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| **MAIL**: Identifying Marginal Lands in Europe and strengthening their contribution potentialities in a CO2 sequestration strategy | |

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# Abbreviations

|  |  |
| --- | --- |
| **Term** | **Explanation** |
| AVHRR | Advanced Very High Resolution Radiometer |
| CFMASK | C Function of Mask |
| ETM+ | Enhanced Thematic Mapper |
| GEE | Google Earth Engine |
| IDL | Interactive Data Language |
| LandTrendr | Landsat-based Detection of Trends in Disturbance and Recovery |
| LT | LandTrendr |
| ML | Marginal Land |
| MODIS | Moderate-Resolution Imaging Spectrometer |
| NBR | Normalized Burn Ratio |
| NDVI | Normalized Difference Vegetation Index |
| NIR | Near-Infrared |
| OLI | Operational Land Imager |
| SWIR | Short Wavelength Infrared |
| TM | Thematic Mapper |
| UI | User Interface |
| USGS | United States Geological Survey |
| YoD | Year of Detection |

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Executive Summary

Being able to detect changes related with the Earth’s surface characteristics is a fundamental step in understanding the way the interaction between human and natural events affects the environment around us. The ***MAIL*** Map Portal includes a series of tools that range from ways to identify potential marginal lands, to estimating biomass volume and calculating the carbon sequestration. However, in order to be able to fully support the user who will be interested in implementing an afforestation or reforestation project, according to the definitions of ***MAIL***, a tool that will support the user in the monitoring phase of the project should be included as well.

The scope of Task 4.4 is to develop a tool that will be able to aid the user in the monitoring (and not only) phase of the project, and to present a pilot case study to validate the functionality of the tool. Since the ***MAIL*** Map portal is developed on Google Earth Engine platform, the tool to be implemented should also be designed to work on GEE. The LandTrendr is a web application developed on GEE, designed to identify changes in a time series of satellite images and to generate trajectory-based spectral time series data with little inter-annual signal noise. LT offers a few change detection UI applications, from which the Change Mapper was utilized for this Task. The various settings of Change Mapper that can be parametrised depending on the study’s scope were described on Chapter 3 Data and software acquisition.

In the pilot case study phase, three different scenarios were explored, representing three different forest succession stages-conditions. These scenarios were the Deforestation, Stable Forest, and Afforestation/Reforestation. The suggested respective settings for the fine-tuning of the tool according to the authors in order to deliver reliable results depending on the scenario to be investigated were discussed in Chapter 4 Workflow development – Tool implementation. Finally, the proposed tool was applied on some pilot areas and some exemplified outcomes were delivered in Chapter 5 Pilot Case Study.

Finally, it is concluded that the Change Mapper application of LT-GEE is a good fit for the scope of this task and it can accompany the rest of the tools on the ***MAIL*** Map Portal.

Introduction

For the realization of the ***MAIL*** project a series of tools have been developed and implemented on the ***MAIL*** Map Portal such as tools for the identification of potential marginal lands, the estimation of sequestered carbon dioxide, the estimation of biomass volume, a carbon calculator and so on. These tools are mainly related with the pre-implementation phase of a afforestation/reforestation project, which leaves a gap in the post-implementation phase of a project.

Forest monitoring is primarily concerned with detecting and calculating land conversion rates, as well as assessing carbon stocks in the forest ecosystem. For detecting forest change and updating existing forest maps, satellite remote sensing is widely used. Change detection research has traditionally centered on comparing two images, one before and one after a change (Coppin et al., 2004; Lu et al., 2004). Some researchers use numerous two-date comparisons in order to summarize multitemporal patterns throughout time, in order to better exploit the extensive archive of satellite data (Jin & Sader, 2005; Olsson, 2009).

Algorithms that can flexibly capture both sudden disturbance events and longer-term stress-induced degradation and ecological change generated by human and natural processes must be developed to characterize and understand our increasingly human-dominated Earth system (Vitousek et al., 1997).

Having said that, the aim of this Task is to develop a tool, that will also be implemented in the MAIL web application, based on the Google Earth Engine platform, which will support the user in the monitoring and management of a forest area. More specifically, the objectives of this task are to:

* Find a change detection algorithm for vegetation monitoring implementable on GEE
* Explore the potential of the algorithm in specific forest monitoring pilot cases
* Adjust the algorithm to the project needs.

