Evaluation of Sentinel-2 Composited Mosaics and Random Forest Method for Tree Species Distribution Mapping in Suburban Areas of Kyiv City, Ukraine

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Abstract. The availability of comprehensive and cost-effective information on the state of suburban forests and their protection and rational use is necessary for policy makers and urban planners to make informed decisions. The lack of this information can be problematic in their efforts to develop sustainable infrastructure and the local economy while improving the environment and general wellbeing of inhabitants. The recently launched Sentinel-2 satellite presents us with the potential for improving inventory and monitoring of suburban forests. We used spatial and spectral powers of this remote sensing data through a Google Earth Engine platform for creating cloudless seasonal mosaics of Sentinel-2 imagery for the year 2015. The non-parametric Random Forest classification algorithm was used for creating continuous dominant tree species composition raster map of Kyiv suburban forests. The developed methodology, including data collection and analysis showed substantial time-savings compared to traditional inventory methods while achieving high accuracy of trees species mapping (97.8 % of overall accuracy). In summary, our approach could be considered as an application that would greatly satisfy inventory, monitoring and sustainable management of suburban forests.

1. Introduction

Managing urban and peri-urban forests requires comprehensive spatial and biophysical information for ensuring long-term sustainability of these natural spaces. These forests are an integral part of the urban framework and provide social, environmental and economic benefit to its inhabitants. Comprehensive knowledge of the status and trends of species distribution, composition, regeneration, health, growth and development of urban and suburban forests is essential for policymakers and urban planners [1]. Remote sensing technologies provide researchers with an alternative solution for solving forest inventory tasks that are less time-consuming and more cost-effective for medium to large scale analysis.

The scale and detail of mapping have gradually evolved with development of finer spatial and spectral resolutions of sensors. Freely available imagery such as Landsat and Sentinel have been applied for mapping large areas of diverse types of forest cover such as tropical, temperate,

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deciduous, coniferous etc. [2]. Landsat-8 and Sentinel-2 images are also used in mapping land use types for managing natural resources [3]. The recent Sentinel-2 mission, which started in June 2015, provides great potential for the land cover type classification at large and medium scales. Because of its high spatial resolution, wide coverage and quick revisit time (about 5 days), Sentinel-2 offers innovative features for environmental remote sensing techniques and can be successfully used for vegetation sensing, monitoring and forest cover mapping purposes [4]. Recent studies have shown successful use of Sentinel-2 imagery for solving various mapping tasks [5].

Based on time series of satellite images received during one calendar year or longer, various tasks of the thematic classification can be solved. Thus, the annual set of images informs users about phenological changes in the vegetation cover or the seasonal condition of the surface of various objects (e.g. ice, snow cover, arable land, tree species distribution) during the year. However, perennial sets reflect the average long-term dynamics of their spectrum and the most significant changes. Phenological changes help in identifying the differences between similar types of terrestrial cover, and as a result improves the accuracy of the thematic decoding of satellite images. Given the large number of variable required, non-parametric methods provide reliable results without the assumption that the forms of the underlying densities are known, even for arbitrary data sets [6]. Hence, these methods (e.g. Random Forest) provide a simple and effective means for accurately classifying forest types [7].

This research explores the potential gains in using medium to high spatial resolution multispectral imagery provided by the newly lunched Sentinel-2 satellite systems for suburban forest mapping. We hypothesised that using Sentinel-2 multi-temporal multi-seasonal imagery, in combination with the Random Forest classifier, the tree species distribution thematic raster map can be produced efficiently with a high accuracy.

2. Methodology

2.1. Study area

The study area was located in the western part of Ukraine's capital city of Kyiv (50°27′00″N 30°31′24″E), covering approximately 12,510 hectares, of which 11,700 hectares is forest cover (Figure 1). These suburban forests consist of mostly middle-aged, mature and over-mature coniferous and deciduous stands and are managed by Sviatoshynske State Forest-Park Enterprise. The most common forest tree species are Scots pine (*Pinus silvestris*), European oak (*Qurcus robur*), silver birch (*Betula pendula),* European black alder (*Alnus glutinosa*) and poplar (*Populus tremula*). Forest cover control maps were obtained as ESRI ArcGIS shape-files from the official Government Forest Inventory's ("Ukrderzhlisproekt") database.

