CROP TYPE MAPPING BY PROBA-V SATELLITE DATA WITH 100 M AND 300 M SPATIAL RESOLUTION AT ZLATIA TEST SITE, BULGARIA

Petar Dimitrov[1], Ilina Kamenova[1], Vassil Vassilev[1], Eugenia Roumenina[1], Martin Banov[2], Georgi Jelev[1]

[1]Space Research and Technology Institute – Bulgarian Academy of Sciences
e-mail: petar.dimitrov@space.bas.bg; ilina.kamenova@hotmail.com; vassilev_vas@yahoo.com; eroumenina@gmail.com; gjelev@space.bas.bg
[2]Institute of Soil Science, Agrotechnologies and Plant Protection "Nikola Poushkarov" – Agricultural Academy, Bulgaria
e-mail: banovm@abv.bg

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Abstract: *This paper presents some of the results obtained during a study carried out in 2014 in the framework of the "PROBA-V 100 m Exploration Exercise" initiative. The aim of the study was to assess the potential of PROBA-V satellite data with 100 m spatial resolution for crop type mapping. Distribution of four main crops was mapped over the territory of Zlatia test site in western Danube plain using multispectral images from 21 March and 8 July 2014. Using a maximum likelihood classifier, overall classification accuracy of 86% and 82% was achieved for the two dates. Classes to be distinguished in the 21 March image were wheat, rapeseed, and soil, while for the 8 July image maize, sunflower, and soil/stubble were sought. For comparison purposes, PROBA-V images with 300 m spatial resolution were also classified achieving accuracy of 80% and 70% for 21 March and 8 July respectively. The wheat and rapeseed areas estimated based on the classifications were compared with independent data for harvested areas from the Ministry of Agriculture and Food. Very good correspondence was observed between the two datasets for wheat, but the deviation for rapeseed was large.*

КАРТОГРАФИРАНЕ НА ЗЕМЕДЕЛСКИ КУЛТУРИ ПО СПЪТНИКОВИ ДАННИ ОТ PROBA-V С ПРОСТРАНСТВЕНА РАЗДЕЛИТЕЛНА СПОСОБНОСТ 100 М И 300 М В ТЕСТОВИ УЧАСТЪК ЗЛАТИЯ, БЪЛГАРИЯ

Петър Димитров[1], Илина Каменова[1], Васил Василев[1], Евгения Руменина[1], Мартин Банов[2], Георги Желев[1]

[1]Институт за космически изследвания и технологии – Българска академия на науките
e-mail: petar.dimitrov@space.bas.bg; ilina.kamenova@hotmail.com; vassilev_vas@yahoo.com; eroumenina@gmail.com; gjelev@space.bas.bg
[2]Институт по почвознание, агротехнологии и защита на растенията „Никола Пушкаров" – Селскостопанска академия
e-mail: banovm@abv.bg

Ключови думи: *Картографиране на земеделските култури, Управлявана класификация, PROBA-V 100 m*

Резюме: *Докладът представя част от резултатите от изследване проведено през 2014 г. в рамките на инициативата „PROBA-V 100 m Exploration Exercise" целящо да оцени потенциала на данни от спътника PROBA-V с пространствена разделителна способност 100 m за картографиране на земеделските култури. Разпространението на четири основни вида земеделски култури е картографирано за територията на тестови участък „Златия", разположен в западната част на Дунавската равнина ползвайки две многоканални изображения – от 21 март и от 8 юли 2014 г. Класификациите на двете изображения по метода на максималното правдоподобие имат точност съответно 86% и 82%, като при първата, търсените класове са пшеница, рапица и почва, а при втората – царевица, слънчоглед и почва/стърнище. За сравнение, идентичен анализ е извършен с данни от PROBA-V с разделителна способност 300 m, като точностите са съответно 80% и 70%.*

Оценките на площите заети с пшеница и рапица получени на базата на класификациите са сравнени с официалните данни на Министерството на земеделието и храните, като за пшеницата съответствието е много добро, докато за рапицата има значително разминаване.

Introduction

Acquiring timely and accurate information for the spatial distribution of crops in a given area is important for practice and represents significant challenge to the monitoring and management systems in agriculture. Spatially explicit information for crops in the form of maps and GIS layers is needed to estimate areas of different crops, check area-based subsidies, generate input data for crop production forecasting models, monitor agricultural practices like crop rotation [1] and other applications.

