República de Moçambique
Ministério da Terra, Ambiente e Desenvolvimento Rural

# Designing and implementing an accuracy assessment of a change map and estimating area based on the reference sample data

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Following the recommended practices for estimating area and assessing accuracy of land change pointed out by Olofsson *et al.* (2014), we summarize below the key elements of this process (sampling design, response design and Analysis).

## Sampling design

The objectives of our analysis are to estimate overall accuracy, user's accuracy (commission error), producer's accuracy (omission error) and area of each class of land change.

As first step we should define the protocol for selecting a subset of the region of interest – ROI, where we are going to apply the response design; a subset of spatial units that will form the basis of the accuracy assessment.

It will be desirable to divide the ROI into discrete, mutually exclusive strata, using land cover change classes because of interest for reporting results (accuracy and area reported by land cover change class) and for improving the precision of the accuracy and area estimates. Strata will be defined based on generalized change categories (1.Deforestation, 2.Forest Gain, 3.Forest degradation, 4. Enhancement of forest carbon stocks, 5. Stable Forest, 6.Stable non-forest), but the sample size will be allocated proportional to the area of each individual change type within one of those generalized strata (increasing the sample size for the rarer classes). So, a stratified random sampling (probability sampling design; inclusion probability known for each unit selected in the sample and greater than zero for all units in the ROI) will be our practical design. We will use the variance estimator for user's accuracy to decide the sample size needed to achieve certain standard errors for the assumed estimated user's accuracy for that class (iterative process).

For stratified random sampling Cochran (1977) provides the following sample size formula, assuming the cost of sampling each stratum is the same:

$$n = \frac{(\sum W_i S_i)^2}{[S(\hat{O})]^2 + (1/N)\sum W_i S_i^2} \approx \left(\frac{\sum W_i S_i}{S(\hat{O})}\right)^2$$

Where N is the number of units in the ROI, $S(\hat{O})$is the standard error of the estimated overall accuracy that we would like to achieve, $W_i$ is the mapped proportion of the area of class i, and $S_i = \sqrt{U_i(1-U_i)}$ (where $U_i$ is the user's accuracy of class i) is the standard deviation of stratum i. Because N is typically large, the second term in the denominator can be ignored.

We can specify a priori target standard error for overall accuracy of 0.01 and user's accuracies of 0.7 for deforestation, 0.6 for forest gain and forest degradation (and enhancement of forest carbon stocks) and 0.9 for stable classes.

## Response design

It provides the best available classification of change for each spatial unit sampled.

The spatial assessment unit will be almost the equivalent a 3 x 3 block of Landsat pixels (100 x 100 m), where a plot of same dimensions and an internal grid of 5 x 5 points will be overlapped.

The entire area of the country has been visually assessed on a 4 x 4 km grid at national level (the same grid used to allocate the NFI clusters from the Stratified Random Sampling design) using high and medium resolution imagery. This precise set of data which characterizes the current LULC and the changes produced in the historical series, will be used both to decide the training areas for the LULC 2016 (sentinel-2) and for the image stack of Landsat 8 OLI and Landsat 5 TM ; training subset (70%). A subset of data will be used for validation purposes of both products; test subset (30%).

Reference data will be high and medium resolution image repository available through Google Earth and Earth Engine, automatically accessible through the Collect Earth tool (www.openforis.org) along with scripts accessible through Earth Engine code that facilitate vegetation type's interpretation (e.g. MODIS or Landsat NDVI time series). A protocol has been stablished for reference labelling and rules for defining agreement between map and reference classifications for a given spatial unit will be specified before proceeding to the analysis that quantify accuracy.

