LIFE14 ENV/IT/000414
Demonstrating Remote Sensing integration in sustainable forest management FRESh LIFE

ACTION D4
Technical Report and Training

Deliverable Technical Report

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Introduction

Climate change is an unprecedented challenge and significantly impacts the functioning of forest ecosystems and the services they provide. The complex nature of climate change increases the uncertainty associated with predicting future forest ecosystem dynamics and requires an adaptive management approach moving forward (Marchetti et al., 2012; Maes et al., 2012).

Forest managers therefore need monitoring and analysis tools that can support them in assessing the current conditions of forest resources and their capacity to supply ecosystem services. Geographic information systems (GIS) and remote sensing are especially useful tools to support forest management decisions and can be used to evaluate the effectiveness of forest management through the well-established indicators of sustainable forest management (SFM) (Corona, 2010). Sustainable forest management is widely recognized as a key objective of forestry policy and practices. To monitor, evaluate, and track progress toward SFM in Europe at the regional, national and international levels, the Ministerial Conference on the Protection of Forests in Europe adopted six key criteria measured through a suite of quantitative (34) and qualitative (11) pan-European indicators of forest management (MCPFE, 2015). Because several of these indicators require information about forest type, a classification system based on 14 European forest types (EFTs) was tested to estimate a subset of forest indicators as part of Forest Europe's 2011 assessment (Forest Europe, UNECE & FAO, 2011). It was found that EFT stratification substantially improved the quality of information reported through indicators and provided an ecologically sound framework to implement SFM indicators and interpret their temporal trends (Barbati et al., 2014).

The FRESh LIFE – Demonstrating Remote Sensing Integration in Sustainable Forest Management (LIFE14/IT000414) project aims to develop innovative methods to integrate forest inventory data collected in the field with remote sensing information to estimate selected SFM indicators across space at the local scale. Within the project, high-resolution data were collected at three sites in central Italy using drones equipped with light detection and ranging (LiDAR) and optical sensors. Automated and semi-automated mapping methods were then used to spatially characterize the variables used to assess forest physiognomy and conditions at the scale of the forest management unit. At the demonstration sites, forest areas were classified based on the EFT classification scheme (Barbati et al., 2014) and a set of SFM indicators were estimated, including forest areal extent, species composition, structure, health status, naturalness, growing stock, increment, and deadwood. Newly collected data were integrated with existing information

regarding the demonstration sites into a forest information system (FIS) that was then made available to support local organizations, managers, experts, and practitioners in achieving SFM goals. This paper outlines the objectives and methods of the FRESh LIFE – Demonstrating Remote Sensing Integration in Sustainable Forest Management (LIFE14/IT000414) project, and presents and discusses some results and their implications.

Materials and Methods
Demonstration Sites

Three demonstration sites were selected in three Italian regions: Toscana, Lazio, and Molise (Fig. 1). The sites were chosen to be representative of different forest types, enabling the applicability and reproducibility of the experimental methods to be tested across a broad range of environmental conditions.

One site was selected in collaboration with the municipalities of Valdarno and Valdisieve and was located within the state property of Rincine, in the Toscana Region. Due to its long-established tradition of sustainable management practices, the site was included in the International Model Forest Network (www.imfn.net). The site, which has an area of 275 ha and is characterized by mixed oak, chestnut, and beech stands, as well as coniferous reforestations, is representative of the forest ecosystems typically found in the central Apennines.

The Bosco Pennataro site (277 ha) was chosen in collaboration with the Molise Region administration and is characterized by mixed forests, with a prevalence of Turkey oak and beech. The University of Molise routinely conducts research in this area to study old-growth forests and monitor biodiversity, and the site was recently identified as a core area of the Collemeluccio-Montedimezzo Alto Molise Man and Biosphere Reserve.

The third demonstration site, located in the Lazio region, falls within the administrative boundary of the Municipality of Caprarola, on the southern face of the Cimini Mountains, east of Lake Vico. The site (240 ha) is characterized by a mosaic of ecologically distinct habitats dominated by mesophilous woods where beech and Turkey oak are the most abundant trees, followed by chestnut, maple, and other broad-leaved species. The Municipality of Caprarola has a long tradition of forest planning and in 1982 most of Caprarola's forested area was included in the Regional Natural Reserve of Lake Vico.

Fig. 1 Map of the demonstration sites

Forest inventory data collection

Field surveys were conducted by surveying all trees with a diameter at breast height (1.30 m) ≥ 2.5 cm in 50 23 × 23 m plots (plot area = 529 m^2) at each demonstration site. Each plot was georeferenced by recording the coordinates of the plot's center through a Global Navigation Satellite System (GNSS) receiver with sub-metric precision. Sampling plots were selected using a probability sampling scheme to ensure sample representativeness and the statistical validity of SFM indicator estimates. The plot selection scheme was designed in collaboration with the Italian Council for Agricultural Research and Economics (CREA) and the University of Siena and was based on a one-per-stratum stratified sampling scheme (Brus et al., 1999; Barabesi et al., 2012; Fattorini et al., 2015). Specifically, the sampling area was split into equal-sized cells using a 23 × 23 m grid, so that the extent of the sampling area (530 m^2) was comparable to that adopted by the National Inventory of Forests and Forest Carbon Pools. Cells were then clustered into 50 equal-sized strata and one sampling plot was randomly selected in each stratum. Maps of the sampling plots selected at each demonstration site by means of the one-per-stratum stratified sampling method are shown in Fig. 2. To ensure uniform sampling procedures across sites, a sampling protocol was developed, with detailed instructions of field survey procedures and methods, target variables, and data analysis.

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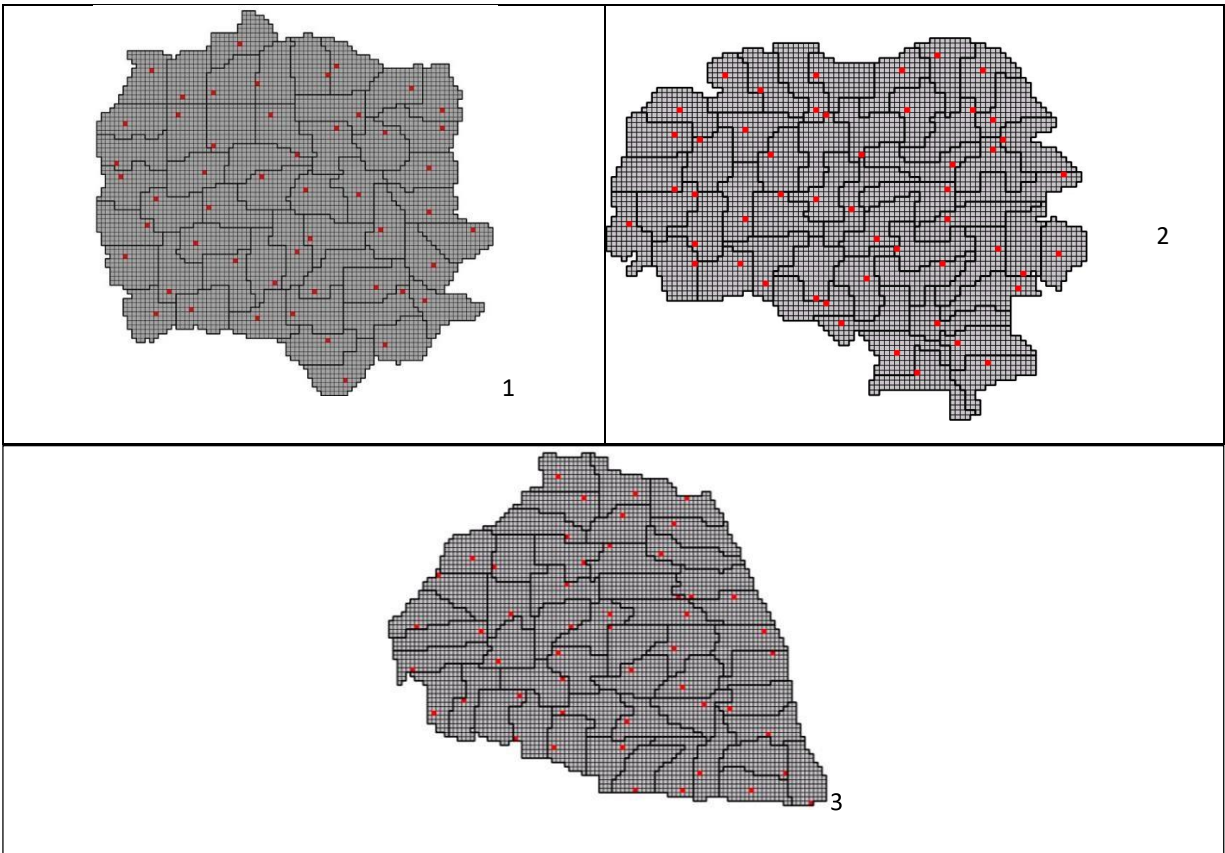
Fig. 2 Map of the sampling plots selected at the three demonstration sites. 1) Rincine; 2) Caprarola; 3) Bosco Pennataro

The following parameters were measured in each plot:

- position, species, diameter, height, crown area, health status, and microhabitat of live trees
- position, diameter, height, and decay class of standing dead trees
- position, diameter, origin, and decay class of stumps
- position, orientation, length, and decay class of down deadwood.

Several qualitative parameters that are useful in monitoring and quantifying biodiversity indices relevant to SFM goals were also recorded, such as the presence and type of microhabitats (Santopuoli et al., 2018a, 2019; Spina et al., 2019).

