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Detection And Characterization of Forest Harvesting In Piedmont Through Sentinel-2 Imagery: A Methodological Proposal

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ABSTRACT This study evaluated the effectiveness of Sentinel-2 (S2) as a tool for early detection and estimation of forest harvesting in the Piemonte Region, which can be used by the regional forest administration. The priority was the detection, at the regional scale, of annual forest cover changes with the following goals: *i)* mapping of irregular (in respect of the regional Forestry Regulation) forest cuts; *ii)* quantification of the intensity of the silvicultural interventions. Results are expected to support forest police controls.
The proposed procedure is based on a supervised classification approach based on Random Forest algorithm. Accuracy of harvested areas detection proved to be high (overall accuracy 98%). Characterization of the occurred forest cuts was obtained computing the local coefficient of variation of the normalized difference vegetation index (NDVI) after harvesting, that showed to be a good predictor of forest harvesting intensity.

KEYWORDS: Forest Harvesting detection, Forest Change detection, Sentinel 2, Forest, harvesting characterization

Introduction

Remote sensing is known to be a powerful tool to detect forest changes and supporting their interpretation. Forest harvesting has long been monitored by satellite remote sensing, with accuracies suitable for operational mapping in many different types of forest and with a great variety of sensors (Franklin 2001). Many studies concerned the detection of forest cuts (Banner and Ahern 1995, Drieman 1994, Fransson et al. 1999) and associated changes of forest cover, which are often validated by aerial imagery. According to Hall et al. (1989), remotely-sensed images offered a 12:1 cost saving in data acquisition in respect of aerial imagery. In fact, information from satellite remote sensing is greatly cheaper than other methods (Holmgren and Thuresson 1998). Identification of the deforestation agents is important for programming public policies aiming at environment preservation (dos Santos Silva et al. 2008). From this point of view remotely-sensed data can effectively support forest controls by land administrations and forest police authority. Remotely-sensed data peculiarities in forest monitoring can be summarized as: *i)* it guarantees a synoptic territorial vision at the regional scale; *ii)* pre-processed (both geometrically and spectrally) data can be accessed for free from the public archives (e.g. Copernicus Sentinel-2 mission); *iii)* available dataset can supply image time series that are internally coherent in terms of temporal, spatial and processing features. This work was aimed at testing the potential of Sentinel-2 (S2) in the ordinary workflow of the Piemonte Region Forest administration, with special concerns about early detection and control of forest harvesting activities. Priority was the detection, at the regional scale, of annual forest cover changes with the following goals: *i)* mapping of irregular (in respect of the regional Forestry Regulation) forest cuts; *ii)* quantification of the intensity of the interventions. Results are expected to support forest police controls.

Materials and methods

Study area

The study area is located in Val Tanaro (CN) and sizes about 95 km^2 (Fig. 1) covering an altitudinal range between 700 m and 2,000 m mostly located in mountain zone. Five administrative units are included in the area: Garessio, Pamparato, Priola, Roburent, Viola, representing the 4.7% of total regional forest surface. The zone has been selected as paradigmatically area because it's present about 7% of regional harvesting biomass (IPLA 2000). The study area is characterized by the dominance of beech and larch stands, which are usually managed respectively as coppice with standards and little clear cuts (about 2,000 m^2) (Camerano et al. 2017).

Available Data

For this work, two S2 images in the T32TMQ tile were used, showing the area at its maximum vegetative activity, i.e during summer (August), for the 2016 and 2017 years. Change detection is intended to map the harvested areas related to the 2016-2017 silvicultural season. Forest cutting requests received by forest authority are needed to make a forest har-

