University of Natural Resources and Life Sciences, Vienna

Department of Landscape, Spatial and Infrastructure Sciences

Institute of Geomtics

Master thesis

Tree species mapping using multispectral data in the Forest Demonstration Center Rosalia

Submitted by:

Ivica Kocic MSc

Student registration number: 01441072

Supervisor:

Univ. Prof. Dr. rer. nat. Clement Atzberger

Co-Supervisor:

Dipl. -Ing. Dr. Markus Immitzer MSc

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Author: Ivica Kocic

Zahvalnost ~ srpski jezik

(Acknowledgments ~ Serbian language)

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Abstract

Tree species diversity and up-to-date information about their spatial distribution are some of the most important parameters for sustainable forest management. Nowadays, remotely sensed data and area-based data acquisition methods, are very applicable for such forest management tasks and their importance goes beyond traditional forest inventory of tree species and other field-based data acquisition methods. Providing such detailed and cost-efficient information over large areas, remotely sensed data have become one of the most important tools and the basis for management of forests. Satellite-borne sensors, with very high spatial resolution, provide great potential for tree species mapping. The satellite sensor WorldView-2 (WV2), launched in October 2009 by Digital Globe, provides data with high spatial and spectral resolution which are suitable for mapping tree speciesdiversity. The aims of this study are to analyze the suitability of WV2 imagery for individual tree crown classification and a comparison with standard orthophotos and to check the overall accuracy that can be achieved by applying object-based image analyses using the non-parametric random forest classifier. The study area is located in the University Forest Demonstration center Rosalia (Lower Austria). The random forest classification has been performed on 32 variables, derived from 530 manually delineated reference trees of the 10 most common tree species in the study site. The achieved overall accuracy (OA) was around 49,4% using the orthophoto and 50,6% for the WV2 imagery. Additional calculation and application of eight Vegetation Indices did not significantly improve the result. The highest OA of 51,7% could be achieved using additionally Vegetation indices, but was still lower as expected, compared to published studies, which obtained accuracies between 45-96%. In some of these studies very promising results have been obtained and researchers have been demonstrated the high potential of WV2 data for tree species mapping. A comparison with these studies has been made, based on a number of analyzed tree species, forest characteristics, acquisition date, and acquisition geometry. Possible improvements could be achieved with multi-temporal data sets, better acquisition date, or better acquisition geometry, but also by increasing the number of reference trees per species.

Keywords: Tree species mapping, Remote sensing data, WorldView-2, Random Forest, Support Vector Machine, Vegetation Indices, Rosalia

Rezime ~ srpski jezik

(Abstract ~ Serbian language)

Raznolikost vrsta drveća i aktuelne informacije o njihovom prostornom rasporedu, jedan su od najvažnijih parametara za održivo gazdovanje šumama. U današnje vreme, podaci dobijeni daljinskom detekcijom i prikupljanjem podataka iz vazduha, su veoma primenljivi za potrebe gazdovanja šumama i njihov značaj prevazilazi tradicionalnu inventuru šuma i druge metode bazirane na ternskom prikupljanju podataka. Pružanjem tako detaljnih i ekonomski isplativih informacija na velikim površinama, podaci dobijeni daljinskom detekcijom postali su jedan od najvažnijih alata i osnova za održivo gazdovanje šumama. Satelitski senzori, sa visokom prostornom rezolucijom, pružaju veliki potencijal za mapiranje vrsta drveća. Satelitski senzor WorldView-2 (WV2), koji je u Oktobru, 2009. godine lansirao Digital Globe, pruža veliku tačnost, okretnost, kapacitet i spektralnu raznolikost potrebnu za klasifikaciju i mapiranja vrsta drveća. Cilj ovog rada je analiza prikladnosti slika dobijenih pomoću WV2, za pojedinačnu klasifikaciju krošnji stabala, uporedjivanjem sa standardnim ortofotografijama i odredjivanje tačnosti, koja se može postići primenom neparametarskih (baziranih na objektu) Random Forest (RF) and Support Vector Machine (SVM) klasifikatora. Lokacija istraživanja, nalazi se u Univerzitetskom šumskom istraživackom centru Rosalia (Donja Austrija). Random Forest klasifikator, baziran na objektima, je primenjen na 32 varijable, dobijene iz 530 ručno obelezenih referentnih stabala, deset najzastupljenijih vrsta drveća. Dobijena je ukupna tačnost od oko 49,4% na bazi ortofotografija i oko 50,6% na bazi WV2 podataka. Dodatno izračunavanje i primena osam Vegetacijskih Indeksa (VIs) nije značajno poboljšalo rezultat. Najveća ukupna točnost od 51,7% postignuta korišćenjem svih WV2 podataka sa implementiranim VIs bila je niža od očekivane, na bazi uporedjivanja sa ranije objavljenim sličnim istrazivanjima, a čija je tačnost u rasponu između 45-96%. U nekim od ovih istraživanja, dobijeni su vrlo obećavajući rezultati, a istraživači su dokazali veoma visok potencijal WV2 podataka za mapiranje vrsta drveća. Bilo je zanimljivo uporediti dobijene rezultate sa ovim uporedivim studijama, po pitanju analiziranih vrsta drveća, karakteristika šuma, datuma prikupljanja i geometrije snimanja podataka. Moguća poboljšanja bi mogla biti postignuta, boljim datumom prikupljanja podataka, boljom geometrijom akvizicije, kombinacijom dva senzora (na primer WorldView-3 i Sentinel-2), kao i povećanjem (optimiziranjem) broja referentnih stabala po vrstama drveca.

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1. Introduction

Forest is one of the most important natural resources and without it, life on the earth cannot be imagined. Oxygen production, carbon dioxide absorption, drinking water filtration, biomass production, a habitat of flora and fauna, protection against pollution, protection against erosion, mitigation of climate change - these are just some of the many ecological, economic and social functions of the forest. Therefore, proper use and management of forests are crucial for maintaining their biodiversity, productivity, vitality, and potential to fulfill all these functions. Nowadays, under the concept of "Sustainable forest management", one tries to implement the proper management of forests, to optimize the benefits and use of their current potential for the present generation and planet, but at the same time to preserve, improve and leave forests in the good conditions to future generations.

The focus of current sustainable forest management is on prompt, detailed, trusty, and up-to-date information about tree species, such as composition, spatial distribution, ecology, structure, vitality, biomass estimation, fire damage detection, detection of deforested areas and other various disturbances, etc. Such detailed information is valuable, for example, to assure protection and conservation of forest, over large areas; for protection of certain tree species or animals; for predicting species responses to environmental change; for hazard and stress management; for conservation sector; to monitor the health status and biotic disturbances; for modeling wildlife habitat; to describe forest ecosystems and especially for the close-to-nature managed forests for multiple ecosystem services (Immitzer et al., 2012; Cabello et al., 2012; Verlic et al., 2014; Fassnacht et al., 2014).

Data collection by traditional forest inventory and other field-based data acquisition methods has been the basis for forest management, for a very long time. Well-established forest inventories are widespread and have a long tradition in many European countries, providing very good and useful results. Systematic collection of qualitative and quantitative data, through forest inventories, is the key information for decision making, planning, and implementation of long-term sustainable forest management. But, acquiring detailed tree species information, based just on these methods is almost impossible over large and difficult to reach areas. They are not suitable enough for such important forest management tasks, mostly because of the inaccessibility of the terrain, ownership structure, and time-consumption, requiring substantial financial investment (Alonzo et al., 2014; Hartling et al., 2019).

Conversely, remotely sensed data and area-based data acquisition methods, such as satellite and aerial imagery, are very applicable for such important forest management tasks. Remote sensing approaches have the potential to provide detailed and up-to-date information about the forest over large areas, in a cost-efficient and dependable way (Franklin, 2001; Maschler et al., 2018). In addition to allowing data to be recorded from difficult and hard-to-reach places, they provide the possibility that various measurements can be repeated periodically, insuring timeliness of the data and the ability to detect changes that occurred in the meantime (Stych et al., 2019). With development, application, and improvement of remote sensing technology and remote sensing data, the field-based acquisition methods were replaced or combined with a new, time-efficient and cost-efficient remote sensing methods (Sedliak et al., 2017). In the last few decades, the use of high-resolution optical satellite data, digital aerial images, hyperspectral images, and airborne laser scanning applications is constantly increasing. The publication of a large number of scientific papers focusing on remote sensing and tree species classification is made possible by the higher availability of multispectral and hyperspectral data (Fassnacht et al., 2016). However, mapping individual tree species in a very complex forest environment remains challenging due to the fine-scale spatial variation and highly heterogeneous background.

Satellite-borne sensors, with a high spatial and spectral resolution, provide great potential for tree species mapping. Currently, a wide range of different types of sensors and satellite data are available. They differ from each other in spatial, spectral, radiometric, and temporal resolution. In terms of *spatial resolution*, it depends on the size of the analyzed objects. For effectively solving the problems of the influence of neighboring crowns (for individual tree crown approaches), it has to be a minimum of 0.5m (Wang et al., 2004; Immitzer et al., 2012). Data with a pixel size less than 1m has a very high resolution, those with spatial resolution from 1m to 10m are considered high, from 10m to 100m moderate, from 100m to 1000m coarse, and greater than 1000m are considered very coarse (Warner et al., 2009;

Immitzer, 2017). The *spectral resolution* of a sensor refers to the number of individual bands and spectral range of data. Multi-spectral satellite data generally has a higher number of spectral bands. Some of the sensors provide only the four standard bands (Blue, Green, Red, Near Infrared) and have a high spatial resolution, such as IKONOS or QuickBird. Also, some of them provide more bands but have a lower spatial resolution, such as MODIS or ASTER (Immitzer et al., 2012). Finally, some sensors provide less expensive data, but have lower spatial and spectral resolutions, as in the case of Rapid Eye. *Temporal resolution* refers to the number of different time points at which images have been acquired. Finally, *radiometric resolution* refers to the number of intensity levels that a sensor can record. Anyhow, one unique sensor is not capable to fulfill all the requirements for potential application purposes.

The WorldView-2 (WV2) satellite-borne sensor, launched in 2009 by DigitalGlobe, offering incredible accuracy, agility, capacity, and spectral diversity. It is equipped with eight spectral bands, who have a spatial resolution of 2m in the multispectral bands and 0.5m in the panchromatic band. In addition to four standard bands (Blue, Green, Red, and Near-Infrared), it contains four new bands (Coastal, Yellow, Red Edge, and Near-Infrared 2). These additional four bands are strongly related to vegetation properties and increase the ability of the WV2 sensor to distinguish tree species even more precisely (Cho at al., 2011; Immitzer et al., 2012).

Image segmentation and classification is an effective and frequently used method of the derivation of the tree and stands characteristics from the remote sensing data. Currently, the object-based image analysis (OBIA) is a more preferred method than the pixel classification (Yu et al., 2006; Petr et al., 2010; Pippuri et al., 2016). The OBIA method works with homogenous objects, which are represented by groups of pixels with similar properties (Benz et al., 2004). These objects should represent real objects, which are the subject of forestry mapping (e.g. tree crowns, forest stands). Using this method, much better results of forest and landscape classification were achieved (Cleve et al., 2008; Myint et al., 2011).

The success of some image classification depends on many considerations and the choice of the appropriate classifier. For the needs of working with high dimensional data and complex images, machine learning algorithms have been developed. They are a more accurate and efficient alternative to conventional parametric classifiers. Popular non-parametric classifiers, such as Support Vector Machine (SVM) and Random Forest (RF), are very applicable for image classification because they do not rely on data distribution assumptions and produce high classification accuracies (Friedl et al., 1997; Hartling et al., 2019).

RF classifier is one of the very accurate and recently used classification algorithms. In the last few decades, its importance and use in remote sensing increase constantly. It can be used as classification or regression algorithm to classify land cover (Pal, 2005; Rodriguez-Galiano et al., 2012) and ecological zones (Miao et al., 2012), to identify spectral differences of tree species, to map landslides (Stumpf et al., 2011), to create forest canopy fuel maps for fire forecasting (Pierce et al., 2012), to quantify aboveground forest carbon pools (Hudak et al., 2012), or to analyze urban areas (Guo et al., 2011; Verlic et al., 2014).