The territory exhibits a moderate continental climate with relatively high average annual temperature (+6.7 °C) and annual rainfall (400-800 mm), thus suitable conditions for most temperate forests species. The average length of the growing season is 204 days with winter frosts averaging around 140 days. The relief of the study area is relatively flat with altitudes ranging from 130-160 m.

2.2. Field data

Field data were collected in the summer 2014. A total of 31 polygonal plots were established with the average area 0.9 ha and were distributed above the whole study area (Figure 1). We used the Forest Inventory's database to allocate forest polygons occupied by four dominant tree species: pine, oak, birch and alder. The forest stands were selected if proportional basal area of the tree species was more than 90%. We therefore considered only pure forest stands forming four stratums for collecting field data. The sampling plots were distributed proportionally to the total area of each strata using random locations.

Each plot was established using a GPS receiver *MAGELLAN Triton-400*. In each sample plot, the basic forest inventory characteristics were reordered (e.g. dominant tree species, age, diameter at breast height (DBH), mean height, basal area, growing stock volume, etc.). Since forest canopy of approximately 70% and higher was an important criterion of establishing plots. Summarized characteristics of all plots as a training field dataset were organized into a KML-file with the appropriate attribute table for further settings of the classification model.

A total number of 10x10m pixels covered by training polygons was 2790 with the distribution among the main tree species: Scots pine (n=1183), European oak (n=927), silver birch (n=465), and European black alder (n=216). We used random bootstrapped samples of 2/3 of this dataset for the training classifier and 1/3 – in the out-of-bag sample for accuracy assessment.

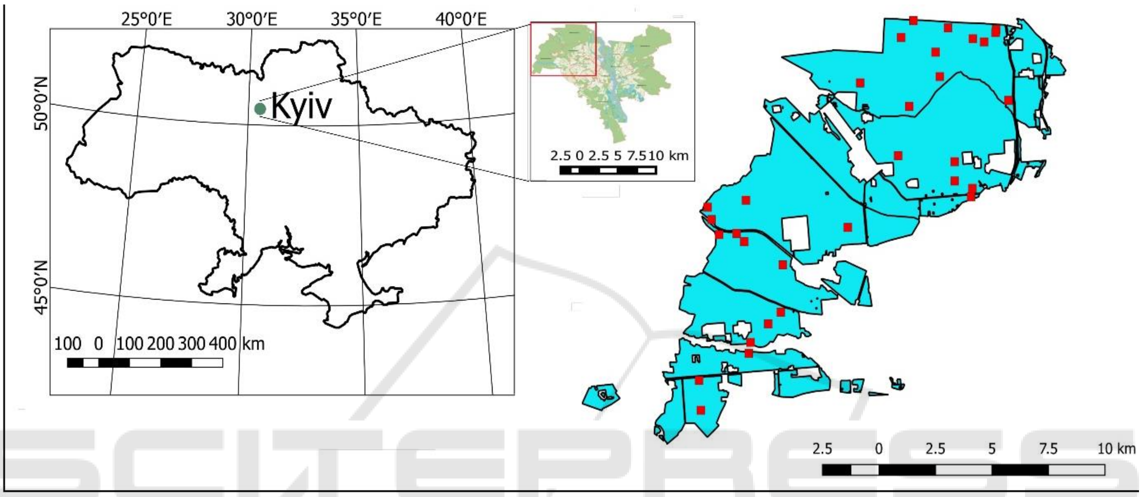


Figure 1. Study area showing a general map of Ukraine (left panel) and close-up panel of Kyiv city and the suburban forest study area in red outline (middle); (right panel) forest cover map of Sviatoshynske Forest-Park Enterprise polygon (in light blue) and sample plots distribution (red points).

