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Species Level Classification of Mediterranean Sparse Forests-Maquis Formations Using Sentinel-2 Imagery

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Essential forest ecosystem services can be assessed by better understanding the diversity of vegetation, specifically those of Mediterranean region. A species level classification of maquis would be useful in understanding vegetation structure and dynamics, which would be an indicator of degradation or succession in the region. Although remote sensing was regularly used for classification in the region, maquis are simply represented as one to three categories based on density or height. To fill this gap, we test the capability of Sentinel-2 imagery, together with selected ancillary variables, for an accurate mapping of the dominant maquis formations. We applied Recursive Feature Selection procedure and used a Random Forest classifier. The algorithm is tested using ground truth collected from site and reached 78% and 93% overall accuracy at species level and physiognomic level, respectively. Our results suggest species level characterization of dominant maquis is possible with Sentinel-2 spatial resolution.

Keywords: Mediterranean forests, maquis, random forest, Sentinel-2, image classification

Introduction

Sustainable Forest Management (SFM), which encompasses a wide spectrum of concerns, from timber to non-timber forest products, and further towards forest related ecosystem services and functions (Wang and Wilson, 2007), requires management of the regenerative capacity of forests for an array of demands of goods (i.e. timber, food) and services (i.e. water regulation, soil protection) for current and future generations (MacDicken et al., 2015). To fulfil these requirements, it is important to understand the diversity of forests for three reasons. First, the compositional and structural diversity of forests serve multiple ecosystem services (Lindenmayer et al., 2000; Burrascano et al., 2011). Second, the composition and structure of forests are important indicators to be monitored for guiding the adaptive management imposed by SFM (Rist and Moen, 2013). In this context, the composition and structure of maquis (defined here as a dense evergreen sclerophyllous cover of small trees and shrubs at various heights and densities) correspond to various stages of regressive succession and degradation (Tomaselli, 1977; Scarascia-Mugnozza et al., 2000). Third, diversity contributes to the resilience of the system (Ciancio and Nocentini, 2004), and it is important to identify the ecologically vulnerable and resilient sites, a crucial topic in Mediterranean because of its susceptibility to fire, degradation, and desertification, as a direct consequence of climate change (Peñuelas et al., 2010).

Despite management shifts towards a SFM perspective, the planning process and inventory principles largely continue to be tied to the conventional methods. National Forest Inventories (NFI) and derived management maps are still dependent upon timber increment interest (Laamanen and Kangas, 2011) and only partially meet the requirements of a sustainable management perspective (Siry et al., 2005; Groot et al., 2015). This is especially evident in Mediterranean sparse forests characterized by tree canopy closure of less than 10% while maquis generate a dense vegetation layer underneath. To classify, plan and manage such ecosystems considering only the sparsely distributed tall trees but ignoring the shrub/small tree layer causes a serious shortcoming due to several reasons: (1) maquis play an important role in ecosystem functioning since they prevent soil erosion (Gabarrón-Galeote et al., 2013), (2) enhance soil quality (García-Orenes et al., 2012), (3) control surface runoff (Casermeiro et al., 2004) (4) create a microclimate for further vegetation generation (Tomaselli, 1977), (6) enhance overall biodiversity (Goberna et al., 2007) and (7) provide indispensable economic resources to local livelihoods, i.e. non-timber forest products such as seeds, fruits, gums, resins, dyes, medicines and aromatic plants (Özturk, 1995; Palahi et al., 2008).

Forests in the Mediterranean basin cover approx. 88 million hectares (FAO, 2018) and according to Bontemps et al. (2011) sparse trees (including shrublands and grasslands) cover across 17.7% of the Mediterranean basin. Turkey's Mediterranean region covers 5.7 million hectares of forest where 41.85% belong to "sparse forest" and are managed as if only tall trees (eg. *Pinus brutia*) exist (GDF, 2019). However, according to the SFM principles, it is necessary to map the maquis distribution and incorporate their compositional diversity into management practices. Since recreating the maps that reflect the complex structure of maquis via surveys is impossible, remote sensing should be employed for this purpose.

The use of remote sensing techniques to delineate maquis is not a novel attempt for the Mediterranean region. Earlier efforts comprise: (1) land use change detection (Sluiter and de Jong, 2007; Tzanopoulos and Vogiatzakis, 2011), (2) vegetation mapping (de Jong and Burrough, 1995; Grignetti et al., 1997), (3) assessing vegetation dynamics (Kadmon and Harari-Kremer, 1999) particularly during recovery from fire (García and Caselles, 1991; Laurin et al., 2018), (4) detection of the flammability for fire management (Koutsias and Karteris, 2003; Bajocco et al., 2017), (5) biomass estimation (Calvão and Palmeirim 2004, Meer at al., 2001) and (6) monitoring land degradation and restoration management (Fava et al., 2016). However, in all previous studies in our knowledge, maquis were treated as a single group (Telesca and Lasaponara, 2006; Bajocco et al., 2012) or they were classified into maximal three categories on the basis of height (Maselli et al., 2000), density/coverage (Laurin et al., 2018) or physiological classes (*maquis/garrrigue/phyrgana*) (De Jong and Burrough, 1995; Esbah et al., 2010). Only Manevski et al. (2011) applied a species level classification scheme based on field spectrometry that requires costly fieldwork.

This study introduces a detailed species level classification scheme for the dominant maquis species (*Genista acanthoclada*, *Erica* spp., *Phillyrea latifolia*, *Quercus* spp., *Olea europea* and *Arbutus andrachne)* based on Copernicus Sentinel-2 time series and a machine learning approach. As a multi-spectral satellite constellation Sentinel-2 provides an opportunity for heterogeneous forests with its 10 m resolution and the short revisit cycle of five days. Applying a multi-temporal methodology helps to catch the spectral variances in phenology and thus increase accuracy in vegetation mapping (Grabska et al., 2019). Due to these reasons Sentinel-2 imagery has been widely used in the forestry sector to classify tree species composition (Immitzer et al. 2016, Persson et al. 2018; Kampouri et al., 2019), quantify forest extent (Suresh and Hovenbitzer, 2018), estimate above ground biomass (Chang and Shoshany, 2016; Laurin et al., 2018), and monitoring forest disturbances from fire (Colson et al., 2018) or logging (Lima et al. 2019).

The main objective of this study is to map the compositional diversity in complex Mediterranean maquis ecosystems with high accuracies based on Sentinel-2 images, and ancillary data. The specific aims comprise:

(1) to create a species level classification for maquis in order to increase our knowledge in compositional data, especially for the relevant formations “sparse forests” in forest stand maps, although they are maquis from an ecological perspective,
(2) to present a semi-automated approach based on open software and freely available global remote sensing data to guarantee that the method can be applied to similar formations over large areas in the Mediterranean region and easily be repeated for monitoring purposes,
(3) to assess the explanatory power of remote sensing and ancillary features in the context of the present mapping task.

The contributions of this paper to the state-of-the-art are as follows:

(1) It is a pioneering study that shows the feasibility of remote sensing methods to species level maquis classification using machine learning techniques and ancillary data in addition to satellite multi-temporal images,
(2) It introduces new features designed to accentuate the subtle spectral differences among maquis species,
(3) It determines the remote sensing variables along with anciellary variables, that has a significant effect on species distribution in maquis.

Materials and Methods

Overview

In this study, a workflow (Figure 1) to produce an accurate and detailed composition map for Mediterranean woodlands, which distinguishes six dominant maquis species was developed. Since no detailed information about maquis distribution at the species level exists, a field survey was carried out to collect Ground Truth (GT) data. The main focus of the field survey was laid on “sparse forests” in NFI where the tree canopy cover is marked as less than 10%. Then, based on orthoimages, GT polygons were delineated around the sampling points. Finally, Sentinel-2 imagery Level 1C products for the time period between 01-01-2016 and 30-05-2019 were acquired via Google Earth Engine (GEE), which is a cloud computing platform for geospatial analysis which has been widely used to monitor deforestation, disaster risk, food security, etc. at the global, regional and local scales (Gorelick et al. 2017).

