The use of unmanned aerial vehicles for precision agriculture: An overview and a preliminary cost analysis

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Abstract: In recent years, interest in techniques and approaches capable of ensuring the efficiency and sustainability of agri-food chains has grown considerably. In this paper, we explore the opportunities offered by the use of unmanned aerial vehicles (UAVs) for precision agriculture. First of all, we provide an overview about the possible alternatives in terms of aerial platforms and sensors for image acquisition. Secondly, starting from the technical constraints, a preliminary cost analysis is carried out. We refer to a hypothetical small-medium farm in the olive sector, which wants to adopt a UAV to make its agricultural practices more efficient. In particular, we make a comparison between two types of UAV, fixed-wing and rotary-wing. The main result of our analysis is that the purchase of a UAV for own use is still quite expensive, especially if the field to be monitored is limited in size. However, the production capacity of the UAV can be better exploited if nearby farms are also served. Finally, we identify the main current limitations of UAV technology in agriculture and the possible challenges that should be faced in the future in order to achieve large-scale spread.

Keywords: Unmanned Aerial Vehicles, Precision Agriculture, Remote Sensing, Crop Monitoring, Cost Analysis

1. Introduction

According to the Food and Agriculture Organization of the United Nations (FAO), food production should increase by 70% by the year 2050, due to the expected growth of the world's population (FAO, 2009). However, due to many inefficiencies in the food chains (Papargyropoulou et al., 2014), up to a third of the food produced in the world is still wasted (Gustavsson et al., 2011): in the production process, crops often remain unharvested because of the bad work organization, while in the distribution phase, due to information asymmetries between producers and consumers, much of the food that reaches retailers remains unsold until decaying (Alexander et al., 2017). Basically, a large amount of water and energy is wasted and a great quantity of greenhouse gases is still generated. Within this difficult and extremely complex scenario, new technologies and approaches are spreading to make agricultural supply chains sustainable and safe: modern traceability systems (Mirabelli and Solina, 2020; Vizza et al., 2018; Tradigo et al., 2019), wireless sensor networks (Ojha et al., 2015), remote sensing (RS) (Zarco-Tejada et al., 2012). Precision agriculture (PA) is one of the many possible applications of RS, being a research topic, whose interest has considerably grown in recent years. According to Zhang and Kovacs, (2012), PA is "the application of geospatial techniques and sensors to identify variations in the field and to deal with them using alternative strategies". Basically, PA is a novel approach, where everything is performed at the right time, at the right place, and with the right intensity. Field is not treated homogeneously as in the past, but is divided into zones, according to different needs and local features. This implies reduction in the use of resources, limitation of environmental impact, increase in yield (Mulla, 2013). For example, it is possible to irrigate only the areas of the field which really need water, and this is crucial, considering that agriculture consumes the majority of the world's water resources (about 70%) (Gilbert, 2012). Other PA's common applications are: weed mapping and management, vegetation growth monitoring and yield estimation, vegetation health monitoring and disease detection, crops spraying (Tsouros et al., 2019). Satellites and manned aircrafts have been PA's enabling technologies in the past, while current research is focusing on the opportunities offered by the internet of things (IoT) and unmanned aerial systems (UASs) or vehicles (UAVs).

The aim of this paper is twofold: (1) we present an overview about the use of UAVs in precision agriculture, namely we illustrate the possible alternatives in terms of aerial platforms and sensors for image acquisition. (2) Moreover, we provide a preliminary cost analysis on the use of the UAVs in agriculture, with reference to a small-medium farm in the Southern Italy. Such an analysis can be very useful for any farmer who wants to approach PA for the first time. Current technology limitations and possible future challenges are also detected.

The remainder of this paper is organized as follows. Section 2 shows the main possibilities in terms of aerial platforms and sensors for PA, the related work and our contribution. In Section 3, we present a preliminary cost analysis, exploring also some technical aspects. Section 4 detects the main current limitations and some possible future challenges. We outline the conclusions in Section 5.