In addition to the RF classifier, very effective and useful for tree species classification is the SVM classifier. Based on its capability to solve problems with a small number of training samples, it is increasingly used for both land cover and tree species classifications (Xie et al., 2019; Heinzel et al., 2012). In several studies, published in the last decade, the results achieved based on SVM exceed the results achieved with RF classifier - making it one of the most common classifiers used in vegetation classifications (Ballanti et al., 2016; Raczko et al., 2017; Lim et al., 2019).

Numerous studies, based on tree species classification using WV2 data, were published in the last few decades. In some of them, very promising results have been obtained. For example, Immitzer et al. (2012) achieving an overall accuracy of 82% (ten tree species, eight bands, object-based, RF), have been demonstrated the high potential of WV2 data for tree species mapping. Even, in the same research, they achieved an overall accuracy of 96% by analyzing the four main tree species. In the second example, Ballanti et al. (2016), were achieved an overall accuracy above 90% (eight tree species, pixel-based reflectance, hyperspectral images), with the statistically significant advantage of SVM (95.02%) over the RF (92.91%) classifier. Additionally, in the research, conducted by Heuman (2011), the overall accuracy of 90% (to distinguish true mangroves from other vegetation) was achieved, using the WV2 sensor, object-based image analysis, and SVM for the classification of mangrove in the Galapagos Archipelago, Ecuador. Contrary to these, some studies obtained lower accuracies. The overall accuracy achieved by Hartling et al. (2019), was 48.2% (eight tree species, eight bands object-based, SVM) and 48.6% (eight tree species, eight bands, object-based, RF). Also, the lower overall accuracy of 58% was achieved by Verlic et al. (2014), analyzing five tree species (eight bands, object-based, SVM). Consequently, it was interesting to make a comparison with these and with other similar comparative studies, especially those published in Central Europe, in terms of the number of analyzed tree species, size of the classes, choice of appropriate classifiers, acquisition date, and acquisition geometry.

Based on all mentioned above, the following objectives were set in this work:

- to analyze the suitability of WV2 imagery for individual tree species classification by comparing with "standard" orthophotos;
- to analyze and compare the potential and performance of two machine learning algorithms, such as SVM and RF, analyzing multispectral data from the WV2 imagery;
- to compare achieved results with comparable studies, published in the last decade.

2. Material

2.1. Study area

Tree species mapping in this research was carried out in the heterogeneous forest of *Forest Demonstration Center Rosalia*, in the east of Austria (Figure 1). This study area is located on the western slope of the mountainous ridge called „Rosaliengebirge“ (BOKU, 2008) in the southeastern part of the province Lower Austria (47°42’N, 16°17’E), near the Lower Austria/Burgenland border in the district Wiener Neustadt, in the communities Ofenbach, Schleinz, Walpersbach and Hochwolkersdorf (source: http://www.wabo.boku.ac.at/lehrforst).

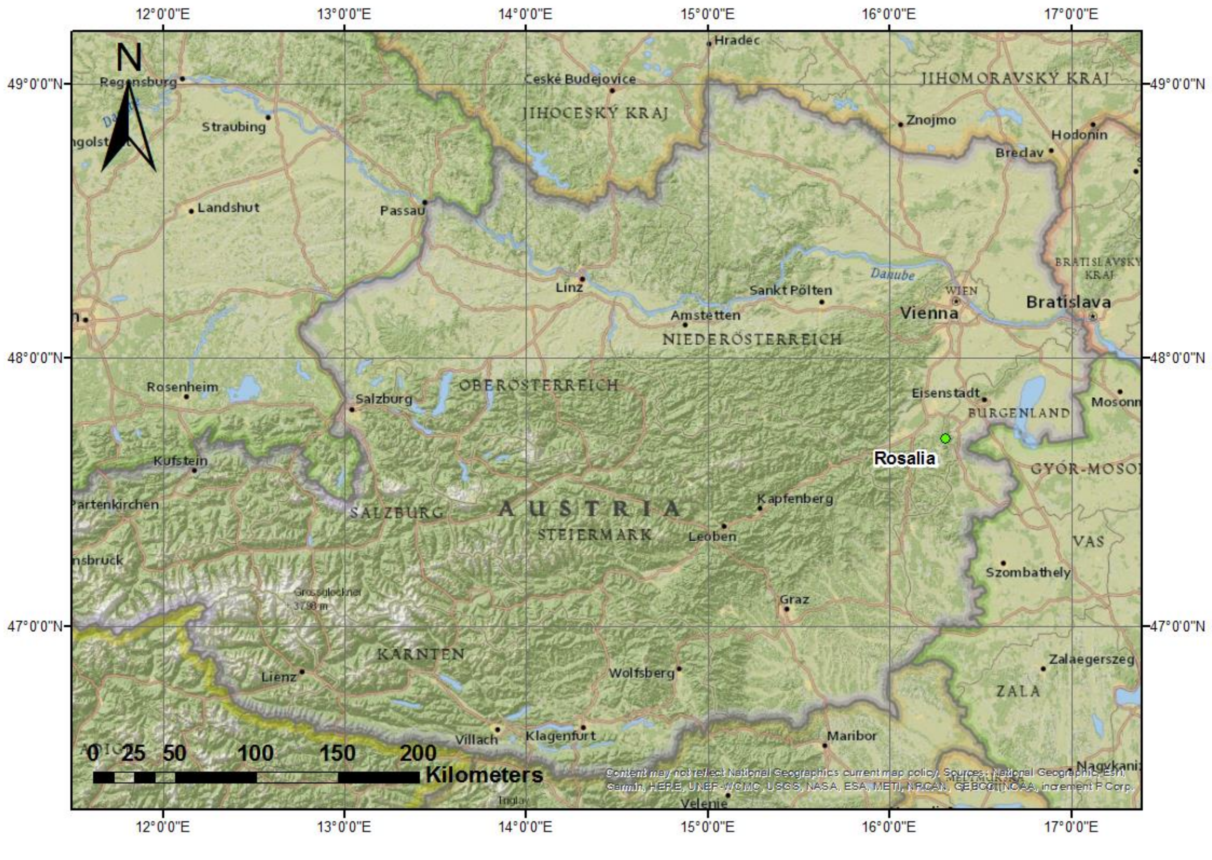

Figure 1. Study area - located in Forest Demonstration Center Rosalia, Austria (the green point indicates the position of the study area)

The beginnings of the Center date back to 1972 and agreement between the Federal Forest of Austria (ÖBf) and the University. Nowadays, this forest is a part of the 3.500ha forest district. The main task of this Demonstration Centre is to support the education and researches of the University of Natural Resources and Life Sciences - especially the Department of Forest and Soil Science. Among other things, the tasks of the center are also independent research work; coordination with the forest owner (ÖBf); and management of the seminar building (shown in Figure 2).

Figure 2. Forest Demonstration Center Rosalia – infrastructure (Google Maps, 2020)

The research focus of the Center lies in the following areas: collection and provision of environmental data; development of user-supporting applications; establishing and monitoring of sample plots; characterization of local microclimates; environmental impacts upon forest ecosystems; monitoring and modeling of small forested watersheds.

The size of the forest is about 930ha. The terrain lies in the submontane life zone, with an elevation between 320m and 725m above sea level. The sum of annual precipitation is around 800m. Soils are composed of soils on tertiary sediments, soils on carbonate rocks, soils on silicate material (brown soils, semipodsol, pseudogley, groundwater affected soils, and strong brown clay influenced soils). The current annual volume increment is 7,8m³/ha. Since it is an experimental forest, the forest practice promotes uneven-aged mixed-species stands (BOKU, 2008). All major tree species and forest types, characteristics of Austria, are presented here as well. The potential natural forests are beech associations (Fagetums) and spruce-fir-beech forest associations (Abieti-Fagetum).

According to the recent forest inventory, the most frequently occurring tree species are Norway spruce *(Picea abies L.)* - covering around 41% of the area, European beech *(Fagus sylvatica L.)* - covering around 36% of the area, and Scots pine *(Pinus silvestris L.)* - covering around 10% of the area, as can be seen in Figure 3. Secondary tree species are European larch *(Larix decidua Mill.)*, Silver fir *(Abies alba Mill.)*, Sessile oak *(Quercus petraea Liebl.)*, European hornbeam *(Carpinus betulus L.)*, Douglas fir *(Pseudotsuga menziesii (Mirb.) Franco)*, Austrian pine *(Pinus nigra A.)*, European ash *(Fraxinus excelsior L.)*, maple-species *(Acer sp.)*, poplar-species *(Populus sp.)* and elm-species *(Ulmus sp.)*. The list of tree species analyzed in this work is presented in Figure 3.

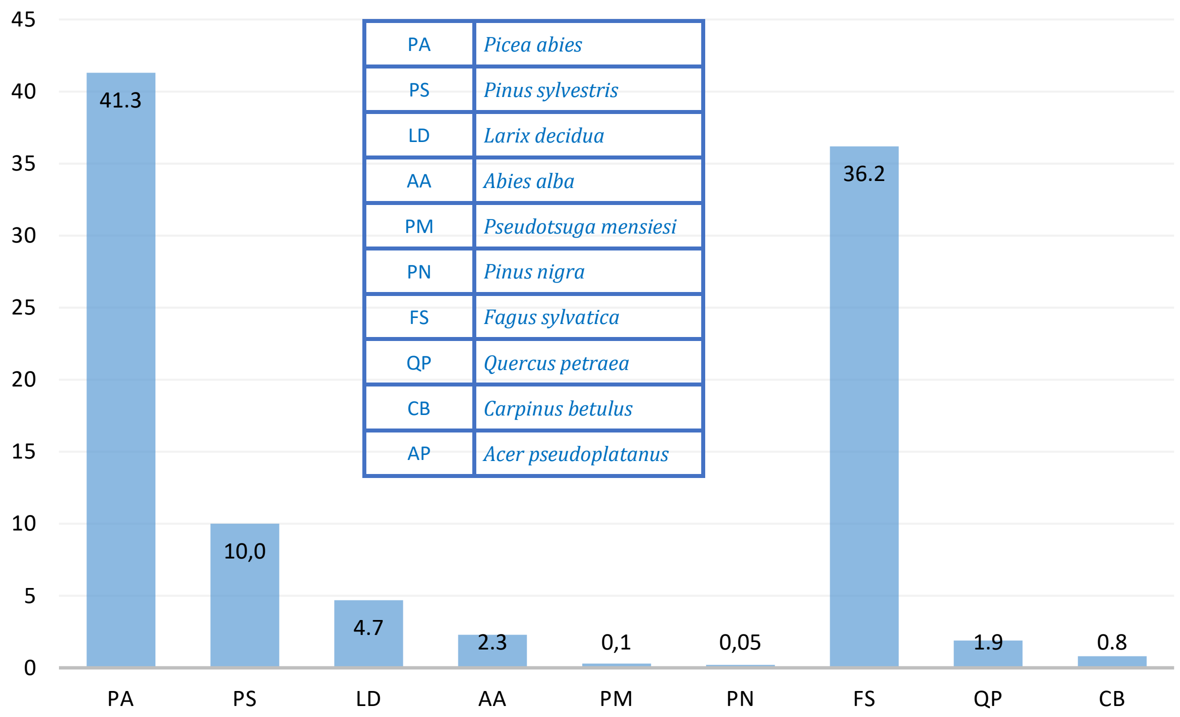

Figure 3. Participation of tree species in the percentage of the total area (BOKU, 2008)

2.2. WorldView-2 imagery

The satellite sensor WorldView-2 (shown in Figure 4) was launched in October 2009 by Digital Globe. It operates at an altitude of 770km, with an orbit lasting 110min. Its average revisits time is between 1.1 and 3.7 days, collecting up to 1 million km² of eight band imagery per day (Digital Globe, 2009). Obtained full-color images supply unprecedented detail and geospatial accuracy, very useful as a basis for land-use planning, mapping and monitoring applications, visualization and simulation environments, enhanced spectral analysis, and many other applications in commercial and government markets. The WV2 satellite is operated in a constellation with other satellites such as GeoEye-1, WorldView-1, WorldView-3, and WorldView-4 (DigitalGlobe, 2016).

