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Article

Precision Agriculture Workflow, from Data Collection to Data Management Using FOSS Tools: An Application in Northern Italy Vineyard

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Abstract: In the past decades, technology-based agriculture, also known as Precision Agriculture (PA) or smart farming, has grown, developing new technologies and innovative tools to manage data for the whole agricultural processes. In this framework, geographic information, and spatial data and tools such as UAVs (Unmanned Aerial Vehicles) and multispectral optical sensors play a crucial role in the geomatics as support techniques. PA needs software to store and process spatial data and the Free and Open Software System (FOSS) community kept pace with PA's needs: several FOSS software tools have been developed for data gathering, analysis, and restitution. The adoption of FOSS solutions, WebGIS platforms, open databases, and spatial data infrastructure to process and store spatial and nonspatial acquired data helps to share information among different actors with user-friendly solutions. Nevertheless, a comprehensive open-source platform that, besides processing UAV data, allows directly storing, visualising, sharing, and querying the final results and the related information does not exist. Indeed, today, the PA's data elaboration and management with a FOSS approach still require several different software tools. Moreover, although some commercial solutions presented platforms to support management in PA activities, none of these present a complete workflow including data from acquisition phase to processed and stored information. In this scenario, the paper aims to provide UAV and PA users with a FOSS-replicable methodology that can fit farming activities' operational and management needs. Therefore, this work focuses on developing a totally FOSS workflow to visualise, process, analyse, and manage PA data. In detail, a multidisciplinary approach is adopted for creating an operative web-sharing tool able to manage Very High Resolution (VHR) agricultural multispectral-derived information gathered by UAV systems. A vineyard in Northern Italy is used as an example to show the workflow of data generation and the data structure of the web tool. A UAV survey was carried out using a six-band multispectral camera and the data were elaborated through the Structure from Motion (SfM) technique, resulting in 3 cm resolution orthophoto. A supervised classifier identified the phenological stage of under-row weeds and the rows with a 95% overall accuracy. Then, a set of GIS-developed algorithms allowed Individual Tree Detection (ITD) and spectral indices for monitoring the plant-based phytosanitary conditions. A spatial data structure was implemented to gather the data at canopy scale. The last step of the workflow concerned publishing data in an interactive 3D webGIS, allowing users to update the spatial database. The webGIS can be operated from web browsers and desktop GIS. The final result is a shared open platform obtained with nonproprietary software that can store data of different sources and scales.

Keywords: precision agriculture; smart farming; FOSS; very high-resolution (VHR) multispectral images; Unmanned Aerial Vehicle (UAV); WebGIS; information management; vineyards

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1. Introduction

Open Source (OS) software is a name for applications in which source code is available for users, who can use, modify, and implement it. OS software lays its foundations in collaborative programming of the early 1980s; since then, open source software has rapidly widespread in many domains, including the geospatial field [1]. Today, under the label of OS geospatial software, a broad range of libraries, tools, applications, and platforms are developed and released with different Open Source Initiative (OSI) licenses [1]. Numerous OS geospatial software packages for processing, analysing and visualising geospatial data are available and promoted by governments, academia, and industry [2].

The variety and plentiful number of OS geospatial solutions stimulated the birth of related organisations, such as the Open Source Geospatial Foundation (OSGeo, https://www.osgeo.org/, accessed on 2 February 2021), which aim to promote the collaboration and interoperability of OS geospatial software [1]. OSGeo includes much software for geospatial data, classified in [3,4]:

- The *Desktop GIS applications*, mapping software installed on a PC, allow users to display, query, update, and analyse geographic information such as Quantum GIS [5].
- The *open-source libraries*, which are tools for vector and raster data processing as well as SAGA [6], Grass [7] and Gdal [8].
- The *Spatial Data Base Management Systems (SDBMS)* include systems to manage and store data, such as the open-source object-relational database PostgreSQL [9] with its graphic interface PgAdmin and the spatial extension PostGIS.
- The *WebMap Servers are* tools to share maps. They support the OGC standards described in paragraph 2.1.
- The *Server GIS and WebGISclient*, in the GIS domain, allow access to maps and databases via the web. Some examples are Geoserver [10], MapServer [11] and GeoNode [12].
- The *Structure from Motion (SfM) OS solutions* are photogrammetric software for 3D reconstruction. Some examples are MicMac [13], Visual SfM [14] and Open Drone Map [15].

The spread of Open Source geospatial software has not yet been stopped, and in the future, growth for Open Source geospatial software is predicted in terms of users and services [1]. The OS software is expected to keep pace with geospatial technology advancements such as the Global Navigation Satellite System (GNSS); Remote Sensing (RS), digital image processing and photogrammetry; 3D Geographical Information Systems OSGIS) [2], and digital mapping. This spread of OS geospatial software is expected to happen in public and private sectors, and academia. This trend is already verified by several recent OS applications [1] dealing with different research fields, such as hydrology [16], urban studies [17–19], forestry management [20], and the development of dedicated software for geospatial data treatment. RTKlib [21] for GNSS processing, Orfeo toolbox [22] and Qgis Semi-Automatic classification plugin [23] for remote sensing, and Visual SfM [14] and Open Drone Map [15] for SfM are only a few of the available OS geospatial software packages.

One of the sectors that should benefit the most from OS geospatial software is the agricultural domain. Modern technology-based agriculture, known with different names such as smart, digital or Agriculture 5.0 [24], needs geospatial information for crop management and precision agriculture. Indeed, advanced sensing technologies and data management tools in smart farming can collect and store a wide range of agricultural parameters. In addition, the United Nations has recognised the pivotal role of OS in Precision agriculture. Indeed, the Sustainable Development Goal (SDG) 12 calls for the provision of ICT services in agriculture [25,26] and, since OS software ensures universal access to information and knowledge, it contributes to digital inclusion remarked by SDG 16 [26].

Smart agriculture is based on the combination of Precision Agriculture (PA), Information and Communications Technologies (ICT), and data management. PA applies sensors and innovative techniques to obtain data on land and crops in a complete, correct and timely way for strategic and operational decisions. It can be defined as a green

cyclic optimisation approach based on both spatial-wise and time-wise variability within crops. It is made possible by using geospatial technologies such as GNSS, digital image processing and photogrammetry, Geographical Information Systems (GIS), and digital mapping [27,28]. These geospatial technologies can cover the whole precision agriculture process that consists of three main steps:

- Data acquisition can be performed using either proximal sensing or remote sensing techniques;
- Information extraction can be achieved by processing and transforming the raw data acquired through sensing techniques and GIS software;
- Crop management can be performed using the information acquired as decision support.

Hence, in this scenario of innovative technologies' progress in managing and sharing spatial data, a crucial role could be identified in developing new free, open and user-friendly tools. Such platforms can archive, share, analyse, manage, and visualise knowledge and information of detailed data regarding vineyard or crops [27,29].

The evolving concept of digitalization and the advanced techniques of automatic information extraction lead to improving the efficiency, productivity and quality of the PA process. The stakeholders indeed can be supported by tools for a rapid decision-making process. As presented by [24], significant efforts have been made to accelerate Smart Farming's move from academics to actual farms in the past decade. Analysing and visualising the data are operations that can be performed using mainly commercial software and services. Indeed, the main limitations of using smart farming technologies (SFT) in real farms are related to the costs of storing and analysing data, and the release of private data to a commercial company [30,31]. In this realm, new affordable tools for small-scale agriculture are needed. Since many OS geospatial software is free, called Free and Open Source Software (FOSS), geospatial FOSS can be a powerful solution for the technology call of real farms.

