Ministerio de Ganadería, Agricultura y Pesca
Dirección General FORESTAL

Ministerio de Ambiente
Dirección Nacional de Cambio Climático

Native Forest Mapping 2021 Methodology and Results Report

Performance indicator associated with the Sovereign Sustainability-linked Bond (SSLB)

KPI-2 Native Forest Area in Hectares

March 2023

Table of contents

1. INTRODUCTION

The General Forestry Directorate (DGF) of the Ministry of Livestock, Agriculture and Fisheries (MGAP), in coordination with the National Directorate of Climate Change (DINACC) of the Ministry of Environment (MA), submit this report linked to the native forest key performance indicator (KPI-2) of the Sovereign Sustainability-linked Bond (SSLB). This KPI (KPI-2) is based on native forest area estimates (in hectares), through the use of satellite mapping and remote sensing techniques, following the provisions of the Intergovernmental Panel on Climate Change (IPCC, 2006) and the IPCC Good Practice Guidance on Land Use, Land Use Change and Forestry (IPCC, 2003). The methodologies used to calculate KPI performance are the same as those used by Uruguay to report progress on its Nationally Determined Contributions (NDCs) to the United Nations.

The framework for the issuance of the SSLB was prepared by the Ministry of Economy and Finance (MEF), the Ministry of Industry, Energy and Mining (MIEM), the Ministry of Foreign Affairs (MRE), the MA and the MGAP . It is a cornerstone for Uruguay's access to the sustainable sovereign finance market and, above all, it aspires to become an alternative approach to sustainability-linked debt financing. Uruguay seeks to implement a symmetrical rate reward and penalty structure, tying the country's cost of capital to achieving the climate and nature conservation targets based on the commitments made under the Paris Agreement. The main goal is to tie sustainable finance to achieving concrete, material, and visible climate performance targets, sustained by a robust reporting and verification system and driven by the actions, policies, and investments needed. The Inter-American Development Bank (IDB) and the United Nations Development Programme (UNDP) provided critical technical assistance for this project.

This document describes the methodology used to map native forest cover in Uruguay in 2021—based on satellite image processing techniques—to estimate KPI-2 of the SSLB: Preservation of native forest area (in hectares) compared to the baseline year (in %).

Mapping efforts were coordinated by the Evaluation and Information Unit of the DGF of the MGAP together with the DINACC of the MA and carried out by a team of 6 technical experts: a mapping technical supervisor, a statistics expert in charge of the validation, and five interpreters trained in the interpretation of land use/land cover from satellite images, who were involved in post-classification, editing, and validation.

2. MATERIALS AND METHODS

The proposed workflow resulted in the supervised object-based classification of satellite images captured through Sentinel sensors by the European Space Agency (ESA) to map native forest cover.

Image classification entails extracting classes of information from a multiband image. The methodology used was specifically developed and adjusted to the characteristics of the Uruguayan forests.

The processing and analysis of open-access satellite imagery were conducted using the Google Earth Engine (GEE) cloud computing platform (Gorelick et al., 2017), while geoprocessing tasks were performed using QGIS and ArcGIS Pro software. The following figure (Figure 1) outlines the different stages of the methodology used to build the native forest map, further described later in this report: Data search and selection; Supervised classification; Post-classification; Accuracy assessment.

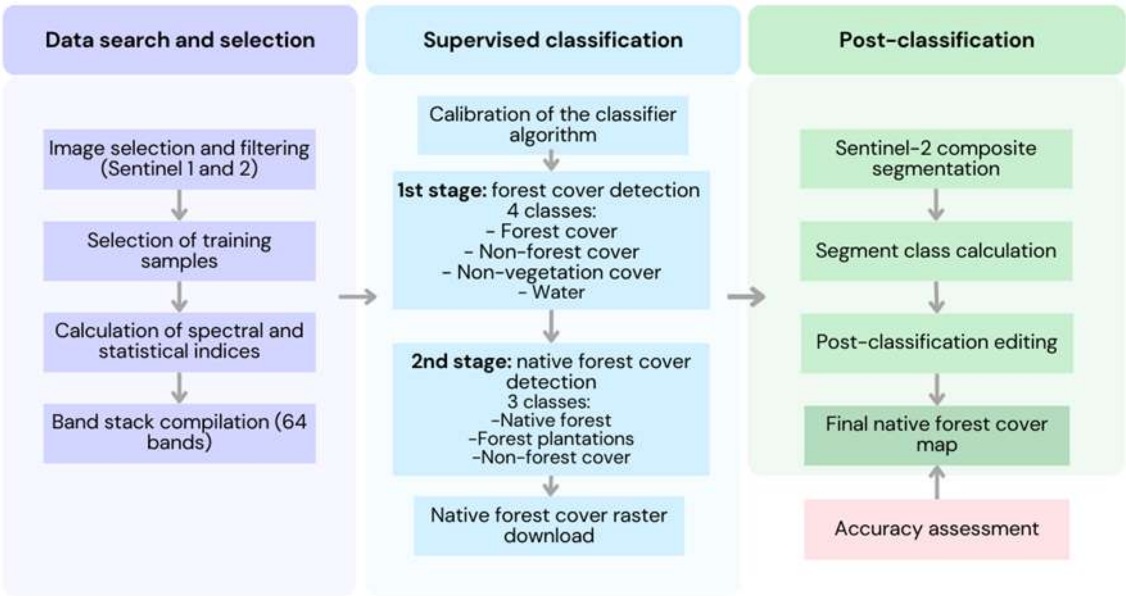

Figure 1: 2021 Native forest mapping process outline

The "Validation of Uruguay's Native Forest Mapping through Sentinel 2021 imagery" report describes the accuracy assessment process for validating the map and its results.

2.1. Data search and selection

2.1.1. Satellite data

The search for prepared data for analysis, intercalibrated, that meets geometric and radiometric quality requirements was carried out in the cloud using the GEE platform. Scenes were selected considering factors such as the presence of clouds and nearest dates amongst the chosen images, taking the period between October 2021 and February 2022 as a reference. Time series images close to the spring-summer period were selected so that spectral signal reflecting the photosynthetic activity of the native forest was clear. In this way, the leaf senescence period of many species is avoided, and classification errors due to misinterpretation with other coverages are reduced. This makes it possible to obtain a more accurate mapping of the native forest.

It has been shown that the integration of SAR (synthetic aperture radar) satellite imagery with multispectral imagery (such as Sentinel-2 imagery) can improve the accuracy of land use/land cover classifications (e.g., Dobrinić et al., 2020; Heckel et al., 2020; Solórzano et al., 2021). Based on the study's objectives, satellite data from different sensors (Sentinel-1 and Sentinel-2) was merged in the same working environment. Sentinel-2 sensor images were used to take advantage of the spectral discrimination potential of its optical instruments, combined with images from the Sentinel-1 sensor (SAR) for cloud-free data.

