Information Technology for Land Degradation Assessment Based on Remote Sensing

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Abstract: Since the launch of ESA Copernicus program, satellite data of high resolution became publicly available and methods and tools for their automated processing to solve a wide range of applications have developed rapidly. An important scientific task is to assess land degradation and achieve zero levels of degradation. There are many methods for determining land degradation. Known approaches to the tasks of environmental land monitoring usually use the same methodology for all types of land cover. The paper represents the approach to the calculation of land degradation based on remote sensing data and modelling results taking into account the specifics of land degradation for different land cover and land use types. Our method is based on the classification of different land cover and land use types from satellite imagery and application of different schemes of land degradation assessment for each of them. We consider forest cuts as land degradation for forests and assess them using deep learning models. Land degradation for croplands is estimated by comparison of real leaf area index (LAI) and ideal LAI, calculated with the bio-physical crop development model. And land degradation for grassland is determined with a traditional approach based on vegetation index NDVI extracted from satellite imagery. The proposed approach was implemented for the territory of Ukraine.

1 INTRODUCTION

Since the advent of publicly available satellite data, methods and tools for their automated processing to solve a wide range of applications have developed rapidly [1]. There are a large number of scientific publications on this topic, including [2], [3], [4], etc. An important scientific task is to assess land degradation and achieve zero levels of degradation [5].

There are many methods for determining land degradation [6]. Known approaches to the tasks of environmental land monitoring usually use the same methodology for all types of land cover. In particular, an analysis of existing approaches to the calculation of quantitative indicators (eg sustainable development indicators) shows that all these indicators are calculated in the same way for all territories. It is natural to assume that each of the types of land cover has its own characteristics at the level of the subject area, which is reflected at the level of relevant mathematical models and can potentially be used to improve the performance of methods of processing these data.

For example, the inaccuracies of the productivity map, which can be traditionally built only on the basis of the NDVI index, include the following: in Volyn and the Carpathians (forest regions) productivity dynamics calculated on the basis of the NDVI index will be low, but this result is due to the index NDVI for forests. In the south (Zaporizhzhya and Mykolayiv oblasts), the productivity calculated on the basis of the NDVI index will be the best in Ukraine, but this is due to the fact that most of the fields in these regions are irrigated. Irrigation, in turn, is one of the factors of sustainable development, so it is advisable to consider it for agricultural fields. Therefore, the urgent task is to develop a differentiated approach to assessing the degradation of different types of land cover.

2 METHODOLOGY

This study proposes a comprehensive method for determining land degradation based on Sentinel satellite data [7], which takes into account the specifics of degradation of different types of land cover. The algorithm for determining the level of land degradation consists of the following steps.

1) Based on satellite data, a land cover classification map is built, which includes various types of crops, uncultivated land (meadows, pastures, grassland, etc.), forests, shrubs, man-made objects, water bodies, swamps, bare land. To deliver a crop classification map we use deep learning neural network model which has been trained on time series of satellite imagery and in-situ data [8], [9].

Three groups are separated of the received classes: agricultural land (which includes the main majority crops - cereals, sunflowers, maize, rapeseed, and soybeans), uncultivated lands (meadows, pastures, grassland), and forests. Given that these three groups cover 90.5% of the entire territory of Ukraine, and other lands are artificial and water objects, wetland, and bare land, we will consider that all strategically important territories of Ukraine are considered.

2) Each of the above groups has its own method of analysis.

3) The general map of land degradation is built by reducing the quantitative indicators for each of the groups (diapason of values of indicators in the general case are different) to some common set of values (the same for each group).

Quantitative indicators of agricultural land productivity will be the ratio of the real LAI index (according to satellite data) to the "ideal" for the relevant conditions of the LAI index. To calculate the latter in this study, it is proposed to use biophysical modeling Crop Growth Modeling System based on the WOFOST model. If the values of the real and "ideal" LAI indices differ slightly, the relevant agricultural area is considered not degraded, and if they differ significantly - degraded.

As deforestation is a significant problem, deforestation in some areas can be considered as an indicator of degradation. However, when searching for felling, it is necessary to take into account the fact that the area cut down but planted with new trees cannot be considered as degraded. In this study, it is proposed to use a neural network of U-Net architecture with an Efficientnet B3 encoder to search for fellings.

