Revista Brasileira de Cartografia (2017), Edição de Fotogrametia e Sensoriamento Remoto, Nº 69/6: 1223-1230
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto
ISSN: 1808-0936

INFLUENCE OF THE TOPOGRAPHIC CORRECTION STRATEGY ON THE LAND COVER CLASSIFICATION: A SPECTRAL APPROACH

Influência de Métodos de Correção Topográfica na Classificação de Coberturas de Solo: Uma Abordagem Espectral

Ana Carolina Moreira Pessôa & Flávio Jorge Ponzoni

[1]Instituto Nacional de Pesquisas Espaciais – INPE
Divisão de Sensoriamento Remoto - DSR
Avenida dos Astronautas, 1758 – CEP 12227-010, São José dos Campos – SP, Brasil
acmoreirapessoa@gmail.com, flavio@dsr.inpe.br

Received on February 13, 2017/ Accepted on July 17, 2017
Recebido em 13 de Fevereiro, 2017/ Aceito em 17 de Julho, 2017

ABSTRACT

Topographic correction methods applied to orbital imagery have been evaluated by several authors. The evaluation criteria have been based on the correlation decreasing between shade and reflectance at different spectral bands or, in some cases, it has included the performance of digital classifiers trying to separate specific land cover types. Some topographic correction methods include sampling procedures based on the original image to be corrected and results are dependent on how they are conducted. The influence of the topographic correction on the land cover types spectral characterization is frequently neglected although it is relevant, specially in "quantitative remote sensing" in which empirical or physical relations between radiometric data and biophysical or geophysical data are explored. The objective here was to evaluate the classification results achieved from original and topographic corrected images using the C-correction method exploring two sampling procedures. The influence of the spectral characterization of some land cover types was also evaluated. Results indicated that pixels under high and low illumination conditions presented bigger spectral dynamics, specially in the infrared spectral region (near and SWIR). Topographic correction based on a single land cover class (vegetation) did not present better classification result when compared to that classification based on the original images. Sampling procedures based on different land cover classes presented lower mapping accuracy and low matching level with the other classification results.

Keywords: Topographic Correction, C-Correction, Digital Classification, Mata Atlântica, Vegetation.

RESUMO

Métodos de correção topográfica aplicados às imagens orbitais vem sendo estudados por diversos autores. O critério de avaliação frequentemente é baseado na correlação negativa entre sombra e reflectância em diferentes bandas espectrais, ou, em alguns casos, incluindo o desempenho de classificadores digitais, que tentam separar tipos de coberturas do solo específicas. Alguns métodos de correção topográfica incluem procedimentos de amostragem baseados na imagem original a ser corrigida, e os resultados dependem em como esses procedimentos são realizados. A influência da correção topográfica na caracterização espectral de tipos de cobertura do solo frequentemente é negligenciada, apesar de ser relevante, sobretudo no "sensoriamento remoto quantitativo", no qual relações empíricas e físicas entre dados radiométricos e dados biofísicos ou geofísicos são exploradas. O objetivo deste trabalho foi avaliar os resultados de classificação obtidos de imagens originais e de imagens submetidas à correção topográfica. O método de correção utilizado foi a Correção-C explorando dois procedimentos de amostragem. A influência da caracterização espectral de algumas classes de cobertura do solo também foi avaliada. Os resultados indicam que pixels sob condições de iluminação alta e baixa apresentaram maiores dinâmicas espectrais, principalmente na região espectral do infravermelho (próximo e SWIR). A correção topográfica baseada em uma única classe de cobertura do solo (vegetação) não apresentou melhoria para o resultado da classificação, quando comparado com a classificação baseada nas imagens originais. Procedimentos amostrais baseados em diferentes classes de cobertura do solo apresentaram menor precisão, e baixo nível de compatibilidade com os outros resultados das classificações.

Palavras-chave: Correção Topográfica, Correção-C, Classificação Digital, Mata Atlântica, Vegetação.

