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**Robust Forest Classification using Hyperspectral Imaging, Laser Scanning and Satellite Imagery**

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**Abstract**

Wood products are an important export for Russia. Understanding the status of trees and their classification is an ongoing task for many organizations. Currently, documentation of forests is done manually and there is a number of initiatives to implement automatic forest classification. A particular case described in the present paper showcases how aerial survey data supplements satellite imagery in order to achieve higher classification accuracy of forest tree species. Moreover, applicability of different data types, such as LiDAR, RGB, and hyperspectral (NIR and VIS) for the task at hand is investigated.

In the paper, we present the experiment to use hyperspectral forest classification (using a UAV), which is then used in the context of satellite imagery, airborne laser scanning, and manual identification. We actively employ machine learning algorithms for classification and recognition tasks.

The project began with an expedition to the northern region of Arkhangelsk (Russia) in August 2018. The main goals of the expedition were data acquisition with the help of UAVs (one RGB and one hyperspectral), as well as observing various weather conditions and their effect on the data collected.

Validation of the results was performed in four separate polygons, where in-situ data was collected by manually recording tree locations and species. In this project we evaluated the precision of trees identification from UAV hyperspectral data, helped by ALS and high-resolution satellite imagery (50 cm).

Supervised machine learning algorithms, namely Support Vector Machine (SVM) and Random Forest (RF), were applied and evaluated for automatic tree species classification task. Preliminary exploratory data analysis using unsupervised techniques was also done and described. An object-based classification has been performed by delineating individual tree crowns beforehand with the help of LiDAR data. Various hyperspectral features have been identified for use in classification algorithms complemented by on-ground spectroscopic benchmark data.

In this paper, we prove applicability of the proposed method and workflow in real life application. Results validation was done using data from the observation parcels, where trees were manually labeled. The next step is design of a system with finely tuned filters, which will make possible robust species classification at a cost much lower than hyperspectral imaging. We aim at classification accuracy of 90% that will allow for change proposal for current forestry policy and legislature to enable the use of UAVs in forestry for classification purposes.

**Keywords:** hyperspectral imagery, LiDAR data, machine learning, forest inventory, tree species, tree detection

**Acronyms/Abbreviations**

ALS Airborne Laser Scanning

CHM Canopy Height Model

DBH Diameter at Breast Height

DTM Digital Terrain Model

DSM Digital Surface Model

LIDAR Light Detection and Ranging

NDVI Normalized Difference Vegetation Index

NIR Near Infrared

RF Random Forest

RGB Red, Green, Blue

SVM Support Vector Machines

UAV Unmanned Aerial Vehicle

1. **Introduction**

Forest inventory plays an important role in terms of economical and environmental sustainability both regionally and globally. It is especially relevant in case of Russia, since its territories cover around 20% of world’s forest reserves [1]. According to the current forestry legislation in Russia, forest inventory shall be done manually, hence, time consuming and expensive. In this project, an attempt to build an automatic trees detection and classification technology, based on remote sensing and machine learning is presented and tested. In order to allow a widespread use of this technology in the industry for forest inventory, classification accuracy of 95% shall be achieved. A combination of machine learning and remote sensing has demonstrated a great potential for solving different tasks in such areas as precision agriculture, land cover changes detection, urban environment monitoring, maritime navigation and control, etc. Additionally, it has application in forest classification, a particular case of land cover classification. In general, any land cover classification task can be categorized either as pixel-based or as object-based, but the latter usually shows better results [2, 4]. Moreover, in forestry applications object-based trees species classification is more valuable, since it gives more detailed information about a forest structure. There are two approaches for object-based forest classification: classification at the individual tree level, classifying every tree separately, or area-based classification, when dominant tree species are predicted for different areas of a forest. In this work, the case of individual tree level forest species classification is considered, because forestry legislation requires to have information for each tree rather than general statistics for whole parcels of a forest. Nowadays, hyperspectral data has become extensively used in different land cover classification tasks, as it contains more information than multispectral imagery and, therefore, allows to catch subtle differences in akin materials. For example, Utsav et al. [5] have described different remote sensing scenarios, in which a high number of spectral bands is important. Also, Kang et al. [6] have presented a performance comparison of different algorithms applied on hyperspectral imagery for land cover classification, providing a benchmark data. Moreover, there are various deep learning approaches for hyperspectral data processing [7–9]. Furthermore, current research on forest classification is based on hyperspectral imaging. Existing investigations describe different approaches based on using different instruments and algorithms classifying different tree species in different regions. For instance, Support Vectors Machine (SVM) algorithm was applied on hyperspectral imagery with 160 bands (410-990 nm) to classify 3 groups of trees (Spruces, Pines, and Deciduous trees) in Norway and the accuracy of 92% was achieved [10] .89% classification accuracy was obtained when classifying 13 tree species (8 Deciduous and 5 Coniferous) in Austria using the same hyperspectral imaging, as in the previous example, but with Random Forest (RF) classifier [11]. Nevalainen et al. [12] have managed to achieve 95% accuracy for tree species classification in Finland. They classified 4 tree species (Spruce, Birch, Pine, and Larch) by RF algorithm using hyperspectral imagery with spectral resolution of 33 channels (500-900 nm). The approach for trees detection and classification presented in this work consists of two steps. First, individual trees are detected using LiDAR data.

