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MAPPING CROP CONDITION USING QUICKBIRD-2 AND WORLDVIEW-1 SATELLITE IMAGES AND DERIVED PRODUCTS. A PRECISION AGRICULTURE CASE STUDY FOR PART OF ZHITEN TEST SITE IN NORTHEAST BULGARIA

Vassil Vassilev, Eugenia Roumenina

Space Research and Technology Institute – Bulgarian Academy of Sciences
e-mail: vassilev_vas@space.bas.bg; roumenina@space.bas.bg

Abstract

The purpose of this article is to investigate the possibilities of mapping crop condition using high resolution (HR) satellite images for Zhiten test site situated in Northeast Bulgaria. The chosen satellite images are acquired from multispectral QuickBird-2 and panchromatic WorldView-1 sensors on 31/05/2009 and 30/11/2011, respectively. The methodology of this article includes the following working stages: 1) applying arable mask from CORINE 2006 land-cover database; 2) conducting per-pixel supervised classification using the Maximum Likelihood Classifier (MLC) algorithm for crop identification; 3) applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistics; 4) mapping crop condition using Normalized Difference Vegetation Index (NDVI), Renormalized Difference Vegetation Index (RDVI) and Soil Adjusted Vegetation Index (SAVI) indices. The overall classification accuracy for the QuickBird-2 image is 90.86 % and overall Kappa statistics is 0.8538, while for the WorldView-1 image is 86.71 % and overall Kappa statistics is 0.7721. The SAVI shows better sensitivity for the spring crops cultivars with less than 40 % vegetation cover. Meanwhile, the NDVI gives good results for winter crops, but saturates at high vegetation dencity and gives generalized results for values less than 0.40. Overall RDVI gives better crop condition results for winter crops at flowering and grain filling phenophases and spring crops at vegetative phase compared to NDVI and SAVI.

1. Introduction[1]

Currently a major challenge in agricultural applications is forecasting crop production using low and coarse resolution satellite images, while for high

[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
RDVI – Renormalized Difference Vegetation Index
SAVI – Soil Adjusted Vegetation Index

resolution (HR) satellite images one of the hottest topics is controlling area-based subsidies and applying precission agriculture practices amongst others. 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, high quality information on agriculture, evenly over broad-scale territories. The Monitoring Agriculture with Remote Sensing (MARS) project of the European Union was established in order to define and demonstrate how RS can be used operationally to supplement, interpret, and standardize 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). Additonally, 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).

Vegetation types can be characterized using their seasonal variations in the Normalized Difference Vegetation Index (NDVI) time-series, which include a series of images, acquired on weekly or decadal basis and showing the crop development dynamics. For example, the winter wheat phenophases, such as 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 and 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 differently 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 European Union member states (Blaes, 2005). The basis for separation 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 quality satellite images. Thus, high-resolution satellite images are the key to the above mentioned difficulties.

The purpose of this case study is to investigate the possibilities of mapping crop condition using HR satellite images for a test site in North-East Bulgaria, and it includes the following tasks:
(1) Applying arable mask from CORINE 2006 land-cover database;
(2) Conducting per-pixel supervised classification using the maximum likelihood classifier (MLC) algorithm for crop identification;
(3) Applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistics;
(4) Mapping crop condition using NDVI, RDVI and SAVI vegetation indices.

2. Materials and methods

The study area – part of Zhiten test site is situated in North-East Bulgaria. The area represents intensively cultivated area sowed mostly with cereals and sunflower. This territory is one of the main agricultural regions of the country. The area is part of the European-continental climatic province of the temperate climatic belt. Climate is moderately warm with no distinctive dry season. Mean annual air temperature is 10.2 °C. The main soil types are chernozems from the zonal ones and fluvisols from the azonal ones.

The major cultivated winter crops (wheat and oilseed rape) and spring crops (sunflower and maize) were investigated in the present case study.

