LIFE 14ENV/IT/000414
Demonstrating Remote Sensing integration in sustainable forest management
FRESh Life

ACTION B3

Mapping SFM indicators

Report on the technical and economic viability of using high resolution optical data to stratify by European Forest Types (EFTs) medium-to large size forest management units

Viterbo, 28/02/2017

Summary

1. Goals

University of Tuscia is the Beneficiary responsible for implementation of Action B3 - Mapping SFM indicators.

The goals of the Action B3 are to test and evaluate methods coupling remote sensed infomation collected from RPAS with plot-level data to derive:

- maps of European Forest Types for the pilot study areas;
- maps of selected Forest Europe SFM indicators;

This report summarizes the technical results achieved in the production of forest types maps in the pilot study areas of Caprarola, Bosco Pennataro and Rincine by segmentation and semi-automatic classification of true color orthomosaics (ground resolution 10 cm/pixel), processed from image data collected in the visible spectrum by a camera equipped on eBee (SenseFly) small fixed-wing unmanned aerial vehicle. The map accuracy levels of products derived from segmentation and semi-automatic classification approaches (hereafter referred to as 'semi-automatic classification') are compared with those of maps derived by visual interpretation. Technical details on the visual interpretation mapping methodology were provided in the Report of the Deliverable "Maps of the European Forest Types for the pilot study areas".

2. Milestones and Deliverables

The B3's Project Milestone is

Milestone name	*Deadline*
Report on the technical and economic viability of coupling remote sensed information, collected from RPAS, with plot-level data to map selected Forest Europe SFM indicators at operational scale	09/2017

The B3's Project Deliverable Products are

Deliverable name	*Deadline*
Maps of European Forest Types for the pilot study areas	12/2016
Report on the technical and economic viability of using high spatial resolution optical data to stratify by European Forest Types (EFTs) medium- to large size forest management units	2/2017
Maps of SFM indicators "Defoliation (# 2.3)", "Forest damage (# 2.4)", "Number of tree species (# 4.1)" and "Area covered by introduced tree species (# 4.4)" for the pilot study areas	3/2017
Report on the technical and economic viability of using very high spatial resolution optical data for mapping forest health and tree species related SFM indicators at the forest compartment level	4/2017
Maps of SFM indicators: "Growing stock (# 1.3)" and "Above ground biomass (# 1.4)" for the pilot study areas	6/2017
Report on the technical and economic viability of using geostatistical methods and techniques for the spatial estimation of growing stock and above ground biomass, at the	7/2017

forest compartment level	

3. Methodology

3.1 Segmentation and semi-automatic classification

The multi-resolution segmentation and object-based image analysis of the orthomosaic was performed using eCognition developer. Only pixels within the limits of the pilot study area were included in the analysis, in order to reduce data processing time.

Objects (polygons) were obtained by applying a segmentation algorithm. Optimal parameters (scale factor, geometric/spectral homogeneity, compactness) for the segmentation were selected after iterative testing of in each study area (Table 1). As the forest types can be best discriminated by the reflectance in the green-wavelength region, the colour feature appeared as more relevant than shape related characteristics. However, the feasibility of forest types mapping by semi-automatic classification proved to be significantly constrained by the target classes to be mapped in each pilot study area (number, spectral differences among classes), by the image acquisition period (phenological differences between forest types classes) and by factors affecting the sensitivity of the image quality the orthomosaic. In Rincine pilot study area, namely, relief shadows negatively affected the image quality of the orthomosaic, causing some forest zones in the pilot study area to look dark. In Pennataro different light and atmospheric conditions occurred in different flights, caused high per-class variability in the colour tone of EFTs classes. Thus, in Rincine pilot study area, where about 25% of the study area look dark, the semi-automatic classification attempt was targeted to distinguish coniferous vs broadleaved deciduous dominated forest types only. Dark areas were preliminary automatically detected using a brightness threshold of 83. In Caprarola and Pennataro, target classes to be mapped were all the field observed EFTs (Table 1).

In the case of Caprarola we also assigned a different relative weight to the three RGB spectral bands (2, 3 and 1, respectively). This choice derives from the different reflectance observed for the two EFTs in Caprarola (7.3 e 8.2) in these bands. In the period when the orthofoto was acquired (last week of May 2016), in fact, a different spectral response of the two species can be identified mainly in the Green band due to the phenological differences between Turkey oak (8.2) and beech (7.3). Image acquisition in Pennataro was carried out later in June and phenological differences between the same EFTs were no longer visible in the RGB image. For this reason, an equal weight was assigned to the three RGB spectral bands for these study areas.

