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Complex method for land degradation estimation

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Abstract. Satellite data of high spatial resolution have become publicly available since the launch of the EU Copernicus program, and their automated processing methods for solving a large number of diverse applied problems have received further development. Our task in this article is to analyze the dynamics of the land degradation level using land degradation assessment approaches based on satellite monitoring and taking appropriate measures. Within this work authors have developed the complex method for land degradation estimation that uses different schemes for separate land cover and crop types at country level based on satellite and modelling data. The deforestation was considered as land degradation in forest areas. For agricultural land, land degradation is determined by comparing the actual leaf area index (LAI) with the simulated (ideal) LAI, and for uncultivated land it is based on normalized difference vegetation index trend analysis from satellite information.

1. Introduction

Methods and their automated processing for solving a wide range of problems began to develop rapidly since the appearance of publicly available satellite data [1, 2]. The main goal of research and the scientific task in publications [3, 4] is the land degradation assessment and the achievement of a zero level of land degradation [5]. Studies in modern publications have shown that there are several definitions of land degradation, each of which gives its own meaning to this complex concept. From the point of view of the land degradation assessment using satellite data, the following are the most important.

Definition 1. Land degradation is a long-term decrease in the functioning of the ecosystem, which can be expressed in a decrease in the biophysical indicators of the vegetative biomass [6].

Definition 2. Land degradation is a complex phenomenon that typically involves the loss of some or all of the following: productivity, soil, vegetation cover, biomass, biodiversity, ecosystem services, and environmental sustainability [7].

Definition 3. Land degradation is the reduction or loss of biological or economic productivity and complexity of rainfed arable land, irrigated arable land or pasture, grassland, forest, and woodland as a result of a combination of pressures, including land use and management practices [8]. This definition is accepted and used by 196 member countries of the UN Convention to Combat Desertification [9]. Such degradation includes the following 3 types [10]:

- *Physical degradation* is a reduction in the content of important organic substances, which can be caused by felling or removal of vegetation and excessive cultivation of inappropriate crops (crop rotation violation).
- *Chemical degradation:* processes leading to soil chemical imbalance, including salinization, nutrient loss, oxidation, and toxicity.
- *Biological degradation* occurs as a result of increased mineralization of humus existing in the land surface layer, which is a direct consequence of physical degradation. These soils experience nutrient loss and lead to increased runoff and erosion.

According to existing methods for land degradation estimation, the state-of-the-art approaches use the same methodology for different land cover types [11]. According to the UN Sustainable Development Goals indicator system (definition 3), land degradation is defined as the reduction or loss of productivity of different types of land (agricultural, forest and uncultivated land) [12]. That is why an important component for a comprehensive assessment of land degradation is the analysis of the trend of its productivity [13]. A positive trend in land productivity reflects favorable changes in ecosystem functioning (for example, an increase in plant biomass), while trends in declining productivity can be a defining characteristic of land degradation [14, 15]. One of the most common ways to analyze the trend of land productivity is based on the use of satellite data and the determination of the dynamics of changes in the normalized difference vegetation index (NDVI) of the land cover [16, 17].

The inaccuracies in productivity maps, which are based on the analysis of the dynamics of average annual vegetation indices (in particular, based on normalized difference vegetation index - NDVI [18]), arise for different types of land cover. In particular, in forest and mountain areas (Volyn region and the Carpathian Mountains), productivity dynamics based on NDVI will be low due to the specifics of the forest cover. For irrigated agricultural land in the southern part of Ukraine (Zaporizhia and Mykolaiv regions), productivity based on the NDVI index will be the best for Ukraine. Irrigated fields are one of the sustainable development factors, so it is appropriate to explore such areas separately. The emergence of such ambiguous conclusions reinforces the relevance of developing a complex approach for different land cover and crop types degradation assessment.

2. Scheme of complex land degradation assessment

In this work, a complex method for determining land degradation for the territory of Ukraine is proposed, which foresees different essential variables and criteria of degradation depending on the type of land cover/land use. It is based on the use of satellite products, such as productivity maps, land cover classification maps, values of the LAI index from various sources (based on satellite information and the WOFOST biophysical model [19]), and the trend of the vegetation index NDVI. All these products could be delivered based on freely available satellite data of Sentinel-1 and Sentinel-2 satellites with 10 m resolution. The general scheme of the complex method of determining land degradation is presented in Figure 1, and its essence consists in performing the following steps.