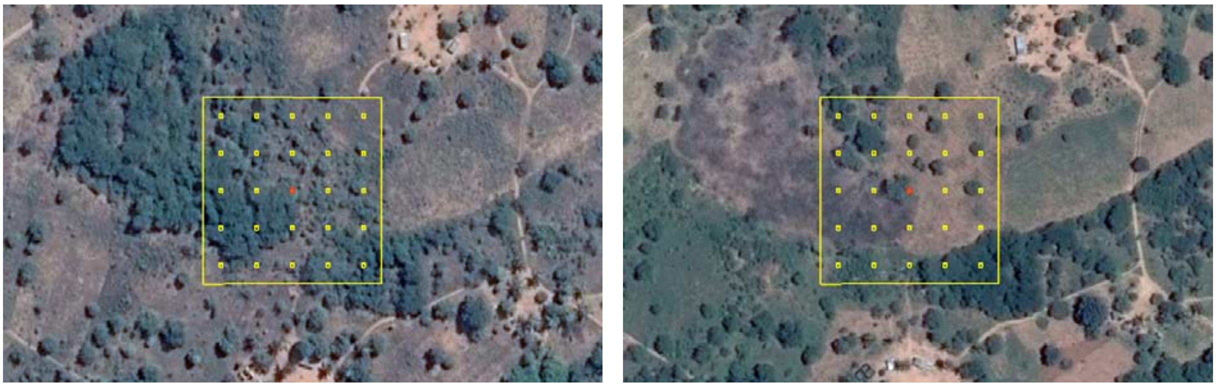

Figure 1. LULC changes detection using Collect Earth Tool. (www.openforis.org). High resolution imagery from Google Earth.

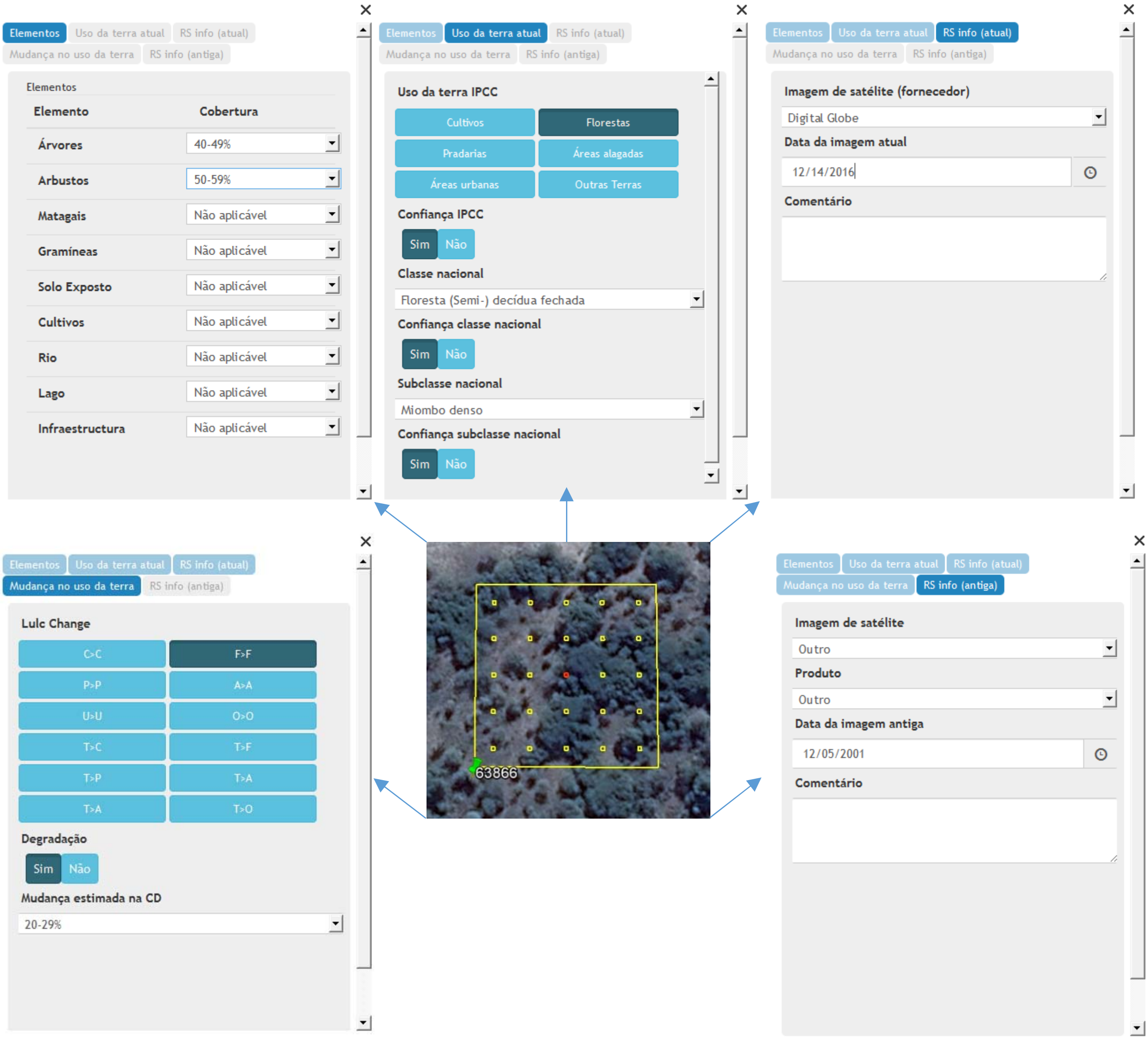


Figure 2. LULC changes detection using Collect Earth Tool. (www.openforis.org). Forms designed with Collect Tool.