Figure 4. WorldView-2 satellite sensor (Digital Globe, 2009)

The WV2 carries a sensor that captures data in eight spectral bands with an 11-bit dynamic range and provides high spatial resolution data with eight spectral bands. At nadir, the ground resolution is 46cm (resampled to 50cm) for the panchromatic band (0.46–0.80μm) and 186cm (resampled to 200cm) for the multispectral bands. Besides four standard bands: Blue (0.45–0.51 μm), Green (0.51–0.58μm), Red (0.63–0.69μm), and Near-Infrared 1 (0.77–0.90 μm), it is also equipped with 4 new bands. These additional four bands are represented by Coastal (0.40–0.45μm), Yellow (0.59–0.63μm), Red Edge (0.71–0.75μm), and Near-Infrared

2 band (0.86–1.04μm). With such high spatial and spectral resolution, the commercial satellite WV2 is very suitable for many applications in forestry, such as mapping forest cover, monitoring forest health status and biotic disturbances, supporting forest inventories, etc. A detailed overview of WV2 bands is presented in Figure 5.

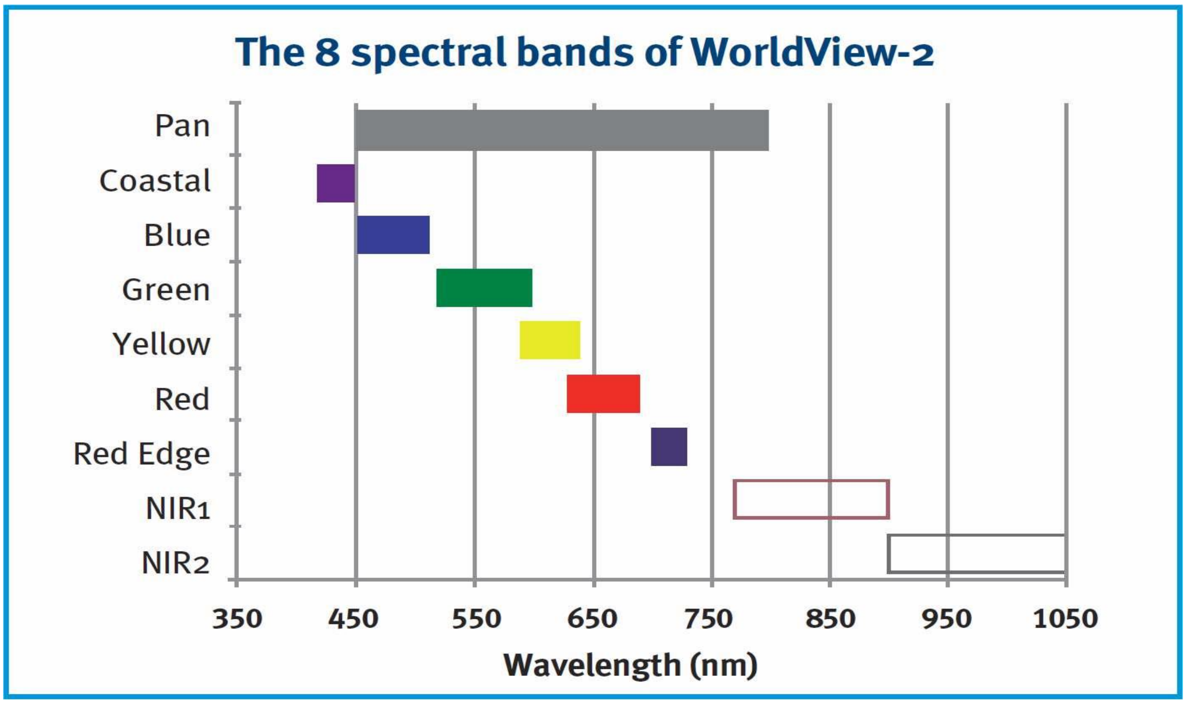

Figure 5. The panchromatic and eight spectral bands of WorldView-2 (Digital Globe, 2009)

According to the producer's specifications, additional four bands are strongly related to vegetation properties. For example, the reflectance measured in the Coastal band is related to the chlorophyll content of plants. The reflectance measured in the Yellow band provides an opportunity for the detection of „yellowness“ of objects (e. g. tree crowns caused by insect diseases). The Red Edge band is more sensitive to biophysical parameters of forests than other traditional bands, offering the possibility of better differentiation between healthy trees and trees infested with disease, and increasing the possibility of separation between different species and age classes. The Near Infrared 2 band is less affected by atmospheric influence and provides an opportunity for sophisticated vegetation analysis, such as biomass studies (DigitalGlobe, 2009). In some previous studies has been shown that improvement with the added-value of four new bands was species-dependent. The research, published by Immitzer et al. (2012), showed that the four new WV2 bands improved classification when a larger number of tree species were analyzed. On the other hand, use of them could simultaneously bring extra-data costs and because of that requires careful evaluation of their use and benefits.

Due to the high price of around 30USD/km² for the heigh performance of commercial WV2 data set, some other data sets achieved for example from S2 and LS8 satellites (that are available for free, with the advantage of covering large areas and providing short global revisit intervals) are a very interesting alternative. WV2 data can be ordered either with the four standard bands or with all eight bands. On the website of the provider (http://worldview2.digitalglobe.com/) can be found additional information about the sensor.

For this work, the pan-sharpened WV2 images served as a basis for all investigations. They have been recorded under conditions without clouds, close to the end of the growing season, on August 29, 2012. It can be said that in this period of the year the conditions for classification are satisfied, based on full developments of crowns, maximally covered with leaves. Basic metadata are represented on the DigitalGlobe scene in Figure 6. One can see the following information: Mean Off-Nadir View Angle (18,3°), Max Target Azimuth (288,7°), and Sun Elevation (50,4°).

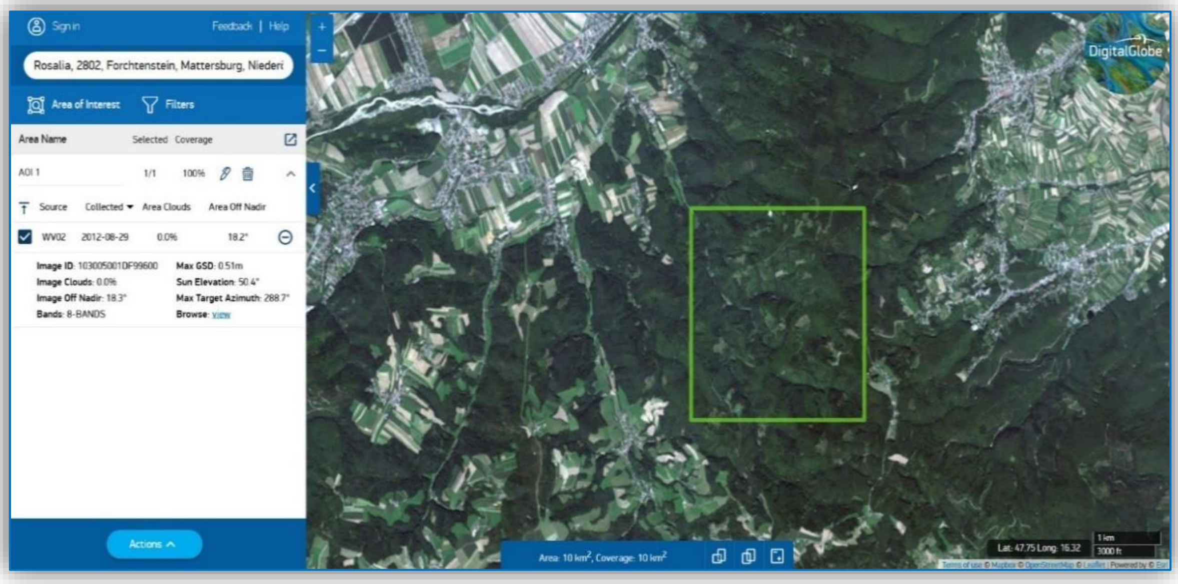

Figure 6. DigitalGlobe WV2 scene with metadata (source: https://discover.digitalglobe.com/)

2.3. Orthophoto imagery

Orthophotos are a very important basis for various applications in Geographical Information Systems (GIS), fulfilling the increased need for up-to-date, accurate, fast acquired, reasonable data and maps for environmental planning and monitoring, and resource management (Kersten et al., 1996). They have a long tradition in forestry and are one of the most important data sources for purposes such as stand delineation and forest planning, through the use of visual interpretation and automated analytic techniques (Hall, 2003).

An orthophoto, orthophotograph, or orthoimage is an aerial photograph geometrically corrected (orthorectified) such that the scale is uniform and the photo has the same lack of distortion as a map. The software can process and display the orthophoto and allow an operator to digitize or place linework, text annotations, or geographic symbols such as hospitals, schools, and fire stations (MapDglobe, 2018).

For tree species classification in this work, the potential reference data were analyzed using visual interpretation of orthophotos. Afterward, representative samples of reference trees species found in the field, have been marked directly on orthophotos.

The baseline of this study is orthophoto images with a spatial resolution of 20cm, with four standard bands, collected in 2011/2012.

2.4. Reference data

The chosen reference trees (also called ground truth data or training samples) were located over the whole study area, trying to satisfy the condition that training points for each class should be equally spatially distributed**.** These trees belong mainly to the old or middle age classes. The location (distribution) of the reference samples is represented in Figure 7.

