STRATIFICATION FOR EVALUATION OF NUTRITIONAL STATUS OF FOREST PLANTATIONS

M. B. Garcia [a] *, P. R. Silva [b], L. M. T. de Carvalho [b]

[a] Dept. Ciências do Solo, Universidade Federal de Lavras
[b] Dept Ciências Florestais, Universidade Federal de Lavras

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ABSTRACT:

The identification of nutritional status of cultures is performed more precisely through chemical analysis of vegetal tissue. However, studies have demonstrated that there is a correlation between chemical content of leaves and their spectral signature, through chemometric techniques. Furthermore, other studies have been pointing a higher spatial stability on chemical content of leaves. Therefore, the current study evaluated the segmentation of satellite images as a tool for identification of homogeneous strata in *Eucalyptus* sp. plantations aiming to reduce variability, the error and the number of parcels in collects of vegetal tissue for chemical analysis.

1. INTRODUCTION

In order to be well succeeded in whatever enterprise, it is fundamental a good planning, good execution and good monitoring. In the case of agricultural or forest enterprises we can apply this analogy. A good planning includes the right choice of the area and culture or variety to be implanted, planting season, spacing, analysis and recommendation of fertilization and management. The well done execution is the warranty that all the panning will be implemented inside the correct schedule. Monitoring, in this case, is mainly based on the evaluation of nutritional status of the implanted culture. The direct evaluation may be used through soil analysis, however the most recommended technique is the evaluation of vegetal tissue (Malavolta et al., 1997).

Many studies have correlated spectral signatures of cultures with their nutritional status, both *in situ* (Gong et al., 2002; Dury & Turner, 2001) and *ex situ* (Mistele & Schmidhalter, 2008; Kokaly et al., 2009), inferring through chemometrical techniques as partial least squares regression (PLS) and multiple regression, achieving very precise estimates. Therefore, the values of each band of a satellite image may be highly correlated to the nutritional status of the culture, serving as parameter for segmentation, stratification and identification of homogenous areas for the collect of vegetal tissue.

Other known question aspect is the spatial variability of soil fertility, culture nutrition and productivity, that is why we must care about representative samplings. Statistical assumptions appoint randomization as the element that guarantee the sample representativeness. However, this sampling may be done by a systematic way in a grid (Systematical Casual Sampling – SS), in which only the first sample is drafted, or in a systematic and stratified way (Stratified Casual Sampling – SCS), in which samples are grouped in homogeneous strata.

However, the stratification strategy has presented good results on diminishing the number of samples and improving their representativeness, as Silva et al. (2009), stratifying and area on *cerrado sensu strictu*, reduced on 45% the error of the area inventory. Other studies highlight this spatial variability and show the importance of the identification of homogeneous areas (Araújo et al, 2005; Montanari et al, 2008; Liu et al, 2008).

Until the present studies focused on stratification are unknown. However, this study aimed to identify homogeneous areas in relation to the biochemical content of leaves in *Eucalyptus* sp. plantations through segmentation and analysis of spectral signature of identified objects in images of the sensor HYPERION in order to suggest stratification of the vegetal tissue collect for nutritional analysis of the plantation.

2. MATERIAL E METHODS

2.1 Image

An image of the sattelite RapidEye was used with five spectral tracks, they are: blue (440–510nm), green (520-590nm), red (630-685nm), Red-Edge (690-730nm), and next infrared (760-850nm), with spatial resolution of 5m, located on the region of Montes Claros – MG (Figure 1). The image was selected based on the empiric knowledge of the area and one subset of an *Eucalyptus* sp. plantation of about 1463 ha was selected.

2.2 Grid plots

Based on the subset, the algorithm Chessboard segmentation was used (from the software eCognition with parameter object size = 5) in order to generate a grid of 25 x 25 m where the mean value of each band was extracted and each grid cell was considered as a parcel.

* garcia.floresta@gmail.com

Figure 1. Image from RapidEye satellite showing the study area with *Eucalyptus* sp. plantation on the colorful composition 5-4-3 located on the region of Montes Claros – MG.

2.3 Segmentation

Two segmentatios were done, one based on NDVI and other on the five bands. For the segmentation based on NDVI the software eCognition was used. The algorithm used on segmentation was Multresolution Segmentation with the parameters Scale = 75, Shape = 0,2 and compactness = 0,2 (Figure 2). After segmentation the objects were grouped in four strata of the same amplitude and varying from 0.5 to 0.75 on NDVI value, these values were growing from stratum one to four (Figure 3). While in segmentation based on the five bands the software ENVI EX was used with the parameters of *Scale Level* = 20 and *Marge Level* = 85 (Figure 4).