Background – Literature Review

The process of detecting differences in the condition of an object or phenomenon by watching it at various times is known as change detection (Singh, 1989). Change detection of Earth's surface characteristics in real time and with high accuracy lays the foundation for better understanding the links and interactions between human and natural events in order to better manage and utilize resources (Lu et al., 2004). Change in the ecosystems is defined as a change in the surface components of the vegetation cover or "a spectral/spatial movement of a vegetation entity over time” (Milne, 1988). Fire is an example of a dramatic and/or abrupt change; biomass accumulation is an example of a subtle and/or gradual change. As a result, change can be seen as a categorical or as a continuous variable.  Land-cover adjustments are more common than land-cover conversions in general. Some environmental changes are caused by humans, such as tree clearance for agricultural growth. Others are the result of natural disasters such as flooding, epidemics etc (Coppin et al., 2004).

The main difficulties in monitoring ecological change from space come from the need to (Coppin et al., 2004):

* detect changes in addition to conversions (e.g., quantify forest cover degradation due to selective logging or fires),
* monitor rapid and abrupt changes in addition to gradual and incremental changes (e.g., compare the impact of a flood, drought, or fire versus a gradual expansion of agriculture),
* given the shortness of the available time series, 20 to 30 years, distinguish inter-annual variability from secular trends (e.g. assess dry land degradation);
* recognize and correct for scale dependency in statistical estimates of change generated from remote sensing data at various spatial resolutions, and
* match the temporal sampling rates of observations of processes to their intrinsic scales (e.g. monitor rapidly evolving processes such as floods or biomass burning).

Change detection identifies spatial changes in multitemporal satellite images and in general, analyzes the temporal effects of a phenomenon using multi-temporal datasets. It is a critical analysis for remote sensing, environmental monitoring, and land use - land cover change detection. Satellite images of varied resolutions are acquired by remote sensing satellites and used for change detection (Asokan & Anitha, 2019).

An effective change detection research should include the following information (Lu et al., 2004):

* area change and change of rate,
* spatial distribution of changed types,
* land-cover change trajectories, and
* accuracy assessment of change detection results

Three major steps are involved in developing a change detection project (Lu et al., 2004):

* image preprocessing, such as geometrical rectification and image registration, radiometric and atmospheric correction, and topographic correction if the study area is in mountainous regions,
* selection of appropriate methodologies for change detection analyses, and
* accuracy assessment

Many factors influence the accuracy of change detection results, including (Lu et al., 2004):

* precise geometric registration between multi-temporal images,
* calibration or normalization between multi-temporal images,
* availability of quality ground truth data,
* the complexity of landscape and environments of the study area,
* change detection methods or algorithms used,
* classification and change detection schemes,
* analyst’s skills and experience,
* knowledge and familiarity of the study area, and
* time and cost restrictions.

The expansion and intensification of agriculture, the conversion of agricultural land and forest to developed land, and agricultural land abandonment have all been linked to climate change, CO2 concentrations, and land use and land cover change (Chen et al., 2019; Grădinaru et al., 2019; Horion et al., 2016; Liu et al., 2015; Zhang et al., 2017; Zhu et al., 2016). Satellite remote sensing data have become an important source of information for more precisely quantifying and better understanding environmental change, particularly to monitor vegetation dynamics from regional to global scales, and to distinguish the impacts of humans and climate change (Hansen et al., 2013; Kuemmerle et al., 2016; Rogan & Chen, 2004).

Change detection analysis allows to find areas which differ between two images or changes over time in one or the other direction. Changes can be described quantitatively and qualitatively. During the analysis of land cover changes it is crucial to exclude changes which are caused i.e. by changes: in atmospheric conditions, the angle of incidence of the sun’s rays, in soil moisture or which result from the cycle of phenological vegetation and hydrological cycle. The methods for change detection can be divided into two main approaches: comparative analysis of two separately classified images or “bi-temporal change detection” and simultaneous analysis of time series imagery or “temporal trajectory analysis”.

* 1. Bi-temporal change detection

Change detection, which involves finding substantial differences in two images, is a common use of remote sensing data. The images were taken at two different points in time. A change map is made up of the changes that have been recognized. The procedure starts with picture acquisition, which is a collection of photos taken at different times of the same location (Figure 1). Atmospheric interferences impact the images, which must be rectified to remove them. The image pre-processing stage is applied to circumvent these interferences. The substantial changes are then identified using the change detection algorithm, and the significant changes are separated using the segmentation algorithm to separate them into change and no change areas (Asokan & Anitha, 2019).

Diagram, schematic

Description automatically generated

Figure 1. Workflow of change detection method. Source: (Asokan & Anitha, 2019)

In terms of color, brightness, and wavelength representations in the image, the images collected from the satellite are highly diverse. The amount of information in each pixel is determined by the image's resolution. The type of sensor used, and the altitude of the satellite's orbit determine the resolution of satellite images.