Open hardware and OS software are used for monitoring many agricultural parameters, such as biomass, Leaf Area Index (LAI), and chlorophyll [32–35]. Despite the fact that OS software, and hardware, are widely applied for PA measures, the OS component is seldom analysed in geospatial analysis and data management for PA. Although workflows for agriculture geospatial data collection and management have been studied and carried out using proprietary software [36–39], as far as the authors know, none has focused on the open source issue. An open and free solution for agriculture data collection and management could permit the reuse of existing knowledge from regional and local geoportal, datasets, SDIs (Spatial Data Infrastructure), and examples from consolidated case studies. This knowledge can be later compared and combined with information of selected areas of interest and real case studies of different crops or vineyards (both public and private). The existing free and open tools for farming data management [40,41] do not consider the spatial component of data and the relation between the information and its spatiality.

In this framework, the present research aims to propose an open source geospatial workflow to create a free and open GIS platform for mapping, visualisation, and agricultural information management. The paper considers three geomatics techniques (photogrammetry, remote sensing, and GIS), which, although deeply related to each other, need to be treated by several different OS geospatial software tools and require different types of expertise.

The final goal is to create a unique web-based framework in which different actors can share results, and advanced characteristics and parameters. Indeed, to reach and validate the OS workflow, a selected vineyard area was chosen as a case study. In this way, each step of the workflow was tested and evaluated showing the reliability of the whole process. Section 2 of this paper presents the materials used, including some considerations regarding the PA's spatial database and the methodology's workflow, showing FOSS tools adopted from data acquisition to data store. Section 3 illustrates this method's outcomes

by the data analysis and classifications results, data visualisation and web publication. Section 4 describes discussions, conclusions, and future developments.

2. Materials and Methods

2.1. Spatial Database and Smart Agriculture Data Sharing

The request for geospatial information systems and open spatial data to support crops and vineyard management in precision farming is increasing everywhere. Recent studies [37,42] reported the adoption of GIS application for precision viticulture and agriculture and WebGIS solution; these examples demonstrate the massive demand for new practical solutions. In this sense, the present research focuses on the fruition of structured and classified spatial data in an OS and shared GIS platform. This solution could allow different users involved in smart farming activities to query, manipulate, and access, for instance, geographic data, documents, and historical archives stored in a unique database.

In the past decades, many works presented application case studies of GIS and WebGIS platforms to represent and query archaeological sites, built heritage, landscape, crops, and city areas with different aims and purposes (such as documentation, preservation, fruition, urban planning, and agriculture management) [43–47]. Many of these applications have been selected for WebGIS solutions. It is a significant GIS milestone that provides tools for people (technicians or not) to use geographic systems in real time and using the only Web mean (without installing any software). These web geographic information systems allow storing, processing, analysing, visualising, and spatial query data [42]. Furthermore, thanks to the WebGIS or open datasets from national or regional SDIs or geoportals, it is also possible to take advantage of the web services. The standards of the OGC (Open Geospatial Consortium) are internationally widespread in the field of GIS and WebGIS. They are Web Map Service (WMS), Web Feature Service (WFS) and Web Coverage Service (WCS). These concern access to data via the Web (HTTP) [48].

Moreover, the geographic information spatial standards play a crucial role in the scenario of open spatial data. They have a significant impact on the interoperability among different types of data. For example, the European Directive 2007/2/EC INSPIRE (Infrastructure for spatial information in Europe) aims to create a European Union spatial data infrastructure [49].

In the framework of the investigation of datasets and spatial information systems able to manage smart agriculture data, it is possible to mention the works of [50] and [51]. They reported many useful parameters and data functions to drive viticulture activities and production quality that could be taken into consideration. The main limitation of these examples is the lack of a unique multiscale spatial system that stores the different sets of data and their changes during the times. Despite this, these works could be the base to potentially define entities and relations of a spatial database to manage precision agriculture data.

2.2. Study Area

A vineyard located in Grugliasco (Northern Italy) is the test site of this work. It is located inside the University of Turin campus (Figure 1), specifically at the School of Agriculture and Veterinary Medicine in the Department of Agricultural, Forest and Food Science.

The vineyard extends for half a hectare and consists of 20 rows of different vine varieties, mainly Barbera, Nebbiolo, Moscato, Pinot Noir, and Sauvignon Blanc. The presence of many types is due to research purposes.

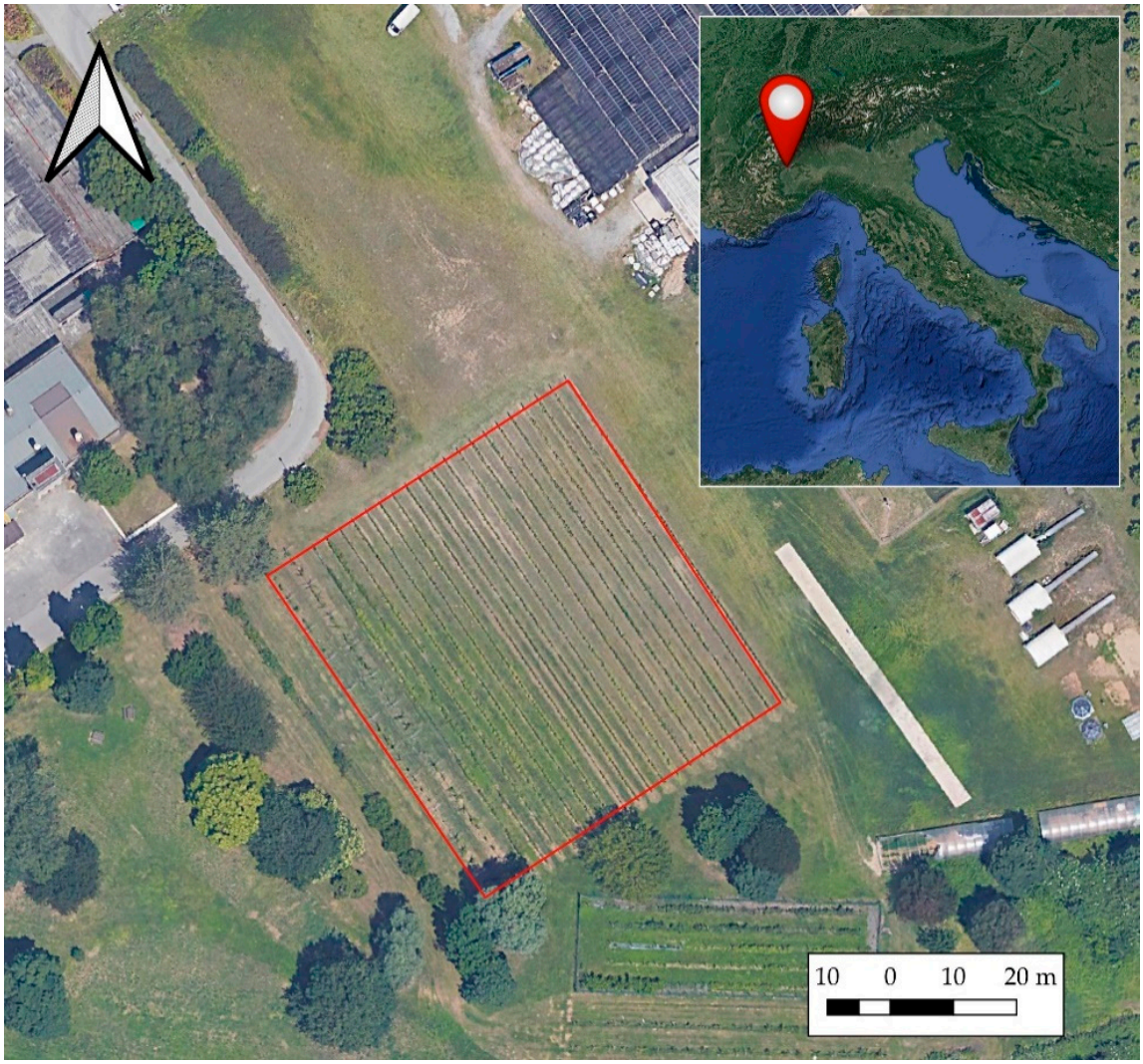


Figure 1. Case study area: the vineyard in Grugliasco University (Piedmont Region, Italy), contoured by red line.

