GEOSPATIAL MONITORING OF SUSTAINABLE AND DEGRADED AGRICULTURAL LAND

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ABSTRACT

In this study, the assessment of sustainable development goal (SDG) indicator 2.4.1 for Ukraine and Germany is conducted using geospatial and satellite data. The traditional methodology for the SDG indicator 2.4.1 calculation cannot be directly applied to the Ukrainian territory due to the lack of systematic data collection of the essential indicators. Therefore, the authors have developed an integrated approach to estimate land degradation, that uses different schemes for various land cover and crop types at the national scale, utilizing satellite data and employing the WOFOST model for crop growing simulation. The research describes the information sources used for creation crop type classification maps and the necessary data for modeling leaf area index (LAI) based on the WOFOST model. The calculated indicators are determined for each Ukrainian region from 2018 to 2022. Observations in 2022 show a decline in the indicator 2.4.1 across nearly all regions of Ukraine, directly attributed to the military conflicts within the Ukraine. To assess the possibility of applying the developed technology to a large area, the indicator was calculated for a European country (Germany).

***Index Terms*—** Geospatial Data Analysis, Machine Learning, Land Degradation, Remote Sensing, Land Cover, SDG 2.4.1.

1. INTRODUCTION

The issue of food security is one of the most important problems of humanity as a whole and many countries, including developing countries. To monitor the sustainable development of the environment in the world the global indicator framework for Sustainable Development Goals was developed by the Inter-Agency and Expert Group on SDG Indicators (IAEG-SDGs) and agreed upon at the 48th session of the United Nations Statistical Commission held in March 2017 [1]. According to the proposed methodology, each country evaluates the indicators for its country, thereby receiving an assessment of the improvement or deterioration of the corresponding indicator for its country.

In the study [2], it is indicated that geospatial data and data from citizens hold significant potential as major sources of big data for the assessment of SDG indicators. The limited number of SDG indicators can directly benefit from alternative data sources such as mobile phone data, web data (including information on prices or employment), postal data, and electricity data.

Regular assessment of agricultural land quality, its suitability for cultivation, and the evaluation of potential losses and yields [3] are crucial tasks, particularly for Ukraine, which stands as one of Europe's major grain product exporters. The outbreak of war has raised global concerns regarding the potential shortage of grain for importing nations, leading to the risk of famine [4] and other food security challenges. Goal 2 of the Sustainable Development Goals (SDGs), titled "End hunger, achieve food security and improved nutrition and promote sustainable agriculture" bears overarching responsibility for the agricultural sector. Specifically, Indicator 2.4.1, which examines the proportion of agricultural land under productive and sustainable agriculture, is the focus of this study conducted within the territory of Ukraine and Germany.

The established framework for calculating SDG indicators is outlined in reference [5], with specific guidelines for SDG 2.4.1 detailed in document [6], recommending data collection at least once every three years. Through a consultative process that has lasted over two years, 11 themes and sub-indicators have been identified, which make up SDG 2.4.1. But for Ukraine, there is no available data for calculating the indicator in a standard way, and the use of general global land use products is not accurate in terms of spatial resolution. Therefore, the authors of this study developed their own technology for land productivity assessment [7], which takes into account crops types information, soil parameters, and meteorological indicators during the growing season.

2. DATA

2.1. Land Cover / Crop Type Classification

The land cover and crop type classification maps based on own classification methodology [8] were used. For classification processing 2 bands (VV, VH) of SAR Sentinel-1 descending data was used with revisit time 12 days. Also, for classification processing 4 bands (Red B4, Green B3, Blue B2, InfraRed B8) of Sentinel-2 data with preprocessing Level-2A and 10-meters spatial resolution are used. The revisit time of Sentinel-2 is 5 days, but due to high cloud cover, monthly composites was used obtained as the median value of all possible values in the respective bands. The multilayer perceptron (MLP) is used for training neural network. Compared to deep neural network algorithms, in particular convolutional neural networks, the MLP algorithm loses in accuracy by 1%, but requires much more powerful computing resources and time to obtain the final product. That is why we use MLP neural network algorithm. We consider cereal (wheat and barley), maize, sunflower, rapeseed and soybeans to be the major crops for Ukraine.

For the territory of Germany, publicly available classification maps for 2016 [9], 2017-2019 [10], 2020 [11] were used, which were created by German specialists, also with a spatial resolution of 10 meters. The major crop classes for Germany are: cereal (wheat, barley), rapeseed, maize, beet, and potato.

