ERS-1 OBSERVATIONS AND POTENTIAL FOR USE IN TROPICAL FOREST MONITORING

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SHEFFIELD CENTRE FOR EARTH OBSERVATION SCIENCE

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1 INTRODUCTION

In the last few decades the Brazilian Tropical Forest has presented intense dynamic alterations, resulting from human disturbance due to the installation of farms for agriculture and cattle raising, and to the implantation of several settlement projects. Many of these areas have been abandoned for several reasons, and their vegetation cover is presently under regeneration by secondary succession. Not much is known about the extent of disturbance to the primary forest or the regeneration of these areas. The study of the stages of secondary forests is justified by the impact that these areas have in the regional carbon budget which, in turn, may have consequences on the global climate change and in the carbon storage in the atmosphere. Satellite imagery can be a powerful tool in the identification of deforested areas, and this study concerns the role of ERS-1 in this task, as an ancillary or substitute sensor to Landsat TM.

This general aim of the study has the following particular components:

- (1) To illustrate the role of models in understanding radar backscatter from tropical forests, and to use them to investigate:
 - The significance of meteorological parameters at acquisition time;
 - The conditions necessary to discriminate forest from non-forest;
 - The information sources actually and potentially present within the imagery and their physical interpretation.
- (2) To define and assess processing techniques for automatic forest/non-forest discrimination and change detection;
- (3) To compare the suitability of different sensors (ERS-1, Landsat TM and SAREX) for discriminating land cover types;
- (4) To investigate the relationship between secondary forest regeneration age and the backscatter observed using ERS-1, using a forest age map derived automatically from a time series of Landsat TM images;
- (5) To define procedures needed in an operational forest monitoring system using spaceborne radar.

2 TEST SITE AND DATA DESCRIPTION

2.1 Test Site

The area of interest for this study is the Tapajos National Forest (FLONA Tapajos), on the bank of the River Tapajos, at approximately 3° South and 55° West. The joint INPE/SCEOS project concerning remote sensing of tropical forest has concentrated on the Tapajos test site, which was chosen by the Brazilian collaborators for its accessibility and its wealth of cleared and regenerating plots of land alongside the protected FLONA Tapajos. INPE personnel also had previous ground data and knowledge from this area.

Geologically FLONA Tapajos lies on Cenozoic sediments of the *Barrieras Formation* and some smaller areas of Amazon Planalto (Belterra Clay). It has an average annual temperature of 26°C

and an average precipitation of 1600–2000 mm per year. Following the UNESCO classification of 1980 [18] FLONA Tapajos and its surrounding area belong to a seasonal forest type, as a foliage reduction is noticeable during the dry season, which occurs between June and October. FLONA Tapajos consists of a high and dense forest type, mainly consisting of broadleaf evergreen trees. The height of the main canopy varies between 15 and 25 m; emergent trees of 35–40 m are also present. There is very little relief in this area, although an escarpment runs through the forest, separating the lower lying river-level forest, and the ‘Terra Firme’ forest on the Amazonian plateau. The canopy closure is almost complete in areas of primary forest and the undergrowth is sparse due to the ensuing light reduction. In certain areas (often indicative of human activity) babacu palm forms an important part of the vegetation. Further information can be found in the 1987 ESA/INPE Amazonian fieldwork report [19].

2.2 ERS-1 PRI data

The primary data source for this study is a multi-temporal sequence of ERS-1 PRI images of the Tapajos region. Images from the 35-day repeat cycle are used as they are of nearly identical geometry and thus remove the problems encountered in registering multi-temporal satellite imagery. Imagery from three dates (22/05/92, 31/07/92 and 18/12/92) is examined; eight frames acquired in 1993 of similar geometry (from the 35 day repeat cycle) are also on order with ESA. The complete ERS-1 dataset from the Tapajos region that is currently available at SCEOS/INPE is summarised in Table 1 :

Date	Orbit	Frame	Track	Media	PAF	Coverage	Pass
01/05/92	4141	7119	489	Exabyte	D	Good	A
	4141	7137	489	Exabyte	D	Good	A
22/05/92	4449	3663	296	Exabyte	D	V.Good	D
	4449	3681	296	Exabyte	D	V.Good	D
05/06/92	4642	7119	489	Exabyte	D	Good	A
	4642	7137	489	Exabyte	D	Good	A
31/07/92	5451	3663	296	Exabyte	D	V.Good	D
	5451	3681	296	Exabyte	D	V.Good	D
29/11/92	7183	3663	24	CCT	D	V.Poor	D
	7183	3681	24	CCT	D	V.Poor	D
02/12/92	7226	3663	67	CCT	D	V.Poor	D
	7226	3681	67	CCT	D	V.Poor	D
16/12/92	7419	7119	240	Exabyte	D	Poor	A
	7419	7137	240	Exabyte	D	Poor	A
18/12/92	7455	3663	296	CCT	D	V.Good	D
	7455	3681	296	CCT	D	V.Good	D
14/03/93	8686	3663	24	CCT	D	V.Poor	D
	8686	3681	24	CCT	D	V.Poor	D
26/05/93	9731	3663	67	CCT	D	V.Poor	D
	9731	3681	67	CCT	D	V.Poor	D

Table 1. Summary of available ERS-1 SAR PRI data over Tapajos

The dates, orbits and frame numbers are all self explanatory, as is the medium on which the raw data is stored. The track number refers to the subsatellite track. Some of the images have the same track number since the image acquisition dates are a multiple of 35 days apart. All the images from Tapajos have come from the German Processing and Archiving Facility (D-PAF). The coverage refers to the amount of the FLONA Tapajos that is covered by the imagery and the pass refers to the orbit direction, ascending (A) or descending (D). The three images used in this

study have been calibrated, using the information included in the image headers (which can be extracted using ESA's RCEOS program), and the method outlined in [10].

2.3 Landsat Thematic Mapper Data

A time series of relatively cloud-free Landsat TM images of Tapajos has also been acquired, one from each year between 1986 and 1992. The most recent image is used to support the work in Section 3; the full series of images is used in Section 5. Due to the cloud cover at the Tapajos test site all the images acquired subsequently have been of no use (which emphasises why the cloud cover penetration of the ERS-1 SAR makes it a potentially valuable data source for use in tropical forest monitoring).

