

# Key Biodiversity Areas

The monthly monitoring of the Key Biodiversity Areas Amboseli National Park and Dakatcha Woodland

# Overall Condition Score (OCS)

## Overview

The Overall Condition Score is used to present complex information from multiple indicators as a single metric that measures progress toward a goal and to facilitate decision-making. One reason why this combined index is used is because different organizations have different priorities and want different indices to be displayed first, so this should be a compromise for everyone. This score is made up of different sub-scores and tries to be a score that contains the information content of those different pieces of information in one. These different sub-scores are:

- **Infrastructure Score**

This score indicates how likely an infrastructure object is to exist in a specific geographical area. This score is calculated from the object recognition and how likely it is that the AI recognized one or more objects (boma, fence, building, etc.) as such.

- **NDVI Outlier Score**

The NDVI (Normalized Difference Vegetation Index) outlier value is a value that compares the current NDVI value with the average value from previous years for the same month. Large deviation will be called an outlier.

- Normalized Burn Ratio (NBR) – will be added in the future

The Normalized Burn Ratio is used to identify burned areas and provide a measure of burn severity and is calculated as a ratio between the NIR (near-infra red) and SWIR(short-wave infra red) values.

# Overall Condition Score (OCS)

## Requirements and Limitation

The calculation of an Overall Condition Score includes requirements that should/must be adhered to in order to be accepted as an acceptable and trustworthy score.

Following you can find all requirements for an OCS score:

- Req\_1: The OCS is a compound index which will be calculated by the usage of sub-indices which are thematically group variables
- Req\_2: Only the sub-scores (range of [0:1]) are permitted for the calculation: Infrastructure\_Score, NDVI\_OutlierScore, NBR\_Score
- Req\_3: Weighting the sub-indices can be done (if so, then the sum of all weights have to be 100% or 1)
- Req\_4: OCS is a value in the range of 0 to 1
- Req\_5: If all sub-scores are 0, the OCS must have a value of 0
- Req\_6: If all sub-scores are 1, the OCS must have a value of 1
- Req\_7: High values of one sub-score must not be canceled out by low values of another sub-score

# Overall Condition Score (OCS)

## Evaluation

After testing different calculation methods by reviewing the results of the different methods with varying input sub-score values and checking which method fulfills the most requirements, the following method was chosen:

### Weighted Max-Ln-Exp

this kind of a softmax function uses  $\ln(2)$  and 0.62 to translate the result into the correct range [0:1]

$$x = \text{Min}(1, (\text{Max}(\ln(1 + e^{v^{1-w}})) - \ln(2))/0.62)$$

Notation:

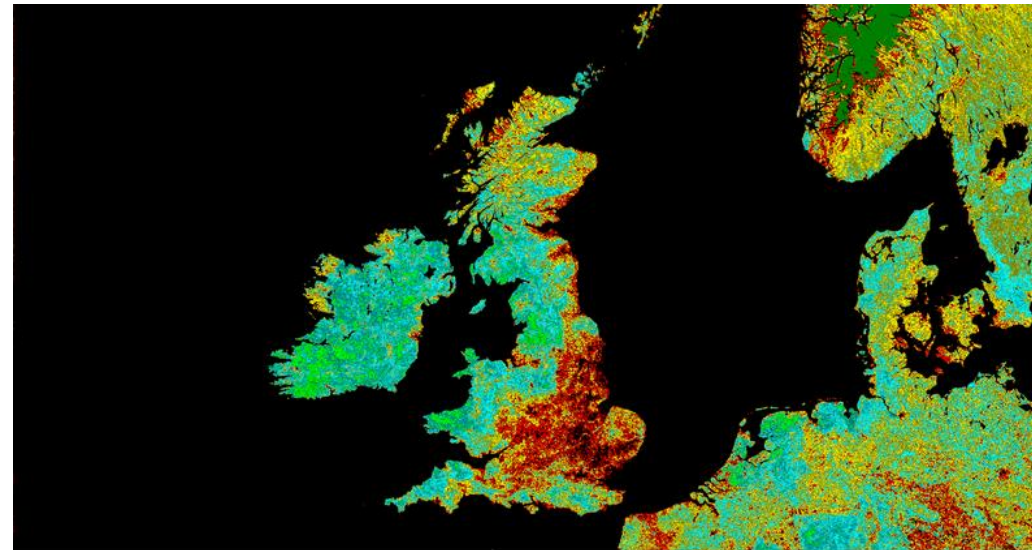
- x is the calculated Overall Condition Score
- v is the input vector – in more detail it is the vector of all sub-scores
- w are the weights of each sub-score where the sum of all weights shall be 1
- $\ln()$  is the natural log

This is the final calculation method of the OCS that is used. As for now, the **sub-scores are not weighted** differently and are calculated into the OCS equally. Including the weight in the calculation obviously has an impact on the result, because the weighting reflects a prioritization of the sub-scores. The weighting should therefore be done by an expert who knows the different scores and can quantify the relationship between them. If prioritization is not desired or possible, then the sub-scores should not be weighted, and these should be viewed as equivalent.