The choice of sensor, change categories, and change detection algorithms is just as important in a bitemporal change detection approach as the choice of images acquisition dates. The calendar acquisition dates, and the change interval duration are two aspects of the challenge. Two criteria stand out among the different features of pre-processing for bi-temporal change detection: multi-date image registration and radiometric correction. It should go without mentioning that accurate spatial registration of multi-date imagery is critical for detecting digital changes. Spatial, spectral, temporal, and thematic constraints affect all digital change detection. The approach used can have a significant impact on the qualitative and quantitative estimations of the disturbance (Colwell, J. E., Weber, 1981). Various approaches to the same environment might result in different change maps. As a result, the selection of the right procedure becomes extremely important. Per-pixel classifiers and pixel-based change information included in the spectral- radiometric domain of the pictures are used in the majority of reported digital change detection systems (Coppin et al., 2004).

* 1. Temporal trajectory analysis

According to research studies based on satellite time series, between 25% and 50% of worldwide vegetated regions have greened during the 1980s, whereas only a small fraction of the global vegetated area has suffered decreased vegetation growth or decline. Agricultural land abandonment is defined as the full suspension of agricultural management for a few years followed by natural succession processes that may lead to forest growth (Kolecka, 2021). In various landscapes across Europe, vigorous vegetation recovery has been seen following the end of intense management. Agricultural land abandonment is a common phenomenon, but it is also geographically distributed, since it commonly affects severely fragmented land or tiny plots in marginal areas (Gellrich et al., 2007).

Due to its intricate features and local distinctiveness, measuring and quantifying agricultural land abandonment across wide geographical scales may be challenging. The establishment of successional vegetation on abandoned land may be traced using satellite data as a progressive increase in vegetation index over time (Kolecka et al., 2017). The Normalized Difference Vegetation Index (NDVI), which is defined as the normalized difference of measured reflectance in the near infrared and red channels and is significantly connected with chlorophyll content and photosynthetic capability, is the most widely used vegetation index (C. J. Tucker & Sellers, 1986; Compton J. Tucker, 1979). It's been widely used in research on vegetation change at various scales.

Because of its accessibility, near-global coverage, long operation, and regular imaging, Landsat time-series have been used in several recent investigations. Trend- or trajectory-based techniques utilizing aggregated yearly or seasonal spectral indices have evolved to overcome data shortages and successfully eliminate intra-annual signal noise. Non-parametric trend-based methods such as the Mann–Kendall (MK) trend test (Kendall, 1975; Mann, 1945) and the Theil–Sen median slope estimator (TSE) (Sen, 1968; Theil, 1992) allow for the detection of significant monotonic (increasing or decreasing) trends in time series data and provide estimates of trend intensity (de Beurs & Henebry, 2005). The Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr, LTR) method tool provides a more precise definition of greenness trends (R. E. Kennedy et al., 2010).

Some researchers have used seasonal development curves or profiles to compare seasonal development curves or profiles to avoid the challenge of selecting appropriate imagery acquisition dates. These need time series of remotely sensed indicators of relevant land surface attributes, which are produced from daily imaging acquisitions given by sensors such as the Advanced Very High Resolution Radiometer (AVHRR), Moderate-Resolution Imaging Spectrometer (MODIS), and others (Coppin et al., 2004). Change detection using such profiles has been shown to be effective for regional investigations of predominantly climate-driven land surface attribute changes, phenology changes, and inter-annual net primary production variability (Behrenfeld et al., 2001; Kawabata et al., 2001; Lambin & Ehrlich, 1997; Myneni et al., 1997).

Because time-profile-based change detection approaches use data from a high number of observation dates, proper pre-processing is critical. Pre-processing involves geometric registration of subsequent images at the sub-pixel level, just like bi-temporal approaches. Roy (2000), for example, demonstrated that when mis-registered data is composited, high contrast boundaries on images from wide field-of-view sensors can be shifted. This might accentuate or obfuscate reversal or change events. Data artefacts that are intrinsic to the sort of imagery used and make comparing data observations or measurements at various periods difficult must be eliminated when working with a series of images. Furthermore, a method of temporal compositing is required to eliminate cloud and other atmospheric influences (e.g., water vapour content, aerosols) (Coppin et al., 2004).

The comparison of temporal development curves, also known as time trajectories or time profiles, of different important indicators across successive growth seasons or years is required for temporal trajectory analysis. The high temporal frequency of data capture not only speeds up the identification of ecosystem changes, but it also makes phenological fluctuations in ecosystem condition much easier to characterize. A seasonal or inter-annual change event or process is discovered when the temporal trajectory of one or more remotely sensed indicators for a given pixel deviates from the normal (or average, or ideal, depending on the study's aims) (Lambin & Strahlers, 1994).

