

## Potential of SAR data (L-hh-hv-vv) to discriminate iron-mineralised laterites in the Amazon Region (Carajás Province) based on textural attributes

Maria Carolina de Morais<sup>1</sup>  
Paulo Martins Pereira Junior<sup>1,2</sup>  
Waldir Renato Paradella<sup>3</sup>

<sup>1</sup> Universidade Federal de Ouro Preto - UFOP  
Campus Universitário Morro do Cruzeiro, s/n  
Departamento de Geologia – DEGEO, 35400-000 - Ouro Preto – MG, Brasil  
mcarolina@degeo.ufop.br

<sup>2</sup> Fundação Centro Tecnológico de Minas Gerais- CETEC  
Avenida José Cândido da Silveira 311700-000, Horto – Belo Horizonte – MG, Brasil  
paulo.martins@cetec.br

<sup>3</sup> Instituto Nacional de Pesquisas Espaciais - INPE  
Caixa Postal 515 - 12245-970 - São José dos Campos - SP, Brasil  
waldir@ltid.inpe.br

**Abstract.** The Carajas Province is located on southeast of Brazilian Amazon with a dense forest cover at humid weather. In this environment, radar has a potential for geological surveys due the all-weather sensing capability to and to the enhancement of the terrain, specially topography and roughness. The N1 deposit is located in the Carajás Province, which encompasses the world's largest iron deposits, with a lateritic cover showing units related to iron mineralizations and to specific savanna-type vegetation. The research was based on the degraded airborne SAR obtained from Surveillance of the Amazon System (SIVAM/SIPAM, L – hh, hv, vv) aiming of simulation of orbital Multi-Application Purpose SAR (MAPSAR). The images were analysed through textural classifications derived from second order measures (GLCM) aiming at the mapping of the laterites. Textures were sensitive to the sensor and can be used as a practical tool for a preliminary mapping, but the surface roughness measurements were not sensitive at L band to discriminate the laterites.

**Key-words:** radar, remote sensing, image processing, geology, lateritic cover.

### 1. Introduction

Airborne and spaceborne C-band SAR data have played an important role in the acquisition of geological information in the Carajás Province of Brazil (Paradella et al., 1997; Paradella et al., 2000). The Province, located on the easternmost border of the Amazon Region, is the most important Brazilian mineral province with the world's largest iron deposits. The area has a mountainous terrain (altitudes near 800 m), surrounded by southern and northern lowlands (altitudes around 150-200 m), and has thick oxisols ("latosols") as a result of deep chemical weathering and few outcrops. The vegetation cover is typical of the Ombrophilous Equatorial forest with complex, multilevel canopies and numerous species (Paradella et al., 1994).

The iron deposits were discovered in 1967, when a remarkable geobotanical control given by the iron-mineralised laterites and specific vegetation types has been recognised. The deposits are related to a set of plateaux covered by thick hard iron-rich crusts developed over volcanic rocks and ironstones. A specific low-density savanna-type vegetation, called "Campus Rupestres" (Silva et al. 1996) is associated with the deposits, and shows a strong contrast ("clearing") with the dense equatorial forest.

The Province was almost completely covered by. Details of the SAREX' 92 can be found in Wooding et al. (1993). The preliminary evaluation of C band, conduced by airborne imageries during the SAREX' 92 (South American Radar Experiment) campaigns, has shown that the backscattered responses are sensitive to this geobotanical contrast in depicting variations in the duricrust/ vegetation associations (Morais, 1998, 2002). As changes in the lateritic compositions play an important role in the expression of the macro and micro (roughness) topography, it was considered worthwhile to evaluate SAR texture classification aiming at the automatic mapping of the lateritic units through L band.

Due of the economic importance of this area, there is a practical need to provide accurate and up-to-date surface maps to support mineral exploration and environmental programs. The province has been extensively covered by various airborne (RADAMBRASIL, INTERA, SAREX) and spaceborne (ERS-1, JERS-1, RADARSAT-1) systems and the practical utility of textural SAR classification for mapping remains to be demonstrated. In addition, with the advent of the forthcoming satellites that will carry SAR systems (ALOS

PALSAR, RADARSAT-2, and MAPSAR) with new characteristics (resolution, polarisation, incidence, wavelength), textural classification will also receive much attention for applications in the moist tropics.

## 2. Objectives

The research was based on the degraded airborne SAR obtained from Surveillance of the Amazon System (SIVAM/SIPAM, L – hh, hv, vv) aiming the simulation of orbital Multi-Application Purpose SAR (MAPSAR). The characteristics of SAR data were showed on **Table 1**. The images were analysed through textural classifications derived from second order measures (GLCM). Further, roughness measures collected in the field were used for the evaluation of the classification results. Thus, the main is the mapping of the laterites from N1 as tool for mapping similar areas.