During the 2010–2011 agricultural season and in particular in the period between March–July 2011 four exhaustive field surveys were carried out and ground data was collected and organized in a GIS geodatabase. Field data was collected in the framework of a project financed by the Belgian Federal Science Policy Office (BELSPO) under the PROBA-V Preparatory Programme, with acronym – PROAGROBURO (Roumenina et al. 2013). 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. Two satellite images were used in this study: a WorldView-1 panchromatic satellite image with 0.50 m spatial resolution, acquired on 30/11/2011 and QuickBird-2 multispectral (2.4 m spatial resolution) and panchromatic image (with 0.60 m spatial resolution), acquired on 31/05/2009.

The most commonly used RS vegetation index for agricultural applications is the NDVI, expressed by the following formula: $NDVI = (NIR\text{-}VIS)/(NIR+VIS)$, 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 commonly used measure for the amount of green vegetation. It ranges typically from 0.15 (bare soils) to 0.80 (dense vegetation). Additionally, the Renormalized Difference Vegetation Index (RDVI), expressed by the following formula: $RDVI = (NIR\text{-}RED)/\sqrt{(NIR+RED)}$ (Rougean and Breon, 1995) and Soil Adjusted

Vegetation Index (SAVI), expressed by the following formula: *SAVI = NIR-RED/NIR+RED+L * (1+L)*, where L is a constant value equal to 0.5 (Huete, 1988).

An arable land mask using CORINE data was applied on the QuickBird-2 and the WorldView-1 images in order to classify only the arable land and reduce the occurrence of mixed pixels with other non-arable classes.

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 classification with five 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. Per-pixel supervised classification using the Maximum Likelihood Classifier (MLC) algorithm was applied on the arable territories of the test site for both images 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. Around 160–170 randomly distributed points were used for accuracy assessment for both classified images. The multispectral QuickBird-2 satellite image and the derived NDVI, RDVI, and SAVI vegetation indices were used to map crop condition.

3. Results and discussions

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

An arable land mask using CORINE 2006 land-cover data was applied on the QuickBird-2 and the WorldView-1 images in order to classify only the arable land and reduce the occurrence of mixed pixels. In Fig. 1 all the land cover classes present in the test area are shown and '2.1.1. Non-irrigated arable land' class was used to build the mask layer.

3.2 Conducting per-pixel supervised classification using the maximum likelihood classifier algorithm for crop identification

The crop identification process was accomplished firstly by conducting unsupervised classification (using ISODATA algorithm) with 4-5 classes/clusters for both the multispectral QuickBird-2 and panchromatic WorldView-1 images. This spectral information was used together with the ground data as an indicator where to draw training samples for the supervised classification.

