Land Use and Land Cover Map of Mount Namuli and surroundings 2022

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1_ Introduction

This report presents the land use and land cover mapping of the Gurué region and the Mount Namuli, using remote sensing. Gurué is located in the northwest of the Zambezia province and 150 km from the Malawi border (Figure 1). The tea production is the main economic activity. This was initiated by the Portuguese in 1930, then in 1980-90 managed by the state and currently managed by private Mozambican and other companies (Timberlake et al., 2009). Apart from a few contract jobs in tea plantations, people live mainly from subsistence and local market agriculture.

The Mount Namuli Massif, located in the north of the city, covers an area of about 200 km² at an altitude above 1200 m (Timberlake et al., 2009). The highest point of the massif, Mount Namuli, reaches 2,419 m. It is the second highest peak in Mozambique after Mount Binga (2,436 m) located in the Chimanimani National Reserve (Manica Province). The region surrounding Mount Namuli is inhabited by local communities who rely on it heavily for ecosystem services. Although, the area's biodiversity is greatly threatened by conversion of forests and grasslands by these communities for subsistence and local market agriculture. There is minimal local government involvement in the area for conservation activities or social services, and thus there has been no effective management of natural resources. Mount Namuli is relatively small in extent but incredibly diverse and a part of the unique mountain island chain of inselbergs in northern Mozambique. Mount Namuli's slopes are covered by a mosaic of forests, grasslands, and agricultural land. Rates of habitat loss, particularly across high conservation value areas above 1,200 meters, are increasing, driven primarily by the introduction of crops, such as the Irish potato, which exhaust the soils. The high rates of forest conversion underway on the mountain's upper slopes must be halted immediately and long-term plans for natural resource management must be implemented if Mount Namuli's remaining biodiversity is to be retained.

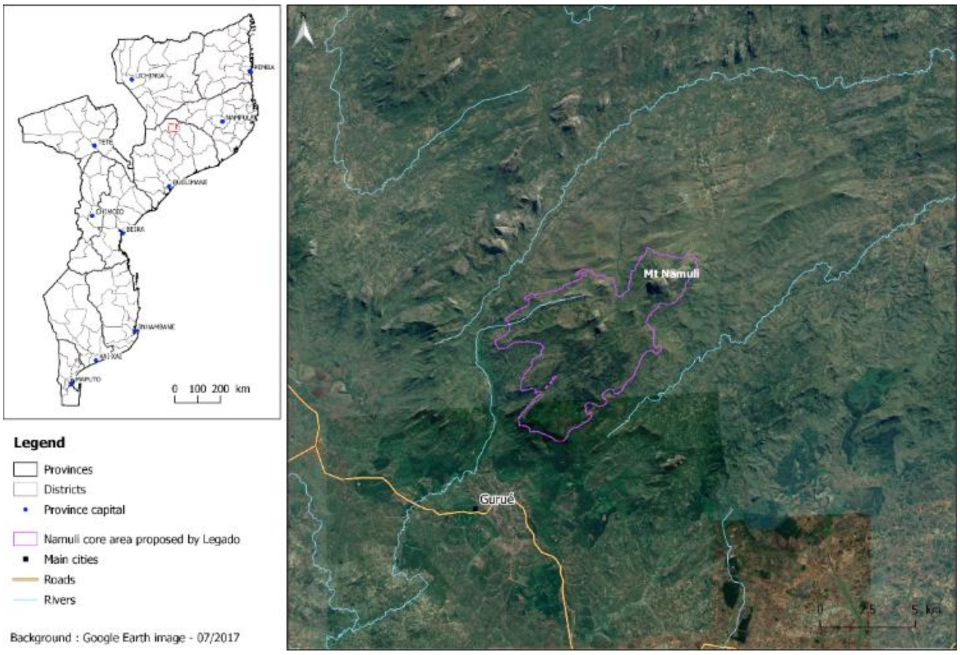

Figure 1: Location of Namuli area

Figure 2 : Landscape of Gurué and Mount Namuli

2_ Methodology

The methodology used in this study is based on a classical approach of remote sensing: satellite image collection, identification of land use typology, delineation of training plots, supervised classification of land use using a statistical model and finally, calculation of land occupation statistics. The methodology is summarized in the following figure:

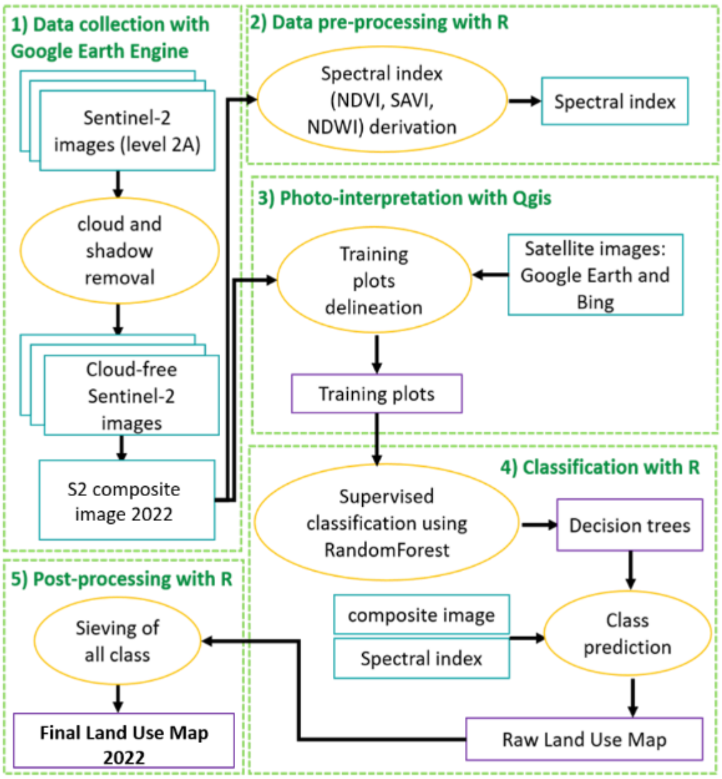

Figure 3 : Processing chain applied for the land use mapping

2.1. Satellite image database

Sentinel 2 :

