

## CROP TYPE MAPPING IN BULGARIA USING SENTINEL-1/2 DATA

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### ***Abstract***

*Advanced possibilities have emerged in recent years for semi-automatic crop type mapping at the national level due to the availability of Sentinel-1 and -2 satellite data. In this study, 14 crop type classes were mapped over Bulgaria using three bi-monthly composite image mosaics for 2019 generated in the Google Earth Engine (GEE) cloud computing platform. The overall accuracy, when both Sentinel-1 and -2 mosaics were used, was 78%, while the accuracy was slightly less when only Sentinel-2 data were used (75%). The accuracy was highest for “Cereals”, “Maize”, “Sunflower”, “Winter rapeseed”, and “Rice” – over 80% for both user’s and producer’s. However, the accuracy for classes such as “Vegetables”, “Technical crops”, “Forage crops”, “Fallow”, etc. was low. These classes represent categories suitable for agricultural practice and statistics, but are too general and difficult to distinguish using satellite data. It was also found that accuracy tends to be higher for larger parcels. Using composites with higher frequency and adapting the legend classes to include only crops similar in phenology and morphology are suggested as possible ways forward.*

### **Introduction**

The potential of Sentinel-2 for crop type mapping has been demonstrated in recent years by numerous studies. The high temporal resolution (5 days when both Sentinel-2 A and B satellites are used) is one of the key characteristics of the Sentinel-2 imagery, which makes it particularly useful for crop mapping because it provides multiple snapshots of crop development during the growing season. These benefits are clearly demonstrated by the multi-date approach, where (all) available cloud-free images during the season are used for classification, e.g. [1, 2]. While this approach is relevant for relatively small study areas, national scale or large area applications, e.g. [3–5], should deal with images from different orbits (thus different date), large volumes of data, and the cloud cover. Cloud storage and computing facilities, such as Google Earth Engine (GEE) [6] facilitate significantly such applications. Additionally, Sentinel-1 Synthetic Aperture Radar (SAR) data have also been used to map crop types [7, 8]. Van Tricht et al. [3] found that

combining radar and optical data for crop classification led to increasing classification accuracies compared to optical-only classification.

A previous case study from Bulgaria [9] demonstrated the utility of Sentinel-2 imagery for crop type mapping in small regions using selected cloud-free scenes. The authors suggested that future studies should address the problems related to mapping at national scale and also to integrate Sentinel-1 data in the classification in an attempt to increase the accuracy. This study, therefore, tries to build on past results and its aim is to produce and evaluate a national scale crop type map of Bulgaria based on Sentinel-1 and Sentinel-2 imagery. The results are also compared with those obtained using only Sentinel-2 imagery. Finally, the map accuracy is analysed with respect to the field size.

### **Data and methods**

The CORINE Land Cover (CLC) 2018 dataset is used to define the area of interest, which includes only agricultural areas. Thus, only the regions with code 200 according to the CLC level 1 are further considered for the image classification.

Based on the agroclimatic zoning of Bulgaria [10] the country is divided into four agroclimatic regions: 1. cool and moderately cool, wet region (mountain areas); 2. Moderately warm and warm region, less liable to droughts (most of the Danube plain and the basins and low mountain parts in southern Bulgaria); 3. moderately hot and hot region, liable to droughts (the northernmost part of the Danube plain, the Upper Thracian lowland, and lowland of Burgas); and 4. Hot, arid region (the lower part of Struma valley). The data pre-processing and classification are repeated for each region and the final crop map is obtained after merging the maps of the individual regions.

