RADARSAT-1 applied to the mapping of tropical rain forest: a case study in Guyana

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Abstract

The potential of RADARSAT-1 Fine mode images for application to the assessment of tropical forest types and the monitoring of industrial selective logging were investigated using data acquired over Mabura Hill, Guyana. This study area supports a nearly complete tropical moist forest cover that comprises a total of six forest types, i.e. five types of primary forest and logged-over forest. Image texture, not backscatter, was identified as the principal source of information for the applications at issue. Texturally enhanced RADARSAT-1 Fine mode image products were found to offer moderate potential for both the assessment of tropical forest types and the monitoring of selective logging by means of visual interpretation. Furthermore, RADARSAT-1 Fine mode images were found to make moderate bases for automated classification of tropical forests by means of textural attributes computed per region.

1.0 Introduction

Tropical rain forests are well known to play prominent roles in global cycles, to have an exceptional biodiversity and to offer great economic potential in the form of timber and other products. Nevertheless, mankind continues to demolish this important natural resource on a large scale and at high speed. The need for programs and procedures aimed at sustainable tropical forest management is widely acknowledged but the development of such programs and procedures is hindered by a lack of accurate and up to date information on the forest's state, extent and rate of change. As a rule, the collection of information on tropical rain forests is complicated by their enormous extent, limited accessibility, intricate constitution, and dynamic nature. Remote sensing systems have the capability to collect information in a systematic, synoptic and repetitive manner and thus make potentially outstanding tools to support tropical forest management. Due to the prevalence of clouds and smoke in the atmosphere, radar remote systems make more reliable tools for application in tropical environments than optical remote sensing systems.

This paper discusses the findings of a study into the potential of RADARSAT-1 Fine mode data for application to the assessment of tropical forest types and the monitoring of industrial selective logging. Analysis of data from airborne experiments has shown that texture, not backscatter, is the most important source of information for the mapping of tropical forests in high frequency (e.g. C-band) and high resolution radar images (van der Sanden and Hoekman, 1999). Thus the study reported here focussed on the evaluation of the textural information as contained in RADARSAT-1 images. According to Haralick and

Bryant (1976) image texture may be defined as 'the pattern of spatial distributions of grey-tone'. Texture in radar images results primarily from radar "layover", "shadowing" and "foreshortening" effects. However, these effects occur only when the object imaged comprises structural elements with sizes greater than or equal to the size of the resolution cell. Texture in radar images of forested areas (on flat terrain) is a function of the forest's canopy architecture in general and canopy roughness in particular.

At present, the Canadian RADARSAT-1 satellite provides the highest resolution commercially available space borne radar data. Others have reported on the use of RADARSAT-1 Fine mode data for the assessment of land cover in tropical forests environments (e.g. Amaral et al., 1997; Malcolm et. al., 1998; Shimabukuro et al., 1998; Toutin and Amaral, 2000). However, few researchers have attempted to apply the data for mapping at a level as detailed as in this study, i.e. the forest type level.

2.0 Study Area

The studied forests are located near the township of Mabura Hill in the Republic of Guyana (see Figure 1). Based on mean annual precipitation, mean annual biotemperature and altitude above sea level, Holdridge et al. (1971) would categorize these forests as "Tropical Moist Forests". Mean annual biotemperature is defined as the mean of unit-period temperatures with the substitution of zero for all unit-period values below 0°C and above 30°C. The study area is part of the Demerara Timbers Ltd. (DTL) logging concession and includes an untouched forest reserve that has been handed over to the Dutch Tropenbos Foundation for research (Tropenbos, 1991). The general topography of the area is gently undulating with relief intensity less than 50 m.

Table 1: Structural characteristics of primary forest types studied

The study area comprises a total of six forest types, that is, five types of primary forest and logged-over forest. According to Fanshawe (1952) the primary forests found in the Mabura Hill area are also well represented in Venezuela (State of Guyana), Trinidad, Surinam, French Guiana and Brazil (States of Para and Amazonas). Table 1 lists the encountered primary forest types found together with a selection of their structural characteristics. The distribution of these forest types is governed by soil properties such as drainage and nutrient content. Mixed forest typically predominates on sites with favourable growing conditions. Wallaba forest and Xeric mixed forest occur on sites with a consistent soil water deficit, whereas Low swamp forest and Mora forest are found on seasonally waterlogged or inundated soils.

