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Article

Single- and Multi-Date Crop Identification Using PROBA-V 100 and 300 m S1 Products on Zlatia Test Site, Bulgaria

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Abstract: The monitoring of crops is of vital importance for food and environmental security in a global and European context. The main goal of this study was to assess the crop mapping performance provided by the 100 m spatial resolution of PROBA-V compared to coarser resolution data (e.g., PROBA-V at 300 m) for a 2250 km^2 test site in Bulgaria. The focus was on winter and summer crop mapping with three to five classes. For classification, single- and multi-date spectral data were used as well as NDVI time series. Our results demonstrate that crop identification using 100 m PROBA-V data performed significantly better in all experiments compared to the PROBA-V 300 m data. PROBA-V multispectral imagery, acquired in spring (March) was the most appropriate for winter crop identification, while satellite data acquired in summer (July) was superior for summer crop identification. The classification accuracy from PROBA-V 100 m compared to PROBA-V 300 m was improved by 5.8% to 14.8% depending on crop type. Stacked multi-date satellite images with three to four images gave overall classification accuracies of 74%–77% (PROBA-V 100 m data) and 66%–70% (PROBA-V 300 m data) with four classes (wheat, rapeseed, maize, and sunflower). This demonstrates that three to four image acquisitions, well distributed over the growing season, capture most of the spectral and temporal variability in our test site. Regarding the PROBA-V NDVI time series, useful results were only obtained if crops were grouped into two broader crop type classes (summer and winter crops). Mapping accuracies decreased significantly when mapping more classes. Again, a positive impact of the increased spatial resolution was noted. Together, the findings demonstrate the positive effect of the 100 m resolution PROBA-V data compared to the 300 m for crop mapping. This has important implications for future data provision and strengthens the arguments for a second generation of this mission originally designed solely as a "gap-filler mission".

Keywords: PROBA-V; single- and multi-date crop identification; NDVI time series; cluster analysis; GSD

1. Introduction

The demand for accurate and readily available satellite-derived agricultural intelligence is rising steadily [1]. Main information requests relate to yield predictions [2,3], area estimates [4,5], cropping patterns and farming systems [6,7], indicators of environmental degradation [8], the provision of agricultural insurance products [9] as well as indicators detecting and quantifying agricultural intensification [10,11] and high value crops [12]. Reliable and up-to-date information is even more precious in times of unpredictable hazardous impacts caused by climate change and socio-economic perturbations.

The linkages of climate change, vegetation and crop phenology and the feedbacks to the climate machine have been studied by climate modelers and remote sensing scientists alike [13–17]. These efforts, however, cannot resolve the existing gap between timely acquisitions and spatial resolution of satellite sensors. The trade-off between spatial and temporal resolution is difficult to address with current remote sensing technologies [18]. In the past decades, the performance of the coarse and medium spatial resolution satellite data at different types of cultivation practices with different crop types has been extensively studied [19,20]. Contemporary satellite missions, such as the recently launched European Sentinel-2A, are designed to address these issues [21]. The possible benefits of the Sentinel-2 mission for the agriculture domain across a range of crops and agricultural practices are currently addressed in ESA's Sen2-Agri project [22]. Simultaneously, innovative solutions, such as data fusion methods or unmixing approaches, also have been developed by the scientific community to address the trade-off [23–26].

The newly deployed PROBA-V satellite is a supporting mission for the European COPERNICUS program originally conceived as a "gap-filler mission" between SPOT-VGT and Sentinel-3 (the latter to be launched in 2016 while the former stopped recording in 2014). PROBA-V has the capability to collect data at a medium (hecta-metric) spatial resolution of 100 m at 2–3 days revisit interval in addition to daily imagery at 300 m [27]. The 100 m spatial resolution will possibly enhance land monitoring programs compared to the 250 m resolution offered for example by MODIS. The PROBA-V data is freely available to the COPERNICUS (formerly "Global Monitoring for Environment and Security" a.k.a. GMES) users through ESA's GMES Space Component Data Access (GSCDA) [28]. The unique characteristics of PROBA-V open a new set of opportunities for scientists to explore various Earth surface phenomena at finer spatial and temporal resolutions.

The monitoring of crops is of vital importance for food security in a global and European context [29–31]. Although the agricultural sector is well developed in Europe, the new EU member states are still catching up with the agriculture sector of the well-developed West-European countries. This process includes adapting agricultural practices (e.g., precision agriculture) and making more intense use of satellite imagery for crop monitoring and yields forecasting [30–32]. Together this necessitates exploring the full-potential of present-day remote sensing missions.

The main goal of this study is to assess the additional information provided by the 100 m spatial resolution of PROBA-V compared to coarser resolution data (e.g., PROBA-V at 300 m). The focus is on winter and summer crop mapping using (single- and multi-date) spectral data as well as NDVI time series. Major tasks include:

- single- and multi-date crop identification using PROBA-V multispectral 100 m and 300 m daily syntheses (S1) Top of Canopy reflectance product acquired on different dates;
- multi-date crop identification using PROBA-V S1 100 m and 300 m satellite NDVI time series.

The various classification experiments permit (1) assessment of NDVI time series information against single/multi-date spectral data; (2) quantification of the added value offered by 100 m PROBA-V data compared to coarser resolution (MODIS type) images; and (3) identification of optimum acquisition periods for crop type mapping in the new EU member states. As the study was conducted in a relatively small area, the findings are obviously only valid for the study region.

2. Study Area and Data Used

2.1. Study Area

For conducting this experiment the Zlatia test site was chosen. The territory of the test site is part of the Pleven aerospace test site (ATS), which belongs to the ATSs network in Bulgaria. This test site in particular has been designated and used for testing and validation of remote sensing data for agriculture applications. The territory has agricultural landscape typical for the intensively cultivated regions of Bulgaria in terms of topography, crop types and field size. The study area has a size of approximately 45 × 50 km (2250 km^2) and is located in northwest Bulgaria. The test site occupies part of the drainage basin of the Bulgarian part of the Danube River (Figure 1). The Zlatia test site is characterized by intensive agriculture due to the favorable climatic and soil conditions. The agro-climatic conditions favor sowing of winter wheat, winter rapeseed, grain maize and sunflower. The annual precipitation for the meteorological station Knezha is 579 mm with maximum in June and minimum in February. The yearly average temperature is 10.7 °C. The duration of the vegetation season (mean temperatures above 5 °C) is 245–255 days. The major soil types observed on the territory according to the WRBSR 2014 soil classification are Calcic Chernozems, Haplic Chernozems, and Mollic Fluvisols [33].

