MAPPING BEE-KEEPING FOREST PLANTS FROM MEDIUM SPATIAL RESOLUTION MULTISPECTRAL SATELLITE DATA

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ABSTRACT:

Apiculture is one of the main branches of agriculture and crucial to rural development since it provides farmers with unique products like honey, wax, pollen, royal jelly, propolis and bee venom. Due to pollination services provided by honeybees, environmental sustainability and diversity are also increased, as well as crop production. In Greece, approximately 2.000.000 bee colonies (second in the E.U.) are reported with a relatively high density per km^2. There are more than 20.000 beekeeping operators that produce about 20.000 tons of honey every year, while more than 65% of Greek honey is produced from honey dew. To this end, this study aims to identify and map major honeybee flora in the Greek mainland and the Greek islands (Fir forests, Pine forests and Oak forests) for the year 2019, in order to examine best regions to deploy honeybee colonies. In particular, a classification framework for mapping the main honeybee flora is introduced that is exploiting annual moderate-resolution satellite multi-temporal data. Additionally, a methodology is presented to generate a coarser training dataset by utilizing a high-spatial resolution, detailed land cover map. This process specifically focuses on the integration of honeybee flora classes that are not present in the land cover map but are of significant great importance for honey flora mapping. The goal was to enable large-scale classification without the computational resource constraints typically associated with such national scale frameworks. Experimental results are quite promising with the quantitative validation indicating overall accuracy of more than 85%.

1. INTRODUCTION

Apiculture, as a subsector of agriculture, is an integral part of primary production in Greece. Honeybees (Apis mellifera L.), apart from honey products, (honey, pollen, wax, propolis, royal jelly and bee venom) constitute the most efficient pollinators of wild flora and crops in the world (Maheshwari, 2003), maintaining biodiversity. Honeybees fly in a range of 6 kilometers (Beekman and Ratnieks, 2000) away from the beehive, depending on the topography of the ground. It is worth mentioning that bee flora mapping has been necessary to beekeepers for a long time for yielding better honey quality and production. In Greece, forests (pine, fir, oak) cover a big amount of land, providing forage for insect pollinators, including honeybees (Hanula et al, 2016). The number of apiaries in a certain area is a phenomenon that needs to be examined. As Xydias (1965) states, beekeeping productivity of an area is not solely indicated by the number of bee colonies but also by the average number of bee colonies per area. Therefore, knowing the types, places, and flowering/budding season of melliferous plants facilitates beekeepers to place their honeybee colonies. To this end, mapping the beekeeping flora serves as a tool for the beekeepers to better place their bee colonies in regions according to blooming periods.

More specifically, in the varied Greek honeybee flora, pine trees (*Pinus* spp.) are considered to be the most important honey-producting trees. Almost 60% of the annual Greek honey production is from pine trees. *Marchalina hellenica* (Gennadius) (Hemiptera: Margarodidae) as an endemic sap-sucking insect which feeds mainly on pine trees, contributes to the production of high-quality honeydew honey. Honeybees collect these secretions mainly from mid-August till the following spring, although the best collecting period is from August to October. Blooming period of pine trees is very beneficial for beekeepers and honeybees, since there is a stable flow regarding the quantity of honeydew produced every year. What is more, the long period of secretions, as well as the number of honeybees that can feed on pine trees in a region with pine forests in Greece, are also beneficial to honeydew honey production (Harizanis, 2015).

Equally useful to apiculture are scale insects that feed on fir forests which cover a large area in Greece (Samaras et al., 2015). The well-known fir honeydew honey is nearly 5% of the honey produced annually. More specifically, scale insects such as aphids and *Physokermes hellenicus (*Kozár & Gounari) (Hemiptera: Coccidae) feed on trunks of Greek fir trees (*Abies cephallonica*) producing large amounts of honeydew (from May to June thanks to high temperatures) which is collected by honeybees (Santas, 1983; 1991).

Oak forest honey has also received increased interest following studies over the past few years that have shed light on the antioxidant properties of dark-colored honey (Can et al., 2015), but limited research has been carried out so far, so there is no adequate data regarding oak tree honey production.