1. INTRODUCTION

The increasing in availability of orbital data collected from different sensors has enforced remote sensing users to be familiar with the Digital Number (DN) conversion to physical parameters such as radiance or reflectance (PONZONI *et al.*, 2014). That conversion has allowed the comparison between data generated from several sensors and has improved the so called “quantitative approach” in which physical or empirical relations between orbital radiometric data and biophysical and/or geophysical parameters are explored.

Multi-temporal studies using orbital imagery have frequently required radiometric consistency between data acquired at different periods of time. As mentioned by Hantson and Chuvieco (2011), any multi-temporal change detection study relies on comparing images acquired at different dates and such comparison assumes that images are geometrically matched and radiometrically consistent. Meeting such requirements becomes almost impossible when the target area has rough terrain, since local illumination change along seasonal sun positioning.

Topographic correction methods have been proposed by several authors (TEILLET *et al.*, 1982; CIVCO, 1989; RIANO *et al.*, 2003; GAO; ZHANG, 2009), in order to minimize radiometric differences between temporal set of images from mountainous regions. Despite of having some particularities and performance differences between them, all of them try to increase the reflectance of shaded pixels and to decrease it of high illuminated pixels promoting a convergence of both to a “middle” reflectance that at least hypothetically should represent the “typical” reflectance of the targets under study. The way they are based to do that varies significantly and some of them are strongly influenced by both the land cover types and the sampling strategy.

One of the most popular topographic correction method was proposed by Teillet *et al.* (1982) being named the C-correction. Its formulation includes the estimation of coefficients from correlations between reflectance values and terrain shade and these correlations are materialized from linear regression analyses that are carried out from arbitrarily sampling procedure. This sampling procedure can be based on randomly or arbitrarily sampling. In the random sampling pixels from different land cover type has the same chance to make part of the regression definition while in the arbitrarily sampling one or a specific group of land cover type can be defined as source of pixels to compose the linear regression analysis.

Moreira and Valeriano (2014) evaluated some topographic correction methods to improve land cover mapping using object-based classification. They concluded that choosing different sampling strategies will affect the final classification result. The author also evaluated the performance of topographic shade removal as carried out by McDonald *et al.* (2000)old-growth forest and disturbance history layers. The data are also used as an information layer in a Geographical Information System (GIS and several others authors observing the decreasing in the correlation coefficient between the incidence angle and the reflectance values at each spectral band under study. Hantson and Chuvieco (2011) explored an additional approach on that evaluation assuming that changes in shade of pixels within the same land cover type in different slopes and aspects should decrease and that the temporal stability of a time series for individual pixels should increase after a successful shade removal.

Despite of so many alternatives to evaluate the performance of topographic correction methods, they have not included a spectral approach to fully understand the impact of them on the spectral characterization of land cover frequently adopted as items of mapping legends. Topographic correction can impact the spectral characterization of land cover types increasing and decreasing the performance of digital classifiers adding constrains on multi-temporal analysis and on physical or empirical relationships between radiometric and biophysical/geophysical data.

In this paper we applied the C-correction method to minimize the topographic effect on reflectance values of a TM/Landsat 5 scene acquired in September 2011 from a specific region in Brazil that presents a rough terrain characterized by different land cover types. The method was applied considering two sampling strategies. The original images and those resulting from C-correction method were classified in order to produce thematic maps. A qualitative spectral evaluation was also performed to better understand the classification results.

2. MATERIAL AND METHODS

Following, the methodology is explained in five topics: study area, digital number conversion, topographic correction strategies, classification and spectral evaluation.

2.1 Study area

The study area is part of a TM/Landsat 5 scene (path 218, row 76) from September 5th, 2011, and is indicated with a yellow rectangle on Figure 1. The central coordinates are 23° 06´59´´ S and 44° 58´49´´ W including partially the territories of São Paulo, Minas Gerais and Rio de Janeiro states, Brazil.