The first step of the algorithm is the identification of land cover/land use for each separate pixel. To determine the land cover type to assess land degradation, a *land cover classification map* is used, which is obtained based on the satellite data Sentinel-1,2 time series of the Copernicus program and using a deep learning algorithm [3]. Such a map includes major agricultural crops (cereals, sunflower, maize, rapeseed, soybeans and other agricultural lands), uncultivated lands (meadows, grassland, etc.), forests, artificial objects, reservoirs, wetland, bare land (Figure 2). In-situ data collected along the roads are used for the neural network training, validation and testing. The resulting accuracy estimates for the main

land cover and crop classes, as well as the distribution of in-situ data for test and training for different years and classes, can be found in article [20].

According to classification map, available land use and crop type classes are grouped into three main categories: agricultural lands (which contain major crops, such as cereals, sunflower, maize, rapeseed and soybeans, as well as other crops), uncultivated lands (meadows and grassland) and forest. In terms of coverage area, these three main categories cover more than 90% of Ukraine (artificial, water, wetland, bare land are not included here). Thus, it can be concluded that for the study of land degradation in Ukraine it will be quite enough to consider these three main categories of land cover, and to apply a separate approach and essential variables for each of them.

Productivity maps for *agricultural areas* of Ukraine is be based on the difference between real maps of the LAI index based on MODIS data (LAI_{real}) [21], as well as "potential" (the ideal) LAI maps ($LAI_{perfect}$) for each crop separately. To model the "ideal" LAI index, the WOFOST open-source model is used, by combining Copernicus reanalysis data [22], Crop Growth Modeling System (CGMS) biophysical models [23] and data from existing weather stations and soil maps [24].

By analyzing the differences between the actual LAI from MODIS data and the "ideal" modeled LAI index, it is determined whether a given agricultural area is degraded. In this way, we obtain separate maps of the degradation of the main agricultural crops for the studied year, combining which allows us to obtain a map of the degradation of agricultural land. The area of interest is defined as $\Omega = I \times J$, and $i \in I$, $j \in J$, and (i, j) - coordinates of one pixel within our area. A quantitative indicator of agricultural land degradation is the function $f_{crop}(LAI_{real}, LAI_{perfect}) = LAI_{real} - LAI_{perfect}$ (pixel based difference), where LAI_{real} is the real LAI index calculated from satellite data for pixels (i, j), $LAI_{perfect}$ is the perfect (or simulated) LAI index for pixels (i, j) according to the WOFOST model [25].

For uncultivated areas that are covered with vegetation, the productivity map is calculated using the trend of the NDVI vegetation index NDVI ($\{NDVI\}_{time\_series}$) [11, 26] based on time series of Sentinel-2 satellite data [27]. The negative trend of the NDVI vegetation index indicates the degradation of uncultivated land. A quantitative indicator of the degradation of uncultivated land is the function $f_{grassland}(\{NDVI\}_{time\_series})$, where $\{NDVI\}_{time\_series}$ is the time series of NDVI indices for pixels (i, j).

For *forests*, we will consider deforestation as an indicator of degradation. However, it is worth considering that places where trees were cutted and then replanted should not be considered as degradation. In this work, for deforestation detection we proposed to use a neural network of the U-Net architecture with the Efficientnet B3 encoder. Test results for deforestation detection tasks show that the most accurate results can be obtained by combining radar and optical images. At the same time, radar images provide acceptable accuracy even in the absence of optical data. This allows us to use the developed method based on deep learning for the tasks of detecting forest cuts in the presence of clouds, as well as in autumn and winter, that is, in those cases in which the use of optical images is ineffective or impossible due to their absence.

