Bulgarian Academy of Sciences. Space Research and Technology Institute.
Aerospace Research in Bulgaria. 27, 2015, Sofia

MAPPING SOFIA PLAIN ARABLE LAND DYNAMICS USING LANDSAT-8 OLI IMAGES AND GROUND DATA

Vassil Vassilev

Space Research and Technology Institute – Bulgarian Academy of Sciences
e-mail: vassilev_vas@yahoo.com

Abstract

The purpose of this article is mapping the arable land dynamics using satellite and ground data. The methodology of this article includes the following working stages: 1) Choosing appropriate satellite images; 2) applying arable land mask from CORINE 2006 land-cover database; 3) Deriving Normalized Difference Vegetation Index (NDVI) images and composing unsupervised classifications on the chosen satellite images; 4) Conducting per-pixel supervised classification using the Maximum Likelihood Classifier (MLC); 5) Applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistics; 6) Mapping the arable land dynamics. The investigation shows good results for mapping arable land dynamics. The overall accuracy for the LANDSAT-8 Operational Land Imager (OLI) satellite image, acquired on 23.03.2014, is 77.66 % and Kappa statistics is 0.6906, while the image acquired on 14.08.2014 was estimated at 86.02 % overall accuracy and Kappa statistics of 0.7646. The analysis on the LANDSAT-8 image, acquired on 14.08.2014 shows that it can be used for controlling and monitoring the agricultural threathments accomplished by the farmers like harvest, for example. The presented research shows the big potencial using LANDSAT-8 OLI data for crop identification and mapping arable dynamics purposes at a relatively high accuracy.

1. Introduction[1]

Currently a major challenge in agricultural applications using high resolution (HR) satellite images is controlling area-based subsidies and applying precision agriculture practices. Satellite Remote Sensing (RS) provides synoptic, objective and relatively homogeneous data which can be geographically and temporally registered. Therefore, RS is an efficient tool for providing standard,

[1] Abreviations used:
MARS – Monitoring Agriculture with Remote Sensing
LACIE – Large Area Crop Inventory Experiment
CITARS – Crop Identification Technology Assessment for Remote Sensing
NDVI – Normalized Difference Vegetation Index

high quality information on agriculture, evenly over broad-scale territories. The Monitoring Agriculture with Remote Sensing (MARS) project of the European Union (EU) was established in order to define and demonstrate how RS can be used operationally to supplement, interpret, and standartize agricultural statistical data provided by conventional techniques (Meyer-Roux and Vossen, 1994; De Winne, 2004). Satellite RS techniques have been proven to be effective and useful in broad-scale agricultural surveys such as: Large Area Crop Inventory Experiment (LACIE) project in the USA and MARS project in Europe (Cohen and Shoshany, 2002). Furthermore, experiments from LACIE and Crop Identification Technology Assessment for Remote Sensing (CITARS) projects have also been conducted to demonstrate the capabilities of RS for crop inventory and forecasting (MacDonald, 1984; Blaes, 2005).

Winter wheat phenophases like tillering and flowering as well as harvest, can be successfully identified using sensors with different spatial resolution in various band combinations and severe ground surveys, including collecting information for defining training samples for the supervised classification (Townshend et al., 1991). A number of different methods have been developed during the last two decades to discriminate crop types using NDVI data from the Advanced Very High-Resolution Radiometer (AVHRR). These methods employ a variety of different approaches including temporal profiles of crop phenology manifested in the NDVI (DeFries et al., 1995; Reed et al., 1994), and classification of multi-temporal data (Brown et al., 1993; Loveland et al., 1995), which can be applied on variously managed crop areas worldwide.

Crop identification during the growing season is a major challenge for forecasting crop production as well as for controlling area-based subsidies in the EU member states (Blaes, 2005). The basis for separation of one crop from another is the supposition that each crop species has a unique visual appearance and spectral signature on the image. However, separating these species may be difficult because of variations in soil properties, fertilization, pest conditions, irrigation practices, planting dates, as well as intercropping, and tillage practices (Ryerson et al., 1997), all of which can be adopted in precision farming using high resolution satellite images. Thus, high resolution satellite images are the key to the above mentioned difficulties.

