Geospatial intelligence and data fusion techniques for sustainable development problems

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Abstract. Knowledge on spatial distribution of land cover and land use is extremely important for solving applied problems in many domains such as agriculture/food security, environmental monitoring, and climate change. Geospatial data including satellite imagery play an important role since it can provide regular, consistent and objective information. Identifying geospatial patterns and quantifying changes that occur in space and time require special techniques to be exploited. These techniques are associated with the area of geospatial intelligence and deal with multi-source data fusion and exploitation of advance intelligent methods. This paper presents the use of these techniques for processing archived and up-to-date satellite imagery for large-scale land cover and crop classification in Ukraine. The main purpose of this paper is to not only show potential of geospatial intelligence, but to pay attention of educators to this extremely important area.

Keywords. Geospatial intelligence, land cover, crop mapping, image processing, satellite imagery, big data.

Key Terms. HighPerformanceComputing, MachineIntelligence, InformationTechnology, Intelligence, Data.

1 Introduction

Geospatial information is a very important source of data for distributed systems development, education, decision making and competitive business. Due to regular acquisition of satellite data all over the world for the last couple of decades as well as new communication, navigation and crowdsourcing techniques, it has become possible to monitor the current state of the large territories development, estimate trends, analyze available scenarios for future development and manage things to provide sustainability. The approach is based on modern IT, namely geospatial intelligence [1] and data fusion [2] techniques. By geospatial intelligence we consider all aspects of geospatial data processing including intelligent methods and technologies to fuse/integrate data and products acquired by multiple heterogeneous sources using machine learning techniques and emerging big data and geo-information technologies. In this paper we exploit geospatial technique to address two important applications for Ukraine, in particular land cover/land use mapping and crop mapping. The purpose is to not only show the potential of geospatial intelligence, but to pay attention of the educators to this powerful IT and bridge the gap between market needs for such specialists and professionals.

Ukraine is one of the main crop producers in the world [3], so agricultural monitoring is a very important challenge for Ukraine. One of the most promising data sources to solve the underlined tasks at large scale is remote sensing data, namely the satellite imagery [4-12]. This is mainly due capabilities to timely acquire images and provide repeatable, continuous measurements for large territories. At present, there are only coarse-resolution satellite imagery (500 m spatial resolution), that has been utilized to derive global cropland extend, e.g. GlobCover, MODIS [13]. But, low-resolution maps always underestimate or overestimate certain land cover or crop type areas. Also several global land cover maps have been made using higher resolution data such as from Landsat-series satellites [14-15], but they are not accurate enough at regional level for Ukraine. Therefore, creation of global products, such as land cover maps and crop maps, based on high resolution satellite images (at 30 m) is very important task for sustainable economic development of Ukraine. This paper presents the results of regional retrospective high resolution land cover mapping and large scale crop mapping for Ukrainian territory using multi-temporal Landsat-4/5/7/8 images and also some supporting data and knowledge obtained during our own investigations [7-8]. The main results of the work were obtained within EC-FP7 project “Stimulating Innovation for Global Monitoring of Agriculture and its Impact on the Environment in support of GEOGLAM” (SIGMA).

2 Objective of the study and data description

The paper covers two different studies: retrospective land cover mapping and crop mapping. These two problems are solved using the same geospatial intelligence approach that encompasses the use of advanced machine learning techniques. In particular, we use a combination of unsupervised and supervised neural networks to first restore missing values in multi-temporal images, and then to provide a supervised classification with an ensemble of multilayer perceptrons (MLPs). One of the advantages of this approach is possibility for automatic processing taking into account of large amount of satellite imagery that need to be processed.

At the first study, we used atmospherically corrected Landsat-4/5/7 products to produce land cover maps for land cover change detection. This was performed for all territory of Ukraine and required processing of about 500 Landsat scenes to cover it completely for three decades: 1990s, 2000s and 2010s. Also, we manually formed training and test sets for supervised classification using the photo interpretation method. Train and test sets were created with uniform spatial distribution over the territory of interest and proportional representation of all land cover classes, namely artificial surface, cropland, grassland, forest, bare land and water.