The Shuttle Radar Topography Mission (SRTM; Farr et al., 2007) digital elevation model was also employed for the classification. It was used for the following topographic variables: elevation (meters) and slope (degrees). The SRTM is an open-access global product using radar interferometry with a spatial resolution of 30 meters. The model was acquired for the territory of Uruguay, resampled to a spatial resolution of 10 meters, and added to the data stack within the GEE platform . This type of topographic information, combined with multitemporal imagery, can help differentiate native forests from other land uses that may lead to misinterpretation and have been successfully used in classifications by forest type (Liu et al., 2018; Hościło and Lewandowska, 2019).

Images from the Sentinel-1 Ground Range Detected (GRD) collection available in the GEE data catalog are already pre-processed regarding thermal noise, radiometric calibration, and terrain correction. C-band images obtained from this sensor between October 2021 and February 2022 were used, with a spatial resolution of 10 meters in the downward mode, in dual polarization (VH and VV polarizations separately).

Subsequently, a median reducer was applied to each polarization to generate time series data (median composite image), which are less susceptible to image acquisition conditions. The image time series median is a commonly used statistical indicator successfully applied in land use classification (Mahdianpari et al., 2018; Liu et al., 2019).

A composite of Sentinel-2 MultiSpectral Instrument (MSI) images was made, using reducers to choose the median values from the pixel stack collection. . This collection is structured to obtain full image composites for the entire area under study without gaps by selecting all images that met the date (October 1, 2021, to March 1, 2022) and cloud filter parameters. Level 2A images (with radiometric and atmospheric corrections) were used. Level 2A products are delivered with a constant ground sampling distance of 10, 20, and 60 meters, depending on the native resolution of the different spectral bands. Multispectral images from Sentinel-2 have 13 spectral bands: four 10-meter bands, six 20-meter bands, and three 60-meter spatial resolution bands (Table 1).

All Sentinel-2 bands with 10- and 20-meter spatial resolution (resampled to 10 meters) were selected, using surface reflectance values, i.e., already incorporated atmospheric corrections. In addition to traditional bands of the visible and near-infrared (NIR) spectrum, *Red Edge* bands (B5, B6, B7, and 8A) were employed, which are related to chlorophyll content of the vegetation, along with SWIR bands (B11 and B12), related to water content. Since these collections are geometrically and radiometrically corrected, the only correction required was cloudy pixels masking (clouds and cloud shadows). The presence of clouds and cloud shadows in satellite images is one of the processing drawbacks. This is why GEE has a feature for filtering or masking cloudy pixels. The *maskS2clouds* function of the GEE platform was used for filtering.

Table 1. Wavelength and spatial resolution of Sentinel-2 bands. Source: National Geographic Institute of Spain (IGN).

Sennel -2 Band	**Central wavelength (μm)**	**Spaal r esoluon (m)**
Band 1 - Coastal Aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetaon R ed Edge	0.705	20
Band 6 - Vegetaon R ed Edge	0.740	20
Band 7 - Vegetaon R ed Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetaon R ed Edge	0.865	20
Band 9 - Water vapor	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

Similar to the Sentinel-1 data, a temporal median reducer was applied to all Sentinel-2 scenes, producing seasonal optical features for classification tasks. The median reducer function enables the production of cloud-free seasonal datasets, where noisy, very dark, or very bright pixels are also removed. Sentinel-2 median composite for the visible spectrum bands (RGB) was downloaded as a raster for further segmentation.

In addition, several spectral indices were calculated from the original Sentinel-2 image bands to add this information into the multiband stack and use them as input data for the classifier algorithm. A spectral index results from remote sensing data through spectral band calculations (Jackson and Huete, 1991). The indices used were: NDVI *(Normalized Difference Vegetation Index*) (Rouse et al., 1974), EVI *(Enhanced Vegetation Index*) (Justice et al., 1998), NDWI *(Normalized Difference Water Index*) (Gao, 1996), and MSAVI *(Modified Soil-Adjusted Vegetation Index*) (Richardson and Wiegand, 1977).

The multiband stack was completed by calculating statistical indicators of the time series (median, min, max, and variance) for each of the Sentinel-2 bands used and for each of the spectral indices for the entire image time series (from October 1, 2021, to March 1, 2022). For NDVI, four monthly medians for the November/2021 to February/2022 period were also added to the multiband stack. These metrics can be directly applied to the bands or derived indices, and represent the different seasonal stages of land cover influenced by vegetation phenological regimes, hydrological regimes or land use (Muro et al., 2020). A total of 64 satellite data bands (Figure 2 and Figure 3) were used as input elements by the classifier algorithm.

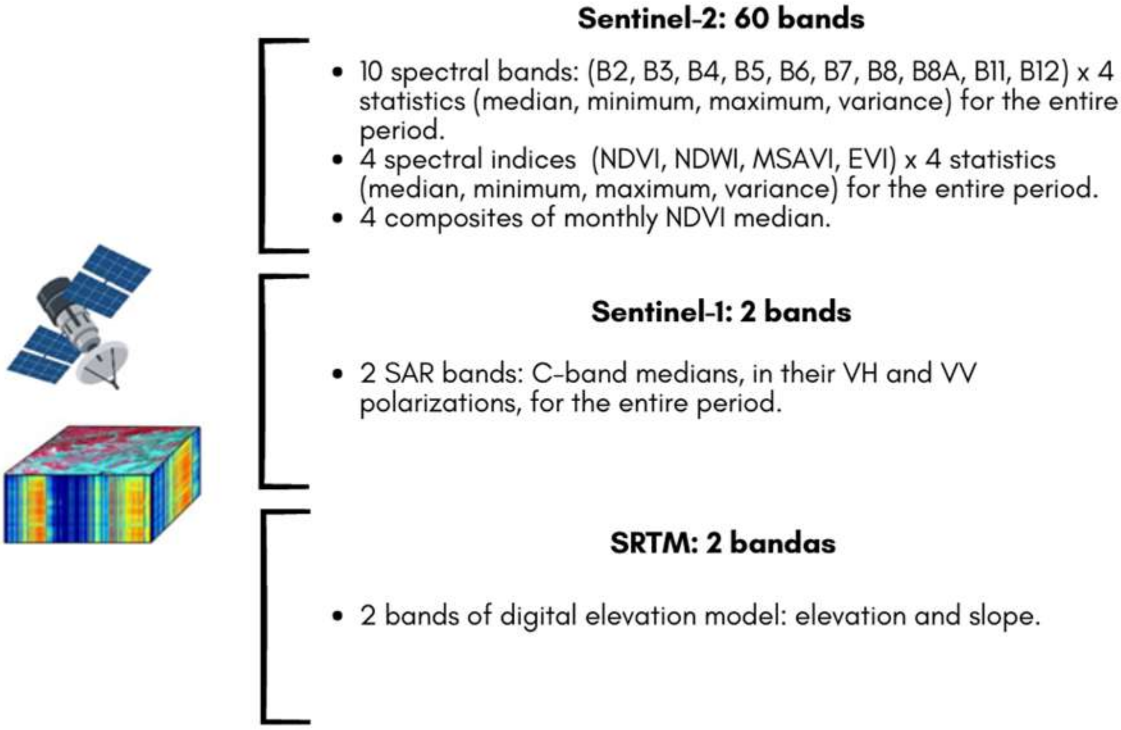

Figure 2. Summary of satellite data used by the classifier algorithm.