Hence, for all the reasons aforementioned, the systematic mapping of beekeeping flora and, specifically, of main forest tree species in Greece is crucial. Remote sensing classification mapping can contribute towards this direction. Many recent studies have been addressed with the use of satellite imagery combined with machine learning frameworks for crop mapping (Karakizi, 2022; Defourny et al., 2019), while studies for the specific detection of beekeeping flora are limited with only a few applications (Papachristoforou et al. 2023).

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In this direction, in the current study a classification framework for the mapping of the main honeybee flora in Greece is presented. The proposed pipeline aims to enable large-scale classification, without the computational resource constraints typically associated with such frameworks, by utilizing annual moderate-resolution satellite multi-temporal data. Additionally, a pipeline for the generation of a coarser training dataset by utilizing an existing higher spatial resolution classification map is presented.

2. MATERIAL AND METHODS

2.1 Multispectral data and digital elevation model

The study area of the research paper is the entire Greek territory consisting of 130,800 km^2 of land. The acquired multispectral data correspond to a temporal range of 12 months, between 11/2018 and 10/2019. Taking into consideration that land use classification with satellite data is a demanding task in terms of available computational resources, it was chosen to utilize multispectral medium spatial resolution data from the Terra MODIS satellite of the American Aeronautics and Space Administration (NASA).

In particular, MODIS Terra MOD09A1 Version 6 product provides an estimate of the surface spectral reflectance, corrected for atmospheric conditions and scattering, with a spatial resolution of 500 meters. This product consists of seven spectral bands (R, G, B, NIR, and SWIR) and is an 8-day composite since MODIS has a revisit frequency of 1-2 days. Each pixel value was selected from all the acquisitions within the 8-day composite period, depending on several criteria, like cloud presence.

Additional auxiliary data used is the digital elevation model Shuttle Radar Topography Mission (SRTM) provided by the United States Geological Survey (USGS), with a spatial resolution of 3 arc-seconds (~90 meters).

2.2 Reference data

The produced reference data consist of 12 classes: Artificial surfaces (AFS), Grass/Wood land (GWL), Bare land (BRL), Water bodies (WBD), Agricultural land (AGR), Mixed forest (MIX), Dense fir (FIR1), Sparse fir (FIR2), Sparse pine (PNE1), Dense pine (PNE2), Dense oak (OAK1) and Sparse oak (OAK2) (Figure 2). In order to produce the reference data, two layers of information are used. The first layer consists of manually annotated data using photo interpretation and prior knowledge about forest regions where pine trees, fir trees, and oak trees are grown. For splitting forest regions into detailed honeybee flora classes, namely FIR1, FIR2, PNE1, PNE2, OAK1, OAK2, and MIX, a second layer of information is used. This layer is a map product made by Karakizi (2022) and is a land cover classification map of 10 meters spatial resolution. The classified map (hereafter referred to as LCM) depicts 42 land cover and crop categories (Figure 2). The LCM has a user accuracy (UA) of 82%, and the corresponding accuracy for natural vegetation categories exceeds 95%. The high spatial resolution of the LCM allowed the quantification of the classes contained in each MODIS pixel.

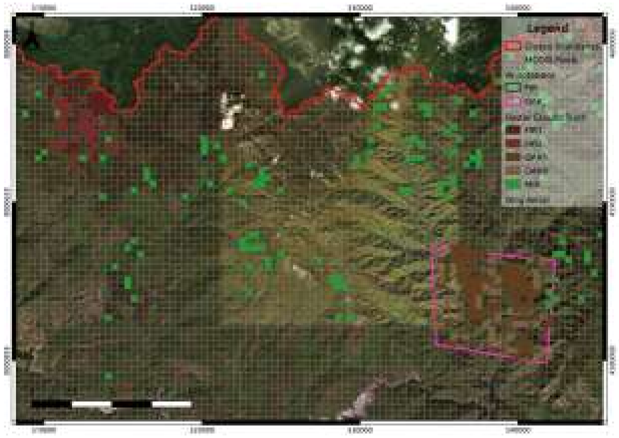

Figure 1. An indicative region of the study area with two annotated polygons for class FIR (green) and OAK (pink). Certain MODIS pixels (red grid) categorized as FIR1, FIR2, OAK1, OAK2 or MIX are also presented.

