Methodology For Extracting Poplar Planted Fields From Very High-Resolution Imagery Using Object-Based Image Analysis and Feature Selection Strategy

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Abstract

Poplars (Populus sp.), a tree that grows rapidly species, are significant as industrial forest products. The delineation and monitoring of poplar cultivated areas are invaluable for decision-making processes. With the remote sensing technology, accurate detection of poplar planted areas could be determined much faster, more economically, and with minimum labor requirements. The objective of this research is to create a map of poplar plantations in the Sakarya region of Turkey utilizing Worldview-3 satellite imagery. Object-based image analysis (OBIA) through the application of the multi-resolution segmentation method (MRS) was employed to generate image segments, and then three prevailing machine learning algorithms, namely Support Vector Machine (SVM), Random Forest (RF) and Rotation Forest (RotFor) were implemented to produce LULC maps of the study area including 11 landscape features. The most effective and contributing object features that assure high separability between landscape features were determined using a filter-based Chi-square algorithm for the prediction models constructed with SVM, RF, and RotFor classifiers. Results revealed that the SVM classifier achieved the highest overall accuracy (91.73%) with 38 features out of 88 features, about 3% improvement compared to the other algorithms. According to the SHAP analysis, the IHS feature was the most effective one in the constructed RF model, followed by the CI (red edge), NDVI-1 and NDVI-2 vegetation indices.

1. Introduction

To decrease the strain on forest ecosystems and satisfy the rising demand for wood products, the cultivation of fast-growing tree species, including poplar, has emerged as a prominent worldwide forestry technique (Tonbul et al., 2020). They have become a favored species due to their rapid growth, ease of production and hybridization, easy adaptation to different soil and climatic conditions, abundant species, varieties, cultivars and colonies, and wide range of uses (Ercan 2014). As one of the main sources of productive afforestation worldwide, poplar industrial plantations are planted with thousands of hectares for plywood, round wood, or biomass. Poplar plantings serve as a crucial essential component for timber production and considerably enhance ecosystem functions and ecological services, including biodiversity, carbon sequestration, elimination of waste, and the cycling of nutrients (Isebrands and Richardson, 2014). According to the 2016 report of the International Poplar Commission having 27 member countries; poplar and willow, which are fast-growing species in the world, have a spread of 103 million hectares, 54.5 million hectares of which is poplar cultivations, 8.5 million hectares of which is willow and 1 million hectares of poplar and willow mixed forest. Of the poplar areas in the world, 25 million hectares are located in Russia, 17.3 million hectares in Canada, 10.2 million hectares in the USA and 1.4 million hectares in China. Turkiye ranks the 4th in the world in terms of poplar areas and over 3.5 million m3 of poplar wood raw material is produced annually (Atmaca, 2018).

Today, different methods are used to determine, monitor, and evaluate all kinds of plantation areas and to establish a future perspective. In Turkiye, methods based on field studies and observations have been employed in the determination of poplar fields grown and inventory applications. Although these methods are costly and require high labor force, the consequences vary and are usually insufficient in terms of the generated accuracy (Kunwar et al., 2010). At this point, with the help of remote sensing technology, high-accuracy detection of poplar-planted areas can be determined much faster, economically and with minimal labor needs. The most widely used of these approaches is the use of remote sensing-based image classification techniques (Kavzoglu and Tonbul, 2018). With the help of remote sensing technology, detection of poplar planted areas with high accuracy can be determined with great efficiency. In this context, some important studies have been carried out recently on the classification and mapping of tree species with machine learning algorithms using remotely sensed images. The reliability and accuracy provided by these maps are crucial for the achievement of forthcoming applications at both local and global scales.

