
APPLICATION OF SATELLITE OPTICAL AND SAR IMAGES FOR CROP MAPPING AND AREA ESTIMATION IN UKRAINE

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Abstract: *Crop area estimation is a key element in crop production forecasting and estimation. Satellite imagery can provide valuable information for stratification purposes and can be used as a source of proxy variables for a-posteriori correction of area estimates. In this regard, efficiency of crop area estimation using satellite imagery depends on the accuracy of crop classification. In this paper, we apply optical and SAR satellite imagery for discriminating major crop types in Ukraine. First, we compare efficiency of several optical image types (MODIS, Landsat TM, AWiFS, LISS-III and RapidEye) combined with a field survey on a stratified sample of square segments. Additionally, field data were collected "along the road" as training data for image classification algorithms. The results show particular difficulties in discriminating summer crops in Ukraine such as maize, soy beans, sunflower, sugar beet, using only optical satellite images. Therefore, we incorporate satellite SAR images (RADARSAT-2 quad-polarization) in order to improve discrimination between summer crops. Obtained results show that omission and commission classification errors can be reduced by adding radar imagery to optical ones.*

Keywords: *remote sensing, agriculture, statistics, estimation.*

ACM Classification Keywords: *I.4.8 [Image Processing and Computer Vision] Scene Analysis - Sensor Fusion.*

Introduction

The knowledge of the crop area is a key element for the estimation of the total crop production of a country and therefore the management of agricultural commodities markets. Ukraine is one of the most developed agriculture countries and one of the biggest crop producers in the world. According to the 2011 statistics provided by the U.S. Department of Agriculture (USDA) Foreign Agricultural Service (FAS), Ukraine was the 8th largest exporter and 10th largest producer of wheat in the world. In past decades, the use of satellite remote sensing data for crop area estimation has been assessed in many studies that have identified which methods are statistically consistent [Gallego, 2004; Carfagna and Gallego, 2005; Gallego et al, 2008; Haack and Rafté, 2010]. In the period 1988-1998 the methods studied by the MARS Project for crop area estimation tested the use of images for stratification, as a source of proxy variables for a-posteriori correction of area estimates and for the production of field documents. At that time the cost-efficiency threshold was not reached in Europe [Taylor et al, 1997]. In the US cost-efficiency of remote sensing was not reached in the 80's [Allen, 1990], but was achieved in the 90's [Hanuschak et al, 2001]. The US program is the largest operational application on agricultural statistics [Johnson, 2008; Boryan et al, 2008]. Considering Ukraine, no similar studies have ever been conducted previously on a large scale basis.

In this paper we discuss results of a pilot study conducted by Ukrainian Space Research Institute of NASU-NSAU, in collaboration with the MARS team of the JRC, to explore the feasibility, cost-efficiency and specific

difficulties of crop area estimation assisted by optical satellite remote sensing in Ukraine. Efficiency of applying SAR satellite imagery to discriminate between summer crops in Ukraine is explored as well.

Description of the study area

The study covered three administrative regions (oblasts): Kyivska, Khmel'nitska and Zhytomyrska, for a total geographic area of 78,500 sq. km with 2.5 Million ha of cropland. The proportion of different land cover types significantly changes across the study area: the Northern part of Kyivska and a half of Zhytomyrska oblasts contain more than 30% forest area. The central part is densely populated. Khmel'nitska oblast is relatively uniform in crop land percentage except for the small Northern part. None of the oblasts has a strongly dominant crop. Field size generally ranges between 50 and 150 ha, land cover classes are quite heterogeneous (including crop, forests, grassland, rivers, lakes and wetlands). A large part of the area (approximately 10-15%) is occupied by small private farms, and the so called family gardens which represent mixed cultivations at small scale mainly for self consumption. These farms are primarily responsible in Ukraine for potatoes and vegetables production (about 90% of total production).

For exploring capabilities of satellite SAR imagery to discriminate summer crops in Ukraine, a test site of the Vasylkiv district in the Kyivska oblast was selected. The test site incorporates all major summer crops (maize, soy beans, sunflower, sugar beet), and has total area of about 1,200 sq. km.

