Ethel Ogallo
12413884
Application Development (Earth Observation)

GUI for Agricultural Land Cover Change Detection using Object-Based Time Series Analysis in eCognition

Introduction

This report documents the development of a graphical user interface (GUI) for detecting agricultural land cover change using Object-Based Image Analysis (OBIA) on Satellite Image Time Series (SITS) in eCognition. The main aim of the application is to automate the import of SITS data, calculate relevant multi-temporal vegetation indices, detect change using these indices, classify land cover change and export these results for further use.

Study Area and Data

The study area selected was Burgenland Austria because of its heterogenous agricultural landscape as shown in figure 1.

For the SITS, Sentinel-2 imagery was downloaded from Copernicus EO Browser monthly for the year 2023. Nine cloud-free images were selected excluding January, March, April which were too cloudy for the analysis.

Vector land parcel data for Austria was also downloaded from data.gov.at to be used as the reference layer for OBIA workflow.

Figure 1 Study area: Burgenland, Austria in Copernicus Browser

The S2 images downloaded as SAFE files were pre-processed in QGIS where the images were clipped to the AOI as well as the Land parcel shapefile. For the S2 images, the relevant spectral bands were stacked: **B2**(Blue), **B3**(Green), **B4**(Red), **B8**(NIR), **B11**(SWIR1), **B12**(SWIR2). The resulting images for each month were the base SITS image for the analysis in eCognition.

Methodology

1. Project setup

The project followed the structure below to ensure clarity and effective data management especially useful in the architect GUI.

```
\ProjectFolder\
│
├── ChangeDetection_App\
│   └── Action_Library\
│       ├── ChangeDetection_ruleset.dcp
│       ├── ChangeDetection_Solution.dax
│       └── ...
│
├── Customized_Import\
│   ├── GRVI_ChangeDetection_Import.xml
│   ├── Import_Satellite_Images.xml
│   ├── NDVI_ChangeDetection_Import.xml
│   └── SAVI_ChangeDetection_Import.xml
│
└── Data\
    ├── 202302.tif
    ├── 202305.tif
    ├── ...
    ├── 202312.tif
    └── INSPIRE_SCALEGE_2023-2.shp
```

2. Rule set development

2.1 Import data

A custom import was created to allow batch loading the multiple images and the land parcel. The images and the land parcel shapefile are stored in one folder, ~*\Data* and this was selected as the root folder with one image chosen as the master file as shown in figure 2. The land parcel shapefile was the defined in the thematic layers tab. This custom import was then saved under the folder ~*\Customized Imports\ Import_Satellite_Images.xml+*

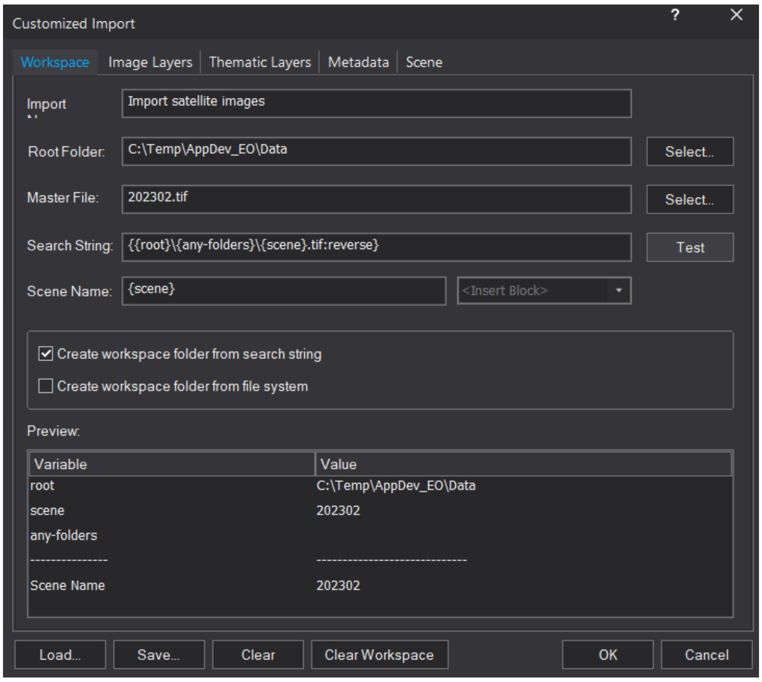

Figure 2 Custom import for the SITS data

2.2 Indices Computation

For analysing change in agricultural land cover the vegetation indices computed were Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Green Red Vegetation Index (GRVI) using the index layer calculation algorithm.

