Land Use and Land Cover Map of Ribaue Mountains (Mount Ribaue and Mount M'paluwe)

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1_ Introduction

This report presents the land use and land cover mapping of the Ribaue Mountains and surroundings (Ribaue district, Nampula province), using remote sensing.

The Ribaue massif is a series of granite inselbergs in northern Mozambique near the town of Ribaue in Nampula Province (Figure 1). The main area of the massif is made up of the Serra de Ribaue to the west and the Serra de M'paluwe to the east. The inselbergs rise from a relatively flat landscape at ca 500-600 m altitude up to 1675 m on Monte M'paluwe. They form part of a belt of granite rock outcrops, inselbergs and mountains, running NE-SW across Nampula and Zambezia provinces and including Mt Inago (1804 m) and Mt Namuli (2419 m) to the southwest of the Ribaue massif (Kew Botanical Garden, 2018).

This belt is considered as a center of endemism (Darbyshire et al., 2019). Overall the site supports 15 nationally endemic plant taxa (plants that only occur in Mozambique), 11 near-endemics (plants that are restricted to Mozambique and neighbouring countries) and 10 taxa that are threatened with extinction on the Global IUCN Red List (Kew Botanical Garden, 2018).
Steeply sloping granite rock outcrops, mid-altitude moist forest and miombo woodland are the dominant habitat types at the Ribaue massif. The site also includes smaller areas of gallery forest, marsh, seasonal stream gullies, seepage on granite rock, and shaded granite cliffs (Kew Botanical Garden, 2018).