Table 1 – SAR characteristics.

Platform	Sensor	Acquisition Date	Incident Angle (deg)	Spatial Resolution(m)	Image Format	Illumination Geometry
EMB -145	SAR-R99B L(hh, hv, vv)	march 2005	48/53 <sup>0</sup>	11 x 11	8-bits	Look Azimuth =282 <sup>0</sup>

## 3. Study Area

The Carajás Province is located on the Southeast part of the Amazonian Craton, which is part of the Brazilian Platform, subdivided into the Guyana and the Central Brazil Shields (**Figure 1**). Based on geochronological data, the tectonic model for the area is characterised by marginal mobile Proterozoic belts surrounding Archean cratonic nuclei (Cordani and Brito Neves, 1982). Thus, granulites and migmatites in the northern border of the Carajás Mountain range are related to the Maroni-Itacaiúnas Belt of Early Proterozoic age. The gneisses, metavolcanic and metasedimentary rocks from the bulk of the Carajás area are related to the Central Amazonia Province of Early Proterozoic/Archean age. A distinct model has been proposed based on geophysical and structural data (Hasui et al., 1984). It is characterised by several independent Archean crustal blocks. Granitoids and volcanic-sedimentary sequences are common in the nucleus of these blocks.

The N-1 is the first of a series of similar plateau related to these sequences, located in the northern border of the Province. It has an iron-ore deposit with an estimated reserve of 854 million metric tons with 66.4 % iron concentration. The plateau area is 24 km<sup>2</sup> with altitudes around 700 m. The N1 area is related to rocks of the Grão Pará Group, displaying complex patterns of folding and faulting. The Grão Pará Group has been subdivided into two units: volcanic rocks of the Parauapebas Formation (Meirelles et al. 1984), and the ironstones of the Carajás Formation (Beisiegel et al., 1973). The volcanic rocks are a bimodal sequence of basalts, dolerites and rhyolites. Based on geochemical data, these volcanic rocks are related to continental tholeiites. The ironstones of the Carajás Formation are composed of several types of iron ore from oxide facies. They are mainly jaspelite and interlayered hematite and silica, which are distinguished by hardness (soft hematite, hard hematite, etc.). Under the humid tropical climate of the Amazon region, ferruginous duricrusts and latosols are extensively developed in the plateau. These weathered products show varying degrees of alteration that are responsible for the differences in composition, hardness and textures.

The N-1 plateau was mapped during the economic evaluation of the iron reserves in the Province (Resende and Barbosa, 1972). The following types of ferruginous crusts were identified in the area: duricrust (in situ duricrust with limonite blocks), chemical crust (hematite fragments with goethitic pisolites), iron-ore duricrust (hematite ore blocks and subordinately specularite, cemented with hydrous ferric oxides), and hematite (mainly hematite outcrops). In addition, a latosol unit was also mapped in a restricted area, associated with arboreal vegetation. The surficial map of the plateau is seen in **Figure 2**.

## 4. Methodology

The investigation was based on textural descriptors extracted from the GLCM and GLDV used as input for an unsupervised classification scheme. The textural analysis based on an statistical approach known as Grey Level Co-occurrence Matrix (GLCM) is a common technique which showed to be effective in earlier studies, e.g. Shanmugan et al. (1981), Ulaby et al. (1986), Yanasse et al. (1993), Baraldi & Parmiggiani (1995), and Kurvonen & Hallikainen (1999), but few examples have focussed on geological applications in tropical environments (Azzibrouck et al., 1997).