NDVI measures vegetation health and density using bands NIR and Red returning values ranging from -1 to +1.

$$\mathbf{NDVI = (B8 - B4) / (B8 + B4)}$$

SAVI, useful for partially vegetated areas, modifies NDVI with a correction factor to reduce interference of soil brightness.

$$\mathbf{SAVI = [(B8 - B4) \times (1 + L)] / (B8 + B4 + L), \text{ with } L=0.5}$$

GGRVI, useful for differentiate crop types., using red and green bands.

$$\mathbf{GRVI = (B3 - B4) / (B3 + B4)}$$

The analysis job process was used to batch compute each of the indices per scene. The result was a project for each index containing a layer for each time step therefore in total a project would include nine layers.

In preparation for the next step, using customized import, the exported projects were imported into the workspace where each layer was named after the scene to identify which time step it was from.

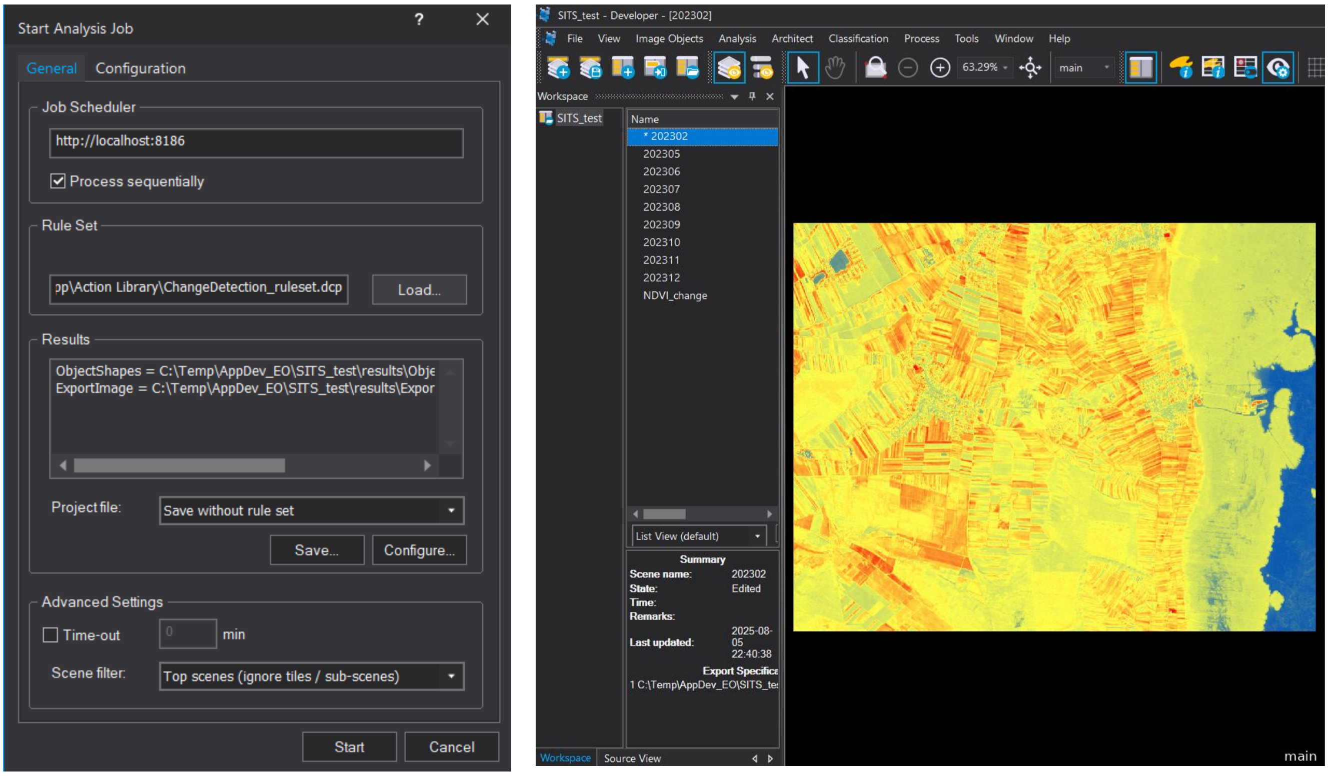

Figure 3 a) Analysis job window, b) Computed NDVI layer for one image.

2.3 Difference Layers

For temporal change detection, the difference layers were calculated between consecutive months using the layer arithmetic algorithm for all the time steps.

The difference layers were such that:

$$\mathbf{\Delta Index}_{\mathbf{T1\ to\ T2}} = \mathbf{Index}_{\mathbf{T2}} - \mathbf{Index}_{\mathbf{T1}}$$

Figure 4 shows the NDVI difference layers visualization where distinct variations are observed in some areas which could be the agricultural land with different crop types.

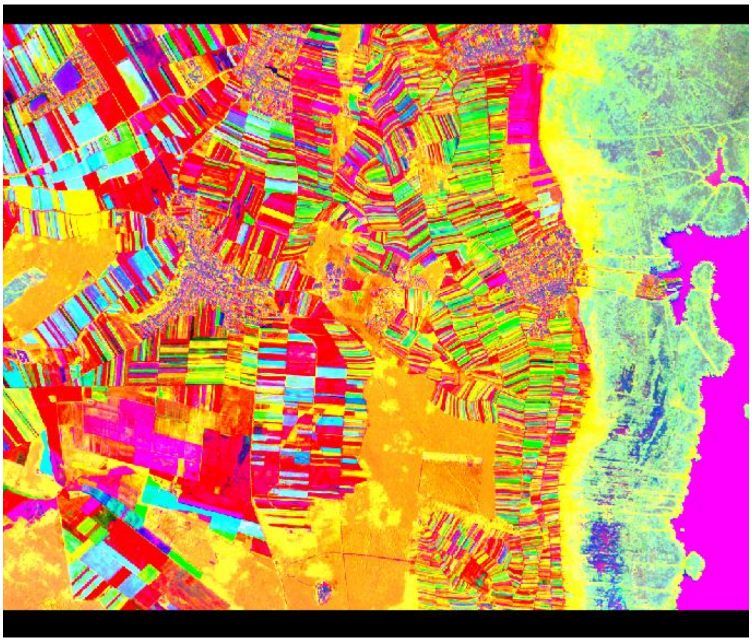

Figure 4 NDVI difference layer where Layer 1 = T1 to T2, Layer 2 = T2 to T3, layer 3 = T3 to T4

2.4 Multi-resolution Segmentation

Multi-resolution segmentation using scale parameter 50, shape 0.1 and compactness 0.5 and including the land parcel as thematic layer. The thematic layer acts as a guide in the segmentation giving objects within the land parcel boundary but also outside this.

