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Alternatives to Medium Resolution Images for Crop Area Estimation: Very High and Coarse Resolution Images.

Francisco Javier Gallego
Joint Research Centre of the EC
Via Fermi 2749
I-21027 Ispra, Italy
Email: Javier.gallego@jrc.ec.europa.eu

ABSTRACT

Classified satellite images with a pixel size between 20 m and 60 m are often used as covariates for crop area estimation combined with field data from an area frame survey (AFS). We explore the cost-efficiency of two alternatives. Two examples of application of coarse resolution images (MODIS images, 250 m resolution in Ukraine and SPOT-VEGETATION, 1 km resolution in Spain) and samples of very high resolution (VHR) images, with a pixel size around 1 m and covering an area of 10 km × 10 km to 20 km × 20 km. Coarse resolution images are comparable to medium resolution if the field size is very large. The combination of local expert data with coarse resolution images appears promising, although this approach is also applicable to medium resolution. Very high resolution images have few chances to be cost-efficient with the current prices.

Keywords: Area estimation; Satellite images; Spatial Resolution

1. Introduction

Agricultural statistics has always appeared as a major application of Earth Observation (EO). In the 70's many scientists believed that satellite images would produce reliable agricultural statistics with very few field data (Mac Donald and Hall, 1980). The risk of bias of pixel counting became soon clear ant therefore the need to combine images with a consistent area frame survey. Calibration estimators are suitable when the units for the field survey are points (Card 1982, Hay, 1988, Czaplewski, 1992, Stehman, 2013), while regression estimators are better adapted when the survey elements are pieces of territory covering several agricultural plots (Wall et al, 1984, Germain and Julien 1988, Allen 1990, Haack and Rafter, 2010). Pure remote sensing approaches provide sufficiently accurate results only for crops that can be clearly distinguished on the images, such as paddy rice (Fang, 1998). Methods without a consistent ground survey are also useful when the access to the fields is problematic. For example, coarse area estimates could be made for Kosovo only based on image analysis at the end of war, when sending surveyors to the fields was dangerous (Geosys, 2000). Nearly-pure remote sensing estimates have been also applied in North Korea, where authorizations were difficult to obtain (Kerdiles et al., 2013). A general overview of the different ways to use remote sensing for agricultural statistics is provided by Carfagna and Gallego (2005). For potential users who wish to have a general idea of what is feasible in this field, the GEOSS community of practice has produced an easy-to-read general document (GEOSS, 2009).

Landsat TM images, with a spatial resolution of 30 m and a swath of 180 km, are probably the images that are most frequently applied to crop area estimation. Other sensors offer similar resolution with slightly different characteristics, but have been less often used for this purpose.

2. Comparing different sensors in Ukraine.

This section presents the main results and conclusions of a pilot study carried out in 2010 on 3 oblasts in Ukraine, covering a total area of 78,500 km^2. (Kussul et al., 2012). The study compares the cost efficiency of several image types: MODIS (250 m resolution), Landsat TM (30 m resolution) , AWiFS (56 m resolution) and RapidEye (6 m resolution). The study area included three oblasts (Kyivska, Khmelnytska, and Zhytomyrska) were selected in the study with total area of 78,500 km^2 and a cropland area of 2.45 Million ha according to official statistics.

Field surveys were conducted in July 2010, and included surveys along the roads and area frame sampling (AFS) surveys (Figure 1). Data collected along the roads were used to train satellite images classifiers while data collected during AFS surveys were used for testing purposes and for area estimation. The units of the AFS were cells of a 4 km x 4 km grid, that were stratified using the GLOBCOVER land cover map at the 300 m resolution (Arino et al., 2008). Three strata were defined: no cropland, some cropland up to 50% and more than 50% cropland.

The acquisition of AWiFS images did not meet the expectations because of technical problems. Rapideye images were acquired in a rather small area with the specific purpose of testing the usefulness of the so-called red-edge spectral band for the discrimination of crops. The expected improvement thanks to the red-edge band was not confirmed. Here we focus on the comparison between Landsat TM and MODIS.