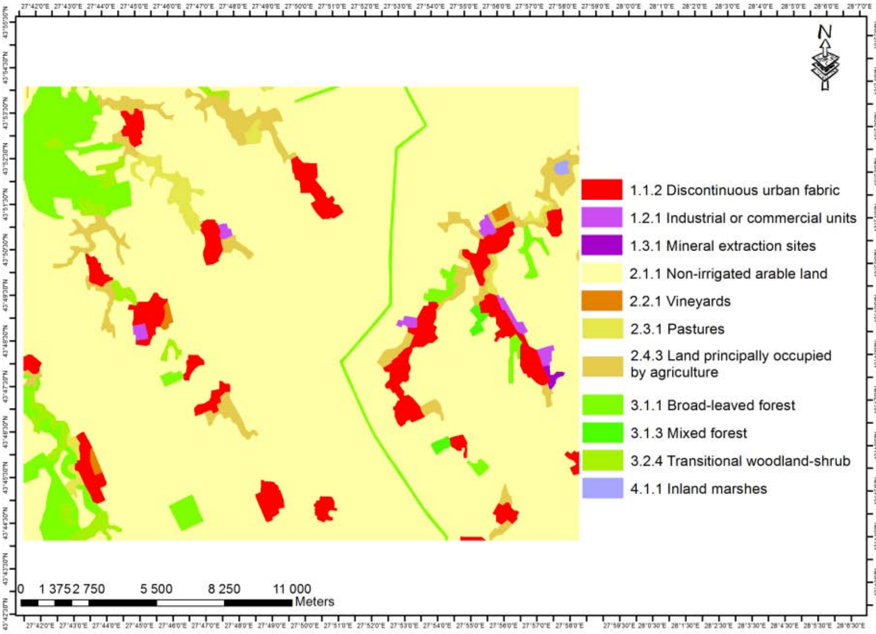

Fig. 1. CORINE 2006 land cover classes

The unsupervised classification is traditionally the first step and is accommodating the interpretation of the images. Supervised classification using the Maximum Likelihood Classifier (MLC) algorithm was applied to the arable land images. In the MLC procedure, a key concern is to collect a training set comprising of at least 10–30 independent training cases per class per discriminatory variable (e.g. band) to allow the formation of a representative description of the class, so that its mean and variance can be reasonably 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 and 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 and the derived NDVI image helped to choose and delineate appropriate training samples for the supervised classification of the QuickBird-2 image. The investigated phenological stages based on the image acquisition dates are: flowering and grain filling phenophases for winter crops and vegetative phase for spring crops for the QuickBird-2 image and emergence phenophase for winter crops for the Worldview-1 image.