Because of the user needs for high-level and reliable information, the focus has recently switched to a new and emerging paradigm, namely object-based image analysis (OBIA). To classify images with a high resolution, OBIA approach exists to manage the intricate hierarchical structure. In contradistinction to the pixel-based image classification, which only considers the spectral information introduced by the image bands or channels, classification in the spatial domain can take into account the shape, size, texture, and patterns of the pixels as determined by some neighboring analyses (Kavzoglu, 2017; Kavzoglu and Tonbul, 2017). It is recognized that in the classification of high-dimensional data, classification accuracy diminishes beyond a certain threshold of dimensionality, a phenomenon referred to as the Hughes phenomenon. For this reason, during the evaluation of the high-dimensional data in question, feature selection is preferred to both reduce the processing load and increase the classification accuracy by avoiding the dimensionality problem. It is crucial to examine the use of high-resolution satellite images and high-dimensional data sets containing auxiliary data, to determine which bands or features contribute the classification accuracy, to regulate the optimum number of bands and to reveal the performance of the classification algorithms according to the selected features.

The objective of the present research was to locate and delineate poplar regions in the Akyazı district of Sakarya province, Turkey, utilizing WorldView-3 (WV-3) imagery. For this purpose, OBIA was applied jointly with SVM, RF and RotFor for producing thematic maps for 11 land cover and land use (LULC) features and thereby mapping poplar cultivated fields. To estimate the most effective object features among the spectral bands and estimated ones, the filter-based Chi-square algorithm was first applied, and thus the most important features were extracted and used in classification stage.

2. Study Area and Data Set

A high-resolution ortho-ready Level-2A WV-3 image that was obtained on August 15, 2021, and is clear of clouds, was downloaded, and used to determine the poplar fields in Akyazı District, one of the regions with the highest number of the poplar planted areas in Turkiye (Fig. 1). The WV-3 satellite has a 0.31 meters spatial resolution panchromatic band. It also includes eight visible and near-infrared bands (i.e., Coastal, Blue, Green, Yellow, Red, Red-edge, NIR-1 and NIR-2) with a spatial resolution of 1.24 meters, and eight shortwave infrared bands (i.e. SWIR-1/2/3/4/5/6/7/8) with a spatial resolution of 3.7 meters.

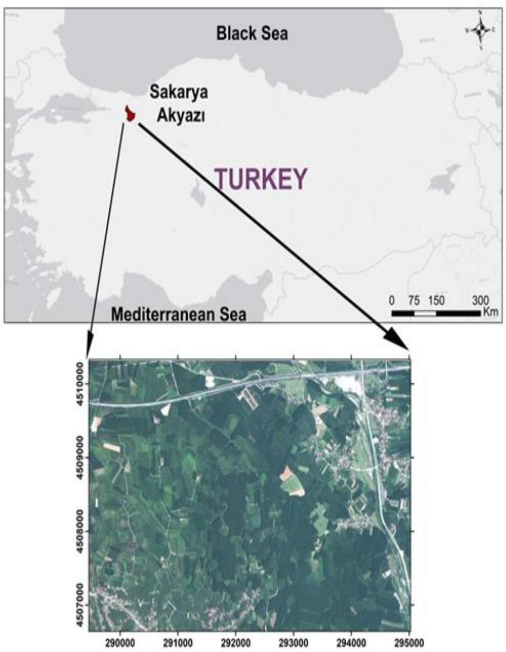

Figure 1. WV-3 satellite image of the study area acquired on August 15, 2021.

The atmospheric correction was applied to the raw pixel values so that the WV-3 image can be used in classification processes. At this stage, the panchromatic and multi-spectral bands of the WV-3 image were first converted to above-atmospheric radiance (TOA) values using the FLAASH module in the ENVI 5.6 program. Afterwards, Gram-Schmidt image sharpening algorithm was performed using SWIR and NIR-2 bands. Once the preprocessing step was completed, the primary training data needed for the classification process was prepared.