The purpose of this case study is mapping the arable land dynamics, and it includes the following tasks:1) Choosing appropriate satellite images; 2) Applying arable land mask from CORINE 2006 land-cover database; 3) Deriving NDVI images and composing unsupervised classifications on the chosen satellite images; 4) Conducting per-pixel supervised classification using the Maximum Likelihood Classifier (MLC); 5) Applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistics; 6) Mapping of the arable land dynamics.

2. Materials, methods and data used

2.1. Study area

The study area is part of the *Sofia* plain, surrounding the capital city of *Sofia*. The major cultivated winter crops (winter wheat and winter barley) and spring crop (sunflower) were investigated in the present case study.

2.2. Ground data used

On 30.06.2014 a field survey was conducted where ground data was collected and organized in a GIS geodatabase. The ground-truth data consists of descriptions of the LU/LC types, phenological stages and vegetation cover of crops, GPS measurements, and photos. The collected ground data will contribute of selecting appropriate training samples for the supervised classification on the chosen satellite images.

2.3. Satellite data used

There are two LANDSAT-8 Operational Land Imager (OLI) satellite images chosen for the present study for the year 2014 acquired on: 23.03.2014 and 14.08.2014 (Fig. 1.).

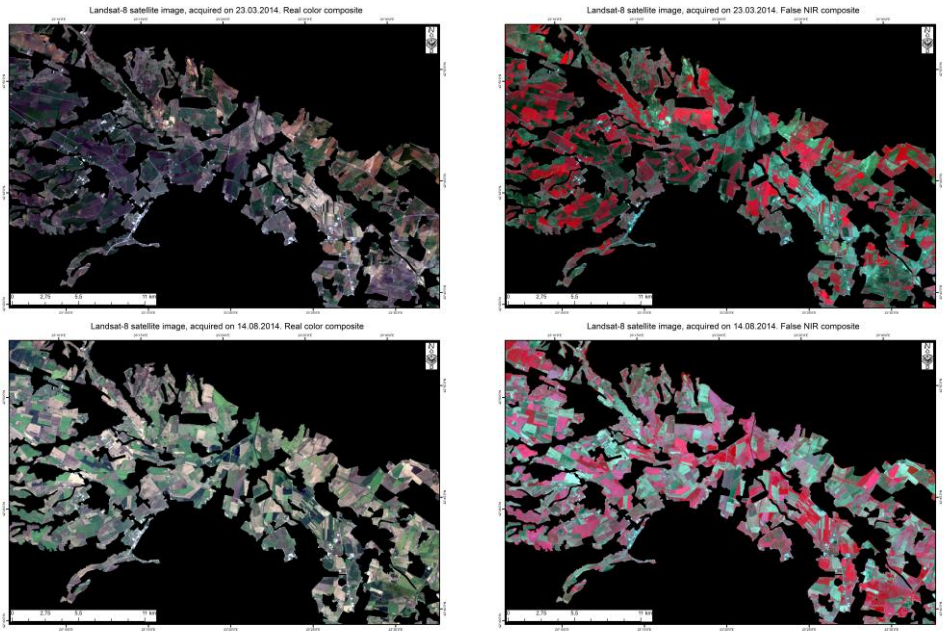

Fig. 1. Selected satellite images from LANDSAT-8 OLI, acquired on 23.03.2014 (top) and 14.08.2014 (bottom)

Table 1. LANDSAT-8 OLI main characteristics

	Bands	Wavelength (µm)	Resolution (m)
LANDSAT-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Band 1 - Coastal aerosol	0.43 – 0.45	30
	Band 2 - Blue	0.45 – 0.51	30
	Band 3 - Green	0.53 – 0.59	30
	Band 4 - Red	0.64 – 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 – 0.88	30
	Band 6 - SWIR 1	1.57 – 1.65	30
	Band 7 - SWIR 2	2.11 – 2.29	30
	Band 8 - Panchromatic	0.50 – 0.68	15
	Band 9 - Cirrus	1.36 – 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 – 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 – 12.51	100 * (30)

3. Results and discussions

3.1. Applying arable land mask from CORINE 2006 land-cover database

The “2.1.1. Non-irrigated arable land” class was used to build the mask layer from the CORINE Land Cover (CLC) 2006 database in order to classify only the arable land and reduce the occurrence of mixed pixels.

