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Preliminary considerations about costs and potential market of remote sensing from UAV in the Italian viticulture context

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ABSTRACT

UAVs have already demonstrated to be effective in many fields. Nevertheless, at the moment, it is not still clear the type and the value of benefits they can provide for remote sensing purposes in agriculture. In particular, in the Italian context, this technique has still to demonstrate that derivable information can improve ordinary crop management. Furthermore, it is not still clear if costs are consistent with the ones of the agricultural sector and if any actual benefit can be really obtained. Some basic questions have to be answered: (a) are costs consistent with sector incomes? and (b) which is the related economic/environmental value? In this work reference values for UAV costs and productivity are proposed. A cost simulating model, based on both technical and economic considerations, and parameterized in respect of the size of the imaged area is proposed. Different UAV company paradigms are considered demonstrating that sustainable costs can be obtained only by making remote sensing skills internal to company. A brief discussion is also given, concerning (a) UAV potential market in the Italian viticulture context and (b) expected minimal composition that a company, basing its business on this type of service, should have.

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Precision viticulture; UAV; UAV productivity; UAV cost analysis; UAV potential market

Introduction

It is commonly known that unmanned aerial vehicles (UAVs), or remotely piloted aerial systems (RPASs), are entering the ordinary professions, demonstrating their potentialities in different fields of applications. UAV success is mainly due to their relative low cost and, above all, on the total independence of user from external operators (i.e. no flying company is required). Combination of UAV and low-cost sensors has the great merit of having introduced aerial digital photogrammetry and remote sensing to professionals, activating a virtuous path of technology transfer from the scientific to the operative context. UAVs have already demonstrated to be extraordinarily effective for aerial photogrammetry and survey and for mapping hardly accessible areas (Gruen, Zhang, & Eisenbeiss, 2012; Ryan et al., 2015; Sauerbier, Siegrist, Eisenbeiss, & Demir, 2011). The high level of automation that software for data processing has reached enormously favoured the process (Lee, Lee, Kim, & Hong, 2013). Nevertheless, especially concerning remote sensing applications, some critical issues persist. Even if some authors tried to focus this point (Mesas-Carrascosa et al., 2017), it is not still completely clear if spectral information that low-cost multispectral sensors mounted on UAV, and flying close to surfaces, is reliable enough. Uncertainty is mainly due to (a) the high degree of automation that the ordinary workflow proposed by system/software sellers accomplishes and (b) a general lack of proper information about sensors technical features (especially related to radiometry) from producers. These two limitations make measures coming from multispectral imagery not completely reliable. This is the reason why we strongly believe that, while dealing with "quantitative" remote sensing, operator still has to play an important role in data interpretation that cannot be completely automated. In particular, in the agricultural context, these systems are imagined to address precision farming practices by mapping vegetation or soil properties (Grenzdörffer, Engel, & Teichert, 2008). Since information coming from this approach can directly lead to economic lost or environmental damages for farmers, it is highly recommended that technology transfer follows a rigorous way, leaving improvised operators outside the market and deprecating completely automated workflows. In spite of these considerations, a new deal for precision farming assisted by UAV remote sensing, aimed at adapting cultural practices to crop/soil conditions mapped in space and time, can be imagined (Cook & Bramley, 1998). Rationalization of agronomic practices and improvement of production are the expected benefits (Arnò et al., 2005; Delenne, Durrieu, Rabatel, & Deshayes,

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2010; Song et al., 2014), together with the consequent mitigation of environmental impact and maximization of farmer's profit. These factors are particularly important in viticulture, where the final product (wine) is characterized by a high added value, further improvable by taking on time decisions based on spatial variability of vineyards (Hall, Lamb, Holzapfel, & Louis, 2011; King, Smart, & McClellan, 2014; Profitt et al., 2006).

Optical remote sensing has already proved to be effective for this task, mapping vegetation behaviour in space and time; particularly in the last decades remote sensing data demonstrated to be able to generate good predictors of some plants' biophysical features. Many spectral indices obtained from multispectral imagery were proposed, generally based on red and near infrared bands recorded by sensors (Bannari, Morin, Bonn, & Huete, 1995; Zhang et al., 2005). Some of them are used to estimate plant vegetative vigour, that is said to be correlated with biophysical parameters (Haboudane, Miller, Pattey, Zarco-Tejada, & Strachan, 2004; Hall, Lamb, Holzapfel, & Louis, 2002; Johnson, Bosch, Williams, & Lobitz, 2001; Montero et al., 1999; Pinter et al., 2003). In particular, in the viticulture research field many experiences, aimed at understanding the role of remote sensing in ordinary agronomic practices, can be found (Bramley, 2001; Bramley, Pearse, & Chamberlain, 2003; Borgogno-Mondino et al., 2017; Rey et al., 2013). Some works also try to define and map uncertainty of spectral indices to separate significant differences in crops from not-significant ones and better calibrate relationship with ground parameters (Borgogno-Mondino, Lessio, & Gomarasca, 2016).

