Sustainable Development Goal 2.4.1 for Ukraine Based on Geospatial Data

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Abstract: In this work, the indicator of sustainable development goal (SDG) 2.4.1 for Ukraine is calculated based on geospatial and satellite data. The generally accepted technology for calculating the given indicator cannot be applied for the territory of Ukraine due to the lack of systematic collection of the necessary indicators. Therefore, the authors have developed the complex method for land degradation estimation that uses different schemes for separate land cover and crop types at the country level based on satellite and modeling data using WOFOST model. The paper describes the sources of information used to create crop type classification maps and the data required for leaf area index (LAI) modeling for the WOFOST model. Calculated indicators from 2018 to 2022 for each of the regions of Ukraine. In 2022, the decrease of the indicator is monitored in almost all regions of Ukraine, which is a direct result of military actions on the territory of Ukraine.

1 INTRODUCTION

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.

According to the study [2] geospatial data and data supplied by citizens are the most potential big data sources for SDG indicators assessment. Only a few SDG indicators may benefit directly from other large data sources such mobile phone data, web data (for example, data on prices or employment), postal data, and electricity data.

The climate change initiative land use data, data from the European Space Agency and the 30-meter global land cover dataset (GlobeLand30) [3] were included for multi-scenario simulation of land use [4]. The data source used to create multispectral photos included photographs from the China Environmental Disaster Mitigation Satellite, Landsat TM5, ETM+, and OLI, as well as HJ-1 multispectral images.

The relationship between agricultural interventions, dietary changes, and nutrition, which incorporates a few complex issues both within and outside of SDG-2, cannot be adequately captured by any one set of metrics (food production, diet diversification, biofortification, food safety). On the other hand, indicators 2.4.2 and 2.4.3 appear to be included into indicator 2.4.1 in the sense that sustainability has social, environmental, and economic components, which permeate every SDG and SDG-2 indicator [5]. However, access to high-quality assessment data is crucial for the SDG11 implementation to be successful [6]. Three SDG11 indicators were measured between 2013 and 2020 in Guilin's urban functional boundary. The main data sources employed were geospatial big data and high-resolution remote sensing pictures. After preprocessing, image fusion was used to combine the panchromatic and multispectral pictures.

In the analysis of urban growth processes, for example, remote sensing photos are combined with geoinformation systems and machine learning. In work [7], [8] authors developed a technique for land productivity assessment and land cover classification using deep learning techniques and satellite data with medium and high spatial resolution.

Ukraine is one of the largest exporters of grain products in Europe, so regular analysis of the quality of agricultural land and its suitability for growing agricultural products, assessment of possible losses and yield [9] is an important task. With the onset of the war, the whole world was shaken by the problem of the possibility of a shortage of grain for importing countries, and as a result of the emergence of famine [10], as well as any other problems in the field of food security. The goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture is generally responsible for the agricultural sector. In particular Indicator 2.4.1: “Proportion of agricultural area under productive and sustainable agriculture”, which is calculated in this study for the territory of Ukraine.

The generally accepted scheme for calculating indicators of sustainable development goals is set out in reference [11], in particular for SDG 2.4.1 in document [12] and it is recommended to be collected at least 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 (Table 1).

Table 1: Themes and sub-indicators for SDG 2.4.1 assessment.

№	Themes	Sub-indicators
1	Land productivity	Farm output value per hectare
2	Profitability	Net farm income
3	Resilience	Risk mitigation mechanisms
4	Soil health	Prevalence of soil degradation
5	Water use	Variation in water availability
6	Fertilizer pollution risk	Management of fertilizers
7	Pesticide risk	Management of pesticides
8	Biodiversity	Use of agro-biodiversity-supportive practices
9	Decent employment	Wage rate in agriculture
10	Food security	Food Insecurity Experience Scale (FIES)
11	Land tenure	Secure tenure rights to land

Unfortunately, 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 [13], which takes into account crops types information, soil parameters, and meteorological indicators during the growing season.

2 DATA USED

2.1 Land Cover / Crop Type Classification

The land cover and crop type classification maps based on own classification methodology [14] were used. For classification processing 2 bands (VV, VH) of SAR Sentinel-1 descending data with main preprocessing steps (correction of coordinates in orbit, specl-filtration, calibration, the Range-Doppler Terrain Correction, data transfer in decibel, creating a data stack, saving imagery bands, and merging of bands VV and VH within a single granule) with 10-meters spatial resolution are used. 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 for every 5 days in the respective bands. A Scene Classification Map (SCL) band with a spatial resolution of 20 meters is used to mask clouds from optical data. Optical composites are obtained in the Google Earth Engine cloud platform.