Then, detected trees are classified by their hyperspectral properties using machine learning classifiers. With the aim to compare results of airborne technologies with technical characteristics of cheaper and more scalable one, the same experiment was performed using space-borne technology, in this case, using a sub metric multispectral sensor. Section 2 surveys methods and algorithms used for trees detection and classification in this project as well as an expedition for collection of LiDAR, hyperspectral and reference trees data together with instruments characteristics and data pre-processing procedures. Section 3 contains results of the experiments done in this project and description of evaluation schemes and performance metrics. Sections 4 and 5 are devoted to discussion of the results and conclusions accordingly.

1. **Data and Methodology**

At the beginning, a special expedition to Arkhangelsk region (northern Russia) was performed in August 2018 for data collection purposes. Experimental area belongs to Krasnoborsky district forestry division (Figure 1).

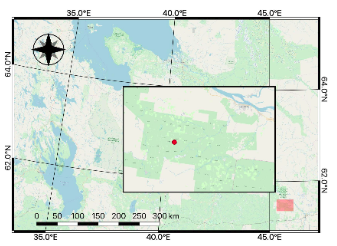


Figure 1. Geographic location of Arkhangelsk region, Russia with the highlighted area (red rectangle) corresponding to Krasnoborsky district at 61◦28′N 45◦34′E

This territory is covered by plain cultivated boreal forests. Four test polygons with a size of 150 m by 200 m each were selected for experimental data collection (Figure 2).

Detailed descriptions of the data collection procedures, instruments characteristics, as well as pre-processing steps for LiDAR, airborne hyperspectral, spaceborne multispectral, and reference trees data are given in Sections 2.1, 2.2, 2.3, and 2.4 respectively. Individual Tree Crowns (ITCs) detection strategy is described in Section 2.5. Section 2.6 is devoted to tree species classification procedure.

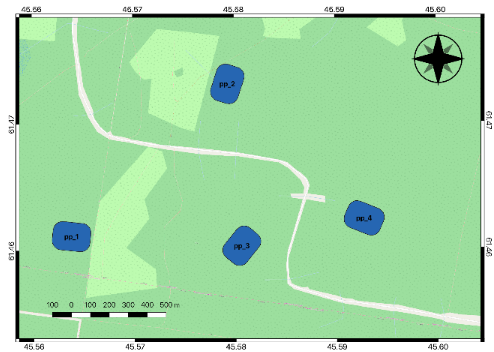


Figure 2. Location of the four experimental polygons, each of them with an area 0.03 Km2

* 1. *Airborne Laser Scanning*

Canopy Height Model (CHM) enables the analysis of trees height and crowns area. It is obtained by calculating the difference between the Digital Surface Model (DSM) and Digital Terrain Model (DTM). In our case, it was derived from a point cloud sampled using airborne laser scanning (ALS) LiDAR sensor Leica ALS70, onboard a manned aircraft. The overall result of mapping was a 5 points/m2 density point cloud.