In addition to remote sensing features such as original spectral bands and spectral indices, also ancillary data such as soil type, geological information, bio-climatic surfaces and topographic variables were prepared and in total, a set of 44 features were used. Multi-collinearity was reduced by applying a feature selection procedure that identified the 20 most important variables. We applied a Random Forest (RF) classifier (Liaw and Wiener, 2002) with 10-fold cross-validation using R 3.3.2 (R Core Team, 2017) and Caret Packages (Kuhn, 2008).

The Study Area

Köyceğiz Forest Management Unit is located between 36.77 - 37.12^{0} E and 28.41 – 29.07^{0} N in the southwestern part of Turkey (Figure 2a) and covers 118,081 hectares. Elevation starts from sea level and reaches up to 2296 m above sea level (a.s.l.). 44.9% of the unit is under various protection status (National Park, Specially Protected Area and Wildlife Reserve) due to the region’s ecological significance for threatened species. A mosaic of freshwater, coastal, and woodland habitats contributes to the exceptional biodiversity of the region. The mean annual temperature is 18.3°C, while the absolute minimum and maximum temperatures are -7.0°C and 43.0°C, respectively, and the annual mean precipitation is 1032 mm (Turkish State of Meteorological Service, 2016). Wooded vegetation covers 74.7% of the area and are composed mainly of *Pinus brutia* (81.8%) and *P. nigra* (19.5%) woodlands, of which approximatively a quarter is managed under the “sparse forest” label (GDF, 2013). The maquis vegetation starts from the sea level and reaches up to 1000-1200 m. a.s.l. (Davis, 1965). A heterogeneous composition of maquis forms a multi-layered vegetation structure in the region. The study area hosts many maquis species in diverse physiognomic stages: dense and open shrublands (<2m) of *Genista acanthoclada* and *Erica* spp.; low tree formations (>5m) of *Olea europea*, *Arbutus andrachne, Phillyrea latifolia* and *Quercus* spp. Apart from these dominant species other characteristic species include *Juniperus, Cotinus, Ceratonia, Cistus, Daphne, Laurus, Myrtus, Pistascia* and *Sarcopoterium* spp.

Material

Field Survey and Ground Truth Polygon Drawing

The field survey was carried out to collect the GT reference data in August 2018. Prior to the survey, the canopy closure information of the study area was derived from forest management maps produced by the GDF (2013). Sparse forests with less than 10% canopy closure were marked and the fieldwork was carried out within this boundary (Figure 2b-c). If any maquis species covered more than 60% of the patch and with a minimum radius of 10-15 m, then the centre of the vegetation cluster was geolocated by GPS and the maquis patch’s radius was recorded for further polygon drawing. Habitat and specimen photos were taken at each location. **Considering the time and labor constraints, we decided to collect a high number of samples that represent all dominant formations of the study area instead of only using few samples from a completely random design. Kadmon (2004) states that if a geographically biased (i.e. roadside) dataset is relatively unbiased as far as it reflects the environmental gradients of the study area, then accurate results are achievable. When we plot histograms of elevation as a major environmental gradient for the ground truth points (n = 375) and sparse forests, we assume except for the highest elevations, our sampling adequately reflects the present environmental heterogeneity (Figure 3).**

Following the fieldwork, GT polygons were drawn by visual interpretation by means of RGB orthophotos of the year 2013 with 90 cm resolution and the photographs taken during the survey. Species classes with samples less than 10 polygons were eliminated from the sample set (e.g. *Laurus nobilis*, *Myrtus communis* and *Cistus sp.*). Figure 4 shows the eight different maquis species used in the classification scheme. Their abundance and coverage reflect the dominance of each species within the studied stands.

Remote Sensing Data

Sentinel-2 Level 1C images between 01-01-2016 and 30-05-2019 were acquired from GEE. The images more than 20% cloud coverage were eliminated from dataset. Totally 167 distinct days were derived for two Sentinel-2 tiles (T35SPA and T35SPB) (Figure 2b). A further cloud mask and shadow mask were applied at the pixel level (Chastain et al. 2019). Sentinel-2 bands B2, B3, B4, B6, B8, B9, B11, B12 (corresponding to blue, green, red, red edge 2, NIR, water vapour, SWIR1 and SWIR 2 respectively) were used in the analysis.

Ancillary Features

Apart from RS features, 25 environmental features in total (Soil-1, Geology-1, Bioclimates-19, Emberger-1, Topographic-3) were prepared to precisely model the distribution of maquis. This type of environmental features are frequently used in species distribution models (Morin et al., 2007). Several studies revealed the usefulness of combining remote sensing features with the environmental features at species level vegetation mapping (Zimmermann et al., 2007), especially in larger scales where the characteristics of the study area cannot be distinguished by moderate scale RS images alone (Engler et al., 2013). In Mediterranean region, many studies reveal the limiting factors of plant growth as the precipitation, the soil depth and formation (Di Castri, 1981; Sluiter and De Jong, 2005).

Table 1 lists the potential features used in this study. Soil and geology polygons were rasterized and other raster layers were resampled to 10 m resolution, which is the highest spatial resolution of Sentinel-2.

Method

Feature Extraction

The pixel values of each raster layer were computed for each GT polygon. Since the digestible Sentinel-2 library in Level 2A was limited in GEE, we used Level 1C images. These images are neither atmospherically nor radiometrically corrected, so a $\pm 3\sigma$ outlier removal algorithm was applied to remove extreme radiometric effects in the daily time series image dataset. Then, polygon spatial means of original image bands (B2, B3, B4, B6, B8, B9, B11, B12) and representative subset of Spectral Indices (SI) (Table 2) were computed. Spectral indices are frequently used for vegetation, soil and water body mapping and comprise band ratios, where confounding issues such as atmospheric effects or soil background reflectance are reduced (Meyer et al., 2019).

The phenological traits such as leaf senescence, colouring, flowering, etc. of each species might enable to filter ideal dates or seasons for remotely sensed data acquisition (Gärtner et al., 2016). This is particularly challenging since the focal species are evergreen sclerophylls and some of them present similar morphological features and biomass accumulation (*Quercus coccifera, Q. infectoria, and Phillyrea latifolia*). To perceive the reflectance behaviour of the target species and understand the subtle differences among each other, the time series of indices are plotted on a monthly basis (Figure 5). In this step, after assessing the distributions visually, and considering their relatively smaller representations in the GT, we grouped the above three species into a single class named "*mix*", hence the final classification is based on six maquis species classes. Furthermore, seven additional spectral features were calculated (Table 2) to accentuate the phenological differences between certain species. In total, 21 features were extracted for each GT polygon: annual median values for eight basic spectral bands, annual mean values for six spectral indices, and seven newly computed indices inferred from time series graphs of spectral indices.

Random Forest Classification

Random forest (RF) (see e.g. Breiman, 2001) is a fast and powerful machine learning algorithm that successfully overcomes high dimensionality and multicollinearity, thus intermittently used in both regression and classification problems (Colditz et al., 2015; Räsänen et al., 2013). The RF model was run in R software (R Core Team, 2017). Major RF tuning parameters have been set to default values as suggested by Belgiu and Drăguţ (2016). Such that; *mtry* (Number of variables randomly sampled as candidates at each split) is equal to the square root of the total number of features, and *N* (number of trees to grow) is set at 500.