In the last decades remote sensing has established itself as an effective tool for mapping land cover/land use mainly because of its possibility to quickly provide information over vast areas. For example, one of the main applications of the data from satellite sensors with low spatial resolution (SR) like AVHRR, VEGETATION and MODIS is the generation of global land cover maps [2-5]. Recently, global land cover product with SR as high as 30 m has been realized based on the Landsat TM/ETM+ archive [6]. Most of these products, however, are not generated regularly and cannot reflect changes within arable lands from one year to another. Moreover, they present agricultural land as a single, aggregated class and therefore are of little practical use for the specific agricultural applications.

Despite the considerable progress in land cover mapping, attempts for thematically detailed crop mapping are still relatively sparse [7]. An example for a standard crop map generated by satellite data is the United States Department of Agriculture's Cropland Data Layer (CDL), which is used for the reports of the National Agricultural Statistics Service [8].

Different approaches for automatic crop recognition based on satellite data can be found in the literature. They propose the usage of different classification algorithms and types of images. For example, the CDL product (56 m SR) is generated using supervised decision tree classification and multispectral images, mostly from the Advanced Wide Field Sensor (AWiFS) onboard the Indian Remote Sensing Satellite (IRS) RESOURCESAT-1 [8]. Many studies emphasize the fact that reflectance characteristics of crop canopies have crop-specific temporal dynamic [9]. For example individual crops can be distinguished based on time profiles of satellite data, usually spectral vegetation Index (SVI) sensitive to vegetation cover and state. Making use this seasonality, Vassilev [10] combine unsupervised classification on NDVI time series from VEGETATION and agro-phenological information in order to map four main crops over the territory of Bulgaria.

Achieving appropriate ratio of the SR of image and the field size is an essential precondition for successful crop recognition and mapping. However, tradeoff should be made when choosing appropriate satellite image. In particular, sensors with high SR capable to discriminate individual fields are restricted in terms of the number of usable, cloud-free images per growing season and coverage of single scene [9]. It is clear that the question of what satellite data and methods are most suitable for crop mapping has no single answer and decision depends on the specific conditions in the area.

In this context, a study was conducted in 2014 in order to evaluate the potential of the recently launched PROBA-V satellite for crop mapping in Bulgarian agricultural setting. One of the objectives of the PROBA-V mission is to assure continuation of the data archive generated by VEGETATION 1 and 2 sensors onboard the *Système Pour l'Observation de la Terre* (SPOT) 4 and 5 satellites [11]. PROVA-V provides improved SR compared to the VEGETATION instruments, namely 300 m for the visible and near infrared (VNIR) and 600 m for the shortwave infrared (SWIR) band. The optical instrument consists of three cameras placed so that their overall field of view covers a swath of ~ 2300 km, which is needed for daily global coverage [11]. The instrument's design, thus, allows using data from the central camera having SR of 100 m (VNIR) and 200 m (SWIR). This data can be very useful when SR is more important than global coverage and daily revisit frequency [11]. They also present great opportunities for crop recognition and mapping.

The aim of this research is to assess the possibilities for mapping arable lands with both winter and spring crops grown on it using supervised classification of PROBA-V satellite images with 100 m and 300 m pixel size. Our specific objectives were to: (i) assess the accuracy of maximum likelihood classifier for recognition of four main crop types; (ii) find whether significant difference exists between classification accuracy achieved with 100 m and 300 m PROBA-V data; (iii) compare estimates of crops' areas derived from the classified images with those provided by Ministry of Agriculture and food.

Study area

The study was conducted on the territory of Zlatia test site (2214.7 km^2), situated in the western part of Danube plain, Bulgaria. Although the agro-climatic conditions vary across Bulgaria, the chosen site is considered representative for lowlands where the intensive agriculture is concentrated. Moreover, our focus is on the major crops, which are common for the country and on the typical field size and spatial structure characteristic for intensively managed agricultural areas. On the territory of *Zlatia* test site, winter wheat, rapeseed, maize, and sunflower are mostly grown. Predominant soil types are carbonate and typical *Chernozem* (not eroded), followed by leached *Chernozem* and alluvial soils.

Data

Ground data. For our study, information for crops sown in 128 fields was available for the 2013-2014 season. The data was organized in GIS layer containing the field boundaries. For 44 fields information was provided by a local farmer and additional data was available: planting date, dates of occurrence of different phenological stage, harvesting date, yield, tillage practices, and winter crops sowing in the next season. For the remaining fields the sown crop was noted during two visits of the test site in March and August 2014. Most fields (75%) have a size up to 100 ha. Statistic data for harvested areas of winter crops in 2013-2014 season was provided by the Ministry of Agriculture and Food (MAF).

