E1.1 – Relatório com descrição do problema, condicionantes, dados de input e especificações técnicas dos outputs

Inês Silveira & Manuel Campagnolo

1. Introduction

Motivation and problem description

Given Portugal's initiative to establish a land cover monitoring system delivering annual products for its mainland territory (Costa et al., 2022), it becomes crucial to ensure an adequate representation of areas experiencing vegetation loss (Moraes et al., n.d.).

The goal of this report is to set an initial framework and reviewing available bibliography in support of creating, maintaining, and validating a land cover vector product for forest and shrubland vegetation losses with a minimum unit area of 0.5 ha and updated every 2 months. The major input is Sentinel-2 imagery.

The problem at hand consists of creating and updating, using Sentinel-2 imagery, a vegetation loss mask. Towards that end, data must be analyzed with change detection algorithms applied to satellite imagery while incorporating additional available ground truth information.

In the domain of monitoring land cover, recent progress in satellite data and enhanced computing capabilities have opened avenues for a new paradigm centered on the continuous identification of change, as an alternative to conventional land cover mapping from a single date satellite image. This review aims to analyze the advantages and limitations of a variety of methods to identify and classify changes in land cover from satellite imagery, specifically focused on vegetation change of forest and shrubland, along with an analysis of the required input data and types of outputs. Other topics of relevance to the project will be addressed in further deliverables. Those include developing effective methodologies on a national scale that are computationally efficient for the systematic creation of a national product in vector format.

Types of change detection algorithms

Detection algorithms can be grouped into two main categories: (1) algorithms that model single-pixel time series to identify changes through divergences about the standard reference spectrum (Brown et al., 2020), and (2) Algorithms that input a series of images instead of a single pixel-based time series. Those are deep-learning algorithms where the inputs are pairs of successive images and the output is a change detection mask.

At the pixel level, algorithms are either applied to long time series (typically Landsat), which are pre-processed to obtain only one observation per year. Examples include the Vegetation Change Tracker (VCT) (Huang et al., 2010), LandTrendr (Jin et al., 2017), and Verdet (Hughes et al., 2017). Those algorithms do not model the intra-annual behavior of the series.

Recently, the focus has been on pixel-based algorithms that decompose the time series into a trend, a periodic component, and noise. Examples are:

1. BFAST Monitor (Verbesselt et al., 2012) and variants (Lin et al., 2020).

2. CCDC or Continuous Change Detection (Zhu & Woodcock, 2014a) implements the Continuous Change Detection and Classification temporal breakpoint algorithm. This algorithm finds temporal breakpoints in an image collection by iteratively fitting harmonic functions to the data. Fit coefficients are produced for all input bands, but the bands used for breakpoint detection can be specified with the 'breakpointBands' argument.
3. EWMACD or Exponentially Weighted Moving Average Change Detection (Brooks et al., 2014). This algorithm computes a harmonic model for the 'training' portion of the input data and subtracts that from the original results. The residuals are then subjected to Shewhart X-bar charts and an exponentially weighted moving average. Disturbed pixels are indicated when the charts signal a deviation from the given control limits.

Deep learning approaches for change detection can be organized into three groups based on the learning techniques and the availability of training data (Khelifi & Mignotte, 2020).

1. Supervised methods that solve the problem by learning from a labeled training dataset. The efficiency of supervised deep networks is particularly evident in the case of the availability of a large amount of labeled data used to properly train the model.
    A. Convolutional Neural Networks (CNN) based studies have shown superior performances to the classical supervised classification methods. The U-net model is considered one of the standard CNN architectures used for change detection tasks, having an encoder that extracts spatial features from the image, and a decoder that builds the segmentation map from the encoder feature. Many developments of CNNs and the standard U-net in particular have been proposed as discussed in (Khelifi & Mignotte, 2020). Comparison among U-net models for forest change detection with Sentinel-2 (Kalinaki, Malik, Lai, et al., 2023), and evaluation of U-net models in comparison to alternative

models also for forest change detection with Sentinel-2 in Ukraine (Isaienkov et al., 2021). (Torres et al., 2021) compare U-net, SegNet, ResU-Net, FC-DenseNet and DeepLabv3+ for deforestation detection over the Amazon with Sentinel-2 and Landsat imagery. (Onojeghuo et al., 2023) compare different bands and spectral indices for Sentinel-1 and 2 for classification of paddy rice fields in China with ResU-net.