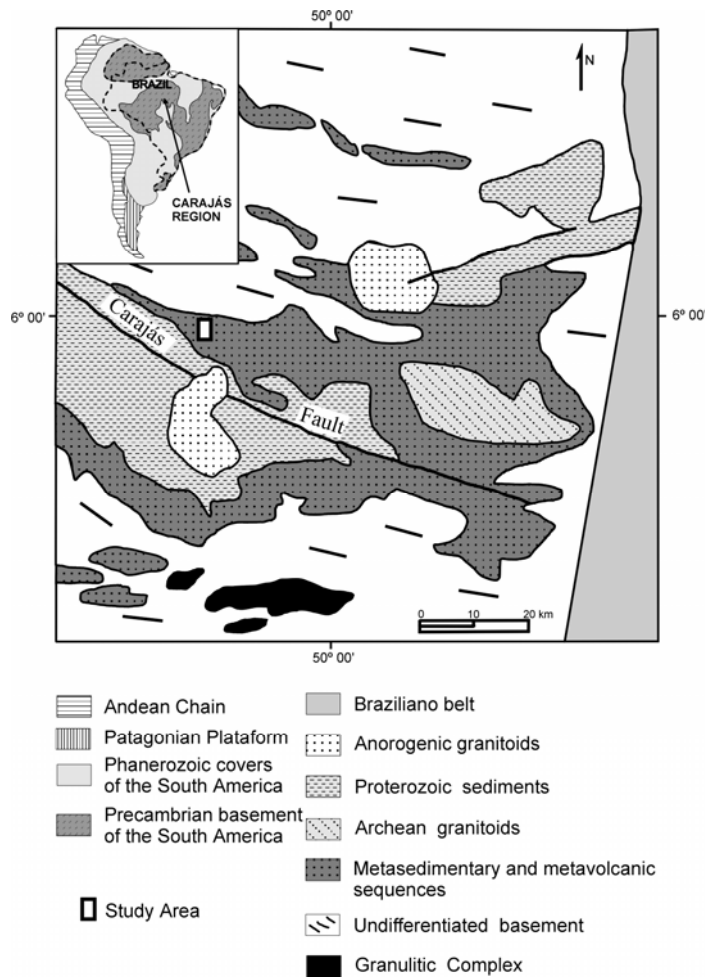


Figure 1. Main tectonic units related to the study area. *Source:* Dall'Agnol et al. (1994).

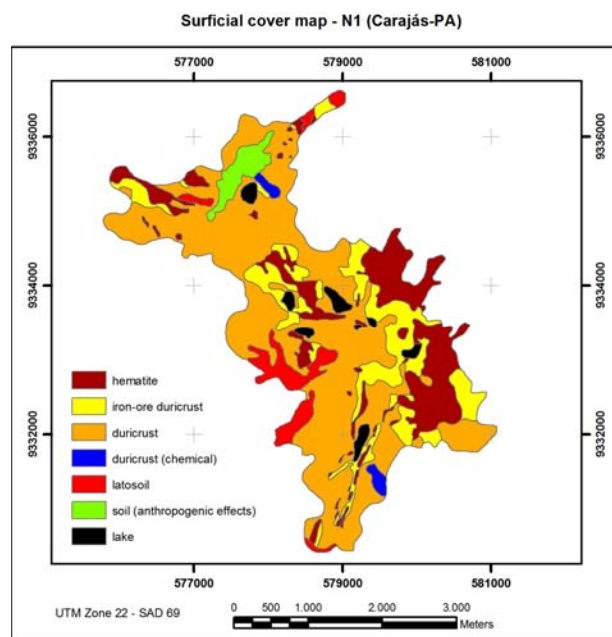


Figure 2. Lateritic units in the N1 plateau (adapted from Resende and Barbosa 1972).

The gray tone spatial dependence approach characterises texture by the spatial relationships among gray tones in a local area. The gray tone co-occurrence can be specified in a matrix of relative frequencies  $P_{ij}$  in which two neighbouring resolution cells separated by distance  $d$  occur on the image, one with gray tone  $i$  and the other with gray tone  $j$ . Such matrices of spatial gray tone dependence frequencies are symmetric and are a function of the angular relationship between the neighbouring resolution cells as well as a function of the distance between them (Haralick, 1979). Several statistical parameters can be extracted from the GLCM, which can be used as input data in automatic classification process. However, the main disadvantages of the GLCM parameters are the requirement of large memory and computational time (Weska et al., 1976; Welch et al., 1990). Thus, the authors consider a class of local properties based on absolute differences between pairs of gray levels. The Grey Level Difference Vector (GLDV) is based on the absolute differences between pairs of grey levels  $i$  and  $j$  at a distance  $d$  and at an angle  $\theta$ .

No speckle filtering was applied to the images. Representative samples of nine classes were chosen, on the basis of field observations and the geological map: C1 = Latosol, C2 = Soil (anthropogenic effects), C3 = Duricrust (chemical), C4 = Duricrust, C5 = Iron-ore duricrust (with shadow), C6 = Iron-ore duricrust, C7 = Hematite (with shadow), C8 = Hematite, and C9 = Lake. Based on these samples, second order measures derived from GLCM (mean, homogeneity, contrast, dissimilarity, entropy, energy, correlation) and from Gray-Level Difference Vector-GLDV (energy, entropy, mean, contrast) were analysed. The second order measures were computed with nine configurations of distance ( $d$ ), i.e., (-2,0), (-2,1), (-2,2), (-1,2), (0,2), (1,2), (2,2), (2,1), and (2,0). Since 82 measures were made, it became impracticable to use such a large number of measures in the classification.