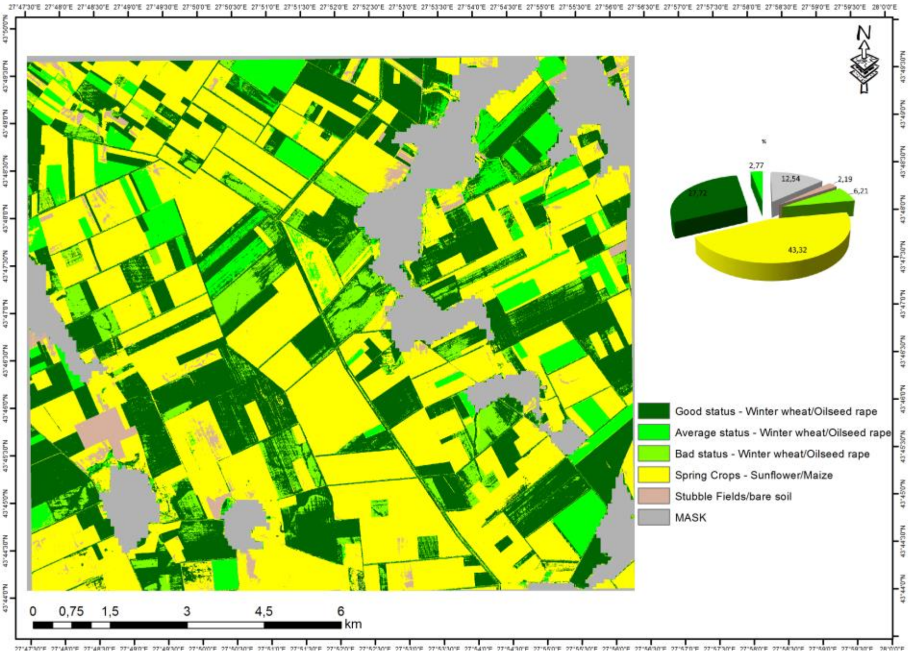

Fig. 2. Per-pixel supervised classification of QuickBird-2 satellite image

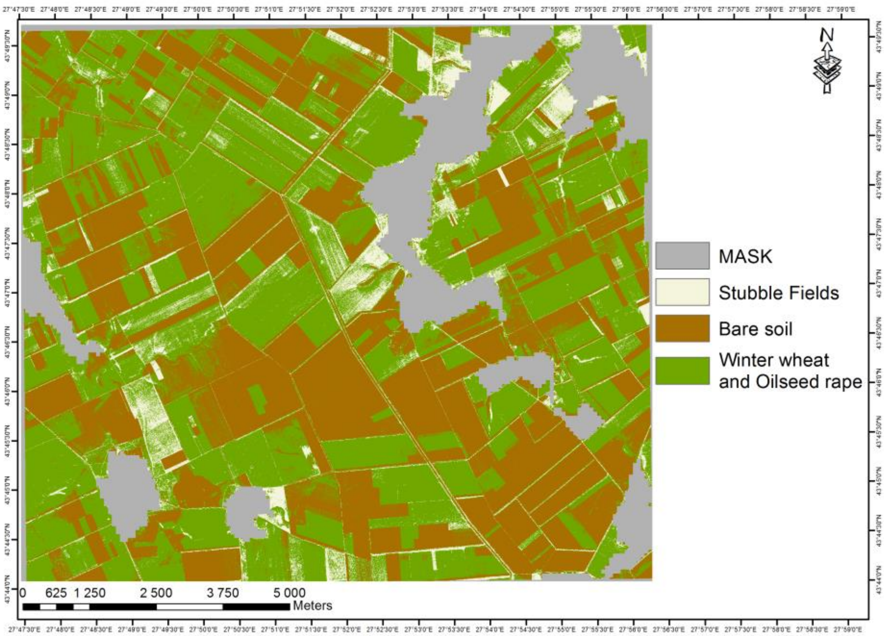

Fig. 3. Per-pixel supervised classification of WorldView-1 satellite image

The identified classes and their distribution in percentage for the QuickBird-2 satellite image are: good status - winter crops (wheat and oilseed rape – 27.72 %),) average status - winter crops (wheat and oilseed rape – 2.77 %); bad status - winter crops (wheat and oilseed rape – 6.21 %); stubble fields/bare soil – 2.19 % and spring crops – sunflower and maize – 43.32 % (Fig. 2), while for the Worldview-1 satellite image are: winter crops (wheat and oilseed rape) class; bare soil and stubble fields classes (Fig. 3).

3.3. Applying accuracy assessment tool in ERDAS Imagine and deriving accuracy totals and Kappa statistics

Accuracy assessment tool in ERDAS Imagine software was utilized for assessing the accuracy of the per-pixel classified images of QuickBird-2 (Fig. 4) and WorldView-1 (Fig. 5.). Around 160–170 randomly distributed points were assessed for both classified images. Accuracy assessment was applied on the WorldView-1 classified image for crop identification using its high spatial resolution by applying visual interpretation on the panchromatic and both on the unsupervised and supervised classifications in combination with the ground data.