As practice shows, for the grassland class (uncultivated land), the use of a standard approach based on the NDVI index gives qualitative and adequate results. Degradation of uncultivated land is determined by the negative trend of the NDVI vegetation index.

2.1 Calculation of Land Degradation for Different Land Cover/Land Use Types

The main idea of the construction of the general map of land degradation is to combine the results for each of the groups of classes of the land cover and to build a general map of land degradation on the basis of general quantitative indicators. The procedure for combining the results can be formally presented as follows.

Quantitative indicators of degradation of territories are:

- for agricultural land: $f_{crop}(LAI_{real}, LAI_{perfect})$, where LAI_{real} is the real LAI index for the pixel (x, y), $LAI_{perfect}$ is the "ideal" (simulated) LAI index for the pixel (x, y). Real LAI is extracted from the satellite imagery (monthly composites for the corresponding growing year), and $LAI_{perfect}$ – is simulated with CGMS system based on WOFOST bio-physical model for each crop independently. The simulated $LAI_{perfect}$ was determined for each day, after which the maximum value for each month was calculated. The model utilizes information on meteorological parameters for each day of the vegetation period as well as profiles for different crops and soil types. A quantitative indicator of degradation of agricultural areas will be the difference between satellite LAI and simulated LAI.
- for uncultivated land (grassland): $f_{grassland}(\{NDVI\})$, where $\{NDVI\}$ is the time series of NDVI indices for the pixel (x, y) during the vegetation period. For each year (from 2001 to 2021), the maximum value of NDVI in each pixel is calculated and the trend of its change is analyzed.
- for forests: $f_{forest}(d)$, where $d=0$ in the case of forestcut, and $d=1$ otherwise. Using our own neural network approaches to forest cover, a "change detection" approach was applied for each year separately.

2.2 Unification of Land Degradation Indicators

Let's areas of available values of these functions: $E(f_{crop})$, $E(f_{grassland})$, $E(f_{forest})$, respectively. As described in Section 2.1, we obtained the following input data for each pixel (x, y):

$$I(x, y) = \{LAI_{real}, LAI_{perfect}, \{NDVI\}, d\},$$

calculated on the basis of available input data (satellite images, meteorological data), or form standard methods (such as time series of NDVI indices).

The general indicator of degradation of the territory to which the pixel (x, y) on the raster map corresponds is f (x, y) with the range of possible values of E(f). The function f (x, y) must satisfy the following conditions: be monotonic, take the minimum value for the most degraded areas, take the maximum value for the areas with the most sustainable development.

Taking into account the above, for each degradation index f_{crop}, $f_{grassland}$, f_{forest} it is necessary to set the appropriate conversion functions:

$$K_{crop}: E(f_{crop}) \to E(f),$$
$$K_{grassland}: E(f_{grassland}) \to E(f),$$
$$K_{forest}: E(f_{forest}) \to E(f).$$

Then the total conversion function K can be written as:

$$K(\varphi(\cdot)) = \begin{cases} K_{crop}(f_{crop}(\cdot)), \varphi = f_{crop}, \\ K_{grassland}(f_{grassland}(\cdot)), \varphi = f_{grassland}, \\ K_{forest}(f_{forest}(\cdot)), \varphi = f_{forest} \end{cases}$$

Given the fact that a set {agricultural lands, grasslands, forests} within the subject is a complete group of events, and that for each element to calculate the quantitative rate of degradation requires only part of the information $I(x, y)$, to reduce the computational complexity software implementation for each pixel (x, y) it is advisable to calculate only part of it, namely:

$$I(x,y) \mid \varphi(x,y) = \begin{cases} \{LAI_{real}, LAI_{perfect}\}, \varphi = f_{crop}, \\ \{NDVI\}_{time\_series}, \varphi = f_{grassland}, \\ d, \varphi = f_{forest}, \end{cases}$$

The total degradation rate can be calculated by the formula:

$$f(x,y) = K(I(x,y) \mid \varphi(x,y)),$$

and the general map of land degradation is actually a graph f(x, y) on the set X × Y, which corresponds to the area of interest.

3 EXPERIMENTAL RESULTS

3.1

3.1 Validation of Classification Map

The efficiency of land degradation assessment is depending on the accuracy of the classification map. That is why the first experiment has been done for validation of the land cover/land use classification map. The main classes on the classification map are maize, winter wheat, soybeans, sunflowers, winter oilseed rape, sugar beet, peas, man-made objects, forests, uncultivated land (grassland), swamps, water bodies, and open ground.