Therefore, texture measure selection was based on a decision rule based on Discriminant Factor which evaluates the separability between classes (Rennó et al., 1998). Thus, for two hypothetical classes  $A$  and  $B$ , and one texture measure  $k$ , the Factor Discriminant was computed according to the variation between and within these classes, given by equation:

$$DF_{AB,k} = \frac{n_A \cdot \sum_{i=1}^{n_A} (X_{Ai,k} - \bar{X}_{B,k})^2 + n_B \cdot \sum_{i=1}^{n_B} (X_{Bi,k} - \bar{X}_{A,k})^2}{n_A \cdot \sum_{i=1}^{n_A} (X_{Ai,k} - \bar{X}_{A,k})^2 + n_B \cdot \sum_{i=1}^{n_B} (X_{Bi,k} - \bar{X}_{B,k})^2}$$

where  $X_{\omega i,k}$  is the  $i^{\text{th}}$  sample of class  $\omega$  for the measure  $k$ ,  $\bar{X}_{\omega,k}$  is the mean value of measure  $k$  class  $\omega$ , and  $n_{\omega}$  is the number of samples of class  $\omega$ . Details of this method can be found in Rennó et al. (1998)

The next step was the generation of the selected textural channels through the Texture Analysis. For a better control of the grey levels, the textural channels were processed with 32-bits. A cell of size  $7 \times 7$  pixels was selected in order to keep the GLCM sensitivity to the smallest details of the targets while reducing both noise effects and computation time. An unsupervised Isoclus classifier was used for the classification. The classifications were based on the best sets of texture measures for each polarisation isolated (hh, hv, and vv) and combined (hh and hv; hh and vv; hv and vv; hh, hv, and vv). In order to refine the results, a post-classification Mode filter algorithm was also applied.

The classification results were analysed through confusion matrix to estimate the amount of correctly and incorrectly classified pixels for each class. The method used to evaluate the accuracy classification with confusion matrix was the Kappa coefficient of agreement (Foody 1992) which was evaluated through test samples extracted from the Surficial Cover Map (see **Figure 2**). On each classified maps, 50 points were randomly allocated for two classes: hematite and no hematite. The test statistic used for evaluate the significant differences for two classifications is given by equation below. All tests for significant difference between results of classifications were carried out at 95 % confidence level. At this level, two results may considered significantly different if  $\Delta \hat{k} > 1.96$  (Benson & DeGloria, 1985).

$$\Delta \hat{k} = \frac{|\hat{k}_1 - \hat{k}_2|}{\sqrt{\hat{\sigma}_{\infty}^2 [\hat{k}_1] + \hat{\sigma}_{\infty}^2 [\hat{k}_2]}}$$

Where  $\hat{k}$  kappa and  $\hat{\sigma}_{\infty}^2 [\hat{k}]$  is the variance kappa.

As roughness is a very important target parameter that influences the performance of the textural classification, roughness measurements were also collected at 73 representative sites of the main classes. Surface roughness is generally difficult to measure accurately at the field, but the in situ measurements were considered a first approximation to categorise a natural crust surface as smooth, intermediate and rough. The height values from each unit were obtained, in RMS (root mean square) values, by inserting a thin plate into the surface, photographing it, and digitising the profile. The roughness classification was based on the criterion proposed by Peake and Oliver (1971). This kind of field information was fundamental to the understanding of the causes of the textural variations in the SAR data.

## 5. Results

**Table 2** shows, for each SAR configuration, the best selected textural measures used in the classifications, with the distances  $d$  (distance in pixels at considered direction for measures related to GLCM). The mean and GLDV contrast measures were sensitive for all data.

Table 2 - Best selected textural measures with the distances  $d$  for each SAR configuration used in the classification.

SAR data set	Measures	$d$
L-hh	Mean	-2,1
	Dissimilarity	1,2
	GLDV contrast	1,2
	GLDV energy	2,1
L-hv	Mean	1,2
	Contrast	-2,1
	GLDV Contrast	2,2
	Entropy	-2,2
L-vv	Mean	-1,2
	Entropy	-2,0
	Homogeneity	1,2
	GLDV contrast	-2,1

The set of selected measures was used as input for the unsupervised classification with hh, hv, vv - L bands and their combinations, hh and hv, hh and vv, hv and vv, hh, hv and vv. The best textural classification for L band is shown on **Figure 3** (hh and vv). The results indicate that not all classes were discriminated on SAR images when compared with the Surficial Cover Map (see **Figure 2**). The latosol, duricrust (chemical), iron ore duricrust, and lake were not classified. Although the soil (anthropogenic effects), duricrust, and hematite were relatively well classified, they presented confusion with another classes. For this reason, the statistical analysis was made between hematite and no hematite. These results are due:

- The soil (anthropogenic effects) presented a grassy cover that occurs on others areas, like the dry lakes and duricrust (chemical).
- The duricrust presents a high occurrence in the Surficial Cover Map and the occurrence of grassy in some areas with duricrust caused confusion with the soil.
- The iron ore duricrust exhibits stronger influence of the macro-topography on the east of plateau (**Figure 4**) given by bright returns and shadows (front/back slopes).
- The hematite, which is the most relevant class in economic context, has presented areas on the ground which were well classified.