2. Literature review

Remote sensing is used in PA, by mounting sensors on aerial platforms, with the aim to acquire information about soil and crop characteristics. Such sensors can collect energy, reflected (i.e., visible and near-infrared (NIR)), emitted (thermal infrared (TIR)), backscattered.

The first technologies for remote sensing in agriculture were satellites and manned aircrafts. The main restriction of satellites is the limited spatial resolution, which makes monitoring of many field crops ineffective (Gago et al., 2015). Moreover, they have a restricted temporal availability (real-time monitoring is not possible) and their performance usually depends on weather conditions. Basically, the use of satellites for images acquisition is considered expensive, not flexible, and poorly practicable, with reference to PA (Stafford, 2000). Manned aircrafts have similar limitations. In particular, multiple and expensive flights are necessary to obtain a high number of images (Tsouros et al., 2019).

Today, agriculture needs monitoring and sensing systems, which are able to collect data in a cheap and effective manner. For these reasons, investments in unmanned aerial vehicles (UAVs) have been growing in recent years. One of the main advantages of UAVs is the ability to fly at low altitude, which improves the quality and resolution of the acquired images (Gago et al., 2015). Furthermore, they are extremely more flexible, cheap and easy to use than manned aircrafts or satellites (Tsouros et al., 2019).

2.1 UAVs: a classification

Next, we list and briefly describe the main types of unmanned aerial vehicles, useful for PA. In literature, several classification criteria exist: Watts et al. (2012) classify the UASs according to their size, features, and flight endurance; Mukherjee et al. (2019) distinguish between fixed- and no-wing systems, while Cai et al. (2014) make a size-based classification (i.e., small tactical, miniature, micro). In this research work, we distinguish between fixed- and (F-W) rotary-wing (R-W) UAVs, as in (Tsouros et al., 2019). This is a quite recognized classification, useful for the aims of this paper.

Fixed-Wing: these UAVs have a fixed wing and need a runway for takeoff and landing. They are quite expensive, but have several advantages, such as high endurance (battery), ability to fly at high speeds, and significant payload. For these reasons, they are preferred when monitoring large areas (Tsouros et al., 2019; Zarco-Tejada et al., 2012).

Rotary-Wing: these UAVs have one (helicopter) or more rotors (multi-copter). In this case, take-off and landing are vertical, then there are no special runway requirements. On one hand, they are easily maneuverable and quite cheap; on the other hand, they only guarantee low speed and a more limited flight time. However, considering the frequent limited size of the areas to be monitored, they are currently the most used for PA (Gago et al., 2015; Tsouros et al., 2019; Mukherjee et al., 2019). Multi-copters are usually built out of light materials (aluminum, carbon fiber) and equipped by 4 (quadcopter), 6 (hexacopter), or 8 (octocopter) engines.

Other systems: balloon (or blimp) and bio-mimicry-based UAVs belong to this category. Such systems are slightly used in PA. Lightness, high endurance, and low speed are the main characteristics of the balloon-based UAVs (Tsouros et al., 2019). Bio-mimicry-based UAVs are instead bio-inspired, as they attempt to replicate the structure of birds, in order to have less wind resistance.

2.2 Sensors: main solutions

Each UAV is equipped with primary and secondary sensors. Primary sensors are essential for UAV functioning, especially for its positioning (e.g., Global Positioning System), and motion (e.g., accelerometers and gyroscopes). Secondary sensors add functionality to the UAV, depending on the purposes to be achieved. Some examples are temperature, humidity, proximity, and stabilization sensors (Mukherjee et al., 2019). However, in this subsection we briefly focus on spectral sensors, which are very useful for PA since they can acquire images beyond the visible spectrum of light.

Multi-spectral and hyper-spectral sensors: the main difference between these two types of sensors lies in the number and width of the bands they can acquire. Multi-spectral sensors can capture 5-12 bands, while hyper-spectral ones can capture hundreds or thousands of bands, even if the bandwidth is narrower (Yang et al., 2017).

Thermal sensors: all objects with a temperature above -273 °C emit radiation. Thermal remote sensing means measuring the radiation emitted by the surface of an object and converting it into temperature, without having direct contact with the object (Prakash, 2000). The possibility of monitoring the temperature of soil and crops allows to efficiently support irrigation and harvesting planning activities.

