Losses Assessment for Winter Crops Based on Satellite Data and Fuzzy Logic

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***Abstract*—This paper considers the method of the winter crop classification map producing in terms of climatic and weather abnormal conditions in 2020. Given that the traditional method of construction involves the use of a training sample, which is collected in ground surveys along the roads. This sample could not be collected under the strict quarantine regime, that is why the classification map was created based on the sample obtained as a result of the photointerpretation. Both, optical Sentinel-2 and SAR Sentinel-1 satellite data were used. This is due to the fact, that the period of the winter crop classification map producing fell exactly on the period of time (April and May 2020), when the area of study Odesa region (as well as the whole territory of Ukraine) had a high percentage of cloud cover. At the same time, radar imaging techniques allow us to bypass obstacles such as clouds, but also have lower sampling quality. Therefore, it was decided to combine the obtained classification maps based on radar and optical data by fuzzy logic, considering the degree of belonging of each pixel by the value of the normalized difference vegetation index (NDVI).**

As a result, the obtained classification maps based on photointerpretation sample have an accuracy close to 95%. The fuzzy logic method allows to increase this value by selecting only the best pixels from classification maps based on radar and optical satellite data.

***Keywords*—winter crops; winter crop state; satellite monitoring; classification maps; climate change; fuzzy logic**

I. Introduction

Available satellite data and significant changes in meteorological conditions in winter and spring of Ukraine (increase of droughts, floods, sandstorms) became an impetus for scientists to study a growth dynamic of an agricultural fields, to analyze a crop state due to weather conditions, as well as to analyze a volume of winter crop losses using train data based on photointerpretation and fuzzy logic methods to build winter crop classification maps.

Often satellite data are used to estimate the crop area [1-4]. This approach allows to get an objective information about the crop type area for major crops by different division (country level, oblasts or regions level, etc.) [5, 6]. Typically, these crop estimates made at the end of a growing season, but lately, there are "in-season" publications. For example, in publication [7] authors considered the method of crop yield estimation to improve prognosticating of agricultural yield. To ensuring national food security authors of publication [8] considered three spatial sampling methods as well as the Kriging method for improving the estimation accuracy of crop area. In order to increase growth of a digital agriculture, authors of [1] proposed to enhance the accuracy of crop identification by using convolutional long-short term memory networks. The yield forecasting was obtained including the regional territory of Ukraine as well described in publication [9, 10].

The works of other authors allow us to see that, on one hand, research is conducted on the topics of the crop yield forecasting, improving the estimation accuracy of crop identification or crop area. The predictors of crop yield variability for all growing season have one of the main directions of crop losses assessment [11-13]. Also, in publications [14-16] discussed the weather-related crop losses and offered the estimation methods based on operational satellite-based vegetation health (VH) indices [17]. Also, crop estimation provides after hailstorms, floods [18, 19], water-logging [20] or other weather disasters for statistics and decision-makers' authorities or to led small-holder and subsistence farmers to the design of mitigation strategies [21-23].

On another hand, the assessment of crop losses during the growing season is less common, although for 2020 this task is quite relevant for several time and location sets, as well as for the spring period in the territory of Ukraine.

A deterioration of weather and climatic conditions in Ukraine has begun in autumn 2019, when due to soil drought there were unfavorable conditions for sowing in necessary time to ensure optimal growth of winter crops. Also, the negative impact on winter crops of Odesa region was frosts from March 15 to April 16, which lasted for 22 days. All these factors affected the winter crop state and led to its losses.

As a result, the climatic condition change in the territory of Ukraine is an opportunity to estimate not only the cropland areas, but also to calculate agricultural losses area.

The idea of the study is to build classification maps for April and May 2020 and to compare the areas of winter crops. If some winter crops were lost then the area will be decreased.

As optical satellite images for April and May 2020 have a high cloud cover percentage, there is a need to use radar satellite data to refine the resulting classification maps. The combination of winter crop classification maps based on optical and radar satellite data is possible through the use of fuzzy logic based on the normalized difference vegetation index (NDVI) [24].

II. DATA

A. Area of Interest (AOI)

To monitor the winter crops condition and losses, a study area is chosen Odesa region (Fig. 1), which has suffered the most from climate change. The region area is 33,314 km^2, it is located in the steppe climate zone of Ukraine. According to statistical data of 2019 the winter crop area in this region is around 11.6 % of the total area of the country (rapeseed, barley, rye, wheat). Odesa region ranks first in Ukraine in the winter crop area.