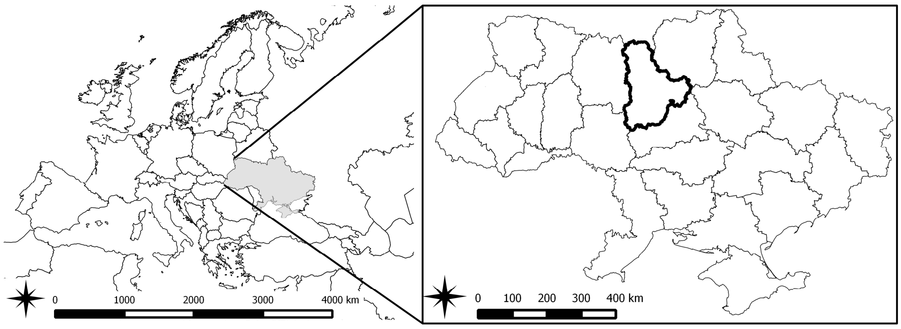

Fig. 1. Location of Ukraine and JECAM test site in Ukraine (Kyiv oblast, marked with bold boundaries.

The second study is the pilot project on large scale crop mapping for JECAM test site [16] in Ukraine for 2013 (Fig. 1). The Joint Experiment for Crop Assessment and Monitoring (JECAM) is an initiative of GEO Agriculture Monitoring Community of Practice with the intent to enhance international collaboration around agricultural monitoring towards the development of a "system of systems" to address issues associated with food security and a sustainable and profitable agricultural sector worldwide (http://www.jecam.org). The JECAM test site in Ukraine was established in 2011 and covers administrative region of Kyiv oblast with the geographic area of 28,100 km2 with almost 1.0 M ha of cropland. For large scale crop mapping over the study region we used two data sources – remote sensing images acquired by Operational Land Imager (OLI) sensor aboard Landsat-8 satellite and data acquired at ground surveys. We used Fmask algorithm for clouds detection and masking [17]. Ground surveys were conducted in June 2013 to collect the knowledge about crop types and land cover types (Fig. 2) over the interested area. In this study we used European LUCAS nomenclature as a basis for land cover / land use types.

3 Method and results

The main scientific challenges for geospatial intelligence problem solving are geospatial data fusion and correct interpretation of geospatial information. To address them for big data satellite monitoring problems we propose the novel approach, based on combination of three machine learning paradigms for geospatial information analysis: big data segmentation, neural network classification and data fusion. Data fusion is performed at the pixel and at the decision making levels. During preprocessing stage, Landsat-4/5/7 and Landsat 8 scenes were merged to multi-channel format for each path, row and date. First, we restore cloudy pixels from time-series of images using self-organizing Kohonen maps [18] and after provide classification based on the time-series of restored images available for the certain year and required area. Classification was done by using an ensemble of neural networks (MLPs). The method of pixel and decision making level data fusion is proposed in [16].

Table 1. Accuracy comparison of Land Cover30-2010 and GlobeLand30-2010

Product	Land Cover30-2010		GlobeLand30-2010	
Class	UA, %	PA, %	UA, %	PA, %
Artificial	100	87.8	79.5	3.4
Cropland	93.5	96.2	99.4	85.3
Forest	95.4	96.2	89.9	95.9
Grassland	81.4	71.2	34.4	60.5
Bare Land	91.7	96.4	0.4	57.1
Water	99.5	99.6	96.6	99.9
Overall accuracy, %	94.7		89.7	

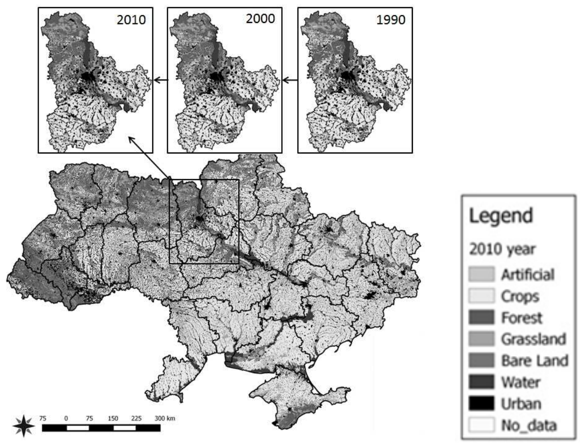

Fig. 2. The land cover map of Ukraine for 2010 year (and also land cover maps of Kyiv oblast for 2010, 2000 and 1990 years).

To estimate the accuracy of land cover classification for Ukrainian territory, we used two approaches: accuracy assessment on independent test (testing) set and comparison of the class areas in land cover with official statistics. The overall classification accuracy achieved in this study was approximately 95%. Accuracies for each individual class were more than 70%. The lowest classification accuracy was for grassland, because it is difficult to separate grassland from some of spring crops. We also compared (Table 1) our result, taken for Ukraine with global land cover map GlobeLand30-2010 at 30 m resolution. The overall classification accuracy of our land cover map was 5% higher than GlobeLand30-2010. Also accuracy of grassland from our maps was +10% (producer accuracy, PA) and +45% (user accuracy, UA) [19] better than GlobeLand30-2010. Our final land cover map is shown at Fig. 2.