The information contained in the images acquired by the sensors is often not visible to the human eye therefore it must be properly processed and transformed into something usable (Mukherjee et al., 2019). The acquired data usually support the monitoring of plant nitrogen content, water stress in crops, soil moisture, crop height, weed presence. In other cases, the acquired images allow the mapping of crop species or fires, the geo-referencing. From a sustainability point of view, real-time identification of plants state allows a more diversified and efficient use not only of water resources but also of pesticides and fertilizers (Mukherjee et al., 2019; Tsouros et al., 2019). Basically, the large amount of data and images, collected through the use of the above sensors, is frequently "translated" into a set of remote indices, which can support decision-making in the field (Mukherjee et al., 2019). The Normalized Difference Vegetation Index (NDVI) is one of the most frequently used indicators and exploits the leaf reflectance to detect the greenness areas on the ground (Zarco-Tejada et al., 2012).

2.3 Related work and our contribution

Precision agriculture is very promising, especially in terms of environmental sustainability, however its advantages are often not fully perceived by farmers. According to Paustian and Theuvsen (2017), the likelihood of adopting practices related to precision farming increases if the farmer's experience is very high (i.e. greater than 16 years) or very low (i.e. less than 5 years). This refers on one hand to experienced and well-educated farmers, on the other to young farmers, who are used to rapid changes and well aware of the economic advantages that modern technologies can bring. Therefore, there are many other farmers who tend to be less likely to implement precision farming approaches. The analysis carried out by Caffaro and Cavallo, (2019) shows that the farmer's low education is strongly associated with the perception of strong economic and commercial barriers. Furthermore, the authors underline that small farmers are often less likely to use new technologies due to the lack of capital to invest, which implies the widening of the digital divide between small and large agricultural producers. According to Long et al. (2016), there are some important barriers that prevent the adoption and spread of technological innovations in agriculture. Some common examples are: perceived high initial investments, long pay-back periods, switching costs, lack of clear regulatory framework, lack of required competences/skills. For these reasons, in recent years some studies have emerged in which the economic convenience in the use of aerial systems, for precision agriculture purposes, is assessed. The most relevant are listed below. Ristorto et al., (2015) estimate the costs of adopting a rotary-wings UAS for crop monitoring tasks in paddy fields. They make a comparison between two different commercial sensors. Ireland-Otto et al. (2016), with reference to a hypothetical farm located in Northeastern Kansas (United States), compare the costs of manned aerial systems and UASs, which can be used to determine whether and where a nitrogen deficiency is occurring during corn production. The main result of their analysis is that UASs are cheaper. Griffin et al. (2018) discuss the profitability of a hypothetical investment in precision technology for agriculture, highlighting potential costs and benefits. However, their analysis is quite generic because it does not refer to a specific equipment. Borgogno Mondino and Gajetti, (2017) propose a cost simulating model and demonstrate that economic sustainability can be obtained only if the skills about remote sensing are internal to the company. They also explore the UAV potential market in the Italian viticulture landscape.

Some important considerations can be drawn from our literature review. The number of studies specifically devoted to the discussion of the economic aspects related to the adoption of UAVs for precision agriculture is quite limited. In fact, many farmers are not aware about the costs related to the use of UAVs for precision farming and this is one of the main barriers, for a large-scale adoption of this technology. Therefore, our paper aims to: (1) provide a preliminary economic analysis about the adoption of two alternative aerial platforms by a hypothetical small-medium farm in the olive sector, (2) make farmers aware of investments and costs under multiple application scenarios, also exploring the possibility of becoming service providers for other farmers.