A quantitative indicator of forest degradation is a function $f_{forest}(d)$, where

$$d = \begin{cases} 0, \text{ if deforestation}, \\ 1, \text{ in the other case} \end{cases}. \quad (1)$$

Consider that for each pixel (i, j) the type of land cover and information $LC(i, j) = \{LAI_{real}, LAI_{perfect}, \{NDVI\}_{time\_series}, d\}$ is available, which is pre-determined based on the input data (satellite images, meteorological data, output of the WOFOST model, time series of the vegetation index NDVI). Areas of permissible values of the specified functions, which correspond to quantitative indicators of degradation of agricultural land, uncultivated land, and forests are $E(f_{cropland})$, $E(f_{grass})$, $E(f_{forest})$ accord.

By combining the obtained results for each land cover group of classes, we will create a complex degradation map based on general indicators. The construction of a general classification map and the procedure for obtaining degradation maps for different land cover groups will be presented as follows.

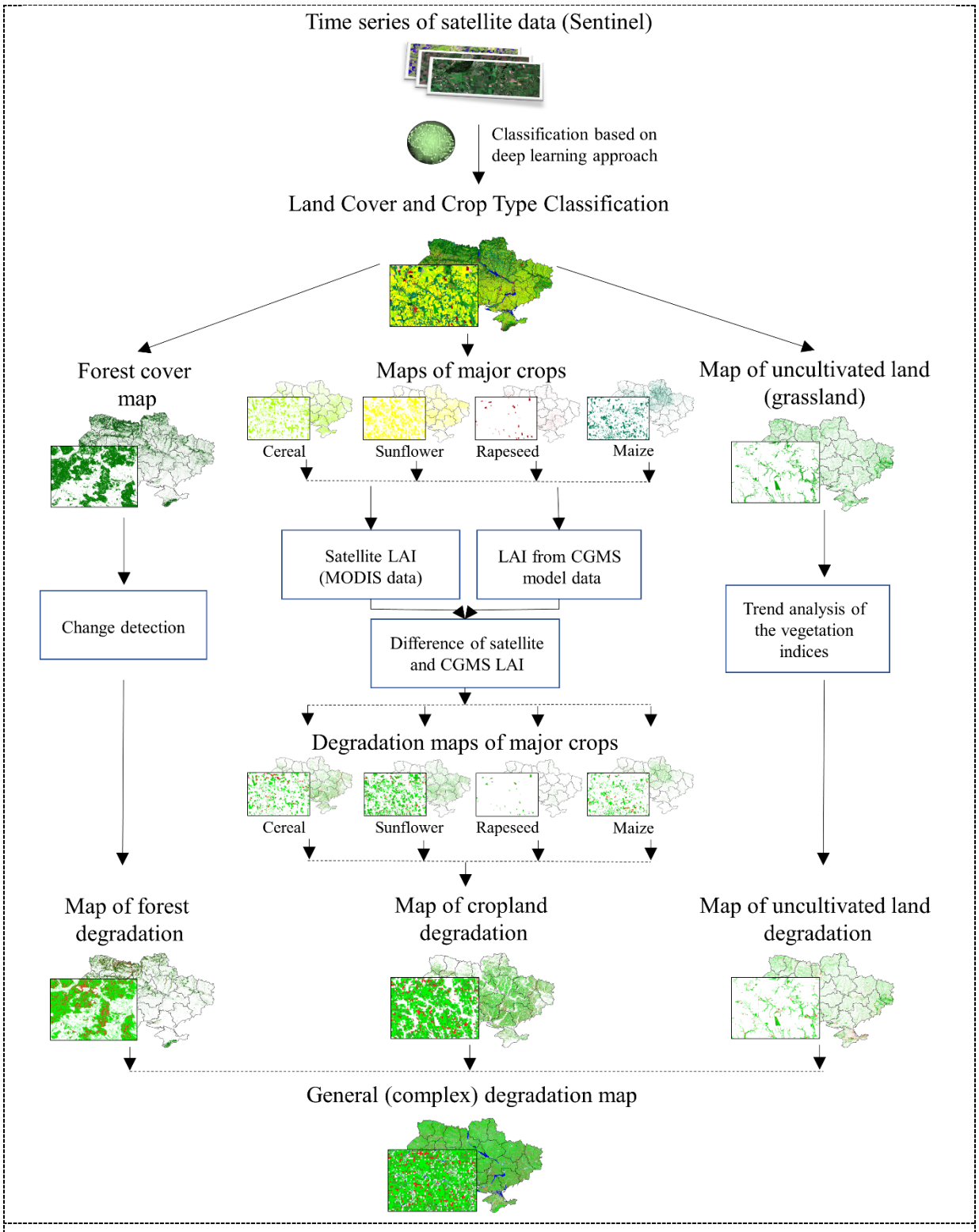

Figure 1. General scheme of the complex method of land degradation estimation.

