COMBINED SUPERVISED CLASSIFICATION METHODS IN REMOTE SENSING FOR THE EVALUATION OF FOREST DYNAMICS ALONG THE SLOPES OF MOUNT CAMEROON

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ABSTRACT

The Mount Cameroon forests risk being disappeared. This threat results from aspects such as lava destruction, the creation of vast plantations, farms and extension of settlements. Being 4095m high facing the Atlantic Ocean with marked differences in reflectances between the windward and the leeward sides, Mount Cameroon is very rich in biodiversity. This threat constitutes a major preoccupation of the Cameroonian Government as she opts to know many issues surrounding the region among which is the annual rate of deforestation. The population (300 000 inhabitants) will be more exposed to environmental hazards in case the forest disappears. This does not guarantee a favourable environment for productive investment.

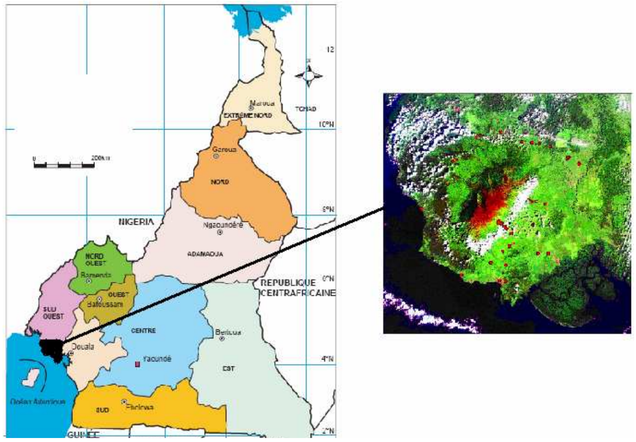
This study of an evolution between 1986 and 2003, done through Remote Sensing depended on satellite images (Landsat and Radar). Before the combined techniques of classification, the images used were first of all subsetted then corrected radiometrically and geometrically. Sampling was carried out on both subsets from their respective scenes which ended up with unsupervised classification and post classification. The preliminary results obtained guided the field trip and the same exercise was repeated in the laboratory which ended up with supervised classification. The validation of field phenomena was aided by the taking of GPS points and photographs. The findings proved the quantitative change of forest cover mentioned above. It showed that 92.5km² of forest was destroyed by the 1999-2000 lava flow. Annual rate of deforestation being 19.25km² (1.12%) occurs at different rates on the different slopes of the mountain. From this study, conservative measures initiated for the region are being implemented to rescue the rich and endemic plant and animal species.

1. Introduction

Forests cover about 40% of the earth's surface. To this tropical humid forests constitute about 60 million hectares. This forests stand out as the richest ecosystem of the planet (World Bank, 1989). It disposes 50 to 90% of animal and vegetal species in the world, with about 8000 species of plants which 80% are endemic. The hot and rainy climatic ambiance of the tropical regions, greatly account for this great wealth of biodiversity.

Tropical humid forests stretch to about 60 countries of the world. They concentrate in Central and Southern America, Central and West Africa and in SE Asia. Among these, about 200 million hectares are concentrated in Central and West Africa. This renders the region the second in terms of surface area in humid tropical forest coming after the Amazon Basin. These forests, as it should be noted, has a great socio economic and environmental importance at the regional, national and at local scales. It also plays a determinant role at the global scale. For almost 30 years now, about half of this forest has been lost due to irrational exploitation and demographic growth (WRI, 1994-95). Between 1981 and 1990, about 15 441 million hectares were destroyed (FAO, 1995; 1997). But most often, experts and researchers do not often agree on the methods and validity of statistical evaluation of the global rhythm of deforestation.

Cameroon, which is within the Central African Sub Region, (fig.1) has often relied on the global evaluation of deforestation carried out by international organisations. Thus, following the FAO Report of 1995, her annual average rate of deforestation stood at 0.6%. It is only of late that detailed studies of evaluating deforestation became adopted by the government. Cameroon government which works in collaboration with the FAO and GFW has adopted Remote Sensing as a technical means of evaluating forest change. This is illustrated by various measures taken at the national level to follow up forest evolution. In this light different studies have been carried out in different sections of the country to evaluate forest change. This study which points to this light focuses on the Mount Cameroon region.



integrated
Landsat image of the Mount
Cameroon Region with GPS Points

Cameroon

Fig.1: Location of the Mount Cameroon region in Cameroon

The Mount Cameroon region stands out of great interest for such a diachronic study for the following reasons:

- The massive projection of the relief provides the region with a unique climatic as well as biodiversity differentiation with altitude within the West and Central African Sub Region.
- The active volcanic nature of the mountain provides the surroundings with volcanic fertile soils that act as a pull factor to immigrant population and the creation of vast agro-industrial plantations.
- Agriculture practised by the resident population is largely detrimental to the rich humid forest though natural causes such as lava destruction resulting from eruptions (once every 11 years) cannot also be ignored.

