Crop inventory at regional scale in Ukraine: developing in season and end of season crop maps with multi-temporal optical and SAR satellite imagery

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**ABSTRACT**

Along the season classification maps based on satellite data is a challenging task for countries with large diversity of agricultural crops with different phenology (crop calendars). In this paper, we investigate feasibility of delivering early and along the season crop specific maps using available free satellite data over multiple years, including Landsat-8, Sentinel-1 and Sentinel-2. For this study, a test site in Kyiv region (Ukraine) is selected, for which we have been collecting ground data on crop types every year since 2011. Crop type maps are generated through a supervised classification of multi-temporal multi-source satellite data using previously developed artificial neural network algorithms. It is shown, how multi-year crop classification maps are used for crop rotation violation detection. The study shows that in case of considerable cloud cover, synthetic aperture radar (SAR) data, for example acquired by Sentinel-1 satellite, can be interchangeably used with optical imagery to achieve the target 85% accuracy for crop classification.

**Introduction**

**Crop mapping with remote sensing data**

Availability of reliable and accurate crop maps at regional and national scale is a prerequisite for efficient monitoring of agricultural land use. A wide range of agricultural applications, including crop area estimation, crop yield forecasting, crop state assessment, land use intensity rely heavily on the use of crop maps. Information on crop frequency derived from historical maps can be effectively used for stratification purposes in crop area estimation (Boryan, Yang, Di, & Hunt, 2014; Gallego et al., 2012). Knowing geographical distribution of given crops can help optimize available resources, when performing large-scale ground observations (Song et al., 2017). For instance, early season crop masks are required to provide crop yield prediction and, consequently, crop production forecasting in the operational context which is important for food security (Becker-Reshef, Vermote, Lindeman, & Justice, 2010; Franch et al., 2015; Johnson, 2016; Kogan et al., 2013; López-Lozano et al., 2015; Shao, Campbell, Taff, & Zheng, 2015). Crop maps can be incorporated into the drought risk assessment models to quantify and map the risk at different scales (Skakun, Kussul, Shelestov, & Kussul, 2016a). Availability of multi-year crop maps can be used to estimate land use intensity, which includes crop planting frequency and crop rotation (Kuemmerle et al., 2013). Also, time-series of such maps is essential for detection of crop rotation violations, which usually lead to soil degradation and decrease of crop production.

Earth observation (EO) remain one of the most important data sources for developing crop maps and crop inventories (Cohen & Goward, 2004). This is mainly due to capabilities to timely acquire images in different spectral bands and provide repeatable, continuous, human independent measurements for large territories. In particular, optical instruments onboard remote-sensing satellites provide imagery in multiple spectral bands, usually in visible, near-infrared, short-wave infrared, and thermal infrared. However, these data can be contaminated with cloud cover that, in many cases, makes it very difficult to acquire imagery in an optimal time range to discriminate crops (Paxlenney & Woodcock, 1997; Prischchepov, Radeloff, Dubinin, & Alcantara, 2012). On the other hand, synthetic aperture radar (SAR) instruments offer unique features to image crops due to their all-weather capabilities and ability to capture crop characteristics different from those derived from optical instruments (Skakun, Kussul, Shelestov, Lavreniuk, & Kussul, 2016b; Stefanski, Chaskovskyy, & Waske, 2014). Thanks to this,
SAR imagery can be captured at the best suited dates.

To this end, several programmes exist that target the development of crop inventories utilizing EO data, both optical and radar. The creation of the Cropland Data Layer (CDL) of the US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) is considered as one of the most successful applications of remote sensing data for crop mapping at national scale (Boryan, Yang, Mueller, & Craig, 2011; Johnson & Mueller, 2010). The CDL product provides crop maps for 47 states at 56 m spatial resolution from 2008 until 2010 and at 30 m spatial resolution after 2010. The primary source of remote sensing images is Advanced Wide Field Sensor (AWiFS), Deimos-1, Landsat-5/7/8, UK Disaster Monitoring Constellation (UK-DMC) and Moderate Resolution Imaging Spectroradiometer (MODIS). Supervised classification based on the classification and regression tree (CART) decision trees (DTs) is used to classify multi-temporal images into 25 crop-specific classes with accuracies for 2009 ranging from 85% to 95% for the major crops (corn, soybeans, and winter wheat). To train the classifier for satellite image classification, administrative data from Farm Service Agency-Common Land Units (FSA-CLU) are used. For crop area estimation, however, the main source of information is the June Area Survey (JAS) in which approximately 11,000, 1 sq mi sample segments are visited by enumerators to collect crop type and acreage information (Boryan et al., 2014). These JAS data provide the main variable for the regression estimator in crop area estimation. In general, CDL is used to drive the sampling strategies within the JAS surveys, and a key component for crop yield modelling (Johnson & Mueller, 2010). Agriculture and Agri-Food Canada (AAFC) provides the Annual Crop Inventory product, which is developed using optical (Landsat-5, AWiFS, DMC) and SAR (Radarsat-2) images. Multi-temporal satellite images are classified using the DT (CART) approach enabling the overall target accuracy of at least 85%. The product is delivered at 30 m spatial resolution (56 m in 2009–2010) (AAFC, 2013). The main source of ground truth data for training and validation of the product is annual crop insurance data derived from farmers. In Europe, regional crop inventories (Taylor, Sannier, Delince, & Gallego, 1997) utilized the USDA approach with area frame samples as main variable and classified satellite imagery as a co-variable. Attempts to produce rapid estimates of inter-annual crop area for the European Union (EU) using images without current field data showed that the results had depended more on the a priori belief of the analyst than on the information provided by the images (Gallego, 2006). Currently, the main usage of remote sensing imagery in the EU within the Land Use and Cover Area-Frame Statistical Survey (LUCAS) lies in stratification, while ground surveys remain the main source of information for land cover and crop area estimation (Gallego & Delincé, 2010).