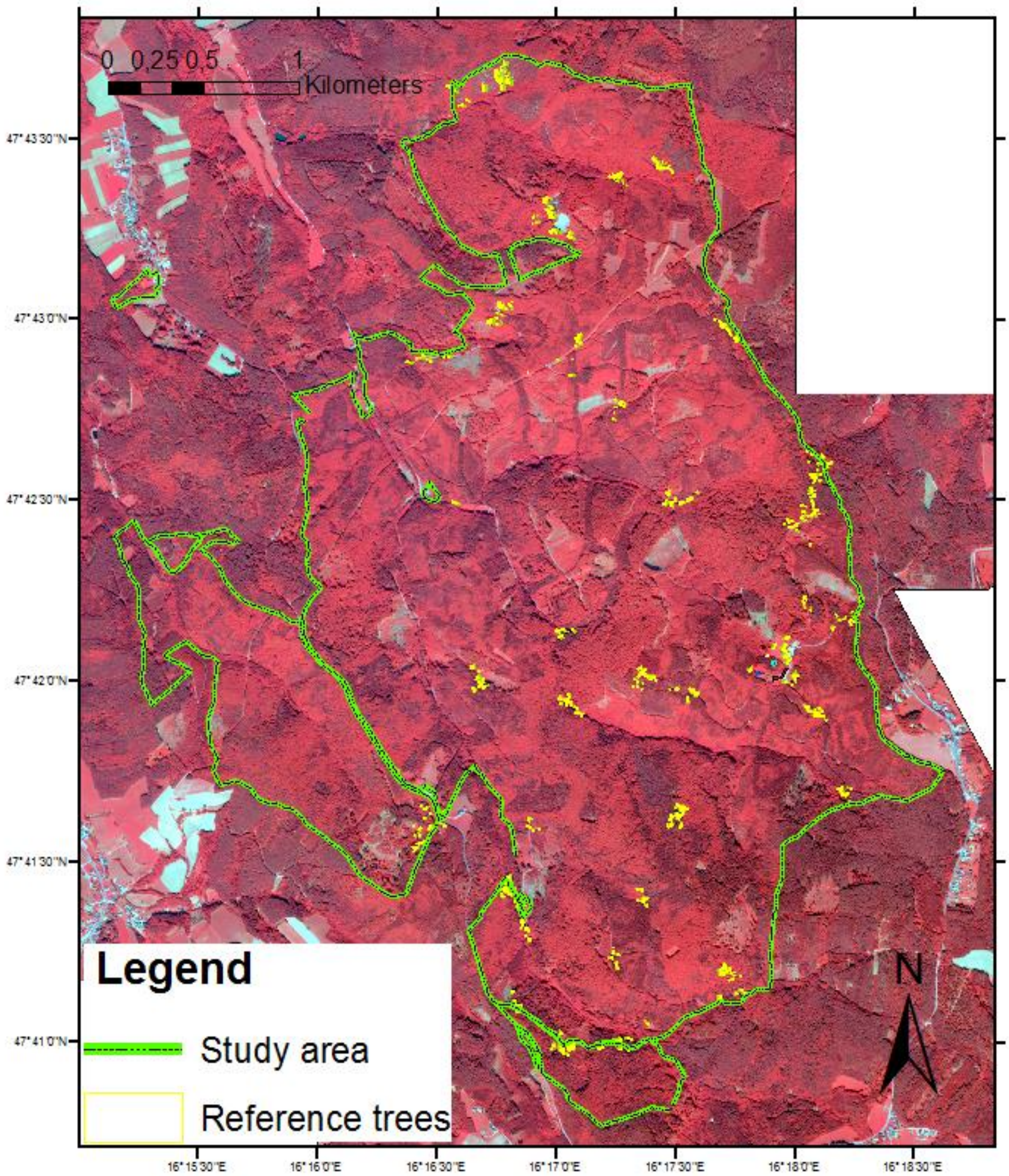

Figure 7. Reference samples - location of reference tree species and their distribution over the study area. Band combination: Band 7 (NIR), Band 5 (Red), Band 3 (Green)

This work covers the ten most common tree species – four coniferous and six broadleafs, based on their percentage of the total surface of the study area. The scientific and common name of reference tree species and the number of the polygon per species are shown in Table 1.

Table 1. Names, acronyms, and number of polygons (reference trees) of the ten tree species

Scientific Name	Common Name	Acronym	Type	Polygons	[%]
Picea abies	Norway spruce	PA	Conifer	71	13,4
Pinus sylvestris	Scots pine	PS	Conifer	59	11,1
Larix decidua	European larch	LD	Conifer	54	10,2
Abies alba	Silver fir	AA	Conifer	47	8,9
Pseudotsuga menziesii	Douglas fir	PM	Conifer	49	9,2
Pinus nigra	Black pine	PN	Conifer	47	8,9
Fagus sylvatica	European beech	FS	Broadleaf	72	13,6
Quercus petraea	Sessile oak	QP	Broadleaf	54	10,2
Carpinus betulus	European hornbeam	CB	Broadleaf	28	5,3
Acer pseudoplatanus	Sycamore maple	AP	Broadleaf	49	9,2
				530	100,0

First of all 890 reference trees were identified in the field. It was not easy to identify qualitative reference tree species on the field due to roads, accessibility, forest structure, tree healthy, missing trees, density, canopy, and overlapping tree crowns. These 890 reference polygons were manually delineated on orthophotos. Afterward, due to the large number of two dominant species (Norway spruce and Beech), the number of polygons was reduced to 530. The distribution of these 530 reference samples corresponds approximately to the distribution of tree species in the study area.

The manual delineation has been done first on orthophoto images. For each reference tree, the sunlit part of the crown has been delineated. Thereafter, in the office, delineated crowns have been represented by polygons using ArcGIS Desktop software. Drawn polygons were transferred to WV2 images. To each tree crown of the tree species, the spectral information from the WV2 image was assigned. For the object-based approach, the mean band values for each crown polygon were calculated.

Scenes of manually delineated polygons, representing sunlit regions of the crowns of reference trees on WV2 and orthophoto image, are presented in Figure 8. and Figure 9.

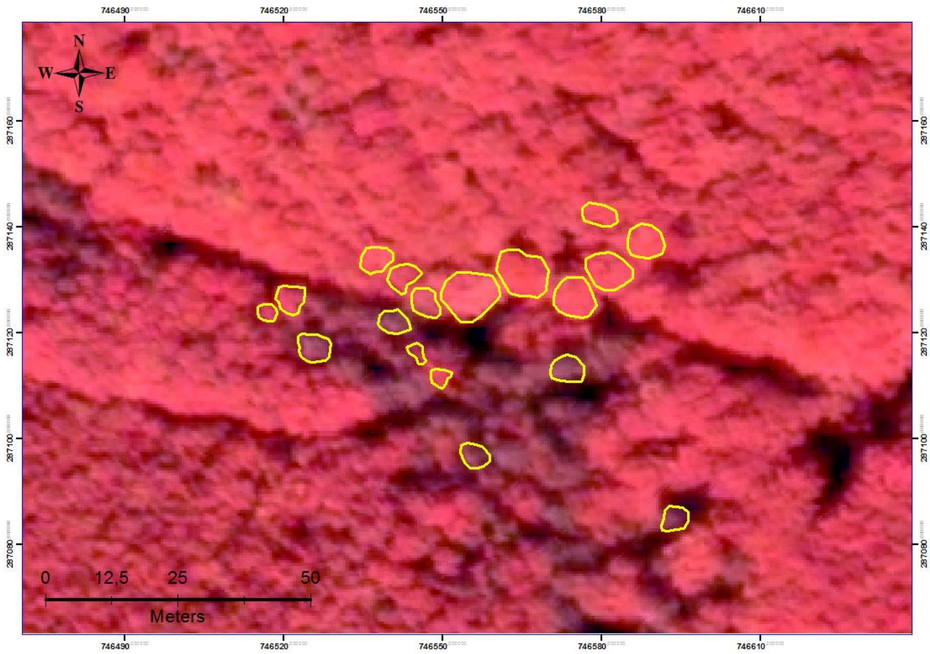

Figure 8. Reference trees - manually delineated polygons on the WV2 image. Band combination: Band 7 (NIR), Band 5 (Red), Band 3 (Green)

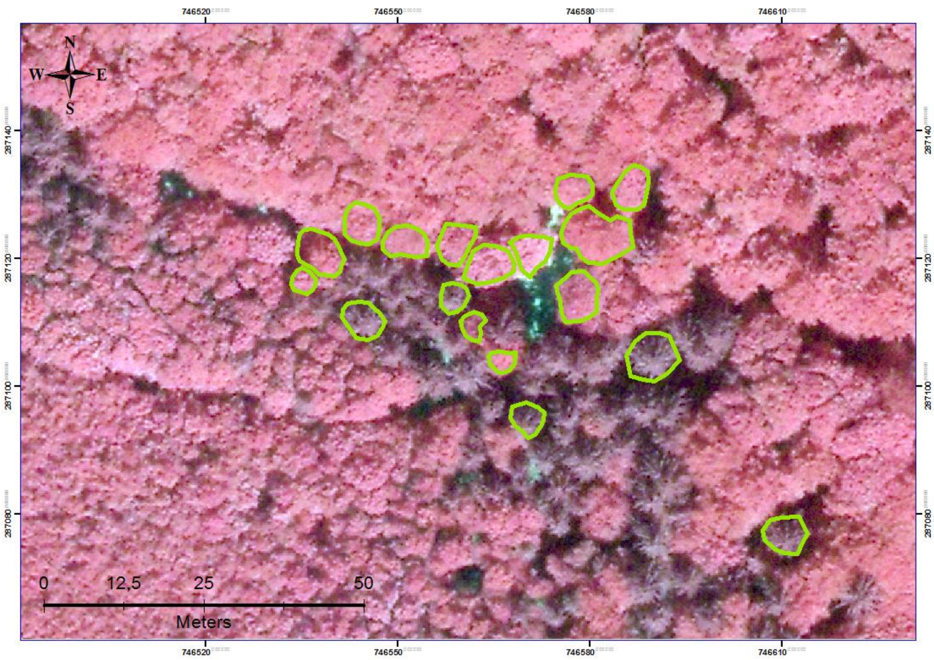

Figure 9. Reference trees - manually delineated polygons of the sunlit region of crowns of reference trees, on the orthophoto image

2.5. Software packages

R programming language is a free and open-source software environment for statistical computing and graphics. It is an integrated suite of software facilities for data manipulation, calculation, and graphical display. R provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering) and graphical techniques. It can be very easily extended via packages, for specific functions or specific areas of study. Also, users are allowed to add additional functionality by defining new functions. R is available as free software under the terms of the Free Software Foundation's GNU General Public License in source code form. It compiles and runs on a wide variety of UNIX platforms and similar systems (including FreeBSD and Linux), Windows, and MacOS.

In this work, statistics were done using R 3.4.3 (R Core Team, 2017), the raster (v2.6.7; Hijmans, 2017), the rgdal (v1.2.16; Bivand & Keitt & Rowlingson, 2017) and the dplyr (v0.7.7; Wickham & Francois, 2018) packages. Official web page: https://www.r-project.org/

ArcGIS Desktop 10.6

This is one of the most well-known software for viewing, editing, creating, analyzing, and sharing geospatial data, maintained by the Environmental Systems Research Institute (ESRI). It provides a lot of possibilities in fields of spatial analytics, mapping, and visualization, 3D modeling, satellite image processing, data collection, and management. Its functionality can be increased by adding many software extensions that can be added to ArcGIS Desktop. It consists of several integrated applications (e.g. ArcMap, ArcToolbox, ArcCatalog, ArcGlobe) and is available at different product levels (e.g. Basic, Standard, Advanced, ArcGIS Online, ArcGIS Web Mapping Apis, ArcGis Mobile, ArcPad).

Official web page: http://desktop.arcgis.com/.

3. Methodology

3.1. Processing steps

The workflow diagram presented in Figure 10, describes the processing steps of this research. The basis for the research were forest inventory data and stand maps. Data set, composed of orthophotos and WV2 data were used.

The image preprocessing was already done by scientists from the Institute of Geomatics. In this process, the pixel gray values were converted to ‘at-sensor’ radiance (Updike et al. 2010). Atmospheric correction was performed with the ENVI module (ENVI 4.8) FLAASH, resulting in top-of-canopy reflectance, to obtain meaningful spectral reflectance signatures of the tree species. For pansharpening, the Hyperspherical Color Space algorithm (HCS) was used (Padwick et al. 2010). This algorithm is dedicated to WV2 data and is implemented in ERDAS Imagine 2010.

At the beginning of practical work, visualization, and interpretation of objects on orthophoto images were done. Afterward, the identification of representative reference samples has been made in the field. Based on the very intensive fieldwork, precisely delineation of individual tree crowns on orthophoto images (higher spatial resolution) was done. Based on that, the reference polygons were transferred, from the orthophoto to WV2 images. Spectral information of reference data set was extracted from the WV2 dataset, using the R environment. In the next few steps, the calculation, creating models, and producing confusion matrics have been made. Finally, achieved results were analyzed and compared with similar studies.