As first step, raw point cloud was pre-processed with Terrasolid software. This software takes LiDAR raw data, and outputs a file in *las* format, which contains position and classification of every point based on ASPRS Standard [13]. For later steps, a pipeline to automatically generate the CHM was developed, taking as input a *las* file, and producing a raster.

In order to generate the DTM, all points classified as *ground* were selected. As the density of points in this classification was only 0.5 points / m2, the rasterization was performed using a linear interpolation method with a resolution of 1 m by 1 m.

As for the DSM calculation, all points classified as *high vegetation* were processed. For the rasterization, cell size of the grid is a key parameter, an appropriate cell size will help to avoid raster gaps and preserve sufficient details. Grid cell size was obtained from , *c* is grid cell size, and *n* is the density of points [14], that in this area was 6.3 points / m2, obtaining a 0.4 m grid cell size. Per each cell, the highest point within its area was selected (Figure 3).

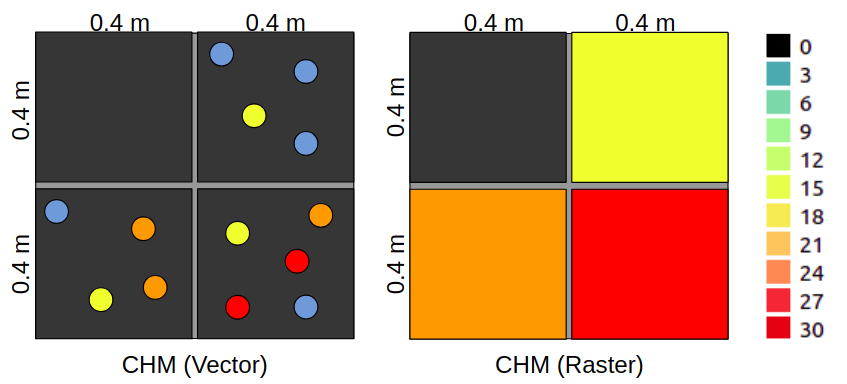


Figure 3. Process of DSM rasterization, from a point cloud gathered from ALS, by selecting points with highest value per each square. Per each cell of 0.16 m2in the grid, the highest point in the vector is selected, and its height value is assigned to the raster.

Finally, CHM in raster format was calculated with the operation *CHM = DSM - DTM*, having the same DSM resolution of 0.16 m2. After generating the raster, data noise or errors may still exist in the CHM. A first attempt of filtering using Gaussian smoothing was performed as described by Wu et al. [14], but due to the low density of points, the top and mean height of trees was considerably decreasing, up to 30\%. For this reason, another approach was followed, instead grey dilation was used for filtering. As shown in Figure 4, it improved the persistence of canopy height, since it only enlarges bright regions (tree crowns), and without altering the height of the top of the trees.

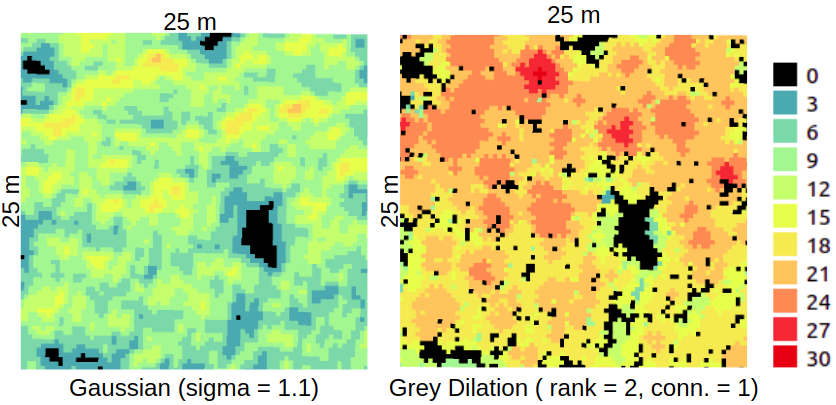


Figure 4. Comparison of results between Gaussian smoothing and grey dilation for resulting CHM filtering in the same region, with an area of 625 m2

* 1. *Airborne Hyperspectral Imagery*

For hyperspectral data collection, a OXI VNIR-40 hyperspectral camera from Gamaya company, mounted on a fixed-wing drone Geoscan-101 was used. The camera has 16 bands in visible range (450-670 nm) and 25 bands in near-infrared range (600-900 nm). The flights were done in early afternoon when the sun was at a maximum elevation angle, in order to minimize shadowing effects. The flights were performed at the constant altitude of 250 m with the speed of 60 Km/h. The spatial resolution of hyperspectral sensor was set to 5.5 cm/pixel.