Nevertheless, at the moment UAV-based remote sensing, differently from the satellite-based one, has still to prove that obtainable information can drive farmer's management choices better than their own experience can do. Second, it has still to demonstrate that associated costs are consistent with the ones ordinarily affecting agricultural practices, or, at least, that economic or environmental convenience is enough to cover the costs (Bramley, Proffitt, Hinze, Pearse, & Hamilton, 2005; Erena et al., 2016; Matese et al., 2015; Ristorto, Mazzetto, Guglieri, & Quagliotti, 2015; Zorbas, Pugliese, Razafindralambo, & Guerriero, 2016).

Whatever are the limitations UAV can still suffer from in agriculture, in this work we only focused on the cost of operations. In particular, our research, based on a collaboration between the Department of Agricultural, Forestry and Food Sciences of the University of Torino and Deloitte Consulting S.r.l. Aviation & Transportations, was aimed at defining some reference values for costs and productivity of this technology; we retain that this type of information is mandatory to understand if an actual diffused transfer to the productive sector is possible and which systemic economic impact (Borgogno-Mondino & Gajetti, 2016) it could have. For this task we developed a computational model where technical and economic issues were considered to generate estimates of costs related to the adoption of UAV-based remote sensing in agriculture.

Our analysis is voluntary limited to UAV systems that, in terms of costs, are consistent with the agriculture sector and, in the meantime, well represent the present situation in Italy of the existing UAV operators. High-performance UAV like Medium-Altitude Long-Endurance (MALE) or High-Altitude Long Endurance (HALE) or any other having a price higher than 15,000 € was, appositely, not considered. Similarly, multispectral sensors having a price higher than 10,000 € were not considered. Reference sensors used to argue our results are limited to those that Italian operators demonstrated to be more familiar with: MicaSense SEQUOIA, TETRACAM Lite and MAPIR Survey2.

Thermal cameras were not considered too in this work, since their main usage, in the agriculture context, concerns water balance and/or evapotranspiration estimates. For these purposes they are generally used jointly with optical multispectral ones to operate the required heat flux balance (Baluja et al., 2012; Gago et al., 2015). This determines that, in this case, cost estimates of operation by UAV will be higher (then possibly more critical in agriculture) than the ones generated by our economic model.

Material and methods

Exploring limiting factors to flight

UAV cannot fly continuously. They basically suffer from the following limitations: (a) daily scene lighting conditions; (b) weather/atmospheric conditions (no rain, weak or absent wind, etc.); and (c) technical limitations related to the "standard" number of hours that UAV should fly in a year in safety conditions. Favourable lighting conditions for image recording from UAV require that shadows are minimized. This is particularly important in vineyards where, depending on management type, vertical development of cultivated lines is not negligible. Shadow minimization relies on the hour of the day UAV is programmed to fly. Best hours for flight are those when the Sun is as more nadiral as possible, therefore, the central ones of a sunny day. We can assume that suitable hours in a day (daily flight hours [DFHs]) are no more than 5 (optimistically, from 10.30 to 15.30 at the Italian latitudes during the growing season of vines). Limited shadows over the scene are mandatory when working with remote

Table 1. Technical features of the considered UAV multispectral sensors.

Sensor	Sensor size (columns × rows)	Pixel size (micron)	Focal length (mm)	Minimum time lap (s)	Cost (€)
MicaSense SEQUOIA	1280 × 960	3.75	3.98	2	5000
TETRACAM Lite	2048 × 1536	3.20	8.00	2	3200
MAPIR Survey2	4608 × 3456	1.34	3.97	3	500

sensing and multispectral acquisitions. In fact, in shadow areas signal-to-noiseratio could be too low and therefore producing a not reliable signal, improper for any spectral deduction concerning phenology or physiology of plants.