In the collection of the real-world reference dataset for the LULC classes in the study region, all samples were collected through in-situ measurements from locations of the LULC classes using GPS and spectral measurements by ASD field spectrometry (Fig. 2). 11 LULC classes covering most of the study site were determined depending on the land characteristics and OBIA was carried out using three different classifiers (Fig. 3). A total of 1,741 image segments corresponding to inventory data were employed in the training stage. Since accuracy assessment was conducted using pixel-wise evaluation, a total of 3,000 test pixels from each class (33,000 pixels in total) were used to estimate the accuracy metrics. At the final stage, the Shapley Additive exPlanations (SHAP) method originating from the game theory was conducted for providing an explainable decision-making mechanism for the fine-tuned classification model (Kavzoglu and Teke, 2022).

Figure 2. LULC classes for the study area.

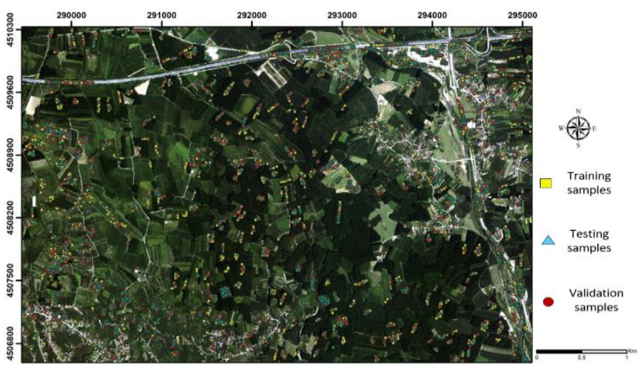

Figure 3. Samples collected within the scope of the study.

3. Methodology

To meet the main objective of this study, mapping poplar plantation areas in an agricultural landscape through a segmentation process, Multi-resolution Segmentation (MRS) was carried out using eCognition software, instead of employing rule set based segmentation. The segmentation process was then followed by the computation of object features. In the classification stage, three machine learning methods were applied to conduct LULC classification based on segment features.

In the method of training of machine learning model training, a supervised classification process is aimed, and the parameters of the models are determined by grid-search method. In addition, the processes used in this methodology are performed using Python language. To achieve this goal, OBIA approaches via three ensemble machine learning classifiers, such as SVM, RF and RotFor were used to produced thematic maps of the research location. To decrease the computation burden, minimize the dimensionality effects and produce high-accurate thematic maps, a feature selection process through Chi-squared algorithm was applied to the dataset. Following the creation of resulting thematic maps, the confusion matrix was formed and accuracy metrics, including both individual (the accuracy of producer and user, - F-score) and overall accuracy measures (overall accuracy and Kappa coefficient), were estimated.

3.1 Image Segmentation Using OBIA

OBIA has the capacity to handle more challenging image analysis tasks and generate thematic maps with higher accuracy. Due to its effectiveness in providing improved and reliable geospatial intelligence, it has gained popularity and drawn considerable interest in the scientific community (Kavzoglu, 2017; Kavzoglu and Tonbul, 2017). As one of the most widely used segmentation methods in literature, the MRS algorithm was utilized in this investigation (Baatz and Schäpe, 2000). It uses local homogeneity criteria to create image segments. Starting with a single pixel, it combines resembling pixels of various sizes, shapes, and characteristics into image objects until they achieve a user-defined homogeneity level or threshold. This leads to the determination of the maximum permitted heterogeneity for the created image objects. The three basic factors that make up the MRS process are scale, shape, and compactness. The mean object size is effectively controlled by the scale parameter (Kavzoglu and Tonbul, 2018). The size of the objects increases with high scale values. The shape parameter influences class separation considering color and texture information. On the other hand, the compactness parameter determines whether the borders of the image objects are sharper or softer. It should be noted that the shape and compactness parameters have values between 0 and 1.

3.2 Feature Selection

In this study, the chi-square algorithm, a widely used filter-based feature selection algorithm in the literature, was used to select the most important or contributing features for providing high separability between the landscape features. The algorithm is based on the chi-square (χ^2) statistic, and it evaluates each feature independently according to the class labels (Plackett, 1983; Sahin et al., 2017). The test examines the distribution of values of classes in a band. As the calculated statistical value increases, it means which the assessed feature includes more useful information about the LULC classes. The null hypothesis is that there is no correlation. In other words, the value in a certain band belongs to only one of the classes. The χ^2 statistic measures how far the true value is from the expected value as shown in Equation 1.