2.3. The Workflow

The workflow, shown in Figure 2, comprises three main phases:

- drone mapping, data analysis, and information extraction;
- database construction;
- web-sharing.

Each step requires specific FOSS software, which differs in functionality and purpose.

2.3.1. Data Collection

As a first operation, it is necessary to acquire a complete representation of the area and therefore, a comprehensive survey of the entire area was carried out using a UAV.

Fifteen plastic markers, used as Ground Control Points (GCPs), were placed on the ground to allow a subsequent georeferencing of the digital model. The coordinates of the centre of each target were acquired using a Real-Time Kinematic (RTK) Global Navigation Satellite System (GNSS) technique [52]. For this application, which aims, as full detail, to identify the different plants within the rows, an accuracy of about 3–4 cm was enough for the elevation model and the orthophoto.

The UAV platform and the embedded sensors were selected according to the needs of the survey. Specifically, information regarding the infrared part of the electromagnetic spectrum was required to describe the vegetation efficiently [53]. Based on this, the

multispectral camera SlantRange 4p+ was chosen. The kit of the camera consists of three elements (Table 1):

- a multispectral camera with four optical sensors:
  1. RGB (Center 470 nm (Blue) 520 nm (Green) 620 nm (Red), Width 110 nm);
  2. Red (Center 650 nm, Width 40 nm);
  3. Red Edge (Center 715 nm, Width 30 nm);
  4. Near IR (Center 850 nm, Width 70 nm);
- a Precision Navigation Module (LiDAR Rangefinder and Integrated Dual Antenna RTK GPS), which allows for obtaining better accuracy and quality of results in areas of uneven terrain [54];
- An Ambient Illumination Sensor (AIS) that allows for gaining sunlight-calibrated spectral images.

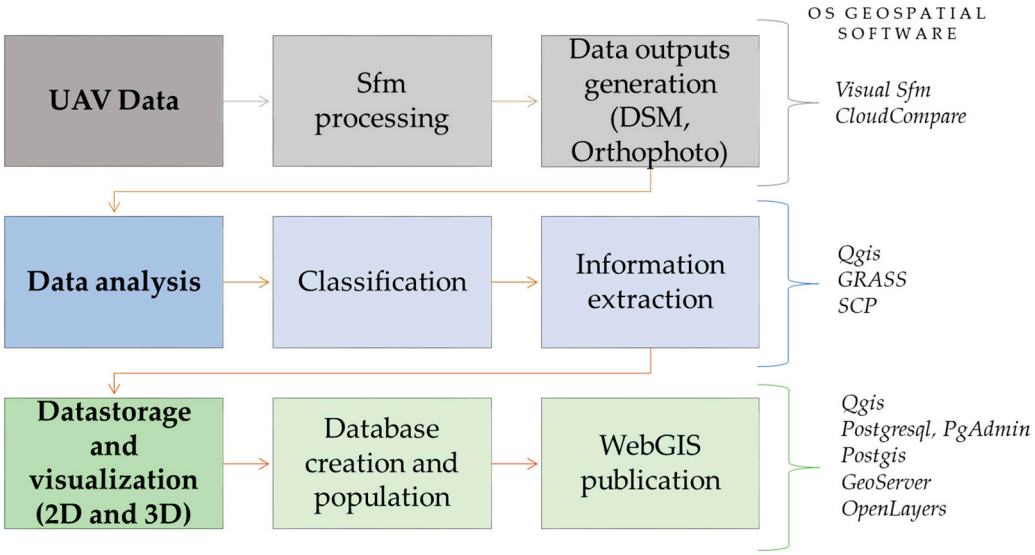
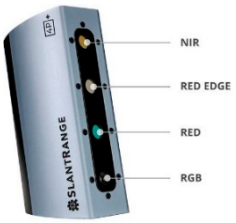


Figure 2. The workflow of the methodology. SfM = Str5ucture from Motion; DSM = Digital Surface Model; SCP = Semi-Automatic Classification Plugin.

Table 1. Data acquisition system specifications.

DJI Matrice 210 V2		• Take-off weight: 4.8 Kg • Payload: 1.34 Kg • Flight autonomy: 34 min • Flight distance: 8 Km • Max speed: 81 Km/h
SlantRange 4P+		• Spatial Resolution (GSD@100m AGL): 2.2 cm • Sensor Type: Si-CMOS • Shutter Type: Global • Positioning & Pointing: GPS/IMU + EKF
Precision Navigation Module(LIDAR) + Ambient Illumination Sensor (AIS)		• Embedded sensors which allow obtaining centimetre-level accuracy and quality of the results in areas of uneven terrain and sunlight-calibrated spectral images

The SlantRange system needs the compatibility of the DJI SKYPORT as regards the UAV on which it is mounted. For this reason and, according to the SlantRange system weight of about 350 g, a DJI Matrice 210 V2 was used.

Then, based on the sensor and UAV's characteristics, the flight was planned. The distance above the ground was about 70 m, to ensure a Ground Sample Distance (GSD) of about 1.5 cm on the object, in agreement with the survey requirements. A grid-schemed flight was carried out to obtain a total coverage of the area and an optimal overlap of the acquired images. The flight resulted in 465 images acquired for each SlantRange 4p+ sensor.

2.3.2. Data Processing

As a first pre-processing operation, the images acquired by the SlantRange system were calibrated with the software SlantView [54]. The sensor producer supplies this software, and it is part of the SlantRange system product. It processes the raw data recorded by the LiDAR module, the GPS/GNSS module and the Ambient Illumination Sensor, and extracts images radiometrically calibrated [55]. Moreover, Slantrange software allows separate of each band of the captured pictures in a single TIFF file.

After extracting the sets of calibrated images grouped by the band, the six datasets (one for each band of the electromagnetic spectrum: Blue, Green, Red W, Red N, Red Edge and NIR) were processed separately using the photogrammetric well-established Structure from Motion (SfM) approach [56]. SfM is now implemented in several commercial and FOSS software packages and, regardless of the software nature, it leads to the image alignment and generation of dense point clouds.

In this study, the photogrammetric process was carried out using Visual SfM [14,57] (FOSS). Several GCPs were collimated in the photos to georeference the photogrammetric block.

3D dense point clouds were produced with a high level of detail (about 28 million points for each set of images) (Figures 3 and 4).