**Objective of the study**

Ukraine is one of the most developed agricultural countries in the world. According to the U.S. Department of Agriculture (USDA) Foreign Agricultural Service (FAS) statistics, Ukraine was the largest sunflower producer (11.6 MT) and exporter, and the ninth largest wheat producer (22.2 MT) in the world in 2013. Providing multi-annual crop inventory is extremely important for managing agricultural resources at regional and national scale in Ukraine. A Joint Experiment for Crop Assessment and Monitoring (JECAM) test site was established in Ukraine in 2011 with the aim to develop and validate different methodologies for monitoring agricultural resources with the help of remote sensing data (Kussul et al., 2016; Skakun et al., 2016b). These include techniques for delivering in season and end of season crop maps by classifying multi-temporal optical and SAR satellite imagery. In this paper, we aim at creating a crop inventory for multiple seasons at regional scale in Ukraine using multi-temporal remote sensing images to provide similar maps available for USA and Canada. Direct application of the US or Canada-based approaches for Ukraine is difficult because of unavailability of data from farmers that leads to exploiting other sampling strategies, e.g. collecting data along the roads (Waldner et al., 2016). The similarity lies in using all freely available satellite imagery, both optical and SAR, and exploiting different machine learning algorithms such as random forest and neural networks (Kussul, Lavreniuk, Skakun, & Shelestov, 2017). The maps, both in season and end of season, are produced utilizing all available moderate spatial resolution satellite data, namely 30 m Landsat-8 Operational Land Imager (OLI) (2013–2015), 10 m Sentinel-1A C-band SAR (2015–2016), and 10 m Sentinel-2 Multi-Spectral Instrument (MSI) (2016). A machine learning technique based on ensemble of artificial neural networks (multi-layer perceptrons – MLPs) (Kussul et al., 2015) is used to classify satellite images into major crop types for 2013–2015 seasons. An application of using these maps for crop rotation violation detection is considered as well.

**Study area and materials description**

**The experimental site**

One administrative districts (Bilotserkivskiy) in Kyiv region has been selected for this study (Figure 1).
Kyiv region with geographic area of 28,100 km$^2$ and almost 1.0M ha of cropland is located in the north-central part of Ukraine. The area of Bilotserkivskiy district is 1,276 km$^2$. Soybeans, maize, winter wheat, sunflower, spring wheat and spring barley are the main crops in this region with major non-crop classes being grassland, forest and water. Our test site is located not far from the Dnipro river, and in general vegetation period is September–July for winter crops, and April–October for spring and summer crops.

**Satellite data**

For this study, we used 10 m SAR and optical satellite data from the Sentinel-1A and Sentinel-2 with the revisit time 12 and 10 days, respectively (Figure 2). Level-1 Interferometric Wide mode Ground Range Detected (IW-GRD) Sentinel-1A products in VV and VH polarizations have been used. All Sentinel-1A images were processed using the Sentinel-1 Toolbox (S1TBX) 1.0.3. Images were multi-looked with a 2 × 2 window, and filtered using a single product Refined Lee filter with a 3 × 3 window to reduce speckle level (Moreira et al., 2013). SAR images were further geometrically corrected using a Range-Doppler terrain correction procedure with the SRTM 3Sec Digital Elevation Model (DEM). The last step of SAR images pre-processing involved calibration to a backscatter coefficient (Moreira et al., 2013). In the experiment with the fusion of Sentinel-1 and Landsat-8 data, we re-sampled SAR images to Landsat-8 spatial resolution at 30 m. Multi-spectral high-resolution optical observations were provided by Sentinel-2. Level-1C top of atmosphere (TOA) reflectance product that consists of 100 × 100 km$^2$ tiles was used for crop mapping. We considered three
visible bands (red, green, blue) and near-infrared band which all have 10 m spatial resolution. For the Bilotserkivskiy district in Kyiv region in 2013 Landsat-8 satellite images were pre-processed to remove the effect of atmosphere using the Simplified Model for Atmospheric Correction (SMAC) (Rahman & Dedieu, 1994). Therefore, each pixel value was converted to the surface reflectance (SR) value; for 2014–2015 we used only top of atmosphere (TOA) reflectance values (Table 1). Multi-temporal Landsat-8 OLI 2–7 bands were reconstructed using self-organizing maps (SOMs) to restore missing reflectance values due to clouds and shadows (Kussul et al., 2017), and used for classification of satellite imagery. Landsat-8 bands 1 and 9 were not used due to the strong atmospheric influence. The panchromatic band and thermal bands from the Thermal Infrared Sensor (TIRS) were not utilized either.