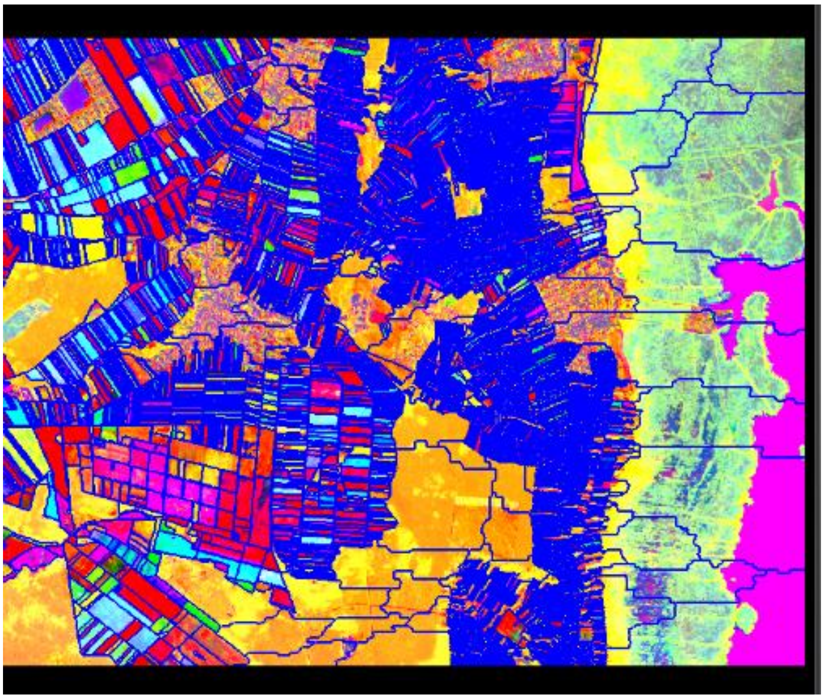

Figure 5 Multiresolution segmentation using thematic layer

2.5 Classification

Using the "Assign Class" algorithm, segments not overlapping land parcel layer were classified as *non-agricultural*. These were merged into one class object as shown in figure 6.

The remaining objects were categorized, example figure 7, based on index difference statistics:

The classification process used a simple uniform threshold applied to difference layers for easier interpretation. The classification rules applied to each difference layer was such that:

- Mean ≤ **-0.1** → Extreme Negative Change
- Mean ≤ **-0.01** → Negative Change
- Mean = **0** → No Change
- Mean ≥ **0.01** → Positive Change
- Mean ≥ **0.1** → Extreme Positive Change