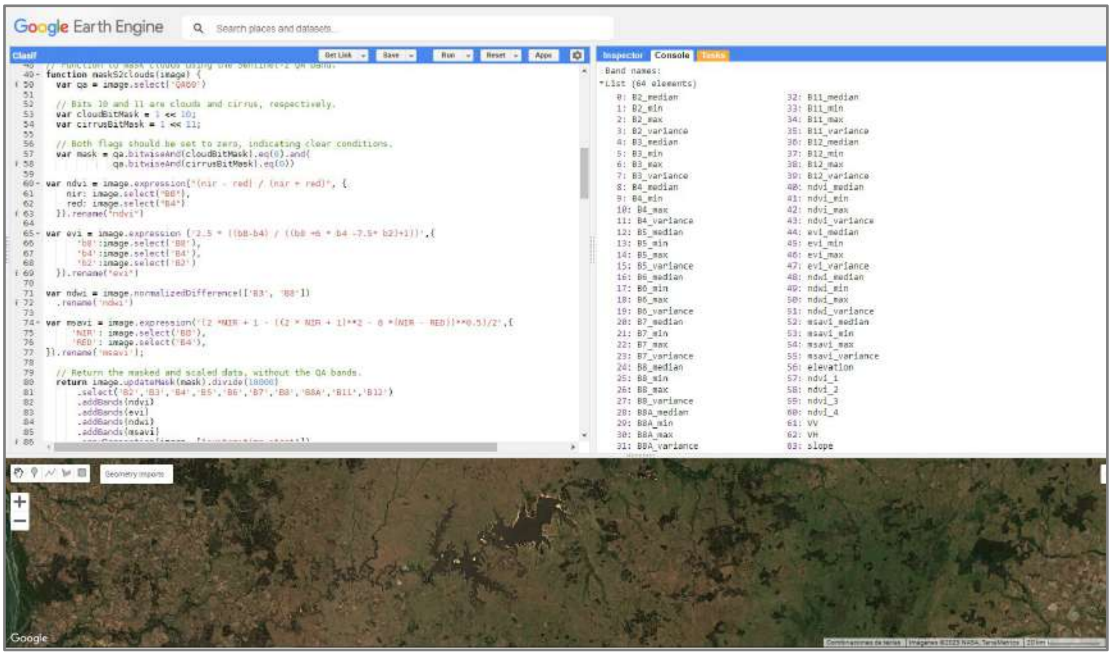

Figure 3: Google Earth Engine Screenshot showing the bands used for classification.

2.1.2. Selection of training samples

For the design of the classification legend, the following conceptual definitions were used to differentiate land use/land cover categories.

Native forest: areas covered by vegetation associations dominated by trees that maintain their natural characteristics. All types of native forests are included in this category.

The following operational definition of native forest was used for selecting training samples and post-classification editing: area with a canopy cover of native species greater than or equal to 30 % and a minimum land area of 0.5 ha. This definition does not consider tree height or other thresholds, such as minimum width.

Forest plantations: areas primarily made up of planted alien species trees, mostly *Pinus* and *Eucalyptus*. This includes standing commercial plantations, shelterbelts, and shade trees of exotic species, as well as established protective forests.

*"Native forest" and "Forest plantations" make up the "Forest cover" category used in the first stage of the classification.

Non-forest cover: this class includes those areas that showed above-ground biomass but no predominant tree component when satellite images were taken (natural grasslands, wetlands, scrub or shrublands, agricultural crops, vegetable crops, implanted pastures, and urbanized areas covered with herbaceous or shrub vegetation, without a predominant tree component).

Non-vegetation cover: this class includes those areas that did not show above-ground biomass when satellite images were taken (bare soil, urbanized area and sand).

Water: includes inland water bodies, both natural and artificial. Given the spatial resolution of the images used and within the scope of the supervised classification process, some watercourses with a channel width of at least 10 m were included.

Some examples (Figure 4 and Figure 5) of the categories used in the native forest map are shown below, using a visualization of Google Earth images (left) compared to Sentinel-2 subscenes (right) in a false-color visualization (combination of B8/B11/B3).

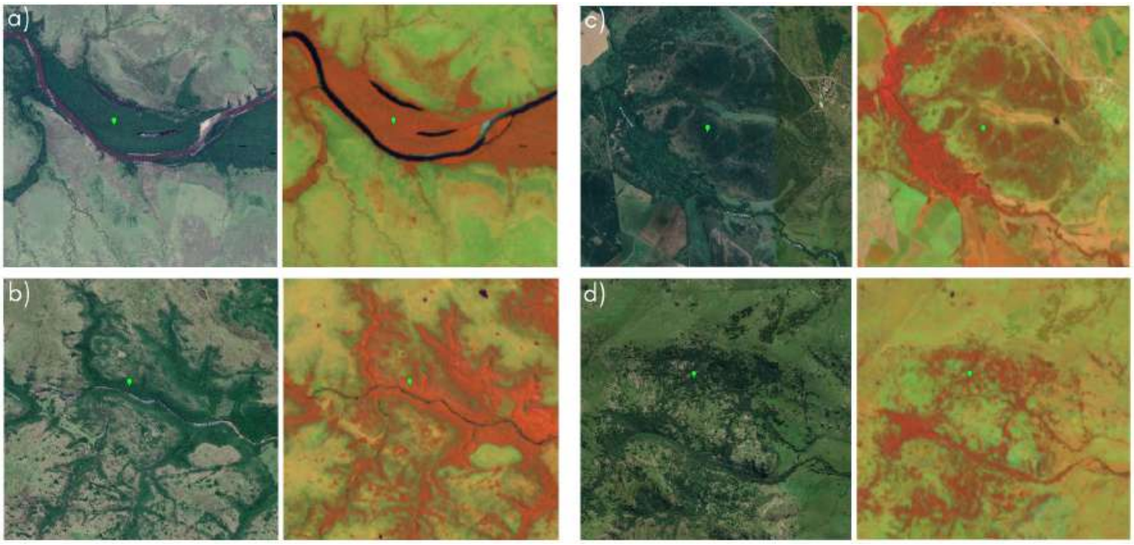

Figure 4: Visualization of Google Earth images and Sentinel-2 subscenes, showing the native forest class: a) riparian or riverside forest; b) ravine forest; c) open or “park” forest; d) hills forest.