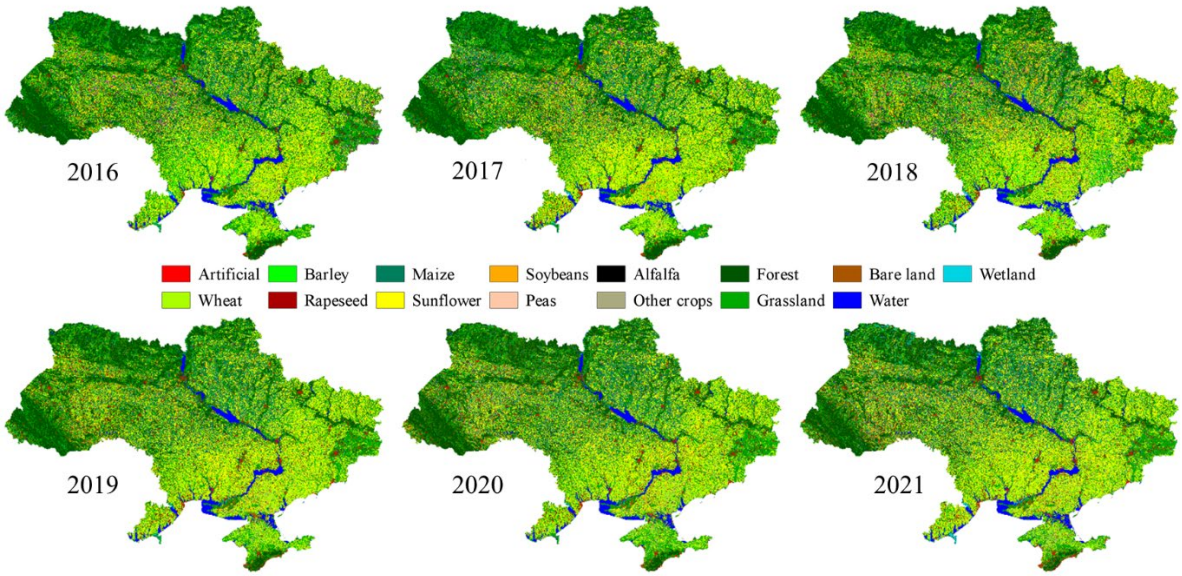

Figure 2. Land cover and crop type classification maps for Ukraine, 2016–2021.

The land degradation function will be denoted as *f(i, j)* for each pixel (*i, j*) on the raster map with a range of possible values *E(f)*. This function should acquire the minimum values for the most degraded areas, acquire the maximum values for the most sustainable development areas, and be monotonic.

Taking into account the above, for degradation indicators $f_{cropland}, f_{grass}, f_{forest}$ we set the corresponding functions:

$$F_{cropland}: E(f_{cropland}) \rightarrow E(f),\ F_{grass}: E(f_{grass}) \rightarrow E(f),\ F_{forest}: E(f_{forest}) \rightarrow E(f). \quad (2)$$

The general conversion function *F* can be represented by the next formula:

$$F\left(\phi(\cdot)\right) = \begin{cases} F_{cropland}(f_{cropland}(\cdot)), & if\ \phi = f_{cropland}, \\ F_{grass}(f_{grass}(\cdot)), & if\ \phi = f_{grass}, \\ F_{forest}(f_{forest}(\cdot)), & if\ \phi = f_{forest} \end{cases} \quad (3)$$