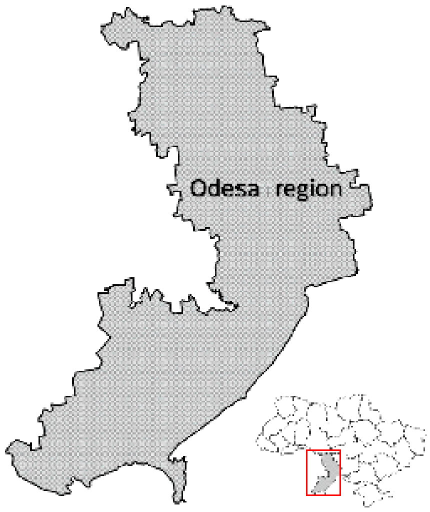

Figure 1. Area of interest – Odesa region, Ukraine.

According to meteorologists, the moisture lacks in Odesa region lasted during the entire vegetation period of winter crops, from crops to the maturation state (Table I).

TRAIN AND VALIDATION DATA

Month	Precipitation (mm)	% of precipitation norm
September 2019	10	23
October 2019 – November 2019	6-10	unsatisfactory
December 2019 – February 2020	66	63
March 2020	4	15
April 2020	5	16

B. Satellite Data

The optical Sentinel-2 and radar SAR Sentinel-1 satellite data for two time periods starting from April 1, 2020 to May 14, 2020 with a spatial resolution of 10 meters are used in this work (Table II).

TABLE I. SATELLITE DATA

	Sentinel-1	Sentinel-2
Dates	01.04.2020 – 10.04.2020 01.05.2020 – 14.05.2020	

This choice of satellites is due to the fact of high number of clouds in spring 2020. In this case, the data from the Sentinel-2 satellite are insufficient, as there were few unclouded images to build a classification map. That is why it is necessary to use the radar data of the Sentinel-1 satellite, for which clouds are not an obstacle.

C. Train and Validation Data

For high-quality producing of the classification map, it is required to have in-situ data [25], which are used as training and validation data. To build the winter crop classification map of Ukraine, such data are usually collected from mid-April to mid-May. Given the extraordinary conditions in 2020, due to the quarantine measures, it was not possible to collect data properly. Therefore, various experiments on the construction of winter crop map, as algorithms that do not use train data, as well as using a sample based on photointerpretation.

This is another scientific challenge that will show whether it is possible to construct relevant classification maps using photointerpretation.

After the end of the strict quarantine, in-situ data were collected along the roads of Odesa region (Fig. 2), and used to validate all obtained classification maps.

The total route length for in-situ data collection is 1650 km. The number of summer fields is 490, and of winter – 1176. A quantitative characteristic of the collected data on the AOI territory are presented in the Table III.

TABLE II. VALIDATION DATA FROM GROUND SURVEY

	Number of fields
Winter crops	1176
Summer crops	490
Total	1666

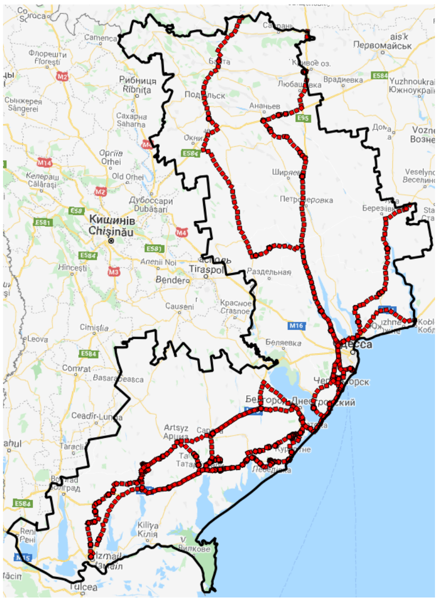

Figure 2. The route of in-situ data collection, 2020.

III. METHODOLOGY

A. Research Method

Traditionally, Random Forest method [26-28], as well as Random forest transfer [29], implemented on Google Earth Engine cloud platform, is used to build classification maps. One way to get yield forecasting assessment is to use biophysical model [30] and complementing operational flood mapping [31, 32].

In this case, the novelty of the study is obtained two different winter crop classification maps based on optical and radar satellite data using the training set of photointerpretation. It is necessary to combine and validate obtained results using vegetation index NDVI.

To solve this problem, the authors propose to combine different data sources: remote sensing data for processing classification maps; fuzzy logic model data for improving maps; in-situ data for validation. Thereby, the research approach is as follows.

Firstly, to build the winter crop classification map in the period for April 2020, because during this period it is possible to analyze all crops during their highest vegetation.

Secondly, to make an assumption that as a result of worsening climatic conditions, the area under crops will decrease next month. Therefore, the next step will be to build the winter crop classification map for May 2020.

To build winter crop classification maps, it is more appropriate to use optical satellite data [33], which for the studied period of time were clouded. That is why it is necessary to use an additional source of radar data [34-37], which is less relevant for such task, but allows to obtain a complete sample of data [38, 39]. Thus, it is necessary to combine the classification maps based on optical and radar satellite data, using a fuzzy logic scenario. Classification maps are refined using the values of NDVI, which, in turn, is selected using fuzzy logic based on the obtained optical and radar data.