Table 1. Parameters used for the segmentation and semi-automatic classification. The description of the variables used for the classification is reported in Definiens (2010).

Study area	Scale factor	Geometric homogeneity	Compactness	Forest types target classes	N of samples for EFT	Variables used for the classification
Caprarola	200	0.3	0.9	7.3 Apennine Corsican mountainous beech forest; 8.2 Turkey oak, forest;	6	Max Diff.; Roundness
Pennataro	300	0.3	0.9	7.3 Apennine Corsican mountainous beech forest; 8.2 Turkey oak, forest; 8.8 Other termophilous deciduous forest	3	Mean of Digital Numbers (DN) of the Red Band; Standard Deviation of Digital Numbers (DN) of Red, Green; Blue Bands; Max Diff.; Asymmetry; HSI transformation Saturation; HSI transformation Hue
Rincine	500	0.3	0.9	Coniferous forest[1] Broaleaved deciduous forest[2]	3 (conifers) 5 (broadleaves)	Roundness; Standard Deviation of Digital Numbers (DN) of the Blue Band; Max Diff.; Asymmetry; Ratio index derived from Blue and Green bands

The subsequent classification of the objects produced by the segmentation was performed through the Standard Nearest Neighbour (STD.N.N.) algorithm. The classifier was trained based on polygon sample for each target class (training sites), selected manually by on-screen visual interpretation.

Feature space optimization tool was used to identify the most suitable spectral and geometric variables for distinguishing, on the basis of the selected training sites, the considered forest types (see Table 1).

[1] The coniferous forest includes in Rincine the following EFTs: joint class including:10.2 Mediterranean Black pine forest; 14. Introduced tree species forest.

[2] The broadleaved deciduous forest includes in Rincine the following EFTs: 7.3 Apennine Corsican mountainous beech forest, 8.2 Turkey oak forest, 8.7 Chestnut forest,8.8 Other thermophilous deciduous forest.

The objects with surface lower than minimal mapping unit (0.5 ha) were dissolved with adjacent polygons.

The three forest types maps produced by semi-automatic classification for the pilot test area of Caprarola, Bosco Pennataro, and Rincine are presented in Annex 1 and are provided also in shapefile format (Deliverable Forest Types Maps_segmentation.zip).

3.2 Classification of ground plots

In order to quantify how well the semi-automathic classification and the visual image interpretation worked in the different pilot test areas, ground truth data collected in fifty sampling units for each pilot study area, during Action B2, were processed to assign each plot with a EFT class. Sampling units size is 23 m^2, corresponding to a square region of 230x230 10 cm^2 pixels in the orthomosaic.

Dominant tree species at plot level was identified using relative basal area proportion. Two alternative approaches were tested to identify the forest species with the highest relative value of basal area in each plot:

A. Relative basal area proportion out of total plot basal area;

B. Relative basal area proportion out of the basal area of the 5 trees with the largest diameter in the plot (dominant trees).

The rationale of using two different approaches for sampling unit classification into EFTs is to evaluate whether differences in classification of reference data might appear when using dendrometric based (A) vs more forest cover based (B) criteria for the identification of the dominant tree species at plot level.

3.3 Validation

The accuracy of EFTs classification was assessed by four indices:

- Overall accuracy (OA); OA quantifies the percentage of plots classified correctly according to ground plot based EFTs classification;
- Kappa index of agreement (KIA); KIA reflects the difference between actual agreement and the agreement expected by chance; KIA= (OA-c)/(1-c) where c is the overall probability of random agreement. The use of KIA index is especially relevant when some classes are more likely to be encountered than others in the investigated area. Thus, some of the apparent classification accuracy given by OA measures could be due to chance, rather than to the ability of the classifier (photo-interpreter or semi-automatic algorithm). We quantified the probability of random agreement (c) using as an *a priori* estimate of the marginal proportions of forest types in each pilot study area (based on approach A, see §). Accordingly, the joint probability of a point being correctly mapped in the target classes, simply by a chance assignment based on given marginal proportions, was calculated.
- Producer's accuracy (PA); PA quantifies how accurate is the map from the perspective of the producer; i.e. for a given mapped EFTs PA quantifies the percentage of plots that are labelled correctly on the map;

- User's accuracy (UA); UA classifies how accurate is the map from the perspective the user; i.e. number of plots correctly identified in a given map EFTs class out of the number of ground plots assigned to that map class.

