Crop Monitoring as an
E-agricultural tool in
Developing Countries

ACCURACY AND COST EFFICIENCY REPORT

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TABLE OF CONTENT

EXECUTIVE SUMMARY

Objective and timely information on crop acreages is an important component in crop production forecasting and plays a key role in decision support toward agricultural management and policy-making. Different approaches on the crop area assessment have been investigated, on the local, regional and national levels. The most classical way for estimating the agricultural areas is statistical survey. Using the modern geo-location instruments based on the GPS, such field survey can generate very accurate results, while the approach can become very costly. The information derived satellite imagery, on the other side, has been increasingly showed advantageous as the data costs for finer resolution image covering a large area become lower. However, the methods used for extracting area information from satellite imagery are highly parameterized, from where subjective elements can be possibly introduced. In this report, we analyse the possible approaches for assessing the crop acreage and its underlying accuracy and cost-efficiency.

1. Introduction

Objective and timely information on crop acreages is an important component in crop production forecasting and plays a key role in decision support toward agricultural management and policy-making. Hence, an operational crop acreage assessment would benefit agricultural and agri-environmental policy makers, institutions dealing with food security and food traders.

Obviously, operational crop acreage estimations are especially of interest in regions with a strong inter-annual variability. In Anhui province of China, one of our study regions, urbanization is taking place at the expense of agricultural land (Figure 1) and at the same time, the population with a fast growing economy demands an increasing crop production. Moreover, volatility on the agricultural commodity market and the biofuel demand are adding sources of instability on crop acreages issues.

Figure 1: One of examples of land-use change in the study area: the agricultural field has been transformed into expressway.

Traditionally, the crop area statistics are made using sampling and non-sampling methods. The non-sampling methods include census of farmers, visual enumeration by experts and other administrative sources. Sampling methods can be constituted by list frame sampling or area frame sampling. List sampling is based interviews providing information on series of agricultural data such as crop areas, yields, livestock or other agricultural policy and production variables. Area frame sampling is more accurate against errors such as, spatial overlapping and missing frames. Since the end of year 80', the earth observation approach has entered more and more into the stage of agricultural area estimation accompanying by increasingly lower cost and better quality of satellite imagery. However, the use of remote sensing information as the primary data input sources for crop area assessment appears to be not solid or not accurate enough from statistical point of view. The limitation for use remote sensing as unique variable for estimating the area lies on the possibilities of introducing biasedness during the satellite image classification process. This study tends to show that:

- In general, remote sensing information alone is not sufficient to generate accurate and unbiased crop area estimates.

- Remote sensing can be used as one of variables in estimation of agricultural areas to increase the accuracy of estimation and reduce at same time the costs of area frame sampling. Furthermore, the remote sensing provides also the information on other land uses, helps for ground sample design and stratification.

2. Sub-pixel classification of coarse resolution imagery for estimating crop acreage

2.1. Introduction of the method of sub-pixel classification

High resolution images (e.g. Landsat-OLI, SPOT-XS, RapidEye) acquired at key phenological stages are often used for producing detailed land cover maps and derived crop acreage estimates. However obtaining cloud free coverage of large areas at right periods of time may be a challenge due to the low revisiting frequency of these instruments. The study case of Mengcheng that we show in the next chapter demonstrated the impossibility to acquire a single cloud free image during a whole growth season.

Low or moderate resolution sensors such as SPOT-VEGETATION, TERRA-MODIS or NOAA-AVHRR provide consistent information on a high temporal resolution (short revisiting period). These data are usually freely available and few additional pre-processing steps are needed prior to their utilisation. However, for crop mapping purpose the spatial resolution of the pixels derived from these sensors is too coarse (250m to 1km).

The development of the sub-pixel classification approach is supposed to bridge the gap between sparse resolution and dominant field sizes. The sub-pixel approach deals with mixed pixels. It does not assign each pixel to a single pure class but rather gives account of the fractions of all (pure) classes (also called end members) that could be found in the pixel. The exact locations of these classes within the pixel remains however undetermined. Both linear as non-linear algorithms are used for this purpose. In this study neural networks (NN) with a Multi-Layer Perceptron with Back-Propagation (MLP-BP) approach was tested. The main advantage of using neural network approach is its capacity to be modelled in an operational context. Once the model is calibrated, the application of the model for crop area estimation would be straightforward. However, we will see from this study that the collection of reference data based on ground truthing or other reliable local crop maps derived from very high resolution imagery and its subsequent parameterisation, limit the potential of its operational use.

2.2. Data and method for sub-pixel analysis

As the coarse resolution imagery has a large scan swath (more than 2000 km), the test location is set to the whole North China Plain (Figure 2).