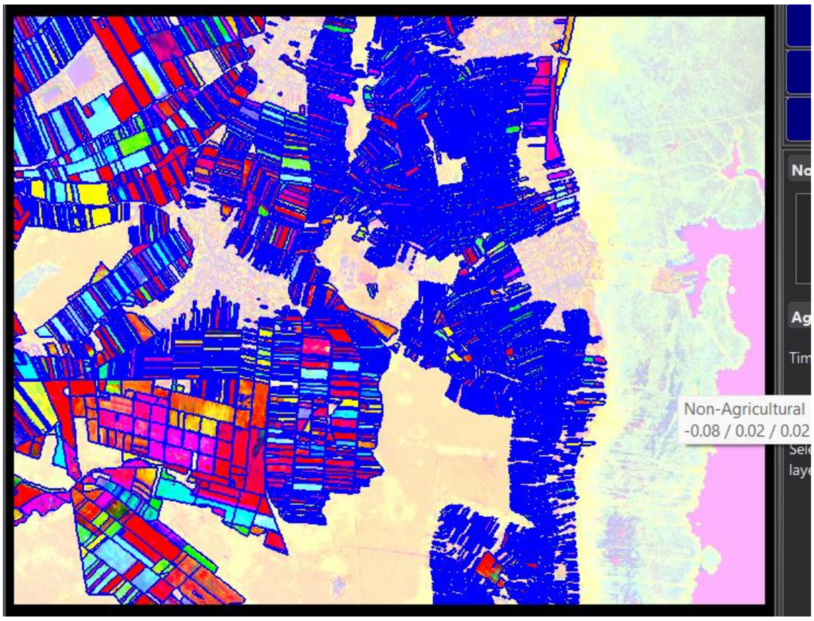

Figure 6 Classification of the non-agricultural land (in white

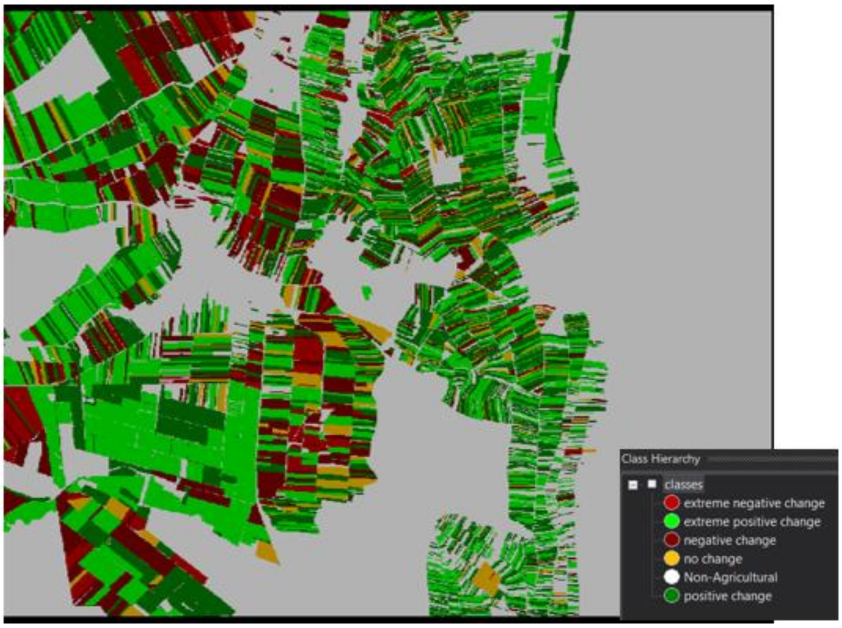

Figure 7 NDVI classification result (T4 to T5)

2.6 Export results

The classification results were exported for all the difference layers as a shapefile with each mean difference layer per time step as an attribute for each object. This can be used for further analysis or reporting.

Results

Architect GUI

The main goal was to develop a GUI using eCognition for change detection classification. This was developed by implementing the ruleset described in the methodology above. The main steps were organized in buttons and actions that execute the processes described in the methodology as well as shown in the figures 8-13.

