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Implementation of Land Degradation Cloud Mapping with Earth Observation Data Cubes

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ABSTRACT The software implementation of land degradation cloud mapping with Earth observation data cubes is described. The software implementation was performed on the ArcGIS Online platform as an external geospatial toolbox. The toolbox was developed in the Python programming language using ArcGIS-compatible Python libraries. The toolbox runs a previously proposed probabilistic model. This probabilistic model leverages the synergy between observed distributions of biogeophysical characteristics of the Earth's surface, i.e., indicators, and existing knowledge of the causes and drivers of land degradation. Land degradation indicators are Earth observation (EO) data products that are aggregated into geospatial EO data cubes and analyzed jointly. The developed geospatial toolbox was applied to the long-term mapping of land degradation over the Kryvyi Rih (Ukraine) test region with EO data cubes of seven selected indicators.

KEYWORDS land degradation; Earth observation; data cube; probabilistic model; cloud mapping; software implementation; online toolbox.

I. INTRODUCTION

LAND degradation poses a significant threat to countries in the European Union located in the east and especially in the south of the continent. The land degradation issue concerns not only scientists but also the broader community vanguard. In the contemporary context, land degradation is provoked by two main drivers: ongoing climate change and increasing anthropogenic impact. For this reason, the EWALD project identified two test regions for land degradation assessment and learning. The first one is the Zagora Province in Morocco, where climate change is the primary driver. The second one is the Kryvyi Rih district of the Dnipropetrovsk region (Ukraine), which is experiencing harsh anthropogenic environmental pressure due to the intensive mining industry.

The Kryvyi Rih mining-industrial landscapes are a unique example of land degradation under anthropogenic pressure. Currently, there are alarming circumstances regarding the unsatisfactory environmental condition of the soils and hydrosphere in the Kryvbas region [1]. This region is also experiencing degradation of vegetation cover and agricultural land [2].

Achieving land degradation neutrality requires efficient land use planning, which, in turn, is impossible without monitoring the condition of natural and anthropogenic ecosystems [3]. In modern Ukraine, land degradation is exacerbated by military actions as well [4]. Under such circumstances, remote assessment and mapping of land degradation using satellite data are a good option, and sometimes the only one. Therefore, the development of a cloud-based system for remote mapping of land degradation is an extremely urgent problem in Ukraine, which is an important element of the European frontier [5].

Although the prevailing drivers of land degradation vary across different test sites, our efforts are focused on developing a single unified methodology for land degradation assessment and mapping based on Earth observation satellite data. The foundation for such unification could be the use of a generic set of land degradation indicators – changes in land

cover classes, physiography, vegetation condition, water balance, soil fertility, and so on. In addition, there are a number of purpose-oriented satellite data products that more or less uniformly represent these indicators, regardless of the sensors, models embedded, or algorithms used to obtain them. Some of the most highly sought-after data products are described in Table 1.

Table 1. Satellite data products for land degradation mapping

Land degradation indicator	Data product	Physical units	Satellite system	Spatial resolution, m	Temporal resolution, days
Land cover change	Google Dynamic World	class probability	Sentinel-2/MSI	10	6
	IGBP MCD12Q1	class code	EOS/MODIS	500	365
Vegetation condition	Gross Dry Matter Productivity	kg/ha/day	Sentinel-3/OLCI	300	10
	Gross Primary Productivity MOD17A2H	$g/m^2/day$	EOS/MODIS	500	8
Physical condition	Land Surface Temperature MOD11A1	K	EOS/MODIS	1000	1
	Land Surface Temperature VNP21L2	K	SNPP/VIIRS	750	1
	Landsat L2C2 Surface Temperature	K	Landsat-8,9/TIRS	100	16
Hydrological condition	Surface Soil Moisture	%	Sentinel-1/C-SAR	1000	12
	Soil moisture L2SMA	fraction	SMAP/L band radar	3000	1
	TerraClim Water Precipitation	mm/month	TRMM/MSWEP	11 100	30
	Total Precipitable Water MYD05L2	mm/day	EOS/MODIS	1000	1
Soil fertility	SoilGrids 2.0 Soil Organic Carbon	t/ha	ISRIC reanalysis	250	365
Terrain morphology	SRTM v4.1 Digital Elevation Model	m	Shuttle/SIR-C/X	90	single (2000)
	ASTER GDEM v3 Digital Elevation Map	m	EOS/ASTER	30	single (2011)
	AW3D v4 Digital Terrain Model	m	ALOS/PALSAR	18	single (2019)