Data and software acquisition

Land cover change can be detected in various ways. There are two main approaches; comparing the conditions between only two points in time, hence two images, and investigating continual processes, which may include long-term trends, short-duration events, or a combination of those two, requiring a time series of images. The aim of this Task is to find a tool that would be able to identify where and how the land has changed over a longer period of time, and not only between two points in time. For such an analysis a time series of images has to be processed what requires adequate processing resources.

Therefore, since each application/tool in the project was designed to work in the Google Earth Engine (GEE), the initial assumption was that the change detection algorithm should also work in this environment. Hence, the goal was to find some suitable method to deal with time-series of data in GEE.

LandTrendr

LandTrendr (LT) is a collection of spectral-temporal segmentation algorithms that may be used to identify changes in a time series of moderate resolution satellite images (primarily Landsat) and to generate trajectory-based spectral time series data with little inter-annual signal noise. LT was initially written in IDL (Interactive Data Language), but it was transferred to the GEE platform with the aid of Google developers. The IDL implementation's onerous data management and picture preparation features are largely eliminated using the GEE framework. Moreover, It is orders of magnitude quicker than the IDL implementation, which measures compute time in minutes rather than days (R. Kennedy et al., 2018).

Each pixel in a time series image has a story to tell, and LandTrendr strives to convey it clearly. The full story of a pixel includes many other minor changes given the precision of the satellite sensor and processing methods; the provided description is the type of pixel history interpretation that is well represented in the image time series. LandTrendr is a brevity algorithm that listens to a pixel's annual, verbose, noisy detail and produces a shortened version of it. In practice, LandTrendr takes a single point-of-view from a pixel's spectral history, such as a band or an index, and runs it through a procedure to find breakpoints, dividing periods of long-term change or stability in the spectral trajectory, as well as the year those changes happened. The spectral history of a pixel may be represented as a series of vertices enclosing line segments using these breakpoints, which are specified by year and spectral index value (R. Kennedy et al., 2018).

Chart, waterfall chart

Description automatically generated

Figure 2. Pixel time series segmentation with LandTrendr. Breakpoint (vertex) identification is used to reduce image data to a single band or spectral index, which is then separated into a series of straight-line segments. Source: (R. Kennedy et al., 2018)

This segmented perspective of spectral history generates two interesting characteristics. The simple geometry computations on line segments provide information about distinct spectral epochs and the ability to interpolate new values for years between vertices.

* 1. Values interpolation for years between vertices

It's really beneficial to be able to interpolate new values for years between vertices. It guarantees that each observation follows a path that is compatible with where the pixel has been and will go. This may be thought of as image time series data with hindsight enhancement. It has two useful features:

* It can fill in data from missing observations in the time series (masked by cloud or shadow) and
* maintain predictive mapping consistency over time

for example, an annual forest classification is unlikely to bounce between mature and old-growth conifers due to minor differences in spectral reflectance from the atmosphere or shadow differences (R. Kennedy et al., 2018).

Chart

Description automatically generated

Figure 3. Image time series data with hindsight enhancement. The interpolation of observations between vertices is enabled by the identification of time series breakpoints or vertices, which removes unnecessary information and places each observation in the context of the trajectory it is a part of. Source: (R. Kennedy et al., 2018)

Since breakpoints or vertices are specified by a year, breakpoints discovered in one spectral band or index can be imposed on any other. For example, a pixel time series cast as Normalized Burn Ratio (NBR: [NIR-SWIR]/[NIR+SWIR]) may be segmented to identify vertices, and the NBR-identified vertices can subsequently be used to segment a short-wave infrared (SWIR) band. This is useful because it allows to make the entire data space for a pixel's time series consistent from a single perspective and summarize starting, ending, and delta values for all spectral representations for the same temporal segments, which can be useful predictors of land cover, agent of change, and state transitions (R. Kennedy et al., 2018).

Chart

Description automatically generated

Figure 4. Impose one spectral representation's segmentation structure on another. Using NBR, four breakpoints or vertices for a pixel time series are identified, and the year of those vertices is used to segment and interpolate the values of a SWIR band time series for the same pixel. Source: (R. Kennedy et al., 2018)

* 1. Spectral Epochs

The second useful aspect of a segmented spectral history world view is that simple geometry computations may summarize spectral epoch attributes. Based on the vertex time and spectral dimensions, each segment's temporal duration and spectral magnitude may be calculated. These properties make it simple to query the data for information such as when changes occur, how frequently they occur, how long they persist on average, the average amplitude of disturbance (or recovery) segments, and so on. It can also give the information on segments that are close to the focus segments. For example, it can check what the average rate of recovery after a disturbance segment is, or what the trajectory of a pixel time series was previous to disturbance segments attributable to fire (R. Kennedy et al., 2018).