Satellite images. In 2014, in the framework of the „PROBA-V 100 m Exploration Exercise" initiative, VITO (*Vlaamse Instelling voor Technologisch Onderzoek*) provided limited access to PROBA-V products with 100 m SR. The aim of the initiative was to demonstrate the potential of these 100 m data products and to justify the need for their operational production and distribution to the wider user community in the next years. As part of this initiative an evaluation study of the possibilities for crop recognition in Bulgaria was conducted. This report presents results from the analysis of two PROBA-V scenes acquired on 21 March 2014 and 8 July 2014. They were selected to be suitable for mapping winter crops (wheat and rapeseed) and spring crops (maize and sunflower) respectively. PROBA-V 300 m products for the same dates were also downloaded from the VITO's Product Distribution Portal[1]. Both 100 m and 300 m data used in this study are S1 TOC products and represent daily synthesis top of canopy reflectances in the four PROBA-V spectral bands (Table 1). Image preprocessing included: stacking separate bands into one file, spatial subsetting, reprojecting the images to UTM zone 34N projection, and masking pixels outside the arable land based on the CORINE 2006 land cover dataset [12]. Additionally, Landsat 8 images were used in the assessment of accuracy of crop recognition.

Table 1. PROBA-V spectral bands [11].

	Band center (nm)	Band width (nm)
BLUE	463	46
RED	655	79
NIR	845	144
SWIR	1600	73

Methods

Supervised maximum likelihood classification (MLC) of multispectral PROBA-V images was used in this study to identify crop types. For the image from 21 March, three agricultural cover categories (classes) were distinguished in the classification: wheat, rapeseed, and soil. Three classes were also used in the classification of the image from 8 July: maize, sunflower, and soil/stubble. Training samples were generated by manually drawing polygons on the image using the GIS dataset with ground data as a guide. Besides the single date classifications, attempt was made to classify stacked images combining the spectral information from both dates (hereafter referred to as two-date stack (TDS) classification). In this case the sought cover classes included wheat, rapeseed, maize, and sunflower.

Classifications' quality was assessed in two ways. First, crop type information for the fields from the GIS layer was used. Test dataset was obtained by extracting the pixels within the fields with different crops. From this *ground dataset*, pixels used to train the classifier and pixels along the field borders were excluded. Error matrix and the percent of correctly classified pixels were calculated. Second, accuracy statistics were calculated for the entire classification based on a simple random

[1] VITO Product Distribution Portal - http://www.vito-eodata.be/PDF/portal/Application.html#Home

sample of pixels. Sampled pixels were selected using the ArcGIS tool for generation of random points. The same random points were used for both 100 m and 300 m classifications, thus the two test samples are related. The category of agricultural cover in each test pixel for 21 March and 8 July was determined by visual interpretation of a series of seven Landsat 8 images spanning the period 23 March – 30 August 2014. The ground truth information from the GIS layer was used to gain knowledge of spectral and temporal behaviour of different cover types and train the interpreter. The opportunity to track temporal changes using the Landsat 8 dataset was the key for gathering reliable referent information for the test pixels. The dominant fraction criterion was used to assign a pixel to a cover type in those cases when more than one cover type is present in a pixel. Based on this *random sample dataset,* error matrix, overall accuracy, and Kappa coefficient were calculated. Confidence interval of overall accuracy was calculated following a simplified procedure for estimation of confidence interval of proportions as presented in Fleiss et al. [13]. In this case 95% confidence interval was used, where the upper bound is:

(1) $p - 1.96\sqrt{\frac{p(1-p)}{n}} - \frac{1}{2n}$, and the lower bound is: $p + 1.96\sqrt{\frac{p(1-p)}{n}} + \frac{1}{2n}$,

where p is the proportion of correctly classified pixels and n is the number of pixels in the sample. The calculated confidence interval contains the true overall accuracy value with probability at least 95% [13, 14]. The statistical significance of the difference in overall accuracy values achieved for the 100 m and 300 m classifications was tested using the McNemar test for proportions [15].