Data about parcel borders and the crop sown in each parcel in 2018/2019 agricultural year are available in a vector format from State Fund “Agriculture” (SFA). The data are based on declarations made by farmers who apply for aid under Common Agricultural Policy (CAP) and national programmes and have complete coverage of the country’s agricultural area. These data are collected as part of the Integrated Administration and Control System (IACS). A special nomenclature of crops is used in this dataset, which, at the lowest level, includes more than 200 crops, which are aggregated in groups (e.g. technical crops) and subgroups (e.g. industrial crops, oil crops, etc.) at the higher levels. For this study, the crops were aggregated in a customised legend, including some important individual crops and some wider classes based on the groups and subgroups of the original nomenclature. The 14 classes are as follows: “Cereals”, “Maize”, “Grain legumes”, “Technical crops”, “Sunflower”, “Winter rapeseed”, “Forage crops”, “Meadows and pastures”, “Alfalfa”, “Vegetables”, “Fallow”, “Vineyards and orchards”, “Perennial medical and aromatic crops”, and “Rice”. The legend is

constructed to be maximally close to the nomenclature used by the state authorities in the agricultural sector. Fig. 1 presents the major stages in the phenological cycle of some crops and crop types. The parcels are divided by random in two parts: for training and for the validation of the classification algorithm (70:30), and are converted to raster format.

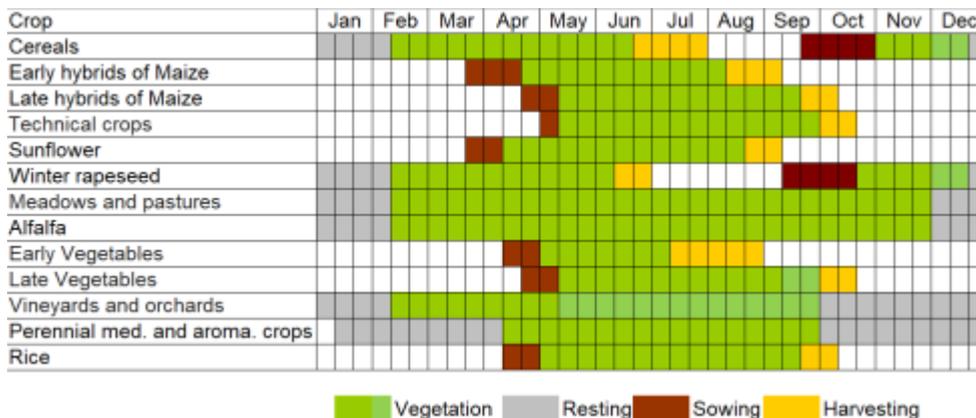


Fig. 1. Crop calendar of some crops and crop types in Bulgaria for 2019

The next steps, including satellite image pre-processing, training of the classifier, and classification, are performed in Google Earth Engine (GEE). The following GEE collections are used: “COPERNICUS/S2” consisting of Sentinel-2 A&B scenes at level 1C, and “COPERNICUS/S1\_GRD” consisting of Sentinel-1 Ground Range Detected (GRD) scenes. The pre-processing steps for the Sentinel-2 imagery include 1. Selection of scenes with cloud cover lower than 20%; 2. Applying the cloud and cirrus masks, which are part of the dataset (band QA60); 3. Generating three multiband temporal composite images using the median compositing rule, each containing bands B02-B08, B11, and B12: March-April, June-July, and August-September 2019. The pre-processing steps for the Sentinel-1 imagery include 1. Filter the scenes by orbit type and selecting only “ascending” imagery; 2. Clipping the edge of the scenes to remove bad pixels (an inland buffer); 3. Apply a function (provided by Kristof Van Tricht, VITO) to make sure all acquisitions in one pixel result from the same relative orbit; 4. Generating three multiband temporal composite images using the median compositing rule, each containing VV and VH polarisations: March-April, June-July, and August-September 2019. Note that May is omitted from the compositing periods due to the frequent cloud cover this month. Two datasets were constructed from the imagery. The first has 27 bands and includes the Sentinel-2 composites. The second has 33 bands and includes both Sentinel-2 and Sentinel-1 composites.