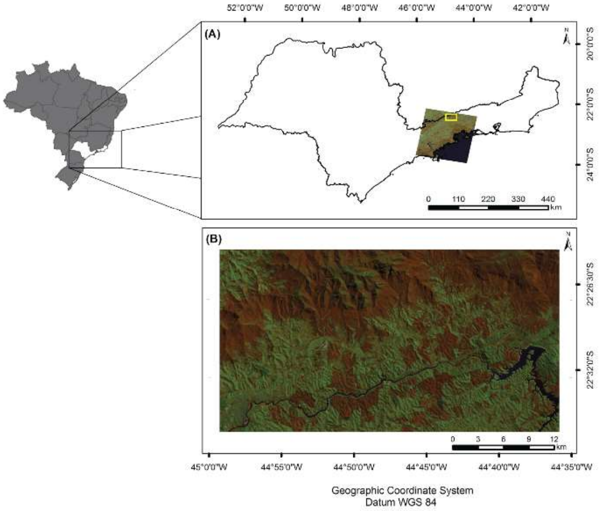

Fig. 1 – Study area localization in the regional context.

This partial scene includes different environments and topographic conditions. In the northern portion of that scene there is a relatively great altitudinal change from the river (Rio Paraiba) level toward the north (around 800m). That mountainous regions is known as "Serra da Mantiqueira" and it is composed by peaks and valleys covered by a very dense tropical forest. The relief is characterized by great variation in slopes and aspects. The land cover is dominated by different land use categories, including pasture, urban areas, dense tropical forest and commercial Eucalyptus plantations. Almost in the middle of the scene there is an elongated valley in the SW-NE direction ("Vale do Rio Paraiba"), presenting a relatively flat topography.

2.2 Digital Number conversion

The Digital Numbers (DN) of the TM/ Landsat 5 optical images (TM spectral bands 1-5 and 7) from September 5th, 2011 were converted to Top of Atmosphere (TOA) reflectance, according described by Chander *et al.* (2009) Top-Of-Atmosphere (TOA. The TOA reflectance images were converted to surface reflectance through the application of the 6S (Second Simulation of the Satellite Signal in the Solar Spectrum) atmospheric correction code. The evaluation of that conversion consistency was analyzed by the spectral characterization of well-known targets such as water bodies, bare soils and different kinds of vegetation cover.

2.3 Topographic correction strategies

We opted for the C-correction topographic correction method proposed by Teillet *et al.* (1982) that is strongly spectrally dependent. This method was described by Hantson and Chuvieco (2011) as:

$$\rho_{\lambda,h,i} = \rho_{\lambda,i}\left(\frac{cos\theta s + c_\lambda}{cos\gamma_i + c_\lambda}\right) \tag{1}$$

where $\rho_{\lambda,h,i}$ is the reflectance of a pixel i in horizontal terrain at spectral band λ; $\rho_{\lambda,i}$ is the reflectance of a pixel i in rugged terrain at spectral band λ; θ_s is the solar zenith angle; γ_i is the incidence angle (according the solar positioning and the topographic conditions for pixel *i*) and c_λ is a ratio of the coefficients of a linear regression between $cos\gamma_i$ and the surface reflectance at band λ. Here $cos\gamma_i$ is given by:

$$cos\gamma_i = cos\theta_s . cos\eta_i + sen\theta_s . sen\eta_i . \cos(\phi_a - \phi_o) \quad (2)$$

where γ_i is the incident angle, θ_s is the solar zenith angle, η_i is the slope angle, ϕ_a is the solar azimuth and ϕ_o is the slope aspect.

The mentioned linear regression is given by:

$$\rho_{\lambda,i} = b_\lambda + m_\lambda . cos\gamma i \quad (3)$$

So, c_λ is given by:

$$c_\lambda = \left(\frac{b_\lambda}{m_\lambda}\right) \quad (4)$$

This method is dependent on the illumination/spectral reflectance relationship and, since the regression is established by a limited number of $cos\gamma i$ x $\rho_{\lambda,i}$ sample points and any random sampling strategy implies extracting data from different land-cover types, the resulting $\rho_{\lambda,h,i}$ is strongly dependent on the sampling procedure (HANTSON; CHUVIECO, 2011).