Data Description

Satellite and in-situ data for the study were collected during 2010-2012 years within two international projects: JRC contract "Crop area estimation with satellite images in Ukraine" within GEOLAND2 project and GEO JECAM project for Ukrainian JECAM site [Kussul et al, 2012; Gallego et al, 2012].

Ground surveys. Two extensive field campaigns in July 2010 and August 2012 were carried out to collect ground data. Ground observations from 2010 were used to compare efficiency of several optical image types for crop identification and crop area estimation. Ground observations from 2012 were used to assess efficiency of using SAR satellite imagery to improve discrimination between summer crops.

Two types of field surveys were run in 2010 (Fig. 1). The first set of ground observations was collected along roads distributed in the whole study area, but not following a proper sampling scheme. This data set comprised nearly 2400 crop fields or other land cover patches and was used to train the image classifiers. The second field data set was a stratified area frame sample (AFS) of 90 segments of 4 km x 4 km (18 of them reduced to 2 km x 2 km) used for validation and regression estimators. The following three strata were defined: 1st stratum — agricultural land (percentage of cultivated area more than 50%); 2nd stratum — semi-agricultural land (percentage of cultivated area more than 0% and less than 50%); 3rd stratum — non-agricultural land (percentage of cultivated area is equal to 0%).

In 2012, only along roads surveys were carried out to collect data on different crop types. In total, data on 271 fields were collected. The following crop types were present: maize, soy beans, sunflower, sugar beet, harvested winter and spring crops, and minor crops like buckwheat.

A specific difficulty for the field survey was the impossibility to have access to aerial orthophotos. Landsat-TM images were used as a graphic support for the survey. Such images were suitable for the very large fields, but not for the approximately 20% of the area that has been split into extremely small fields that could not be individually reported and represents a major challenge for the operational use of AFS and remote sensing.

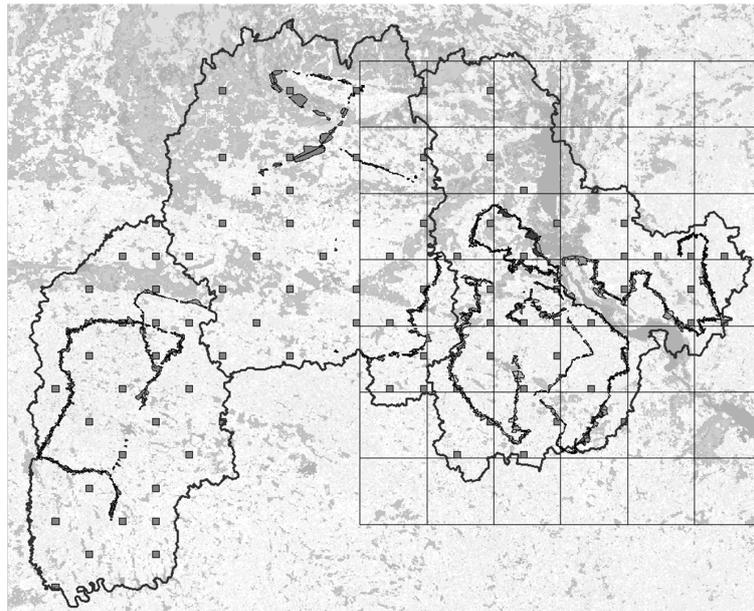


Figure 1. Distribution of the ground surveys data. Shown in the figure are boundaries of the oblasts, AFS segments (squares), along the road field data (curves), along the road grid for Kyivska oblast.

Satellite images. Satellite images used in the study were as follows:

- Moderate-resolution Imaging Spectroradiometer (MODIS) on board Terra and Aqua satellites – orthorectified MODIS Normalized Difference Vegetation Index (NDVI) images that are temporally aggregated to a decade period at the 250 m resolution;
- Advanced Wide Field Sensor Satellites (AWiFS) onboard IRS-P6 (ResourceSat-1) satellite – images were acquired on 2010-06-05, 2010-06-28, and 2010-08-15;
- Linear Imaging Self-Scanning Sensor - 3 (LISS-III) onboard IRS-P6 (ResourceSat-1) satellite – images were acquired on 2010-08-11 and 2010-09-04 and covered southern part of Kyivska oblast;
- Multi-spectral push broom imager onboard RapidEye satellites – images were acquired within two time windows in April and June: 25 and 30 April 2010, and 5 and 6 June 2010;
- Thematic Mapper (TM) onboard Landsat5 satellite – 75 images were acquired from April to September 2010 with the path/row coordinates ranging from 180/025 to 184/026. The images were further temporally aggregated for each oblast: Kyivska (2010-04-10, 2010-06-15, 2010-08-01), Khmel'nitska (2010-06-18, 2010-07-20, 2010-08-21, 2010-09-13), Zhytomyrska (2010-05-01, 2010-06-18, 2010-07-20, 2010-08-21, 2010-09-13);
- RADARSAT-2 quad-polarization – image was acquired on 27 July 2012;
- Advanced Land Imager (ALI) onboard EO-1 satellite – image was acquired on 28 July 2012.