The Random Forest (RF) classification algorithm [11, 12] as implemented in GEE is used to classify the satellite image datasets. The raster with the parcels designated for training is imported in GEE and a stratified random sampling is performed with 1000 pixels per class (note that in some of the agroclimatic regions this number cannot be attained for some classes, which have limited distribution). The values of the image bands are extracted for each training pixel. These data are then used to train the RF classifier. The number of trees is set up to 100, which is considered good compromise between accuracy and computational time [13]. All other parameter values are left by default. The final map is exported from GEE in GeoTiff format with 10 m pixel size.

The final crop map obtained after the four agroclimatic regions have been merged is “smoothed” by eliminating patches smaller than 10 pixels. This is performed using the Sieve tool of QGIS. Accuracy assessment is also performed in QGIS. For that purpose, the raster with the parcels designated for validation and the crop map raster are compared pixel by pixel and a confusion matrix is generated. Over 100 million pixels are used for this validation. Overall accuracy and class-wise accuracies (User’s and Producer’s) are calculated. Additionally, We repeated the same validation procedure several times but using only parcels with specific size: less than 0.5 ha, 0.5-1ha, 1–3 ha, 3–5 ha, and over 5ha.

## **Results and discussion**

The overall accuracy of the map based solely on Sentinel-2 data is 74.8%, while the overall accuracy of the map based on a combination of Sentinel-1 and -2 data is 78.1%. This confirms the added value of SAR data in crop type mapping. All results and discussions further on concern the map based on the combination of Sentinel-1 and -2 data which is shown in Fig. 2. A visual examination of the map shows that the agricultural land use pattern is well portrayed in most of the territory where large parcel sizes dominate. For example, Fig. 3A shows a map excerpt representing a small area near the town of Knezha in the Danube plain. Here, parcel borders and shapes are realistically represented and within-field heterogeneities caused by errors in the classification are rare. More importantly, in most parcels the crop type is accurately determined by the RF classifier if we compare it with the IACS dataset used in this study as a reference. In other parts of the country, however, the classification results are characterised with much noise. A typical example is to be found in the Upper Thracian lowland near Plovdiv, where parcel sizes are much smaller (Fig. 3B). The post-processing (i.e. the smoothing with the “sieve” tool) reduces noise but due to small parcel size, it resulted in disturbance of the parcels’ shape. Also, compliance with the IACS dataset is poorer.

The performance is not constant among classes and the accuracy varies for the different crop types. Both user’s and producer’s accuracy are above 80% for the

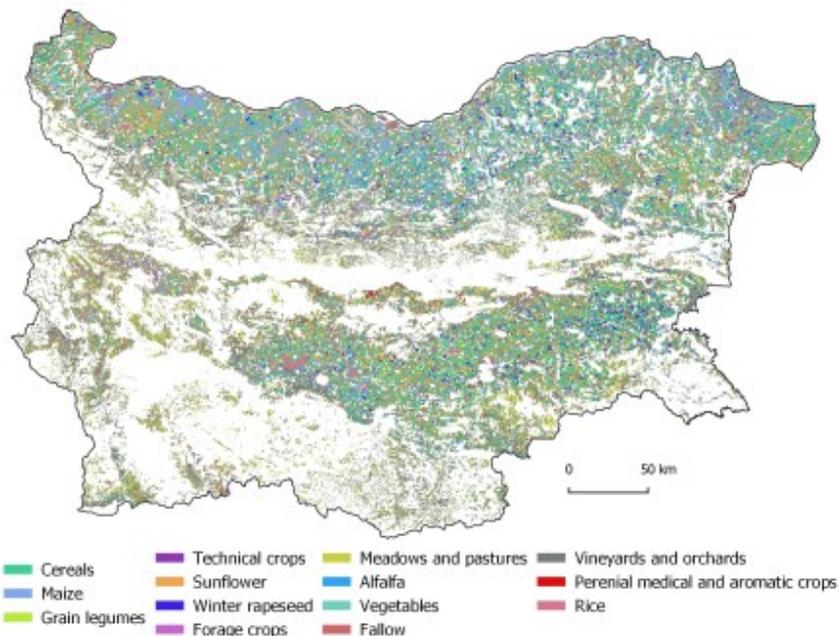
classes “Cereals”, “Maize”, “Sunflower”, “Winter rapeseed”, and “Rice” (Fig. 4). Cereals, (which include mostly winter wheat and winter barley), maize, and sunflower represent the most important crops in the country in terms of area. Rice is particularly well classified, which is due to its specific method of cultivation. The class “Meadows and pastures” is mapped with moderate accuracy (70% and 75% for producer’s and user’s accuracy respectively; Fig. 4). The accuracy for the other classes is lower. In particular, their user’s accuracies are low, which indicates that their occurrence is overestimated. For example, most of the pixels belonging to class “Vegetables” in the map are actually other crop types. The classes for which the RF classification has low accuracy are rare classes, which mean they represent a small part of the arable land in Bulgaria. This can be seen in the area distribution shown in Fig. 5.