Feature Selection

RF's variable importance approach is highly beneficial for ranking features, applying stepwise approaches, and setting certain thresholds to feature space. By means of these, it is possible to find out (1) respectively correlated variables, (2) explanatory features for the prediction, and (3) to optimize the feature space with the minimum number of variables (Genuer et al., 2010). Feature selection is an important step for machine learning applications (Kohavi and John 1997). In total, 46 remote sensing and environmental features are computed. Inherently some of them might be highly correlated with each other, so to highlight the indispensable features, feature selection algorithm was applied. In this study, we applied a wrapping approach, i.e. Recursive Feature Selection (RFE) as described in Gregorutti et al. (2017). RFE uses a backward iteration approach and it is highly capable of removing noisy and highly correlated features. The RF classifier is trained and feature ranking is computed by permutation importance. As a consecutive step, the least important features are eliminated and this recursive process is repeated until all the features contribute significantly to the model (Gregorutti et al., 2017).

Accuracy Assessment

We applied 10-fold cross-validation to provide an unbiased estimation of RF model performance based on the entire sample of the limited GT set. To assess the accuracy of the output classification a further independent validation was applied by placing 500 random points within sparse forest stands. By visual interpretation we categorized each point by means of orthophotos. However due to the limitations in delineating maquis we labelled these points as either trees or shrubs, thus a physiognomic ontology was produced (tree and shrub) which is also highly beneficial in understanding the dynamics of various vegetation stages. The classification map was also grouped namely, shrubs (*Genista* ssp, *Erica* ssp, Mix) and trees (*Olea europea*, *Arbutus andrachnea*, *Pinus brutia*). The classification map predicted by the model were compared to these independent random set and assessed with the accuracy statistics aforementioned above.

Results

Classification map

The species level classification map of the maquis is presented in Figure 6. The most widespread species is *Genista acanthoclada* (34.4%), followed by the "mix" class (26.6%), *Erica sp*. (15.9%), *Arbutus andrachne* (7.9%) and *Olea europaea* (3.3%). Although these vegetation types are labeled as "sparse *Pinus brutia* forests" by the foresters, our study reveals that pines only cover 11.8% of the masked area.

Classification Accuracy

Species Level Classification Accuracy

Overall accuracy (OA) of the model is 0.78 and Cohen's kappa coefficient (K) is 0.73 (Table 3). For each class, the accuracies are greater than 0.70. The classes *Genista acanthoclada* and *Pinus brutia* achieved highest accuracies indicating a successful classification. Commission errors are in the range of 0.0% to 28%, with the largest error for *Pinus brutia* and the smallest for *Olea europea*.

Physiognomic Classification Accuracy

The species level classification can be easily adapted into a physiognomic classification which is a basic way of describing the vegetation condition. This scheme is useful for various application areas in forestry and restoration ecology. Furthermore, with this generalized categorization, we produced an independent sample set that enables further validation. To assess map accuracy at the physiognomic level, an independent validation set was generated that is based on 500 randomly selected points and labelled by image interpretation. Table 4 shows the accuracy metrics of this independent validation set on physiognomic level. OA is 0.93 and the K value is 0.86. These results confirm that this classification is highly capable to discriminate the physiognomic (shrub-tree) stages of the maquis.

Explanatory Features

The RF classification for six species of the maquis enables to assess the power of the predictor features. The total number of features used in the final RF model generation is assessed by RFE performance. To reduce the effect of fluctuations in the performance of the RF caused by the random nature of the algorithm, the model is run 12 times with different seed values and the results are averaged. Figure 7 represents the relative contribution of features to the model accuracy. Trend lines are depicted on the curve and the first intersection is observed around 20 features. The intersection point illustrates that the first 20 features seem to be highly important (steep trend line). Using more than 20 features results in an almost horizontal trend line and feature importance even begins to decline.

As for variable importance, spectral indices appear to be the most important features with the blue band (B2). Visible (red, green and blue bands), NIR and SWIR spectrum of Sentinel-2 also contribute to the model. On the other hand, red edge spectrum is eliminated. With respect to characteristics of the evergreen species, the mean annual indices are more descriptive than specific seasonal features such as Feat 2, 4 and 1. Among the ancillary variables, geology, soil, BIO19 (Precipitation of Coldest Quarter), BIO12 (Annual Precipitation) and DEM (elevation) are prominent (Figure 8).

Discussion

Utility of the Classification Map

This study presents an algorithm to classify six species of maquis and contributes to a consistent solution to the problem of classifying complex woody vegetation in the Mediterranean ecoregion. Thus, the output of this research is of great importance and will enable to develop an enhanced ecosystem management and policy, in particular SFM at stand level in Turkish Mediterranean region. Moreover, the use of freely available and high-quality multi-temporal Sentinel-2 images offers new perspectives to discriminate maquis vegetation down to the species level. The spatial resolution of the map (10 m) is sufficient to discriminate the composition of most maquis types. Although higher spatial resolution might produce even better classification results at the species level, the current resolution is absolutely sufficient for forest management units to infer management decisions. The potential utility areas of species and physiognomic level maps are suggested in Table 5.

RS based classification is more successful when most pixels are pure, i.e., composed of one single class only. However, even for tree species classification, it remains challenging to find pixels consisting of a single tree species and/or single age class (Fassnacht et al., 2016). Also in our study, obtaining pure sample points consisting of a single maquis species was not always feasible due to the heterogeneous and inherently mixed maquis vegetation with varying heights. To overcome this problem, we focused on patches dominated by a single species (>60% cover of a single type of vegetation) and generated target classes accordingly. Although canopy closure for each class is even, the height of target species varies significantly for some of the classes. The greater variance occurred for oak species (between 1 and 10 m), probably due to their specific management (coppice regime or grazing pressure) in the past. *Phillyrea latifolia* also vary substantially in their height (between 0.6 m and 5 m). The vertical leaf area density of those species changed during their life cycle and thus might affect classification performance.

Another issue is the spectral inter class variability due to the clutter caused by the bare soil or other plants underneath the target species (Fassnacht et al., 2016). In our case, presence of bare soil causes problems for the classes *Genista acanthoclada* and *Erica* spp. However, other maquis plants and herbs contributing to the mixture in the sampling locations of other classes (i.e. *Arbutus, Olea, Quercus* etc.) are the major challenge and increase intra-class variability. In order to reduce the background signal (clutter) caused by bare soil, we chose sampling locations with canopy closure higher than 75%. We tolerated the natural variability caused by species heterogeneity as typical characteristics of the Mediterranean region and did not further categorize or eliminate species classes to remove this effect.

Similar to the findings of Manevski et al. (2012) obtained with field spectrometer, VIS and SWIR are highly prominent for the maquis species. This is especially evident for *Olea europea* in our study. Similarly *Genista* and *Erica* classes are well distinguished (Table 5).

Classification Accuracy

Our classification for both species and physiognomic levels are highly accurate. In general, the accuracies are higher in biomes which have lower biodiversity (Fassnacht et al., 2016). As Mediterranean maquis has high biodiversity, we found it more applicable to compare our results with the similar studies conducted in the Mediterranean region. The classification schemes, spectral and spatial resolutions of imagery used and classification algorithms vary greatly in previous literature. Nevertheless, Table 6 presents a comparison, with an emphasis on the accuracy statistics.

To increase the accuracy and usefulness of the classification map we recommend three issues regarding the sampling set. The acquisition of sampling set is a time and money consuming process and a relatively subjective task (Belgiu and Drăguţ, 2016). We collected 382 samples from 11 different maquis types. However, as aforementioned above, we could not draw polygons for every sample point and include that number (382) of training samples in the classification scheme. Recording the locations of cluster centres just as points is not a good sampling methodology for the Mediterranean region where the spatial heterogeneity is high. For some of the target species visual interpretation is hardly possible at the inter-specific level (e.g. between *Quercus* and *Phillyrea*, or between *Erica* and *Genista*). The easiest case of discrimination by photo interpretation is between *Olea* and *Arbutus* due to different hues of their leaves. Also, the shadows generated by the taller trunks of *Olea* and *Arbutus* are easily discriminated from shrub formations.