The MODIS dataset was obtained from the JRC Agri4Cast image server, and contained ortho-rectified MODIS Normalized Difference Vegetation Index (NDVI) images. The data are temporally aggregated to obtain a composite image every 10 days. Data from the end of 2009 were also used in order to better identify winter crops. Data with heavy clouds were excluded from the study. As a result, a time-series of 13 NDVI values for each pixel were used as an input to classifiers. MODIS was expected a priori to be the best suited sensor for the Ukrainian agricultural landscape because the coarse spatial resolution is not a major drawback in a landscape dominated by plots around 100 ha. In exchange MODIS should provide a better picture of the temporal evolution of the vegetation.

The Thematic Mapper (TM) instrument onboard Landsat-5 satellite was a very senior sensor, but still giving good performances. In total, 75 Landsat-5 scenes over the study area were downloaded from April to September. The number of images in each point of the area of interest ranged between 2 and 4.

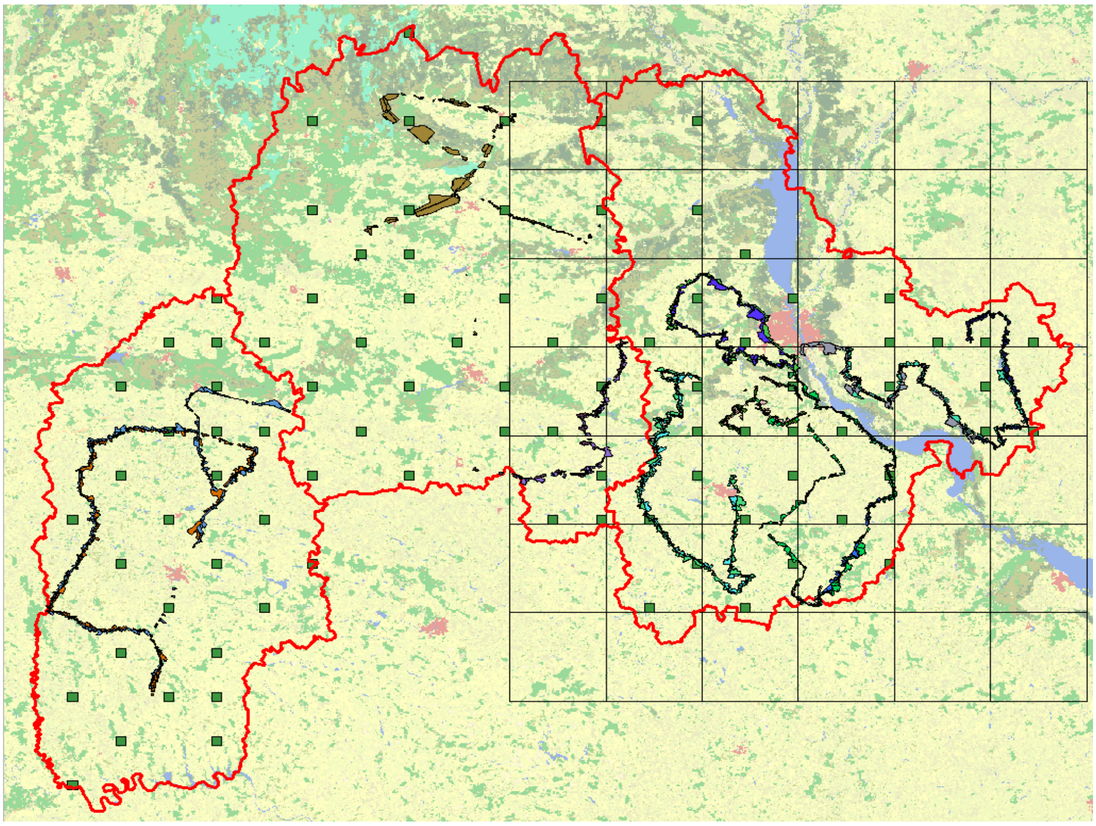

Figure 1: *Distribution of the ground data. Boundaries of the oblasts, AFS segments (squares), along the road field data (curves),*