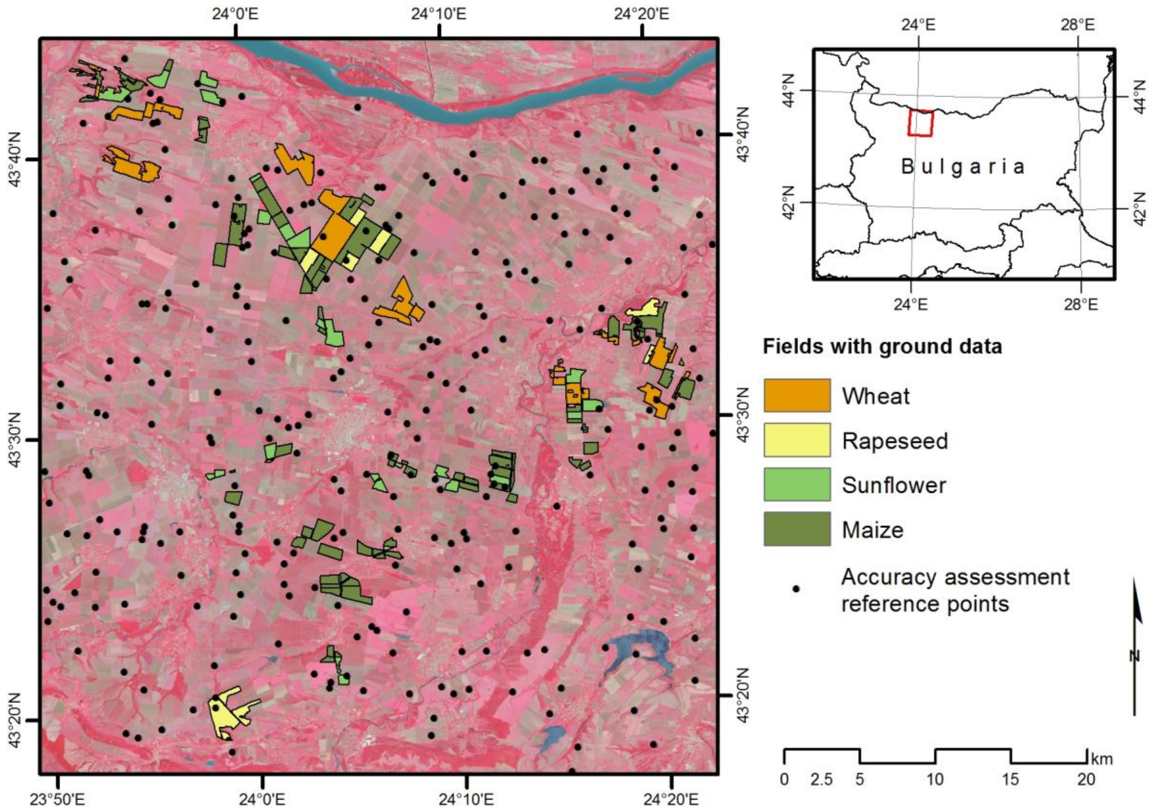


Figure 1. Zlatia test site in Bulgaria. Background false color (RGB) composite (bands 5-4-3) from Landsat-8 OLI acquired on 11 June 2014. The colored polygons correspond to four crop types with *in situ* (ground) data available (e.g., winter wheat, rapeseed, sunflower, and maize). Data from these areas are used for training purposes. The dots indicate reference points where the crop mapping accuracy was evaluated.

2.2. Data

2.2.1. Ground Truth

Crop information for 132 individual fields in the study area was available for the agricultural year 2013–2014 as a vector layer. The information for part of the fields was provided by a local farmer, whereas for the other fields data was collected during two field campaigns in March and August 2014. Adjacent fields sown with the same crop were not merged together. The mean area of the individual fields was 74.4 ha (min 11.2 ha; max 504.6 ha). The 132 individual crop fields are delineated in Figure 1. In total, the field data consisted of 29 fields (2827 ha) sown with winter wheat, 11 fields (1048 ha) were sown with winter rapeseed, 67 fields (4397 ha) were sown with maize and 25 fields (1553 ha) sown with sunflower cultivars.

To complement the information, crop calendars were prepared for the agricultural year 2013–2014 including the following information: sowing dates, onset dates of the major development stages, and date of harvest. The major development stages are reported in Table 1 for each of the four major crops studied: winter wheat, rapeseed, maize and sunflower. The data in Table 1 are from the fields for which ground data were provided by a local farmer and thus do not completely represent the variability of crop development in the study area. More specifically, late maize cultivars are also present in the region and they are usually sown in May.

Table 1. Phenophases of the major crop cultivars in the 2013–2014 agricultural year on the fields used in the study. The observation dates (N) are numbered from I to X and correspond to PROBA-V acquisitions used in the study (see Section 3).

N	Date	*Winter Wheat*	*Winter Rapeseed*	*Maize*	*Sunflower*
I	21 March	*Heading*	*Vegetative*	*Bare soil*	*Bare soil*
II	30 March	*Heading*	*Vegetative*	*Sowing*	*Bare soil*
III	4 April	*Flowering*	*Flowering*	*Vegetative*	*Sowing*
IV	19 May	*Grain filling(milk development)*	*Grain filling*	*Vegetative*	*Vegetative*
V	7 June	*Grain filling (dough development)*	*Grain filling*	*Vegetative*	*Vegetative*
VI	11 June	*Ripening*	*Ripening/Maturity*	*Vegetative*	*Flowering*
VII	8 July	*Maturity harvest/stubble fields*	*Stubble fields*	*Flowering*	*Grain filling*
VIII	5 August	*Bare soil*	*Bare soil*	*Ripening*	*Ripening*
IX	14 August	*Bare soil*	*Bare soil*	*Ripening*	*Maturity*
X	27 August	*Bare soil*	*Bare soil*	*Maturity*	*Harvest*

2.2.2. Satellite Data

The PROBA-V 100 m and 300 m daily (S1) Top of Canopy reflectance products were downloaded from the VITO’s Product Distribution Portal in GeoTIFF file format [34]. The main characteristics of the PROBA-V mission are summarized in Table 2 [35]. The PROBA-V satellite has three cameras aligned to each other to cover the full swath of 2250 km. The PROBA-V 300 m product combines the image stripes of the three cameras and the resulting full-width image is resampled to 300 m pixels. The 100 m product use data solely from the central camera. In this case the original resolution of 100 m is retained.

From all images covering the Zlatia test site only images with less than 5% cloud cover were selected and processed (Table 3). The images cover most of the 2014 agricultural season (March–August) but are not evenly distributed because of extended periods with persistent cloud cover. No attempts were made to filter and gap-fill cloudy/partly-cloudy images [17,36].