2.3. Remote sensing data acquisition and preprocessing

Compilation of the remote sensing data was performed using the Google Earth Engine API (GEE) platform. GEE uses state-of-the-art cloud-computing and storage capabilities that have been archived in a large catalogue of earth observation data [8]. It was accessible to the scientific community to work on petabytes of satellite imagery rapidly using parallel processing [9]. The Sentinel-2 mission, launched on the 23rd of June 2015, was a land monitoring constellation of two satellites (Sentinel-2a and Sentinel-2b) providing global optical imagery with 13 spectral bands using a Multispectral Imager (MSI). Temporal resolution of Sentinel-2 was 10 days with one satellite alone, whereas it would be 5 days with combining two satellites [10]. As a result, it created a large amount of earth observation data with a spatial resolution ranging from 10m to 60m that could be used for several research applications. For our study, we collated Sentinel-2 image data for the period ranging from June 1st – October 31st, 2015. To reduce the influence of atmospheric effects on the classification results, data were collected with a cloud cover of less than 20%.

All selected images were organized in three seasonal cloudless mosaics based on the algorithm that maximizes the effect of pixels with the highest values of the index NDVI and allows for selecting the "best" observations [11]. The three seasonal composites were organized as follows: a) Summer (Su), b) Autumn (Au), c) April-October (ApOc). Accordingly, the series of observations for each spectral channel were selected only for those pixels that did not contain cloud cover. If this criterion for the *i*-th pixel satisfied several images at once, then observations with the largest value of NDVI were chosen. For Su and Au seasonal mosaics, the training sample is formed according to the following channels: Band 4 (red), Band 8 (NIR), Band 11 (SWIR1), Band 12 (SWIR2); channel relations Band 4 / Band 8, Band 4 / Band 12, Band 8 / Band 11, Band 8 / Band 12, Band 11 / Band 12, NDVI index. For the ApOC mosaic, special metrics were selected using the following statistics: the median, the 1^{st} and 3^{rd} quartiles of the bands: Band 4, Band 8, Band 11, Band 12 and the NDVI index. The ApOc approximately corresponds to the growing season in Kyiv region. We therefore aimed to capture the dynamics of spectral features of different tree species within this timeframe (April to October). The mosaics we extracted were three metrics corresponding to the start of the season (1^{st} quartile), middle (median), end (3^{d} quartile). The minimum and maximum values were not applied because they would potentially highlight extreme pixel values. We believe this set of predictors is effective in detecting the seasonal variability of the spectral properties of various categories of the forest cover, particularly in identifying the dominant tree species.

In the GEE computing environment, all characteristics (metrics) of seasonal composite mosaics were composed into one multichannel image with 10m resolution. The total number of channels we selected was 45. Prior to collating the images, each Sentinel-2 image was converted to Top-of-Atmosphere reflectance values to enable supervised classification.

2.4. Settings of the classification algorithm

Given the large number of predictors, exclusively non-parametric methods for classifying satellite images were considered. Recently, the Random Forest (RF) machine learning algorithm has been widely used as an enhancement of traditional decision trees consisting of many of decision trees [12]. For the construction of each decision tree, an individual bootstrap sample (usually two thirds) was drawn from the original dataset (i.e. sampling with replacement). The rest of the observations were used to estimate OBB (out-of-bag) classification errors. Bagging was repeated *n* times, after which results from all classification trees were averaged. Finally, the predicted class of an observation was determined by the majority case from all the decision trees developed within the RF [13].

In the RF method, the decision of classification trees is weakly correlated due to the double realization of a random selection process, i.e. at the stage of the formation of training subsets and the selection of predictors for branching. However, the optimization of the training sample of a large set of predictors is important [8].