The data products listed in Table 1 provide the minimum necessary coverage of remote indicators of land degradation, as they together account for almost all natural and anthropogenic drivers of land degradation. The main drivers of land degradation are terrain topography, water scarcity, climate change, soil erodibility, unsustainable land management, infrastructure development, disasters, warfare, and socioeconomic challenges [6, 7].

The general methodology for land degradation mapping ensures the current state assessment using a set of indicators. Both spatial and inter-indicator relationships must be taken into account. The most convenient and versatile tool for assessing and analyzing complex phenomena in geosystems is the relevant geospatial data cube. The use of the data cube technique in Earth observation enables the efficient analysis of vast amounts of satellite and other geospatial data by processing them as a single multidimensional structure [8]. Although the involvement of EO data cubes in remote sensing applications is not pioneering itself [9], it has been significantly modified in our research. We formalized the data cube structure, established interrelations with the land degradation drivers, embedded a novel probabilistic model to convolve the entire cube into a single land degradation map, and built an end-to-end cloud processing pipeline that implements a distributed mapping system. This enables sophisticated analysis of the entire data stack at once, supports the identification of hidden dependencies and enhances the reliability of outcomes. Moreover, sequential data cubes easily form a multidimensional time series and support unified extraction of trends and other temporal functions. Thus, the data cube technique is ideally suited for land degradation mapping. A specific constraint on the joint analysis of multidimensional data is to avoid duplicating the influence of the same driver, which mathematically, as a rule, manifests as a strong correlation across different layers of data. Therefore, before data products selection to include into a data cube, the physical nature of their data must be compared, and the inter-layer correlation must also be estimated.

The continuous improvement of methods and technologies for remote Earth observation is characterized by a gradual transition from raw satellite imagery to sophisticated, high-quality, well-validated data products that reflect the actual physical and biophysical parameters of the Earth's surface, under the analysis ready data (ARD) concept [10]. Therefore, in the approach proposed in this study, the original satellite images were not used, but rather the derived higher-level data products. From the indicators described in Table 1, seven ones were selected as most suitable for land degradation mapping and did not duplicate each other. Fig. 1 illustrates the composition of the data cube layers utilized for land degradation assessment within the study area.