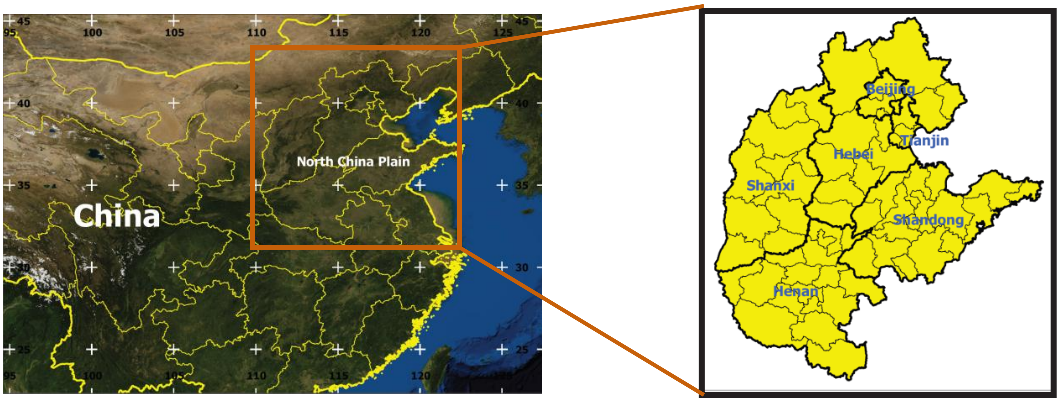

Figure 2: Location of the North China Plain (Hubei Plain).

The reference land-use data were derived from a classification of two LANDSAT TM images of 14 March and 17 May 2009 were classified (Figure 3), using the supervised Maximum Likelihood classifier. The overall accuracy of this mapping exercise was around 88%. The analyses allowed distinguishing 10 land cover or crop classes. These land-use / crop distribution data were used to train the neural network during the sub pixel classification analysis.

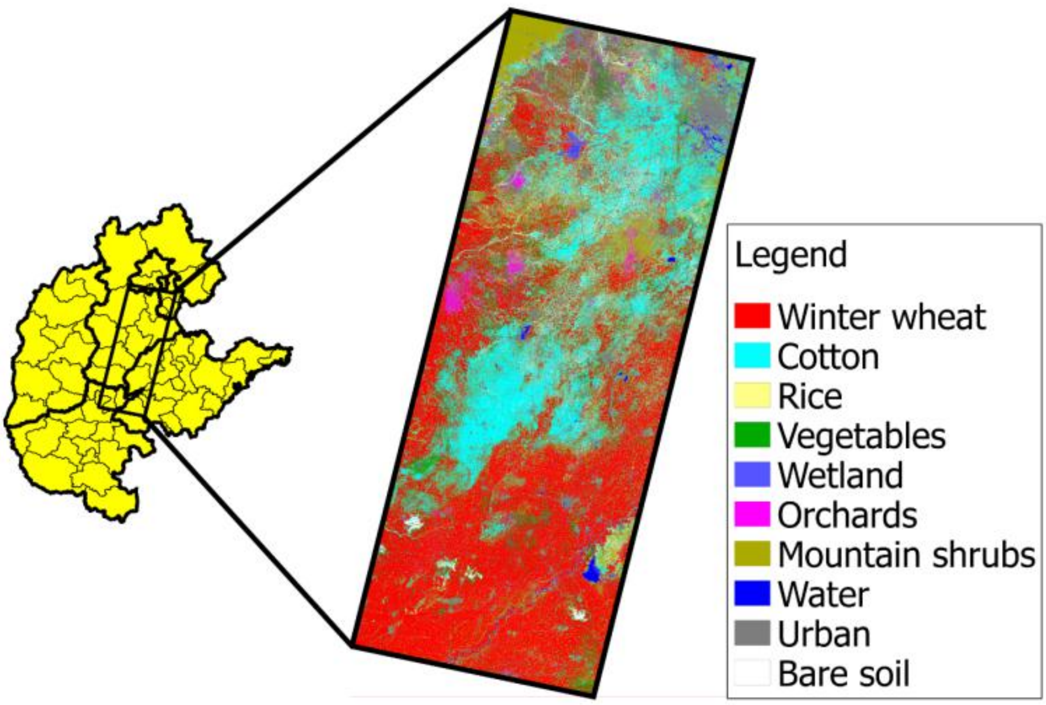

Figure: 3: The high resolution Landsat TM based land cover map in the North China Plain.

The neural network consists of a structure of multilayer perceptron with error back propagation (MLP-BP). In our case, an interconnected group of artificial neurons was structured in three layers: the input layer (11 nodes), one hidden layer (11 nodes) and an output layer (10 nodes).

As input coarse resolution imagery, Ten-day Maximum Value Composites of Normalized Difference Vegetation Index (NDVI) derived from SPOT-VEGETATION sensor was used. The input dataset was composed by 10 daily NDVI images for the period 11 February to 31 May for the years 2005-2010. The output layer are the area fractions of the various land-use or crop classes, one node for each class.

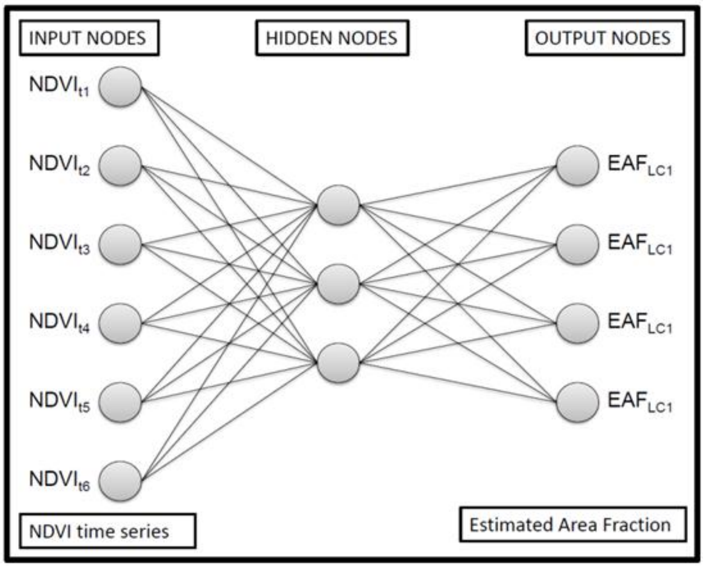

Figure 4: Example of a three-layered neural network used for sub-pixel classifications. NDVI time series are used as input. The output is estimated area fraction images.