2.4 Results of field campaign, August/September 1994

Visual interpretation of the TM data and observations of areas showing dynamic behaviour in the ERS-1 multi-temporal imagery were used to guide fieldwork undertaken in the Tapajos region in August 1994 [5], in collaboration with INPE and the UK Remote Sensing Applications Development Unit (RSADU). This involved an extensive land use survey, primarily to enable INPE to produce a ground data map for use in this and future work using remotely sensed data from the Tapajos region. Areas showing change in ERS-1 and areas of primary and regenerating forest (of various ages) were visited. At each plot the following measurements were taken :

- Common names of between three and seven of the most prevalent species at the plot ;
- Weights of a small amount of leaf material and stem material from one tree of each of the species ;
- Leaf thicknesses of five leaves picked at random from each species (thickness was measured twice, on either side of the main 'stem' of the leaf) ;
- Leaf dimensions, major and minor axes of five leaves picked at random from each species (the leaves were predominantly oval in shape).

After drying, the leaves and stems were weighed again. This enables leaf and stem moisture content to be calculated. This can be related to dielectric moisture content, which along with the leaf thickness and area measurements could then be used as parameters in backscatter modelling.

2.5 SAREX-92 Airborne data

The Tapajos test site was imaged during the SAREX-92 (South American Radar EXperiment) campaign. This data is examined, and compared to the lower resolution satellite imagery. The Tapajos test site was denoted BRA1; data was collected using the Canadian Centre for Remote Sensing (CCRS) C-band airborne SAR operating in HH and VV polarisations.

In this study BRA1.1, BRA1.2 and BRA1.3 at both HH and VV polarisation are examined. These three flight passes were all carried out with the radar in different acquisition modes. BRA1.1 was imaged with the radar in wide swath mode. This has angles of incidence of 45° at near range and 85° at far range, giving a swath width of approximately 65 km. The slant range resolution is 20 m and the azimuth resolution is 10 m; the pixel size is approximately 16 m in slant range by 7 m in azimuth. BRA1.2 was imaged in narrow swath mode. This has angles of incidence of 45° at near range and 74° at far range, giving a swath width of approximately 18 km. Both the range and the azimuth resolution is 6 m; the pixel size is approximately 4.5 m in slant range and azimuth. BRA1.3 was imaged with the radar in nadir mode. This has angles of incidence from nadir (0°) at near range to 72° at far range. This gives a swath width of approximately 22 km; the range and azimuth resolutions are 6 m as in the narrow swath data. All the SAREX data is calibrated, using the methods outlined in [11]. The data necessary for this calibration (concerning noise value

at each pixel in range, and a further calibration factor which corrects for antenna pattern, etc.) for each flight line at each polarisation was supplied by CCRS.

2.6 Additional data sources

As well as the remotely sensed data and fieldwork results, other valuable data sources have been acquired. Daily rainfall measurements for May, July and December 1992 from the Belterra meteorological station in the Tapajos region were supplied by the Brazilian Meteorological Office. These months contain the dates of acquisition of the ERS-1 multi-temporal data used in this study. Furthermore, an airborne 35mm. colour photographic data set, at 1:10,000 scale, collected in September 1991, has been made available. There is a 60% overlap along track, which will enable photogrammetric techniques to be used to extract the forest canopy topography. It is over a specific area in the North of FLONA Tapajos, with good congruence with SAREX BRA1.2 (narrow swath) imagery.

JERS-1 satellite borne radar imagery of Tapajos is also available but not used in this study. This is of a longer wavelength (24 cm.) than the ERS-1 and SAREX data so different scattering mechanisms will be operating, and different information will be contained in the data. Multi-frequency polarimetric data will shortly be available from the Tapajos test site, as it was imaged as part of the SIR-C campaign.

3 DATA ANALYSIS TECHNIQUES

3.1 Measuring temporal change in radar cross section

A multi-temporal overlay of a section from three ERS-1 PRI frames from 22/05/92 (shown in blue), 31/07/92 (green) and 18/12/92 (red) is shown in Figure 1. Certain areas within the Tapajos region are readily distinguished due to their multi-temporal fluctuations in backscatter. Some of these areas were visited during the field campaign of August/September 1994 [5]. It was found that the areas showing dynamic behaviour were predominantly areas of bare soil, pasture or similar low vegetation. An example of this is the large, square area of farmland towards the bottom of the image shown in Figure 1 (which was visited during the 1994 field campaign). It is clearly visible in the multi-temporal image due to its blue-green appearance, relating to a lower backscatter in the December image. The areas of regeneration near to the small tributary of the River Tapajos (below left centre of Figure 1) are also visible, again by their blue-green appearance. As the areas showing dynamic behaviour appear to be the areas of non-forest, various analysis and processing techniques are investigated and their use for forest/non-forest discrimination is compared.

The previously mentioned area of farmland and its surroundings was chosen for change detection analysis. The size of the area operated upon is approximately 12 km by 11 km; it is shown in Figure 2(a). Of the three available ERS-1 SAR images from the 35 day repeat cycle, those from 31/07/92 and 18/12/92 were chosen for analysis since visually they showed the largest changes. In order to carry out a quantitative comparison of algorithms, a ground cover map is needed. This can be prepared from the Landsat TM image acquired on 29/07/92, shown in Figure 2(b). Band 3 is displayed in red, band 4 in green and band 5 in blue. The frame displayed in the Figure encloses the section of the image corresponding to the ERS-1 test area. Areas of farmland (pasture, crops and bare soil) can be identified by their pink colour in the image, areas of forest regeneration appear bright green and primary forest areas appear dark green with a different texture.

Four approaches to change detection were considered, based on the following types of preprocessing:

- Simple averaging;
- Filtering using the gamma maximum a posteriori filter;
- Simulated annealing;

- Image segmentation.

One technique for speckle reduction is simple averaging of pixels, although this operation is obviously at the cost of decreased spatial resolution. Previous studies [12] have indicated that for change detection using image ratios (or differences in log images), the data need considerable averaging to give useful classification results. Table 2 shows the number of independent looks that need to be averaged to give an error rate of 10% or less when classifying regions whose radar cross section is separated by x dB, along with the corresponding approximate region size in 3-look ERS-1 PRI data:

x	No. of looks	Approx. no. of pixels
4	16	5×5
3	32	7×7
2	64	9×9
1	256	18×18
0.6	675	30×30

Table 2. No. of looks needed to classify regions separated by x dB with a 10% (or lower) error rate.

Pixel averaging simply takes the mean value within a window and returns it to the central pixel within that window. This window is stepped across the whole image producing a smoothed output image. Images were smoothed using 7×7 , 11×11 , 18×18 and 30×30 pixel windows.

Figure 3 shows the result of applying a 7×7 smoothing filter to intensity data. The ERS-1 PRI image from 18/12/92 (after smoothing and conversion to decibels) is shown at the top left of the figure; the corresponding image from 31/07/92 is shown at the top right. The difference in backscatter over the square pasture area between the two dates can be seen. Other areas of non-forest lying along the Santarem-Cuiaba highway (running from top to bottom of the image on the right hand side of the pasture area) and on two other perpendicular roads are just discernible due to their lower backscatter than the surrounding forest in the December image. These non-forest areas (including the large pasture area) are barely visible in the July image.