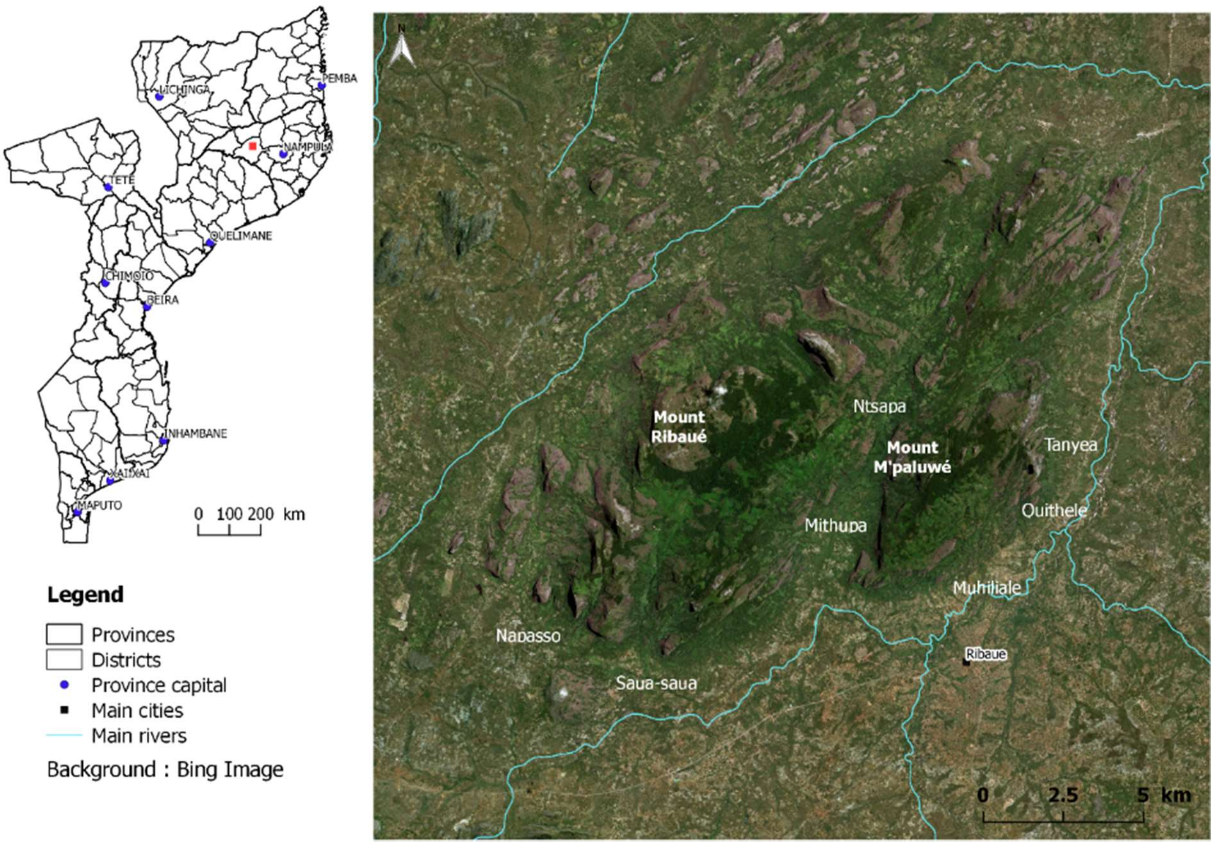


Figure 1 : Location of Ribaue Mountains

Figure 2 : Landscape of Ribaue Mountains

2_ Methodology :

The methodology used in this study is based on a classical approach of remote sensing: 1) satellite image collection, 2) data pre-processing, 3) delineation of training plots, 4) supervised classification of land use using a statistical model and 5) post-processing. In order to reach our objectives of characterization of land use, we chose to work on two different seasons (dry and wet season). The methodology is summarized in the following figure:

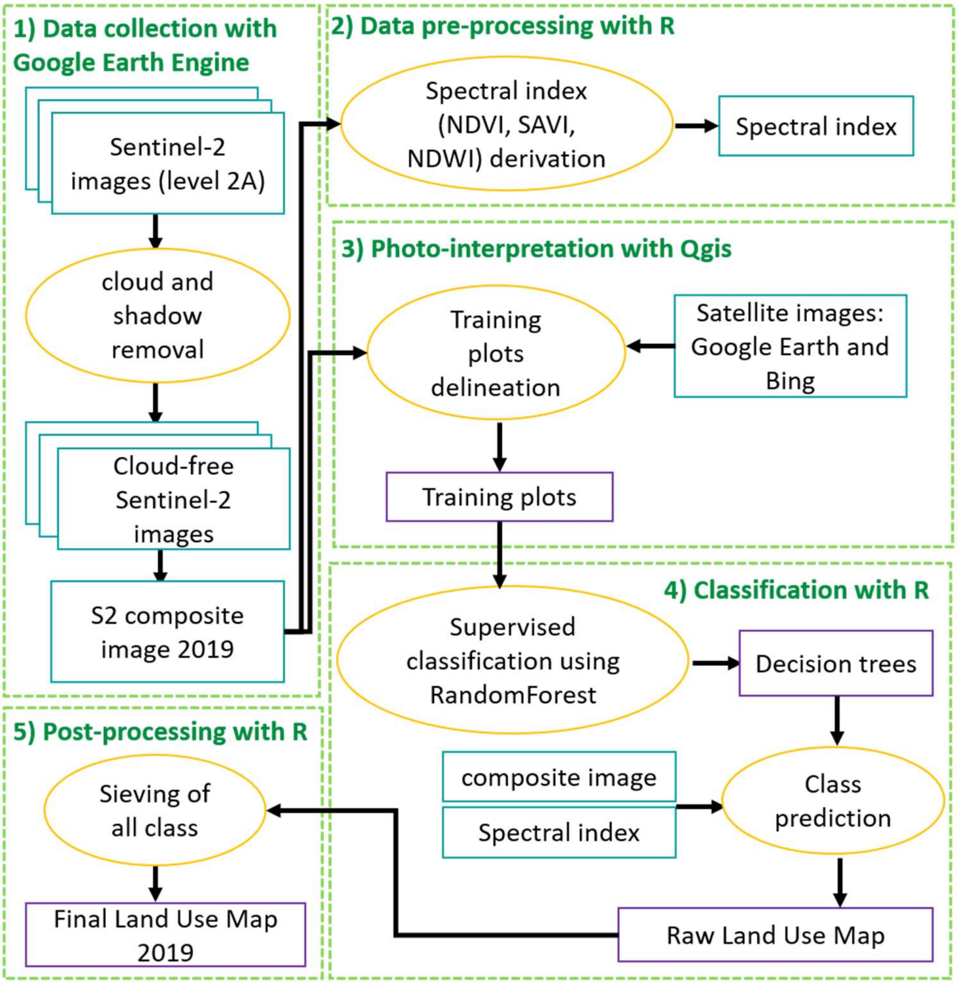


Figure 3 : Processing chain applied for the land use mapping

2.1. Satellite image database

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 2019 (3 month period – Dry season) and image acquired between September and December 2019 (4 month period – Wet 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

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 categories, 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

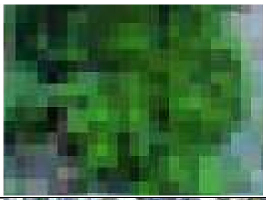
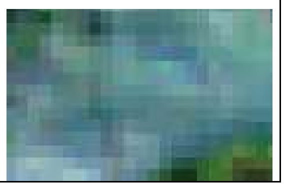
After data pre-processing, the method to establish a deforestation map follows three main steps:

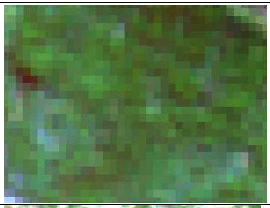
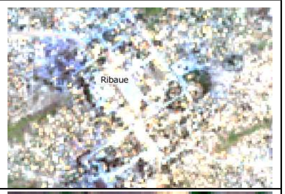
- Definition of land use and land cover categories;
- Delimitation of training plots;
- Classification with a specific algorithm (Random Forest).

2.3.1. Definition of land use and land cover changes categories

A field survey was conducted in February 2019, to collect information on land use and land cover. Theses information were supplemented by information recorded by Stephanie Mladinich during the pre-landscape analysis conducted in July 2019 (Mladinich, 2019). All information collected were compared to the different types of patterns visible on the satellite images. The use of satellite imagery acquired in the dry and rainy seasons allows the differentiation between miombo forests (dominated by deciduous trees) and evergreen forests. Areas invaded by the shrubs *Vernonanthura polyanthes* in the moutains was identified in the field but could not be dissociated on satellite images, these areas are included in the secondary vegetation class. Land use and land cover (LULC) categories existing in the areas and detectable on Sentinel-2 images are presented in the following table:

Table 3 : Nomenclature of land use and land cover categories for the study

Code	Short Name	Category description	Field photos	Image satellite (S2)
1	Moist evergreen forest	Dense mature moist evergreen forest (montane forest) that have not been perturbed.		
2	Miombo forest	Dense mature miombo vegetation (dominated by deciduous trees) that have not been perturbed.		
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	Grassland	Area with herbaceous plant types, but without crop cultivation		

5	Secondary vegetation or woodland	Secondary vegetation is regenerated forest or other woody land that has been disturbed by human activities. It includes a wide vegetation gradient , limiting the ability for class differentiation		
6	Swampy lowland	Cultivated (without specific management) and uncultivated lowlands		
7	Rivers and riparian area	This class includes rivers and the strip of natural vegetation located along a river		
8	Urban area, Settlement	Urban area and settlement comprises all developed land, including areas of human habitation and transportation infrastructure.		
9	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 categories.		