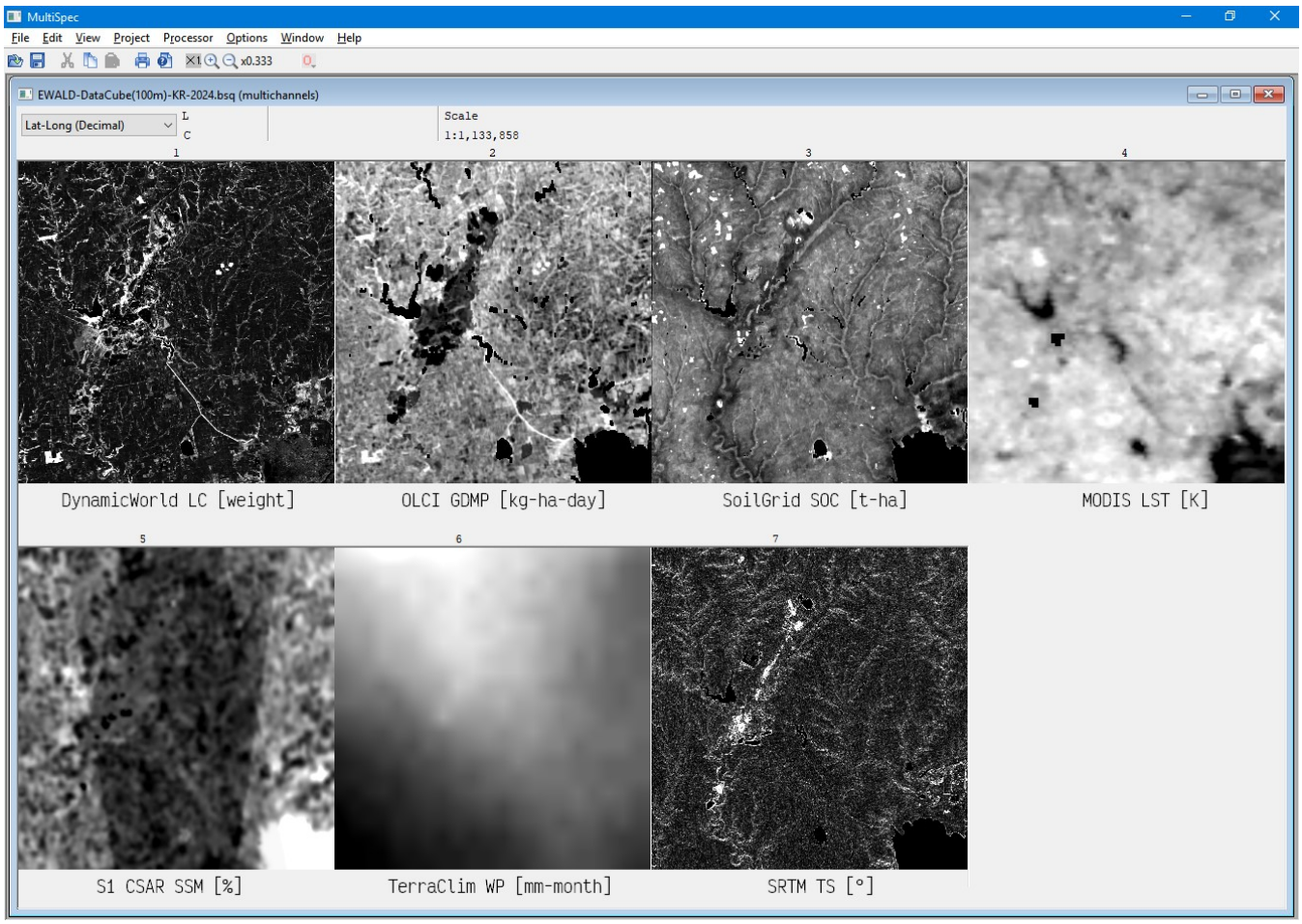

Figure 1. Data cube for land degradation assessment, loaded into MultiSpec software.

The approach used in our study differs from commonly practiced ones because it involves mapping not the actual land degradation according to definitions from agriculture, forestry, geobotany, urban planning, and so on, but the geoecological conditions that provoke and conserve it. This is considerably determined by the limitations of remote sensing methods, but in some cases it even offers an advantage: for example, degradation has not occurred yet, but the conditions for it have already taken shape. This is especially important for the early warning of land degradation, which is precisely the focus of the EWALD project.

So, the European research project EWALD – Earth Observation for Early Warning of Land Degradation at European Frontier (https://cordis.europa.eu/project/id/101086250) is precisely focused on developing such a system. Conceptually, the land degradation mapping in this project is based on the statistical fusion of biogeophysical geospatial data to reveal conditions in a specific land area under threat of degradation.

Several approaches to assessing land degradation with Earth observation data are known [11]. These approaches include the visual interpretation of satellite images [12], the application of land degradation indicators defined by the UN [13], and geospatial modelling of processes leading to land degradation, such as deforestation and soil erosion [14] among others. Most of them are based on the methodology implemented in the Trends.Earth geospatial tool, for example, in [15, 16]. Trends.Earth uses land productivity and other indicators recommended by the United Nations Convention to Combat Desertification (UNCCD) [17]. The weaknesses of Trends.Earth are a limited set of rather primitive remote indicators, such as the normalized difference vegetation index (NDVI), and the consideration of changes without regard to the absolute land condition. The advantages of Trends.Earth are its simplicity, implementation as an open QGIS plugin, and numerous actualizations in cloud-based geospatial services, for example, as [18].