The C-correction method was performed twice in order to generate two sets of corrected images for the same TM/Landsat 5 scene (September 5th). The difference between both was based on the sampling strategy to calculate c_λ. During the first application of the C-correction method $cos\gamma i$ and $\rho_{\lambda,i}$ values were randomly collected from the respective images, i.e., from different land cover types. The second application of the C-correction method included an oriented arbitrarily sampling collecting data from vegetated surfaces, mainly forested surfaces.

The $cos\gamma i$ was calculated considering the geometric illumination conditions of September 5th and the study area central coordinates. The resulting $cos\gamma i$ image was sliced in three illumination classes: High Illumination, Illuminated and Low illumination. These illumination classes were important during the classification procedure as will be described later.

2.4 Classification

The digital classification was performed on three TM/Landsat 5 image sets: one set composed by the original images that were just converted to surface reflectance values, a second set composed by topographic corrected images using the C-correction method being c_λ calculated from different land cover types, and a third set composed by topographic corrected images again using the C-correction method, but being c_λ calculated from vegetated surfaces.

It was used the Maximum Likelihood classification algorithm. Its training step was carried out taking into account the illumination classes from which around 10 sample regions of interest for each land cover type were identified arbitrarily. The idea here was collecting data from each land cover type positioned in different illumination conditions and the samples positioning was maintained the same for the three image sets. Table 1 shows the number of sample regions of interest for each land cover type that were defined.

Table 1: Number of maximum likelihood training samples for each land cover type

Land cover	High Illumination	Illuminated	Low Illumination	**Total**
Initial	10	9	7	26
Intermediate	10	7	10	27
Advanced	9	10	10	29
Water	6	14	10	30
Soil	10	11	12	33
Urban Area	4	10	11	25
Reforestation	10	10	9	29
Shade	0	0	20	20
Total	59	71	89	**219**

From each of these sample regions of interest a variable number of pixels were randomly collected for the Maximum Likelihood training step.

Classes Initial, Intermediate and Advanced refer to forest secondary succession stages and they were included due to their spectral similarity. The spectral characterization of such classes is frequently demanded.

The classification result achieved for the non-topographic corrected image (surface reflectance image) was assumed here as a reference to be compared to the results achieved for the topographic corrected images, since the first one has been commonly applied by the remote sensing user community.

The classification accuracy of each image set was estimated visiting 100 checking pairs of coordinates, randomly selected, on Google Earth (from 2011). The Kappa Coefficient and the Global Accuracy were calculated from confusion matrices that were elaborated from these 100 checking points.

Additionally, in order to evaluate the adjustment degree between the classifications with and without topographic correction, it was performed a pixel to pixel comparison among them. It was also calculated the Kappa Coefficient ang Global Accuracy, but here, they are used to indicate the similarity between the classified images, not the accuracy. The idea here was to evaluate expected differences between a conventional classification to those performed with topographic corrected images.

2.5 Spectral evaluation

Surface reflectance values from the classification classes (including forest secondary succession stages) were plotted as reflectance curves to qualitatively evaluate the effect of the topographic correction strategies.

3. RESULTS

The results are presented below.

3.1 Classification

Figure 2 shows the classification results.

According Table 2, classification performed from Original (surface reflectance) and topographic corrected from C-correction method exploring vegetation sampling presented similar Kappa and Global accuracy values. Despite being lower than both Kappa and Global Accuracy estimated for classifications resulted from Original and Vegetation sampling, the classification achieved from topographic corrected images exploring total sampling, there was no significant difference between Kappa Coefficient values.

The objective of the second strategy was to compare the classification results assuming that resulted from the original data as a reference. So, the Kappa Coefficient and the Global Accuracy were calculated (not estimated) building confusion matrices from the entire study area pixel to pixel. Table 3 shows the results of that comparison.

