ANALYSIS OF RAPIDEYE IMAGERY FOR ANNUAL LANDCOVER MAPPING AS AN AID TO EUROPEAN UNION (EU) COMMON AGRICULTURAL POLICY

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ABSTRACT:

The Common Agricultural Policy (CAP) of the European Union (EU) was established to maintain balance between farming industries and the environment as well as to provide economic sustainability in rural areas. EU Regulations for agricultural and rural development, adopted by countries upon their admission to the EU, allow payments to farmers for each eligible hectare of agricultural land (CAP reform), under different payment schemes. Remote sensing data is currently used as an efficient tool in determining areas potentially eligible for payments, through land cover identification and mapping. Launched in August 2008, RapidEye consists of five constellation multispectral sensors with a ground sampling distance (GSD) of 6.5m and a daily overpass. The satellite has a predicted lifespan of 7 years and with the target application of the sensor being agriculture; contains a high potential for the application of agricultural monitoring, necessary to some new Member States, such as Bulgaria and Romania. Analysis of RapidEye imagery, combined with local ancillary data over pre-selected test zones lead to determination and classification of land cover features which have potential or no potential to be eligible under the Single Area Payment Scheme (SAPS). This classification was completed using object oriented analysis and was run concurrently alongside a pixel based (self-organizing maps) analysis for comparison.

1 INTRODUCTION

The European Union (EU) established the Common Agricultural Policy (CAP) to support the agricultural sector in Europe, assess its impact to the environment and ensure economic sustainability in rural areas. One of the principal payment schemes under the CAP is the Single Area Payment Scheme (SAPS) which regulates payment of uniform amounts per eligible hectare of agricultural land. For most EU member states applying SAPS, the agricultural area eligible for payments is the utilised agricultural area, maintained in good agricultural condition (GAC) at a given reference date. As a consequence, the land which can be declared by the farmers and is the subject of the administrative and control processes that manage the CAP payments is limited to the historical extent, fixed at the reference date. Two exceptions are Bulgaria and Romania where the requirement for the reference year was omitted in their accession treaties. As a result, for these countries any utilised agricultural area, maintained in good agricultural condition at the time of the farmer declaration, regardless of its past status, can be considered eligible for payment. This creates a particular challenge for land management in the years following the EU accession, as agricultural land eligible for payment should be assessed on annual basis.

The objective of this study is to investigate and develop an operationally efficient methodology for annual monitoring and assessment of land eligible for subsidy payments under SAPS in Bulgaria. In order to ensure a correct assessment of the agricultural land suitable for SAPS payments, a necessary preliminary step is to clarify the concept of what is 'good agricultural condition' (GAC) in the national context, as there is no common legal definition of GAC at EU level. The proposed methodology envisages remotely sensed imagery, as an efficient source of up-to-date information, to detect and quantify (for the entire country) the agriculture land, that may represent eligible area, through monitoring of land cover dynamics. The recently launched constellation of RapidEye satellites was considered particularly suitable for this study, as the satellites were designed to be used mainly for monitoring of agricultural and natural resources at relatively large cartographic scale. The methodology was based on multi-temporal analysis of RapidEye time-series.

In order to detect eligible agricultural land and estimate their impact at reference parcel level, two different approaches were considered: *i)* object oriented classification techniques (Gamanya et al., 2007, Mathieul and Aryal, 2005) based on red edge normalized difference vegetation index (Wu et al., 2009, Gitelson et al., 1996) and *ii)* automated clustering of self-organizing maps (Taşdemir and Milenov, 2010). The proposed methodology was tested using zones selected according to the variability of land cover features across the country, which potentially represent eligible land (Milenova et al., 2001).

The outline of the paper is as follows: Section 2 introduces the concept of Good Agricultural Condition (GAC) elaborating on a proposal for its legal definition; Sections 3 and 4 briefly overview the test areas of the study and RapidEye sensor specifications; Section 5 describes proposed methodology for detection and quantification of the GAC/non-GAC land cover types and features, using object oriented approach; Section 6 briefly presents the first results of the study and the ongoing validation, Section 7 provides results from a concurrent testing using Self-Organizing Maps, as an alternative of the object oriented approach; Section 8 concludes the paper.