Three classification algorithms were selected for this study: neural networks, Support vector machine (SVM) and decision tree. Neural networks have been successfully applied in remote sensing for decades (Foody and Arora, 1997, Lu and Weng, 2007, Mas and Flores, 2008, Bishop, 2006). The MLP classifier behaved generally better than the SVM and the classification tree, therefore the reported results correspond to the application of the MLP algorithm. The area estimates were computed combining the AFS field data with classified images (separately for each sensor) with a regression estimator.

$$\bar{y}_{reg} = \bar{y} + b\left(\bar{X} - \bar{x}\right)$$

where $\bar{y}$ is the AFS field survey estimate for a given crop, X refers to the covariate (proportion of pixels for the same crop in the classified image; $\bar{X}$ and $\bar{x}$ are the population and the sample means of X, and b is the slope of a linear regression between Y and X. Because the sample of segments was rather small, we used the variance estimator

$$V(\bar{y}_{reg}) = \frac{N-n}{N \times n}\left(1 + \frac{1}{n-3} + \frac{2G_x^2}{n^2}\right)\sigma_y^2\left(1-\rho^2\right)$$

where $G_x = \frac{k_{3x}}{\sigma_x^3}$ is the relative skewness, less biased than the more often used simplified approximation

$$v(\bar{y}_{reg}) \approx \frac{1}{n} s_y^2 \left(1 - \rho_{xy}^2\right)$$

that provides the relative efficiency

$$Eff = {v(\bar{y})} \big/ {v(\bar{y}_{reg})}$$

Oblast	**MODIS**		**Landsat-5**	
	Training accuracy	**Test accuracy**	**Training accuracy**	**Test accuracy**
Kyivska (K)	74.67%	57.64%	71.3%	62.8%
Khmelnitska (KH)	65.07%	40.14%	68.63%	40.7%
Zhytomyrska (ZH)	75.91%	54.99%	82.37%	55.3%

Table 1: *Overall accuracy of image classification based on MODIS and Landsat TM*

	MODIS			Landsat-5		
Crop\Oblast	K	ZH	KH	K	ZH	KH
Winter wheat	1.44	2.66	1.13	1.90	3.74	1.39
Spring barley	1.05	1.00	1.00	1.23	1.00	1.00
Maize	1.35	1.27	4.19	1.38	1.73	1.37
Soybeans	1.23	1.68	1.03	1.45	1.22	1.05

Table 2: *Relative efficiency of the regression estimator for main crops.*

The classification accuracy on test pixel sets is significantly better for Landsat TM than for MODIS, although the comparison results are not clear when we look at the efficiency of the regression estimator (Table 2).

3. Downscaling subjective estimations per commune.

In this section we present a test case carried out in Andalucia, Spain (87,000 km^2). We applied an unsupervised classification to a stack of daily images from SPOT VEGETATION, with 1 km resolution. Every 10 days a composite image is built with the maximum value of the NDVI (Normalised Difference Vegetation Index). The images were classified into 45 classes using an ISODATA algorithm (Duda et al., 2001), a modified version of k-means clustering. Each class k has a time profile $NDVI_{kt}$ t=1….36. For each crop c there was a first selection of K_c time profiles that were roughly compatible with the phenological cycle of the crop.

The Spanish Ministry of Agriculture provided data for a sample of 1800 segments of 700 m x 700 m and crop area data per commune (780 communes) from local experts. Such expert estimates have a strong risk of bias, but they are useful to provide an idea of the geographical distribution of a crop. Field data were available for a stratified sample of 1800 segments of 700 m × 700 m visited for the ESYRCE survey (Ministerio de Agricultura, 2007). This sample provides the basic data for official crop area estimates, currently with a straightforward extrapolation. A potential improvement might come from a geographic covariate such as a classified image. We also used CORINE Land Cover (CLC), a land cover map produced with common rules across the European Union (JRC-EEA, 2005). This work is a follow-up of a method proposed by Khan et al. (2010).

