Assessment of Sustainable Development Goals Achieving with Use of NEXUS Approach in the Framework of GEOEssential ERA-PLANET Project

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Abstract. In this paper, we propose methodology for calculating indicators of sustainable development goals within the GEOEssential project, that is a part of ERA-PLANET Horizon 2020 project. We consider indicators 15.1.1 Forest area as proportion of total land area, 15.3.1 Proportion of land that is degraded over total land area, and 2.4.1. Proportion of agricultural area under productive and sustainable agriculture. For this, we used remote sensing data, weather and climatic models' data and in-situ data. Accurate land cover maps are important for precisely land cover changes assessment. To improve the resolution and quality of existing global land cover maps, we proposed our own deep learning methodology for country level land cover providing. For calculating essential variables, that are vital for achieving indicators, NEXUS approach based on idea of fusion food, energy, and water was applied. Long-term land cover change maps connected with land productivity maps are essential for determining environment changes and estimation of consequences of anthropogenic activity.

Keywords: ERA-PLANET · Classification maps · Essential variables GEOEssential

1 Introduction

Aimed at reaching Sustainable Development Goals (SDGs) accepted in Sendai Framework for 2015–2030, ERA-PLANET project implements use of earth observation data in tasks of Environmental Management[1,2]. In this paper, we present a methodology for calculating indicators of reaching the following goals: end hunger, achieve food security and improved nutrition, promote sustainable agriculture aimed on

[1] Group on Earth Observation, https://www.earthobservations.org/.
[2] The European Network of observing our Changing Planet, http://www.era-planet.eu.

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ensuring sustainable food production systems and implementing resilient agricultural practices [1–5].

Our main targets are ensuring the conservation, restoration and sustainable use of inland freshwater ecosystems and their services; combating desertification by 2020; restoration of degraded lands by 2030. These goals can be indicated by proportion of agricultural area under productive and sustainable agriculture, the forest area as a proportion of total land area, and the proportion of land that is degraded over total land area.

For calculating indicators for these goals, we use land cover maps [6–9], NDVI trend productivity change map, essential variables by output of our NEXUS approach model, which include stochastic climate simulation model, and biophysical model for crop simulation WOFOST[3].

There are many global and open sources for land cover data, that require a time series of satellite and ground measurements that can be used in research purpose. But in this study, we used land cover maps, achieved by our machine learning methodology for Ukraine territory due to higher accuracy on a country scale and better spatial resolution in 10 m.

2 Data

In study of land cover change, we use classification maps built for territory of Ukraine, using methods of machine learning developed by us for classification of time series of Sentine-1 and Sentinel-2 images with 10 m spatial resolution. For the territory of Ukraine, 9 paths of Sentinel-1 were used. Each of these paths consist of several images and is constructed by merging for one date (Fig. 1). For learning and validation of model, we used in-situ data collected by us. More than 800 images were used for covering the territory of Ukraine with Sentinel-1A data during the vegetation season. The data amount used for land cover classification for 2016 and 2017 is over 29 Tb in total.

Fig. 1. Coverage of the territory of Ukraine by Sentinel-1A data with relative orbit number

3 BioMA (Biophysical Models Applications) framework, http://bioma.jrc.ec.europa.eu/.

In case of use biophysical models and climatic models in NEXUS approach, we used time series of weather data provided by Copernicus and NASA-POWER that begin from year 1997, and that include daily minimal and maximal temperature, daily wind speed, daily precipitation, daily incoming global shortwave radiation, daily mean vapor pressure, and daily mean wind speed. All the data were collected from open data providers such as NASA Prediction of Worldwide Energy Resource and Copernicus for 100 km grid for Ukraine.

3 Methodology

3.1 Deep Learning Approach for Land Cover Classification

For providing more accurate land cover maps on the country level, we proposed methodology based on deep learning idea that is very popular nowadays in other tasks like voice recognition, face detection, buildings detection, and so on. The most popular deep learning approaches are convolutional neural networks (CNN), deep auto-encoders (DAE), recurrent neural network with Long Short-Term Memory (LSTM) model and deep belief networks (DBN). They outperform traditional classification approaches such as random forest (RF), support vector machines (SVM), and multi-layer perceptrons (MLP) [10–13].