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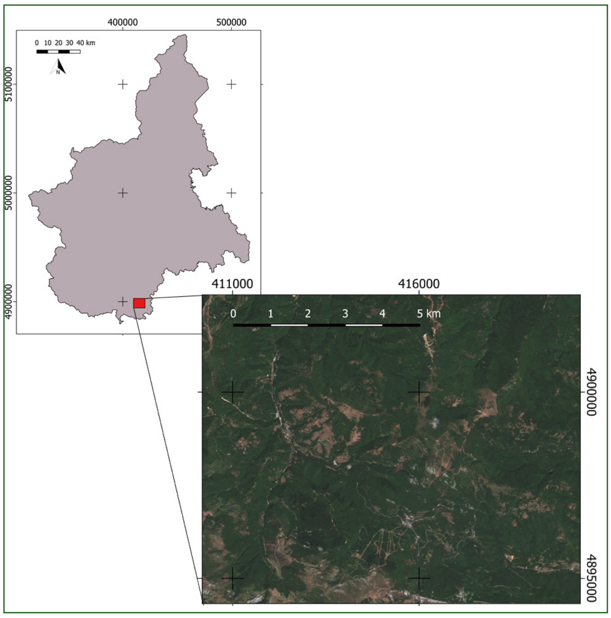
Figure 1 - The study area is located in Val Tanaro (CN), South Piemonte, Italy (Reference frame: WGS84 UTM 32N).



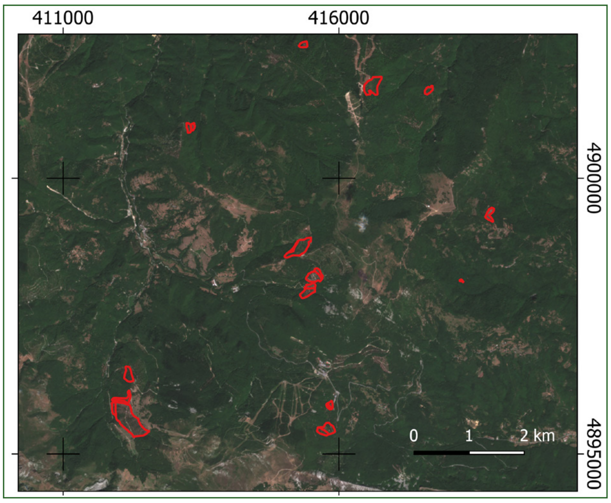
vesting legally in Piemonte region according to the actual regional forest regulation (DPGR 20.09.2011 n. 8/R). The same regulation defines the harvesting periods that are made, at these zones, between autumn and winter. For this reason, we considered two representative images acquired respectively before and after this silvicultural season intending to map only all cuts made in this period. Copernicus S2 data processed at level 2A were obtained already calibrated in at-the-ground reflectance by CNES for THEIA Land data center. Technical features of the available images are reported in Table 1.

Table 1 - Technical features of the available S2 images. Each image is a stack of 10 bands with 10 m geometrical resolution.

Band ID	Central wavelength (nm)	Bandwidth (nm)	Nominal Geometric resolution by Theia CNES provider
B2	490	98	10 m
B3	560	45	10 m
B4	665	38	10 m
B5	705	19	10 m (20 m native resolution)
B6	740	18	10 m (20 m native resolution)
B7	775	28	10 m (20 m native resolution)
B8	840	145	10 m
B8A	865	33	10 m (20 m native resolution)
B11	1610	143	10 m (20 m native resolution)
B12	2200	242	10 m (20 m native resolution)

Forested areas were preventively mapped according to the available Piemonte Forestry Map (Camerano et al. 2017) and the correspondent mask generated. The Forest map of the Piemonte Region was completed in 2016 by IPLA under assignment of the Forest regional sector, it was acquired as vector format with 1:10,000 nominal map scale (WGS84 UTM 32N reference frame). In this preliminary phase, 20 reference areas (ROI, *Regions of Interest*) representing authorized (by forest regional administration) cuts were recognized and mapped by photointerpretation of high resolutiontrue color satellite orthoimages (updated to 2018) available from Google Earth (Fig. 2).

