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Detecting olive grove abandonment with Sentinel-2 and machine learning: The development of a web-based tool for land management

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A R T I C L E I N F O

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A B S T R A C T

The abandonment of rural areas is an important environmental and socio-economic issue in Europe, threatening the stability and profitability of agricultural production. The identification and quantification of abandoned land is key for temporal and spatial monitoring of the process and for applying alternative management measures. Italy is one of the most important European countries for the production of high quality olive oil, accounting for a large slice of the current certificated production (i.e., PDO, PGI). In this study, we present a machine learning model (i.e., Random Forest) for the identification of abandoned olive tree groves using field observations and NDVI time series, tested in a typical agroecosystem in central Italy dominated by olive groves. An application for smartphones able to record the geographic position was developed and used to collect field points, which in turn were utilised to train the model. The data of NDVI from January to December 2020, calculated on Sentinel-2 images, were extracted for each monitoring point and gap-filled to obtain a 10-days interval time series. The Random Forest model used the annual NDVI time series as features and classified the sampling points in the test dataset with an accuracy of 0.85. The model showed a higher capacity of classifying cultivated than abandoned points, sensitivity being equal to 0.88 and specificity equal to 0.82. Results demonstrated the applicability of the combined approach for discriminating cultivated from abandoned olive tree groves, in case that the parcels destined for olive tree cultivation are known. A web-based tool was implemented to support land monitoring and management.

1. Introduction

Olea europaea L. (olive tree) is deeply rooted in the cultural identity of Mediterranean countries for its landscape, socioeconomic, and dietary values [1]. This crop occupies 1,145,520 hectares in Italy [2], contributing to a large extent to the overall world production together with Spain and Greece [3]. Italy accounts for the largest share of protected olive oil labels, i.e., approximately 40% of the EU Protected Designations of Origin (PDOs) and Protected Geographical Indications (PGIs) [4]. Although the production of olive oil is strategic for EU countries, the sector is characterised by fragmentation and the predominance of smallholding. The average farm size in the three main European olive oil producing countries—Spain, Italy, and Greece—is just 5.8, 1.8, and 1.5 ha, respectively [5].

Global and regional, environmental and socioeconomic changes led to a vulnerable situation for the olive sector, especially for smallholder farmers, as a result of the volatility of both production (dependent on the annual harvest) and prices (due to global market uncertainty) [6]. The resultant low profitability is leading to the abandonment of many olive tree farms [7,8]. Farm abandonment also entails a loss of cultural services [9], in addition to a total drop of provisioning services, especially in regions where high quality olive oil can be produced. Regulating services are as well threatened by the abandonment of farming systems, with scrub encroachment that enhances the risk of fire. Abandonment of olive tree groves is an ongoing process in traditional sloping olive tree production systems, in which mechanisation of agricultural practices is an issue. In hilly and mountainous areas, the abandonment of olive tree production has adverse economic, social, environmental, and cultural effects [10].

Time and cost effective methods are urgently needed to measure and map the abandonment of olive groves, to provide land managers and policy makers with information on land use changes, and to continuously update the Common Agricultural Policy (CAP) [11]. About 11% of agricultural land in the EU is under high risk of abandonment [12]. Temporal- and spatial-explicit information on land abandonment may help customise policy instruments for counteracting or reversing the process. Accurate mapping of abandoned agricultural land is fundamental to implement tailored monitoring and management measures of the landscape. Traditional techniques for detecting abandoned agri-

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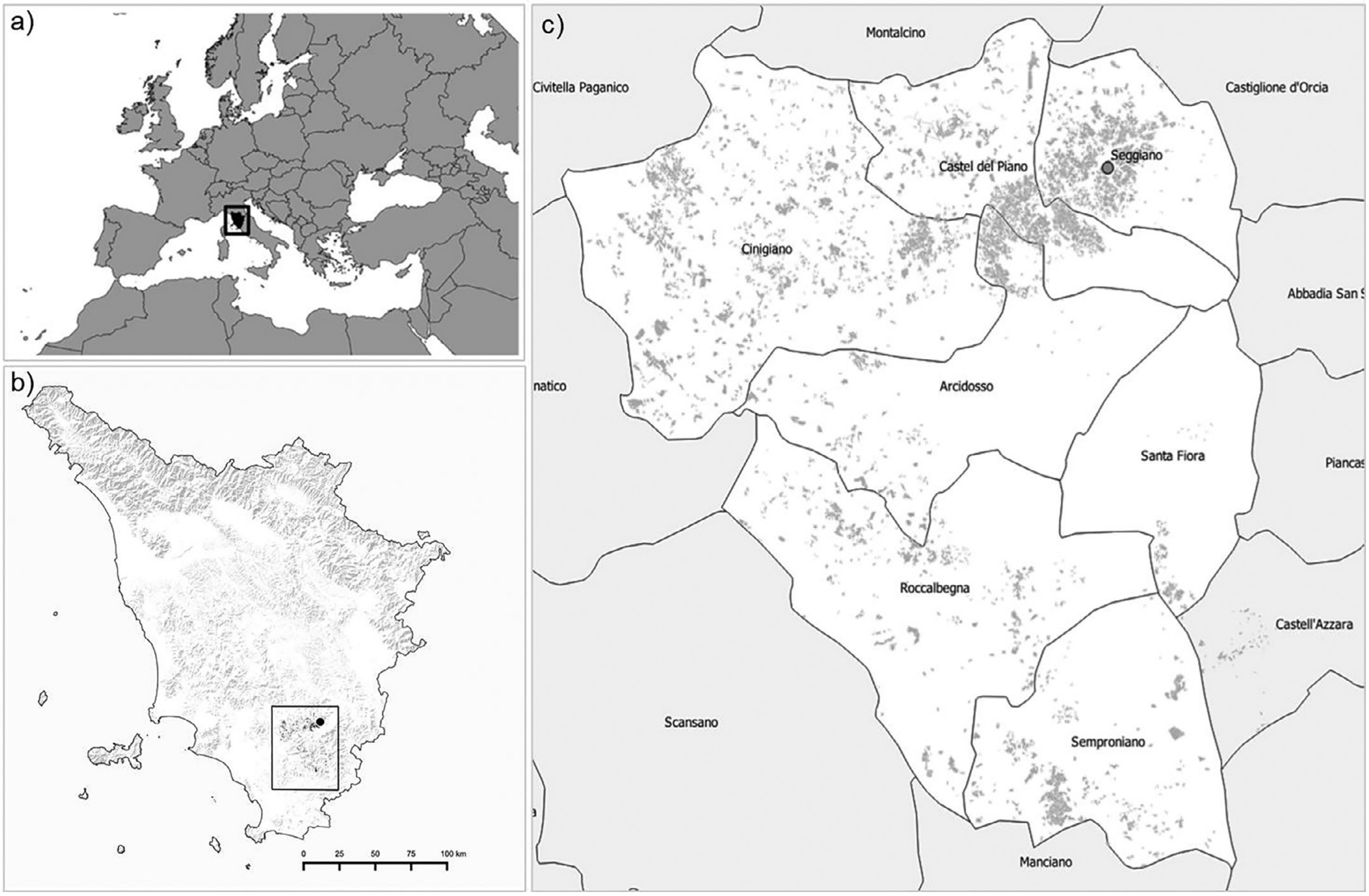