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2 GOOD AGRICULTURAL CONDITION

In order to suggest a robust and plausible concept of GAC, current legal definitions within regulations were consulted. The driver behind the need for a GAC concept in Bulgaria is Council Regulation 73/2009, Article 124 paragraph 1, which states:

"For Bulgaria and Romania, the agricultural area under the single area payment scheme shall be the part of its utilised agricultural area which is maintained in good agricultural condition, whether or not in production, where appropriate adjusted in accordance with the objective and non-discriminatory criteria to be set by Bulgaria or Romania after approval by the Commission."

According to this statement, 'utilised agricultural area' subject to the Single Area Payments Scheme (SAPS) must be maintained in 'good agricultural condition', even if the land is not in production. The *utilised agricultural area* is defined as 'the total area taken up by arable land, permanent grassland, permanent crops and kitchen gardens ...' in Regulation 73/2009 Art 124 with definitions of other terms in current EU regulations: arable land [380/2009 Art 1 s2(a)], permanent grassland [380/2009 Art 1 s2(b)], permanent crops [370/2009 Art 1 (b)] and kitchen gardens [1444/2002 Annex 1]. This definition is important to the foundation of GAC concept as it lists the main land cover types, which can represent eligible land, but also can be easily detected (monitored) on the ground or though remote sensing data. By integrating the definitions from regulations, GAC (for Bulgaria) can be defined as follows:

Definition: *Good Agricultural Condition shall apply to accessible land which is maintained as active, or has the potential to become active, agricultural area or agricultural activity within a reference parcel.*

Definitions for agricultural area and agricultural activity are defined in Regulation 73/2009 Art 2 while the reference parcel is defined in Regulation 796/2004 Art 2 (26). The two key elements in the proposed GAC definition are:

- *the potential of the land to become agricultural:* the land shall have the potential to produce biomass either due to its natural properties or due to the implementations of certain standard agriculture activities, a general European farmer can implement.
- *the accessibility of the land:* there are no obstacles, neither natural nor man-made, preventing the access and use of the land for agriculture activities.

For a consistent technical framework, which will allow a proper classification of the agricultural land in GAC, the proposed definition lays a good foundation to build methodology. However, another challenge for GAC analysis in Bulgaria (as well as Romania) is the significant decline of the Utilised Agricultural Area (UAA) in Bulgaria (as well as Romania) in the last few decades mainly due to farmland abandonment and soil sealing. There are two types of "abandoned" land in Bulgaria: (1) land, not-cultivated for a maximum of 3 years, which could be easily recovered with the minimum agronomic measures applied; and (2) "deserted" land, not-cultivated for more than 3 years, and is more difficult to be recovered. The first case could be definitely considered as long fallow and part of arable land (according to EU definition), while the second case is considered really "abandoned".

Since Bulgaria became an EU member, the interest to the "abandoned" land increased, due to the possibilities given by EU Common Agriculture Policy to receive subsidies for its utilization. In this respect, a certain portion of this "abandoned" land, even if currently not utilised, can be brought back into use by the farmers, at any given moment, and thus should be considered potentially part of the "SAPS envelope". From a physiognomic-structural (biotic or abiotic) aspect, land not cultivated for several years, may acquire certain land cover properties, common to natural vegetation. This means that an estimation of the land in GAC, based on detection of the land currently under cultivation (using remote sensing), will not be correct, as it will omit the former agricultural areas (presently appearing as naturally vegetated), which can be brought back into use through the application of common agriculture practices. Supplementary information from the LPIS or other sources such as NATURA 2000[1] may be needed to support the interpretation. To incorporate and manage correctly all possible cases of land cover, the features captured during the classification, will be grouped in three distinctive categories according to the physiognomic-structural point of view and to the LPIS information:

- *GAC* includes land cover features which can be classified as agricultural land being in GAC,
- *Potential non-GAC* includes land cover features which are unlikely to represent agricultural land in GAC; however, a cross-check using up-to-date VHR data or a rapid field visit is necessary to finalise conclusions,
- *Non-GAC* includes land cover features which cannot be, and have no potential to be, agricultural land in GAC.

