UAV saffran monitoring process

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***Abstract*—The use of Unmanned Aerial Vehicles (UAVs) in the field of Precision Agriculture (PA) is becoming more widespread, as the great benefits they offer are recognized by more and more farmers around the world. A UAV can fully inspect or spray arable land and crops, in just a few minutes. Farmers can use the spatial maps, photos and reports that can be produced with the help of these inspections to collect useful information in order to increase productivity and reduce costs. Drones have already been used for remote sensing in many different types of crop and environments, with great results. In this paper, we present the process adopted for monitoring remotely saffron cultivations with the use of UAVs in the Western Macedonia region of Greece, in an effort to reduce labor and costs.**

Keywords— Precision Agriculture (PA), UAV, drones, saffron

I. INTRODUCTION

Precision Agriculture (PA) is a management strategy that encompasses information technology, such as Unmanned Aerial Vehicles (UAVs) and sensors, to gather geospatial, remote and close-range data for improved resource usage in an agricultural holding. PA technologies aim to optimize the efficiency of production factors and potentially reduce the environmental impact. UAV remote sensing refers to the measurement and recording of quantitative and qualitative variables remotely. By using special cameras that record wavelengths in the visible range and beyond, they can capture phenomena on a farm that are not immediately and timely perceived with the naked eye. In the visible range, UAVs can record information related to the topography of the field (i.e. exact dimensions, altitude differences, water collection basins), the flowering of the plants, and the estimation of the phytomass. Additionally, they can identify sowing problems in planting lines as well as provide an estimate of the survival rate of young plants. They can capture the effects of specific diseases, detect water stress and assess the ripening stage of fruits and vegetables. Furthermore, they can capture the efficiency of a fertilizer or of a plant protection recipe by producing useful conclusions about whether the recipe should be repeated [1][2]. Finally, the benefits of the above applications are multiple including: inputs reduction, decreased costs, production increase, product quality upgrade, thus contributing to the wider goal concerning the sustainability of agricultural production [3].

In this paper, we present the results of the pilot study performed in the region of Western Macedonia targeting to monitor saffron fields. We will describe the procedure followed to gather the necessary field and crop data that will allow for the creation of spatial maps that depict the various objects that can be recognized in saffron fields such as flowers, weeds, mammals and anomalies.

II. METHODOLOGY

This section presents the methodology adopted to obtain and analyze the necessary data acquired from saffron fields. The overall methodology is depicted in Figure 1 and consists of three steps:

- **Step 1. Remote Sensing**
- **Step 2. Application of Photogrammetry**
- **Step 3. Machine Learning Estimation**

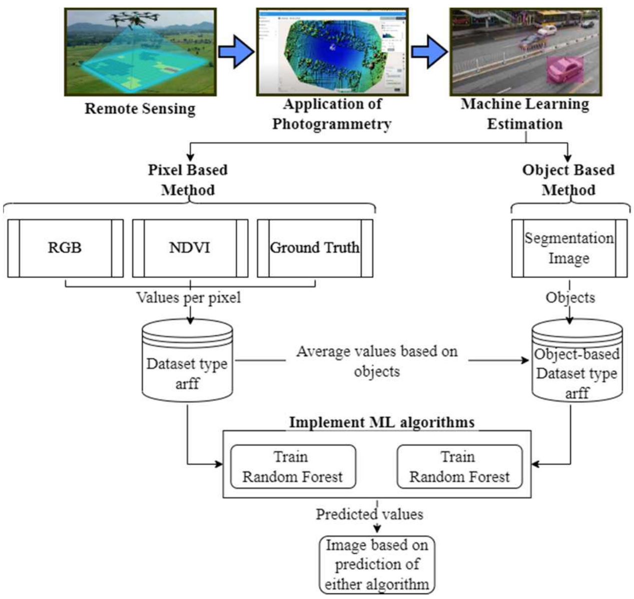

Fig. 1. Process followed for the research.

A. Remote Sensing

In this step, data collection is performed with the help of UAVs, ground sensors and other instruments such as meteorological stations. During this step the fields are photographed with the help of UAVS. For the purpose of the pilot study an *RGB* sensor was used to capture the required photographs. The *RGB* sensor detects light in the three basic color spectrums *red*, *green* and *blue*. It is used to take realistic photos of the area of interest and is usually pre-installed on the UAV. *RGB* sensors are the simplest and usually less expensive sensors to capture image compared to other types. Additionally in this step we can also obtain data from the ground. Several types of sensors can be used (i.e. pH sensors, temperature sensors, humidity sensors, wind velocity sensors). In the context of this study we used temperature and humidity ground sensors. The outputs of this step are photographs and measurements (i.e soil temperature and humidity).