We used SAR scenes from the 36th and 007th relative orbit numbers, Landsat-8 images with 181/25 path/row coordinate and Sentinel-2 data with 36TVT and 35UQR tiles (https://sentinel.esa.int/web/sentinel/missions/sentinel-1-observation-scenario/acquisition-segments).

**Ground reference data**

Ground surveys for *insitu* data collection to support crop classification using satellite imagery were conducted in 2013–2016. The European Land Use and Cover Area frame Survey (LUCAS) nomenclature (Gallego & Delincé, 2010) was used in this study as a basis for land cover/land use types. For 2013–2015 years, we had 13 land cover classes, including the following crops: winter wheat, winter rapeseed, maize, sugar beet, sunflower, soybeans, other spring crops and other cereals (Table 2). For 2016, we had only 7 land cover classes: winter wheat, winter rapeseed, winter barley, spring and summer crops, forest, grassland and water (Table 3).

### Methodology description

One of the main challenges in classification of multi-temporal optical satellite imagery is the presence of missing values caused by clouds and shadows. In previous works, we proposed an approach that combines unsupervised and supervised neural networks for missing data restoration and supervised classification, respectively (Kussul et al., 2015; Skakun et al., 2016b). First, self-organizing Kohonen maps (SOMs) are applied to restore missing pixel values in a time series of optical satellite imagery. However, with persistent cloud cover, especially during an early season, optical imagery is not enough to achieve the desirable accuracy of 85%. Therefore, SAR imagery is fused with optical ones to improve discrimination of crops when optical images are not available (Kussul et al., 2016; Skakun et al., 2016b). *In situ* samples have been randomly divided into two independent subsets: training set (50% of polygons for each class) and test set (50% of polygons for each class). Then, a supervised classification is performed to classify multi-temporal satellite images (Skakun, Nasouro, Lavrenyuk, & Kussul, 2007). For this, a committee of NNs, in particular multi-layer

### Table 1. Landsat-8, Sentinel-1A and Sentinel-2 data availability for the Bilotserkivskiy district in 2013–2016.

| Year | Landsat-8 | Sentinel-1A | Sentinel-2 |
|------|-----------|-------------|------------|
| 2016 | 24.05, 9.06, 25.06, 28.08 | 07.03, 19.03, 31.03, 12.04, 24.04, 06.05, 18.05, 30.05 | 01.03, 13.03, 25.06, 06.04, 18.04, 30.04, 12.05, 24.05, 05.06, 17.06, 29.06, 11.07, 23.07, 16.08, 28.08 |
| 2015 | 03.04, 06.06, 08.07, 10.09, 12.10, 28.10 | – | – |
| 2014 | 16.04, 02.05, 18.05, 19.06, 05.07, 06.08 | – | – |

### Table 2. Number of polygons and total area of crops and land cover types collected during the ground surveys for the Bilotserkivskiy district in 2013–2015.

| # | Class       | 2013 | 2014 | 2015 |
|---|-------------|------|------|------|
|   | Class       | Area, ha | Area, ha | Area, ha |
| 1 | Artificial  | 6   | 23.0 | 15  | 53.0 | 0    | 0    |
| 2 | Winter wheat| 51  | 3960.8 | 125 | 7589.4 | 102 | 3695.9 |
| 3 | Winter rapeseed | 12 | 937.3 | 36 | 1686.6 | 22 | 715.9 |
| 4 | Spring crops | 9 | 455.9 | 44 | 1358.0 | 11 | 296.0 |
| 5 | Maize       | 87  | 7253.3 | 76 | 4030.4 | 98 | 4329.1 |
| 6 | Sugar beet  | 8   | 632.5 | 18 | 1624.5 | 8   | 860.7 |
| 7 | Sunflower   | 30  | 2549.0 | 31 | 1338.2 | 53  | 1954.0 |
| 8 | Soybeans    | 60  | 3252.3 | 108 | 2965.3 | 87  | 3606.9 |
| 9 | Other cereals | 32 | 1364.0 | 12 | 451.9 | 0    | 0    |
| 10 | Forest     | 17  | 1014.3 | 35 | 1750.7 | 49  | 2012.3 |
| 11 | Grassland  | 48  | 747.5 | 67 | 1528.8 | 64  | 952.3 |
| 12 | Bare land  | 10  | 67.2 | 10 | 69.6 | 10 | 71.4 |
| 13 | Water      | 16  | 448.3 | 31 | 578.9 | 43  | 1072.1 |
| **Total** | **386** | **22,705.3** | **608** | **25,025.3** | **547** | **18,966.6** |
Table 3. Number of polygons and total area of crops and land cover types collected during the ground surveys for the Bilotserkivsky district in 2016.