In addition to Trends.Earth, other approaches can be applied for land degradation assessment. These include the revised universal soil loss equation (RUSLE) [19], evidence convergence [20], composite land degradation index (CLDI) [21], and optimal land degradation index (OLDI) [22] models, among others. Mapping land degradation using deep learning technologies, such as convolutional neural networks and/or transformers seems quite promising [23]. Unfortunately, as with other deep learning applications, the problem lies in the preparation of high-quality labeled datasets. While for relatively simple detection and classification tasks, datasets with millions of examples can still be created, developing and labeling the necessary amount of multidimensional data cubes for complex and non-obvious conditions inside geosystems is very challenging.

The objective of our research is to extend the scope of engaged Earth observation data, ensure a unified approach to their handling, formalize and algorithmize processing, and

develop a cloud-based geospatial tool for land degradation mapping with EO data cubes.

II. FORMALIZATION

The general paradigm of land degradation mapping involves transitioning from natural and anthropogenic drivers to remote indicators, which are EO data products, and then assessing the conditions of degradation occurrence in each spatial element of the study area according to an observed set of indicators [24].

The possibility of jointly considering heterogeneous data of various physical natures is ensured by a probabilistic model, through which the physical value of any indicator is transformed into a partial probability of land degradation [25]. The histogram of indicator value distribution is analyzed, from which the empirical probability is reconstructed [26], and then approximated by a smooth function over the entire range of indicator values, as shown in Fig. 2.

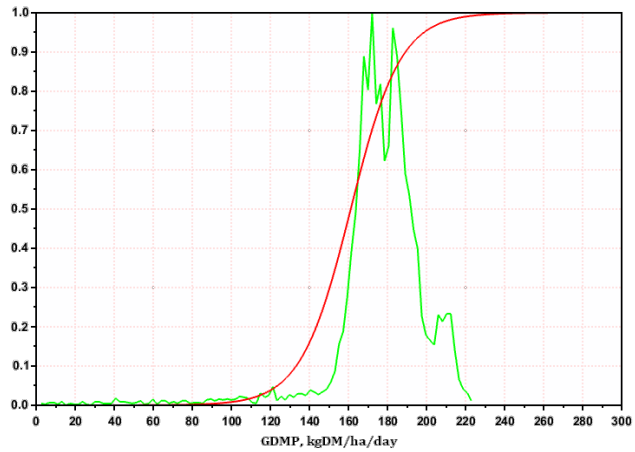

Figure 2. Indicator's histogram transformation into a probability distribution.
— – indicator's value histogram, — – approximated probability distribution

The partial probabilities for each indicator are fused into a single posterior probability of land degradation according to the Bayesian rule [27]. For simplicity and reliability of the probabilistic model, it is recommended to choose uncorrelated indicators corresponding to different drivers of land degradation.

The formalized workflow for mapping land degradation probability within the study area is described in the Fig. 3 flowchart.

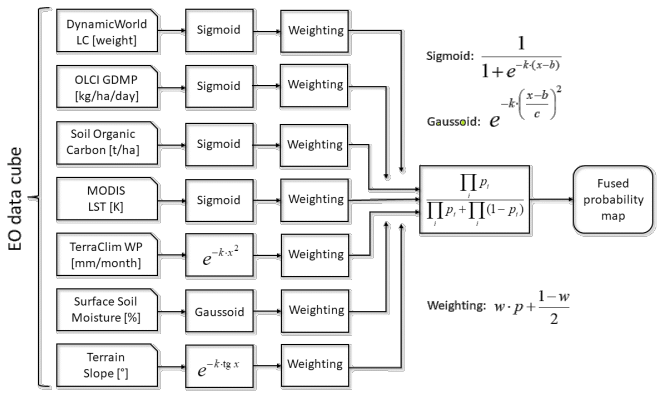

Figure 3. Flowchart of land degradation mapping with EO data cube.