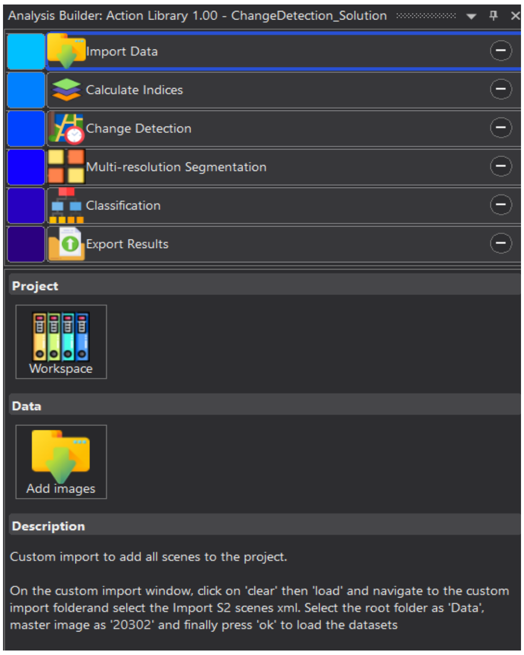

Figure 8 Import Images

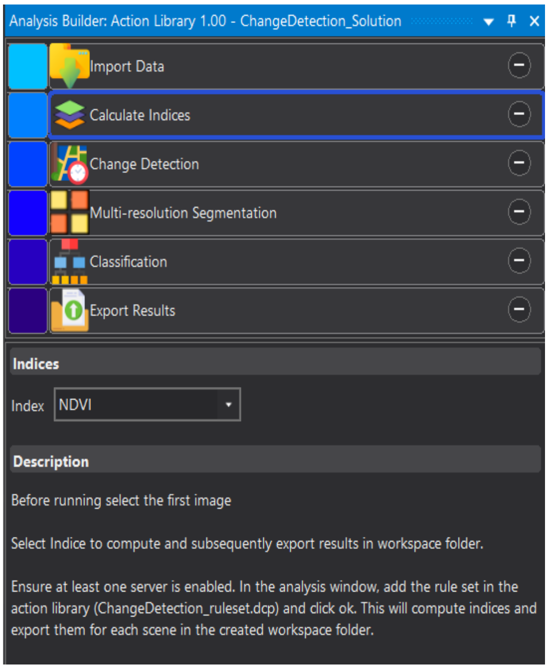

Figure 9 Calculate Indices

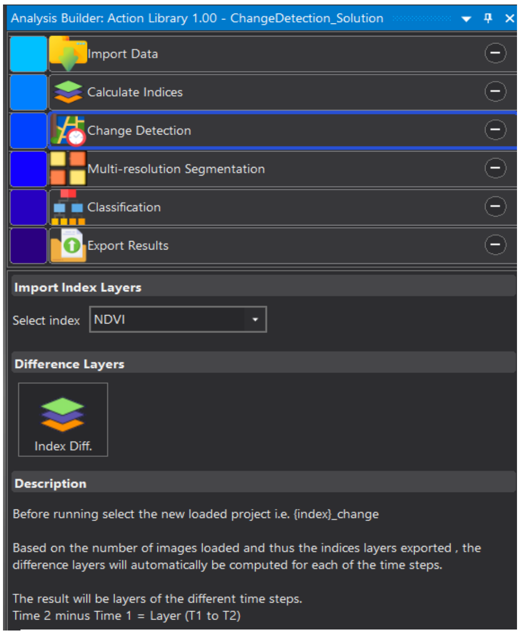

Figure 10 Change Detection

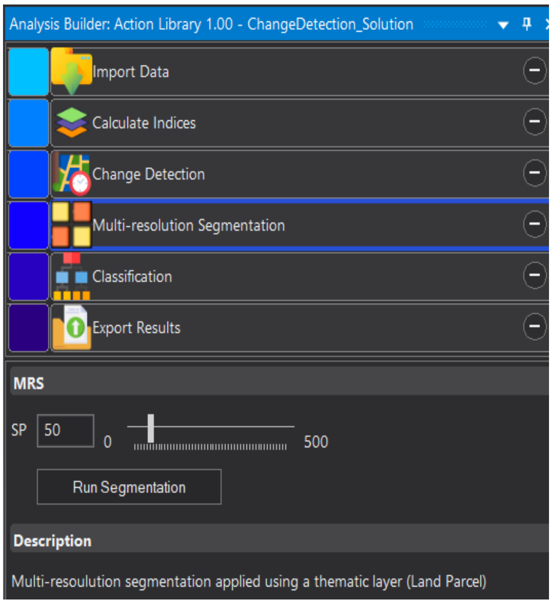

Figure 11 Segemnetation

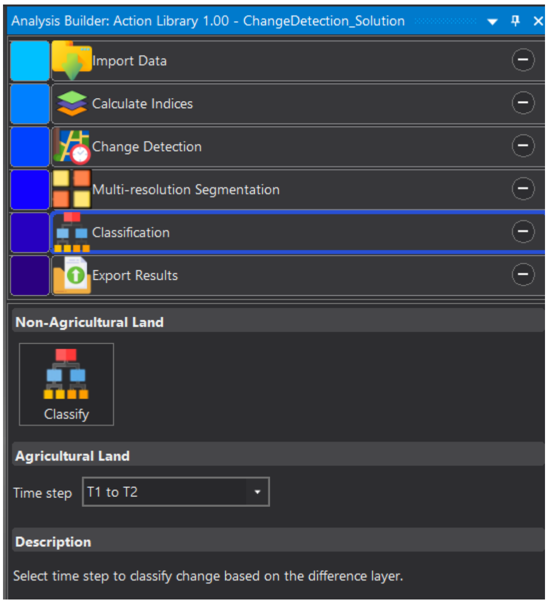

Figure 12 Classification