Figure 2 - Forest harvested area used as ROI (Reference frame: WGS84 UTM 32N).



As validation data, the Global Forest Change (GFC) 2000-2017 dataset-v1.5 (Hansen et al. 2013) was obtained from the Hansen/UMD/Google/USGS/NASA system in raster format. GFC is divided into 10 x 10 degree tiles, consisting of seven files per tile. All files are supplied with a spatial resolution of 1 arc-second per pixel (approximately 30 meters per pixel at the equator) and a radiometric resolution of 8 bits. Year of gross forest cover loss event grid (*loss year*, hereinafter called GFC-YL) is defined as a disaggregation of total forest loss to annual time scales. In this dataset, zero values mean "no forest loss", values in the range 1–17 (2000-2017) indicate the year when a forest loss detection occurred. Forest loss detection was defined as both stand-replacement disturbance, or changes from a forest to non-forest state occurred only in the 2017; the other values (2001-2016) in the reference map were excluded. The GCF-YL raster layers were preventively projected into the WGS84 UTM 32N reference system, setting a Ground Sampling Distance (GSD) of 10 m with a nearest neighbor resampling method. Image processing, results and intermediate steps were managed by free GIS software (QGIS 2.18.4 and SAGA GIS 6.3.0).

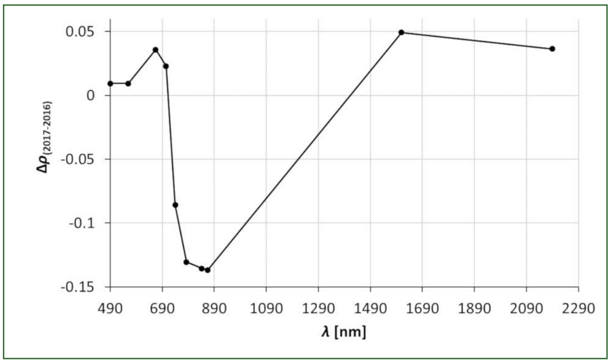
Detection of harvested areas

Many algorithms to detect forest cover changes are present in literature. Most diffuse ones include support vector machines (SVMs), decision trees (DTs) or the maximum likelihood classifier (MLC) (Otukei and Blaschke 2010). Another powerful approach is based on the multi-temporal image analysis (De Petris et al. 2019) that shows high overall accuracy especially in contexts with high vegetation cover (e.g. equatorial forests). From this point of view, the most used algorithm in forest disturbances analysis is called LandTrendr (Landsat-based detection of Trends in Disturbance and Recovery) (Cohen et al. 2018, Kennedy et al. 2018 and 2010) a new approach to extract spectral trajectories of land surface change from yearly Landsat time-series stacks (LTS), which is mainly based on Landsat data retrieved by the U.S. Geological Survey (USGS) archive. This method was developed assuming that many forest changes have a distinctive temporal progressions before and after the change event, and that these lead to characteristic temporal signatures in spectral space (Kennedy et al. 2007). Land Trend is less suitable for Italian forests as it is not calibrated for coppices forests (Fabbio, 2016) due to the fast regrowing that early close gaps (i.e. harvested areas) in vegetation cover, attesting no detectable variation in the time series. The authors decided to detect forest changes using a multi-temporal approach analyzing the spectral change between two silvicultural years (i.e. 2016 and 2017).