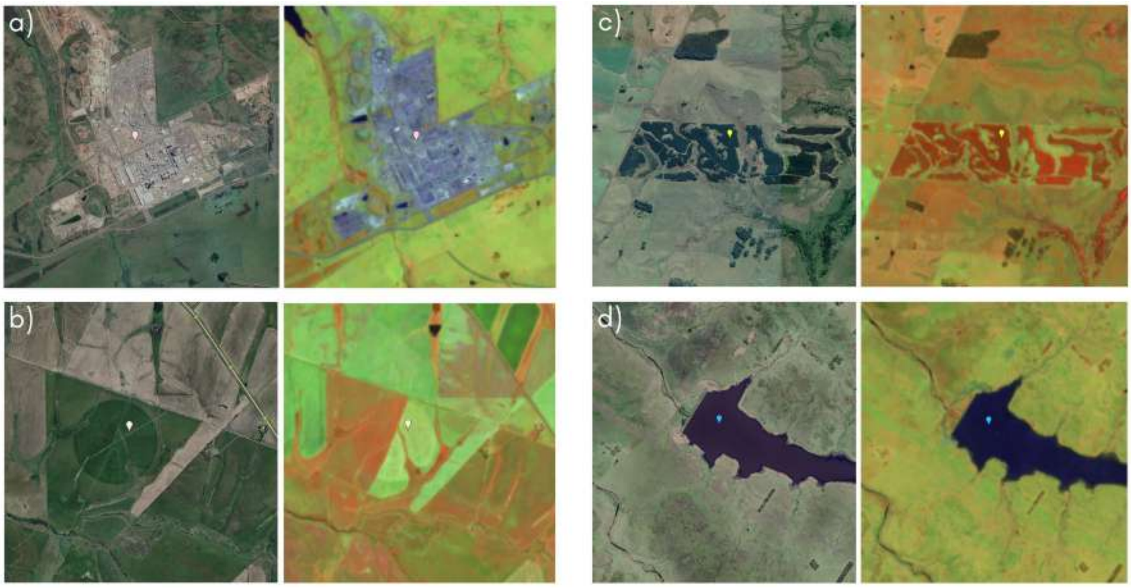

Figure 5: View of Google Earth images and Sentinel-2 subscenes, showing the classes corresponding to: a) Non-vegetation cover (urbanized area); b) Non-forest cover (agricultural crops); c) Forest plantations; d) Water surfaces.

Some of the challenges involved in mapping native forests in Uruguay are: their low relative surface area compared to the total territory; confusion with forest plantations of exotic species, both commercial and non-commercial; low tree density in some cases (“park” forests); fragmentation and distribution in "patches" of certain forests (hills forests) (Betancourt, 2021). Additionally, there is a certain similarity in the spectral response of some native forests (mainly riparian zones) with certain wetlands in the country, which makes it even more difficult to discriminate between them using remote sensing techniques.

Given the nature of these ecosystems and the difficulties in accurately identifying them through remote sensing, it is quite possible that a pixel-based classification that attempts to predict areas of native forest cover includes possible false positives (e.g., forest plantations scrub or shrublands, wetlands). Below are some examples of potential confusion between different vegetation cover classes that can hinder the remote sensing of native forests in Uruguay (Figure 6).

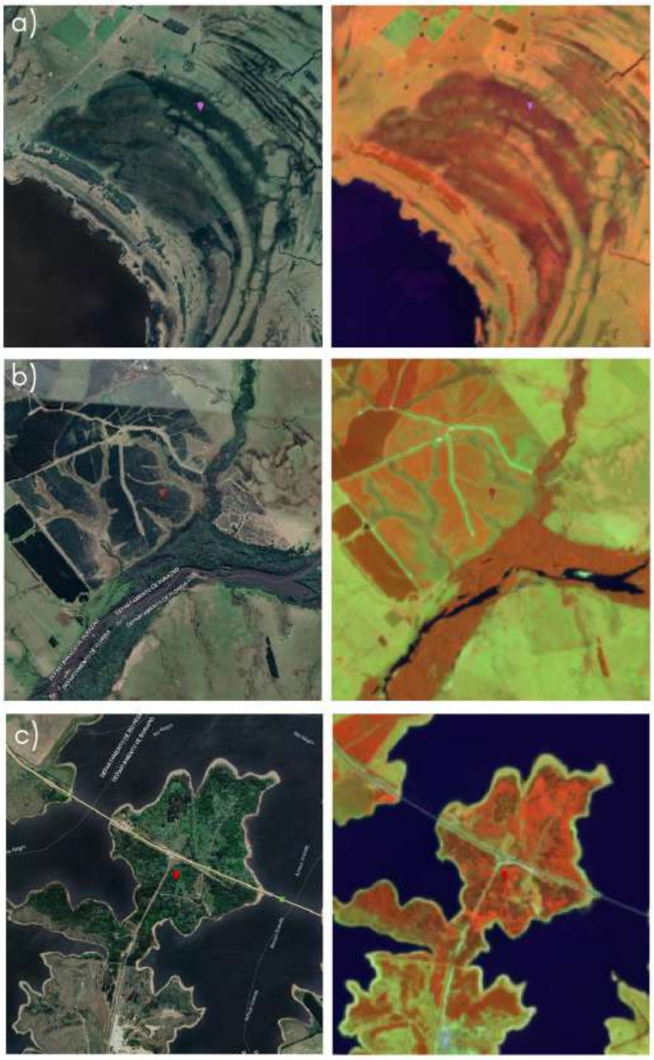

Figure 6: View of Google Earth images and Sentinel-2 subscenes, showing some land covers often confused with native forests: a) wetlands; b) young forest plantation; c) mix of exotic and native tree species.

Considering the above mentioned challenges, special care was taken in selecting training samples for this classification.

The selection of training samples was performed by manual digitization of training polygons in the GEE platform based on accurate visual interpretation of Sentinel-2 image composites (in their true-color and false-color displays) for the period under study. In addition, high-resolution satellite images, available in Google Earth base maps within the GEE platform, were also used as supplementary information.

On these composites, polygons were selected on the types of land cover representing the different classes to be identified in each classification stage. Homogeneous sites were considered for reference sample collection to mitigate the effect of mixed pixels by avoiding fragmented or heterogeneous land cover areas.

T raining polygons were homogeneously and randomly distributed throughout the territory, trying to cover all regions of the country and forest types, as shown in Figure 7.