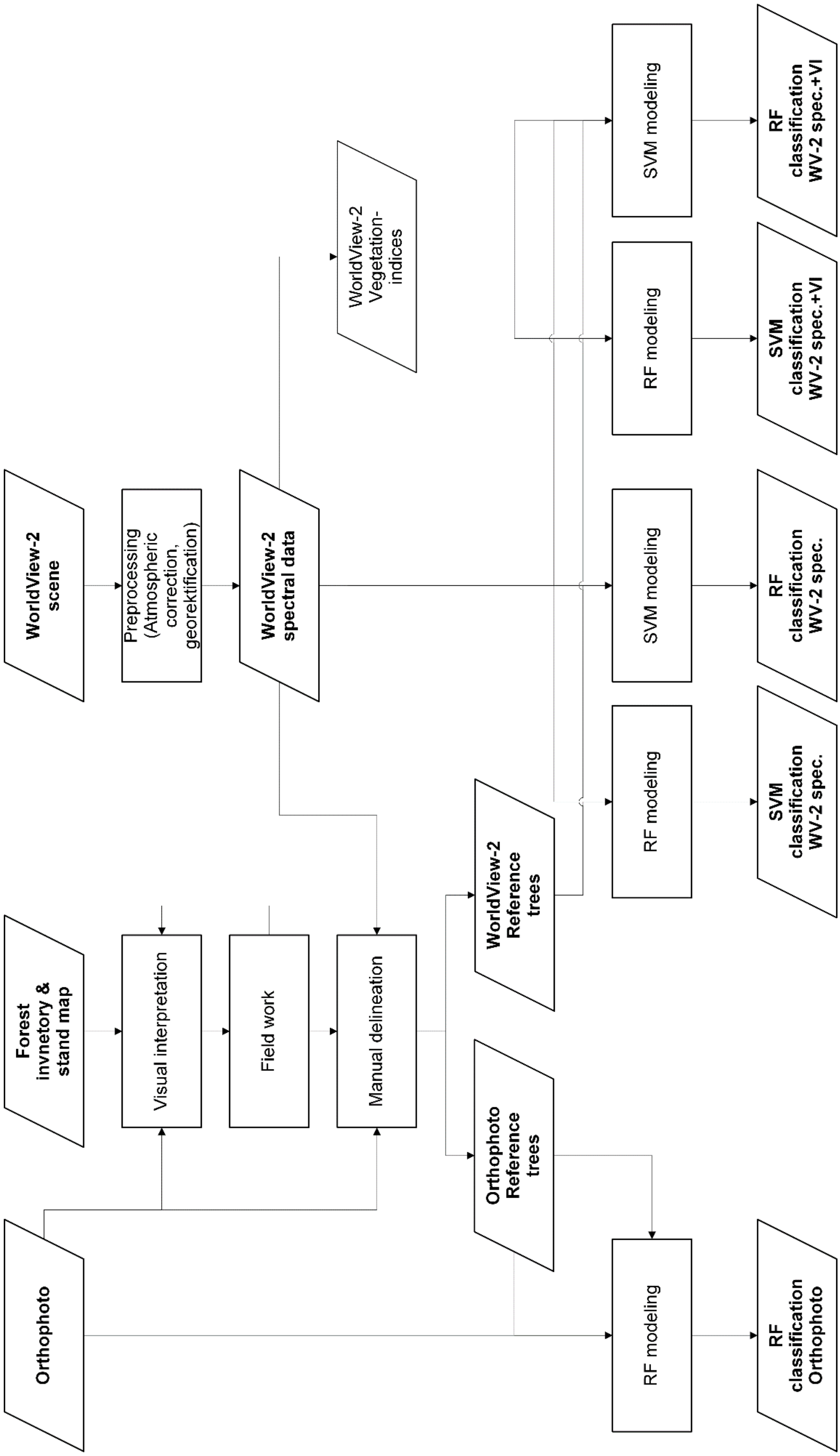

Figure 10. Workflow diagram - the main processing steps of tree species classification using multispectral, orthophoto, inventory and field data

3.2. Spectral signature

The opportunity for tree species mapping with remote sensing techniques is based on the distinctive spectral signature of a tree species, which depends on its biochemical and biophysical characteristics. Under the same or similar site conditions, the same tree species may feature different spectral signatures (based on their different age or health state, for example) while the overall shape of the reflection curve is widely conserved across species borders (Jones at all., 2010). However, the remotely recorded signal is rarely the pure signature of a tree. One can say, that observed spectral radiance is some kind of the mixture of different signals coming from the tree itself (useful signal) and the understory. Together with shading effects, the understory is the main disturbing factor for tree species discrimination. The strong effect of understory reflectance on the overall signal has been demonstrated experimentally and using physically-based radiative transfer models (Spanner at all., 1990).

As input features, for objected-based SVM and RF classification (using manually delineated sunlit regions of tree crowns), spectral information of the orthoimages and the eight WV2 bands was used. For each polygon, the mean band values were calculated. The mean spectral signature of ten tree species is presented in Figure 11.

As can be observed from the spectral signature of analyzed tree species, the reflectance values in the NIR2, NIR1, and RE bands are higher for the broadleaf species than for the conifers. Tree species, that show the highest values and differ significantly from the other tree species, are oak (QP), maple (AP), European beach (FS), and European hornbeam (CB). Among conifers, black pine (PN) and European larch (LD) show the highest reflectance values in the NIR bands. In the visible part of the spectral signature, the largest differences are in the yellow band, but this differentiation is not so clear as in the NIR bands. Based on these reflectance values, separation of the tree species has been possible. However, it should be taken into account that the mean values between the two species are different, but the variance could be big and leading to a large overlap of the two species (the mean values of the mean value of the tree crowns of one species were calculated and presented in Figure 11).

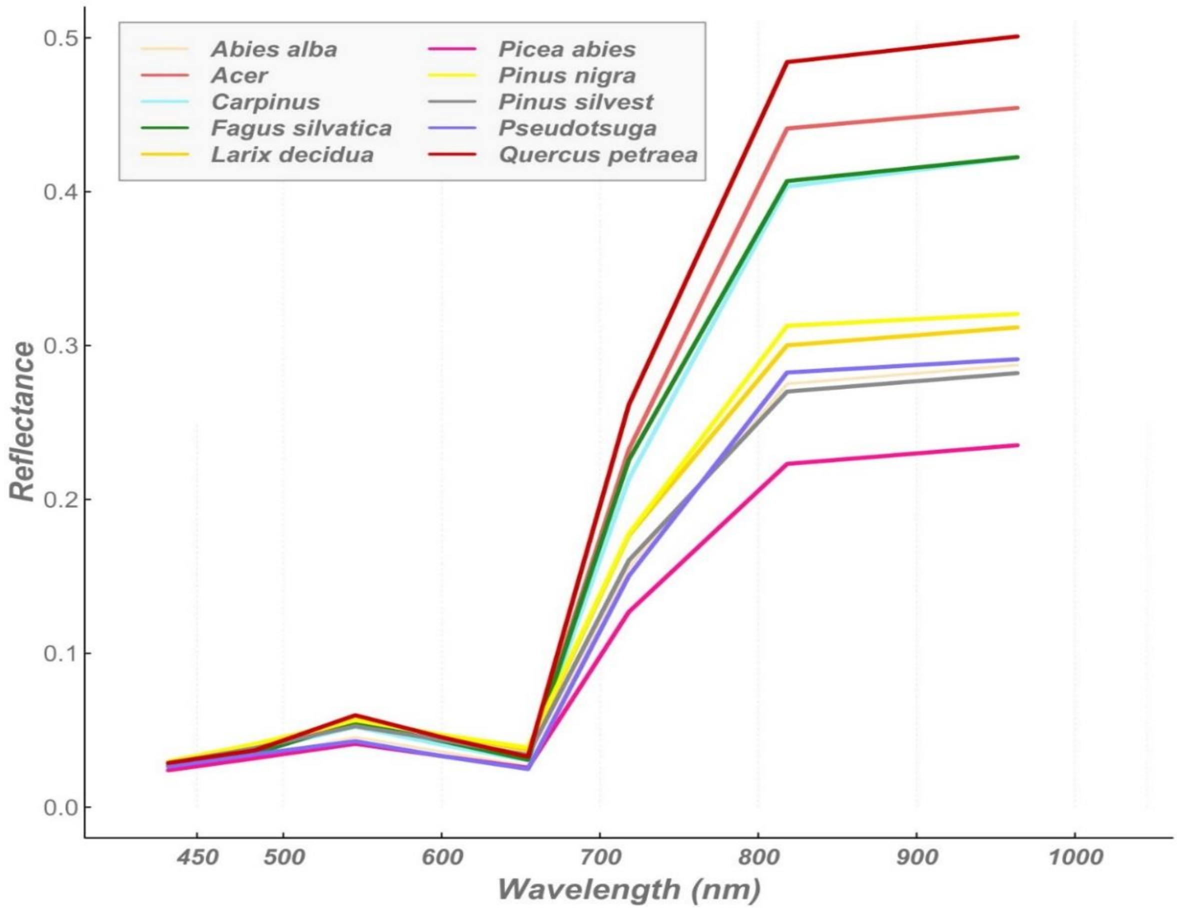

Figure 11. The mean spectral signatures for ten tree species derived from the eight WV2 bands using the reference polygons

3.3. Vegetation Indices

To explore spectral signature characteristics of vegetation, for the needs of various remote sensing applications, lots of vegetation indices have been developed and have been extensively used, in the last 50 years.

Vegetation Indices (VIs) are quantitative measurements indicating the vigor of vegetation (Campbell et al., 1987). They qualitatively and quantitatively evaluate vegetative covers using spectral measurements and try to enhance vegetation response and minimize the effects of disturbing factors. They use transformations of spectral bands of the electromagnetic spectrum that are measured as reflectance from the Earth's surface by satellites. The spectral response of vegetated areas presents a complex mixture of vegetation, soil brightness, environmental effects, shadow, soil color, and moisture. Many studies have focused on evaluating spectral indices in terms of their sensitivity to vegetation biophysical parameters (Bannari et al., 1995). For example, the reflectance of healthy leaves in the NIR region is high relative to other wavelengths, due to the effects of leaf structure and multiple scattering in plant canopies. On the contrary, reflectance in the visible wavelengths region tends to be very low due to absorption by leaf pigments such as chlorophyll.

Besides, VIs are affected by the atmosphere, sensor calibration, sensor viewing conditions, solar illumination geometry, soil moisture, color, and brightness. Theoretically, the ideal vegetation index should be particularly sensitive to vegetative covers, insensitive to soil brightness, insensitive to soil color, little affected by atmospheric effects, environmental effects, solar illumination geometry, and sensor viewing conditions. (Jackson et al., 1983; Bannari et al., 1996). One of the most used indices calculated from multispectral information is the Normal Difference Vegetation Index (NDVI). It is calculated as a ratio between the Red and Near-infrared bands. Since it is a ratio, this index is invariant to the difference in illumination conditions, slope, seasons, etc. and thus very suitable for crop monitoring throughout the growing season.

In several studies, the benefits of the VIs application were shown. For example, in the research published by Waser et al. (2014) usefulness of calculated VIs is demonstrated through a slight improvement of classification of seven tree species, but significant improvement of the accuracies classifying four different levels of damaged ash. Aditionally, Immitzer et al. (2019) demonstrated that the use of vegetation indices improved the classification performance compared to the sole use of spectral signatures. Analyzing scenes collected by Sentinel-2 satellite, they found a very useful band combination involving the SWIR (Shortwave infrared), NIR, and Red Edge bands for broadleaves species and on the other hand, indices based on Red and NIR bands for the coniferous species.

In this research, the eight VIs from WV2 imagery were calculated. The selected VIs are commonly related to vegetation status, canopy structure, canopy foliage content, leaf pigments, and vegetation greenish. They were chosen based on recently published studies (shown in the column Reference), with a focus on forestry applications. The names and corresponding formulas for the calculation of used VIs, are presented in Table 2.

Vegetation Indices	Formula	Reference
NDVI	(NIR1 - R)/(NIR1 + R)	Friedl et al., 1997
Green NDVI	(NIR1 - G)/(NIR1 + G)	Friedl et al., 1997
RedEdge NDVI	(NIR1 - RE)/(NIR1 + RE)	Greenberg et al., 2006
Green red ratio	(G - R)/(G + R)	Cho et al., 2012
Red Edge - yellow ratio	(RE - Y)/(RE + Y)	Cleve et al., 2008
NIR2 - yellow ratio	(NIR2 - Y)/(NIR2 + Y)	Cleve et al., 2008
Simple Ratio Index - SRI	NIR2/R	Greenberg et al., 2006
Modified RedEdge SRI	(RE - C)/(R + C)	Greenberg et al., 2006

Table 2. The overview of calculated Vegetation Indices derived from WV2 bands (C – coastal, G – green, Y – yellow, R – red, RE – red-edge, NIR1 – near-infrared, NIR2 – near-infrared)

3.4. Random Forest Classification

For addressing classification problems in remote sensing, RF classifier has become increasingly important and popular in the last few decades. It has great potential for getting a rapid initial idea about the suitability of the particular classification model, delivering usually good results in models based on all available input data.

