# Training Guide Book on processing Satellite Imagery for Forest Monitoring using IMPACT Toolbox.

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This Guide Book presents 5 exercises that offers training on different techniques to map forests and its degradation. Training is based on working with the IMPACT toolbox, processing Landsat and Sentinel data. Each of the exercises is shown on real case in particular area in Eastern Africa. Different types of landscapes are reviewed, and a series of tools and methods available in IMPACT are tested.

For each exercise the necessary data are available for download. The data exercises for 2., 3. and 4. are provided also in lighter version, where some heavy files are missing (details under each exercise).

**Contents**

# 1. Installing IMPACT tool – review of new features

## What is IMPACT tool?

Developed at JRC, in the iForce team, to support activities linked to the mapping of forests and their degradation.

## Installing and updating

IMPACT is available from [http://forobs.jrc.ec.europa.eu/products/software/](http://forobs.jrc.ec.europa.eu/products/software/)

IMPACT as an auto-update mechanism: each time you launch it, it connects to the internet and checks if a newer version exists. In this case, it will download and install it.

## Overview

We will test the features in the exercises. We make a tour of functionalities through examples.

- Selecting a Sentinel image from JRC web site (CID portal)
- Generalities on IMPACT tool: the 3 panels
- Importing the image: band selections, resolution
- Note on Landsat and Sentinel spectral properties.
- Displaying raster images. IMPACT has default behaviour
- Data repository DATA/. Rules, moving files in the file panel, renaming, deleting files.

Working with rasters:

- Recoding
- Creating legends

Working with vectors:

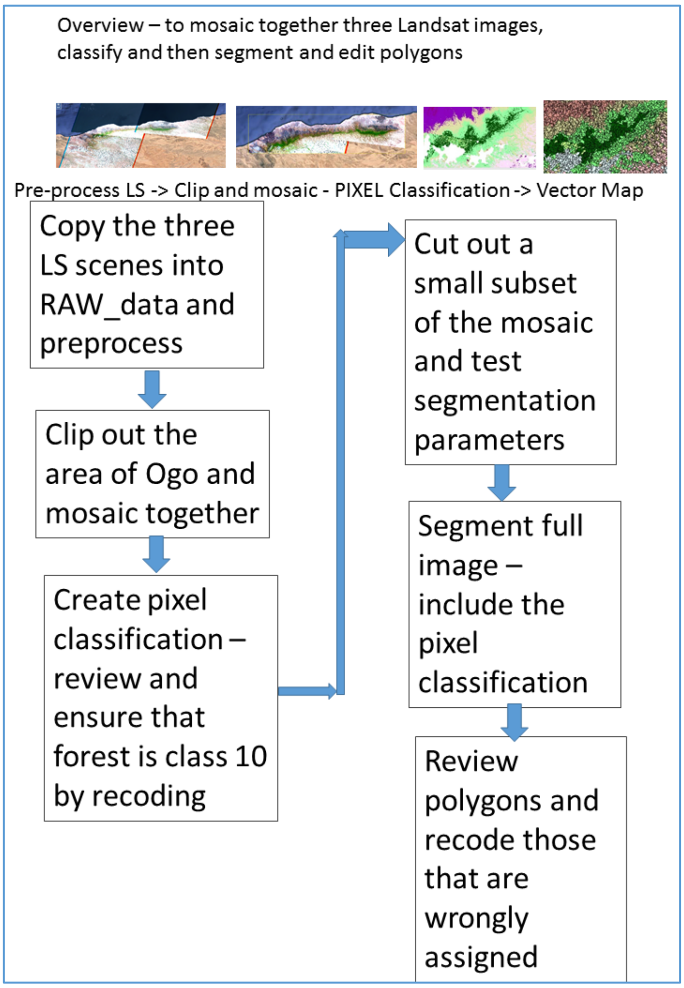
- Creating a vector
- Legends
- Editing a vector

Description of the S2 archive. How to display images in Google Earth.

## 2. Creating a basic raster and vector Forest / non-forest map

***Data: ex2_Ogo.zip (670 MB)***

***Data: ex2_Ogo_light.zip (50 MB)*** *Light version of the dataset contains only one image which is already process and is covering only one part of Ogo area. The provided processed image can be clipped by Ogo shape file and then the exercise can be continued from the step g.)*




**Overview** – we will take three LS scenes from the year 2000, which cover the Ogo mountains forests. These are to be preprocessed and mosaicked together. A decision tree algorithm is used to produce a pixel classification. We review the results and recode the classification into forests / non-forest. The image mosaic is then segmented with the raster classification being used to give the resulting polygons a class. This vector layer is then reviewed in conjunction with a Sentinel2 image from 2015.

**Source Directory**: ex2_Ogo

Files:

Landsat (original, zipped)

LT05_L1TP_162052_20000914_20161213_01_T1.tar.gz

LT05_L1TP_163052_20000820_20161213_01_T1.tar.gz

LT05_L1TP_163053_20000921_20161213_01_T1.tar.gz

Sentinel 2

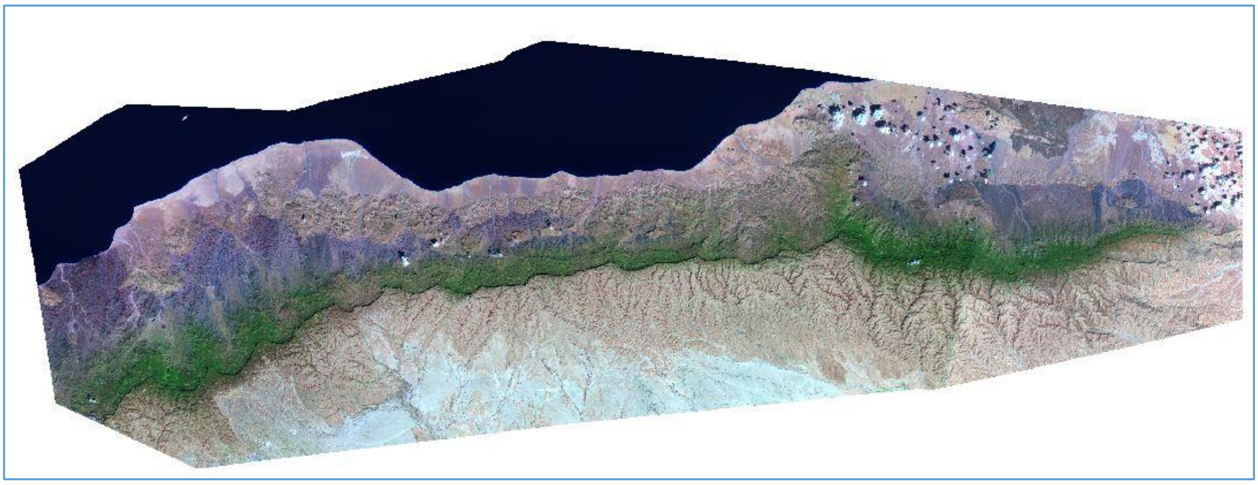
S2A_OPER_PRD_MSIL1C_PDMC_Mosaic1.tif

This is from 2015; Bands 2;3;4;8;11;12 (G;R;NIR1;SWIR1;SWIR2)

Vector

ogarea.shp

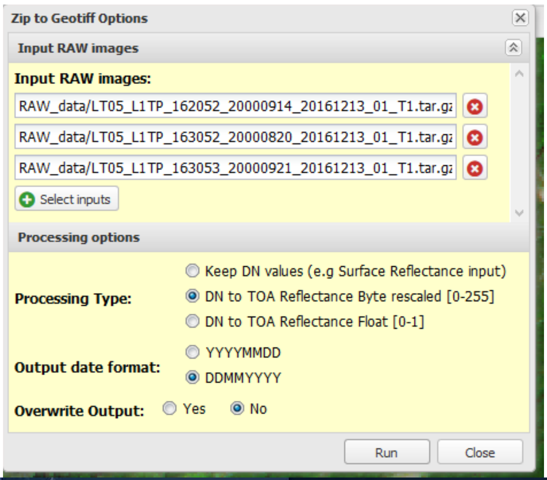
If you have Google Earth available, you can review the area using the ogomountainforest.kmz file