The image on the centre left of the figure is the result of applying a per-pixel difference to the two images shown above (July image - December image). This differencing of log data is equivalent to ratioing of intensity data. The difference image shown is scaled between -3 and 5 dB; the histogram of the pixel values within the difference image is also shown.

Change detection between the two dates is then carried out by applying a threshold to the difference image. In the image shown at the bottom left of the figure all pixels where the backscatter in the July image is 1.5 dB higher (or more) than the December image are white; the remainder are black. The result of reducing the threshold to 1 dB is shown at the bottom right of the figure. The square pasture area and other non-forest areas are visible in both thresholded images, but the image is very noisy with many white pixels appearing in areas believed to be primary forest. As the threshold is reduced the detection of non-forest areas becomes more complete but more false detections occur, due to the different speckle patterns at the different dates.

Figures 4 and 5 show the same information as Figure 3, with the original (intensity) data smoothed over an 18×18 and 30×30 window in each case. The pre-processed images from December and July are shown, as is their difference image and a histogram of its pixel values. The smoothing effect of the increasing window size is visible in both the appearance of the images and the increasing sharpness of the histogram (as the more extreme values in the difference image are smoothed out). In Figure 4 the square pasture area and other non-forest areas along the Santarem-Cuiaba highway and other perpendicular roads appear clearly in the image thresholded at 1.5 dB; the noise is beginning to cause problems as the threshold is reduced to 1 dB. According to theory [12], using an 18×18 pixel smoothing window in ERS-1 data (roughly corresponding to 256 looks) 1 dB differences between the images should be detected with a 10% error rate. Further noise reduction is visible in the thresholded images of Figure 5, although the large window used has the

effect of 'smearing out' some of the non-forest areas detected, and could not be used for small area detection. Note that at a threshold of 1 dB several areas of change in forest areas are detected after 30×30 averaging. The large averaging window used implies that we are observing real temporal changes; at present any relation between these areas and forest properties is unknown.

The next approach investigated was based on the gamma maximum a posteriori filter [13]. The image is modelled as the product of a gamma distributed underlying mean intensity and n -look speckle which is also gamma distributed. The degree of local smoothing is controlled by the coefficient of variation estimated within a square window. Structural features (edges, lines and points) are detected and the size of the smoothing window is reduced when structure is present. As the filtering process expects independent samples pre-averaging of the data is necessary, in order to remove correlation between adjacent pixels in the ERS-1 PRI imagery. After conversion to intensity and reduction by a factor of four (averaging over a 2×2 window), the image contains nearly uncorrelated samples. The results of applying GMAP over a 9×9 pixel window in the pre-averaged image (corresponding to an area of 18×18 pixels in the PRI image) can be seen in Figure 6. The December and July images, after filtering and conversion to decibels are shown. The filtering was carried out with a probability of false alarm (for edges and points) set at 10^{-4} . The difference image (July image - December image, scaled between -3 and 5 dB) and a histogram of its pixel values are also shown. Both the smoothing effect of the GMAP filter and the preservation of image structure (i.e. streams running through the pasture area) are visible in the images. Once again change detection is carried out by thresholding the difference image at 1.5 and 1 dB. This image appears noisy, becoming more so as the threshold decreases. The large square area of pasture in the image is reliably detected at both threshold levels, but many areas within the primary forest are also above the threshold.

Figure 7 shows the results of applying GMAP over a 15×15 window in the pre-averaged data (corresponding to an area of 30×30 pixels in the original data) with the same probability of false alarm for edges. Once again the December and July images, and their per-pixel difference (along with a histogram of the difference image) are shown. The effect of increasing the size of the smoothing window (in areas where structure is not detected) is visible when comparing the difference image histogram with that in Figure 6. It is more peaked, corresponding to a higher degree of smoothing. The difference image thresholded at 1.5 and 1 dB is shown. As with the previous example, non-forest areas are detected, but the image is still noisy. The feature preserving smoothing which GMAP attempts does not appear too successful, and other methods to preserve structure while removing speckle were investigated.

Simulated annealing is essentially an attempt to find the global MAP reconstruction of the image [14]. Two versions of simulated annealing have been supplied to the University of Sheffield by NA Software of Liverpool, UK. The earlier program includes the option of setting the number of iterations which the program would perform and models image speckle as a Gaussian random process. The updated version runs to convergence, and models the speckle as Gamma distributed with an order parameter equal to the number of looks in the data (defined by the user). The updated version also runs at a vastly reduced machine time. Figure 8 shows the results of applying 1 iteration of the older annealing algorithm to the December and July images. Its smoothing effect is clear. The non-forest areas to the north (above) the square pasture area are hardly visible, even in the December image. The difference image shown is produced by applying a per-pixel differencing after logging the annealed data, and the histogram of pixel values within this difference image is also shown. The degree of structure that has been retained in the annealed difference image can be seen from the histogram as well as the image itself. The spikes seen at the sides of the histogram correspond to well defined areas in the image, not simply many fragmented areas. At present we have no information to indicate whether these areas are artefacts of the algorithm or correspond to forest properties.

The difference image thresholded at 1.5 and 1 dB is shown. Non-forest areas are readily detected, even in some areas where this is not obvious by visual inspection of the difference image. A small number of 'false alarms' occur (pixels above the threshold in areas believed to be the pri-

mary forest), although some of these appear to correspond to areas of rapidly changing backscatter values (such as the slopes around drainage features) where mis-registration of the images, even of a sub-pixel level, will produce large per-pixel differences between the two. As the threshold is reduced from 1.5 to 1 dB the non-forest areas are more completely detected, and there are still relatively few 'false alarms'.

Figure 9 shows the results of applying the simulated annealing for two iterations. More small scale structure is found in the image, although the spikes that were previously apparent on the histogram of the difference image have now nearly disappeared. More 'false alarms' occur in the thresholded difference image than for the previous case. This suggests that increasing the number of iterations leads to detection of too much structure in the image for this application.

The results of applying the updated simulated annealing to the images are shown in Figure 10. As the number of looks is required the images are first reduced by a factor of four (2×2 window) to produce nearly uncorrelated pixels of approximately 5 looks. The annealing is applied to both the December and July intensity images in turn and to convergence. The per-pixel difference of the July and December (log) images is shown, along with a histogram of its pixel values. The smoothness of the histogram also relates to the degree of smoothness of the image. The difference image, thresholded at 1.5 and 1 dB, is shown once again. The areas of non-forest along the Santarem-Cuiaba highway and the two perpendicular roads are clearly visible and there are only a small number of 'false alarms'.