The input spatial datasets selected are Sentinel 2 images (S2). This satellite and sensor was launched in April 2015 and deliver free of charge satellite images since November 2015. This satellite offers a great opportunity to map subtle and timely land use and land use change in an unprecedented manner since it has record reflectance values at 10 meters ground resolution for visible and near infra-red bands, and has a 10 days revisiting period.

A Google Earth Engine script has been adapted and executed to produce a cloud-free and shadow-free Sentinel-2 composite using precise parameters. We selected image acquired between June and August 2022 (3 month period – Dry season). All the spectral bands of the Sentinel-2 sensor have not been used. Only the 6 bands, highlighted in blue in the following table, were used to perform a composition in a multi-band image resampled at 10 m.

Table 1 : Sentinel-2 spectral band (spectral bands used in blue)

Name	Scale	Resolution (meters)	Wavelength	Description
B1	0.0001	60	443.9nm (S2A) / 442.3nm (S2B)	Aerosols
B2	0.0001	10	496.6nm (S2A) / 492.1nm (S2B)	Blue
B3	0.0001	10	560nm (S2A) / 559nm (S2B)	Green
B4	0.0001	10	664.5nm (S2A) / 665nm (S2B)	Red
B5	0.0001	20	703.9nm (S2A) / 703.8nm (S2B)	Red Edge 1
B6	0.0001	20	740.2nm (S2A) / 739.1nm (S2B)	Red Edge 2
B7	0.0001	20	782.5nm (S2A) / 779.7nm (S2B)	Red Edge 3
B8	0.0001	10	835.1nm (S2A) / 833nm (S2B)	NIR
B8a	0.0001	20	864.8nm (S2A) / 864nm (S2B)	Red Edge 4
B9	0.0001	60	945nm (S2A) / 943.2nm (S2B)	Water vapor
B10	0.0001	60	1373.5nm (S2A) / 1376.9nm (S2B)	Cirrus
B11	0.0001	20	1613.7nm (S2A) / 1610.4nm (S2B)	SWIR 1
B12	0.0001	20	2202.4nm (S2A) / 2185.7nm (S2B)	SWIR 2

SPOT 6:

To improve identification of the remaining forest patches in the Namuli core zone, we used a SPOT 6 image, a very high spatial resolution image. SPOT-6 is an optical imaging satellite with a resolution of 1.5 meter panchromatic and 6 meter multispectral (blue, green, red, near-IR). These images are distributed by Airbus Defence and Space and GEOSUD/DINAMIS.

They have 5 spectral bands acquired simultaneously

- Panchromatic (PA): 0.450-0.745 µm
- Blue (B0): 0.450-0.520 µm
- Green (B1): 0.530-0.590 µm
- Red (B2): 0.625-0.695 µm
- Near infrared (B3): 0.760-0.890 µm