3.2. Deriving NDVI images and composing unsupervised classifications on the chosen satellite images

The *k*-mean and Iterative Self-Organizing Data Analysis (ISODATA) clustering algorithms are the most frequently used ones in RS. The ISODATA algorithm was selected in this study because it allows different number of clusters, while the *k*-mean algorithm assumes that the number of clusters is known *a priori* (Groom et al., 1996; Garcia-Consuerga and Cisneros, 1999; Yang et al., 1999). Unsupervised ISODATA cluster classification with six classes was applied to spectraly discriminate the crops and to collect the necessary information in order to delineate the training samples for the supervised per-pixel classification.

The crop identification process was accomplished firstly by conducting unsupervised classification (using ISODATA algorithm) with 5–6 classes for each satellite image (Fig. 2 and Fig. 3). This spectral information was used together with the ground data as an indicator where to draw training samples for the supervised classification. The unsupervised classification is traditionally the first step and is accommodating the interpretation of the images. The most commonly used RS vegetation index for agricultural applications is the NDVI, expressed by the following formula: NDVI=(NIR-VIS)/(NIR+VIS), where VIS and NIR stands for the spectral reflectance measurements acquired in the visible red and near-infrared regions, respectively (Rouse et al., 1973). NDVI is a commonly used space-observed measure of the chlorophyll activity (Fig. 4 and Fig. 5). It ranges typically from 0.15 (bare soils) to 0.80 (dense vegetation).

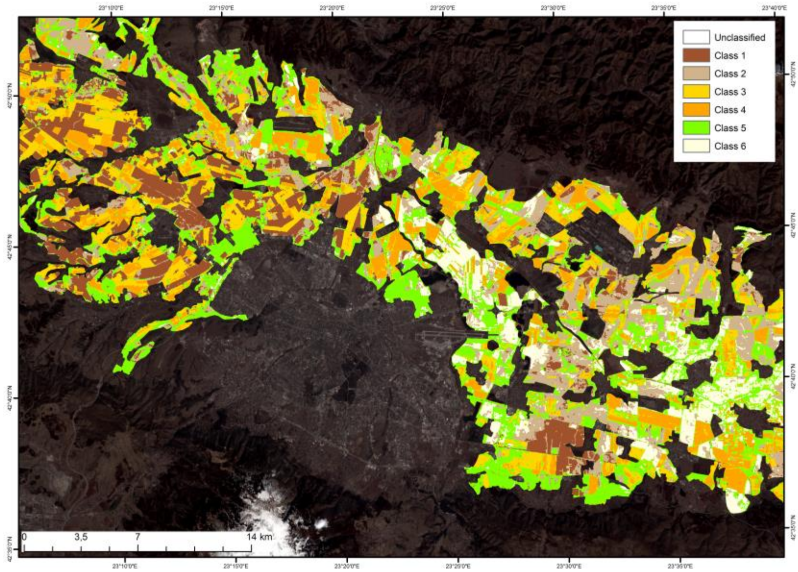

Fig. 2. Unsupervised classification of LANDSAT-8 OLI image acquired on 23.03.2014

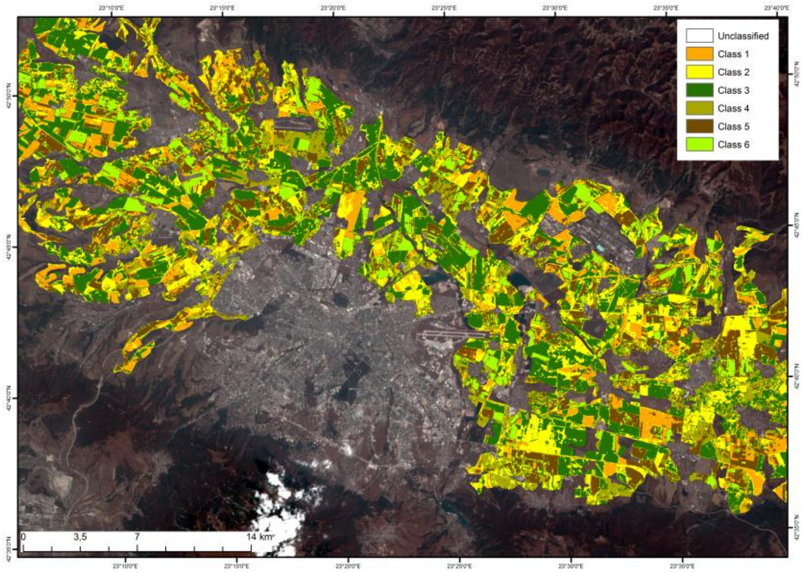

Fig. 3. Unsupervised classification of LANDSAT-8 OLI image acquired on 14.08.2014