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{n_c}\frac{(O_{i,j}-E_{i,j})^2}{E_{i,j}}, \tag{1}$$

where r is the number of different values in a feature (band), n_c is the number of LULC classes, $O_{i,j}$; the observed number of pixels with i value in class j and $E_{i,j}$ represents the expected number of samples with class j and value i.

3.3 Machine Learning Algorithms for Classification

In recent years, machine learning algorithms including support vector machines, neural networks, random forest, and deep learning have been widely employed in the classification of image since they are good at discovering the hidden and inherent relationship in the data sets. Moreover, multiple learning algorithms have been used in ensemble approaches to improve the prediction accuracy. The ensemble methodology relies on the use of multiple classifiers and combining their output by employing voting procedures (Kavzoglu, 2017). Three machine learning algorithms, namely SVM, RF and RotFor were utilized in this study to classify segmented image segments according to their properties.

SVM is a method for classifiers that has found extensive application in the classification of satellite images, with its effectiveness in classification demonstrated by several researches (Kavzoglu et al., 2015; Norman et al., 2020). It is a new generation classification algorithm based on non-parametric and statistical learning theory. The basic working principle of the algorithm is based on the determination of a hyperplane that can optimally separate the pixels of the two classes from each other. The main classification problem considered in the development of the SVM algorithm is the process of classifying the data set containing two classes and having a linear structure. At least two support vectors are required for problem-solving, but in practice, a much larger number of support vectors is considered (Mether and Koch, 2011).

The RF algorithm, a popular ensemble learning algorithm, uses decision trees as the base classifier. The algorithm uses more than one decision tree in the training phase and can be defined as a decision tree forest with this structure. In the RF algorithm, random subsets are generated from the original training dataset for training each decision tree in the forest. While 2/3 of these subsets are used to construct the decision tree structure, the other part is used to test the validity of the tree structure. Each decision tree in the forest receives one vote as a result of classification, and the tree structure that is the basis for classification is established by determining the one with the most votes (with the lowest error rate) from all trees in the forest. Any instance (pixel) whose class label is unknown is classified by assigning it to the class with the most votes in all tree predictions (Breiman, 2001).

The RotFor algorithm, which was introduced as a new generation ensemble learning algorithm, is based on the creation of the classifier ensemble using a feature extraction technique, specifically principal component analysis (Kavzoglu and Colkesen, 2013; Tonbul et al., 2018). The fundamental operational concept behind the algorithm resembles that of the random forest method. However, the data set to be used in the training of each decision tree in the forest is subjected to the principal components. With the RotFor algorithm, during the training phase of the decision trees in the forest, the training dataset is split into random groups, and feature extraction is performed using principal component analysis on each group. As a result of feature extraction, the features (i.e., bands) with the highest distinctiveness are determined. All components are considered to preserve the variability information in the dataset. With feature extraction, diversity is preserved for each classifier in the classifier set.

4. Results

OBIA was carried out using a WV-3 image to extract poplar areas in Akyazı District of Sakarya province. The image segmentation process was performed with MRS algorithm. At the end of the segmentation process, a total of 133,949 image segments were obtained. The ESP-2 tool developed by Drăgut (2014) was employed to identify the most proper scale parameter for performing the segmentation stage and thus the optimum scale value was determined as 40 (Figure 4). It should be noted that the compactness and shape were arranged to 0.7 and 0.5, respectively after a trial-and-error strategy applied. After the image objects were created, the properties of the image objects to be used in the classification stage were determined. In this study, a total of 88 image object features were selected from the WV-3 image in the first place. These features were brightness, mean, minimum, maximum, standard deviation and GLCM texture values, NDVI-1, NDVI-2, Green Chlorophyll Index (GCI), Red Edge Chlorophyll Index (CI red edge), IHS, length of pixel, and area of pixel. In the feature selection stage, a statistical-based chi-square algorithm determined 38 features, which were subsequently used as input to the machine learning algorithms in the classification stage. All available features and the selected ones were shown in Table 1. Classification was performed with machine learning classifiers using the selected features. The parameters of the classifiers were determined using a grid search optimization method.

