Development of Croatian Land Information System

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doi: 10.5281/zenodo.11585039

Abstract: One of the main goals of the LIFE CROatian Land Information System (CROLIS) project is development of a harmonized land monitoring data model that enables integration and processing of Land Cover (LC), Land Use (LU) and land management data from different data sources (national spatial data and publicly available spatial data within the Copernicus mission and services) and its use for a variety of purposes such as Land Use, Land-Use Change and Forestry (LULUCF) reporting and accounting purposes in line with the requirements of international (United Nations Framework Convention on Climate Change, UNFCCC and Paris Agreement, PA) and EU legislation, robust basis for planning and implementation of Greenhouse Gas (GHG) mitigation actions in the land use sector, etc.

Within the project the LU conceptual model was created by the recommendations of European Environment Agency (EEA) when creating CLC+ layers while the LC conceptual model includes (in this early stage of development) a minimum of 6 LC categories identified using newly Object Based Image Analysis (OBIA) approach methodology. The newly developed methodology is applicable throughout the Republic of Croatia, where Accuracy Assessment is correlated with input vector data.

Keywords: Life CROLIS; LULUCF; LC; LU; OBIA.

1 Introduction

To meet the EU's goals of at least a 55% reduction in greenhouse gas emissions by 2030 and creating conditions for climate neutrality by 2050 and fulfilment of the LULUCF reporting requirements under the UNFCCC and PA (Penman et al. 2003), member countries need to establish a comprehensive national geographically explicit system for land monitoring by 2030. In response to the obligations, Croatia in close partnership with the Croatian land monitoring community that includes all authorities and major stakeholders concerned by the monitoring of Land Cover and Land Use changes launched the CROLIS project. One of the main achievements of the CROLIS project is development of a harmonized land monitoring data model which follows EAGLE concept (the goal of EAGLE is to provide tools for resolving ambiguities within nomenclature, and for comparisons and translations between different nomenclatures) that enables integration and processing of Land Cover (LC), Land Use (LU) and land management data from different data sources and its use for a variety of purposes. This new model will be designed by integrating the existing LC and LU information systems and data in Croatia in combination with freely available products (SPOT, Landsat, Aster and Sentinel-2 satellite imageries) and upcoming multi-temporal observations in order to be able to trace back and identify LC and LU changes. Layers for historical years will also be created within the project.

2 CROLIS Land Use Layer

CROLIS Land Use layer was created according to the principles of creating Corine Land Cover + (CLC+) layer. CLC+ layer is the next generation product within the CORINE (Coordination of Information on the Environment) Land Cover (CLC) product. CLC is a comprehensive, detailed, and harmonized dataset on the land cover and land use of the European continent created within COPERNICUS in 1980. CLC product offers a pan-European land cover and land use inventory with 44 thematic classes with new status and change layers updates for every six years (Büttner et al. 2021). In order to improve spatial resolution and separation of land cover from the land use, the EEA made recommendations for the creation of the CLC+ layer.

The CLC+ layer should represent the land use map of each country within the EU Copernicus Land Monitoring Service (CLMS). The basis for creating the CLC+ layer is the spatial data of the relevant national institutions which are categorized by EAGLE (Arnold et al. 2023) translation table. Spatial data are mapped in a raster format according to a hierarchical table of categories.

The CROLIS Land Use layer for the Republic of Croatia (Figure 1) was created based on the spatial data of Croatian Forests, the Paying Agency for Agriculture, Fisheries and

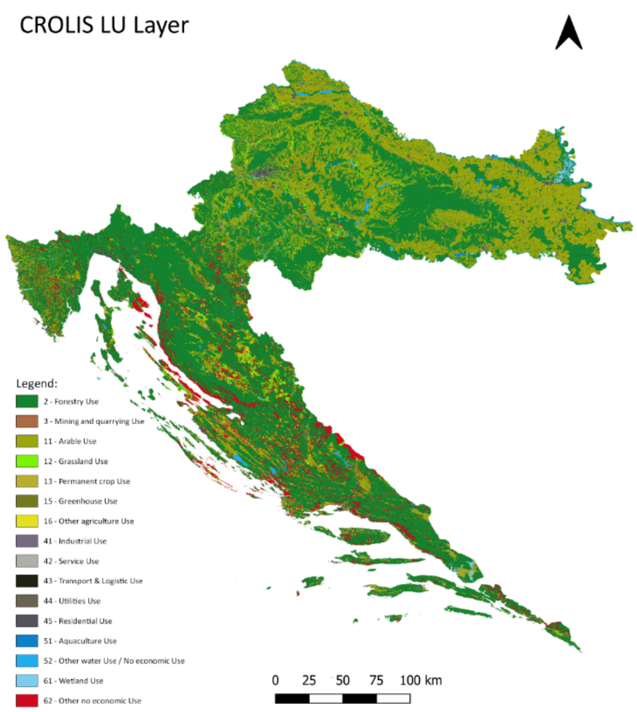

Figure 1. CROLIS LU Layer.

