Sampling transects for crop area estimation with drones.

Javier Gallego[1], Aldo Giovacchini[2], Michele Downie[2]
[1]Joint Research Centre of the European Commission.
[2]ITA Consortium

DOI: icasVII.2016.g44c

ABSTRACT

Small Unmanned Aerial vehicles (UAV), better known as drones, have invaded very quickly the public debate. Besides the headlines on their military use, the potential civil applications are widely discussed. Agriculture is one of the fields in which drones appear to be very useful. In particular many agricultural statisticians would like to understand how much information can be extracted from UAV images and how cost-efficient such images may be.

This paper has several purposes:

- Discussing the cases in which UAV images can substitute field surveys.
- Analysing suitable sampling schemes for such image acquisition.
- Presenting practical implications and limitations in a test by the ITA consortium in Malawi.

Sampling long thin stripes to be surveyed with UAV has a good efficiency in terms of variance, but the feasibility is linked to two conditions that appear to be very difficult to meet: possibility to identify all major target crops on images with 2-3 cm resolution and flight regulations in the country that allow flying long distances far away from the operator. Small traditional airplanes with pilot might be a more realistic approach than UAV for surveys based on a sample of aerial photographs.

Keywords: Crop area estimation, Drones, Area frame sampling, Transects.

1. Introduction

The scientific community is paying attention to Unmanned Aerial Vehicles (UAV) and the possible civil applications of the images they can provide (Floreano and Wood, 2015). The debate on the use of UAV, better known as drones, includes the agricultural applications (Malveaux et al., 2014, Anderson, 2014), and the health aspects of agricultural practices (Capolupo et al., 2014). The limitations imposed by flight regulations are also analysed by the scientific literature (Freeman and Freeland, 2014). The image processing technology is well advanced and should not be a major limitation for practical applications (Zarco-Tejada et al., 2012, Hruska et al., 2014, Liu et al., 2014). Most applications of drone images to agriculture refer to local crop monitoring (García-Ruiz et al., 2013, Duan et al., 2014, Uto et al., 2013), in particular for precision agriculture (Zhang and Kovacs, 2012, Stehr, 2015). The possible application to agricultural statistics is often discussed, but at the time of drafting this paper, we have not been able to find any published paper that specifically addresses the topic.

If we consider the standard approaches to use imagery for agricultural statistics (Carfagna and Gallego, 2005), the requirements for yield estimation or forecasting seem far from the characteristics of low altitude flights because a large number of images along the cropping season is a critical condition and this would be too expensive. The use of images as a covariate in regression or calibration estimators appears also unfeasible at the current stage of the technology because it requires covering a very large area, in principle the whole targeted geographical domain

The most realistic use of drone images is substituting field visits in an area frame survey. At the current status of technology it is reasonable to cover for example an area of 1 km x 1 km with a single flight by mosaicking stripes of about 100 m width with a resolution that can range between 2 and 5 cm. Such resolution may be enough to identify single crops in some cases. The usability of such images to identify single crops depends very much on the type of agricultural landscape. One of the purposes of this paper is presenting the conclusions of a test run by the ITA consortium in Malawi. The conclusions of this test are likely to be useful for many countries in sub-Saharan Africa.

If we assume that most crops of interest, or at least some key crops, in a given region or country can be identified, several points still need to be discussed:

- Is a drone-based survey cost-efficient compared with a standard field survey?
- How can we optimize a sampling plan of spatial units to be observed with drones?

Analysing survey costs on the basis of pilot studies is not easy. The cost per sampling unit tends to be lower when a survey becomes operational (Taylor et al., 1997), but with a very heterogeneous pace. Pilot surveys in developing countries may be more expensive than in developed countries due to difficulties linked to transportation infrastructures and logistics, but the cost can be also very different when a pilot study is paid by an external donor.

The idea of using samples of aerial photographs have been used for agricultural and environmental estimates is not new. It has been applied already in the 70's (Jolly and Watson, 1979), but needs to be revisited taking into account the technological advances.

2. Pilot Test in Malawi.

A test has been carried out by the ITA consortium in Malawi. A subsample of 20 clusters of 4 x 4 points 250 m apart was covered with UAV flights. The leaf shape of maize, by far the most important crop in the country, can be reliably recognised with the 2-3 cm resolution images, but associated crops (less visible than maize) were very difficult to identify and distinguish from weeds. Other crops such as ground nuts, soya and cassava are difficult to discriminate for different reasons including the relevant presence of the intercropping practices and the different phenological stages for the same crop types during the drone overpass. Figure 1 provides an example of image acquired by a drone in the Malawi test. The fields in the right side of the image can be clearly identified as maize, but it is very difficult to identify if the associated vegetation are simultaneous crops or weeds.