This classifier is a very accurate, non-parametric, ensemble learning classifier, robust against noise (Breiman, 2001). It operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Contrary to parametric classifiers, it does not make any assumption about data distribution and provides a reliable measure of variable importance, i.e., the Mean Decrease in Accuracy (MDA) which is very helpful for feature selection. Some studies have shown the best results applying recursive feature elimination procedure and involving step-by-step elimination of the least important features, preferring the MDA value (Guyon et al., 2002; Hastie et al., 2009; Immitzer, 2017).

In addition to the suitability and high accuracy that it provides, RF has many other advantages. Some of the advantages, based on comparing with other classifiers are insensitivity to the small sample size problem; simple to use; production of rapid results; handling large amounts and different types of input data, without assumptions about the statistical distribution of input data and potential collinearity in the data; low risk of model overfitting; providing reliable measures of variable importance important for feature selection, etc. (Breiman, 2001; Hastie et al., 2009; Immitzer, 2017; Fassnacht et al., 2016). A detailed description of RF in particular for remote sensing applications can be found in studies published by Paul, 2005. and Rodríguez-Galiano et al., 2012. To perform the classification, the “randomForest” and “caret packages” within the free and open-source statistical software package R were used. The algorithm was executed in R (version 3.4.3). The following parameters were set to allow maximum performance. Each RF model was built using the following parameters:

ntree - number of bootstrap iterations (it was set to 1000, in this work) and

mtry - number of input variables used at each tree node (square root of the total number of input variables; in this work it was set to 5).

For tree species classification the object-based approach using manually delineated sunlit regions of the tree crowns was applied. As input features, the spectral information of the eight WV2 bands was used. The object-based classification was performed on 32 explanatory variables, derived from 530 manually delineated reference trees. For each polygon was calculated the summary statistics. Explanatory variables extracted from the polygons were:

- *min* - the minimum value of the data for each band,
- *max* - the maximum value of the data for each band,
- *mean* - mean value of the data for each band,
- *sd* - the standard deviation of the data for each band.
- *VIs* – vegetation indices.

Finally, to evaluate the results of RF, confusion matrices were produced, with calculated producer's and user's accuracy for each class, and overall accuracy (correct classification rate).

3.5. Support Vector Machine

The SVM is a supervised machine learning algorithm effective for solving non-linear, high dimensional space classifications. It is very effective at handling complex multispectral and hyperspectral datasets and multi-class problems, where spectral differentiation of target characteristics can be difficult (Hartling et al., 2019*)*. Generally, the SVM contains a machine learning algorithm that separates classes by defining an optimal hyperplane between classes, based on support vectors that are defined by training data (Mountrakis et al., 2011). It is widely used for land cover and tree species classifications since it produces higher classification accuracies and does not rely on data distribution assumptions (Friedl et al., 1997).

The great potential of SVM has been demonstrated in several studies. Even, in some of those studies, the accuracies achieved using SVM were slightly better than accuracies achieved using RF or some other algorithms. For example, findings in the study published by Pal and Mather (2005) demonstrate the overcoming of SVM against the Maximum Likelihood and Neural Network classifiers using Landsat TM. Additionally, the study published by Foody and Mathur (2006) shows that SVM outperforms Discriminate Analysis and Decision-tree algorithms for airborne sensor data.

4. Results

4.1. RF classification results for orthophoto data

The results, for classifying tree species based on values extracted from orthophotos, are summarized by the confusion matrix, presented in Table 3. The achieved overall accuracy was around 49,4%. There could be observed only small misclassification between broadleaf and coniferous tree species, while the species-specific results show large differences. The producer's accuracy ranges from 18% for European hornbeam (CB) to 82% for Norway spruce (PA), while the user's accuracy ranges from 28% to 72% for the same tree species. The European hornbeam shows the highest misclassification rate, while the Spruce shows the highest percentage of both accuracies. Among the broadleaf species Sessile oak (QP) shows the highest user’s accuracy and European beech (FS) the highest producer’s accuracy. Among the coniferous species, the European larch (LD) shows the lowest user’s accuracy and Silver fair (AA) the lowest producer’s accuracy.

Ortho-photo	PA	PS	LD	AA	PM	PN	FS	QP	CB	AP	*Total*	*User´s Acc.*
PA	**58**	2	0	6	13	0	1	0	0	1	81	**72%**
PS	2	**40**	8	6	2	5	0	0	0	0	63	**63%**
LD	0	5	**19**	3	2	12	2	1	0	1	45	**42%**
AA	3	1	2	**14**	5	0	1	1	0	3	30	**47%**
PM	7	0	3	8	**22**	1	3	0	3	2	49	**45%**
PN	1	11	16	4	0	**28**	0	0	0	1	61	**46%**
FS	0	0	5	1	3	1	**39**	14	16	15	94	**41%**
QP	0	0	0	1	0	0	10	**24**	1	13	49	**49%**
CB	0	0	0	2	2	0	9	0	**5**	0	18	**28%**
AP	0	0	1	2	0	0	7	14	3	**13**	40	**33%**
Total	71	59	54	47	49	47	72	54	28	49	**530**	
Prod. Acc.	**82%**	**68%**	**35%**	**30%**	**45%**	**60%**	**54%**	**44%**	**18%**	**27%**		49,4

Table 3. Confusion matrix for the ten tree species using the orthophoto imagery and object-based RF classification algorithm

4.2. RF classification results for WV2 data

The overview of the results based on the object-based classification using WV2 imagery is presented in Table 4. The overall accuracy of 50.6% was slightly better then accuracy achieved based on the orthophoto imagery. One can see the narrow range of achieved results among all species. Again, the European hornbeam (CB) shows the lowest users (33%) and producers (32%) accuracy, as expected, but at the same time, it can be observed slightly increasing of these percentage values in comparison with the results achieved based on orthophoto data. The highest values off achieved accuracy show Douglas fair (PM) with 60% of the user‘s accuracy and Spruce (PA) and Black pine (PN) with 68% of the producer‘s accuracy. Among broadleaf species, the highest accuracy shows Maple (AP) with 53% of the user‘s and Oak (QP) with 67% of the producer’s accuracy.

WV2	PA	PS	LD	AA	PM	PN	FS	QP	CB	AP	*Total*	*User´s Acc.*
PA	**48**	9	9	12	8	2	0	0	0	1	89	**54%**
PS	6	**24**	12	3	2	6	0	0	1	0	54	**44%**
LD	4	11	**24**	3	1	6	3	0	0	1	53	**45%**
AA	5	1	1	**16**	4	0	2	0	0	1	30	**53%**
PM	7	1	0	4	**29**	0	3	0	2	2	48	**60%**
PN	1	13	3	1	0	**32**	0	0	2	2	54	**59%**
FS	0	0	4	4	2	0	**33**	10	9	12	74	**45%**
QP	0	0	1	1	0	0	18	**36**	3	10	69	**52%**
CB	0	0	0	3	2	1	6	3	**9**	3	27	**33%**
AP	0	0	0	0	1	0	7	5	2	**17**	32	**53%**
Total	71	59	54	47	49	47	72	54	28	49	**530**	
Prod. Acc.	**68%**	**41%**	**44%**	**34%**	**59%**	**68%**	**46%**	**67%**	**32%**	**35%**		50,6

Table 4. Confusion matrix for the ten tree species using the eight bands of WV2 and object-based RF classification

The use of eight calculated Vis just slightly enhanced the results. The confusion matrix in Table 5. shows just a slight improvement in the overall accuracy for one percentage point, compared with the previous confusion matrix based on WV2 data without integrated VIs. Here, one can observe, that broadleaf and coniferous trees were almost perfectly separated. The Spruce (PA), with 75%, shows the highest producer’s and Black pine (PN) with 64% the highest user’s accuracy. On the other hand, the lowest results show Silver fir (AA) with 28% of producer's and European hornbeam (CB) with 33% of user's accuracy. The best agreements were obtained for Spruce (PA) and Black pine (PN).

VIs	PA	PS	LD	AA	PM	PN	FS	QP	CB	AP	*Total*	*User´s Acc.*
PA	**53**	8	8	11	11	2	0	0	0	1	94	**56%**
PS	3	**30**	13	5	2	3	1	0	1	0	58	**52%**
LD	5	10	**25**	2	1	7	2	0	0	1	53	**47%**
AA	4	1	1	**13**	4	0	3	0	0	1	27	**48%**
PM	5	1	0	8	**26**	0	3	0	1	2	46	**57%**
PN	1	9	5	0	0	**34**	0	0	2	2	53	**64%**
FS	0	0	2	4	3	0	**32**	12	10	12	75	**43%**
QP	0	0	0	1	0	0	17	**34**	4	9	65	**52%**
CB	0	0	0	3	1	1	6	3	**8**	2	24	**33%**
AP	0	0	0	0	1	0	8	5	2	**19**	35	**54%**
Total	71	59	54	47	49	47	72	54	28	49	**530**	
Prod. Acc.	**75%**	**51%**	**46%**	**28%**	**53%**	**72%**	**44%**	**63%**	**29%**	**39%**		51,7

Table 5. Confusion matrix for the ten tree species using the eight bands of WV2, using calculated Vegetation Indices and object-based RF classification

Finally, the overall accuracy, achieved by analyzing just five main tree species, was around 65%. The values for the Producer's accuracy ranged from 44% to 83%, and for the User's accuracy ranged from 53 to 73%. The confusion matrix presented in Table 6. shows the increasing of producers and users accuracies for almost all species comparing with results achieved analyzing all ten tree species. Now and again, spruce (PA) shows the highest accuracies, with 83% of producer's and 73% of user's accuracy, followed by Beech (FA) and Pine (PS), while Larch (LD) shows the lowest percentage of accuracy.

RF	PA	PS	LD	FS	AP	*Total*	*User´s acc.*
PA	**59**	11	9	1	1	81	**73%**
PS	4	**36**	16	0	2	58	**62%**
LD	6	11	**24**	3	1	45	**53%**
FS	1	0	4	**55**	21	81	**68%**
AP	1	1	1	13	**24**	40	**60%**
Total	71	59	54	72	49	**305**	
Prod. Acc.	**83%**	**61%**	**44%**	**76%**	**49%**		64,9

Table 6. Confusion matrix for the five dominate tree species using the eight bands of WV2, with calculated Vegetation Indices and object-based RF classification

4.3. SVM classification results for WV2 data

For the purpose of this work, the SVM classifier was performed on 32 variables extracted from the WV2 data set. The achieved an overall accuracy of 51.1% shown a similar result with the result achieved using the RF classification algorithm. As can be observed from Table 7. Douglas fair (PM) showed the best producer's accuracy of 82%, followed by Black pine (PN) and European larch (LD). Among broadleaf species, the highest producer's accuracy achieved Oak (QP), with 64%. On the other side, the best user's accuracy of 88% was achieved by black pine (PN). Among broadleafs, European beach (FS) achieved the highest accuracy of 50%. One more time European hornbeam (CB) shows the highest misclassification rate.