Rural Development, Croatian Roads, Croatian Waters, Croatian Railways, Croatian Highways, the State Geodetic Administration, the Ministry of Economy. The CROLIS LU layer consists of 6 Level-1 categories and 16 Level-2 categories. The hierarchical table proposed by the EEA was used to create the wall to wall CROLIS LU layer, and the spatial resolution of the final raster layer is 5m.

3 CROLIS Land Cover Layer

One of the main components of the CROLIS land information system is the Land Cover status layer, as well as a land cover layers for the historical period. Historical land cover layers will be created as a sample grid system.

At this stage of CROLIS development, the Land Cover status layer includes 6 LC categories: Woody surfaces, Crops surfaces divided into Annual Crops Surfaces and Perennial Crops Surfaces, Grassland Surfaces, Water Surfaces, Artificial Surfaces and Bare land Surfaces. Figure 2 shows the present state of the Land Cover Conceptual model. The final number of LC classes will be defined in cooperation with all project partners upon the implementation of all necessary activities (development of the layer for 2020 and implementation of sampling for the historical period) in the test areas.

Land cover status layer has been crated based on Object Based Image Analysis (OBIA). Object-based image analysis is a method for classifying satellite imagery by segmenting neighboring pixels into shapes with a meaningful representation of the objects. OBIA is usually performed in two steps: (1) image segmentation, and (2) classification. Image segmentation is defined as a method of dividing an image into homogeneous regions. Classification is the process of adding predefined categories to segments. Classification can be done based on threshold; it can be supervised (machine learning) as well as unsupervised (Blaschke 2010, Blaschke et al. 2014).

Input raster data for creating the LC status layer are:

- The digital state orthophoto map (DOF) in RGB and CIR production, official state map with the spatial resolution 0.5 m
- LIDAR nDSM. Normalized Digital Surface Model (nDSM) represents the relative height of natural (vegetation) and constructed (buildings, bridges, etc.) objects located on the Earth's surface in relation to the Earth's surface itself. nDSM is obtained as difference between Digital Surface Model (DSM) and Digital Terrain Model (DTM). NDSM created for the needs of the CROLIS project has spatial resolution 1 meter.
- Sentinel-2 satellite imageries with 13 bands in the visible, near infrared, and short-wave infrared part of the spectrum, spatial resolution of 10 m, 20m and 60m with revisit time 5 days.

In addition to raster data, national vector data from reference national institutions are also used to create the LC status layer.

Within preprocessing, from the raster bands DOF5 and Sentinel-2, corresponding radiometric spectral indices NDVI, NDWI, NDSI, NDBI, SAVI and EVI were made.

Normalized difference vegetation index (NDVI) is sensitive to vegetation greenness and is useful in understanding vegetation density and assessing changes in plant health. NDVI is calculated according to the formula (Gandhi et al. 2015):

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \quad (1)$$

Normalized Difference Water Index (NDWI) is sensitive to liquid water. NDWI is calculated according to the formula (Picoli et al. 2019):

$$NDWI = \frac{(G - NIR)}{(G + NIR)} \quad (2)$$

Normalized Difference Soil Index (NDSI) is sensitive to soil moisture, organic matter content, and texture. NDSI is calculated according to the formula (Deng et al. 2015):

$$NDSI = \frac{(R - B)}{(R + B)} \quad (3)$$

Normalized Difference Built-up Index (NDBI) is sensitive to artificial objects. NDBI is calculated according to the formula (Bhatti and Tripathi 2014):