In the first run of the classifier, the number of training polygons was evenly assigned for each class defined in the two classification stages. Subsequently, based on expert judgment, a greater number of samples were added for the classes of interest and those with higher spectral heterogeneity (forest stratum classes and non-forest cover) in areas where confusion between classes was observed.

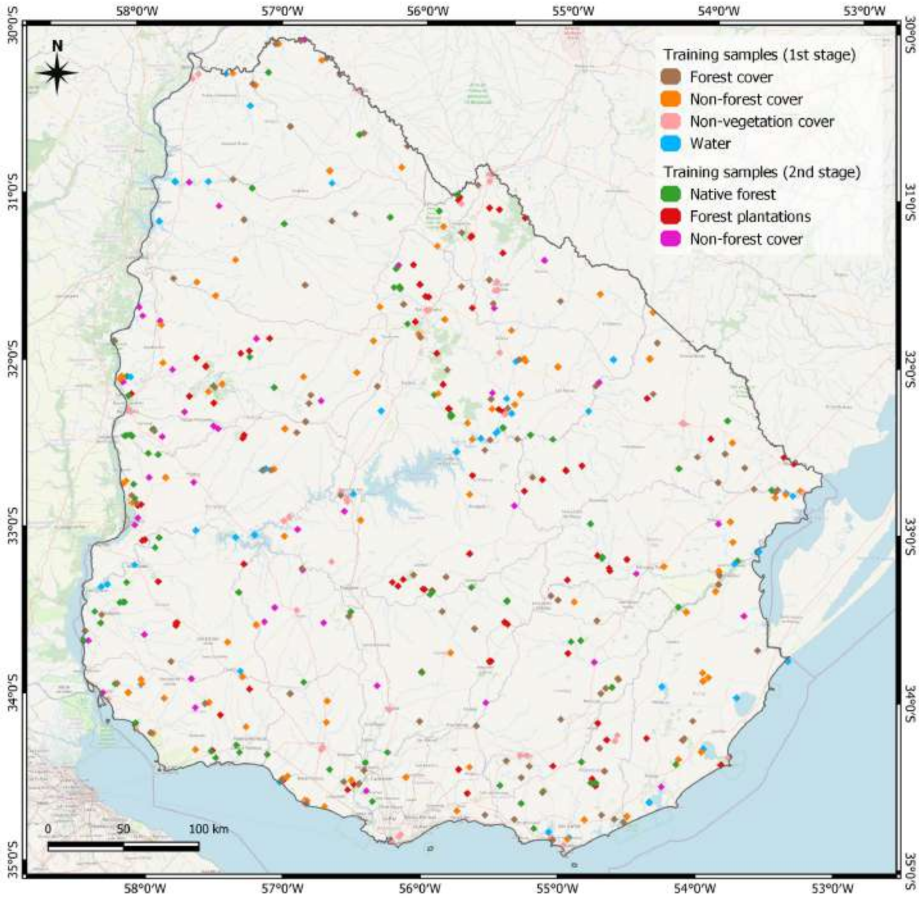

Figure 7: Location of the selected training samples by class.

A total of 498 polygons were digitized to train the classifier algorithm for the two classification stages; each pixel (10 meters on a side) within these polygons was the sampling unit .

As outlined in the following section, the native forest map was built based on two supervised classifications: the first to obtain a base layer of forest cover and the second to distinguish between native forest and forest plantations for more accurate discrimination between these two classes.

The following were interpreted in the first stage: 102 polygons for the "Forest cover" class (14,823 pixels); 89 polygons for the "Non-forest cover" class (12,472 pixels); 46 polygons for the "Non-vegetation cover" class (6,550 pixels); 41 polygons for "Water (6,955 pixels). For the second stage, the following were defined for the "Forest cover" class: 93 polygons of the "Native forest" class (10,195 pixels); 83 polygons of "Forest plantations" (9,207 pixels); 44 polygons of "Other cover/non-forest cover" (5,887 pixels), corresponding to areas of confusion in the initial classification, where no predominant tree cover was observed when interpreting the reference images.

Table 2. Summary of selected training samples for each class.

Class	Number of polygons	
1st stage		
Forest cover	102	14,823
Non-forest cover	89	12,472
Non-vegetaon c over	46	6,550
Water	41	6,955
2nd stage		
Nav e forest	93	10,195
Forest plantaons	83	9,207
Non-forest cover	44	5,887

2.2. Supervised classification

Classification of digital satellite data is the process in which image pixels are grouped into individual classes or categories based on their similarity in data values (Chuvieco, 2010). Supervised classification uses spectral information obtained from samples corresponding to different types of coverage to classify an entire image or a mosaic of photos. In this case, the classifier used the data from the combination of bands and indexes established for each image in the stack (Figure 2), assigning a class to each composite pixel. This stage was also carried out on the GEE platform.

A two-level classification scheme was selected to produce a layer corresponding to native forest cover. In the first stage (forest cover detection), a supervised classification was applied to distinguish a forest layer (area covered by forest plantations and native or natural forests), distinguishing it from the rest of the land cover and then masking over this layer and applying a new supervised classification. The second stage (native forest detection) implied distinguishing native forests within the forest cover mask. Thus, the classes for the first classification comprised : Water , Forest cover, Non-forest cover, and Non-vegetation cover. The second stage of the classification comprised three classes: Native Forest, Forest Plantations, and Other Cover/Non-forest Cover (this class included sites that were not clear during the first classification stage, where the cover did not correspond to forest cover).

2.2.1. Forest cover detection

The first stage of the classification consists of an initial stratification into four land cover classes: Water , Forest cover, Non-forest cover, and Non-vegetation cover.

A "mask" is created based on this classification to detect all areas whose cover corresponds to the forest layer (planted or native). For this purpose, training samples were selected for each layer based on the types of coverages of the different classes to be detected at this stage. Supervised classification relies on all the information in the multiband stack—obtained from the training samples corresponding to other land use/land cover types—to classify the entire image composite.

The GEE platform was used, applying the non-parametric Random Forest classification model (Breiman, 2001) with 100 decision trees as the main parameter and the aforementioned subset of training samples. This algorithm is a powerful classification tool; it is highly accurate, can handle large data sets, and is less computer-intensive than other methods (Gislason et al., 2006). Random Forest is a learning method that operates by averaging many randomly generated decision trees for a single low-variance, high-accuracy final model (Breiman, 2001; Liaw and Wiener, 2002).

2.2.2. Native forest cover detection

Once the "mask" layer of the forest cover is available, it is classified into three classes: Native Forest, Forest Plantations, and Other Cover/Non-forest Cover. A very similar process to the previous one is performed, with the same Random Forest classifier algorithm (and same parameters), but with the training samples corresponding to the second stage of the classification (Table 2) and masking based on the previous mosaic so that only pixels corresponding to tree cover area are classified. The selection of training samples for classification was also made through visual interpretation based on the composite image and high-resolution images available.