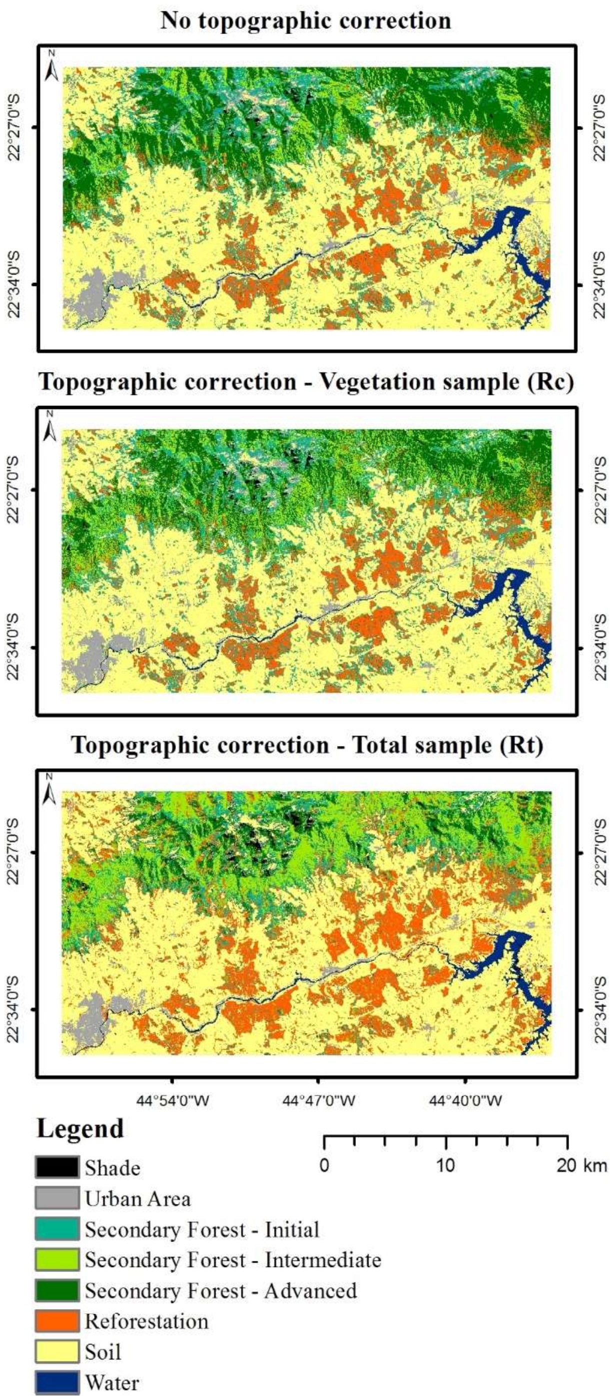

Fig. 2 – Classification results.

Table 2: Kappa Coefficient, Global Accuracy values and Z Test results.

	No correction	Rc[1]	Rt[2]
Kappa Coefficient	0.4901	0.5082	0.3808
Global Accuracy	0.63	0.63	0.53
Var(Kappa)	0.00328027	0.00319363	0.00269755
Z Test to compare Kappa values (Alpha = 0.05)			
p-value		0.41070202	0.07885941

[1]Vegetation sample; [2]Total sample

Table 3: Kappa Coefficient and Global Accuracy calculated to the pixel to pixel classification comparisons.

	Rc[1] x No correction	**Rt[2] x No correction**
Kappa Coefficient	0.8353	0.6151
Global Accuracy	0.87	0.71

[1]Vegetation sample; [2]Total sample

As expected the classifications resulted from topographic corrected images (C-correction) exploring the vegetation sampling and from the Original data were quite similar, while that resulted from the topographic corrected images (also C-correction) exploring the total sampling was different.

3.2 Spectral evaluation

Some pixels from Urban area, Soil, Reforestation, Water and Shade were arbitrarily selected and their surface reflectance (original and topographic corrected by both strategies) were plotted as shown in Figure 3.