A further limitation is in the evenness of the remaining samples. RF classifier is less sensitive to imbalance in training, noise in the training set or overfitting problems (Belgiu and Drăguţ, 2016). However, the distribution of samples within the training set might improve the performance of the model. Colditz (2015) suggested that the best accuracy was reached by the generation of area-proportional allocation of training samples over classes, i.e. more samples allocated for commonly occupied classes. On the other hand, Jin et al. (2014) showed that the area-proportional allocation reduced the commission error and the equal allocation of classes reduced the omission error for low-represented classes. While noting these findings, we again underline the complex vegetation patterns in our study area. Given in Figure 4, the widespread species are *Genista acanthoclada, Erica sp.* and the rare ones are *Phillyrea latifolia*, *Q. coccifera* and *Q. infectoria*. On the other hand, due to the species community traits, some of them generates wide clusters (*Genista acanthoclada, Erica sp.*) on the other hand for some species it was hard to find even 100 m^2 coverage (*Q. infectoria*). We followed the area-proportional allocation guides, our sampling scheme reflects the plants' occurrences.

However, there are several other species such as *Laurus nobilis*, *Myrtus communis*, and *Pistacia terebinthus* in the study area but they do not cluster explicitly or show dominance and also they are very rare in the study area. Since, we note these species as minorities or odd distributions during the field survey, we dismiss their representation in the sample set. In further studies detection of these rare species should be targeted as they have a potential to contribute to the local livelihoods as non-timber forest products. These shortcomings in the sampling set might be improved with more intensive fieldwork.

Explanatory Features

Although RF is insensitive to high dimensionality, an iterative backward selection is highly recommended (Belgiu and Drăguţ, 2016). With the optimization of feature space, the predictors with substantial importance were identified, so we can understand the main drivers of the species distribution and prevent the overfitting problem caused by a limited number of samples in relation to the number of predictor features, as well as prevent multicollinearity.

Remote Sensing Features

The important wavelength regions are VIS and SWIR which explains the reaction of plant pigments and water content (Schmidt and Skidmore, 2003; Fassnacht et al., 2016; Manevski et al., 2011). Similar to Pu and Liu (2011) and Waser et al. (2011)'s findings, the blue wavelength region is remarkable to the construction of the model. This might be related to the lower photosynthesis in the blue light. The least important portion of the wavelength is red edge spectrum which is also noted in the study of semi-arid woodlands' tree classification (Peerbhay et al., 2014).

Grignetti et al. (1997) highlighted the autumn and winter periods as the best seasonal descriptors for maquis. On the other hand, Calvão and Palmeirim (2004) recommended the summer period to better discriminate between sclerophylls and semi-deciduous scrubs. Our results revealed that the annual mean features are more descriptive than specific seasonal descriptors, i.e., Feat 1-7 inferred from time series graphs in our case.

Ancillary features

In this study, the use of ancillary features substantially increases model performance. Single use of spectral features is not able to reflect the high environmental heterogeneity of the study area. These findings support Sluiter and De Jong (2005); they also suggested that the spectral confusion in heterogeneous vegetation patterns can be overcome by adding ancillary data. The depth and type of soil bounds the niche for particular maquis species (e.g. Rundel et al., 2016). Another limitation in plant growth is the precipitation (Pausas, 1999). Thus, geology, soil type, annual precipitation (BIO12), the precipitation of coldest quarter (BIO19) and elevation appear as important features in Figure 8in terms of variable importance.

Conclusions

As an important ecological formation, maquis provide substantial services such as soil protection, runoff control or the provision of non-timber forest products to Mediterranean communities. Therefore, maquis ecosystems should not be ignored in the context of climate change because the forest trees are highly prone to climate change and interlinked to land degradation and desertification process. Their high biodiversity, various fire and drought prone traits may enhance resilience of Mediterranean region.

In the present study a detailed classification for Mediterranean maquis was developed based on a machine learning approach and freely available multi-temporal Sentinel-2 images that meets the requirements for a future Sustainable Forest management. The classification approach enabled to distinguish between six maquis classes and produced 78% overall accuracy. An additional output of the approach was the identification of required spectral indices, spectral bands and environmental factors a successful classification for typical Mediterranean maquis region. Our results demonstrate that several prominent maquis species can be successfully discriminated with remote sensing.

Based on the promising results, we anticipate that increasing the number of samples in low represented classes will further improve the accuracy of the classification product. Existing forest inventories, focusing only on the presence of a few woody tree species in Turkey, have to be improved and adapted by better reflecting the diversity of maquis ecosystems,

The increasing availability of remote sensing products and the launch of user-friendly data downloading and processing tools such as the cloud sourcing platforms (Google Earth Engine) will provide a common basis to improve our knowledge on understanding the complex ecosystems and will enable us to test the performance of the model in the wider Mediterranean Basin. Also the ingestion of Sentinel-2 Level 2A images, when available, into GEE may increase accuracy of species classification.

Disclosure statement

No potential conflict of interest was reported by the authors.

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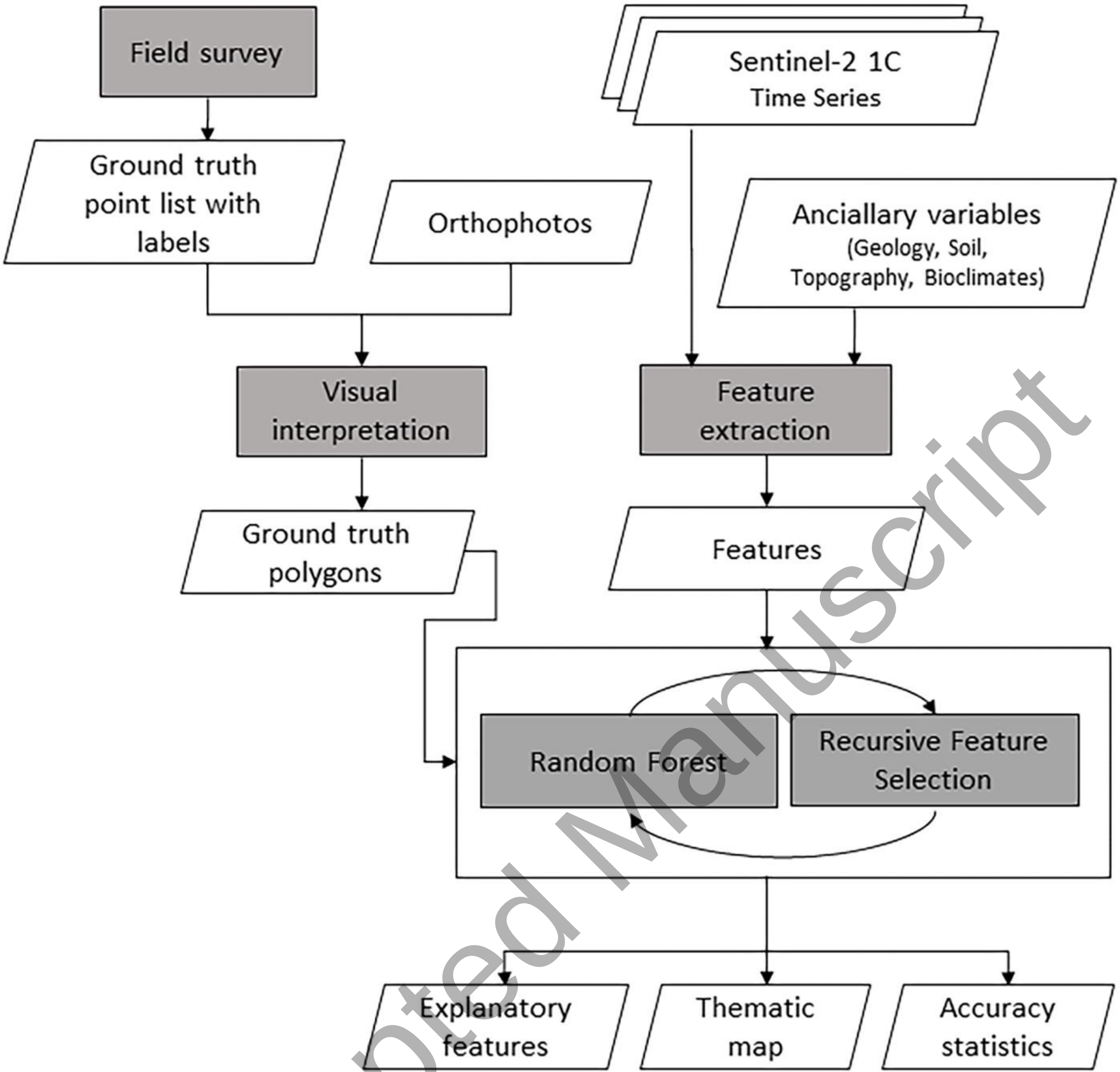

