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Mapping of areas degraded by gold mining through remote sensing techniques along rio revue – Mozambique

Mapeamento de áreas degradadas pela mineração de ouro através de técnicas de sensoriamento remoto ao longo do rio revue – Moçambique

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Abstract: In Mozambique, specifically in Manica, gold is currently extracted on an industrial and artisanal scale, being the artisanal most predominant. The extraction and processing stage of this mineral has created changes in land use and land cover classes. This study aims to map areas degraded by artisanal gold mining between 2000 and 2019 in the Revue river sub-basin. For this purpose, images from the Landsat 5 (TM) and Landsat 8 (OLI) satellites were used. The images were pre-processed, and radiometric calibration was performed using the ENVI 5.1 platform. For atmospheric correction were used the Dark Object Subtraction (DOS 1) algorithm of the QGIS Semi-Automatic Classification Plugin (SCP). The images were later classified using the supervised maximum likelihood classification (MAXVER) method. The calculation of the Normalized Difference Vegetation Index (NDVI) allowed obtaining quantitative values of the vegetation removed by the practice of artisanal mining. The results showed that the current pattern of land use is markedly characterized by the presence of artisanal mining areas and by the planting of eucalyptus and pine trees that expand towards areas of sparse natural vegetation and exposed soil.

Keywords: Changing detection. Artisanal mining. Degraded área.

Resumo: No Distrito de Manica – Moçambique, o ouro é atualmente extraído na escala industrial e artesanal, sendo a última a mais predominante. A etapa de extração e processamento deste mineral tem criado alterações nas classes de uso e cobertura de terra. Este trabalho visa mapear áreas degradadas pela mineração artesanal de ouro entre os anos de 2000 a 2019 na sub-bacia do rio Revue. Para o efeito, foi utilizada imagens do satélite Landsat 5 (TM) e Landsat 8 (OLI). As imagens foram pré-processadas, tendo sido feita a calibração radiométrica utilizando a plataforma ENVI 5.1 e correção atmosférica utilizando o algoritmo Dark Object Subtraction (DOS 1) do Semi-Automatic Classification Plugin (SCP) do QGIS. As imagens foram posteriormente classificadas por meio do método da classificação supervisionada por máxima verossimilhança (MAXVER). O cálculo do Índice de Vegetação por Diferença Normalizada (NDVI) permitiu obter valores quantitativos da vegetação removida pela prática da mineração artesanal. Os resultados mostraram que o atual padrão de uso e ocupação da terra é marcadamente caracterizado pela presença de áreas de mineração artesanal e pelo plantio de eucaliptos e pinheiros que se expandem em direção a áreas de vegetação natural esparsa e de solo exposto.

Palavras-chave: Deteção de mudanças. Mineração artesanal. Área degrada..

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1. Introduction

The artisanal mining activity in Manica province is secular and practiced by local communities and other practitioners who come from other regions of the country. Despite being a source of wealth, this activity generates negative, adverse and severe impacts on the environment that manifest themselves in the destruction of riparian forest, topography modification, soil degradation, siltation of rivers, pollution and contamination of ground and surface water, causing ecosystem disturbances and loss of biodiversity.

The knowledge of the spatial dynamics and quantification of the mining area is extremely important for territorial and environmental planning. Remote sensing products (satellite imagery) have been in recent decades a rich and constant source of information about the earth's surface.

Remote Sensing techniques combined with Geographic Information Systems (GIS) have been shown to be extremely relevant and widely applied, because they provide a synoptic view of very large areas, allowing to evaluate areas of difficult access and also to detect small coverage changes (RYAN et. al, 2011)

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In remote sensing, objects interact spectrally differently with incident electromagnetic energy, as objects have different physicochemical and biological properties. These different interactions enable the distinction and recognition of the various terrestrial objects remotely detected, as they are recognized due to the variation in the percentage of energy reflected in each wavelength (MORAES, 2002).