A different approach to obtaining the underlying radar cross section is to first segment the image [15]. As for GMAP, the data is pre-averaged to produce an approximately 5-look image of uncorrelated pixels. A multi-dimensional segmentation is then performed (in this case using all 3 dates) to learn all the edges in the image, at a user defined false alarm rate. The RCSEG program, prepared by Dr. R. G. Caves of SCEOS, the University of Sheffield, was used [16]. The program involves an iterative process of edge detection and segment growing, starting from an amplitude image. After each iteration an overall measure of segment homogeneity is calculated, and the program continues iterating while this measure decreases. The number of looks must be set as it is used to calculate the coefficient of variation of single pixel segments. Output consists of a segmented image (each segment labelled with a separate integer), and the edge map used to form the segmentation. This edge map can be used to generate an image where the mean value of backscatter is calculated within each segment. The ensuing images from December and July, after segmentation has been performed with a false alarm rate set at 10^{-4} , are shown in Figure 11. The difference between the July and December images (after conversion to decibels) and the histogram of pixel values is also shown. Each spike on the histogram, in general, corresponds to the pixels within a few segments, which are all set to the mean backscatter within those segments. Visual comparison with the original data confirms that segments faithfully reproduce image structure. The difference image, thresholded at 1.5 and 1 dB, is shown at the bottom of the figure. The large square pasture area, and other areas of non-forest, appear clearly in both images, but there are a few segments in areas believed to be primary forest.

The segmentation was run again with the probability of false alarm reduced to a value of 10^{-3} ; therefore more, and smaller, segments were detected. This can be seen in both the December and July images (shown in Figure 12). After a per-pixel differencing of log images there is more structure present in the difference image. When this image is thresholded more small segments within the areas believed to be primary forest are seen. In this case the image appears to have been over-segmented for our purposes.

3.2 Comparison of Data Analysis methods

A ground cover map, containing the classes of primary forest, regeneration, and pasture/crops/bare soil, can be prepared from the Landsat TM imagery. A simple threshold of band 3 separates pasture, crops and bare soil from the other classes; after thresholding band 5 areas of forest regeneration are also detected (see Figure 13). The Santarem-Cuiaba highway and the two perpendicular roads are also clearly visible in the thresholded TM imagery. At present the Landsat TM and

the ERS-1 data used in this study have not been registered, so a pixel by pixel comparison is not possible. However, a comparison of the forest/non-forest discrimination achieved by thresholding the Landsat TM data (band 5) and that achieved by thresholding difference images produced after pre-processing the data by various methods is shown in Figure 14. The threshold is applied to the pre-processed radar difference images at 1.5 dB in all cases. The TM image is shown at the top left of the figure and the box within the image corresponds to the edges of the area over which the ERS-1 data analysis was carried out. At the top right of the image is the difference image of the calibrated ERS-1 PRI data. It is very noisy, due to the different speckle patterns of the two images.

On the centre left the data has been smoothed over a 30×30 pixel window. On the centre right the GMAP filter has been applied to a 15×15 pixel window of pre-averaged data (averaged over a 2×2 window to produce nearly uncorrelated pixels); this therefore corresponds to a 30×30 pixel area in the PRI image. Simulated annealing is applied to the pre-averaged data to produce the image shown at the bottom left; the bottom right shows the result of subtracting mean values within segments, when image segmentation with a probability of false alarm of 10^{-4} is carried out.

All of the pre-processing techniques applied give an obvious increase in accuracy when compared to the raw data, although none preserve the level of detail visible using the Landsat TM imagery. The smoothing filter removes the problems of speckle as the window size increases, but at the largest window sizes investigated it will also remove small areas where change has occurred and 'smear out' the edges of larger areas of multi-temporal change. Using the GMAP filter a higher level of detail is preserved (i.e. streams running through the pasture area are visible, edges of the non-forest areas are sharper) but many areas within the primary forest appear above the threshold level. When using simulated annealing a large degree of detail is preserved with relatively few 'false alarms' (pixels above the threshold within the area believed to be primary forest). Similarities can be seen between the results of simulated annealing and image segmentation, where image structure is preserved and relatively few 'false alarms' are occurring. Some of these false alarms are in areas of rapidly changing backscatter, and in these areas mis-registration, even on a sub-pixel level, will produce large backscatter differences between the images.

To give a quantitative comparison, Figure 15 shows the proportion of pixels falling above a threshold after each of the various analysis techniques has been applied to the data. The proportion of the test area that corresponds to areas of pasture, bare soil and crops (by analysis of band 3 of the Landsat TM image) is 19%. The proportion of the test area that is non-forest, including areas of forest regeneration, is 23% (by analysis of band 5 of Landsat TM).

At the top left of the Figure the result of increasing the size in the averaging window can be seen. The number of pixels falling above the threshold falls as the window size increases, due to the removal of speckle effects. This indicates that, as window size increases, detection performance of large areas based on averaging tends towards the performance of the more sophisticated methods. However, at the largest window sizes investigated the removal of small areas of multi-temporal change acts to further reduce the number of pixels falling above the threshold.

Changing the size of the window over which the GMAP filter operated has little effect on the number of pixels above the threshold, although differences can be seen between the thresholded images seen in Figures 6 and 7. The number of pixels falling above the threshold level is higher than that found using averaging over a large window, simulated annealing or segmentation at all threshold levels above zero.

Similar results are found using annealing of one iteration ($n=1$ on the graph) or annealing to convergence using the updated method. After annealing to two iterations ($n=2$) more pixels lie above all threshold levels greater than 1dB. This is possibly due to the increased amount of small scale structure annealing to two iterations finds in the image. The numerical proportion of pixels falling above the threshold is higher for image segmentation with a probability of false alarm for edge detection (pe) set at 10^{-3} than when it is set at 10^{-4} ; this is again due to an increase in the small scale structure that is detected in the image. The number of pixels falling above the threshold when the image is segmented with a probability of false alarm for edge detection (pe)

set at 10^{-4} is similar to that found for annealing of one iteration or annealing to convergence.

3.3 Computational Aspects

A table showing the run times (clock time and CPU time) of each of the processing techniques is shown below:

	Clock time	CPU usage	CPU time
Averaging (7×7)	0:01:25	48%	40.0
Averaging (18×18)	0:04:26	80%	212.2
Averaging (30×30)	0:09:40	93%	542.5
GMAP (9×9)	0:00:54	51%	27.1
GMAP (15×15)	0:01:24	79%	66.5
Annealing (1 iteration)	2:46:05	97%	9755.8
Annealing (2 iterations)	5:55:39	93%	19968.4
Annealing (updated)	0:26:09	80%	1259.7
Segmentation	1:27:18	92%	4855.9

Table 3. Run times of each of the processing methods used

All these timings were taken on a Sun Sparc10 machine. Images of size 880 by 992 pixels were operated upon using the simple averaging method, pre-averaged images (of 440 by 496 pixels) were used for GMAP, anneal, and segmentation. Pixel averaging, GMAP and annealing all work on single frame images, while the segmentation was applied to three frames simultaneously. The updated version of simulated annealing runs in a vastly reduced machine time.