The images were cropped to the study area borders, projected to Universal Transverse Mercator (UTM) Zone 34N projection, and resampled using the Nearest Neighbor method. CORINE 2006 Land cover database was used to mask all cover types outside the class “211: Non-irrigated arable land”. In addition, seven Landsat-8 Operational land Imager (OLI) images spanning the period 23 March–30 August 2014 were used to support the crop identification accuracy assessment (see “Methods”).

3. Methods

Two types of classification were conducted to assess the added value of 100 m data against 300 m PROBA-V data:

(1) single- and multi-date supervised maximum likelihood classification (MLC) of the multi-spectral data, and
(2) multi-date maximum likelihood classification (MLC) and Iterative Self-Organizing Data Analysis Technique (ISODATA) clustering [36,37] of NDVI time series.

Table 2. PROBA-V mission main characteristics.

Launch Date	**02:06 GMT on 7 May 2013**	
Weight	33 kg	
Size and Volume	33 cm × 22 cm × 11 cm/0.05 m^3	
Altitude	820 km	
Orbit type	sun-synchronous	
Local overpass time	10:45 h	
Field Of View	102 °	
Swath width	2295 km	
Number of cameras	3	
Temporal resolution	daily near-global coverage (90%) and full global coverage is achieved every 2 days if data from all three cameras are combined (e.g., at 300 m Ground Sampling Distance)	
PROBA-V spectral bands	Centered at (nm)	Width span (nm)
BLUE	463	46
RED	655	79
NIR	845	144
SWIR	1600	73

Table 3. PROBA-V 100 m and 300 m image acquisitions used in the study.

n	**Date**	**Cloud Coverage**	**Use in Classification Scheme Based on**	
			Multi-Spectral Data	**NDVI Time Series**
I	21 March	cloud free	+	+
II	30 March	<5%	−	+
III	4 April	cloud free	+	+
IV	19 May	<5%	−	+
V	7 June	cloud free	+	+
VI	11 June	<5%	−	+
VII	8 July	cloud free	+	+
VIII	5 August	<5%	−	+
IX	14 August	cloud free	−	+
X	27 August	<5%	−	+

3.1. Single and Multi-Date Supervised MLC Classifications

Supervised classification of the multi-spectral PROBA-V data with an MLC algorithm was applied on single- and multi-date images (Table 4). More than 10–15 training samples for each class were selected within the fields with available (*in situ*) ground truth data (Figure 1). The focus of the study was on the impact of ground sampling distance (100 m data against 300 m data) and number/timing of image acquisitions. For this reason, alternative classifiers such as Random Forest (RF) or Support Vector Machines (SVM) [38] were not tested.

Four single-date MLC image classifications of the spectral data sets were run, abbreviated as SINGLE1 to SINGLE4. The timing of the PROBA-V image acquisitions for these four single-date classifications is indicated in the first part of Table 4 together with the distinguished crop types. As the name indicates, for these single-date classifications, only one image was used at a time.

Regarding the multi-date MLC classifications (second part of Table 4), three to four stacked PROBA-V images were composed into multi-date layer stacks representing different combinations of the selected scenes (same scenes as those used for the single-date classifications). Three experiments were conducted abbreviated as MULT1 to MULT3. The analyzed images are indicated in Table 4 together with the distinguished crop types.

Table 4. Overview of the classification experiments conducted using either (i) single-date spectral data or (ii) multi-date spectral data. The roman numbers identify the individual PROBA-V images used for the classification (see Table 3). The classified crops and cover types are also indicated.

Single-Date Spectral Classification Experiments		**Abbreviation of Classification Experiment**			
		SINGLE1	**SINGLE2**	**SINGLE3**	**SINGLE4**
Image used	21 March (I)	+	−	−	−
	4 April (III)	−	+	−	−
	7 June (V)	−	−	+	−
	8 July (VII)	−	−	−	+
Distinguished classes		Wheat, Rapeseed, Soil	Wheat, Rapeseed, Soil	Wheat, Rapeseed, Soil, Maize, Sunflower,	Maize, Sunflower, Soil/crop residue

Multi-Date Spectral Classification Experiments		**Abbreviation of Classification Experiment**		
		MULT1	**MULT2**	**MULT3**
Images used	21 March (I)	+	+	−
	4 April (III)	+	+	+
	7 June (V)	+	+	+
	8 July (VII)	+	−	+
Distinguished classes		Wheat, Rapeseed, Maize, Sunflower		

For the single- and multi-date classifications, the MLC performance was assessed based on simple random sampling, where 275 randomly distributed points were assessed by computer aided visual interpretation of several high-quality Landsat-8 OLI images from 2014 (black dots in Figure 1). The process was simple and not error prone. The statistical significance of the difference between overall accuracy achieved with PROBA-V 100 m and 300 m was tested using the McNemar test for proportions [38–40].

3.2. Cluster Analysis of PROBA-V NDVI Time Series

A maximum likelihood classification (MLC) and ISODATA unsupervised cluster analysis was undertaken for crop identification purposes on the PROBA-V (S1) 100 m and 300 m NDVI time series data. A similar approach has also been used in other regional studies based on satellite image time-series and multi-date images [41]. For this purpose, ten relatively cloud-free NDVI images indicated with circles in Table 3 were used (possibly occurring clouds were masked out). The NDVI time series for the 2014 agricultural year were created separately for the 100 and 300 m data by stacking the ten NDVI images. Afterwards, maximum likelihood classification (MLC) and the ISODATA algorithm were applied. Following the supervised and unsupervised classifications, crop maps were prepared and their accuracy assessed using the same dataset as for the single- and multi-date classifications.

4. Results

4.1. Single- and Multi-Date Supervised MLC Classifications of Multi-Spectral Data

Two of the four PROBA-V 100 m and 300 m multi-spectral images were used to assess the possibilities for winter crop identification at the time after the spring resumption of vegetation growth. The two images were acquired on 21 March and 4 April 2014 (experiments SINGLE1 and SINGLE2).