This study falls within the context of evaluating forest dynamics with the use of Remote Sensing. Recourse is given to an azonal ecosystem (mountain region). This is because mountains host about 1/10 of the world's population and the Mount Cameroon region in particular with a surface area of 5695.5 km² hosts more than 400 000 inhabitants. Further more, mountains within the tropical forest zone constitute rich biodiversities comparable to non in the world. Remote sensing being the technique used here is a technique that enables us to obtain information about the earth's surface without direct or material contact with that surface. It consists of capturing and registering energy of electromagnetic waves emitted or reflected by the earth surface. It then processes and analyses the information registered before their application and use (Klein, 2002; Tommpo and Czaplewski, 2002).

Given that quantitative and qualitative changes of a surface can be evaluated through Remote Sensing, this study used Landsat images for two periods, 1986 and 2000 and radar image for 2003.

The optical images were extracted from Landsat scenes p187r57_861212 of 1986 and p187r057_20001210 of 2000. These images coupled with the radar image of 2003 were treated using the following computer softwares – ENVI, ArcView, MapInfo and VOIR to come out with statistics of the evolution of surface phenomena between 1986 and 2003. This ended up with realisation of spatio-maps for the Mount Cameroon region

2. Methods

In order to arrive at expected results, four major aspects constituted the methodology. The first was the acquisition of data to be treated in the LETS laboratory, classification of the optical images, classification of the radar image and the fieldtrip to validate certain phenomena seen on the images. The National Advance School of Engineering (NASE) Yaounde is the structure that hosted this research work. Fig.2 shows the images used. Other materials implicated were GPS, Digital camera and Computer with appropriate softwares.

2.1: Treatment of the optical images

After subsetting the desired zone, a colour composit of 753 and 543 band combinations were realised which provided a good base for sampling. By using the polynomiale approximation of the 1st order method, the edges of the images were ignored and pixels of 0 radiometric values were eliminated. Then we proceeded to the physical recognition of 4 points (A, B, C and D) on the 1986 image and (A1, B1, C1 and D1) on the 2000 image, given that the two images of this work were of the same spatial resolution (28.5m). The Mount Cameroon Region was extracted of 2922*2330 sizes of the two images and rendered superposable.

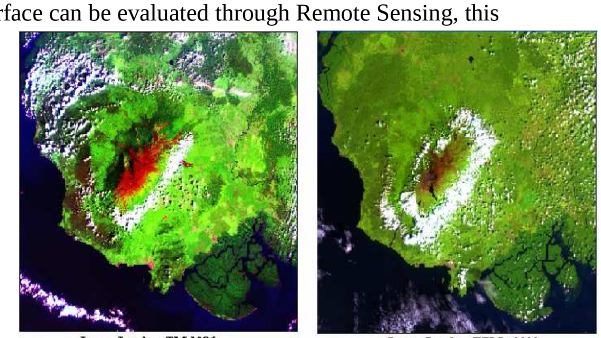
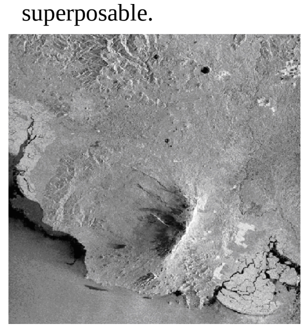


Image Landsat TM 1986 Image Landsat ETM+ 2000



ERS 1 Radar image 2003

Fig. 2: Extracted images of the Mount Cameroon Region

The images were then pre-treated as follows using the ENVI software: interactive stretching from 0 to 255 points in all the 3 bands (RGB). The "High Pass" filter was applied in order to render all the different plantation layers clearer as well as enhancing the savannah zones. Other filters were also applied especially to differentiate similar phenomena on the surface such as settled areas and lava surfaces, young plantations and tea plantations or savannahs with tea plantations, dense forest and matured rubber plantations etc. Still with the ENVI software, sampling of different objects was realised with the ROI Tool and various colours were attributed to each sample. (Table 1).