			Main canopy		Emergent trees	
Cover type	Number of trees ha^{-1}	Above ground dry biomass ($t\ ha^{-1}$)	Total height (m)	Crown diameter (m)	Total height (m)	Crown diameter (m)
Mixed	3350 1)	645	25 - 35	10 - 15	40 - 50	15 - 20
Wallaba	5675 1)	460	25 - 30	10 - 15	—	—
Xeric mixed	5050 1)	240	15 - 20	5 - 10	25 - 30	10 - 15
Low swamp	n.a.	n.a.	10 - 20	n.a.	—	—
Mora	2885 1)	575	30 - 40	10 - 15	40 - 60	20 - 30

1) Excluding trees with a diameter at breast height ≤ 2 cm.

Table 1: Structural characteristics of primary forest types studied

Logged-over forests are forests that have been subject to industrial *selective* logging, not clear-cut. According to DTL's management plan felling is restricted to trees with a diameter at breast height of ≥38 cm and carried out with an intensity of circa 20 $m^3 ha^{-1}$ (≈8 trees ha^{-1}, ≈22 t ha^{-1} total dry biomass above the ground). The average size of the resulting canopy openings is approximately 800 m^2 (Hammond and Brown, 1992). Like in other parts of Guyana, logging is concentrated in Mixed forests dominated by Greenheart (*Chlorocardium rodiei*).

3.0 Radar Data

The Canadian RADARSAT-1 satellite acquired the radar studied on 21 February 1997 and 3 October 2000 at approximately 5.30 a.m. local solar time (descending overpasses). The Synthetic Aperture Radar (SAR) onboard of RADARSAT-1 operates in a single frequency and polarization (C-band HH) but offers a range of user-selectable beam modes and beam positions. Beam modes are defined by spatial coverage and spatial resolution while the incidence angle range defines beam positions. The 1997 and 2000 data for Mabura Hill were acquired in the high-resolution Fine beam mode (ground resolution 8.4 by 8.4 m, spatial coverage 50 by 50 km) at incidence angles ranging from 42.2° to 44.1° and 41.5° to 43.4°, respectively. The raw SAR signal data were processed in-house to absolutely calibrated, ground range image products with a pixel spacing of 3.125 by 3.125 m.

4.0 Analysis approach

The study adopted two complementary approaches that may be denoted as Gross Textural Analysis (GTA) and Moving Window Analysis (MWA). GTA is intended to quantify the texture for predefined image regions while MWA is meant to do so for a relatively small spatial window around each image pixel. In this study GTA was used as a precursor for MWA. The goals of GTA were the following. First, to establish whether or not the forest types studied had different textural properties. Second, to determine the optimal settings for MWA. GTA and MWA were applied to 8 bits image products with pixel values ranging from 0 to 127. These products were generated through the rescaling of 32 bits logarithmically scaled RADARSAT-1 intensity images, i.e. images with pixel values representing backscattered power in decibels (dB). Logarithmically scaled intensity images were chosen as a starting point for textural analysis to account for the effect of radar speckle. Only in this particular type of image, the total grey level variance is a function of a *fixed* speckle variance and a variable texture variance (Hoekman, 1991; van der Sanden, 1997). Hence, textural descriptors derived from these images are effectively unaffected by speckle induced grey level variations.

GTA was preceded by the definition of image regions representing the forest types studied. These regions were located on maps and black-and-white aerial photographs and subsequently digitised on the screen of an image processing system. The number of regions defined for Xeric mixed forest equalled seven. For each of the other forest types 10 image regions were identified. GTA was restricted to the image acquired on 3 October 2000. MWA was applied to both of the RADARSAT-1 images available.