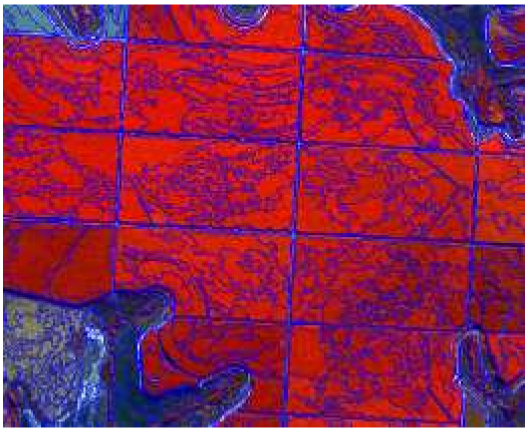

Figure 2. Segmentation detail of the image made based on the NDVI value.

2.4 Classification

It was necessary to create a raster image with mean values of each band on each segmented object in order to create the segmentation pallets of ENVI EX, and posterior classification not-supervised with IssoData with four strata (Figure 5).

2.5 Parcels

Systematic parcels in a grid of 150 x 125 m exported on eCognition were sample with the aid of the tool *Hawths Tools* on the software ArcGis.

Data from each parcel, mean of bands, were processed as a forest inventory with Simple Casual Sampling, without considering extracts and with Stratified Casual Sampling in order to evaluate the influence of stratification on variation coefficient, on sampling error, number of parcels and on estimation of the value of each band.

Only parcels entirely contained in an unique substratum were considered as valid, creating a "n" of 382 parcels for segmentation based on NDVI and 402 for the ones based on the bands. The estimate error was fixed on 2%.

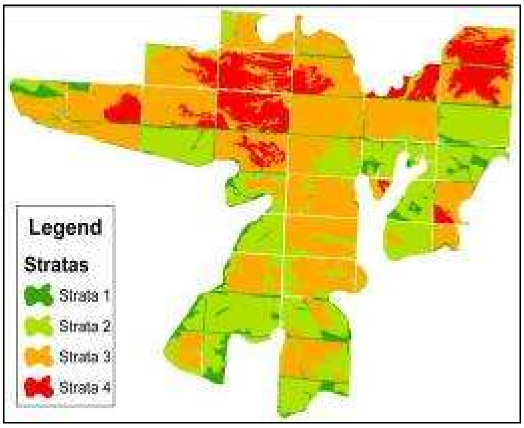

Figure 3. NDVI strata obtained through image segmentation without stratum 1, which presented the lower value.

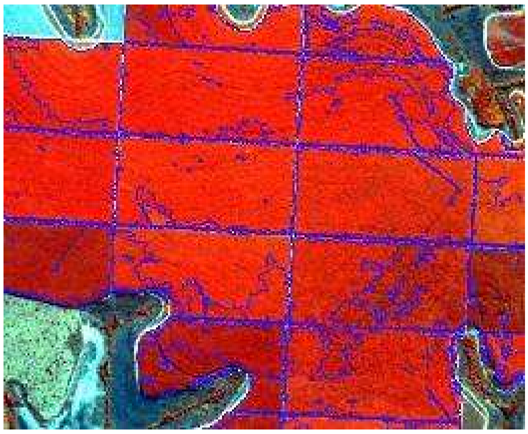

Figure 4. Segmentation detail of the image made based on the values of the five bands.

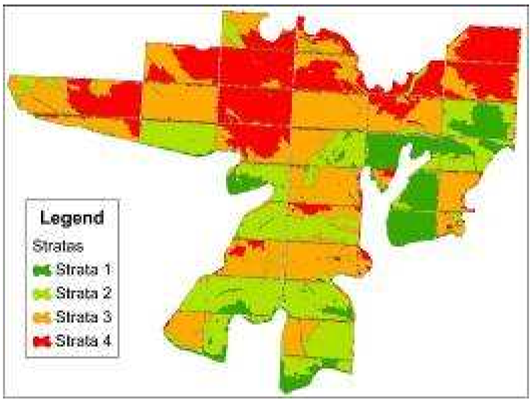

Figure 5. Strata obtained through the non-supervised classification with IssoData.