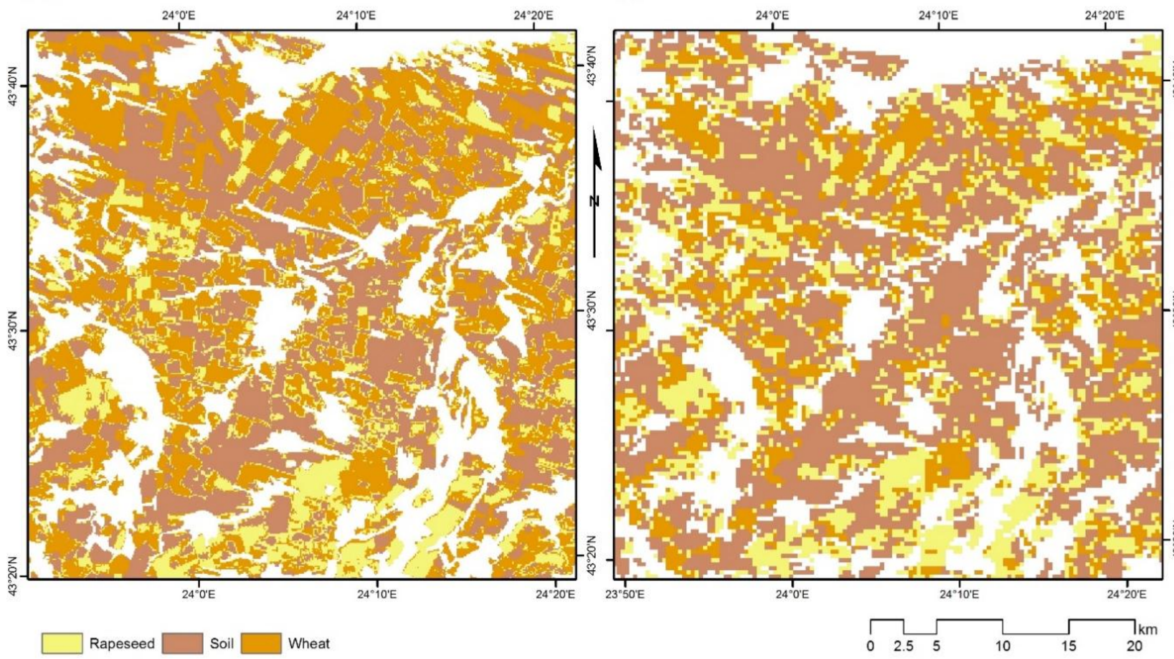
Table 5. Overall accuracy for the supervised MLC. Confidence intervals at the 5% significance level are shown in parentheses [39,40]. All differences between 100 and 300 m are statistically significant at the 0.05 probability level.

Data Sets Used for Classification	Number of Distinguished Classes	Accuracy Assessment based on Computer Aided Visual Interpretation of Landsat OLI Data	
		100 m (n = 275)	300 m (n = 275)
SINGLE1	3	86.2 (81.9–90.5)	79.3 (74.3–84.3)
SINGLE2	3	79.6 (74.7–84.5)	67.6 (61.9–67.8)
SINGLE3	5	72.4 (66.9–77.9)	62.2 (56.3–68.1)
SINGLE4	3	82.5 (77.8–87.2)	70.2 (64.6–75.8)
MULT1	4	76.7 (71.5–81.9)	69.8 (64.2–75.4)
MULT2	4	74.9 (69.6–80.2)	69.1 (64.0–75.0)
MULT3	4	73.5 (68.1–78.9)	66.2 (60.4–72.0)

The overall accuracy for the 21 March and 4 April 2014 PROBA-V images is 86.2% and 79.6%, respectively (100 m) and 79.3% and 67.6%, respectively (300 m). For both image acquisitions, in March and April, the 300 m classifications were less accurate than the 100 m results (Table 5). In summary, the March image (SINGLE1) gave higher classification accuracies compared to the April image (SINGLE2) demonstrating the importance of an early image acquisition for mapping winter crops.

The crop map produced using the March multi-spectral PROBA-V image is shown in Figure 2 for (a) the 100 m data and (b) the corresponding 300 m data. One can clearly see that the 300 m data is not well suited to resolve the agricultural fields, whereas the agricultural landscape can be relatively well depicted using the 100 m data.

The experiment SINGLE3 was conducted to assess the possibilities for identification of all four crop types. For the experiment, the 100 m and 300 m PROBA-V images acquired on 7 June 2014 were used. The error matrix using the random sampling dataset (Table 6) reveals that the relatively low accuracies were due to a significant underestimation of maize cultivars at the expense of soil.



(**a**) (**b**)

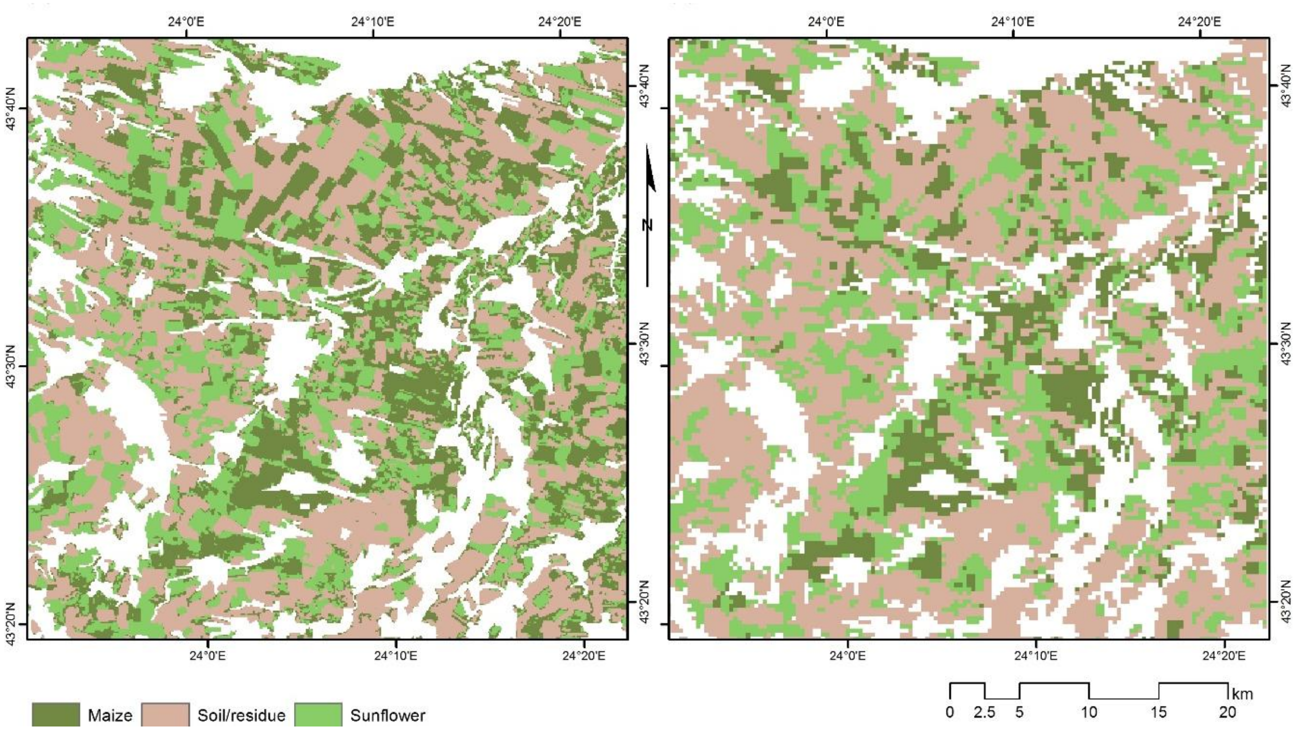
Figure 2. Classification results using PROBA-V (**a**) 100 m and (**b**) 300 m multi-spectral images from 21 March 2014 (SINGLE1 experiment) for mapping bare soil, wheat and rapeseed. Note that areas outside the CORINE class 211 (agriculture) were left blank.