Diagram

Description automatically generated

Figure 5. Diagram of segment attributes that summarizes and checks change per pixel over the landscape. Source: (R. Kennedy et al., 2018)

* 1. Image Collection

LT requires an annual image collection (data is provided through GEE) and a set of parameters to control segmentation. The image data that makes up a collection must indicate a consistent observation throughout time. Noise from the atmosphere, clouds and shadows, sensor discrepancies, and other oddities should not be included. Annual changes in a time series should be due to changes in a landscape's physical features.

The dataset used is the USGS Landsat Surface Reflectance Tier 1 (L5, L7 and L8). These are atmospherically corrected imagery and include a cloud, shadow, water and snow mask produced using CFMASK that can be applied to the image collection. TM and ETM+ data are included without alternation, but OLI bands 2-7 are subset and transformed to the spectral properties of ETM+ bands 1-5 and 7 respectively using method elaborated by Roy et al., (2016). The annual image composite is generated using the medoid approach. Medoid (of a given image pixel) is the value for a given band that is numerically closest to the median of all corresponding pixels among all images considered (between a provided annual data range).

LandTrendr merely reduces the given time series to a minimal number of segments and records when the signal changes. Each year, only one observation must be collected. Because clouds are frequently present in any given image, it is ideal to collect numerous images for a season, filter off clouds and cloud shadows from each, and then produce a composite of those images to ensure that clear-view pixels are covered in a suitable yearly spatial coverage. LandTrendr will segment the first band in the image collection and generate values to interpolate years between vertices for each subsequent band (R. Kennedy et al., 2018).

## LT-GEE applications

LT-GEE, the name of the algorithm that is available for running on GEE, has five different applications:

* UI LandTrendr Download MultiTool
* UI LandTrendr Pixel Time Series Plotter
* UI LandTrendr Change Mapper
* UI LandTrendr Fitted Index Delta RGB Mapper
* UI LandTrendr Time Series Animator

After analysis of all five tools, the LandTrendr Change Mapper was selected to be used in this task. This application allows to display map layers of change (vegetation loss or gain) attributes, namely: Year of Detection, Magnitude, and Duration of change event.

This tool provides a set of parameters that the user can modify according to the scope of the study. The first parameter is the Year Range which is used for building a Landsat time series dataset to identify change. Then the Date Range over which to generate annual Landsat image composites must be defined. The third parameter that needs to be provided by the user is the Band (e.g. SWIR) or Index (e.g. NDVI) that will be used for the change detection. The best representation may differ among the various types of land cover. The output may also differ due to different date windows and widths for generating annual composites.

The tool also allows to mask out some features from the imagery from the CFMASK quality band included with each image. Then there is the option to define the area of interest by inserting pixel coordinates (decimal degrees of latitude and longitude based on the WGS84, EPSG 4326). This is an optional step since the user can also select the area by clicking on the map if the Inspector button is turned off. Afterwards, is the option to define the Buffer Around the centre Point (in km) that the algorithm will draw and clip the map to the bounds of the square region.

Naturally, the Vegetation Type Change (gain or loss) of interest can be selected, as well as the Vegetation Change Sort (greatest, least, longest, etc.). However, the latter applies only if there are multiple changes of a given type in a pixel time series.

In addition, five filtering options are available; Filter by:

* Year of detection,
* Magnitude,
* Duration of event,
* Pre-change spectral value, and
* Minimum Mapping Unit (MMU), which is the minimum disturbance patch size (defined by 8-neighbor connectivity of pixels having the same year of change detection).

The UI comes also with an Inspector mode selector that allows, when activated, for retrieving change event attributes for the clicked pixel in a form of chart with values in the right-hand panel. Information regarding the segmentation parameters can be found on LT-GEE webpage.

It should be noted that the Magnitude values are multiplied by 1000 for ratio and normalized difference spectral indices, while surface reflectance bands are multiplied by 10,000 according to LEDAPS and LaSRC processing.

Workflow development – Tool implementation

Task 4.4 is mainly oriented towards the monitoring and management of a forest ML. Therefore, three different forest monitoring scenarios, stemming from two general and opposite processes have been investigated, representing the different states or events related with the forest succession. These are the “Deforestation”, the “Stable Forest” and the “Afforestation/Reforestation” scenarios. The chosen tool, more specifically the Change Mapper UI application of LandTrendr, should be able to provide meaningful information related with the three aforementioned scenarios. In this Chapter, the different scenarios in which the Change Mapper can be of use for the stakeholder will be described, alongside with the proposed settings, based on each scenario.