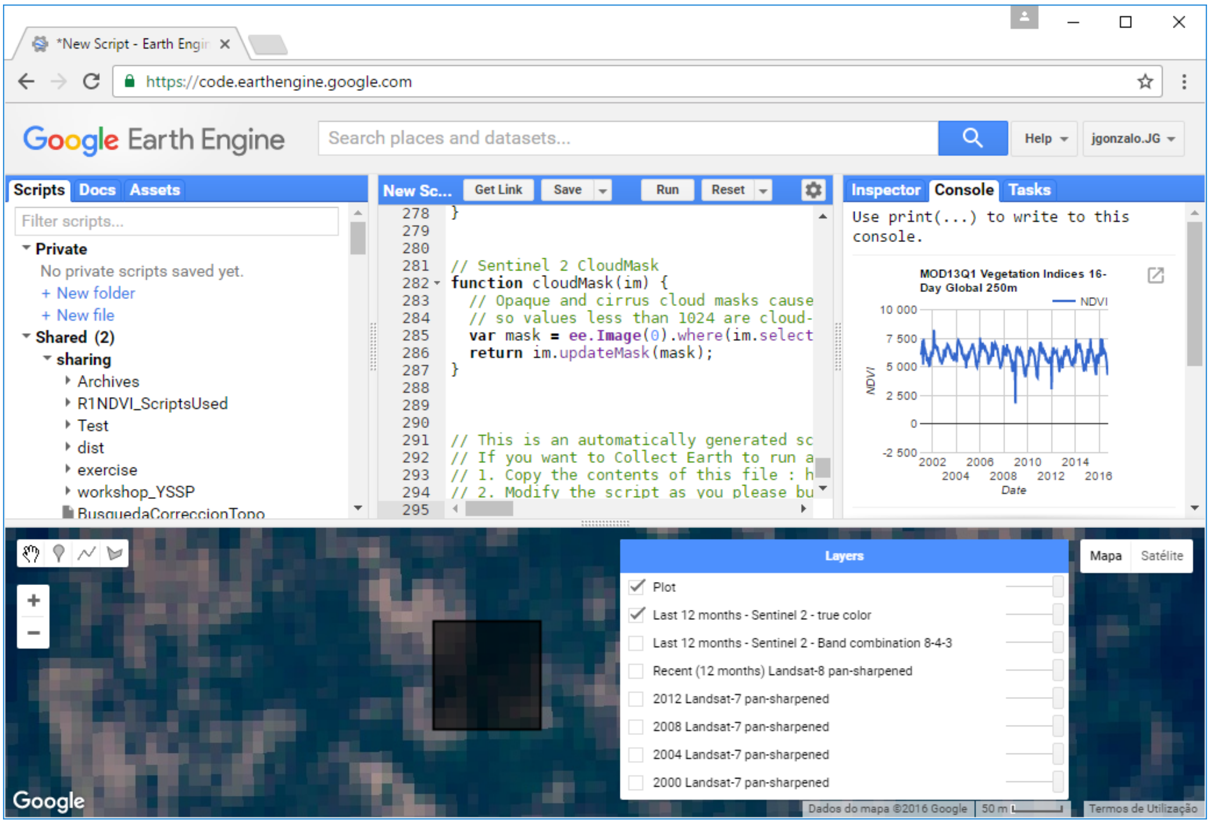


Figure 3. Earth Engine code accessible trough Collect Earth Tool. (www.openforis.org). Scripts of NDVI series.

## Analysis

We consider here the protocols for specifying the measures to be used to express accuracy and class area, and the procedures to estimate these measures from the sample data.

The error matrix (confusion matrix), cross-tabulation of the class labels allocated by the classification of the RS data against the reference data for the sample sites, summarize the key results, and aids the quantification of accuracy and area.