Healthy vegetation has high absorption of electromagnetic energy in the visible spectrum region, which is captured by chlorophyll for photosynthesis. Within the visible spectrum the absorption is weaker in the region that characterizes the color of the vegetation. The high reflectance in the near infrared (up to 1.3μm) is due to the cellular structure, and from this wavelength on, it is the water content in the vegetation that modulates the absorption bands present in its spectral behavior (MORAES, 2002).

The use of vegetation indices has been frequent in studies on the detection of change in multispectral imaging. The Normalized Difference Vegetation Index (NDVI), proposed by ROUSE et al. (1974), is one of the most applied and has been explored in climate studies and agricultural and forestry cultures (PONZONI et al., 2012).

NDVI is calculated by the difference in reflectance between the range of NIR (near infrared) and RED (red). This difference is normalized by dividing the sum of the NIR and RED ranges, according to the equation below:

$$NDVI = \frac{(\rho NIR - \rho RED)}{(\rho NIR - \rho RED)}$$

Where ρ represents the reflectance factor in the near infrared (NIR) and red (RED) bands.

The index can theoretically vary between -1 and 1. Values equal to or less than 0 (zero) indicate the absence of vegetation or exposed soil. Values close to 1 indicate a large amount of photosynthetically active vegetation.

Among the economic activities directly related to the exploitation of natural resources, mineral extraction is one that is capable of causing major disturbances in the environment in specific situations or not.

The deterioration in the quality of life that usually accompanies environmental degradation justifies the need to monitor mineral extraction activities frequently. Therefore, this study aims to map the areas degraded by artisanal gold mining between the years 2000 to 2019, in the Revue river sub-basin, Manica District.

2. Methodology

2.1. Study area

The study area is located between Latitudes 18°30'48.24" and 19° 6'15.22" South and Longitude 33°12'39.28" and 33° 8'11.71" East, Manica Province, central Mozambique. It comprises an extension of 45 km, in a 2 km buffer of the main bed of the Revue river, in the district of Manica (Figure 1). It is an artisanal gold mining area, characterized by mountainous formations, sparse natural and anthropogenic vegetation (eucalyptus and pine plantations).

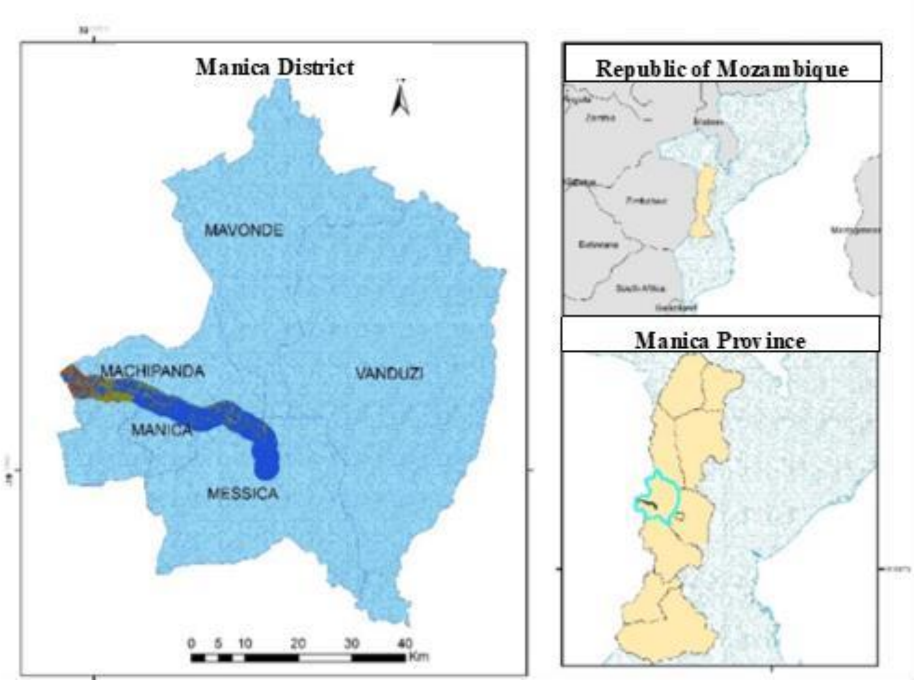

Figure 1: Location of the study area
Source: author (2020).