2.3. Results of the sub-pixel classification

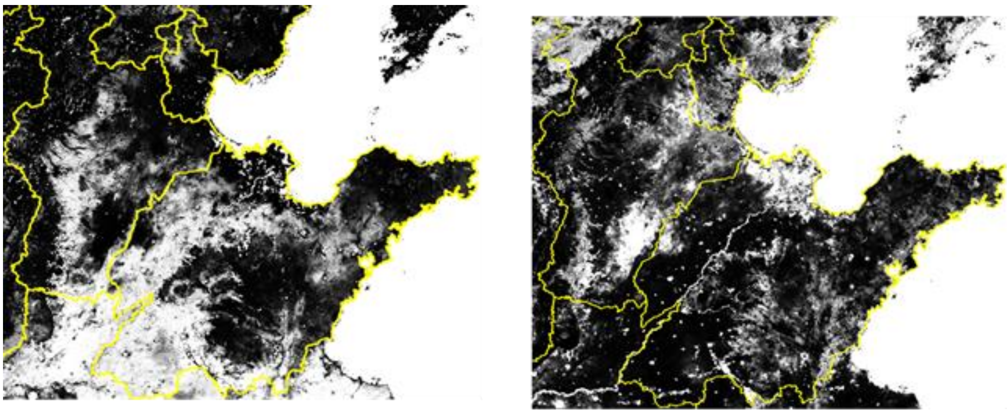

Figure 5: Estimated area fraction images (AFI's) for maize (left) and cotton (right).

Figure 5 shows the example of sub-pixel classification results with the Area Fraction Image for the classes of maize and cotton.

2.4. Accuracy of the sub-pixel classification

To analysis the accuracy of the sub-pixel classification, a scatter plot of the estimated area fractions versus the official statistics for the selected counties is shown in Figure 6.

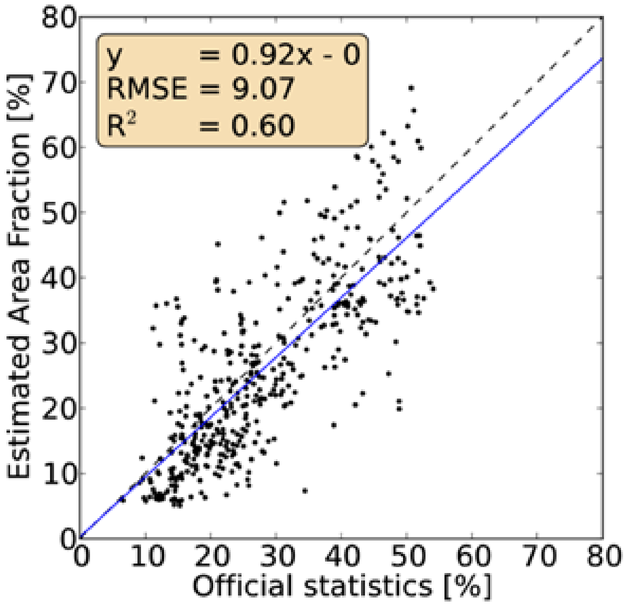

Figure 6: accuracy analysis of the estimated area fractions on county level with official statistics for the years 1999-2009. The dotted line is the 1:1 line, the blue line is the linear regression line.