In order to assign one of the 5 classes (AFS, GWL, BRL, WBD, and AGR) to a MODIS pixel, the higher resolution pixels of the LCM are examined. For instance, for a MODIS pixel to be categorized as WBD it should contain 99%-100% of LCM pixels characterized as wetlands, water courses/bodies, or coastal water. The same principle was applied to the other 4 classes, but with varying LCM pixel ratios. The reason for applying different pixel ratios was the challenge of identifying MODIS pixels that solely consisted of the aforementioned LCM classes and the production of a balanced training dataset.

More specifically, the criteria for the 5 classes, were:

- AFS (Artificial surfaces): 93-100% of LCM classes; dense/sparce urban fabric, industrial/commercial units, asphalt, photovoltaic units and greenhouses
- GWL (Grass/Wood land): 99-100% of LCM classes; natural grasslands, sparse/dense sclerophyllous vegetation

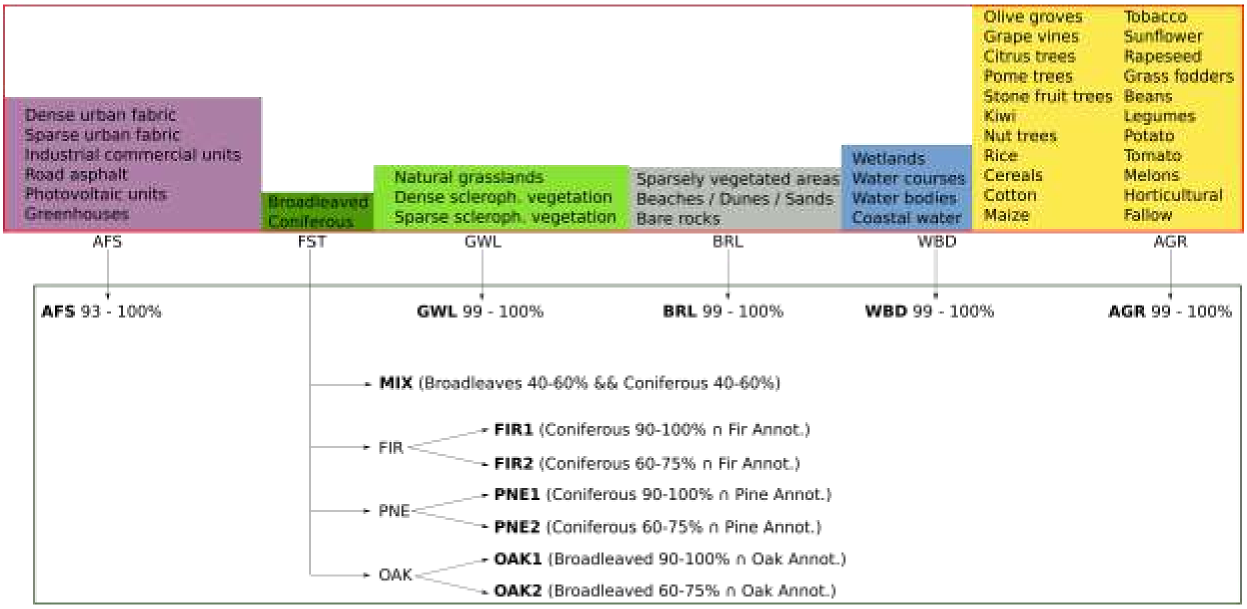

Figure 2. A detailed presentation of the reference data nomenclature. Land cover map (LCM) 42 classes are in the red box, aggregated in 6 classes named as AFS, FST, GWL, BRL, WBD, and AGR. In the green box, the rules based on how the final 12 MODIS pixels classes were extracted, are presented.

- BRL (Bare land): 99-100% of LCM classes; bare soils, sparse vegetation, rocky/sandy areas
- WBD (Water bodies): 99-100% of LCM classes; water bodies, rivers, lakes, wetlands, coastal waters
- AGR (Agricultural land): 99-100% of LCM 22 crop type classes

A different approach is followed for the forest region classes FIR1, FIR2, PNE1, PNE2, OAK1, OAK2, and MIX. To further classify the Forest (FST) category into the specific classes related to fir, pine, and oak, the annotations were utilized. For instance, for a MODIS pixel to be categorized as FIR1, it should contain 90%-100% of LCM pixels characterized as coniferous and should also be annotated as fir. Similarly, for a MODIS pixel to be categorized as FIR2, it should contain 60%-75% of LCM pixels characterized as coniferous and should also be annotated as fir. For the MIX class, only the LCM was utilized, and for a MODIS pixel to be categorized as MIX, it should contain 40%-60% of LCM pixels characterized as broadleaves and 40%-60% coniferous vegetation, without annotation needed. Figure 1 depicts an indicative, relative small, region of the study area, with an example of two annotated polygons for class FIR and OAK. Certain MODIS pixels categorized as FIR1, FIR2, OAK1, OAK2 or MIX are also presented.