The textural descriptors employed were computed according to the grey level co-occurrence (GLCO) technique (e.g. Haralick et al., 1973). This technique proved to be effective in earlier studies (e.g. Weszka et al., 1976; Conners and Harlow, 1980; Kushwaha et al., 1994; van der Sanden and Hoekman, 1999). For each region of interest a series of ten GLCO matrices corresponding to displacement lengths ranging from 1 to 15 pixels was computed. Displacement was first in range and then in azimuth, so the matrices comprised the summed entries of displacement in both these directions. Subsequently, the GLCO-Contrast and GLCO-Correlation statistics were calculated from each of the matrices. Hence, the total number of textural attributes extracted per region equalled 30. Previous analysis of airborne radar images had shown GLCO-Contrast and GLCO-Correlation to be the preferred GLCO statistics for tropical forest type discrimination (van der Sanden and Hoekman, 1999).

The potential of the extracted textural attributes to classify the forest types was evaluated with the help of a class separability measure known as pairwise transformed divergence (TD_{ij}). Two classes were considered separable if the TD_{ij} value was equal to or greater than 1900. A TD_{ij} value of 1900 can be shown to correspond to a lower bound for the likelihood of correct classification of close to 78%. Attributes that offered good classification potential were then used in Gaussian maximum-likelihood classifications. Successive evaluation of the results by means of contingency tables and the KHAT or Kappa statistic ($\hat{K}$) allowed for a direct assessment of the classification capacity of the attributes in question (cf. Lillesand and Kiefer, 1994). Since the aim was to assess relative rather than absolute classification capacities, the same data set could be used both for the design of the classifier and the evaluation of the classification results.

The test statistic for significant difference between two classification results is given by:

$$\Delta\hat{K} = \frac{\left|\hat{K}_1 - \hat{K}_2\right|}{\sqrt{\hat{\sigma}_\infty^2\left[\hat{K}_1\right] + \hat{\sigma}_\infty^2\left[\hat{K}_2\right]}} \qquad (1)$$

where $\hat{\sigma}_\infty^2\left[\hat{K}\right]$ is the approximate large sample variance of $\hat{K}$. In the present study all tests for significant difference between results of classifications were carried out at the 95% confidence level. At this level of confidence, two results may be considered significantly different if $\Delta\hat{K} > 1.96$ (Benson and DeGloria, 1985).

5.0 Results and discussion

5.1 Potential for the assessment of forest types

Results of GTA show that best and worst performing GLCO attributes successfully discriminate seven and zero out of the 15 forest class pairs, respectively. As the displacement length increases from 1 to 15 pixels, the performance of GLCO-Contrast and GLCO-Correlation, respectively, improve and worsen at the onset and then stabilize. For reasons of comparison, the performance of regionally averaged values for the mean radar cross-section per unit projected area (gamma, $\bar{\gamma}$) was assessed too. Like the worst performing GLCO attributes this radiometric attribute did not facilitate the discrimination of any class pairs.

The discriminating capacities associated with $\bar{\gamma}$, GLCO-COR[1] (GLCO-Correlation, displacement length 1 pixel), and GLCO-CONT[11] (GLCO-Contrast, displacement length 11 pixels) are illustrated in Figure 2. The probability density functions (pdf's) for GLCO-COR[1] and GLCO-CONT[11] reflect the canopy architecture of the different forest cover types well. Forests with large emergent trees (cf. Table 1), and, hence rough upper canopies, are found to the right in Figures 2b and 2c. In contrast, forests with relatively smooth upper canopies are situated to the left. Selective logging results in enhanced canopy roughness. Consequently, the pdf's for Logged-over forest are located to the right of those for Mixed forest, i.e. the forest type being logged. In van der Sanden (1997) it is shown that plots of GLCO-COR and GLCO-CONT as a function of displacement length do allow for more detailed observations with regards to canopy architecture. For example, the average size of the canopy openings resulting from selective logging was derived from such plots.