Inventory data were collected using Field-Map (IFER Ltd., Prague, Czech Republic), which allows for automated digital recording of field measurements and provides output in the form of Excel spreadsheets and shapefiles, thereby significantly decreasing the time required to input raw field data into a database. Prism-based positioning of individual trees resulted in low sampling error and improved precision when correlating field estimates with remote sensing data

(Santopuoli et al., 2018b). Forest inventory data collected at the three demonstration sites were organized in a single georeferenced database and imported into a GIS software (Fig. 3).
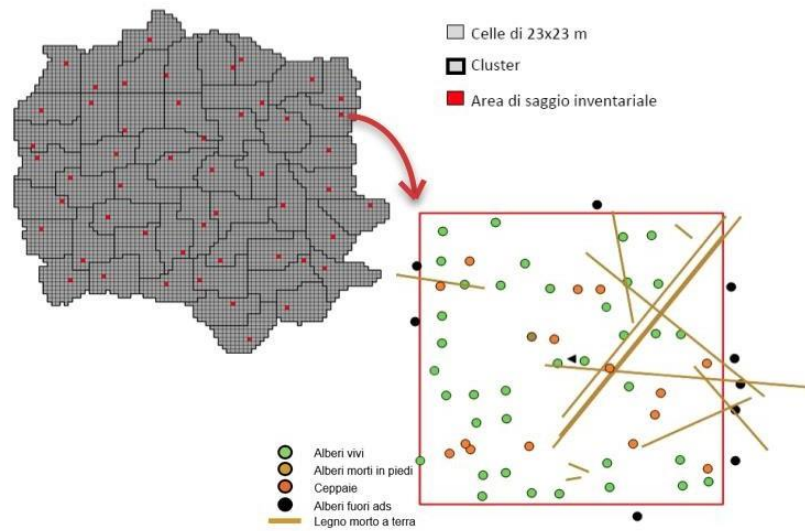
Fig. 3 Visualization of forest inventory data imported into a geographic information system (GIS) software

Remote sensing surveys

Unmanned aerial vehicles

An increasing number of studies have shown the benefits of using unmanned aerial vehicles (UAVs), or drones, in forestry research (e.g., Tang & Shao, 2015), especially when coupled with remote sensing images. The use of UAVs in forestry research is particularly valuable for several reasons:

- the spatial resolution of drone-borne optical images is remarkably high (a few cm) because of the low flight altitude. This feature substantially enhances image interpretation, especially when it comes to the identification of tree species and delineation of areas exhibiting forest damage or different land uses

- the temporal resolution is enhanced because the low maintenance requirements and flight costs of UAVs allow for more frequent image acquisition compared to manned aircraft or remote sensing. Event-specific image acquisition at relatively short notice can also be readily accommodated

- UAVs equipped with multispectral optical instruments or LiDAR technology allow for multi-sensor data acquisition.

Within the FRESh LIFE project, two UAVs were used: an octocopter and a fixed-wing UAV (Fig. 4). The octocopter, made by Oben s.r.l., has a diameter of 1.8 m, take-off weight of about 15 kg, flight time of approximately 20 min, and flight altitude generally around 20 m above the

canopy. When performing a set of sequential flights using multiple batteries, the octocopter is capable of image acquisition across a surface area between 20 and 50 ha per day, depending on the orography and accessibility of the study area. The octocopter was equipped with an ultra-light Yellowscan LiDAR sensor that can acquire point clouds with densities up to 50 points/m^2 under conditions typically encountered in forest surveys.

The second UAV used in this project, purchased by the University of Firenze, was the fixed-wing eBee Ag model made by senseFly. The eBee Ag was equipped with a camera with visible range (RGB) and near infrared (NIR) sensors that can acquire multispectral images with extremely high definition. The eBee Ag has a wingspan of 98 cm, weight of approximately 700 g, flight time of about 45 min, and can cover around 60 ha in one flight. The eBee Ag was specifically developed for photogrammetric applications that convert aerial images into 3D digital models and orthophotos with very high resolution.

Both UAVs were operated autonomously using the appropriate software, while pilots supervised the flight and intervened as needed.
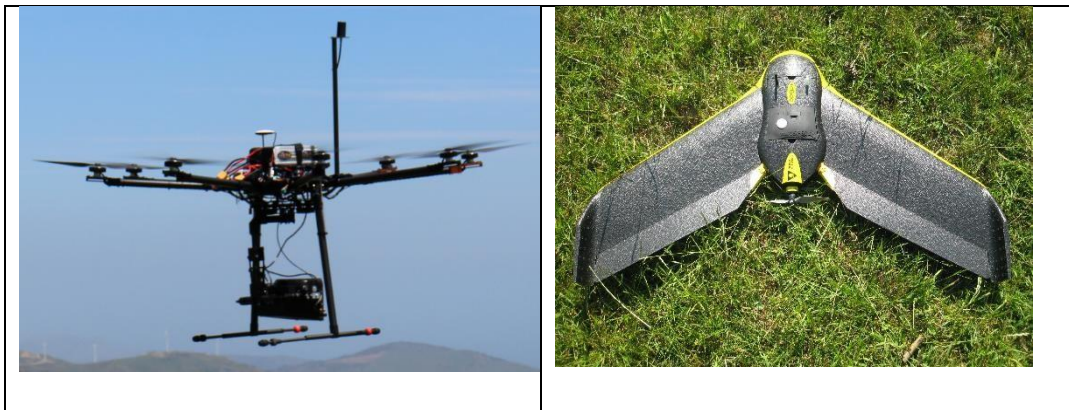
Fig. 4 Octocopter with a light detection and ranging (LiDAR) sensor (left) and fixed-wing eBee drone (right)

Drone regulations established by the Italian Civil Aviation Authority (ENAC) prohibit flying drones beyond the visual line of sight and require that a distance of no more than 500 m is maintained between the drone and the pilot at all times. Because of these restrictions, the octocopter could cover 75% of the overall demonstration area, while no images could be acquired in the remaining 25% because local geographic features, such as deep valleys and a lack of clearings suitable for piloting, prevented pilots from operating within regulatory limits. In such cases, LiDAR data acquisition was performed using a light helicopter with technical

specifications (e.g., flight profile, flight altitude above the canopy, cruise speed) that mimicked drone flights (Balsi et al., 2018b).

Multispectral data

For multispectral data acquisition through the eBee Ag, 12 ground control points (GCPs) were established at each demonstration site using 50×50 cm targets. The coordinates of each GCP were recorded by means of a GNSS receiver with sub-metric precision. The eMotion 2 version 2.4.2 software (senseFly) was used to simulate, plan, and monitor flights. Throughout the project, the total flight time was 23 h 40 min and the overall surface area covered was 1298 ha.

Table 1 Details of image acquisition flights performed with the eBee Ag drone and ground control point (GCP) acquisition through the Global Navigation Satellite System (GNSS)

Type of data acquired	Demonstration Site	Number of flights	Total flight and GCP acquisition time	Number of images
GCP	Caprarola	-	10 h	-
RGB	Caprarola	5	3 h 20'	483
NIR	Caprarola	5	4 h 20'	564
GCP	Bosco Pennataro	-	11 h	-
RGB	Bosco Pennataro	6	3 h 50'	608
NIR	Bosco Pennataro	7	4 h 35'	689
GCP	Rincine	-	8 h	-
RGB	Rincine	4	3 h 25'	506
NIR	Rincine	5	4 h 10'	682
	Total	27	52 h 40'	3532

Images were processed with the Agisoft PhotoScan software (Agisoft LLC, St. Petersburg, Russia) to generate 3D point clouds. Agisoft Photoscan combines Structure from Motion (SfM) and photogrammetric algorithms to generate 3D spatial data from properly overlaid images. The software has a user-friendly processing workflow that combines computer vision SfM and stereo-matching algorithms for imagery alignment and multi-view stereo reconstruction. Image alignment involved the sparse reconstruction of 3D geometry by detecting and matching homologous points across overlaid images by means of SfM techniques. At this stage, GCPs

were used to improve the estimates of camera position and orientation, thereby resulting in a more accurate reconstruction of the 3D model (Giannetti et al., 2017, 2018a). The GCP coordinates were imported and positioned using a guided approach and a dense point cloud and digital surface model (DSM) were generated with Agisoft Photoscan. The DSM was used to perform orthorectification of the images acquired by the eBee Ag.

The image processing steps described above resulted in the generation of the following data products at each demonstration site:

- two dense point clouds (NIR and RGB), with an average of 20–40 points/m^2
- two DSMs with a resolution of 50 cm
- two orthophotos (RGB and NIR), with a resolution of 10 cm (Fig. 5).
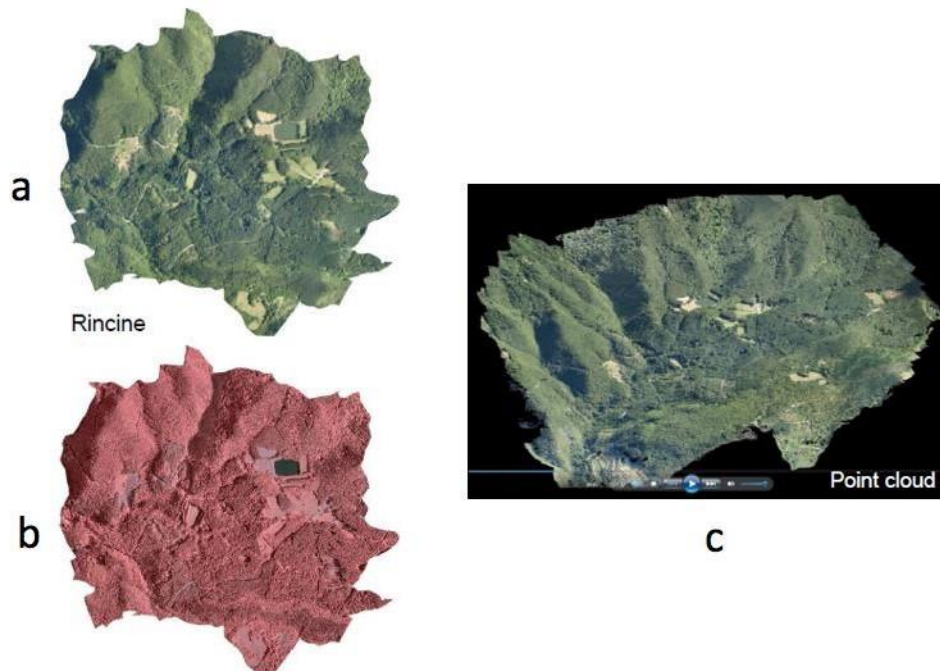
Fig. 5 Examples of data products generated by processing eBee Ag images at Rincine. a) RGB orhophoto; b) NIR orthophoto; c) 3D point cloud model

LiDAR data

Tables 2 and 3 provide a summary of the survey flights carried out at the three demonstration sites with the octocopter and light helicopter.

Table 2 Details of light detection and ranging (LiDAR) data acquisition with the octocopter

Demonstration site	Flight altitude (m)	Total acquisition time	Number of flights	Number of swaths	Area covered by the octocopter (ha)	Area covered by the octocopter and the light helicopter (ha)
Bosco Pennataro	70	4 h 40'	24	97	195	259
Rincine	70	4 h 00'	20	88	178	236
Caprarola	70	5 h 00'	30	60	140	241

Table 3 Details of light detection and ranging (LiDAR) data acquisition with the light helicopter. For technical reasons related to flight trajectories, some areas were covered by both the octocopter and the helicopter.