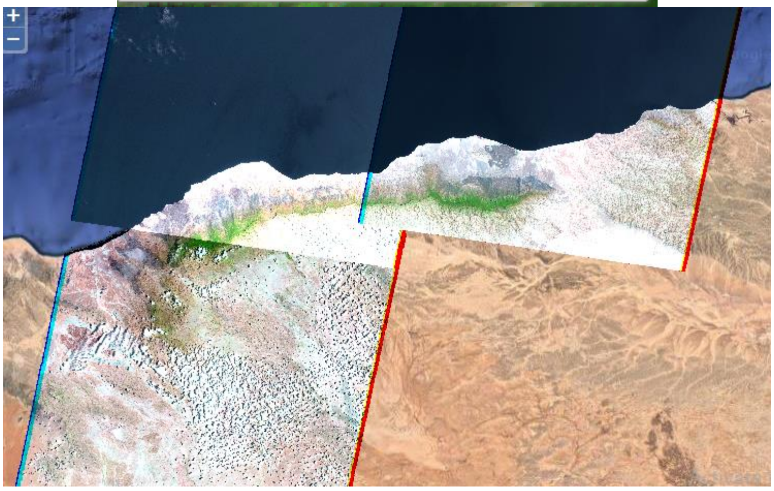


Ogo Mount range in northern Somalia

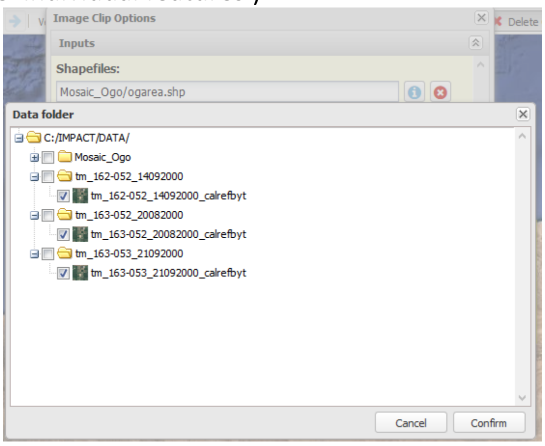
**Creating a Landsat Image Mosaic of the Ogo Mountain area**

a) Retrieve the Landsat (LT05**) zipped files and Sentinel2 images from the ex2_Ogo directory. The Landsat images must be placed in the C:\IMPACT\DATA\RAW_data directory. Actually, IMPACT needs you to put in RAW_data any files that will be imported with its import functions (see the procedure in step c, hereafter);
b) Copy the ex2_ogo to the C:\IMPACT\DATA\ Place the shapefile ogo_area.shp (be sure to copy all files, with extensions shp, dbf, shx and prj) in the DATA directory, or in the ex2_Ogo directory;
c) Run the Landsat Preprocessing Function on the three Landsat scenes (DN to Top of Atmosphere TOA). Once imported, you may want to reorder your data and put the imported images in the ex2_Ogo directory;
d) Display and review.
   Note that the stretch for PR163-53 needs to be different from the other two scenes, as it has no sea in the image.
   If you imported the images as byte, displaying bands 5 as red, 4 has green and 3 as blue (which is the default) and imposing a manual stretch from 0 to 255 would give a pseudo natural colour display.



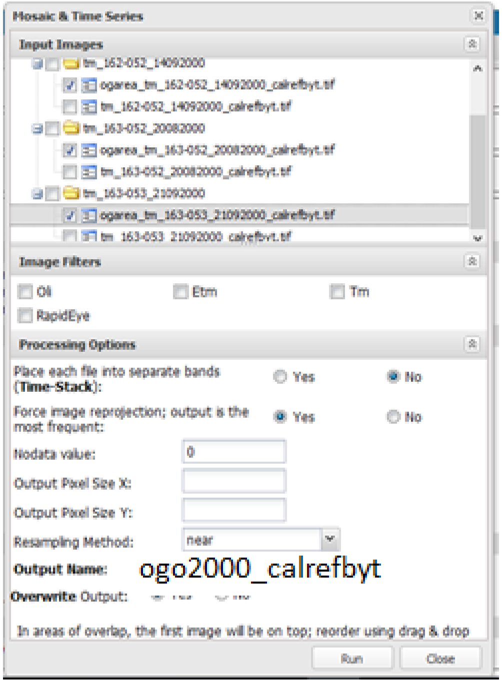



e) Use the Image clip function to clip the 3 Llandsat scenes to the Ogo area using the ogoarea.shp (do not use 'individual features')




f) Use the Mosaic Function from the General Tools to mosaic the 3 Landsat sub-scenes together – in the processing options you will need to use the Second option – Force Image Reprojection as the input images are in different UTM zones. The mosaic is done by flattening the stack of images: the image on the top of the list will be on the top of the mosaic. As a result, pixels from the top image mask pixels underneath. Play with the order, in the IMPACT view, to decide what you prefer: less cloud, more vegetation visible.

Make sure to name the output file with a suffix **_calrefbyt**, for example LS_2000_ogo_calrefbyt.tif.
This is necessary to indicate to the auto-classification tool that the data is a Landsat reflectance, encoded on byte. If you imported your data as float, use the file extension _calrefflt.




**Producing a pixel based classification and editing the classes**

Use the Automatic Classification from the Classification Tools to produce a raster classification map – the input is your image mosaic: LS_2000_ogo_calrefbyt.tif

g)

| ID | Class description | Color | ID | Class description | Color |
|---|---|---|---|---|---|
| 0 | No data | | 14 | Shrub / open forest | |
| 1 | Cloud - core | | 16 | Shrub / open forest | |
| 2 | Cloud - edge | | 21 | Shrub / Grass | |
| 3 | Snow - ice | | 22 | Grass | |
| 5/6/7 | Deep Water | | 30/31 | Soil | |
| 8 | Turbid Water | | 34 | Soil | |
| 9 | Bright veg. Humid Grass/Shrub | | 35 | Dark soil | |
| 10 | Forest | | 40 | Shadow on vegetation | |
| 11/12 | Forest | | 41 | Shadow on bare soil | |
| 13 | Shrub dense | | 42 | Shadow / Low illumination | |

Ideally, the classes in the raster map are those set out in the table above. However, often, due to problems of calibration, atmosphere and lack of metadata, the classes are not always correct. We will now check the classes by visual interpretation and ensure that the class which relates to the forested area is set as class 10.

h) Identify which of the classes in the new raster is most closely associated with forest and recode it to class 10 using the Start Raster Recode menu which opens on right clicking the classification file name

**Testing Segmentation parameters**

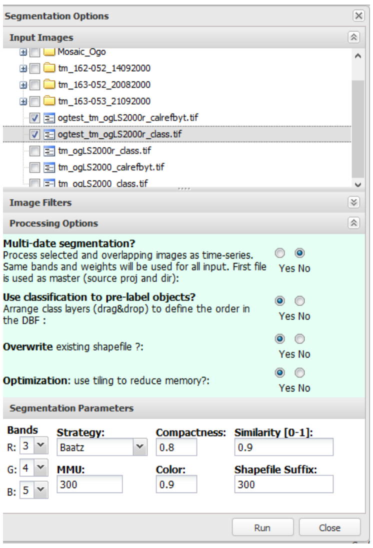
Image segmentation can require extensive computer memory and processing time – therefore before segmenting our whole area, we need to test the parameters on a small subset, so as to obtain settings that give us polygons that adequately reflect the landscape units.

a) Create a small test data set (image and classification) so as to test the segmentation parameters by creating a small rectangle (draw rectangle) over an area of the mosaic. Save the rectangle;
b) Use the rectangle to clip the mosaic to a smaller test image.

Segmentation – you can run several segmentations with different parameters until you find one that you feel is adequate for mapping purposes – a compromise has to be made between not have too many small polygons, and not have huge mixed polygons.

Here are some explanations about the functioning, options and parameters:

The segmentation module identifies consistent elements (segments, saved as polygons in a shapefile) in the image. The consistency is defined with the set of parameters at the bottom of the image. The identification of the segments can be done using a single image or a series of images (multi-date segmentation).




The segmentation is controlled by the following parameters:

- Image bands. You can select up to 3 bands which allow to contrast the landscape elements you want to segment. The pre-selected bands 3, 4 and 5 (green, red and near infrared) correspond to a Landsat image default setting. You may want to use different combination depending on the landscape, application or sensor;
- The minimum size for a segment, in number of pixels (MMU). This allows the algorithm to regroup pixels;
- The similarity parameters:  from 0 to 1. This parameters controls how/when connected segments are merged together: 0 allows grouping spectrally heterogeneous segments while 1 regroups only segments with same spectral properties;
- Strategy: the segmentation algorithm itself
  - Region growing: a basic and rather fast algorithm based only on spectral properties;
  - Baatz: more sophisticated, depending on two parameters: compactness, controlling the morphological component of the detection from 0 (any shape is accepted) to 1 (tries to find more compact, rounded, polygons); colour, controlling the contribution of the colour (band combination): 0 no influence, 1 maximum weight of the colour in the detection. This algorithm finds a balance between spectral and morphological information.

The segmentation algorithm identifies segments from the input image, and save them as a shapefile of polygon. Each polygon can receive a value, corresponding to a reference classification (this is an option). You can choose among 3 rules: attributes to a polygon the majority of the pixels values in the classification corresponding to this polygon, or the minimum or the maximum of this value.