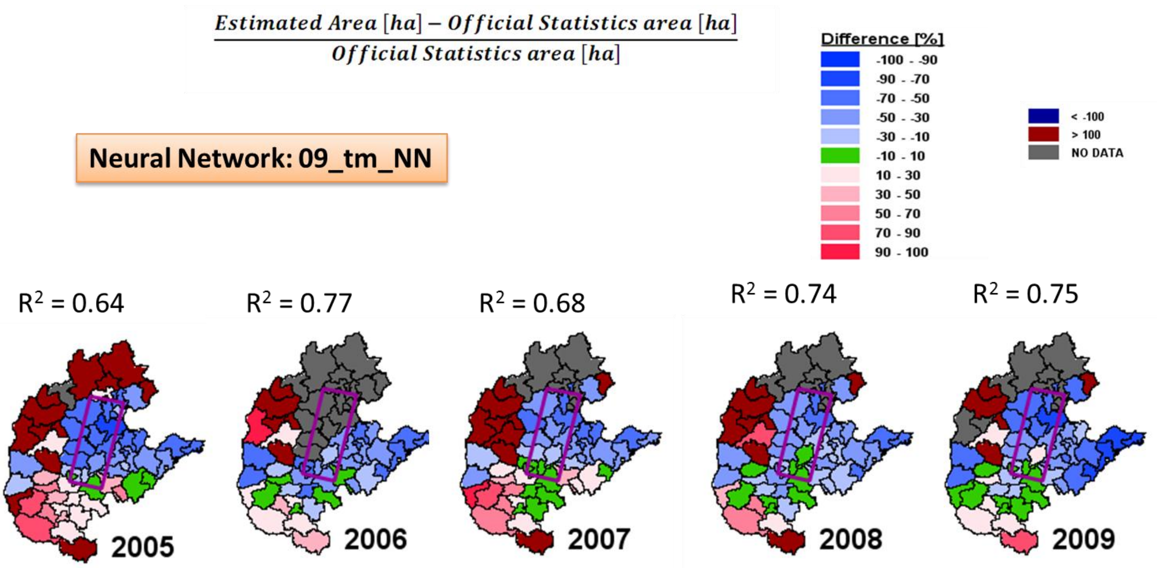

Figure 7: application of the neural network trained with 2009 reference data over other periods.

When the neural network calibrated using 2009 reference data is used to classify data from other years, the coefficient of correlation varies from 0.64 to 0.75.

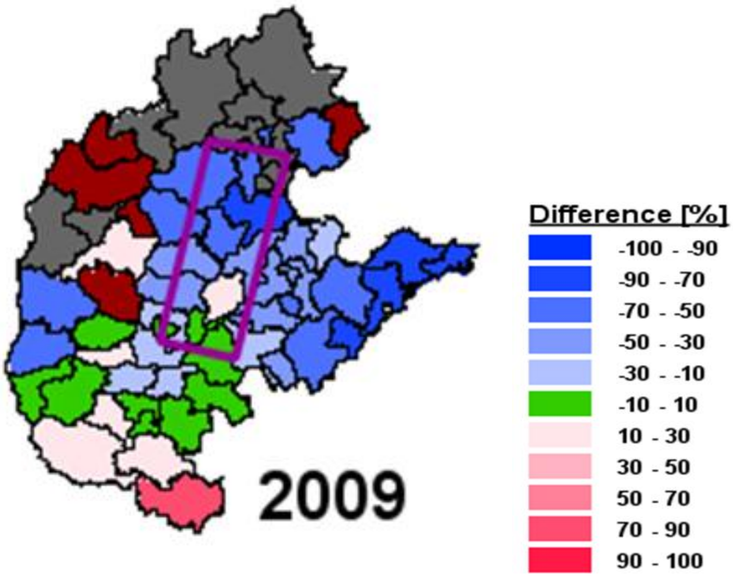

Figure 8: Relative difference between the estimated crop acreage versus the official statistics using the network calibrated

This investigation showed that sub-pixel classifications based on single TM-frame classifications are not appropriate to provide accurate and reliable crop area estimates. The poor performance can be partially explained by the differences in phenology, which seem determinant for the sub-pixel classification approach. The neural networks calibrated using one dataset (from one location) can poorly be applied to other areas. The approach is therefore not suitable for application on agricultural statistics although the costs for this application are very low.

3. Using high resolution imagery for deriving crop acreage estimates

3.1. Introduction of high resolution imagery for estimating crop acreage

Classical high-resolution imagery such as LANDSAT TM (30m resolution), followed by LANDSAT OLI, can produce spatial cropping details. However with a low temporal resolution (16 days for Landsat), these sensors produce image data with low ability to discriminate the crops based on phenology. As the coverage per scene of these sensors is also limited, crop mapping on large areas using high number of scenes is not a cost-efficient approach.

At the levels of county or district in China and commune or province in Morocco, the high-resolution imagery can provide relatively accurate crop area information. In this study, two cases of analyses for estimating crop area are demonstrated and their accuracy and cost efficiency are analysed.

3.2. Use of (very) high resolution for crop area statistics in Mengcheng County

Mengcheng is located in the north of Anhui province. The county has a representative landscape of the North China Plain, the main crop producing region in the country. The main cropping pattern in this county of 2150 km2 is winter wheat (harvested in May) followed by maize and soybean (harvested in October). According to the available official statistics, the maize area has grown from 55,000 ha in 2008 to 73,000 ha in 2010 while the soybean area has remained more stable around 32,000 ha (2009).

3.2.1. Data and method of analysis on high resolution imagery

From the beginning of satellite data collection, the short come of the use of high resolution data appeared. Because of cloud interference, the optical image acquisition was not possible during the whole growth season, even with the programing. At the end, two satellite images were obtained: a Spot 5-HRG acquired on 22 September 2011, close to the period of harvest for summer crops, and a Landsat 5 TM image acquired on 1st June 2011. Two resolutions were present for the Spot 5 image: the standard 10m multispectral image, and the 2.5m pan-sharpened image. Both images are geo-referenced. The images were classified with the maximum likelihood algorithm with no prior probability; 41 segments collected during the ground survey were used to train the classifier while the other 42 were used ulcerously for assessing the classification accuracy. For the classes “woodland”, “water bodies” and “artificial surfaces” that were nearly not present in the arable segments, polygons were selected by photo-interpretation of the Spot 2.5m image (taking care of the overall proportion of these land cover types for the validation data set). Three combinations of the 10m Spot and the TM5 images were tested: the Spot image alone, the Spot image combined with TM band 4, the two images together (7 bands).