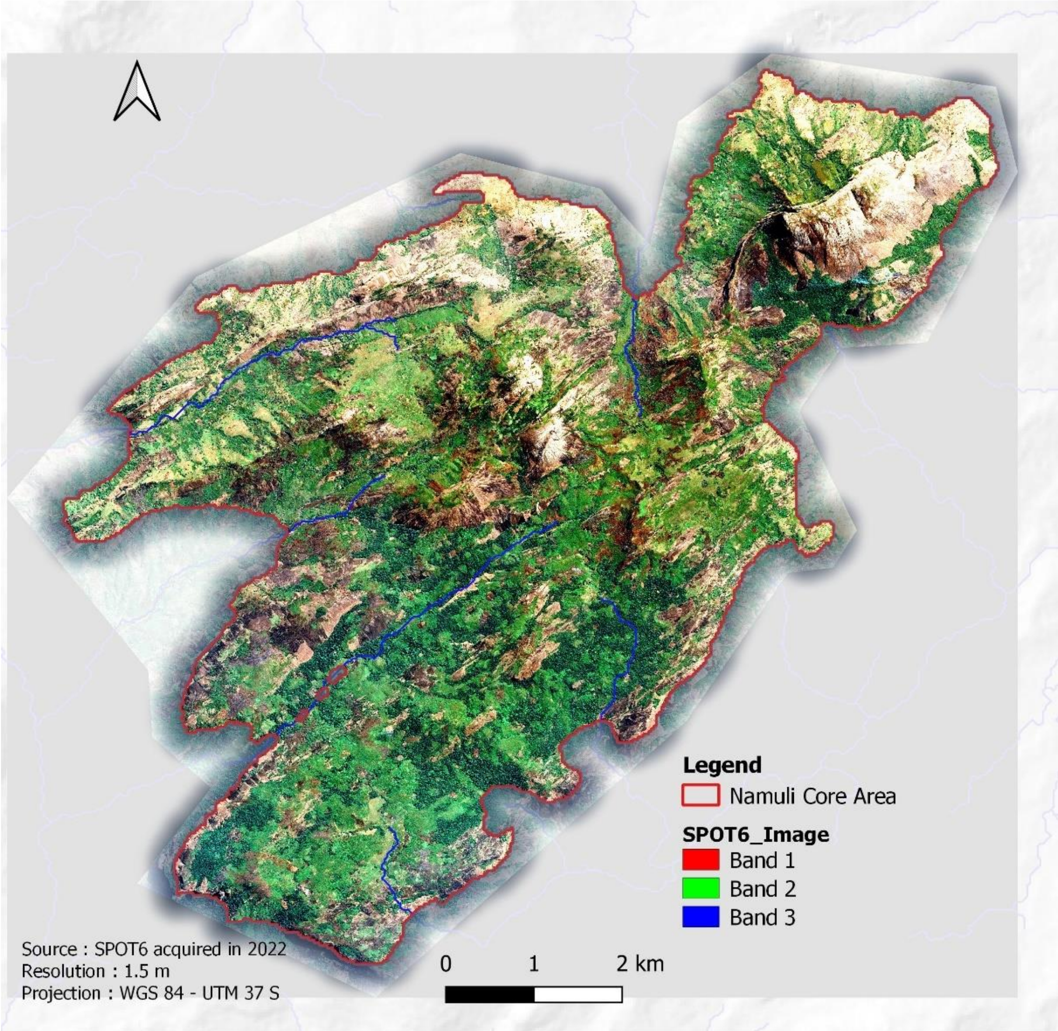

Figure 4: SPOT6 Satellite image

2.2. Data pre-processing and variables

For the classification, three categories of variables have been used: the Sentinel 2 spectral bands, soil, water and vegetation indices, and topographic indices such as altitude, slope and the relative height. In order to improve the classification and increase the spectral differentiation between classes, several spectral indexes were derived from the primary bands of the two satellite images, as presented in the following table.

Table 2 : Spectral indexes calculated

Index	Formula	References
NDVI (Normalized Difference Vegetation Index) – Vegetation spectral enhancement	NDVI=(NIR-R)/(NIR+R)	Rouse et al., 1974
SAVI (Soil Adjusted Vegetation Index) – Soil spectral enhancement	SAVI = (NIR - R) / (NIR + R + L) * (1.0 + L)	Huete, 1988
NDWI (Normalized Difference Water Index) – Water spectral enhancement	NDWI = (NIR - SWIR) / (NIR + SWIR)	Gao, 1996

2.3. Supervised classification

After data pre-processing, the method to establish a deforestation map follows three main steps:

- Definition of land use and land cover classes;
- Delimitation of training plots;
- Classification with a specific algorithm (Random Forest).

2.3.1. Definition of land use and land cover changes classes

A field campaign was conducted in November 2018, to collect information on land use and land cover. Then, these information were compared to the different types of patterns visible on the satellite images. Land use and land cover (LULC) classes that exist in the areas and are detectable with Sentinel imagery are presented in the following table:

Table 3 : Typology of land use and land cover classes for the study

Code	Short Name	Description	Photos	Color code
1	Forest	Forest includes all land with dense mature woody vegetation (mainly moist evergreen forest – Montane forest) that have not been perturbed.		
2	Grassland	Grassland is an area with herbaceous plant types, but without crop cultivation. Trees and shrubs can be present but cover is less than 10%.		
3	Mosaic of culture and fallow	This class includes land covered with temporary crops followed by harvest and a period of bare soil or fallow.		
4	Eucalyptus plantation	Eucalyptus plantation		
5	Tea plantation	Tea plantation		
6	Macadamia plantation	Macadamia plantation		

7	Secondary vegetation or woodland	Secondary vegetation is regenerated forest or other woody land that has been disturbed by human activities. Includes a vegetation gradient but it's difficult to go further in class differentiation		
8	Irrigated crop / Flooded area	Lowland irrigated crop or flooded area		
9	Water	This class includes areas covered by water during all the year.		
10	Urban area, Settlement	Urban area and settlement comprises all developed land, including areas of human habitation and transportation infrastructure.		
11	Bare soil, rock, sands and others	This class includes bare soil, rock, and all unmanaged land areas that do not fall into any of the previous classes.		

2.3.2. Delimitation of training plots

Delimitation of trainings plots is a necessary step to calibrate the classification algorithm when applying a supervised classification. The accuracy of the classification mainly depends on the quality of the delimitation of these training plots. Therefore, a standardized and rigorous photo-interpretation work was conducted. Photo-interpretation was carried on the basis of field knowledge, Sentinel image patterns and high-resolution images from Google Earth. Number of polygons and area delimitated are presented in the table below.

Table 4 : Number of polygons and associated delimitated area used as training plots

Code	Class	Training plots number	Cumulated area (ha)
1	Forest	60	100
2	Grassland	30	50
3	Mosaic of culture and fallow	115	660
4	Eucalyptus plantation	46	320
5	Tea plantation	58	631
6	Macadamia plantation	20	75
7	Secondary vegetation, woodland	107	237
8	Irrigated crop, flooded areas	41	123
9	Water	31	10
10	Urban area, settlement	35	230
11	Bare soil, rocks, sands	51	234
Total		594	2670

First, in order to improve the localization and determination of changes, those area where highlighted by performing a multi-dates color composite. Then, training plots were located in cluster i.e. by grouping several plots of different categories on a same landscape unit or small area (Figure 4). In order to reduce noise in training data, plots contours were verified by superposition on very high-resolution images available on Google Earth.