Forest condition scenarios

The first scenario in which a stakeholder can deploy this tool is the “Deforestation” scenario. These are abrupt changes that interfere with the natural trend of the vegetation and are identifiable in plots of time series as a sudden drop in the vegetation biomass indicator used. Using the Change Mapper tool, the user can monitor and get valuable information in the case of a deforestation event, be that because of natural (wildfire, wind, tornado, etc.) or human-induced factors. This way the user is able to identify the extent of the forest area that was lost, the point in time the decrease in forest biomass occurred, and what was the magnitude of change. If the magnitude of the deforestation event is high, it indicates that significant portion of the vegetation was destroyed.

The theoretical background for the utility of this scenario is twofold. Its first use concerns the user that is already managing a healthy forest area, while the second use is not related with the monitoring of an existing project, rather than with the investigation phase of a new project. This could be of interest for a user who is looking for an area that was a forest but turned recently into a ML due to a sudden catastrophic event, be that because of natural or human-induced factors. Depending on the legal context of each country, there are cases where a forest was destroyed because of a wildfire and there is a need for a quick rejuvenation of the forest area. In such cases, reforestation projects are funded by local, national, or European funding programs, and attract the attention of potential stakeholders.

The second scenario is the “Stable Forest” scenario, meaning that the condition of an old forest is under investigation. In this scenario slow and gradual changes are expected, hence the time series plot of the given vegetation index manifests a flat and stable trend, without abrupt changes and without a significant, increasing or decreasing, trend. The values of such pixels are expected to have high values, indicating a healthy, stable, and already developed forest.

The primarily interested users of such scenario are the users that have already implemented an afforestation or reforestation project few years ago and are interested in monitoring its condition. These areas include forest pixels that exhibit low magnitude of change throughout the whole time spectrum specified.

Finally, the third scenario of interest for the potential user of this tool is the “Afforestation/Reforestation” scenario. This scenario encompasses areas that either an afforestation or a reforestation project was recently implemented. This is also a long-term trend investigation scenario, in which stable trends are expected to prevail, however the trend of the pixel values is expected to be a steadily increasing one. The magnitude of such changes is expected to vary from low to high, depending on the type of the forest, the time range and successfulness of the project. Potential users of such scenario are the stakeholders that recently carried out either an afforestation or a reforestation project.

Change Mapper parameters / fine tuning

The UI application of Change Mapper of the LandTrendr algorithm provides a variety of settings to the user, offering many options depending on the study that it will be applied on. Since this application is going to be implemented in the web application of the ***MAIL*** project, it was decided that not all of these settings are relevant to the potential user of the ***MAIL*** Map portal. Moreover, it is understood that the level of programming and scientific understanding of the potential user is not expected to be necessarily on the level of an experienced remote sensing scientist. Therefore, some of the options offered in the original version of the Change Mapper will not be accessible to the user, in order to prevent him from making a set of choices that would affect negatively the outcome of his research. On the other hand, though, all the relevant with this task options, will be open for the user to modify according to the project’s needs and requirements, striking a balance between ease of use and customizability.

Non modifiable

Starting from the general settings that will be “locked” to the user, a summary of which is presented on Table 1, the starting date of the Year Range will be fixed to 2000, instead of the 1985 original value, since for this project we are interested in relatively recent events and projects. This way the computation time is reduced, and more relevant and useful information is delivered to user. The Date Range is fixed to the whole summer period, from 1st of June until the 30th of September in order to include the summer period of all European regions. Out of all the provided indexes, the NDVI and the NBR are proposed as options to the user since those were found to provide consistent results for the purposes of this task applied over any European region. The option to mask specific elements, like clouds, shadows, snow and water, is also advised to remain locked in the default values, as well as the value of the option to buffer around a point, to 50 km. The option to define pixel coordinates is a useful one under any scenario, so it will remain open. The Segmentation Parameters on the other hand is advised to stay “locked” in their default values, as defined by the LandTrendr authors, in order to avoid potential errors. Finally, the Inspector mode on the right should always be enabled since the plot it produces is very informative and one of the major assets of this tool.

Table 1. Constant Change Mapper parameters in MAIL Map Portal and their respective values

|  |  |
| --- | --- |
| **Field** | **Value** |
| **Year Range** | 2000 – 2021 (latest) |
| **Date Range** | 06/01 - 09/30 |
| **Index** | Reduced to NBR & NDVI |
| **Mask elements** | Keep all |
| **Pixel Coordinates** | User input |
| **Buffer around point** | 50 |
| **Segmentation Parameters** | Default |
| **Inspector Mode** | On |

Proposed settings

In this chapter, the proposed settings for the parameters offered by the Change Mapper will be described, based on the desired forest condition-stage scenario described in the previous chapter. It should be noted that the settings and the values proposed here are by no means absolute and should serve as starting point examples for a user not already familiar with LandTrendr. The user is encouraged to experiment with these settings and fine tune the values according to the needs of the study or project. The proposed settings according to the requirements of each scenario are summarized in Table 2.