3. A preliminary cost analysis

We aim to explore the economic feasibility of using a UAV for PA. We refer to a hypothetical and small-medium olive company, located in the province of Cosenza (Calabria Region), in Southern Italy. In recent years, UAV-based smart farming has been significantly spreading in the olive sector, to achieve various purposes, like estimation of olive crown parameters (Diaz-Varela et al., 2015), early disease detection (Calderon et al., 2013), estimation of incoming solar radiation in a plot of land (Ortega-Farias et al., 2016). The olive sector is one of the main sources of revenue in the Calabrian territory, also because the olive oil produced is in many cases extra-virgin and organic (Guido et al., 2020). The cultivation of the olive tree in Calabria is very fragmented and covers about 186,000 hectares, which are distributed among approximately 138,000 farms, with an average size of 1.3 ha (Perri et al., 2009). In Italy, the activities of the UAVs are regulated by the Italian Civil Aviation Authority (Ente Nazionale per l'Aviazione Civile, ENAC). As discussed in Section 2, the aspect that most distinguishes UAVs from each other, concerns the characteristics of the wing. In this paper, we explore two alternatives: fixed-wing and rotary-wing. In particular, with the aim to avoid any drone-sensor incompatibility, we refer to two well-known and commercially popular solutions identified in (Mukherjee et al., 2019) and outlined in Table 1. For both cases the use of the Parrot Sequoia multi-spectral sensor is assumed, in order to make the comparison homogeneous.

Table 1: Main features of the two explored alternatives

Name	UAV type	Battery autonomy [min]	Speed [m/s]	Price [€]
senseFly eBee SQ	F-W	55	1-30	11,000
DJI M100	R-W	35	1-22	7,500

3.1 Technical aspects

The economic assessment of this study depends, above all, on the characteristics of the mission to be conducted. In this paper, the term "mission" indicates the set of three phases represented in Figure 1. The preparation phase includes a set of operations preceding flight, like checking the condition of the vehicle, positioning the battery, planning the flight in terms of path and any stops for battery change and/or recharge. The flight phase lasts from the first take-off of the UAV to the last landing. Multiple take-offs/landings may indeed be necessary if the battery autonomy is not sufficient to guarantee the completion of the entire flight. Therefore, flight time is the period in which the UAV is actually in flight, while idle time takes into account the stop(s) due to the battery restrictions. A closing phase is also necessary because the UAV must again be checked, and the battery removed. Our estimation about the pre-flight time and post-flight time, based on interviews with twelve drone pilots, is 25 minutes and 20 minutes, respectively. Flight time mainly depends on the path of the aerial vehicle.

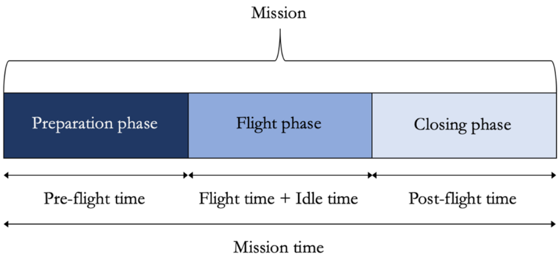

Figure 1: Mission structure

In this paper, for simplicity, we suppose to consider a rectangular ground, which is not an unusual assumption (Borgogno Mondino and Gajetti, 2017; Ristorto et al., 2015). We assume that the long side (l_1) of the rectangle is double the short one (l_2), while the area is 1.3 ha, which is the mean for olive fields in Calabria. I is the distance between two flight lines.

In Figure 2, the flight path is shown.

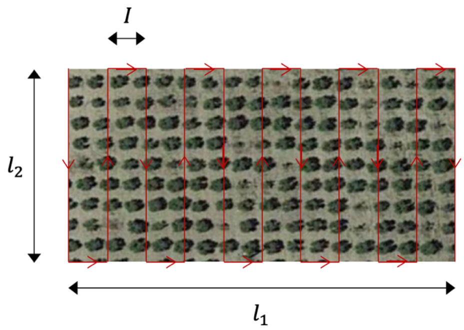

Figure 2: Path flight over the rectangular ground

The distance D travelled by the UAV can be computed by using the following formula:

$$D = \left\lceil \frac{l_1}{I} \right\rceil (l_2 + I) + l_2 \tag{1}$$

While l_1 and l_2 are fixed, since they depend on the size of the ground, it is possible to make a decision about I. The choice of I is quite critical, because it determines how "dense" the path is. Basically, the lower I is, the greater the overlapping rate of the images acquired; in this case, both distance to be travelled and flight time increase. I is strongly influenced by the flight height (fh). Another important choice concerns the time τ between two consecutive shots (by the spectral sensor), which determines the coverage rate of the ground. τ is related to fh and the aerial vehicle speed σ. Table 2 outlines, for each flight height, the recommended I and σ, according to the user guide of the Parrot Sequoia multi-spectral sensor (MicaSense, 2019), in order to have an image overlapping and a coverage rate of 80 % (we set $\tau = 1$ second). We point out that some of the values in Table 2 have been obtained by interpolating the graphs provided in (MicaSense, 2019).

Table 2: Recommended I and σ for each flight height

fh [m]	30	50	70	90	110
I [m]	5	10	14	16	20
σ [m/s]	5	10	13	18	20

In Figure 3, we show the flight time (in minutes) necessary to travel D and for take-off and landing, for each pair (fh, I), by varying σ (in minutes per second). Observe that when $\sigma \in [23{,}30]$, the mission can be carried out only by the fixed-wing UAV. On the basis of the technical characteristics of the UAVs of the study, take-off speed and landing speed have been set to 5 m/s and 4 m/s, respectively. If we only refer to the recommended speed for each pair (fh, I), we can extract the flight time marked in red. As it can be seen, when referring to very limited land sizes such as that considered in this study (i.e., 1.3 ha), the strengths of the fixed-wing UAV are not fully exploited. The maximum flight time is about 9-10 minutes (at a height of 30 meters), hence the battery of the rotary-wing UAV, albeit limited, allows to complete the mission. Therefore, under the examined conditions, the higher fixed-wing UAV's price does not seem to be adequately justified.

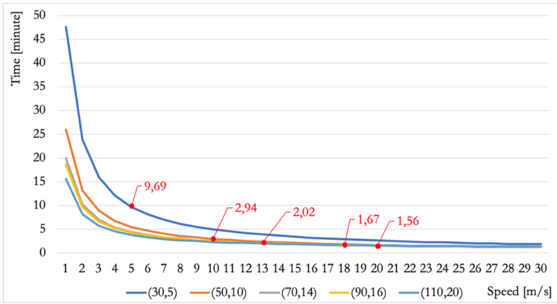

Figure 3: Flight time by varying the flight speed

3.2 Cost-based considerations

Below, the costs related to the PA activities are discussed. The use of the UAVs in agriculture can have multiple purposes: activities such as real-time irrigation management or vegetation growth monitoring involve fairly frequent aerial surveys, while to make a 3D reconstruction of the field or to map grass species, even occasional surveys are enough. In order to make our analysis purpose-independent (i.e. general purpose), we analyze 4 different scenarios, in terms of flight frequency: 1 mission/month (S1), 1 mission/week (S2), 2 missions/week (S3), 3 missions/week (S4). We refer to the olive growing/harvesting season, which usually lasts from May to December. First of all, the purchase of the UAV must be taken into account. In the literature, there is not a single commonly shared idea about the length of the useful life of a UAV, but the various scholars formulate different hypotheses. Basically, it ranges between 2 and 7 years (Ristorto et al., 2015; Borgogno Mondino and Gajetti, 2017; Doole et al., 2018). Considering that the regulations are constantly evolving, we assume that the drone can provide utility for 5 years at the end of which it has a residual value equal to 5% of the purchase cost. The estimate on the residual value is linked to the possibility of reselling the drone to reuse it for purposes other than precision agriculture, in fact in the last few years the drone market for recreational purposes has had considerable development (Liu et al., 2015). According to our estimation on pre-flight time, flight time, and post-flight time, we can say that the mission time is not greater than one hour, in any case. As for the cost of the pilot, we refer to (Xiang et al., 2016), where the annual cost was estimated at $ 34,000. Then, if the pilot worked full time (22 days per month, 8 hours per day), he/she would cost around 14-15 €/h. Therefore, we suppose to pay a specialized drone pilot 15 €/mission. The cost of the assistant was estimated to be 20% lower (i.e., 12 €/mission), considering the less responsible tasks to be performed. For each mission, an expert must take care of processing the collected data through appropriate methodologies (e.g., machine learning). The average salary for an expert data scientist is around 55,000 €/year in Italy (Uva, 2019). Then, if the data scientist worked full time (22 days per month, 8 hours per day), he/she would cost around 26 €/h. We estimate a work of about 2-3 hours to process the data of each mission, therefore we suppose to pay a data expert 60 €/mission. According to the ENAC regulation, maintenance operations include: revision, inspection, replacement, modification or correction of aircraft defects. For the rotary-wing UAV, we suppose to replace for wear: the battery TB47D twice per year (400 €/year), the motor DJI 3510 (35 €/year) and the 4 propellers (20 €/year) once per year. For the fixed-wing UAV, we suppose to replace the battery Venom 3S twice per year (300 €/year). Any extraordinary maintenance work is included considering an additional fee equal to 20% of the yearly depreciation. According to the ENAC regulation, it is not allowed to conduct operations with an UAV, unless an insurance concerning liability to third parties has been stipulated. As indicated in (Borgogno Mondino and Gajetti, 2017), the yearly insurance fee usually ranges between 400 and 1000 €/year. Then, we estimate a yearly insurance fee of 900 and 600 €/year, respectively for F-W and R-W UAV, then proportionally to their market value. In Table 3, a summary of the costs is shown.