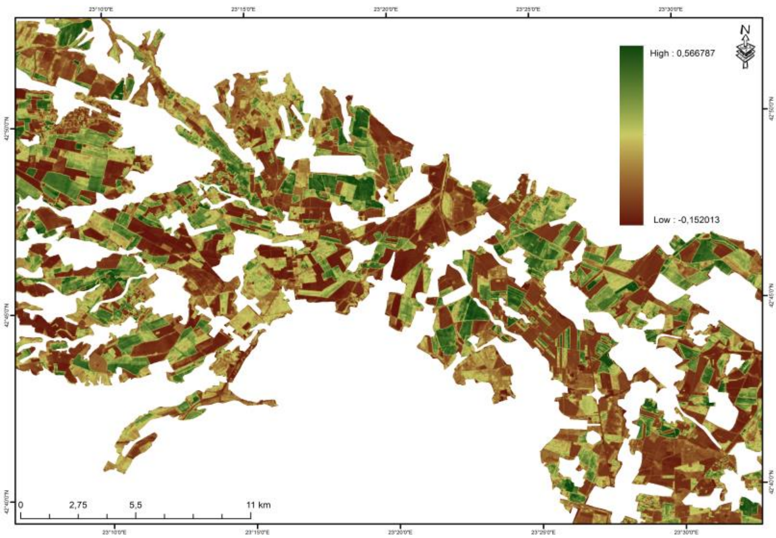

Fig. 4. NDVI image derived from LANDSAT-8 OLI satellite image acquired on 23.03.2014

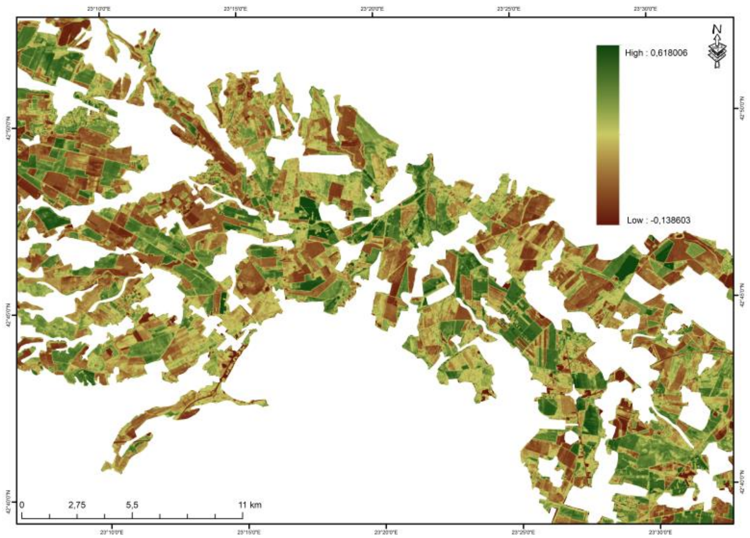

Fig. 5. NDVI image derived from LANDSAT-8 OLI satellite image acquired on 14.08.2014

3.3. Conducting per-pixel supervised classification using the Maximum Likelihood Classifier (MLC) algorithm for crop identification

Per-pixel supervised classification using the MLC algorithm was applied on the arable territories of the test site for crop identification purposes. In the MLC procedure, at least 10–15 independent training cases per class were used, so that its mean and variance can be estimated (Piper, 1992). For example, the spectral response of an agricultural crop class in an image might vary as a function of variables such as: the crops growth stage, topographic position, density of vegetation cover, health, impact of management activities, substrate conditions and instrument view angle (Foody, 2002). The gathered training set from the field data was good enough to make representative training samples for the arable land classes. The unsupervised classification in combination with the ground information helped to choose and delineate appropriate training samples for the supervised classification of the chosen satellite image. The identified classes for the LANDSAT-8 image, acquired on 23.03.2014 are: ‘winter crop condition classes’ (normal state; good state, and very good state), ‘bare soil asphalt and roads’, ‘cultivated arable land/shrubs, grass and meadows’, and ‘cultivated arable land’. For the LANDSAT-8 image, acquired on 14.08.2014 the identified classes are: ‘tillage fields’, ‘spring crops’, and ‘stubble fields’.