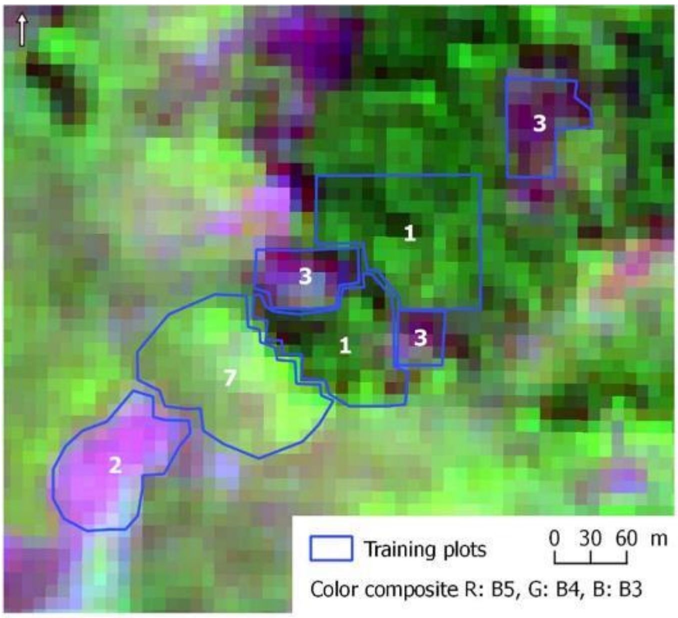

Figure 5: Example of training plots delimitation

2.3.3. Supervised classification

Afterward, the training plot spatial database was correlated with the multi-date stacked image database using a statistical algorithm. The Random Forest algorithm, developed by Breiman (2002) and available in R software was used. It is a data-mining algorithm that combines bugging techniques and decision tree. It was successfully applied in land cover change studies in humid forests of Madagascar (Grinand et al., 2013) and in the Miombo forest biome (Kamusoko et al., 2014). First, the Random Forest algorithm must be calibrated to predict the different land-use categories to be classified. The calibration of the model is done from the database regrouping the previously delimited training plots. The Random Forest algorithm allows, during the calibration, to analyze the quality of the prediction by an indicator of global precision (explained variance) and a confusion matrix calculated from individuals (pixels) drawn at random and left out (sample "Out-Of-The-Bag"). This step is called internal validation (see paragraph below). Once the model is calibrated, the algorithm can be used to produce the land cover map with satellite data for all the study area.

2.3.4. Internal validation

Random Forest calibration was performed using 2/3 of randomly selected training plots. The remaining plots (1/3) were used to perform an "internal validation" by the algorithm. Based on a confusion matrix, this validation enabled the operator to identify the remaining confusions in order to add, remove or change the training plots on the GIS and redo the classification until satisfactory results were obtained.

2.3.5. Post-classification treatments

After classification, some isolated pixels of forest were found, giving a noisy appearance to the map. To respect the requirements on Minimum Mapping Unit (MMU - linked to the forest definition), those pixels were removed during post-classification processing. In the present study, MMU is 1 ha for forest (GoM, 2016). A majority filter with a 3x3 window was first used to remove isolated pixels. The classified image was filtered with a Grass/R script for forests patches.

3_ Results

3.1 Land Use and Land Cover map and statistics - Sentinel 2 image

The distribution of the land use and land cover classes around the town of Gurué and the Namuli massif, in 2022 (Figure 5), is largely dominated by agricultural land composed by cropland, fallow and some areas of settlement, which accounts for 44 % (35427 ha) of the total area studied. Cropland areas are dedicated mainly to subsistence farming and local market agriculture (Timberlake et al., 2009). Area of secondary vegetation or woodland are the second most represented class with an area of 17337 ha or 21 % of the total area. Tea and tree plantation cover an area of 9520 ha or 12 %. Forest land cover only 1.3 % of the study area, mainly located above 1400 m altitude. Land use and land cover statistics are presented in Table 5.

Table 5 : Area and proportion of land use and land cover classes of Mount Namuli and surroundings area calculated from the LULC 2022 map

Code	Classe	2022 Area (ha)	2022 % of total area
1	Forest	1077	1.3
2	Grassland	3370	4.1
3	Mosaic of culture and fallow	35427	43.6
4	Eucalyptus plantation	2804	3.4
5	Tea plantation	6716	8.3
6	Macadamia plantation	147	0.2
7	Secondary vegetation, woodland	17337	21.3
8	Irrigated crop, flooded area	1470	1.8
9	Water	1490	1.8
10	Urban area, settlement	1617	2.0
11	Bare soil, rock, sand	9832	12.1
Total		81289	100