B. Photogrammetry

In this step the data collected from **Step 1** serve as input to photogrammetry techniques. Photogrammetry is the method of obtaining reliable information about an object or a location through the analysis of two-dimensional photographs. This information is actually accurate measurements of the three-dimensional characteristics of the ground or object of interest. More specifically, with the photogrammetric calculation of coordinates, distances, heights and areas can be quantified and topographic maps, digital elevation models and orthophotos can be produced.

There are two types of photogrammetry, aerial and terrestrial, depending on whether the camera is in the air or on the ground. In this study we focus in aerial photogrammetry techniques (due to the usage of UAVs) that presents many advantages related to high-resolution images, low cost and flexible data analysis [4]. The outputs of this step are:

- **Orthomosaics:** Orthomosaics or orthophotos correct any geometric deformation inherent in aerial images. Using a process called orthodontics this techniques can create a highly detailed map that refers to the real world. Proofreading removes perspective from each individual image to create continuity throughout the map, while maintaining the same level of detail from the original image. The final product is a seamless mosaic sewn with matching edges and color balance.
- **Digital Surface Model (DSM):** A DSM represents the physical and structural features of the Earth's surface including their height. For example, the height may come from the top of the buildings, the tree canopy and the power cables.
- **Normalized Difference Vegetation Index (NDVI):** NDVI is the most common vegetation index and the one that was used in this project. Vegetation indices analyze the interaction of electromagnetic radiation. They are mathematical and quantitative combinations of absorption and scattering in different bands of the electromagnetic spectrum. Utilization of vegetation spectral behavior has proven to be very efficient in remote sensing applications and more specifically in precision farming applications using UAVs. NDVI has the ability to minimize the effect of topography and in addition, the value scale is from -1 to 1 with 0 being the limit of absence of vegetation. The NDVI index is defined by the following general equation:

$$NDVI = NIR - RED / NIR + RED \quad (1)$$

Where *NIR* is the near-infrared spectral channel and *RED* is the spectral channel in the red visible area. The sum of the denominator mainly compensates for the changes that exist in the conditions, in the surface slopes and in their orientation. Healthy vegetation absorbs most of the visible light, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light.

C. Machine Learning (ML)

In this step the maps produced in **Step 2** are used as input to train the machine learning models so as to estimate the existence of different objects in the fields (i.e. flowers, weeds, mammals). ML is often applied in PA to exploit information from the vast amount of data acquired by UAVs. ML techniques are usually classified into different broad categories, depending on the type of learning (supervised / unsupervised), learning models (classification, regression, and grouping) or the learning models used to carry out the selected task. In this pilot study, two types of analysis was applied: pixel-based and object-based methods.

Pixel-Based Image Analysis: Pixel-based method is based on classifying images pixel by pixel, by using a set of rules to decide whether different pixels can be grouped for having similar characteristics.

Object-Based Image Analysis (OBIA): Object-based analysis was the first methodology to start using objects as an elementary unit. Objects are considered neighboring pixels which are grouped according to criteria, defined by the user. The resolution of the image depends on these objects which constitute its primary data. Each of these objects contains information related to the shape, the object's neighbors, spectral characteristics, and relationships with the environment. Through the creation of these objects, which are a result from a segmentation process, the possibility is given to the user to draw a lot of information from them, in contrast to the information they received from the individual pixels.

Random Forests and Neural Networks algorithms were then applied to the produced data to train models in weed, cultivation, and mammal detection in a field.

Random Forests Algorithm: Random forests are a group categorization algorithm that ranks in supervised learning and uses decision trees. As its name implies, it consists of a large number of unique decision trees that function as a whole thus creating a forest. The fact that it uses a large number of decision trees, reduces the error from the occurrence of overtraining phenomena in individual trees.

Artificial Neural Networks (ANNs): Artificial neural networks [5] are an attempt to approach the human learning process. They essentially mimic biological neural networks by assigning nerve functions to a single element (neuron) which is only capable of summing its input and normalizing its output. Neurons are interconnected in arbitrary complex artificial neural networks.

