APPLICATION OF MULTISPECTRAL REMOTELY-SENSED IMAGERY IN AGRICULTURE

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ABSTRACT:

Most classification projects now make use of digital classification procedures guided by human interpretation. Because of remotely - sensed data could be particularly efficient for land use mapping, evaluation of crop status, the objectives of the study are represented by agricultural crops within the crop rotation during the spring-summer period. The use of various classification techniques is shown in the study. The satellite images considered for this paper were IRS-P6/LISS-4 and IRS-1D/LISS-3. The final stage of the classification process involves an accuracy assessment.
Die meisten Klassifikationsprojekte verwenden heutzutage digitale Klassifikationsvorgänge, die durch menschliche Interpretation geleitet werden. Da auf Distanz gewonnene Daten von besonderer Effizienz für Landwidmungen, sowie die Evaluierung von Ernteerträgen sind, werden die Ziele der Studie am Beispiel von landwirtschaftlichen Ernten in der Anbaurotationsfolge während der Frühjahr-/Sommerperiode dargestellt. Die Anwendung verschiedener Klassifikationstechniken wird in der Studie gezeigt. Die Satellitenbilder, die in diesem Paper betrachtet werden, sind IRS-P6/LISS-4 und IRS-1D/LISS-3. Die letzte Stufe des Klassifikationsprozesses schließt eine Genauigkeitsbewertung mit ein.

1. INTRODUCTION

Remotely-sensed data and satellite imagery is an important input to many analyses. It can provide timely as well as historical information that may be impossible to obtain in any other way. The availability of this data provides opportunities for environmental studies particularly in the areas of change detection, landuse mapping, land evaluation, land survey that would have been unknown only a few decades ago.

Crop distribution maps are widely used for agricultural management. Remotely-sensed data and satellite imagery in particular have proven their efficiency for crop mapping. A large number of algorithms for image classification have been developed and their application has been shown in the literature (De Wit and Clevers, 2004; Conrad et al., 2010). New image processing techniques have been developed during the last few years. They provided the increase of classification accuracy.

The crop average spectral reflectance per field was used in the study. Validation of classification was performed with field observations for all crop types.

2. MATERIALS AND METHODS

The objectives of the study are represented by crop types within the field boundaries in the crop rotation of Forest-Steppe of Ukraine. The high resolution image IRS-P6 (6.0 m) was used for obtaining field boundaries. Data of medium spatial resolution (IRS-1D, 23 m) was used to classify crop types. Multispectral images were collected for three stages of development for winter cereals and spring crops over the growing season (in May, June and July in 2008). Erdas Imagine software was used to georeference image with ground-control points, for image geometric correction, image enhancement (radiometric enhancement and Ehlers fusion), and image classification. Field boundaries were digitized in ArcGIS 9.3 from reference IRS-P6 image after Ehlers fusion application.

High pass filter (Laplacian) of the IRS-P6 data was used to delineate boundaries of crops within fields (Kokhan, 2010). Boundaries of fields and crops were evaluated and checked with the plan of the territory organization for Mankivka State Crop Variety Station.

The station is located in the Central part of Ukraine in the Forest-Steppe zone. Soils are mainly represented by chernozem typical. Climate of the region is moderately continental. Winter is mild with frequent thaws. Summer is warm, which is some times hot with precipitation. The annual mean temperature is 7.7°C with minimum in January and maximum in July. The annual rainfall is 517 mm with the maximum amount received in July.

Cereals and pulse crops are grown in 60% of the cultivated areas in the region. Industrial crops (sugar beets, corn) comprise 22% of crops grown in the cultivated area. Crops in the research station are represented by sugar beets, peas (two fields), radish, winter wheat (two fields), winter rape, spring barley (two fields) and sunflower.

3. RESULTS AND DISCUSSION

Land cover and other types of maps may be developed from the classification of remotely-sensed imagery. The majority of image classification is based on the detection of the spectral response patterns of land cover classes. Classification depends on distinctive signatures for the land cover classes in the band set being used, and the ability to reliably distinguish these signatures from other spectral response patterns that may be present (Eastman, 2006).