3 STUDY AREA

After joining to the EU in 2007, Bulgaria adopted the legislation of the European Community for management and monitoring of their agricultural land and benefit payments. Bulgaria is approximately 111.000 km^2 in size, extending from the western boundaries of the Black Sea to Serbia and FYROM on the East. The country borders Romania on the North and Turkey and Greece on the South. The northern boundary follows closely the Danube River. To capture the diversity of landscape within the country, the study area has been divided (stratified) into three testing zones: Zone 1–Kardzhali (KARD); Zone 2–Plovdiv (PLOV) and Zone 3–Varna (VARN). Two additional 'back-up' zones, were also selected in the event suitable RapidEye imagery over the main zones could not be obtained. This paper presents the analysis and results obtained for the KARD zone.

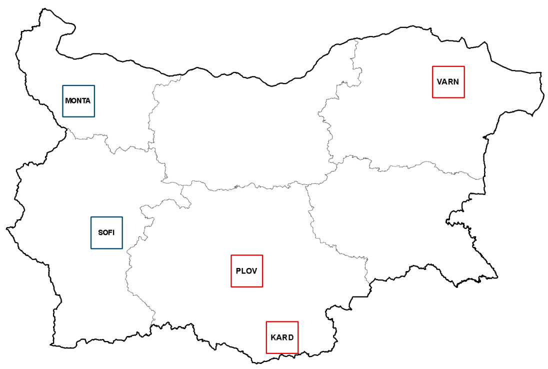

Figure 1: Map of Bulgaria and Test zones.

The KARD zone is located in a highly segmented part of Strumni Ridge, situated in the area of Eastern Rhodope, Bulgaria. The landscape is hilly to mountainous, with an average altitude of 444 meters. The climate is mild to Mediterranean with an average annual temperature about 11°C, and an average annual rainfall between 650-700mm. Droughts are common during the summer. The soil, having limited mineral chemical elements, makes

[1] http://ec.europa.eu/environment/nature/index_en.htm

the area suitable for the cultivation of vines, tobacco (main cultivation in the region), fruits and grains. Slopes are deforested and eroded; with areas prone to landslides. Most of the hills are covered by low-productivity grassland used for grazing. There are alluvial and deluvial-meadow soils along the major rivers in the region, where vegetables and hemp can be grown, due to the larger quantity of moisture, they receive from the soil layers.

4 REMOTE SENSING IMAGERY

A constellation of 5 multispectral satellite sensors were launched by RapidEye in August 2008 with a primary focus on agricultural applications. These satellites have a lifespan of seven years; a ground sampling distance of 6.5m resampled to 5m; and a daily overpass. A new feature in RapidEye sensor is the Red Edge band (690-730nm), which could allow better estimation of the ground cover and chlorophyll content of the vegetation (Haboudane et al., 2002, Vinal and Gitelson, 2005). All 5 satellites have the same calibration coefficients. The radiometric scale factor converting the image DN values into reflectance is 0.01.

Imagery was obtained from RapidEye AG at standard processing level 3A [2] (orthorectified) for the dates indicated in Table 1. Pre-processing of imagery was carried out in ERDAS Imagine and ESRI ArcGIS software. This entailed further geo-referencing of the satellite imagery to the national orthoimagery provided by the Bulgarian government, thus ensuring data consistency between the RapidEye imagery and the LPIS datasets. Nearest neighbour approach was used for the resampling. In addition to the RapidEye imagery, VHR data from IKONOS has been acquired in the frame of the annual CwRS campaign and was also provided for the study. The availability of this imagery was an important source of ground truth. An orthorectification of this VHR data was carried out using the reference national orthophoto, additional ground control points and the SRTM DEM provided freely.