3.2.2. Accuracy of classification for Mengcheng County

Different combinations of bands contained in the LANDSAT TM and SPOT 5 HRG were tested. The classification of the combination containing the 4 bands of SPOT 5 and the band 4 of TM (Figure 9) resulted in the highest overall accuracy (81%). The combination containing the 4 bands of SPOT 5 and all 3 bands of TM obtained an accuracy of 79.5%. The accuracy of the classification combining only the bands of SPOT 5 reached an accuracy of 75.5%. Table 1 shows the overall accuracies for three most accurate classification tests.

Table 1: Summarized validation accuracy results for all the classifications

Classification layers	SPOT 5: B1, B2, B3, SWIR TM: bands 3, 4, 5.	SPOT 5: B1, B2, B3, SWIR TM: band 4	SPOT 5: B1, B2, B3, SWIR
Maize	77.1	**79.3**	70.9
Soybean	72.6	**72.5**	71.1
Other crops	18.1	**23.1**	29.6
Overall accuracy /Kappa	79.5 / 0.65	**81.0 / 0.68**	75.5 / 0.61

Table 2: Confusion matrix (expressed in % of the number of pixels of a given land-use or crop class) for the Spot + TM band 4 image, derived from the 42 validation segments

Class	Maize	Other crops	Soybean	Woodland	Water bodies	Artificial	Total (% classified pixels)
Maize	79.3	31.2	24.4	1.9	0	0.1	57.9
Other crops	3.3	23.1	2.5	1.9	0	0.1	3.3
soybean	16.9	41.9	72.5	0.7	0	0.3	22.6
Woodland	0.1	0	0	95.5	0	0	9.2
Water bodies	0	0	0	0	96.5	0	0.6
Artificial	0.4	3.8	0.7	0	3.5	99.5	6.5
Total (%)	100	100	100	100	100	100	100

Table 2 displays the confusion matrix for the combination resulted in the highest producer accuracy for maize and soybean, with 79.3% and 72.5% of the maize and soybean pixels respectively being correctly identified. Confusions between summer crops appear to be relatively high with 20% of the maize pixels assigned to other summer crops, mainly soybean; 27% of soybean pixels assigned to maize and other crops and 73% of other crops pixels classified as maize and soybean. The classifier underestimated the majority class (maize) and overestimated the minority ones (e.g. soybean); this could be partly corrected through the use of prior probabilities (e.g. using crop statistics from the previous year); in such a case however, the opposite bias (overestimation of large classes, underestimation of small ones) is obtained.

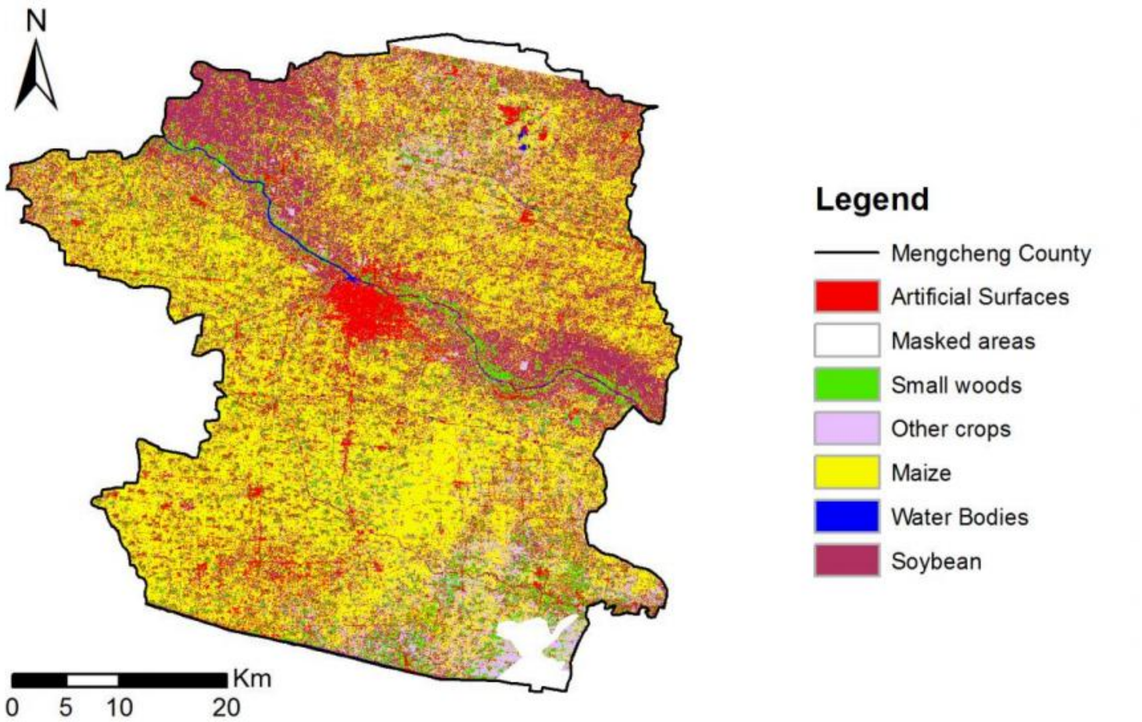

Figure 9: Classification of Spot5 + TM band 4 image. The masked areas correspond to the missing data due to the image edge (north) or cloud (south east)

This study showed that the classification of high resolution images, can achievement accuracy of 75 to 80% for dominant crops. The results correlate very well with other studies carried out in Europe in the framework of MARS programme. Image classifications of LANDSAT TM or SPOT -4 XS in Europe had produced an accuracy of 70% to 80% when the region is not too complex and the classification legend is not too detailed, for example containing only 4-6 dominant crops. When the study regions become large or heterogeneous, the accuracies will be lowered to 50-60 percent.