More specifically, the criteria for the 7 classes, were:

- FIR1 (Dense fir): 90-100% of LCM coniferous and fir annotation
- FIR2 (Sparse fir): 60-75% of LCM coniferous and fir annotation
- PNE1 (Dense pine): 90-100% of LCM coniferous and pine annotation
- PNE2 (Sparse pine): 60-75% of LCM coniferous and pine annotation
- OAK1 (Dense oak): 90-100% of LCM broadleaves and oak annotation
- OAK2 (Sparse oak): 60-75% of LCM broadleaves and oak annotation
- MIX (Mixed forest): 40-60% of LCM coniferous and 40-60% of LCM broadleaves

In this manner, MODIS reference pixels are generated to emphasize forest honeybee flora classes. This is achieved by utilizing a high-resolution classification map where these specific classes are absent, as the map solely provides information regarding coniferous and broadleaved forests.

ID	Class	MODIS pixels
1	FIR1	1439
2	FIR2	854
3	PNE1	280
4	PNE2	700
5	OAK1	1217
6	OAK2	524
7	MIX	1000
8	GWL	1000
9	AFS	1000
10	AGR	1000
11	WBD	1000
12	BRL	1000
		Total: 11014

Table 1. The total amount of MODIS pixels per-class that were used as reference data.

Table 1 illustrates the amount of MODIS reference pixels for each class. The total amount of pixels sums up to 11014. The amount of reference pixels for fir, pine and oak classes reveals the representation of these classes in the annotated regions, based on LCM map. For example, class PNE1 is low represented comparing to class FIR1, since areas of 500x500 meters, annotated as pine and consisting of 90-100% coniferous LCM pixels are rare.

2.3 Satellite data pre-processing

Prior to the classification stage, satellite data preparation is required since the entire Greek territory is depicted partially in 3 different MODIS acquisitions (Figure 3). In these terms, a satellite image mosaic is created for each 8-day composite and then is delineated at the border of the country. Also, the single digital elevation layer is resampled from 90 to 500 meters spatial resolution using the MODIS images geometric transformation.

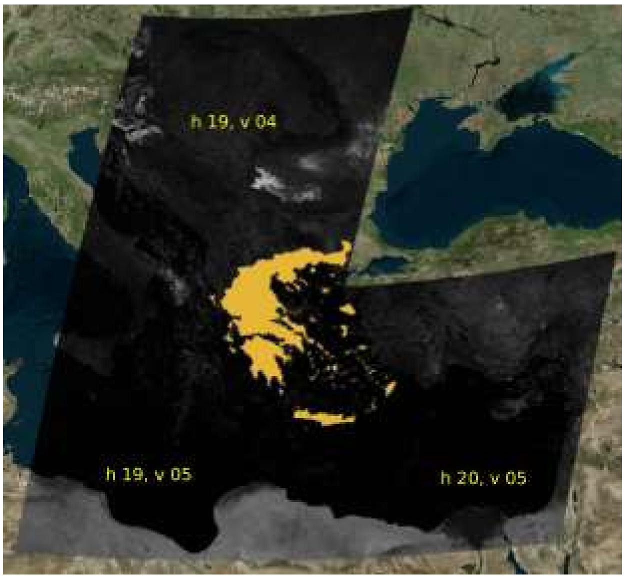

Figure 3. The corresponding 3 MODIS tiles (h 19, v 04; h 19, v05; h 20, v05) that cover the study area.