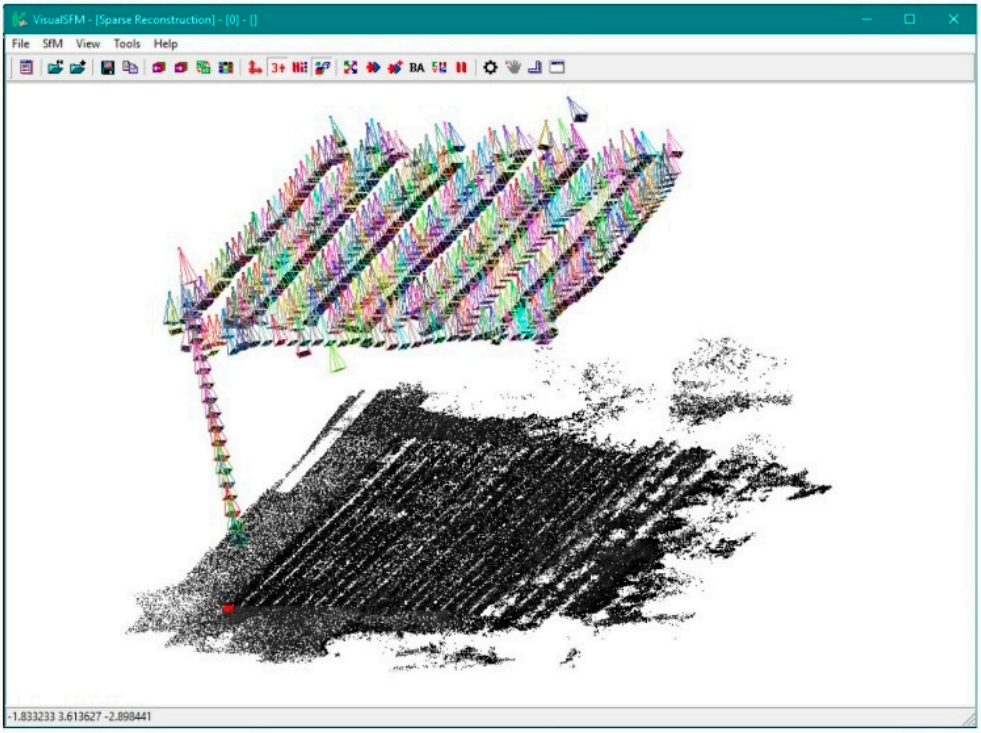


Figure 3. Sparse cloud and cameras of the set relative to the RED W band.

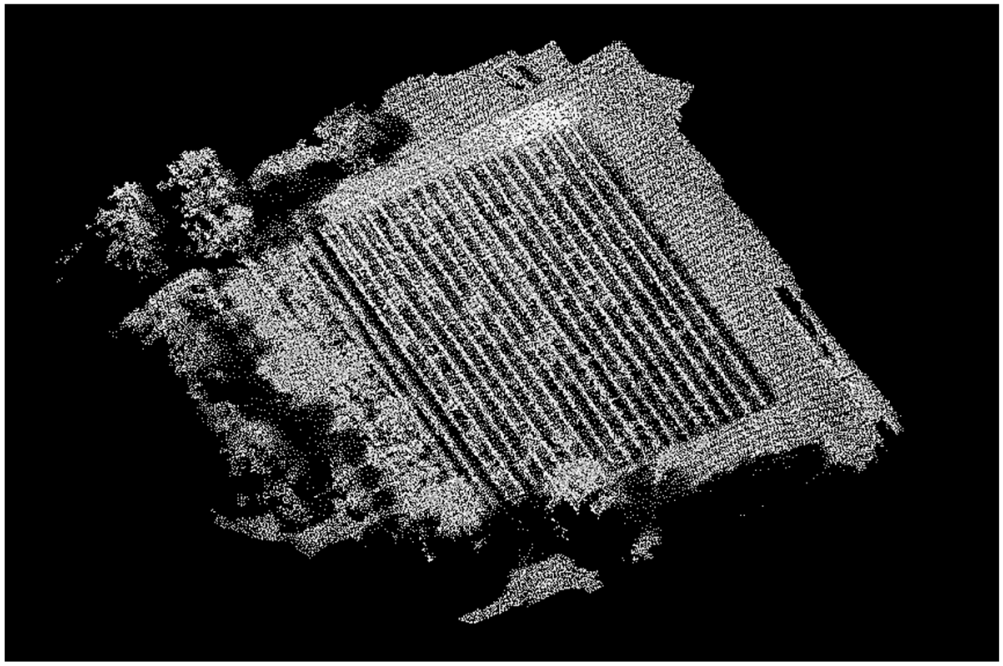


Figure 4. Dense cloud relative to the RED W band in grey-level visualisation.

After generating six dense clouds, one for each set of images, they were imported in CloudCompare, an Open-source tool for the point cloud and mesh processing first developed by Daniel Girardeau-Montaut [58,59]. Finally, using the "rasterize" tool in Cloud Compare, which allows for transforming a point cloud into a 2.5D grid by setting the pixel size and the projection directions, the orthomosaics and the Digital Surface Model (DSM) were generated with a pixel size of 3 cm.

2.3.3. Mapping and Classification

The orthomosaics generated with the SfM technique were used to (i) map the vineyard rows and the single trees, and (ii) extract punctual information regarding the phenological conditions of the inter-row herbaceous vegetation.

First, a pixel-based supervised classification was performed that identified six classes (Table 2) using a Minimum Distance algorithm [60]. The classification was carried out in QGIS environment (version 3.14.0), using Gdal and Grass algorithms, and the QGIS semiautomatic classification plugin (SCP) developed by Luca Congedo [23].

The structure of the classification was organised at two levels. The first level defined four classes (*Shadows*, *Rows*, *Dense Herbaceous Vegetation*, and *Sparse Herbaceous Vegetation*). The second level consisted of the reclassification of *Shadows* class to distinguish between *Shaded Dense Herbaceous Vegetation* and *Shaded Sparse Herbaceous Vegetation*. The *Rows* class helped in the definition of health condition of the vines. *Shadows* classes served the single-tree segmentation process and were used as geometry input, while the *herbaceous vegetation* classes described where under-row weeds needed to be mowed at the time of the survey.

Five derivative features were extracted from the Slantrange spectral bands to improve the classification's final accuracy. These features are spectral indices that, along with the six Slantrange spectral bands and the DSM, constitute the final classification input dataset. Table 3 reports the list of the derivative features computed.

Table 2. Qualitative description of the classes according to first level classification (Classification I) and second-level classification (Classification II).

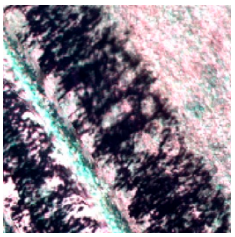
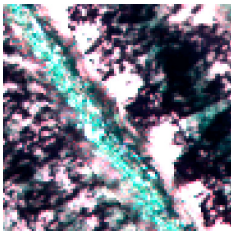
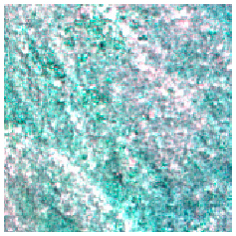
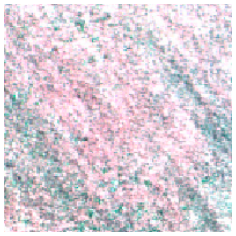
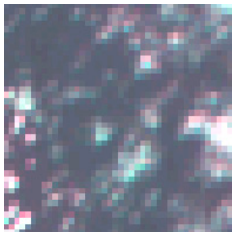
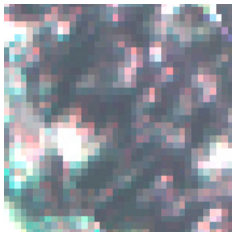
	Class	Description	
I classification	Shadows	The flight was realised in the afternoon. Well-defined shadows are present on the scene.	
	Rows	The vineyard rows are constituted by several grape trees in which vines grow together on three metal wires parallel to the ground. This cultivation structure is typical and does not allow the detection of single trees from aerial nadiral views (like the one of the present UAVs survey).	
	Dense Herbaceous Vegetation	To facilitate the mechanisation of farming activities and the use of tractors, the vineyards are mowed, or herbicides are used. This class indicates the area in with the herbaceous vegetation is at an advanced stage of development.	
	Sparse Herbaceous Vegetation	This class indicates the area in which the herbaceous vegetation is dry or at an early stage of development.	
II classification	Shaded Dense Herbaceous Vegetation	Same characteristics of *Dense Herbaceous Vegetation* class, but in shade condition. It is a service sub-class created to facilitate the classification. The *Shaded Dense Herbaceous Vegetation* is merged with the *Dense Herbaceous Vegetation* in the post-processing phase.	
	Shaded Sparse Herbaceous Vegetation	Same characteristics of *Sparse Herbaceous Vegetation* class, but in shade condition. It is a service sub-class created to facilitate the classification. The *Shaded Dense Herbaceous Vegetation* is merged with the Sparse herbaceous vegetation in the post-processing phase.	