Feature	**B-1**	**B-2**	**B-3**	**B-4**	**B-5**	**B-6**	**B-7**	**B-8**	**B-9**	**B-10**	**B-11**	**B-12**	**B-13**	**B-14**	**B-15**	**B-16**
Min.								✓	✓	✓	✓	✓	✓	✓	✓	
Max.	✓	✓	✓	✓	✓	✓	✓	✓				✓				
Mean			✓	✓		✓	✓	✓		✓		✓				
Std. Dev.				✓			✓	✓								
GLCM homogeneity		✓				✓	✓								✓	✓
NDVI-1									✓							
NDVI-2									✓							
GCI									✓							
CI (red edge)									✓							
Brightness																
IHS									✓							
Length of pixel																
Area of pixel									✓							

Table 1. Features used in the OBIA process using WV-3 image of Akyazı district of Sakarya province.

Class	**SVM**			**RF**			**RotFor**		
	Producer's Accuracy	***User's Accuracy***	***F-Score***	***Producer's Accuracy***	***User's Accuracy***	***F-Score***	***Producer's Accuracy***	***User's Accuracy***	***F-Score***
Hazelnut	95.9	87.9	91.7	88.5	74.3	80.8	91.0	85.0	87.9
Corn	82.8	97.1	89.4	70.1	93.3	80.1	75.9	92.0	83.2
Pasture	89.3	92.2	90.7	86.9	91.0	88.9	87.1	90.1	88.6
Poplar	93.0	92.7	92.8	95.1	85.8	90.2	92.8	91.2	92.0
Red Roof	97.9	92.8	95.3	96.0	92.5	94.2	97.4	92.0	94.6
Shadow	96.5	94.1	95.3	97.5	96.1	96.8	96.8	95.4	96.1
Road	70.8	90.3	79.4	71.9	86.2	78.4	71.6	83.9	77.3
Bare Soil	87.3	97.1	91.9	89.9	91.5	90.7	84.0	95.1	89.2
White Roof	96.2	67.9	79.6	90.1	73.3	80.8	95.8	73.0	82.9
Water	99.5	95.3	97.4	98.9	97.6	98.2	98.9	99.2	99.0
Young Poplar	98.8	95.5	97.1	99.7	74.3	85.1	99.3	92.7	95.9
Overall Accuracy (%)		91.73			87.38			88.95	
Kappa Coeff.		0.90			0.87			0.88	

Table 2. Object-based classification results.

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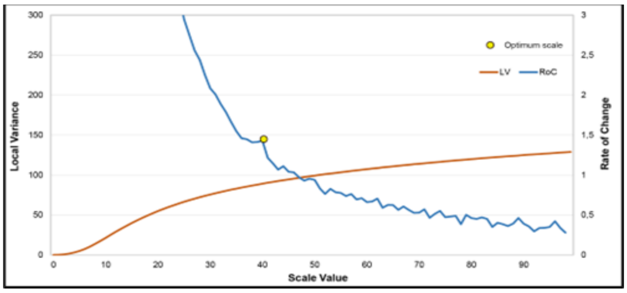

Figure 4. Optimum scale estimation using ESP-2 tool.