4. Comparison of the relative accuracy of maps

In the following sections, we compare the accuracy parameters of the EFTs maps derived from visual interpretation and semiautomatic classification in the pilot study areas of Caprarola and Pennataro, and report accuracy levels of the semiautomatic classification for coniferous vs broadleaved deciduous map in the study area of Rincine.

4.1 Caprarola

Table 2 reports OA and KIA indices calculated for the two mapping methods according the two validation approaches (A, B). The validation accuracy is the same for A and B approaches, as in Caprarola pilot test area there is a full agreement in the classification of fifty sampling units into EFTs between the two approaches. Table 3 reports PA and UA values for each EFTs class.

The overall accuracy is high, exceeding 85%, though visual image interpretation performed better. The KIA value (0.69) also confirm to the good performance of both classification approaches compared to would be expected by a chance assignment of ground truth points to the two mapped classes.

PA and UA calculated for the semi-automatic classification are lower for the "8.2 Turkey oak, Hungarian oak and Sessile oak forest" (around 80%) if compared to "7.3 Apennine Corsican mountainous beech forest" (around 90%). The PA and UA obtained for the map derived by visual interpretation are similar or just slightly higher, highlighting that the semi-automatic classification yielded results that are comparable with visual image interpretation.

Table 2. OA and KIA calculated according the two tested validation approaches.

Field data	Classification			
	Semi-automatic classification		Visual image interpretation	
	OA	K	OA	K
A) Total basal area/ B) Basal area of dominant trees	0,86	0,69	0,92	0,82

Table 3. EFTs per-class PA and UA in Caprarola pilot study area.

Forest Types	Classification			
	Semi-automatic classification		Visual image interpretation	
A) Validation based on total basal area/ B) Validation based on basal area of dominant trees				
	PA	*UA*	*PA*	*UA*
7.3 Apennine Corsican mountainous beech forest;	0,88	0,91	0,94	0,94
8.2 Turkey oak, Hungarian oak and Sessile oak forest;	0,82	0,78	0,88	0,88

4.2 Pennataro

Accuracy results for the study area of Pennataro are reported in Table 4 and Table 5.

The two approaches (A, B) applied to assign EFTs by field data give similar outcomes in the case of semi-automatic classification, with an OA index around 50%. A value of zero of KIA, however, indicate that this overall accuracy is as high as what would be expected from a pure random assignments of pixels to EFTs. Accuracy of visual image interpretation is higher considering both OA and KIA, demonstrating how, in this case, this method is more suitable to detect EFTs.

Accuracy results for “other termophilous deciduous forest” show how this EFT is very difficult to be discriminated. PA and UA are in the range of 0,3-0,4 according to both the approaches (A, B) for the semi-automatic classification. The class has not been mapped at all by the visual interpretation. Regarding the other two EFTs, Turkey oak forest has been detected better by visual interpretation both according to the approach A and B (0.7<PA<0.8, UA>0.95), than by semiautomatic classification (0.4<PA<0.5, 0.7<UA<0.8). On the other hand, PA and UA for the Apennine Corsican mountainous beech forest mapped by semi-automatic classification are similar to (approach A) or higher than (approach B) those provided by visual image interpretation. However the PA of the beech dominated forest class is significantly higher (0.7<PA<0.8) than the UA (0.32<UA<0.36) in both methods.

Table 4. OA and KIA calculated according two tested validation approaches in Pennataro pilot study area.

Field data	Classification			
	Semi-automatic classification		Visual image interpretation	
	OA	KIA	OA	KIA
A) Total basal area	0,48	0	0,74	0,49
B) Basal area of dominant trees	0,48	0	0,76	0,53

Table 5. EFTs per-class PA and UA in Pennataro pilot study area.

Forest Types	Classification			
	Semi-automatic classification		Visual image interpretation	
A) Validation based on total basal area				
	PA	*UA*	*PA*	*UA*
7.3 Apennine Corsican mountainous beech forest;	0,70	0,32	0,71	0,36
8.2 Turkey oak, Hungarian oak and Sessile oak forest;	0,46	0,72	0,74	1,00
8.8 Other termophilous deciduous forest	0,33	0,40	-	0,00
B) Validation based on basal area of dominant trees				
Forest Types	Classification			
	Semi-automatic classification		Visual image interpretation	
	PA	*UA*	*PA*	*UA*
7.3 Apennine Corsican mountainous beech forest	0,80	0,36	0,57	0,36
8.2 Turkey oak, Hungarian oak and Sessile oak forest	0,41	0,78	0,79	0,97
8.8 Other termophilous deciduous forest	0,33	0,20	-	0,00

4.3 Rincine

The validation accuracy (Table 6 and Table 7) is the same for A and B approaches, as in Rincine there is a full agreement in the classification of fifty sampling units into conifeours and broadleaved dominated forest types.