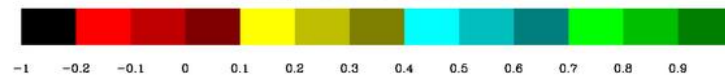
# Normalized Difference Vegetation Index (NDVI)

## Overview

The Normalized Difference Vegetation Index (NDVI) is a widely used metric for quantifying the health and density of vegetation using sensor data. It's calculated from spectrometric data at two specific bands: red and near-infrared. Essentially, NDVI helps assess vegetation cover by normalizing green leaf scattering in the near-infrared wavelength and chlorophyll absorption in the red wavelength.



average NDVI of October 2003



[https://commons.wikimedia.org/wiki/File:NDVI\\_102003.png](https://commons.wikimedia.org/wiki/File:NDVI_102003.png)

# NDVI

## Calculation

There are 3 different NDVI values that are displayed. The heatmap displays the NDVI outlier score, which shows the deviation of the value from usual/expected NDVI value of this month. When one hexagon is then selected, the expected and the measured NDVI value of this area can be seen.

- **Measured NDVI value**

The NDVI calculation is performed for each pixel within the image. Calculation of NDVI will be done through subtraction and division of the values.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Notation:

- *NDVI* is the calculated NDVI value for one pixel
- *NIR* is the pixel value of band 4 of a TIF-file: Containing Near Infra-red (NIR) data
- *RED* is the pixel value of band 3 of a TIF-file: Containing RGB data

The result is an array of NDVI values within a range of -1 and +1. Values closer to +1 indicate a greater density of vegetation of higher level of “greenness”, values less than 0 are, by definition, water or non-vegetated features and are not used for further calculation. The valid NDVI values for each hexagon are now averaged and the result is the measured NDVI value for that hexagon.

# NDVI

## Calculation

- **Expected NDVI value**

This is the mean value of all NDVI values from previous years of the same/current month.

$$ndvi_{expected} = \frac{\sum_i^n x_i}{n}$$

Notation:

- n is the number of years where the NDVI of this month was already measured and can be added to the historical data
- $x_i$  is the i-th NDVI value of all n historic NDVI values

- **NDVI outlier score**

This is a scoring value which is calculated by the current value in comparison to the previous year's values for the current month. A strong deviation from the historical values is then referred to as an outlier. An outlier is an observation that lies abnormally far away from other values in a dataset. The output range is in the interval from 0 to 1. Zero means that there is no outlier, and the actual value is in the range of the historical values. One means that this is an outlier. The current implementation is based on the calculation of the z-score. The z-score can be used to identify outliers by measuring how many standard deviations a single observation or data point is away from the mean of the distribution. The result of the z-score calculation is scaled by a continuous function (sigmoid) and resulting in values between 0 (no outlier) and 1 (certain outlier).

# NDVI

## Calculation

$$ndvi_{z-score} = \frac{ndvi_{measured} - ndvi_{expected}}{\sqrt{ndvi_{var}}}$$

$$ndvi_{os} = \frac{1}{1 + e^{-k(|zScore| - z_0)}}$$

Notation:

- $ndvi_{var}$  is the mean variation of the historical values until the processing month, it is calculated as follows:  $\frac{\sum_i^n (x_i - ndvi_{expected})^2}{n}$
- $k$  is the slope of the sigmoid function  
The larger the value the faster get result is getting to the limits of [0,1]



# Infrastructure Score

## Overview

This score is used to measure the human made infrastructure in each area by converting the number of objects and their confidence score in an area into a score between 0 and 1. Zero means there is no detectable human-made infrastructure, and one means there is some kind of hotspot where the human footprint is highly visible. To detect changes, monthly object detections are done to monitor the key biodiversity areas.

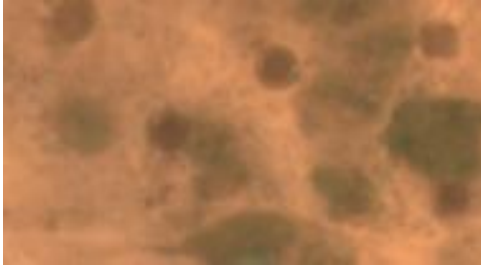
The object detection is done by an AI model which was trained with labelled images from the Dakatcha Woodland and the Amboseli National Park. The images are provided monthly by Planet.com and have a resolution of approximately 3m/pixel.

The classes of objects that were labelled and that the model was trained on are **bomas**, **buildings** and **fields**. The object class fence will be added in the future.