The set of defined categories is a complete group of events, and every group needs just part of the information about land cover *LC(i, j)* for the degradation index calculation. Therefore, to reduce the computational complexity in the software implementation, only a part of it was calculated for pixels *(i, j)*, namely:

$$LC(i,j) \mid \phi(i,j) = \begin{cases} \{LAI_{real}, LAI_{perfect}\},\ if\ \phi = f_{cropland}, \\ \{NDVI\}_{time\_series},\ if\ \phi = f_{grass}, \\ d,\ if\ \phi = f_{forest}, \end{cases} . \quad (4)$$

At the same time, the total indicator of territory degradation is calculated according to the formula for pixels *(i,j)*:

$$f(i,j) = F\left(LC(i,j) \mid \phi(i,j)\right), \tag{5}$$

and the complex land degradation map represents as a function $f(i, j)$ on the set $I \times J$, which corresponds to the area of interest.

3. Results

To assess land degradation based on time series of satellite data, land cover and crop type classification maps were created for Ukraine for 2016-2021 based on Sentinel satellites. The overall accuracy of these classification maps is more than 90%, which is a reliable indicator of this kind of products in other countries, in particular in the USA and EU [28]. For major crops (sunflower, maize, cereals, soybeans, and rapeseed), maps with real LAI indicators were obtained, and biophysical modeling was performed to estimate ideal LAI values. The accuracy of the LAI maps was evaluated based on the comparison of the LAI index values simulated by CGMS and the data of ground LAI measurements collected by conducting ground surveys within the JECAM test site [29]. The average value of the correlation coefficient is 0.72, while the value of the correlation coefficient is the maximum for soybeans - 0.88, and the lowest for winter wheat - 0.58. A productivity map was obtained separately for each crop, based on which a degradation map of the major crops was constructed using the threshold segmentation method. The final degradation map of agricultural land is the result of combining the obtained degradation maps for each crop type. The general map of the degradation of agricultural territories for 2021 is presented in Figure 3.

Calculated productivity maps based on the NDVI vegetation index trend for uncultivated areas. Lands, where NDVI has had negative dynamics for many years, are considered degraded. Based on the productivity map of uncultivated territories, a map of the degradation of uncultivated territories was constructed using the threshold segmentation method (Figure 4). To analyse changes in forest cover and create the forest degradation map for Ukraine, the data set "Global Forest Change 2000-2020" [30] was used, and our own maps were obtained using deep learning methods (Figure 5). The calculated F1-score accuracies on independent test data for the forest class from 2016-2021 range from 90 to 98%. As a result of the summation of quantitative indicators for each of the groups $f(i, j)$ to a common set of values, a general map of land degradation is constructed.

Figure 6 shows the general land degradation map for 2021. According to the land degradation assessment methodology, degraded lands are marked in red, and productive lands are marked in green color. According to this, the most territory of Ukraine remains sustainable, and the greatest land degradation is observed on cultivated lands as a result of environmentally unfavourable farming methods, as well as during deforestation in forest.