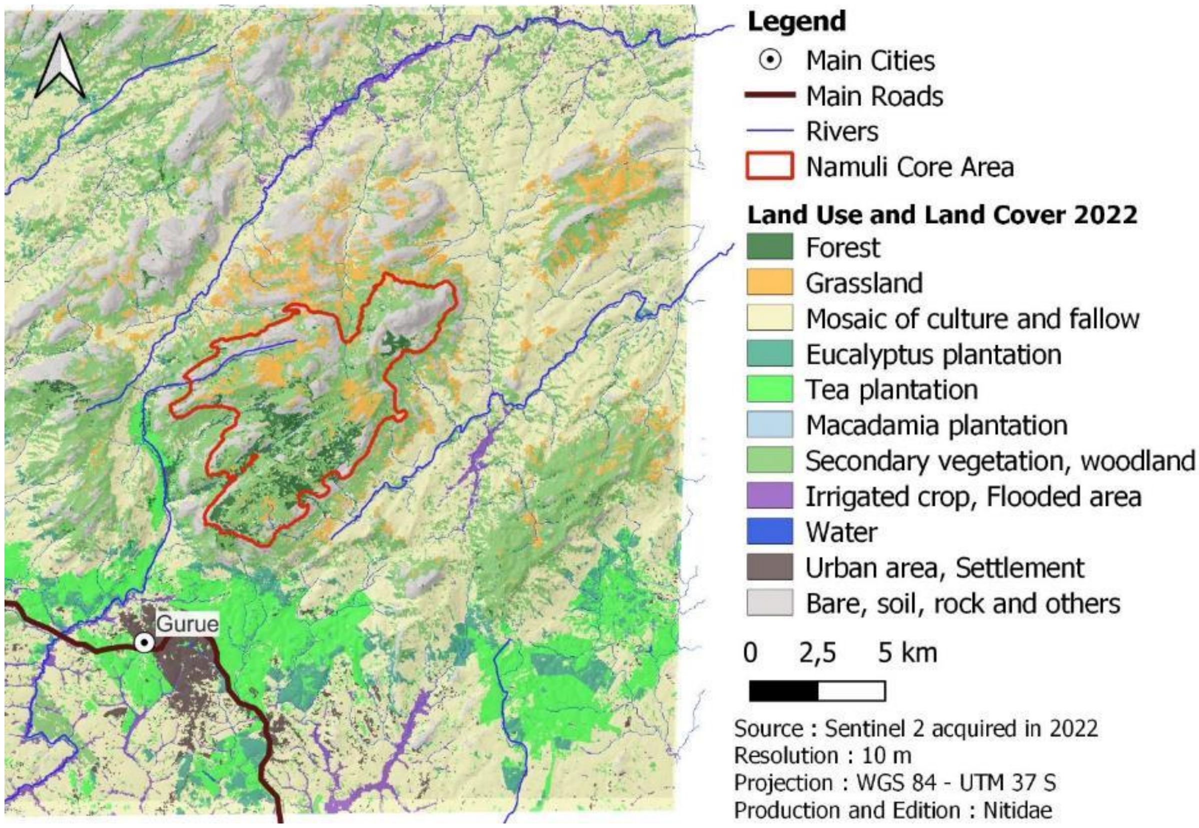

Figure 6 : Land Use and Land Cover map of Mount Namuli and surroundings (2022)

3.2 Land Use and Land Cover map and statistics of Namuli Core area - Sentinel 2 image

The land use and land cover of the Namuli core area in 2022, can be broadly categorized into five main classes: forest, grassland, cropland area, secondary vegetation or woodland and other areas (mainly rocks) (Figure 6). Land use and land cover statistics are presented in Table 6. Remaining forest areas cover 663 ha and account for 13 % of the total area. The Namuli core area is located above 1600 m altitude. Forest above this altitude are mainly montane Forest, with close canopy at around 20-25 m high (Timberlake et al., 2009). Areas of secondary vegetation of woodland can be natural area or area partially cleared, cultivated of frequently affected by fire, these areas cover 2155 ha or 42 % of the core area. Grassland cover 526 ha (10,5 % of total area), many patches can be find in the Namuli core area. Cropland in the core area that could be detected, cover a total area of 54 ha and patches do not exceed 0.5 ha. Due to their smaller size, some cropland may not have been detected during the analysis or may have been confused with secondary vegetation.

Table 6 : Area and proportion of land use and land cover classes in the Namuli core area, calculated from the LULC 2022 map

Code	Short Name	Area (ha)	% of total area
1	Forest (Montane Forest)	733	13.2
2	Grassland	738	10.5
3	Mosaic of culture and fallow	15	1.1
7	Secondary vegetation, woodland	1928	42.9
11	Bare soil, rocks, sands	1 604	31.7
Total		5020	100