Table 6. Error matrix of the supervised MLC classification for PROBA-V 100 m SINGLE3 (7 June 2014) using the random sampling dataset (e.g., n = 275 in Figure 1).

	Reference Data						
	Maize	**Rapeseed**	**Sunflower**	**Wheat**	**Soil**	**Total**	**User Acc. (%)**
Maize	16	0	5	1	3	25	64.0
Rapeseed	0	25	0	1	0	26	96.2
Sunflower	5	3	53	2	0	63	84.1
Wheat	9	6	6	72	0	93	77.4
Soil	22	1	2	10	33	68	
Total	52	35	66	86	36	275	
Prod. Acc. (%)	30.8	71.4	80.3	83.7			
Overall Accuracy 72.4%							

Using the random validation dataset, the overall accuracy assessment for the PROBA-V 100 m was 72%, compared to 62% for the PROBA-V 300 m data. Similar to the results obtained using the *in situ* data, confusion between maize and soil was observed (Table 6). The confusion can be explained by the low canopy cover formed by the emerging plants and the soil contribution to reflectance in those fields sown with late maize cultivars. As in the previous experiments, the PROBA-V 300 m classification gave a lower accuracy compared to the PROBA-V 100 m classification and the difference was significant.

To test the mapping of summer crops, grown after the harvest of winter crops, a PROBA-V 100 m and 300 m scene from 8 July was used (experiment SINGLE4) (Figure 3). Using the 275 visually assessed validation points, the overall accuracy of the 8 July PROBA-V 100 m and 300 m classifications was 82% and 70%, respectively. The error matrix confirmed that the low accuracy of the 300 m classification was due to an underestimation of maize at the expense of sunflower (not shown). The difference between overall accuracies of the two classifications was statistically significant. The resulting maps are shown in Figure 3.



(**a**) (**b**)

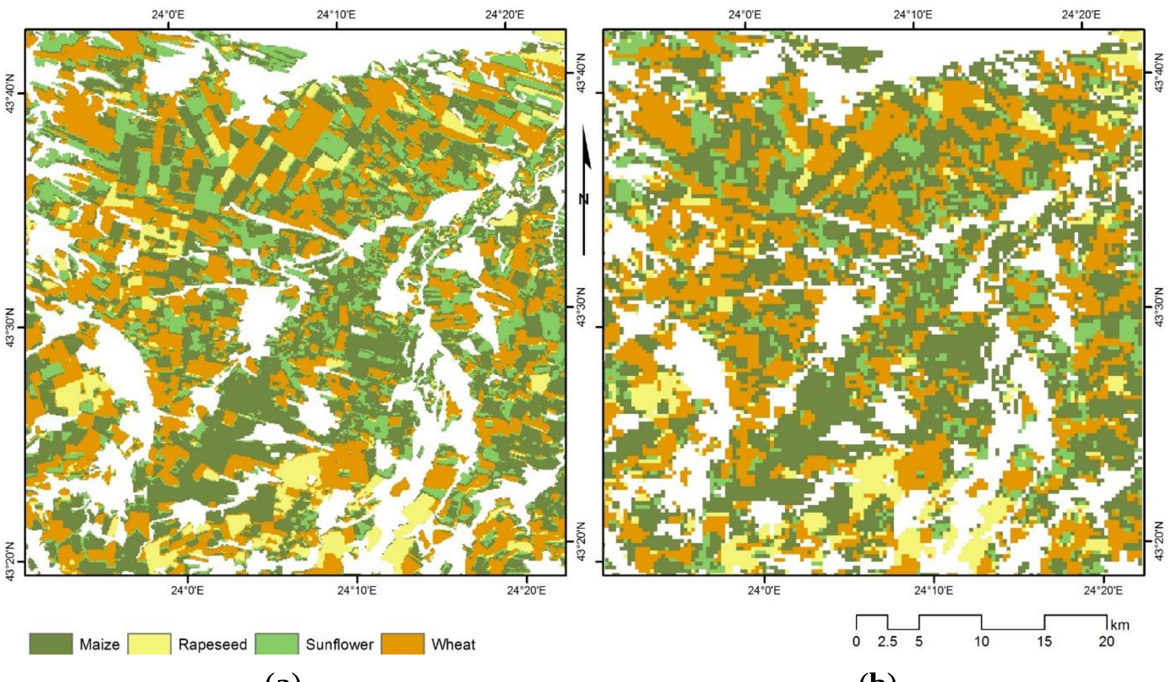
Figure 3. Classification results using PROBA-V 100 m (**a**) and 300 m (**b**) multi-spectral images from 8 July 2014 (SINGLE4 experiment) for mapping maize and sunflower. Note that areas outside the CORINE class 211 (agriculture) were left blank.

In addition to the four single-date classifications, three multi-date experiments were conducted using spectral information from more than one acquisition date for crop classification (e.g., experiments MULT1 to MULT3) (Table 4). The aim of these multi-date classifications was to improve crop discrimination compared to single-date experiments, by depicting crop phenology in addition to their spectral signatures. Results for the three multi-date experiments are summarized in Table 5.

Assessed against the validation data set (275 random points—marked as dots in Figure 1), we found the overall accuracy varied between 74% and 77% for the 100 m multi-date classifications. The highest overall accuracy assessment was found for the complete, four-date stack (MULT1). However, even using four images for classification, some overestimation of maize at the expense of sunflower still was observed. On the other hand, the winter crops were well separated. The accuracy of the MULT classifications were higher than the accuracy of the SINGLE3 classification. Therefore, the recognition of the four crops benefits from the usage of several images distributed over the season (e.g., higher accuracy in comparison to the sole use of one early June image).