SVM	PA	PS	LD	AA	PM	PN	FS	QP	CB	AP	*Total*	*User´s Acc.*
PA	**28**	8	0	20	8	0	4	0	0	0	68	**41%**
PS	16	**28**	16	0	0	4	0	0	0	4	68	**41%**
LD	0	4	**48**	8	0	0	8	0	0	0	68	**71%**
AA	16	4	4	**24**	0	0	3	0	0	0	51	**47%**
PM	4	0	0	8	**36**	0	0	0	8	4	60	**60%**
PN	0	4	0	0	0	**28**	0	0	0	0	32	**88%**
FS	0	0	0	8	0	0	**28**	0	8	12	56	**50%**
QP	0	0	0	0	0	0	20	**28**	8	8	64	**44%**
CB	0	0	0	0	0	0	8	0	**4**	4	16	**25%**
AP	0	0	0	4	0	4	0	16	3	**20**	47	**43%**
Total	64	48	68	72	44	36	71	44	31	52	**530**	
Prod. Acc.	**44%**	**58%**	**71%**	**33%**	**82%**	**78%**	**39%**	**64%**	**13%**	**38%**		51,1

Table 7. Confusion matrix for the ten tree species using the eight bands of WV2 and SVM classifier

Finally, applying the SVM classifier, using the WV2 data set with integrated eight VIs, brought the result in an overall accuracy of 48.1%, lower as expected. The best accuracies were achieved for Black pine (PN) with 75% of the Producer's accuracy, and Larch (LD) with 73% of the User's accuracy. The wide range of accuracies obtained for ten tree species, calculated based on 32 explanatory variables and integrated VIs, can be seen in the confusion matrix presented in Table 8.

SVM & VIs	PA	PS	LD	AA	PM	PN	FS	QP	CB	AP	*Total*	*User´s acc.*
PA	**28**	16	0	16	4	0	0	0	0	0	64	**44%**
PS	8	**28**	4	8	0	8	0	0	0	0	56	**50%**
LD	0	12	**44**	4	0	0	0	0	0	0	60	**73%**
AA	20	0	8	**20**	8	0	8	0	0	4	68	**29%**
PM	8	0	0	0	**36**	0	0	0	0	0	44	**82%**
PN	0	8	4	0	0	**24**	0	0	0	0	36	**67%**
FS	4	0	8	4	0	0	**28**	24	8	4	80	**35%**
QP	0	0	0	0	0	0	4	**28**	0	16	48	**58%**
CB	0	0	0	0	8	0	8	8	**4**	7	35	**11%**
AP	0	4	0	0	4	0	8	4	4	**15**	39	**38%**
Total	68	68	68	52	60	32	56	64	16	46	**530**	
Prod. Acc.	**41%**	**41%**	**65%**	**38%**	**60%**	**75%**	**50%**	**44%**	**25%**	**33%**		48,1

Table 8. Confusion matrix for the ten tree species using the eight bands of WV2 with integrated VIs and SVM classifier

5. Discussion and conclusions

5.1. Discussion

Based on all these results, presented in confusion matrices above, one can observe a large species-specific difference, as a consequence of less separability of some species than others. An obtained wide range of achieved accuracies was from 28% to 72% for the user's accuracy and 18% to 82% for the producer's accuracy. Dominant tree species, Spruce (PA) and European beach (FA) achieved better accuracies, while some species, as in the case of European Hornbeam (CB), are characterized by constantly lower accuracies. In passing, CB shows lower accuracies than other analyzed tree species in Central Europe, which was also observed in many other studies (Fassnacht et al.,2017; Immitzer et al., 2012). For coniferous, using VIs has improved the results. As well, the better accuracy for broadleaf tree species was achieved using WV2 data, than in the case of using orthophoto data. Even though analyzed tree species showed big differences in the values of accuracies, while the separation between coniferous and broadleaf species was satisfactory, only with small misclassifications. A comparison of the results produced in confusion matrices based on 32 variables, extracted from orthophotos and WV2 datasets, are presented in Table 9.

RF	Orthophotos		WV2	
	User's acc.	*Producer's acc.*	*User's acc.*	*Producer's acc.*
PA	72	82	54	68
PS	63	68	44	41
LD	42	35	45	44
AA	47	30	53	34
PM	45	45	60	59
PN	46	60	59	68
FS	41	54	45	46
QP	49	44	52	67
CB	28	18	33	32
AP	33	27	53	35
Overall acc.	49,4		50,6	

Table 9. Comparison of accuracies achieved using the RF classifier, based on 32 variables extracted from orthophotos and WV2 dataset for ten dominant trees species

It can be observed that some slight improvement has been achieved in the percentage of overall accuracy using WV2 data. Among tree species, a wide range of accuracy values has been achieved. For some of the species, the producer's accuracy was higher based on analysis with orthophoto data, as in the case with dominant Norway spruce (PA) and especially Scots pine (PS), with decreasing of 27%. Contrary to that, for oak (QP) and hornbeam (CB), the use of WV2 data has brought a better producer’s accuracy. Comparing the user’s accuracy, it can be observed an increase in accuracy values using WV2 data for some species, especially for Maple (AP), Douglas fair (PM), and Black pine (PN). At the same time, a decrease in the accuracy of dominant tree species, Norway spruce (PA), and Scots pine (PS) were obtained.

The use of the SVM classifier resulted in accuracy similar to the accuracy achieved using the RF classifier (Table 10). In many of recently published studies can be found that the use of both classifiers in a forest and land cover classifications results in high accuracies with no large difference between them (Ghosh et al., 2014; Ballanti et al., 2016).

WV2	RF		SVM	
	User’s acc.	*Producer’s acc.*	*User’s acc.*	*Producer’s acc.*
PA	54	68	41	44
PS	44	41	41	58
LD	45	44	71	71
AA	53	34	47	33
PM	60	59	60	82
PN	59	68	88	78
FS	45	46	50	39
QP	52	67	44	64
CB	33	32	25	13
AP	53	35	43	38
Overall acc.	50,6		51,1	

Table 10. Comparison of user’s and producer’s accuracies achieved with SVM and RF classifiers, based on 32 extracted variables from ten dominant tree species, using eight bands WV2 dataset

From this confusion matrix can be observed some slight improvement in the percentage of overall accuracy achieved in the model created with the SVM classifier. Some tree species show heigh increasing of accuracy by using the SVM algorithm, as in the case of Black pine (PN), with an increase from 59% to 88% of user's accuracy and Douglas fair (PM) with an increase from 59% to 82% of producer's accuracy. On the contrary, some species show a high decrease in achieved accuracy, which is most pronounced in species as Norway spruce (PA) and European hornbeam (CB) and their producer's accuracy.

The comparison of overall accuracies achieved using both RF and SVM classifiers, based on the WV2 dataset with implemented VIs is presented in Table 11. The use of additionally calculated VIs brought the increase in the percentage of accuracy just for half of the tree species. Achieved overall accuracy of 48.1% using the SVM classifier was lower than the accuracy of 51.7% achieved by applying RF classifier. But, for some species, as in the case of Douglas fair (PM) and European larch (LD) much better results were obtained by applying the SVM classifier. On the other side, some species show a high decrease in achieved accuracy, which is most pronounced in species Norway spruce (PA) and European hornbeam (QP) and their producer's accuracy.

WV2 + VIs	RF		SVM	
	User's acc.	*Producer's acc.*	*User's acc.*	*Producer's acc.*
PA	56	75	44	41
PS	52	51	50	41
LD	47	46	73	65
AA	48	28	29	38
PM	57	53	82	60
PN	64	72	67	75
FS	43	44	35	50
QP	52	63	58	44
CB	33	29	11	25
AP	54	39	38	33
Overall acc.	51,7		48,1	

Table 11. Comparison of user's and producer's accuracies achieved with SVM and RF classifiers, based on 32 extracted variables and calculated VIs from ten dominant tree species, using eight bands WV2 dataset

In the end, higher results were achieved analyzing the spectral signature of five dominant tree species, as expected. Many recently published studies, demonstrate higher overall accuracies, analyzing a smaller number of tree species. For example, Immitzer et al. (2012) were able to separate the four tree species with an overall accuracy of about 95%. Fassnacht et al. (2017) analyzing five tree species, achieved an overall accuracy of 86%, while Cho et al. (2015) reached an accuracy of 89% analyzing three tree species. The comparison of accuracy achieved in this work, analyzing five and ten dominant tree species using RF classifier, based on the WV2 dataset is presented in Table 12.

RF / WV2	5 tree species		10 tree species	
	User's acc.	*Producer's acc.*	*User's acc.*	*Producer's acc.*
PA	73	83	54	68
PS	62	61	44	41
LD	53	44	45	44
FS	68	76	45	46
AP	60	49	53	35
Overall acc.	64,9		50,6	

Table 12. Comparison of user's and producer's accuracies for five dominant tree species, using RF classifier, based on WV2 dataset

5.2. Comparison with other studies

In the last decade, it was published lots of studies that demonstrate the high suitability of WV2 satellite data for classification and mapping of tree species. Consequently, it was interesting to analyze obtained results and metadata used in this work, with some of these studies, especially in terms of the number of analyzed tree species, acquisition date, and acquisition geometry. The overall accuracies, reported in the listed studies, shown in Table 12, range between 49% and 96%. All analyzed studies are based on WV2 data. The number of analyzed tree species is mostly between four and ten. The applied classification algorithms are non-parametric methods, Support Vector Machines and Random Forest classifiers.

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Sensor	**Acquisition date**	**Viewing angle [°]**	**Number of tree species**	**Number of polygons per species**	**Overall acc. [%]**	**Reference**
WV2	10/07/2010	11.0	4	80-250	96	*Immitzer et al., 2012*
WV2	10/07/2010	11.0	10	80-250	82	*Immitzer et al., 2012*
WV2	04/06/2011	8	7	80-380	83	*Waser et al., 2014*
WV2	08/06/2013	0	10	12-59	80	*Fassnacht et al., 2017*
WV2	08/06/2013	0	5	12-59	85	*Fassnacht et al., 2017*
WV2	01/08/2010	19.3	5	100	58	*Verlic et al., 2014*
WV2	11/11/2011	23	8	50-180	84	*Zhu et al., 2017*
WV2	22/09/2012	18.4	8	130-350	48	*Hartling et al., 2019*
WV2	*29/08/2012*	*18.3*	*10*	*30-70*	*51*	**:::**
WV2	*29/08/2012*	*18.3*	*5*	*30-70*	*65*	**:::**

Table 11. The overview of results and metadata of comparable studies (the last two rows shows the data based on this study)

Results achieved in this work are lower then results achieved in the studies which demonstrate the high potential of the WV2 dataset, but at the same time in the line with some other studies that had various explanations for achieved lower accuracy values. However, in many of these studies very promising results have been obtained.

For example, Immitzer et al. (2012), achieving an overall accuracy of 82% (ten tree species, eight bands, object-based, RF) have been demonstrated the high potential of WV2 data for forest tree species separation. Even, in the same research, they achieved an overall accuracy of 96% analyzing the 4 main tree species. As possible reasons for relatively high values of achieved accuracies, the authors state the spectral and spatial properties of the WV2 sensor, making it very suitable and acceptable for the tree species classification tasks; the large sample size per class, that had a positive impact on the classification results; consideration of the sunlight regions of the tree crowns, that significantly contributed to heigh classification accuracies; manually delineation of the tree crowns, that gives very accurate object boundaries, avoiding the fusion of neighboring crowns in the reference polygons, resulting in almost unmixed reference samples.

Further, Waser et al. (2014), analyzing seven tree species, riched the overall accuracy of 83% and an accuracy of 77% for four different levels of damaged ash. As possible reasons for misclassifications in that study, the authors state the similar spectral properties of sample crowns among the tree species, and among the different damaged ash and other species; while as less, but theoretically possible reasons could be mixed crown segments from a neighboring tree of a different species or different level of damage.

Finally, Fassnacht et al. (2017) obtained accuracies of nearly 80% for the classification of ten tree species, using SVM classification. With the reduction to the five main tree species, they achieved an increase in accuracy to 85%. The input variables included the eight WV2 spectral bands and eleven textural metrics obtained from the panchromatic channel via the standard grey-level co-occurrence matrix procedure.