OA index is just above 65%, but the KIA value (0,26) highlights that a large proportion of the apparent classification accuracy could be due to chance agreement. Conifers were more accurately discriminated than broadleaves, as showed by higher PA and UA values: 0,79 and 0,70 for conifers and 0,50 and 0,63 for broadleaves, respectively.

Table 6. OA and KIA in Rincine pilot study area.

Field data	Classification	
	Semi-automatic classification	
	OA	KIA
A) Total basal area/ B) Basal area of dominant trees	0,67	0,26

Table 7. Per-class PA and UA in Rincine pilot study area.

Forest Types	Classification	
	Semi-automatic classification	
A) Validation based on total basal area/ B) Validation based on basal area of dominant trees		
	PA	*UA*
Conifers	0,79	0,70
Broadleaves	0,50	0,63

5. Time to produce classifications

A quantification of the time required to produce EFT classification using the two methods is reported for each study area in table 8. In general, classification in e-cognition environment required less time if compared to visual image classification.

Table 8. Estimation of time to produce EFT classification using the two selected approaches.

Study area	Visual image classification	Classification in e-cognition environment		
		Segmentation	Semi-automatic classification	Total
Caprarola	8 h	45 mins	3 h	3 h 45 mins
Pennataro	8 h	45 mins	3 h	3 h 45 mins
Rincine	10 h	1 h	3 h	4 h

6. Conclusions

Summarizing and comparing results from the three pilot areas we can draw the following conclusions:

from the map producer's point of view

- EFT "7.3 Apennine Corsican mountainous beech forest" is reliably mapped by semi-automatic classification and visual interpretation: PA is higher than 0.7 in most cases.
- EFT "8.2 Turkey oak, Hungarian oak and Sessile oak forest" is reliably recognized in Caprarola by both methods (PA>0.8 according to the two validation approaches). However, in the case of Pennataro semi-automatic classification was less accurate (0.41<PA<0.46) if compared to visual image classification (0.74<PA<0.79).
- EFT "8.8 Other termophilous deciduous forest" is not accurately detected in Pennataro.
- forest dominated by coniferous species was more accurately mapped than one covered by broadleaved deciduous species in Rincine, as showed by higher PA values: 0,79 for conifers and 0,50 for broadleaves.

from the map user's point of view

- UA is very high for EFT "7.3 Apennine Corsican mountainous beech forest" in Caprarola (UA>0.9) according to both classification approaches. In the case of Pennataro this class is over-mapped, resulting in UA just above 0.3. An explanation can be the lower image quality of the orthomosaic, but also the presence of thermophilous deciduous class being confused with beech.
- UA of EFT "8.2 Turkey oak, Hungarian oak and Sessile oak forest" is higher than 0.7 in all cases both in Caprarola and Pennataro.
- EFT "8.8 Other termophilous deciduous forest" is over-mapped based on semi-automatic classification (UA<0.4) while it is not recognised by visual interpretation.

- forest dominated by coniferous species was more accurately mapped than one covered by broadleaved deciduous species in Rincine: UA=0,70 for conifers; UA=0,63 for broadleaves.

Final remarks

- Visual interpretation resulted generally more accurate than semi-automatic classification;
- Semi-automatic classification required less time to be performed than visual image classification;
- Semi-automatic classification of true color orthomosaics appears a feasible and economic (less time consuming) alternative to visual interpretation for mapping widespread European Forest Type classes (beech and turkey oak dominated forest), provided that images are acquired by the drone under optimal conditions (different phonological status of the species, resulting in a diverse spectral response; absence of clouds; homogeneous light and atmospheric conditions between flights).

7. References

Definiens, A.G., (2010). eCognition Developer 8.0.1—user guide, 1.2.1 ed. Definiens AG, Munich.

Annex 1

Figure 1. EFTs mapped by segmentation and semi-automatic classification in the study area of Caprarola.