The **Table 3** shows the kappa values for all classifications, where the classes duricrust and soil (anthropogenic effects) were grouped into no hematite and evaluated with hematite class. According this table, the classifications were successful and the hh polarisation was superior to vv and hv, and the cross polarization presented the worst result. The best result is the classification obtained from hh and vv data. The confusion matrix for this classification was obtained by test samples based on the points investigated in the field and it is shown on **Table 4**. The application of the Kappa ranking, as proposed by Landis and Koch (1977), indicates the following: (1) the best results (very good in the ranking) were obtained when the classifications were based on both polarisation under hh and vv, (2) the best classification with only one band occurred when using hh (bad in the ranking), and (3) the cross polarisation was considered the worst result on classifications.

According this results, textural L-band SAR attributes may not be totally sufficient to express the physico-chemical variations of laterites as expressed in Surficial Cover Map, except for hematite. It was possible to observe from these classifications that the textural features are sensitive to the sensor properties (frequency, polarisation, and illumination geometry). The influence from grassy caused strong returns on the vv data and it caused confusion with another classes.

**Thematic Map from lateritic cover - N1 (Carajás-PA)**  
Obtained from textural classification of L-band (HH and VV) data

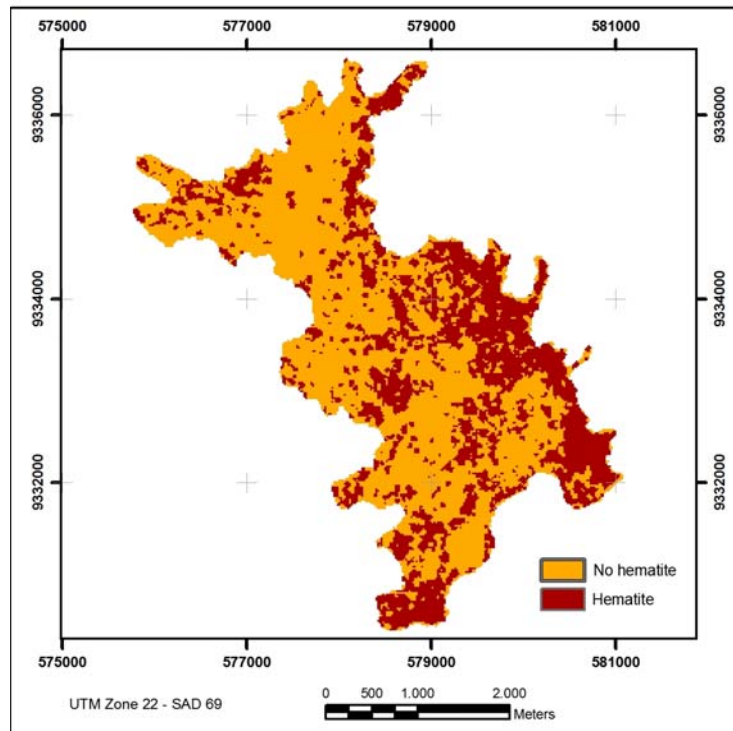


Figure 3 - Textural classification for the L (hh and vv) data.  
N1 (Carajás\_PA)  
Obtained from L-hh data.

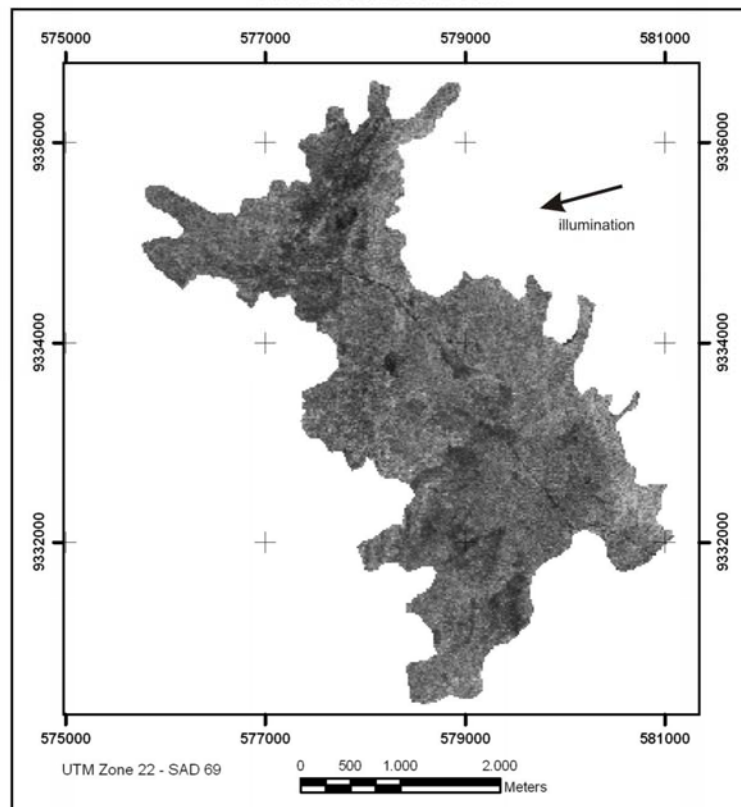


Figure 4 - N1 obtained from L-hh SAR.