Fig. 1. The picture represents: a) the localization of the Tuscany region (Italy); b) the localization of the study area in which the black dot is the village of Seggiano (Grosseto); c) the municipalities (administrative boundaries) totally included in the PDO “Olio Seggiano”, highlighted in white (the parcels with olive trees are colored in grey).

cultural lands include field sampling and photo-interpretation methods, both characterised by a high labour demand. On the other hand, cost-effective methods for the detection and mapping of abandoned land through the use of remote sensing techniques and easy to use digital tools are currently missing for olive tree grove-dominated agroecosystems.

The availability of high spatial resolution imagery has recently enabled researchers to develop analysis tools on agricultural parcels and at tree level. The use of Normalized Difference Vegetation Index (NDVI) and change detection analysis have made it possible to identify the change in agricultural use and/or abandonment of land at large scale across Europe e.g., [13], integrating remote sensing techniques and Geographic Information System (GIS). Recently, medium and high-resolution satellite images have become popular to map small areas of abandoned land due to their higher information quality. Löw et al. [14] combined Random Forest and Support Vector Machine algorithms to map abandoned agricultural land in Kazakhstan based on Landsat and RapidEye data. Yusoff et al. [15] monitored abandoned oil palm lands with multi-temporal Landsat and SPOT-6 satellite imagery. Morell-Monzó et al. [12] used Sentinel-2 and airborne imagery to map land abandonment (citrus cultivation) in fragmented landscapes in Spain, applying the Random Forest algorithm for the classification of pixels. Li et al. [16] applied field-based and pixel-based classification of field boundaries to estimate the percentage of abandoned jujube fields with multi-temporal high spatial resolution satellite images (Gaofen-1 and Gaofen-6) and the Random Forest algorithm.

Advances in remote sensing, providing high spatial resolution (e.g., Sentinel-2) and very high spatial resolution (VHSR) images, open new ground for the monitoring of farmland by parcels (i.e., small agricultural fields) and for mapping highly fragmented agricultural landscapes and other ecosystems [17,18]. Nevertheless, the spectral and texture of complex abandoned land in remote sensed images may change with time and space, resulting in considerable internal variability, making pixel-based classification approaches misleading [19].

The integration of machine learning models and Sentinel imagery for classifying land use and detecting abandonment, e.g., [20,21], provides a pipeline easily integrable in digital tools for land monitoring and management, based on open data, allowing large-scale automated analysis of satellite imagery. The overall goal of the present study is to develop an automatic technique for the recognition of abandoned olive tree groves using remote sensing, field mapping, and digital tools, based on the hypothesis that a machine learning model, trained with field observations, may discriminate abandoned from cultivated olive tree groves, using NDVI annual series as features. With the aim of providing technological and practical solutions for the design of sustainable agricultural policies, we also propose a web-based tool for monitoring the level of land abandonment.

2. Materials and methods

2.1. Study area

The research was conducted in a typical agroecosystem in central Italy (Tuscany), dominated by olive trees, included in the Protected Designation of Origin (PDO) “Olio Seggiano” area (Fig. 1). Traditionally managed and abandoned olive tree groves in the study area are located at an altitude ranging from 400 m to 800 m a.s.l. All orchards are rainfed, the majority of those cultivated has a spontaneous herbaceous layer maintained through the year, subjected to weed mowing. The olive tree parcels were mapped merging the land use dataset of Tuscany Region (http://dati.toscana.it/dataset/ucs) with the declarations of the LPIS (Land Parcel Identification Systems) derived from ARTEA (Tuscany Region rural payment agency), both of 2019. Over the study area, there are 7,465 olive tree parcels with an average size of 0.55 ha and a total surface of 4,158.18 ha.