**Producing final map and comparing to S2 image from 2015**

a) Run the segmentation for different MMU / Color and Compactness factors on the test image – until you have a satisfactory result.
b) Run the segmentation on the full mosaic using the selected parameters and include the recoded classification that you produced in the first part of the exercise.
c) Use the apply classification legend to layer by right clicking on the segmentation result – apply the 0-50 classification scheme. The legend can be reviewed by clicking on Vector Legends in the window bar
d) You can review the vector classification over the mosaic by unclicking the T1_class box along with the Start Editing option by using right click on the file name. Here you can recode polygons that you think are wrongly labeled.

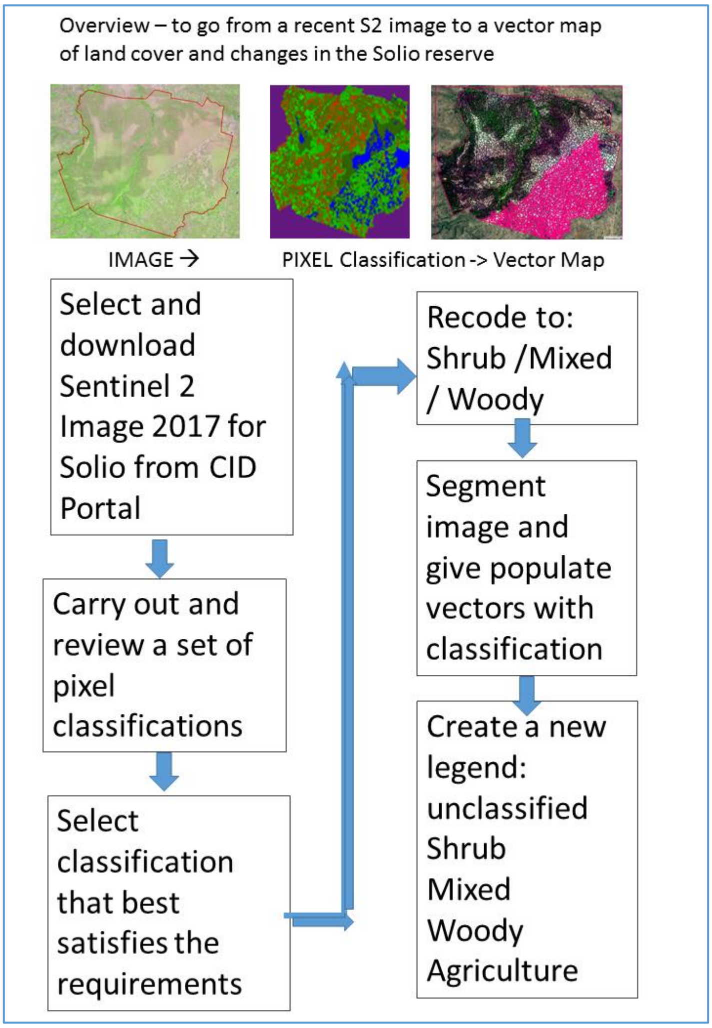
e) Read in the Sentinel 2 image S2A_ogo2015_Mosaic1.tif, to see if there have been any changes.

For several areas we have provided LS and S2 images for you to review the same process.

# 3. Resource mapping and monitoring in protected areas – a case study over the Solio protected area

***Data: ex3_solio.zip (609 MB)***

***Data: ex3_solio_light.zip (16 MB)*** *Light version of this dataset contains all necessary images to run all the steps of the exercise. The only difference is that the Landsat images are already processed and clipped for the Solio area*




For park managers the resources available for wildlife (water and fodder) are often difficult to assess.

In this exercise we will use Sentinel-2 data to map the proportions of a wildlife reserve that are predominantly grass dominated or woody species dominated. We will also review the potential sensitivity of the reserve to the encroachment of surrounding human activities, and see their changes in relation to previous years.

COPY the ex3_solio_inputs directory to IMPACT\DATA

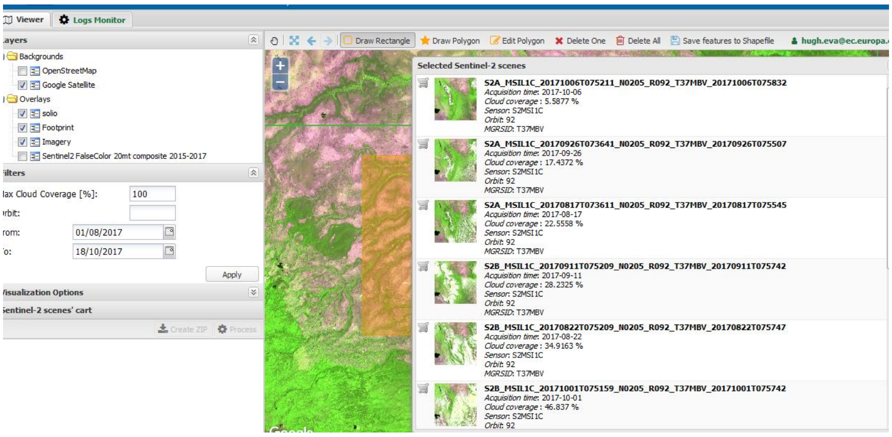
Folder ex3_solio_inputs contains raw inputs, such as 3 Landsat images from 1995, 2000 and 2011 and 2 Sentinel image, all 4 from 2017, and a shapefile delineating the area of the Solio park.

## Selecting Imagery

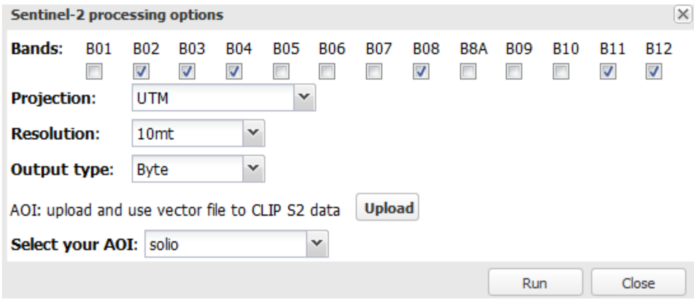
The next steps show how to obtain the Sentinel images from JRC servers. If the internet connection does not allow to obtaining these data from JRC server, you can use the raw data found in directory ex3_solio_inputs.

https://cidportal.jrc.ec.europa.eu/forobsdev/sentinel.py

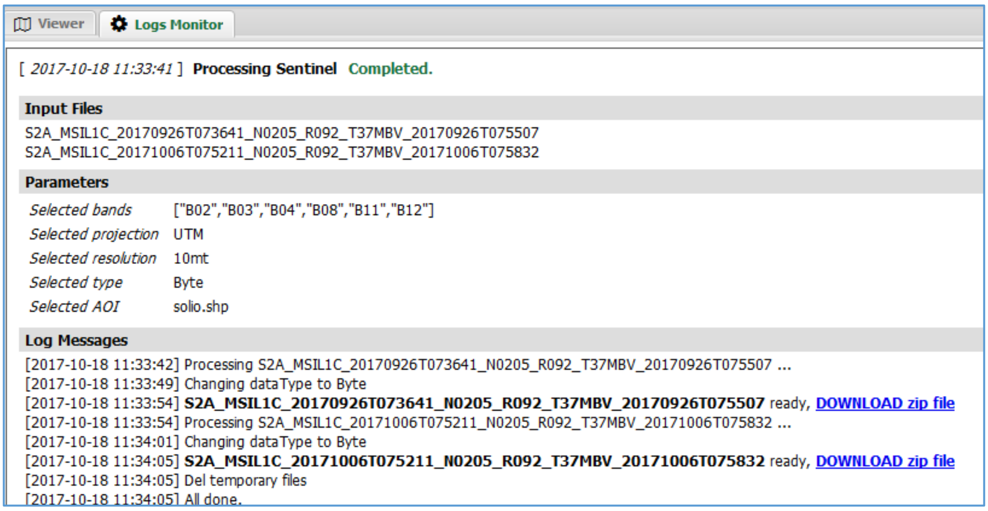
a) Using the JRC image repository we select the most recent cloud-free S2 image. To facilitate the process we use a restricted number of bands and a shapefile that covers our area of interest.




Using the 'Process' function we use the default options and load the solio.shp / shx / dbf / prj files to restrict the processing to the required area.




b) Check to Logs Monitor tab and download your image when it's ready - copy the file to C:\IMPACT\DATA\ex3_solio and unzip




If you cannot download the image, one is already prepared in the ex3_Solio directory – S2A_MSIL1C_20170926T073641_N0205_R092_T37MBV_20170926T075507_TOA.zip
This file was already imported, you only need to unzip it with the output remaining in the ex3_solio directory DATA repository or any subdirectory.

c) The S2 image should now display in IMPACT
d) We have provided you with 3 other satellite images. These are Landsat from three epochs 1995, 2000, and 2011:

   LT05_L1TP_168060_19950522_20170109_01_T1.tar.gz

   LE07_L1TP_168060_20000205_20170213_01_T1.tar.gz

   LT05_L1TP_168060_20110110_20161010_01_T1.tar.gz

Copy these files to the \\IMPACT\DATA\RAW_data directory – then run the Landsat pre-processing routines in the FUNCTION panel.