Results

The image from 21 March coincides with the period of resumption of crops growth after the winter dormancy. The main crops of interest at that time are winter wheat and rapeseed. In addition, class “soil” was used in the classifications in order to represent the land cover in fields allocated for sowing of spring crops. The assessment based on the *ground dataset* shows that almost 100 % of the test pixels are correctly classified in both 100 m and 300 m classification from 21 March (Table 2). Thus, the classifications perform very well within the fields where ground truth data was available. More complete picture of classification accuracy is provided by the overall accuracy statistic, calculated using the *random sample dataset*. The overall accuracy was 86 % and 79 % for the 21 March 100 m and 300 m classification respectively (Table 3). For the 100 m classification, user and producer accuracies are close to or higher than 80%, and only the “rapeseed” class has relatively low producer accuracy (73%). The most accurately recognized class is “soil” (over 90%). For the 300 m classification accuracies of separate classes are lower. For example, producer accuracy of “wheat” and “rapeseed” is only 62 %. For the “wheat” class the low producer accuracy is mainly due to misclassification as “soil”, while for the “rapeseed” class, the incorrectly classified pixels are equally distributed between “soil” and “wheat”.

The PROBA-V data for 8 July represents the period just after the harvest of winter crops. Land cover of the harvested fields is presented by stubble or soil-crop residue mixture depending on the time and type of tillage performed. Since spectral variations between these fields are present we decided to use subclasses so that spectral signatures satisfy the normal data assumption. Once the image is classified, subclasses are merged into one class denoted as “soil/stubble”. This was done because the classification of the image from 8 July focuses on the two summer crops – maize and sunflower and detailed description of harvested fields was beyond the scope of the study. The classification quality assessment based on the *ground dataset* shows that the success with which the three classes are identified is different for 100 m and 300 m PROBA-V data. Ninety-six percent of the test pixels extracted from the fields with ground data was correctly classified in the 100 m classification. For the 300 m classification the corresponding value was 82% (Table 2). Visual check of the 300 m classification shows that several maize fields are classified as sunflower. The difference of classification performance between the 100 m and 300 m PROBA-V image is confirmed by the overall accuracy, which was 82% and 70% respectively (Table 3). The error matrix generated using the randomly sampled pixels confirms that the 300 m classification tend to overestimate the “sunflower” at the expense of “maize”. Most of the referent pixels of class “maize” are not recognized and the producer accuracy for that class is only 42%. The user accuracy of the “sunflower” class is only 49%. In the 100 m classification less misclassification is observed and the accuracies for “maize” and “sunflower” are between 69% and 78%.

When the aim is to map the distribution of both winter and summer crops for a particular agricultural season one should best use several images acquired on different dates. One possible approach is to perform separate single-date classifications and then combine the results in a final map fowling predetermined procedure [1]. Decision should be made when a pixel is assigned to different classes in each classification. More simple and less time consuming layer stack approach was used in this study. The spectral data from 21 March and 8 July was first combined in a single image and then classified to distinguish the four crops. The resulting TDS classifications are very accurate in recognizing the crops in the fields from the ground truth dataset (98% and 91% for the 100 m and 300 m data respectively, Table 2). The overall accuracy however is relatively low – 75% and 72% for the 100 m and 300 m PROBA-V data (Table 3). Examination of the error matrix shows that the main reason for the low accuracy of the 100 m classification is the underestimation of “sunflower” (producer accuracy=52%) at the expense of “maize” (user accuracy=62%). Unlike spring crops, the recognition of the winter crops is relatively accurate. Similarly to the 100 m classification confusion between “maize” and “sunflower” is observed in the 300 m classification.

The overall accuracy of the TDS classification with 100 m SR was not particularly high. However, the full potential of multitemporal PROBA-V data for crop classification has yet to be realised. Using larger number of scenes acquired in key periods of the growing season is expected to enhance crop separability but may necessitate the use of different analysis methods, for example Bayesian model averaging or co-training [16]. Other possibility is the use of vegetation indices time-series [10].

In this study, the overall classification accuracies achieved using the 100 m PROBA-V data were higher than accuracies achieved using the 300 m data. The differences were 7% and 12% for the scenes from 21 March and 8 July respectively (Table 4), and the statistical test shows they are significant ($p<0.05$). Accuracy of the stacked-image classifications differed by only 3% which value is not significant. This result is somewhat confusing, but in general, it seems that better classification results in terms of overall accuracy can be achieved with PROBA-V 100 m images. Advantages of the PROBA-V 100 m classification become apparent when it is visually compared with the 300 classification (Figure 1). Even relatively small fields with area below 1 km^2 and irregular or narrow shape are clearly distinguished on the classified 100 m images. Contrary to this, the exact borders and shape of even large fields are not apparent on the classified 300 m images. For the studied agricultural landscape, the number of mixed pixels in the PROBA-V 300 m products may by significant. Overlaying the TDS classifications with 100 m and 300 m spatial resolution it was found that 61% of the 300 m pixels contain more than one class or one class and mask according to the 100 m classification.