The classification process can be represented by determining the set to which each pixel belongs. The sets in supervised classification assumed to be known before the process is begun. In the case of supervised classification we delineated fields with different crops based on statistical characterization data drawn from known training sites. Ground truth data was collected nearly

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time-synchronous to receiving IRS images. Vegetative period for spring crops usually starts at the end of April - beginning of May. Fields are mainly bare at that time and vegetation has low value of dry matter as well as leaf area index.

Phenological observation of crops during the spring and summer period (Table 1) were used for crop classification

Crops	Field	Vegetation		
		May	June	July
Sugar beets	I	Very low	Low	Dense
Peas	II	Very low	Low	Medium
Radish	III	Low	No vegetation	No vegetation
Peas	IV	Very low	Low	Dense
Winter rape	V	Medium	Dense	Dense
Sunflower	VI	Very low	Low	Medium
Spring barley	VII	Very low	Low	Dense
Winter wheat	VIII	Medium	Dense	Dense
Spring barley	IX	Low	Medium	Medium to dense
Winter wheat	X	Medium	Dense	Dense

No vegetation   Medium
Very low   Medium to dense
Low   Dense

Table 1. Vegetation development during the spring and summer period.

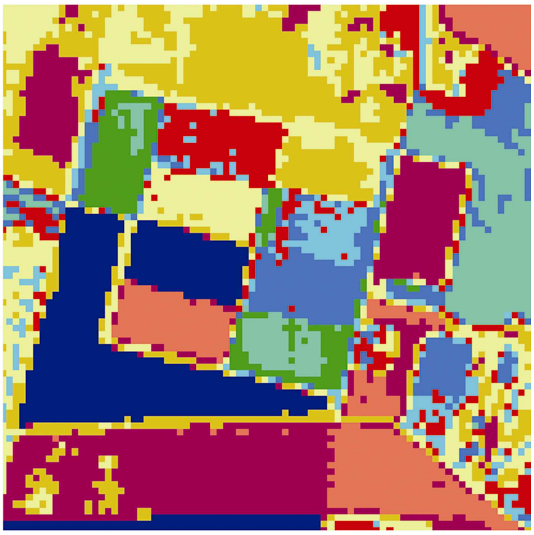
based on IRS-P6 and IRS-1D data. Multispectral data was obtained on May 18, June 16 and July 7. To evaluate the status of vegetation within the period of crop sampling we measured plant height, leaf area index, aboveground biomass and dry matter.

Peculiarities of crop development were used to analyze per field vegetation development. Information on crop cover types and vegetation density (very low, low, medium, medium to dense, dense) based on ground truth data provided information for image classification.

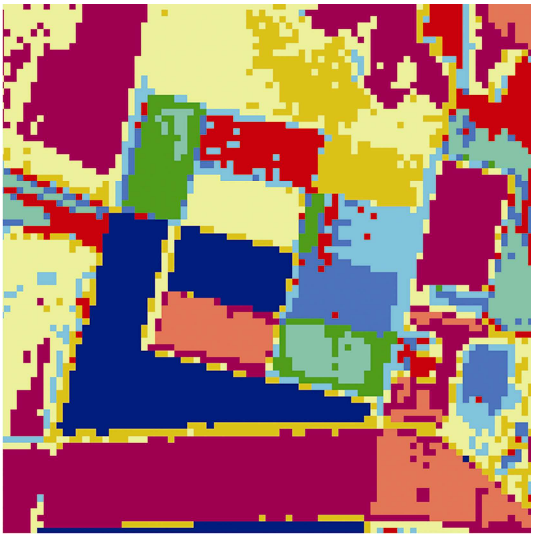
Ten training classes for crop classification were used in spite of that seven crop were cultivated. Peas, winter wheat and spring barley were located within two fields but they differed by the level of fertilization, crop variety and previous crop. It gains to differences in development of aboveground mass and yield components.