You can now review the changes around the park since 1995

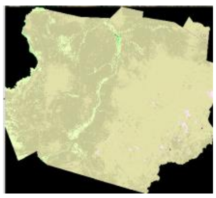
**Classification options**

e) Use the S2 image to test the different classifications and image enhancement: Automatic; K-means (10 classes); NDVI cluster (10 classes) – for this use bands 4 (near infrared) and band 3 (red) in the interface to create and NDVI – then select 10 classes for cluster. You can also create a PCA image and a spectral unmix image and then classify each of these with K-means – use 10 classes.

You can first apply an image enhancement, then a classification. Of course, such an approach can't be applied to the automatic classification. **Why?**

Also, NDVI clusters, which is a histogram binning of the NDVI image, can be considered either as an image enhancement and classification. **Can you comment this point?**

**Classification**



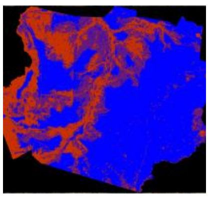
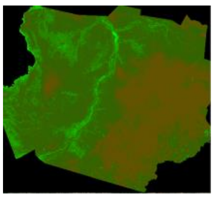
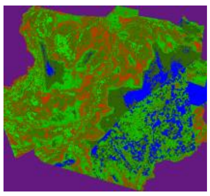
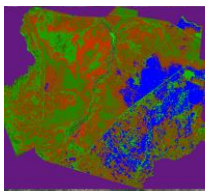


**Image enhancement**







**Automatic** **K-means** **NDVI clusters** **PCA clusters** **UNMIX cluster**

**Image classification and enhancement**

f) You now have five different classifications – Automatic; K-means; NDVI_cluster, PCA_cluster, UNMIX cluster. Review these against the background satellite image and determine which is better for repartitioning the image into three classes:

    1: grassland;

    2: mixed grass and shrub;

    3: woody vegetation.

It may also make sense to combine operation. For example, PCA on 3 bands only, then k-means, or unmixing followed by a kmeans.

**Test different combination of image enhancement and classification. Compare the classification result with the actual land cover.**
The kmeans classifier will create an image of 10 classes, we need to associate a class to its corresponding landcover.
One approach is to write down the list of the 10 classes, decide for 4 land cover we want to keep at the end, and explore the image to associate each k-means class value together with a landcover.
Say we want to keep the following classes:

| **Landcover** | **Code (arbitrary)** |
|---|---|
| No data | 0 |
| Grassland/bare soil | 1 |
| Mixed grass and shrub | 2 |
| Woody | 3 |
| Other | 4 |

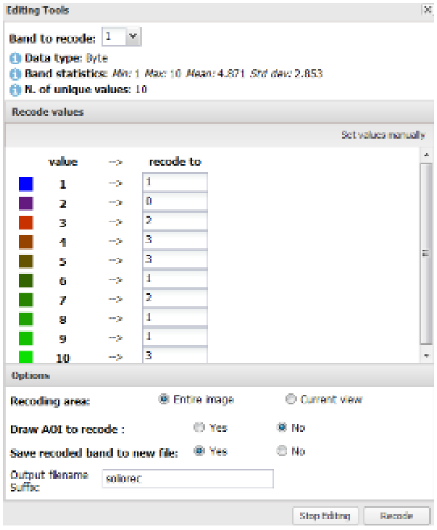
It is a good practice to have a no data class (in our case, the black border around the image). Class ”other” is for anything we don’t want to assign to a class.

Explore the image, and try to fill the following table:

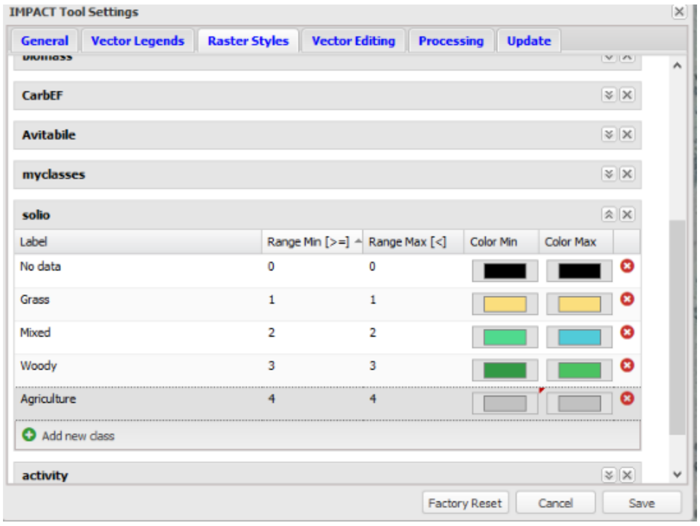
| **Kmeans class** | **Our classification (0, 1, 2, 3, 4)** |
|---|---|
| 0 | |
| 1 | |
| 2 | |
| 3 | |
| 4 | |

| **Kmeans class** | **Our classification (0, 1, 2, 3, 4)** |
|---|---|
| 5 | |
| 6 | |
| 7 | |
| 8 | |
| 9 | |
| 10 | |

g) You can now recode the image into the final classes (no data, grassland/bare soil, mixed grass and shrub, woody and other). Right-click on the best classification and select Raster Recode – unique values.



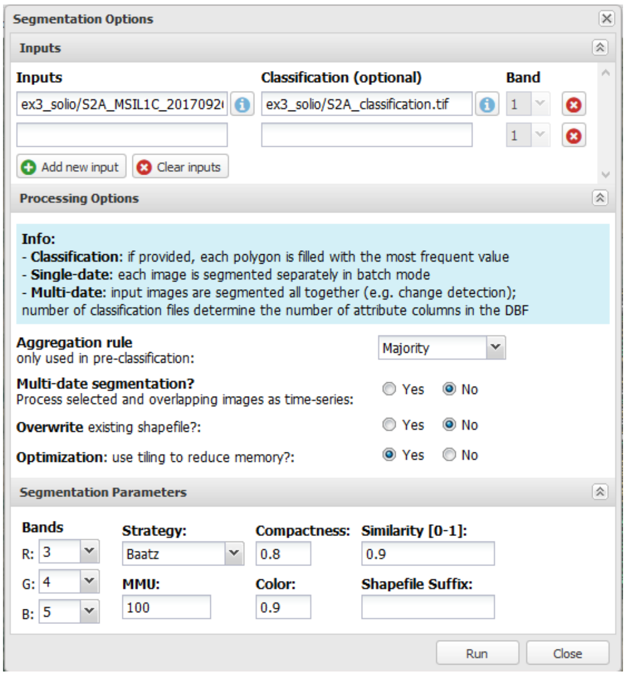

h) Create a new raster style with 4 classes: grassland, mixed (grass and woody), woody and agriculture. Save it with the name *solio*.



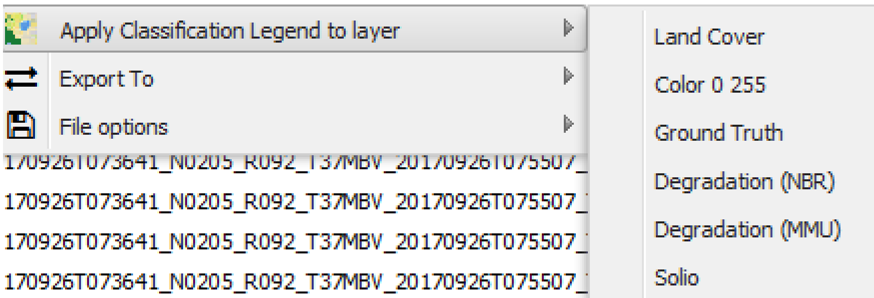

At a later stage, you'll need also a vector legend, to assign legend to the result of the classification. You can now create a vector legend that matches the raster legend. Name it solio. Think about giving a name to each legend class, as some interfaces in IMPACT use the class labels.

i) Now create a segmentation based on the original Sentinel2 image – *the polygon classes will come from the majority of the class from the recoded raster image* – we suggest MMU of 100