For the traditional regression estimator to be efficient, we need a geographical covariate that is well correlated with the spatial distribution of the crop. If we take wheat an example, an easy solution is considering the class "rain fed arable land" in CLC. This is probably a weak covariate for several reasons: too generic, spatially coarse and old, but may be cost-efficient because it is free and easy to use. A new covariate needs to provide better results to be useful. We build a covariate that combines subjective estimates by commune and classified images. For commune m A_{km} is the area classified in class k and Y_{km} the subjective estimate for crop c. The coefficients b_{ck} of a regression.

$$Y_{cm}=\Sigma_k \ b_{ck} A_{km} + \varepsilon_m$$

with restrictions $0 \leq b_{ck} \leq 1$ can be interpreted as an indication of the link between class k and crop c. We do not say that it is the estimated share of crop c in class k, but it will be useful if the correlation is good. Table 1 reports the adjusted r^2 for this regression. Some of the values are very high and can lead to a very optimistic assessment. The comparison with the r^2 between the crop area per commune and the relevant CLC class moderates the optimism. For some crops, such as wheat, barley and cotton, we still have a solid indication of usefulness, but this is not the case for sunflower, maize and rice. Failing to compare with a benchmark would have led to a fake positive message.

Attributing the coefficient b_{ck} to each pixel of class k we build a geographical covariate (Figure 2) that can be combined with the segments (49 ha each) of the ESYRCE survey. The values of r^2 at the segment level are much lower (table 2) and give a more practical indication of the usefulness of the b_{ck} map through the classical approximation of the relative efficiency of the regression estimator $eff \approx 1/(1-r^2)$.

… Crop	*CLC*	*VGT-classification*
Wheat…	0.93	0.97
Barley…	0.33.	0.57
Cotton…	0.65	0.91
Maize…	0.50	0.47.
Sunflower	0.72	0.72
Rice	0.99	0.97

Table 1: Values of r^2 between crop area per commune and two covariates.

… Crop	*CLC*	*VGT-classification*
Wheat…	0.26	0.45
Barley…	0.06	0.10
Cotton…	0.14	0.25
Maize…	0.06	0.04
Sunflower	0.22	0.20
Rice	0.74	0.66

Table 2: Values of r^2 between crop area per segment and two covariates.

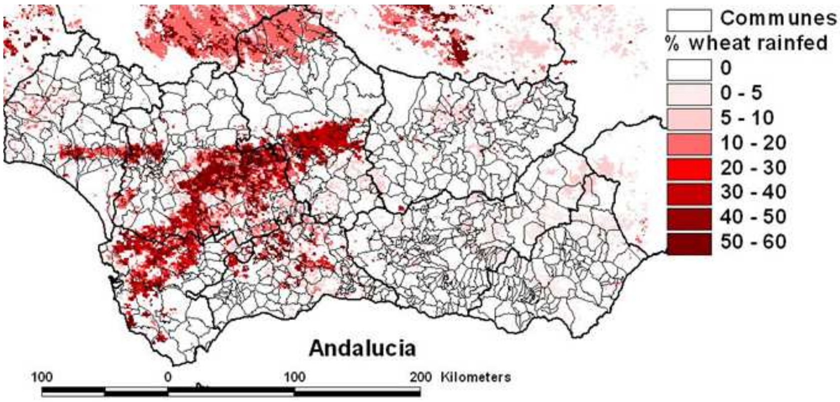

Figure 2: *Distribution of the b_k coefficients for rainfed wheat*

We can draw two main conclusions from these simple results. One conclusion is that an apparently high correlation (e.g. r^2=0.8) does not necessarily mean that the method used to obtain it is good and useful. A critical view requires at least comparing it with the r^2 that can be obtained with a basic inexpensive method that provides a benchmark. In the scientific literature we can find papers that conclude that classifications of coarse resolution images is valid for crop area estimation because they obtain correlations of the order of 0.8 (Verbeiren et al., 2008)

A second conclusion is the usefulness of combining two different data sources that are separately rather weak: subjective estimates by commune and classified coarse resolution images, in which individual fields cannot be identified. The relative efficiency is substantial only for dominant crops (wheat) and for crops that can be easily identified on images (rice). The procedure may become cost-efficient because the cost of coarse resolution images is low and the NDVI profiles are anyhow produced to monitor the status of vegetation and yield forecasting. Other coarse resolution images are being tested, in particular MODIS, with a resolution of 250 m, that were expected to give a better correlation than VGT (1 km resolution), but did not.