Methodology

Optical satellite data classification and crop area estimation. Classification of optical satellite imagery for 2010 was done using per-pixel approach. Several classification algorithms were tested [Shelestov et al, 2006; Kussul et al, 2009; Kussul et al, 2010; Hluchy et al, 2010]: neural networks (MLP: Multi-layer perceptron), support vector machine (SVM) and decision trees (CART). The best results were obtained with MLP classifiers and TM images.

In order to further improve estimators computed from a ground survey a regression estimator that utilizes classified satellite images was applied. For each segment i of the sample we know y_i proportion of land use c in ground survey. We assume now that the auxiliary variable x_i is known for the whole population on segments; x_i is most often the proportion of pixels classified into c , although other choices are possible. For example if y_i is the proportion of winter wheat in the ground survey, x_i may be the proportion of pixels classified as winter cereals, if we were not able to discriminate different winter cereals in the image classification, or some arithmetic index computed from radiometric values, if we found a good correlation for that particular landscape.

We call μ_y (μ_x) the population mean of $Y(X)$ and \bar{y} (\bar{x}) the sample mean. Regression estimators of the mean μ_y of Y can be written as:

$$\hat{y}_{reg} = \bar{y} + b(\mu_x - \bar{x}) \quad (1)$$

where b is a least squares estimate on a sample.

Under the hypothesis of a linear model $y = \alpha + \beta x + \varepsilon$, the variance can be written [Cochran, 1977]:

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

where $G_x = \frac{k_{3x}}{\sigma_x^3}$ is the relative skewness.

The ratio between the variance of the ground survey area estimate and the variance after correction with the aid of satellite images using Eq. (1) is named the relative efficiency of the regression estimator:

$$rel\ eff = \frac{V(\hat{y}_{sample})}{V(\hat{y}_{reg})} \quad (3)$$

where $V(\hat{y}_{sample})$ is the variance of area estimates using ground samples only.

An efficiency of 2 means that the same precision would have been obtained multiplying by 2 the number of segments in the sample and not using remote sensing data. Therefore, relative efficiency is the main tool to assess if remote sensing has been economical. However, it must be taken into account that remote sensing provides more than an improvement of the statistical precision, since information on the location of the crops, or other land uses, is given.

SAR satellite data classification. Unlike the previous per-pixel classification approach for optical imagery, SAR images were classified using per-field classification [Kravchenko et al, 2008; Shelestov and Kussul, 2008; Skakun et al, 2007; Kussul et al, 2005]. Many previous studies have shown that efficiency of SAR classification can be improved using per-field approach due to the presence of speckle at the pixel level [Blaes et al, 2005]. For each field, a median value of backscatter coefficient was estimated for each polarization (VV, VH, HV, and HH), and was used as an input to classification algorithm. Classification was done using the SVM classifier.

Obtained Results and Discussion

Crop identification and crop area estimation using optical satellite images. In almost all cases MLP outperformed SVM and decision tree on test data showing better generalization ability (Table 1). Decision tree showed best results on training data comparing to MLP and SVM but failed to produce better results on test data that were not used for training and were not spatially correlated with training data. This confirms to theoretical investigations in

which it is shown that MLP represents a universal approximator, i.e. any piecewise continuous function could be approximated using MLP, while decision tree classifier has disadvantage of overfitting on training datasets having, thus, lower generalization ability comparing to MLP and SVM. The MLP classifier on Landsat-5 data showed slightly better results comparing to other satellite data in terms of classification accuracy for test datasets (up to 63%, see Table 2). As to analysis of confusion matrices by classes, all satellite data showed similar results (with commission and omission error of approximately 35-40%) for winter crops. Better results (30% and 20% of commission and omission errors respectively) were achieved for summer crops. For all satellite data, the classifiers were unable to discriminate spring crops. This is due to the time period when the satellite images were acquired and a cloud cover. Due to technical problems AWiFS and LISS-III satellite provider did not serve certain time periods which resulted in not optimal dates for crops identification. Fig. 2 shows results of classification of Landsat-5 data for Kyivska oblast using MLP.