# Infrastructure Score

## Object Classes

### Boma



- The image above shows a cluster of Bomas in the Amboseli National Park (the dark circles)
- A boma is a livestock enclosures
- Very frequent in the Amboseli National Park, uncommon in the Dakatcha Woodland

### Building



- The image above shows a small town in Amboseli
- The coloured dots are the individual buildings
- These three images are the actual satellite images from Planet.com which were included in the training

### Field



- The image above shows fields in the Dakatcha Woodland
- Field stands for any human-made clearings that are mainly used for agricultural purposes
- Fields shape the landscape of the Dakatcha Woodland

# Infrastructure Score

## Calculation

For each hexagon and each object class the number of detected objects and the object class score is saved. The object class score is a metric which combines the number of objects in that area with the corresponding confidence scores and stays in the range [0:1]. After comparing different methods, the following formular was chosen:

$$x = \text{Min}\{1, \mu \cdot \ln(1 + n)\}$$

Notation:

- x is the calculated object class score
- n is the saved object count
- $\mu$  is the average confidence, so the sum of all the confidence values of the detected objects divided by the count
- $\ln()$  is the natural log

The overall infrastructure score is calculated by combining all the object class scores in the following way:

$$\text{Infrastructure\_score} = 1 - ((1 - \text{boma\_score}) * (1 - \text{building\_score}) * (1 - \text{field\_score}))$$

As for now, the **object classes are not weighted** differently and are calculated into the infrastructure score equally. Including the weight in the calculation obviously has an impact on the result, because the weighting reflects a prioritization of the object classes. Weights can be added in the future by experts who know the domain and believe a prioritization is beneficial.

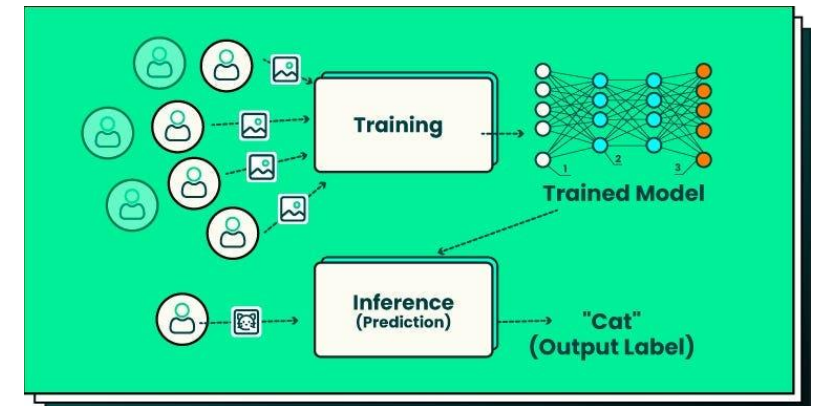
# Object Detection

## Training Process

The object detection is done monthly on images from Planet.com of the current month. Therefore, to get the best results possible, the training is done on labelled Planet.com data. For the training and the inference, we use the tool Detectron2 which is a PyTorch based modular computer vision model library.

The machine learning model uses these human-made labels to learn the underlying patterns in the model training. The result is a trained model that can be used to make predictions on new data. The prediction on new data is called inference and, in our case, will be done each month on the current satellite data. For each detected object its class, geo-coded polygon and bounding box, date and the confidence (=accuracy) are saved to the database. The confidence is a number between 0 and 1 that represents the likelihood that the output of the model is correct.

The trained model is a file where the trained weights are saved in. The weights are numerical values that the model learns and adjusts during its training. They are the inputs that determine the strength of connections an AI model makes between different things.