Atmospheric/weather conditions, differently, heavily condition the possibility of flying: normally, one operates by UAV when it does not rain and wind speed is weak enough. We therefore looked for average values of number of rainy, fully cloudy and windy days for the Italian national context, considering, separately, North, Centre and South of Italy. At this point only synthetic statistics concerning raining days were found and reported (see the "Results and discussion" section).

As far as technical limitations to flight are concerned, in Italy UAVs are regulated by the National Institute for Civil Aviation (ENAC) laws (Circolare 23 Dicembre 2015 e succ.); philosophy underlying this regulation is the same adopted for manned airplanes, therefore it encourages virtuous and safe management actions. One of these concerns the maximum number of hours that an UAV can fly in safe condition in a year. A reference value that can be derived considering experiences from ordinary flight procedures is 200 h/year. Therefore, even if the number of hours that UAV could fly in a year, in respect of the previously mentioned factors, is higher, this threshold should be supposed to not be overcome. Consequently, if this is needed, UAV operators have to operate with more than one drone, making costs increasing. Consequently, we can easily define the minimum number of UAVs that an operator should possess to be operative every day of the available ones within the growing season of vines.

UAV productivity

While evaluating convenience of remote sensing from UAV, one has to carefully consider productivity (*Pr*), expressed in terms of number of hectares per hours (ha/h) potentially imaged by sensors. *Pr* strictly depends on UAV flying speed, battery pack performance and spatial continuity of the imaged area. Concerning UAV flying speed, this mainly relies on flight plan whose design is given by photogrammetric considerations responding to geometric resolution and image overlapping requirements. These result from the combination of sensor technical features and UAV flight height. For this study, we considered three of the most common multispectral sensors for UAV, whose cost is consistent with the agronomic sector: MicaSense SEQUOIA, TETRACAM Lite and MAPIR Survey2. Main technical features of these sensors are reported in Table 1.

Our simulator operates by varying progressively the size of the imaged area from a minimum of 1 to a maximum of 100 ha. This value is somehow consistent with the maximum admitted distance between pilot and UAV as defined by Italian laws. Law states that operation has to be run within the volume around pilot defined by a cylinder with a base of 500 m radius and a height of 150 m. Our forcing hypothesis is that imaged area is continuous.

The process is iterative and operates in a fractal way. This necessarily introduces some approximations that we retain not important for the goal of this work. The flight path is decomposed in blocks, each corresponding to a distance calculated as two times the longer size of the rectangular area (A) summed with two times the distance between two adjacent image strips (I, depending on the lateral image overlapping). The UAV is supposed to operate with a speed = v, alimented by batteries having an actual endurance, battery endurance (BE), assumed equal to 65% of full charge. According to these assumptions, we can say that the total number of blocks that can be acquired along the flight can be iteratively calculated using Equation (1).

$$N_k = \frac{\left(BE \cdot v - 2I \sum_{j=1}^{k-1} N_j\right)}{2(A + 2I)}, \qquad (1)$$

where N_k is the number of blocks acquired with k battery changes, N_j the number of blocks acquired with j battery changes (preceding the last one), v is UAV speed, I the distance between strips, A the strip length (see Figure 1) and BE the battery endurance.

From this value the total distance covered by UAV can be determined once the area to be imaged is fixed; consequently the number of needed battery changes, digital size of acquired images and time of flight (UAV type depending) can be easily determined too. In particular, as far as time of flight is concerned it depends basically on the height of flight that is set depending on the expected geometric resolution of images; the main limiting factor to UAV speed is sensor time lap, i.e. time step between two consequent images. Cheap multispectral sensors can acquire an image every 2–3 s being the most of time cost due to data transfer to memory. In Table 2 we report *maximum* flying speeds needed to obtain proper image overlapping (values are