The majority tool was used at this classification stage; it is a pixel filter to remove the so-called "salt and pepper" or isolated pixel effect, thus smoothing the resulting product. As a result, a layer corresponding to the forests considered within the scope of this activity (i.e., only the category "Native forest") was obtained, , which was downloaded in raster format for further processing.

2.3. Post-classification

2.3.1. Segmentation

Sentinel-2 composite image was segmented using the ArcGIS Pro software segmentation tool based on its spectral information, to perform an object-based image assessment.

Object-based image assessment provides an alternative methodology to pixel-based assessment, using a combination of shape , size, and spectral information to classify image data (Hay et al., 2005). Objects or segments are regions produced by one or more homogeneity criteria in one or more dimensions (Blaschke, 2010). These objects originate from an image segmentation process in which pixels close to each other and similar spectral characteristics are grouped into a segment, representing land elements.

Ideally, a segmented image will represent discrete objects while representing them completely and separately from neighboring objects. A group of neighboring pixels (grouped based on their spectral homogeneity and spatial arrangement) can better represent object features than individual pixels (Whiteside et al., 2011), making it easier to manage the resulting data. One of the advantages of segmentation is that it creates objects representing land cover types that can be spectrally variable at the pixel level, thus removing the so-called "salt and pepper" effect, which is very common in pixel-based classifications (Whiteside et al., 2011).

The parameters used to segment the Sentinel-2 image composite were: Spatial Range (20), Spectral Detail (18), and Minimum Segment Size (50).

Spatial Range refers to the relevance you want to assign to the proximity between image features, with a range of values from 1 to 20. Smaller values produce uniform and spatially smoother results between clustered areas, while higher values are more appropriate when the elements under study are small and must be combined (Wessel et al., 2018).

Spectral Detail sets the relevance given to the spectral differences of the image features, with values from 1 to 20. Lower values result in more smoothing and longer processing times, while higher values are appropriate for features that must be classified separately but have similar spectral characteristics (Wessel et al., 2018; ESRI, 2022).

Minimum segment size is directly related to the minimum mapping unit. Smaller segments of this size are merged with their best-fitting neighboring segment. The unit of this parameter is expressed in pixels; since we have 50 pixels in this case, the minimum mapping unit is equivalent to 0.5 hectares, as described in the operational definition of native forest.

The result is a finite set of objects that do not have yet a classification category assigned, which is done in a subsequent process. Both the segmentation products (shapefile) and the supervised classification were exported for further editing/corrections in a GIS environment. Figure 8 shows a Sentinel-2 composite sample site, and Figure 9 shows the result after segmentation.

Figure 8: Sentinel-2 composite subscene (true color display B4/B3/B2).

Figure 9: Example of Sentinel-2 image segmentation with true color display as basemap.

2.3.2. Segment type calculation

In this phase of the process, the Zonal Statistics tool in QGIS software was used to assign a class to each object (segment) by calculating the majority statistic, determining the majority class for each segment. In this case, the classes were Native forest/Non-forest

To do this, the vector file (shapefile format) generated in the previous step and the native forest classification in raster format, downloaded from the GEE platform, were used. This produced a new column in the input vector file—in this case, in the file containing the segments—with the binary value of the majority numerical class for each segment (1=Native forest; 0=Non forest). The "Non-forest" category of the preliminary map encompasses all segments where most cover belongs to other land covers that are not "native forest."

2.3.3. Post-classification editing

Once the categorized segments were obtained (Native forest/ Non-forest), a review was carried out by a team of five interpreters to verify whether their classification was aligned with the supporting data (high-resolution satellite and aerial images). To facilitate the review of the categorized segments, a grid was created to maintain organization for the editing work, dividing the territory into five zones, with each interpreter assigned to a specific zone.

Corrections were made by visual interpretation of the segments that had been misclassified in the previous stage, based on the high-resolution images available (Google Satellite, ESRI Satellite, aerial orthophotos of the Spatial Data Infrastructure of Uruguay [IDEUy]) and the Sentinel-2 image composite from the same dates used for classification. These misclassified objects were assigned the correct cover type class (Native Forest/Non-Forest).

The same operational definitions of native forests mentioned earlier in the document were used in this stage. As several interpreters were involved, they were trained and were in communication throughout the process to ensure consistency and agree on a common approach to labeling those segments.

This methodology was developed to overcome the challenges involved in accurately mapping native forests in Uruguay and distinguishing them from other land use/land cover types that may have similarities in their spectral behavior measured through remote sensing sensors.

In this final stage of post-classification editing, the objective was to correct the confusions of the preliminary map. In particular, certain confusions that may persist between native forests and forest plantations are detected in this stage through visual interpretation based on differences in texture, stand shape, and planting scheme.

Figure 10 shows an example of the post-classification visual editing process of the segments. There, a segment misclassified in the preliminary map as "Non-forest" is shown , which actually met the criteria of the operational definition of native forest, and it was manually assigned the class of "Native forest" (Figure 10(c); purple segment). There are also two segments (Figure 10(c); orange segments), which had been misclassified in the preliminary map as "Native Forest" but were then labeled as "Non-forest" in the final map because they did not meet the minimum percentage of native tree cover of the operational definition. The remaining segments of the preliminary map were considered to be correctly classified for both the "Native forest" class (Figure 10(b, c, d); green segments) and the "Non-forest" class.

Figure 10: Example of the post-classification editing process: a) Sentinel-2 subscene in true color display; b) preliminary result of the native forest map (in green); c) preliminary result, highlighting misclassified segments, as Native Forest (in orange) and as Non-forest (in purple); d) post-editing result of the native forest map (in green).

The necessary modifications (changes from one class to another) were made directly in the shapefile table containing the segments with QGIS software. Once the segment editing was completed, a post-processing stage of the map was carried out, where geometric and topological corrections were also performed in QGIS.

2.3.4. Accuracy assessment

The last step consists of validating or assessing the resulting map to estimate the accuracy of the classification. The "Validation of Uruguay's Native Forest Mapping through Sentinel 2021 imagery" report outlines the methodological details and results.

The thematic accuracy assessment consists of comparing the information on the map with reference information considered highly reliable. This reference information is typically based on verification site sampling, where the classification is obtained from field observations or more detailed satellite image analysis than those used to generate the map (Peralta-Higuera et al., 2001).

To accomplish this, a reference or "ground truth" information source was used, which consisted of independent land cover data with higher spatial resolution than the one used for generating the classification. This reference information was obtained from sources such as Google Earth imagery, ESRI data, or aerial orthophotos from the IDEUy. It should be noted that although the IDEUy nationwide aerial photography survey was conducted during the 2017-2018 period, the aerial photographs taken have very high definition (spatial resolution of 0.2 meters).