2.2. Datasets of field data

Field points were gathered with a smartphone application, allowing the recording of the geographic coordinates for each observed point. The app (http://cosedimoda-app.aedit.it/) was developed as a Progressive Web App, designed and delivered by Google to overcome the limitation of mobile browsing and native application. This technology provides features, such as background synchronisation, offline support, home screen installation for mobile platforms, allowing the users to work easily also in areas with no or limited bandwidth. The app facilitated the collection of the ground control point by different types of users, providing a guided data entry format to describe abandoned olive tree groves, which was carried out integrating GPS data, field survey, and user guidelines. Field monitoring was carried out by trained technicians of Scuola Superiore Sant'Anna and those of the Consortium "Olio Seggiano" PDO, taking points at least 20 m away from each other. A few sampling points fell out of the study area. The field campaign lasted from 1 December 2020 to 20 March 2021.

The points were recorded in the smartphone application as (i) "woodland" when the point was in semi-natural woodland patches; (ii) "cultivated" when the point was in managed olive tree groves, where the crown was pruned (at least once in the last three years) and the soil was managed with no undergrowth, (iii) "abandoned" when the olive tree grove was not subjected to management (i.e., crown not pruned in the last three years and development of thick undergrowth with scattered shrubs). The application was designed for recording ancillary traits, which go beyond the modelling exercise and respond to specific requests made by the Consortium "Olio Seggiano" PDO. In particular, these traits allow gathering supplementary information on olive tree groves in the area, e.g., whether the olive tree grove was under recovery (when the restoration of an abandoned olive tree grove was started) or the olive tree varieties.

Since the aim of the study was to train and test a model for discriminating among abandoned and cultivated olive tree groves, the points collected in the study area were classified as "cultivated", when the point referred to a cultivated olive tree grove, and "abandoned", when the point referred to an abandoned olive tree grove or to woodland.

For model training, testing, and validation, the dataset was divided into three parts (Fig. 2). We used the term "validation" to indicate a final testing of the model, carried out in an independent area within the same study area, not used for training and testing.

The dataset including points, used for training and testing the model, was composed of 277 cultivated and 277 abandoned sampling points. 70% of these points were selected randomly, for training, maintaining the proportion between the two classes. The remaining 30% was used for testing the model. The dataset splitting for training and testing was carried out using Orfeo ToolBox (OTB) [22], through the function "SampleSelection".

The training and testing datasets were balanced, since machine learning models are often unable to cope with imbalanced datasets, favouring the most representative class [23]. The validation set was represented by an independent area, individuated by selecting sampling points in the neighbourhood of Seggiano, including 197 points: 60 cultivated and 137 abandoned.

Table 1
List of the evaluation metrics. True positive (TP) means correctly classified as abandoned, true negative (TN) means correctly classified as cultivated, false positive (FP) incorrectly classified as abandoned, false negative (FN) means incorrectly classified as cultivated.

Evaluation metric	Description
Accuracy	$\frac{TN+TP}{TN+TP+FN+FP}$
Positive Predictive Value (PPV) = Precision	$\frac{TP}{TP+FP}$
Negative Predictive Value (NPV)	$\frac{TN}{TN+FN}$
Sensitivity = Recall	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
F1	$\frac{2\times Precision\times Recall}{Precision+Recall}$

2.3. Sentinel-2 data acquisition and modelling

The latitudinal extent of the study area is 42.612:43.000, while the longitudinal extent was 11.255:11.669. Sentinel-2 (Level-2A Bottom-Of-Atmosphere) images captured between January 2020 and December 2020 (65 images) were downloaded using Google Earth Engine (GEE; https://earthengine.google.com) [24] functions, implemented in Python, applying Hollstein mask for cloud masking [25]. Moreover, through GEE, the NDVI was computed using near-infrared (NIR) and red bands: $\frac{NIR - Red}{NIR + Red}$.

Possible impacts on non-synchronous field sampling and satellite images were avoided, since abandonment is not recognizable in less than one year to be recognized, and olive tree groves eventually recorded as "under recovery" were excluded by the modelling exercise.

All the steps needed for model training and evaluation were addressed using OTB. The function "ImageTimeSeriesGapFilling" of OTB was used to gap-fill missing data (e.g., due to clouds) and for temporal resampling, with the aim of sampling data on a regular temporal grid of 10 days, using linear interpolation. Then, data of NDVI for each day in the time series was extracted for each monitoring point, using a pixel-based approach. The feature extraction for each point in the three datasets (training, test, and validation) was carried out using the function "SampleExtraction" of OTB.

A Random Forest model was trained using the training dataset, through the function "TrainVectorClassifier" of OTB, with the values of NDVI in the annual series as features. Random Forest is a machine learning method based on a collection of tree-structured classifiers, which operate as an ensemble [26]. The hyperparameters of the Random Forest model were: 100 trees ("ntree"), 5 as maximum depth of the tree, and the number of variables randomly sampled as candidates at each split as the square root of total number of features. Then, the function "VectorClassifier" of OTB was used to classify the points included in the test and validation datasets. The performance of the model in the test and validation datasets was evaluated using the metrics listed in Table 1, with the class "abandoned" as reference.