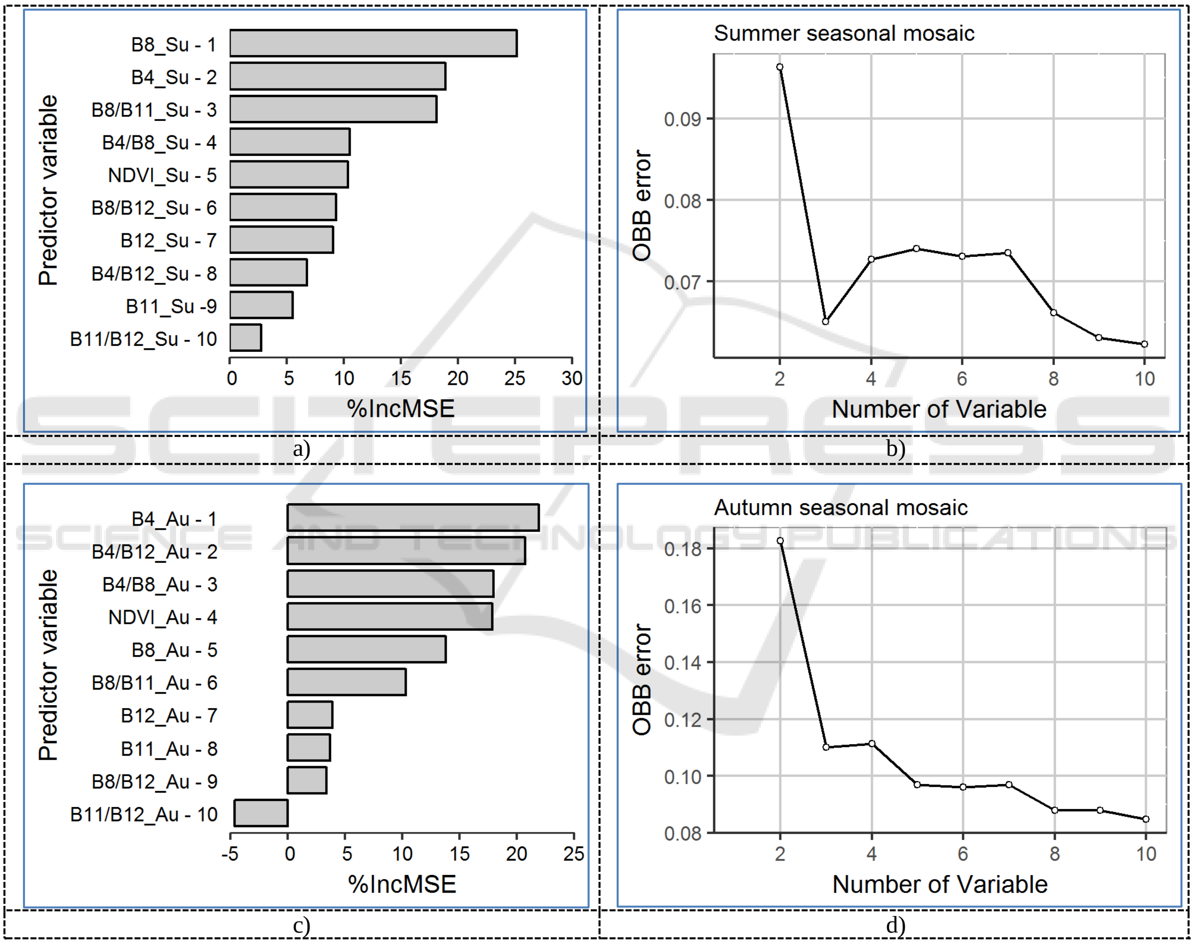
In order to evaluate the relative impact of each predictor on the accuracy of the RF model, the *%IncMSE* indicator was used. It indicates how many percentages the mean square error of classification will increase if we excluded the corresponding variable from the model, and is the most commonly used indicator in studies to interpret the accuracy of RF classifiers [14], [15].

In order to select the optimal values for the parameters of the RF model, we used the *tuneRF* function from the *randomForest* statistical package in the R programming language. The magnitude of the relative influence of the predictors on the accuracy of the classification was estimated by the mean arithmetic error value (OBB error), calculated as a result of 50 repetitive launches of the *randomForest* algorithm. Subsequently, each variable was assigned a rank according to the decrease of *%IncMSE*.