3.4. Applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistic

Around 100 randomly distributed points were assessed applying the accuracy assessment tool on the classified images for crop identification using visual interpretation on the image, the unsupervised classifications, derived NDVI image, and the ground collected data as a reference.

The achieved results for the per-pixel supervised classification from 23.03.2014 show overall classification accuracy of 77.66 % and overall Kappa statistics of 0.6906 (Table 2). While, the per-pixel supervised classification from 14.08.2014 shows overall classification accuracy of 86.02 % and overall Kappa statistics of 0.7646 (Table 3). For the classification on 23.03.2014 there are not enough reference points to assess reasonable accuracy for winter crops classes – ‘very good state’ and ‘cultivated arable land’.

Table 2. Accuracy totals for supervised classification on NDVI from LANDSAT-8 OLI acquired on 23.03.2014

Class Name - state	**Reference Totals**	**Classified Totals**	**Number Correct**	**Accuracy (%)**	
				Producers	**Users**
Winter Crop – very good	2	2	2	100.00	100.00
Winter Crop – normal	19	23	15	78.95	65.22
Winter Crop – good	12	10	5	41.67	50.00
Bare soil, asphalt, and roads	41	36	33	80.49	91.67
Cultivated land/shrubs/grass/meadows	19	22	17	89.47	77.27
Cultivated arable land	1	1	1	100.00	100.00
Overall	**94**	**94**	**73**	**Accuracy – 77.66 %**	**Kappa – 0.6906**

Table 3. Accuracy totals for supervised classification on NDVI from LANDSAT-8 OLI acquired on 14.08.2014

Class Name	Reference Totals	Classified Totals	Number Correct	Accuracy (%)	
				Producers	Users
Tillage fields	12	7	7	58.33	100.00
Spring crops	46	38	38	82.61	100.00
Stubble fields	35	48	35	100.00	72.92
Overall	**93**	**93**	**80**	**Accuracy – 86.02 %**	**Kappa – 0.7646**

3.5. Mapping of the arable land dynamics

The mapping of the arable land dynamics is presented in Fig. 8 and Fig. 9.

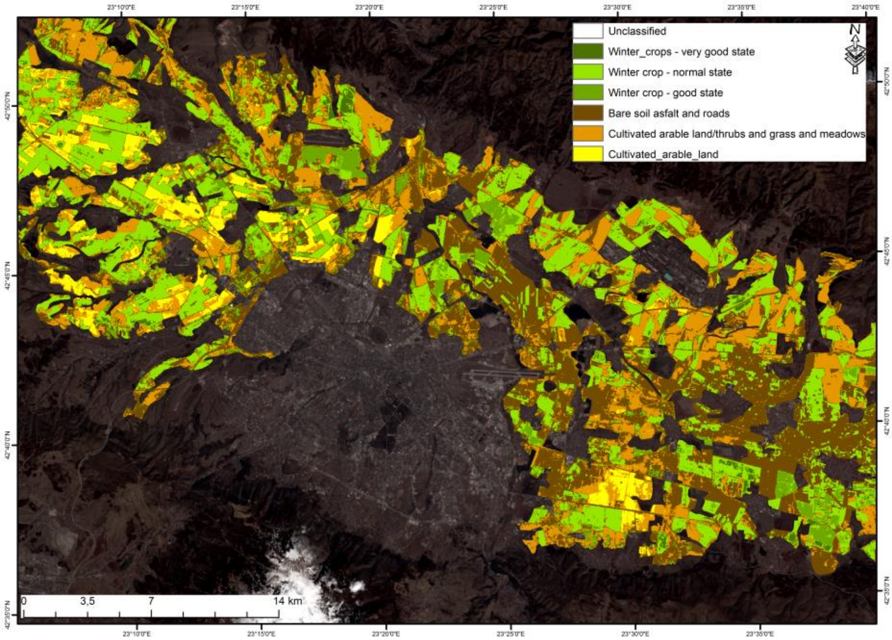

Fig. 6. Supervised MLC on satellite image from LANDSAT-8 OLI acquired on 23.03.2014