Demonstration site	Flight altitude (m)	Total acquisition time	Number of flights	Number of swaths	Area covered (ha)
Bosco Pennataro	70	6 h 00'	5	22	94
Rincine	70	5 h 00'	4	20	82
Caprarola	70	10 h 00'	7	41	120

Processing of LiDAR data was conducted with the CloudCompare software and Terrascan and the following data products were generated at each demonstration site (Fig. 6):

- a dense point cloud, with an average of 70–120 points/m^2
- a digital terrain model (DTM), with a spatial resolution of 50 cm
- a DSM, with a spatial resolution of 25–50 cm
- a canopy height model, with a spatial resolution of 50 cm (Balsi et al., 2016).
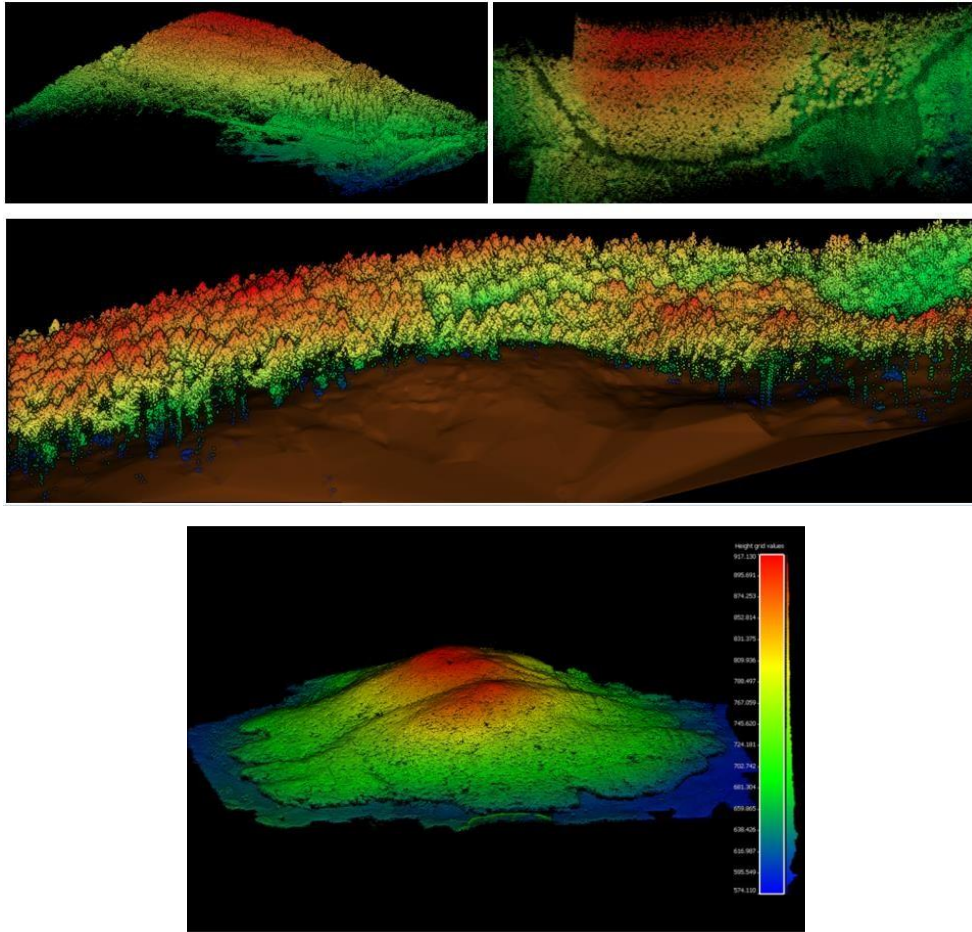
Fig. 6 Data products obtained by processing light detection and ranging (LiDAR) images acquired at Rincine (upper panel) and Caprarola (lower panel)

The acquired data were validated by comparing them to existing airborne laser scanner (ALS) data available for the Rincine site. The results of these comparisons, including qualitative comparisons of LiDAR profiles and orthophotos, extraction of geometric features, and rugosity analyses, confirmed the quality of the data and the validity of the image acquisition techniques tested within the project (Balsi et al., 2017, 2018a).

Important technical aspect to design SAPR acquisition and data validation

The main phases of an aerial SAPR survey are:

• flight plan planning

• Materialization and measurement of control points (GCP) with high precision GNSS receiver for photogrammetric acquisition

• high precision GNSS base station for LiDAR acquisition

• Flight execution

The flight planning phase

• identify the areas suitable for the materialization of the control points that must be located at different altitudes, scattered throughout the area of interest and in clearings, in several not less than 8;
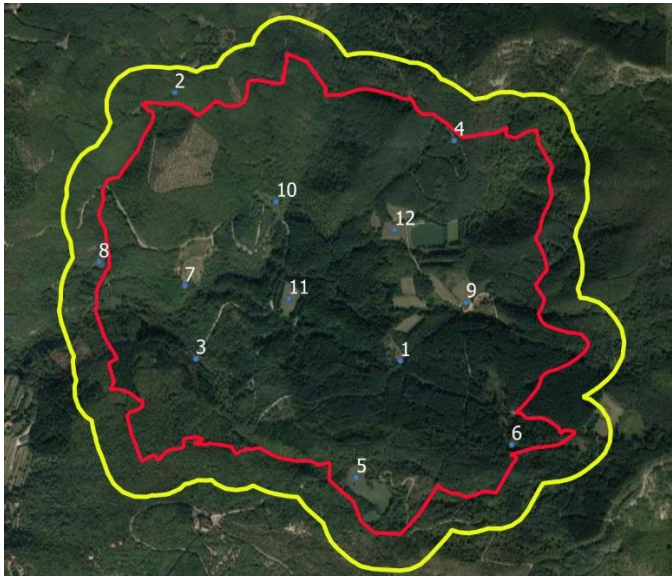
Fig. 7 planning GCP and Buffer area to avoid holes in the acquisition in the area of interest

• analysis of the conformation of the terrain, in order to program the flight parallel to the slope, to avoid deformities in the scale of the acquired images or LiDAR data point densities;
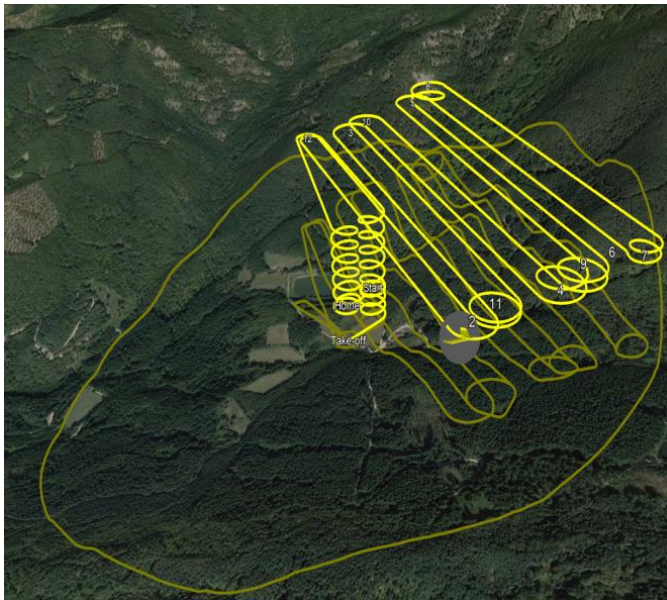

Fig. 8 planning of flight line parallel to the slope

• identification of take-off and landing points in order to comply with the ENAC regulation on the distances allowed between the pilot and the SAPR (distances up to 500 m in VLOS mode are allowed, which means that the pilot must always be in visual contact with the SAPR without no device);
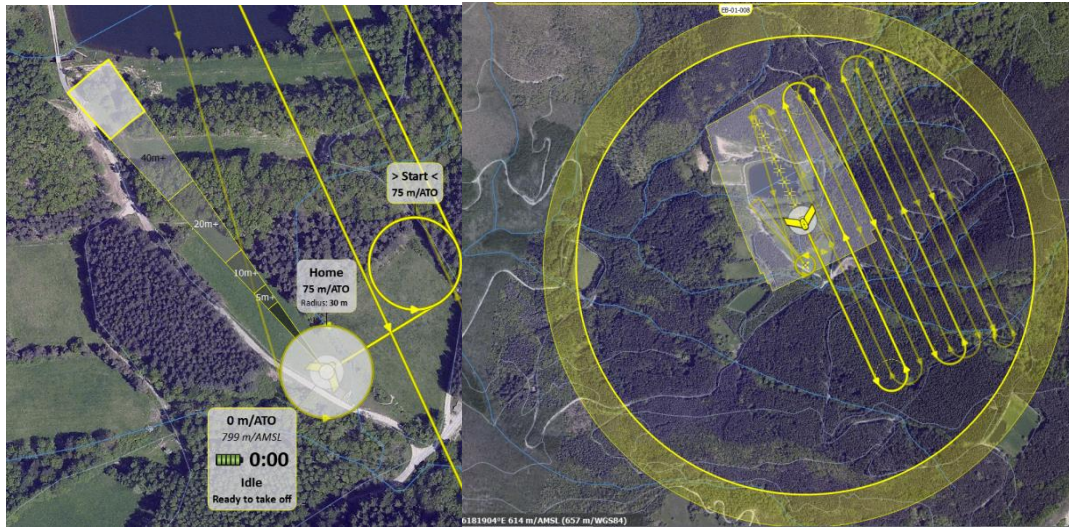
Fig. 9 planning area flight according to ENAC regulation (the circle rappresents the area of 500 m around the pilot) and planning the correct landing path.