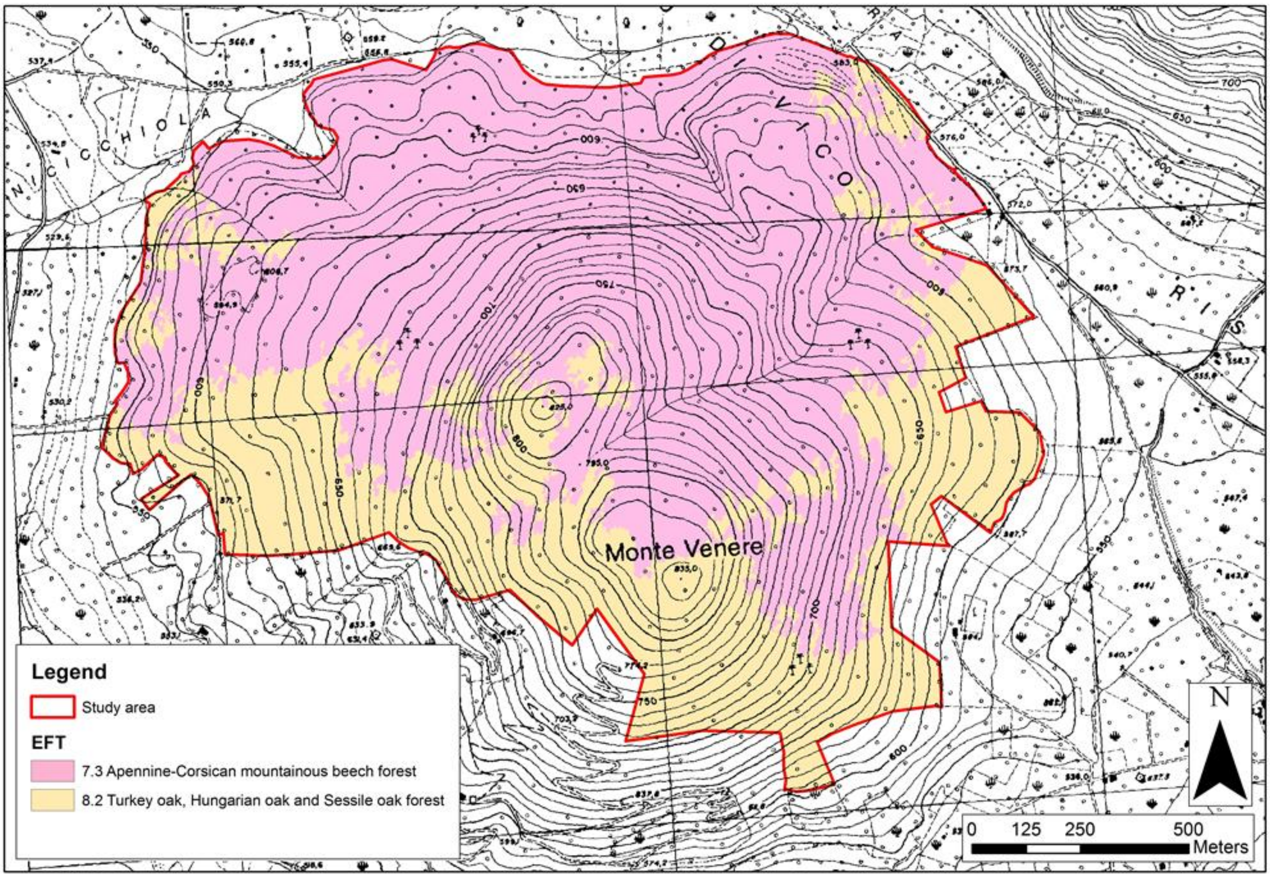

Figure 2. EFTs mapped by segmentation and semi-automatic classification in the study area of Caprarola displayed on high-resolution image acquired by eBEE.