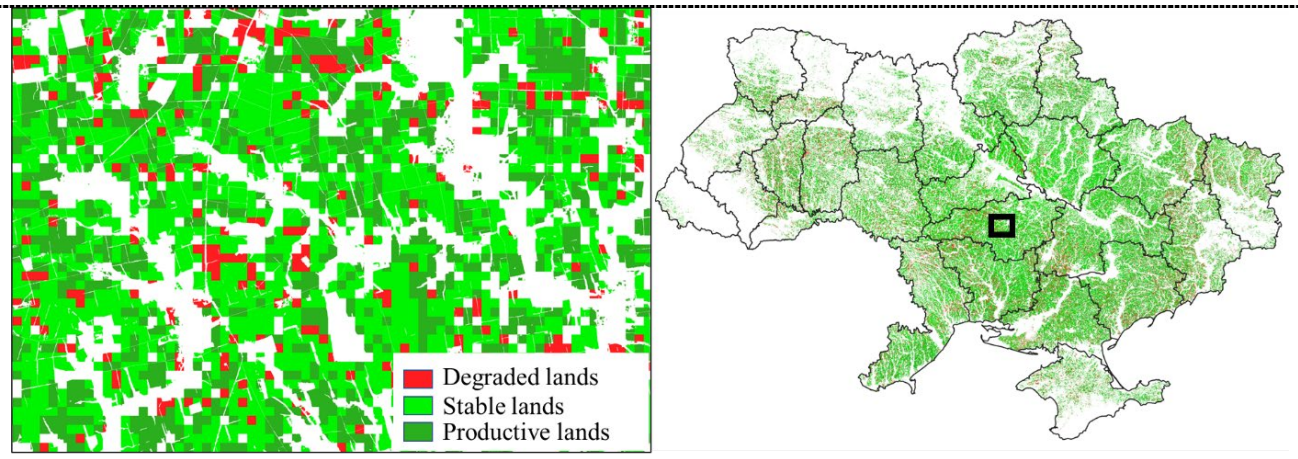

Figure 3. Map of agricultural land degradation for Ukraine in 2021.

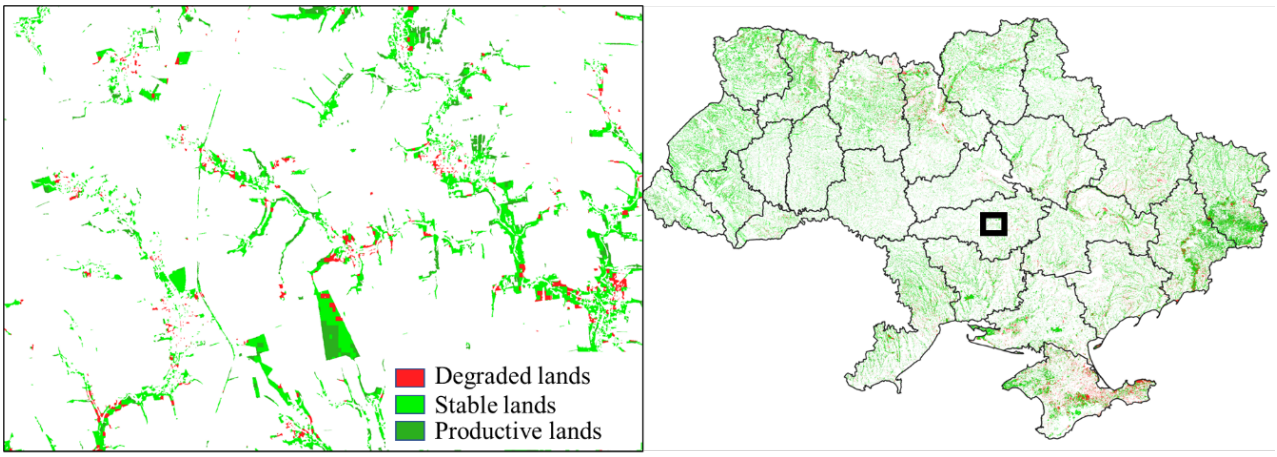

Figure 4. Map of uncultivated land degradation for Ukraine in 2021.