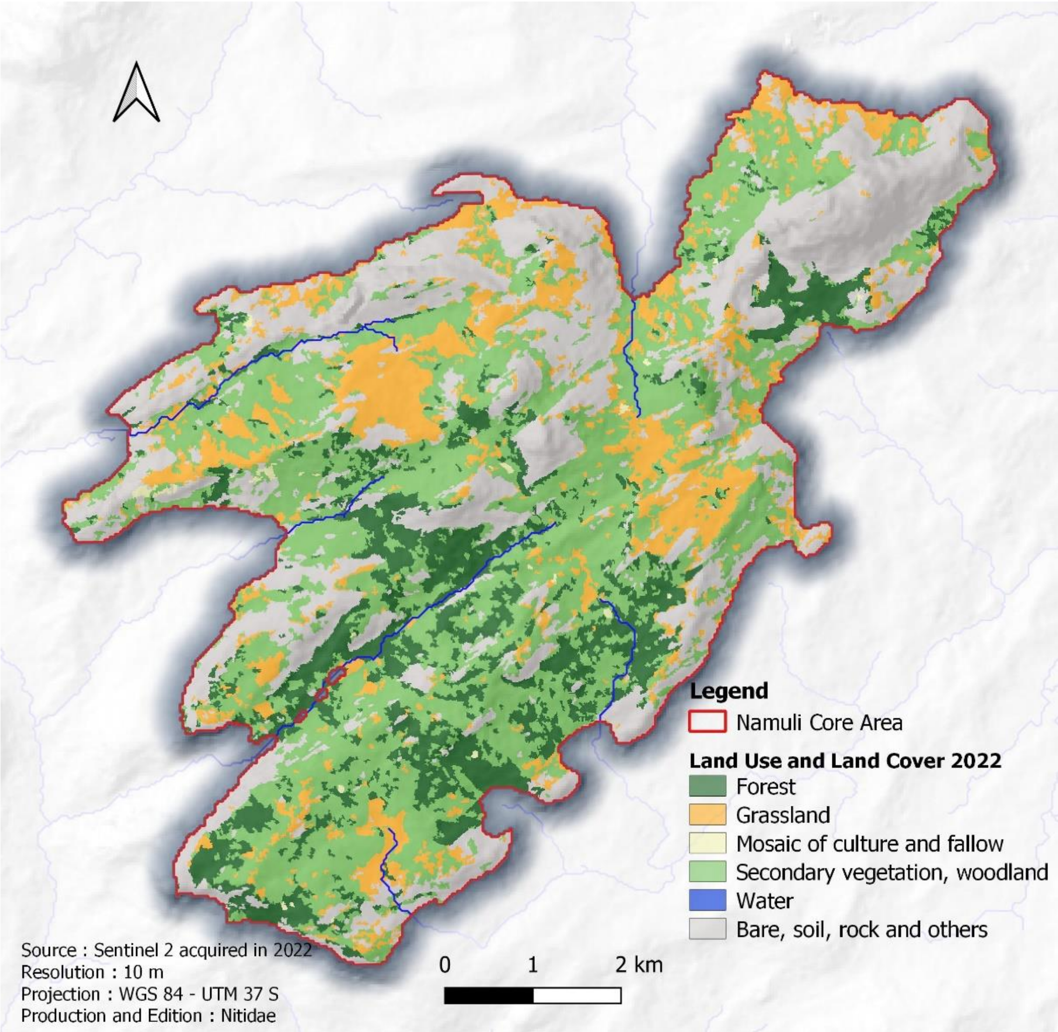

Figure 7 : Land Use and Land Cover map of Namuli core area (2022)

3.3 Internal validation – Sentinel 2 image

The results of the evaluation of pixel-level classification accuracy (referred as internal validation) are presented in Table 7. The overall accuracy of the classification results is 93 %, which confirms the acceptability of classification results. This means, among the 267 848 pixels observed 91 % are ranked well and 7 % are misclassified. For most of the classes, the user accuracy is above 90 %, except for the urban area classes which present the lowest accuracy (89 %). Forest category present a high spectral separability, with a user accuracy value of 98 % (correctly classified pixel).

Table 7 : Confusion matrix between land use categories

Class map	Observation (plot)											Total	User accuracy	Commission error
	1	2	3	4	5	6	7	8	9	10	11			
1	9573	2	8	9	53	0	300	0	1	0	20	9966	0,96	0,04
2	5	5280	23	0	0	0	65	0	0	0	25	5398	0,98	0,02
3	111	3	62863	139	1433	65	508	238	1	694	28	66083	0,95	0,05
4	15	0	577	28897	2123	105	231	13	7	91	8	32067	0,90	0,10
5	43	0	1502	1191	59663	139	432	58	2	162	4	63196	0,94	0,06
6	0	0	109	193	647	6474	9	1	0	35	1	7469	0,87	0,13
7	228	29	1341	228	733	11	20975	37	4	27	75	23688	0,89	0,11
8	0	0	703	20	265	3	19	11356	3	30	3	12402	0,92	0,08
9	1	0	24	20	7	0	39	24	897	26	0	1038	0,86	0,14
10	0	0	1617	77	461	11	39	34	4	20835	7	23085	0,90	0,10
11	19	29	78	14	138	0	109	0	0	69	22973	23429	0,98	0,02
Total	9995	5343	68845	30788	65523	6808	22726	11761	919	21969	23144	267821		
Producer accuracy	0,96	0,99	0,91	0,94	0,91	0,95	0,92	0,97	0,98	0,95	0,99			
Omission error	0,04	0,01	0,09	0,06	0,09	0,05	0,08	0,03	0,02	0,05	0,01			
Overall accuracy												0,93		

* 1: Forest; 2: Grassland, 3: Cropland, 4: Eucalyptus Plantation, 5: Tea plantation, 6: Macadamia plantation, 7: Secondary vegetation/Woodland, 8: Flooded area, 9: Water, 10: Urban area, 11: Bare soil, rocks, others

3.4 Land Use and Land Cover map and statistics of Namuli Core area - SPOT6 image

The same methodology described previously was used to produce the LULC map of Namuli core area using a SPOT-6 satellite image. Land use and land cover statistics are presented in Table 7. According to this map, remaining forest areas cover 818 ha and account for 16 % of the total area.

Comparing two LULC maps produced from images of different resolutions can give different results in terms of statistics because of the differences in resolution. The high-resolution SPOT-6 image (1.5x1.5m) enables the different classes to be mapped more precisely and minimises the disturbance observed with the 10x10m resolution image, particularly when differentiating certain classes present on our map.

Table 8 : Area and proportion of land use and land cover classes in the Namuli core area, calculated from the LULC 2022-SPOT6

Code	Short Name	Area (ha)	% of total area
1	Forest (Montane Forest)	818	16.3
2	Grassland	934	18.6
3	Mosaic of culture and fallow	57	1.1
7	Secondary vegetation, woodland	1521	30.2
11	Bare soil, rocks, sands	1 690	33.7
Total		5020	100