The EO data cube consisting of seven data layers x, namely – land cover type, vegetation gross dry matter productivity (GDMP), soil organic carbon (SOC) content, land surface temperature (LST), water precipitation (WP), surface soil moisture (SSM), and terrain slope (TS) – is transformed into a cube of partial probabilities p using sigmoidal, gaussoid and exponential approximations. These probability maps are weighted by prior probabilities w and then fused into a single land degradation probability map.

III. IMPLEMENTATION

A geospatial tool for land degradation cloud mapping was elaborated in the framework of the ArcGIS Online platform. It was uploaded to the ArcGIS environment accessible to all users of this platform through a web-based interface [28]. Geospatial data cloud processing and result visualization were carried out according to the Formalization section workflow.

The developed tool was programmed in the Python programming environment. The Python programming language is used for computational logic, data normalization, and implementation of necessary functions [29]. The Python libraries were included for the development:

- NumPy for working with large arrays of data and applying mathematical transformations,
- ArcPy is used to link the script to the toolbox's graphical interface.

The geospatial tool structure has been defined and described by a UML diagram in Fig. 4.

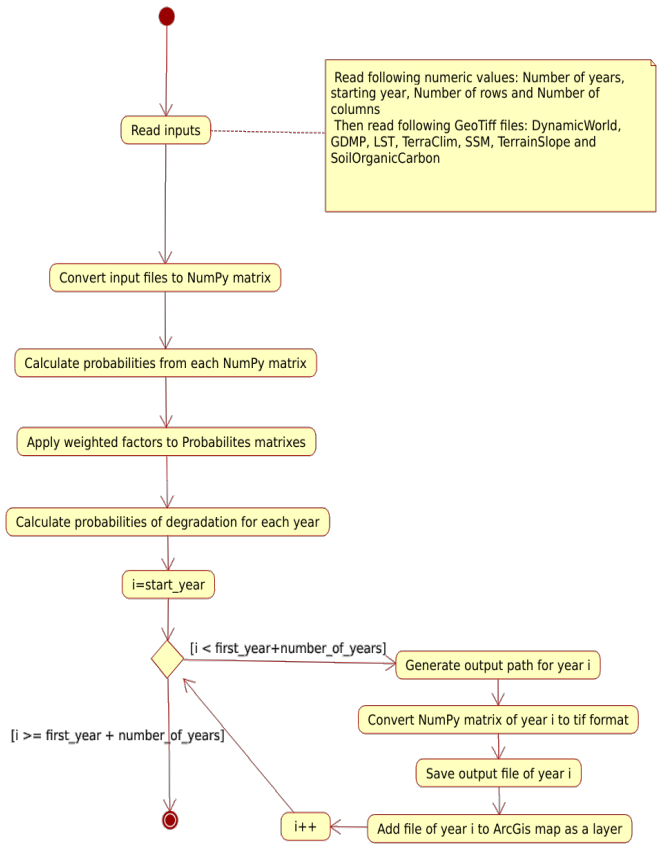

Figure 4. UML diagram of the developed geospatial tool.

Overall, the current implementation corresponds to the previously proposed architecture for land degradation early warning [30].

IV. DEMO

To provide a user-friendly interface, a custom toolbox has been created in ArcGIS Pro (Fig. 5). ArcGIS is a sophisticated geospatial software platform developed by ESRI, enabling comprehensive mapping and geographical data management. It provides advanced capabilities for visualizing spatial information, analyzing geographic patterns, and uncovering underlying trends. According to a benchmarking study [31], ArcGIS ranks highest among geographic information systems in terms of analytical tools, cartographic quality, editing functions, imagery integration, innovation potential, and technical support, as summarized in Table 2. The main functionalities of ArcGIS relevant to constructing an early warning system prototype include:

- Designing maps and visualizing spatial information;
- Performing spatial analysis and automated geographic data processing;
- Managing large-scale geographic datasets effectively;
- Facilitating web-based GIS for online sharing of maps and applications;
- Supporting applications in diverse domains such as urban planning, environmental monitoring, transportation logistics, and public health management;
- Analysis of geospatial raster data, including satellite imagery.