Table 1: Sampling of objects

Sample colour	Object determined	Number of pixels for 1986 image	Number of polygons for 1986 image	Number of pixels for 2000 image	Number of polygons for 2000 image
Deep green	Dense forest	911	10	938	10
Light green	Degraded forest	256	5	267	5
Light yellow	Savannah	458	5	465	5
Red	Lava	439	15	437	15
Light purple	Adult palms and rubber plantations	672	8	668	8
Light Sienna	Banana plantations	163	3	171	3
Light cyan	Young plantations	246	4	306	4
Light Maroon	Mangrove	496	6	579	6
Thistle	farm	192	4	194	4
Magenta	settlement/ bare surface	200	5	211	5
White	Clouds	751	9	797	9
Blue	Sea and water bodies	907	7	1016	7

This operation proceeded to a classified classification-maximum likelihood and then post classification.
The next operation consisted of segmenting the two images and again conducting post classification to arrive at another set of results to be compared to the first operation. Fig.3 shows results of the supervised classification and segmentation respectively.

Fig.3: Classification results of the optical images

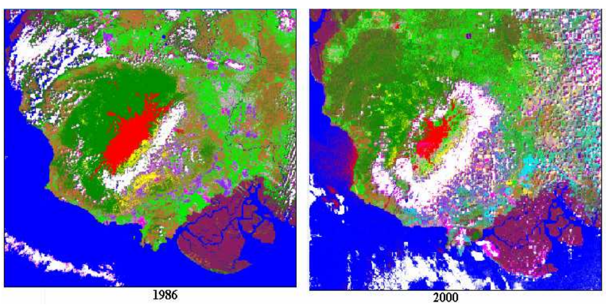
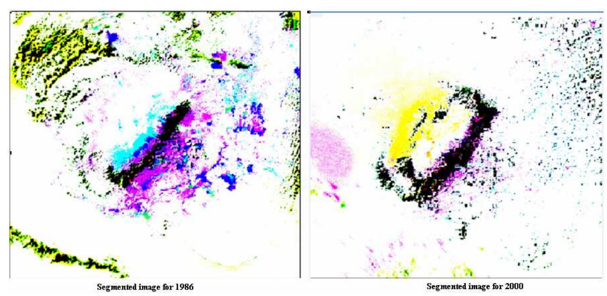


Fig.4: Segmented optical images



2.2: Treatment of the Radar Image

Processing here started with texture analysis as Akono et al., (2003) states its importance in classification. Anys and He**,** D.C. (1995) were the first to use texture parameters for the classification of crops. Their results were satisfactory as texture parameters were integrated in to classification process. Given that much literature exist in the supervised classifications methods, our study of the Mount Cameroon region focused on a new classification approach of the radar image. This approach emphasized on the concept of proper "texture values" in a supervised classification. By presenting the texture parameters to be used we chose exercise sites followed by window image and the classification algorithms.

2.2.1 Order of textural parameters

This refers to the number of pixels that enter the evaluation process of this parameter. The 2nd order which is the most classical and most solicited (Haralick, 1979) does not still identify all the constituents of an image even if the treatment takes into consideration all the pixels of the image. Thus, no order is considered best. Orders ranging between 2 and 5 are often used but in our case it was realised that each order provided complementary information that was different from the others. This led to the testing of many orders and the results compared.

There are no universally accepted criteria in selecting texture parameters. Basing on several tests, it is the visual appreciation that determined our choice. This depended for example on the aptitude to enhance image discontinuities of each parameter in a given image, the aptitude to enhance obscured zones in the image etc. Our choice of a parameter highly depended on the image itself, the theme envisaged and the use intended. The choice ensured that only one representative was selected (that with less calculations) since the others will not provide supplementary information.

Without ignoring the size of the window in image classification, statistical parameters become significant when the sample size is large. The window image regularly used in radar images comprise between 5*5 and 11*11, but for practical reasons we used (2k + 1) * (2l + 1), with k and l being natural integers. We used 2 algorithmic approaches which were equivalent – one said to be "non exclusive" which consisted of extracting each class of information separately and fusioning them in order to obtain a globally classified image; and the other said to be "exclusive" which consisted of direct classification.

2.2.2: Algorithm of "non exclusive" classification

Entry data: non classified IMG image. Exit data: classified IMG image. Local variables: ξ - any information class. Other: complementary class at ξ
Pix: a pixel in the image. S: a natural integer

Start:
1. Choose the texture parameter to be used
2. Identify the main information classes
3. Characterize each information class identified
4. Define the S threshold of tolerance
5. For each information class ξ, do;

a) for each pixel "pix" of the image extract and chacterize a window F centered on "pix"; b) evaluate the degree D_F^{ξ} of F nearness in relation to ξ class. c) if D_F^{ξ} π S ,then attribute ξ class to "pix"

d) if not, attribute the class "other" to "pix" e) store the I_{ξ} image obtained