Table 1. Comparison of overall classification accuracy (in %) of MLP for MODIS, Landsat-5 and AWiFS satellite data (TR = training datasets; TT = testing datasets)

Oblast	MODIS		Landsat-5		AWiFS		RapidEye		LISS-III	
	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT
Kyivska (K)	74.7	57.6	71.3	62.8	72.2	54.6	64.9	52.6	66.3	49.3
Khmelnitska (KH)	65.1	40.1	68.6	40.7	62.0	36.2	-	-	-	-
Zhytomyrska (ZH)	75.9	55.0	82.4	55.3	85.2	60.2	-	-	-	-

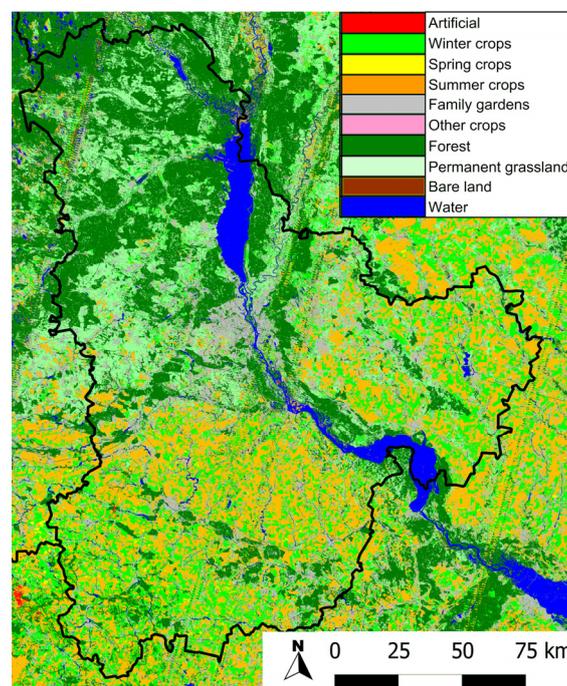


Figure 2. Results of classification of Landsat-5 data for Kyivska oblast using multilayer perceptron (MLP).

A regression estimator with satellite classification data as a co-variate (Eq. 1) was used to improve area estimation. Table 3 shows relative efficiency (Eq. 3) of using satellite data for area estimation for major crops: wheat, barley, maize and soybeans. Mean relative efficient for major crops was 1.59 for MODIS data, 1.54 for

Landsat-5 data, and 1.49 for AWiFS data. The obtained final area estimates were compared to official statistics provided by the State Committee of Statistics of Ukraine for 2010. In almost all cases, our estimates corresponded to official statistics lying within the $\pm 2\sigma$ range of the standard errors. The exceptions were potato, vegetable and sugar beet. The reason is that potato and vegetable in the selected oblasts are mainly produced by small farms and family gardens, and fields with sugar beet are mainly located near sugar mills. For these crop types a special stratification scheme is required in order to account for such geographical distribution.

Table 2. Comparison of classification accuracy by classes of MLP for MODIS, Landsat-5 and AWiFS satellite data (where UA and PA are the user's and producer's accuracies respectively)

	Class	MODIS		L-5		AWiFS		RapidEye		LISS-III	
		UA,%	PA,%	UA,%	PA,%	UA,%	PA,%	UA,%	PA,%	UA,%	PA,%
1	Artificial	0.0	0	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	Winter crops	59.7	60.8	54.5	64.9	58.7	59.0	40.6	37.6	60.4	66.8
3	Spring crops	23.3	6.3	19.7	4.8	0.0	0.0	5.5	12.5	0	0
4	Summer crops	68.2	82.5	68.9	87.6	79.2	74.8	68.8	74.1	67.9	63.2
5	Family gardens	32.0	79.1	51.9	50.2	29.2	79.5	48.8	55.2	21.4	70.5
6	Other crops	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	Forest	78.7	83.5	77.5	86.1	76.8	81.3	83.1	70.0	91.8	74
8	Permanent grassland	49.2	12.7	58.3	56.3	54.2	25.5	43.1	46.0	0	0
9	Bare land	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	Water	71.6	29.1	73.2	42.1	73.6	28.0	49.7	39.0	83.8	37.2