Figure 1. Workflow for the classification (Grey rectangle denotes process and rhomb denotes data)

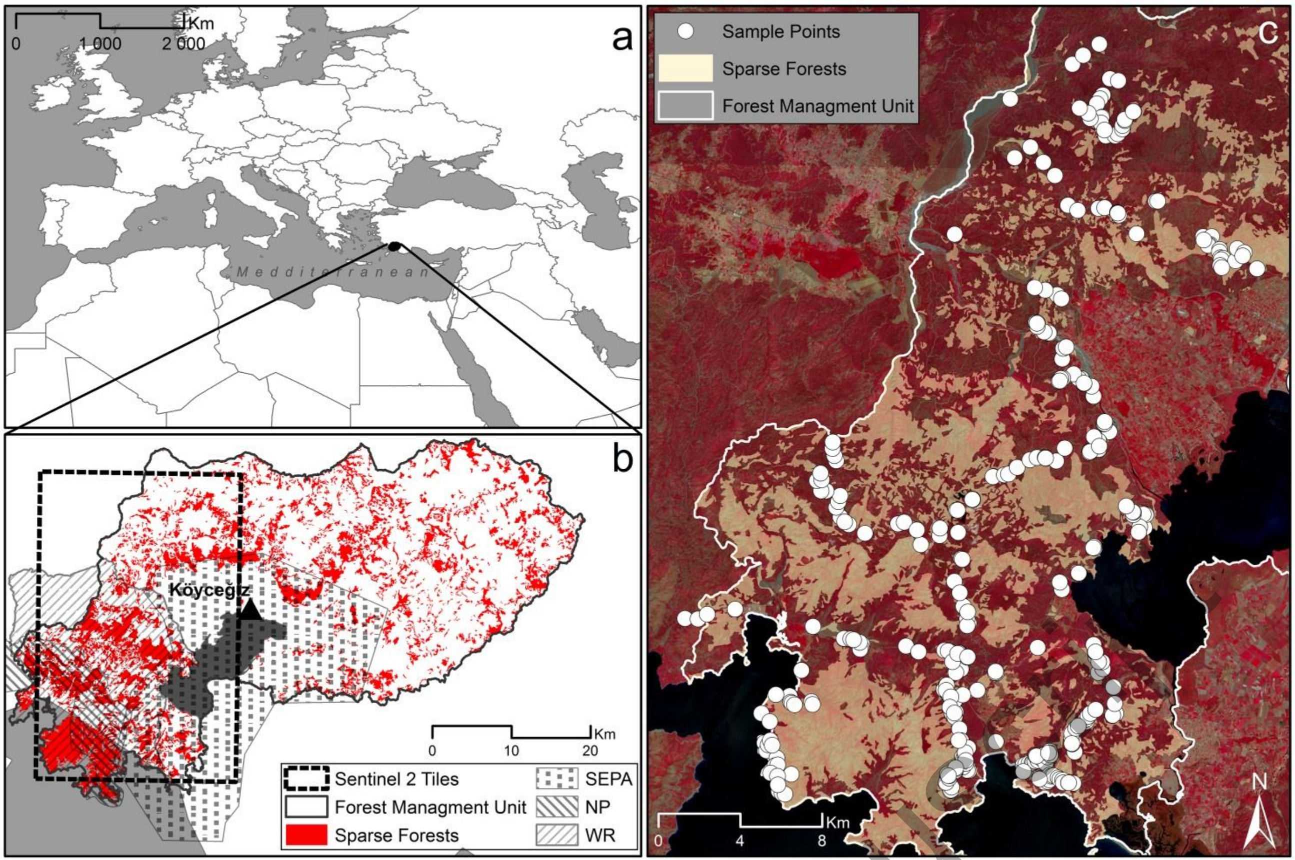

Figure 2. The study area and the sampling points within the "sparse forests" a) The location of the study area, b) Dark grey polygon: Köyceğiz Forest Management Unit. Red polygons: "sparse forest" stands identified in stand management maps. Dashed lines: various protection status (SEPA: Specially Environment Protection Area, NP: National Park, WR: Wildlife Reserve. c) White dots: sampling points.