Hyperspectral imagery pre-processing included optical and radiometric calibration. On ground spectroscopy measurements were acquired during each flight and it was used as a calibration information to transform raw pixel values into reflectance values. However, changing weather conditions (sunny and cloudy) during the flights have resulted in significant brightness differences in hyperspectral values along the same flight, and between flights. Nevertheless, these effects were partially mitigated by normalization procedure applied when performing tree species classification. Optically and radiometrically calibrated images were then stitched together into orthophotoplans. Afterwards, bad quality spectral bands were removed and the resulting dimensionality of hyperspectral cubes was reduced to 32 (15 VIS and 17 NIR) spectral bands and 10 cm ground resolution.

Due to low geolocation accuracy, additional georeferencing procedure using ground control points (GCPs) was applied to collocate LiDAR and hyperspectral imagery. CHM rasters computed from LiDAR point clouds served as a base layer for this georeferencing procedure. For each test site, between the 5 and 7 most recognizable tree tops were found on both CHM rasters and hyperspectral cubes and used as GCPs.

* 1. *Satellite-based Multispectral Imagery*

Satellite multispectral imagery is extensively used in remote sensing area for land cover classification tasks [26]. For example, medium-resolution spaceborne optical data, from such satellites as Sentinel 2 or Landsat 8, can be used to perform object-based classification of agricultural field parcels [27].

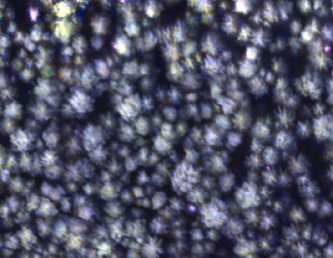
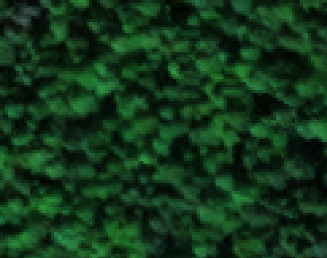
 

Figure 5. Examples of true color composites from airborne hyperspectral imagery (left) and spaceborne multispectral imagery (right) for the same area.

* 1. *Reference data*

For every polygon described in Figure 2, there is a sub polygon, 100 m by 50 m size that contains annotations of the four main tree species presented in test region: *Spruce, Birch, Fir, and Pine*. All trees with diameter at breast height (DBH) larger than 6 cm were labeled, 3000 trees in total. Table 1 contains the amount of different reference tree species for every test polygon.

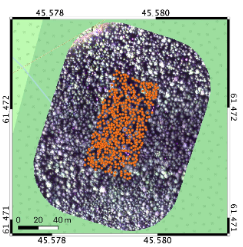


Figure 6. Example of the test polygon (red dot on the left map) with true color composite obtained from hyperspectral imagery (Red: 622 nm, Green: 578 nm, Blue: 461 nm) and the labeled reference trees location.

Table 1. Distribution of reference trees by class in every polygon

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Polygon | Spruce | Birch | Fir | Pine | Total |
| pp1 | 603 | 224 | 20 | - | 847 |
| pp2 | 464 | 322 | 89 | - | 875 |
| pp3 | 210 | 98 | - | 227 | 535 |
| pp4 | 528 | 153 | 7 | - | 688 |
| Total | 1805 | 797 | 116 | 227 | 2945 |

One of the issues with the labeling process on field was that there was no information about the tree height. Moreover, trees were labeled regardless their visibility from above. For this reason, non-visible trees from remote optical sensors were filtered out. Heights of the labeled trees were estimated using regression models based on DBH values and heights information for some of the model trees in the test polygons. Locations of remaining trees were adjusted visually in QGIS software using CHM rasters and true color composites from hyperspectral imagery for exact matching their positioning with the corresponding tree crowns. Table 2 presents the final numbers of the reference trees collected.