Table 2. Results from the classification accuracy assessment based on ground truth data,

Image	100 m	300 m
	percent of correctly classified pixels	
21 March	99	98
8 July	96	82
TDS (21 March + 8 July)	98	91

Table 3. Results from the classification accuracy assessment based on the simple random sample of pixels (n=275) and visual interpretation of Landsat 8 images.

Image	100 m	300 m
Overall accuracy (%)*		
21 March	86.2 (81.9-90.5)	79.3 (74.3-84.3)
8 July	82.5 (77.8-87.2)	70.2 (64.6-75.8)
TDS (21 March + 8 July)	74.9 (69.6-80.2)	71.6 (66.1-77.1)
Kappa		
21 March	0.76	0.64
8 July	0.73	0.52
TDS (21 March + 8 July)	0.65	0.61

* 95% confidence interval of overall accuracy is shown in parentheses.

Table 4. Results from the McNemar test for difference of overall accuracy between each 100 m classification and its 300 m counterpart (n=275). The method of comparison based on related samples as described by Foody [15] was used. Continuity correction was applied.

Image	Difference of the overall accuracy of 100 m and 300 m classifications (in %)	Chi-squared	*p*-value (2 tails)
21 March	6.9	6.11	0.013
8 July	12.3	14.72	0.000
TDS (21 March + 8 July)	3.3	0.93	0.336

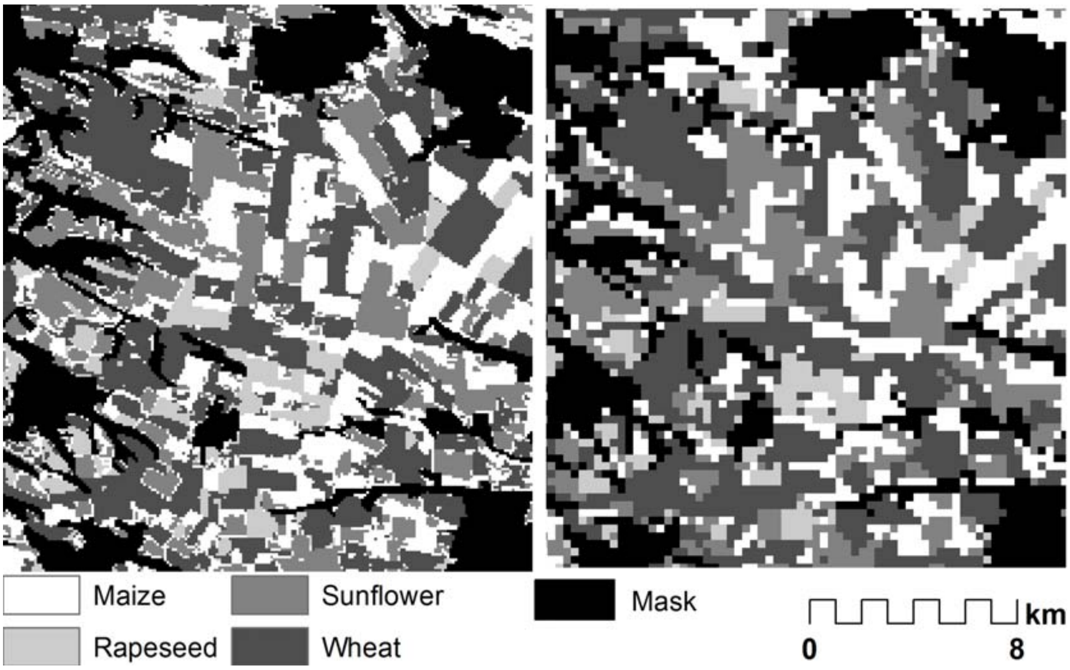

Fig. 1. Subsets from the classifications of the PROBA-V image stacks (21 March+8July) with 100 m (left) and 300 m (right) spatial resolution