Compared to the pdf's for $\bar{\gamma}$, the pdf's for GLCO-COR[1] and GLCO-CONT[11] have considerably less overlap. The two textural attributes can therefore be expected to make better bases than $\bar{\gamma}$ for region-based classification of the forest cover types studied. This is confirmed by the Gaussian maximum-likelihood classification results presented in Table 2. At the 95% confidence level the classification results for both GLCO-COR[1] and GLCO-CONT[11] prove to be significantly better than those for $\bar{\gamma}$. Yet, the difference in the overall classification results for GLCO-COR[1] and GLCO-CONT[11] is not significant. The overall results of the classifications based on GLCO attributes may be denoted moderate as some 50 to 60% of the data points are classified correctly. For comparison, the maximum total percentage correct resulting from classification of GLCO-COR and GLCO-CONT attributes computed from airborne C-band HH data and space borne ERS-1 C-band VV Precision data

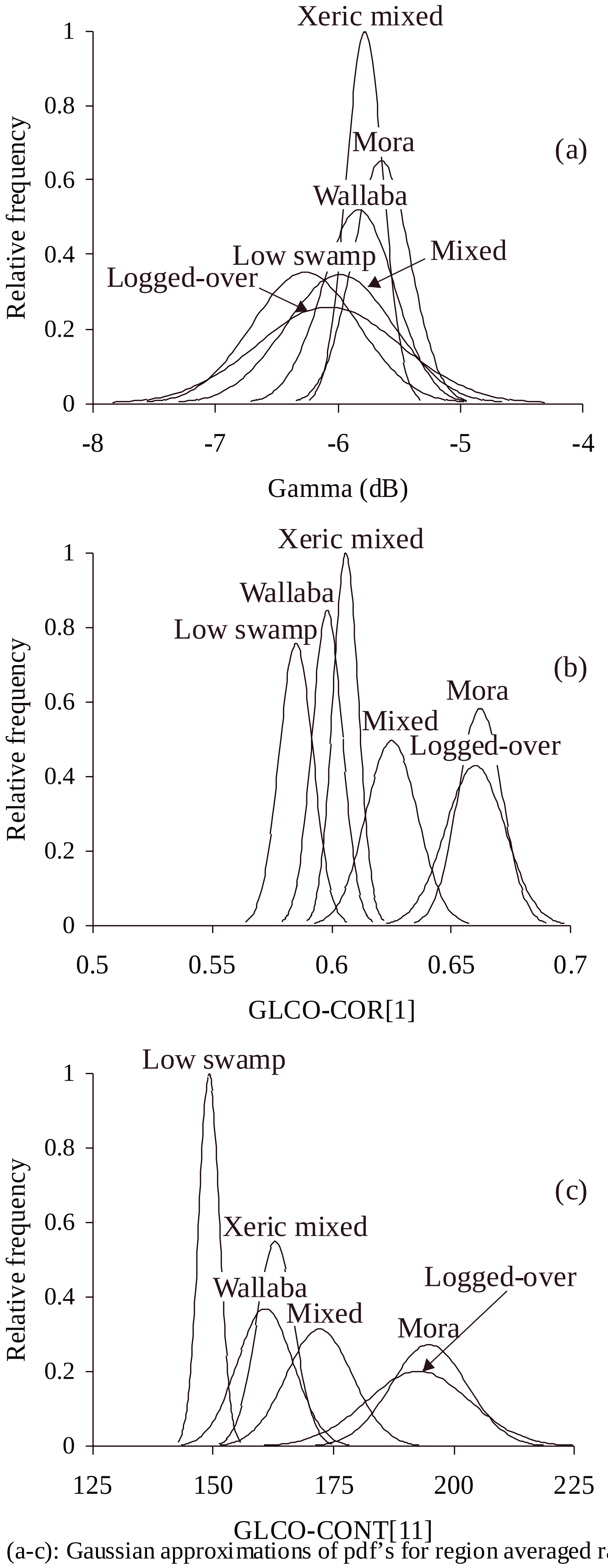


Figure 2 (a-c): Gaussian approximations of pdf's for region averaged radiometric and textural attributes associated with the forest types studied: (a) pdf's for $\bar{\gamma}$; (b) pdf's for GLCO-COR[1]; (c) pdf's for GLCO-CONT[11]

was 84% and 42%, respectively (van der Sanden, 1997; van der Sanden and Hoekman, 1999). The GLCO attributes fail to uniquely describe the texture of Logged-over forest, in particular. In the classifications, Logged-over forest is primarily confused with Mora forest and to a lesser extent with Mixed forest, i.e. the forest type being logged. Two other frequently confused classes are Xeric mixed forest and Wallaba forest. The classification results for Logged-over forest and Mora forest can be improved through application of a time series of radar images (see section 4.2).