Table 2. Final number of the labeled reference trees

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Polygon | Spruce | Birch | Fir | Pine | Total |
| pp1 | - | - | - | - | - |
| pp2 | 424 | 181 | 41 | - | 471 |
| pp3 | 66 | 43 | - | 139 | 248 |
| pp4 | 231 | 19 | 3 | - | 327 |
| Total | 539 | 324 | 41 | 39 | 1046 |

Unfortunately, it was not possible to co-locate most of the reference trees with the hyperspectral imagery in the first test polygon, thus it was decided to exclude all the labeled trees in this polygon from further analysis completely.

* 1. *Individual Tree Crowns Detection*

Individual tree crowns detection (ITCd) is a preliminary step for object-based tree species classification. Most of the existing methods for ITCd are based on local maximum (LM) filtering applied either on CHM rasters obtained from LiDAR data [15-17] or on high spatial resolution imagery [18-21]. The results are more stable when using LiDAR data, since LM points correspond to the real tree crown tops in this case. While in the case of using imagery for ITCd, LM points may actually be just the brightness peaks and not the real tree crown tops. Moreover, it was shown that detection accuracy using imagery is more or less comparable with detection accuracy using LiDAR data only if imagery resolution is high (around 5-15 cm) and for lower resolution imagery (less than 30 cm) detection accuracy is significantly lower [20]. There is another approach for ITCd using deep learning [22, 23], but it requires a considerable amount of training data.

In this work, the following approach for ITCd was used. Firstly, non-vegetation areas, such as roads, dead trees, etc., were excluded by masking out Normalized Difference Vegetation Index (NDVI) raster using threshold value of 0.6. NDVI is calculated for every pixel according to:

where NDVI - pixel's NDVI value, NIR - pixel's value in near-infrared range, RED - pixel's value in red range.

After, low vegetation areas, with value lower than 10 m on CHM, were masked out. Therefore, only the areas containing high vegetation are left for further analysis. Finally, for these areas ITCs were detected on CHM rasters using the approach based on LM filtering described by Popescu et al. [15].

* 1. *Tree Species Classification*

There are two approaches for classification tasks in remote sensing as it was discussed in Section 1. In pixel-based classification each pixel is classified separately. This approach is usually applied with coarse resolution imagery, for instance field crop classification using 30 m resolution Landsat 8 satellite. In the other hand, object-based classification is performed using the information about the whole object, for either individual crowns, or areas. In general, it was shown that object-based approach is more stable and outperforms pixel-based approach in most cases; for this reason, object-based tree species classification is used along this work.

First of all, boundaries of the classified objects shall be defined to be able to extract features inside these regions. Tree crowns delineation methods are usually applied for segmentation of exact shapes of the crowns, and can follow different approaches, including point clouds obtained from LiDAR [15-17], and some others methods just relying on the image brightness values in the absence of structural information [19, 20, 21]. However, in case of high resolution imagery, it is enough to use more simple strategies to define object boundaries, as, for example, Nevalainen et al. [12] extracted features for tree species classification inside a circle area around detected tree top. In Figure 7 it is shown how tree crowns areas for both hyperspectral airborne and multispectral satellite imagery are cropped using 1 m radius distance, and in Section 3 it is explained how to determine the optimal radius dimension based on cross validation for different classification algorithms. In case of satellite imagery tree crowns areas are represented by only several pixels due its low resolution comparing to airborne imagery (Figure 7).

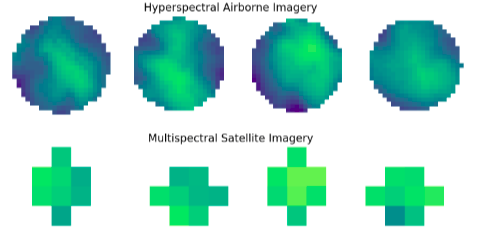


Figure 7. Examples of differences in amount of extracted pixels of tree crowns in hyperspectral airborne and multispectral satellite data during features calculation step due to different imagery resolutions