As mentioned before the C-correction method is dependent on a relationship between the topographic position ($cos\gamma i$) and the surface reflectance. After the topographic correction application, it is expected that this correlation decreases and that decreasing is explained by the spectral dynamic that can be visually observed on Figure 3. Note that in High illumination condition the topographic correction decreased the Original surface reflectance values and increased them under Low illumination condition. No significant dynamic was observed in the spectral characterization of those pixels under Illuminated condition as expected. Such spectral dynamic in fact influences the Maximum Likelihood classifier performance. It is important to emphasize that these spectral dynamics are dependent on the sampling strategy adopted during the C-correction method application.

Considering land cover classes presenting spectral similarity as that verified in the forest secondary succession, the topographic correction did not contribute to discriminate themselves. Figure 4 shows the surface reflectance values of each successional stage under the three illumination conditions and of each set of images (original and topographic corrected).

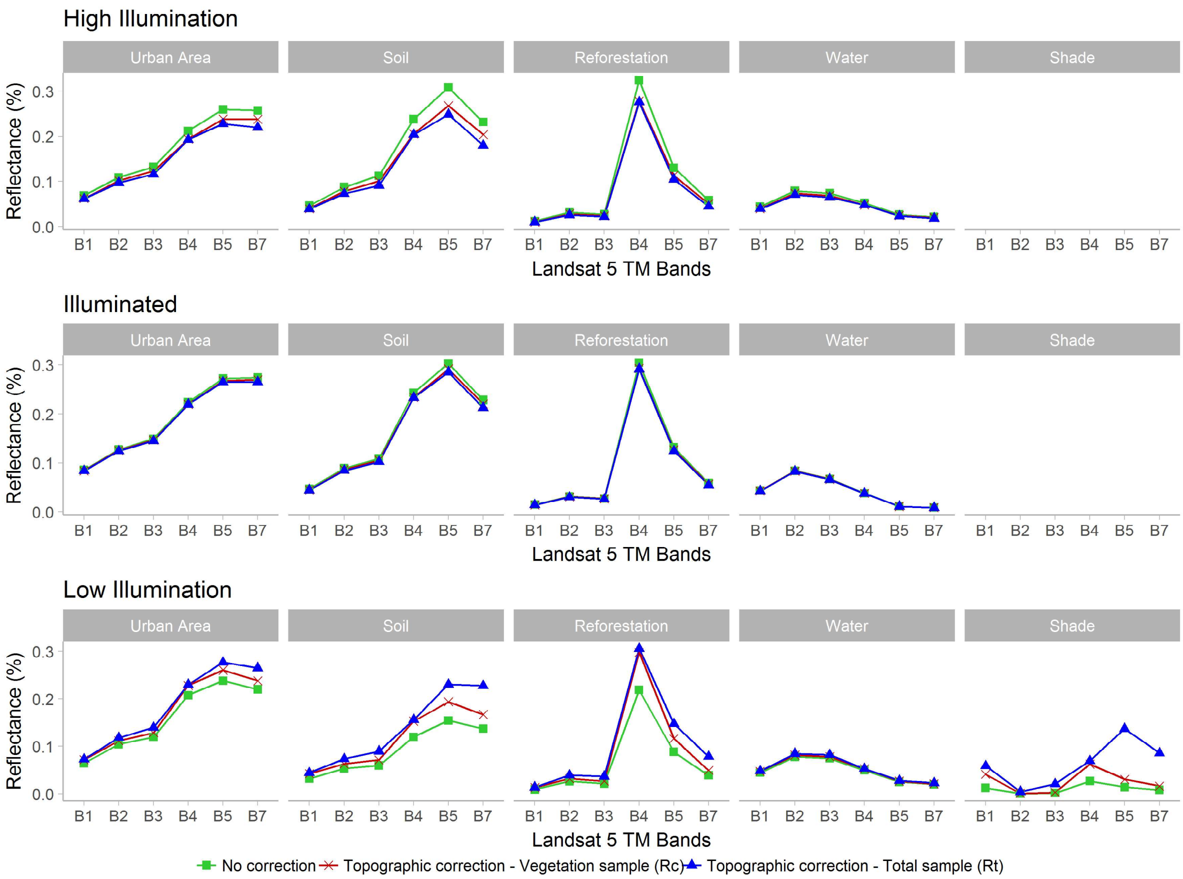

Fig. 3 – Surface reflectance from Original and topographic corrected images.

