IMPROVING SUSTAINABILITY OF FIELD CROP PRODUCTION BY INTEGRATING REMOTELY COLLECTED DATA

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Abstract

Sustainability of field production could be improved ifthe amount of data collected is greatly increased. Mass data collection could allow for following much more closely crop and pest development together with tracking the effects exerted by abiotic stresses. This could further provide for better crop management with optimized pesticide, water, and fertilizer applications.

Remote data collection is possible in a number of different ways (i.e. ground-, air-, and space-based). Each of these approaches has its benefits and limitations and the current report discusses some of them. It further elaborates on the use of "copter" drones for real-life applications. Examples of the actual application of such drones in various settings are presented and discussed. Possibilities opened by dynamic tracking of the crop condition are demonstrated in relation to the monitoring of water and nutritional regime. The capacity to track in near real-time of the presence and development of weeds, emergency and spreading of diseases, damages from insects, rodents, etc. is discussed as related to the estimation of actual crop density – mostly in closed canopy crops(i.e. winter cereals and rapeseed). Sustainable crop production is presented as depending on the possibility to determine the total volume of the biomass accumulated during the vegetation/year (particularly in wood species) and thus – the capacity to adequately plan for timely ceasing of applications of agrochemicals and for harvesting the crop.

Further discussion on the possibilities to develop prognostic and response applications of drone systems and what benefits they can bring to real-life farming is provided.
Keywords: Precision agriculture, hexacopter drones, sustainable farm management.

1. Introduction

Sustainability of field production could be improved ifthe amount of data collected is greatly increased. Mass data collection could allow for following much more closely crop and pest development together with tracking the effects exerted by abiotic stresses. This could further provide for better crop management with optimized pesticide, water, and fertilizer applications.

Optimized and efficient crop management requires good knowledge of crop development. Data can be remotely collected in a number of different ways (i.e. ground-, air-, and space-based). However, each of these approaches has its benefits and limitationsand they should be taken into account before selecting the most appropriate one in each particular case. Satellites, for example, are collecting datawith relatively low resolution (on the multi-meter scale), thus providing general overview of large areas(Ahamed, Tian, Zhang, & C. Ting, 2011). Even with the latest developments in the resolutions achieved it still is in the meter-decameter range (Sousa, Gonçalves, & da Silva, 2017). While very useful at regional/state scale their usability for on-farm applications is limited by the fixed intervals at which data is collected. Yet another usability restriction for satellite-based data acquisition is that in many cases it can be compromised by the presence of cloud coverage over particular fields, therefore creating data collection gaps.

Ground-based data acquisition, on the other hand, can provide high precision (in the centimeter range) by attaching sensors to GPS guided agricultural machinery, or by directly integrating GPS data modules in hand-held data collection appliances. First of these two approaches is often preferable as the GPS guidance systems for the machinery are already adjusted for high precision positioning – a rather significant investment that is mandatory if precision agriculture is to be implemented at farm level. While providing for very good precision and for integration of data collection with other farm activities, this approach is limited by the fact that data is collected only when the machinery actually is in the particular field to be observed. This limits both the number of passes for data collection and the areas over which it can be done as the machinery has limited speeds and area coverage due to the main purpose it is implemented for at any particular moment.

Unmanned Aerial Vehicles (UAVs) have several advantages over satellites and piloted aircraft: they can be deployed quickly and repeatedly; they are less costly and safer than piloted aircraft; they are flexible in terms of flying height and timing of missions; and they can obtain imagery at sub-decimeter resolution (Rango et al., 2009). The first UAV to take photography for aerial reconnaissance was the Radioplane in 1955 in the United States. Similar capabilities were developed by the French in the later 1950s, the Italians in the 1960s, and the Russians in the early 1970s (Newcome, 2004). Most unmanned aerial platforms allow the operation height to be very low (e.g. 30m), enabling low-altitude aerial photography (LAAP) (Verhoeven, 2009)to acquire image data that can resolve thefinest details.