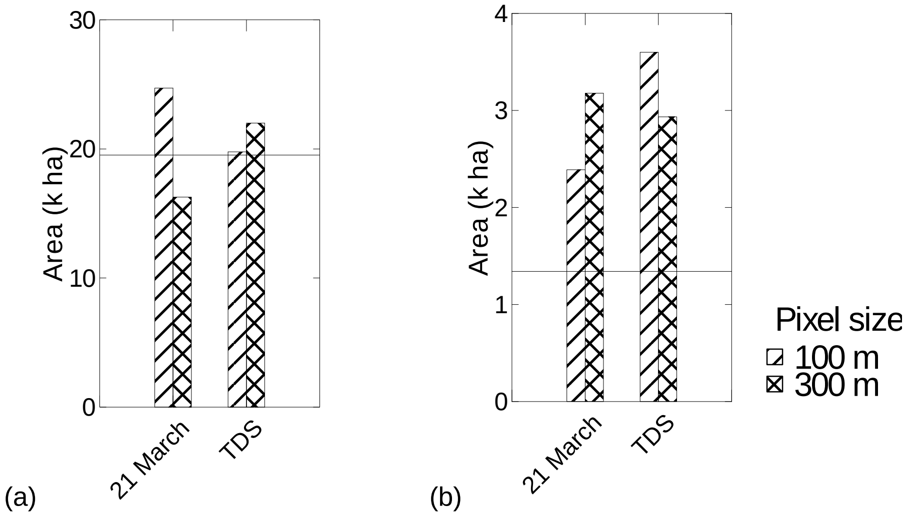

Fig. 2. Comparison between crop area estimates derived from the classifications and harvested area reports of the Ministry of Agriculture and Food (marked by horizontal line) for (a) wheat and (b) rapeseed. TDS – image stack combining data from 21 March and 8 July 2014

Harvested area reports of the MAF are the only source of data for the areas of different crops in the country provided on annual basis. This data were used as a reference to assess the accuracy at which areas are estimated using PROBA-V classified images and a pixel count method. Results for wheat and rapeseed are shown in Figure 2. The analysis was performed for three municipalities, Knezha, Oryahovo, and Iskar. Their overall arable land is 64.5 thousand ha according to the CORINE dataset. Wheat area estimates derived from the classifications are within 1 to 27 % of the reference MAF data. More accurate area estimates for wheat are achieved by the TDS classifications. As seen in Table 3, the TDS classifications have lower overall accuracy compared with the 21 March classifications. The error matrices, however, show that user and producer accuracies for "wheat" are higher in the TDS classifications, thus, for this particular class these classifications provided better area estimates. In order to be useful, crop area estimates derived from remote sensing data should have inaccuracy smaller than the inter-annual variability of the area of that crop [17]. The average rate of inter-annual change of the total area of wheat in Bulgaria for the period 2000-2011 is 12.6%[2]. The

[2] www.mzh.government.bg/MZH/bg/ShortLinks/SelskaPolitika/Agrostatistics/Crop/Results_copy3.aspx

wheat area estimated based on the 100 m TDS classification was within 1% of the official MAF data. This accuracy suggests that using PROBA-V 100 m data one can detect small changes in wheat area from one season to the next. On the contrary the rapeseed area estimated from the classifications deviates strongly from the figures reported by the MAF. The rapeseed area was overestimated with up to 170%. It should be noted that rapeseed covers only about 1300 ha in the three municipalities (according to the MFA data). As shown by Czaplewski [18] the bias in areal estimates for rare classes can be relatively high, even with high producer/user accuracies. At the time when this paper was prepared no complete data for harvested areas were available for maize and sunflower and comparison with the classification area estimates was not possible.

Conclusion

Results from this study show that the PROBA-V 100 m products may be successfully used for crop mapping under agricultural setting (mean field size, crop types, etc.) similar to that of *Zlatia* test site. Two scenes were selected within the growing season in order to map winter and spring crops respectively. For both scenes the overall accuracy of maximum likelihood classification was greater than 80%. Thus, all four major crops in the region can be mapped with reasonable accuracy. The PROBA-V 100 m images provide surprisingly good spatial details over the agricultural landscape of *Zlatia* test site, allowing most fields to be clearly distinguished. This is an important advantage over the PROBA-V products with 300 m spatial resolution. Moreover, significantly higher overall accuracy was achieved with 100 m data in two of the three classifications. Our results also suggest that multitemporal PROBA-V data are useful for crop mapping, however further studies are needed to review their full potential. Wheat area estimate derived from the classified stacked PROBA-V 100 m image was quite accurate judging from the close correspondence with the MAF data. However rapeseed area estimates deviate substantially from the referent data. The higher temporal resolution and wider coverage of PROBA-V 100 m data make them valuable complementary data source to Landsat-like sensors for crop mapping and monitoring exercises. The PROBA-V 100 m products are good alternative to Terra/Aqua MODIS, PROBA-V 300 m, etc for crop mapping and area estimation over large territory, for example at national level.

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