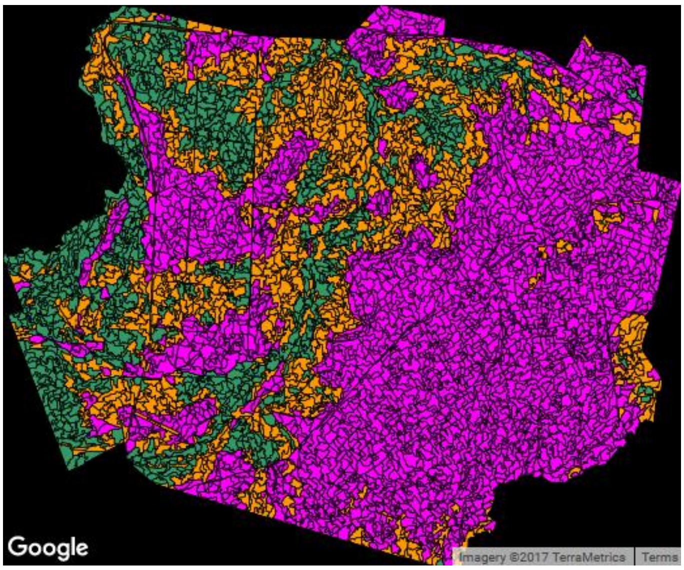
**Input image**: your Sentinel 2 image **Classification:** your recoded pixel classification **Legend:** solio




When the segmentation is finished click on the vector file and “Apply classification legend to the layer”: solio



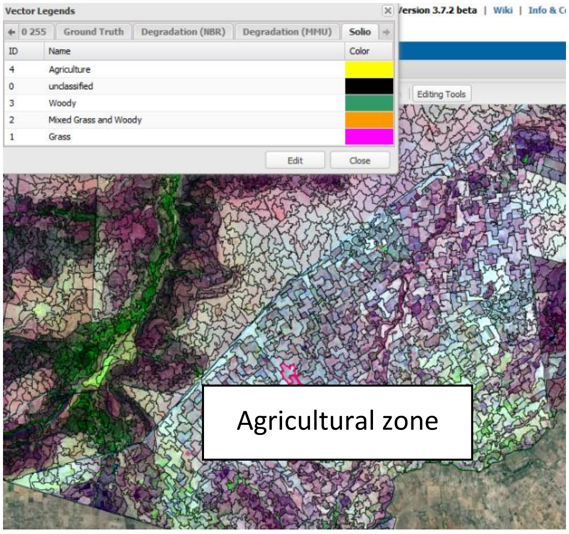

The result will be something like this – where much of the south of the park is classed as grassland – in fact we see that it is agriculture.



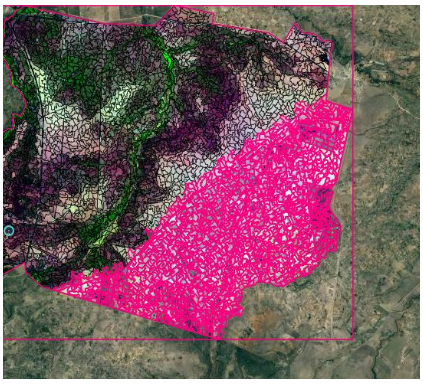
**Editing the vector layer – and extracting statistics**

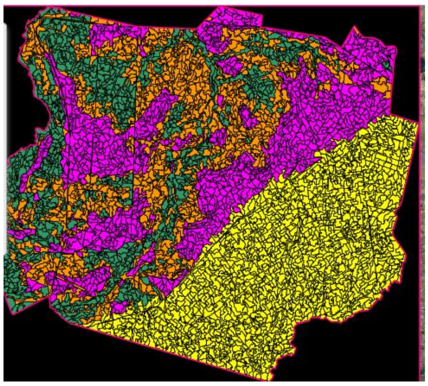
We now need to edit the vector layer so as to differentiate between grassland and agriculture (the initial classification did not allow to make the difference). This section shows you how to manually correct the result of an automatic classification.

j) In first place, edit you legend to add a new class for agriculture. Let's rename our class "other" as "agriculture";
k) We need to select manually polygons we identified as agriculture, and assign them to the class "agriculture". Move the vector layer on top of the Sentinel 2 image and unclick T1class. We can now see which areas of the park are under agriculture.

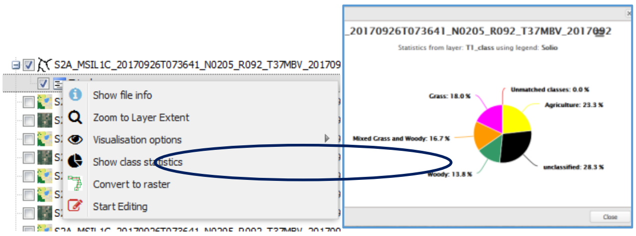



l) Right click on vector layer T1 and 'start editing' - we use the AOI tool with the mouse to select those polygons that are agriculture- then recode them to agriculture - then 'stop editing'





We can now review the percentage of each class in the vector cover by right clicking and selecting 'show class statistics'.

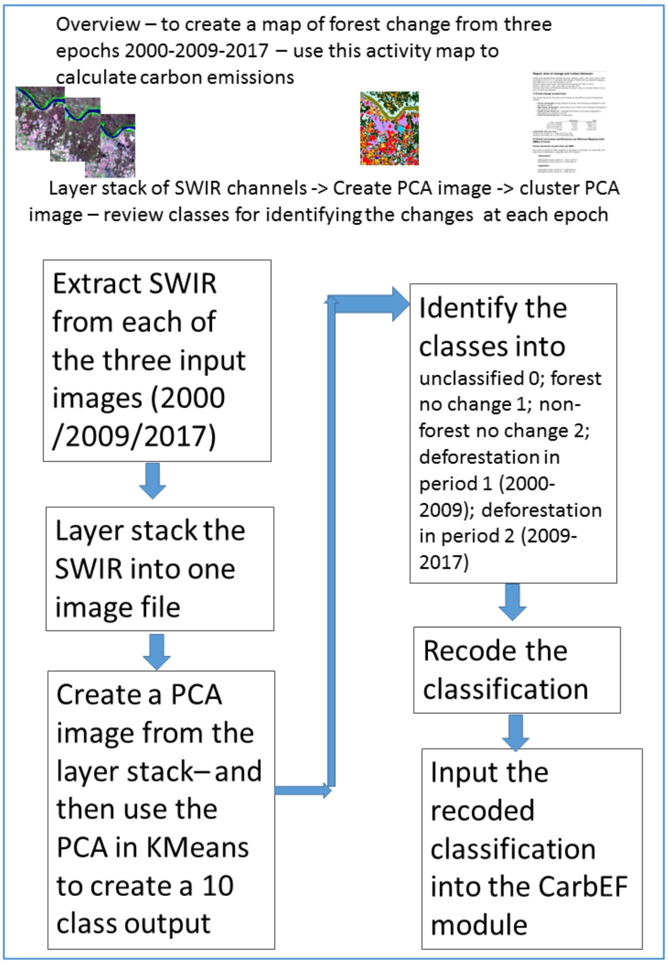



m) Within the ex3_Solio folder we have three Landsat TM files (1995, 2000, 2010). These can be reviewed and the changes in agriculture can be observed. By editing the vector legends menu, you can add classes – agriculture 2010 etc. so as to have a classification that documents the expansion of agriculture. The full Solio area covered by the shapefile is 236 $km^2$ – so we can calculate the areas that are under each land cover class.

# 4. Monitoring dry forest changes with the aim of producing an activity map for use in CarbEF – calculating forest change and emissions

***Data: ex4_dryforest.zip (919 MB)***

***Data: ex4_dryforest_light.zip (44 MB)*** *Light version of the dataset include everything except General data folder which is needed only for very last part of this exercise. General data folder contains activity and biomass maps for Kenya, Sudan, Ethiopia, Mozambique, Rwanda and Uganda*




In this exercise, we will estimate the areas of forest removed or degraded and the corresponding amount of carbon released, for two periods of time, a historical period of change and a recent period of change. The carbEF module will be used for this estimation. It requires the following inputs:

- A map of forest change;
- The value of the biomass per hectare, either as a constant or as a map;
- The definition of two periods of time;
- The definition of a minimum mapping unit.

Optionally, a land use shapefile can be used to break down the emissions with respect to different sources (protected areas, forest exploitation, etc.), and an exclusion map can be used to put apart detection that should not be summed-up in the grand total of emission (eg. Burnt areas).

We review changes to a forest area between 2001 and 2017. We set up a legend and then create a random sampling grid with a MMU of 1 ha.

This exercise simulates a requirement for a forest reference level (FREL) and a recent change – as required by the IPCC. The test site is in the Mwingi region of Kenya. We use recent Sentinel 2 data in conjunction with historical Landsat data to map forest changes from 2000 to 2009 and 2010 and to 2017. We map the forest change using a PCA on the short wave infrared bands extracted from the three dates. The resulting PCA image is then clustered using K-means into 10 classes. We then visually interpret these 10 classes into the five classes required by the CarbEF module.