Taking into account that land cover proving task is similar to visual pattern recognition tasks, in this paper, we propose a deep learning architecture in the form of ensembles of CNNs (4 neural networks) for optical and SAR time-series classification (Fig. 2) [14]. Each CNN from the committee is a 2-d CNN with 7 layers implemented within the Google's library TensorFlow. Different CNN has been trained on different subset of training data. In this experiment, two convolutional layers were used with kernel size 5×5 and 3×3, respectively. After each convolutional layer, a max-polling layer follows with kernel size 2×2. Finally, CNN ends with two fully connected layers and softmax function, which produces a distribution over the output class labels. The rectified linear unit (ReLU) function has been used in CNN architecture.

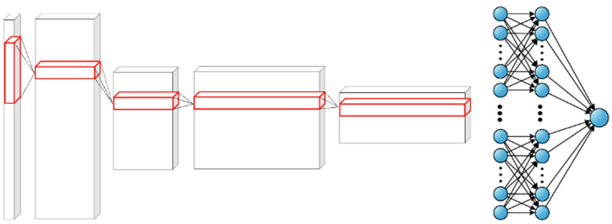

Fig. 2. Deep convolutional neural network architecture

All the images were preprocessed using standard technology. For optical images, we provided atmospheric correction and cloud masking using sen2cor tool, for SAR data we utilized radiometric correction, filtration, terrain correction, converting to backscatter coefficients with ESA SNAP toolbox. After preprocessing step, time series of optical and SAR data were formed based on in-situ data. Further, these data were divided into sets for training phase as inputs into classifier, for validation, and independent set for final test. During training phase, validation set was used for best hyper-parameters selection.

Taking into account large volume of satellite data that are necessary for land cover classification and in order to decrease the time of satellite imagery downloading, it makes sense to deploy a classification system in the cloud environment, for example, Amazon, where Sentinel-1 and Sentinel-2 data are already available for free. An architecture component diagram of the proposed classification system is shown in Fig. 3. With such cloud-based approach, geospatial research can be moved from data to analysis with way smaller delay from the beginning of the study.

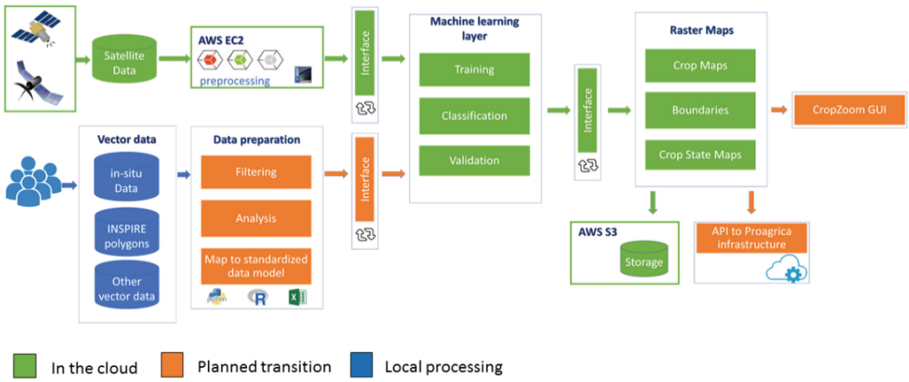

Fig. 3. Typical architecture component diagram for crop classification system

3.2 NEXUS Approach for Calculating Essential Variables

The core part of our NEXUS approach model that provides essential variables for food, water, and energy, is a WOFOST biophysical model, which is supplemented by stochastic climate simulation model and weather data from global models' products of Copernicus and NASA-POWER. We combine these results with models, NDVI productivities maps, and land cover maps in one data processing chain for essential variables calculating like in Fig. 4.