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.

As an input to the neural network model, we have a stack of rasters - a time series of satellite data. Together with the satellite data stack, training in-situ data is fed to the input of the neural network model, which is collected along the roads every year in the form of vector contours of the fields, indicating the corresponding land cover or crop type class. The output of the model is a raster georeferenced image, where each pixel contains the corresponding land cover or crop type class. The validation independent in-situ data set is used to obtain class accuracies and the overall accuracy of the resulting classification map.

2.2 Leaf Area Index Modelling

The simulation model for the quantitative analysis of the growth and production of annual field crops WOFOST (WOrld FOod STudies) [15] was used to simulate LAI for agricultural crops. The main input parameters for this model are soil profiles (including various soil characteristics), crop profiles (including sowing dates, flowering, maturity and other important characteristics), as well as meteorological indicators.

2.2.1 Soil Profiles

Soil parameters are important input data for estimating the model value of LAI. There are 40 main types of soils for Ukraine (Figure 1). 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 [16].

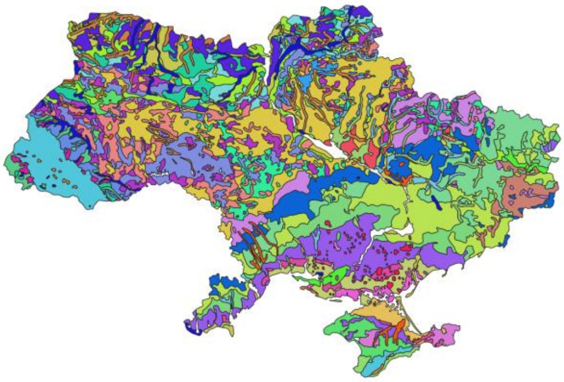

Figure 1: Soil map for Ukraine.

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 [17], 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). The Figure 2 shows the geospatial ratio of meteorological data pixels to oblasts of Ukraine.

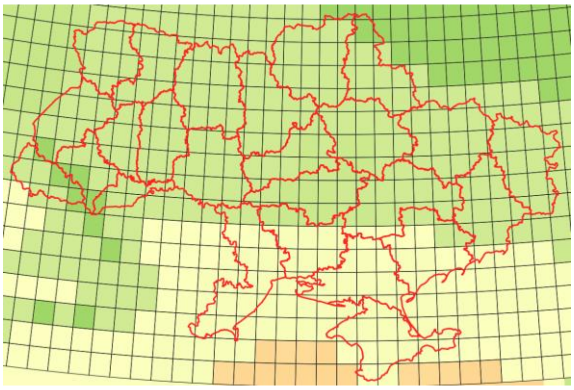

Figure 2: Soil map for Ukraine.

2.2.4 Grid Creation for Ukraine

Considering the rather low spatial resolution of meteorological data, as well as the fact that a single soil can extend over a long area, a new markup is created for the use of the WOFOST model, which is the intersection of meteorological data and soils (Figure 3). Thus, we increase the variability and taking into account the agro-climatic zones of Ukraine. For each polygon created, a point for which a soil profile, crop profile and meteorological indicators are assigned is set in accordance.

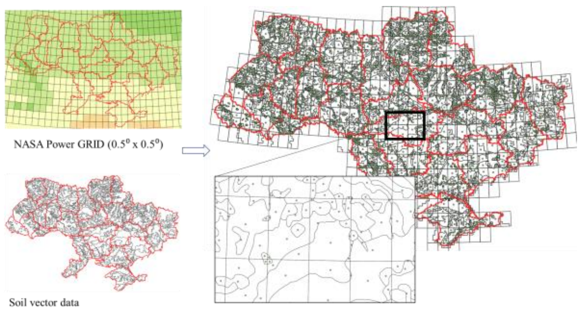

Figure 3: Grid for WOFOST model using for Ukraine.

3 METHODOLOGY

Our method of land productivity assessment is based on the land cover and crop type classification from satellite imagery and application of different schemes of land degradation assessment for each of them [13] (Figure 4).