Table 3. List of derivative features selected and used in the classification dataset.

Feature Name	Formula
Chlorophyll Index Red edge (CI Re) [34]	$\frac{NIR}{RedEdge} - 1$
Enhanced Vegetation Index (EVI), [61]	$2.5 \times \frac{NIR-RED}{NIR+RED-1}$
Hue Index [62]	$arctan\left(\frac{2\times RED-GREEEN-BLUE)}{(GREEN-BLUE)}\right)$
Normalised Difference Vegetation Index (NDVI), [63]	$\frac{NIR-RED}{NIR+RED}$
Normalised Difference Water Index (NDWI), [64]	$\frac{GREEN-NIR}{GREEN+NIR}$

Once the input dataset was created, a supervised classification was performed. Supervised classification algorithms require the definition of training samples. Thus, areas of class-homogeneous pixels and regions of interest (ROIs) were manually identified and made up the training dataset. Each ROI extends for 4180 pixels on average. Figure 5 shows the spectral signature of the classes and the scaled distance between each other.

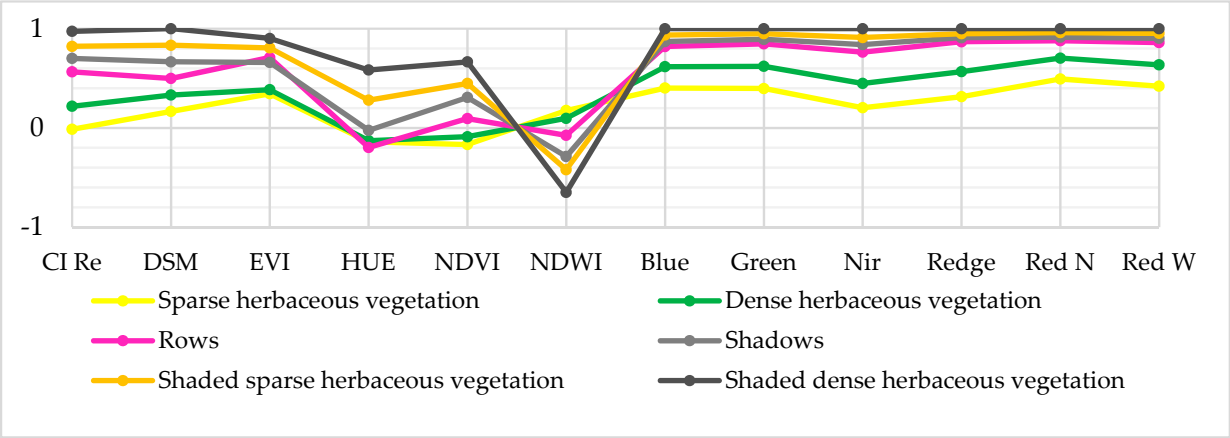
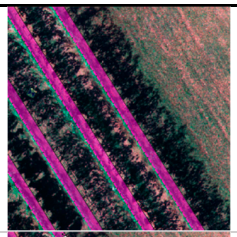


Figure 5. Spectral signatures of the classes. The values were scaled on a −1—1 range to facilitate the reading of the graph.

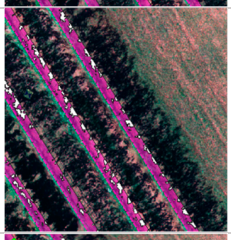
The first level classification (Classification I) was performed using the Minimum Distance algorithm, with a threshold (standard deviation from the mean) of 2-sigma for classes *Rows*, *Shaded Sparse Herbaceous Vegetation*, *Shaded Dense Herbaceous Vegetation*, and *Sparse Herbaceous Vegetation* and 3-sigma for *Shadows* and *Dense Herbaceous Vegetation*. The result was then postprocessed applying a 15-pixel sieving filter and 4-pixel dilation on the *Rows* class. The areas classified as Shadows were masked and used for the second classification (Classification II). It was realised with the same algorithm and settings of Classification I. The main accuracy measures based on the error matrix (Producer's accuracy, User's accuracy, Overall accuracy, and F1-score) were computed for both classifications using 100 randomly placed points per class. The resulting classifications were merged.

The database built in this work also needs to store information at the single-tree level. The cultivation structure consisted of several grape trees in which vines grow together on three metal wires parallel to the ground. This structure made it impossible to detect each tree from the nadiral view of the rows. Thus, the single trees were segmented using the information derived from the shadows. The segmentation was performed on vector data. First, an intersection between the directional buffer of each row's major axis and the shadows was computed and the centroids of the intersections were extracted.

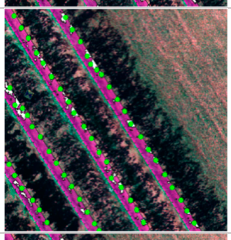
Then, the centroids were snapped on the major axis of the rows. Voronoi polygons were computed on the centroid and clipped according to the row borders. Finally, the results were transformed from multipolygons to single polygons and visually checked. Figure 6 summarises the entire segmentation process.



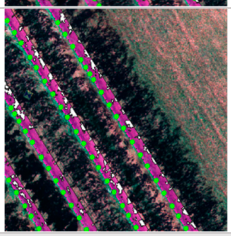
Directional buffer of the major axis of each row on the direction of the shadows



Intersection analysis between shadows and the buffered axis and polygons smoothing

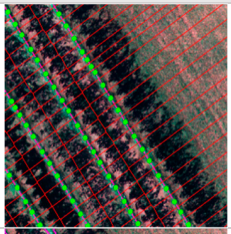


Centroids extraction

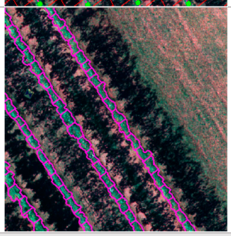


Snap of the centroids on the major axis of the rows

Visual check and manual correction



Voronoi polygons creation on the centroids



Mask of Voronoi polygons on the rows

Transformation of multi-polygon geometry in single-polygon geometry

Visual check

Figure 6. Workflow for the detection of the single tree.

The modal values of the spectral indices EVI, NDVI, NDVI Red Edge, and Chlorophyll Index were then calculated and plotted for each object (tree) to scale the tree health [65].

3. Results and Discussion

The following sections present the outputs and outcomes of the described FOSS methodology: UAV survey processing products, classified data of rows and single-tree identification, and 2D and 3D web visualisation of data and attributes according to a structure geodatabase.

3.1. Orthophoto and DSM

Thanks to the operations described in Section 2.3, it was possible to extract orthophoto and DSM with the pixel size of 3 cm for each of the six bands separately. Figure 7 shows the DSM and the RGB orthomosaic obtained by the multichannel visualisation of Red, Green, and Blue bands.