Additionally, in order to enhance the model's ability to distinguish between the 12 defined classes, five spectral indices are calculated alongside the MODIS bands. Three of these indices, namely the Normalized Difference Vegetation Index (NDVI), Modified Soil-adjusted Vegetation Index (MSAVI), and Enhanced Vegetation Index (EVI), are computed specifically for the vegetation classes. Additionally, the Normalized Difference Built-up Index (NDBI) is calculated as an extra feature for artificial surfaces, while the Normalized Difference Water Index (NDWI) is calculated for water bodies. These indices are commonly used and well-documented as highly useful for this type of studies (Pelletier et al., 2016; Defourny et al., 2019; Hermosilla et al., 2022).

Finally, to input the data into the model, a spectralcube is generated by stacking the 12 spectral layers for each date along with one layer for the digital elevation model. This process yields a spectralcube with a size of 3.9 GB, encompassing 37 selected dates spanning from 11/2018 to 10/2019. The spectralcube, in conjunction with the reference data, offers the classifier both the annual spectral variation and the elevation information of the pixels.

2.4 Classification

The Random Forest classifier was employed as the machine learning algorithm for the classification process. The algorithm is parameterized using default values that have been recommended in relevant literature to achieve a balanced trade-off between accuracy and computation cost (Liaw and Wiener, 2002; Rodriguez-Galiano et al., 2012; Pelletier et al., 2016, Karakizi, 2022). In particular, as far as the Random Forest classifier is concerned, the number of estimators is set to 200, and the number of features randomly selected at each node is equal to the square root of the total number of features. Default values are chosen for the maximal depth of each tree (set to None) and the minimal number of samples per node (set to 1). Finally, the reference data are divided into 67% as train data and 33% as test data randomly.

3. EXPERIMENTAL RESULTS AND DISCUSSION

This section provides a comprehensive analysis, both quantitative and qualitative, which is conducted by applying the classification framework and examining the resulting outcomes.

3.1 Quantitative analysis and accuracy metrics

The confusion matrix (Table 2) is generated by comparing the test dataset with the model's predictions. A total of 3892 MODIS pixels were used to validate the model.

Among the 5 aggregated classes, namely GWL, AFS, AGR, WBD, and BRL, which are created solely by using the LCM and are unrelated to forest regions, the highest F1 scores range from 92.7 to 98.3. The class with the highest F1 score of 98.3 is

truth\pred.	FIR1	FIR2	PNE1	PNE2	OAK1	OAK2	MIX	GWL	AFS	AGR	WBD	BRL	All	PA	f1
FIR1	**381**	84	0	0	0	0	0	2	0	0	0	0	467	81.58	77.67
FIR2	124	**252**	0	5	0	0	10	11	0	0	0	3	405	62.22	65.71
PNE1	1	2	**24**	60	0	0	0	0	0	0	0	0	87	27.59	37.8
PNE2	1	3	16	**260**	0	0	4	11	0	0	2	0	297	87.54	81.76
OAK1	0	0	0	0	**350**	46	6	0	0	1	0	0	403	86.85	85.79
OAK2	0	0	0	0	46	**167**	20	2	0	7	0	0	242	69.01	71.52
MIX	7	14	0	4	16	10	**291**	2	0	1	0	1	346	84.1	85.84
GWL	0	7	0	5	0	1	0	**324**	1	5	0	0	343	94.46	92.7
AFS	0	0	0	0	0	0	0	0	**320**	15	2	0	337	94.96	96.39
AGR	0	0	0	1	0	1	0	2	2	**311**	0	0	317	98.11	93.96
WBD	0	0	0	4	1	0	1	0	1	3	**311**	0	321	96.88	97.8
BRL	0	0	0	0	0	0	0	2	3	2	0	**320**	327	97.86	98.31
All	514	362	40	339	413	225	332	356	327	345	315	324	3892	81.76	
UA	74.12	69.61	60	76.7	84.75	74.22	87.65	91.01	97.86	90.14	98.73	98.77	83.63	**OA** 85.07	**Avg f1** 82.68

Table 2. Confusion matrix for the RF experiment. Diagonal values (pink colour) represent true positive values for each class.