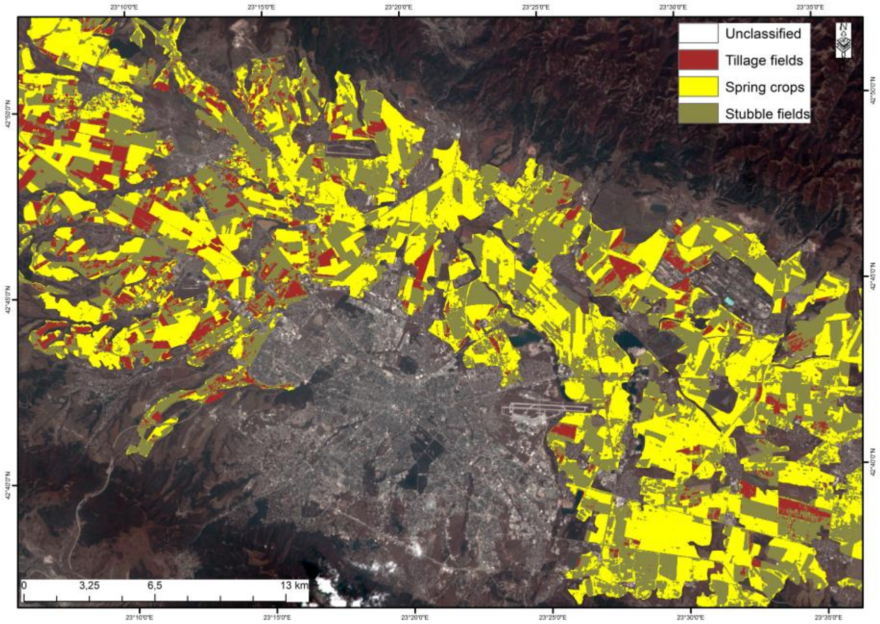

Fig. 7. Supervised MLC on LANDSAT-8 satellite image acquired on 14.08.2014

The distrubutuion of classes of each resulted classification derived from the LANDSAT-8 OLI images are presented in Fig. 8.

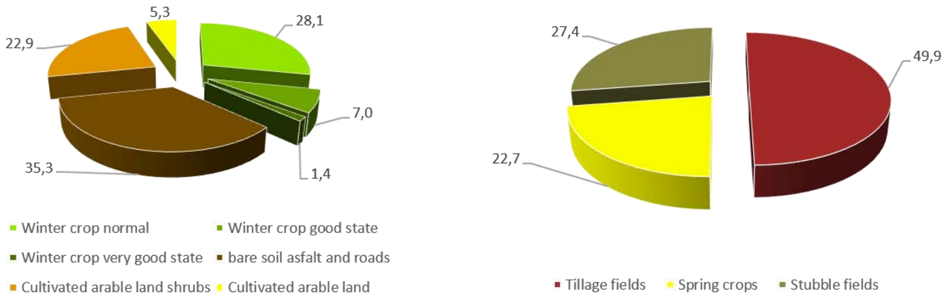

Fig. 8. Distribution of classes (%) for classification on 23.03.2014 (left) and 14.08.2014 (right)

4. Conclusions

The applied methodology emphazises on extracting valuable arable land dynamics information that can be directly utilized by the authorities. The arable land mask can increase the quality of the crop identification process, consequently on the accurate extraction of arable land dynamics information. The analysis on the LANDSAT-8 OLI satellite image acquired on 14.08.2014, shows that it can be used for controlling and monitoring the agricultural threathments accomplished by the farmers like harvest, for example. The presented research shows the big potencial using LANDSAT-8 OLI data for crop identification and mapping arable dynamics purposes at a relatively high accuracy.