We consider forest cuts as land degradation for forests and assess them using deep learning models [18]. Land degradation for croplands is estimated by difference of real leaf area index (LAI) based on MODIS data [19] and ideal LAI, calculated with the biophysical crop development model WOFOST [15], which takes into account the biophysical characteristics of the soil (soil moisture content at saturation, at wilting point, and at field capacity), meteorological conditions (precipitation, temperature, wind direction and strength), altitude above sea level.

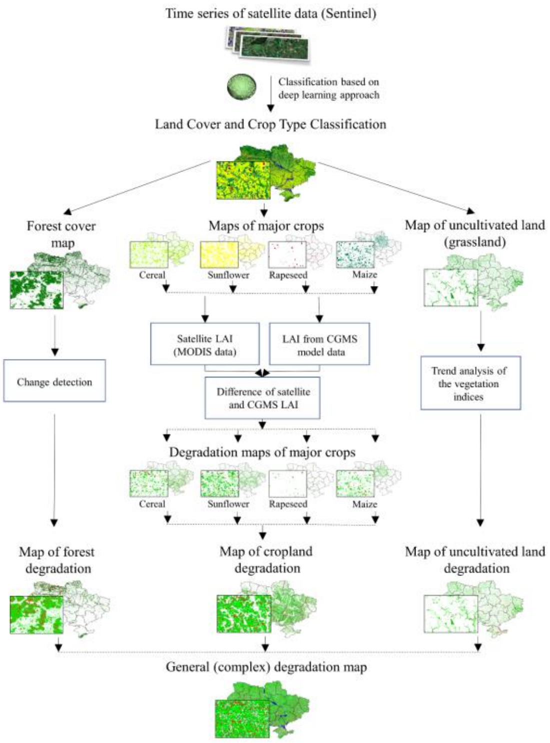

Figure 4: General scheme of the complex method of land degradation estimation [13].

The sustainability criteria are the distance from the 90th percentile of the national distribution [12]:

- Green (desirable or productive): Sub-indicator value is ≥ 2/3 of the corresponding 90th percentile.
- Yellow (acceptable or sustainable): Sub-indicator value is ≥ 1/3 and < 2/3 of the corresponding 90th percentile.
- Red (unsustainable or degradation): Sub-indicator value is < 1/3 of the corresponding 90th percentile.

The land degradation for grassland is determined with a traditional approach based on trend of vegetation index NDVI [20] extracted from satellite imagery.

The indicator 2.4.1 is defined by the (1):

$$SDG_{2.4.1} = \frac{Area\ under\ productive\ and\ sustainable\ agriculture}{Agriculture\ land\ area}, \quad (1)$$

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

According to the developed technology for indicator 2.4.1 calculation, the land degradation maps were calculated, which include three classes (productive, sustainable and degradation land) for the calculation of which the crop type maps for 2018 - 2022 were used. On the basis of the obtained maps, according to (1), the SDG indicator 2.4.1 was calculated for each region of Ukraine (Figure 5).

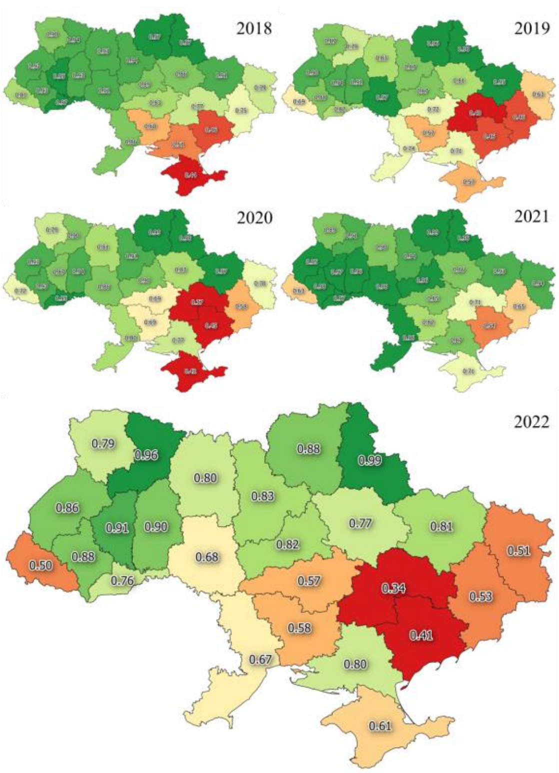

Figure 5: SDG 2.4.1 indicator for Ukraine (2018 – 2022).