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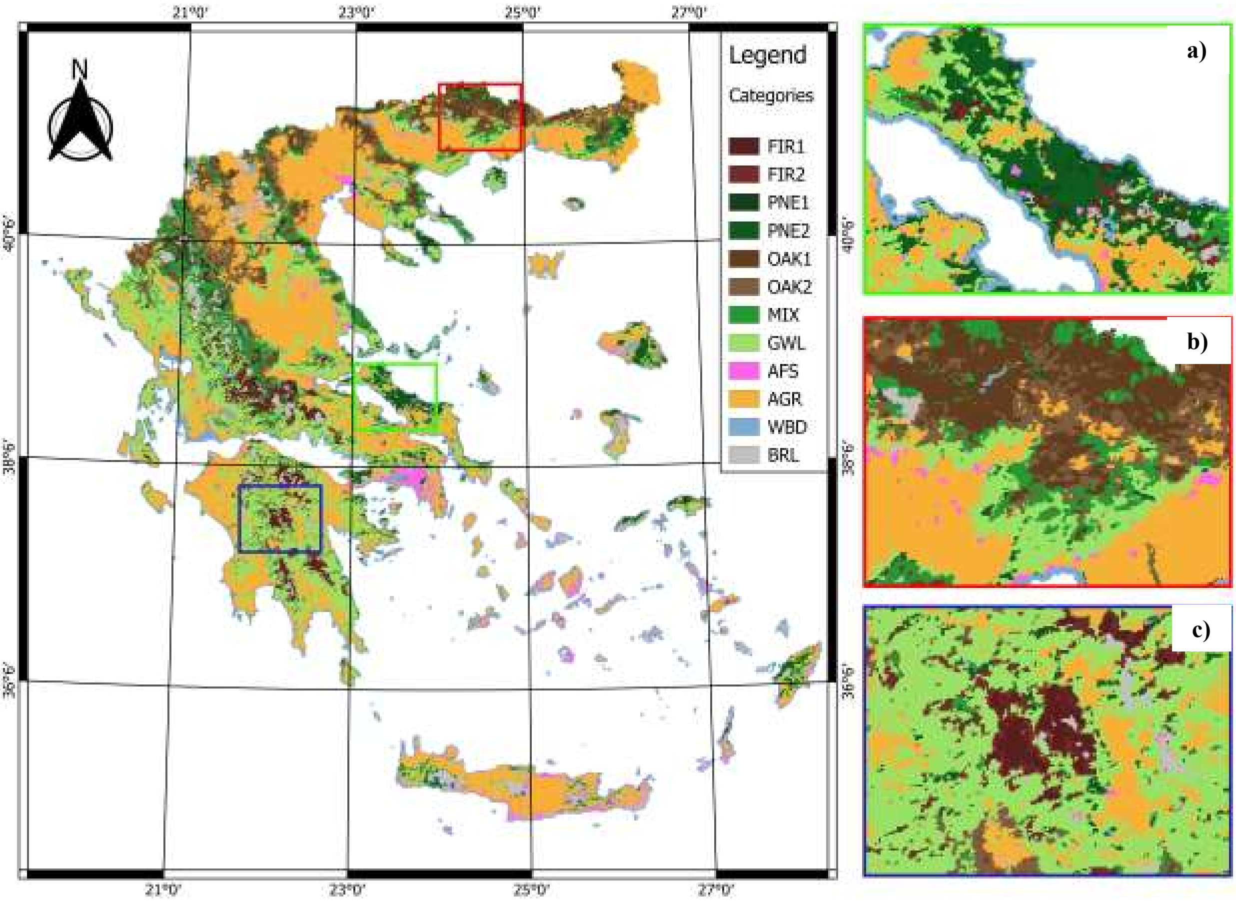

Figure 4. The classified map of the study area with the derived 12 categories of this study. In subfigures a), b), c) indicative sub-regions in Evia, northern Greece and central Peloponnese are presented, respectively.

the Bare land (BRL), which is easily distinguishable from other categories. The second highest F1 score of 97.8 is the Water bodies (WBD) class, as water has distinctive spectral properties that allow for clear identification. The third highest F1 score of 96.4 is the Artificial surfaces (AFS) class, which also has a unique spectral signature and remains consistent over time. The fourth highest F1 score of 94.0 is the Agricultural land (AGR) class. However, this category presents challenges, particularly when different crop types are grouped together. Interestingly, the User Accuracy (UA) for the AGR class is the lowest among these 5 classes, indicating that some MODIS pixels classified as AGR in the final map are false positives.