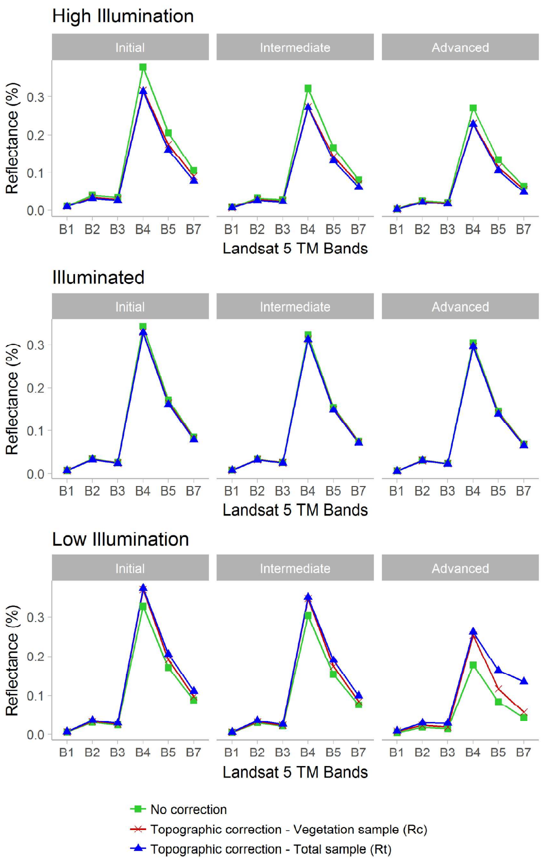

Fig. 4 - Surface reflectance values of each successional stage under the three illumination conditions and of each set of images (original and topographic corrected).

As observed with the other and cover classes (Figure 3) the topographic correction influenced more significantly those pixels positioned under High and Low illumination conditions, but in low illumination condition, in the infrared spectral region (TM spectral bands 4, 5 and 7) the increase of the surface reflectance values was bigger for the Advanced successional stage, becoming more difficult the distinction between it and the other successional stages. That influence can be observed on the confusion matrices presented on Table 4.

The total number of pixel of each land cover class of the reference classification (made from the Original data) is at the end of each column. At the end of the lines are found the number of pixels of the same classes that were found in the classifications resulted from the topographic corrected images.

The numbers highlighted in yellow represent the number of pixels specifically confounded with the successional stages themselves. It is clear that the mutual confusion was greater when adopting the total sampling, assuming the Original classification as a reference.

Table 4: Confusion matrices resulting from the comparison between the classification results, assuming the classification resulted from the original data as a reference

Classified image topographic corrected with vegetation sample (Rc)

PIXELS	Shade	Urban area	Initial	Intermediate	Advanced	Reforestation	Soil	Water	**TOTAL**
Shade	2124	5	0	0	1490	0	27	0	3646
Urban area	0	38801	2739	0	122	20	14401	6	56089
Initial	0	1517	**115172**	6212	3418	8245	2770	0	137334
Intermediate	0	0	10713	**45152**	28986	3943	0	0	88794
Advanced	9	19	1444	8706	**116629**	1863	13	0	128683
Reforestation	0	2	4167	903	4775	98128	134	0	108109
Soil	0	7512	2495	0	78	171	414926	1	425183
Water	0	267	0	0	0	0	222	16371	16860
TOTAL	2133	48123	136730	60973	155498	112370	432493	16378	**964698**

Classified image topographic corrected with total sample (Rt)