Table 3: Cost summary [€/mission]

Item	S1	S2	S3	S4
F-W depreciation	261.25	65.31	32.66	21.77
R-W depreciation	178.13	44.53	22.27	14.84
Manpower	87.00			
F-W maintenance	90.00	22.50	11.25	7.50
R-W maintenance	92.50	23.13	11.56	7.71
F-W insurance	112.50	28.13	14.06	9.38
R-W insurance	75.00	18.75	9.38	6.25
F-W total	550.75	202.94	144.97	125.65
R-W total	432.63	173.41	130.21	115.80

As expected, the fixed-wing UAV is more expensive than the rotary-wing one. However, the limited size of the field does not allow to fully exploit neither its greater battery endurance nor the highest achievable speed. Moreover, it is important to highlight that under each of the 4 scenarios considered, the yearly net use of the aerial vehicle, in terms of flight time, is extremely limited. This means that a large amount of the UAV "production capacity" remains unused. For example, under S4 and when $fh = 30$ m, the annual flight time is approximately 16 hours. Therefore, the agricultural company, object of this study, could sell the PA service to its near farmers. In this case, some time constraints must be taken into account. First of all, a mission can be successfully carried out only during a non-rainy and non-windy day. According to the technical characteristics of the considered UAVs, we have then excluded the days with wind higher than 30 km/h. In the province of Cosenza, in the last 5 five years (2015-2019), the non-rainy and non-windy days were on average 145 in the period May-December (source: www.ilmeteo.it). Furthermore, a limited number of sunny hours are available for each day, then we assume a limit of 4 missions/day, considering also the transfer time field-to-field. Therefore, not more than 580 missions/year can be carried out, by using a single UAV. In Figure 4, we show the trend of the cost per mission, by varying the number of customers from 0 to 10, under the 4 scenarios, and for each type of UAV, F-W and R-W. Observe that we consider the average case, then also the customers' field is 1.3 ha.

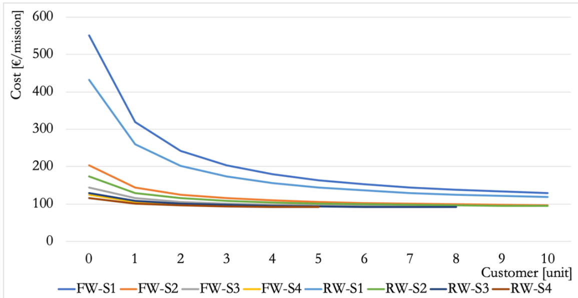

Figure 4: Cost per mission, by varying the number of customers, under the 4 scenarios

As expected, the trend is decreasing and the incidence of the manpower cost (with particular reference to the data processing expert) appears very significant. Observe that the constraint related to the weather conditions limits the number of customers to 8 and 5 for the third and fourth scenario, respectively.