The 7 classes that are of particular interest in this study, namely FIR1, FIR2, PNE1, PNE2, OAK1, OAK2, MIX, exhibit consistently lower F1 scores compared to the previously mentioned 5 classes. The highest F1 score of 85.85 is achieved by the Mixed Forest class, for which reference data are generated solely using the LCM without annotated regions. The second highest F1 score of 85.79 belongs to the Dense Oak Trees (OAK1) class which is easy to annotate and identify due to the loss of canopy during winter months. The third highest F1 score of 81.76 is obtained by the Sparse Pine Trees (PNE2) class, which is a prominent category within the study area. The fourth highest F1 score of 77.67 is associated with the Dense Fir Trees (FIR1) class, identifiable and annotated based on texture and commonly found at high elevations. The fifth highest F1 score of 71.52 is achieved by the Sparse Oak (OAK2) class, followed by the Sparse Fir (FIR2) class with an F1 score of 65.71. Notably, the class with the significantly lower F1 score of 37.80 is Dense Pine (PNE1), which has a low representation in terms of reference MODIS pixels and poses challenges in identifying areas consisting solely of densely grown pine trees within a 500x500-meter region.

The omission and commission errors are more pronounced for the 7 Forest (FST) classes compared to the 5 aggregated classes, particularly between the sparse and dense tree classes, and especially within the sparse-dense classes of the same tree type. This outcome is expected despite making efforts to define dense-sparse classes with a 15% gap in terms of the ratio of LCM pixels (as shown in Figure 2) and avoiding the use of MODIS pixels consisting of 75-90% coniferous or broadleaved LCM pixels as reference data. Additionally, smaller omission and commission errors are observed between the sparse tree classes and the Mixed forest (MIX) class. This result is also anticipated as the definition of the MIX class (40-60% coniferous and 40-60% broadleaved) closely aligns with the definition of the sparse classes (60-75% coniferous or broadleaved and annotation). The definition of Forest (FST) categories strikes a balance between the available MODIS pixels and the spectral signature of each class.

By examining the confusion matrix, it is useful to extract a summary regarding the commission and omission errors of each class, specifically focusing on the two most confusing classes. In terms of commission errors, FIR2 and MIX are false positively classified as FIR1, FIR1 and MIX as FIR2, PNE2 as PNE1, PNE1, FIR2, and GWL as PNE2, OAK2 and MIX as OAK1, OAK1 and MIX as OAK2, OAK2 and FIR2 as MIX, FIR2 and PNE2 as GWL, BRL and AGR as AFS, AFS and GWL as AGR, PNE2 and AFS as WBD, and finally FIR2 and

MIX as BRL. The corresponding User Accuracy (UA) for each class can be found in Table 2.

Regarding omission errors, the FIR1 class is false negatively classified as FIR2 or GWL, FIR2 as FIR1 or GWL, PNE1 as PNE2 or FIR2, PNE2 as PNE1 or GWL, OAK1 as OAK2 or MIX, OAK2 as OAK1 or MIX, MIX as OAK1 or FIR2, GWL as FIR2, PNE1, or AGR, AFS as AGR or WBD, AGR as GWL or AFS, WBD as PNE2 or AGR, and finally BRL as AFS, GWL, or AGR. The corresponding Producer Accuracy (PA) can be found in Table 2.

Noteworthy observations regarding commission errors involve MODIS pixels that are classified as Agricultural land (AGR) instead of Artificial surfaces (AFS). Noteworthy omission errors include pixels from the Water bodies (WBD) class being misclassified as Agricultural land (AGR). The confusion between AGR and AFS is well-known due to temporary coverage of agricultural crops with man-made materials. The confusion between WBD and AGR could be attributed to the presence of rice crops in the study area.

3.2 Map Validation and discussion

The last step of the proposed methodology is the production of the map by applying the Random Forest (RF) classifier. In order to extract the map product, the spectralcube was utilized.