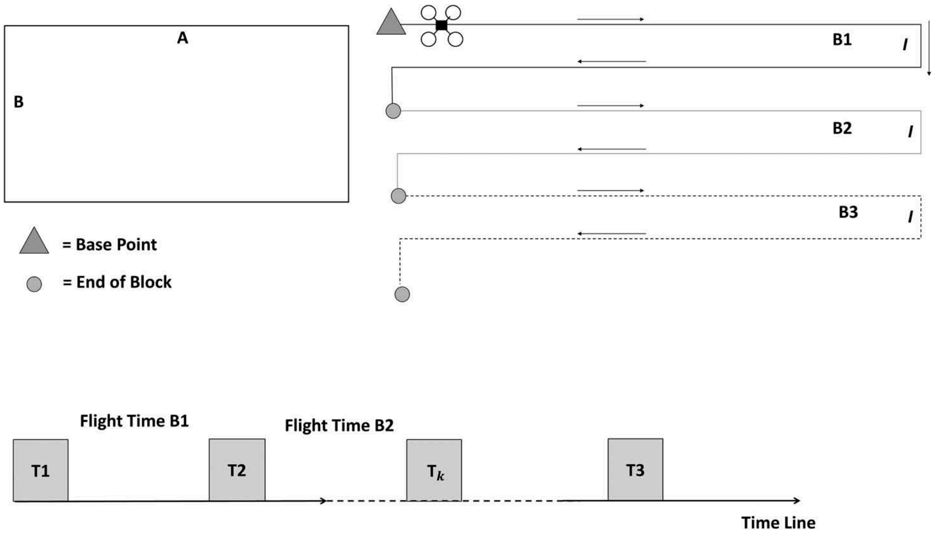

Figure 1. (above) Flight plan geometry considered for simulation. A and B are, respectively, the longer and shorter size of the overflown area (supposed continuous and rectangular). The minimum flying unit is the block (B1, B2, etc.). UAV is supposed to return to the take-off area (base point) after an integer number of blocks. (below) Time blocks along the flight. Flying periods alternate with battery pack changes and UAV activation ($T1$) and packaging ($T3$).

Table 2. UAV maximum speed values that are required for 70% and 80% image overlapping (needed to properly adjust image block during orthoimage generation). Grey cells report values that more commonly correspond to RUAVacquisitions; white cells report values that more commonly correspond to F-UAV acquisitions.

	UAV speed (km/h) 80% overlapping			UAV speed (km/h) 70% overlapping		
Flight height (m)	TETRACAM	SEQUOIA	MAPIR	TETRACAM	SEQUOIA	MAPIR
25	7.4	10.9	14.00	11.1	16.3	21.0
50	14.8	21.7	28.00	22.1	32.6	42.0
75	22.1	32.6	41.99	33.2	48.8	63.0
100	29.5	43.4	55.99	44.2	65.3	84.0

given for 70% and 80% overlapping). Maximum speed corresponds to the highest potential *Pr*.

Simulation was achieved under the following conditions: (a) time for UAV pre-flight preparation (rotor arms folding and blocking + battery installation + pre-flight checks (rotors and sensor)) is set to 600 sec ($T1$); (b) time for battery change and UAV intermediate set-up is set to 600 s ($T2$ and T_k); (c) time for UAV/RPAS Recovery and Packing (post-flights checks (rotors) + battery removal + rotor arms folding for hull packing and transport) is set to 600 s ($T3$). While $T1$ and $T3$ occur only once, $T2$ has to be repeated as many times (k) as imposed by the combination of battery charges and weather conditions, i.e. endurance (Figure 1).

Cost of flight: from time to unitary cost (€/ha)

Every simulation necessarily introduces simplifications and, generally, given estimations represent extreme values of the simulated parameter. In the context of UAV costs simulation, estimates in general can be read as the lower limit of real costs. This largely depends on the fact that we cannot preventively imagine in which operative conditions flight will occur. In particular, we cannot consider: (a) costs for approaching the area that has to be imaged (this depends on the distance between the operator location and the area of operations) and (b) costs to maintain on the site the operating team (minimally formed by two persons). Furthermore, the optimistic estimates potentially given by the model are related to the assumption that all expected 200 hours that a single UAV can fly in a year are completely flown. Given these mandatory specifications, our model takes into account average costs from market (May 2016); market analysis was achieved by Deloitte Consulting S.r.l. Aviation & Transportations. The following reference prices were considered in the simulation proposed in this work: UAV price = 10,000 € (market range = 1000–15,000 €); multispectral sensor price = 5200 € (market range = 400–15,000 €); UAV and sensor depreciation is calculated over 4 years, supposing that, at the end of the period, a remaining profit (10% of the initial cost) can be obtained by selling parts of the system to other operators; a safety fee is considered for unexpected accidents (10% of the UAV yearly depreciation fee); yearly insurance fee = 500 €/year (market range = 400–1000 €/year); one rotors replacement per year (150 €

for a single UAV); and three battery packs per UAV contemporary available for one mission and one replacement for year. Furthermore, our simulation admits that UAV company operates with four UAVs (minimum number of vehicles to operate all of the available hours in a year; see the section "UAV productivity"). Two flying company paradigms (CPs) were considered, focusing on the minimum number of people that necessarily has to be considered to make them operative.