UAVs, also called small Unmanned Aircraft Systems (sUAS) or drones(Mulero-Pázmány et al., 2017)can be divided in two main groups, depending on the propelling/lifting principle. Fixed wing drones are using the airplane principle of creating lifting force from the differences in pressure above and below the wings of the appliance (relatively) fast moving through the air. The quick deployment and the ability to fly for extended times, unobstructed by the cloud coverage, are two of the main benefits of using this approach. However, sharing the benefits of such approach (i.e. low energy/kg equipment in the field and ability to cover large areas in a limited amount of time), means sharing also its limitations. Some of the most relevant to agricultural settingsof them include the requirement for alevelled landing strip and the difficulties of precise positioning when side- and gusty winds are occurring during the flight.

Multi-rotor UAVs (MRUAV) are propeller-lifted(or “copter”) drones that on the other hand do not require any specific take-off/landing path preparation. They are better at dealing with gusty winds and have lower relative ground speed, thus providing for a more precise following of the pre-defined observation path. As a consequencethey meet the critical requirements of optimum resolution, which makes them ideally suited for identifying within-field variations in vegetation health and condition resulting from non-optimal growing conditions(Houborg, Fisher, & Skidmore, 2015). On the negative side, using the energy of propellers to generate not just forward thrust, but lifting force as well, they have higher energy/kg equipment ratio, which converts to shorter flying times and lower area coverage capacity per flight.

With the quick developments in satellite, aerial and ground-based remote sensing systems they have to be regularly compared and decisions made based on the spatial and temporal resolutions of imagery to be adopted for site-specific management(Ahamed et al., 2011).

Taking into account benefits and limitations of different systems and aiming to provide a solid foundation for choosing the right technology the current report concentrates on the use of multi-rotor UAVs (MRUAV) for real-life farm applications. Main advantages and disadvantages of such systems are presented, followed by the examples of the actual application of such UAVs in various settings.

2. Materials and Methods

2.1. Equipment

For the purposes of evaluating the potential of MRUAVs6-rotor BUTEO drone (ProDroneSys, Sofia, Bulgaria) was used that was assembled as follows:

- Weight, including sensors and batteries – 4.2 kg;

- Diagonal size – 660 mm;
- Satellite positioning systems – GPS & GLONASS;
- NIR/RGB combined camera:
  - NIR sensor: photographing spectrum 780-800nm
  - RGB sensor – 8 Mpx with fixed lens
  - Matrix resolution: 3280 × 2464 pixels
  - Combined sensor size 3.68 x 2.76 mm (4.6 mm diagonal)
  - Lens focal length –3.04 mm
  - Pixel size – 1.12 µm x 1.12 µm
  - Horizontal angle – 62.2 degrees
  - Vertical angle – 48.8 degrees.
- Damping system for vibrations absorption

The fully loaded system has maximum speed of 22 m/s and can reachmaximum flight height (from take-off position)of 1000 m with a climbing speed of up to 3 m/s. The equipment operates in the temperature rangeof -10°Cto +40°C and can resist sustained winds at up to 18 m/s. Maximum flight durationis 45 min.

Duringdatacollection ground speed of 6 m/s was usedwith a flight duration in observation mode of 30 min.

For the fertilizer application a tractor John Deere model 6130 was used equipped with GreenStar 2630 navigation display and assembled with Kubota DSX-W GEOspread applicator.

2.2. Survey Area

Observation area is situated in Sredna Gora Mountain, “Karach” ground, at 400 m altitude where sunflower was grown in 2015-2016. For the 2016-2017 season wheat variety Avenue was planted at 600 plants/m^2 with seeds of C1 grade.

3. Results and Discussion

Before planting the crop for the 2016-2017 season soil samples were taken and a number of fertility parameters determined (Table 1). Sampling was done following W-shape tracks trough the fields and the results were averaged per plot.