3.3 Wider fields: brief considerations

With the aim to make our analysis more exhaustive, we provide also the flight time necessary for wider fields. In Table 4, we show how the flight time varies, by varying the field size, for each pair (fh, I). As it can be noted, when the size of the ground increases, the flight time considerably grows and additional needs emerge. First of all, one battery is not always enough to complete a single mission; this means that in the economic analysis, the purchase of more batteries should also be considered. Furthermore, the characteristics of the fixed-wing UAV are better exploited; for example, if a ground of 50 ha must be monitored at a flight height of 30 m, 6 and 9 stops are needed to change the battery for the F-W and R-W UAV, respectively. Therefore, there is a significant difference about the production capacity of the two alternatives. In this context, it would also be necessary to redefine the number of potential customers and the service frequency, taking into account that a UAV should not exceed 200 flight hours per year, for safety reasons (Borgogno Mondino and Gajetti, 2017).

Table 4: Flight time for each pair (fh, I), by varying the field size

(fh, I)	Flight time [min]				
[m]	5 [ha]	10 [ha]	20 [ha]	50 [ha]	100 [ha]
(30,5)	35.22	69.51	137.16	339.91	673.84
(50,10)	9.67	18.24	35.37	86.50	171.17
(70,14)	5.80	10.63	20.44	48.27	95.27
(90,16)	4.15	7.26	13.37	31.43	60.78
(110,20)	3.34	5.68	10.12	23.21	44.72

4. Current limitations and future challenges

The study of the current state of the art and the preliminary economic analysis, above conducted, are very useful for detecting some current limitations of the UAV technology for PA purposes. Substantially, a farmer who wants to invest in the purchase of a UAV must face the following issues, which characterize the current state of technology: training, investment, battery, data processing, regulation, maneuverability, sensors and payload. They are briefly described in Appendix, at: https://drive.google.com/file/d/1YMMtODfoPQyAL4GNlPYEILY-uAxr1HXd/view?usp=sharing

Future challenges concern several aspects. First of all, UAV technology should become more user-friendly, in order to stimulate adoption by farmers (Gago et al., 2015). Considering the undoubted benefits of PA, an increase in sales of remote sensing devices is expected in the coming years; therefore, the costs of aerial platforms and sensors will decrease, due to the higher competition among manufacturers. However, probably the most important challenge is the definition of a standardized and harmonized pipeline, which concerns the most important operational steps: flight preparation and execution, data processing and interpretation. In fact, currently there is no a well-defined and recognized workflow for PA applications (Tsouros, 2019).

5. Conclusions

In this paper, we have presented an overview about the use of the unmanned aerial systems for precision agriculture. First, we have focused our attention on the different alternatives in terms of UAVs and sensors for image acquisition. Then, we have presented a preliminary cost analysis, with reference to a hypothetical small-medium farm, located in the South of Italy, who wants to use a UAV in order to exploits the benefits of precision agriculture. Our analysis has also taken into account technical and regulatory constraints. Currently, the number of studies in literature, which analyse the economic potential of UAVs for precision agriculture, is quite limited. Therefore, this paper aims to fill this gap. Moreover, from a practical point of view, this study can be a reference for any farmer who wants to apply UAV-based precision farming techniques for the first time. In fact, it provides a summary of: current state of technology, main limitations and investments to be faced. The main result of our analysis is that the purchase of a UAV for own use is still quite expensive, especially if the field to be monitored is limited in size. The production capacity of the UAV can be better exploited if nearby farms are also served. We have also detected the current technology limitations and the possible future challenges. Basically, the benefits of precision farming are not yet clear to many farmers, because this technology is still in its infancy. Implementations costs are currently high, and regulations are constantly evolving, any investment is uncertain. Future developments include the use of a drone, equipped with visual and spectral sensors to acquire images and support the decision-making of a real farm. Field-tests will clarify both the technical aspects and the cost items, which are only hypothesized and estimated in this study.

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Some icons have been retrieved from the Flaticon website (www.flaticon.com)

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