Zone	Acquisition dates in 2009				
	April	May	June	July	September
KARD	12.04	20.05	10.06	15.07	10.09
				23.07	16.09
				24.07	

Table 1: Acquisition dates of all RapidEye images over KARD

5 METHODOLOGY

The proposed methodology is based on the key elements derived from the GAC definition in Section 2. From the adopted GAC definition, we can conclude that, a land could be considered in GAC, if at least the following two criteria are met: *i)* vegetation is growing or can be grown on that land; *ii)* the land is accessible for agriculture activities (cropping, grazing, etc.). Both criteria can be evaluated by monitoring the development of the vegetation during the year (phenological cycle), together with the analysis of the texture properties of the land cover and the relevant spatial context. Thus, the methodological approach was based on a multi-temporal analysis of RapidEye time-series, using object oriented classification techniques in order to detect and qualify the land cover features in respect to their potential to represent agriculture area in GAC. Considering that the proposed definition of GAC is quite broad, it was agreed that the first estimation of the land potentially useful for agriculture (and being in GAC) can be done through detection and quantification of the non-GAC (and potential non-GAC) features. From land cover (physiognomic-structural) point of view, land which is not in GAC is constantly bare or non-vegetated during the (cultivation) year (for example sealed surfaces; natural bare areas) and contains features preventing the agricultural activity even though it is vegetated (for example closed forest, woodland, wetland, etc.)

An overview of the proposed methodology used for decision-making and analysis can be seen in Figure 2. The selection, acquisition and pre-processing of imagery was important to provide a solid foundation for future analysis. The acquisition windows were carefully defined on the base of crop calendars, provided by ReSAC. Imagery from April, May, June, July and September were acquired over the test zones to reflect the phenological cycles of the vegetation (see Table 1).

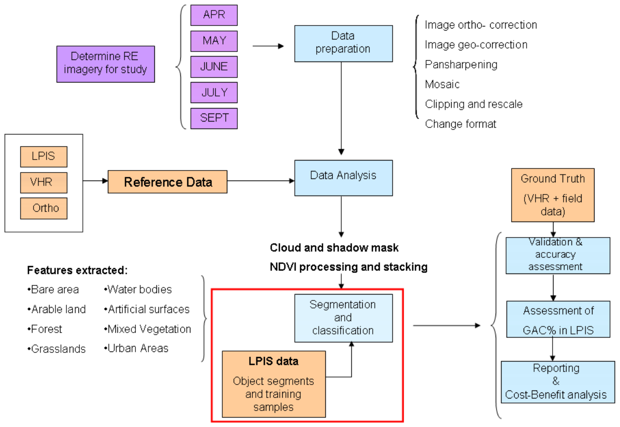

Figure 2: Proposed methodology

Data analysis: Capture and qualification of the permanently non-vegetated areas and the areas not accessible for agriculture were the primary targets. Most of the non-vegetated area with artificial anthropogenic origin, as urban structures, roads, hardpans, etc. can be efficiently extracted from a single RapidEye image, if acquired in the correct period of the year. The same is also valid for the naturally vegetated areas, not suitable for agriculture activities (such as forested areas, wetlands), or water bodies. However, for most of the natural bare areas, unsuitable for agriculture (such as as eroded surfaces, degraded soils), the analysis has to be based on several time series, in order to filter out temporary bare areas, for example, harvested agricultural fields. Another important land cover, requiring multi-temporal approach, is low-productivity grassland, quite common in the area of KARD. This type of mountain grassland, used for grazing, appears vegetated (on the satellite imagery) only during particular periods of the year (early spring); usually its spectral signature is similar to bare surface, especially during the summer when it becomes dry. The only option to efficiently capture those areas is through the use of multi-temporal imagery covering the entire active agriculture period so that various aspects of the vegetation growth and climatic conditions can be considered.