2.2. Methods

For this study, images from the LANDSAT 05 TM and LANDSAT 08 OLI satellites were used, acquired from the website of the U.S. Geological Survey – USGS. All images acquired are from the dry period (August to October) Point 74 and Orbit 167. The choice for the referenced period was due to the low cloud cover and atmospheric noise. The images were pre-processed and radiometric calibration was performed using the ENVI 5.1 platform, in which the digital numbers (ND) of the image were transformed into radiance values. The images were subjected to atmospheric correction using the DOS1 (Dark Object Subtraction 1) method, coupled with QGIS's SCP Plaguin program. The other data used in this study were obtained from the geographic database of CENACARTA (National Center for Cartography and Remote Sensing of Mozambique).

In order to analyze the expansion of mining areas between 2000 and 2019.Land use and land cover mapping was carried out through supervised classification - (MAXVER) of Landsat satellite images. In the classification, four main classes were defined, namely: mining, bare soil, shrubland and planted forest.

To estimate the amount of native vegetation suppressed by the mining activity, the NDVI calculation method was applied. Depending on the NDVI value of each pixel, it was reclassified into six classes, namely: moderate high, high, moderate, moderately low, low and exposed soil. Some of these classes had to be regrouped in order to express greater similarity with the terrain reality, as shown in Table 1. Using the zonal geometry as table tool of the spatial analyst tools of ArcGis 10.2.2, the area was determined in hectares of each class.

Table 1 - Reclassification of NDVI intervals, for all years of analysis.

NDVI Range Reclassification Notes	Range	NDVI classes
1	-1 a < 0.3	Bare Soil to low
2	0.3 a < 0.5	Moderately low
3	0.5 a < 0.7	Moderate
4	0.7 a 1	Moderately high to high

Source: author (2020).

Finally, changes in coverage were quantified in hectares using the post-classification comparative method between maps of the years under analysis. To estimate how much one class changed to another during the period under analysis, the transition matrix was calculated in the DINAMICA EGO software.

For all classifications, thematic accuracy analyzes were performed using confusion matrices, from which the agreement coefficients were extracted. The reference samples were selected randomly, using the pixel as a reference and sampling unit. These samples were used as reference data (field truth) to compose the confusion matrix. This matrix made it possible to calculate the total agreement accuracy indices. For this work, the Kappa Index was chosen to assess thematic accuracy, as it is more sensitive to variations in omission and inclusion errors (COHEN, 1960).

3. Results and discussion

Through supervised classification method, by maximum likelihood (MAXVER) of Landsat 05 and Landsat 08 satellite images, the corresponding set of pixels for each defined use class was obtained (Figure 2), which allowed the analysis of variation of land use and land cover classes.

Regarding the accuracy of the classification of images, the Kappa coefficients determined for the classifications from 2000 to 2019, showed good classification quality according to the results of Table 2. In Table 3, it is possible to observe the variation of land use and land cover classes between 2000 to 2019.

Tabele 2 - Kappa índex.

Year	2000	2011	2015	2019
Kappa	0.76	0.64	0.73	0.75

Source: author (2020).

Tabele 3 - Classes of land use and land cover in hectares (ha)

Class	**2000**	**2011**	**2015**	**2019**
Mining	41	201	360	734
Bare soil	9962	10124	8300	8370
Shrublands	7064	6428	8600	7422
Planted forest	2984	3299	2791	3525

Source: author (2020).

Os dados demonstram aumento da área de mineração e floresta plantada na ordem de 3%, de 2000 a 2019. Em 2000, a classe de mineração ocupava uma área menor, sendo que a atividade era praticada em pequenos poços de dimensão menor que a resolução espacial do Landsat 05. A floresta plantada ocupava cerca de 15%, passando a ocupar 18% de área total em 2019.