Table 3 - Kappa Coefficients for the supervised classifications obtained by test samples from field.

Sar data	K (%)	Kappa variance (%)
L-hh-vv	0.720	0.009
L-hv-vv	0.560	0.011
L-hh-hv	0.450	0.013
L-hh-hv-vv	0.400	0.012
L-hh	0.372	0.013
L-vv	0.360	0.013
L-hv	0.320	0.016

Table 4 - Confusion Matrix for the classification based on textural attributes extracted from airborne SAR data (hh, hv, and vv). The rows present the results of the classification in percent and the columns are the truth obtained from random test samples.

Classified data	Reference data		
	No hematite	Hematite	Totals
No hematite	24	6	30
Hematite	1	19	20
Totals	25	25	50

In relation to surface roughness, the texture attributes were not sensitive to the variations at L-band. **Figure 5** shows the roughness classification for the lateritic units derived from 73 situ measurements, based on a scheme proposed by Peake and Oliver (1971), and **Figure 6** shows the roughness characteristics on N1 plateau. According to these results, the most classes were classified as intermediate and the duricrust (chemical) and soil (anthropogenic effects) were classified as smooth. As the plateau was located in the centre of swath, it shows a small variation of incident angles. As a consequence, the influence of the macro-topography, given by bright returns and shadows (front/back slopes) is most perceptible on the east of the plateau that presented medium slopes.

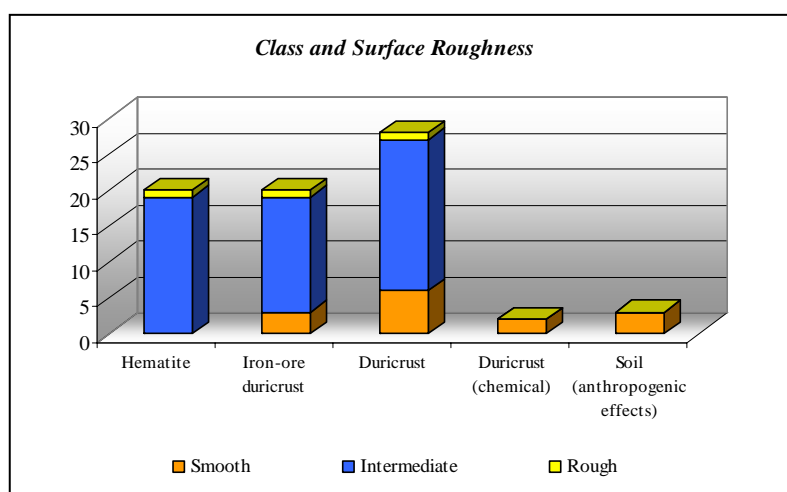


Figure 5 – Roughness classification for all classes.