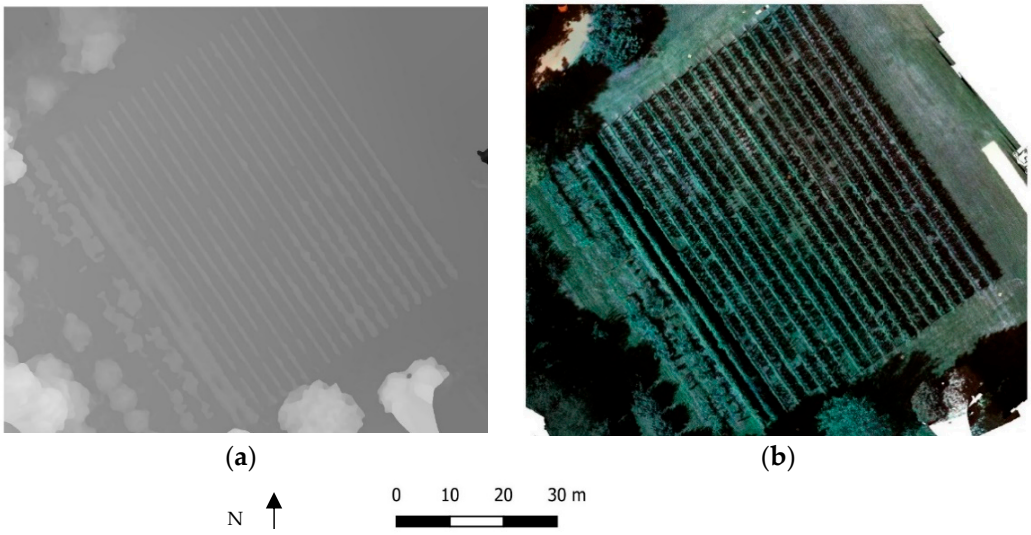


Figure 7. (**a**) Digital Elevation Model (DEM), and (**b**) RGB orthophoto obtained by combining Red W, Green and Blue orthophotos.

It is worth notice that the SfM process required some practical measures to process multispectral data. The five multispectral bands were processed separately since Virtual SfM cannot deal with the 4p+ dataset.

3.2. Classification of the Rows and Single Tree Detection

The first classification was performed using the Minimum Distance algorithm on four classes with about 16,000 pixels as training. Its result shows some "salt and pepper" effect; indeed, some single pixels were not classified and some were misclassified (see Figure 8).

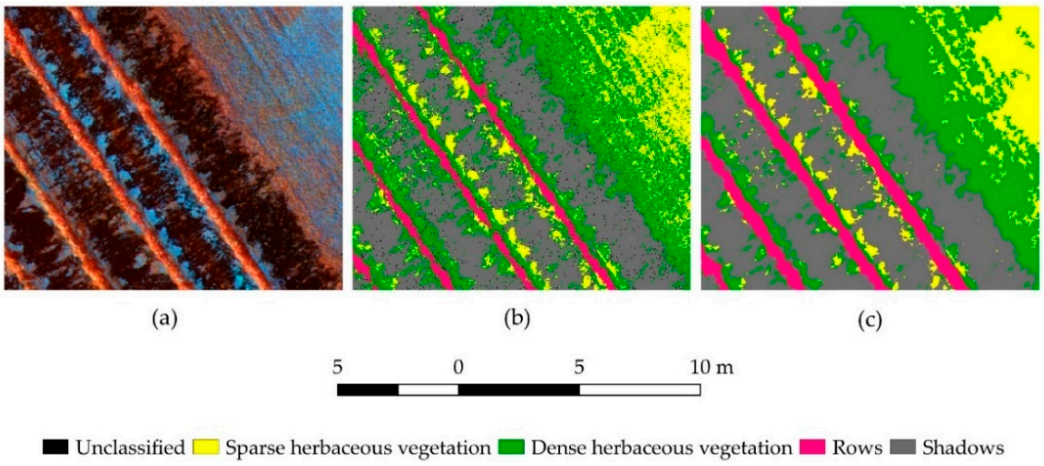


Figure 8. Detail of the results of classification I. The (**a**) is the orthophoto in false colour (red-Edge, Green, Red); (**b**) shows the classification I without postprocessing; (**c**) shows postprocessed classification I.

Nevertheless, these inaccuracies were corrected in the postprocessing phase through the sieving and dilation processes.

The final accuracy assessment on classification was measured on 400 points randomly placed, and it had an overall accuracy of 95% (Table 4). The Dense Herbaceous Vegetation represents the most critical classes and the Shadows as the F1-score indicates (respectively, 90% and 94%). This is mainly due to the difficulty of classification in the edge areas between the two classes. It is worth underlining that the shadows of the canopies' upper parts are irregular and the illumination conditions are not uniform. The Producer's accuracy is particularly low for the Dense Herbaceous Vegetation (only 0.87).

Table 4. Error matrix of classification I. PA = Producer's Accuracy; UA = User's Accuracy; OA = Overall Accuracy.

Classification I	Sparse Herbaceous Vegetation	Dense Herbaceous Vegetation	Rows	Shadows	Total
Sparse herbaceous vegetation	95	4	0	1	**100**
Dense herbaceous vegetation	2	94	1	3	**100**
Rows	0	3	96	1	**100**
Shadows	0	7	0	93	**100**
Total	**97**	**108**	**97**	**98**	
PA	0.979	0.870	0.990	0.949	OA=
UA	0.950	0.940	0.960	0.930	0.945
F1-score	0.964	0.904	0.975	0.939	

Classification II was realised using the Minimum Distance algorithm on the pixels classified as Shadows from classification I. Only two classes are included in classification II: Shaded Sparse Herbaceous Vegetation and Shaded Dense Herbaceous Vegetation. Similarly to classification I, the results present some "salt and pepper" effect all over the scene of unclassified pixels, which was corrected in the postprocessing phase.

The accuracy assessment was measured on 200 randomly placed points, and it has an overall accuracy of 95% (Table 5). Eight validation points of Shaded Dense Herbaceous Vegetation were classified as Shaded Sparse Herbaceous Vegetation, and only two are in the opposite condition. The results of the accuracy measures are outstanding: both User's and Producer's accuracies were never below 92%. The presence of only two classes undoubtedly influences these positive results.

Table 5. Error matrix of classification II. PA = Producer's Accuracy; UA = User's Accuracy; OA = Overall Accuracy.

Classification II	Shaded Sparse Herbaceous Vegetation	Shaded Dense Herbaceous Vegetation	Total
Shaded sparse herbaceous vegetation	98	2	**100**
Shaded dense herbaceous vegetation	8	92	**100**
Total	**106**	**94**	
PA	0.925	0.979	OA=
UA	0.980	0.920	0.950
F1-score	0.951	0.948	

The segmentation of single trees resulted in 1269 plants distributed on 20 rows. It is worth mentioning that the method does not provide the precise size of the canopies, but it assumes that the canopy of a grapevine is symmetrically developed on the metal wires and it extends until mid-distance to the next plant. This assumption is the base for using Voronoi polygon construction. Figure 9 shows the results of the classification and the segmentation.

Finally, the EVI, NDVI, NDVI Red Edge, and Chlorophyll Index were calculated on the entire scene. The pixels' mode value corresponding to single-tree geometries was calculated and scaled to identify the unhealthy plants.

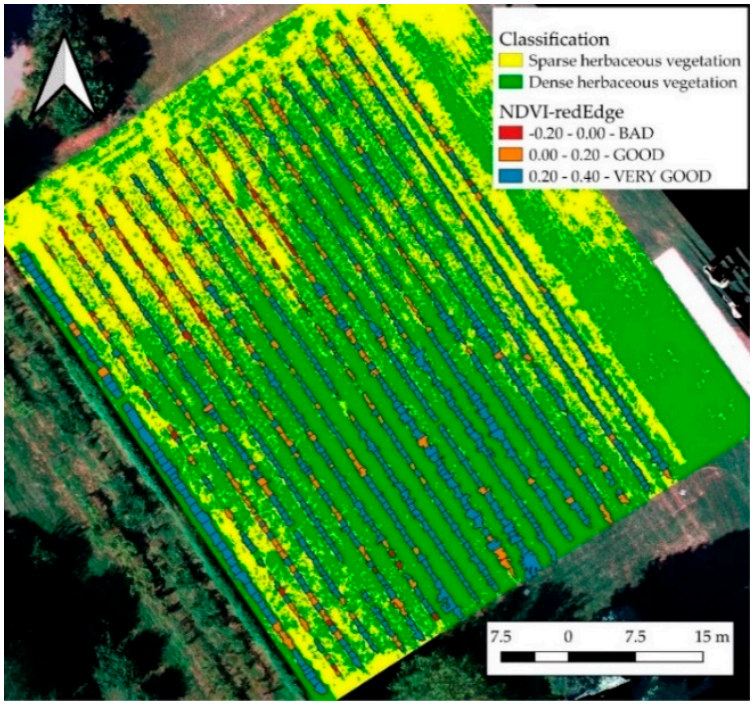


Figure 9. The result of the classification and the segmentation of the single trees. The image shows the example of NDVI values calculated on the Red Edge band for each plant. NDVI-Red Edge was classified in BAD (<0.00), GOOD (0.00–0.20) and VERY GOOD (>0.20).