4 USE OF MODELLING IN TROPICAL FOREST MONITORING

Models have been used in this study to attempt to define the information carried by the mean backscatter and to understand the varying degrees of multi-temporal change seen in the images. Both volume and surface scattering models have been needed, as described below.

4.1 Description of models

4.1.1 MIMICS canopy scattering model

The volume scattering model that has been used in this study is the Michigan Microwave Canopy Scattering model, or MIMICS [21]. This is a first order radiative transfer model, calculating backscatter from a tree canopy modelled as layered regions (a trunk region, a crown region and a ground region). A single scattering event is allowed in each region, or double scattering from pairs of regions.

Backscatter is calculated by dividing the problem into two parts. Firstly backscatter from the whole canopy is calculated, including the interactions between the separate regions, treating the ground as specular (only scattering in the forward direction). Secondly the direct backscatter from the ground is calculated, the forest canopy attenuating the radiation on its two way path. The two contributions are added incoherently. A choice of surface scattering models (Kirchhoff model, Small Perturbation model and an empirical model) is included within MIMICS.

The characterisation of the forest canopy is one of the most difficult problems for this (or any other) forest backscattering model. The problem is reduced by splitting it into smaller components; leaves, needles, primary and secondary branches and trunks. Sizes and moisture contents (or dielectric permittivities) for each component are needed and statistical distributions are used to represent the spatial orientations of the components used to build up the canopy. Trunks and branches are treated as dielectric cylinders of uniform diameter, leaves are represented by flat

discs and needles by oblate spheroids. The trunk and branch surfaces are treated as specular, scattering in the forward direction only. Therefore there is no direct scattering from the trunks, but the trunk-ground 'corner reflector' type mechanism can still be the dominant component in backscattering in some cases.

In addition to characterising the forest, details of the sensor used (incidence angle, frequency) and other environmental factors (temperature, the presence of standing water/snow on the surface, etc.) must be included in the model. In all 41 parameters are needed. This obviously reduces the degree to which we can trust the results, as the amount of data that would have to be collected to fulfil all of the input requirements with a high degree of accuracy is vast. This does not render the MIMICS model useless, however. After a sensitivity analysis it is possible to define the most critical input parameters and therefore reduce the difficulty of input data collection, while still achieving meaningful results.

Ground data collection was included as part of the fieldwork carried out in FLONA Tapajos during August/September 1994. Six test plots were visited, of primary forest and forest in various stages of regeneration. Leaves were recovered from the upper part of the canopy of a number of trees at each area, allowing leaf dimensions and moisture content to be measured. Full details of the measurements made and of the methods employed are given in the SCEOS/INPE fieldwork report [5].

The parameters for collection were chosen by a combination of their influence on backscatter in the MIMICS model, and their ease of collection. Preliminary runs of the model (and previous results [25], [26], [27]) indicated that the majority of scattering from a forest canopy at C-band was from the tops of the tree crowns. Therefore it was decided to measure the moisture contents of leaves and twigs from the crowns, and also leaf sizes and thicknesses. Dielectric constant of the leaves could be found from their moisture content, using the method outlined in [22].

4.1.2 Surface Scattering models

A variety of surface scattering models, each with their own regions of validity, have been used in this study. The models used are basically of two types; mathematical models where, after some simplifying assumptions, the exact solution to scattering from a surface is sought, and an empirical model, prepared by fits to a large database of measurements from soil under various conditions.

The Kirchhoff model makes the fundamental assumption that the surface is made up of smooth 'facets', large when compared to a wavelength. These facets scatter in the manner of an infinite plane tangential to the point of incidence of the radiation on the surface. Even after this assumption further simplification is needed to obtain analytic solutions. For surfaces with a large RMS deviation in surface heights (this corresponds to approximately one third of the peak to peak variation in height when examining a cross section of the surface) the Geometrical Optics or Stationary Phase approximation is used, and for surfaces with a medium or small RMS deviation in surface heights and small surface slopes the Physical Optics solution is used.

The Kirchhoff model applies to surfaces with horizontal scales of roughness large when compared to a wavelength (thus the facets can be approximated as infinite). When both RMS deviation in surface heights and horizontal roughness is small a different approach is needed. Here the Small Perturbation model must be used. The mathematical formulation of the scattering problem is different from the Kirchhoff case. The problem is to calculate the amplitudes of plane waves transmitted and reflected from the surface. These field amplitudes can be found using the boundary conditions and the divergence relations. This gives an exponential term, but provided the surface is relatively smooth (when compared to a wavelength) this can be reduced to a Taylor series expansion, and truncated at first order.

The University of Michigan Empirical Soil Model was also used. This model does not attempt to find the solution to the mathematical scattering problem, but relies instead on fitting functional forms to experimental observations. This model has been validated for a frequency range of 1–10 GHz, angles of incidence between 20° and 70°, a range of roughnesses (RMS deviation in surface height) from 0.3 cm to 4 cm and a moisture range from 0.05 to 0.31 g/cm³.

4.2 Simulation Study: Scattering from bare soil

Daily rainfall data, with the help of radar backscatter modelling, can be used to explain the multi-temporal behaviour observed in some areas of the imagery. The Brazilian Meteorological Office supplied rainfall measurements taken at the Belterra test station, located approximately 60 kms to the north of our ground control points. The data for rainfall (in mm.) each day for the months of May, July and December (all 1992) are given in Table 8. A graphical illustration of rainfall for the day of image acquisition, and the ten preceding days, is given in Figure 16. It can be seen that on the day of acquisition of the December image (and in the two days immediately preceding it) there was no rainfall recorded. In the May image there was rainfall on the day of acquisition and in the July image there was rainfall one day before. Therefore the soil moisture content would have been lower when the December image was acquired than on the other two dates. The empirical bare soil model shows that, as soil moisture content increases, so does radar backscatter (see Figure 17). This suggests that the multi-temporal signature seen in some areas of the image is related to soil moisture.

However, some other areas of pasture and bare soil, visited during the 1994 field campaign, do not exhibit this multi-temporal signature. These were located approximately 10 kms to the South of the large, square pasture area showing strong multi-temporal fluctuations. A modelling approach to explain these differences is used, varying the soil conditions until the model results best fit the observations. Results using the University of Michigan empirical soil model, the Small Perturbation model and Kirchhoff surface scattering model are presented and compared.