3. RESULTS AND DISCUSSION

3.1 Segmentation and variability

According to the analogy between band values and nutritional status coming from chemometrics, we can affirm that the variability of nutritional values on *Eucalyptus* sp. plantations could be evidenced by image segmentation. Patterns among band values and also among NDVI were responsible by the grouping on homogeneous areas and posterior segmentation (Figures 2 and 4).

3.2 Segmentation based on NDVI

Table 1 shows the results of processing through Simple Casual Sampling for each band. We can verify that in all bands the sampling is significantly low, with all the values lower than 1%.

Parameters	VC%	E%	n
Banda 1	8,465	0,841	68,947
Banda 2	5,439	0,541	28,538
Banda 3	6,464	0,642	40,276
Banda 4	3,426	0,340	11,334
Banda 5	2,037	0,202	4,009

Table 1. Estimated values of Variation Coefficient (VC%), Error (E%) and NUmber of Parcels 9(n) of Systematic Casual Sampling for segmentation based on NDVI.

Table 2 shows the results of processing through Stratified Casual Sampling, in which we can verify a small reduction on Variation Coefficient and Error.

Parameters	VC%	E%	n
Band 1	4,324	0,430	36,058
Band 2	5,132	0,514	50,744
Band 3	4,799	0,484	44,394
Band 4	2,935	0,294	16,628
Band 5	1,875	0,187	6,793

Table 2. Estimated values of Variation Coefficient (VC%), Error (E%) and Number of Parcels (n) of Stratified Casual Sampling for segmentation based on NDVI

Analyzing data we can verify on Table 3 that the mean of VC%, E% and n values, for the two sampling methods did not differ in significant values. However we can verify the efficiency of stratified sampling, in which VC% and E% were reduced keeping approximately the same number of parcels.

Parameters	SCS	ACE
VC%	5,166	3,813
E%	0,513	0,382
n	30,621	30,923

Table 3. Mean values of the parameters Variation Coefficient (VC%), Error (E%) and Number of Parcels (n) for Systematic Casual Sampling (SS) and Stratified Casual Sampling (SCS) for segmentation based on NDVI.

3.3 Segmentation based on bands

Table 4 shows the results of processing through Simple Casual Sampling for each band. We can verify that despite of the short variation on number of valid parcels between the two segmentations, NDVI and bands, result of Simple Casual Sampling was similar to the segmentation based on NDVI.

Parameters	VC%	E%	n
Band 1	8,469	0,823	69,018
Band 2	5,124	0,510	25,335
Band 3	6,932	0,689	46,321
Band 4	3,578	0,356	12,364
Band 5	1,970	0,196	3,749

Table 4. Estimated values of Variation Coefficient (VC%), Error (E%), and Number of Parcels (n) of Systematic Casual Sampling based on the bands.

However, Table 5 shows the results of processing through Stratified Casual Sampling, in which we can verify that only estimates for band 1 and 2 were better than segmentation based on NDVI.

Parameters	VC%	E%	n
Band 1	3,241	0,316	20,278
Band 2	4,712	0,469	42,802
Band 3	6,442	0,645	79,820
Band 4	3,355	0,337	21,734
Band 5	1,930	0,193	7,197

Table 5. Estimated values of Variation Coefficient (VC%), Error (E%) and Number of Parcels (n) of Stratified Casual Sampling for segmentation based on bands.

The summary presented on Table 6 shows the worst result for estimates of SCS (antes ACE) in relation to the number of parcels when segmentation was based on bands values. However, values are next to the ones found with segmentation based on NDVI.

Parameters	SCS (antes ACS)	SCS (antes ACE)
CV%	5,215	3,936
E%	0,515	0,392
n	31,357	34,366

Table 6. Mean values of Variation Coefficient (VC%), Error (E%) and Number of Parcels (n) parameters for Systematic Casual Sampling (SS) and Stratified Casual Sampling (SCS) for segmentation based on bands.

4. CONCLUSION

Small differences on statistical parameters between two segmentation criteria suggest that segmentation based on NDVI promotes a lower error on estimating values of bands with less parcels and consequently of nutritional status. However, few simulations and the impossibility of confirming the variability of nutritional status in the field indicate to us the need of more studies in order to confirm this possibility.

In contrast, due to the reduced knowledge about the relation between spectral signature and nutritional status of cultures, we can evaluate the small reduction on the statistical parameters evaluated as a gain.

Other analysis, simulations and confirmations may be developed with segmentation based on other bands separately and together, and other spectral indexes related to the theme in order to identify strata that obtain better gains on reducing the tested parameters.

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