3.3. Data Storage, Visualisation, and Querying

Following data generation, analysis and classification, the ending phases of the presented workflow aim to organise, store, visualise and query the postprocessed data. This final step, carried out by adopting open-source software, aims to develop a spatial database storing knowledge of vineyard and publishing information in a web- and user-friendly platform. This last process consists in the steps reported in Figure 10.

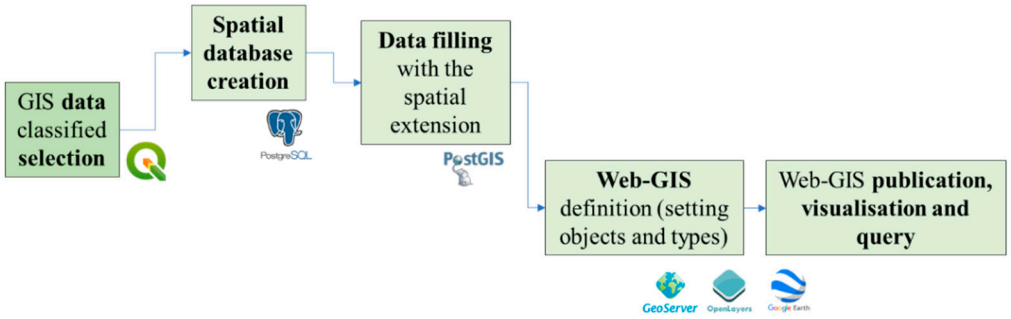


Figure 10. Data visualisation and querying process.

For the generation and publication of the spatial dataset of the vineyard, different FOSS solutions were adopted. QGIS (version 3.14.0) was used for the database creation and for visualising 2D and 3D data, as Figure 6 shows (Section 2.3), while for the data publication, PostgreSQL with its interface PgAdmin, was selected. The spatial extension PostGIS was added for the geometry population. GeoServer, OpenLayer and Google Earth were used for the online publication of the database with three-dimensional visualisation and query elements. Figure 11 graphically describes the data storage, visualisation, and querying process.

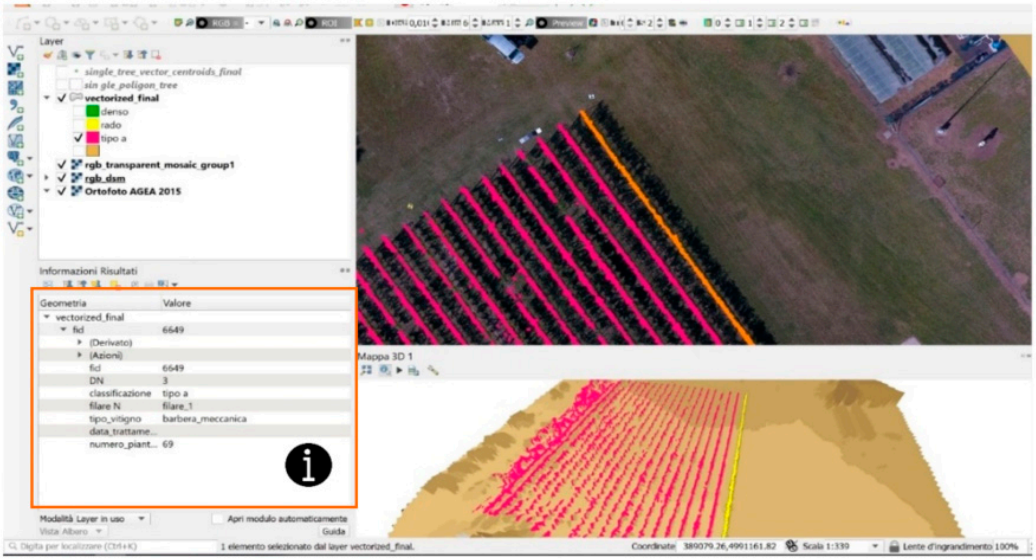


Figure 11. QGIS project with 2D and 3D visualisation and querying of Grugliasco vineyard data.

3.3.1. 3D Visualisation of Data in QGIS and Spatial Database Creation

The first part of the methodological workflow regarded the QGIS project creation (Figure 11). This operation aimed to defined entities useful for the database creation to store information of the site area. Thanks to the 2D and 3D maps of Qgis, it was possible to plan a possible user-friendly web interface (explained in the next section). The following entities were selected to populate the table of attributes of the GIS project:

- DSM, raster data from drone acquisition;
- orthomosaic, raster data resulting from the SfM elaboration (Section 3.1) visualised in real colour (RGB);
- vineyard row, polygons obtained from the vectorisation of the class Rows;
- single trees and plants, centroid-points of the single tree;
- state of health, a classified vector composed polygons of single trees. It contains information regarding vegetation health indices.

In addition to the attributes derived from the data collected in the field, the classified vectors contain new attributes useful for the vineyard's agricultural management, such as the identification number (ID), the grape variety, the number of rows, the history of phytosanitary treatments, and the number of vines. Further information can be added anytime. For example, as reported in the studies analysed in Section 1, it is possible to add additional data from national and international standards or based on the necessity of the performed analysis (such as soil description, climate conditions, characteristics of treetops, and variety of grape). Thanks to the new 3D Map implemented in QGIS, it was possible to visualise vector data on the surface model in 3D.

Then, the structure of the database was designed to support queries and data retrieval. A table of entities was created in PostgreSQL (Figure 12), and the column geometry was added thanks to the PostGIS extension. Then the geometries were populated connecting the database in QGIS by the DB manager tool, by setting the correct reference system (for this area WGS84-32N) and adding user and password of the localhost (PostgreSQL server works on port 5432).

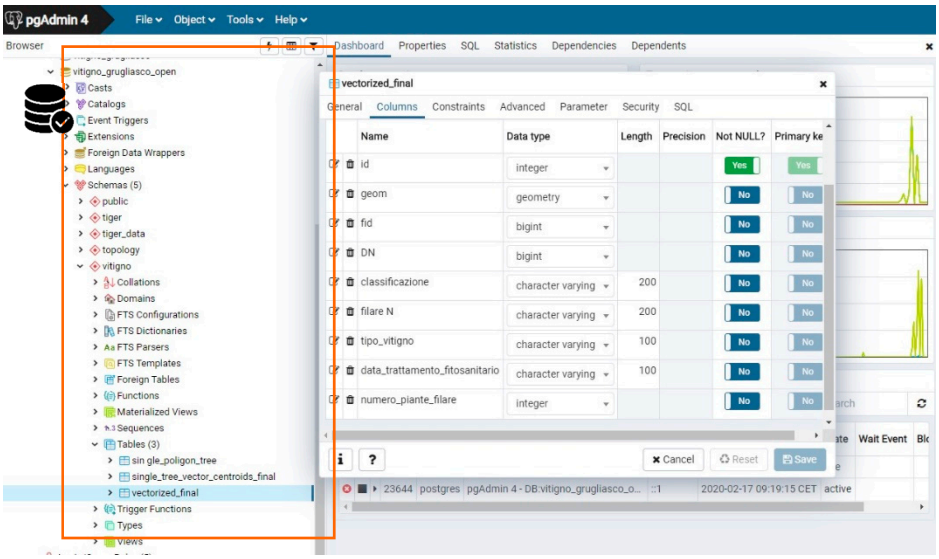


Figure 12. Database tables creation in PostgreSQL (in the PgAdmin interface).