WOFOST Model with data used on a regular grid covering the territory of Ukraine is also named Crop Growth Modeling System (CGMS). During WOFOST model simulation of crop growth, we accept values of total biomass and leaf area index for every day, on levels of sub models like soil water content model, soil temperature model, etc. In this simulation, we also get values for water and energy essential variables like soil moisture, soil temperature evaporation and evapotranspiration [15, 16].

Stochastic climate simulation model is a statistical model based on Markov chains constructed using time series of weather data. In realization of this part, we face the problem of the lack of complete global data that cover the territory of Ukraine and contains all the necessary components such as daily minimal and maximal temperature, daily wind speed, daily precipitation, daily incoming global shortwave radiation, daily mean vapor pressure, and daily mean wind speed. Our weather data cover for Ukraine contain time series built from Copernicus and NASA-POWER data, starting from year 1997, and this is enough for use in stochastic climate model for long range statistical forecast of these weather parameters. These weather parameters not only are needed for WOFOST model simulation, they are separate essential variables for water and energy [17–23].

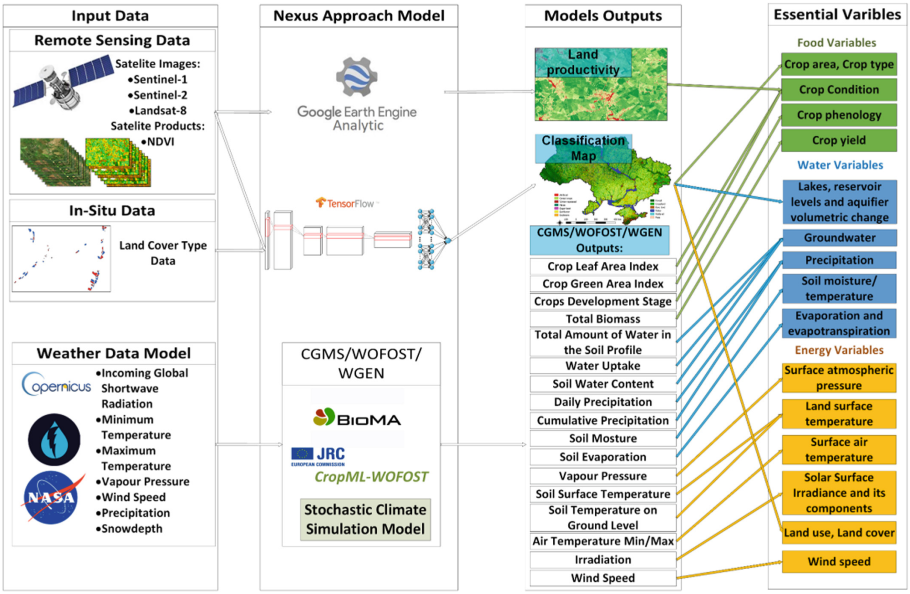

Fig. 4. Data processing chain for essential variables calculating

4 Results

In Table 1, results of cross-comparison of global land covers maps (ESA CCI-LC) and national land cover (SRI LC) maps is presented. In terms of User Accuracy (UA), Producers Accuracy (PA), and Overall Accuracy (OA), national datasets are more accurate than global products and possess higher correlation with national statistics data. In particular, difference between maps is obvious for grassland (Fig. 5). Also, our national land cover map has higher resolution compared to Global land cover map. Using our land cover classification maps for years 2000 and 2016, we detected all problematic areas for Ukrainian territory with deforestation. An example of deforestation for Kherson region is shown in Fig. 6.

Using total area of Ukraine, excluding inland water, we calculated indicator 15.1.1 Forest area as proportion of total land area by forest area calculated with our land cover maps and government statistics. We can see positive trend of forest area as a proportion of total land area indicator change by our classification maps and government statistics, and although the data for the 2000 s and 2010 s are very close to the statistics, our results differ for 2016.