Table 2. The comparison of GIS

Feature / Tool	ArcGIS	QGIS	Google Earth Engine	GRASS GIS	MapInfo Pro
License	Commercial	Open-source	Free (research)	Open-source	Commercial
Ease of Use	High	Medium	Medium	Low	Medium
Customization	Medium	High	High (API-based)	High	Low
Web Integration	Excellent	Good	Excellent	Limited	Limited
Best For	Enterprise GIS	Flexible GIS	Remote sensing	Scientific GIS	Business GIS

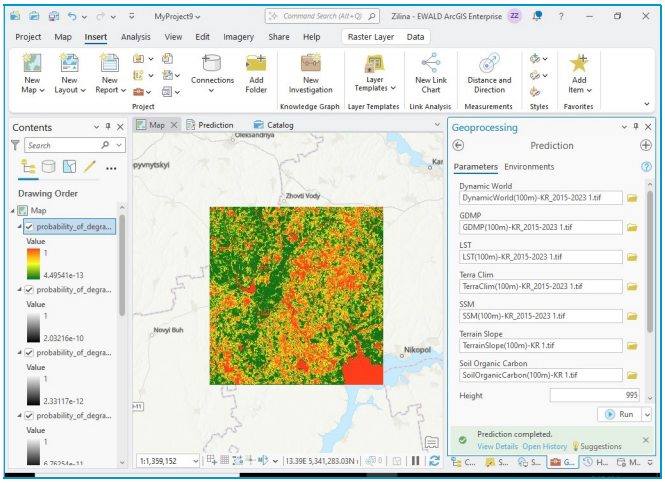

Figure 5. Developed geospatial toolbox in the ArcGIS environment.

This toolbox serves as an application interface for running calculations allowing the user to select input parameters, define the area of interest, and perform degradation probability calculations. The advantage of this solution is its integration into the GIS environment [32], which significantly simplifies the practical application of the analysis results. The toolbox was written in Python. The Python programming language is used for computational logic, data normalization, and the implementation of transformation functions. This language offers a wide range of scientific and numerical libraries [33], as well as broad support for geospatial data processing. Land degradation probability calculations were implemented as stand-alone Python modules, enabling easy replicability, transparency, and automation of the computational process. Python scripting integration into the Google Earth engine significantly enhances geospatial analysis capabilities [34].

The developed toolbox can be accessed online at the EWALD project official website (https://ewald-hub-ewald.hub.arcgis.com/). Currently, EO data cubes have been collected and regularized for two test regions of the project, namely Kryvyi Rih (Ukraine) and Zagora (Morocco). Land degradation probability maps covering a 10-year period have been produced, and land degradation forecasts for the study area for 2025-2028 have been obtained using ArcGIS tools (Fig. 6).

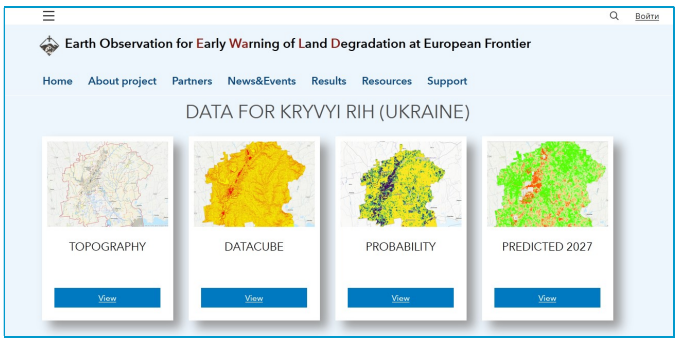

Figure 6. Online toolbox demo for land degradation mapping.