• identification of obstacles and possible problems (eg power lines, pylons).
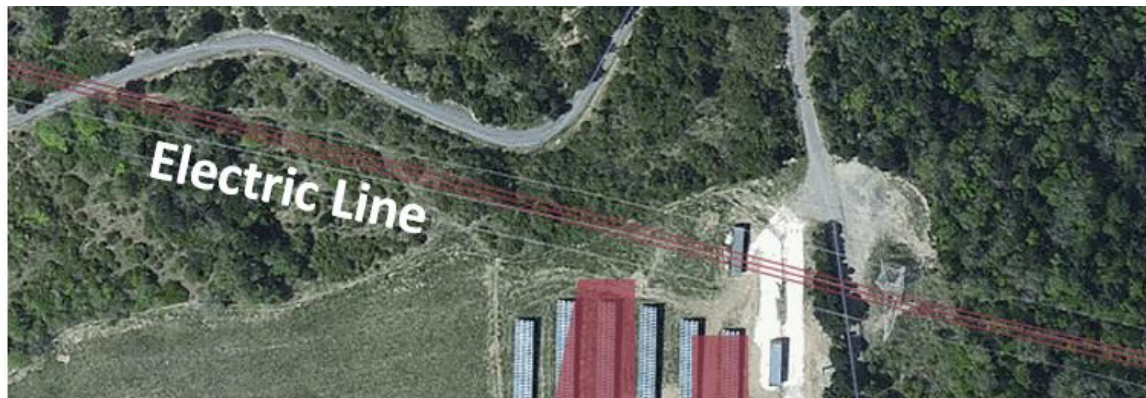
Fig. 10 identification of obstacle in the area to avoid collisions

Materialization of ground control point for photogrammetric acquisitions

Before the drone acquisitions, it is necessary to acquire between 8 and 12 ground control points (GCP) located at different altitudes and scattered throughout the area of interest in clearings, and / or roads not covered by vegetation, in order to be able to collimate well the GCP in post-processing and avoid distortions in photogrammetric data (Figure 7). The targets need to be materialized on the ground with panels with a black and white checkered pattern black and white numbered 50×50 cm in size to ensure maximum contrast in the images and therefore easy identification in post-processing. The target panels need to be fixe to the ground in open areas and their coordinates need to be recorded with a high precision GNSS receiver. It is important to emphasize that in one area the GCPs can be marked permanently in order to use the same data to collect future flights. In fact, in our case we used the same GCP for RGB acquisition and NIR acquisition. Moreover, if the GCP will be permanently, that will allow to align better future flights, and thus make change analyzes easier.

GCP accuracy measures is important to georeferenced well the photogrammetric data. Errors in GCP

accuracy will reflect high errors in the position of data derived by the survey.

High precision GNSS base station for LiDAR acquisition

The correction and accuracy of data acquired by LiDAR SAPR depends on two main aspect: one related with the flight line and the side lap between the strips and one based on the accuracy of the base stations used to correct the points cloud. In fact, LiDAR points are correct as a normal RTK GNSS field survey. So, the base station used during the flight need to be a high accurate GNSS receiver (double frequency). Moreover, it is important to switch on the base station at least 30 minutes before starting the flights to avoid errors in the corrections. Moreover, the base station needs to be place in an open space, without tree nearby to avoid multipath errors.

Flight execution of eBee Photogrammetric SAPR

Firstly, it should be noted that it is necessary to build a buffer zone around the area of interest to avoid deformations in the data that we need to derive. For our experience, we suggest using a buffer area of at least 150 m on the border of the area of interest in order to avoid distortions in areas to be detected (Figure 7).

The flights need to be done around 12.00 in summer or in spring to avoid problems of shadowing the slopes. Moreover, it is important to note that passing clouds in the images can affect the alignment of the images in post-processing and therefore "holes" in the aerial SAPR survey.

The overlap and sidelapof the images in forestry activities for our experience need to be set between (65-95 %). High overlap and sidelap allow to obtain more dense point cloud, and avoid errors related with some problematic image (i.e. blurry images) that can affect the alignment of images in post-processing. Moreover, the flight lines need to be parallel to the slope, to avoid deformities in the scale of the acquired images.

Flight execution with LiDAR octocopter

The sidelap the flight lines need to be set between 85-95% in order to align without problem the different strip and avoid holes in the survay. (65-95 %). Moreover, the flight lines need to be parallel to the slope, to avoid different densities of point in the different area of point clouds.

Data validation of aerial survey

In our experience, we validate the aerial survay of eBee and Octocopter in two different way.
The eBee data accuracy was evaluate using additional GCP acquired in the area and analyzing the error in terms of x, y and z, reveled high level of accuracy (i.e. z=10 cm, y=0.5 cm, x=0.5 cm). However, it could be possible to evaluate the accuracy of photogrammetric data also with available data of the area acquired for example by airplane (old ortomosaic). The validation is important to understand if the data are georeferenced in a right way or not.
The data LiDAR octocopter were evaluate using available LiDAR data, as we present before, moreover additional analysis related to the sidelap between the streep can be done in order to evaluate holes in the survay.

SFM indicators

Forest type classification

Data acquired at the three demonstration sites were used to classify forested areas according to the

EFT classification scheme. Classification was conducted through a visual interpretation of high-

resolution color orthophotos (ground resolution of 10 cm/pixel) acquired through the eBee Ag drone. Photo-interpretation is a qualitative classification technique widely used in forestry research to characterize forest cover. Forest inventory data collected in 50 plots at each demonstration site were used to evaluate the accuracy of the maps obtained through photo-interpretation.

The EFTs correspond to ecologically distinct forest communities that exhibit homogeneous features in terms of species composition and forest cover (EEA, 2006; Barbati et al., 2014). The main criterion typically used for classification through photo-interpretation is the variation in tone due to the different spectral responses in the green band, but the high resolution of the RGB orthophotos used in this project warranted the use of additional diagnostic parameters, such as the size, shape, and structure of individual tree crowns. This made it possible to identify the main canopy taxa to the genus or species level. A photo-interpretation protocol based on the following criteria was developed to harmonize procedures across demonstration sites:

- minimum mapping unit of 0.5 ha, based on the FAO definition of forest land, i.e., area > 0.5 ha, tree height > 5 m, and tree canopy cover > 10% (FAO FRA, 2005)
- photo-interpretation scale of 1:1500
- development of a legend of the forest types present at the demonstration sites based on previously available information (Table 4).

Table 4 Legend used to classify the demonstration sites according to the European Forest Type (EFT) scheme (species present at the demonstration sites are reported in parentheses)

Code	Forest Type
7.3	Apennine-Corsican mountainous beech forest (*Fagus sylvatica* L.)
8.1	Downy oak forest (*Quercus pubescens* Willd.)
8.2	Turkey oak, Hungarian oak, and sessile oak forest (*Quercus cerris* L.)
8.7	Chestnut forest (*Castanea sativa* Mill)
8.8	Other thermophilous deciduous forests (*Fraxinus ornus L., Ostrya carpinifolia Scop.*)
10.2	Mediterranean and Anatolian black pine forest (*Pinus nigra* spp.)
13.2	Italian alder forest (*Alnus glutinosa* L.)
14	Introduced tree species forest (*Pseudotsuga menziesii* Mirb. *Chamaecyparis lawsoniana* Murray*)

99.2	Non forest

In addition to photo-interpretation, semi-automated EFT classification methods were also tested. Specifically, a multi-resolution segmentation and object-based analysis of orthophotos was performed using the eCognition software (Trimble, Munich, Germany). Objects (polygons) were obtained through a segmentation algorithm whose parameter values (scale parameter, geometric/spectral homogeneity, compactness) were set based on several tests performed at each demonstration site (Giuliarelli et al., 2017). The classification of polygons obtained through segmentation was performed using the standard nearest neighbor algorithm. The classifier was trained on a set of polygons (training sites) manually selected through visual interpretation for each forest type. Two additional classifiers (random forest and k-nearest neighbors) were tested to classify the dominant forest species at Rincine (Del Perugia et al., 2017, 2018).

Defoliation

Forest Europe indicator 2.3 (defoliation) is defined as "Defoliation of one or more main tree species on forest and other wooded land in each of the defoliation classes: "moderate", "severe" and "dead"". This indicator is a proxy for the health and vitality status of trees and is generally evaluated through a visual assessment of tree crown status during field surveys. Within the FRESh LIFE project, defoliation data were collected during forest inventory field surveys based on a percentage scale, where 100% indicates standing dead trees. The degree of defoliation of live trees was mostly ≤10%, suggesting a limited impact of defoliation at the demonstration sites. To verify the feasibility of estimating defoliation from high-resolution RGB orthophotos acquired by the eBee drone, plots with trees that had >50% defoliation were selected, but preliminary results showed that defoliation was readily detected only for severely damaged trees, i.e., with a degree of defoliation between 70 and 99%. Based on these preliminary results, photo-interpretation of RGB orthophotos was only used to detect the highest defoliation classes (70–100%). A map showing the spatial distribution of this indicator was generated for each demonstration site.

Forest damage

Forest Europe indicator 2.4 (forest damage) is defined as "Forest and other wooded land with damage, classified by a primary damaging agent (abiotic, biotic and human induced)". The only

large-scale disturbance event recorded at the demonstration sites was a windstorm in March 2015 at Rincine. A map of this indicator was generated through RGB orthophoto interpretation (ground resolution of 10 cm) using a minimum mapping unit of 0.25 ha. Clearing operations after the windstorm, which removed all trees from the damaged areas and were completed before our drone surveys, facilitated the delineation of the areas damaged by the windstorm.

Tree species composition

Forest Europe indicator 4.1 (diversity of tree species) is defined as "The area of forest and other wooded land, classified by the number of tree species present" to distinguish forested areas dominated by a single species from those characterized by multiple tree species. This indicator is typically assessed during field surveys by quantifying the fraction of the basal area occupied by each species in a plot. The use of orthophoto interpretation to map this indicator is limited by the fact that some tree species are only represented in the lower layers of a forest and never reach the canopy layer. Because of these limitations, the number of EFTs was used as a proxy for the number of species.

Introduced tree species

Forest Europe indicator 4.4 (introduced tree species) is defined as "The area of forest and other wooded land dominated by introduced tree species". Because these areas are captured by the EFT category 14, this indicator was mapped by delineating the areas classified in that category, which only occurred at Rincine.

Growing stock and above ground biomass

While the estimation of other SFM indicators was based on RGB and NIR orthophotos, Forest Europe indicators 1.3 and 1.4 were estimated using LiDAR data acquired with the octocopter and supplemented by data obtained with the light helicopter in areas not reached by the octocopter. Remotely sensed and field inventory survey data were integrated by relating variables measured in the field (growing stock volume and total above ground biomass) to LiDAR-derived metrics obtained in the corresponding grid cells. The resulting regression model was used to spatially extrapolate indicator estimates throughout each demonstration site.