Accuracy assessment was conducted on the test data sets using confusion matrices (Table 2). The WV-3 image was employed to produce thematic maps, which yielded an overall accuracy of more than 87%. While the SVM algorithm produced the highest overall accuracy (91.73%), for the RF algorithm, the lowest accuracy was determined to be 87.38%. When the F-score values of LULC classes were examined, it was found that the highest accuracy (92.8%) of the poplar class was obtained with the use of SVM algorithm, and the highest F-score value (97.1%) for the young poplar class was also produced by the SVM algorithm. The thematic map produced by the SVM algorithm is shown in Figure 5. When the figure is analyzed, the LULC classes are generally classified correctly, but the classification errors occur between man-made structures, such as the road and the white roof. As a result, a total of 601 ha of young and mature poplars were determined by the classification process using WV-3 image in the mid-vegetation period. SHAP analysis, which estimates the predicted marginal contribution of a feature relative to all characteristics, was utilized to elucidate the significance of the features in the RF classification outcomes (Fig. 6). The SHAP summary plot displays the most notable characteristics in descending order, highlighting each feature's contributions to the classifier. It exhibits the characteristics on the x-axis, the estimated Shapley values on the y-axis, and the color indicates the extent of influence on LULC classes. The colors indicate various LULC classes in the plot, allowing for a detailed interpretation of the influence of each feature on LULC classes through the classification stage. The plot illustrates that IHS produced a stronger impact than the others, succeeded by the CI (red edge), NDVI-1, and NDVI-2 vegetation indices, signifying that variations in this feature can significantly affect the outcomes. However, GLCM features indicating the texture characteristics were ranked in the least effective ones together with standard deviation of bands 4 and 7 (Yellow and NIR-1).