2.4. Classifying the olive tree parcels in the study area

All the pixels included in the polygons of the olive tree parcels in the study area were classified using the trained Random Forest model, through the function "ImageClassifier" from OTB. The classification of all pixels of the study area, falling within the polygons of the parcels declared as olive tree groves, allowed us to classify the parcel by calculating the predominant class of pixels within each parcel, following the most frequent pixel value criterion inside the field, calculated with the Python library "rasterstats".

The area of olive tree parcels classified as abandoned over the total, was calculated only for those municipalities whose administrative boundaries were totally included in the PDO.

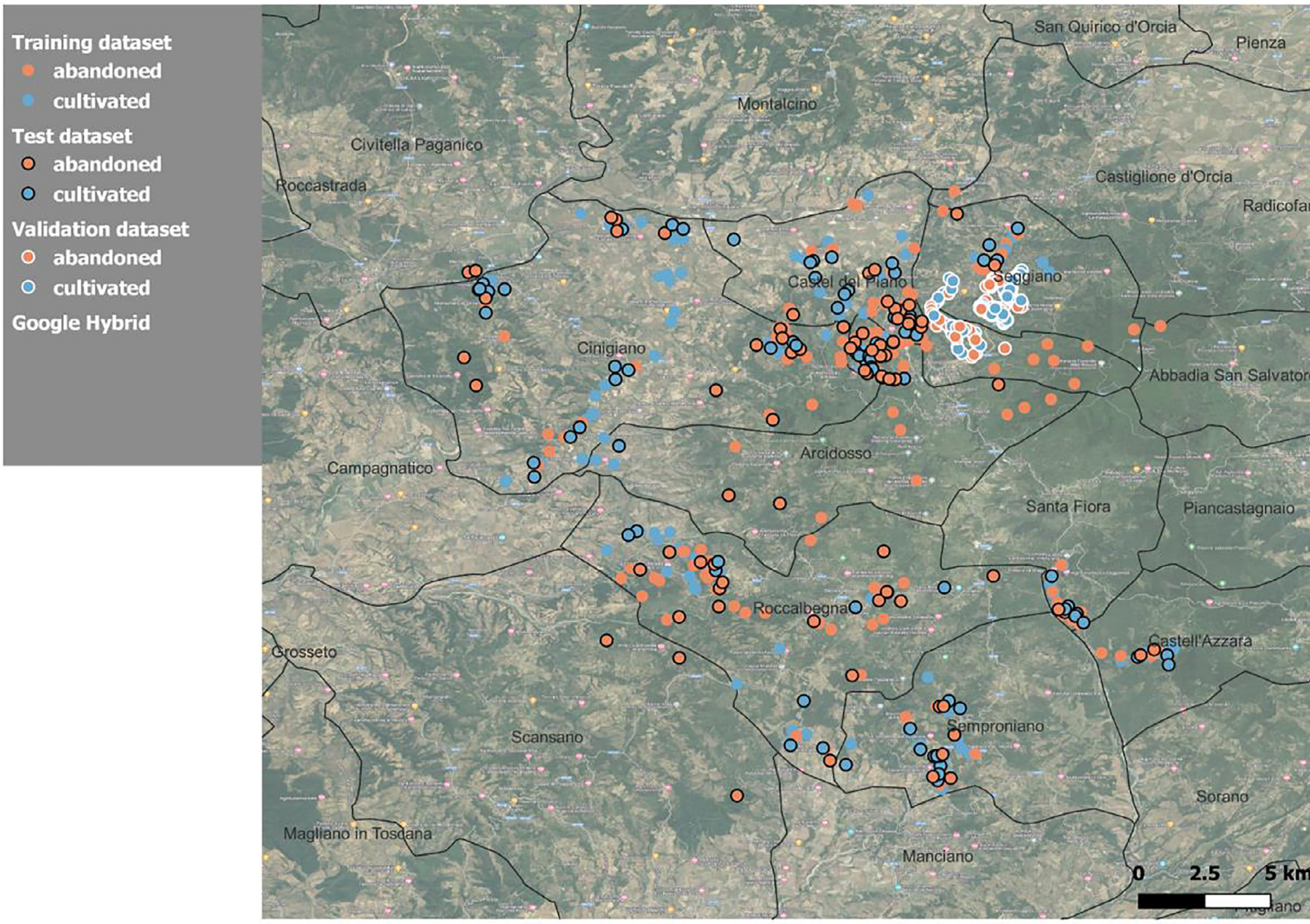

Fig. 2. Ground truth data for training, testing, and validation.

2.5. Development of the web-based tool

The result of the modelling exercise was published on the web (https://cosedimoda.aedit.it/mod_cosedimoda_carto?lang=en) to make it available for end users. The tool consists of a web-based GIS (Geographic Information System), using the OpenStreetMap open source data as a base map [27], enabling the acquisition of the map generated by the data analysis system and making it available through a web interface. The web-based tool allows the collected points of monitoring campaigns to be shown in real time. The spatial data was published using the standard protocol Web Map Service (WMS), established by the Open Geospatial Consortium to facilitate the interoperability with other webGIS.

3. Results and discussion

A web-based tool was developed for the discrimination of cultivated from abandoned olive tree groves in a typical olive tree-dominated area in central Italy, targeting local authorities, consortia, and association of producers. The tool is aimed at supporting the monitoring, managing, and decision making for sustainable olive tree growing in the territory of the “Olio Seggiano” PDO. Such a tool can be potentially applied to other areas affected by agricultural land abandonment, as long as the parcels with olive trees are known (e.g., LPIS).