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

LULC Class ID	Number of training polygons	Cumulated area (ha)
1	79	76
2	48	45
3	109	254
4	84	74
5	71	10
6	34	6
7	44	92
8	49	77

9	81	28
Total	599	661

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. In order to reduce noise in training data, plots contours were verified by superposition on very high-resolution images available on *Google Earth*.

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 RandomForest 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 RandomForest 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 RandomForest 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 call 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

RandomForest 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 were found, giving a noisy appearance to the map. A majority filter with a 3x3 window was first used to remove isolated pixels, using a Grass/R script. Furthermore data concerning roads (OSM data) and rivers extracted from the MNT with the Grass r.watershed tool were add to the map.

3_ Results

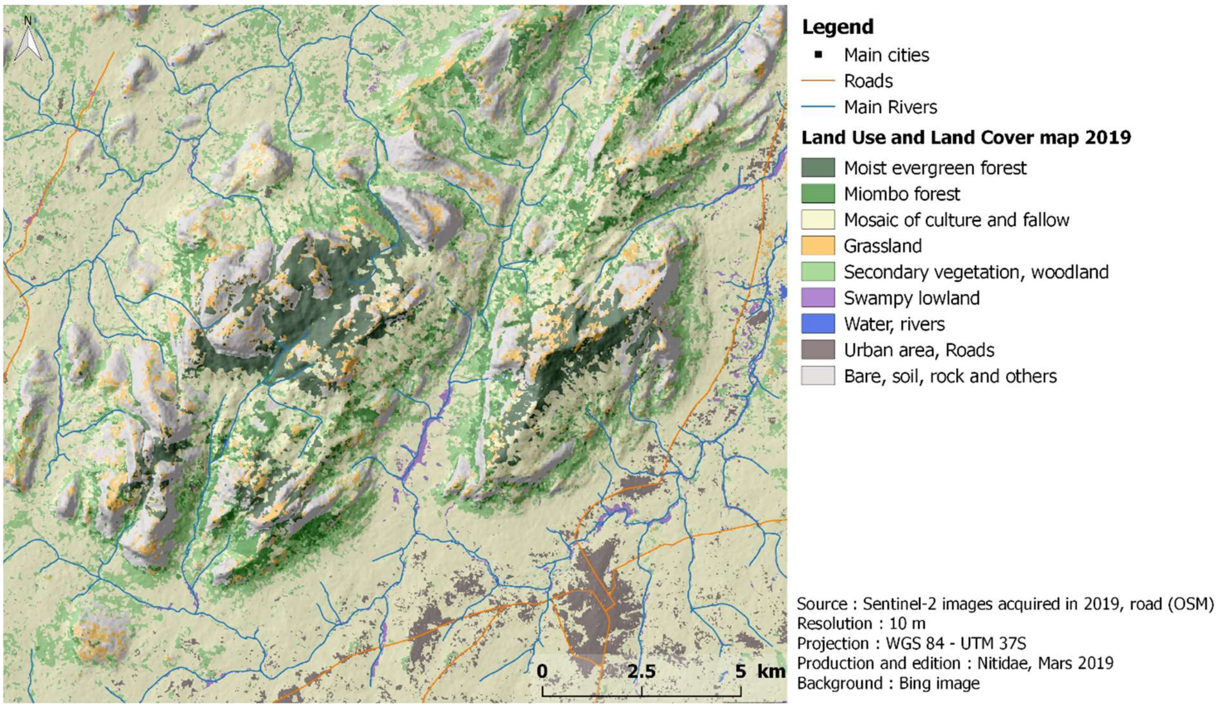
3.1.1. Land Use and Land Cover map and statistics

The landscape of the Ribaue Mountains, in 2019 (Figure 4), was largely dominated by agricultural land composed by cropland, fallow and some areas of settlement, which accounted for 54 % (22 519 ha) of the total study area. Cropland areas are dedicated mainly to subsistence farming and local market agriculture. Area of secondary vegetation or woodland were the second most represented class with an area of 6 777 ha or 16 % of the total area. Moist evergreen forest covered 1 708 ha (4.1 %) of the study area and Miombo forest 1 436 ha (3.5%). Land use and land cover statistics are presented in Table 5.