In the arid regions, where the vegetation is sparse, the climate variation is important, the analysis of the high resolution image can achieve a rather high accuracy compared to the temperate and humid regions.

From cost point of view, the very high resolution (pixel resolution from 1-5 meters) images' costs remain relatively high approximately from 1 to 5 EUR per square km. However, the availability of other high resolution images such as new LANDSAT OLI (freely downloadable), although with a coarsest space resolution (30 m), will push definitively the data costs downwards.

4. Combing field sampling and remote sensing analysis: regression estimator

4.1. Introduction of regression estimator

We have seen in the previous stages of our research, the accuracy of image classifications, are usually described by a confusion matrix. The key parameters, such as user and producer accuracy, can be computed from the confusion matrix. In favorable conditions, such as a homogenous land-use pattern with a few dominant vegetation types, the overall accuracy can reach 80 even 90%. In the case where the maximum likely hood classified is applied, such as in this study, with uniform a priori probability, large classes tend ti be underestimated and the small classes tend to be overestimated.

We demonstrated here that combining the remote sensing information with area frame sampling approach, the assessment of crop area can be carried out in a cost efficient with a pre-determinate accuracy. Before the sampling stage, the remote sensing can help to design an efficient and low-cost stratification approach, from which a stratum of agricultural land can be identified. The relative efficiency of stratification is the ration between the variance that would have been obtained without stratification and the estimated stratifies variance. The efficiency depends strongly on the complexity of land-use pattern. In the European Union, the efficiency is generally low; while in the northern China some cropping pattern is largely dominant, the winter wheat is the only crop during the winter season followed by maize or soybean in summer.

Furthermore, regression estimator approach integrates the classified satellite images as auxiliary information to improve the accuracy of the estimates from ground sampling.

4.2. Data and method of regression estimator for crop area estimation

The field data were collected in the county of Mengcheng in the summer 2011. The remotes sensing image from GoogleEarth were used to perform the stratification. Other satellite imagery included Landsat TM registered on 1st June 2011 at 30m resolution and with coverage of 180km x 180 km. Three spectral bands (RED, NIR, and SWIR1) out of seven produced by the TM sensor were used. Two resolutions of a same SPOT5 registration are provided:

- 2.5m resolution resulting from a merging of two 5m panchromatic band and 10m multi-spectral resolution at level 3 (ortho-rectified)

- Original 10m multi-spectral image (4 bands) in level 1A.

Stratification was performed with five strata:

- Agriculture (arable land)
- Non agriculture (urban, artificial, water)
- Permanent vegetation (orchard, poplars)
- “thematic” doubt (doubt between arable and non-arable land)
- “geometric” doubt (point falling on arable/non arable border)

All 235 grid points are assigned to one of 5 strata listed above.

83 of grid points belonging to the stratum “arable land” in two grids are randomly selected and further surveyed. Each point was attributed with a percentage of crops by surveying the field where the point is located.

The regression estimator improves the accuracy of area estimates by adjusting the estimate of mean $\bar{y}$ and reducing the variance. In other words, the introduction of the remote sensing information (here the use of image classification) as an auxiliary variable enabled to reduce the amount of ground samples to be collected if the accuracy of estimation is a constant. On the other hand if the ground sample size is a constant, introduction of remote sensing allows improvement of estimation accuracy.

In this study:

$$\bar{y}_{reg} = \bar{y} + b\left(\bar{p}_{pop} - \bar{p}\right) \quad (1)$$

where $\bar{y}_{reg}$ is the regression estimate for a target crop area mean; $\bar{y}$ the crop area mean derived from ground survey; $\bar{p}_{pop}$ is the proportion of pixels classified as the target crop in the arable land stratum of the county; $\bar{p}$ is the average proportion of pixel classified as the target crop in the surveyed segments (in the arable land stratum). b is the slope of the regression p (crop proportion in the segment according to ground survey) and y (crop proportion in the segments according to the image classification).

For large random samples (n>50), the variance of the regression estimator can be approximated by:

$$\mathrm{var}\left(\bar{y}_{reg}\right) = \mathrm{var}(\bar{y})\left(1 - R^2_{py}\right) = \frac{1}{n}\mathrm{var}(y)\left(1 - R^2_{py}\right) \quad (2)$$

where R^2_{py} is the coefficient of determination for the regression.

4.3. Results of regression estimator

Stratification led to the assignment of 93 points among 132/in total (**73%**) to the stratum "arable land". 83 agricultural point frame are surveyed. The results of survey are summarized in the Table 3.