PIXELS	Shade	Urban area	Initial	Intermediate	Advanced	Reforestation	Soil	Water	**TOTAL**
Shade	2012	1637	359	1	2445	74	879	316	7723
Urban area	0	26396	2087	0	108	411	6562	1	35565
Initial	0	1276	**48485**	10223	22232	11380	659	0	94255
Intermediate	0	0	6726	**49236**	66070	6412	0	0	128444
Advanced	0	2505	16228	607	**46911**	2211	1377	0	69839
Reforestation	7	2998	59090	906	16966	89861	12615	0	182443
Soil	114	13239	3755	0	766	2021	410209	0	430104
Water	0	72	0	0	0	0	192	16061	16325
TOTAL	2133	48123	136730	60973	155498	112370	432493	16378	**964698**

4. CONCLUSIONS

Despite of having no significant differences between the Kappa Coefficients (estimated to mapping accuracy evaluation from Google Earth data) of the classification maps, total sampling presented worse results in terms of mapping accuracy.

The classification result based on vegetation cover sampling was very similar than that carried out with the Original data, indicating that there was not significant gain in applying this topographic correction strategy on this TM/Landsat 5 scene, at least for the mapping legend adopted.

In spectral terms pixels under high and low illumination conditions presented bigger changes, mainly in the infrared (near and SWIR) spectral region. As those spectral changes are dependent on the sampling procedure, users must be aware when applying topographic correction methods based on similar criteria such as those in which the C-correction method is based on.

ACKNOWLEDGMENTS

The authors are scholarship holders of CNPq, the Brazilian Council for Science and Technology. We also express our gratitude to Dr. Márcio de Morisson Valeriano and Mr. Eder Paulo Moreira for exchanging ideas and concepts that have been incorporate to this paper.

REFERENCES

CHANDER, G.; MARKHAM, B. L.; HELDER, D. L. Summary of current radiometric calibration coefficients for landsat mss, tm, etm+, and eo-1 ali sensors. **Remote sensing of environment**, v. 113, n. 5, p. 893–903, maio 2009.

CIVCO, D. L. Topographic normalization of landsat thematic mapper digital imagery. **Photogrammetric engineering and remote sensing**, v. 55, n. 9, p. 1303–1309, 1989.

GAO, Y.; ZHANG, W. A simple empirical topographic correction method for etm+ imagery. **International journal of remote sensing**, v. 30, n. 9, p. 2259–2275, maio 2009.

HANTSON, S.; CHUVIECO, E. Evaluation of different topographic correction methods for landsat imagery. **International journal of applied earth observation and geoinformation**, v. 13, n. 5, p. 691–700, out. 2011.

MCDONALD, E. R.; WU, X.; CACCETTA, P.; CAMPBELL, N. Illumination correction of landsat tm data in south east nsw. In: PROCEEDINGS OF THE TENTH AUSTRALASIAN REMOTE SENSING CONFERENCE. 2000…. **Anais...** . [S.l: s.n.], p. 13 pp., 2000.

MOREIRA, E. P.; VALERIANO, M. M. Application and evaluation of topographic correction methods to improve land cover mapping using object-based classification. **International journal of applied earth observation and geoinformation**, v. 32, p. 208–217, out. 2014.

PONZONI, F.; SILVA, C.; SANTOS, S.; MONTANHER, O.; SANTOS, T. Local illumination influence on vegetation indices and plant area index (pai) relationships. **Remote sensing**, v. 6, n. 7, p. 6266–6282, 3 jul. 2014.

RIANO, D.; CHUVIECO, E.; SALAS, J.; AGUADO, I. Assessment of different topographic corrections in landsat-tm data for mapping vegetation types (2003). **Ieee transactions on geoscience and remote sensing**, v. 41, n. 5, p. 1056–1061, maio 2003.

TEILLET, P. M.; GUINDON, B.; GOODENOUGH, D. G. On the slope-aspect correction of multispectral scanner data. **Canadian journal of remote sensing**, v. 8, n. 2, p. 84–106, dez. 1982.