			Percentage correct						
	$\hat{K}$	$\hat{\sigma}_{\infty}^{2}[\hat{K}]$	Total	Mixed	Wallaba	Xeric mixed	Low swamp	Mora	Logged-over forest
$\bar{\gamma}$	0.1893	0.0035	32	0	0	71	70	60	0
GLCO-COR[1]	0.5593	0.0057	63	90	50	71	80	60	30
GLCO-CONT[11]	0.4535	0.0057	54	70	20	57	100	70	10

Table 2: Gaussian maximum-likelihood classification results. Classification based on $\bar{\gamma}$ values and textural attributes computed per region from RADARSAT-1 Fine mode image acquired on 3 October 2000.

In practice, analysis of image texture by means of predefined image regions is only feasible if the required boundary information is available in geographically referenced databases or can be generated with the help of automated image segmentation techniques. In absence of boundaries, analysis of texture by means of a moving spatial window is the only alternative. Figure 3 shows an image product resulting from a Red-Green-Blue (RGB) colour space transformation applied to a subset of the 2000 RADARSAT-1 image, the corresponding its GLCO-CONT[11] textural transform and a grey channel with digital values equal to 127. The window size used to generate the textural transform was 55 by 55 pixels. Image regions marked by squares demonstrate the appearance of forest types studied. Blue, green/yellow and red colours correspond to low, intermediate and high GLCO-CONT[11] values, respectively.

The value of GLCO-CONT[11] increases with an increase in canopy roughness. Therefore, blue colours predominate in areas covered by forests with a relatively low degree of canopy roughness, e.g. in areas covered by Low swamp, Wallaba and Xeric mixed forest. For similar reasons, red colours prevail in areas of Logged-over and Mora forest, whereas green/yellow colours are preponderant in Mixed forest areas. The forest patterns shown in Figure 3 are in good agreement with those shown in available maps. However, certain forest types cannot be uniquely identified without additional information, e.g. Wallaba and Low swamp forest, and Logged-over and Mora forest. Hence, it is concluded that texturally processed RADARSAT-1 Fine mode images offer moderate potential for the mapping of tropical primary forest types by means of visual interpretation. GLCO statistics resulting from MWA will generally provide poorer bases for automated classification than those resulting from GTA. In the MWA approach the attributes are computed from considerably less pixel pair realisations than in the GTA approach. Consequently, MWA attributes are less capable of capturing the essence of texture in question and more susceptible to textural anomalies.

5.2 Potential for the monitoring of industrial selective logging

In section 4.1 it was shown that the texture of Logged-over forest resembles that of Mora forest but is differs from the textures of all other forest types. Yet, the risk of confusion between Logged-over forest and Mora forest in a single date RADARSAT-1 image does not obstruct the potential of RADARSAT-1 the monitoring of logging activities. A time series of RADARSAT-1 fine mode images will support the explicit identification of new logging areas since forest types do not change from one year to another and logging is concentrated in forest types other than Mora forest. Consequently, a forest area with the textural appearance of, for example, Mixed forest in year one and with the textural appearance of Logged-over or Mora forest in the year following must have been subject to selective logging. Furthermore, the discrimination of Logged-over and Mora forest is greatly facilitated by the use of contextual information. Logged-over forests generally occur as patches and are always found in the vicinity of logging roads. The riparian Mora forests, on the other hand, are elongated and always found in connection with streams. As a rule, both roads and the locations of streams are clearly visible in Fine mode RADARSAT-1 images.