Refferences

1. Meyer-Roux, J., Vossen P. (1994). The first phase of the MARS project, 1988–1993: overview, methods and results. In: Official Publications of the E.U., Luxembourg (Ed.), Report EUR 15599 EN. Conference on the MARS project: Overview and prospectives, Belgirade, 1994, 33–79.
2. De Winne, P. (2004). Les Besoins de la Direction Generale VI: Agriculture. In: Office for official publications of the E.U., Luxembourg (Ed.), Report EUR 15599 EN, 2004. Conference on the MARS project: Overview and prospectives, Villa Carlotta, Belgirate, Lake Maggiore, Italy, 17–22 (in French).
3. Cohen, Y., M. Shoshany. (2002). A national knowledge-based crop recognition in Mediterranean environment International Journal of Applied Earth Observation and Geoinformation, 4, 75–87.
4. MacDonald, R. (1984). IEEE Transaction on Geoscience & Remote Sensing, GE-22, 473–481.
5. Blaes, 2005. Efficiency of crop identification based on optical and SAR image time series. Remote Sensing of Environment, 96 352–365.
6. Townshend, J., Justice C., Li W., Gurney C., McManus J. (1991). Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sens Environ, 35, 243–255.
7. DeFries, R., Hansen M., Townshend J. (1995). Global discrimination of land cover types from metrics derived from AVHRR pathfinder data. Remote Sens Environ, 64 (3), 209–222.
8. Reed, B. C., Brown J. F., VanderZee D., Loveland T. R., Merchant J. W., Ohlen D. O. (1994). Measuring phenological variability from satellite imagery. Journal of Vegetation Science, 5, 703–714.
9. Brown, J. F., Loveland T. R., Merchant J. W., Reed B. C., Ohlen D. O. (1993). Using multisource data in global land-cover characterization: Concepts, requirements, and methods. Photogramm Eng Remote Sens, 59(6), 977–987.
10. Loveland, T. R., Merchant J. W., Brown J. F., Ohlen D. O., Reed B. C., Olson P., Hutchinson J. (1995). Seasonal land-cover regions of the United States. Annals of the Association of American Geographers, 85, 339–355.
11. Ryerson, R. A., Curran P. J., Stephens P. R. (1997). Agriculture. In: Philipson W.R. (Ed.) Manual of Photographic Interpretation. 2nd ed. Americal Society for Photogrammetry and Remote Sensing, Bethesda, MD, 365–397.

12. Rouse, J., Haas R., Schell J., Deering D. 1973. Monitoring vegetation systems in the Great Plains with ERTS. In: Third ERTS Symposium, 1973, NASA SP-351 I, 309–317.
13. Groom, B.G., Fuller R. M., Jones A. R. 1996. Contextual correction: techniques for improving land-cover from remotely sensed images. Int J Remote Sens, 17, 69-89.
14. Garcıa-Consuegra, J., Cisneros G. (1999). Establishing spatially continuous in a non-supervised way. In: Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS'99), 1999, Hamburg, Germany.
15. Yang, H., Khorram, S., Dai X.L. (1999). Applications of simulated annealing minimization technique to unsupervised classification of remotely sensed data. In: Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS'99), 1999, Hamburg, Germany.
16. Piper, J. (1992). Variability and bias in experimentally measured classifier error rates. Pattern Recognition Letters, 13, 685–692.
17. Foody, G. M., (2002). Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201.

КАРТОГРАФИРАНЕ НА ДИНАМИКАТА НА ЗЕМЕДЕЛСКАТА ТЕРИТОРИЯ НА СОФИЙСКАТА КОТЛОВИНА ПО СПЪТНИКОВИ ИЗОБРАЖЕНИЯ ОТ LANDSAT-8 И НАЗЕМНА ИНФОРМАЦИЯ

В. Василев

Резюме

Целта на настоящето изследване е картографиране на динамиката на земеделска територия по спътникови и наземни данни. Методологията на изследването включва следните работни етапи: 1) Избор на спътникови изображения; 2) Прилагане на маска с обработваемите земи в района на изследването от базатаданни на CORINE 2006 земно покритие; 3) Създаване на NDVI изображение и прилагане на неконтролирана класификация върху избраните изображения; 4) Прилагане на пикселно-ориентирана класификация по принципа на максималното подобие; 5) Прилагане на инструмент за оценка на точността в програмния продукт ERDAS Imagine и извличане на общата точност и капа статистиката; 6) картографиране на динамиката на земеделската територия.

Резултатите от проведеното изследване показват добра точност на картографиране на динамиката на земеделската територия. Общата точност за изображението заснето на 23.03.2014 г. е 77.66% с Капа статистика от 0.6906, докато това заснето на 14.08.2014 г. има обща точност от 86.02% и Капа статистика от 0.7646. От анализа проведен върху изображението заснето на 14.08.2014 г. може да се контролира и следи кога земеделските собственици са извършили определена дейсност, като жътвата, например. Проведеното изследване показа големия потенциал на LANDSAT-8 OLI за разпознаване на земеделски култури и картографиране на динамиката на земелските култури с относително висока точност.