Here are the four classes we want to obtain:

No data; forest – no change; non-forest no change; deforestation period 1; deforestation period 2.

a) The input images are a Sentinel 2 image from 2017, and Landsat images from 1986, 2000, and 2009 (path/row is 167/60) – the images are already pre-processed, so we can use them directly.

    dryclipkenya_S2A_MSIL1C_20170718_TOA.tif

    dryclipkenya_tm_167-060_14011986_calrefbyt

    dryclipkenya_etm_167-060_09092000_calrefbyt.tif

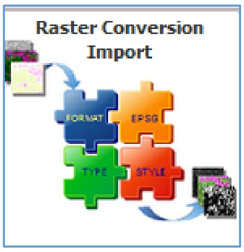
    dryclipkenya_tm_167-060_06062009_calrefbyt.tif

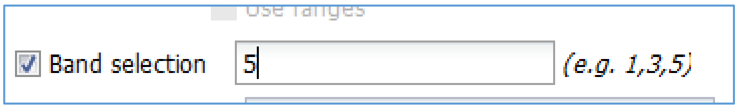
Note: the original S2 image is dryclipkenya_S2A_MSIL1C_20170718T075211_N0205_R092_T37MDV_20170718T075752_TOA – we have shortened the name for convenience.

We also provide an historical Landsat (dryclipkenya_tm_167-060_14011986_calrefbyt) image from 1986 for comparison.

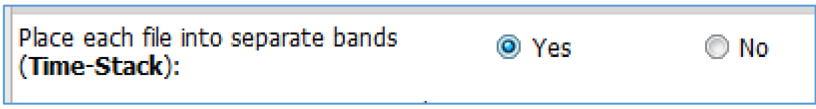
b) Copy the **ex4_dry_activityforest** directory to the DATA directory in IMPACT. Review the images over the area and <u>note the changes that have occurred from 1986 to date</u>.

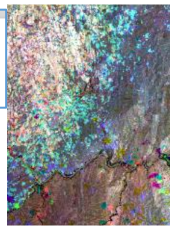
c) For each of the three later images (2000, 2009 and 2017) we will extract the SWIR channel, which gives good differentiation between *forest* and *non-forest*. Use the file info to find the bands that are actually available in each image. Which ones correspond to SWIR? The band graphics at the end of this document can help you. We use the RASTER CONVERTION function in the general tools; for the two Landsat images the SWIR is Band 5, for the Sentinel 2 image the SWIR is also Band 5; extract these bands into separate files one at a time.



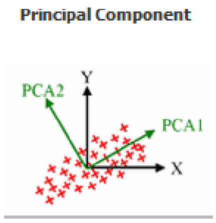




a) The three SWIR channels must now be layer stacked in the same file; we use the tool Mosaic; time stack; 320m pixel and force reprojection to ensure that we have the same output projection. If you display the layer stack, it has colors, why is that?

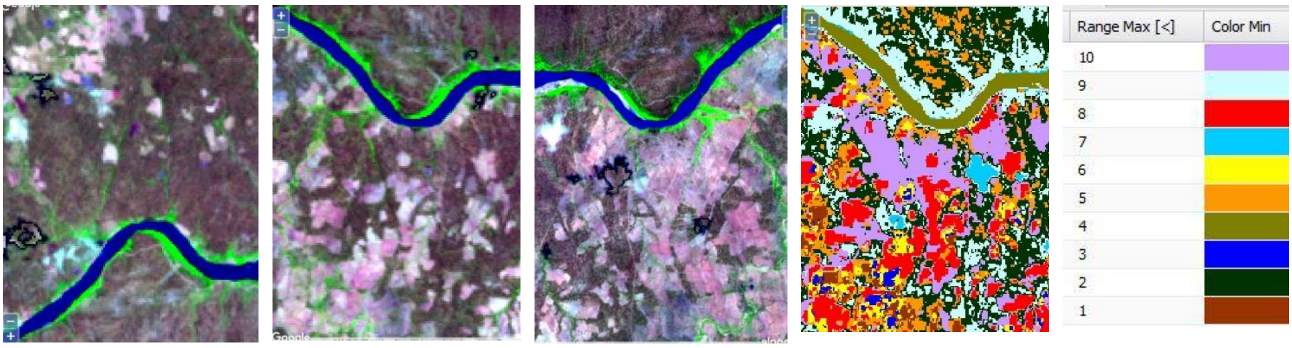


b) We use the PCA algorithm on the SWIR layer stack to enhance contrast between forest and non-forest. The function is found under the Analysis and Enhancement tool.

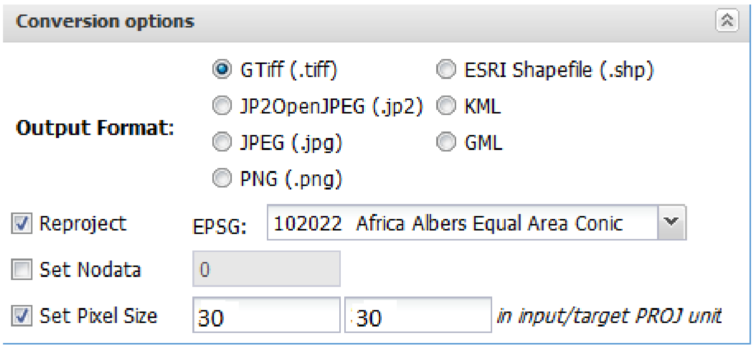



c) We can review the PCA results in the interface. We now classify the PCA result into 10 classes using the K-means classifier.




By examining the images (above 2000; 2009; 2017, with the classification and the colour table, we can see which class relates to changes in which period.

d) Create a new Raster Style – with classes; unclassified 0; forest no change 1; non- forest no change 2; deforestation in period 1 (2000-2009); deforestation in period 2 (2009-2017). Review the classes in the output from K-means so as to recode the image into the 5 classes above. Exactly those 4 classes are necessary to run CarbEF module (late in the last steps of this exercise).
e) Recode the image and review the activity map.
f) The activity map needs to be in Equal Area Projection to calculate the areas – Under General Tools – Raster Conversion – you can reproject the activity map – scroll down the list of projections until you find the Africa Equal Area projection – we use a 30m pixel.




g) Now, run the CarbEF module, under Degradation and Reporting. Select an emissions factor for dry forests that seems reasonable – 20 t/ ha? Indicate the years of the two periods – Each period starts at the beginning of a year and end at the end of a year. So start=2010 end =2011, means that the period spans from January 2010 to December 2011. To define a period of 1 year, say 2016, use start=2016, end=2016. In our case we use 2000-2009 and then 2010-2017 (approx.).

h) Review the raster results, and go into the log file to find the report on the calculations of emissions. The report can also be found in your working directory.

## This exercise shown you how to create an activity map to go into the CarbEF – you can now use a different area or time period. Application to other regions.

You can apply a similar approach to other regions. The principle is to create a map of forest change for 2 periods, and obtain a value for the biomass factor (either a constant or a map).

As a first approach, you can use global datasets. The quality of those data is sufficient for educational purpose. However, a good quality estimate requires that you create your own activity maps and collect your own biomass data.

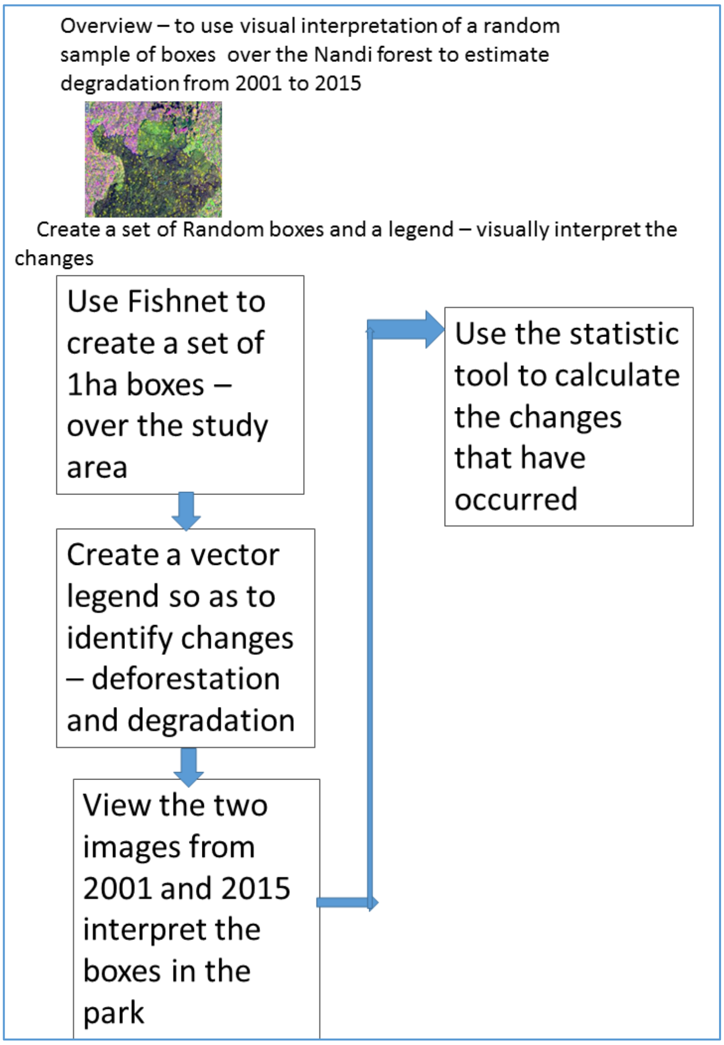
General data:

- Activity derived from Global Forest Watch, assuming a minimum of 30% for the forest cover, and periods 2011-2013 and 2014-2015
- Biomass from Avitable et al., “An integrated pan-tropical biomass map using multiple reference datasets. Glob Change Biol, 22: 1406–1420. doi:10.1111/gcb.13139”: above ground biomass density of vegetation in Mg/ha. Conversion factor: multiply by 0.47 to get tC/ha, by using the raster calculator.