An additional point that requires further work is the efficiency of classifications earlier in the year. For the results given above we used images for the whole year. This means that the area estimates can be obtained only at the beginning of the following year. If we want to have area estimates by August in the current year we should use images only up to July. The efficiency in this case still needs to be assessed.

4. Sampling very high resolution images.

Very High Resolution (VHR) images, with a pixel size that ranges between 0.5 m and 2 m, allow a better land cover identification, in particular when the plot size is small. Thus it is natural to think of using VHR images to monitor such areas. Full coverage of a region with VHR images is usually not affordable, and a sample of images can be considered. However the cost-efficiency of a sample of VHR images needs to be assessed. Figure 3 shows an sample of sites that were selected for VHR image analysis in the framework of the Geoland2 project (http://www.gmes-geoland.info/).

In this paper we focus on the potential variance of a sample of spatial units with a size compatible with VHR images (around 10 km x 10 km) compared with a sample of unclustered points, that may be suitable for a field survey. We implicitly assume that the identification accuracy of crops on VHR images is comparable with the identification accuracy on the field. This assumption is very optimistic and corresponds to a stepwise evaluation: if a sampling plan based on units (clusters) of 10 km x 10 km has good chances to be cost-efficient, it is worth assessing the identification accuracy and its impact on the area estimation. Otherwise this exercise is unnecessary and we can disregard the potential use of VHR images.

The "equivalent number of points" is a useful indicator to compare a sampling plan of clusters.

$$Q = V(\bar{y}) / V(\bar{y}_{\text{clus}})$$

meaning that a sample of n clusters gives the same sampling variance as a sample of $n \times Q$ points. For simple random sampling Q is nearly constant when n changes, unless the sampling rate n/N is high. The equivalent number of points can be computed from the intracluster correlation, narrowly linked with the correlogram when we talk about spatial units (Gallego, 2012)