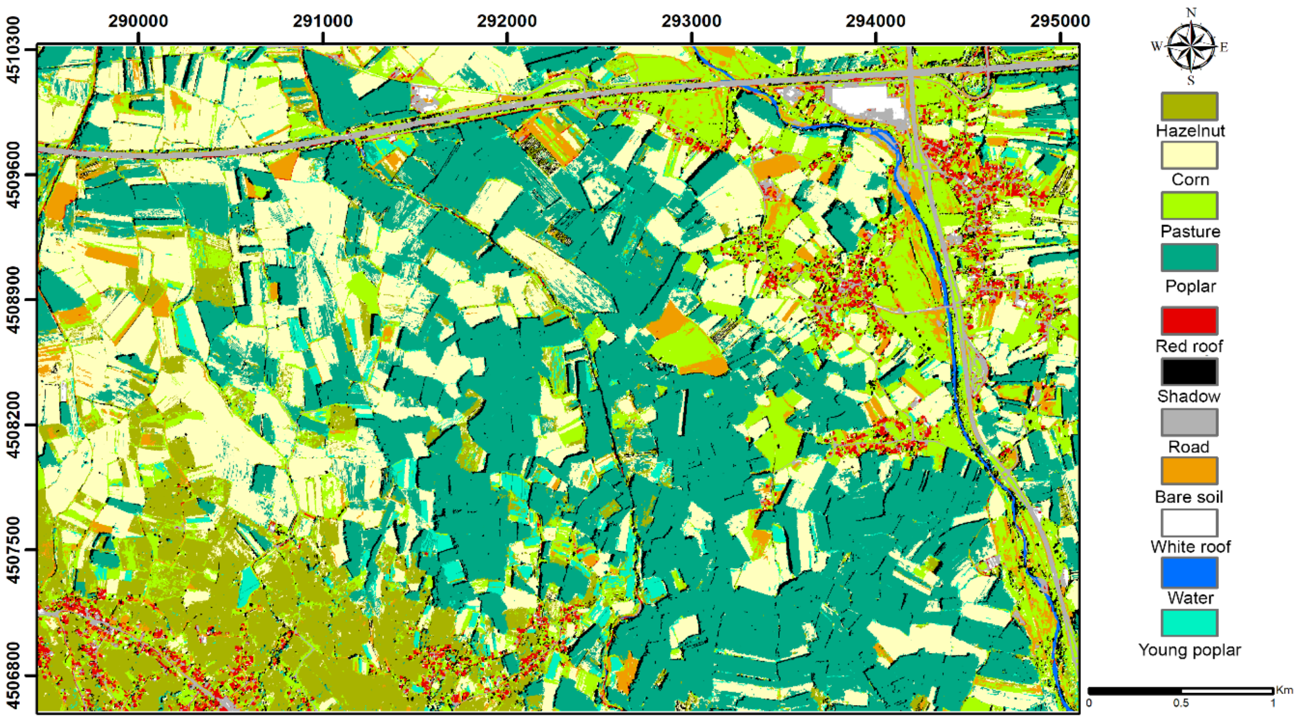

Figure 5. Thematic map of the object-based SVM classifier obtained using WV-3 image of Akyazı district of Sakarya province.

5. Conclusion

Poplar that is among the fast-growing forest types is a tree species that has an important economic value and is cultivated industrially in Turkiye. In this context, it is of great importance in terms of sustainable land management to continuously monitor the industrially planted poplar trees by making inventory planning and examining their spatial distribution (Ateşoğlu et al., 2022). As a result of the study, results of this study showed that the classification results using object-based SVM, RF and RotFor machine learning classifiers and Chi-square feature selection algorithm gave high-accurate results, successful delineating the poplar planted areas. When the performances of the classification algorithms are examined, it was determined that the SVM classifier provided approximately 3% higher overall accuracy compared to the RF classifier. In addition, WV-3 image with the high spatial and spectral resolution was found to be very informative and valuable to distinguish poplar species from the other LULC types and thus identify poplar cultivated areas. Finally, SHAP results revealed that vegetation indices and IHS transformation was the most effective features in the discrimination of LULC classes whilst the texture information estimated through GLCM homogeneity (average value of all directions) and variabilities from the mean of bands 4 and 7 were the least effective ones. To improve the quality of the results with higher individual class accuracies, a region-based multi-scale approach suggesting the utilization of various scale values estimated for each LULC class can be adopted into the OBIA framework in future studies (Kavzoglu et al., 2017; Kavzoglu et al., 2016).

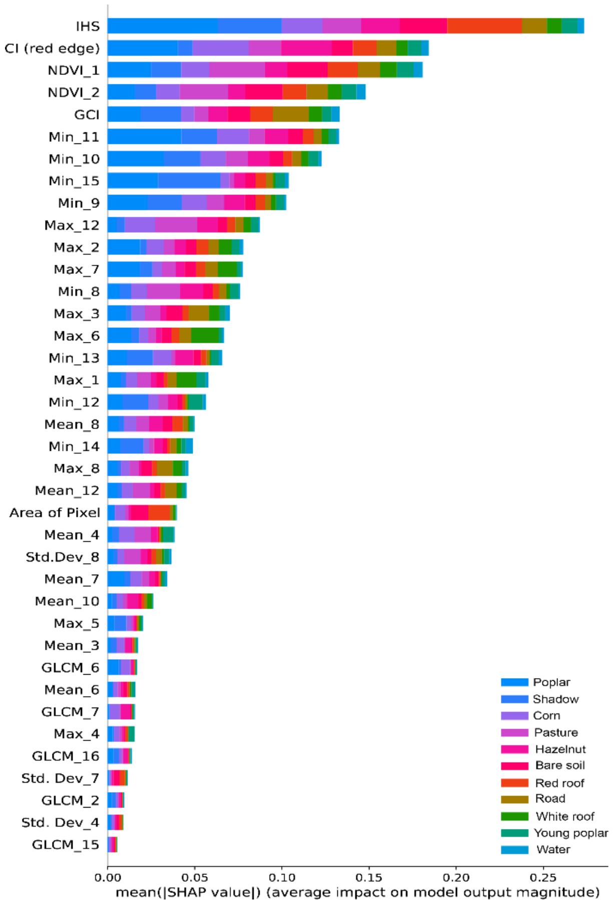

Figure. 6. SHAP graph illustrating the importances of features for RF classification.

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