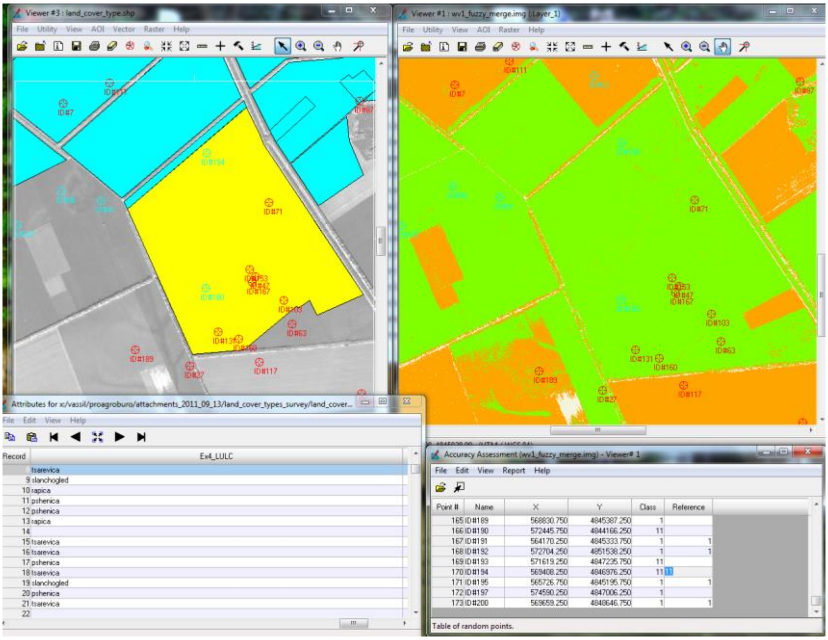

Fig. 4. Accuracy assessment on WorldView-1 image

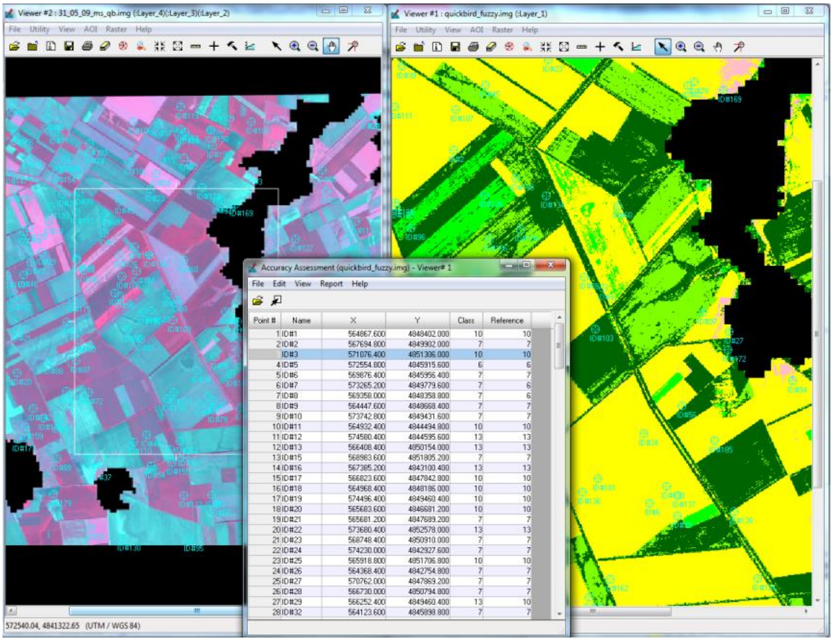

Fig. 5. Accuracy assessment on QuickBird-2 image

The achieved results on the overall classification accuracy for the QuickBird-2 image is 90.86 % and overall Kappa statistics is 0.8538 (Table 1), while for the WorldView-1 image is 86.71 % and overall Kappa statistics is 0.7721 (Table 2).

Table 1. Accuracy totals for QuickBird-2

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	User Accuracy (%)
Stubble fields	6	5	5	83.33	100.00
Bad status – WC	14	8	8	57.14	100.00
Average status – WC	21	15	14	66.67	93.33
Good status - WC	44	48	42	95.45	87.50
Spring crops	90	99	90	100.00	90.91
			Overall Accuracy – 90.86%		**Kappa – 0.8538**

Table 2. Accuracy totals for WorldView-1

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	User Accuracy (%)
Stubble fields	19	15	14	73.68	93.33
Winter crops	73	77	64	87.67	83.12
Bare soil	81	81	72	88.89	88.89
			Overall Accuracy – 86.71%		**Kappa – 0.7721**

The QuickBird-2 accuracy assessment shows that the class 'stubble fields' is with high accuracy, the reasons are that the class is easily identified using the multispectral data and the precise delineation of the training samples in ERDAS Imagine. The class 'spring crops', represented by sunflower and maize are with high users accuracy 100 %, with 90 reference points used for the accuracy assessment. The high user's accuracy is due to the different crop development stage between winter crops and spring crops at the date of image acquisition. The accuracy assessment of the winter crops' classes show that the 'bad status' class is with 100 % user's accuracy, while average status and good status classes are with 93.33 % and 87.50 %, user's accuracy, respectively. The accuracy assessment of the WorldView-1 satellite image shows that the 'bare soil' class is representing territories which are being prepared to be sown with spring crops in the agricultural year 2011-2012 or left for fallow land. The 'winter crops' class represents areas which have already been sown with winter crops (wheat and rapeseed) and are at emergence phenophase.