Since harvestings are supposed to occur where the forest biomass is high, we initially mapped such vegetated areas using the 2016 NDVI map (pre-event) obtained by raster calculation from the calibrated bands of the original S2 available image. This step was intended to refine the previous area selection carried out using the Piemonte Forestry Map. It was achieved by NDVI map thresholding @ 0.5, we appositely used this value to ensures that vegetated pixels were sufficiently pure. In fact in literature NDVI values under 0.5 are generally related to partially vegetated pixels (Borgogno-Mondino et al. 2016, Momeni and Saradjian 2007). To detect forest cover changes occurred between August 2016 and August 2017 (silvicultural season 2016-2017), the 2016 and 2017 average spectral signatures of each ROI was computed by Zonal Statistics tool in SAGA GIS. This operation produced 20 average spectra per year representing denser vegetation in 2016 and sparser vegetation in 2017. An average spectrum for both 2016 and 2017 was finally computed from the previously obtained 20 ones, representing reference spectra of respectively vegetated and harvested areas. They were consequently compared by difference (after - before), band by band, obtaining a difference curve (RD, *reference difference* - Fig. 3) that was used as reference to test similar behavior all over the image. RD trend showed moderate positive values in the visible (VIS), negative in the near infrared (NIR), and strongly positive in the shortwave infrared (SWIR) regions.

RD was computed at image level by grid difference of the 2016 and 2017 multispectral stacks, obtaining a new stack, $\boldsymbol{D(x,y,i)}$, containing as many bands ($i = 1,10$) as the original multispectral images,

Figure 3 - RD trend showing the typical behavior of harvested areas. It was used as reference to map pixels having similar behavior in the area, i.e. to map candidate harvested areas.



representing the local spectral difference of each pixel. To detect the harvested areas, a Random Forest (RF) supervised classification was performed using the previously described ROIs as training areas and the mask generated according to the NDVI map thresholding (only potentially forested areas in 2016 were considered). The target of the classification is binary: harvested (1) and non-harvested classes (0) (Fig. 4). According to Lessio et al. (2017) S2 georeferencing accuracy is generally greater than 7 m, i.e. about one S2 pixel; this positional error can induce a false-positive change between two acquisitions due to pixel displacement. Consequently, all areas smaller than one S2 pixel (100 m^2) were not considered. Refined result was then vectorized for a further check. For each polygon of the obtained vector map, the average $\boldsymbol{D(x,y,i)}$ spectrum ($\boldsymbol{\mu}_P^D$) was computed by zonal statistics and compared with the reference one (RD, Fig. 3) testing the following condition: $\boldsymbol{\mu}_\mathbf{P}^\mathbf{D} > 0$ in VIS & $\boldsymbol{\mu}_\mathbf{P}^\mathbf{D} < 0$ in NIR & $\boldsymbol{\mu}_\mathbf{P}^\mathbf{D} > 0$ in SWIR. If this condition was not satisfied the correspondent polygon was turned to not-harvested. After this step, the Pearson correlation coefficient (r) was computed comparing $\boldsymbol{\mu}_\mathbf{P}^\mathbf{D}$ and RD to somehow map reliability of detection. This information is expected to be operationally exploited to define a priority of controls.

Estimating Local Intensity of Forest Cuts

Many studies have examined the effect of silvicultural activities, or partial harvesting, on the spectral response of forest (Gerard and North 1997). Typically, the reduction in overstory cover resulting from these activities is much less than which occurs during a clearcutting (Franklin 2001). One goal of this work was trying to support forest authority in that part of its controls aimed at testing consistency of forest cuts operations with those defined by Forestry Regulation. The intensity of forest cuts depends on forest type and silvicultural practices, and can be assumed as a first indicator to address controls at the regional scale. In this work, authors operated such investigation at patch level after classification of potentially harvested areas, as reported in similar works (Franklin et al. 2002, Graham and Blake 2001). **A**In fact, forestry authority is used to control the single harvesting operation looking at the characteristics of the entire cadastral parcel where, not contiguous cut areas could fall in. According to this assumption new zonal statistics (σ_{NDVI} and μ_{NDVI}) were computed for each filtered polygon from the 2017 NDVI map. The correspondent coefficient of variation ($CV_{NDVI}=\sigma_{NDVI}/\mu_{NDVI}$) was finally computed as index of polygon internal NDVI variability, assumed as predictor of cut intensity. We defined 3 classes of values for CV_{NDVI} corresponding to low, medium and high intensity. Low intensity upper class value was defined as the 33rd percentile of the whole CV_{NDVI} distribution (computed from all the potentially harvested polygons); medium intensity upper class value was defined as the 66th percentile; higher values of CV_{NDVI} define high intensity cuts. Low intensity harvesting can be related to the shelterwood silvicultural system; medium intensity harvesting can be due to patch cuts or group trees selection cut; high intensity harvesting is usually due to clearcutting, coppicing or land use change from forest to other cultivations.