It was assumed that permanent bare areas should have low NDVI values in all time series. For that purpose Red Edge Normalized Difference Vegetation Index (NDVI) (equation 1) (Wu et al., 2009) was calculated for all images.

$$NDVI_{Red\ Edge} = \frac{NIR - Red\ Edge}{NIR + Red\ Edge} \quad (1)$$

The choice of the Red Edge channel, instead of the Red channel for the NDVI calculation, was mainly driven by lesser saturation of the Red Edge NDVI comparing to the traditional NDVI over highly vegetated (forested) regions, as reported in the literature (Haboudane et al., 2002, Vinal and Gitelson, 2005). Figure 4.b

[2]http://www.rapideye.de/home/products/standard-image-products/standard-image-products.html

shows stacked imagery composed by the NDVI images calculated for four consecutive months from April to July. Analysis of the stacked NDVI imagery clearly highlights permanent bare areas (low NDVI values) as dark features, contrary to the forested or vegetated agricultural areas (high NDVI values), which appear in brighter shades of blue and yellow. After obtaining the Red Edge NDVI images, a 5-band image containing the stacked NDVI images for the months of April, May, June, July and September were created in ERDAS Imagine. It was finally rescaled to the dynamic range of the RapidEye imagery, which is 12 bit.

Segmentation and Classification: The 5-band stacked NDVI image was segmented in Definiens eCognition, using the spatial data of the LPIS as an input thematic layer. The aim was to aggregate into single objects, the image pixels with similar temporal behaviour in respect to the vegetation cover. The segmentation was performed at high detail to preserve features up to 0.1 ha within the imagery; as a consequence the land cover features larger than the minimum mapping unit, were over-segmented (Figure 3).

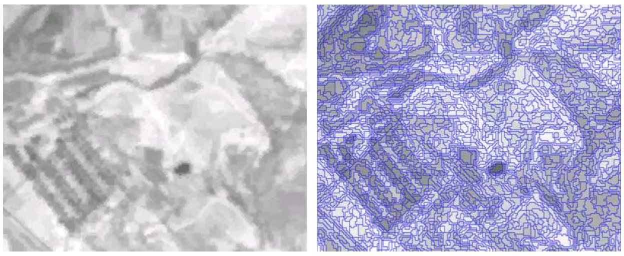

Figure 3: An extracted part from the original stacked NDVI imagery and its segmentation by Definiens eCognition.

The spatial and alphanumeric data from the LPIS plays an integral role in the segmentation and classification of the RapidEye imagery. As a consequence, the resulting land cover segments were coherent with the spatial extent and design of the reference parcels of the LPIS. In addition, valuable information regarding the type of the land use and the farmer restrictions at reference parcel level (stored in the LPIS attribute data), was used in the subsequent classification and aggregation of the image segments into meaningful land cover features at a higher object level.

The resulting segments were further classified in eCognition, to extract various land cover features. Different variables, such as Brightness, Mean value of Red, Relative Border to, Border Index and Thematic Attribute, have been used. The exhaustive toolbox of eCognition, together with the extensive use of abundant RapidEye and LPIS data, gave the possibility to define and extract more land cover types thus, enrich the initial simple binary classification of vegetated and non-vegetated areas. The land cover types were further grouped in GAC, Potential non-GAC and Non GAC categories, based of the pre-defined rules.

6 PRELIMINARY RESULTS

The first results obtained for the test area of KARD (Figures 4.c and 4.d) indicate that non-GAC features can be detected with high success rate. The overall thematic accuracy of the land cover classification is about 81% (See Table 2). The major confusion, which was between natural bare areas and urban areas, was not considered critical as both classes, eventually, are classified into the same (non-GAC) group. For KARD zone 55.1% (10118.8 ha out of 18361.3 ha) is in GAC, 8.8% (1614.2 ha) is in potential non-GAC and 36.1% (6628.2 ha) is in non-GAC group.