| #  | Class                  | Fields | Area, ha |
|----|------------------------|--------|----------|
| 1  | Winter wheat           | 117    | 4255     |
| 2  | Winter barley          | 6      | 203      |
| 3  | Winter rapeseed        | 15     | 454      |
| 4  | Spring and summer crops| 150    | 5611     |
| 5  | Forest                 | 44     | 1100     |
| 6  | Grassland              | 32     | 250      |
| 7  | Water                  | 17     | 109      |
|    | **Total**              | **381**| **11,982**|

perceptrons (MLPs), is utilized to improve the performance of individual classifiers (Kussul et al., 2015). The MLP classifier has a hyperbolic tangent activation function for neurons in the hidden layer and logistic activation function in the output layer. The committee is formed using four MLPs with different number of hidden neurons (10, 20, 30, and 40) trained on the same training data within 250 epochs. Outputs from different MLPs are integrated using the technique of average committee. Under this technique, the average class probability over classifiers is calculated, and the class with the highest average posterior probability for the given input sample is selected. After obtaining a pixel-based classification map, a parcel-based procedure is applied to improve the quality and accuracy of the final map (Kussul et al., 2016). Crop type maps generated for 2013–2015 seasons are used to generate crop rotation violation map. By crop rotation violation, we mean growing the same crop type on the same field during at least 2 years in a row.

For 2016, when producing in season crop maps, we investigated availability of optical and SAR imagery to discriminate different crop type early in the season at acceptable target accuracy of 85%. In other words, in a situation of persistent cloud cover early in spring, can optical data be substituted with SAR imagery and whether the same level of performance can be achieved? In 2016, the test region experienced a lot of clouds during spring, so we considered the difference between using optical data from Sentinel-2 and SAR data from Sentinel-1A. Only one or two optical non-cloud images were available from March to June; at the same time we acquired 8 images from Sentinel-1A satellite (Table 1). For 2016 early season classification, we had three experiment designs: S1 – crop classification mapping using Sentinel-1A data only; S2 – using Sentinel-2 images only; and S1+S2 – crop classification mapping using combination of Sentinel-1A and Sentinel-2 images. Performance metrics were estimated from ground validation datasets that were not used during classifiers training. The confusion matrix used in accuracy assessment provides information on the magnitude of the classification errors that allows an adjustment to be made in the area estimator (Olofsson, Foody, Stehman, & Woodcock, 2013). User’s accuracy (UA) and producer’s accuracy (PA) are ways of representing individual class accuracy. User’s accuracy means the probability that a pixel classified on the map represents the class on the ground whereas producer’s accuracy indicates the probability of a reference pixel being correctly classified.

Results

Table 4 shows performance metrics for classification of satellite data for 2013–2015 seasons. We obtained reliable results with overall accuracy 85.3%, 90.1% and 92.4%, respectively, for 13 classes (Figure 3, Table A1-A3). Producer’s (PA) and user’s (UA) accuracies of winter wheat were always higher than 92%. Using only Landsat-8 optical data (2013–2014) winter rapeseed’s PA and UA values were about 80% and 98%, respectively. When adding Sentinel-1 SAR data (2015), significant improvements were observed in detecting rapeseed (PA = 100%, UA = 94.6%). Also, fusion of SAR and optical data achieved gains of PA +15.4% and UA + 7% for sunflower. At the same time, addition of SAR data had no effect on detecting maize (PA and UA were approximately 90%), sugar beet (PA and UA were approximately 100%) and water (PA and UA were approximately 100%). Accuracy of soybeans (PA – 72.4%, 98.6% and 83.7%; UA – 80.8%, 87.3% and 78.9%) and spring and summer crops (PA – 25%, 76.4% and 66.7%; UA – 33.3%, 70.5% and 84.2%) varied widely from year to year.

Figure 4 shows a crop rotation violation map generated from single-year crop maps for 2013–2015. Winter wheat (with estimated total area of violations at 68,400 ha), winter rapeseed (5700 ha), sunflower (22,200 ha) and maize (85,800 ha) were grown at the same field at least twice during the past 3 years. It means that for these fields crop rotation requirements were not met.