First we must formulate the problem. Considering two areas of pasture (modelled as areas of bare soil for simplicity) imaged on the same day, backscatter differences between them could be produced by :

- Differences in soil moisture content ;
- Differences in soil roughness ;
- Differences in angle of incidence of radiation ;
- Differences in soil composition.

It is possible that rainfall (and hence soil moisture content) was different at each of the pasture areas (and different from that recorded at Belterra), although this is not considered further as we do not have the data necessary to test this. We also have no data on soil composition, and assume a similar soil type across the region (consisting of equal parts of sand, silt and clay). This leaves differences in soil roughness and angle of incidence (although the angle of incidence changes very little across the scene, a change in slope of the field will produce local changes in incidence angle).

Two areas of pasture visited during the 1994 field campaign were chosen for the simulation, one which showed large seasonal variation in backscatter and the other very little. The inputs to the Michigan empirical soil model were systematically varied in order to find the conditions which gave best fits to the observations.

The input parameters for the simulation were varied over a range of soil moisture conditions, soil roughnesses and angles of incidence. Soil moisture contents of 0.05 (dry) to 0.25 (wet) were used. Incidence angle was varied between 10° and 40° , corresponding to a slope of approximately $\pm 15^\circ$ away from the ERS-1 look direction. In the first instance the empirical model was used as soil roughness is parameterised solely by the RMS deviation in surface heights (correlation length is not used); a range of 0.40 cm (very smooth) to 4.00 cm (very rough) was investigated. A summary of the results is given in Table 4, where M_v refers to soil moisture content and θ_i to local incidence angle:

	18/12/92 (dry)	31/07/92 (wet)
Area A	$M_v = 0.125$ $\theta_i = 35^\circ$ RMS height = 0.80 cm	$M_v = 0.200$ $\theta_i = 35^\circ$ RMS height = 0.80 cm
Area B	$M_v = 0.125$ $\theta_i = 40^\circ$ RMS height = 4.00 cm	$M_v = 0.200$ $\theta_i = 40^\circ$ RMS height = 4.00 cm

Table 4. Input parameters achieving best fit of modelled backscatter to observations

The fitted angle of incidence can be seen to be similar in both fields, suggesting that a change in slope between the two fields is not the mechanism producing the observed backscatter differences between different fields. However, a distinct change in soil roughness is seen, the rougher field having higher backscatter (due to a more isotropic scattering of the incoming radiation), and a smaller dependence between backscattered intensity and soil moisture content. Therefore a further run of the simulation was carried out with the angle of incidence set at 23° , the incidence angle of ERS-1. This time the results of the empirical model were compared with results from the Small Perturbation model and the Kirchhoff model (Geometrical Optics solution). For the Small Perturbation and Kirchhoff models a further parameter is included to characterise the horizontal surface roughness, viz. the surface correlation length, l . This was varied between 0 and 30 cm. The best fit of the data calculated using each model is given in Table 5 :

	M_v (18/12/92)	M_v (31/07/92)	RMS height (Area A)	RMS height (Area B)	l (Area A)	l (Area B)
Empirical	0.075	0.125	0.80	2.00	-	-
SPM	0.100	0.125	1.20	1.60	6.00	6.00
Kirchhoff	0.075	0.125	2.80	3.20	26.00	26.00

Table 5. Input parameters achieving best fit of modelled backscatter (using Kirchhoff, Small Perturbation and empirical models) to observations

The Kirchhoff model (Geometrical Optics solution) produced the best fit, giving a total square difference between the four observations and the four modelled values (in dB) of 1.54; for the Michigan empirical model it was 1.81 and for the Small Perturbation model it was 2.00.

The Kirchhoff model predicted the same variation in soil moisture content as the Michigan empirical model, while the small perturbation model gave the same value in July but an increase to 0.100 g/cm^3 in December. The decrease in soil moisture from July to December is in agreement with the daily rainfall data. The three models all predict only a small change in moisture content between the two dates. All three models also predicted that the region showing less dynamic behaviour was rougher than the area showing fluctuations in backscatter, although all quantified the surface roughness differently. Visits to both areas during the 1994 field campaign showed that the 'smooth' area was managed pasture, while the 'rough' area was untended pasture. In the empirical model there is a large difference in RMS deviation of surface heights between the two fields, while the correlation length measure is not used. In the Small Perturbation model the correlation length is relatively small (6 cm, which is of the order of a wavelength), and the RMS deviation in surface heights (1.20 cm and 1.60 cm) is equivalent to a fairly smooth surface in the vertical direction in both cases. In the Kirchhoff model a large correlation length is predicted for both fields (26 cm), although the RMS deviation in surface heights predicts a very high vertical roughness in both fields (2.80 and 3.20 cm). These results show how a relatively small change in surface roughness can produce large changes in observed backscatter, the change in soil moisture content having a greater effect on backscatter from the smoother surface, than the rougher, more isotropically scattering surface.

The modelled angular response of backscatter from areas with these roughnesses at both moisture states, calculated using the Michigan empirical model, is shown in Figure 18. The uppermost

curve in this Figure shows the predicted return from a 10m deep leafy canopy with trunks. Note that at an incidence angle of 23° the forest response lies between the returns from the rougher area at the two soil moisture states, and the small differences between the forest and bare soil would make them hard to distinguish.

In this very simple parametric approach to explaining the multi-temporal variations seen in different pasture areas the soil composition is not taken into account, as previously noted. Different soil compositions can cause the absolute backscatter to vary by up to 3dB, but the functional variation of radar backscatter with soil moisture and soil roughness does not change. Therefore it appears likely that the multi-temporal differences seen in radar backscatter in the Tapajos region are soil moisture related and that differences seen between different areas of pasture (imaged on the same day) are soil roughness related.

This approach also assumes that there was no vegetation present (or that it had negligible effect on the backscattered radiation). At C-band this is perhaps viable for areas of pasture and low grass, but for areas of higher biomass it could not be used. As the levels of biomass rise (such as in areas of regenerating forest) the backscatter quickly saturates, becoming indistinguishable from that of primary forest. The soil is no longer the dominant scatterer in this case, the radiation being almost completely attenuated by the vegetation canopy. Previous studies have quantified the dependence of C-band radar backscatter on vegetation biomass ([25],[26],[27],[28]). The modelling of backscatter from the forest canopy is examined in detail in the following section, and the effect of a low vegetation canopy (of various heights) over bare soil is discussed in Section 4.3.3.