The smartphone application enabled the collection of 751 field observations. The use of this application simplified the field work of users, in comparison with traditional methods employing a GPS tracking device and recording the information on a field book. The application allows the memorization of both the coordinates and the results of the observation, as well as the real-time visualisation of the results in the web-based GIS. Having the ability to easily capture such data with a smartphone may provide a practical and inexpensive tool to measure and easily visualise abandonment processes in agroecosystems.

Averaging the NDVI values computed for all the sampling points in the training set, highlights a different pattern between the two classes of olive tree groves, cultivated and abandoned (Fig. 3).

Pixels corresponding to abandoned olive tree groves had higher yearly average NDVI (0.55) than those corresponding to cultivated olive tree groves (0.51). The average profiles of NDVI had the minimum value on 25 January for abandoned olive tree groves and on 12 August for cultivated olive tree groves, while the maximum value was recorded on 24 May in abandoned olive tree groves and on 24 April in cultivated olive tree groves. In particular, the average NDVI profile of cultivated olive tree groves presented two peaks, one in spring and the other one in autumn. Similar results were reported by Brilli et al. [28] for olive tree groves in central Italy. In our work, the values of NDVI for cultivated olive tree groves included both olive trees and ground vegetation, thus the values were lower than those reported by Brilli et al. [28] for olive tree canopies.

The largest difference in NDVI values between abandoned and cultivated olive tree groves was recorded from the end of April to the beginning of November, where the values of NDVI in abandoned olive tree groves were higher than the ones in cultivated olive tree groves. In abandoned olive tree groves, the encroachment of deciduous tree species might have contributed to differentiate the NDVI seasonality from that of the cultivated olive tree groves. Maselli et al. [29] reported the annual

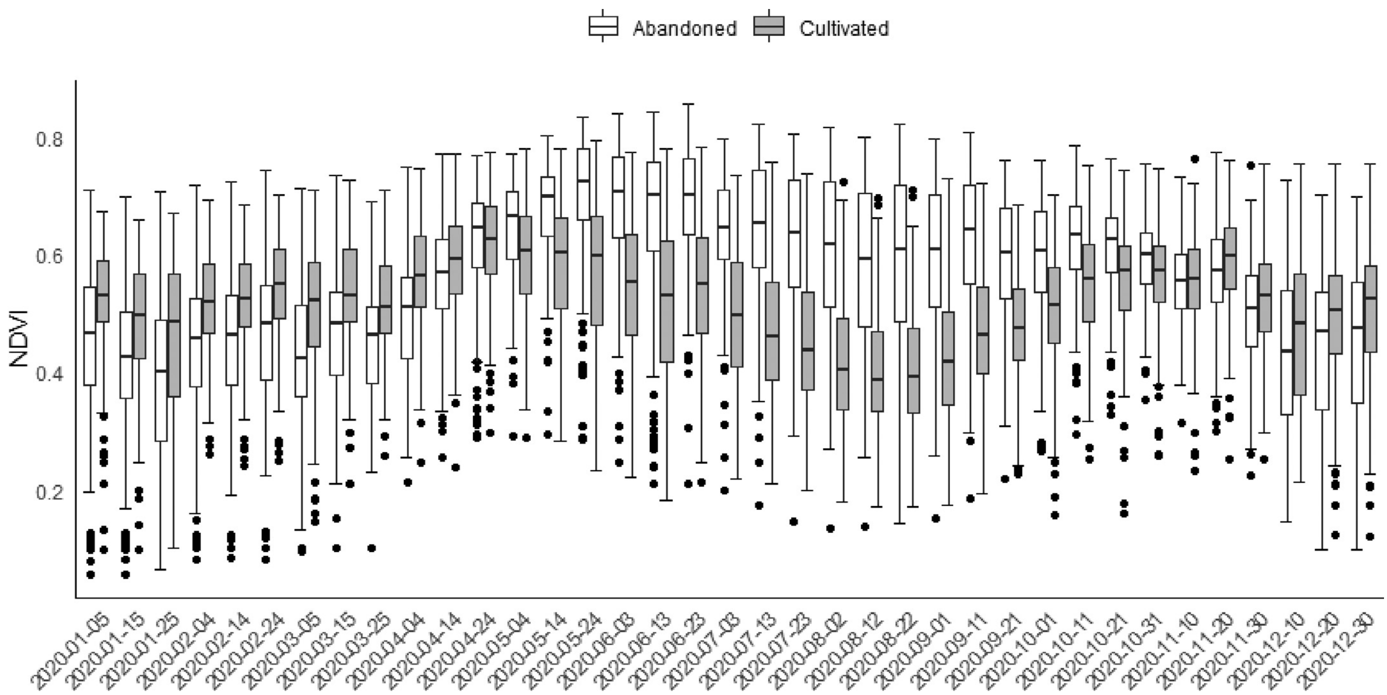

Fig. 3. Boxplot of the NDVI values of observed cultivated and abandoned olive tree groves included in the training dataset for each date in the time series (n=194). Lower and upper box boundaries are 25th and 75th percentiles, respectively. The line inside the boxes is the median. The lower and the upper error lines are 10th and 90th percentiles, respectively.

Table 2
Results on the test and the validation datasets.