There exist several strategies to construct feature vectors for classification from hyperspectral data. For example, Nevalainen et al. [12] used mean, median, and some of their threshold values as features. In this project, it was decided to use only mean values per each spectral band as features, since there is one-to-one correspondence between features and spectral bands in this case and, therefore, the results will be more interpretable and it is possible to estimate the importance of the spectral bands for tree species classification. The number of extracted features for hyperspectral airborne data is 32, which is the total number of bands in hyperspectral imagery used in this project. Additionally, normalization is applied in order to reduce the effects of brightness differences in hyperspectral imagery as well as the shadowing effects. Moreover, normalization improves the overall accuracy of hyperspectral imagery classification, which was demonstrated by Cao et al. [24] where it is recommended to use normalization per spectral bands, but in this project normalization per pixel values is applied, since it gives better results in case of changing weather conditions during the flights. The exact formula for normalization used in this project is the following:

Where - the value of the pixel in the spectral band , - the total number of bands and - normalized value of the pixel in the spectral band . Figure 8 shows mean normalized spectral values averaged from hyperspectral airborne data per tree species for the reference trees in different test polygons.

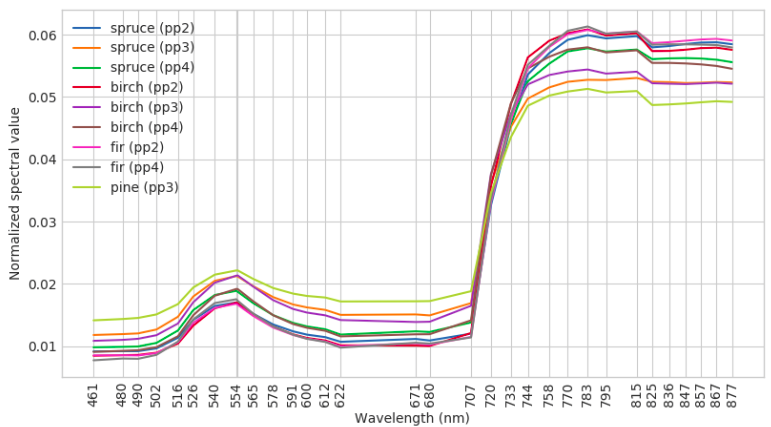


Figure 8. Mean (normalized) spectral values of the reference trees for four tree species in different test polygons using hyperspectral airborne imagery.

In terms of the multispectral satellite data, 8 features were extracted, following the same normalization process as for hyperspectral imagery. Figure 9 shows mean normalized spectral values averaged from multispectral satellite data per tree species for the reference trees in different test polygons.

1. **Results**

Performance of the classification algorithms is estimated using leave-one-out cross-validation (LOOCV) scheme, which is a special case of cross-validation when each sample is used for validation exactly one time. The following two metrics are calculated in order to compare the algorithms: Overall Accuracy (OA) -- the proportion of correctly classified samples and F-score -- harmonic mean of precision, and recall:

where *N* -- the total number of samples, *TP* -- the number of true positive classifications, *FP* -- the number of false positive classifications, *FN* -- the number of false negative classifications.

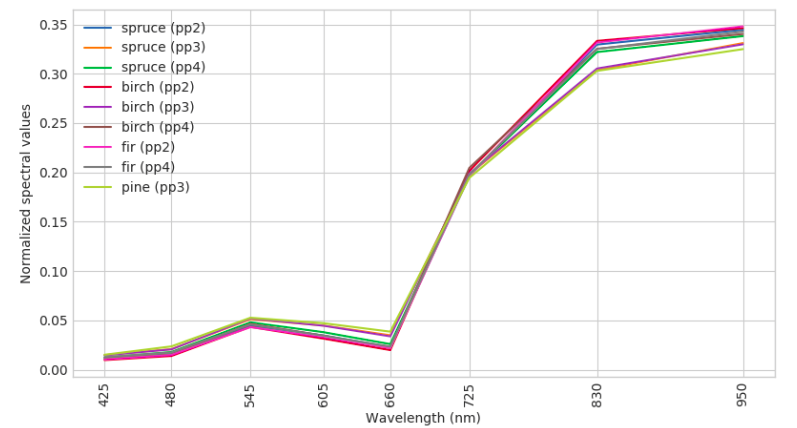


Figure 9. Mean (normalized) spectral values of the reference trees for four tree species in different test polygons using multispectral satellite imagery.