After the training sites had been created, the three methods were used to determine if a specific pixel qualifies as a class member. The minimum distance procedure, the minimum distance method with standardized distances and the method of maximum likelihood known to be hard classifiers were applied. They made a definitive decision about the land cover class to which any pixel belongs (Figures 1 to 3).

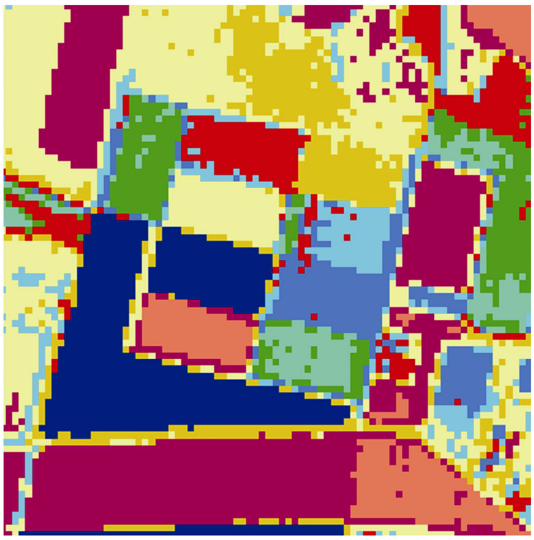
The minimum distance classifier uses the mean vectors of each training site and calculates the Euclidean distance from each unknown pixel to the mean vector for each class. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. The method made some mistakes in classification results because of standard deviation of pixel spectral characteristics within the polygons.



A

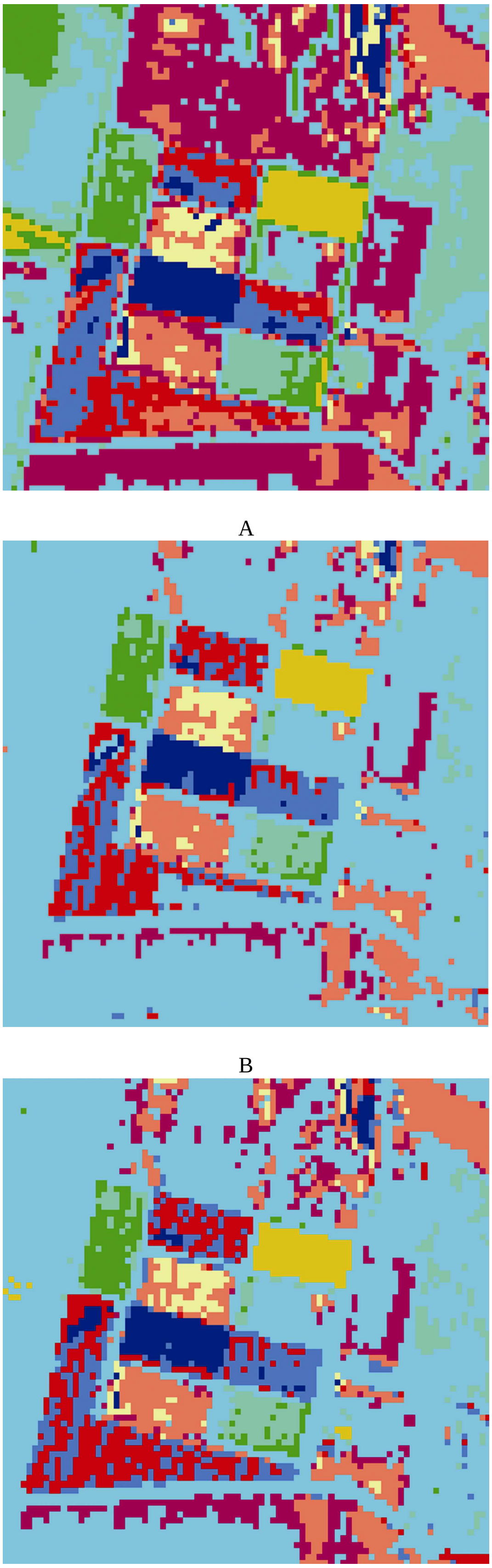


B



C

Figure 1. Crop classification maps derived from IRS-1D image (May 18): A - minimum distance procedure; B - minimum distance method with standardized distances; C - maximum likelihood classifier