B. Transformers are a relatively recent paradigm in deep-learning. This kind of model has been applied to remote sensing change detection in (Feng et al., 2023) by transforming a change detection task into a semantic segmentation problem. They applied their model to very high-resolution imagery of mostly urban areas.

2. Unsupervised methods that learn from unlabeled datasets. Change detection tasks often do not have enough training data to build reliable supervised models. Therefore, in many cases, it is more efficient to learn the change features generated from a remote sensing image in an unsupervised manner. These methods are mainly based on models that may learn feature representations from the patches without any supervision. There are many alternative models for change detection as discussed in (Khelifi & Mignotte, 2020).

   In particular, Convolutional Auto-Encoders (CAE), were used by (Bergamasco et al., 2022), to perform change detection in bi-temporal images with Landsat and Sentinel data for burned and deforested areas over Spain and Italy. The method uses bitemporal samples and extracts deep features, which are compared and fused to detect changed and unchanged pixels.

3. Transfer learning-based methods have the capability of extracting knowledge from one or more source tasks and applying it to a target task. As it is important to reduce the requirement and effort to recollect the training data, transfer learning can be a reliable solution. There are two basic approaches:

a. Transfer learning from pre-trained CNNs: which uses the outputs of one or more layers of a trained network, and train a new shallow model based on these features.
b. The second approach is more involved, and consists of fine-tuning the network pre-trained in general images. An example of transfer learning from Landsat-8 to PlanetScope for detection of burned areas is provided in (Martins et al., 2022).

Algorithms that have been applied to the monitoring of vegetation loss

The Continuous Change Detection and Classification (CCDC) algorithm was specifically designed to process high-temporal frequency satellite data. However, studies utilizing CCDC frequently rely on Landsat data which, in comparison to Sentinel-2 data, has coarser spatial and temporal resolution (Costa et al., 2022).

The Land Change Monitoring, Assessment, and Projection (LCMAP) is a United States program that created a land cover and land surface change dataset. This dataset consists of annual land cover and land cover change products throughout 1985-2017 at 30 m resolution using Landsat data via the CCDC algorithm (Xian et al., 2022; Zhu & Woodcock, 2014a). The CCDC algorithm uses all available Landsat observations and requires several input datasets to perform both change detection and classification (Xian et al., 2022).

While Landsat data were limited by annual and sub-annual frequency of observations, the Sentinel-2 mission may provide high-resolution images every 5 days. The potential of Sentinel-2 in detecting small-scale deforestation regions is shown in (Lima et al., 2019) where Sentinel-2 imagery showed a better performance than Landsat in detecting forest change in the Amazon

Using Sentinel-2 images, (Isaienkov et al., 2021) presents a U-net model for deforestation detection in the forest-steppe zone in Ukraine. This task was solved in a supervised learning manner, having a dataset of training observation with known ground truth deforestation regions. The labeling was carried out manually by analyzing a series of three or more sequential images where each new section of increasing a clearcut was marked as a separate polygon. The results of the study provided the information that the use of pairs of images with close dates can improve the classification performance.

(Xiang et al., 2023) also relies on Sentinel-2 imagery to detect annual forest changes from 2017 to 2021, in a subtropical monsoon climate. The study compared the performance of various deep learning models revealing that the U-net++ model performed the best, with a precision of 0.795, a recall of 0.748 and an F1-score of 0.771. The results of annual and quarterly forest change detection were consistent with the changes in the Sentinel-2 images with accurate boundaries, demonstrating the high practicality and generalizability of the used method.