The data show an increase in the area of mining and planted forest in the order of 3%, from 2000 to 2019. In 2000, the mining class occupied a smaller area, and the activity was carried out in small wells with a dimension smaller than the spatial resolution of Landsat 05. The planted forest occupied about 15%, starting to occupy 18% of the total area in 2019.

The bare soil class was decreasing in function of the increase of the other classes. In other words, eucalyptus and pine plantations that correspond to areas of planted forest and the mining class have increased over areas of bare soil.

To better understand the variation relationship between classes, the results of the transition matrix can be seen in Table 4.

Tabele 4: Transition matrix in percentage (%), between the years 2000 and 2019.

	2019			
2000	**Mining**	**Bare soil**	**Shrublands**	**Planted forest**
Mining	0.30	0.14	0.51	0.05
Bare soil	0.04	0.56	0.29	0.012
Shrublands	0.04	0.24	0.54	0.18
Planted forest	0.00	0.06	0.21	0.73

Source: author (2020).

According to the data from the transition matrix, which took place between 2000 and 2019 (Table 4), it can be seen that the bare soil and planted forest classes had the highest rates of permanence. However, 34% of the bare soil area and 27% of planted forest were transferred to other classes. The mining and shrublands classes had a medium permanence, with mining gaining 4% of bare soil area and shrublands.

In the same period, it is possible to observe the abandonment and migration of previously mined areas that ended up gaining a new vegetation cover. The mining class is the one with the lowest rate of permanence, demonstrating its migratory nature.

The shrublands area gained 51% and 29% of mining areas and bare soil respectively.

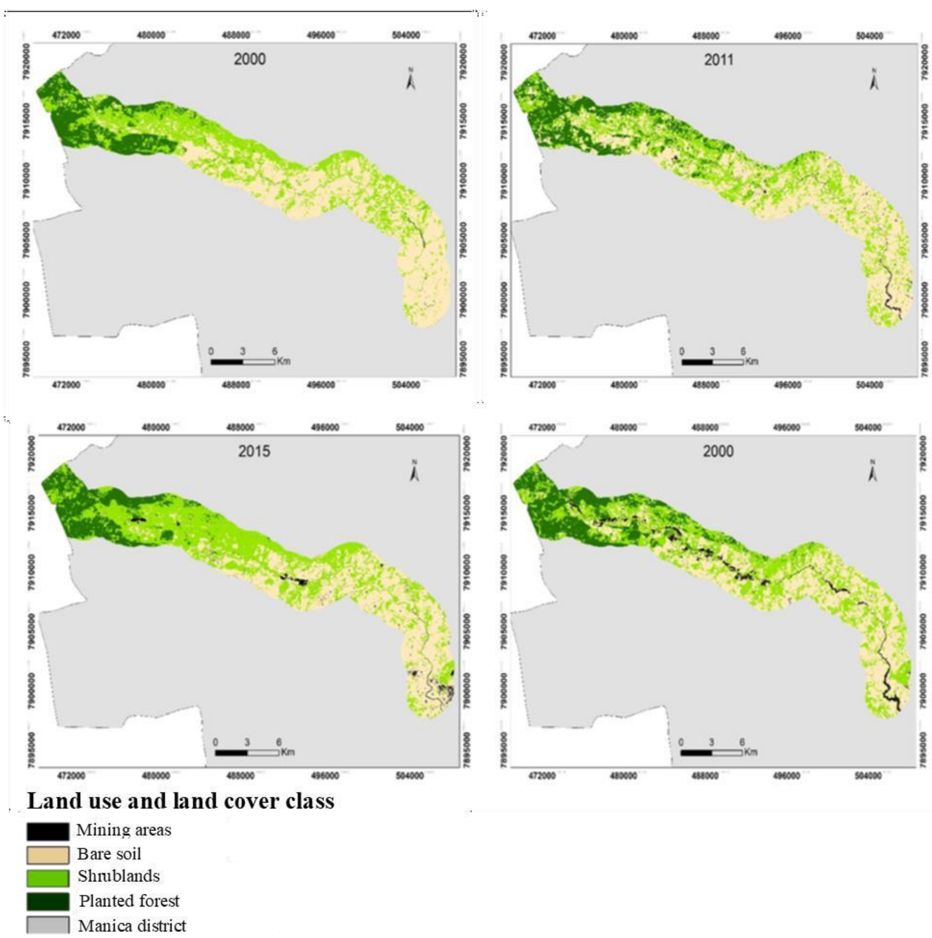

Figure 2 - Evolution of land use and occupation 2000, 2011, 2015 and 2019
Source: author (2020).