The most important misclassifications are as follows: 1. “Alfalfa” is overestimated at the expense of “Cereals” and “Meadows and pastures”; 2. “Technical crops” and “Grain legumes” are overestimated at the expense of “Sunflower” and “Cereals”; 3. “Forage crops” is overestimated at the expense of “Maize” and “Cereals”; 4. “Vegetables” is overestimated at the expense of “Sunflower” and “Fallow”; 5. “Vineyards and orchards” is overestimated at the expense of “Meadows and pastures”; 6. “Perennial medical and aromatic crops” and “Fallow” are mixed with many of the other classes. Most of the mixtures are with “Cereals”, “Sunflower”, and “Maize”, which can partially be explained by the fact that these are the most widespread classes. The similarity of classes in terms of crop phenology and/or physiognomy also plays a part. For example, “Alfalfa” is mixed with “Meadows and pastures”, both classes representing low herbaceous plants with continuous cover and similar phenological cycle (Fig. 1). Another reason for the errors in the classification is that some classes are too general and include crops which are not similar in their spectral characteristics but in their usage. For example, the “Forage crops” class includes, among others, crops as different as clover and corn for silage. This can partly explain the mixture with the “Maize” class. Fig. 6 shows the overall accuracy calculated for different parcel sizes. As the visual inspection of the map suggested the parcel size is related to the accuracy. The accuracy increased from below 60% for the smallest parcels to over 80% for those larger than 5 ha. While the smallest parcels (<0.5 ha) are the most numerous, they account for only 3% of the area of all parcels designated for validation. The largest parcel category (> 5 ha) constitutes by far the largest area (76 %). These results can be explained with the fact that smaller fields have more border pixels, which represent a mixture of land uses.

The application of the national crop map based on Sentinel data could be the calculation of areas of different crops for statistical purposes. To check the accuracy of the calculated areas they are compared with the areas from the IACS dataset (Fig. 5). To guarantee that the areas are comparable the Sentinel-based crop map is clipped to the extent of the IACS dataset. In general, the magnitude of the