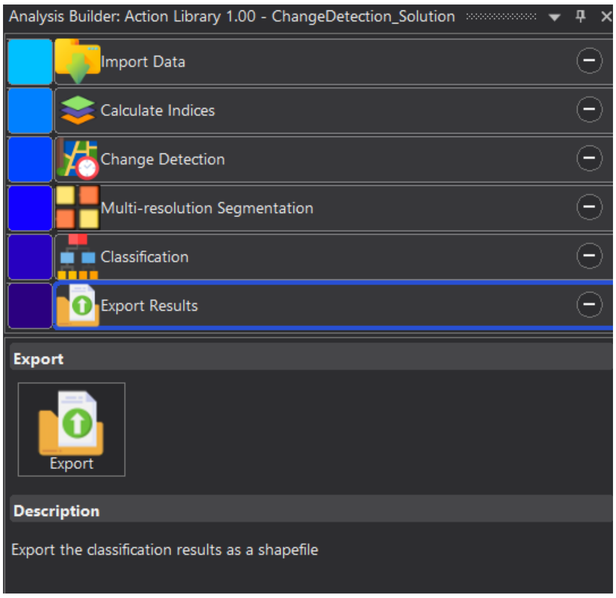

Figure 13 Export Results

Classification results

The steps conducted in the application resulted in the classification of the change detection based on the index. Below in figure 14-16 shows the NDVI change classification for the first four temporal difference layers: February–May, May–June, June–July, and July–August.