For the “Deforestation” scenario, the Vegetation Change Type should be set to “Loss” and the Vegetation Change Sort option to “Greatest”. This way, the biggest vegetation loss event will be displayed. From the Filtering options the ones relevant with this scenario are the Filter by Year, should a user want to focus on a narrower Year Range, than the one indicated in the beginning, the Filter by Magnitude, which is suggested to be set to greater than 200 or 300 since any major event will have higher values than that and the events of lower magnitude will only introduce noise, and the Filter by MMU, which is suggested to be set to anywhere between 4-12 in order to minimize the noise in the resulting map from isolated pixels. Finally, out of the three layers that are mapped on the screen in default by the Change Mapper, only the Year of Detection is advised to be turned on for the following reasons. Firstly, the computation time is reduced, secondly the Duration layer is irrelevant since such events are very short in duration and information about the Magnitude of the event is displayed on the plot provided by the Inspector. However, the latter could be explored by the user for additional information as well.

Table 2. Proposed settings for the Change Mapper parameters in MAIL Map Portal per scenario

|  |  |  |  |
| --- | --- | --- | --- |
| **Field** | **Deforestation** | **Afforestation** | **Stable Forest** |
| **Vegetation Change Type** | Loss | Gain | |
| **Vegetation Change Sort** | Greatest | Fastest | Slowest |
| **Filter by Year** | Optional | Not useful | |
| **Filter by Magnitude** | > 200/300 | | < 200 |
| **Filter by Duration** | Optional | > user input | |
| **Filter by Pre-Dist Value** | Optional | | |
| **Filter by MMU** | > 4 - 12 | Not necessary | |
| **Layers** | Year of Detection, (Magnitude) | Magnitude,  (Duration) | |

As far as the other two scenarios are concerned, the proposed settings for these are very similar, since they both describe similar forest states and processes. Unlike the settings in the Deforestation scenario, the Vegetation Type Change should be set to “Gain” for both scenarios. The Vegetation Change Sort, though, is suggested to be set to “Slowest” for the “Stable Forest” scenario and to “Fastest” for the “Afforestation/Reforestation” scenario. The differences between these two options are expected to be minor, however finer results are expected by tuning them. Filtering either by Year or by Duration may not be useful here, since these are long-term changes and all the information provided is needed. Filtering by MMU is also not necessary since it makes sense that the user would be interested in the values of every pixel in the area. Nevertheless, the Filtering by Magnitude option is the one effectively distinguishing one scenario from the other. As mentioned before, in the “Stable Forest” scenario, no significant change in the vegetation health is expected, thus a filter of lower than 200 or 300 is proposed. Contrarily, setting the Filter by Magnitude to greater than 200/300 would indicate pixels that the vegetation biomass is rapidly increasing year by year and only those pixels will be mapped, delineating a healthy and successful afforestation or reforestation project. For those two scenarios the layer that contains the most relevant information to be visualised to the user, is the Magnitude layer. The Duration layer is expected to be very high for most of the pixels, even though there are possible exceptions to this claim.

Pilot Case Study

In this Chapter the aforementioned settings will be applied on specific regions in order to perform a pilot case study and evaluate visually the performance of the proposed tool. The graph on the right of each figure shows the time series analysis plot related with the pixel inspected based on the position of the cursor.

Deforestation Scenario

The most impressive results are produced under the Deforestation scenario since these are precisely delineated events both in the temporal and the spatial aspect. A major deforestation cause, especially for Mediterranean regions, are the wildfires. As an example, a region in the central Greece, and more specifically around the broader region of Athens, is presented here. This is a region that has been affected by various wildfire events in the recent years and a very recent event of the summer of 2021 is visible as well (Figure 6). The Year of Detection layer (YoD) provides useful information for the year that the deforestation event took place, and the different events are mapped in different colors according to the year the event took place. The Magnitude layer provides information regarding the magnitude of the deforestation event, for each pixel.

|  |  |
| --- | --- |
| Map  Description automatically generated  (a) | Map  Description automatically generated  (b) |

Figure 6. Deforestation example Greece wildfire 2021. (a) Magnitude, (b) YoD

Another natural cause for a deforestation event is the strong winds that can be related with a storm or a cyclone. Such event took place in a forest area in central Poland (approximate longitude and latitude coordinates: 19.97 and 51.33) in 2016. Based on personal testimonies, the whole forest was cleared in this storm. The effects of this storm are clearly delineated with the Change Mapper tool, with an orange colour in the YoD layer, as seen in Figure 7.