The overall accuracy for the 300 m multi-date classifications was between 66% and 70% and therefore significantly lower compared to the 100 m data. Using the 300 m data, no clear relationship with the number of dates in the stack could be found. Even in the four-date classification (MULT1) the sunflower was strongly underestimated and most of its referent pixels were misclassified as maize. Confusion between the two winter crops was also present.

Crop maps depicting the results from experiment MULT1 are shown in Figure 4. The advantage of using 100 m data instead of 300 m PROBA-V data can be clearly seen in the northern part where the larger fields are located.



(**a**) (**b**)

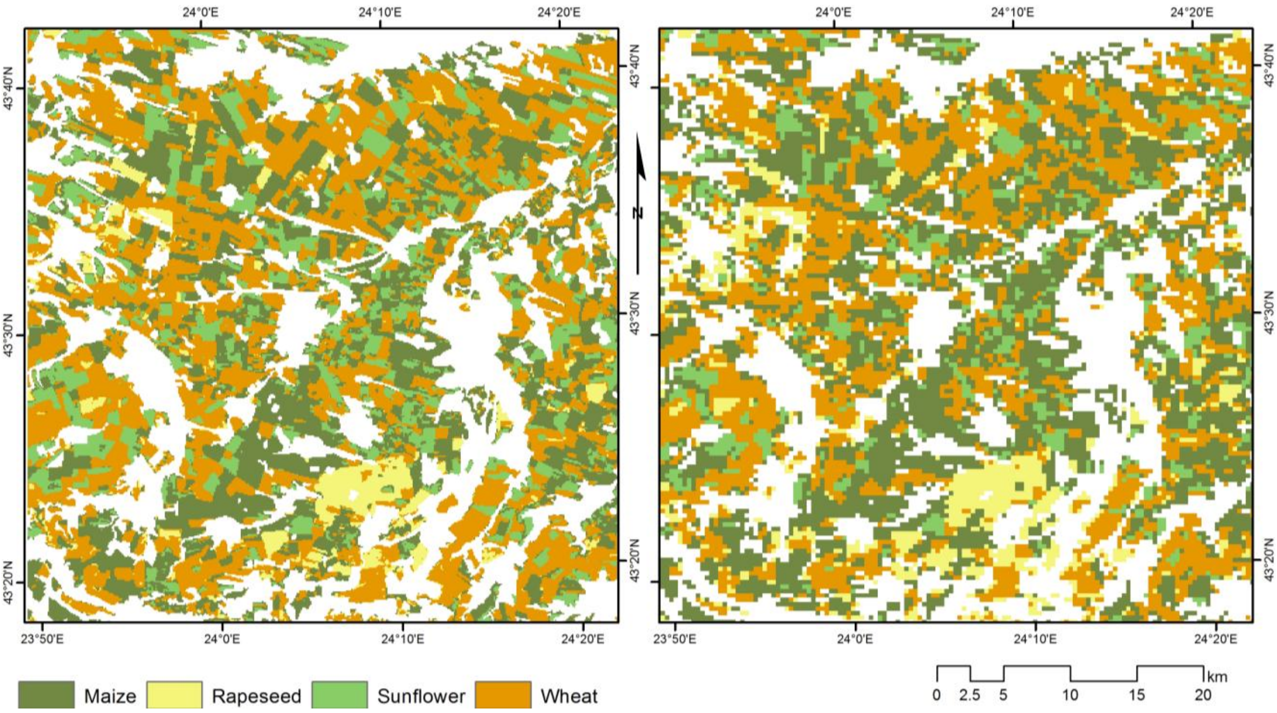
Figure 4. Classification results using multi-date PROBA-V multi-spectral images at (**a**) 100 m and (**b**) 300 m resolution (experiment MULT1: 21 March, 4 April, 7 June, and 8 July 2014) for mapping wheat, rapeseed, sunflower and maize. Note that areas outside the CORINE class 211 (agriculture) were left blank.

4.2. Time Series Cluster Analysis Using PROBA-V NDVI Data

The ISODATA clustering of the NDVI time series was parameterized to yield four clusters. These four clusters were afterwards labeled as winter wheat, winter rapeseed, sunflower, and maize (Figure 5).

For each of the four classes, Figure 6 shows the mean NDVI values from the PROBA-V time-series composites.

Interestingly, the extracted (average) time profiles from 100 m and 300 m are generally very similar (Figure 6a,b). This is not the case for the resulting maps which are indeed quite different (Figure 5). Assessed against the validation data set, the 300 m maps gave only unsatisfactory results (overall accuracy assessment 61.8%—Table 7). The 100 m data preformed significantly better, but still with a relatively low OA of 74.9%.



(**a**) (**b**)

Figure 5. Crop map with four classes for PROBA-V NDVI (**a**) 100 m and (**b**) 300 m time series from unsupervised ISODATA clustering. Note that areas outside the CORINE class 211 (non-irrigated arable land) were left blank.

To minimize confusion between maize/sunflower and rapeseed/wheat, the four classes were recoded into two broader classes: winter crops and summer crops. The recoded maps with two classes at 100 m and 300 m are presented in Figure 7. For each of the two classes, the mean NDVI values from the PROBA-V time series composites are displayed as time series profiles in Figure 6c,d. When only two broad classes had to be classified, the overall accuracy for the 100 m crop map reached 92.4%. The OA of the recoded 300 m crop map reached 84.7% (Table 7). Hence, using a simpler classification scheme, a 17%–23% increase of overall accuracy assessment could be achieved for both PROBA-V 100 m and 300 m.

We also tested whether the supervised MLC classifier could outperform the unsupervised ISODATA clustering when analyzing NDVI time series. The maximum likelihood classification of the PROBA-V NDVI time-series gave only a low accuracy compared to the unsupervised ISODATA with 68.7% and 60.4% overall accuracy for 100 m and 300 m, respectively (Table 7).