Table 3 contains *OA* and *F-score* values for different classifiers on cross-validation when using different crown area sizes for features extraction. As shown in Figure 10 and Figure 11, the optimal radius for RF and SVM is 0.8 m and 0.4 m respectively.

Table 3. Cross-validation results

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | **HSI** | **SAT** |
| Random Forest | OA (%) | - | - |
|  | F-score | 181 | 41 |
| SVM RBF | OA (%) | - | - |
|  | F-score | 181 | 41 |

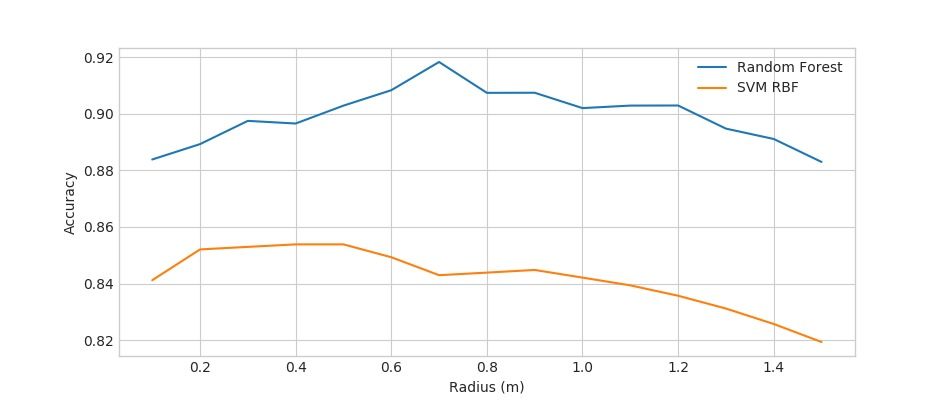


Figure 10. Classification accuracy for hyperspectral airborne imagery in LOOCV with RF and SVM, using a step size of 0.1 m.

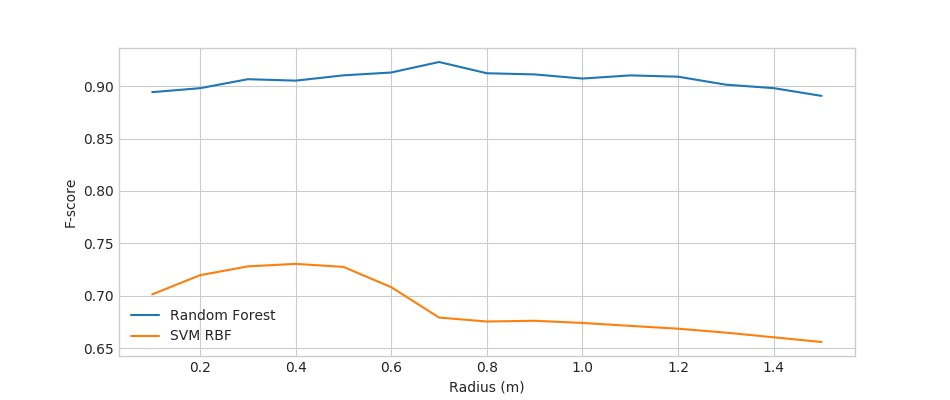


Figure 11. Classification F-Score for hyperspectral airborne imagery in LOOCV with RF and SVM, using a step size of 0.1.



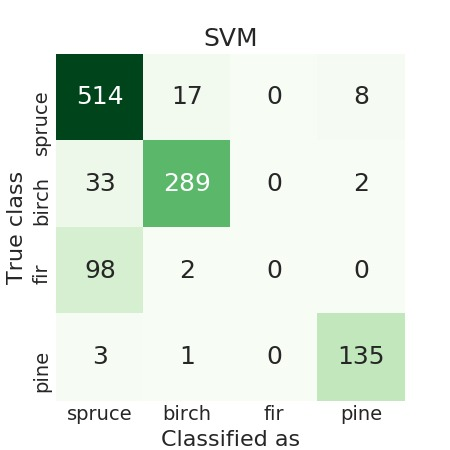
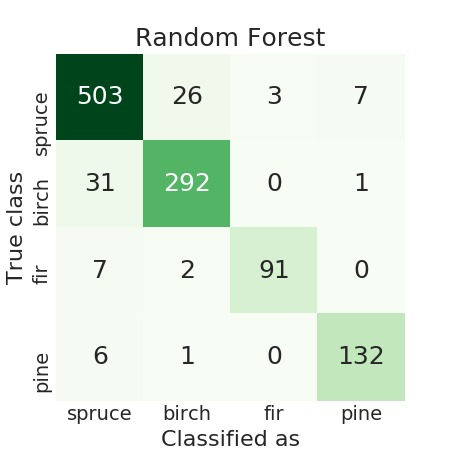
Confusion matrices for Random Forests and SVM classifiers, using its corresponding optimal circle radius tree crown area are calculated for hyperspectral airborne imagery (Figure 12) and multispectral satellite imagery (Figure 13).