Table 1. Results from fertility parameters’ analysis of soil samples taken before planting (05.09 2016).

Total area 22.8 ha	pH	N (ppm)	Zink (ppm)	Na (ppm)	K (ppm)	P (ppm)	S (ppm)	Fe (ppm)	Mo (ppm)	Cu (ppm)	B (ppm)	Mn (ppm)	Mg (ppm)	Ca (ppm)	Cation exchange capacity (meq/100g)
Area M01	7.1	14	1.4	30	211	9	1	188	0.23	9.8	1.02	192	400	6959	32 2
Area M02	7.0	9	1.3	29	189	5	1	251	0.17	8 1	1.08	126	398	5075	23.6

As a result, from soil analyses the plots were divided into two groups for fertilizer application (denoted M01 and M02 – Figure 1). Diammonium phosphate (DAP – $(NH_4)_2HPO_4$) was used as pre-sowing fertilizer. Based on fertility parameters of the plots DAP was evenly applied at 150 kg/ha for M01 and 200 kg/ha for M02.

To assure proper near-infrared (NIR) measurements data on soil reflectance was collected with the BUTEO drone after the last pre-sow treatment in both RGB (Figure 2) and NIR specters.

Figure 1. Area Denotation as a Result from Soil Fertility Analysis.

Figure 2. Areal View of the Test Site. Three Arable Plots Used (Total Area 22.8 Ha), Surrounded Byuncultivated Land, are Visible

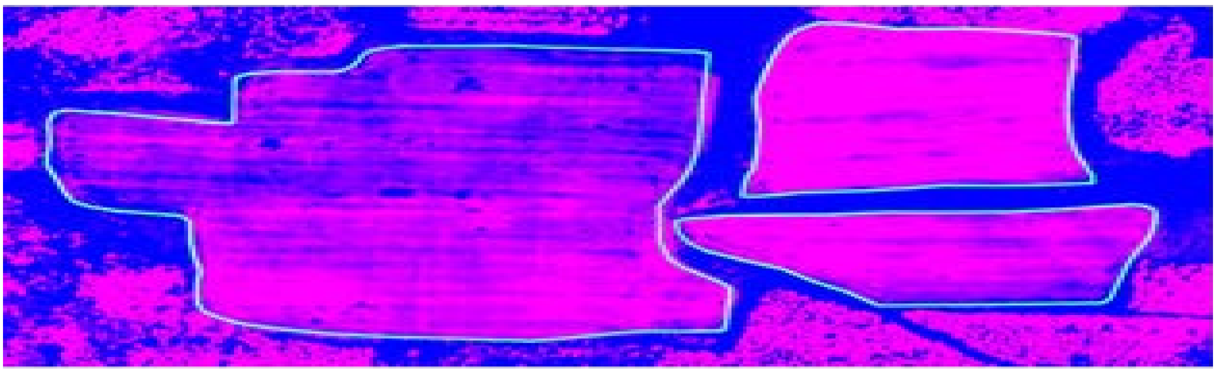

Figure 3. Near Infrared (NIR) observation of the Wheat Crop in Early Spring. Data Collected on March 7, 2017.