	Predicted class			
	Test		Validation	
Actual class	Abandoned	Cultivated	Abandoned	Cultivated
Abandoned	68	15	55	5
Cultivated	10	73	25	112
Accuracy	0.85		0.85	
PPV	0.87		0.69	
NPV	0.83		0.96	
Sensitivity	0.82		0.92	
Specificity	0.88		0.82	
F1	0.84		0.79	

NDVI profiles for evergreen and deciduous tree species in Tuscany, highlighting that the evergreen forest types of plain-hilly areas showed an almost flat profile, while a seasonality was more pronounced for stands in which the deciduous species prevailed. Differences in land cover between cultivated and abandoned olive tree groves might help unravel the NDVI patterns. Cultivated olive tree groves (rainfed) had a lower NDVI during summer, because of either drought-induced decrease in greenness of the herbaceous ground cover or tillage, in comparison with abandoned olive tree groves, where encroachment processes might progressively lead to canopy closure and, in turn, to a higher NDVI.

The Random Forest model classified the sampling points in the test dataset with an accuracy of 0.85, with a higher capacity of classifying cultivated than abandoned points, specificity being equal to 0.88 and sensitivity equal to 0.82 (Table 2). This result demonstrated the applicability of the proposed methodology for identifying cultivated and abandoned olive tree groves, when the olive tree parcels are known.

The accuracy on the validation dataset was equal to 0.85, with a higher capacity to classify abandoned points than cultivated, sensitivity being equal to 0.92 and specificity equal to 0.82. The metric F1 (harmonic mean of precision and recall) resulted in around 0.8 for both the test and validation datasets, highlighting that the model performed well both in terms of precision and recall. The high accuracy of the classification, even in an unbalanced and independent dataset, stressed the applicability of the model in real conditions and with unseen data, and confirmed that remote sensing and machine learning technologies were suitable for mapping farmland abandonment [21].

Results of our work confirmed what was reported in other studies about the good performance of Random Forest in supervised classification, thanks to the high classification accuracy, the robustness to overfitting, and its ability to deal with nonlinearity and multicollinearity of variables [30,31]. The Random Forest model demonstrated a high accuracy in classifying abandoned olive tree groves in the study area. Nevertheless, further work should test the applicability of the proposed methodology to other areas, since the accuracy of Random Forest was sometimes reported to be lower when applied to areas different from those of the training dataset [30].

The raster that resulted from the Random Forest classification of all pixels in the olive tree groves within the study area was included in the web-based GIS, enabling a clear visualisation through a user-friendly interface, and used as a monitoring tool by the associations of producers of PDO “Olio Seggiano” (Fig. 4).

The web-based tool provided a graphical user interface with a navigable map composed of different layers, which could be selected by the users. The integrated layers were: (i) a base map (OpenStreetMap), (ii) the administrative boundaries of the municipalities of “Olio Seggiano” PDO, (iii) the olive tree parcels mapped joining the land use dataset of Tuscany Region and the declarations of the LPIS derived from ARTEA, both of 2019, (iv) the output of the machine learning model with abandoned and cultivated olive tree parcels, (v) the monitored points automatically taken from the application for smartphone.

Further work will be needed to automate the procedure enabling an annual recalibration of the model based on new field campaigns. The latter will be facilitated by the application for smartphones. The use of Progressive Web App in the agricultural domain has been already explored in monitoring and decision making e.g., [32]. This technology offers robust options that enable users to continue working even if the

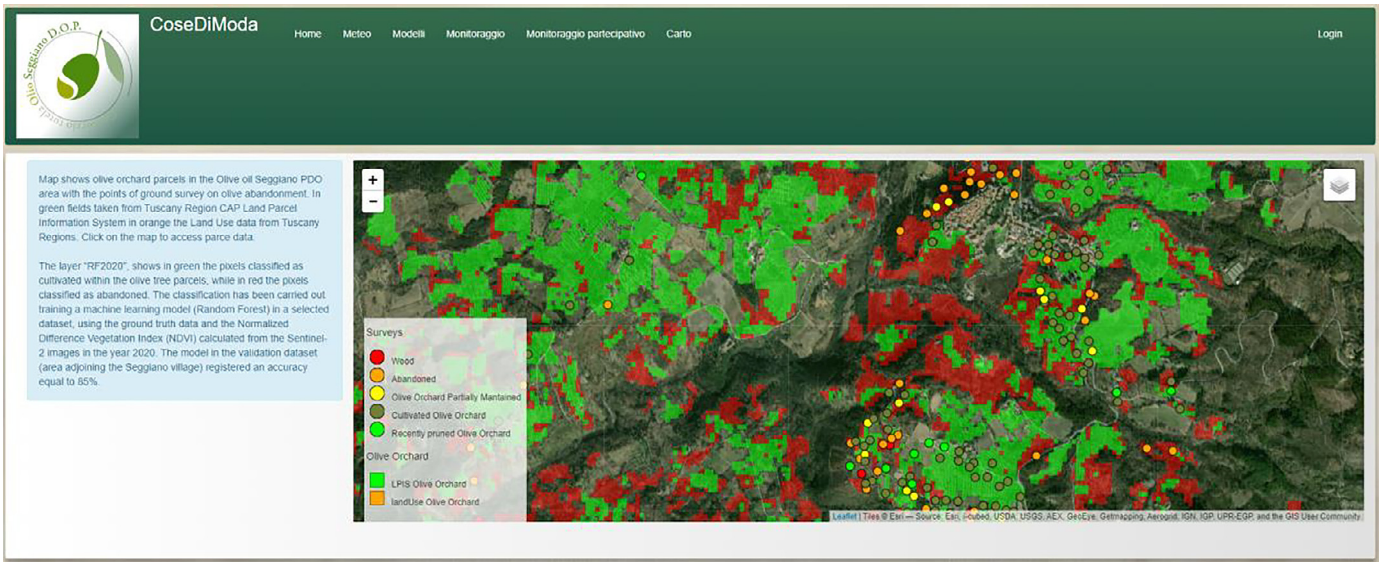

Fig. 4. Screenshot of the web-based tool allowing the consultation of the data collected in the field campaign and the results of the Random Forest model.