Figure 12. Confusion matrices using hyperspectral airborne imagery

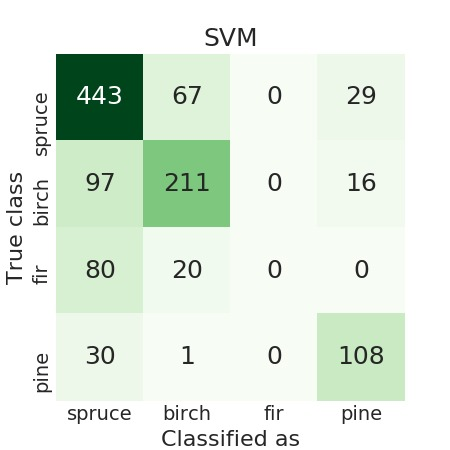
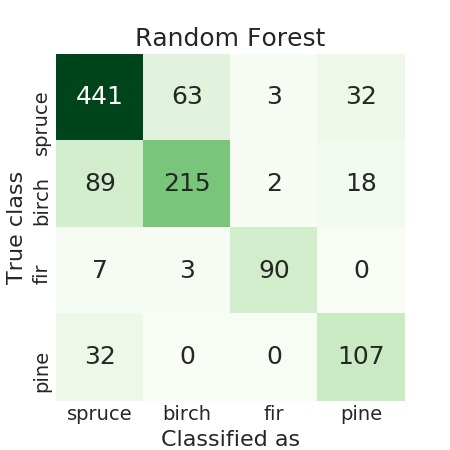


Figure 13. Confusion matrices using multispectral satellite imagery

Spectral bands importance for tree species classification task is estimated using recursive feature elimination(RFE) procedure for the case of the best performing algorithm on cross-validation, which is RF classifier with upsampling of Fir samples using 1.0 m radius circle area of a tree crown for features extraction according to the experiments described above. RFE allows to rank features according to their importance for classification, hence, it is possible to estimate importance of the corresponding spectral bands. Figure 12 (left) demonstrates how classification accuracy changes on 10-fold cross-validation when increasing the number of the most important features from RFE procedure used for classification. In order to estimate relative feature importance values corresponding to different spectral bands, features importance values from one run of RF classifier with the most optimal settings are shown in Figure 12 (right). These features importance values may slightly vary from run to run of RF algorithm since it is a stochastic process, but the general pattern and the ordering stay always the same for the first 6-9 most important spectral bands. RF algorithm with the most optimal settings defined above was chosen to make final tree species classification maps in four test polygons. Firstly, individual trees were identified using the approach described in Section 2.4. Around 70% of the reference trees were detected in 1.5 m far-off the real tree tops. For all of the detected trees in four test polygons, RF classifier with the most optimal settings retrained on the full reference trees dataset was applied calculating hyperspectral features in the same way as it was described in Section 2.5. Table 5 contains the numbers of the detected tree species in each test polygon as well as the mean probabilities of the classification, which represent a confidence of the classifier when making tree species prediction, and their standard deviations. A visual example of trees detection and classification results is presented in Figure

1. **Discussion**

This should explore the significance of the results of the work, not repeat them. A combined Results and Discussion section is often appropriate. Avoid extensive citations and discussion of published literature.

1. **Conclusions**

The main conclusions of the study may be presented in a short Conclusions section, which may stand alone or form a subsection of a Discussion or Results and Discussion section.

**Acknowledgements**

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**Appendix A (Title)**

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**Appendix B (Title)**

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