III. CASE STUDY

The data for our study were captured from a saffron field near the village of Ano Komi in the municipality of Kozani, of the region of Western Macedonia, Greece. The field's exact coordinates are 40.23398743, 21.85294092. The pilot study was part of DIAS research project, funded by the Greek government and European funds.

The remote sensing was performed using the DJI's PHANTOM 4 drone which is equipped with one RGB sensor for visible light imaging and five monochrome sensors for multispectral imaging. In this case study, we present only RGB orthomosaics, DSM and NDVI (figure 2) using an open-source mapping software called OpenDroneMap (ODM) [6] that was reused in the context of DIAS platform.

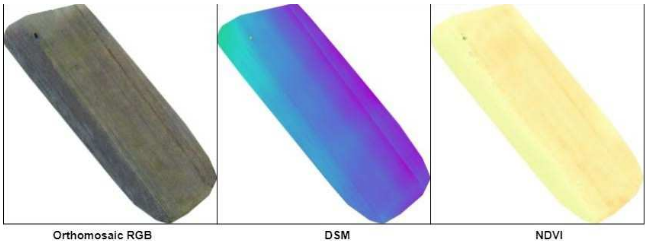

Fig. 2. Images produced by DIAS platform.

The image annotation for the ground-truth image was performed with the help of another open-source software, the Computer Vision Annotation Tool (CVAT) [7], using as input the RGB orthomosaic.

Pixel-Based Image Analysis: For this method we developed a code in python to extract the RGB values of the pixels from the image and created an arff dataset. The input data were orthophotos in the RGB and NDVI spectrum. At the same time a separate image was developed with the annotation of each pixel which essentially represents the real data (ground truth) of the image with the pixels being represented in black blue, red, green depending on which of the four categories (saffron = red, weed = green, field = black, mammal sample = blue) belong. In this way a set of data was created from images which indicates the various characteristics that contribute to the field.

Python's PIL library was used for image analysis, which is suitable for collecting pixel values in each image. With its application, the data were collected from the RGB, NDVI images as well as from the image with the real data of the categorized pixels (ground-truth image). This resulted in the data set with each instance corresponding to one pixel.

Object-Based Image Analysis (OBIA): This method, instead of categorizing each pixel like in pixel-based one, groups small pixels into a common vector object. With the higher resolution UAV images, pixel-based categorization has become significantly less efficient because of the pixel size ratios relative to the object size. OBIA uses the segmentation image method which divides pixels into homogeneous parts. These object segments are then arranged into classes based on shape, spectrum, texture, and other characteristics. There are two basic steps in this method before creating the data set:

1. The segmentation of the image
2. The exportation of features and the categorization

We used the open source approach described in [8]. OBIA is based on objects built as groups of pixels (raster clumps). The properties of each object (clump) are stored inside a raster attribute table (RAT) while each object is associated with the clump ID. The following software packages were used in DIAS platform to create, store, display, and sort objects within the RAT:

- GDAL: raster data model, provides both input and output (I / O) of common image formats.
- RSGISLib: segmentation of images.
- Raster I / O Simplification (RIOS): used to read, write, and sort objects that are rendered.
- Tuiview: used to view data that is in KEA format
- KEA image format: used to store image objects and related attributes.

All packages were deployed in Windows operating system, except RSGISLib which was deployed in Linux. The segmentation algorithm applied to RSGISLib is that of Shepherd et al. [9] (figure 3). The algorithm uses an embodiment of the K-means clustering to generate threads for segmentation where, after mapping the pixels to the relevant cluster center, the clusters are repeatedly deleted if they are below the min- imum matching unit limit in the adjacent cluster that is closer to "color" (as defined by Euclidean distance). After deletion, the final clusters are relabeled to ensure that they are sequentially numbered, with the value zero not defining any data area. The algorithm is repeated, always producing the same result with the same input data and the same parame- ters. The segutils.runShepherdSegmentation function is available, through the RSGISLib package, in Python to per- form all the steps required for partitioning. The algorithm has two basic parameters: (1) the number of k-blocks used to generate the K-means algorithm (numCluster) and (2) the minimum object size in which objects are deleted (minPxls). The scale or size of the segmentation is controlled by k, where smaller values of k produce larger objects.