Results and discussion

Detection of harvested areas

Forest harvested area mapping was achieved using a supervised classification of ***D(x,y,i)*** by Random Forest algorithm method, as illustrated in Figure 4. RF was run in SAGA GIS with the following parameters: tree count = 10; samples per tree = 1; Sample with Replacement flagged; Minimum Node Split Size = 1; Features per Node = square root; Stratification = none.

Classification accuracy assessment was achieved with reference to GFC-YL. GFC-YL represents the forest loss occurred in the 2017, that authors assumed to be potentially, and totally, due to forest harvesting in the same period. In fact, according to forest administration declarations, in this study area forest harvestings are the first reason of forest loss without the presence of other abiotic or biotic disturbances (e.g. wildfire, wind damage, forest diseases). Concerning new harvested area detection, the proposed method, based on supervised classification of ***D(x,y,i)***, proved to be effective. Table 1 reported the classification performance (Espíndola and Ebecken 2005) showing a Geometric Mean (G-Mean) value, defined as measure of the balance between classification performances on both the majority and minority classes, about 0.69. User's and producer's accuracy of detected harvested areas are respectively 0.72 and 0.67, proving to be consistent with values from some other works on similar topics (Cohen et al. 1998, Rogan et al. 2002). According to classification, in the study area, we found that 47 ha of forest were harvested between 2016 and 2017.

Figure 4 - Classification map of forest area harvested using RF method (Reference frame WGS84 UTM 32N).

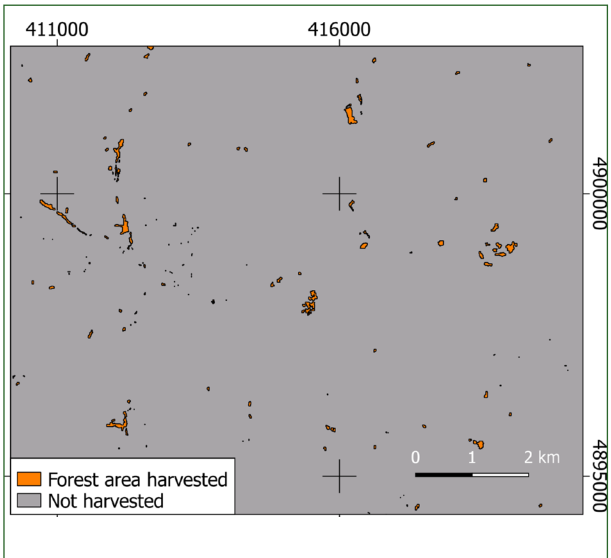


Table 2 - Confusion Matrix of harvested area detection (n° of S2 pixels).

	Classified positive	Classified negative	Producer's Accuracy
Actual Positive	4785	2362	0.670
Actual Negative	1864	939695	0.998
User's Accuracy	0.720	0.997	

Harvested area characterization

Authors assumed CV_{NDVI} as predictor of forest harvesting intensity with this interpretation key: high value of CV_{NDVI} correspond to heterogeneous land cover, likely due to an intensive forest cut exposing bare soil (low NDVI) alternated to some trees (high NDVI); low CV_{NDVI} values correspond to homogeneous land cover possibly related to lower forest harvesting. To support this assumption, we tested the relationship between μ_{NDVI} and CV_{NDVI} in 2017 (post event) for the mapped harvested areas. Figure 5 shows a strong negative correlation (R^2= 0.94) suggesting that CV_{NDVI} high values (intensive forest harvesting) correspond to μ_{NDVI} lower values (i.e. low vegetation fraction).