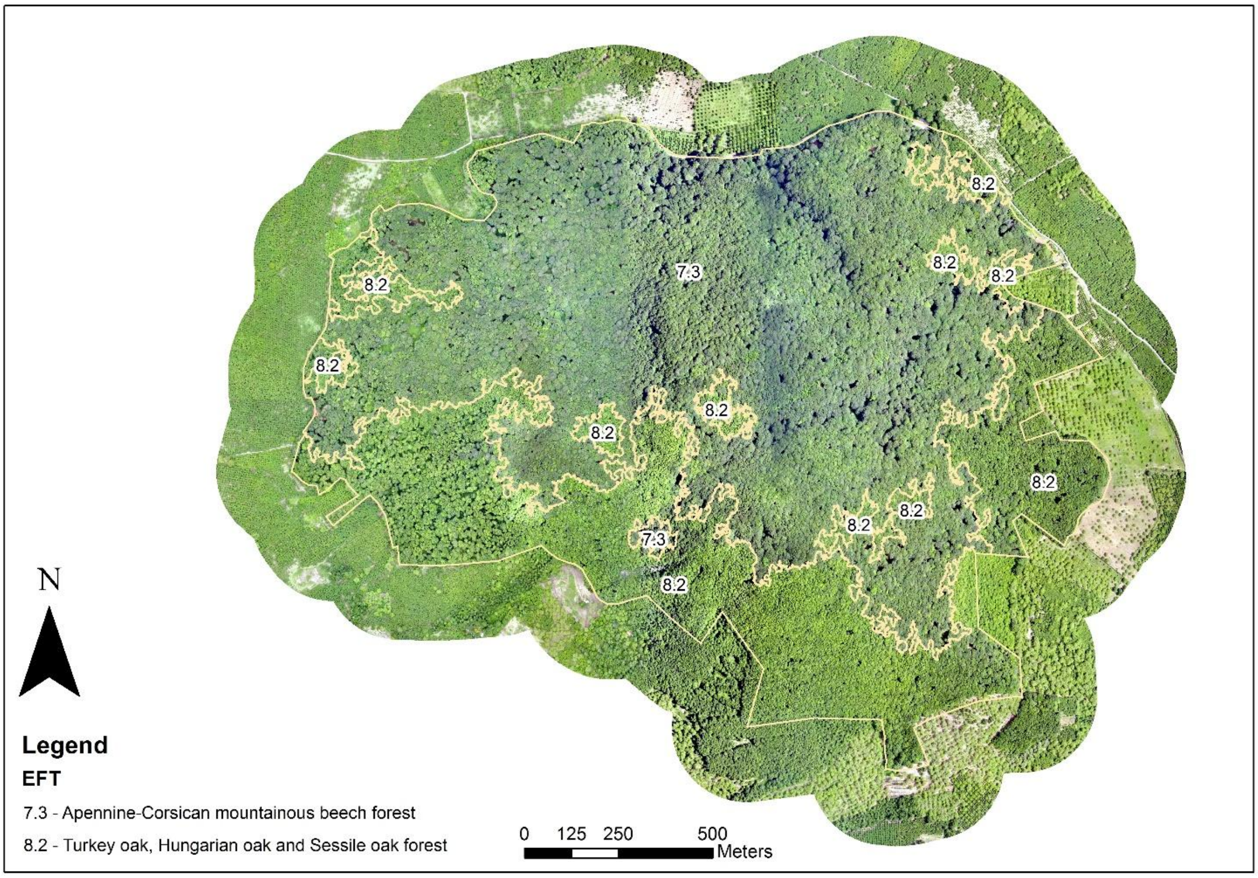

Figure 3. EFTs mapped by segmentation and semi-automatic classification in the study area of Pennataro.