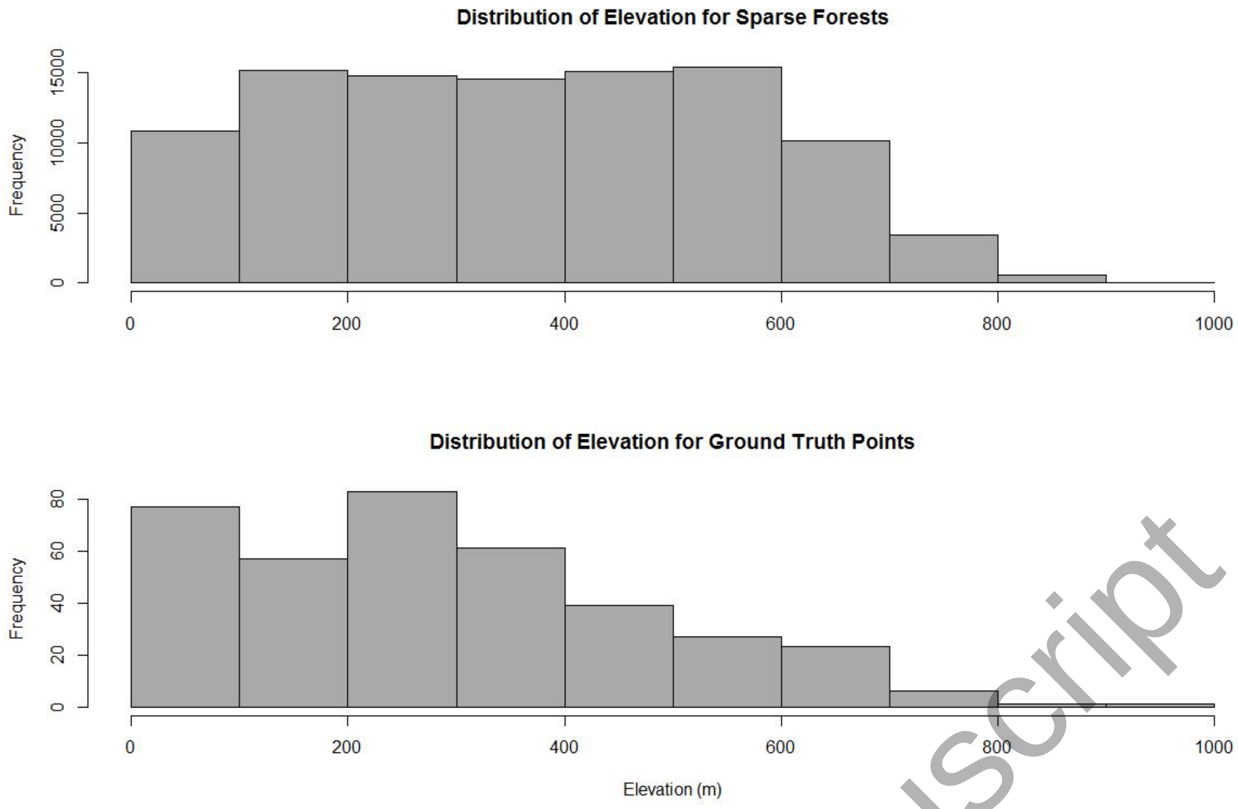

Figure 3. Histograms of elevation classes for sparse forests (upper) and 375 ground truth points (lower).

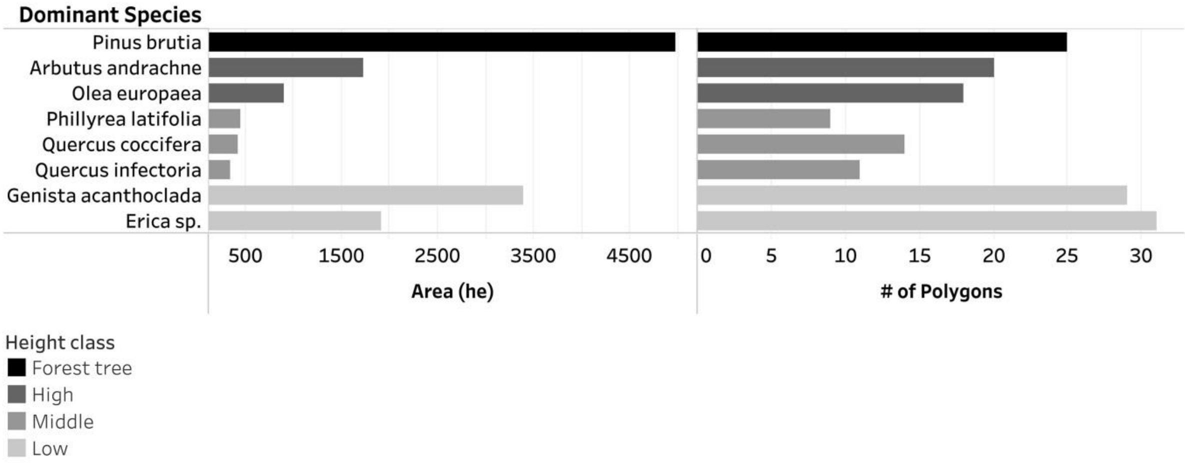

Figure 4. Distribution of ground truth polygons among the eight species classes.

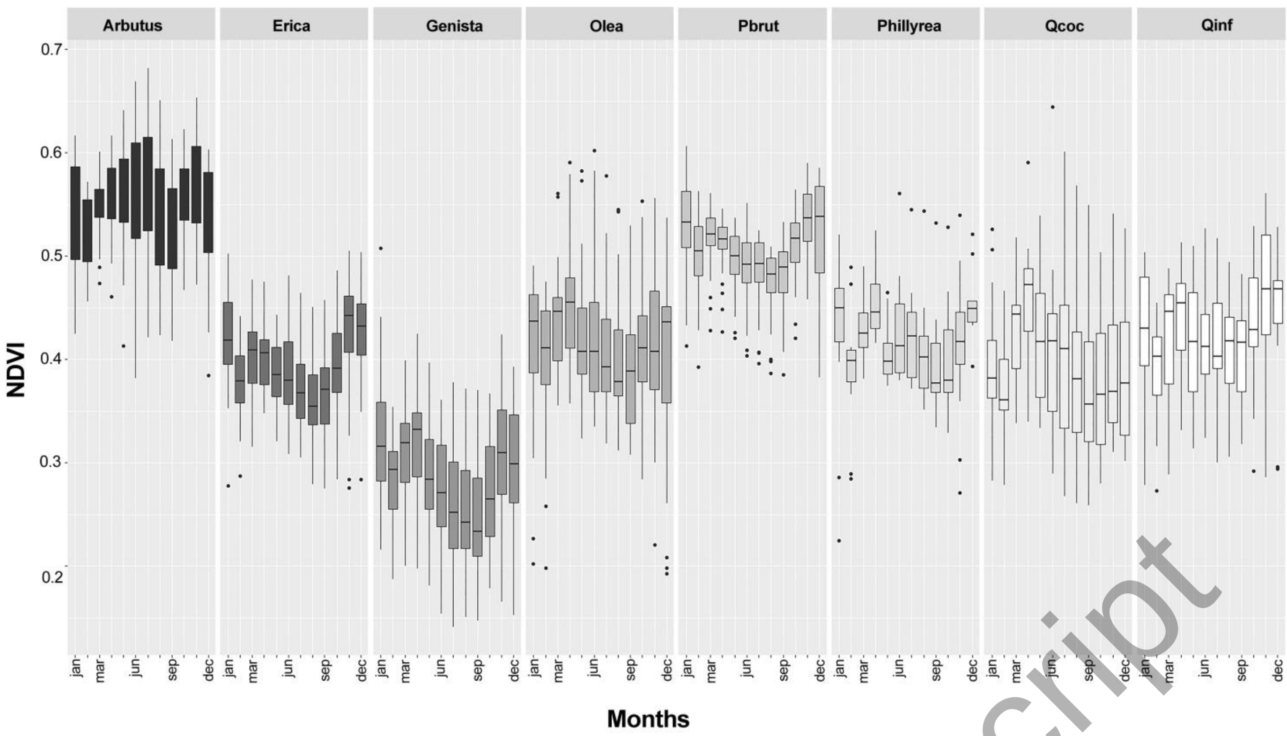

Figure 5. NDVI values distribution per month for each of the eight vegetation classes.