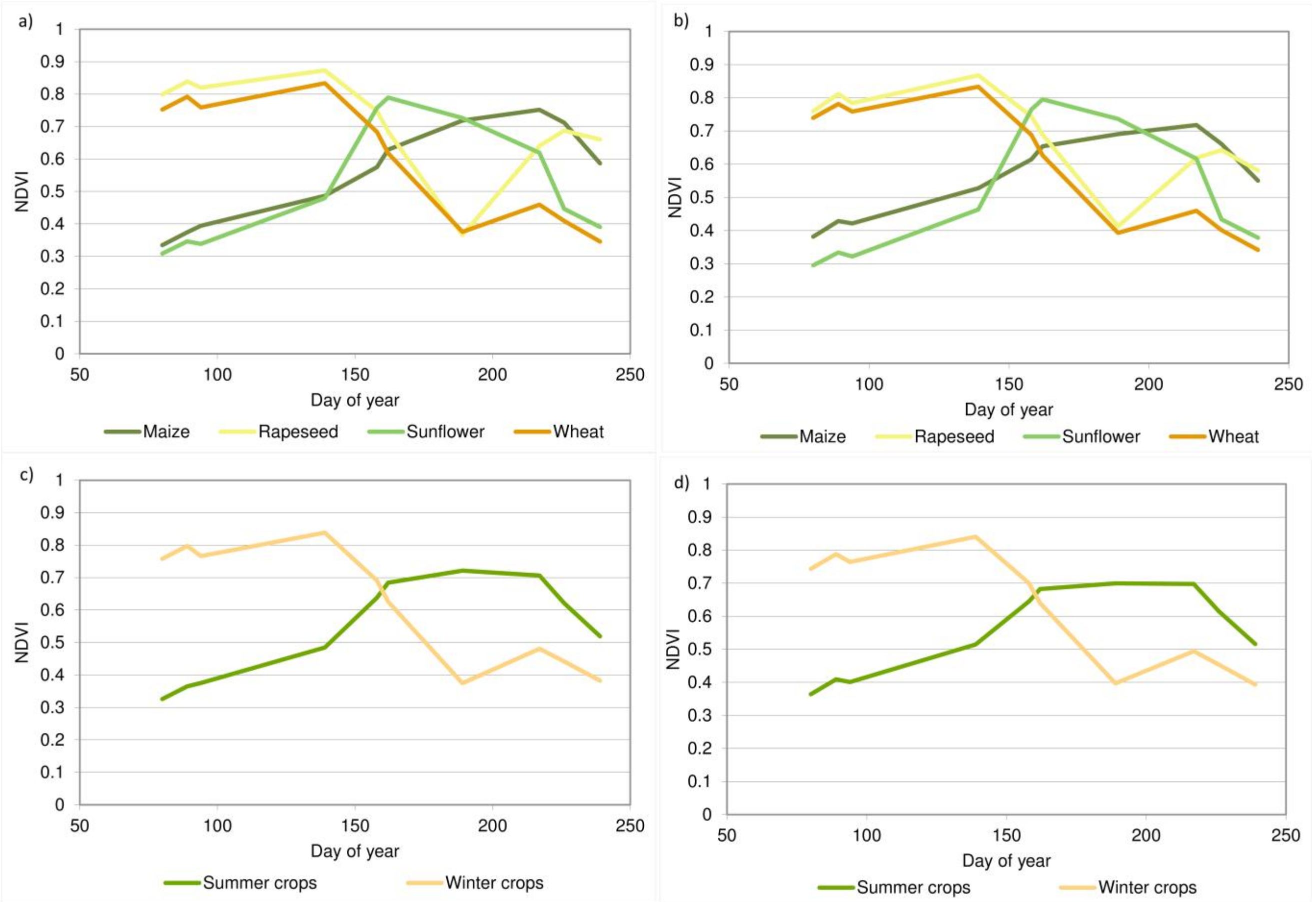
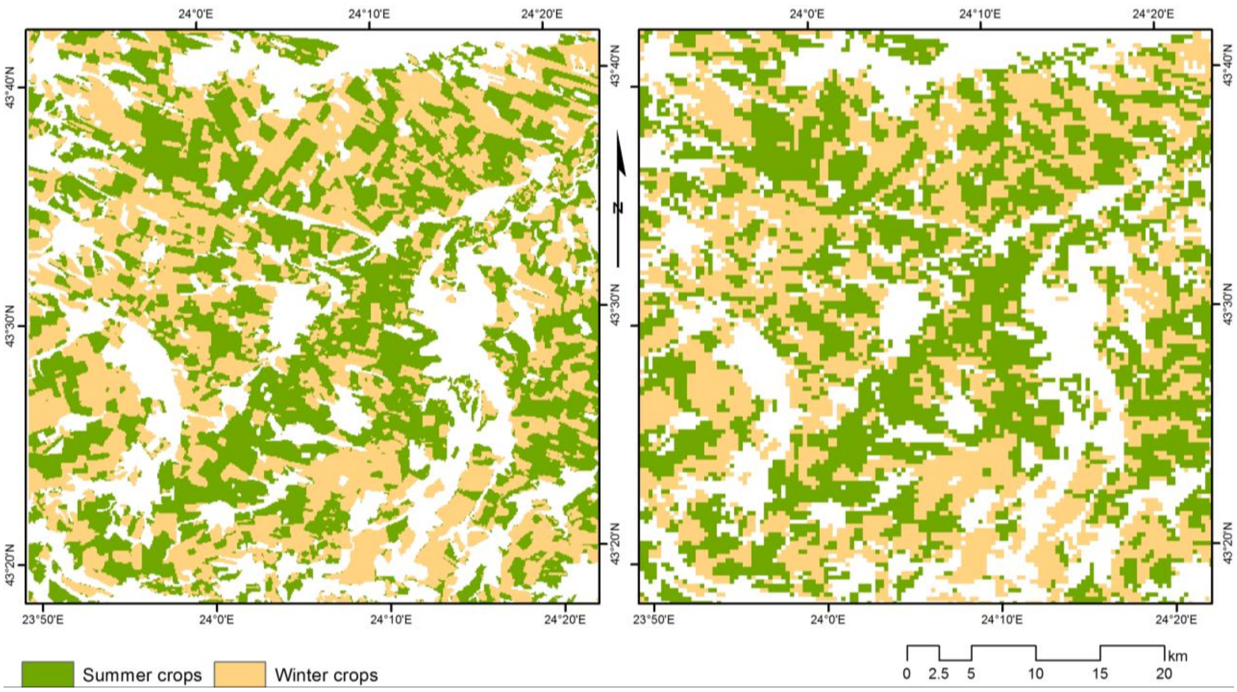


Figure 6. PROBA-V NDVI (**a**) 100 m and (**b**) 300 m time series profiles of four classes from ISODATA clustering and the recoded time series profiles with two classes (**c**) 100 m and (**d**) 300 m.

Table 7. Overall classification accuracies for PROBA-V NDVI time-series against independent validation data (n = 275). Confidence intervals at the 5% significance level are shown in parentheses [38,39]. The differences between the overall accuracies of 100 m and 300 m were statistically significant at the 0.05 probability level.