An element $p_{ij}$ of this matrix represents the proportion of area for the population that has map class i (rows) and reference class j (columns). Population is the full ROI. The sample based estimator of $p_{ij}$ is $\hat{p}_{ij}$, and for stratified random sampling with strata corresponding to the map classes: $\hat{p}_{ij} = W_i \frac{n_{ij}}{n_{i.}}$ (where $W_i$ is the proportion of area mapped as class i, and $n_{ij}$ are the sample counts).

**Estimating Accuracy**

Accuracy parameters derived from a population error matrix o f q classes:

*Map class/Reference class*

| | *class 1* | *class 2* | *class j* | *Total* |
|---|---|---|---|---|
| *class 1* | $p_{11}$ | $p_{12}$ | $p_{1j}$ | $p_{1.}$ |
| *class 2* | $p_{21}$ | $p_{22}$ | $p_{2j}$ | $p_{2.}$ |
| *class i* | $p_{i1}$ | $p_{i2}$ | $p_{ij}$ | $p_{i.}$ |
| *Total* | $p_{.1}$ | $p_{.2}$ | $p_{.j}$ | 1 |

Overall accuracy: $O = \sum_{j=1}^{q} p_{jj}$

User's accuracy of class i (the proportion of the area mapped as class i that has reference class i): $U_i = p_{ii}/p_{i.}$

Producer's accuracy of class j (the proportion of the area of reference class j that is mapped as class j): $P_j = p_{jj}/p_{.j}$

For overall accuracy, the estimated variance is: $\hat{V}(\hat{O}) = \sum_{i=1}^{q} W_i^2\, \widehat{U_i}(1-\widehat{U_i})/(n_{i.}-1)$

For user's accuracy of map class i, the estimated variance is: $\hat{V}(\widehat{U_i}) = \widehat{U_i}(1-\widehat{U_i})/(n_{i.}-1)$

For producer's accuracy of reference class j=k, the estimated variance is:

$\hat{V}(\widehat{P_j}) = \frac{1}{\widehat{N_{.j}}^2}\left[\frac{N_{j.}^2(1-\widehat{P_j})^2\widehat{U_j}(1-\widehat{U_j})}{n_{j.}-1} + \widehat{P_j}^2 \sum_{i\neq j}^{q} N_{i.}^2 \frac{n_{ij}}{n_{i.}}(1-\frac{n_{ij}}{n_{i.}})/(n_{i.}-1)\right]$ where $\widehat{N_{.j}} = \sum_{i=1}^{q} \frac{N_{i.}}{n_{i.}} n_{ij}$ is the estimated marginal total number of pixels of reference class j, $N_{j.}$ is the marginal total of map class j and $n_{j.}$ is the total number of sample units in map class j.

These variance estimator would not apply to a polygon assessment unit or to a mixed pixel situation.

**Estimating Area**

The row total $p_{k.}$ represents the proportion of area mapped as class k (known), and the column $p_{.k}$ represents the proportion of area of class k as determined by the reference classification (estimated from the sample), and it should have smaller bias than $p_{k.}$ . The bias attributable to reference data error is smaller than the bias attributable to map classification error, so it is recommended an area estimation based on the proportion of area derived from the reference classification.

The stratified estimator of the proportion of area of class k is: : $\hat{p}_{.k} = \sum_{i=1}^{q} \hat{p}_{ik} = \sum_{i=1}^{q} W_i \frac{n_{ik}}{n_{i.}}$,

and the standard error is estimated by: $S(\hat{p}_{.k}) = \sqrt{\sum_i w_i^2 \frac{\frac{n_{ik}}{n_{i.}}(1-\frac{n_{ik}}{n_{i.}})}{n_{i.}-1}} = \sqrt{\sum_i \frac{W_i\hat{p}_{ik}-\hat{p}_{ik}^2}{n_{i.}-1}}$ , where

$n_{ik}$ is the sample count at cell (i,k) in the error matrix, $W_i$is the proportion of area mapped as class i, $\hat{p}_{ik} = W_i \frac{n_{ik}}{n_{i.}}$, and the summation is over the q classes.

The estimated area of class k is $\hat{A}_k = A\, \hat{p}_{.k}$, where A is the total map area. The standard error of the estimated area is given by $S(\hat{A}_k) = A\, S(\hat{p}_{.k})$. An approximate 95% confidence interval is obtained as $\hat{A}_k \pm 1.96\, S(\hat{A}_k)$.