Figure 1: *Example of image with 2-3 cm resolution acquired by a drone in Malawi.*

3. Data and Sampling Schemes.

We have made simulations using as pseudo-truth the farmers declarations in the Netherlands in 2012 . The data we have contains approximately 770,000 plots declared by farmers in 2012 in the Netherlands, out of which 345,000 correspond to cropland. The rest corresponds mainly to grassland and a minor part of natural vegetation plots owned or managed by farmers. For the examples based on this data layer we will focus exclusively on cropland. The interest of using this data set is that it behaves very much like the real spatial layout of cropland. The consistency of the data set has been checked by crossing it with the Eurostat point survey LUCAS (Gallego and Delincé, 2010) that has resulted in a nearly perfect match, with the exception of a significant undercover on potatoes. Similar data sets exist in all European Union (EU) member states, but most of them consider these data confidential. The Dutch authorities have considered that these data may be made public if they only contain data that anyone can observe on the field. The layer can be found in http://geodata.nationaalgeoregister.nl/brpgewaspercelen/atom/brpgewaspercelen.xml in a GIS format. It would have been better to use a similar data set for a developing country with a more complex agricultural landscape, but it has not been possible to find such data.

There is a wide variety of spatial sampling schemes for agricultural statistics (Benedetti et al. 2015). In this paper we will limit ourselves to comparing:

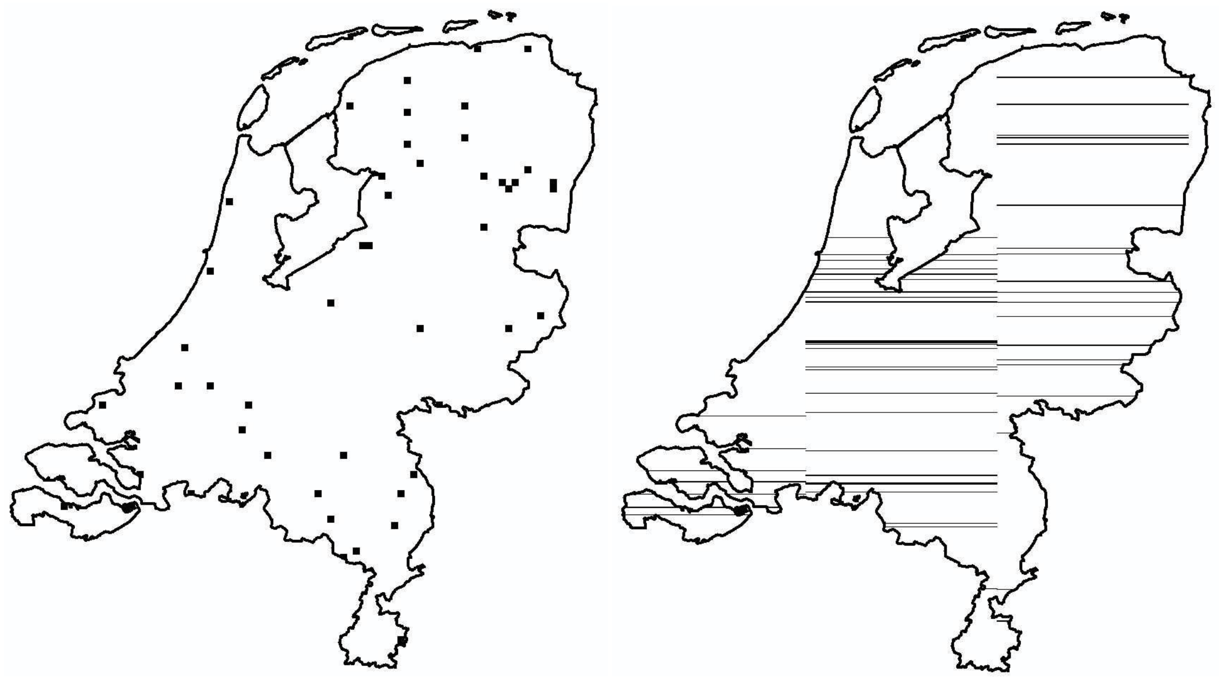
- simple random sampling of points. This is generally not a good choice for the problem we are considering, but we use it as a benchmark.
- Square segments. We have tested segments of 1 km × 1 km and 3 km × 3 km

- Long and thin segments (stripes). We have tested stripes of 10 km × 100 m and 90 km × 100 m that correspond to the same area of the square segments above. Therefore the variance ratio between square segments and stripes may be attributed to the shape and not to the size of the segments.

Long and thin stripes are theoretically better adapted than square segments to low altitude flights. A good quality UAV can fly a straight line of 100 km if the topography is not too complicated. However local or national regulations often forbid such long stripes.