The potential of RADARSAT-1 Fine mode data to support the monitoring of selective logging is illustrated in Figure 4. Figure 4a and 4b show texturally enhanced colour composites produced from corresponding subsets of the RADARSAT-1 images acquired on

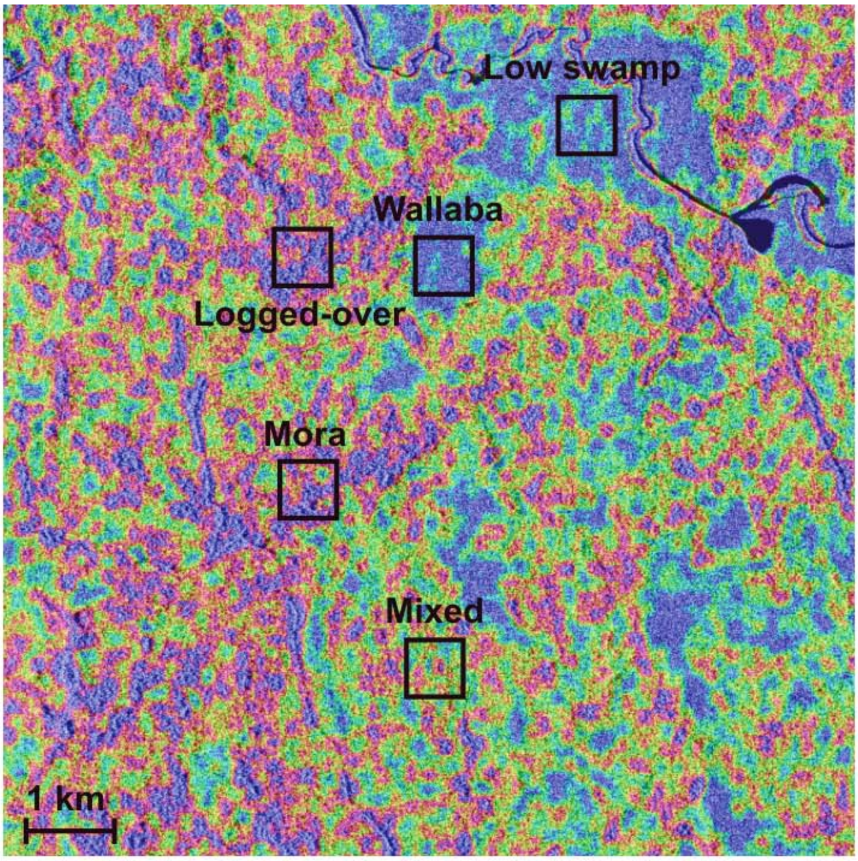
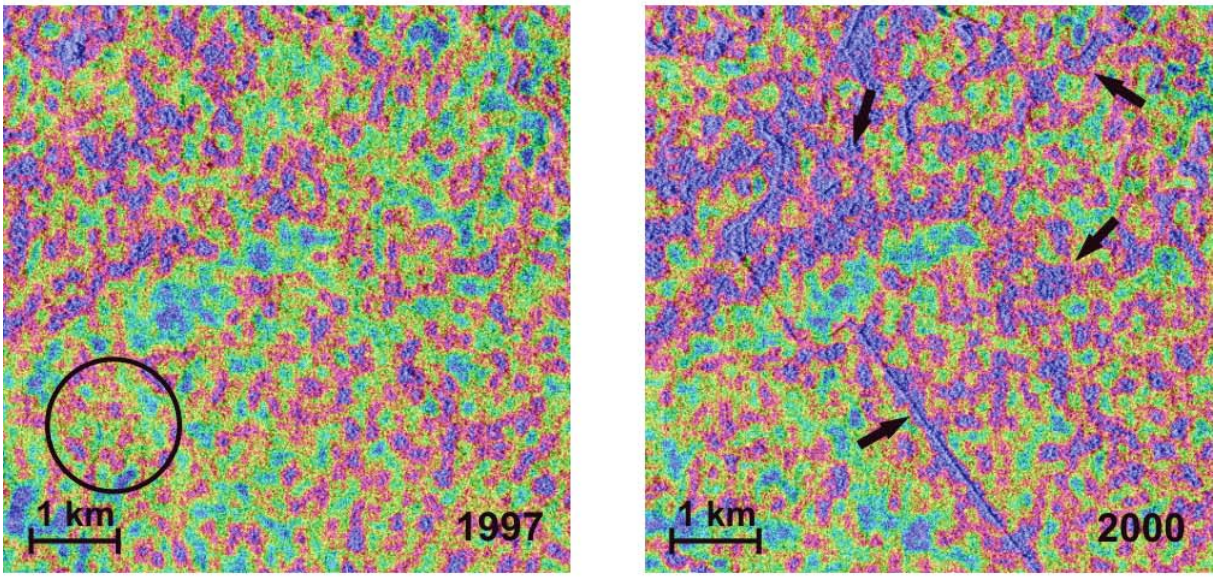