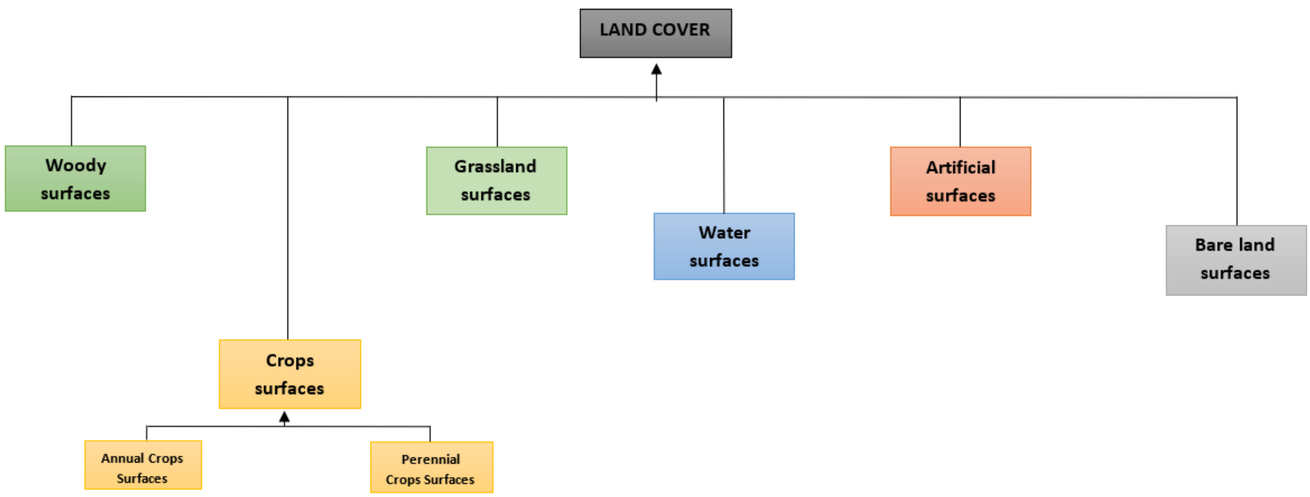

Figure 2. Land Cover Conceptual model.

$$NDBI = \frac{(SWIR - NIR)}{(SWIR + NIR)} \quad (4)$$

The Soil-Adjusted Vegetation Index (SAVI) method is sensitive to vegetation. SAVI minimize soil brightness influences using a soil-brightness correction factor. SAVI is calculated according to the formula (Jiang et al. 2008):

$$SAVI = \frac{(NIR - R)}{(NIR + R + L)} * (1+L) \quad (5)$$

Enhanced Vegetation Index (EVI) is sensitive to vegetation, especially in areas with dense vegetation. EVI is calculated according to the formula (Jiang et al. 2008):

$$EVI = 2.5 * \frac{(NIR - R)}{(NIR + 6R - 7.5B + 1)} \quad (6)$$

In order to separate all the mentioned LC categories, a newly developed methodology has been implemented in the eCognition software. Firstly, the segmentation is performed in 2 steps with a smaller and larger scale parameter in order to separate all the segments well. Categories are assigned to segments based on threshold values and conditions of input data. After this step, there are still uncategorized segments. The categories of uncategorized segments will be assigned in the next step using machine learning classification. All categorized segments are then converted into training samples for machine learning models. Machine learning is performed based on raster input data and its statistics, radiometric spectral indices, and geometric characterization of segments, such as relates to other segments. The Support Vector Machine (SVM) algorithm with Radial basis function kernel (rbf) has been used to train the model. SVM is based on the linear classifier with the optimal margin in the feature space and thus the learning strategy is to maximize the margin, which can be transformed into a convex quadratic programming problem (Wang 2022). The result of the land cover classification in the test area Osijek is shown in Figure 3.

After the classification, the accuracy assessment was carried out on two test fields, the Istra test field and the Osijek test field. On the Istra test field, the kappa coefficient is 0.89, and the overall accuracy is 0.92, while on the Osijek test field, the kappa coefficient is 0.94, and the overall accuracy is 0.96. One of the main reasons for the difference in kappa coefficients is that the input ARKOD layer containing information of the categories Crops surfaces and Grassland surfaces is better defined for the test area Osijek.