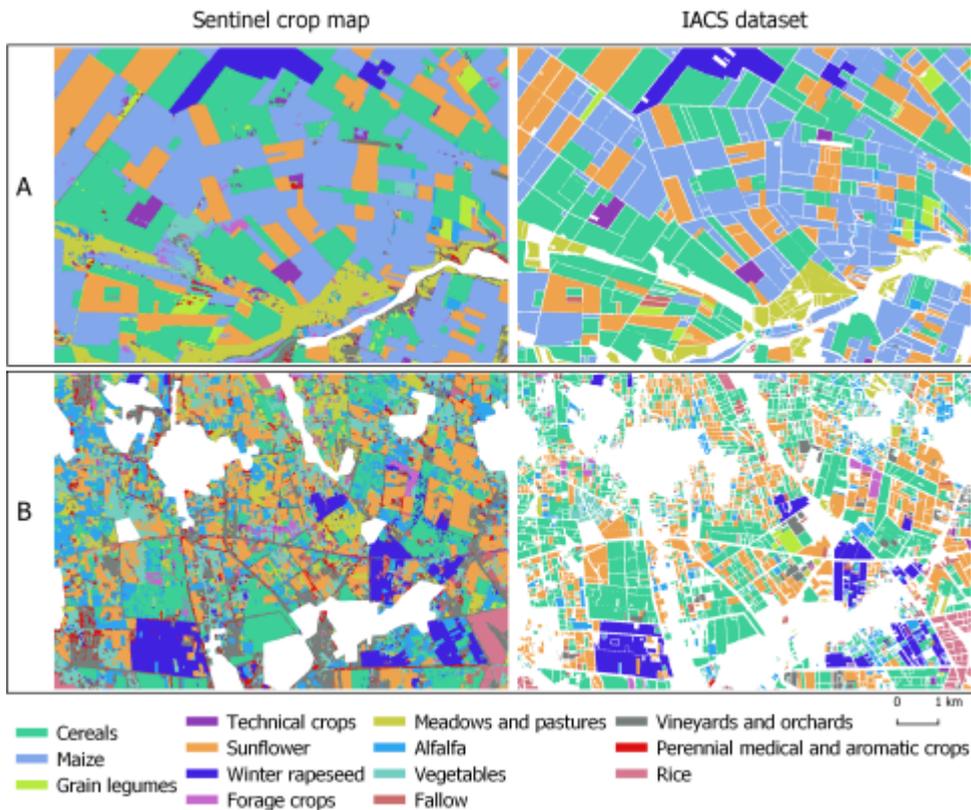
class area differences is well reproduced using the Sentinel-based map. For example, “Meadows and pastures” has roughly half the area of “Sunflower” according to both datasets. However, the area of the three largest classes is somewhat underestimated with the Sentinel-based map data (the difference with IACS areas is 11–14%). The small-area classes are, as a rule, overestimated, this being the most severe for “Vineyards and orchards”, “Vegetables”, “Grain legumes”, and “Forage crops” where the difference from IACS data is more than 100%. The most accurate are the areas of “Winter rapeseed” and “Rice”, which are within 3% and 9% of the IACS data, respectively.

The accuracy of the Sentinel derived crop maps reported in the literature vary depending on the input data, methods and study area specifics. Very high accuracy (95–96%) was reported for example by Vuolo et al. [1], but they used a large number of cloud-free Sentinel-2 images, instead of composites, and mapped small region. In a study, similar to this presented here, Griffiths et al. [4] mapped 12 crop and land cover classes over Germany with 81% overall accuracy. In another national scale exercise Van Tricht et al. [3] classified dense time series of Sentinel-2 NDVI and Sentinel-1 backscatter data to map 12 crops and land cover types in Belgium, achieving overall accuracy of 82%. These results are similar to the accuracy reported here.



*Fig. 2. Crop type map of Bulgaria for 2018/2019 agricultural year derived from Sentinel-1 and -2 data. White areas are non-agricultural land*

The two-month compositing interval used in this study is relatively long to allow fine phenological differences between crops and be captured (Fig. 1). However, it ensured cloud-free Sentinel-2 mosaics over the entire study area with a negligible cloud contamination according to the visual inspection. Other studies have successfully applied shorter compositing periods for Sentinel-2, e.g. 10-day or month, but this may require smoothing and gap-filling the time series or even ingestion of Landsat observations [4, 5]. Griffiths et al. [4] showed that using 10-day composites resulted in higher accuracy for most classes than longer compositing periods. These developments may increase mapping accuracy in the Bulgarian context as well and should be examined in future studies.