Unauthorized users can only view and scale the zoom of the existing maps. It should be noted that the portal can only be used to process data in a specific format such as data cubes. This presentation was described above and also discussed in detail in [30]. And initial data cubes should be downloaded by the tools of ArcGIS (Fig. 7) for the developed toolbox.

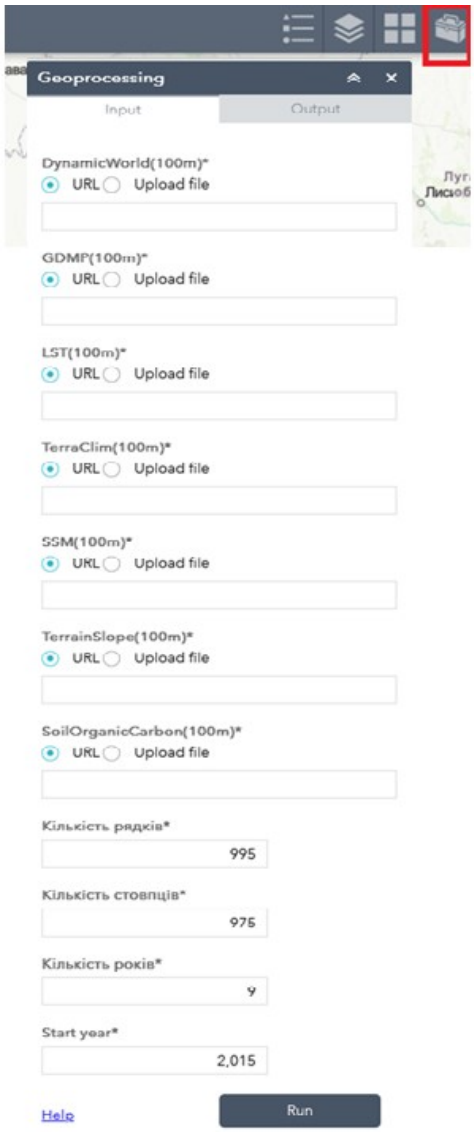

Figure 7. ArcGIS tool for downloading data cubes.

V. RISK ASSESSMENT

Evaluating risk is a critical step in monitoring and interpreting processes of land degradation. The notion of risk, though applied differently across fields, typically encompasses three elements: a set of potential adverse events, their likelihood, and the associated impacts. In this context, risk serves as a metric that captures both the presence and potential of a hazard, factoring in the inherent uncertainty of its occurrence and can be defined as:

$$R = y \cdot p, \tag{1}$$

where y stands for the intensity or occurrence rate of a hazard, and p represents its probability or another suitable evaluative measure.

Landscapes threatened by degradation are complex systems influenced by multiple interacting drivers. A comprehensive risk assessment must therefore account for the combined effect of various biogeophysical and human-induced stressors. The approach adopted here converts measurable EO-derived variables into probabilistic estimates of degradation susceptibility.

For a specific spatial element s, let I_{si} be the standardized value of a chosen indicator in land degradation at time point i. This value is transformed into a conditional probability of degradation using fitted distribution models (e.g., sigmoid or exponential curves), informed by historical data and domain expertise, consistent with the formalization described earlier. This conditional probability is interpreted as a composite hazard score. To evaluate temporal dynamics, two summary metrics are calculated over a given observation window:

$$K = \sum_{i=1}^{T} h_{si}\ , \tag{2}$$

$$K_T = h_{sT} - h_{s(T-1)}, \tag{3}$$

where h_{sT} and h_{si} are the hazard scores for the element (pixel) s at time point T (last interval) and i accordingly:

$$h_{si} = (I_{si} - I_{s(i-1)})/I_{max}, \tag{4}$$

or

$$h_{si} = (I_{si} - I_{s(i-1)})/I_{aver}, \tag{5}$$

where I_{max} and I_{aver} are the maximal and average values of a chosen indicator in land degradation in time interval from 1 to T.