On the contrary, there are some studies with achieved lower overall accuracy. In the research, published by Hartling et al., 2019, an overall accuracy of around 48% was riched, analyzing eight dominant tree species, using both RF and SVM classifiers. A similar low result of 58% of overall accuracy was achieved in the study of Verlic et al. (2014). In this study, just five species (in the dominant layer of the natural, mixed, heterogeneous urban forest in Ljubljana, Slovenia) were analyzed, but probably the time of acquisition (August) and the viewing angle of 19.3° were resulted in obtaining less accuracy. However, the authors assume that the effect of variability of forest conditions has a high impact on the accuracy of the results.

A possible positive factor, for good results in some studies, could be the acquisition date. One can say, that June and July are the months when the vegetation is fully developed and tree crowns are completely covered by green leaves, providing excellent material for analysis. Additionally, a positive impact on the classification results can also have a large sample size per class. Furthermore, considering only the sunlit regions of the tree crowns in the classification process significantly contributes to high classification accuracy, as demonstrated in some studies (Greenberg at al., 2006; Wasser at al., 2011; Immitzer et al., 2012),. On the other side, the acquisition date in late August or September, close to the end of vegetation period, as in this study or a similar one, could be a hampering factor for getting better accuracy.

5.3. Possible reasons for lower accuracy

The achieved results in this research are lower than expected, based on recently published studies on tree species mapping with WV2 data and nonparametric classification algorithms, but in the line with few studies, which demonstrate small results as well. For such results and observed misclassification could be a lot of possible reasons, such as errors in the reference data set, not perfect crown delineation, understory vegetation, the topography of the study site, variety of scales of tree canopy size and tree ages, complex forest structure, small sample size per class, spectral overlaps, acquisition date, and properties of the WV2 sensor, especially the higher view angle.

One of the possible reasons could be a not perfect crown delineation. The quality of the segments is very important for the performance of an object-based classification. But, the crown delineation in this study, was done manually, trying to minimize the shadow effects by focusing only on the sunlit parts of the tree crowns and resulting in objects that were almost ideally suited for classification. the shadow effects were minimized.

Another possible reason for observed misclassifications could be complex forest structure in this area. But, comparing with already existing research, this study area is covered by a forest similar to the forest from other studies. Generally, it was difficult to estimate tree species composition in the field due to roads, accessibility, forest structure, missing trees, density, and overlapping of tree crowns. Consequently, the tree position one can see from the ground can vary greatly from the one, that one can see from above.

Also, a reason can be some errors in the reference data set. To minimize these types of errors, the study area was visited and reference data was chacked several times. Therefore, if small errors exist, they do not significantly affect the results. As well, an attempt was made to avoid multi-stored stands and small tree crowns, because both of these two characteristics could lead to mixed pixels and cause misclassification.

Follows, the sample size could be a reason for lower accuracy. The research published by Immitzer et al. (2017), reported that class-specific accuracy is positively correlated with sample size. The imperative is to have an adequate number of reference samples of high quality, to reach the high potential of data with a high spectral resolution for tree species classification. Additionally, class imbalances negatively affect class-specific results. Especially in the case of classes that are hard for separation, classes with more samples are preferred by RF classifier and obtain higher results (Immitzer et al. 2019). Hence, The sample size of 45–75 polygons per tree species in this work, may harm classification results. Therefore, the size of the sample should be higher, but it is still comparable.

Finally, conditions for data acquisitions could be an important factor that has a strong influence on accuracy. In some studies, a strong influence of the acquisition date and acquisition parameters on the usability of the WV2 data for tree species classification is demonstrated (Immitzer et al. 2017). For example, data collected during the summer (June to August), achieved the highest accuracy values. Also, acquisition near nadir is more preferable for achieving of highest accuracy values.

5.4. Recommendations based on the main findings

Based on all mentioned above, the following findings can be observed:

The results achieved comparing two machine learning algorithms, SVM and RF, to classify ten most common tree species in a mixed forest, demonstrate small differences in the overall accuracy of individual tree species classification.

The number of classes (analyzed tree species) has a big impact on the classification results. With an increase in the number of classes the performance of models and achieved accuracies were decreased.

The size of the samples influences the results obtained in the work. Generally, species with more samples have an increase of the class-specific accuracies. To harness the high potential of WV2 data for tree species classification, it is necessary to have an optimal number of reference samples.

The significance of the acquisition date and acquisition parameters on the usability of the WV2 data is indisputable. For example, data collected during the period from June to August achieved the highest accuracy values. At the same time acquisition close to nadir, ensures better classification results.

Limiting factors, for use of the WV2 dataset for mapping tree species and other forest applications, are the relatively high price, the limited spatial coverage of these data, not appropriate for regional or country-wide analyses, and still skeptical forest community, less familiar with these data. Additionally, forest fieldwork is often separated from remotely sensed data analyses. In the future, better integration and coordination between these two methods would be beneficial and very useful for both parties.

Improvements could be achieved with multi-temporal data sets, better acquisition date and acquisition geometry, or increasing the number of reference polygons per tree species. To confirm the potential of WV2 data for tree species classification, different vegetation types should be analyzed, with a focus on the use of data from sensors covering larger areas.

Last but not least, the influence of the quality of the reference data on the achieved accuracy is also very important. Intensive fieldwork, with precise delineation of reference polygons, are the main prerequisites for the success of the classification.

The new generation of satellites provides data with high spatial, spectral, temporal, and radiometric resolution. Thanks to their developments, these data sets are increasingly used for forest applications. Examples of data sources are very high-resolution satellites such as WorldView-3 (WV3) or Sentinel-2.

The WV3 satellite, launched in 2014, caries 16 bands, consisting of eight VNIR and eight short-wave infrared bands (SWIR), that could improve the separation of tree species and vegetation analysis. Additionally, with the resolution of 30cm in the panchromatic band, tree crown delineation would be more precise and effective.

Sentinel-2A and 2B satellite, launched by European Space Agency, provides high-quality data with high spatial, spectral, and temporal resolution, delivering detailed, cost-efficient, and up-to-date information over a large area. Additionally, it has two SWIR bands, important for tree species classification (Immitzer et al. 2019). With very high revisit intervals and freely available data, it has a high potential for tree species separation.

6. Conclusion

The focus of this master thesis is on the suitability of eight band WV2 data for tree species mapping at a crown level, in a mixed forest, located in Austria. For testing the potential of the WV2 sensor for forest mapping, a large number of individual tree crowns of the ten most common tree species were identified through intensive fieldwork. The spectral signature of these 530 manually delineated reference trees was analyzed. The VIs and 32 explanatory variables were calculated and analyzed with the RF and SVM classifiers. Finally, confusion matrices with accuracies achieved analyzing ten dominant tree species were produced.

Using the spectral resolution of the WV2 sensor and trying to minimize the shadow effects, by focusing only on the sunlit parts of the tree crowns, for some tree species, the relatively very low accuracies were achieved. The possible spectral overlap can be the result of the many biochemical and biophysical properties, that determine the reflectance of trees.

The overall accuracy of 50.4% using RF classifier and 51.1% using SVM have been obtained. There were no big differences in achieved accuracies based on explanatory variables extracted from WV2 and orthophoto imagery. Even though the species-specific results show large differences, coniferous and broadleaf trees were almost perfectly separated. Additionally, eight Vegetation Indices strongly related to vegetation characteristics were calculated and the highest overall accuracy of 51.7%, using RF classifier was achieved. Calculation and application of eight VIs did not improve the results much. In the end, after comparing the results with similar studies, the reduction of the number of classes to five (most common tree species) was made, resulting in a higher accuracy of 64.9%.

With these values of achieved overall accuracy, using the RF and SVM classification algorithm, this study can not demonstrate the high potential of WV2 data for tree species mapping. These results are lower than results reported in comparative studies, with achieved overall accuracy above 80%, demonstrating the high potential of WV2 data for mapping and classification of forest tree species. Therefore, an additional check of the reference data set, characteristics of crowns, forest, and the stand was made.

Additionally, a comparison of acquisition conditions, metadata, and characteristics of the WV2 sensor with comparable studies have been made. Based on the main findings, some recommendations are given at the end.

The potential of the VHR satellite data is expected to continue to increase through future researches, developing the new generation of sensors, with higher spatial, spectral, temporal, and radiometric resolution. Also, a combination of datasets, from two or more sensors in the same area, could have greater potential for successful tree species classification.

7. List of abbreviations

AA - Silver fir - *Abies alba*

AP - Sycamore maple - *Acer pseudoplatanus*

B - Blue band

C - Coastal band

CB - European hornbeam - *Carpinus betulus*

FS - European beech - *Fagus sylvatica*

G - Green band

LD - European larch - *Larix decidua*

MDA - Mean Decrease in Accuracy

NIR1 - Near Infra-Red 1 band

NIR2 - Near Infra-Red 2 band

OBIA - Object-based Image Analysis

OOB - Out of Bag

PA - Norway spruce - *Picea abies*

PM - Douglas fir - *Pseudotsuga mensiesi*

PN - Black pine - *Pinus nigra*

PS - Scots pine - *Pinus sylvestris*

QP - Sessile oak - *Quercus petraea*

R - Red band

RE - Red Edge band

RF - Random Forest

SVM - Support Vector Machine

VIs - Vegetation Indices

WV2 - WorldView-2

Y - Yellow band

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10. Affirmation

I certify, that this Master thesis was written by me, without using sources and tools other than quoted and without using any other illegitimate support.

Furthermore, I confirm that I have not submitted this Master thesis either nationally or internationally in any form.

Vienna, 2020

Author: Ivica Kocic

Personal information

Name:	Ivica Kocic
Date of birth:	24.11.1977.
Address:	1020 Wien
	Feuerbachstraße 10
Nationality:	Serbia
Telefon:	+43 (0) 6604794318
E-Mail:	ivicakocic77@gmail.com
Family status:	Merried, 2 children

Work experience

09/2006 - present

Math Teacher - Nachhilfelehrer für Mathematik
Freelancer, Vienna (Austria)
Agency for education "Sveznanje", Belgrade (Serbia)

- ✓ Additional lessons of mathematics for Primary and Secondary school (for children from 7 to 19 years old)

02/2014 - 08/2014

Data analyst
Velestroj doo, Tyumen, Russia

- ✓ Analysis of the production process
- ✓ Preparation of statistical results and reports

02/2012–08/2012

Scientific officer
Faculty of Forestry, University of Belgrade (Serbia)

- ✓ Project - National inventory of private forests
- ✓ Collecting and processing data

11/2009–02/2012

Front office manager
TUP Avala - Hotel "1000 Roses", Belgrade, Serbia

- ✓ Front Office Manager, Receptionist

02/2007–02/2008

Export/import coordinator
TNT EXPRESS – global express, logistics & mail, Belgrade

- ✓ Export/import coordinator for UN3373 materials
- ✓ Data entry operator

09/2004–02/2007

Secondary school Teacher
School of Agriculture, Leskovac (Serbia)

Education

10/2014 - present

MSc Mountain Forestry
University of Natural Resources and Applied Life Sciences, BOKU, Vienna (Austria)

- ✓ Master thesis
  „Tree species mapping using WorldView-2 multispectral data in the Forest Demonstration Center Rosalia, Austria"

10/2017 - present

MSc Water Management and Environmental Engineering
University of Natural Resources and Applied Life Sciences, BOKU, Vienna (Austria)

10/1996 - 01/2003

Master of Science in Forestry
Faculty of Forestry, University of Belgrade, Serbia

- ✓ Graduation theme: "Dendroflora of North-West part of Mountain Kukavica"

09/1992 - 06/1996

Department of Mathematics
Gymnasium, Leskovac, Serbia

- ✓ Graduation theme: "Checking reversion by Hi–square test"

Computer skills

HTML5, CSS3, JS, Angular, Python, R, ArcGIS, QGIS

Comnex, Lotus, Track&Trace, Fidelio Suite 8 – CRM & Property management system

Language skills

Serbian – mother language (Bosnian, Croatian)
English – fluently
German – B1
Russian – A2

Hobbies and other skills

Sport (statistics and analysis), Sport (football, running), Music (accordion and keyboards)