*Fig. 3. Comparison of the crop type map of Bulgaria for 2019 derived from Sentinel-1 and -2 data with the IACS dataset for selected regions: (A) Danube plain near Knezha and (B) Upper Thracian lowland near Plovdiv*

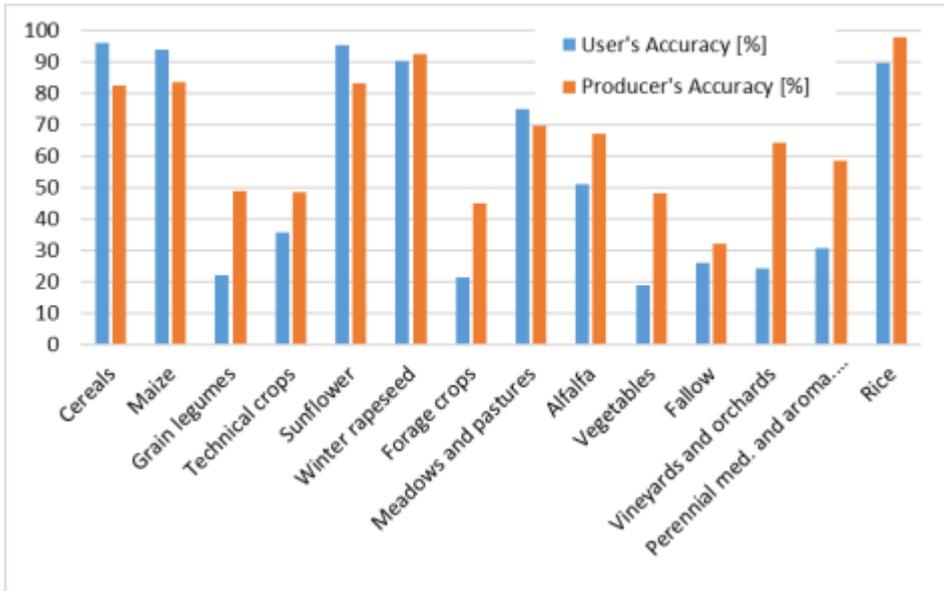


Fig. 4. User's and Producer's accuracy (%) of the 14 classes of the crop map

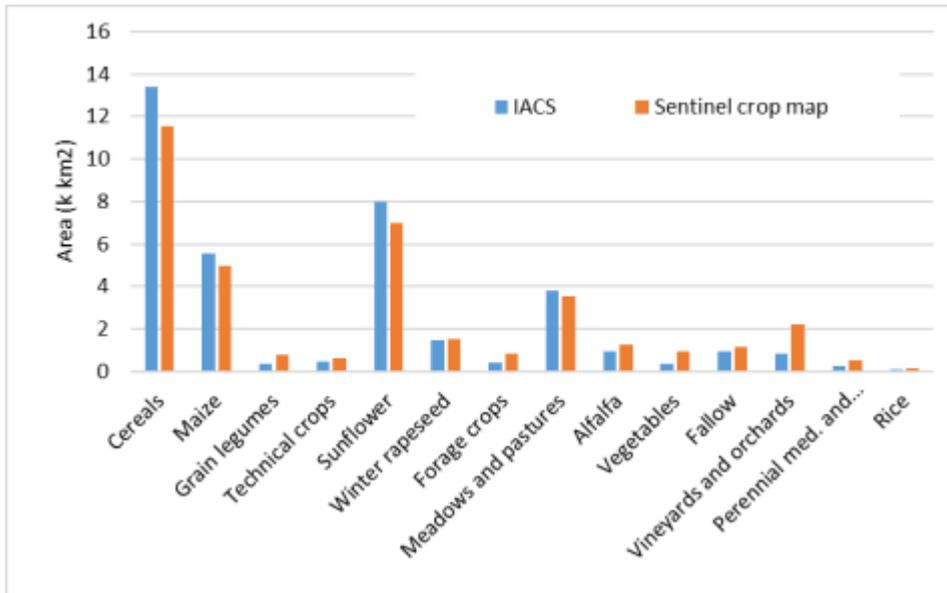
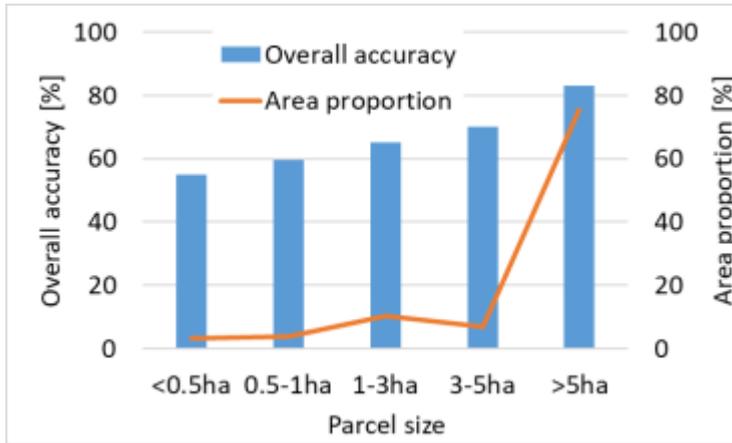