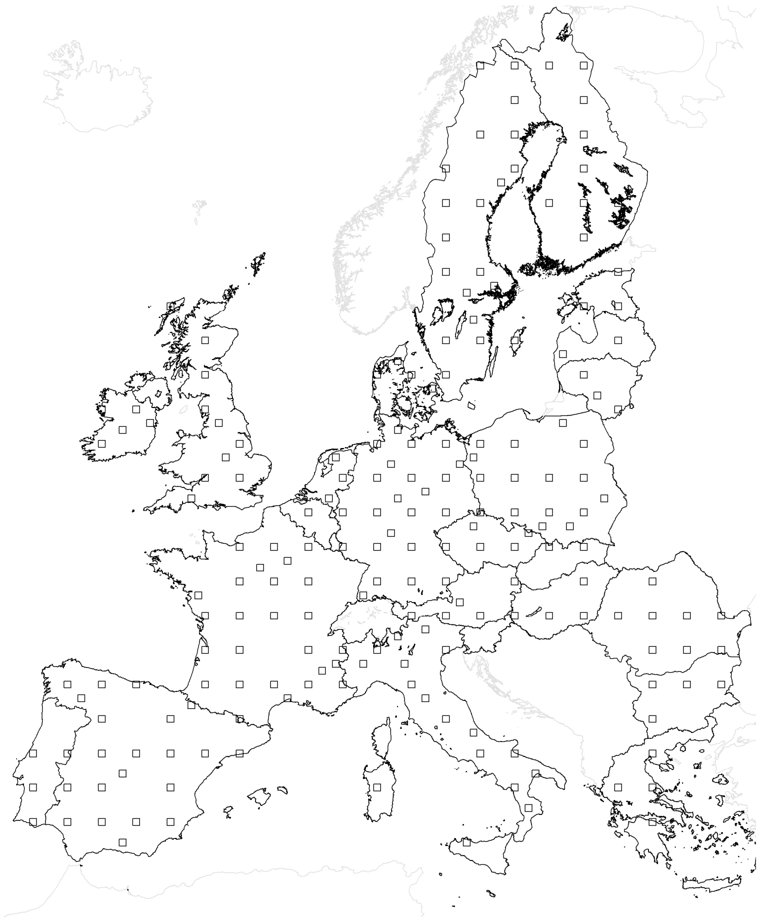

Figure 3:*A sample of sites in the European Union vor VHR analysis.*

Under reasonable conditions (not very high sampling rate, large number M of elementary units in a cluster, i.e. large number of points in a VHR image), the value of each cluster in terms of equivalent number of unclustered points is approximately $Q \approx 1/\rho_M$ where ρ_M is the intracluster correlation. It is interesting to notice that the term M does not explicitly appear, although it has an indirect influence because ρ_M decreases when M increases. For example if M has a large value, e.g.

$M=10^6$ and the ICC is $\rho_M = 0.1$, each cluster has a sampling value approximately equivalent to 10 unclustered points. The intracluster correlation can be estimated as a weighted average of values of the correlogram (Gallego et al., 1999). We obtained low values of the equivalent number of points of major crops or the overall area of arable land in the European Union (EU) with samples of 5 km × 5 km to 30 km × 30 km (Table 5), The correlograms for main crops in the European Union (EU) were calculated on the basis of LUCAS data (Land Use and Cover Area frame Survey).

Intracluster correlation (ICC)			
Site size (km)	Arable LUCAS	Wheat	Sunflower
5	0.425	0.201	0.144
10	0.341	0.126	0.066
20	0.300	0.113	0.060
30	0.266	0.093	0.047
	Equivalent number of points		
5	2.4	5.0	7.0
10	2.9	7.9	15.1
20	3.3	8.9	16.7
30	3.8	10.8	21.3

Table 5: Intra-cluster correlation and "equivalent number of points" for square sites of different sizes. The last three columns were computed using an exponential adjustment to the correlogram computed on the LUCAS sample.

For an economic assessment we need to know the cost of data collection for unclustered points. For the particular case of in-situ observations in the EU we find some useful information in the LUCAS-2006 management report (Eurostat, 2007). This report mentions an observation cost per point of around 14 € for a sample of unclustered points. Actually this figure does not include the general management cost. Also the cost per point has changed in different editions of the survey. Assuming a cost of 25 € per point for in-situ observation, the added value of a 10 km site for the estimation of major land cover classes ranges between 60 € and 400 €. This is not very encouraging if the observation mode is based on VHR images, since the market price of VHR images is generally higher. On this basis it seems that a cost-efficient use of samples of VHR images for land cover area estimation is limited to zones with difficult access, such as mountainous areas or regions where most private property has restricted access and the observation of points from the field boundaries is often impossible.

However it should be taken into account that the cost per point in LUCAS is low because the sample size is very large and the communication infrastructure is good, therefore the travelling time from one point to the next is short. Cost considerations will dramatically change if we consider a different geographic context or a less dense sample. For example ground observations in tropical rainforest or in Siberia are extremely expensive; in this case reaching a cost-efficiency threshold with samples of VHR images is much easier.

When we consider land cover change instead of land cover area, spatial correlation can be much lower and the equivalent number of points can be much higher. Unfortunately at the moment we do not have suitable fine-scale observations to assess the spatial correlation of land cover change. Rare land cover types may also have correlograms with specific behaviour. The "equivalent number of points" might be higher in more fragmented landscapes, such as agricultural landscapes in sub-Saharan Africa. This conjecture needs to be checked when suitable data are available.

The equivalent number of points seems to be slightly higher with stratified sampling, where the strata can be defined from a land cover map. However the improvement is not enough to modify the conclusions (Gallego and Stibig, 2013).

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