|  |  |
| --- | --- |
| A screenshot of a map  Description automatically generated with medium confidence  (a) | A map of a city  Description automatically generated with low confidence  (b) |

Figure 7. Deforestation example Poland storm 2016. (a) Magnitude, (b) YoD

As a third example of mapping a, human-induced, deforestation event with the Change Mapper tool, the authors investigated a mine area in Saxony, Germany. This investigation resulted in an impressive multicolored map showing how the human-induced deforestation events are clearly differentiated from the natural ones, because of the prevailing texture (Figure 8). The progress of the expansion of each mine and the consequent deforestation caused by the clearcuts are mapped effectively in the YoD map, with each color representing each expansion step. An additional peace of information is provided by the Inspector plot, revealing that the vegetation on the specific pixel was disturbed twice in the past 10 years; once in 2012 and once in 2015.

|  |  |
| --- | --- |
| Map  Description automatically generated  (a) | Map  Description automatically generated  (b) |

Figure 8. Deforestation example Germany mine. (a) Magnitude, (b) YoD

Stable Forest Scenario

As it has been already mentioned, the differences in the settings between an old healthy forest and a new afforested or reforested area are minimal. It is only through experimenting with the parameters and after getting familiar with the outputs of Change Mapper that a user can differentiate between those scenarios. A stable healthy forest is expected to have constant high NDVI values for the years under study, without any significant fluctuation. As an example of the output of such area the Black Forest in Germany and a Mediterranean forest region were investigated (Figure 9a). No filter was applied in neither of the regions and the blue colours represent the areas that vegetation is stable for the past 20 years under investigation, while the greener ones indicate a trend towards an increase in vegetation content. In Figure 9b the greener colours are prevailing over the blue ones, which might indicate that the Black Forest is older, hence more stable in greenness forest.

|  |  |
| --- | --- |
| Graphical user interface  Description automatically generated with low confidence | **(a)** |
| A picture containing text, screenshot  Description automatically generated | **(b)** |

Figure 9. Stable Forest example. (a) Black Forest (Germany), (b) Mediterranean forest (Greece)

If the user would be interested to isolate only the stable pixels, then he could enable the Filter by Magnitude and set it to less than 200/300.

Afforestation – Reforestation Scenario

On the other hand, if the user is interested in afforestation monitoring an detection of only of the “greening” pixels, he could set the Filter by Magnitude to greater than 200/300 on previously analysed area. This way a rapidly increasing in vegetation biomass area on the centre-left part of the map would be easier distinguishable (Figure 10). This is an area that little to no vegetation existed before the year 2000, but since then the vegetation has been increasing and becoming more dense year by year.

Map

Description automatically generated

Figure 10. Afforestation example. Albania

In another example, a reforestation project was carried out in one mountainous region close to the city of Athens, Greece, which was hit by a devastating wildfire back in 2008. Soon after the effect of the wildfire was identified and mapped, a reforestation plan was decided and set into motion (Figure 11).

Map

Description automatically generated

Figure 11. Reforestation example, Greece

Conclusions

Task 4.4 is a task mainly oriented towards the monitoring and management of the changes in forest related projects; either an already developed forest, or a recently implemented project. Based literature and algorithms review, the tool proposed for this task is the Change Mapper UI application, part of the LandTrendr application, developed on GEE. The tool is capable of monitoring various vegetation related processes, process data in real time, using satellite imagery and utilizing the temporal trajectory analysis.

Three main scenarios representing different forest succession stages were investigated: namely a Deforestation, a Stable Forest, and an Afforestation-Reforestation scenario. Each represents a different stage of a forest’s life; therefore, different parameters are required in order to monitor such conditions. These parameters were described in this report, and a few examples were presented for each scenario.

To the best of the authors’ knowledge, the processes described are the main forest succession processes that are relevant with the scope of the ***MAIL*** project and can be monitored by utilizing this tool. Nevertheless, this does not mean that the functionality of the Change Mapper is restrained to these scenarios. On the contrary, this was merely a demonstration of the basic utilities of this tool and the user is highly encouraged to apply this tool on individual and more case-specific studies and experiment with the options offered.

Summing up, the LandTrendr is a praiseworthy tool for any change detection project and can serve as an asset in various applications. For the task 4.4 of the ***MAIL*** project, it can serve both as an identification tool of forest areas that have turned into MLs, but also as a monitoring tool of freshly (or not) afforested or reforested ML projects.

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2. **PU** = Public, **PP** = Restricted to other programme participants (including the Commission Services), **RE** = Restricted to a group specified by the consortium (including the Commission Services), **CO** = Confidential, only for members of the consortium (including the Commission Services). [↑](#footnote-ref-3)