Table 5 : Area and proportion of land use and land cover categories of Ribaue Mountains and surroundings area calculated from the LULC 2019 map

Code	Short Name	Area (ha)	% of total area
1	Moist evergreen forest	1 708.1	4.1
2	Miombo forest	1 435.5	3.5
3	Mosaic of culture and fallow	22 518.6	54.4
4	Grassland	1 462.8	3.5
5	Secondary vegetation	6 776.8	16.4
6	Swampy lowland	314.3	0.8
7	Water, rivers	576.7	1.4
8	Urban area, roads	1 400.4	3.4
9	Bare soil, rock, sands and other	5 225.0	12.6
Total		41 4118.2	100

Figure 4 : Land Use and Land Cover map of Ribaue Mountains and surroundings (2019)



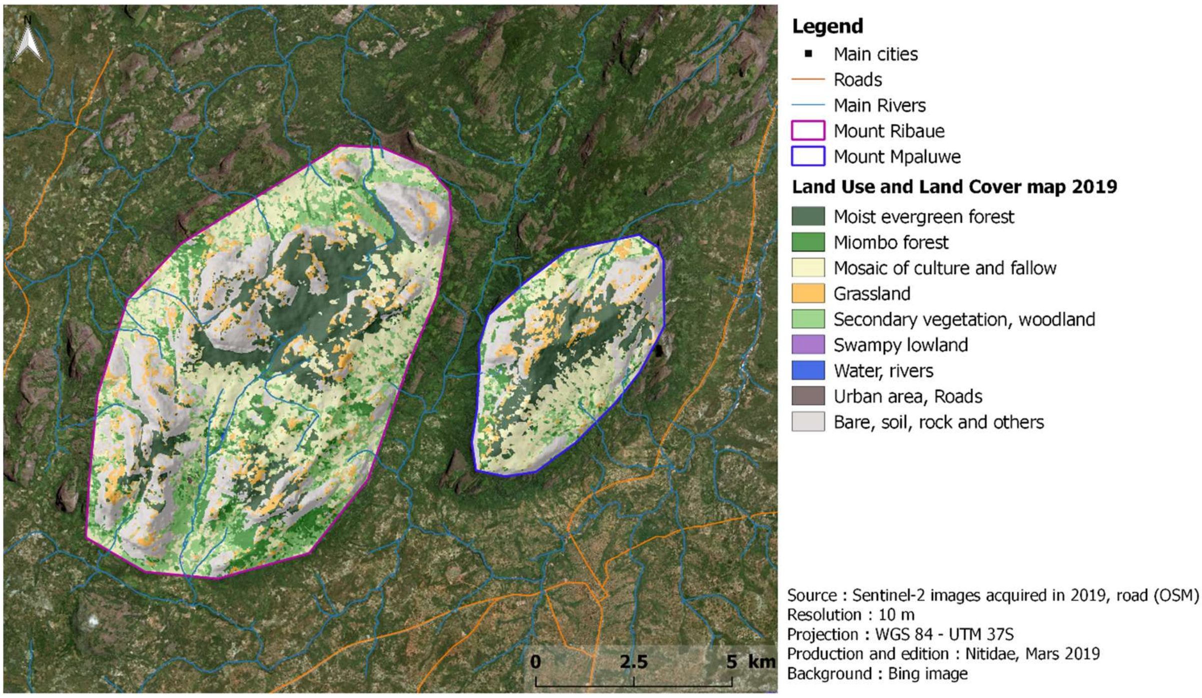
3.1.2. Mount Ribaue and M'paluwe Land Use and Land Cover map and statistics

The land use and land cover of the Mount Ribaue and M'paluwe in 2019, can be broadly categorized into four main categories: forest, cropland area, secondary vegetation or woodland and other areas (mainly rocks) (Figure 5). Land use and land cover statistics are presented in Table 6. On the Mount Ribaue, remaining moist evergreen forest areas and miombo forest covered 1 185 ha (17 % of the total area) and 598 ha (9%), respectively. On the Mount M'paluwe, remaining moist evergreen forest areas and miombo forest covered 473 ha (23 % of the total area) and 144 ha (7%), respectively. Areas of secondary vegetation of woodland can be natural area or area partially cleared, cultivated of frequently affected by fire.