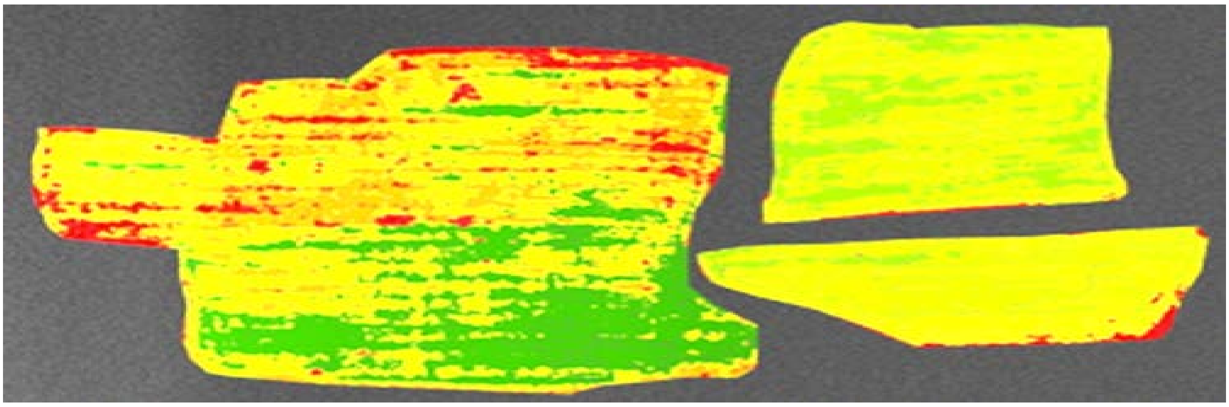

Figure 4. Variable Rate Application (VAR) Map Delivered to the Greenstar 2630 Navigation Display. Areas in Red are With Lowest NDVI and Thus Received the Highest N Fertilizer Rate (250 Kg/Ha), While the Areas in Green Received the Lowest (150 Kg/Ha).

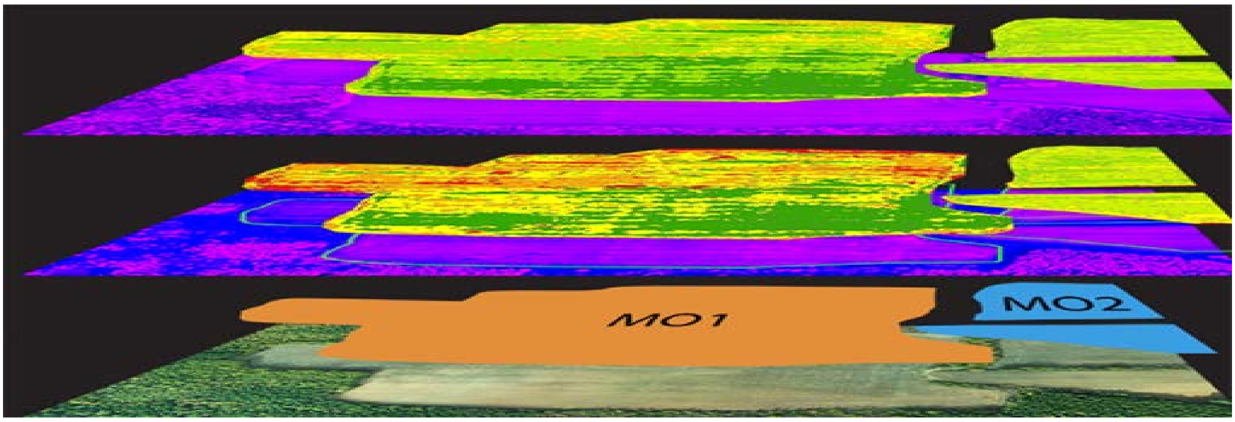

Figure 5. Overlaying Soil, Fertilizer and Pest Maps.