In the first stage, we analyzed how different the accuracy of the classification of individual seasonal mosaics was (Figure 2). The slightest error showed the classification of images of the ApOc period (OBB was approximately 1%), but the two other classifications of seasonal mosaics of Su and Au showed slightly lower accuracy (OBB is approximately 2 and 8% respectively). For some indicators, the *%IncMSE* characteristics acquired negative values and indicated the need to exclude them from the calculations.

In the second stage we used the entire list of predictors for estimating the classification OBB error. Of the 35 variables used, those with the lowest errors were obtained (about 0,1%). This enabled us to determine what the optimal number of variables was and thus provided the highest accuracy of the classification (Figure 3). We can define the needed list of predictors by analysing how the classification error changes with the gradual increase of the number of predictors. To solve this problem, we used the results of the ranking of variables in terms of their contribution to the accuracy of the classification. In our case, it was sensible to choose the first 22 variables because their contribution had the most significant impact on the accuracy, after which the improvement had a little effect. (Figure 3).

Moreover, for the accuracy assessment of the classified study area, the confusion matrix was created on the base of out-of-bag pixels sample that was not included for the training RF classifier (495 reference pixels). As a result, producer's and user's accuracies were calculated for each class as well as overall accuracy and Kappa statistics.



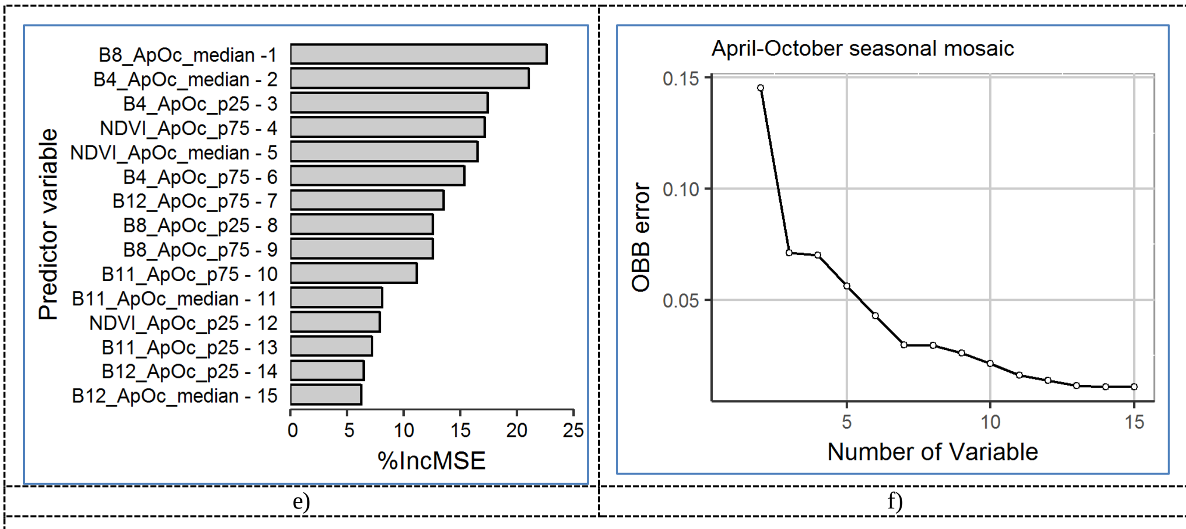


Figure 2. Impact of predictor variables onto the classification accuracy of seasonal mosaics. Left panels (a, c, e) show the ranked predictors' impact onto the decrease of MSE of a model. Right panels (b, d, f) show the relationship between the number of variables and out-of-bag classification error).