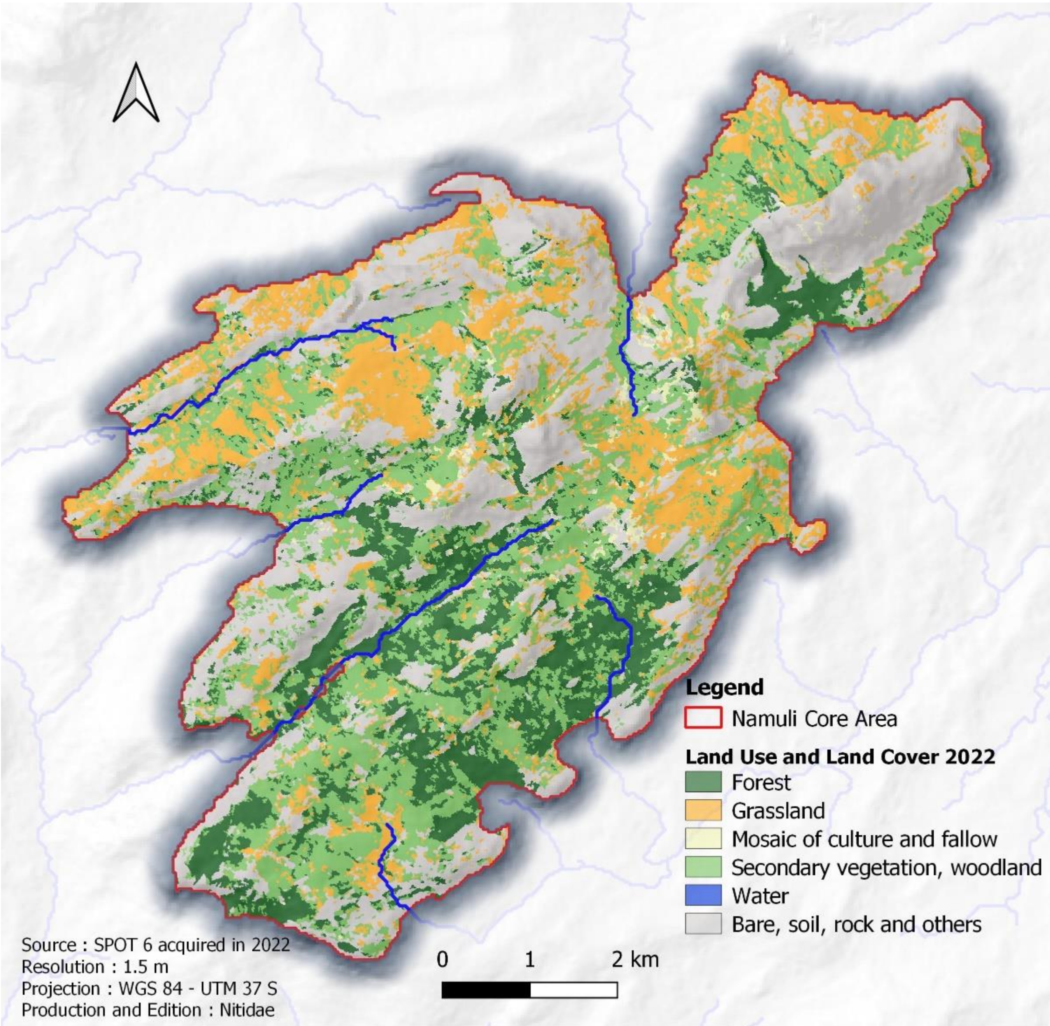

Figure 8: Land Use and Land Cover classes plots – SPOT6

4_Namuli land use 2022 vs 2020, 2018 (Sentinel 2 images)

In this session we will focus on the main differences encountered while comparing the two previous land use and land cover of the Mount Namuli core area produced with Sentinel 2. The first land use and land cover map of Mount Namuli and surroundings was produced in 2018. In 2020 with the same methodology a new land use and land cover was also produced.

Remaining forest land cover of the Namuli core area in 2022 covers 733 ha, 34 ha less from 2020 and 216 less from 2018, this means an average of 54 ha forest loss by year and account for 1 %. Grassland areas in Namuli core area have a slight variation corresponding about 29 ha by year and account for 0.6%.

Cropland area that could be detected in analysis cover 126 ha in 2018, 39 ha in 2020 and 15 ha in 2022, as mentioned in session 3.1.2, due to their smaller size, some cropland may not have been detected or may be confused with secondary vegetation.

During analysis secondary vegetation, woodland is the only land cover that seems to be increasing with an average of 1 % by year from 2018 to 2020. A summary of the statistics is presented in table 8.

Table 9 : Area of land use and land cover classes of Mount Namuli core and surroundings area calculated from the LULC 2022, 2020, 2018 map

Classe (code)	Area (ha) 2018	Area (ha) 2020	Area (ha) 2022
Forest (1)	949	767	733
Grassland (2)	623	560	738
Mosaic of culture & fallow (3)	126	39	15
Secondary vegetation, woodland (7)	1735	2055	1928
Bare soil, rock, sands (11)	1586	1565	1604