Table 3: statistics from 83 surveyed point frames

	Maize	Soybean	Other crops	Non agriculture
Average (%)	76.8%	19.8%	3.0%	0.4%
Standard deviation (%)	2.7%	2.5%	1.3%	0.2%
Total Area (ha)	242.08	61.02	9.53	0.83
Average segment Size (ha)	**3.78**			

According to the **image classification** results discussed above, only the most accurate classification output was used for regression estimator analysis (Table 4).

Table 4: ratio and area of each class derived from the most accurate classification

	Classification based on SPOT 5: B1, B2, B3, SWIR and TM band 4	
	%	Ha
Maize	45.4	97,56
Soy-bean	28.7	61,66
Other crops	7.5	16,16
Woodland	9.1	19,49
Artificial	8.7	18,67
Water body	0.6	1,34
Total	100	214,88

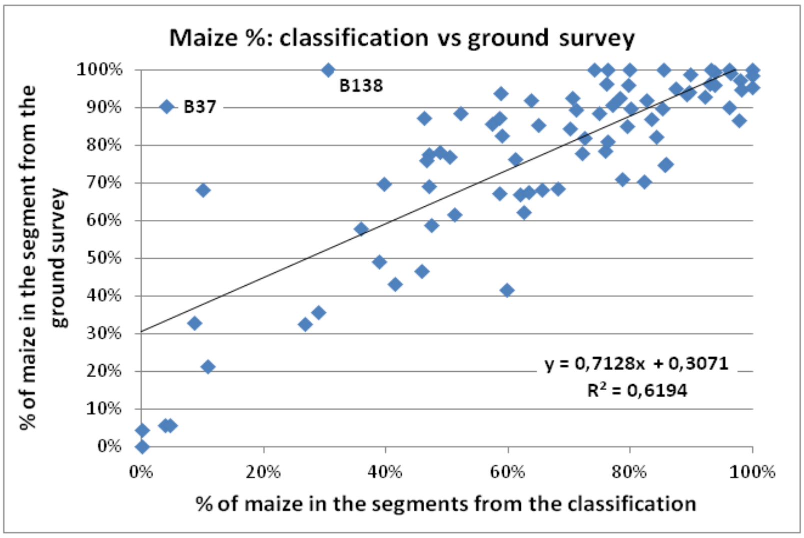

Figure 10: regression of the maize proportion derived from 83 surveyed segments against that derived from the classification for the same segments

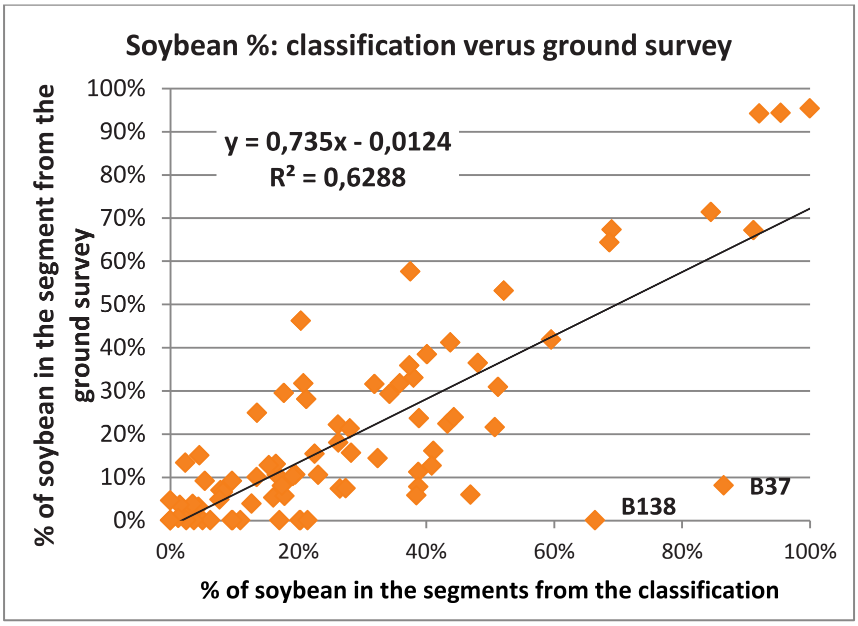

Figure11: regression of the soybean percentage derived from the ground survey against the same percentage derived from the classification for the 83 segments.

Figures 10 and 11 illustrate the regressions between the percentage of crop derived from the point frame survey and from the image classification for the 83 visited segments.

Table 5: crop area proportions derived from ground survey, from image classification and from the regression estimator

	Maize	Soybean	Other crops
Area mean from ground survey (83 segments) and (SD)	76.8% (2.7%)	19.8% (2.5%)	3.0% (1.3%)
Regression slope (b) and coefficient of determination (R^2_{py})	0.71 (0.62)	0.74 (0.63)	0.56 (0.50)
Area mean from image classification in terms of arable land points	59.0%	28.6%	7.9%
Area mean within the 83 (arable) segments	64.7%	28.6%	5.5%
Regression estimator and (SD) in the arable stratum	72.8% (1.7%)	19.8% (1.5%)	4.4% (0.9%)
Relative efficiency of RS & equivalent sampling size	2.6 218	2.7 223	2.0 167
Number of ha in the county (assuming 157057 ha arable area)	114,287 ha (2,602 ha)	31,067 ha (2,418 ha)	6,882 ha (1,398 ha)

The estimation of the crop areas according to the regression estimator approach was carried out using the equation (1) described above. Table 4 summarises the proportions of maize, soybean and other crops in the arable land stratum as derived from the ground survey, from remote sensing (image classification) and from the combination of the ground survey and remote sensing analysis through the regression estimator. Following the regression estimator, the area proportions of maize and soybean are respectively 76.8% and 19.8% within the arable land stratum (157,075 hectares), or 114,287 hectares and 31,067 hectares respectively. The cost efficiency will be discussed in the next section.