4.3 Modelling backscatter from the forest canopy

Surface scattering models can be used to explain the multi-temporal differences (and in some cases the lack of them) seen in the ERS-1 imagery, but this is only related to areas of bare soil, pasture or similar low vegetation. We are mainly interested in forested areas, and what information can be found concerning them using the available SAR imagery. Again, radar backscatter modelling can be a useful tool in this respect, although, as previously mentioned, there are problems concerning collection of the large amounts of data needed to characterise the forest canopy with any degree of accuracy and in validating the results.

This is particularly true in natural tropical forests, which have an extremely heterogeneous mix of species. During the 1994 field campaign parameters were collected to be used as inputs for modelling, but as time and resources would not allow an exhaustive survey, preliminary runs of the model were used to select the most critical parameters to be measured.

As a first approximation to a primary tropical forest a forest canopy of 35m in height (25m trunk layer, 10m crown layer) was modelled. Despite well documented climatic and ecological differences between the Manaus and Tapajos regions [19], the only information available on leaf density and moisture content was for the Manaus area, given in [20], and these were used in our preparatory modelling. All the leaf and branch sizes and thicknesses were set at the default values given in the MIMICS model. For these parameters, it was apparent that the dominant scatterers from this modelled forest canopy were the leaves. Therefore, the primary concern of the field data collection was to measure the leaf size, thickness and moisture content.

During the field campaign six test sites were visited, covering a wide range of forest conditions. Primary forest from the plateau (above the level of the river and never flooded during the year) and primary river level forest were visited, as well as areas of forest regeneration of ages 3, 10 and 30 years. At each site between three and seven of the most prevalent species were selected and identified by local woodsmen. These were then climbed by a woodsman, and a small amount (between 75g and 200g) of leaf and twig material was recovered and weighed at the scene. The moisture content could then be calculated after the leaves had spent 30 hours in a drying oven at the SUDAM (Superintendancy for the Development of Amazonia) Wood Technology Centre at Santarem. Leaf dimensions and thickness were also measured.

Using the input parameters calculated from the fieldwork results (and assuming that the leaves and branches have uniform distributions in solid angle) the model was run once again. The results

are shown in Figure 19. It can be seen that, at angles of incidence above 10° , the modelled VV backscatter is close to following a cosine relationship with respect to the angle of incidence (shown by the solid line). This relationship has been noted before in situations where forest or crop canopies have a very high attenuation [24]. The region where this angular relationship breaks down is when the sensor is looking almost vertically down on the vegetation canopy. In this case there will be greater penetration into the lower part of the canopy, as the path length through the forest crown layer is shorter at these near nadir incidence angles. The HH polarised backscatter deviates from the cosine relationship due to its greater penetration, with ensuing trunk-ground and ground-trunk interaction. Hence angle of incidence variation provides little useful information about the forest canopy at VV, but conceivably could at HH.

4.3.1 Comparison of modelled backscatter with calibrated data

We now compare the model predictions with calibrated radar data from the Tapajos region. The calibrated data is from two sources, the 1992 South American Radar Experiment (SAREX) and the ERS-1 satellite.

The Tapajos test site was overflown on four occasions during the SAREX campaign, with the radar operating in three different acquisition modes. This results in a range of measurements at incidence angles between 0° (nadir) and 85° . These data were calibrated using information supplied by the Canadian Centre for Remote Sensing (CCRS) concerning the residual noise at each pixel in range, and a calibration factor. The three ERS-1 frames used in the multi-temporal analysis were also calibrated, using data available in their header files.

To compare the angular variation of backscatter of each of the sensors and the model, mean backscatter across the whole of each of the ERS-1 images was calculated. This could then be used as a calibrated reference at the 19° – 26° range of incidence angles. Due to the large range of incidence angles covered by each of the SAREX acquisition modes, each image was split into 16 sections, each consisting of 250 lines of constant range (250 azimuth lines of 2048 pixels each). The mean and standard deviation of backscatter in each of these subimages could then be calculated, and the angular range that they covered could be found from the CCRS calibration files (which also give angle of incidence and distance between the sensor and each pixel in range). The three SAREX images used are of VV polarisation to enable direct comparison with the ERS-1 data.

The results of comparing the mean backscatter in each of the SAREX subimages, the ERS-1 images, and the VV polarised output of the MIMICS model (when using the input parameters calculated from the fieldwork results) are shown in Figure 20. It can be seen that the model predictions are of the order of 1 dB below the observations in ERS-1 and the SAREX wide swath ($\theta_i = 45^\circ$ – 85°) and narrow swath ($\theta_i = 45^\circ$ – 74°) data, but very different to the SAREX nadir data.

This result is more clearly visualised when comparing the modelled backscatter to SAREX data averaged along lines of constant range (2048 pixels in azimuth) in each of the SAREX images collected. These variations are displayed against angle of incidence in Figure 21. It should be noted that these images are all from different areas within the FLONA Tapajos. Therefore local differences on the ground will produce local differences in the backscatter at similar incidence angles in the different images. The most obvious example of this is where the SAREX nadir swath is imaging the River Tapajos at far range (approximately 69°), and the backscatter in this image falls rapidly. This also occurs at far range in the SAREX wide swath image (approximately 80°), again where the river is being imaged. An obvious feature is the 'banding' in the SAREX nadir swath data at near range; this banding is clear on the calibrated image and is not a physical phenomenon; it is an artefact of the image acquisition, processing and calibration process. Therefore no useful conclusions can be drawn from the near range data in the narrow swath image. This is unfortunate since only the nadir data contains measurements at the range of incidence angles at which ERS-1 operates.

It has been previously reported that very good agreement (less than 1 dB difference) has been found between the modelled radar backscatter and the calibrated SAREX wide swath measurements [3]. This result was obtained whilst carrying out the preliminary runs of the MIMICS model,

using parameters from the MIMICS model validation experiment and the Institute of Hydrology study at Manaus [20]. The significant parameter that has changed as a result of the field campaign (and has made the model results a poorer fit to the data) is the leaf thickness. The leaf thickness measured at Tapajos was 0.2 mm, while the previous study used a leaf thickness of 1mm. Figure 22 shows how the backscatter increases with leaf thickness, tending towards the observed backscatter when the leaf thickness is approximately 1mm. The MIMICS model treats leaves as flat discs; during the 1994 field campaign the leaf thickness was measured on the 'flesh' of the leaves, and the increase in thickness in areas of 'veins' or the central stem was not taken into account. This may have led to a systematic underestimation of the leaf thickness.