6. Fusion the I_{ξ} images with the preceding results and put the results in IMG
7. Over turn IMG

End

The choice of texture parameters was in function of the image. The identification of information classes was aided by fieldwork and prior knowledge about the region. The characterization of the information classes constituted the knot of the algorithms: Entry data: an information class ξ, exit data: a matrix MC of real that characterizes ξ classes; local values: T_x, T_y, I, N_b: natural integers with T_x and Ty odds. MC: a matrix of reals

Start
1. Identify and extract a series of N_b window images of T_x*T_y size each and put them all in ξ class
2. Identify the connection rules to be used in each other
3. For each window F_i that had been extracted and put in MC_i the characteristic matrix of the F_i window.
4. Put the average of MC_i in Mc and over turn the results.

End

The higher the number of N_b, the more the precision of the classification. The algorithm of the window image characterization was as follows: Entry data: a window image F; exit data: a matrix MC of reals characterizing the windows F; local variables: V_o: natural integers.

Start
For each order "o" of texture parameters do,
1. Evaluate each texture parameter for each connection rule retained
2. Construct V_o vector that constitutes the averages of values obtained through the connection rule and for each parameter.
3. Construct the M matrix from different vectors V_o that had been calculated
4. Calculate M^T matrix transposed of M matrix
5. Over turn the characteristic matrix

$$MC = \frac{1}{2}\left(M + M^{T}\right)$$

End

Definition of the threshold tolerance was done as follows

$$S \;\pi\; \frac{\underset{\xi,\eta=0,1,\ldots,K}{Min}\left\{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\xi}-MC_{ij}^{\eta}\right)^2}\right\}}{\underset{\xi,\eta=0,1,\ldots,K}{Max}\left\{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\xi}-MC_{ij}^{\eta}\right)^2}\right\}}\times 100, \quad \xi \neq \eta$$

k being the number of classes identified; N_p and N_o being the number of parameters and number of orders respectively; $MC_{ij}^{\xi}, MC_{ij}^{\eta}$ is the (i,j) component of the characteristic matrix of the information class ξ respectively.

The degree of nearness was also calculated as follows

$$D_F^{\gamma} = \frac{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\gamma}-MC_{ij}^{F}\right)^2}}{\underset{\xi,\eta=0,1,\ldots,K}{Max}\left\{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\xi}-MC_{ij}^{\eta}\right)^2}\right\}}\times 100, \quad \xi \neq \eta$$

As concerns the algorithm for exclusive classification we had Entry data: non classified IMG image; exit data: classified IMG image; local variables ξ: information class; Γ: all the information classes; other: complementary information class; pix: a pixel in the image; N: a natural integer; S: a real number.

Start:
1. Choose the texture parameters
2. Identify tye main information classes (construction of Γ)
3. Calculate the MC^{ξ} matrices that are characteristic of different information class ξ of Γ
4. Calculate the S threshold of tolerance defined above
5. For each pixel "pix" of the image, do; a) extract and characterize a window F centered on "pix"; b) evaluate the degrees $D_F^{\xi_i}$ (i = 1,2,….N) of nearness of F in relation to diverse classe ξ_i of Γ; c) identify the y class which verifies the following equation

$$D_F^{\gamma} = \underset{\upsilon\in\Gamma}{Min}\left\{\frac{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\upsilon}-MC_{ij}^{F}\right)^2}}{\underset{\xi,\eta=0,1,\ldots,K}{Max}\left\{\sqrt{\sum_{i=0}^{Np}\sum_{j=0}^{No}\left(MC_{ij}^{\xi}-MC_{ij}^{\eta}\right)^2}\right\}}\times 100\right\}, \quad \xi \neq \eta$$

d) if D_F^{γ} S π then attribute y class to "pix" e) if not, attribute the class "other" to "pix"

End

Through the classification of the proper values of texture, we used the following methodology. We took a characteristic data by $MC = \begin{pmatrix} a_{11} & a_{21} & \cdots & a_{n1} \\ a_{12} & a_{22} & \cdots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{nn} \end{pmatrix}$. This matrix which is one of endomorphism can be expressed in a reduced base said to be the Jordan base. The reduction consists of determining the Dunfold determination i.e find a diagonalizable endomorphism and a nilpotent endomorphism such that the sum should equal the initial endomorphism. In other words there exist a D diagonal matrix of the type $D = \begin{pmatrix} d_{11} & 0 & \cdots & 0 \\ 0 & d_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_{nn} \end{pmatrix}$ and an inversible p matrix (det(p).0) such that the following equation can be verified $MC = P\,D\,P^{-1}$ Thus the algorithm was as follows

$$S \le \frac{\underset{\xi,\eta=0,1,\ldots,K}{Min}\left\{\sqrt{\sum_{i=0}^{n}\left(VC_i^{\xi}-VC_i^{\eta}\right)^2}\right\}}{\underset{\xi,\eta=0,1,\ldots,K}{Max}\left\{\sqrt{\sum_{i=0}^{n}\left(VC_i^{\xi}-VC_i^{\eta}\right)^2}\right\}}\times 100\,, \quad \xi \neq \eta$$

where ξ and η are any exercise sites identified and k, the number of the exercise sites. The results obtained were as follows.