Fig. 5. Comparison of the areas of the 14 classes according to the Sentinel-based national crop map and the IACS dataset



*Fig. 6. Overall accuracy as a function of the parcel size. Area proportions are based on the validation dataset*

## Conclusions

This study is, to our knowledge, the first attempt to map crop types over the entire Bulgarian territory using Sentinel satellite imagery. A moderate overall accuracy of 78% is achieved, but results are better for the most important crops and crop types – “Cereals”, “Sunflower”, and “Maize”. Problem for the classification is the recognition of some classes, which are too heterogeneous, e.g. “Vegetables” and “Forage crops”. Such classes are included in the legend to comply with the existing nomenclature of crops used in the country, but the poor accuracy suggests that their usage is impossible in the context of the semi-automated remote sensing-based mapping. Higher overall accuracy was achieved with a combination of Sentinel-1 and -2 data than using only optical imagery. This confirms that SAR data derive important information for crop discrimination. It was also found that accuracy tends to be higher for larger parcels. Future studies should concentrate on the adjustment of the definitions of the classes. Mapping only individual crops, instead of groups of crops, is another approach but this would require a more computational resources. Further improvement of results may require testing of other classification algorithms and/or using composites with higher frequency.

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The contents of the publication do not represent the official views of the European Commission nor do they constitute a commitment of any kind on its behalf. The IACS data were kindly provided by State Fund “Agriculture” of the Bulgarian Ministry of Agriculture, Food and Forestry.

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## КАРТОГРАФИРАНЕ НА ЗЕМЕДЕЛСКИТЕ КУЛТУРИ В БЪЛГАРИЯ ЧРЕЗ ДАННИ ОТ SENTINEL-1/2

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### Резюме

През последните години, благодарение на достъпа до сателитни данни от Sentinel-1 и -2, се появиха нови възможности за полуавтоматично картографиране на земеделските култури на национално ниво. В това изследване са картографирани 14 земеделски култури и групи от култури на територията на България използвайки три двумесечни композитни изображения за 2019 година, генерирани в облачната платформа Google Earth Engine (GEE). Общата точност, когато се използват изображения както от Sentinel-1, така и от Sentinel-2 е 78%, докато точността е малко по-ниска, когато се използват само данни от Sentinel-2 (75%). Точността е най-висока за класовете “Зърнено-житни култури”, “Царевица”, “Слънчоглед”, “Зимна рапица” и “Ориз” – над 80%. Точността при класове като “Зеленчуци”, “Технически култури”, “Фуражни култури”, “Угар” и др. обаче е по-ниска. Тези класове представляват категории, подходящи за използване в земеделската практика и статистика, но са твърде общи и трудни за отличаване чрез сателитни данни. Беше установено също така, че точността е по-висока за парцелите с по-големи размери. Като възможни пътища за подобряване на резултатите са посочени използването на серия от композитни изображения с по-голяма честота и адаптирането на класовете от класификационната система, така че да включват култури, които са сходни по фенология и морфология.