2.2. Leaf Area Index Modelling

The WOFOST (WOrld FOod STudies) simulation model [12] was used for quantitative analysis of the growth and production of annual field crops, specifically to simulate Leaf Area Index (LAI) for agricultural crops. The model relies on several key input parameters, including soil profiles (various soil characteristics), crop profiles detailing sowing dates, flowering, maturity, and other significant attributes, as well as meteorological indicators. These inputs collectively facilitate the accurate simulation of LAI and enable comprehensive assessments of crop development and productivity within the WOFOST model framework.

2.2.1. Soil Profiles

Soil parameters are important input data for estimating the model value of LAI. For each type of soil parameters are recorded in profiles and used as input of the model. The soil parameters, in particular (soil moisture content at saturation, at wilting point, and at field capacity) are available according to European Soil Database [13].

2.2.2. Crop Profiles

The most important characteristic in crop profiles is the accumulated sum of temperature from emergence to anthesis (TSUM1), as well as temperature sum from anthesis to maturity (TSUM2). For winter crops, an important characteristic is the sum of temperatures that exceed 4 degrees Celsius for the continuation of vegetation after wintering.

2.2.3. Meteorological Data

The WOFOST system uses daily meteorological parameters from NASA Prediction of the Worldwide Energy Resources (POWER) Project [12], in particular temperature, precipitation, irradiation, wind power and direction. That resolution is 1.0° latitude by 1.0° longitude for the radiation data sets and 0.5° latitude by 0.625° longitude for the meteorological data sets (or approximately 55.5 km x 69 km).

3. METHODOLOGY

Within the framework of the Horizon 2020 ERA-Planet (GEO-Essential) project a methodology for land productivity assessment based on satellite observations and biophysical modeling has been developed [14]. In "EuroGEO Showcases: Applications Powered by Europe" (e-shape) project (Pilot 1.6 Service for SDG 2.4.1 and 15.3.1 indicators) it was implemented as a pilot service for SDGs indicators assessment. The proposed methodology is based on the use of crop type classification maps with high spatial resolution (10 meters), and the results of biophysical modeling of the Leaf area index (LAI) for the relevant major crops.

Based on the squares of meteorological data and soil vector data, a new grid was created, which is the intersection of the two previous ones (Fig. 1). For each element of the created grid, the centroid is calculated, and for each centroid, LAI values for all major crops will be simulated based on WOFOST model [15], [16]. Annual maximum LAI values based on MODIS data are considered as real LAI value. The difference between modelled and real LAI values will demonstrate the productivity of agricultural land. The sustainability criteria are the distance of the LAI difference from the 90th percentile [6]: desirable or productive land: difference value is ≥ 2/3 of the corresponding 90th percentile; acceptable or sustainable land: difference value is ≥ 1/3 and < 2/3 of the corresponding 90th percentile; unsustainable or degradation land: difference value is < 1/3 of the corresponding 90th percentile. The diagram of the developed technology is shown in the Fig. 1.

Thanks to the developed technology, it becomes possible to determine sustainable and degraded agricultural land at the country level, which makes it possible to evaluate the indicator of the sustainable development goal 2.4.1 "Proportion of agricultural area under productive and sustainable agriculture" at the country level. The indicator 2.4.1 is defined by the formula:

$$SDG_{2.4.1} = \frac{Area\ under\ productive\ and\ sustainable\ agriculture}{Agriculture\ land\ area},$$