3. Results

In 1986, dense forest covered a surface area of 1988.5 km² more than 50% on the NW flank of the mountain. The savannah on its part mostly concentrated at more than 2000 m of altitude. Savannah in general covered a surface area of 777.56 km².

Lava which mostly concentrated on the summit of the mountain covered a surface area of 187 km². Farms which generally did not extend beyond 3000m of altitude, occupied a surface area of 680km². The CDC plantations occupied the lowest altitudes besides the mangroves. They then occupied a surface area of 493.2 km².

The situation in 2003 saw some phenomena increase while others reduced. Table 2 presents the rate of change of phenomena while Fig.4 present the treated images

Table 2: Rate of change of phenomena

Theme	Variation 1986/2002 in km²	Annual change of surface area (km²)	Rate of annual variation	Observation
Dense forest	269.7	19.25	1.12 %	Rapid reduction
Degraded forest	47.6	3.42	0.53 %	Increase
Savannah	70.98	5.07	0.59 %	Increase
Mangrove	18.2	1.3	0.14 %	Reduction
Lava	14.98	1.07	0.62 %	Reduction
Plantation	294	21	2.6 %	Rapid reduction
Settled area/bare surface	7	0.5	1.04 %	Increase
Farms	117.6	8.4	1.49%	Giving way to plantations

Fig.5 Results of treated images

Fig. 6a) : Surface occupation of the Mount Cameroon Region 1986

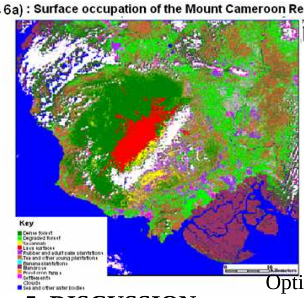
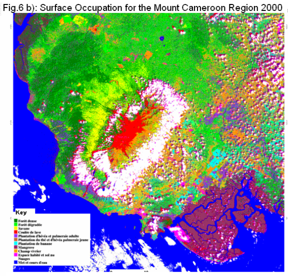
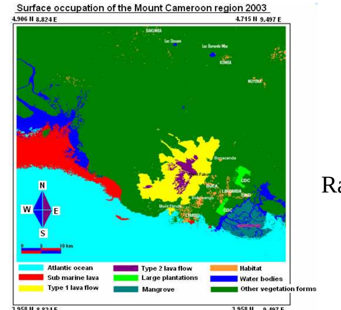


Fig.6 b): Surface Occupation for the Mount Cameroon Region 2000



Optical images

Surface occupation of the Mount Cameroon region 2003



Radar image

5. DISCUSSION

With the advent of the computer, the manipulation and management of certain aspects of life have been facilitated with softwares. To that effect Remote Sensing (RS) and Geographical Information Systems (GIS) have benefited much from this technology. Using Remote Sensing therefore to evaluate surface dynamism is recommendable and results got are often considered to be the most acceptable compared to any other technique (Bauer et al, 2003). Given the structured nature of plantations, one can easily differentiate them from non plantation surfaces on satellite images even at lower resolutions. Pre-treating the images and going to the field add to the authenticity of the expected results as colour composition is not enough to render the clarity of surface phenomena. From the results obtained, one cannot conclude that the Mount Cameroon region witnesses the fastest forest degradation in the Central African Sub Region. The sections of rapid degradation in the region (South, South West, South East) are to a larger extent flat surfaces. The high fertility of the volcanic soils here actually attracts the creation of vast agro-industrial plantations whose crops are mostly destined for exportation which highly contributes to the Cameroon economy in terms of export crops. Thus thousands of immigrants have settled in the region to fortify the plantations with the necessary man power.

On the opposite flanks of the mountain ie in the N, NW, NE, much of the virgin forests still exist and they have been designed into forest reserves with some sections worshipped as sacred forests. Such sections are believed to host important shrines of the Bakundu and Bakweri tribes. Hunters and other trespassers must duly be authorised by the traditional authorities before any form of exploitation. Such reverence coupled with the low population density in this part of the mountain help maintain the forest integrity which certainly can sustain in the next

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