5. Cost efficiency of remote sensing

The relative efficiency of integrating remote sensing constitutes a criteria of cost-efficiency for economic evaluation of the approach. It is a concept based on the ration of estimator's variances and defined as:

$$\text{relative efficiency } \eta_{\text{reg}} = \frac{\textit{Variance of Ground survey}}{\textit{Variance of ground survey corrected with remote bsensing}}$$

An efficiency value of 2 means that the accuracy obtained from sampling 100 segments corrected with remote sensing will be equivalent to the accuracy obtained from sampling 200 segments. In other words, introduction of remote sensing information can reduce the sample size by 2 in this case and the integration of remote sensing will be cost efficient if its costs are less than the costs for surveying 100 segments. In other case where we keep the sample size unchanged (200 segments are surveyed), the variance of the estimation will divided by 2 when the information of remote sensing is integrated.

More generally speaking, the application of regression estimator will be cost efficient if for a pre-fixed variance (thus accuracy), the costs of surveying supplementary segments are higher than the total costs for image acquisition and analysis. Mathematically, this cost-efficiency is established when:

$$(n_1 - n).p > R \qquad (3)$$

Where n is the original sample size, p is the unitary variable cost (cost for adding/surveying one supplementary sample), n_1 is the required sample size to reach the expected accuracy of the regression estimation. R is the remote sensing cost.

When sample size is large enough, we see from the equation (2) that the variance for regression estimator can be approximated by:

$$Var(\bar{y}_{reg}) = \frac{S^2}{n}(1-\rho^2) \qquad (4)$$

Where S^2 is the population variance and S^2/n_1 is the variance of direct survey expansion estimator, ρ is the coefficient of correlation between Y (ground survey measurement) and X (remote sensing measurement).

When n_1 is the sample size that allows the survey estimate to reach the same accuracy of regression estimate, the variance of the direct expansion (of survey) estimators becomes

$$\frac{S^2}{n_1} = \frac{S^2}{n}(1-\rho^2) \qquad (5)$$

Thus,

$$n_1 = n\frac{1}{(1-\rho^2)} \tag{6}$$

Where $\frac{1}{1-\rho^2}$ equals the ration between the variance of the ground survey area estimate and the variance after this estimate has been corrected by satellite image analysis, what we named relative efficiency of regression estimator **η_{reg}** in the beginning of the section.
A substitution between the formulas (6) and (3) leads to:

$$\eta_{reg} > 1+\frac{R}{np} \tag{7}$$

Therefore, 1+*R/np* is the threshold value for cost effectiveness of the use of remote sensing as an auxiliary variable in the regression estimator.

Usually the cost-efficiency of including remote sensing information is higher when field are large and the dominant crop species are few.

In our study case of maize area estimation, the ρ^2 is about 0.6, and the η_{reg} is about 2.6.

Given that:

- Unitary cost for surveying an additional sample are about 75 EUR
- 135-140 additional samples are needed to reach the variance of regression estimator (see Table 5)
- The price for SPOT high resolution imagery (60*60km) is about 3500 EUR (resolution10m)

We can conclude that the use of SPOT imagery is cost efficient for crop mapping at county level (2000 km^2) if the imagery of SPOT 5 10 m resolution is sufficient. The cost efficiency will be greatly raised when the availability of high resolution imagery becomes costs free such as the case with Sentinel 2 imagery (290 km swath and 10m to 20m resolution)

6. Conclusions

Remote sensing is a very valuable tool for estimation the land-use areas. However the direct use of satellite imagery to produce the agricultural or environmental statistics is subject to many debates. A straightforward application of image classification, essentially a pixel counting process including sub pixel classification, while considering the ground data as a secondary role, produces results inaccurate enough for agricultural statistics application. The risk is high that the final estimates contain much of *a-priori* knowledge of analysts. This pixel counting approach should only be used when there is no reasonable alternative available such as in regions where no or few ground truth data can be collected. In this study, the sub-pixel analysis can only produce an overall accuracy about 50 to 60% while the maximum likelihood classification on high resolution imagery led to an area estimation with an accuracy (for two main crops) between 70 and 80%.

Combining the exhaustive but sometimes inaccurate information from remote sensing with accurate information from area frame sampling is the most reliable way for application of remote sensing in crop area assessment. In our study the relative efficiency of integrating remote sensing data reached a value of 2.6.

The cost-effectiveness of integrating satellite information had been for a long time a debated issue, especially in years nineties. It depends on many parameters but essentially on the costs related to the acquisition of high resolution imagery. However with the improvement of computing infrastructure and the automation of analysis process, particularly with the drastic drop of the costs for high resolution image acquisition, the approach integrating the remote sensing information becomes more than ever costs-effective.