Table 2. Classification results

No	Class	PA, %	UA, %
1	Artificial	100.0	97.9
2	Winter wheat	95.7	91.8
3	Winter rapeseed	93.5	99.4
4	Spring crops	40.6	34.6
5	Maize	90.5	86.8
6	Sugar beet	94.9	89.6
7	Sunflower	84.1	85.4
8	Soybeans	69.7	77.1
9	Other cereals	70.9	78.0
10	Forest	96.9	92.9
11	Grassland	91.0	89.0
12	Bare land	86.7	99.0
13	Water	100.0	98.1

3.1 Large scale crop mapping

The use of multi-temporal Landsat-8 imagery and an ensemble of MLP classifiers allowed us to achieve overall accuracy of slightly over 85% (Table 2) which is considered as target accuracy for agriculture applications.

Target accuracy of 85% was also achieved for winter wheat, winter rapeseed, maize and sugar beet. For the spring crops, sunflower and soybeans the accuracy is less, than 85%. Soybeans is the least discriminated summer crop with main confusion with maize. In particular, almost 61% of commission error and 71% of omission error was due to confusion with maize. All non-agriculture classes including forest and grassland yielded PA and UA of more than 85%. The final classification map is shown in Fig. 3.

Comparison of official statistics and crop area estimates derived from Landsat-8 imagery for Kyiv region described at the Table 3.

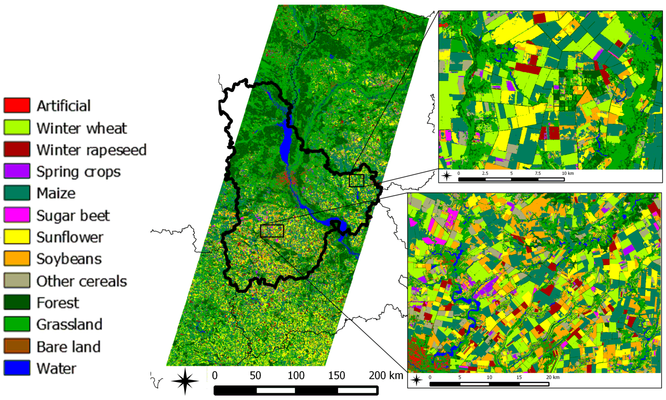

Fig. 3. Final crop map obtained by classifying multi-temporal Landsat-8 imagery.

Table 3. Comparison of official statistics and crop areas derived from Landsat-8 imagery

Class no.	Class	Crop area: official statistics, x 1000, ha	Crop area: Landsat-8 derived, x 1000, ha	Relative error, %
2	Winter wheat	187.3	184.5	-1.5
3	Winter rapeseed	46.7	59.9	28.3
5	Maize	291.7	342.4	17.4
6	Sugar beet	15.5	11.2	-27.9
7	Sunflower	108.2	117.6	8.7
8	Soybeans	145.9	168.5	15.5

4 Application in education process

As well as geospatial intelligence is one of the emerging areas of data science, we actively use it in education process. Developed approach to land cover and crop mapping is actively used for education purposes. We incorporate these topics (geospatial intelligence methods and developed software) into a master and PhD program of “Ecological and economic monitoring” specialization at the National University of Life and Environmental Sciences of Ukraine with the main focus on big geospatial data processing and satellite data analysis.

Also we are actively trying to implement project based education, involving students into scientific projects . Some methods of data fusion are included into laboratory works on intelligent computations. Master and PhD student fulfill their qualification diplomas within international projects. According to our experience more attention should be paid on geospatial data processing and intelligent computations within Bachelor programs on Computer Science in Life Science universities.

5 Conclusions

This paper presents a novel approach for satellite monitoring based on big geospatial data analysis. The main idea of the proposed geospatial intelligence approach is the use of supervised neural networks in order to classify multi-temporal optical satellite images with the presence of missing data. A supervised classification was performed with the use of ensemble of MLP classifiers to create such global products as retrospective land cover and crop maps for the whole territory of Ukraine. Proposed approach allowed us to achieve the overall classification accuracy of 95% for three different time periods (1990, 2000 and 2010) and improve quality of maps comparing to other land cover maps available for Ukraine at 30 m spatial resolution, namely GlobeLand30-2010. The same approach was successfully applied for the JECAM test site in Ukraine for large area crop mapping.

Now geospatial intelligence is a hot topic in big data analysis, but we observe the lack of experts in the area. Therefore, we would like to pay attention of the IT educators to the gap and build a roadmap to fill it.

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