2. Constraints

Identifying changes in vegetation can be constrained at various stages of the process, spanning satellite imagery acquisition, reference to ground truth data, and the model itself.

Reference data

Ground truth data introduces significant limitations, primarily due to its limited availability (Kim et al., 2021), and temporal misalignments with satellite imagery recording dates (Altarez et al., 2023; Kalinaki, Malik, Lai, et al., 2023; Matosak et al., 2022a; Onojeghuo et al., 2023; Waldeland et al., 2022). Even when comprehensive data is accessible, accurate labeling demands an intimate understanding of the ecosystem to discern genuine land cover changes (Moncrieff, 2022).

Satellite observations availability

Collections of satellite images are characterized in particular by their spatial, spectral, and temporal resolutions. For instance, when comparing Landsat and Sentinel-2, the former has more bands (in particular thermal bands) while the latter has better spatial resolution and potentially better temporal resolution.

It is worth mentioning that harmonized products, like the collection of harmonized Landsat and Sentinel-2 products (HLS) with a 30 m spatial resolution (Claverie et al., 2018), are also available for change detection. Those products tend to have a better temporal resolution (2-3 days for HLS) than each single sensor.

Data availability depends on the sensor, and the latitude (lower latitudes have fewer overpasses), and on the cloud cover for the region of interest. (Lewińska et al., 2023) compare image availability for Landsat and Sentinel-2 over the years and over Europe, showing that it has been increasing with the launch of new satellites and that countries in the South of Europe have the densest series of available images.

Topography

Topographical variability emerges as a limiting factor, influencing illumination conditions and altering reflectance and radiometric properties, complicating the accurate detection and classification of vegetation and non-vegetation areas, in forests that exhibit significant elevation, slope, and aspect variations (Kalinaki, Malik, & Ching Lai, 2023).

Computational requirements

The CCDC algorithm is characterized by its high computational cost and substantial data storage requirements, as mentioned by (Zhu & Woodcock, 2014b) and deep learning models like U-nets are known to require a large amount of computational resources (Onojeghuo et al., 2023) . To apply change detection and classification techniques for Portugal with Sentinel-2 10 m resolution collections of images is therefore a challenging task. Computational techniques like arithmetization and parallelization can help overcome the computational constraints. Advanced computational platforms (Google Earth Engine, Copernicus Data Space Ecosystem, the Portuguese RNCA) might be necessary to run advanced change detection and classification algorithms.

3. Input Data

Reference data

A reference data set is a set of labeled examples, where the examples correspond to some temporal series at the pixel or the patch level, and labels can either be a binary mask (e.g. vegetation loss/no loss) and/or a categorical variable that indicates the cause of loss (fire, clear cut, ...).

The labeling type varies from binary classification (forest, non-forest) (Alzu'bi & Alsmadi, 2022; Kalinaki, Malik, & Ching Lai, 2023; Kalinaki, Malik, Lai, et al., 2023; Waldeland et al., 2020) to multi-class categorization (Wagner et al., 2023; Wang et al., 2022). (Altarez et al., 2023) use both approaches, where it first identifies the deforestation areas and then classifies the same region according to their land use/land cover.

In smaller study areas, labeling processes may adopt either manual or semi-automatic methods. (Alzu'bi & Alsmadi, 2022) employed a **manual approach**, crafting a ground truth dataset by manually delineating a forest mask around dense forest boundaries, excluding areas with scattered trees. (Kalinaki, Malik, Lai, et al., 2023) utilized "Apeer annotate" which is an online tool for deep learning image annotation, to create four classes: forest vegetation (forest and grassland), non-forest (roads, buildings, soil, and other land covers), the buffer zone, and the area outside the buffer zone. In the study conducted by (Isaienkov et al., 2021), sequential images from 2016 to 2019 were analyzed, with each clearcut section marked as a separate polygon.