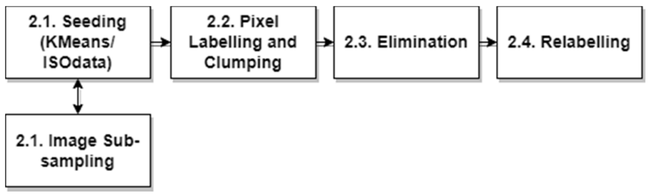

Fig. 3. Shepherd et al algorithm.

After image segmentation, the object property was added into the data and a new dataset was created, whose instances were the objects as categorized by the segmentation. Average values per object were calculated from RGB, NDVI and ground-truth data.

The Random Forests algorithm was applied to the above two different data sets in order to train a model to identify saffron, weeds, mammal presence and field. Since the data was in arff format, scipy.io was used which allows python to read arff files. Python language provides the sklearn package which gives the RandomForestClassifier function that applies the random forest algorithm to pandas data. Pandas is a software library written for the Python programming language for data handling and analysis. Specifically, it offers data structures and functions for manipulating arithmetic tables and time series. The value that the function took as a parameter is the number of trees to be created n_estimators = 100.

The Multilayer Perception algorithm was used for the application of the neural networks, which is also included in the sklearn package within the MLPClassifier function. The parameters accepted by the MLPClassifier function were hidden_layer_sizes = (7,7,7), activation = 'relu', solver = 'adam', max_iter = 500.

Figure 4 presents on the left side the output of the OBIA model that classifies the areas of the field into three different types of objects (mammals, weeds and crops) and on the right side the ground-truth image.

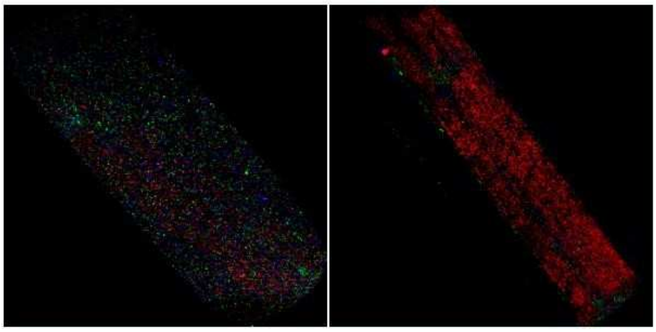

Fig. 4. OBIA model output and calculated ground-truth image

Two evaluation methods were developed for the above algorithms. Initially, the results of all algorithms in each data set were checked with the technique of **10 fold-cross validation** for greater reliability. Cross-validation is a process used to validate results, helping to draw safe conclusions about the behavior of the categorizer in a data set. The general idea is that the data set is divided into ten equal parts and follows an iterative process in which each time one part is used for categorization and evaluation, while the rest is used for the categorizer training. The other concept employed to assess the classification performance is the **confusion matrix table** (Table 1), which depicts the model's predictions versus ground-truth labels. Each confusion matrix row represents the instances in a predicted class and each column represents the instances of a real class. The confusion matrix table is a key tool for evaluating the methods used in this project.

Additional key indicators whose values are shown in Table 2 are:

- **Precision**: is the ratio between all the points that are estimated correctly to be positive (those assigned in a category), to the total number of points that are estimated as positive.

  Precision = True Positive/Predicted Positive

- **Recall**: is the ratio between all the points that are estimated correctly to be positive, to the points that are actually positive.

  Recall = True Positive/ Actual Positive

- **Accuracy**: is the ratio between all the points that are estimated correctly, to the total number of points.

  Accuracy= True Positive + True Negative/ All

In addition to the above popular methods, two programs were created for further evaluation of the results. The first accepts the predictions of the model and recreates the ground truth image for comparison with the original. The second compares OBIA forecasts with the original picture.

Overall the estimation accuracy for this field is:

TABLE 1. CONFUSION MATRIX

Image 1	mammal	field	weed	crop
mammal	**5**	25235	8	323
field	4668	**30393824**	9081	273789
weed	1	14203	**8**	160
crop	37	257622	92	**3408**

TABLE 2. EVALUATION INDICATORS

model	accuracy	precision	recall
RF	1.00	0.97	0.64
NN	0.98	0.85	0.75

IV. CONCLUSION

The purpose of this study was to propose a methodology for obtaining and analyzing data with the use of UAVS. We provided a case study showing the appliance of the proposed methodology in saffron cultivations in Western Macedonia, Greece in order to be able to produce maps that depict the various objects that exist in fields such as crops, mammals, weeds.

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