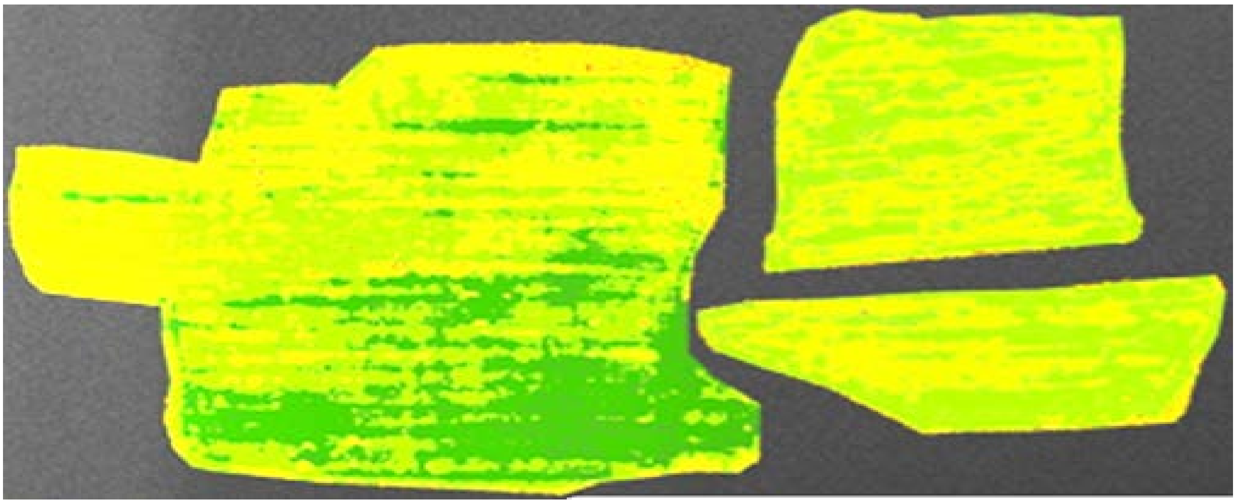

Figure 6. VRA Map Calculated as a Result from Field Observation in the Third Decade of May, 2017.

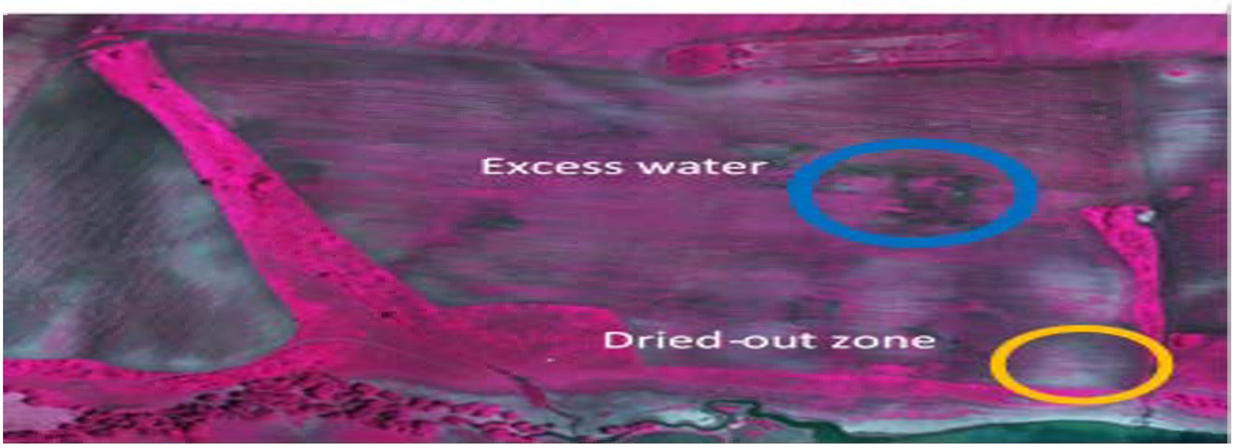

Figure 7. Data Collected from NIR Camera can be Used for Identification of Zones of Excess or Insufficient Water Supply (Areas with Different Water Availability to Plants)