CP1 is supposed to be composed by one UAV pilot (net salary = 1800,00 €/month for 220 working days/year and 13 paid months) and one flight assistant at the ground (net salary = 1450 €/month for 220 working days/year and 13 paid months). One of them is assumed to be in charge of maintaining/revising UAV along the year. No remote sensing skill is present within the team; data processing and image interpretation for agronomic concerns are therefore assigned to an external professional (full cost = 90 €/h for 8 working hours). This cost is assumed fixed once the flight is done and, therefore, does not participate to form the hourly cost.

CP2 is supposed to be composed by one UAV pilot and one flight assistant at the ground. Both UAV maintaining/revising and data processing skills are internal to the team. Net salary for both of them is assumed to be 180,000 €/month for 220 working days/year (13 months are paid). Company gross cost for internal personnel is set to 1.5 times net salary. Resulting hourly costs are reported in Table 3.

If eventually the UAV company decided to demand an external specialist in UAV and sensor maintenance, a further voice of cost should be considered. Since a stop for maintenance is suggested every 60 h of flight (in safety conditions), three stops for each UAV are required in a year (given 200 h/year suggested as safe flight time).

A complete revision of UAV is supposed to take 8 h by a specialist that could be paid (gross hourly cost) about 60 €/h. This cost can be estimated in 8 h × 3 stops/year × 60 €)/200 h = 7.20 €/h for a single UAV (28.80 €/h for four UAVs). In our simulation, we assumed that this task is operated by internal personnel for both CP1 and CP2.

Under the following constraints and conditions, according to the above-mentioned simulator of UAV *Pr*, we modelled unitary cost of flight for four different scenarios: (A) CP1 operating by rotating wings UAV (R-UAV); (B) CP2 operating by RUAV; (C) CP1 operating by fixed wings UAV (F-UAV); and (D) CP2 operating by F-UAV. Unitary cost estimation was modelled for four different flight heights: 25, 50, 75 and 100 m determining, respectively, a Ground Sample Distance (GSD) of about 24, 48, 71 and 94 mm (compliant with technical features of the SEQUOIA sensor).

Results and discussion

Limiting factors to flight

A preliminary analysis over Italy, based on data obtained from http://www.climatedata.eu/, showed that, within the ordinary vines growing season (from April to October included), the average number of days without rainfall (hereafter called DF, days of flight) are the following: 121 in Northern Italy, 137 in Central Italy and 149 in Sothern Italy. Analysis is certainly an overestimation of the number of days suitable for flight: in fact neither windy nor fully cloudy days were considered, being quite difficult to define reasonable and general thresholds both for not-proper cloud density and wind speed. By coupling DFH with DF, we can easily compute the total amount of hours that can be proper for UAV acquisitions within the growing season of vines: 605, 685 and 745 h/year, respectively, for Northern, Central and Sothern Italy. Since from our investigation a single UAV, for safety reasons, has to fly averagely 200 h per year, we can easily estimate the minimum number of UAVs an operator should have to be fully operational, that is 4.

Table 3. Hourly costs for CP1 and CP2. Both company models are assumed to operate with four vehicles and only one sensor which is moved from one to other UAV to guarantee full operation.

		(€/h)	
Costs	*N*	CP 1	CP 2
Pilot	1	19.94	19.94
Safety personnel (at the ground during flight)	1	16.07	19.94
Data processing		90.00 €/h × 8 h	19.94 €/h × 8 h
UAV depreciation (4 years)	4	45.00	45.00
UAV yearly insurance fee	4	10.00	10.00
Safety fee (10% of UAV yearly depreciation)	4	4.50	4.50
Battery replacement (3 packs/year/UAV)	12	24.00	24.00
Rotors replacement	4	2.34	2.34
Sensor depreciation (4 years)	1	3.91	3.91
Total hourly cost		125.76	129.63

Column "*N*" reports the number of items that determined the cost for each voice. Cost for data processing is not considered in the total hourly cost, but must be added separately to form the total cost of a single flight.