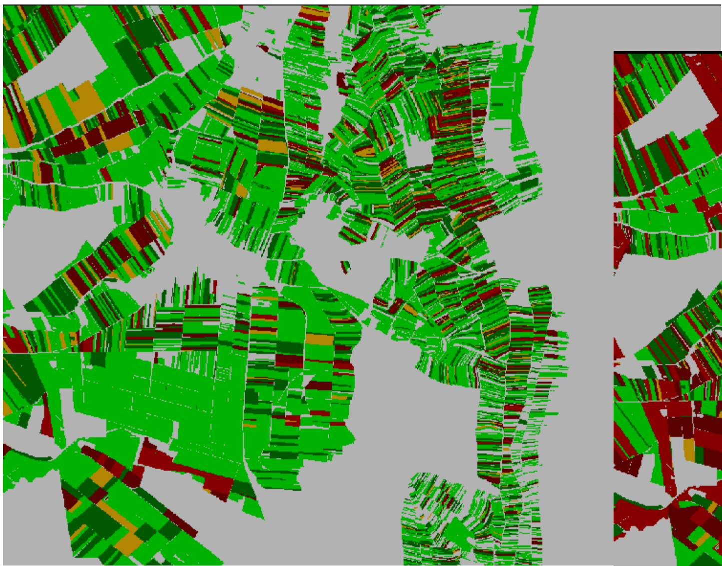

Figure 14 Feb-May NDVI Change

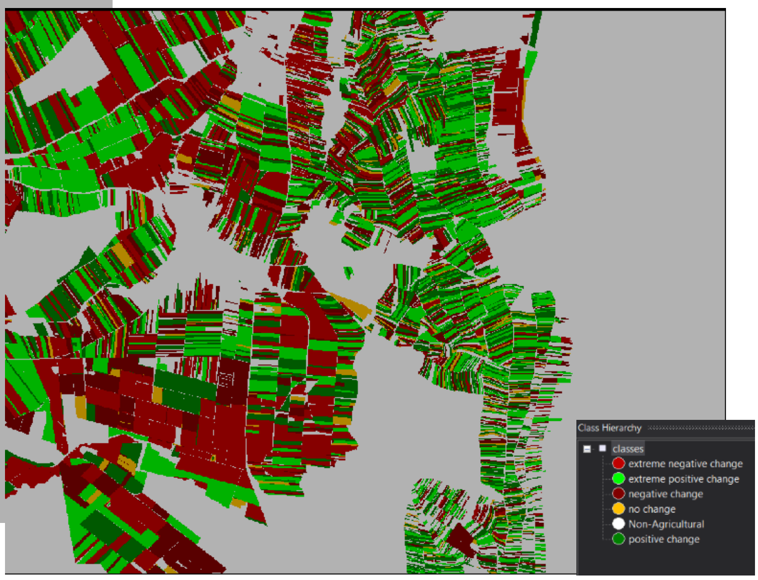

Figure 15 May - Jun NDVI Change

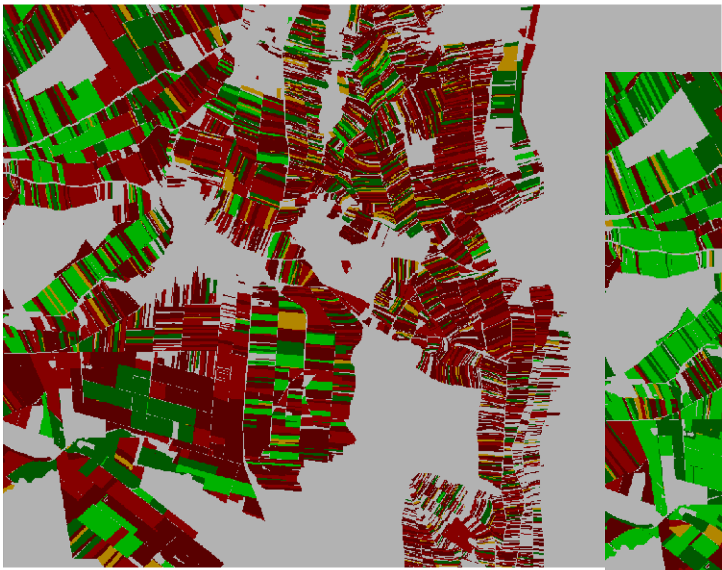

Figure 86 Jun-Jul NDVI Change

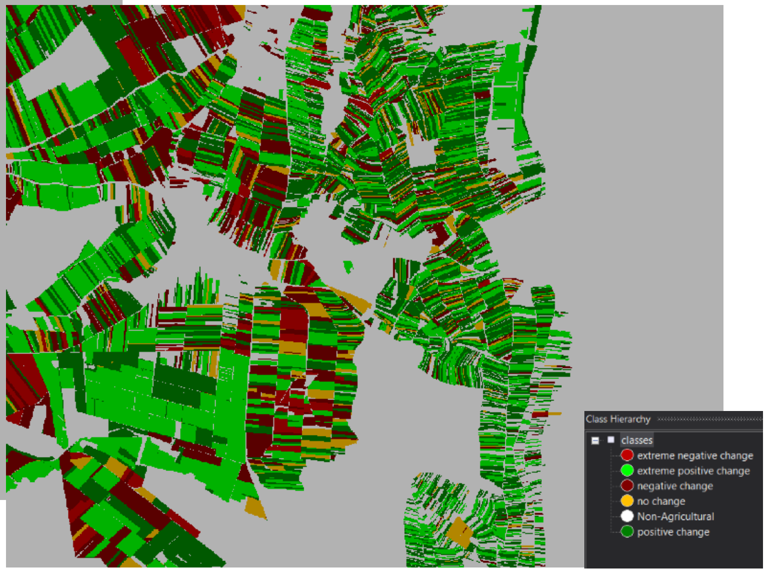

Figure 97 Jul-Aug NDVI Change

Figure 14 (Feb-May) shows more positive changes in NDVI values, indicating an increase in crop growth. On the other hand figure 15 (May-Jun) has an increase in the negative change class but still a moderate presence of positive change class. This could correspond with harvesting of winter crops and increase in temperature as the seasons are shifting into summer. Figure 16 (Jun-Jul) shows a higher increase in extreme negative NDVI change and this could also be accounted to the summer season, crop rotation or harvesting activities. Figure 17 (Jul-Aug) shows an increase in postive and extreme postive NDVI change likely corresponding to planting season.

Conclusion and Limitations

This project developed a simple GUI for agricultural land cover change detection using object-based time series analysis in eCognition in Burgenland, Austria. The integration of multi-temporal Sentinel-2 imagery, selected vegetation indices, and a parcel-based thematic vector layer allowed for robust monitoring of seasonal crop dynamics.

One main limitation was using the Land parcel vector as a thematic layer for segmentation as well as classification. This worked in this context as both the scenes and the land parcels aligned temporally i.e. 2023. However, given that crop land extents vary temporally this may lead to poor segmentation and further misclassification if a different thematic layer is used with temporally different images.

Comparing the change maps generated for the different indices computed (NDVI, SAVI, GRVI), the patterns are similar with minor variations. This could be due to the fact a uniform threshold was used to simplify the workflow. The threshold selected was for detecting broad changes and may not fully capture crop-specific dynamics. Further refinement could integrate crop-specific threshold to improve classification.