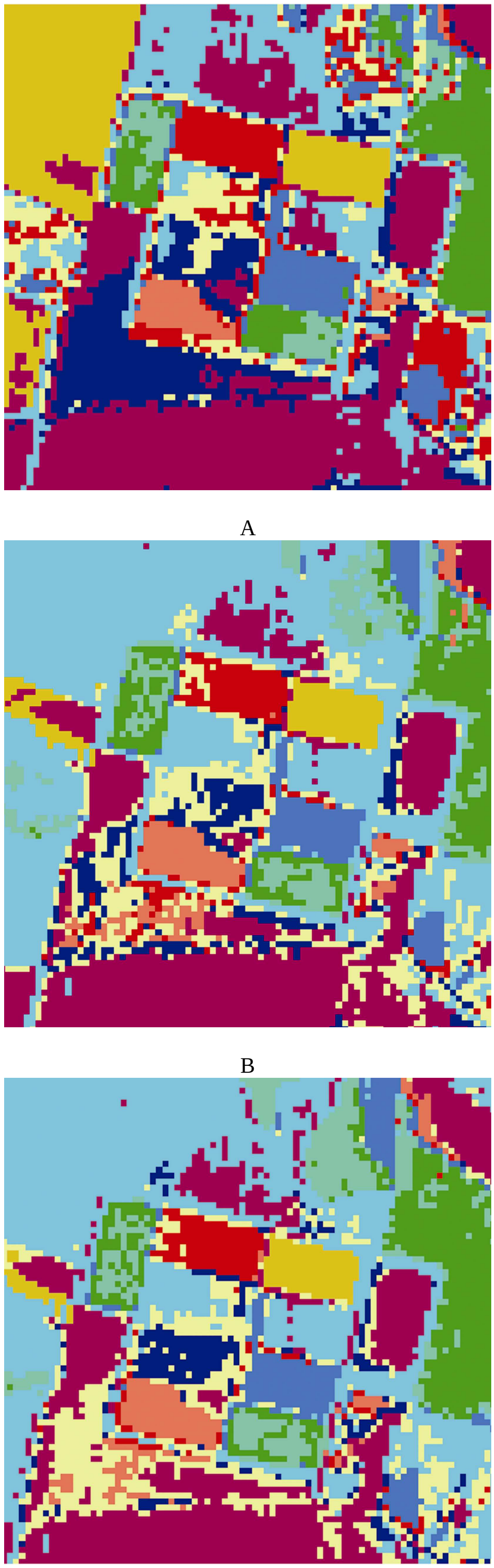


A

B

C

Figure 2. Crop classification maps derived from IRS-1D images (June 16)



A

B

C

Figure 3. Crop classification maps derived from IRS-1D images (July 7)

	Sugar beets (I)		Peas (II)
	Radish (III)		Peas (after barley, IV)
	Winter rape (V)		Sunflower (VI)
	Spring barley (after sugar beets, VII)		Winter wheat (after peas, VIII)
	Spring barley (after cereals, IX)		Winter wheat (after radish)

In the case of normalized distance procedure application the classifier calculated standard deviation for reflectance values around the mean value and made contours of standard deviations. The pixel is assigned to the closest category in the form of standard deviations.

The maximum likelihood procedure is one of the most sophisticated, and the most widely used classifier. The classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability.

Multiple schemes of image classification used in environmental and agricultural mapping are either traditionally statistical or heuristic (region growing, fuzzy classification etc.) (Kovalevskaya and Pavlov, 2002).

Agricultural crops within the fields are not homogeneous objects because of the spatial variability of soil quality and soil moisture. In this research project we used the general schemes of supervised image classification. Training sites included only homogeneous areas within fields.