Table 4. Comparison of producer accuracy (PA), user accuracy (UA) and overall accuracy (OA) for the Bilotserkivsky district in 2013–2015 (based on Landsat-8 and Sentinel-1A).

| #  | Class                  | 2013  | 2014  | 2015  |
|----|------------------------|-------|-------|-------|
|    | PA, %| UA, %| PA, %| UA, %| PA, %| UA, %| PA, %| UA, %|
| 1  | Artificial             | 100   | 89.9 | 100   | 90.1 | 100   | 92.4 |     |
| 2  | Winter wheat           | 96    | 96.4 | 93.5  | 99.2 | 92.4  |     |     |
| 3  | Winter rapeseed        | 83.3  | 80.5 | 98.1  | 100  | 94.6  |     |     |
| 4  | Summer and spring      | 25    | 33.3 | 76.4  | 70.5 | 66.7  | 84.2 |     |
| 5  | Maize                  | 93    | 88.9 | 85.2  | 94.2 | 89.2  | 93.4 |     |
| 6  | Sugar beet             | 100   | 97.2 | 99.9  | 100  | 100   |     |     |
| 7  | Sunflower              | 80    | 75   | 84.6  | 87.5 | 100   | 94.5 |     |
| 8  | Soybeans               | 72.4  | 80.8 | 98.6  | 87.3 | 78.9  |     |     |
| 9  | Other cereals          | 75    | 63.2 | 1.2   | 5.6  | 99.5  | 99.9 |     |
| 10 | Forest                 | 87.5  | 100  | 98.6  | 95.6 | 99.7  | 99.9 |     |
| 11 | Grassland              | 90.5  | 86.4 | 83.4  | 72.7 | 86.3  | 99  |     |
| 12 | Bare land              | 80    | 100  | 100   | 87.2 | 100   | 95.9 |     |
| 13 | Water                  | 100   | 100  | 99.9  | 99.5 | 99.6  | 100 |     |

OA, % 85.6 90.1 92.4
For 2016 early season classification, SAR data provided better results than optical due to the number of available images during the spring, when cloud cover was significant (Figure 5). Fusion of SAR and optical data allowed us to improve classification accuracy by +0.8% (Table 5). Winter rapeseed, spring and summer crops were discriminated with high accuracy (>85%). Winter wheat had higher user and producer accuracy. Unfortunately, reliable discrimination of winter barley and grassland is possible only in the end of the season.

**Discussion and conclusions**

This paper aimed at exploring the creation of yearly crop maps for the same region (Ukraine) utilizing different sets of available satellite imagery (both optical and SAR), and at different time periods (end of season and in season). This is the first such a study for Ukraine for producing multi-year crop type inventories, as previous studies focused on other regions (AAFC, 2013; Boryan et al., 2011; Johnson & Mueller, 2010), single year and end of season crop type maps only (Kussul et al., 2016; Prischchepov et al., 2012; Skakun et al., 2016b; Waldner et al., 2016). The proposed approach is very useful for operational crop mapping, as it can be applied, while satellite imagery being acquired and ingested into the classifier to provide both in season and end of season crop maps. Multi-year crop specific maps have multiple applications. One such application is detection of areas (fields), where crop rotation requirements (not to plant the same crop in consecutive years) were not met. Such maps are important.
developed in Ukraine at national level. Everyone could revise crop information for each parcel for previous years and detect corresponding crop rotation violations. The applications of the developed multi-year classification maps include stratification for ground surveys for crop area estimation and crop rotation violation area estimation, and providing crop-specific empirical crop yield forecasting models.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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**References**

AAFC. (2013). ISO 19131 AAFC Annual crop inventory – data product specifications. Retrieved from [http://www.agr.gc.ca/atlas/supportdocument_documentesupport/aafcCropTypeMapping/en/ISO%2019131_Aafc_Annual_Crop_Inventory_Data_Product_Specifications.pdf](http://www.agr.gc.ca/atlas/supportdocument_documentesupport/aafcCropTypeMapping/en/ISO%2019131_Aafc_Annual_Crop_Inventory_Data_Product_Specifications.pdf)

Becker-Reshef, I., Vermote, E., Lindeman, M., & Justice, C. (2010). A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. Remote Sensing of Environment, 114(6), 1312–1323.

Boryan, C., Yang, Z., Mueller, R., & Craig, M. (2011). Monitoring US agriculture: The US department of agriculture, national agricultural statistics service, cropland data layer program. *Geocarto International*, 26(5), 341–358.

Boryan, C.G., Yang, Z., Di, L., & Hunt, K. (2014). A new automatic stratification method for U.S. agricultural area sampling frame construction based on the cropland data layer. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7(11), 4317–4327.

Cohen, W.B., & Govard, S.N. (2004). Landsat’s role in ecological applications of remote sensing. *Bioscience*, 54(6), 535–545.

Franch, B., Vermote, E.F., Becker-Reshef, I., Claverie, M., Huang, J., Zhang, J., … Sobrino, J.A. (2015). Improving the timeliness of winter wheat production forecast in the United States of America, Ukraine and China using MODIS data and NCAR Growing Degree Day information. Remote Sensing of Environment, 161, 131–148.

Gallego, F.J. (2006). Review of the main remote sensing methods for crop area estimates, remote sensing support to crop yield forecast and area estimates. *ISPRS Archives*, XXXVI, 8/W48, 65–70.

Gallego, F.J., Kravchenko, O., Kussul, N., Skakun, S., Shelestov, A., & Grypych, Y. (2012). Efficiency assessment of different approaches to crop classification based on satellite and ground observations. *Journal of Automation and Information Sciences*, 44(5), 67–80.