Figure 3: Texturally enhanced composite image resulting from an RGB colour space transformation applied to: the 2000 RADARSAT-1 Fine mode image, its GLCO-CONT[11] textural transform (window of 55 by 55 pixels), and a grey channel comprised of pixels with values equal to 127



(a) (b)

Figure 4 (a-b): Texturally enhanced composite images illustrating the potential of RADARSAT-1 Fine mode images for the monitoring of industrial selective logging: (a) image generated using RADARSAT-1 data acquired on 21 February 1997; (b) image generated using RADARSAT-1 data acquired on 3 October 2000. The circle identifies an area of intact Mixed forest while the arrows mark evidence of logging .

21 February 1997 and 3 October 2000, respectively. In both cases, the texture transform was computed using the GLCO-CONT[11] statistic and a window size of 55 by 55 pixels. The arrows in Figure 4b mark evidence of selective logging. The 2000 image clearly shows the new logging roads. Moreover, the proportion of red colours in the 2000 image is larger than in the 1997 image. This increase in red tones can be contributed to an increase in canopy roughness resulting from openings created during logging. The high concentration of red tones in the top left quarter of Figure 4a suggests that logging begun prior to February 21st of 1997. It should be noted, however, that canopy openings are not restricted to Logged-over forest butare also found in intact forest canopies (see circle in Figure 4a). This could lead to confusion between intact and Logged-over forest. Although natural gaps usually exhibit a lower density and are smaller in size than the man-made logging gaps. Field measurements by Hammond and Brown (1992) confirm this for Mabura Hill. The authors report over 50 % more gaps in Logged-over forest than in intact forest and a logging and natural gap size of ca. 800 ± 200 m^2 and 100 ± 20 m^2, respectively. Moreover, natural gaps tend to lack the, for logging gaps typical, clustered and systematic occurrence in the vicinity of roads.

Because of the large data volumes involved, monitoring of selective logging in an operational environment will require the use of automated change detection techniques. Simple differencing or ratioing of images generated by means of moving window textural processing will facilitate the detection of areas with change in terms of image texture, i.e. areas that may have been subject to logging. Techniques for automated detection and extraction of roads from SAR images have been published by e.g. Touzi et al. (1988), Adair and Guindon (1990), and Samadani and Vesecky (1990). Touzi and Sasitiwarih (2001) discuss the optimum imaging geometry for the mapping of roads in a tropical forest environment by means of RADARSAT-1. In general, the detection of roads requires much less knowledge of local conditions and logging practices than the detection of logging gaps. Nonetheless, roads are very distinctive indicators of foregoing and/or forthcoming (selective) logging and other human activities.

6.0 Conclusions

Texturally enhanced RADARSAT-1 Fine mode image products were shown to offer moderate potential for both the assessment of tropical forest types and the monitoring of selective logging by means of visual interpretation. Furthermore, RADARSAT-1 Fine mode images were found to make moderate bases for automated classification of tropical forests by means of textural attributes computed per region. In practice, however, the applicability of this automated approach will often be hampered by the fact that it requires *a priori* information on forest type boundaries. Theoretically this information could be obtained through automated segmentation of remotely sensed images. However, the computerised definition of tropical forest regions is likely to be problematic since these forests are far from homogeneous and rarely have clear boundaries. The future RADARSAT-2 satellite (> 2003) will have the capability to operate in an Ultra-Fine imaging mode (ground resolution 3 by 3 m). The resultant images can be expected to contain more textural information and hence offer increased potential for the applications discussed. From operational point of view, however, it is unfortunate that the swath with associated with this new data type is limited to 20 km.

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