Estimates of the accuracy of the classification map were calculated using a validation dataset, which was not used to train the classifier and construct this classification map. The validation dataset contained 455 polygons with a total area of 5858.16 ha. User and producer accuracy for each class is shown in Table 1.

Table 1: Producer Accuracy (PA) and User Accuracy (UA) for each class at the classification map.

	Class	PA, %	UA, %
1	Artificial	95,9	74,0
2	Winter wheat	96,5	98,8
3	Winter rapeseed	98,4	98,8
4	Maize	98,0	86,2
5	Sugar beet	99,1	100,0
6	Sunflower	98,2	94,0
7	Soybean	72,7	97,0
8	Forest	99,7	99,2
9	Grassland	96,8	66,0
10	Bareland	61,4	100,0
11	Water	100,0	100,0
12	Wetland	83,7	100,0
13	Peas	100,0	99,8
	Overall accuracy, %	94,2	
	Kappa	0,93	

3.2 Productivity Map Based on NDVI

The traditional remote sensing approach to degradation assessment is based on the dynamic of vegetation index NDVI, extracted from satellite imagery. During the last 5 years, the best data source for NDVI calculation is Sentinel 2 imagery, because of its high resolution (10 meters) and good coverage (each point on the Earth's surface is visited every 6-12 days). In our study, we use this data source, but only for nonagricultural lands. The lands, where NDVI has negative trend over the years we consider as degraded. Figure 1 demonstrates the productivity map based on NDVI dynamics for Ukraine for 2021.

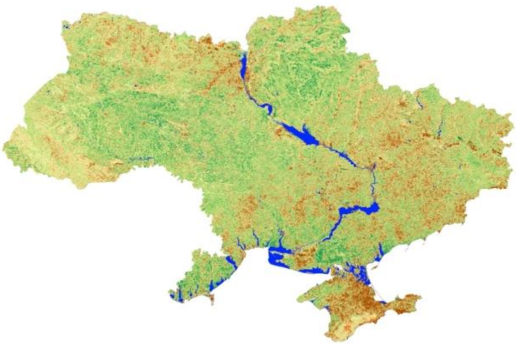

Figure 1: Productivity map based on vegetation index.

3.3 Land Degradation Maps

Figure 2 shows land degradation for the 2020 year. Red color depicts degraded lands, while green – is sustainable and productive land according to the complex methodology of land degradation assessment. As we can see, most of the territory of Ukraine stays sustainable. Most land degradation is observed on croplands due to ecology unfriendly agricultural practices.

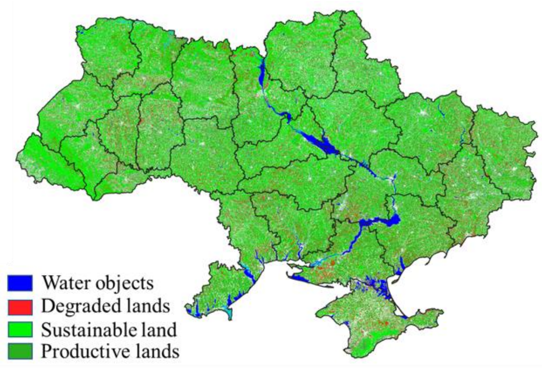

Figure 2: Land degradation for Ukraine for 2021.

4 CONCLUSIONS

In this study, we have developed the geospatial method of land degradation assessment based on remote sensing data, neural networks, and bio-physical modelling. It takes into account different land cover/ land use classes and provides a specific way for land degradation assessment for each of them. Due to the high computation complexity of the method, it is reasonable to implement it in a cloud environment [10]. According to our study, most of the territory of Ukraine stays sustainable. Most land degradation is observed on croplands due to ecology unfriendly agricultural practices.

The developed technology is flexible and applicable to different climatic zones, because during biophysical modeling according to the WOFOST model it takes into account precipitation, temperature, as well as the main stages of crops growth - seedlings, maturation, maturity. Obtaining annual degradation maps according to the described methodology, it is possible to analyze changes for the better or worse, analyze degraded areas and their distribution, as well as make appropriate management decisions to prevent and regulate land quality in Ukraine.

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