UAV productivity

Pr was simulated using a self-developed model assuming the followings: (a) imaged area is rectangular $A \times B$ where $A/B = 1.5$; (b) simulation results were generated for 80% image longitudinal overlapping at four relative flying heights (25, 50, 75 and 100 m); (c) lateral image overlapping is 60%; (d) UAV has to return to the landing/taking off area when battery charge is 35% of the total (safety charge); (e) UAV stop time for battery change is estimated in 10 min; (f) battery charge time is 30 and 55 minutes for R-UAV and F-UAV, respectively; and (g) sensor size is 1280 × 960 pixels, pixel size is 3.75 micron and focal length is 3.98 mm (Parrot SEQUOIA compliant).

Figure 2 shows the results of simulation we did under the conditions reported above. Graphs relate flight time and imaged area size. They show that theoretical productivity of a continuous area by UAV is about 20 ha/h (100 ha/day) and 50 ha/h (250 ha/day) for R-UAV (at a typical flight height of 50 m) and F-UAV (at a typical flight height of 75 m), respectively.

Unfortunately these values only represent the maximum potential productivity that UAV can reach. Reality is drastically different, especially in a highly fragmented landscape like the Italian one (1.6 ha is the average size of a vine farming company, [Italian Agriculture Census, 2010]). In fact, interviews we did to some UAV operators and representatives of ASSORPAS, Italian Association for Light Remotely Piloted Systems, refer that in real situations, the hours potentially exploitable in a day (5 h/day) cannot be flown completely and continuously. On the contrary, it is quite common that UAV operators have to move from one site to another during the day. This determines a productivity reduction that optimistically can reach 25 ha/day.

Comparing potential and actual *Pr* with yearly hours available for acquisition (previously calculated for the Italian national context), we can easily quantify the amount of hectares that can be potentially, or actually, imaged in a year (Table 4).

In Italy, there are about 750,000 (seven hundreds and fifty thousands) ha of vineyards (ISTAT, 2010); comparing this value with the ones of Table 4, we can estimate the potential number of UAV operators that could be absorbed by the market of remote sensing of vineyards (each of them is supposed to operate with four UAVs and one sensor; non-contemporary missions are considered). According to our simulation, about 56, 23 and 222 UAV companies could operate in Italy, respectively considering theoretical R-UAV/ F-UAV and actual *Pr*. Since it is operatively reasonable to imagine that more than one flight is needed above the same vineyard along the growing season, the number of UAV operators could eventually be multiplied per the number of flights/year. At the moment, the authorized UAVs in Italy are 2603.

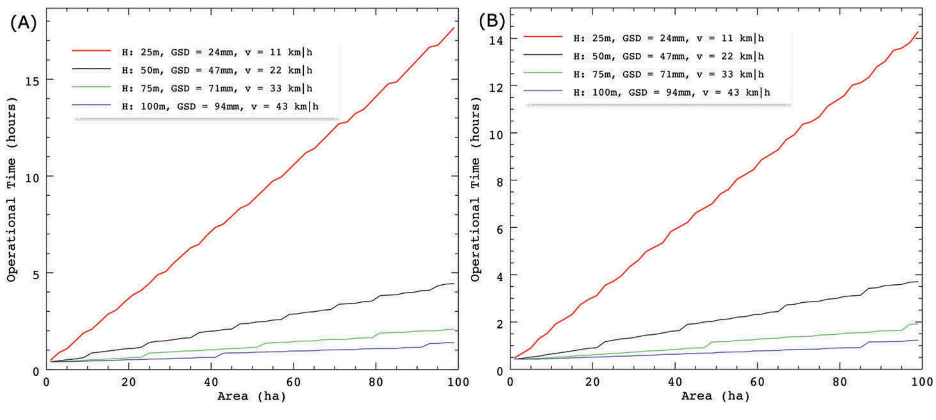

Figure 2. (a) R-UAV productivity. (b) F-UAV productivity. Oscillations around the main linear trend are related to UAV recovering at the take-off/landing station for battery changes. Four different flight heights (25,50,75 and 100 m), determining different GSD are considered. . In general we can say, in respect of flying speed, that R-UAV can operate according to red and black lines, while F-UAV to green and blue ones.

Table 4. Theoretical (potential) and actual (as reported by operators) area that, yearly, can be imaged within the growing season of vines (from April to October). The following *Pr* values were used: F-UAV potential *Pr* = 250 ha/day, R-UAV potential *Pr* = 100 ha/day and actual *Pr* = 25 ha/day. Reported values represent the hectares that a single UAV operator could image if operated in all of the available days within vine growing season. National total amount of hectares is computed by considering contemporary flights in the Northern, Central and Southern part of Italy.