The final stage of the classification process usually involves an accuracy assessment. There are several types of accuracy assessments. Usually it is done by generating a random set of locations in the field conditions to verify the true land cover type. A simple value file is then made to record the true land cover class for each of locations. This values file is then used with the vector file of point locations to create a raster image of the true classes found at the locations examined. This raster image is then compared to the classified map (Eastman, 2006).

The Kappa coefficient is another measure of the accuracy of the classification. The coefficient is calculated by multiplying the total number of pixels in the ground truth classes by the sum of the confusion matrix diagonals, subtracting the sum of the ground truth pixels in a class times the sum of the classified pixels in that class summed over all classes, and dividing by the total number of pixels squared minus the sum of the ground truth pixels in that class times the sum of the classified pixels in that class summed over all classes. We used the Kappa coefficient to estimate the accuracy of the classification and to evaluate the results of applied methods of classification for each crop.

The error matrix produced was used to identify particular crop types for which errors are in excess of that desired. The information in the matrix about which crops are being mistakenly included in a particular class (errors of commission) and those that are being mistakenly excluded (errors of omission) from that class can be used to refine the classification approach.

Results showed that in May winter wheat and winter rape had the highest value of Kappa coefficient compared to another crops in the crop rotation (0.727 and 0.835). For the other crops the very low to low level of aboveground biomass is characterized. Radish can be recognized only during this period because of the early harvesting. The Kappa coefficient is 0.647.

Some fields in May are still bare and some crops have very low aboveground biomass. Therefore, accuracy of the classified fallow land is above 0.760.

Because of the weak biomass development for sugar beet, peas, sunflower and spring barley in the second decade of June the classification results shown that accuracy varied from 0.483 (sugar beet) to 0.614 (sunflower) (Figure 4). Winter rape and winter wheat had the higher value of Kappa coefficient (0.702 to 0.712) compared to the other crops.

Spring barley is one of the main agricultural crops in Ukraine. Results showed that accuracy assessment for this crop in June varied from 0.445 to 0.633. The higher value has been obtained for crop after the previous winter wheat.

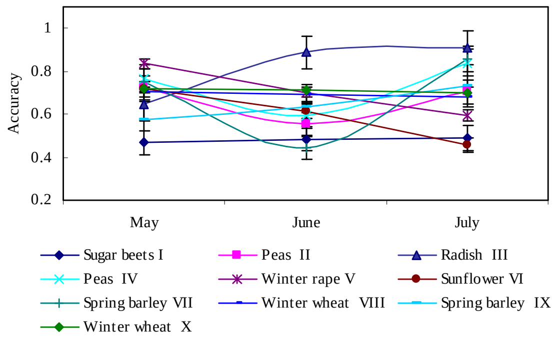


Figure 4. Accuracy assessment of the crop classification

Dense vegetation cover in July was mainly used to classify winter wheat, spring barley and peas with high percentage of identification (from 0.699 for winter wheat to 0.857 for spring barley). Kappa coefficient varied for fields with peas from 0.703 to 0.839. It was related to different nitrogen fertilizer rate applied under crops.

The overall accuracy for cereals and peas was 0.688, for the other crops – 0.608. Low accuracies were obtained for sugar beet, and sunflower. Because of the broad row-spacing and the within-field heterogeneity of crop growth, there was reduced classification accuracy.

4. CONCLUSION

It can be assumed that IRS-1D images acquired in three periods were classified to determine seven different crops. The overall accuracy for cereals and peas was 0.688 and for the other crops was 0.608.

In comparison to the studies (Turker et al., 2005, Conrad et al., 2010) the overall accuracy of classification was lower because of heterogeneity of crops within some fields, differences in agricultural technologies applied to the same group of crops, spatial variability of soil nutrients and moisture.

Additional image acquisition and database development of spectral signatures based on the results received within the experimental stations using sensors with medium resolution can provide images with lower spatial resolution to determine certain crops within the larger territories.

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