The accuracy assessment was carried out by random sampling by class, considering the map segments as the unit of analysis. For each segment of the validation sample, the class assigned in the native forest cover map was compared with the class set based on the visual interpretation of the high-resolution images (reference information or "ground truth"). Based on these results, the confusion matrix was constructed, and the overall accuracy percentage, producer's and user's accuracy of the map were calculated, along with their corresponding confidence intervals (Olofsson et al., 2014).

3. RESULTS

The following map (Figure 11) of Uruguay's native forest cover in 2021 was produced based on the above methodology (highlighted for better visualization). The map shows that native forests cover an area of 847,181 ha, which accounts for approximately 4.84% of the total land area of the country.

Figures 12-15 also show two larger-scale views of the final map for two sample sites with native forest cover, using very high-resolution aerial imagery (IDEUy) as basemap .

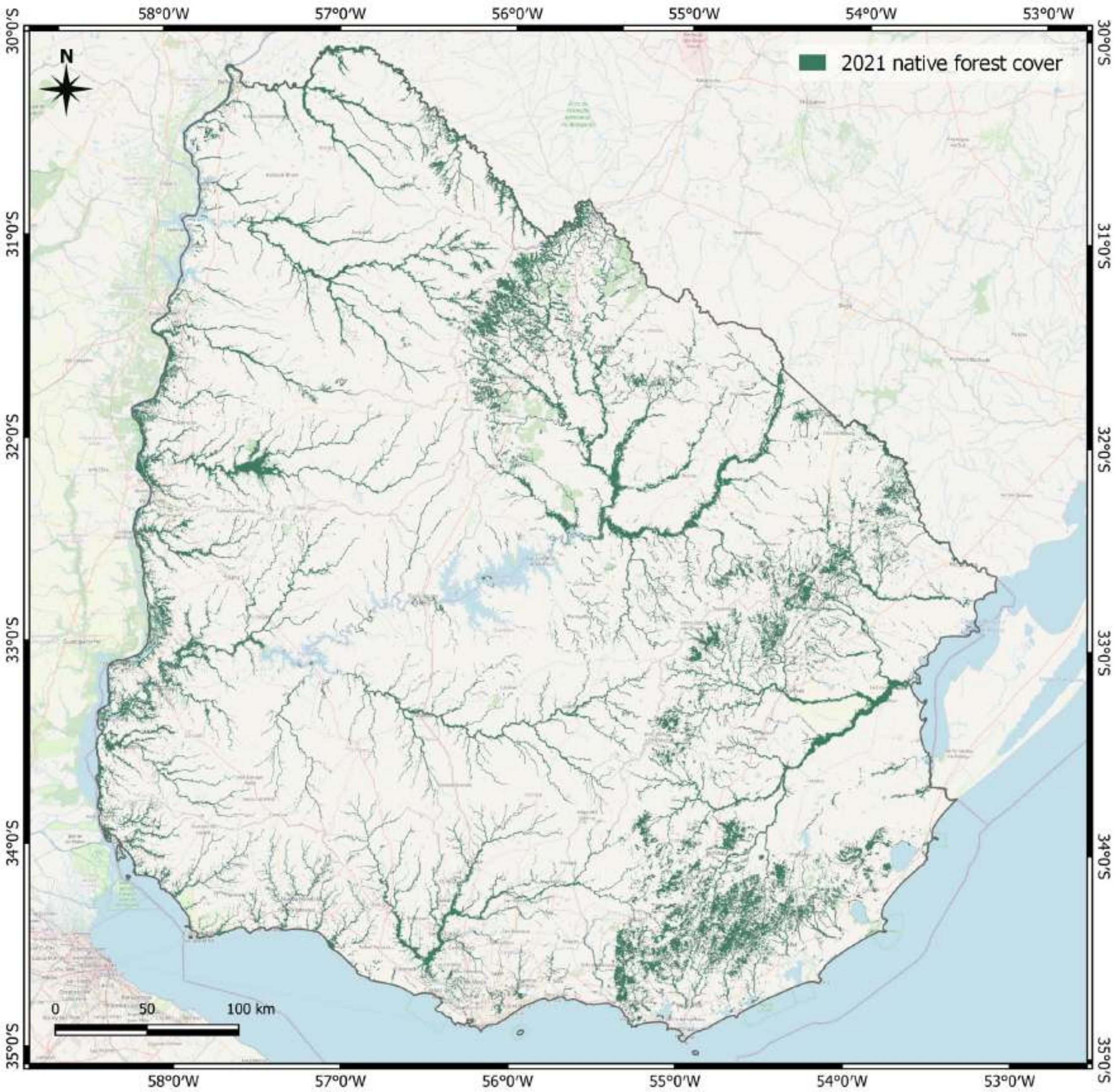

Figure 11: 2021 Native forest cover in Uruguay.

Figure 12: Aerial orthophotos (IDEUy) of a sample site with native riparian forest and forest plantation cover.

Figure 13: Mapping results (in green) on aerial orthophotos (IDEUy) of a sample site with native riparian forest and forest plantation cover.

Figure 14: Aerial orthophotos (IDEUy) of a sample site with ravine native forest cover.

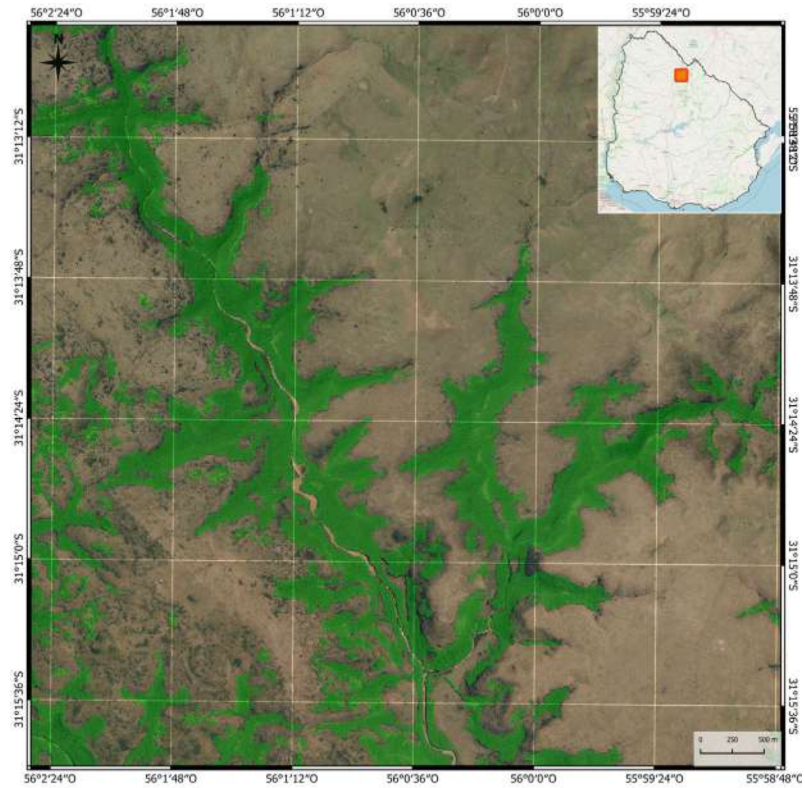

Figure 15: Mapping results (in green) on aerial orthophotos (IDEUy) of a sample site with ravine native stream forest cover.