	Potential *Pr* (ha/year)				Actual *Pr* (ha/year)			
UAV type	North (121 days)	Centre (137 days)	South (149 days)	National	North (121 days)	Centre (137 days)	South (149 days)	National
R-UAV	12,100	13,700	14,900	40,700	3025	3425	3725	10,175
F-UAV	30,250	34,250	37,250	101,750				

Certified UAV operators are 2136: 1810 for not critical and 326 for critical operations [www.operatori-sapr.it].

Cost of flight

Costs of flight can be easily determined within the model by combining productivity with costs of Table 3. If we refer costs to imaged area size (unitary costs), the euros that the acquisition of a single hectare could cost strictly depends on the total area that can be imaged along the same flight. Results of this computation are given in Figure 3. Reported simulation concerns a single mission; consequently, if for agronomic purposes, more than one mission is required along the year, costs have to be multiplied by the number of flights. Costs are estimated for images having a longitudinal and lateral overlapping, respectively, of 80% and 60%, supposing the camera positioned with the longer part along flight direction. Reference sensor in this simulation is Parrot SEQUOIA. Graphs clearly show that unitary cost drastically decreases while imaged area increases, making this issue the most critical one in the Italian national context.

To practically exemplify what our simulation meant, we calculated, according to the model, unitary costs (Table 5) for three scenarios corresponding to three different operational situations corresponding to different area sizes (10, 50 and 100 ha) and supposing five repetitions of the flight along the vine growing season.

Once given a value for unitary cost (e.g. 10 €/ha potentially reachable by CP2 imaging an area greater than 40 ha), an estimation of potential yearly costs

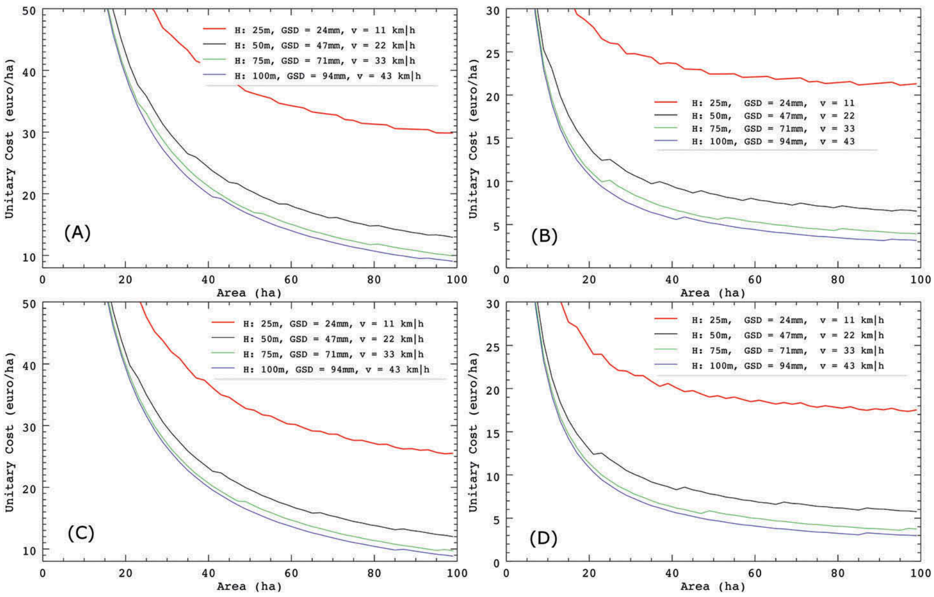

Figure 3. Estimated unitary costs (€/ha). Simulations refer to the following scenarios: (a) R-UAV and CP1; (b) R-UAV and CP2; (c) F-UAV and CP1; (d) F-UAV and CP2. Four different flight heights (25, 50, 75 and 100 m) determining different GSD are considered. In general we can say, in respect of flying speed, that R-UAV can operate according to red and black lines, while F-UAV according to green and blue ones.

Table 5. Paradigmatic CP1 and CP2 scenarios of unitary costs. Three different area sizes (10, 50 and 100 ha) and five flights per year are considered. Costs do not include team transfer and accommodation. Both unitary costs (€/ha) and yearly total costs (ha × unitary cost × number of flights) are simulated for bot R-UAV and F-UAV.