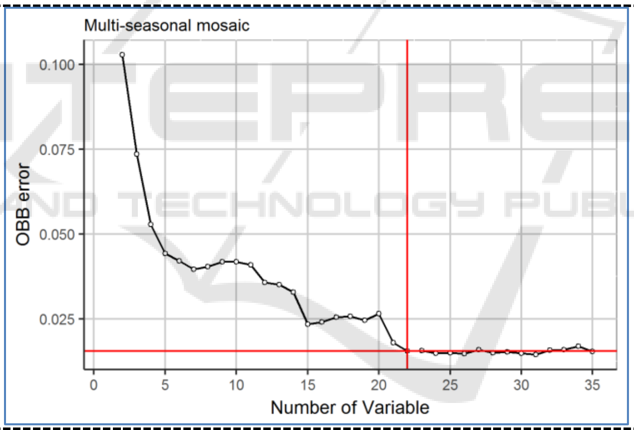


Figure 3. Dependence of the error of tree species distribution classification model (OBB error) on the number of predictor variables. Vertical red line indicates the most efficient number of variables which provide optimal accuracy (horizontal red line).

3. Results and discussion

The study of forest cover area in the Sviatoshynske Forest-Park Enterprise (11,700 hectares) was classified based on the developed random forest classification model and seasonal composite mosaics of Sentinel-2 imagery (22 predictors). As a result, we developed the dominant trees species distribution thematic raster map at 10m resolution (Figure 4). The accuracy assessment of the developed map was performed based on the confusion matrix, which was created from observations of the training sample that was not included in the development of the RF classification model (out-of-bag error). In total, 495 pixels were randomly selected for constructing an error matrix. The overall accuracy of the classification model RF for the entire study area was 97.8% with a Kappa value of 0.97 (Table 1). As expected, accuracy of the coniferous-pine forests identification was the highest (100% for producer's and user's). The classification of European oak and silver birch forests also showed very high accuracies (about 97%). The lowest producer's and user's accuracies were obtained after the identification of black alder forest compartments (87.9 and 82.9%, respectively). Based on the results obtained from seasonal composite mosaics of Sentinel-2 imagery and RF algorithm, we show this method to be an efficient and effective means for medium-scale mapping of dominant tree species distribution with high accuracy. In general, this approach could be considered as meeting expectations for research in this field and has a great potential for future development and applications.

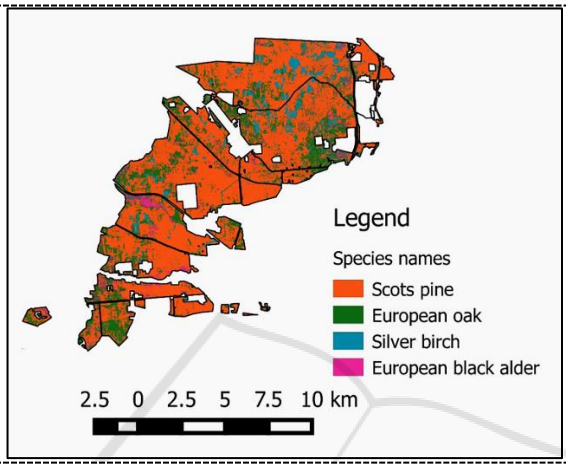


Figure 4. Sviatoshynske Forest-Park Enterprise dominant tree species distribution map.

Table 1. Classification results achieved by RF ensemble learning method for Sentinel-2 seasonal mosaics.

Species name	Prod. acc.(%)	User's acc.(%)	Overall acc.(%)	Kapp Stat.
Scots pine	100	100		
European oak	96.9	97.5		
Silver birch	97.7	98.8	97.8	96.7
Black alder	87.9	82.9		

4. Conclusions

This study assessed the utility of multi-seasonal time-series Sentinel-2 satellite imagery for mapping dominant tree species distribution of Kyiv-city suburban forests, using the Random Forest (RF) algorithm. We concluded that a) the use of Google Earth Engine platform allows us to save a significant time in collating and processing large number of free available Sentinel-2 images; b) RF can be considered a good non-parametric classifier algorithm for tree species composition mapping on the base of seasonal Sentinel-2 image mosaics; and c) with an overall accuracy of 97.8%, we could demonstrate a high potential of Sentinel-2 data for mapping of dominant tree species composition on a medium scale. The described approach could be a foundation for future development and application in suburban forest management system in order to provide sustainable development of urban ecosystems.

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