4 Conclusions

The establishment of such a complex land system requires the involvement and participation of all national institutions. The CROLIS project is the first project of its kind that will include the EAGLE system and will be built in accordance with all recommendations for the creation of CLMS layers so that its final products can contribute to numerous fields. The newly developed land cover classification methodology is based on national raster and vector data, and for the first time, nDSM from Lidar

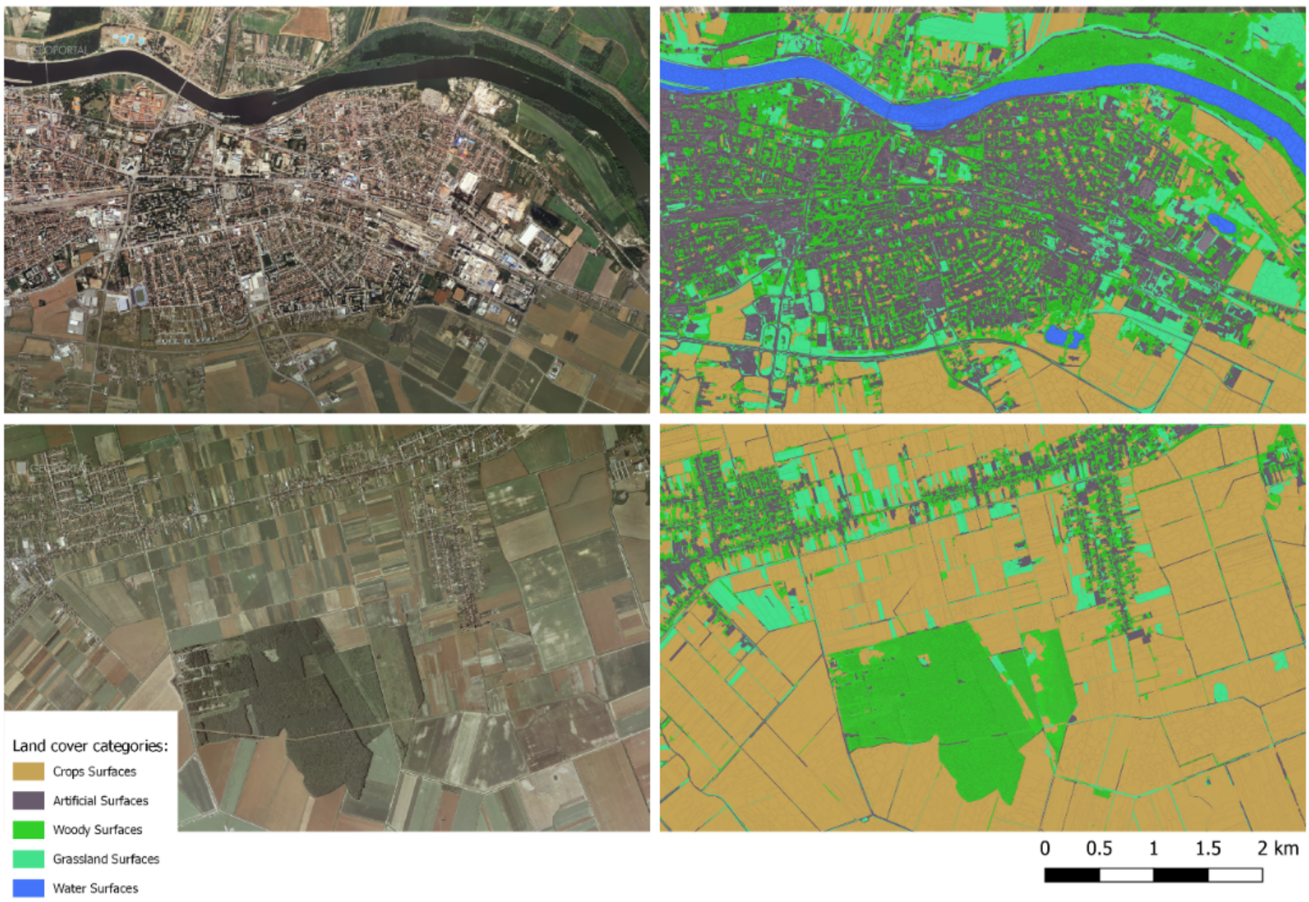

Figure 3. The result of the classification in the test area Osijek.

measurements for the whole of the Republic of Croatia has been used for land cover detection. Within the CROLIS project, the creation of an improved ARKOD+ layer is planned. Therefore, this is only the first version of the developed methodology for land cover detection and will be upgraded according to new input data and future needs that the system should meet.

Acknowledgments: LIFE CROLIS project is co-financed by the LIFE program of the EU.

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