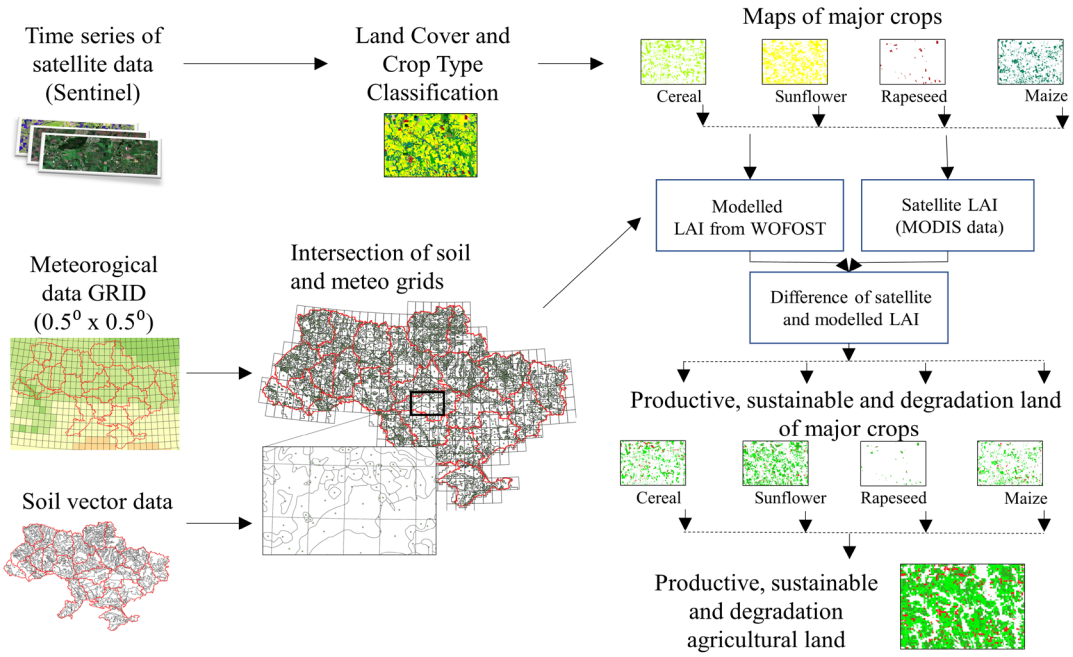

Fig. 1 General scheme of the method of agricultural land degradation estimation.

where area under productive and area under sustainable agriculture calculated based on land degradation map, and agriculture land area based on crop type classification map.

4. RESULTS

Indicators of sustainable development goals 2.4.1 have been calculated for Ukraine (Fig. 2) and Germany (Fig. 3). The most agricultural land degradation in 2022 in Ukraine is observed in the southeastern regions due to environmentally unfavorable methods of farming and military operations. Compared to 2018, indicator 2.4.1 decreased for most regions of Ukraine by more than 8-10%, and in militaries zones - by more than 25%. The greatest deterioration of the indicator in 2020 compared to 2016 in Germany is observed in the central regions (by more than 15%), and the improvement of the situation in the northern regions (by 7 - 24%).

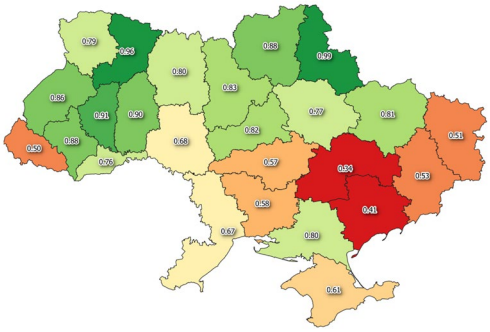

Fig. 2 SDG 2.4.1 indicator for Ukraine (2022) based on satellite data

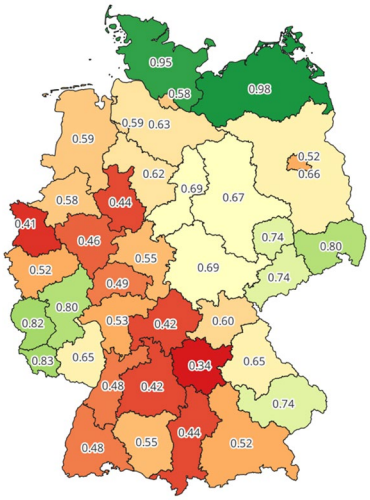

Fig. 3 SDG 2.4.1 indicator for Germany (2020) based on satellite data

CONCLUSIONS

In this study, we calculated indicator 2.4.1 for 2018-2022 for the territory of Ukraine using a previously developed geospatial method for assessing land degradation based on remote sensing data, neural networks, and biophysical modeling [7]. It takes into account different land cover/land use classes and provides land degradation assessment for each of them based on different input. Due to the high computational complexity of the method, it is implemented in the CREODIAS cloud environment, thanks to the

resources within the EO4UA initiative. The most land degradation is observed on arable lands in the southeastern regions due to environmentally unfavorable methods of farming and military operations.

The developed technology is flexible and applicable for different climatic zones, because during the biophysical simulation according to the WOFOST model, it takes into account precipitation, temperature, as well as the main stages of crop growth - seedlings, maturation, maturity. After receiving the annual maps of degradation according to the described methodology, the changes at the level of the regions of Ukraine were analyzed, and as a result it was concluded that in 2022 there was a significant deterioration compared to the previous 4 years. On the basis of the obtained result, it is possible to make appropriate management decisions regarding the prevention and regulation of land quality in Ukraine.

The proposed technology can be used for any country in the world. The only information required is a crop type classification map for the required area. In particular, the data technology is also applied to calculate the indicator of the sustainable development goal 2.4.1 for the territory of Germany within the framework of the Horizon 2020 e-shape project.

5. AKNOWLEDGEMENTS

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