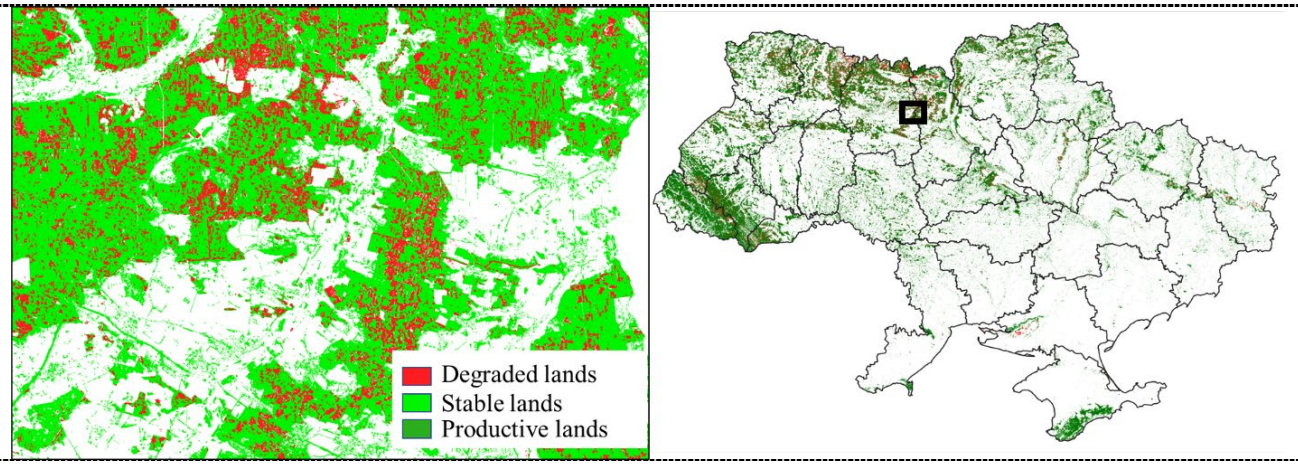

Figure 5. Map of forest degradation for Ukraine in 2021.

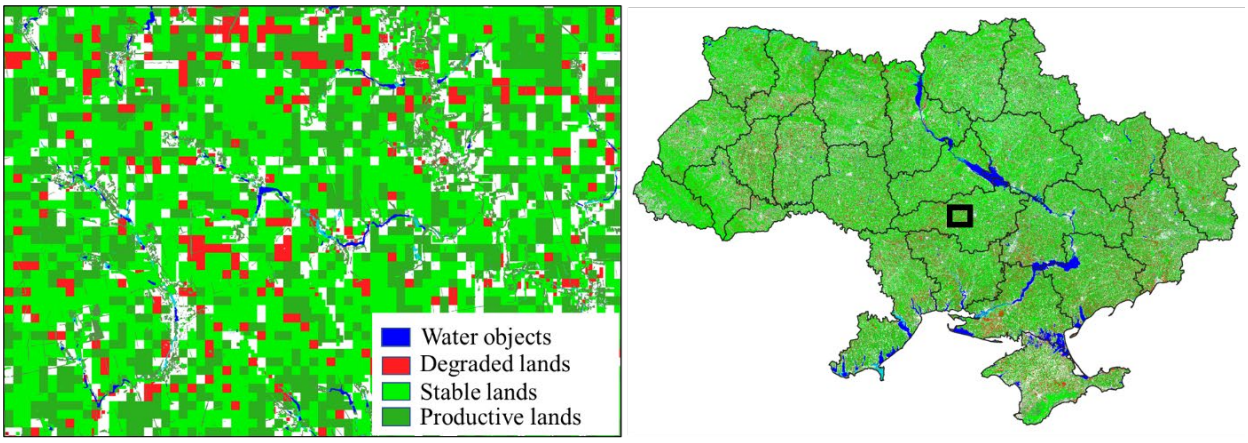

Figure 6. Land degradation map for Ukraine in 2021.

4. Conclusions

Within this article authors described the developed geospatial land degradation assessment complex method based on neural networks, biophysical modelling, and satellite data. This approach takes into account three main land cover types and provides a specific approach for each of them separately. For land degradation monitoring, simple vegetation indices, in particular NDVI, are applicable, which have several limitations, in particular, they can become saturated. This problem is solved through the use of biophysical parameters such as LAI, Green Chlorophyll Index (GCI) [31], Leaf Water Content Index (LWCI) [32] indices, as well as the use of a crop classification map, which allows taking into account different classes of crops and their growth dynamics. The complex method of land degradation assessment allows to improve the results of calculations of indicators of the UN sustainable development goals 15.3.1 "Proportion of land that is degraded over total land area" [33], 2.4.1 "Proportion of agricultural area under productive and sustainable agriculture" [34] and 15.1.1 "Forest area as a proportion of total land area".

Authors used own neural network model for the land cover and crop type classification, as well as the method of filtering agricultural land classification maps, which allow to increase the accuracy and reduce the "noisiness" of the resulting classification raster map, which is an important prerequisite for the analysis of land cover changes. A proprietary algorithm based on a neural network with the U-Net architecture, its modification using the Efficientnet B3 encoder [35], as well as an ensemble of these networks was also used to detect forest cuts.

Due to the high computational complexity of the method and with the need to calculate the corresponding products for the whole country, it is advisable to implement it in a cloud environment, such as CREODIAS [36]. According to this research, the most territory of Ukraine remains stable, and the greatest degradation is observed on cropland due to ecologically unfavorable agricultural methods and tree cutting.

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