Table 3. Relative efficiency of the regressions estimator for MODIS, Landsat-5 and AWiFS satellite data for stratum 1

Crop\Oblast	MODIS			Landsat-5			AWiFS		
	K	ZH	KH	K	ZH	KH	K	ZH	KH
Winter wheat	1.44	2.66	1.13	1.90	3.74	1.39	1.31	3.08	1.48
Spring barley	1.05	1.00	1.00	1.23	1.00	1.00	1.00	1.48	1.00
Maize	1.35	1.27	4.19	1.38	1.73	1.37	1.53	2.32	1.28
Soybeans	1.23	1.68	1.03	1.45	1.22	1.05	1.18	1.27	1.00

A cost-efficiency analysis of using satellite data for crop area estimation in Ukraine showed free MODIS and Landsat-5 to be the most cost-efficient allowing us to reduce costs of ground surveys up to 37% (or 1.59 times). The AWiFS, RapidEye and LISS-III satellite data were not cost-efficient due to their high price. AWiFS will become cost-efficient when its price will be reduced by more than 20%.

Summer crop identification using optical and SAR satellite images. Collected ground data were used for preliminary analysis of the discriminating power of optical, SAR and a combination of them both by visual

interpretation and supervised classification. In contrast to optical images visual interpretation of SAR images allows distinguishing maize, soy beans and combined sunflower & sugar beet crops due to different canopy architecture and different scattering processes. Sugar beet and sunflower could not be discriminated.

Numerical analysis was performed using a Support Vector Machine (SVM) classifier. Classification accuracies, commission and omission errors were estimated using a five-fold cross-validation procedure. Special care has been taken to prevent over-fitting of cross-validation procedure due to spatial correlation in collected data. Three different data sets were examined: combined EO-1 and RADARSAT-2, EO-1 only and RADARSAT-2 only data. Total accuracies appear similar in all datasets because they are heavily influenced by winter and spring crop class that is classified equally well by optical and SAR data. The difference between datasets lies in per crop classification errors. All summer crops are better classified using SAR data rather than optical data. The most profound effect is observed on soy beans that is the second major summer crop after maize in the given area. Using SAR data instead of optical allows decreasing omission error for soybeans from 34% to 13% while maintaining similar level of commission error. Combined dataset shows gradual decrease of errors for most crops 5% to 10%. Combined sunflower and sugar beet class is the most beneficial as combined data allows decreasing classification errors in 1.5-2 times in comparison with optical or SAR data alone. This result is explained by complementary roles of SAR and optical data for discriminating sunflower at flowering phenological stages.

Conclusions

In the paper we described the results of the EC-JRC project on "Crop area estimation with satellite images in Ukraine" carried out by Ukrainian Space Research Institute of NASU-NSAU, in collaboration with the MARS team of the JRC. The best results were obtained with MLP classifiers and TM images that demonstrated to give a cost-efficient contribution to the improvement of the estimators. MODIS images also demonstrated to be cost-efficient. This study provided useful insights in the framework of Geoland2-Crop CIS and updates the conclusions of the MARS project in the mid 90's: at that time the approach had proved to be technically solid, but did not reach the cost-efficiency threshold with the costs of 15 years ago.

The study also showed particular difficulties in discriminating summer crops using satellite optical images. This was due to cloud cover, not optimal dates of satellite image acquisition and inherent limits of optical data. Therefore, feasibility of satellite SAR images was explored to improve discrimination between summer crops. The results on using SAR data for summer crops classification looked very promising allowing classification of major summer crops with 10-15% of commission and omission errors under typical Ukrainian landscape. Further research is required to ensure robustness of proposed approach on larger areas. Additional efforts should be put on investigation of possibility to substitute quad-polarization SAR data with cheaper wide swath dual-polarization data available from RADARSAT-2 and the upcoming Sentinel-1 satellites.

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