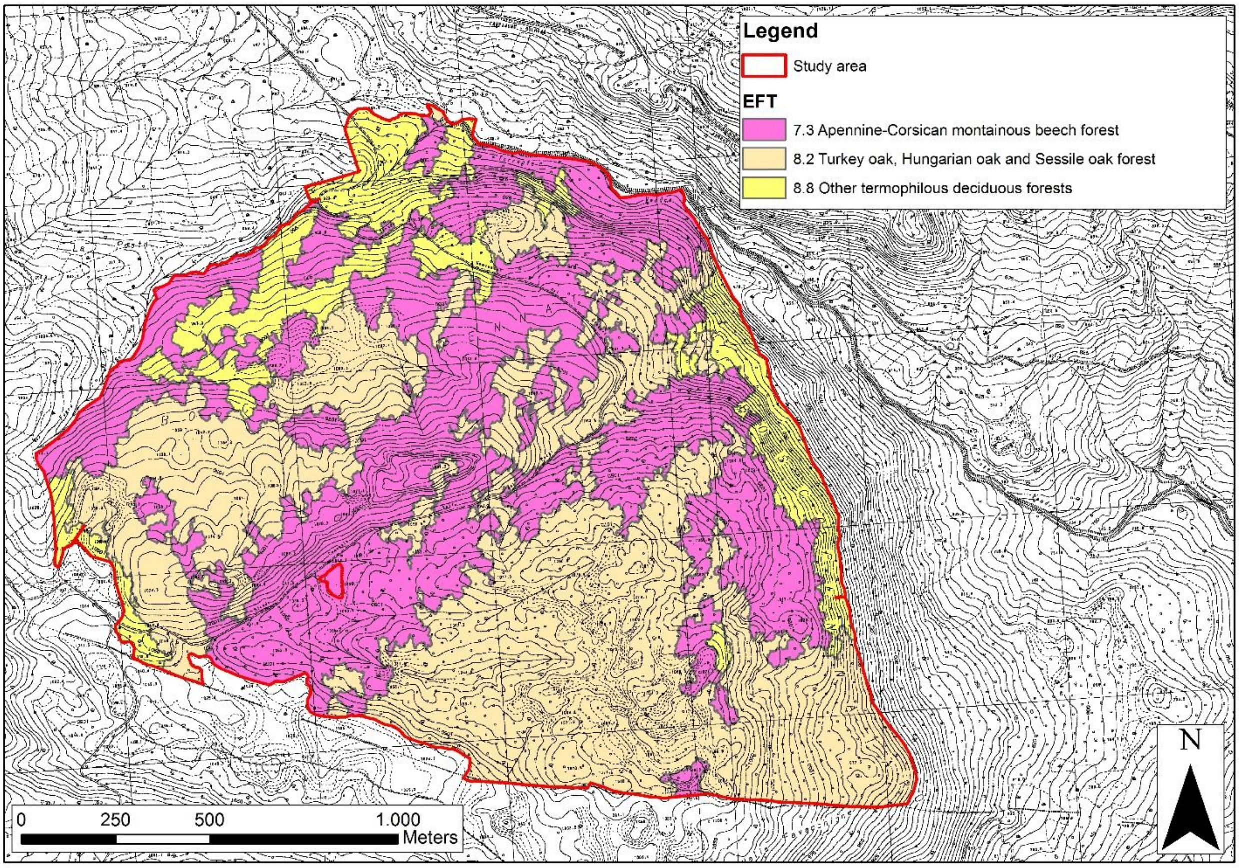

Figure 4. EFTs mapped by segmentation and semi-automatic classification in the study area of Pennataro displayed on high-resolution image acquired by eBEE.