Table 1. Comparison of user accuracy (UA), producer accuracy (PA) and overall accuracy for National land cover and Global land cover maps (ESA CCI) for 2000 and 2010 years

Year	Land cover national 2010		Land cover national 2000		Land cover dataset ESA CCI-LC-2010		Land cover dataset ESA CCI-LC-2000	
Class	PA, %	UA, %	PA, %	UA, %	PA, %	UA, %	PA, %	UA, %
Cropland	97.5	98.5	97.1	98.6	98.9	76.7	98.9	79
Tree-covered	97.2	97.4	98.8	98.4	84.9	95.6	86	97.1
Grassland	90.7	85.4	90.5	84.6	4.9	40.7	7.6	43.5
Other land	93.6	96.9	96.2	89.7	21.5	87.2	20.1	76.2
Water	99.5	99.8	99.5	99.9	96	99.6	96.4	99.8
Overall accuracy, %	97.5		97.7		85		87.3	

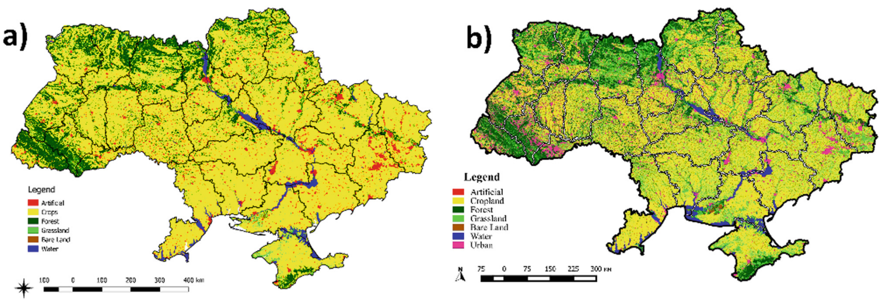

Fig. 5. Example of Global land cover maps (ESA CCI) with 300 m resolution for 2010 (a) and National land cover map for 2010 (b)

The JRC developed methodology for Land Productivity Dynamics (LPD) estimation based on NDVI profile derived from SPOT-VGT time series with course spatial resolution[4]. Taking into account that our national land cover maps have much higher spatial resolution, it is necessary to provide land productivity maps with the same resolution. Thus, we estimate productivity map for Ukraine territory for years

[4] JRC Science for Policy Report, http://publications.jrc.ec.europa.eu/repository/bitstream/JRC80540/lb-na-26500-en-n%20.pdf.

2010–2014 based on NDVI profile derived from Landsat images with simplified methodology. Further, we are going to extend of the JRC approach to Landsat and Sentinel-2 data.

Also, we get 15 essential variables for food, water, and energy that can be used for monitoring state of Ukrainian resources and indicators calculation. Food essential variables will be used for building new productivity map with help of classification map, replacing productivity map based on NDVI trend (Fig. 7). It will be used for calculating indicator 15.3.1 Proportion of land that is degraded over total land area and indicator 2.4.1. Proportion of agricultural area under productive and sustainable agriculture. At the same time, productivity map is sub indicator of achieving a zero level of land degradation.

Crop classification map were obtained on c4.4xlarge Amazon instance (500 Gb SSD drive, 16 threads CPU Intel(R) Xeon(R) CPU E5-2666 v3 @ 2.90 GHz and 30 GB RAM). This task takes approximately two weeks.