3.3.2. The WebGIS Platform

As mentioned before, the final output of this FOSS methodology consists of the WebGIS publication that allows any actors involved in the production of the grapes to interact with the 2D/3D database. To obtain a web address of the 2D model of the project, we selected GeoServer. It is an Open Source server for sharing geospatial data that provides maps and data such as web browsers and desktop GIS. Hence, it is possible to store spatial data in many formats, and users are not required to have GIS data structure knowledge. Moreover, GeoServer provides different types of data as well as vectors; Shapefiles; External WFS; PostGIS, ArcSDE, DB2, Oracle Spatial, MySql, SQL Server; Raster; GeoTiff, JPG and PNG; pyramids, GDAL formats, Image Mosaic, Oracle GeoRaster. It supports the EPSG projection as the WGS84-32N one.

Here the main steps are listed:

- Connection of the PostGIS Database in GeoServer with the localhost http://localhost:8080/geoserver/web;
- Workspace creation: Grugliasco vineyard (URI: http://localhost:8080/geoserver/Grugliascovineyard, accessed on 18 December 2020), Figure 14;
- Inserting layers from PostGIS (vectors and raster) with their style of visualisation. slt as defined in the QGIS project;
- Publication of the Grugliasco vineyard WebGIS in GeoServer;
- Visualisation of the 2D Map with OpenLayers (it is a JavaScript library for viewing interactive maps in web browsers) (Figure 13);
- Downloading.kml, JSON or WFS file and 3D viewing in GIS environment or in Google Earth for a fast and for not-GIS specialised users' immediate visualisation.

Finally, thanks to previous steps, it was possible to query the spatial data and the vineyard's geometries, such as rows, trees, and plants, to gain all the information inserted in the QGIS project for the crop management.

The present research also tested another FOSS WebGIS solution using the QGIS plugin "QGIS2web" viewer and visualising the data of the WebMap with Leaflet (an open-source JavaScript library for mobile-friendly interactive maps [66]).

Despite the fact that this solution is faster and already integrated in the QGIS software, it does not provide the possibility to modify and implement the vineyard data into a spatial relational database structure. Indeed, it is not editable directly on the web using a FOSS GIS server.

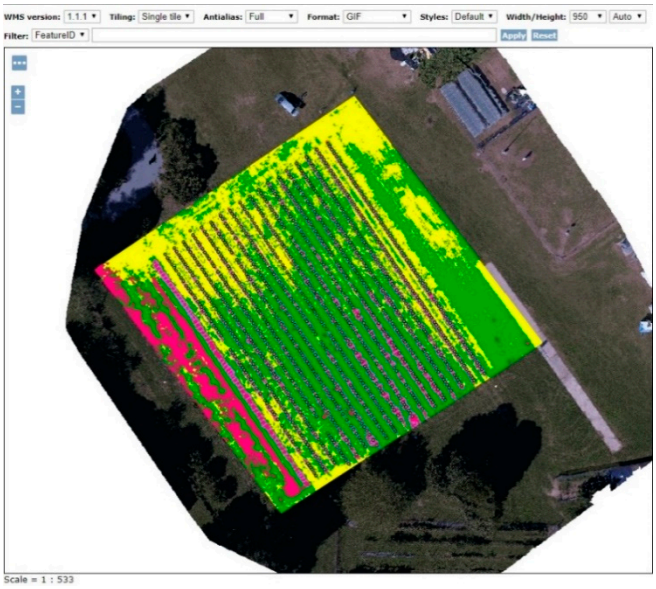


Figure 13. OpenLayers visualisation.

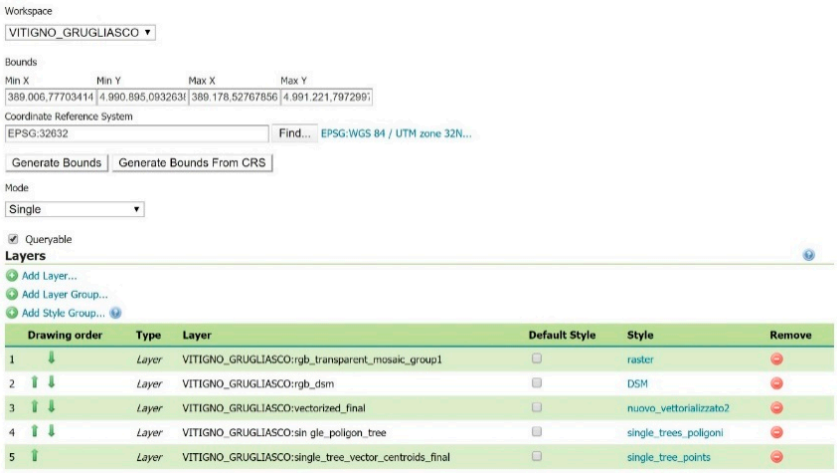


Figure 14. Workspace creation for the Grugliasco vineyard WebGIS.

4. Conclusions and Future Perspective

This paper presents a complete workflow based on FOSS procedure and software compared to the previous knowledge and the already published studies. The structure of the proposed workflow is the base for any applications based on SfM and automatic information extraction techniques. Indeed, it has a wide application range and can also be adapted to non-agricultural purposes, such as inventory management of cargo and urban green monitoring.

The paper aims to present and validate a FOSS workflow for smart farms and, at the same time, to point to possible future developments in this application field. This open-source research workflow starts with the acquisition phase of data with a multispectral sensor and traces the traditional photogrammetric process via SfM, classification of spatial data, and GIS visualization and querying processes adopting OS tools, combined under the precision agriculture hat. Moreover, the present study proposes a webGIS and user-friendly solution for smart farming, capable of garnering, updating, and querying information about crops and vineyard processes in a unique spatial database system. The reliability of the whole process is demonstrated with a real case study used for testing the single steps and validating them.

Although the three main steps of the workflow could be applied and validated separately, the methodology assessment could be improved. With this in mind, the present research tends to set the base for the following developments. Hence, future works should focus on evaluating the workflow in terms of effectiveness and replicability. The effectiveness concerns the workflow's appropriateness to answer the PA's needs and can be evaluated via subjective qualitative methods, such as questionnaires and interviews to final users, and objective methods, through reliable indicators. This evaluation needs to be carried out after a significant time of usage of the webGIS platform and its data implementation.

The presented solution is easily replicable by many use cases and by different stakeholders involved in various tasks concerning precision agriculture. As mentioned in [67], the integration of geomatics techniques and methods (such as remote sensing and aerial photogrammetry by different sensors) with a geographic information system could improve the resilience of modern agriculture, managing and monitoring every step (seeding, crop growth, and harvesting and production).

Additionally, the methods' replicability can be assessed on similar case studies or compared with commercial solutions. It is worth mentioning that the three main steps of the proposed workflow remain unaltered regardless of the study case. Nevertheless, from the replicability point of view, adjustments could be necessary for what concerns the classification. The classification parameters depend on the defining characteristics of the vineyard and the possible input data type (i.e., RGB, multispectral).

Moreover, the spatial database can be implemented and organized to store precision farming information collected by OS hardware, making a step toward OS smart farming. Total OS smart farming is the expected direction for future research.

Another fundamental aspect to take into consideration regards the possibility of targeting a wider audience, now designated to not-academic or not-GIS expert users, enriching the web-GIS DB-based platform with analysis tools and giving different level of access depending on the degree of expertise.

Future steps of our research could consider creating a new web service able to support field operation for treatments of grapes and crops, providing online digital content (also accessible from mobile devices). Even if some valuable examples of digital tools are already developed in the vineyard management field, none of these present map services or spatial datasets.

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