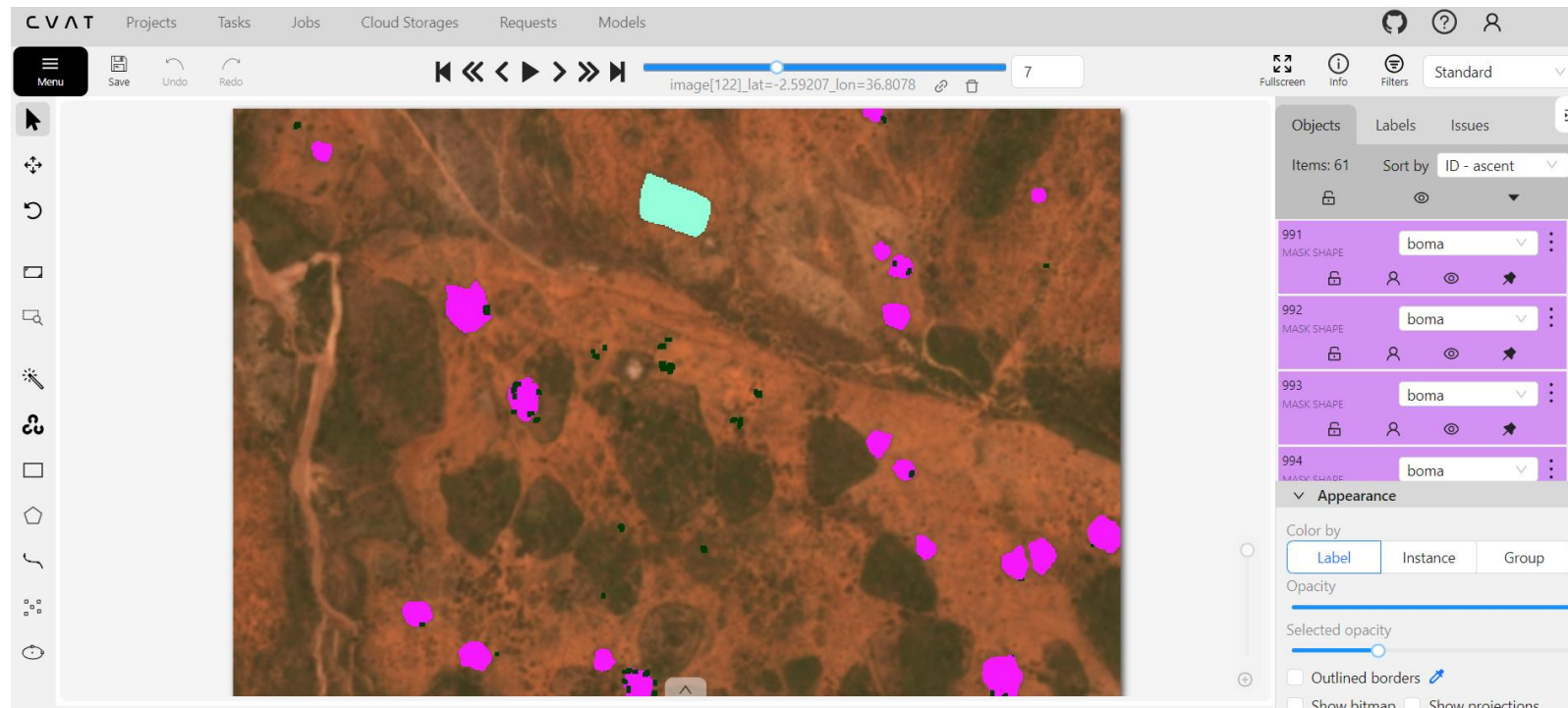


[https://miro.medium.com/v2/resize:fit:1400/0\\*RMtQoNuC5UEtQcs0.jpg](https://miro.medium.com/v2/resize:fit:1400/0*RMtQoNuC5UEtQcs0.jpg)

# Object Detection

## Training Process - Labelling

The used model was trained on 40 labelled images. We identified and labelled over 4000 objects, which were mainly buildings. The tool that was used for the labelling is called CVAT. The following image shows an example of how a labelled image looks like in CVAT. Marked as light green is a field, purple are bomas and the little dark green spots are buildings. Because accurate labelling is essential for a well-trained model and because the objects are difficult to spot, we used some additional tools for a better labelling process.

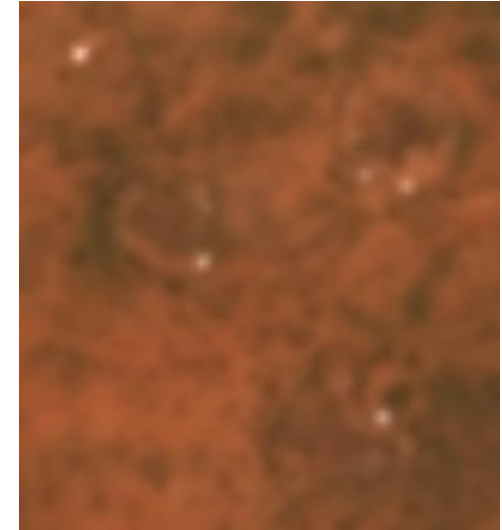


# Object Detection

## Training Process - Labelling

Because of the 3m/pixel resolution of the Planet data, accurately detecting the objects by eye is very difficult. To increase accuracy and to make the labelling process easier, we cross-checked the Planet images against higher resolution images. This was done by generating a GEOJSON file of the TIF image with its exact coordinates and displaying the area on the GeoJSON.io website.

The following images show the drastic difference in the resolution and how much easier the objects can be seen. However, it also shows the downside that the high resolution images are not from an exactly known date, as it can be seen in the upper left corner that there is a building and probably a boma on the Planet image, but not in the high resolution one. This has to be taken into account, but this method still improved the process a lot.



# Flowchart