In figure 4, the map with the 12 categories is presented in the study area. Also, 3 cases of the beekeeping targeted vegetation are highlighted. Figure 4.a showcases a vast pine forest located in Evia, part of the region of Central Greece. This particular forest is renowned for its pine honey production in the region. The RF classifier successfully identified and captured the presence of the dominant PNE1 (Dense pine) and PNE2 (Sparse pine) categories, while also smaller regions with FIR2 (Sparse pir), as depicted in the figure. In figure 4.b, a well-known beekeeping oak forest that produces large quantities of oak tree honey in northern Greece is presented. As presented in the map, the RF classifier managed to capture the oak forest. The selected region is dominated by OAK1 (Dense oak) and OAK2 (Sparse oak) categories while, also, by some Agricultural land (AGR), Grass/Wood lands (GWL) and Mixed forest (MIX). Finally, in figure 4.c, a fir forest on Mt. Mainalon in central Peloponnese is presented, known for the production of the first PDO Vanilla-fir honey. Similarly, the RF classifier successfully classified the forest with FIR1 and FIR2 being the dominant categories within the region. Additionally, substantial areas of mixed forest and bare lands are observed, as depicted in the figure.

In Figure 5, a map produced by the classified map with the total coverage area of the major forest beekeeping plants per Greek prefecture is presented. Important honey production regions in Greece present differences regarding the area coverage of forest beekeeping plants.

As it can be concluded from the map coverage, the leading areas with beekeeping forests in Greece are northern mainland and Peloponnese. More specifically, the prefectures in northern mainland consist of higher percentage of mixed and oak forests compared to Peloponnese, where fir and pine forests outweigh oak and mixed forests.

Some other interesting findings that were obtained in the present study are that the prefectures in central Greece with the highest percentage of fir forest coverage are Evritania and Fokida, with a coverage of 30.7% and 20.4%, respectively. Additionally, the prefecture of Samos (the islands of Samos, Ikaria, Fourni) has the highest percentage of pine forest coverage (20.15%). The prefecture of Evia follows with a percentage of 17.73% coverage of pine trees. Both the prefectures of Samos and Evia produce the well-known Greek pine honey.

Finally, the prefectures with the highest percentage of oak tree forests coverage are Xanthi and Drama (~40%) while findings yielded a 27% of oak tree coverage in Pella, Grevena and Kastoria.

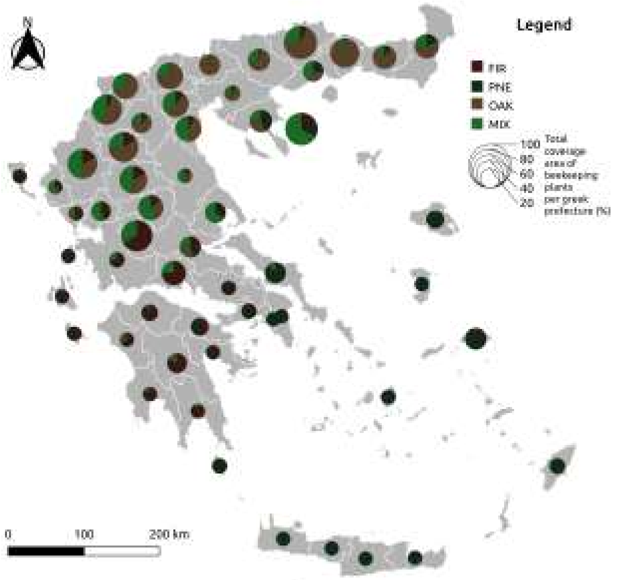

Figure 5. The computed national-scale map with the coverage of forest beekeeping plants in each Greek prefecture.

4. CONLUSIONS

This study aimed to develop a classification framework for mapping the main honeybee flora across the entire Greek territory. The framework utilized moderate-resolution satellite data to address the high computational resources required for large-scale classification. Additionally, reference data are generated by utilizing existing higher-resolution classification maps. With the developed pipeline, a method for producing reference data that focuses on detailed categories which are not present in the utilized map is presented. This was achieved through annotations associated with these classes and fractional rules used to define these specific categories. The definition of the fractional rules considering the available amount of reference MODIS that could describe with clarity the spectral behaviour of a class, is challenging and could lead to omission or commission errors, especially for quite similarly defined classes, like sparse, dense and mixed.

The developed dataset is used for the training and the validation of the Random Forest classifier. Quantitative evaluation demonstrated the efficiency of the proposed methodology by achieving results of high overall accuracy of over 85% and average f1 score over 82%.

Furthermore, through the qualitative analysis of the classified map, the proposed methodology managed to capture major and important forests of honey production in Greece as presented in the previous section. In that direction, extra detailed mapping of the honeybee flora could serve as planning consultant for beekeepers and play a crucial role to rural development.

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