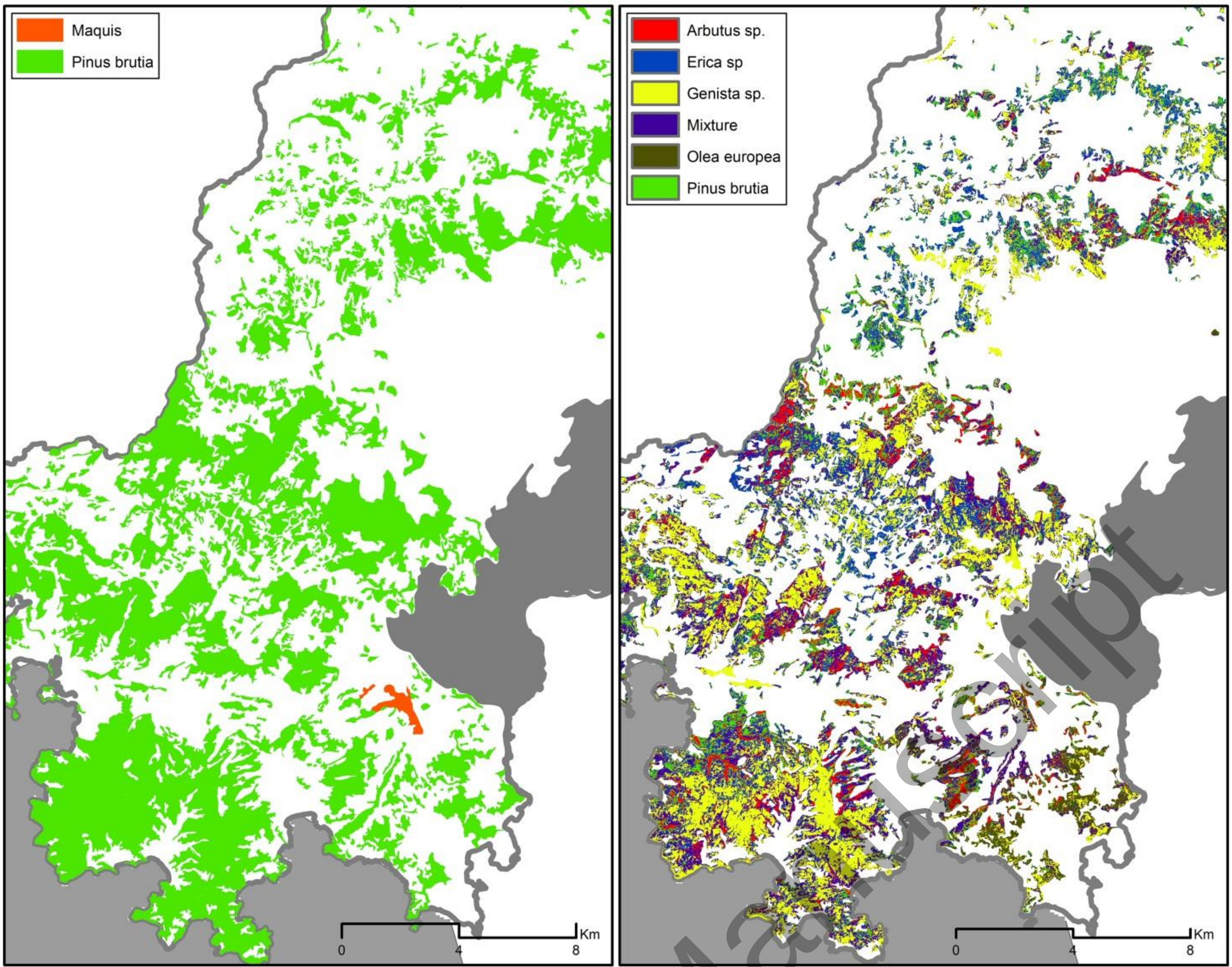

Figure 6. (left) “Sparse forest” mask; green polygons show stands labelled as “sparse *Pinus bruita* forest”, only orange polygon labelled as “maquis”. (right) Classification representing the dominant maquis species and *Pinus brutia*.

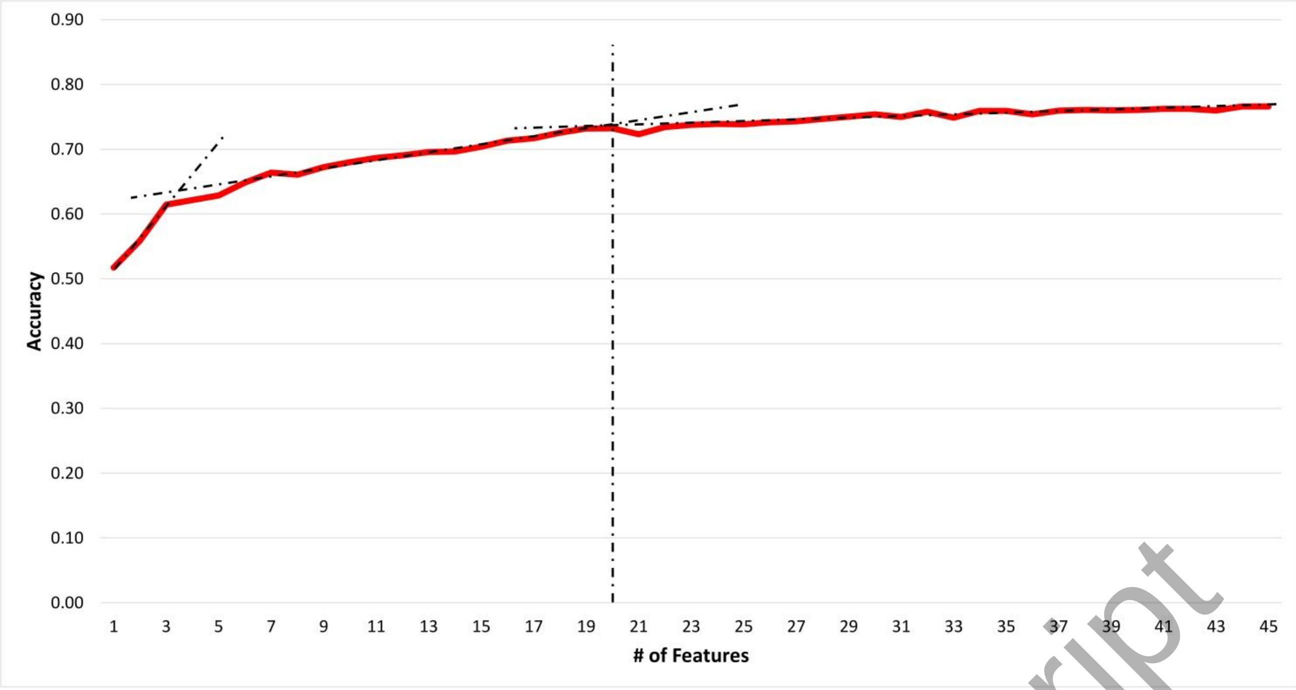

Figure 7. Number of features versus overall accuracy (Red line: change in accuracy with the additive random features. Dashed lines: the trend in the accuracy change).

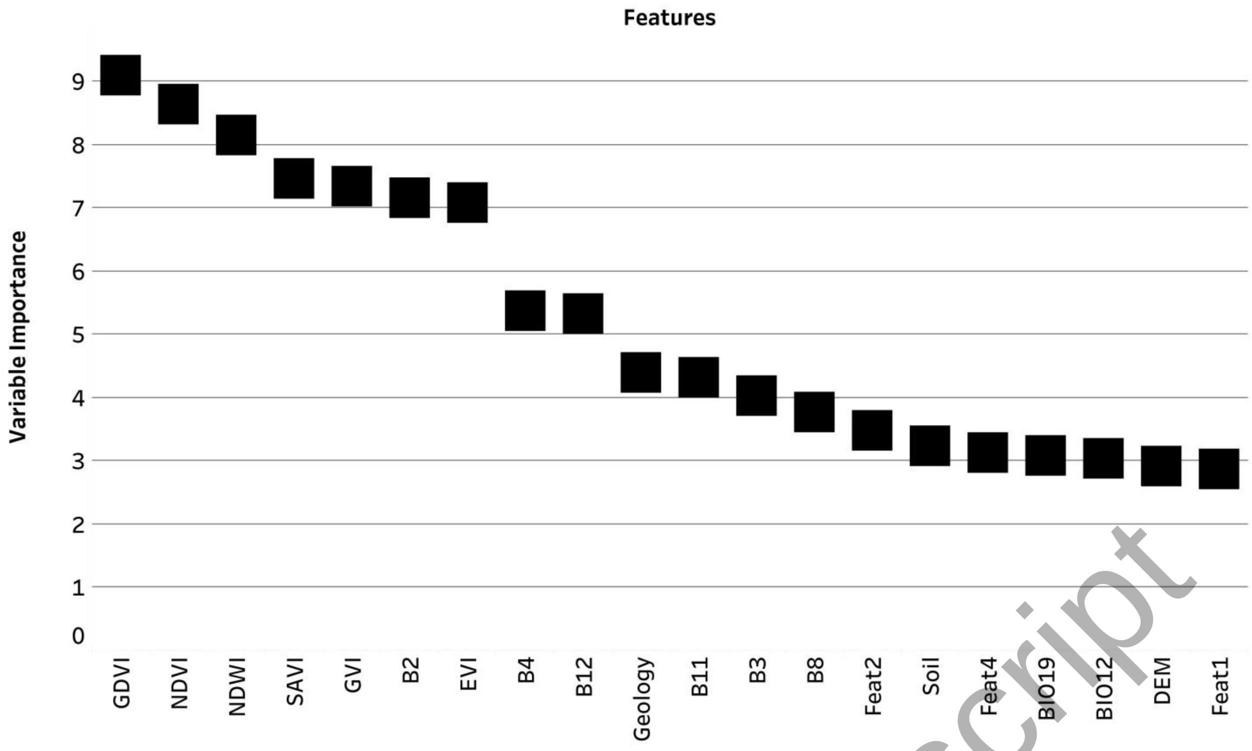

Figure 8. RF Variable importance of the 20 input features.