		CP1			CP2		
Flight height (m)	Imaged area size (ha)	10	50	100	10	50	100
25	R-UAV						
	Unitary cost (€/ha)	107.00	36.00	30.00	40.00	22.00	21.00
	Yearly total cost (€)	5350.00	9000.00	15,000.00	2000.00	5500.00	10,500.00
50	R-UAV						
	Unitary cost (€/ha)	89.00	20.00	13.00	25.00	8.00	6.00
	Yearly total cost (€)	4450.00	5000.00	6500.00	1250.00	2000.00	3000.00
50	F-UAV						
	Unitary cost (€/ha)	81.00	19.50	12.00	23.00	7.50	5.50
	Yearly total cost (€)	4050.00	4875.00	6000.00	1150.00	1875.00	1750.00
75	F-UAV						
	Unitary cost (€/ha)	79.00	17.00	9.50	21.50	5.60	3.50
	Yearly total cost (€)	3950.00	4250.00	4750.00	1075.00	1400.00	1750.00
100	F-UAV						
	Unitary cost (€/ha)	78.00	16.00	8.50	21.00	4.70	2.50
	Yearly total cost (€)	3900.00	4000.00	4250.00	1050.00	1175.00	1250.00

Table 6. Yearly potential and actual costs that an UAV operator (operating by four vehicles) should support, assuming that it can operate every available day in the vine growing season (see Table 1). Estimations were generated assuming an average unitary cost of 10 €/ha. Values can be assumed as a proxy (underestimation) of potential income that yearly an UAV operator can reach.

	UAV company yearly costs (€/year)		
UAV type	North (121 days)	Centre(137 days)	South (149 days)
R-UAV (potential)	121,000	137,000	149,000
F-UAV (potential)	302,500	342,500	372,500
Actually operating UAV	30,250	34,250	37,250

that an UAV operator, working with four vehicles, should support to fly every available day in the vine growing season can be easily derived. This can be obtained by combining (a) the size of those areas that can be potentially imaged in a year; (b) the number of expected repeated flights; and (c) an average unitary cost assumed as reference (e.g. 10 €/ha). Results of this simple exercise are reported in Table 6, where potential R/F-UAV *Pr* (100 and 250 ha/day, respectively) and actual *Pr* (25 ha/day) are considered.

Conclusions

Potential market of UAV operators for viticulture in Italy appears to be promising in spite of some contingent limitations. It could be further more interesting by extending the reasoning to other agricultural segments. Our work showed that only a CP for UAV operator possessing internal skills for (a) geometric and radiometric/spectral processing of images (remote sensing) and (b) technical maintenance of UAVs can generate unitary costs consistent with the agronomic market. A team made of two persons in charge of piloting, safety, maintenance and data processing appears to be the minimal sustainable configuration for an UAV operator company. Further and, probably, more appropriate concerns could be made assuming that this minimal configuration is replicated while market grows.

Moreover, our research highlighted that: (a) potential incomes generated by F-UAV are surprisingly not so higher than those potentially obtainable by R-UAV; (b) height of flight does not generate appreciable economic benefits when height is over 50 m; (c) if operating exclusively in the viticulture field, an UAV operator must be able to operate all of the days suitable for flight, therefore it must have at least four UAVs (if the suggested 200 h/year of flight is respected); (d) at the moment "actual" productivity (25 ha/day) seems to be not enough to ensure economic sustainability of the company; and (e) costs, therefore prices, consistent with the viticulture economic segment can only be obtained when large contiguous areas are flown (possibly higher than 20 ha). Since the Italian average size of viticulture enterprises is 1.6 ha (Italian Census of Agriculture, 2010), future scenario for technology transfer should necessarily consider and drive farmers to aggregate in consortiums.

It is worth to remind that costs presented in this paper have to be interpreted as the potential ones in a future scenario where UAV operators can operate every day along the vine growing season (even with different customers), i.e. when this practice has become systemic. Once more, we want to stress that estimated unitary costs (and consequent deductions) are different (lower) than potential prices that UAV operators will apply for their services while selling to farmers; they have to be interpreted as a cost basis from which to move to generate the final service selling price. Costs concerning team transfer to the area, accommodation and profit fee are excluded from our estimations, since they are strictly dependent on operative conditions (therefore impossible to be modelled in a general way).

At the moment, given the relatively few experiences concerning UAV adoption in the Italian viticulture context, it is not still possible to statistically measure and demonstrate the type and the value of benefits generated.

Disclosure statement

No potential conflict of interest was reported by the authors.

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