Figure 5 - The relationship between μ_{NDVI} and CV_{NDVI} in 2017 (post event) for the mapped harvested areas.

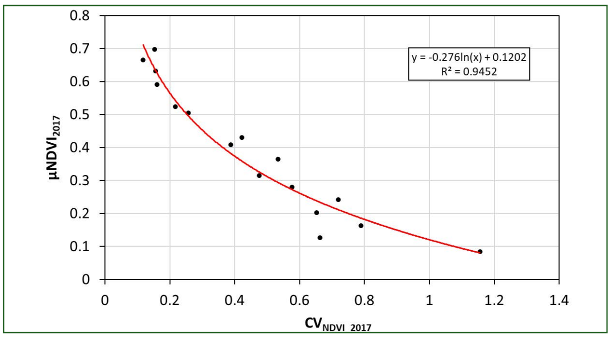


Figure 6 - (Left) Map of forest cut intensity in the detected harvested areas. (Right) Absolute frequency histogram of CV_{NDVI} for all detected patches.

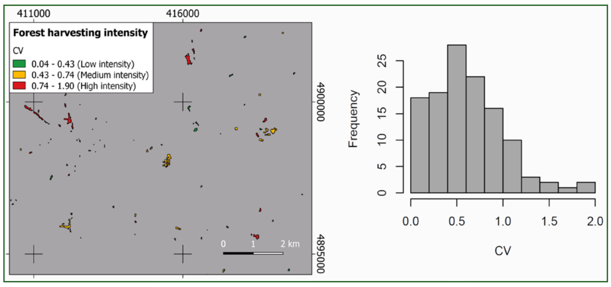
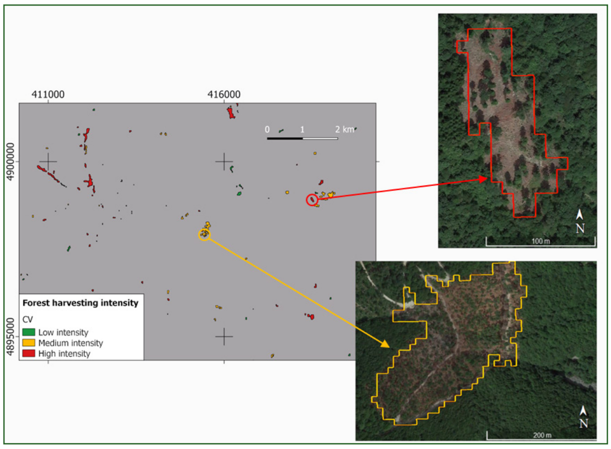


Figure 7 - Forest harvesting intensity map. Two paradigmatic patches: (red polygon) medium intensity of harvesting could be reasonably related to shelterwood cutting; corresponding CV_{NDVI} values from S2 assessment, in this case, are around 0.60; (yellow polygon) high intensity of harvesting could be reasonably related to coppicing with standards cut, corresponding CV_{NDVI} values from S2 assessment, in this case, are around 0.84.



Oppositely, CV_{NDVI} low values correspond to μ_{NDVI} higher value, reasonably related to a high vegetation fraction. The strong relationship between NDVI and vegetation cover is, in fact, well known in literature (Gamon et al. 1995).

It is authors' opinion that the adoption of CV_{NDVI} in place of μ_{NDVI} moves results to a more absolute solution, possibly independent from place, vegetation and time of acquisition. Accordingly, starting from the previously generated map of harvested areas, a new one was generated showing 3 classes of intensity of cut (Fig. 6 left).

The histogram of Figure 6 (right) shows that CV_{NDVI} distribution is skewed towards to medium and high intensity values (CV_{NDVI}> 0.43), proving to be consistent with data supplied by the regional forest authority about cut requests (Tab. 2). It is worth to remind "cut requests" are the procedural tools need to get cut authorization. Table 2 reports correspondent statistics that demonstrate that 81% of requests are related with medium and high harvesting intensity practices.