Gallego, J., & Delincé, J. (2010). The European land use and cover area-frame statistical survey. In R. Benedetti,

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**Table 5.** Comparison of producer accuracy (PA), user accuracy (UA) and overall accuracy (OA) for the Bilotserkivskiy district in 2016 using Sentinel-1A and Sentinel-2 images.

| Class                  | S1 PA | S1 UA | S2 PA | S2 UA | S1+S2 PA | S1+S2 UA |
|------------------------|-------|-------|-------|-------|----------|----------|
| 1 Winter wheat         | 87.5  | 93    | 86.4  | 92.5  | 88       | 93.8     |
| 2 Winter barley        | 76.1  | 63.9  | 69    | 61.1  | 79.9     | 68.1     |
| 3 Winter rapeseed      | 96.4  | 91.6  | 90.9  | 59    | 97.2     | 91.8     |
| 4 Spring and summer    | 96.8  | 99.7  | 87.7  | 98.2  | 97.6     | 99.7     |
| 5 Forest               | 99.9  | 98.9  | 95.5  | 88.4  | 99.8     | 98.5     |
| 6 Grassland            | 61.5  | 25    | 84.3  | 23    | 66.8     | 29.8     |
| 7 Water                | 100   | 86    | 100   | 100   | 100      | 83.2     |
| **OA, %**              | **92.9**| 87.3 | **93.7**|       |          |          |
M. Bee, G. Espa, F. Piersimoni, J. Wiley, L. Sons, & U.K. Chichester (Eds.). Agricultural survey methods (pp. 149–168). doi:10.1002/9780470665480.ch10

Johnson, D.M. (2016). A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. *International Journal of Applied Earth Observation and Geoinformation*, 52, 65–81.

Johnson, D.M., & Mueller, R. (2010). The 2009 cropland data layer. *Photogramm Engineering Remote Sensing*, 76, 1202–1205.

Kogan, F., Kussul, N., Adamenko, T., Skakun, S., Kravchenko, O., Kryvobok, O., … Lavrenyuk, A. (2013). Winter wheat yield forecasting in Ukraine based on earth observation, meteorological data and biophysical models. *International Journal of Applied Earth Observation and Geoinformation*, 23, 192–203.

Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P. H., Estel, S., … Levers, C. (2013). Challenges and opportunities in mapping land use intensity globally. *Current Opinion in Environmental Sustainability*, 5(5), 484–493.

Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*, 14(5), 778–782.

Kussul, N., Lemoine, G., Gallego, F.J., Skakun, S.V., Lavreniuk, M., & Shelestov, A.Y. (2016). Parcel-based crop classification in Ukraine using landsat-8 data and sentinel-1A data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9, 2500–2508.

Kussul, N., Skakun, S., Shelestov, A., Lavreniuk, M., Yailymov, B., & Kussul, O. (2015). Regional scale crop mapping using multi-temporal satellite imagery. *International Archives Photo gramm Remote Sens Spatial Information Sciences*, XL-7/W3, 45–52.

López-Lozano, R., Duveiller, G., Seguini, L., Meroni, M., García-Condado, S., Hooker, J., … Baruth, B. (2015). Towards regional grain yield forecasting with 1km-resolution EO biophysical products: Strengths and limitations at pan-European level. *Agricultural and Forest Meteorology*, 206, 12–32.

Moreira, A., Prats-Iraola, P., Younis, M., Krieger, G., Hajnsek, I., & Papathanassiou, K.P. (2013). A tutorial on synthetic aperture radar. *IEEE Geoscience and Remote Sensing Magazine*, 1(1), 6–43.

Olofsson, P., Foody, G.M., Stehman, S.V., & Woodcock, C. E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, 129, 122–131.

Pax-Lenney, M., & Woodcock, C.E. (1997). Monitoring agricultural lands in Egypt with multitemporal landsat TM imagery: How many images are needed? *Remote Sensing of Environment*, 59(3), 522–529.

Prishchepov, A.V., Radeloff, V.C., Dubinin, M., & Alcantara, C. (2012). The effect of Landsat ETM/ETM+ image acquisition dates on the detection of agricultural land abandonment in Eastern Europe. *Remote Sensing of Environment*, 126, 195–209.

Rahman, H., & Dedieu, G. (1994). SMAC: A simplified method for the atmospheric correction of satellite measurements in the solar spectrum. *International Journal of Remote Sensing*, 15(1), 123–143.

Shao, Y., Campbell, J.B., Taff, G.N., & Zheng, B. (2015). An analysis of cropland mask choice and ancillary data for annual corn yield forecasting using MODIS data. *International Journal of Applied Earth Observation and Geoinformation*, 38, 78–87.

Skakun, S., Kussul, N., Shelestov, A., & Kussul, O. (2016a). The use of satellite data for agriculture drought risk quantification in Ukraine. *Geomatics, Natural Hazards and Risk*, 7(3), 901–917.