3.1. Accuracy assessment

As mentioned above, the "Validation of Uruguay's Native Forest Mapping through Sentinel 2021 imagery" report outlines the accuracy assessment results.

4. REFERENCES

Betancourt, A. (2021). *Evaluación del riesgo de los principales ecosistemas boscosos de Uruguay (Risk assessment of the main forest ecosystems in Uruguay).* Master's thesis in Environmental Sciences. School of Science. Udelar. Montevideo.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS journal of photogrammetry and remote sensing*, *65*(1), 2-16.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.

Chuvieco, E. (2010). *Teledetección ambiental: la observación de la tierra desde el espacio (Environmental remote sensing: Earth observation from space).* Ed. Ariel. Barcelona. 608 p.

Congalton, R.G. (1991) A review of assessing the accuracy of classifications of remotely sensed data. *Remote sensing of environment, 37*(1), 35-46.

Dobrinić, D., Medak, D., and Gašparović, M. (2020). Integration of multitemporal Sentinel-1 and Sentinel-2 imagery for land-cover classification using machine learning methods. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 43*, 91-98.

ESRI (2022). ArcGIS Pro Documentation: Segmentation. https://pro.arcgis.com/en/pro-app/latest/help/analysis/image-analyst/segmentation.htm.

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., ..., and Alsdorf, D. (2007). The shuttle radar topography mission. *Reviews of geophysics, 45*(2).

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote sensing of environment*, *80*(1), 185-201.

Gao, B.C. (1996) NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote sensing of environment, 58*(3), 257-266.

Gislason, P. O., Benediktsson, J. A., and Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern recognition letters*, 27(4), 294-300.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment*, *202*, 18-27.

Hay, G. J., Castilla, G., Wulder, M. A., and Ruiz, J. R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation*, *7*(4), 339-359.

Heckel, K., Urban, M., Schratz, P., Mahecha, M. D., and Schmullius, C. (2020). Predicting forest cover in distinct ecosystems: The potential of multi-source Sentinel-1 and-2 data fusion. *Remote Sensing, 12*(2), 302.

Hościło, A., and Lewandowska, A. (2019). Mapping forest type and tree species on a regional scale using multi-temporal Sentinel-2 data. *Remote Sensing, 11*(8), 929.

IPCC (2003). Good Practice Guidance for Land Use, Land-Use Change and Forestry. Penman J., Gytarsky M., Hiraishi T., Kruger D., Pipatti R., Buendia L., Miwa K., Ngara T., Tanabe K., and Wagner F. (eds). Intergovernmental Panel on Climate Change (IPCC), IPCC/IGES, Hayama, Japan.

IPCC (2006). 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Eggleston H.S., Buendia L., Miwa K., Ngara T., and Tanabe K. (eds). Intergovernmental Panel on Climate Change (IPCC), IPCC/IGES, Hayama, Japan.

Jackson, R. D., and Huete, A. R. (1991). Interpreting vegetation indices. *Preventive veterinary medicine*, *11*(3-4), 185-200.

Justice, C. O., Vermote, E., Townshend, J. R., Defries, R., Roy, D. P., Hall, D. K., ..., and Barnsley, M. J. (1998). The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research. *IEEE transactions on geoscience and remote sensing*, *36*(4), 1228-1249.

Liaw, A., and Wiener, M. (2002). Classification and regression by randomForest. *R news*, *2*(3), 18-22.

Liu, Y., Gong, W., Hu, X., and Gong, J. (2018). Forest type identification with random forest using Sentinel-1A, Sentinel-2A, multi-temporal Landsat-8 and DEM data. *Remote Sensing, 10*(6), 946.

Liu, C. A., Chen, Z. X., Yun, S. H. A. O., Chen, J. S., Hasi, T., and PAN, H. Z. (2019) Research advances of SAR remote sensing for agriculture applications: A review. *Journal of integrative agriculture, 18*(3), 506-525.

Mahdianpari, M., Salehi, B., Mohammadimanesh, F., Homayouni, S., and Gill, E. (2018). The first wetland inventory map of newfoundland at a spatial resolution of 10 m using sentinel-1 and sentinel-2 data on the google earth engine cloud computing platform. *Remote Sensing, 11*(1), 43.

Muro, J., Varea, A., Strauch, A., Guelmami, A., Fitoka, E., Thonfeld, F., ..., and Waske, B. (2020). Multitemporal optical and radar metrics for wetland mapping at national level in Albania. *Heliyon*, *6*(8), e04496.

Olofsson, P., Foody, G., Herold, M., Stehman, S., Woodcock, C., and Wulder, M. (2014). *Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment*, 148, 42-57.

Peralta-Higuera, A., Palacio, J. L., Mas, G. B. J., Velázquez, A., Victoria, A., Bermúdez, R., ... and Prado, J. (2001). Nationwide Sampling of Mexico with Airborne Digital Cameras: an Image Database to Validate the Interpretation of Satellite Data. American Society for Photogrammetry and Remote Sensing. In *18th Biennal Workshop on Color Photography & Videography in Resource Assessment*. *Amherst, Massachusetts* (pgs. 1-9).

Rouse, J. W., Haas, R. H., Schell, J. A., and Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA special publication,* 351, 309.

Richardson, A.J., and Wiegand, C.L. (1977). Distinguishing vegetation from soil background information. *Photogrammetric engineering and remote sensing*, *43*(12), 1541-1552.

Solórzano, J. V., Mas, J. F., Gao, Y., and Gallardo-Cruz, J. A. (2021). Land use land cover classification with U-net: Advantages of combining sentinel-1 and sentinel-2 imagery. *Remote Sensing, 13*(18), 3600.

Stehman, S. (1996). Estimating the kappa coefficient and its variance under stratified random sampling. *Photogrammetric Engineering and Remote Sensing, 62*(4), 401-407.

Wessel, M., Brandmeier, M., and Tiede, D. (2018). Evaluation of different machine learning algorithms for scalable classification of tree types and tree species based on Sentinel-2 data. *Remote Sensing*, *10*(9), 1419.

Whiteside, T. G., Boggs, G. S., and Maier, S. W. (2011). Comparing object-based and pixel-based classifications for mapping savannas. *International Journal of Applied Earth Observation and Geoinformation*, *13*(6), 884-893.