Alternatively, some studies opt for a **semi-automatic approach** to generate ground truth data for model training. (Zhang et al., 2022) and (Khankeshizadeh et al., 2022) leverage previously conducted fieldwork and LIDAR measurements, respectively. Others utilize pre-existing datasets as masks. The Global Forest Change dataset and a Land Use Land Cover (LULC) classification of the study area were used by (Solórzano et al., 2023), where the deforestation polygons had to be visible in a range of a year, as it was assumed those deforestations were the ones the algorithm could detect. From INPE (Instituto Nacional de Pesquisas Espaciais), the PRODES dataset was used by (Matosak et al., 2022b; Wagner et al., 2023). PRODES monitors clear-cut deforestation in the Amazon based on Landsat, providing annual maps with polygons identifying forest, non-forest, current-year deforestation, previous deforestation, clouds, and water (Wagner et al., 2023).

Satellite Imagery

To monitor changes as they occur, and to be able to identify changes in small size, it is necessary to have an algorithm that uses fine spatial resolution data, such as Landsat. It uses as many observations as possible to detect land cover changes accurately (Zhu & Woodcock, 2014b). The CCDC algorithm was developed to advance time series change detection by using all available Landsat - approach used to create LCMAP products (Xian et al., 2022). Landsat-8 imagery is employed more for extensive temporal coverage, as demonstrated in the work of (Alzu'bi & Alsmadi, 2022), monitoring deforestation between 2010 and 2020. Sentinel-2 imagery is predominantly used in multiple studies due to its multispectral capabilities, offering diverse bands and high-resolution imagery. The prevalent resolution for Sentinel-2 imagery is 10 m. Although less common, Sentinel-1 imagery is used with Sentinel-2 imagery, in tropical regions (Altarez et al., 2023).

Cloud Cover

A common concern is the mitigation of cloud cover. There are basically two approaches that can complement each other. The first filters data at the tile level, using the cloud cover percentage. The second acts at the pixel level, masking the cloud-covered pixels of the image.

Considering the approach at the **tile level**, efforts are considered to keep this cover below a specific threshold, as this, among other variables, can lead to an increased rate of false positives and false negatives (Alzu'bi & Alsmadi, 2022). Using Sentinel-2 images some studies detecting forest changes exclude from the analysis all images where overall cloud cover is larger than 15% (Kalinaki, Malik, & Ching Lai, 2023) or 20% (Isaienkov et al., 2021). However, (Altarez et al., 2023) considered both Sentinel-1 and 2 and kept the threshold at 30%. For a change detection in shrubland, the images were discarded if the cloud cover exceeded 50% (Moncrieff, 2022).

A **pixel-level** approach requires the creation of a mask to identify which pixels to eliminate. (Solórzano et al., 2023) masked the pixel clouds in Sentinel-2 images according to the s2cloudless workflow proposed by (Skakun et al., 2022), and cloud probability bands. (Moncrieff, 2022) uses the same approach, where pixels with a cloud probability greater than 40% are masked. (Solórzano et al., 2023) also suggests that, depending on the cloudiness conditions of a study area and the images used, there can be a trade-off between single-date images (with potentially more artifacts due to clouds) and temporal composites with typically larger study area coverage. The s2clouldless is also used in the work of (Waldeland et al., 2020) to map vegetation height with Lidar - where areas with clouded pixels were masked with an ignore value to prevent cloud pixels from being used to train the model.

The missing values caused by cloud shadows can be estimated using the CubicSpline algorithm (Matosak et al., 2022a) or calculated from cloud masks using cloud and solar geometry combined with dark pixel detection (Moncrieff, 2022).

All cloud-contaminated observations on LCMAP products are removed based on the Analysis Ready Data (ARD) pixel quality assessment (QA) band derived from the version 3.3 Fmask algorithm (Zhou et al., 2022; Zhu et al., 2015). A multi-temporal mask model is implemented to remove the outliers, and then Landsat ARD containing invalid or physically unrealistic data values for surface reflectance and temperature bands are also removed (Xian et al., 2022). Due to the non-existing thermal bands, this can not be applied to Sentinel Images.