	Urban Areas	Agri-culture	Forest	Bare area (natural)	Water
Urban areas	44	0	0	9	0
Agriculture	0	141	0	0	0
Forest	0	0	58	0	0
Bare area	0	7	0	27	5
Water	0	0	0	0	26
Other	0	37	0	10	0
Producer acc.	1.0	0.76	1.0	0.59	0.84
User acc.	0.83	1.0	1.0	0.69	1.0
Overall acc.	**0.81**				

Table 2: Producer and user accuracies for the clusters extracted by object oriented analysis

Some mixed land cover of bare areas and natural vegetation were incorrectly validated as agricultural areas because of the vagueness associated with ground truth samples. Unfortunately, due to the limited ground truth taken directly in the field, the validation of the classification was done solely on the base of information obtained from the VHR imagery. Even though having sufficient spatial, spectral and radiometric resolution, the IKONOS imagery represents only a single snapshot of the ground, a limitation, which cannot always ensure that the information available on the VHR image will be sufficient for a proper interpretation of the ground truth. A further validation of the results is planned with more reliable ground truth data, available from the annual field inspection done by the National Administration on selected agriculture parcels from the test zones.

7 CONCURRENT TESTING

In addition to the object oriented analysis of stacked red edge NDVI images, a pixel based method using automated clustering of the Self-Organizing Maps (SOMs) (Taşdemir and Milenov, 2010) has also been utilised. This SOM based analysis has exploited information in all bands, i.e., each pixel has a 20-band (5 RapidEye bands for 4 consecutive months from April to July).

SOMs are unsupervised artificial neural networks that use a self-organizing learning algorithm inspired from the neural maps on the cerebral cortex (Kohonen, 1997). They are successfully used in remote sensing applications due to their two main properties: *i)* providing an adaptive vector quantization of the data samples to approximate the unknown density distribution of the data; *ii)* distribution of these quantization prototypes on a rigid lattice by preserving neighborhood relations in the data space so that high-dimensional data spaces can be visualized in lower dimensions (preferably 2D or 3D). Comprehensive knowledge learned by SOMs can be used for cluster extraction and knowledge discovery from large data sets using interactive or automated methods (Taşdemir and Merényi, 2009, Taşdemir and Milenov, 2010).

An automated hierarchical clustering of SOMs based on detailed local density distribution, proposed in (Taşdemir and Milenov, 2010), was used for GAC detection and extraction from the 20-band stacked RapidEye imagery. A 50×50 SOM was trained by Matlab SOMtoolbox and a cluster map, focusing on the land cover types of permanent bare areas, water, forest and vegetated areas, was extracted. Figure 5 shows the resulting cluster map and compares it to the map extracted by the object oriented analysis. SOM based approach is unable to capture spatial context such as inland grass (for example vegetation within forest) whereas object oriented approach is unable to correctly capture small fields due to its averaging property. Despite these minor details, the resulting cluster maps are quite similar in terms of GAC detection. The SOM based clustering is advantageous because it is a faster, semi-automated method which requires much less user interaction than the object oriented segmentation.