Table 3
Classification of the olive tree parcels in the municipalities (administrative boundaries) included in the study area.

Municipality	Total olive parcels (ha)	Abandoned olive parcels (ha)	Cultivated olive parcels (ha)	Percentage of area abandoned (%)
Arcidosso	400	146	254	36.5
Castel del Piano	768	204	564	26.6
Cinigiano	1281	85	1196	6.6
Roccalbegna	407	170	237	41.8
Santa Fiora	68	40	28	58.8
Seggiano	744	176	568	23.7
Semproniano	382	41	341	10.7

network connection becomes unstable or goes offline, common in rural and remote areas [33]. Integrating the entire process into a dynamic tool to automatically update the spatial database and rapidly map the land abandonment will help managers to routinely identify the changes of land use. Compared with the traditional way, such a digital approach will save time, making decision-making more effective. Results showed how the combined approach of remote sensing, machine learning, and digital tools might become an operational instrument to monitor and map the spread of abandoned olive tree groves, with the advantage of exploiting open access data (i.e., Copernicus), without the need of a specific technology (e.g., drones). Indeed, although land abandonment might have some positive consequences on environmental issues, e.g., limiting soil erosion in the long term, the process had a negative impact on the rural economy of the study area, where olive oil production of high quality holds significant potential for creating productive jobs and contributing to sustainable development and economic growth.

The percentage of area of the olive tree parcels under abandonment varied across the PDO "Olio Seggiano", from a minimum of 7% to a maximum of 59% (Table 3).

Should data on olive tree parcels declaration be unavailable, further efforts would be required to integrate the classification model with a procedure for olive tree grove detection, e.g., [34, 35].