The images being rather large, you should clip them to a region of interest.

# 5. Estimating forest degradation and deforestation using a sampling approach – Nandi forest 2010-2015

***Data: ex5_nandi.zip (26 MB)***




a) The image data are Sentinel 2 from 2015 and Landsat from 2001. Clip_S2_nandi_2015.tif and Clip_LS_nandi_2001.tif;
b) Copy the ex5_nandi directory to IMPACT\DATA;
c) Read in and visually review the changes between the two dates;
d) Create a new vector legend – vector legends->Edit-> Add new legend: We wish to create a matrix of classes to cover the transitions.

Forest – Forest

Forest – Non Forest

Forest – Degraded Forest

Degraded Forest – Degraded Forest


Nandi

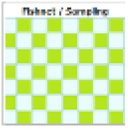
| ID | Name | Color | Opacity |
|---|---|---|---|
| 4 | FNF | | 1 |
| 3 | NFNF | | 1 |
| 2 | FD | | 1 |
| 1 | FF | | 1 |

Non Forest – Non Forest

Non classified (areas outside the study area)

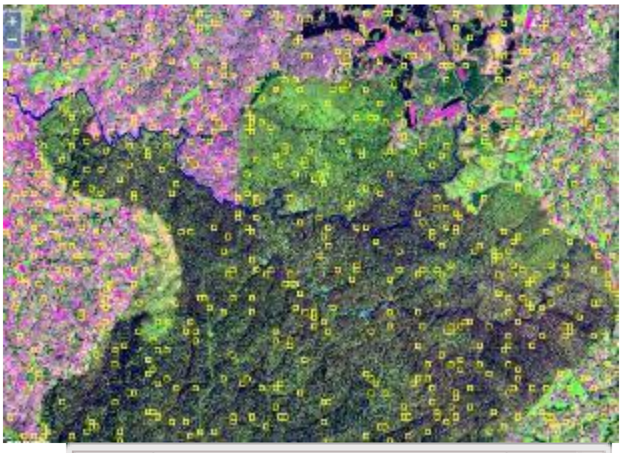
Note: You may find that a legend *Ground Truth* already exists in the Vector Legends

e) We now create a sampling scheme using a 1% sample of 1 ha boxes. Under general tools we use the Fishnet function:



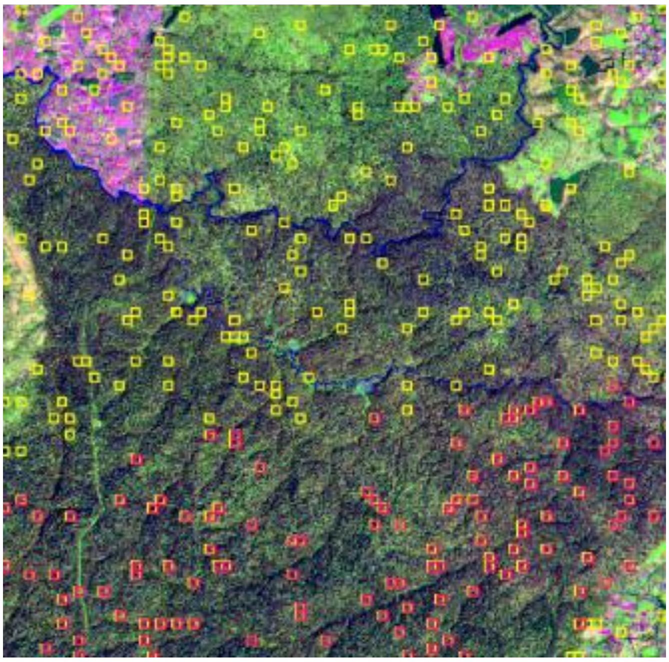

We restrict the grid to the same extent as our Sentinel image. To obtain a 1 ha box we use a cell width of 0.001 decimal degrees if projection is in Lat Lon. If the projection is UTM, we can use a cell width in meters. To find out the projection we can display "Show file info" by right clicking on the layer.

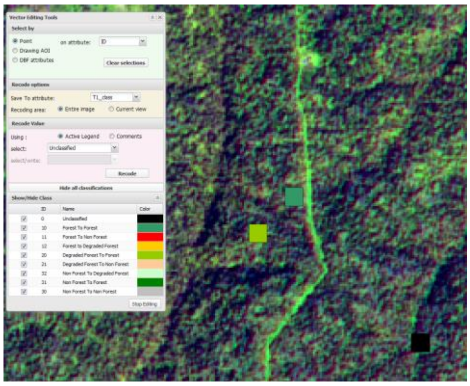
f) We can display the boxes over the 2015 and 2000 images so as to visually interpret changes. Right click on the sample file to Start editing and apply the Nandi legend. Each box within the Nandi forest can be classed according to our scheme. We only class the boxes inside the reserve area – of the original boundary – nandi_original.shp.



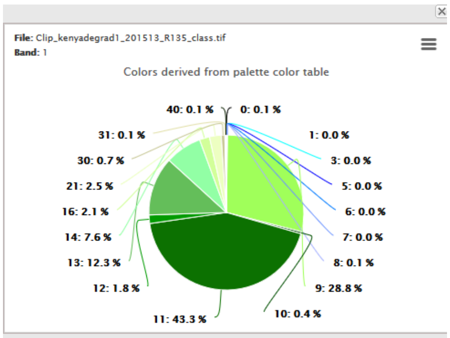
| ID | Name | Color |
|---|---|---|
| 3 | NFNF | |
| 4 | FNF | |
| 1 | FF | |
| 2 | FD | |

g) You can use the AOI selection to change many boxes at the same time.

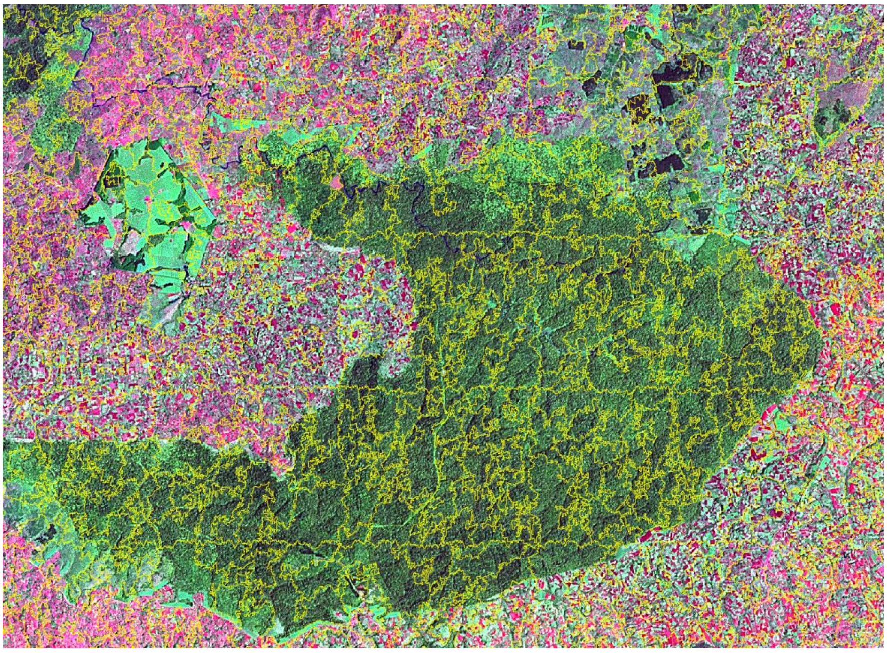




h) When editing is finished, you can right click on the shapefile to obtain the statistics for the park. The original area of the park is 200 km$^2$ – so we can calculate the proportion that has changed.




Note you can use a similar approach, but with a segmentation of the full area



You can use the same legend and classify the individual polygons.