3.4. Mapping crop condition using NDVI, RDVI and SAVI indices

Mapping crop condition was accommodated using the multispectral QuickBird-2 image and the derived Normalized Difference Vegetation Index (NDVI), Renormalized Difference Vegetation Index (RDVI), and Soil Adjusted Vegetation Index (SAVI).

The raw NDVI, RDVI and SAVI indices, respectively (Fig. 6, Fig. 7, and Fig. 8) are presented by color ramp ('no vegetation' to 'dense vegetation'). The highest values of the indices are for winter wheat followed by oilseed rape, sunflower, and maize cultivars. Additionally, the crop condition was mapped using the derived NDVI image and applying histogram reclassification. The crop condition status classes are the following: (1) 'bad condition' and (2) 'good condition' for winter crops and (3) 'low NDVI values' for the other fields, since they are already sown with early spring cultivars or left for fallow land (Fig. 9). The crop condition was analyzed using interpretation between all the indices and comparing them with the collected farmers inquires on applied agricultural practices and observed crop development stages for the agricultural fields in the test area. The SAVI shows better sensitivity for the spring crops cultivars with less than 40 % vegetation cover whereas, the NDVI gives good results for winter crops, but saturates at high vegetation densities and gives generalized results for values less than 0.40. Overall, the utilized vegetation indices show that RDVI gives crop condition assessment results for winter crops at flowering and grain filling phenophases and spring crops at vegetative phase compared to NDVI and SAVI.