FIS

The use of decision support systems has grown substantially in recent years as a result of the increased availability of field and remote sensing data at multiple scales. To provide managers of the demonstration sites with a useful forest management support tool, all data acquired and processed within the FRESh LIFE project were organized in a GIS-based Forest FIS. A georeferenced data package was prepared for each demonstration site by ensuring that spatial layers could be visualized on any GIS software available to managers. In cases where managers did not already have a GIS platform, the QGIS open-source software (QGIS Development Team, 2019) was used and training sessions were organized to familiarize managers with the software. All data collected during the project were stored in the FIS, including preexisting data (e.g., road and traffic information, management plans, and regional topographic and hydrographic maps), newly acquired data (orthophotos, DTM, DSM, and inventory data) and processed data (EFT classification and SFM indicator maps). Wherever possible, data were organized and provided at the scale of the individual forest units. Managers were encouraged to test the tool and provide feedback on how to tailor the FIS to the specific management needs of the individual demonstration areas.

Results

EFT classifications based on photo-interpretation are reported in Figs. 11 and 12. While Caprarola and Bosco Pennataro had only two forest types, Rincine exhibited a higher heterogeneity.
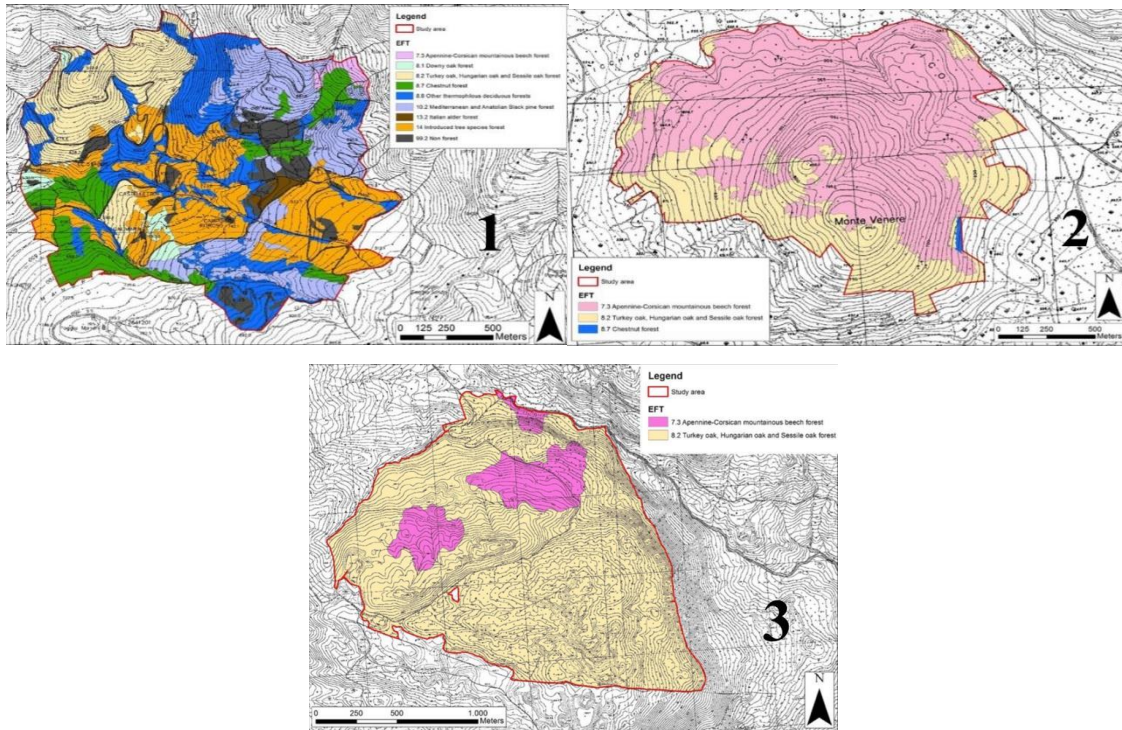
Fig. 11 Results of the photo-interpretation at the three demonstration sites. 1) Rincine; 2) Caprarola; 3) Bosco Pennataro
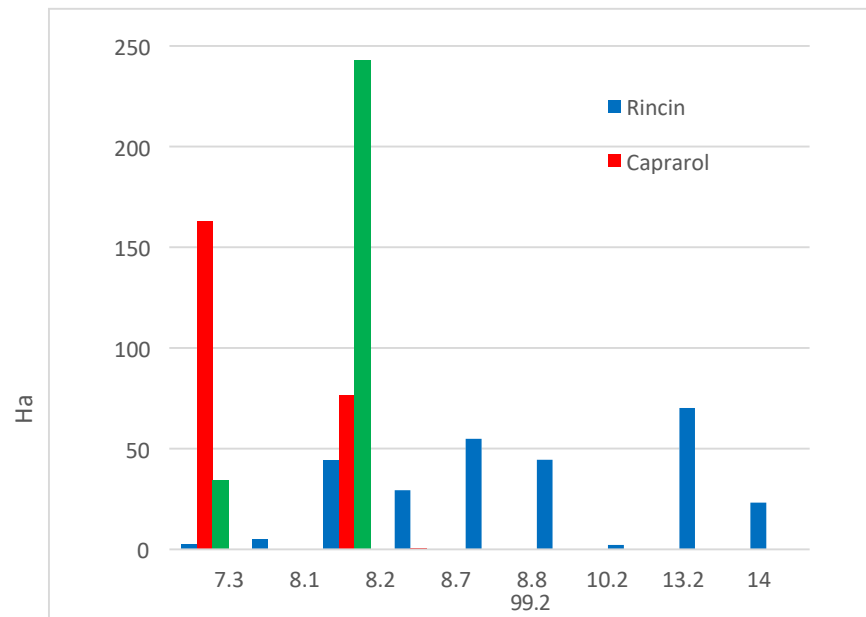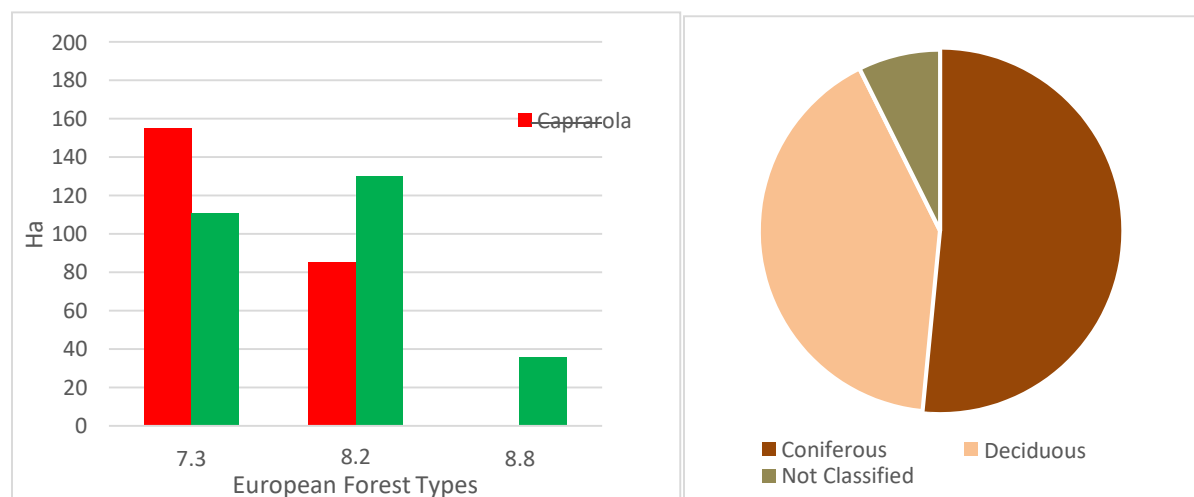

Fig. 12 Results of the photo-interpretation at the three demonstration sites (see Table 4 for code interpretation)

Semi-automated classification led to different results across the demonstration sites. At Rincine, the orography of the area negatively impacted orthophoto quality, with 25% of the surface area shaded by mountains. As a result, in this area the semi-automated classification was limited to distinguishing between coniferous and broad-leaved forest areas, with an overall classification accuracy (OA) of 67%. At Caprarola and Bosco Pennataro, the presence of a limited number of forest types made classification easier and EFTs were assigned with OA = 86%, which was close to the accuracy obtained through photo-interpretation in the same area (92%) (Giuliarelli et al., 2017). Differences in the time of year when images were acquired at Caprarola and Bosco Pennataro led to differences in parameter settings due to changes in species phenological stages. At Caprarola, where flights were conducted at the end of May, the two dominant species (beech and Turkey oak) had different spectral responses in the green band, resulting in a larger weighting being assigned to this band within the classification algorithm.

Fig. 13 Results of the semi-automated classification at the three demonstration sites. Left panel: histogram corresponding to Caprarola and Bosco Pennataro; Right panel: classification of coniferous and broad-leaved forest areas at Rincine, with the corresponding surface areas reported in ha (see Table 4 for code interpretation)

The results of the application of the other semi-automated classification methods (Del Perugia et al., 2017, 2018) showed that Random Forest based on combining three data sources (NIR, RGB, and LiDAR) led to the highest accuracy (OA = 71%) compared to photo-interpretation (Fig. 14).