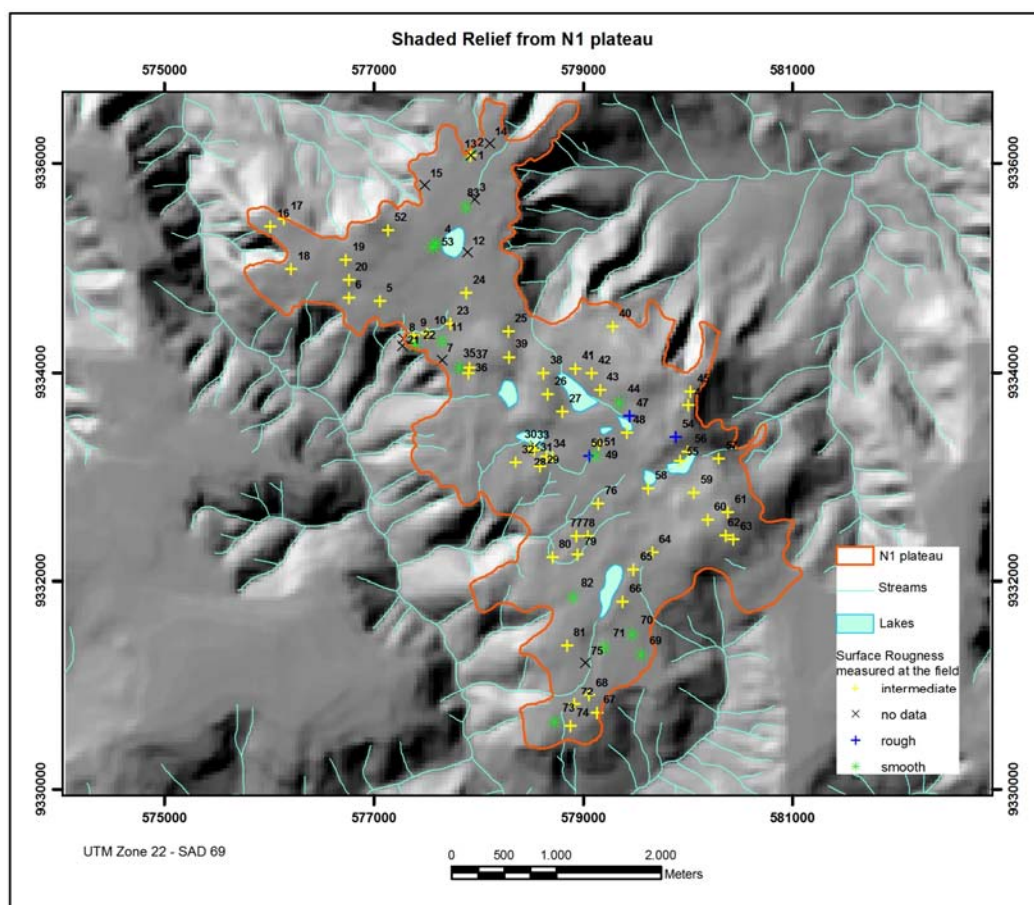


Figure 6 – Roughness characteristics on N1 plateau.

## 6. Conclusions

Textures derived from SAR L-band, especially hh and vv polarisations, derived from the second order measures (GLCM) can be used as a practical tool for a preliminary map as a guide for detailed mapping of iron mineralised laterites, like the hematite, in similar areas of the Amazon. The investigation has also shown that textural descriptors were sensitive to the (1) SAR polarisation, (2) SAR illumination geometry (look azimuth), and (3) target parameters (macro-topography). The surface roughness was poorly classified at L-band, the most of classes were classified as intermediate. Finally, an additional approach will deserve attention for future research in the Province is the use of polarimetric SAR data.

## 7. Acknowledgements

The authors wish to thank to Dr. Camilo D. Rennó (INPE) for the support with the Texture algorithm and kappa statistic. Special thanks to the INPE for the field support and to mining company CVRD (GAJAN), particularly to the senior-geologist Lambertus C. Schardt for the infrastructure in Carajás.

## References

Azzibrouck, G. A., Saint-Jean, R., and Prévost, C. 1997. Analyse de la texture d'une image RADARSAT pour la cartographie géologique dans la Forêt Équatoriale de Ngoutou, est du Gabon. In: **Proceedings** of Geomatics in the era of RADARSAT (GER'97), Ottawa Canada, CD-ROM.

Beisiegel, V. R., Bernadelli, A. L., Drummond, N. F., Ruff, A. W., and Tremaine, J. W. Geologia e Recursos Minerais da Serra dos Carajás. **Revista Brasileira de Geociências**, v.3, p.215-242, 1973.

Benson, A.S.; and DeGloria, S.D. Interpretation of Landsat-4 Thematic Mapper and Multispectral Scanner data for forest surveys. **Photogrammetric Engineering Remote Sensing**, v.51, p. 1281-1289, 1985.



Cordani, U. G., and Brito Neves, B. B. The geologic evolution of South America during the Archean and Early proterozoic. **Revista Brasileira de Geociências**, v.12, 78-88, 1982.

Dall'Agnol, R., Barros, C. E., Magalhães, M. S., Villas, R. N. N., Rios, F. J., Nogueira, A. C., Silva, C. M. G., Soares, A. D. V., Vieira, E. A. P., and Martins, L. P. B. Estudo petrológico da borda oeste do Granito Central e dos corpos máficos associados à Formação Águas Claras, **internal report**, CVRD-UFPA, 1994. Belém, Brazil.

Foody, G.M. On the compensation for change agreement in image classification accuracy assesment. **Photogrametric Engineering and Remote Sensing**, v.6 , p.1459-1460, 1992.

Frost, V. S., Shanmugan, K. S., and Holtzman, J. C. The influence of sensor and flight parameters on texture in radar images. **IEEE Transactions on Geoscience and Remote Sensing**, v. 22, p. 440-448, 1984.

Haralick, R. M. Statistical and structural approaches to texture. **IEEE Transactions on Geoscience and Remote Sensing**, v.67, p.786-804, 1979.

Hasui, Y., Haraly, N. L. E, and Schobbenhaus, C. E. **Geoscience and Remote Sensing**, v. 37, 680-689, 1984.

Landis, J. R., and Koch, G. G. The measures of observer agreement for categorical data. lementos geofísicos e geológicos da região Amazônica: subsídios para o modelo geotectônico. In: **Annals of the II Amazon Geological Symposium**, Manaus, Brazil DNPM/CNPq, Brasília, Brazil, v.2, pp.129-141, 1977.