During the vegetation period data was collectedmultiple times using both RGB and NIR cameras to follow the crop development in near real-time. When a variation in the vegetation growth was detected (i.e. in early spring – 07 March, Figure 3),normalizeddifference vegetation index (NDVI) was obtained according toJ.W. Rouse, Jr., Haas, Schell, Deering, & Harlan (1973) and J. W. Rouse, Jr., Haas, Shell, & Deering (1973), as further developed by Tucker(1979) and Panda, Ames, & Panigrahi(2010). It was used to produce variable rate application (VRA) map (Figure 4)that was uploaded to the GreenStar 2630 navigation display of the tractor guiding the Kubota DSX-W GEOspread fertilizer applicator.We considered the correction of nitrogen supply as the first response becauseimportant synergies of data in the visible to near-infrared and thermal domain for the estimation of plant pigments were suggested as closely linked to leaf nitrogen and productivity(Elarab, Ticlavilca, Torres-Rua, Maslova, & McKee, 2015). Based on the calculated vegetation indices the first vegetation fertilizer application was varied throughout the field in the rate of 150-250 kg/ha ammonium nitrate.Due to the more precise fertilizer distribution, the total amount of fertilizer delivered to the fields was reduced by 400 kg, thus reducing the cost for acquiring fertilizers by ~150 euro.

With the progression of the vegetation observations of the fields continued and in April, 2017 two more fertilizer applications were administered – one with leaf fertilizer containing micronutrients to supplement the deficits, identified during initial soil sampling, and about 10 days later a second N application, based on the calculated NDVIs and the third VRA map generated.

It has been speculated that phenolic concentration may contribute to the assessment of vegetation stress and species discrimination (Houborg et al., 2015). Determination of these specific constituents appears possible by measuring changes in a unique absorption feature near 1.66 μ in spectra of leaves and plants (Kokaly & Skidmore, 2015). BUTEO drone however is not equipped with such a sensor, so changes in NDVI were used instead for monitoring both pest and weed infestations. In our study, sudden changes in NDVIs (within 2-3 days from the previous field observation) were used as indicators of pest/disease/weed development and triggered emergency visits of the agronomists to the crop site. Upon determination of the specific causative agent for the NDVI fluctuation, appropriate plant protection treatments were applied. Furthermore, the plant protection products were only applied to the areas with modified NDVI indices (reduced – incase of pest and increased – in case of weed infestation).This allowed for maintaining the crop in a good condition throughout the rest of the season with reduced both machinery and plant protection products use, thus reducing also soil compaction and the number of working hours needed to assure high productivity. Altogether, this resulted in expense reduction that was estimated to amount to about 20-22 euro/ha.

Field maps, resulting from different surveys were accumulated throughout the season, which allowed for analyzing key elements of the crop development during the vegetation period. The ability to overlay different maps (Figure 5) gives the agronomists and farm managers ability to trace not only short-term effects of nutritional regime / pest development, but also to get a better idea of the interplays between them.

The results from the differential application of the fertilizers, in combination with timely application of pest and weed control formulations (all of them based on the observations of fluctuations in NDVI) during the vegetation were clearly visible at the final stages of crop development. After the fast vegetative growth phase and the flowering of the crop were completed and grain formation has well advanced the crop condition continued to be in very good state as indicated by calculated VRA map (Figure 6).

As demonstrated in the present report the use of MRUAVs was the only adequate approach when quick-response action is needed at farm/field level. In regions like Central and Eastern Europe, where cloud cover is frequent and the fields are relatively small this severely impairs applicability of satellite-based systems (Machwitz et al., 2014).

The use of ground-based equipment was inadvisablebecause it is incapable of covering all the fields on an average-sized farm (500-2000 ha) every two-three days. When weather conditions favor rapid disease/pest spreading, longer time gaps may compromise the entire crops on the farm and thus are unacceptable.Furthermore, in many crops entrance of machinery at the late stages of crop development is impossible – either due to the tall stature of the crop (i.e. maize and sunflower) or because of the closed crop stand (i.e. wheat, barley, and canola) that cannot recover from mechanical damage after certain developmental stage.