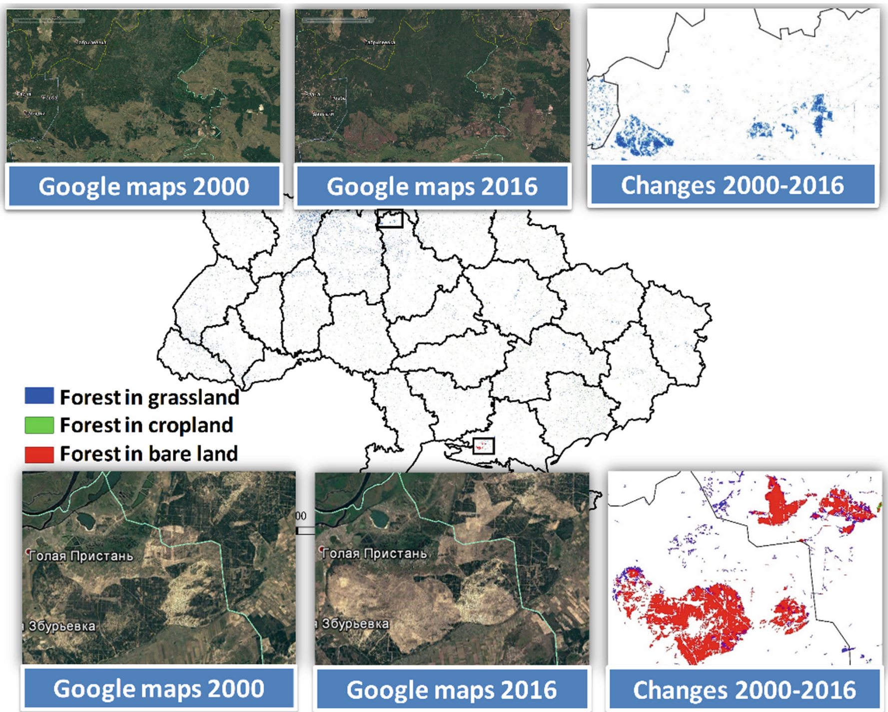

Fig. 6. Example of forest area changes from 2000 to 2016

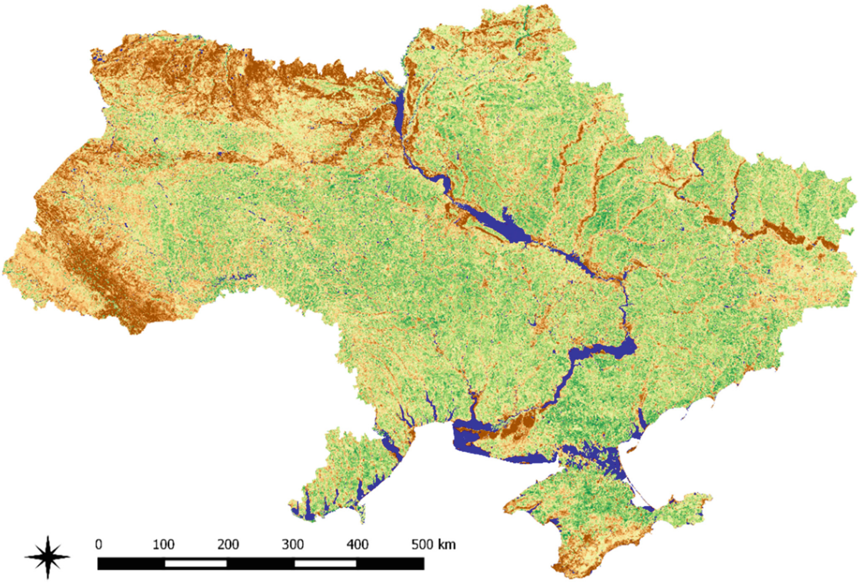

Fig. 7. Productivity map for Ukraine territory for 2010–2014 years

5 Conclusions and Discussion

Accurate and precise land cover and land use maps with high resolution, built with use of remote sensing and in-situ data and deep learning approach, are essential for assessment sustainable development goals. Thus, to improve the resolution and quality of existing global land cover maps, we proposed our own deep learning methodology for country level land cover providing. NEXUS approach that combines three different spheres (food, water, and energy) was used for achieving workflow for fusion of different essential variables and obtaining indicators of approaching to selected goals. For this, we utilized WOFOST crop state model and different weather and climatic models' data, and as a result we obtained a possibility to calculate three indicators 15.1.1 Forest area as proportion of total land area, 15.3.1 Proportion of land that is degraded over total land area and indicator, and 2.4.1. Proportion of agricultural area under productive and sustainable agriculture. Based on this methodology, we could see the positive trend of indicator 15.1.1 for the Ukraine territory from 2000 to 2016.

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