Accuracy further improved (OA = 83%) when classification was limited to the identification of forest types (coniferous, broad-leaved, and mixed forest areas) rather than individual species.
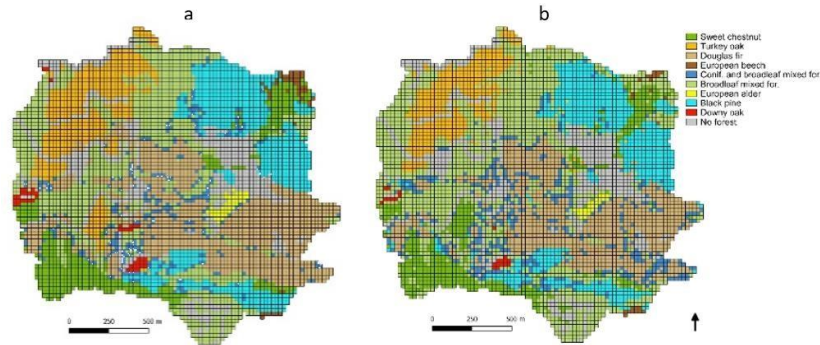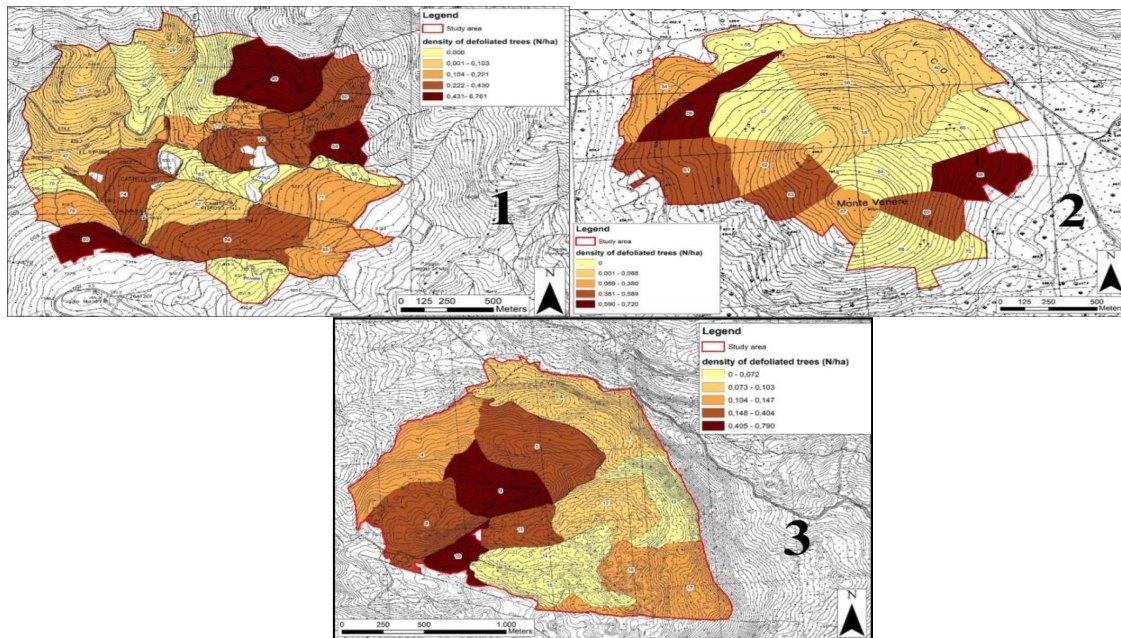

Fig. 14 Comparison of the results of photo-interpretation (a) and Random Forest (b)

The results of the defoliation indicator showed that the average number of trees falling in the highest defoliation classes was <1 tree/ha at Caprarola and Bosco Pennataro and 7 trees/ha at Rincine (Fig. 15).

Fig. 15 Defoliation maps at the three demonstration sites. 1) Rincine; 2) Caprarola; 3) Bosco Pennataro

At Caprarola, automated segmentation methods were tested to identify the additional features of forest cover. Specifically, a study was conducted to test the use of maps of forest canopy gaps as

covariates of variables of interest in remote sensing biodiversity monitoring (Bagaram et al., 2018). The results showed that very small gaps can be readily mapped through object-oriented segmentation methods applied to orthophotos, with a very high spatial resolution obtained with the eBee Ag drone. Similar methods could be tested in the future to estimate defoliation. Rincine was the only site exhibiting forest damage, with a little over 3 ha out of the 270 ha of land within the demonstration site classified as damaged (Fig. 16).
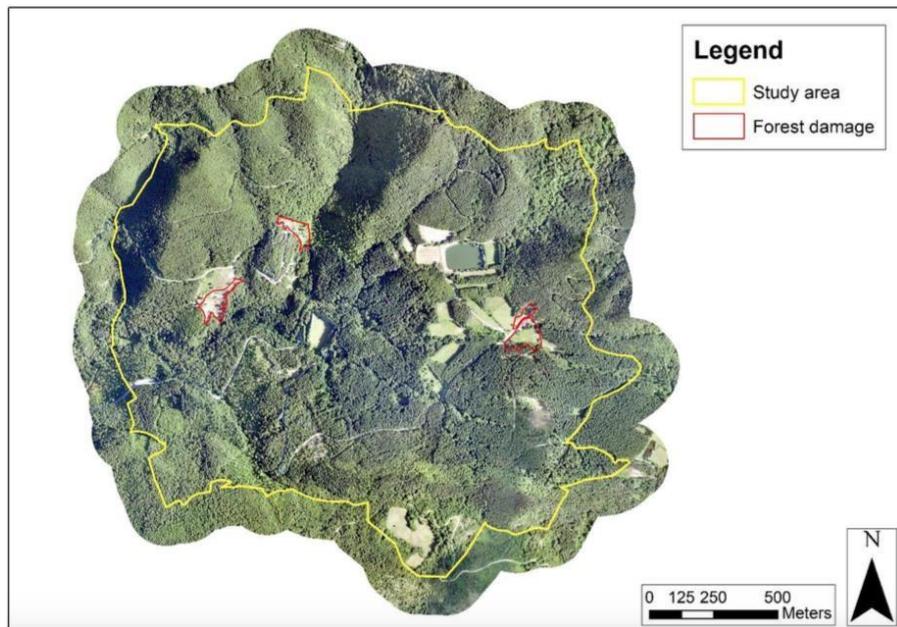
Fig. 16 Forest damage map at Rincine

The number of EFTs present in each forest lot, which was used as a proxy for the number of tree species, varied between one and three at Caprarola and Bosco Pennataro but was five at Rincine (Fig. 17).
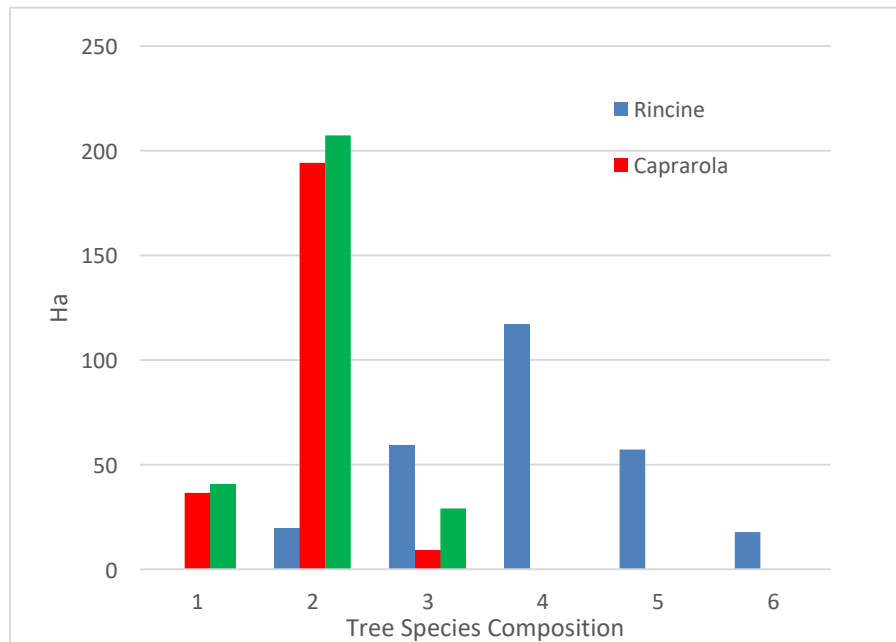

Fig. 17 Classification of the three demonstration sites based on the sustainable forest management (SFM) indicator of tree species composition

Introduced tree species were only found at Rincine, where approximately 25% of the site was covered by reforestation stands of Douglas fir (*Pseudotsuga menziesii*) and other alien conifers (e.g., *Chamaecyparis lawsoniana*) (Fig. 18).
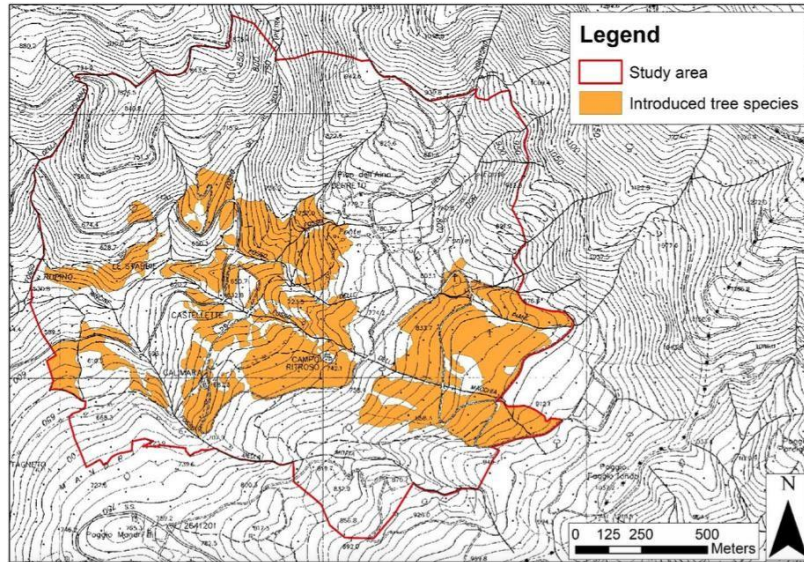
Fig. 18 Map of the introduced (alien) tree species at Rincine