Figure 2 represents the spatial layout of a sample of square segments of 3 km × 3 km and a sample of stripes of 90 km × 100 m. The sample of stripes has been defined with the help of a fixed grid. A large proportion of stripes is incomplete because they are clipped by the country boundary. This is likely to have an impact on the efficiency of the sampling scheme and may need to be reworked with a sampling frame better adapted to the shape of the country. In both cases we have considered simple random samples. Improvements such as stratification or systematic sampling have not been considered in order to focus on the effect of the segment shape.

Figure 2: *Layout of a sample of square segments and a sample of 90 km stripes.*



4. Simulation Results.

For the comparison of variances we use the "equivalent number of points". If a sample of n segments with a given shape and size gives the same variance as a simple random sample of $n \times Q$ points, we say that a segment is equivalent to Q points in terms of variance.

Table 1 reports the equivalent number of points Q of square segments and long stripes for major crops and some less important crops. We can see that Q is generally larger for minor crops. This happens because the spatial auto-correlation is generally higher at short distances for major crops, making clusters less efficient. We can also see that the relative efficiency of stripes compared with square segments is higher when the stripes are very long. This empirical result is fully consistent with the formal link between efficiency of clusters and spatial autocorrelation (Carfagna and Gallego, 1994, Gallego 2012).

Table 1: *Equivalent number of points of square segments and stripes*

		1 km2			9 km2		
	Area (% territory)	*Q* square segment	*Q* stripes	Efficiency stripes	*Q* square segment	*Q* stripes	Efficiency stripes
Maize	7.17	7.2	12.8	1.8	13.8	26.0	1.9
Temporary grass	5.41	6.2	14.1	2.3	14.6	41.8	2.9
Wheat	4.32	4.1	6.1	1.5	6.2	15.2	2.5
Potatoes	4.27	5.7	8.5	1.5	9.0	24.4	2.7
Sugar beet	2.07	8.9	15.1	1.7	18.3	58.5	3.2
Barley	0.84	9.9	18.9	1.9	24.3	69.0	2.8
Flowers	0.65	4.4	6.7	1.5	6.7	20.1	3.0
Orchards	0.51	6.1	12.1	2.0	13.6	43.6	3.2
Pulses	0.19	11.4	25.7	2.2	43.2	115.8	2.7
Flax	0.06	12.6	24.6	1.9	39.3	131.2	3.3

5. Conclusions and Discussion.

Very high resolution images acquired by UAV are a very appealing tool for agricultural statistics. The idea of substituting field surveys with photo-interpretation of geo-referenced images with a resolution of 2-3 cm is attractive, but several limitations appear very strongly:

- The applicability is limited to crops that can be identified on images with a reliability compared to field observations. This is unlikely for associated crops, as in the example of Figure 1.
- National regulations often limit the flights of UAV to the area within the sight of the operator. Square segments of 1 km × 1 km would be feasible, but the statistical efficiency of such segments is not very high.
- A UAV-based survey requires field trips of highly specialized staff and material. The ratio between the cost of field observations in a traditional area frame survey and an UAV-based survey is not easy to estimate with the available information coming from small pilot tests.

For specific food need assessments based on inter-annual changes of maize (assuming maize is the staple food) a sample of UAV-covered stripes can provide a sufficient information if long stripes are compatible with national regulations.

We need to make a reasonable assumption to apply to developing countries with very small plot size the relative efficiency values obtained from data in the Netherlands, where the average field size is around 3-4 ha. We can assume that the spatial correlation structure may be similar if we apply a 1:3 or 1:4 zoom-out. The average field size would become 0.2-0.5 ha, a field size that is much more common in semi-subsistence agriculture. However this “plot reduction” may be not enough to have a landscape similar to a developing country. In particular simultaneous crops are not considered in the results.

The efficiency for long and thin sampling units (e.g. 10 km × 100 m) may be around 2-3 times better than for compact-shaped units (squares). Taking into account the standard operational conditions of UAV (landing near the take-off point), a suitable sampling unit could be a pair of parallel transects of 10 km with a distance of 500 m or 1 km from each other.

When flight regulations are do not allow long distance flights of UAV, small aircrafts with pilot would be an alternative that should be considered. It is less fashionable than UAV and has other requirements (sufficient network of landing fields), but it might be efficient in many cases.

A sampling plan should take into account the orographic characteristics of the surveyed area. A stratification bight be performed to exclude areas with too steep slopes for a smooth operation of UAV. However case by case analysis is needed for an approximate assessment of the potential bias generated by excluding hilly areas.

REFERENCES.

Anderson, C. (2014) Agricultural drones. *Technology Review, 117*(3), 58-60.