Bands and Indices

(Torres et al., 2021) used all seven bands with 30 m resolution from Landsat and B2, B3, B4, and B8 with 10 m resolution from Sentinel-2, to detect deforestation in the Brazilian Amazon and compare two satellite image sources. To map areas of forest change, in China, (Xiang et al., 2023) used the same four Sentinel-2 bands while (Waldeland et al., 2022) used all 13 bands but resampled to 10 m resolution the bands with lower resolution, with the goal of mapping and monitoring forest in Africa.

RGB images are frequently combined with other indices. The Normalized Difference Vegetation Index (NDVI) has proven helpful for evaluating and tracking land degradation (Altarez et al., 2023), and as a greenness indicator (Kim et al., 2021). The Normalized Difference Moisture Index (NDMI) serves as an effective indicator of forest loss due to its ability to detect tree damage and provide data on plant water status, canopy cover, and biomass shift patterns. These indices are used together in studies that detect forest loss and classify land use and land cover (Altarez et al., 2023) and forest clear-cuts (Isaienkov et al., 2021). The Enhanced Vegetation Index (EVI) is commonly considered as is the case for the detection of land cover change in shrubland [8], mapping deforestation (Altarez et al., 2023; Matosak et al., 2022a), and for paddy rice mapping where one of the datasets used optical indices only (Onojeghuo et al., 2023).

Topographical data

For instance, to identify priority afforestation sites, (Kim et al., 2021) utilized topographical data to identify priority afforestation sites, as one of the key features in North Korea is the distribution of highlands at an altitude of 2000m. The Digital Elevation Model (DEM) with 1-ARC resolution to calculate the slope and altitude of the terrain (Kim et al., 2021). To detect changes in wetlands, Pan et al (2023) also used DEM as input data for the model. For a vegetation height map, the Digital Terrain Model (DTM) and the Digital Surface Model (DSM) derived from Lidar data create a canopy height indicator by subtracting DTM from the DSM (Waldeland et al., 2022).

(Altarez et al., 2023) propose the inclusion of topographic parameters to improve the classifier’s capacity. (Matosak et al., 2022a) use the slope information as auxiliary data to improve the results. The hybrid classification of this study is based on LSTM (Long Short-Term Memory) and U-net.

4. Output

In general, there are three possible output sets of classes: 1) a single binary classification that determines where changes occur; the classes are change/no-change; 2) multi-year binary classification map; the precedent years impose constraints on the following years; 3) the classes (in general, multiple classes) correspond to transitions between the land cover before and after the change; in this case, one aims at characterizing the type of change.

In studies addressing the issue of deforestation, it is common to employ a **binary classification map** as the result of the study. Usually, the vegetation change between the dates of bi-temporal satellite images are identified (Khankeshizadeh et al., 2022), and maps are classified as “forest”/”non-forest” where the difference between the two resulting maps will represent a forest loss or gain (Alzu’bi & Alsmadi, 2022; Kalinaki, Malik, Lai, et al., 2023).

As an example of a **multi-year binary classification map**, (Isaienkov et al., 2021) consider past clear-cutting events in the study regions, creating binary maps that identify the evolution of those changes.

A **multiple classification map** can be done, representing types of forest loss. (Matosak et al., 2022a) make the distinction between “old-growth forest loss” and “second forest/plantation loss”, while (Solórzano et al., 2023) represent “deforestation”, “natural vegetation” and “past deforestation”.

Change detection can be performed by analyzing differences between pre and post changes images as in the examples discussed above, or by comparing land cover maps at different dates. This latter approach uses a series of LCLU maps and compares them. (Altarez et al., 2023) created LULC maps from Sentinel 1 and 2 for 2015 and 2022 and estimated deforestation areas in the Philippines. (Wang et al., 2022) creates LCLU maps in agricultural areas for 2019, 2020 and 2021 in China with deep learning techniques from 10 m Sentinel-2 images to monitor land cover.

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