Therefore, the aim of this study is as follows: 1. determining the degree of belonging of each pixel to winter crops with the help of expert knowledge; 2. producing a membership measure map for optical and radar satellite data; 3. obtaining a general membership measure map based on fuzzy inference method.

Consider more detailed algorithm for classification map creation based on fuzzy logic.

To perform geospatial analysis of the obtained classification maps based on radar and optical satellite data, it is necessary to form expert estimates of each pixel membership.

Form semantic values of expert assessments based on the values of NDVI of winter crops (Table IV).

TABLE III. SEMANTIC VALUES OF EXPERT ASSESSMENTS

Semantic value	Expert assessment
Low vegetation level	1
Middle vegetation level	2
High vegetation level	3

As a result of the expert assessment formalization, each pixel of the winter crop classification map acquires a certain value. In this case, it is necessary to ensure the implementation of fuzzy membership function:

$$A_i = \{C(A),\ \mu(C_A)\}, \quad (1)$$

where A_i – a pixel of the corresponding class of the classification map $C(A)$, $\mu(C_A)$ – a reliability measure of the expert assessment.

A priori, the reliability measure is taken equal 1/N, where N – a number of experts. Then:

$$A_i = \{C(A),\ 1/N\}. \quad (2)$$

If the pixel is on the border of several classes, then its reliability measure is equal to 1/kN, where k is a number of neighboring classes.

The next step is to form fuzzy rule base. In this case, use the maximum function. Given that the main selection criterion is the value of the vegetation index of winter crops, the function that determines a probability of including pixel in the resulting classification map is:

$$A_i = \{\arg\max NDVI(C),\ 1/kN\}. \quad (3)$$

The main concept of fuzzy logic is the development of a clear unambiguous control action for any type of control object [40]. Using the rule base, fuzzification and de-fuzzification stages, get winter crop classification map with higher accuracy. Also, this achievement can improve the process of combining statistical and satellite data for Ukraine [41].

B. Experiments and Validation

The experiments have shown the following. The overall accuracy of winter crop classification maps based on sample by photointerpretation and fuzzy logic for April and May 2020 is around 95 %.

Winter crop maps have been produced for two dates: 10 of April and 14 of May. The crop losses (red color) in Odesa region are shown in the Fig. 3 in higher zoom.

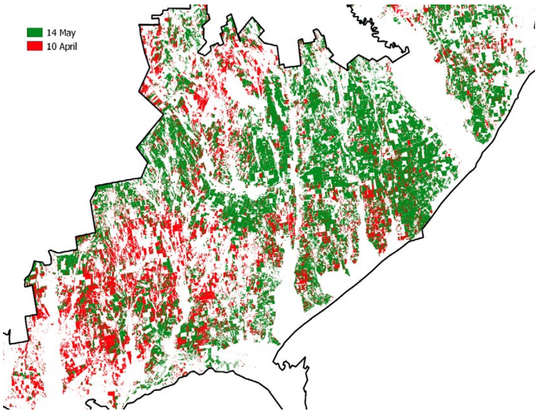

Figure 3. Crop losses (red color) in Odesa region from April to May 2020.

TABLE IV. AREAS OF WINTER CROPS IN ODESA REGION

Area, thousand hectares		
10th of April	***14th of May***	***Winter crop losses***
901.15	538.58	337.94

IV. DISCUSSIONS AND CONCLUSIONS

In this work, the scientific research of the winter crop classification map producing in the period of the adverse climatic and epidemiological conditions is carried out. The state-of-the-art method of classification is Random Forest implemented on the Google Earth Engine cloud platform. However, due to deteriorating climatic and weather conditions, the classification method based on the sample by photointerpretation was considered, using training set taken with satellite images of the required time period (April and May 2020). Two types of satellite data were used for this - the optical Sentinel-2 data and the radar Sentinel-1 data. This choice is due to the fact that the quality of optical data depends on weather conditions, namely the percentage of cloudiness of satellite images. Spring 2020 has high percent of clouds that were present in the satellite images, and for the radar clouds it is not the obstacle.

The resulting maps based on optical and radar satellite data and fuzzy logic have an accuracy of 95 %.

Another method that will increase the accuracy of winter crop classification map was chosen the fuzzy logic: formed the expert assessment table of the membership measure of each pixel to a certain class based on NDVI; the classification map was obtained by combining radar and optical satellite data.

Due to adverse climate change in winter and spring 2020 (dry winter and spring with frosts), the task possible winter crop losses assessment for Odesa region as the most affected was also set. Comparing the classification maps obtained with the fuzzy set knowledge base, the winter crop losses are calculated, which are equal 337.94 thousand hectares.

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