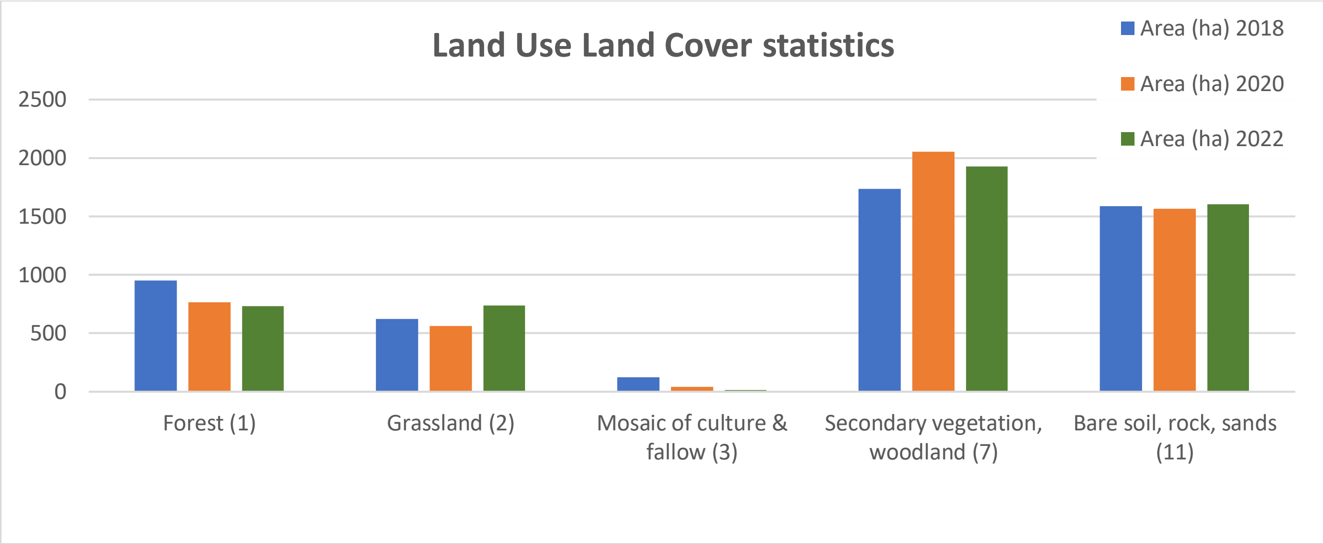

Figure 9: Land Use and Land Cover classes plots

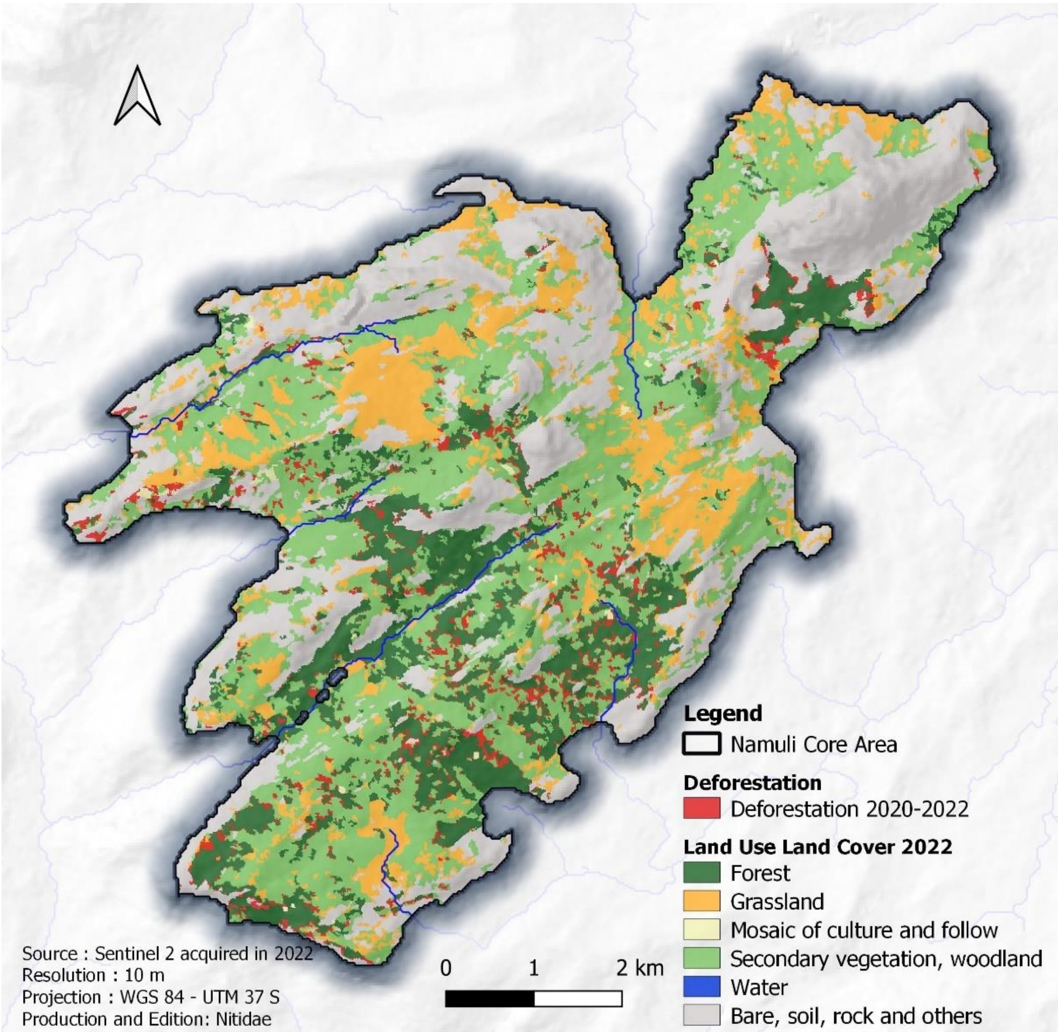

Figure 10: Namuli core area deforestation 2020-2022

5_ Conclusion

The land use and land cover mapping of the Mount Namuli and surroundings, using Sentinel-2 imagery has been used to update the statistics on land cover types in the region. The outputs map is the most recent land use and land cover map at 10 meters ground resolution of the study area. This analysis notably, allows to update extent of remaining forest patches in the Namuli core area, estimated at 733 ha. Forest land use and grassland decrease over time, potentially being converted to crop land which is increasing. Tree plantation is increasing over time with the main specie eucalyptus. This analysis can be done in the coming years to monitoring changes in the extent of montane forest and estimate deforestation rates.

6_ References

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