While fixed wing drones could be used for quick deployment and large area observations, irregularities often experienced in the path followed by the vehicle, varying altitude, and camera attitude (Mancini et al., 2013) lead to an lower average precision that can be achieved by these systems – in the range of ~25 cm (Dunford, Michel, Gagnage, Piégay, & Trémelo, 2009). Furthermore, high shutter speeds are needed to combat the blurring effect of relative ground speed that occurs at lower altitudes in the case of airplane (Verhoeven, 2009).The enhanced cm-scale spatial detail that BUTEO drone can achieve was acknowledged to allow for the separation of soil and canopy contributions and reduce obfuscating effects of soil background, structure, and shadow (i.e., by isolating pure vegetation signals), providing an improved capacity to remotely sense and model vegetation traits and function(Houborg et al., 2015). As vegetation indices are vague in quantitative biophysical meaning, and most of them were formulated to minimize the effect of non-vegetation factors on spectral data (Baret &Guyot, 1991) this capacity is of crucial importance for identifying exact crop condition. Several propositions exist to overcome the abovementioned problems. Jin & Eklundh(2014)for example proposed a new index, named the plant phenology index (PPI), which is derived from radiative transfer equations. PPI is approximately linear to green leaf area index (LAI), and has the same unit as LAI ($m^2 \cdot m^{-2}$). The authors argue that, as LAI is the most dynamic visible canopy variable during the phenological cycle, linearity with green LAI is a fundamental property of a phenology vegetation index. It is for this reason that the index can be used for representing canopy green foliage dynamics for any green terrestrial vegetation. Several other vegetation indices (VIs) were also proposed (i.e. Baret & Guyot, 1991; Houborg et al., 2015; Jin & Eklundh, 2014) as well as ways to incorporate them into crop growth models (Machwitz et al., 2014) and yield prediction neural networks (Panda et al., 2010). Remote data collection could also be used to assess soil conditions both by direct measurement of soil reflectance (Dunford et al., 2009; Mancini et al., 2013; Panciera et al., 2009) and by inference from plant responses – as our own data shows (Figure 7) and discussed by Rango et al.(2009) and Yin, Udelhoven, Fensholt, Pflugmacher, & Hostert(2012).

Remote sensing will be best used by providing accurate, site-specific data that can be converted into information used by decision support systems (Shaw, 2005).In case of the MRUAVs, major advantages include the ability to operate close to the groundand use these devices for photographic situations where low amounts of reflected radiation need to be recorded (Verhoeven, 2009). By providing both higher resolution and longer daytime operational duration than other air- and satellite-based systems,MRUAVs provide two other crucial data streams for the decision support. The first one is the capacity to produce 3-dimensional field topography maps (Mancini et al., 2013) in the centimeter range, thus providing a possibility for erosion prediction and prevention. The second one is the near real-time measurement of the biomass accumulation in the crops (Ahamed et al., 2011; Dunford et al., 2009; Sousa et al., 2017). They were used for example as a low-altitude remote sensing

(LARS) platform to acquire quality images of high spatial and temporal resolution in order to estimate yield and total biomass of a rice crop (Swain, Thomson, & Jayasuriya, 2010).

4. Conclusions

Present report summarizes the results from actual application of propeller-lifted drones in precision agriculture that include:

- Dynamic tracking of the crop condition throughout the season and supporting decision-making process in near real-time
- Monitoring of nutritional regime (zones of excess or insufficient nutrient availability)combined with the capacity to follow water availability to plants
- Near real-time tracking of the presence and development of weeds, emergency and spreading of diseases, damages from pests, etc.

Due to the complexity of factors involved the total direct and indirect economic benefits were difficult to precisely calculate, but were estimated to amount to at least 30 euro/ha. Combined with the lower amounts of fertilizers and pesticides used throughout the season this provides strong evidence that the use of MRUAVs can significantly contribute to the sustainability of the crop production.

It further presents the potential of the multi-rotor unmanned air vehicles to:

- Estimate actual crop density (number of plants/m^2 or ha) in closed canopy crops, i.e. winter cereals and rapeseed.
- Possibility to determine the total volume of the biomass accumulated during the vegetation/year

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