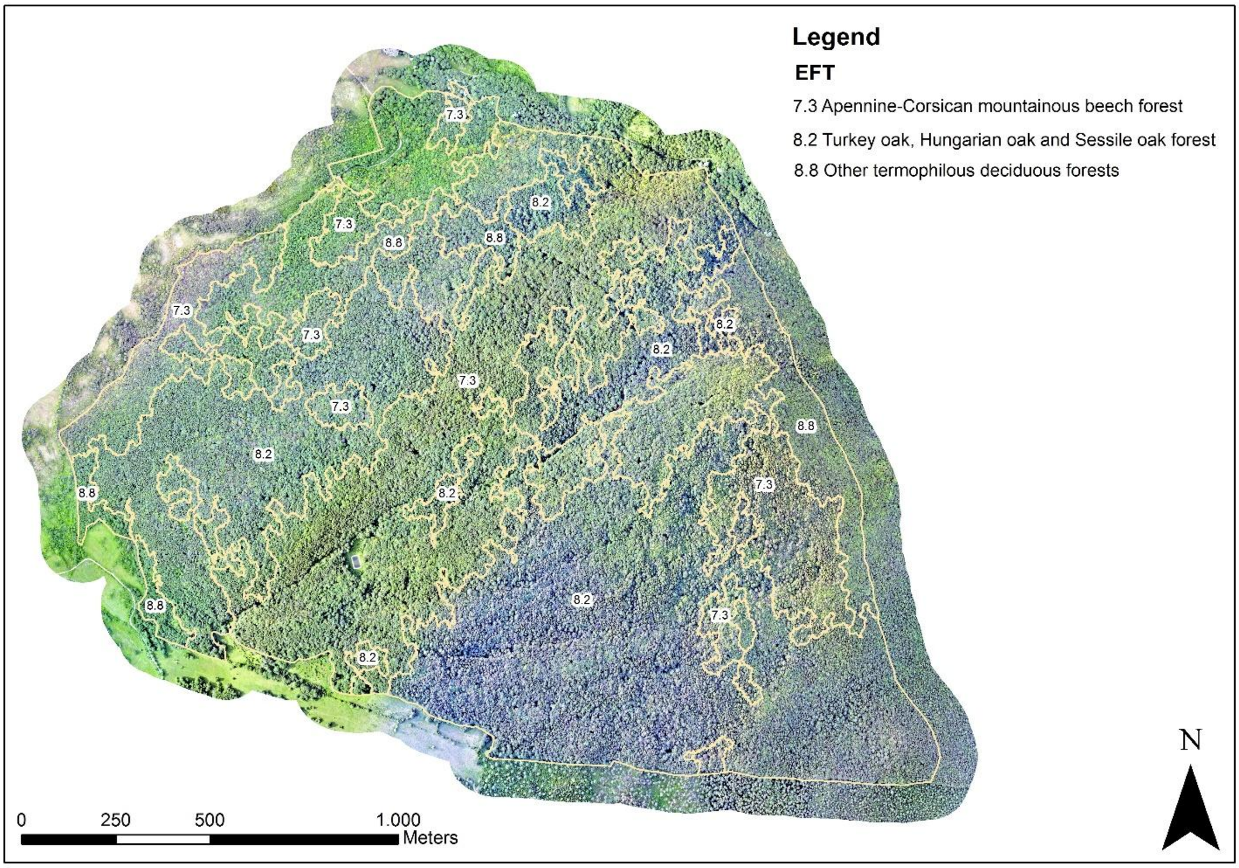

Figure 5. EFTs mapped by segmentation and semi-automatic classification in the study area of Rincine.

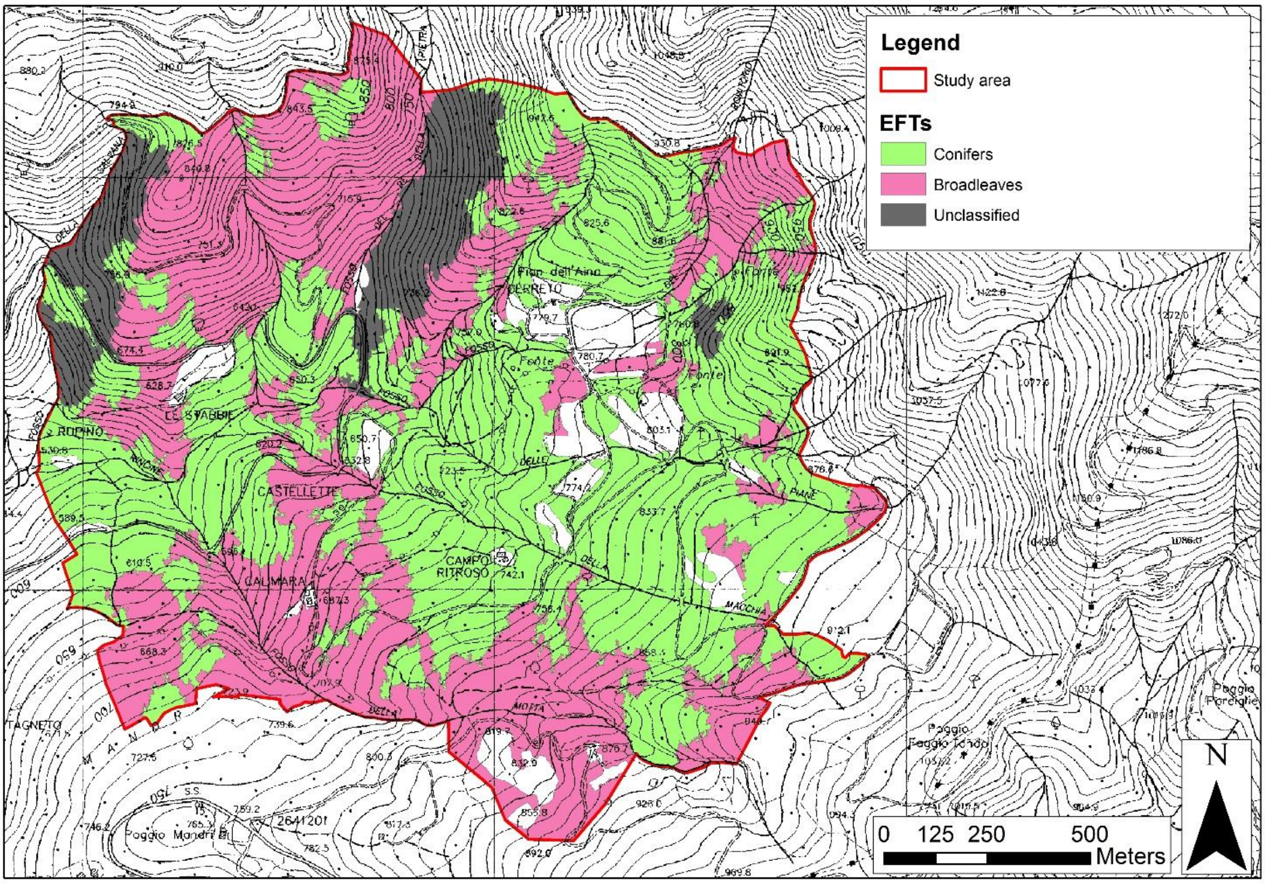

Figure 6. EFTs mapped by segmentation and semi-automatic classification in the study area of Rincine displayed on high-resolution image acquired by eBEE.