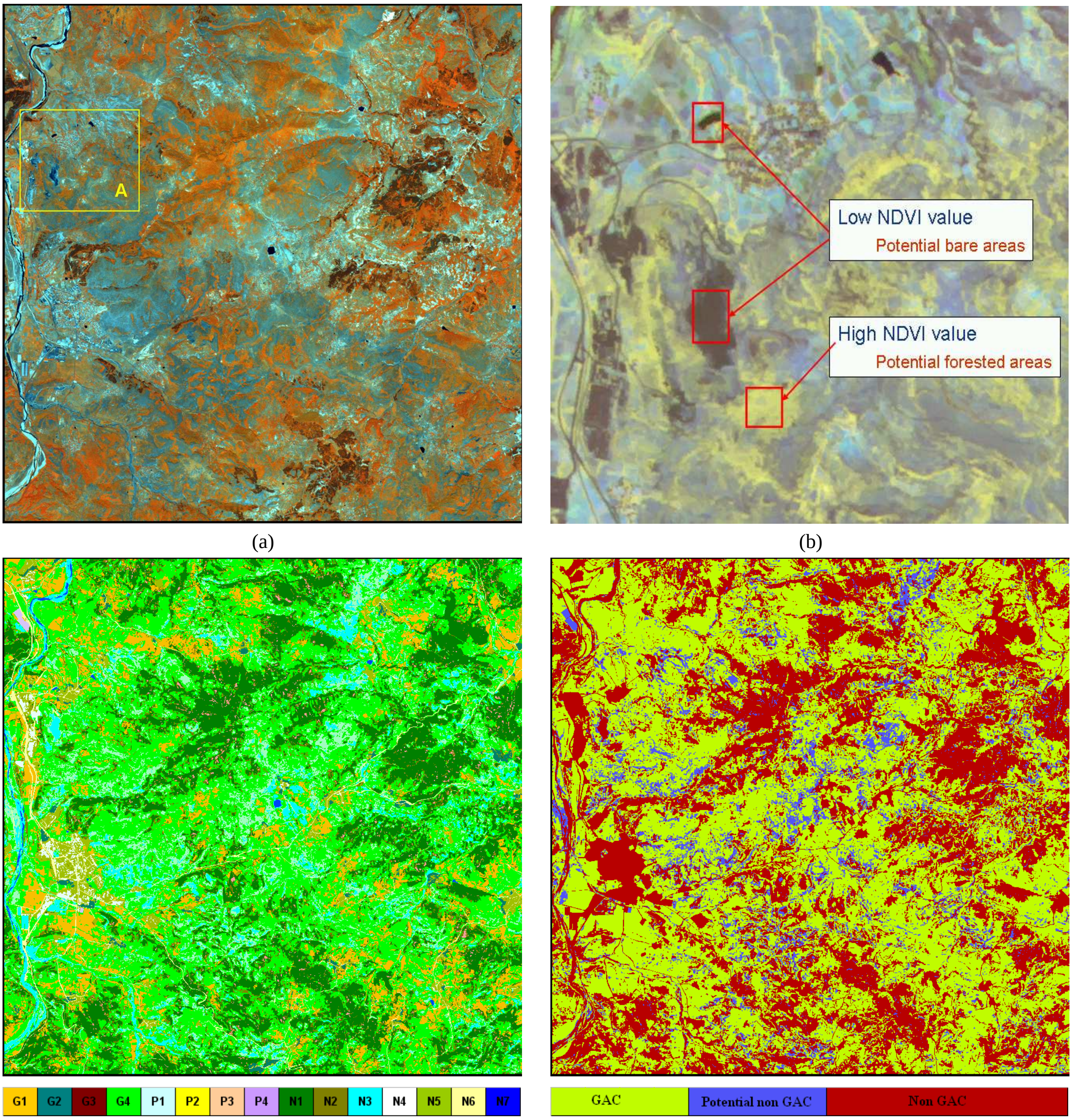

Figure 4: (a) Colour composite (NIR, Red Edge, and Red) image of KARD zone. (b) Colour composite image of the NDVIs from 4 consecutive month (April to July) for a subset (A, outlined on the left) of KARD zone. Dark regions (low NDVI for 4 months) indicate potential bare areas whereas light regions (high NDVI for 4 months) indicate potential forested areas. (c) Preliminary results for the land cover map of KARD. GAC is represented by cultivated land (G1, arable and grassland), family gardens (G2), permanent crops (cultivated) (G3), and mixed pattern of cultivated land, mountain grassland and natural vegetation (G4). Potential non GAC includes mixed pattern of bare area and natural vegetation (P1), fallow land (P2), inland vegetation or grassland (P3), permanent crops (not cultivated) (P4). Non GAC consists of closed (N1) or open (N2) forests, permanent natural bare areas (N3), urban areas (N4), vegetation in urban (N5), other sealed surfaces such as roads (N6), and water bodies (N7). (d) Resulting GAC, Potential non GAC and non GAC mask for KARD zone.