Kurvonen, L. and. Hallikainen, M, T. Textural information of multitemporal ERS-1 and JERS images with applications to land and forest type classification in boreal zone. **IEEE Transations on Biometrics**, v.33, p.159-174, 1999.

Meireles, E. M., Hirata, W. K., Amaral, A. F., Medeiros Filho C. A., and Gato, W. C. Geologia das folhas Carajás e Rio Verde, Província Mineral dos Carajás, Estado do Pará. In: **Annals of the XXXIII Brazilian Congress of Geology**, Rio de Janeiro, Brazil. Sociedade Brasileira de Geologia. p. 2164-2174, 1984.

Morais, M. C. **Discriminação de lateritas mineralizadas em ferro no Depósito N1 (Carajás-PA) por radar imageador: uma avaliação através de classificação textural**. 1998. 190p. (MSc. in Remote Sensing) - National Institute for Space Research, São José dos Campos, Brazil.

Morais, M. C. de; Paradella, w. R.; Freitas, C. C. An assessment of the discrimination of iron-mineralised laterites in the Amazon region (Carajás Province) based on textural attributes from C-band airborne SAR data. **Asian Journal of Geoinformatics**, v.2, n.3, p. 11-20, 2002.

Paradella, W. R., Silva, M. F. F., Rosa, N. A., and Kushigbor, C. A. A geobotanical approach to the tropical rain forest environment of the Carajás Mineral Province (Amazon Region, Brazil), based on digital TM-Landsat and DEM data. **International Journal of Remote Sensing**, v. 15, p.1633-1648, 1994.

Paradella, W. R., Bignelli, P. A, Veneziani, P., Pietsch, R. W., and Toutin, T. Airborne and spaceborne Synthetic Aperture Radar (SAR) integration with Landsat TM and gamma ray spectrometry for geological mapping in a tropical rainforest environment, the Carajás Mineral Province, Brazil. **International Journal of Remote Sensing**, v.18, p.1483-1501, 1997.

Paradella, W. R., Santos A. R., Veneziani, P., Sant'Anna, M. V., and Morais, M. C. Geological investigation using RADARSAT-1 images in the tropical rainforest environment of Brazil. **Canadian Journal of Remote Sensing**, v. 26, p.1483-1501, 2000.

Peake, W. M., and Oliver, T. L. The response of terrestrial surfaces at microwave frequencies. **Technical Report**, Columbus, Ohio, p. 2440-2447, 1971.

Rennó, C. D., Freitas, C. C., and Sant'Anna, S. J. S., 1998. A system for region classification based on textural measures. In: **Annals of the IX Brazilian Remote Sensing Symposium**, Santos, Brazil (INPE, CD –ROM).

Resende, N. P., and Barbosa, A. L. de M. Relatório de Pesquisa de Minério de Ferro, Distrito Ferrífero da Serra dos Carajás, Estado do Pará. **Final report, AMZA**, Belém, Brazil, 1972.

Shanmugan, K. S., Narayanan, V., Frost, V. S., Stiles, J. A, and Holtzman, J. C. Textural features for radar images. **IEEE Transactions on Geoscience and Remote Sensing**, v.19, p.153-156, 1981.

SILVA, M.F.F. da; SECCO, R.S. & LOBO, M.G.A. Aspectos Ecológicos da Vegetação Rupestre da Serra dos Carajás (PA). **Acta Amazônica**, v. 26, n.1/2, p. 17-44, 1996.

Ulaby, F. T., Kouyate, F., Brisco, B. and Lee Williams, T. H., 1986. Textural information in SAR images. **IEEE Transactions on Geoscience and Remote Sensing**, v. 24, n. 2, 235-245.

Welch, R. M., Kuo, S. S., Sengupta S. K., 1990. Cloud and surface textural features in polar region. **IEEE Transactions on Geoscience and Remote Sensing**, 28, 520-528.

Weska, J. S., Dyer, C. R., Rosenfeld A. A comparative study of texture measures for terrain classification. **IEEE Transactions on Systems, Man and Cybernetics**, v.6, n.4, p. 269-285, 1976.

Wooding, M. G., Zmuda, A. D., Attema, E. An overview of SAREX'92 data acquisition and analysis of the tropical forest environment. In: **Proceedings** of the SAREX-92 (South American Radar Experiment) Workshop, 6-8 december, Paris, France, p. 3-14 (ESA WPP-76), 1993..

Yanasse, C.C.F., Frery, A. C., Sant`Anna, S. J. S., Filho, P.H., Dutra, L.V., Statistical analysis of SAREX data over Tapajós – Brazil. In: **Proceedings** of the SAREX-92 South American Radar Experiment) Workshop, 6-8 december, Paris, France, p. 25-40 (ESA WPP-76), 1993.