A further validation came from a preliminary photointerpretation of Google Earth high resolution true color imagery (updated to 2018), carried out over two well-recognizable sites representing respectively

Table 3 - Cut Requests received by regional forest authority for silvicultural season 2016-2017 concerning the study area.

N° requests	Management type	Methods of harvesting	Principal species	Averange harvested area (ha)
1	High forest stands	Regeneration cutting	Ash	2.00
1	Coppice stand	Intermediate cutting or shelterwood cutting	Beech	3.00
4	Coppice stand	Coppicing	Beech	5.89
3	Coppice stand	Intermediate cutting or shelterwood cutting	Beech	4.57
1	High forest stands	Intermediate cutting or shelterwood cutting	Beech	0.40
3	High forest stands	Regeneration cutting	Beech	2.98
1	Mixed management	Intermediate cutting or shelterwood cutting	Beech	0.40
1	Mixed management	Regeneration cutting	Beech	23.38
1	Coppice stand	Coppicing	Birch	0.21
1	Chestnut stand	Intermediate cutting or shelterwood cutting	Chestnut	0.10
1	Chestnut stand	Regeneration cutting	Chestnut	0.50
1	Coppice stand	Coppicing	Hornbeam	1.05
9	High forest stands	Regeneration cutting	Larch	2.37
1	Coppice stand	Coppicing	Manna ash	0.17
5	High forest stands	Regeneration cutting	Norway spruce	0.44
3	High forest stands	Regeneration cutting	Silver-fir	1.93

medium and high intensity of cut (Fig. 7). Concerning medium intensity, looking at Figure 7, it can be noted that: *i)* medium intensity of harvesting could be reasonably related to shelterwood cutting (Fig. 7); corresponding CV_{NDVI} values from S2 assessment, in this case, are around 0.60; *ii)* high intensity of harvesting could be reasonably related to coppicing with standards cut (Fig. 7); corresponding CV_{NDVI} values from S2 assessment, in this case, are around 0.84.

Conclusions

S2 multispectral imagery proved to be effective to detect and characterize forest harvesting in the considered period. Detection of new harvested area based on supervised classification of spectral signature difference revealed to be accurate enough (G-mean = 0.69) confirming that multitemporal spectral differences are much more discriminant than single acquisitions when assessing vegetation. It was also proved that an approximated estimation of harvesting intensity can be obtained, making possible to test consistency of declared cuts with forestry regulation. The proposed methodology could effectively support forest police, that, at the moment, can control only the 5% of the received harvesting requests. Nevertheless, many limitations, at the moment, still persist: a) detected changes in vegetation cover could be also related to abiotic or biotic disturbance like wildfire, plant diseases, human clear cut. Auxiliary data from other maps or institutional sources could certainly help to make result more reliable from this point of view; b) intensity estimates based on CV_{NDVI}, could be calibrated according to ground data specifically referred to the explored area.

Since cutting requests could be, according to Regulation, categorized into 7 functional types, depending on the main and secondary species and type of cut, future developments could concern the investigation about methodology performances in respect of the functional type. The following functional types should be considered:

(i) cutting in pure broadleaf stands;

(ii) maturity cutting in pure broadleaf stands;

(iii) partial harvesting in pure broadleaf stands;

(iv) maturity cutting in pure conifer;

(v) partial harvesting in pure conifer;

(vi) maturity cutting in mixed woods;

(vii) partial harvesting in mixed woods.

Finally, the proposed methodology is intended to standardize forest harvesting monitoring aiming at improving control effectiveness, moving from a control based on few sample areas to a complete control over the regional wooded area. This would permit to assign priority of ground controls making more economically sustainable the ordinary task of the regional Forestry Authority.

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