4. Conclusions

The combination of high-resolution Sentinel-2 imagery and Random Forest was able to accurately discriminate abandoned from cultivated olive tree groves in a typical Mediterranean agroecosystem of central Italy. The development of a smartphone application for field sampling facilitated the collection of 751 geolocated field points used to train, test, and validate the Random Forest model. The model was successfully utilised to classify all pixels falling within declared olive tree grove parcels in the study area, which allowed sorting each parcel by means of the most frequent pixel value criterion. Results highlighted that the percentage of abandoned olive tree groves varied across the PDO "Olio Seggiano" from 7% to 59%. A first version of a web-based tool for effective implementation in practice was developed and offered to the managers of PDO "Olio Seggiano", underlining the potential of the tested technologies to support land monitoring and management.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] A. Loumou, C. Giourga, Olive groves: "The life and identity of the Mediterranean, Agric. Hum. Values 20 (2003) 87–95.
[2] FAOSTAT website, 2020. URL http://faostat.fao.org. Last Access: February 2022.
[3] IOC website URL https://www.internationaloliveoil.org. Last Access: February 2022.
[4] G. Belletti, A. Marescotti, J. Sanz-Cañada, H. Vakoufaris, Linking protection of geographical indications to the environment: evidence from the European Union olive-oil sector, Land Use Policy 48 (2015) 94–106, doi:10.1016/j.landusepol.2015.05.003.
[5] Eurostat 2015. Olive plantations: number of farms and areas by, agricultural size of farm (UAA) and size of olive plantation area. Available at: https://data.europa.eu/euodp/en/data/dataset/FAlvK1ZGLyoeRQ1siGI8qw.
[6] A.A. Rodríguez Sousa, J.M. Barandica, A.J. Rescia, Application of a dynamic model using agronomic and economic data to evaluate the sustainability of the olive grove landscape of Estepa (Andalusia, Spain), Landsc. Ecol. 34 (2019) 1547–1563.
[7] F. Duarte, N. Jones, L. Fleskens, Traditional olive orchards on sloping land: sustainability or abandonment? J. Environ. Manag. 89 (2008) 86–98.
[8] Gennai-Schott, S., Sabbatini, T., Rizzo, D., Marraccini, E., 2020. Who remains when professional farmers give up? Some insights on hobby farming in an olive groves-oriented terraced mediterranean area. Land 9.
[9] J.M.R. Benayas, A. Martins, J.M. Nicolau, J.J. Schulz, Abandonment of agricultural land: an overview of drivers and consequences, CAB Rev.: Perspect. Agric., Vet. Sci., Nutr. Nat. Res. 2 (2007).
[10] B. Rocamora-Montiel, K. Glenk, S. Colombo, Territorial management contracts as a tool to enhance the sustainability of sloping and mountainous olive orchards: evidence from a case study in Southern Spain, Land Use Policy 41 (2014) 313–324.
[11] S. Colombo, M. Perujo-Villanueva, Analysis of the spatial relationship between small olive farms to increase their competitiveness through cooperation, Land Use Policy 63 (2017) 226–235.
[12] S. Morell-Monzó, J. Estornell, M.T. Sebastiá-Frasquet, Article comparison of Sentinel-2 and high-resolution imagery for mapping land abandonment in fragmented areas, Remote Sens. 12 (2020) 2062.
[13] S. Estel, T. Kuemmerle, C. Alcántara, C. Levers, A. Prishchepov, P. Hostert, Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series, Remote Sens. Environ. 163 (2015) 312–325.
[14] F. Löw, E. Fliemann, I. Abdullaev, C. Conrad, J.P.A. Lamers, Mapping abandoned agricultural land in Kyzyl-Orda, Kazakhstan using satellite remote sensing, Appl. Geogr. 62 (2015) 377–390.
[15] N.M. Yusoff, F.M. Muharam, S. Khairunniza-Bejo, Towards the use of remote-sensing data for monitoring of abandoned oil palm lands in Malaysia: a semi-automatic approach, Int. J. Remote Sens. 38 (2017) 432–449.
[16] X. Li, C. Yang, H. Zhang, P. Wang, J. Tang, Y. Tian, Q. Zhang, Identification of abandoned jujube fields using multi-temporal high-resolution imagery and machine learning, Remote Sens. 13 (2021) 1–19.
[17] J.L. McCarty, C.S.R. Neigh, M.L. Carroll, M.R. Wooten, Extracting smallholder cropped area in Tigray, Ethiopia with wall-to-wall sub-meter WorldView and moderate resolution Landsat 8 imagery, Remote Sens. Environ. 202 (2017) 142–151.
[18] Q. Xia, C.Z. Qin, H. Li, C. Huang, F.Z. Su, M.M. Jia, Evaluation of submerged mangrove recognition index using multi-tidal remote sensing data, Ecol. Indicat. 113 (2020) 106196.
[19] J.M. Peña-Barragán, M.K. Ngugi, R.E. Plant, J. Six, Object-based crop identification using multiple vegetation indices, textural features and crop phenology, Remote Sens. Environ. 115 (2011) 1301–1316.
[20] S. Wang, G. Azzari, D.B. Lobell, Crop type mapping without field-level labels: random forest transfer and unsupervised clustering techniques, Remote Sens. Environ. 222 (2019) 303–317.
[21] X. Zhu, G. Xiao, D. Zhang, L. Guo, Mapping abandoned farmland in China using time series MODIS NDVI, Sci. Total Environ. 755 (2021) 142651.
[22] M. Grizonnet, J. Michel, V. Poughon, J. Inglada, M. Savinaud, R. Cresson, Orfeo ToolBox: open source processing of remote sensing images, Open Geospatial Data, Softw. Standards 2 (2017) 0–7.
[23] H. Kaur, H.S. Pannu, A.K. Malhi, A systematic review on imbalanced data challenges in machine learning: applications and solutions, ACM Comput. Surv. 52 (2019).
[24] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, R. Moore, Google Earth engine: planetary-scale geospatial analysis for everyone, Remote Sens. Environ. 202 (2017) 18–27.
[25] A. Hollstein, K. Segl, L. Guanter, M. Brell, M. Enesco, Ready-to-use methods for the detection of clouds, cirrus, snow, shadow, water and clear sky pixels in sentinel-2 MSI images, Remote Sens. 8 (2016) Page 666 8, 666.
[26] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32.
[27] K. Curran, J. Crumlish, G. Fisher, OpenStreetMap, Int. J. Interact. Commun. Syst. Technol. (IJICST) 2 (2012) 69–78.
[28] L. Brilli, M. Chiesi, F. Maselli, M. Moriondo, B. Gioli, P. Toscano, A. Zaldei, M. Bindi, Simulation of olive grove gross primary production by the combination of ground and multi-sensor satellite data, Int. J. Appl. Earth Observ. Geoinf. 23 (2013) 29–36.
[29] F. Maselli, P. Cherubini, M. Chiesi, M.A. Gilabert, F. Lombardi, A. Moreno, M Teobaldelli, R. Tognetti, Start of the dry season as a main determinant of inter-annual Mediterranean forest production variations, Agric. For. Meteorol. 194 (2014) 197–206.
[30] M. Belgiu, L. Drăguţ, Random forest in remote sensing: a review of applications and future directions, ISPRS J. Photogramm. Remote Sens. 114 (2016) 24–31.
[31] A.O. Ok, O. Akar, O. Gungor, Evaluation of Random forest method for agricultural crop classification, Eur. J. Remote Sens. 45 (2012) 421–432.
[32] L.E. Nugroho, A.G.H Pratama, I.W. Mustika, Ri. Ferdiana, Development of monitoring system for smart farming using Progressive Web App, in: 2017 9th International Conference on Information Technology and Electrical Engineering (ICITEE), 2017, pp. 1–5.
[33] J. Kieti, T.M. Waema, H. Baumüller, E.B. Ndemo, T.K. Omwansa, What really impedes the scaling out of digital services for agriculture? A Kenyan users' perspective, Smart Agric. Technol. (2022) 100034.
[34] Aftab Khan, U. Khan, M. Waleed, Ashfaq Khan, T. Kamal, Remote sensing: an automated methodology for olive tree detection and counting in satellite images, IEEE Access 6 (2018) 77816–77828.
[35] T. Caruso, J. Rühl, R. Sciortino, F.P. Marra, G. La Scalia, Automatic detection and agronomic characterization of olive groves using high-resolution imagery and LIDAR data, Remote Sens. Agric., Ecosyst. Hydrol. XVI 9239 (2014) 92391F.