Benedetti R., Piersimoni F., Postiglione P., (2015) *Sampling spatial units for agricultural surveys,* Springer

Capolupo, A., Pindozzi, S., Okello, C., & Boccia, L. (2014) Indirect field technology for detecting areas object of illegal spills harmful to human health: Application of drones, photogrammetry and hydrological models. *Geospatial Health, 8*(3), S699-S707.

Carfagna E., Gallego F.J. (2005) The use of remote sensing in agricultural statistics, *International Statistical Review* 73, 3, 389-404.

Carfagna, E., Gallego F.J. (1998) Sampling Segments in Satellite Image Strips, *Seminario Esquilino*. Rome, 27-29 November 1995. Office for Pubblications of the EC. Luxembourg. pp. 213-222..

Carfagna, E., Gallego, F.J. (1994) On the optimum size of segments in a two-step survey on area frame: Possible improvements for rapid european estimates. *Conference on the MARS Project: overview and perspectives*. Office for Publications of the E.C. Luxembourg. pp. 139-143.

Duan, S., Li, Z., Wu, H., Tang, B., Ma, L., Zhao, E., & Li, C. (2014). Inversion of the PROSAIL model to estimate leaf area index of maize, potato, and sunflower fields from unmanned aerial vehicle hyperspectral data. *International Journal of Applied Earth Observation and Geoinformation, 26*(1), 12-20.

Floreano, D., & Wood, R. J. (2015) Science, technology and the future of small autonomous drones. *Nature, 521*(7553), 460-466. doi:10.1038/nature14542

Freeman, P. K., & Freeland, R. S. (2014). Politics & technology: U.S. polices restricting unmanned aerial systems in agriculture. *Food Policy, 49*(P1), 302-311. doi:10.1016/j.foodpol.2014.09.008

Gallego F.J., (2012) The efficiency of sampling very high resolution images for area estimation in the European Union. *International Journal or Remote Sensing* 33 (6): 1868-1880.

Gallego, F.J., Delincé J. (2010) The European Land Use and Cover Area-frame statistical Survey (LUCAS), in *Agricultural Survey Methods*, ed: R. Benedetti, M. Bee, G. Espa, F. Piersimoni, Ch. 10. pp. 151-168, John Wiley & sons.

Garcia-Ruiz, F., Sankaran, S., Maja, J. M., Lee, W. S., Rasmussen, J., & Ehsani, R. (2013). Comparison of two aerial imaging platforms for identification of huanglongbing-infected citrus trees. *Computers and Electronics in Agriculture, 91*, 106-115.

Hruska, R., Mitchell, J., Anderson, M., & Glenn, N. F. (2012). Radiometric and geometric analysis of hyperspectral imagery acquired from an unmanned aerial vehicle. *Remote Sensing, 4*(9), 2736-2752. doi:10.3390/rs4092736

Jolly, G. M., & Watson, R. M. (1979). Aerial sample survey methods in the quantitative assessment of ecological resources. *Sampling Biological Populations'.(Eds RM Cormack, GP Patil and DS Robson.) pp*, 203-216

Liu, Y., Wang, T., Ma, L., & Wang, N. (2014). Spectral calibration of hyperspectral data observed from a hyperspectrometer loaded on an unmanned aerial vehicle platform. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7*(6), 2630-2638. doi:10.1109/JSTARS.2014.2329891

Malveaux, C., Hall, S., & Price, R. R. (2014). Using drones in agriculture: Unmanned aerial systems for agricultural remote sensing applications. Paper presented at the *American Society of Agricultural and Biological Engineers Annual International Meeting 2014, ASABE 2014, , 6* 4075-4079.

Stehr, Nikki J. (2015) Drones: The Newest Technology for Precision Agriculture. *Natural Sciences Education* 44.1: 89-91.

Taylor J., Sannier C., Delincé J, Gallego F.J. (1997) *Regional Crop Inventories in Europe Assisted by Remote Sensing: 1988-1993*. Synthesis Report . EUR 17319 EN, Office for Pubblications of the EC. Luxembourg. 71pp. http://mars.jrc.ec.europa.eu/mars/Bulletins-Publications/Regional-Crop-Inventories-in-Europe-Assisted-by-Remote-Sensing-1988-1993

Uto, K., Seki, H., Saito, G., & Kosugi, Y. (2013). Characterization of rice paddies by a UAV-mounted miniature hyperspectral sensor system. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6*(2), 851-860.

Zarco-Tejada, P. J., González-Dugo, V., & Berni, J. A. J. (2012). Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. *Remote Sensing of Environment, 117*, 322-337.

Zhang, Chunhua, and John M. Kovacs. (2012) The application of small unmanned aerial systems for precision agriculture: a review. *Precision agriculture* 13.6: 693-712.