The growing stock and above ground biomass estimates varied across the demonstration sites, with R^2 values between 0.80 (Rincine, RMSE = 111 m³/ha) and 0.26 (Caprarola, RMSE = 167 m³/ha) for growing stock (Fig. 19) and between 0.68 (Rincine, RMSE = 64.7 m³/ha) and 0.25 (Caprarola, RMSE = 134.4 m³/ha) for biomass (Fig. 20) (Puletti et al., 2017; Grotti et al., 2018).
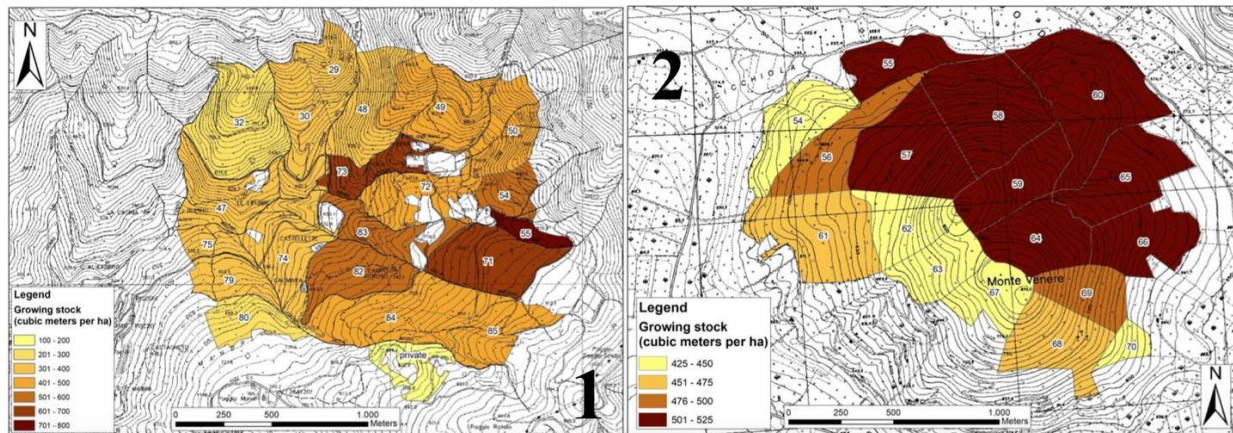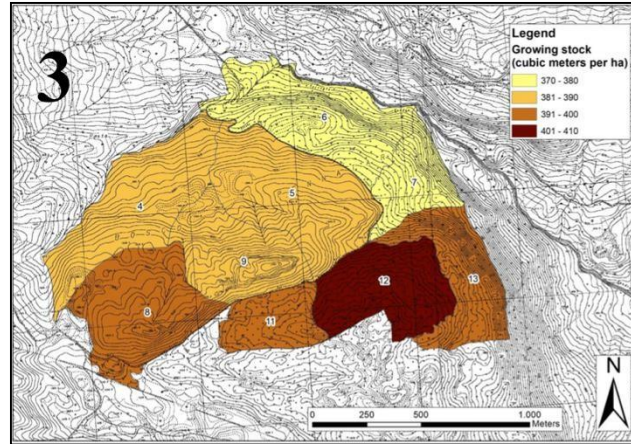
Fig. 19 Maps of growing stock estimates at the scale of the individual lot for the three demonstration sites. 1) Rincine; 2) Caprarola; 3) Bosco Pennataro
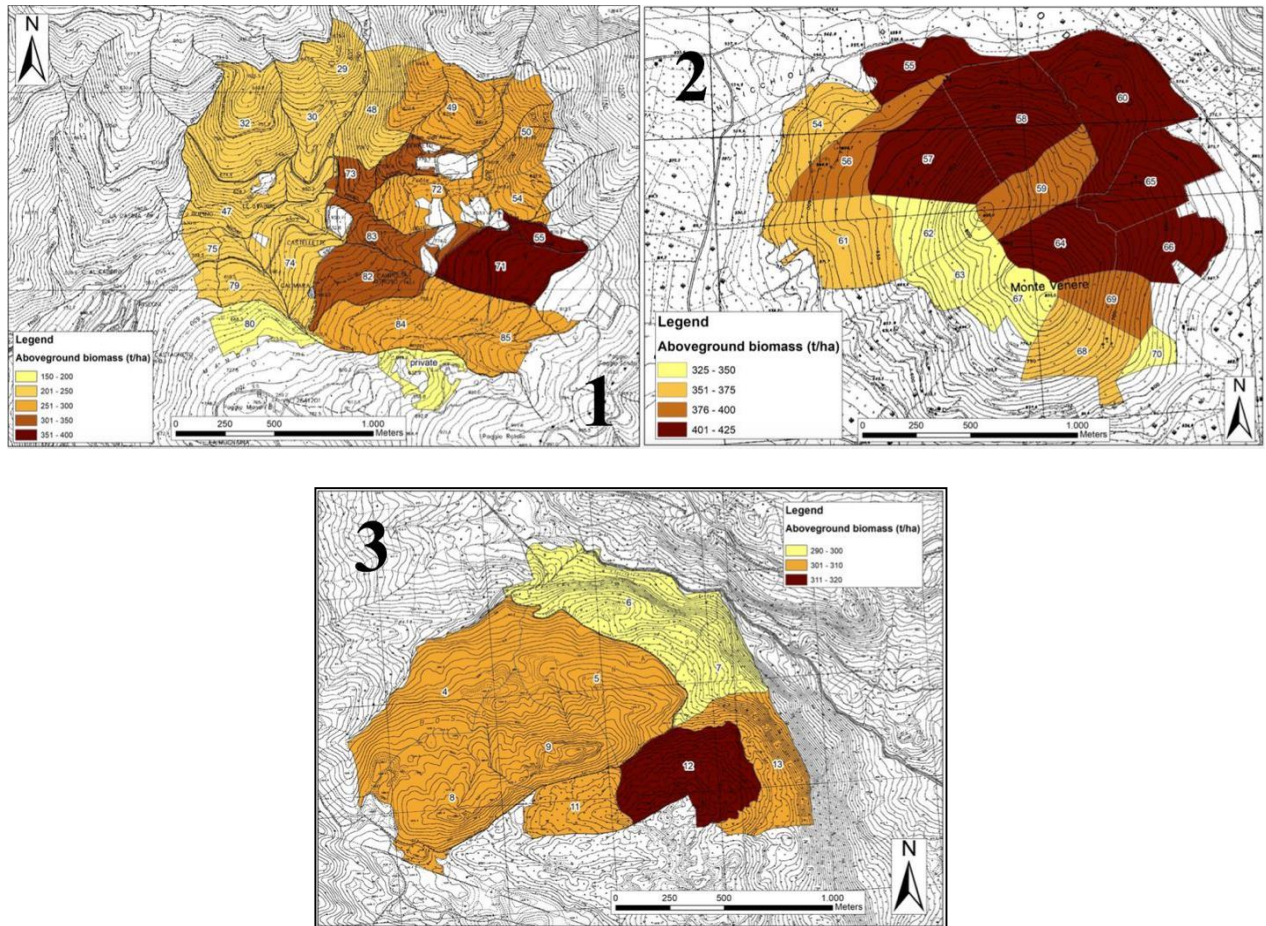

Fig. 20 Maps of above ground biomass estimates at the scale of the individual lot for the three demonstration sites. 1) Rincine; 2) Caprarola; 3) Bosco Pennataro

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Data generated during the project were included in the FIS and provided to the three organizations that manage the three demonstration sites, i.e., the Municipalities of Valdarno and Valdisieve, the Municipality of Caprarola, and the Molise Region Administration. As requested by local managers, the FIS was integrated into the QGIS open-source software, which had already been adopted by managers for daily management activities.
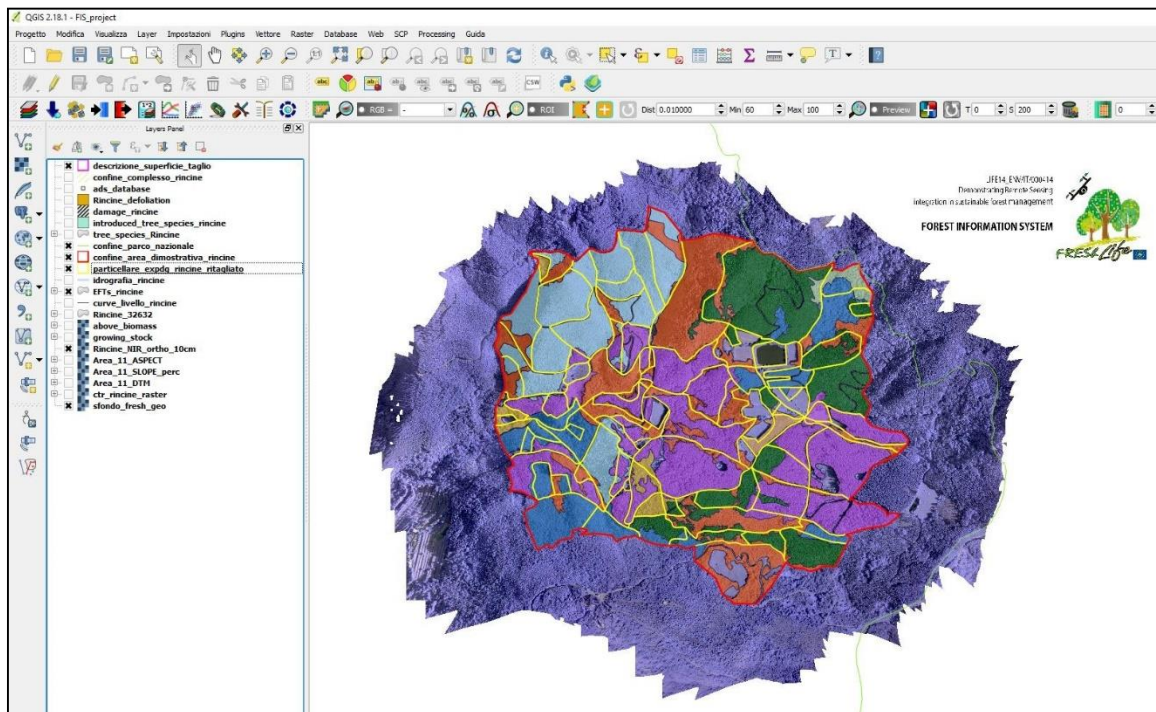
Fig. 21 Example of a screenshot of the Rincine forest information system (FIS)

Discussion and conclusions

The FRESh LIFE project has demonstrated the use of orthophotos acquired with the eBee Ag drone to map SFM indicators related to forest composition and health status. Alternative estimation methods and the combined use of ALS and field data were tested to map growing stock and above ground biomass. The transferability and reproducibility of the methods used in this project were verified in several operational contexts. For example, inventory and LiDAR data were used to estimate the growing stock of coastal stone pine stands in Toscana (D`Amico et al., 2019); individual tree detection algorithms were used to estimate tree volume (Sačkov et al., 2016); and the integration of ALS and field data was tested to estimate individual tree

attributes, such as height and diameter (Giannetti et al., 2018b). Innovative methods were also developed, such as the use of DTM-independent metrics (Giannetti et al., 2018c). These metrics are extremely useful in forestry research because they are based on photogrammetric data, thereby overcoming the restrictions imposed by current regulations that limit the use of heavier drones, which can carry the LiDAR sensors necessary to generate DTMs.

The main goal of the LIFE projects is the transfer of knowledge generated through research to real-world applications. Local managers were included as partners in the FRESh LIFE project and they were actively involved in all phases of the project. Other stakeholders were engaged throughout the project, leading to the development of a network of individuals and organizations operating at different scales and directly interested in the project objectives. In addition, the use of drones and innovative methods, such as 3D modeling, prompted interest from individuals working in fields other than forestry, such as robot and sensor technology.