Skakun, S., Kussul, N., Shelestov, A.Y., Lavreniuk, M., & Kussul, O. (2016b). Efficiency assessment of multi-temporal C-band Radesat-2 intensity and Landsat-8 surface reflectance satellite imagery for crop classification in Ukraine. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9, 3712–3719.

Skakun, S., Nasuro, E., Lavrenyuk, A., & Kussul, O. (2007). Analysis of applicability of neural networks for classification of satellite data. *Journal Autom Information Sciences*, 39(3), 37–50.

Song, X.P., Potapov, P.V., Krylov, A., King, L., Di Bella, C. M., Hudson, A., … Hansen, M.C. (2017). National-scale soybean mapping and area estimation in the United States using medium resolution satellite imagery and field survey. *Remote Sensing of Environment*, 190, 383–395.

Stefanski, J., Chaskovskyy, O., & Waske, B. (2014). Mapping and monitoring of land use changes in post-Soviet western Ukraine using remote sensing data. *Applied Geography*, 55, 155–164.

Taylor, J., Sannier, C., Delince, J., & Gallego, F.J. (1997). Regional crop inventories in Europe assisted by remote sensing: 1988–1993 (Synthesis Report, EUR 17319 EN, JRC). Ispra.

Waldner, F., De Abeleyra, D., Verón, S.R., Zhang, M., Wu, B., Plotnikov, D., … Le Maire, G. (2016). Towards a set of agrosystem-specific cropland mapping methods to address the global cropland diversity. *International Journal of Remote Sensing*, 37(14), 3196–3231.
### Table A1. Confusion matrix for 2013 when classifying multi-temporal Landsat-8 images.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | UA |
|---|---|---|---|---|---|---|---|---|----|----|----|----|----|
| 184 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 21,453 | 33 | 51 | 26 | 0 | 29 | 11 | 1728 | 0 | 2 | 30 | 0 | 91.8 |
| 3 | 0 | 3788 | 1 | 14 | 0 | 5 | 1 | 2 | 0 | 0 | 0 | 0 | 99.4 |
| 4 | 0 | 723 | 0 | 982 | 3 | 0 | 0 | 3 | 1101 | 0 | 2 | 0 | 34.6 |
| 5 | 0 | 0 | 0 | 177 | 33,972 | 2 | 390 | 1027 | 14,668 | 29 | 3 | 0 | 86.8 |
| 6 | 0 | 0 | 0 | 11 | 222 | 3511 | 118 | 3241 | 1672 | 91 | 0 | 0 | 85.4 |
| 7 | 0 | 0 | 0 | 10 | 389 | 71 | 13,241 | 1672 | 91 | 0 | 0 | 0 | 89.6 |
| 8 | 0 | 343 | 2 | 74 | 1279 | 0 | 84 | 15,448 | 4 | 0 | 0 | 0 | 70.5 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| PA | 100.0 | 95.7 | 93.5 | 40.6 | 90.5 | 94.9 | 84.1 | 69.7 | 70.9 | 96.9 | 91.0 | 86.7 | 100.0 | 85.3 |

### Table A2. Confusion matrix for 2014 when classifying multi-temporal Landsat-8 images.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | UA |
|---|---|---|---|---|---|---|---|---|----|----|----|----|----|
| 210 | 12 | 23 | 0 | 139 | 2 | 31 | 4 | 90 | 68 | 163 | 0 | 0 | 28.3 |
| 2 | 36,984 | 0 | 518 | 22 | 0 | 42 | 1683 | 1 | 298 | 0 | 1 | 93.5 |
| 3 | 1 | 37 | 6608 | 0 | 0 | 90 | 0 | 0 | 0 | 0 | 0 | 0 | 98.1 |
| 4 | 0 | 240 | 1242 | 3693 | 45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 70.5 |
| 5 | 0 | 440 | 200 | 16,902 | 0 | 35 | 174 | 33 | 0 | 4 | 0 | 0 | 94.2 |
| 6 | 0 | 3 | 2 | 0 | 0 | 6831 | 0 | 0 | 0 | 0 | 0 | 0 | 99.1 |
| 7 | 0 | 0 | 0 | 785 | 10 | 6702 | 1 | 9 | 0 | 156 | 0 | 0 | 87.5 |
| 8 | 0 | 343 | 2 | 74 | 1279 | 0 | 84 | 15,448 | 4 | 0 | 0 | 0 | 87.3 |
| 9 | 0 | 49 | 0 | 388 | 0 | 0 | 0 | 0 | 27 | 0 | 0 | 0 | 5.6 |
| 10 | 3 | 66 | 0 | 19 | 95 | 0 | 2 | 95 | 10,752 | 208 | 0 | 2 | 95.6 |
| 11 | 15 | 195 | 127 | 0 | 657 | 1 | 1074 | 3 | 393 | 79 | 6762 | 0 | 0 | 72.7 |
| 12 | 51 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 3 | 383 | 0 | 87.2 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| PA | 72.4 | 96.4 | 80.5 | 76.4 | 85.2 | 97.2 | 84.6 | 98.6 | 1.2 | 98.6 | 83.4 | 100 | 99.9 | 90.1 |