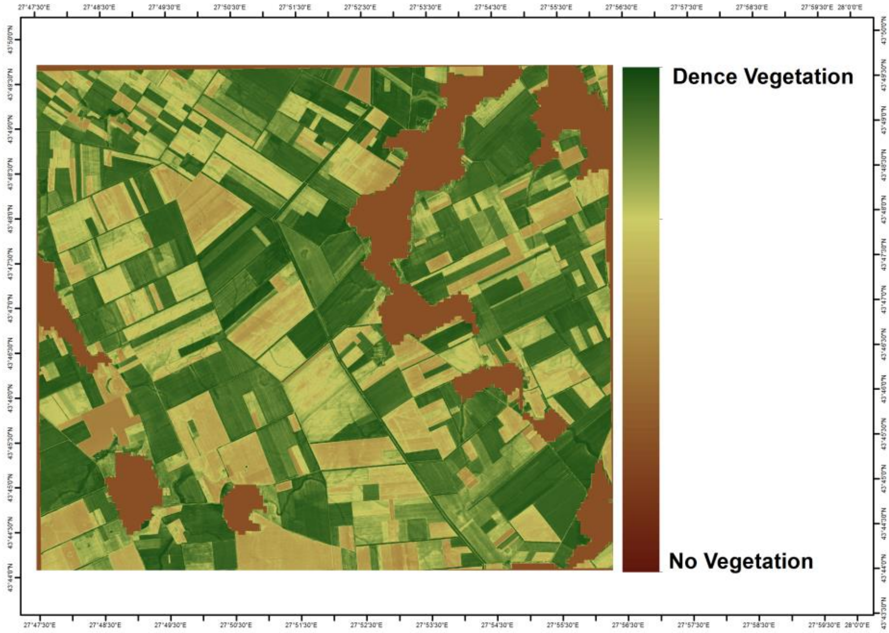

Fig. 6. NDVI image

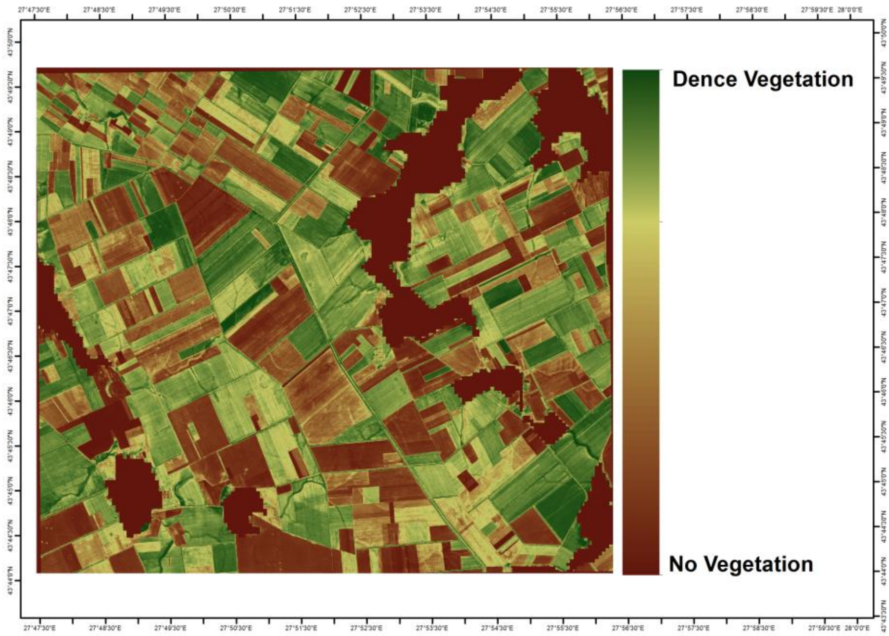

Fig. 7. RDVI image of Zhiten test area, Bulgaria

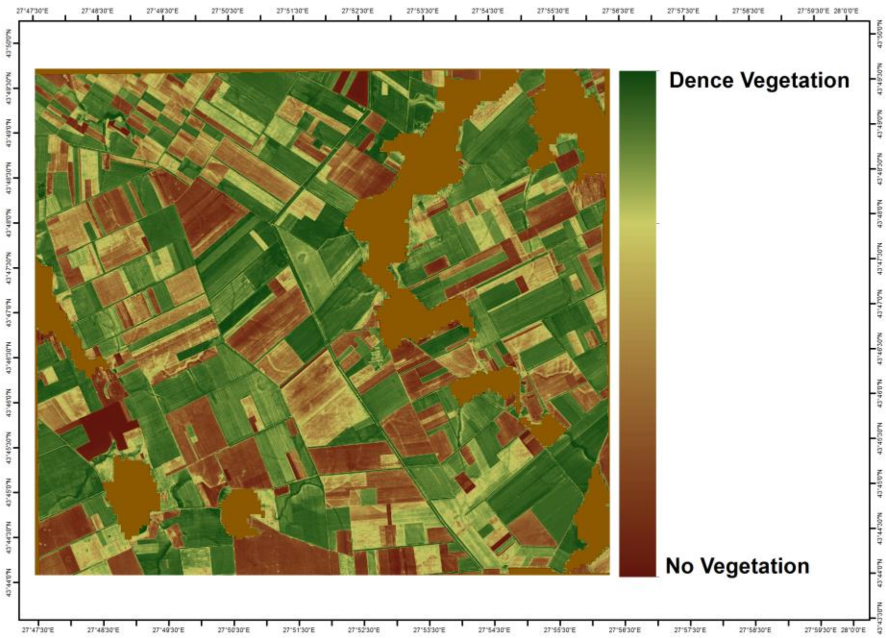

Fig. 8. SAVI image

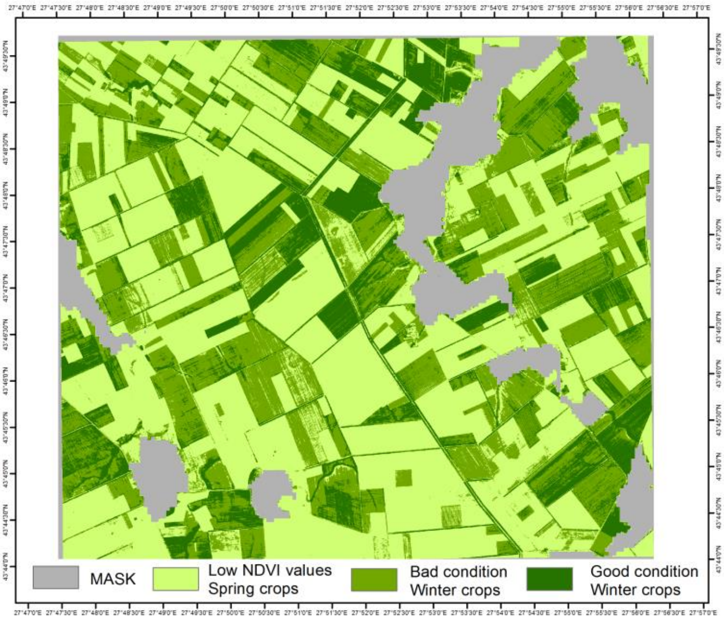

Fig. 9. Reclassified NDVI image

4. Conclusions

The presented methodology using per-pixel supervised classification for crop identification and consequently followed by utilizing the NDVI, RDVI, and SAVI indices provides a rapid tool for accurate and valuable crop condition information for a better crop management and for immediate adoption in precision farming practices. The results show that RDVI vegetation index can better be utilized for crop condition assessment at flowering and grain filling phenophases for winter cultivars and vegetative phase for spring crops compared to both NDVI and SAVI. Furthermore, in near future within the framework of the Copernicus Programme and the launch of *Sentinel-2* mission, with its more sufficient spectral capabilities, will add more possibilities for agriculture related investigations and will allow applying new spectral indices for improved retrieval of vegetation biophysical parameters.

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КАРТОГРАФИРАНЕ НА СЪСТОЯНИЕТО НА ЗЕМЕДЕЛСКИ КУЛТУРИ ПО СПЪТНИКОВИ ИЗОБРАЖЕНИЯ И ПРОДУКТИ ОТ QUICKBIRD-2 И WORLDVIEW-1. ТОЧНО ЗЕМЕДЕЛИЕ ВЪРХУ ЧАСТ ОТ ТЕСТОВИ УЧАСТЪК ЖИТЕН, РАЗПОЛОЖЕН В СЕВЕРОИЗТОЧНА БЪЛГАРИЯ

В. Василев, Е. Руменина

Резюме