During the remote sensing data acquisition phase of the project, the organization of demonstration flights at each demonstration site was especially successful. Each event, organized in collaboration with local partners, included an introduction to the project topics and objectives, followed by drone flights, live data processing, and the generation of final data products. These events, advertised through the project website and social media, were attended by students, scientists, local managers, professionals, and institutions, who became part of a network of contacts that was then included in all project communications. The project website and social media pages are routinely updated with reports, pictures, and videos about project activities. In addition to these dissemination activities, project activities and results are presented at conferences and seminars organized at universities and other institutions.

To date, the project has led to the publication of 10 papers in international peer-reviewed journals and over 30 oral presentations and posters at conferences.

Bibliography

- Bagaram M.B., Giuliarelli D., Chirici G., Giannetti, F., Barbati A. (2018). UAV Remote Sensing for Biodiversity Monitoring: Are Forest Canopy Gaps Good Covariates? *Remote Sens.* **2018**, *10*, 1397.

- Balsi M., Esposito S., Fallavollita P., Giannì C. (2016), "Airborne lidar scanning for forest biomass estimation", Unmanned Vehicles in Research ENVRIPlus Workshop – Livorno, 12th -15th October 2016

- Balsi M., Esposito S., Fallavollita P., Giannetti F., Chirici G. (2017). High-Density Aerial LiDAR Survey for the FREShLIFE Project. In: Fares S, Alivernini A, Chianucci F, Ferrara C, Marchi M, Sallustio L, Bucci G (eds) (2017). La foresta che cambia: ricerca, qualità della vita e opportunità. XI SISEF National Congress, Rome (Italy) 10-13 Sept 2017. Abstract-book, pp. 122+134 [online] URL: htp://www.sisef.it/sisef/xi-congresso/.

- Balsi M., Esposito S., Fallavollita P., Nardinocchi C. (2018a) Single-tree detection in high-density LiDAR data from UAV-based survey, European Journal of Remote Sensing, 51:1, 679-692, DOI: 10.1080/22797254.2018.1474722.

- Balsi M., Esposito S., Fallavollita P., Chirici G. (2018b). High-Density Aerial LiDAR Survey for the FREShLIFE Project. In: AIT2018, IX Conference of the Italian Society of Remote Sensing, Florence 4-6 July 2018, Abstract Book (https://aitonline.org/ait2018-2/).

- Barabesi L., Franceschi S., Marcheselli M. (2012). Properties of design-based estimation under stratified spatial sampling with application to canopy coverage estimation. The Annals of Applied Statistics, 6 (1): 210–228. doi: 10.1214/11-AOAS509.

- Barbati A., Marchetti M., Chirici G., Corona P. (2014). European Forest Types and Forest Europe SFM indicators: tools for monitoring progress on forest biodiversity conservation. Forest Ecology and Management, 321:145-157.

- Brus D.J., Spätjens L.E.E.M., de Gruijter J.J. (1999). A sampling scheme for estimating the mean extractable phosphorus concentration of fields for environmental regulation. Geoderma, 89: 129–148.

- Corona P, 2010. Integration of forest mapping and inventory to support forest management. iForest, 3: 59-64.

- D'Amico G., Del Perugia B., Chirici G., Giannetti F., Travaglini D. (2019). Caratterizzazione delle pinete litoranee di pino domestico della Toscana con dati telerilevati a supporto della Gestione Forestale Sostenibile. In stampa negli Atti del Settimo Simposio "Il Monitoraggio Costiero Mediterraneo: problematiche e tecniche di misura".

- Del Perugia B., Travaglini D., Barbati A., Barzagli A., Giannetti F., Lasserre B., Nocentini S., Santopuoli G., Chirici G. (2017). Classificazione delle specie forestali con dati multispettrali e laser scanning multipiattaforma. In: Fares S, Alivernini A, Chianucci F, Ferrara C, Marchi M, Sallustio L, Bucci G (eds) (2017). La foresta che cambia: ricerca, qualità della vita e opportunità. XI SISEF National Congress, Rome (Italy) 10-13 Sept 2017. Abstract-book, pp. 122+134 [online] URL: htp://www.sisef.it/sisef/xi-congresso/.

- Del Perugia B., Travaglini D., Barzagli A., Giannetti F., Nocentini S., Chirici G. (2018). Classification of dominant forest tree species by multi-source very high spatial resolution remote sensing data. In: AIT2018, IX Conference of the Italian Society of Remote Sensing, Florence 4-6 July 2018, Abstract Book (https://aitonline.org/ait2018-2/).

- EEA, 2006. European Environment Agency (2006). European forest types. Categories and types for sustainable forest management and reporting. EEA, Report No. 9/2006

- Fattorini L., Corona P., Chirici G., Pagliarella M.C. (2015). Design-based strategies for sampling spatial units from regular grids with applications to forest surveys, land use and land cover estimation. Environmetrics, 26, 216-228.

- Forest Europe, UNECE and FAO, 2011. State of Europe's Forests 2011. Status and Trends in Sustainable Forest Management in Europe. In: Ministerial Conference on the Protection of Forests in Europe, Forest Europe Liaison Unit Oslo.

- Giannetti F., Travaglini D., Chirici G. (2017). Use of UAV photogrammetric 3D data for forestry inventory: a case of study. In: Fares S, Alivernini A, Chianucci F, Ferrara C, Marchi M, Sallustio L, Bucci G (eds) (2017). La foresta che cambia: ricerca, qualità della vita e opportunità. XI SISEF National Congress, Rome (Italy) 10-13 Sept 2017. Abstract-book, pp. 122+134 [online] URL: htp://www.sisef.it/sisef/xi-congresso/.

- Giannetti F., Travaglini D., Chirici G. (2018a). Use of UAV photogrammetric 3D data to predict forest structure indices. In: AIT2018, IX Conference of the Italian Society of Remote Sensing, Florence 4-6 July 2018, Abstract Book (https://aitonline.org/ait2018-2/).

- Giannetti F, Puletti N, Quatrini V, Travaglini D, Bottalico F, Corona P, Chirici G (2018b). Integrating terrestrial and airborne laser scanning for the assessment of single tree attributes in Mediterranean forest stands. European Journal of Remote Sensing 51:795–807. doi: 10.1080/22797254.2018.1482733.

- Giannetti F, Chirici G, Gobakken T, Næsset E, Travaglini D, Puliti S (2018c). A new approach with DTM-independent metrics for forest growing stock prediction using UAV photogrammetric data. Remote Sensing of Environment 213:195–205. doi: 10.1016/j.rse.2018.05.016

- Giuliarelli D., Barbati A., Del Perugia B., Ferrari B., Giannetti F., Lasserre B., Mattioli W., Oreti L., Santopuoli G., Tomao A., Travaglini D., Chirici G. (2017). Mappatura degli European Forest Types da drone e applicazioni per la stima di indicatori di biodiversità forestale. In: Fares S, Alivernini A, Chianucci F, Ferrara C, Marchi M, Sallustio L, Bucci G (eds) (2017). La foresta che cambia: ricerca, qualità della vita e opportunità. XI SISEF National Congress, Rome (Italy) 10-13 Sept 2017. Abstract-book, pp. 122+134 [online] URL: htp://www.sisef.it/sisef/xi-congresso/.

- Grotti M., Puletti N., Corona P., Chirici G., Giuliarelli D., Dibiase R.M., Fattorini L. (2018). Design-based approaches for the spatial prediction of stand attributes under forest inventory perspectives. In: AIT2018, IX Conference of the Italian Society of Remote Sensing, Florence 4-6 July 2018, Abstract Book (https://aitonline.org/ait2018-2/).

- Maes J., Egoh B., Willemen L., Liquete C., Vihervaara P., Schägner J. P., Grizzetti B, Drakou E.G., La Notte A., Zulian G., Bouraoui F., Paracchini M.L., Braat L., Bidoglio, G., 2012. Mapping ecosystem services for policy support and decision making in the European Union. Ecosystem Services, 1(1), 31- 39.

- Marchetti M., Sallustio L., Ottaviano M., Barbati A., Corona P., Tognetti R., Zavattero L., Capotorti G., 2012. Carbon sequestration by forests in the national Parks of Italy. Plant Biosystems 146(4), 1001- 1011.

- MCPFE, 2015. Background information for Improved Pan-European Indicators for Sustainable Forest Management. Madrid, Spain.

- Puletti N., Chirici G., Barbati A., Giannetti F., Grotti M., Morletti A., Ventre T., Corona P., Fattorini L. (2017). Stima di risorse forestali ad alta risoluzione tramite informazioni telerilevate multipiattaforma. In: Fares S, Alivernini A, Chianucci F, Ferrara C, Marchi M,

Sallustio L, Bucci G (eds) (2017). La foresta che cambia: ricerca, qualità della vita e opportunità. XI SISEF National Congress, Rome (Italy) 10-13 Sept 2017. Abstract-book, pp. 122+134 [online] URL: htp://www.sisef.it/sisef/xi-congresso/.

-   Sačkov, I.; Santopuoli, G.; Bucha, T.; Lasserre, B.; Marchetti, M. Forest Inventory Attribute Prediction Using Lightweight Aerial Scanner Data in a Selected Type of Multilayered Deciduous Forest. *Forests* **2016**, *7*, 307.

-   Santopuoli G., Di Febbraro M., Alvites Diaz C., Balsi M., Marchetti M., Lasserre B. (2018a). ALS data for detecting Habitat Trees in a multi-layered Mediterranean forest. In: AIT2018, IX Conference of the Italian Society of Remote Sensing, Florence 4-6 July 2018, Abstract Book (https://aitonline.org/ait2018-2/).

-   Santopuoli G., Antonucci, S., Spina, P., Marchetti, M., & Garfì, V. (2018b). Field-Map: riscontri pratici sull'utilizzo in campagne di rilievo. L'esperienza dell'Università del Molise nell'ambito di progetti di ricerca e progetti LIFE. Sherwood, 237 Novembre - Dicembre 2018 pp 15-18.

-   Santopuoli, G., di Cristofaro, M., Kraus, D., Schuck, A., Lasserre, B., & Marchetti, M. (2019). Biodiversity conservation and wood production in a Natura 2000 Mediterranean forest. A trade-off evaluation focused on the occurrence of microhabitats. (iforest in stampa).

-   Spina, P., Santopuoli, G,. (2019, in stampa). Valore habitat e valore economico degli alberi. Esempi pratici per la valutazione dei trade-off sulla base dei microhabitat. Sherwood |238 Gennaio - Febbraio 2019 pp 11-15.

-   Tang L., Shao G., 2015. Drone remote sensing for forestry research and practices. Journal of Forestry Research, 26: 791-797.