Table 1. List of ancillary features

Category	Feature Name	Data Source	Usefulness in vegetation mapping
1/25.000 Soil Map	Soil type	Turkey Ministry of Agriculture and Forestry	Sluiter and De Jong, 2005; Corcoran et al., 2013
1/25.000 Geology Map	Formation category	General Directorate of Mineral Research and Exploration	Sluiter and De Jong, 2005
Bioclimatic features	Bio1: Bio19	CHELSA bioclimatic surfaces (Karger et al., 2017)	Zimmermann et al., 2007
Emberger Index	Calculated from bioclimatic features	Emberger, 1955	Dufour-Dror and Ertas, 2004
Topographic Variables	Elevation (m) Slope (°) Northness	ASTER GDEM (NASA, 2009)	Sluiter and De Jong, 2005; Gislason et al., 2006

Table 2. List of spectral indices and re-computed features from SIs to delaminate vegetation classes.

Spectral Indice (SI)	**Formula**	**Reference**
NDVI	$(B8 - B4)/(B8 + B4)$	Rouse et al., 1974
NDWI	$((B8 - B11))/((B8 + B11))$	Ceccato et al., 2001
SAVI	$((B8 - B4) * 1.5)/((B8 + B4 + 0.5))$	Huete, 1988
EVI2	$((B8 - B4) * 2.5)/((B8 + 2.4 * B4 + 1))$	Jiang et al., 2008
GDVI2	$\frac{(B8^2 - B4^2)}{(B8^2 + B4^2)}$	Wu, 2014
GVI (Tasselled Cap vegetation)	$(-0.283 * \mathrm{B2}) + (-0.2453 * \mathrm{B3}) + (-0.5436 * \mathrm{B4}) + (0.7243 * \mathrm{B8}) + (0.0840 * \mathrm{B11}) + (-0.18 * \mathrm{B12})$	Thenkabail et al., 2002
Computed Features	**Formula**	
Feat_1	$\frac{\mathrm{NDVI}_{\mathrm{std}}^{1} + \mathrm{NDVI}_{\mathrm{std}}^{2}}{2}$	Inferred from SI monthly graphs (e.g. Figure 4) for to distinguish species phenological differences
Feat_2	$\frac{\mathrm{NDVI}_{\mathrm{mean}}^{4} - \mathrm{NDVI}_{\mathrm{mean}}^{9}}{\mathrm{NDVI}_{\mathrm{mean}}^{1:12}}$	
Feat_3	$\frac{\mathrm{NDVI}_{\mathrm{mean}}^{11} - \mathrm{NDVI}_{\mathrm{mean}}^{6}}{\mathrm{NDVI}_{\mathrm{mean}}^{1:12}}$	
Feat_4	$\frac{\mathrm{NDWI}_{\mathrm{mean}}^{2} - \mathrm{NDWI}_{\mathrm{mean}}^{4}}{\mathrm{NDWI}_{\mathrm{mean}}^{1:12}}$	
Feat_5	$\frac{\mathrm{GVI}_{\mathrm{mean}}^{7} - \mathrm{GVI}_{\mathrm{mean}}^{12}}{\mathrm{GVI}_{\mathrm{mean}}^{1:12}}$	
Feat_6	$\frac{\mathrm{SAVI}_{\mathrm{mean}}^{11} - \mathrm{SAVI}_{\mathrm{mean}}^{9}}{\mathrm{SAVI}_{\mathrm{mean}}^{1:12}}$	
Feat_7	$\frac{\mathrm{GVI}_{\mathrm{mean}}^{6} - \mathrm{GVI}_{\mathrm{mean}}^{4}}{\mathrm{GVI}_{\mathrm{mean}}^{1:12}}$	

Table 3. Confusion matrix of species classification

CLASSES	Arbutus	Erica	Genista	Mix	Olea	Pbrut	Row Total
Arbutus	14	0	0	1	0	4	19
Erica	0	24	3	4	0	0	31
Genista	0	2	25	2	0	0	29
Mix	2	1	4	24	0	3	34
Olea	2		1	1	14	0	18
Pinus	0	2	1	1	0	21	25
Column Total	18	29	34	33	14	28	156
Omission Error	0.26	0.23	0.14	0.29	0.22	0.16	
Comission Error	0.22	0.17	0.26	0.27	0.00	0.28	
Overall Accuracy: 0.78				Cohen's Kappa: 0.73			

Table 4. Confusion matrix of the physiognomic classification

CLASSES	Shrub	Tree	Row Total
Shrub	287	8	295
Tree	25	180	205
Column Total	312	188	500
Comission Error	0.08	0.04	
Omission Error	0.03	0.12	
Overall Accuracy:0.93		Cohen’s Kappa:0.86	

Table 5. Potential utility of produced species maps in Mediterranean maquis.

Utility	Species level map	Physiognomic level map
Monitoring land use land cover (LULC)	X	X
Monitoring land degradation	X	X
Landscape restoration	X	X
Vegetation mapping	X	X
Vegetation dynamics	X	
Fire management	X	
Biomass estimation	X	X
Managing non- timber forest products	X	
Mapping ecosystem services	X	X

Table 6. Accuracy statistics and classification scheme. We listed only classes related with maquis.

Classes (Maquis related class labels mentioned)	**Predictors**	**Classification/ discrimination technique**	**Accuracy**	**Reference**
Maquis and three other classes	Aerial Photographs	Object based	OA: 0.83, Kappa: 0.77	Fava et al., 2016
Low maquis High maquis Maquis with open canopy forest sp. and other 11 classes	Landsat TM SPOT	Maximum likelihood	OA: 0.85	Grignetti et al., 1997
Species level discrimination; *Ceratonia siliqua*, *Olea europea*, *Pistacia lentiscus*, *Calicatome villosa*, *Genista acanthoclada*	Hyperspectral air and spaceborn sensors / Field spectometry	Parametric and non-parametric tests	99% confidence level results highlights the spectral discrimination in certain wavelengths	Maneski et al., 2011
Shrublands, Oak Grove and 12 other classses	Landsat TM geostatistical textural features	RF / Maximum likelihood	OA: 0.83- 0.92	Rodriguez - Galiano et al., 2012
6 dense mattoral classes (3 of them directly related with maquis: scattered *Pinus*, *Quercus ilex* dominant by undergrowth species) 4 middle mattoral classes (dominated by *Quercus cocifera*, *Erica arborea*, *Cistus* spp) 3 low mattoral and 13 other classes	HyMap & Some ancillary variables	Spectral angle mapper & Ancillary data classification Model	OA: 0.51- 0.69	Sluiter and De Jong, 2005