### Table A3. Confusion matrix for 2015 when classifying multi-temporal Landsat-8 + Sentinel-1 images.

| 2 | 3 | 4 | 5 | 6 | 7 | 8 | 10 | 11 | 12 | 13 | UA |
|---|---|---|---|---|---|---|----|----|----|----|----|
| 9918 | 1 | 209 | 3 | 0 | 0 | 384 | 0 | 214 | 0 | 0 | 92.4 |
| 3 | 0 | 2177 | 78 | 0 | 0 | 46 | 0 | 0 | 0 | 0 | 94.6 |
| 4 | 0 | 576 | 38 | 0 | 0 | 67 | 3 | 0 | 0 | 0 | 84.2 |
| 5 | 0 | 0 | 17,918 | 0 | 0 | 1257 | 5 | 0 | 0 | 0 | 93.4 |
| 6 | 0 | 0 | 0 | 466 | 0 | 0 | 0 | 0 | 0 | 0 | 100 |
| 7 | 0 | 0 | 0 | 0 | 3191 | 184 | 0 | 3 | 0 | 0 | 94.5 |
| 8 | 73 | 0 | 2128 | 0 | 0 | 10,018 | 7 | 470 | 0 | 1 | 78.9 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10,759 | 208 | 0 | 99.9 |
| 11 | 3 | 0 | 4 | 0 | 0 | 9 | 29 | 4433 | 0 | 1 | 99 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 301 | 11 | 95.9 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 3851 | 100 |
| PA | 99.2 | 100 | 66.7 | 89.2 | 100 | 100 | 83.7 | 99.7 | 86.3 | 100 | 99.6 | 92.4 |

### Table A4. Confusion matrix for 2016 when classifying multi-temporal Sentinel-1A.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | UA |
|---|---|---|---|---|---|---|----|
| 29,711 | 965 | 8 | 1049 | 0 | 0 | 225 | 0 | 93 |
| 2 | 1479 | 3079 | 4 | 49 | 0 | 208 | 0 | 63.9 |
| 3 | 171 | 0 | 1875 | 1 | 0 | 0 | 0 | 91.6 |
| 4 | 94 | 0 | 11 | 60,229 | 0 | 0 | 0 | 99.7 |
| 5 | 28 | 0 | 45 | 1 | 6943 | 1 | 0 | 98.9 |
| 6 | 2485 | 3 | 3 | 851 | 10 | 1115 | 0 | 25 |
| 7 | 4 | 0 | 0 | 22 | 0 | 163 | 1159 | 86 |
| PA | 87.5 | 76.1 | 96.4 | 96.8 | 99.9 | 61.5 | 100 | 92.9 |
Table A5. Confusion matrix for 2016 when classifying multi-temporal Sentinel-2A.

|   | 1     | 2     | 3     | 4     | 5     | 6     | 7     | UA   |
|---|-------|-------|-------|-------|-------|-------|-------|------|
| 1 | 124,170 | 3218 | 482   | 5382  | 372   | 594   | 0     | 92.5 |
| 2 | 4776   | 7296  | 1     | 289   | 1     | 172   | 0     | 61.1 |
| 3 | 0      | 7999  | 0     | 2     | 166   | 0     | 0     | 59   |
| 4 | 2832   | 0     | 61    | 174,228 | 10   | 370   | 0     | 98.2 |
| 5 | 2763   | 3     | 4     | 334   | 24,204 | 60    | 0     | 88.4 |
| 6 | 4955   | 63    | 159   | 18,410 | 758   | 7287  | 0     | 23   |
| 7 | 0      | 0     | 0     | 0     | 0     | 0     | 3727  | 100  |
| PA| 86.4   | 69    | 90.9  | 87.7  | 95.5  | 84.3  | 100   | 87.3 |

Table A6. Confusion matrix for 2016 when classifying multi-temporal Sentinel-1A and Sentinel-2A.

|   | 1     | 2     | 3     | 4     | 5     | 6     | 7     | UA   |
|---|-------|-------|-------|-------|-------|-------|-------|------|
| 1 | 29,902 | 813   | 5     | 1054  | 0     | 112   | 0     | 93.8 |
| 2 | 1233   | 3234  | 2     | 62    | 0     | 221   | 0     | 68.1 |
| 3 | 151    | 0     | 1891  | 17    | 0     | 0     | 0     | 91.8 |
| 4 | 87     | 0     | 7     | 60,713 | 4    | 81    | 0     | 99.7 |
| 5 | 68     | 0     | 36    | 4     | 6937  | 0     | 0     | 98.5 |
| 6 | 2521   | 0     | 5     | 315   | 12    | 1211  | 0     | 29.8 |
| 7 | 10     | 0     | 0     | 37    | 0     | 187   | 1159  | 83.2 |
| PA| 88     | 79.9  | 97.2  | 97.6  | 99.8  | 66.8  | 100   | 93.7 |