During 2018 - 2021, a worse situation is observed in the southern regions in terms of the value of the indicator, which may be caused by the annual crop rotation violation in this zone [21].

The situation in 2022 has significantly worsened in almost all regions of Ukraine, in particular in the south-eastern regions, where hostilities continue. The worsening situation in other regions may also be due to shortages of fuel, resources for productive agriculture, and human resources, as many workers have gone to war.

The Table 2 shows the calculated SDG indicators 2.4.1 for 5 years, as well as their comparison with 2022 in percentage. The cases where the indicator decreased are marked in pink color, and the cases in which the indicator increased are marked in green color. From Table 2, it can be concluded that in almost all regions of Ukraine, compared to the previous 4 years, the condition of the land has deteriorated. Kherson region has higher indicators than other territories under occupation, as it contains the largest areas of irrigated territories in Ukraine, which helped it.

Table 2: Indicator SDG 2.4.1 for Ukraine (2018 – 2022).

Oblasts	SDG 2.4.1					Difference (in %) with 2022			
	2018	2019	2020	2021	2022	2018	2019	2020	2021
Vinnytska	0,92	0,97	0,86	0,98	0,68	-25,7	-29,3	-20,2	-30,5
Zakarpatska	0,81	0,69	0,72	0,63	0,50	-38,0	-26,7	-30,2	-20,3
Kirovohradska	0,83	0,72	0,69	0,85	0,57	-31,5	-21,7	-18,0	-33,6
Luhanska	0,79	0,63	0,70	0,94	0,51	-36,4	-19,8	-28,0	-46,3
Dnipropetrovska	0,77	0,40	0,37	0,71	0,34	-56,4	-14,9	-8,9	-52,8
Kharkivska	0,91	0,95	0,97	0,93	0,81	-10,5	-14,8	-16,2	-12,9
Zaporizka	0,46	0,46	0,45	0,54	0,41	-9,9	-10,8	-7,6	-23,5
Odeska	0,86	0,74	0,80	0,96	0,67	-22,6	-10,1	-16,9	-30,4
Volynska	0,90	0,87	0,79	0,89	0,79	-12,1	-9,1	-0,3	-11,3
Chernihivska	0,97	0,96	0,99	0,99	0,88	-8,9	-8,4	-11,0	-10,7
Chernivetska	0,97	0,82	0,96	0,97	0,76	-21,2	-7,6	-20,3	-21,6
Cherkaska	0,89	0,87	0,90	0,96	0,82	-7,4	-6,0	-8,3	-14,1
Lvivska	0,93	0,90	0,93	0,96	0,86	-7,9	-4,9	-7,1	-9,9
Kyivska	0,94	0,87	0,91	0,94	0,83	-11,5	-4,7	-8,3	-11,2
Poltavska	0,86	0,81	0,84	0,86	0,77	-10,3	-4,4	-7,4	-10,1
Zhytomyrska	0,93	0,83	0,81	0,90	0,80	-14,7	-4,0	-1,6	-11,3
Ternopilska	0,96	0,94	0,87	0,97	0,91	-4,8	-3,7	4,4	-6,7
Khmel'nytska	0,93	0,92	0,94	0,96	0,90	-3,1	-2,1	-3,7	-6,6
Ivano-Frankivska	0,93	0,88	0,93	0,98	0,88	-5,2	-0,7	-6,1	-10,4
Donetska	0,75	0,46	0,58	0,65	0,53	-29,2	14,7	-8,5	-18,2
Mykolaivska	0,60	0,57	0,69	0,82	0,58	-2,7	1,0	-16,4	-29,4
AR of Crimea	0,44	0,57	0,42	0,72	0,61	38,4	8,3	46,0	-14,3
Khersonska	0,51	0,71	0,77	0,87	0,80	56,8	13,0	3,1	-7,9
Sumska	0,97	0,98	0,98	0,98	0,99	2,4	0,6	0,6	0,5
Rivnenska	0,94	0,79	0,90	0,91	0,96	1,7	21,4	6,5	5,7
Ukraine	0,83	0,77	0,79	0,87	0,73	-12,5	-6,1	-8,1	-17,0

5 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 [13]. It takes into account different land cover/land use classes and provides a specific way of assessing land degradation for each of them. 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. According to our research, most of the territory of Ukraine remains stable. 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.

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