Using the NDVI calculation method, values were obtained that reflect the behavior of vegetation cover in the study area, as shown in Figure 3. Regarding the value scales established by the vegetation index, Table 5 presents data on the variation of classes of the index.

Tabele 5 - Area in hectares of NDVI classes 2000 to 2019

Class	2000	2011	2015	2019
Bare soil to low	5054	5785	3715	3559
Moderately low	9791	10278	11588	10840
Moderate	3473	3961	3563	3702
Moderatety high to high	1733	27	1185	1950

Source: author (2020).

The data in table 5 allow us to infer that there was a reduction in the class of bare soil to the low level, which occupied a little more than 25% of the total area, this in 2000, but in 2019 it occupied less than 18%. Similar fact verified in the behavior of the bare soil class in the supervised classification method.

The range of values close to zero (-1 <0.3) shows the presence of bare soils and reduced vegetation cover, mainly represented by mining areas and degraded soils.

The range of the moderately low class (0.3 to <0.5) is characterized by a considerable increase from 48% in 2000 to 54% of the total area in 2019. This class is constituted by low and shrublands that also verified an increase in the supervised classification method.

The range of the moderate class (0.5 to <0.7) groups areas of medium density of vegetation cover consisting mainly of young eucalyptus and pine plantations. This class did not show a significant increase, going from 17% in 2000 to 18% in 2019.

The range of moderatety high to high class (0.7 to 1) comprises areas of high vegetative vigor and higher density of vegetation cover, a characteristic fact of eucalyptus and pine plantation areas. The spectral behavior of this anthropogenic vegetation is more clearly seen in the 2000 image (Figure 3) in which it occupied an area of about 1700 hectares. After more than 10 years, eucalyptus and pine plantations were cut down and the 2011 image shows a low percentage of the moderatety high to high class (Figure 3). In subsequent years, anthropogenic vegetation gained greater expression in the area, increasing from 27 hectares in 2011 to 1185 in 2015 and 1950 hectares in 2019. The transition matrix allows us to understand the evolutionary relationship between NDVI classes (Table 6).

Tabele 6 - Transition matrix in percentage of classes from NDVI 2000 to 2019

	2019			
2000	**Bare soil to low**	**Moderately low**	**Moderate**	**Moderatety high to high**
Bare soil to low	0.36	0.61	0.03	0.00
Moderately low	0.16	0.63	0.15	0.02
Moderate	0.04	0.29	0.46	0.21
Moderatety high to high	0.01	0.12	0.28	0.59

Source: author (2020).

The greatest transition between the two extreme years was found between bare soil and low to moderately low classes, in the order of 61%, demonstrating the reforestation of areas that were previously mined and/or abandoned. There was also a transition between the moderate class to the moderatety high and high, in the order of 21%, which represents the growth of anthropogenic vegetation.