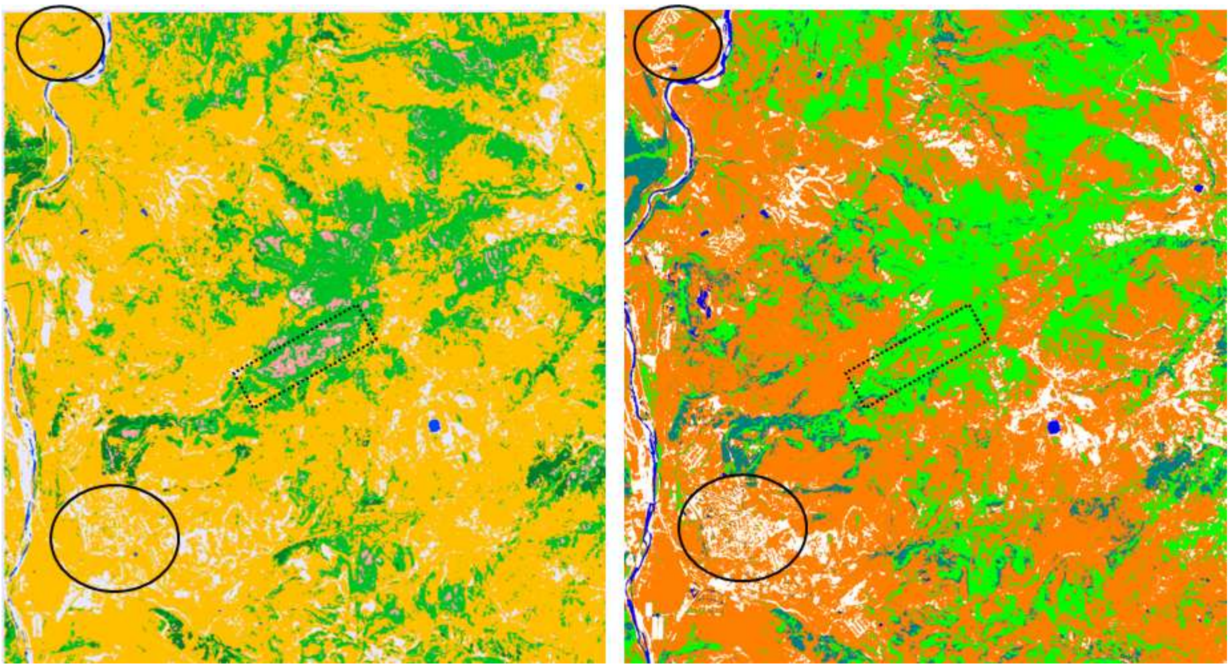

Figure 5: Comparison of cluster maps extracted using object oriented analysis (left) and self-organizing maps (right) for GAC detection. GAC regions are orange, urban areas are white, deciduous forests are light green whereas coniferous forests are dark green, and water bodies are blue. There is high degree of similarity between these cluster maps. SOM correctly extracts urban areas (white regions within ellipses on the right) whereas they are captured as GAC by object oriented analysis (orange within ellipse on the left). However, inland grass, pink regions within the rectangle on the left, cannot be extracted by the SOM (orange on the right) due to the necessity of spatial context whereas SOM clustering is pixel based.

8 CONCLUSIONS

The paper proposed a methodology for annual inventory and monitoring of the land which may be 'eligible' under SAPS in Bulgaria, using RapidEye imagery. A legal definition of "Good Agricultural Condition (GAC)" was introduced as a starting point for assessment of eligible area. An object oriented classification of multi-temporal RapidEye data was performed in order to quantify agricultural area in GAC on annual basis. In addition to the object oriented analysis, an alternative method based on self-organizing maps has also been used. Preliminary results are encouraging and they clearly indicate that multi-temporal remote sensing data can effectively contribute to differentiate currently active and potential agriculture land, and land which cannot be considered suitable for agriculture in the context of SAPS. However further validation of the methodology for the other test zones is necessary. It is envisaged to follow-up discussions of results with the Bulgarian Administration.

RapidEye imagery (in terms of information content) seems to be particularly suitable for feature detection and land cover mapping of agriculture landscapes. As the spatial resolution doesn't correspond to 1:10 000 scale, the imagery cannot be used directly for LPIS update; however it can provide essential information on the overall accuracy of the LPIS in relatively short time frame, provided that the acquisition approach is adapted to the user expectations. The proposed methodology may also help Bulgaria (and Romania) to further develop their concept in respect to the eligibility conditions currently applied under SAPS.

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