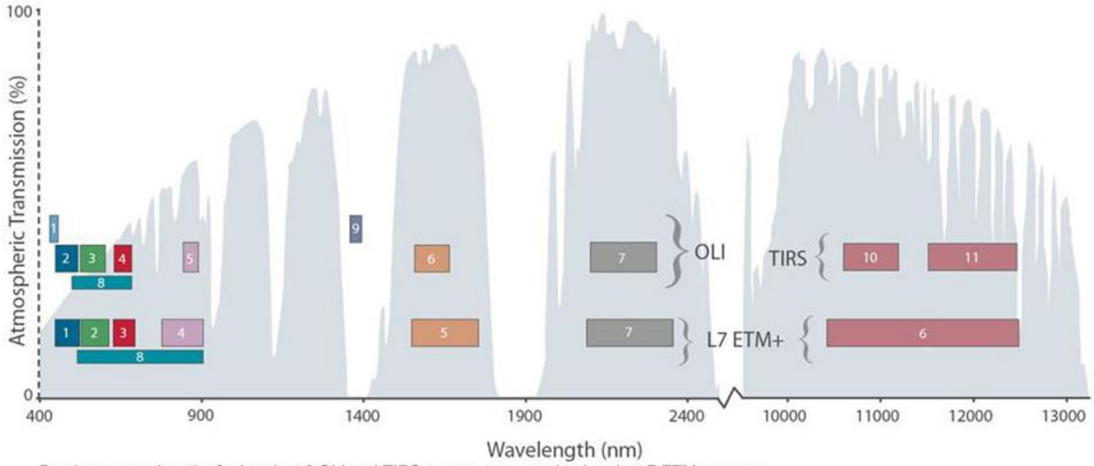
## 6. Carbon fraction of aboveground forest biomass

| TABLE 4.3<br>CARBON FRACTION OF ABOVEGROUND FOREST BIOMASS | | | |
|---|---|---|---|
| **Domain** | **Part of tree** | **Carbon fraction, (CF) [tonne C (tonne d.m.)$^{-1}$]** | **References** |
| **Default value** | All | 0.47 | McGroddy *et al.*, 2004 |
| **Tropical and Subtropical** | All | 0.47 (0.44 - 0.49) | Andreae and Merlet, 2001; Chambers *et al.*, 2001; McGroddy *et al.*, 2004; Lasco and Pulhin, 2003 |
| | wood | 0.49 | Feldpausch *et al.*, 2004 |
| | wood, tree d < 10 cm | 0.46 | Hughes *et al.*, 2000 |
| | wood, tree d ≥ 10 cm | 0.49 | Hughes *et al.*, 2000 |
| | foliage | 0.47 | Feldpausch *et al.*, 2004 |
| | foliage, tree d < 10 cm | 0.43 | Hughes *et al.*, 2000 |
| | foliage, tree d ≥ 10 cm | 0.46 | Hughes *et al.*, 2000 |
| **Temperate and Boreal** | All | 0.47 (0.47 - 0.49) | Andreae and Merlet, 2001; Gayoso *et al.*, 2002; Matthews, 1993; McGroddy *et al.*, 2004 |
| | broad-leaved | 0.48 (0.46 - 0.50) | Lamlom and Savidge, 2003 |
| | conifers | 0.51 (0.47 - 0.55) | Lamlom and Savidge, 2003 |

To convert Avitabile's biomass density into tons of carbon per hectares, multiply the value of the Avitabile's file by 0.47.

# 7. Annex: Sentinel 2 and other sensors spectral properties

Spectral properties of Landsat sensors OLI, L7, ETM+, and TIRS




Bandpass wavelengths for Landsat 8 OLI and TIRS sensor, compared to Landsat 7 ETM+ sensor

*Note: atmospheric transmission values for this graphic were calculated using MODTRAN for a summertime mid-latitude hazy atmosphere (circa 5 km visibility).*

# Spatial Resolution

The spatial resolution of SENTINEL-2 is dependent on the particular spectral band:

**10 metre spatial resolution:**

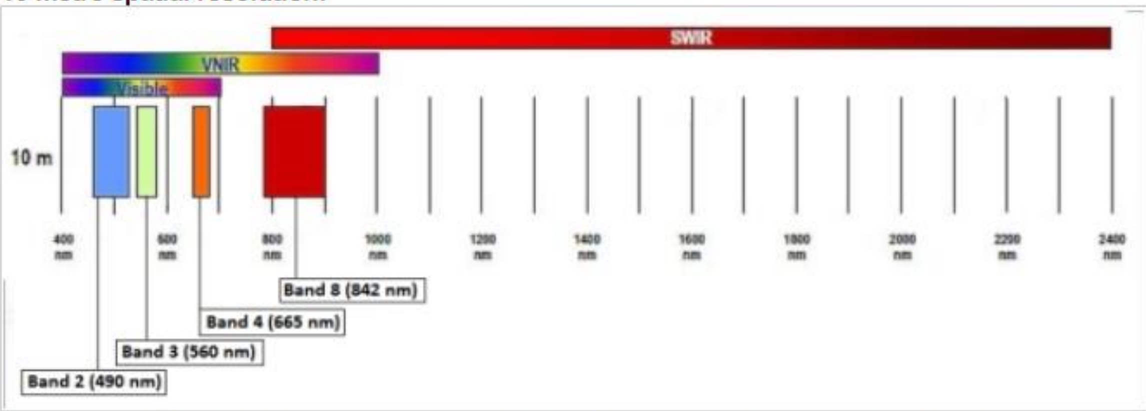



Figure 1: SENTINEL-2 10 m spatial resolution bands: B2 (490 nm), B3 (560 nm), B4 (665 nm) and B8 (842 nm)

**20 metre spatial resolution:**

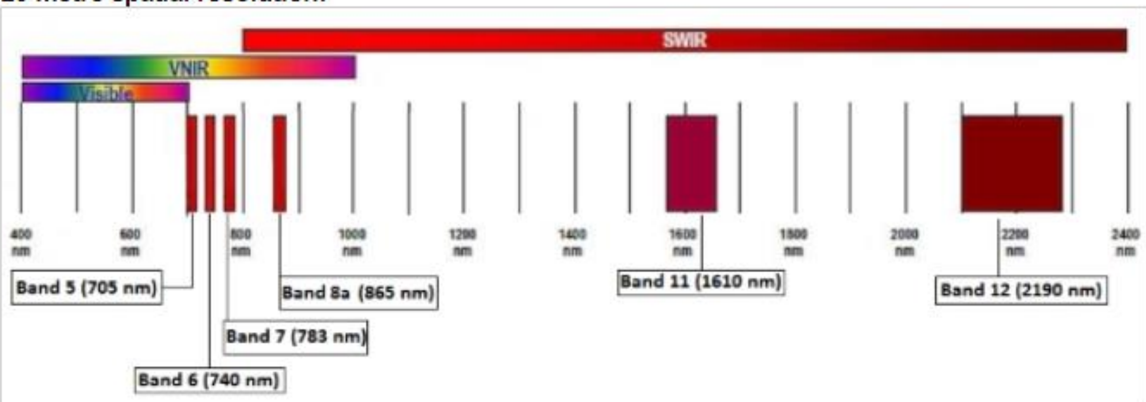



Figure 2: SENTINEL-2 20 m spatial resolution bands: B5 (705 nm), B6 (740 nm), B7 (783 nm), B8a (865 nm), B11 (1610 nm) and B12 (2190 nm)

**60 metre spatial resolution:**

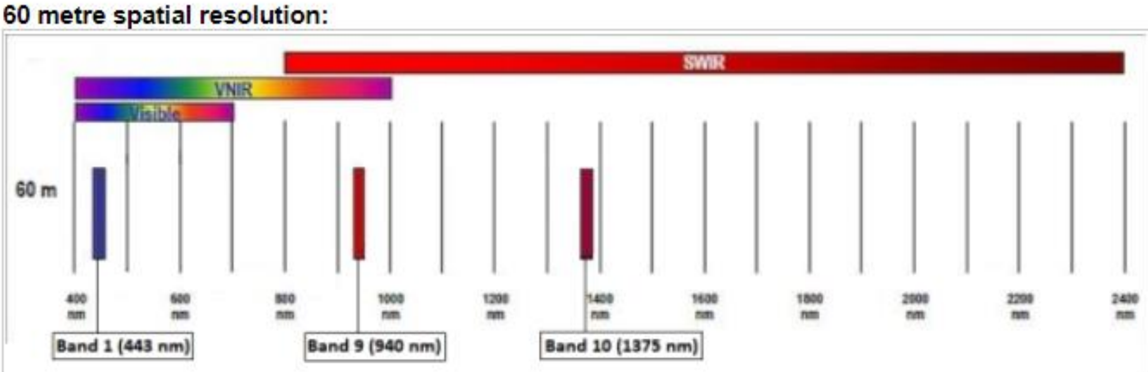



Figure 3: SENTINEL-2 60 m spatial resolution bands: B1 (443 nm), B9 (940 nm) and B10 (1375 nm)

Spectral properties of Sentinel 2. Note that the bands have different spatial resolutions.