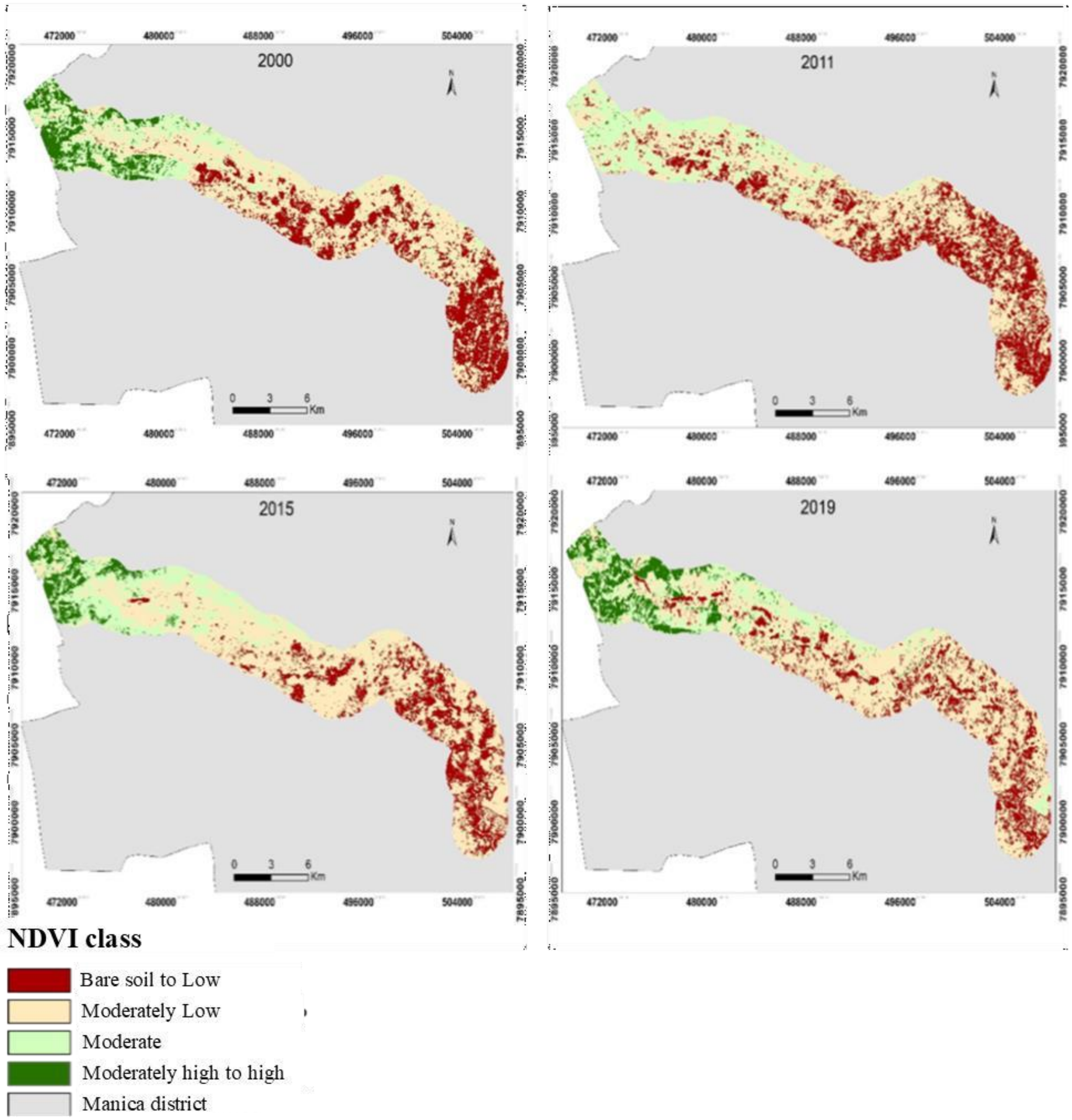

Figure 3 - NDVI Classes 2000, 2011, 2015 and 2019
Fonte: autor(2020).

4. Final considerations

The land use in the artisanal gold extraction areas shows that the shrublands was significantly altered, reflecting the expansion of artisanal mining and eucalyptus and pine plantation areas. This scenario of loss of shrublands and advance of mining activity can assert the degradation of elements of the environmental system. The values of land use and cover classes obtained by the supervised classification method were similar to the intervals defined in the reclassification of the NDVI index, despite small disparities derived from the regrouping of bare soil and low classes in the same interval.

This research proved to be efficient in analyzing the evolution of land use and land cover in a mining area either by the method of classification supervised by maximum likelihood of satellite images, or by calculating the NDVI index.

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