Целта на настоящата статия е да изследва потенциала и възможностите на картографирането на състоянието на земеделски култури по спътникови изображения с висока пространствена разделителна способност върху тестови участък Житен, разположен в Североизточна България. Избрани са спътникови изображения от QuickBird-2 и WorldView-1, заснети съответно на 31.05.2009 г. и 30.11.2011 г. Методологията включва следните работни етапи: 1) Прилагане на маска от CORINE 2006 земно покритие; 2) Извършване на пикселно-ориентирана контролирана класификация по метода на максимално подобие за разпознаване на земеделски култури; 3) Прилагане на инструмент за оценка на точността на класификациите и извличане на обща точност и Капа статистика; 4) Картографиране на състоянието на земеделските култури по генерирани индексни изображения Normalized Difference Vegetation index (NDVI), Renormalized Difference Vegetation Index (RDVI) и Soil Adjusted Vegetation Index (SAVI). Общата точност на изображението от QuickBird-2 е 90.86% и с Капа статистика от 0.8538, докато това на WorldView-1 има обща точност от 86.71% и с Капа статистика от 0.7721. SAVI индекса показва по-добра чувствителност към пролетните култури с общо площно покритие от под 40%. От друга страна NDVI индекса дава по-добри резултати при картографиране на зимните култури, но индекса се насища при високи стойности и гъста растителна покривка. Освен това NDVI индекса дава ниска информативност при стойности по-ниски от 0.40. RDVI индекса дава добри резултати при картографиране на зимните култури при изкласяване и наливане на зърно фенофазите, както и при фазата образуване на съцветия при пролетните култури сравнено с индексите NDVI и SAVI.