	100 m	**300 m**
Unsupervised ISODATA classification of the four crops (maize, sunflower, winterwheat, rapeseed)	74.9 (69.6–80.2)	61.8 (55.9–67.7)
Unsupervised ISODATA classification of the two crop types (summer and winter crops)	92.4 (89.9–96.3)	84.7 (80.3–89.1)
Supervised MLC classification of the four crops (maize, sunflower, winterwheat, rapeseed)	67.3 (61.6–73.0)	60.4 (54.3–66.3)



(**a**) (**b**)

Figure 7. Crop map with two classes from unsupervised ISODATA clustering for (**a**) 100 m and (**b**) 300 m PROBA-V NDVI time series. Note that areas outside the CORINE class 211 (agriculture) were left blank.

5. Discussion

The overall accuracies achieved with 100 m PROBA-V data were in the range of other crop identification studies applying the Maximum Likelihood Classifier (MLC). The Global Agriculture Monitoring (GLAM) initiative, a joint NASA, USDA, UMD and SDSU effort, mainly uses medium resolution satellite data to provide for global coverage for crop type assessment [42]. Their Global Cropland Extent map, based on 250 m MODIS multi-year data, performs with a relatively lower accuracy compared to this study, *i.e.*, 63% over the entire European continent [43]. Recently, using MODIS data but a more sophisticated approach of multi-criteria analysis and LU/LC data on a national level, the team [44] was able to achieve lower commission errors (26%) for the produced Unified Cropland Layer for the year of 2014, and an overall accuracy of 82%–94% (global scale). Similarly, using very-high-resolution QuickBird and similar images >85% up to 90% overall accuracy assessment have been achieved [45–47]. Accuracies over 85% were also reported in studies using SPOT-5 data with 10 m spatial resolution [48]. High overall accuracies of over 95% for crop identification were reported in [49,50] for high-resolution EO-1/ALI images. Our crop identification accuracies estimated against independent reference data from computer aided visual interpretation of Landsat OLI images were in the range of 72.4%–86.2% for the PROBA-V 100 m single-date classifications and between 62.2%–79.3% for the PROBA-V 300 m single-date classifications. Similar results were achieved for MODIS and Landsat over India's test sites [51]. The increased spatial resolution of the PROBA-V 100 m data compared to the PROBA-V 300 m data thus positively contributed to the achieved overall accuracy assessment in the range of 7%–10%. Obviously, those results depend on the specific landscape studied and in particular the average field size and the number and types of crops present.

Regarding the optimum image acquisition time, we set up experiments for separating two winter crops as well as two summer crops. The experiment involving a single image acquired in March gave best overall accuracy assessment for winter crops for both PROBA-V 100 m and 300 m (86.2% and 79.3% respectively). The experiment using data acquired in July, on the other hand, yielded the highest overall accuracy assessment for summer crops (82.5% and 70.2% for 100 m and 300 m, respectively). The results are comparable to another study [52].

Compared to Landsat-type imagery, PROBA-V offers a 100 m ground sampling distance at very high revisit frequency (2–3 days depending on latitude) [35]. This high revisit frequency offers advantages for crop mapping. Multi-date crop identification maps with four crop types and derived from PROBA-V 300 m yielded overall accuracy (OA) between 66.2%–69.8%. Using the same image acquisitions but at 100 m spatial resolution yielded OA in the range 73.5%–76.7%. This complies with the results from other studies [53–55], based on multi-date Landsat MSS/TM/ETM+ images and NDVI products.

The crop identification map with three broader LU/LC classes, based on NDVI time series from PROBA-V 100 m, shows results (overall accuracy of 88.9%) similar to a previous study [56] in which accuracies of 94% for the general crop map and 84% for the summer crop map were achieved using MODIS NDVI products with 250 m spatial resolution. The achieved overall accuracy, from a PROBA-V 300 m crop identification map, was estimated at 74.1%, which represents better results compared to those achieved by [57] (overall accuracy = 52%), while for wheat the estimated thematic accuracy was 41%.

It is well known that grouping of spectrally overlapping classes into broader classes can increase the overall accuracy of the map [56–59]. In our study, the overall accuracy assessment improved by roughly 14%–15%, after recoding the four original classes into two broader crop type classes, based on the PROBA-V NDVI time series analysis.

6. Conclusions

Newly available satellite images from PROBA-V with spatial resolution of 100 m have been comparatively assessed against the 300 m equivalent at a Zlatia test site, Bulgaria. To our best knowledge, this is the first study investigating the spatial resolution effect of PROBA-V for agricultural applications.

The PROBA-V 100 m data used in this study provides an intermediate spatial resolution between Landsat (ca. 30 m) and MODIS data products (ca. 250 m). The PROBA-V 100 m data is thus filling a niche in the current satellite data types available for crop identification and mapping. As this data became available only very recently, we evaluated its benefits for crop mapping compared to the coarser resolution data.

Initially PROBA-V was designed as a “gap-filler” between SPOT-VGT and Sentinel-3 [35]. The study demonstrates that there is a possible advantage of extending the lifeline of PROBA-V beyond the original schedule (e.g., by launching a second satellite in orbit).

In our study, crop identification using 100 m PROBA-V (S1) data reached significantly higher classification accuracies compared to the 300 m PROBA-V (S1) data. The classification accuracy from PROBA-V 100 m compared to PROBA-V 300 m was improved from 5.8% to 14.8%. The PROBA-V multispectral image, acquired on 21 March 2014, was the most appropriate for winter crop identification, while the satellite image acquired on 8 July 2014 was superior for summer crop identification. The stacked multi-date satellite images, with three to four PROBA-V S1 images, did not show significant differences in accuracy. Only a slight reduction in overall accuracy assessment was noted if either the first or the last image of the four-date multi-band layer stack were eliminated. This demonstrates that three (cloud-free) images, well distributed over the growing season, capture most of the spectral and temporal variability in our test site. This requires a high revisit time as offered by PROBA-V in particular in areas with significant cloud coverage.

Based on PROBA-V NDVI time series analysis, summer crops could be well separated, while winter crops behave more similarly and were difficult to separate during the active phase of vegetation growth. Overall accuracy assessment improved by 17%–23% after recoding the four classes from ISODATA clustering into two broader crop type classes based on the PROBA-V NDVI time series. Again, a substantial increase in classification accuracy was noted when increasing the spatial resolution from 300 m to 100 m. The unsupervised ISODATA classification showed superiority in the overall accuracy compared to the supervised maximum likelihood classification (MLC) of the PROBA-V NDVI time series.

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Author Contributions

E. Roumenina and M. Banov conceived and designed the experiments; I. Kamenova and P. Dimitrov performed the experiments; V. Vassilev and L. Filchev analyzed the data; G. Jelev contributed reagents/materials/analysis tools; C. Atzberger and V. Vassilev wrote the paper.

Conflicts of Interest

The authors declare no conflict of interest.

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