Table 6 : Area and proportion of land use and land cover categories of the Mount Ribaue and Mount M'paluwe, calculated from the LULC 2019 map

Code	Short Name	Mount Ribaue		Mount M'paluwe	
		Area (ha)	% of total area	Area (ha)	% of total area
1	Moist evergreen forest	1 185	17.0	473	23.4
2	Miombo forest	598	8.6	144	7.1
3	Mosaic of culture and fallow	1 546	22.2	542	26.7
4	Grassland	589	8.4	195	9.6
5	Secondary vegetation	1 145	16.4	158	7.8
6	Swampy lowland	1	0.01	-	-
7	Water, rivers	57	0.82	7	0.3
8	Urban area, roads	-	-	-	-
9	Bare soil, rock, sands and other	1 857	26.6	508	25.1
Total		6 978,0	100	2 027	100

Figure 5 : Mount Ribaue and Mount M'paluwe Land Use and Land Cover map (2019)



3.1.3. Internal validation

The results of pixel-level classification accuracy evaluation (referred as internal validation) are presented in Table 7. The overall accuracy of the classification is 89 %, which confirms the acceptability of classification results. This means, among the 66 148 pixels observed 89 % are ranked well and 11 % are misclassified. For most of categories, the user accuracy is above 90 %. Moist evergreen 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*		Observation (plot) 1	2	3	4	5	6	7	8	9	Total	User accuracy	Commission error
Class map	1	7490	87	27	30	0	0	0	23	12	7669	0,98	0,02
	2	40	4152	35	71	10	0	0	1	6	4315	0,96	0,04
	3	5	26	25009	52	3	1	285	6	8	25395	0,98	0,02
	4	29	23	154	7059	1	0	15	1	9	7291	0,97	0,03
	5	0	0	37	12	1108	2	2	1	0	1162	0,95	0,05
	6	0	7	14	9	1	699	10	1	0	741	0,94	0,06
	7	0	7	483	24	2	5	8622	0	0	9143	0,94	0,06
	8	49	33	83	35	0	0	3	7101	36	7340	0,97	0,03
	9	40	9	38	15	0	1	0	65	2924	3092	0,95	0,05
Total		7653	4344	25880	7307	1125	708	8937	7199	2995	66148		
Producer accuracy		0,98	0,96	0,97	0,97	0,98	0,99	0,96	0,99	0,98			
Omission error		0,02	0,04	0,03	0,03	0,02	0,01	0,04	0,01	0,02			
Overall accuracy											0.89		

* 1: Moist Evergreen Forest; 2: Miombo Forest, 3: Cropland, 4: Grassland, 5: Secondary vegetation/Woodland, 8: Swampy lowland, 9: Water, Rivers, 10: Urban area, Settlement, 11: Bare soil, rocks, others

4_ Conclusion

The land use and land cover mapping of the Ribaue Moutains and surroundings, using Sentinel-2 imagery has been used to update the statistics on land cover categories in the region. The outputs map is the most recent land use and land cover map at 10 meters ground resolution of the area. This analysis notably, allows to update extent of remaining forest patches of moist evergreen forest on the Mount Ribaue and Mount M'paluwe, estimated in 2019 at 1 185 ha and 473 ha, respectively. This analysis can be done in the coming years to monitoring changes in the extent of montane forest and estimate deforestation rates.

5_ References

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