Here, K represents the mean hazard level over the full period, while K_T reflects the hazard level at the most recent time point. Using these metrics, each spatial unit can be assigned to one of four discrete risk categories:

- **R3 (Acute Risk):** $K < 0$ and $K_T < K_{T-1}$. This signals a consistent and recently worsening trajectory toward degraded states.
- **R2 (Established Risk):** $K < 0$ and $K_T \leq K_{T-1}$. This indicates a historically negative trend that has recently plateaued or shown modest recovery.
- **R1 (Emerging Risk):** $K \geq 0$ and $K_T < K_{T-1}$. This corresponds to an overall past improvement that has recently reversed, suggesting increasing vulnerability.
- **R0 (Minimal Risk):** $K \geq 0$ and $K_T \geq K_{T-1}$. This denotes a sustained positive trend with stable or improving recent conditions.

This probabilistic categorization enables the creation of spatially explicit land degradation risk maps. It enhances early warning capabilities by highlighting regions where degradation is already advanced and where environmental conditions are deteriorating, thereby supporting timely, targeted land management interventions. The proposed evaluation considers the aleatory (statistical) uncertainty of initial data in satellite images, but these resources also entail epistemic uncertainty, which should be accounted for as well. Therefore, for the risk analysis, qualitative methods as Preliminary Hazard Analysis (PHA) or Hazard and Operability analysis (HAZOP) [35] should be used. These methods combine deductive (cause search) and inductive (consequence analysis) approaches to identify the initiating events of undesired sequences, in this case, land degradation. The risk is established as a combination of a given event/consequence and a severity of the same event/consequence. This will enable ranking of events/consequences in a risk matrix (Fig. 8). In the context of the land degradation risk assessment, such a matrix is completed for each risk category introduced above. The frequency characteristic is the number of locations for each risk category in the region under consideration is described by Fig. 8.

	Frequency				
	Very unlikely	Remote	Occasional	Probable	Frequent
Acute Risk					
Established Risk					
Emerging Risk					
Minimal Risk					

Legend:

Acceptable

Acceptable with further monitoring

Not acceptable

Figure 8. Risk matrix for qualitative risk assessment.

So, discrete risk gradations, associated with the input continuous probabilistic value can be obtained in this way. Risk level discretization is especially useful for subsequent visual analysis by an expert [36].

VI. CONCLUSIONS

Thus, the previously proposed approach and architecture for land degradation cloud mapping with Earth observation data cubes have been implemented in an online software toolbox on the ArcGIS platform. The toolbox runs a probabilistic model that converts biogeophysical EO indicators of land degradation into partial probabilities. Subsequently, the partial probabilities are fused into a single final probability of land degradation according to the Bayesian rule. Just the final probability is then mapped. The conducted implementation enables a deeper, more intimate, and visually appealing representation of formalized knowledge about land degradation, thereby increasing awareness of the condition and dynamics of land resources. The proposed approach is relatively simple, updatable, and cost-effective compared to field observations.

The scientific novelty of the proposed approach lies in the substantiation and selection of remotely sensed land degradation indicators from a wide pool of available analysis-ready data products; the algorithmic formalization of geospatial modelling over a heterogeneous data cube; the computational implementation of an end-to-end processing pipeline in a distributed cloud environment; and the coupling of the output land degradation map with geospatial risk assessment.

Future work will focus on large-scale validation of the obtained results within the test regions. Ground-truth data will support the precise calibration of the probabilistic models and may lead to changes or expansions in the selection of the EO indicators involved. Moreover, as is already evident, various physiographical regions will require adaptation and adjustment of land degradation mapping parameters. This represents another necessary direction for future research.

Theoretically, it can be considered not only tuning system parameters for different regions of the Earth but also replacing indicators included in the data cube. Nevertheless, these adjustments will not alter the fundamental structure of the system or its workflow.

Therefore, during the computer implementation, it will be advisable to split off the model core not only from the input data but also from processing parameters such as the set of probability approximating functions and weighting factors.

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