4.3.2 Penetration of radiation

Previous results suggest that the forest crown layer has a high attenuation. To test this, some simple tests were run using MIMICS. Using leaf moisture and size parameters calculated from fieldwork results, and uniform orientation in solid angle for the leaves and branches (as before) the results for crown backscatter and total backscatter were calculated. The amount of backscatter from the crown layer and the total backscatter given by MIMICS can be compared and hence the crown attenuation inferred. The results are shown in Figure 23. The crown is the dominant scatterer at VV polarisation at all angles of incidence (more than 95% of the backscatter from the crown layer at all angles above 10°), although in the HH case the trunk-ground and ground-trunk scattering mechanisms are important for incidence angles up to 50° . Furthermore, the trunks protrude into the crown layer itself (as in the case of a true forest canopy) and alter the scattering from the crown layer. In the HH polarised case, only approximately 60% of the backscattered radiation comes from the crown at angles up to 25° .

4.3.3 Modifications to MIMICS for low vegetation over soil

Removing the trunk layer from the MIMICS model produces a vegetation layer above soil. This can be used to model the first stages of forest regeneration. During the fieldwork little difference was found between the leaf moisture content in areas of regeneration when compared to areas of primary forest. Therefore the same moisture parameters were used as before. A leaf thickness of 1 mm was used; the absolute value of radar backscatter for a full canopy (of thickness 10m) is then in close agreement with that observed using ERS-1 and SAREX. A canopy consisting of leaves only, uniformly distributed in solid angle was constructed and the canopy thickness was varied from bare soil to 10m, in 0.5m steps. The VV polarised backscatter at the full range of incidence angles (0° to 85°), for each canopy thickness, is shown in Figure 24. Note that in the cases illustrated the canopy is assumed to lie over the dry smooth soil surface from the simulation study (Section 4.2), giving the lowest of the bare soil returns in Figure 18.

It can be seen that even a small amount of regrowth causes the backscatter to tend towards that for a full canopy, especially at higher incidence angles. Large differences occur only near nadir. At 23° incidence angle there is less than 1 dB difference between the backscatter from a 2 metre vegetation layer and the backscatter from the forest canopy. This illustrates the problem of using ERS-1 for detection of areas of deforestation, unless images are gathered very soon after the event.

4.3.4 HH/VV Differences (model and SAREX)

A further feature of the SAREX data set is that it was collected with the radar operating at both HH and VV polarisations. This enables us to calculate the HH - VV difference, and compare this result to that obtained using the MIMICS model (see Figure 19). Any insight this information gives concerning the target (the forest) is not of direct relevance to ERS-1 but could possibly be of use when considering future spaceborne SARs, such as ENVISAT.

The mean RCS along lines of constant range (2048 pixels in azimuth) in each of the SAREX images at both HH and VV polarisation was calculated and these means were then subtracted. The

results are shown in Figure 25, along with the HH - VV differences calculated using the MIMICS model. For the SAREX nadir data, the 'banding' in the VV polarised data is once again apparent, causing very large fluctuations in the HH - VV difference. This banding is almost certainly not a physical phenomenon, therefore no conclusions can be drawn using data from this part of the swath. At the higher incidence angles in the nadir data, and in the SAREX narrow swath data, the HH - VV difference fluctuates about zero (except at the farthest range in the nadir data where the river is being imaged).

The most interesting results are found when examining the SAREX wide swath data. Across the majority of the swath (in terms of incidence angle) the HH polarised backscatter is between 0 and 2 dBs higher than the VV, in general agreement with the model results, but at angles of above 80° the difference rises sharply to a value of 4 to 6 dBs. This could be due to a double bounce dihedral type reflection from the forest crown. After specular reflection at near grazing incidence (at an angle close to the Brewster angle) the radiation is returned in the backscattered direction by a further, near normal, reflection from a leaf or branch of an emergent tree in the forest canopy. This effect cannot be reproduced by MIMICS since it is only a first order model (i.e. only a single scattering event within the crown layer is allowed). More details of this work can be found in [7].

Narrow swath data (of angles of incidence between 45° and 74°) show a similar excess of HH over VV as the wide swath data at these incidence angles, though less marked. Some indication that this is not just a calibration effect is that MIMICS shows the same phenomenon.

Previous studies [29] have shown that a leaf has a higher radar cross section to horizontally polarised radiation (with respect to the leaf) than to vertically polarised radiation. The leaf orientation used is uniform in solid angle, but not in the look direction. This leads to a greater proportion of the radiation being sensed (with respect to the leaves) in its transmitted polarisation than vice versa, and hence higher HH polarised scattering from the forest crown layer than VV polarised scattering. Furthermore, there is a greater modelled ground-trunk/trunk-ground backscattering in HH than VV polarisation.

4.4 Comparisons between ERS-1 and SAREX data

The radiometric distortions that are present in the SAREX nadir swath VV polarised data (the characteristic 'banding' that has been previously mentioned) make a direct comparison between SAREX and ERS-1 data imaged at the same angle of incidence impossible. However, the modelling carried out has indicated that the crown layer is the dominant scatterer within a tropical forest, and the backscatter varies with a cosine relationship over almost the complete range of angles of incidence. Therefore, a simple comparison in terms of relative calibration is carried out by fitting a cosine curve to the SAREX wide swath data, by eye. The ERS-1 data is also shown, see Figure 26. The SAREX data is once again shown as the average of 2048 pixels in each azimuth line (lines of constant range). The ERS-1 and SAREX wide swath data both fall on the cosine curve shown; this is an encouraging result in terms of the relative calibration of the two data sets.

The primary forest in the Tapajos region has many emergent trees, leading to an undulating canopy topography. Probably because of enhanced scattering from the front of these trees and radar shadows behind them there is a characteristic textural forest signature in the SAREX data, which is easily discriminated from other land use classes using simple statistical measures such as coefficient of variation. This texture is absent in the ERS-1 data as it is imaged at a lower resolution with a steeper angle of incidence. Future work will investigate this more fully using an airborne 35mm colour photographic data set of an area within FLONA Tapajos. There is a 60% overlap along track, which enables photogrammetric techniques to be used to extract the forest canopy topography. This will then be related to the limiting angles of incidence/resolution combinations needed to enable imaging of the forest texture and to predict whether the textural information seen in the SAREX imagery will be visible using future spaceborne SARs, such as ENVISAT or the high resolution mode of RADRSAT.

5 COMPARISON OF SAR AND OPTICAL DATA

At this stage, only a preliminary visual comparison of the classification capabilities of Landsat TM, ERS-1 PRI and SAREX wide and narrow swath data has been carried out. On this basis, Table 6 summarises the suitability of using different sensors to discriminate land cover types.

	ERS-1	Landsat TM	SAREX/Wide	SAREX/Narrow
drainage	****	***	****	****
palm trees	*	**	*	*
pepper	*	***	*	*
pasture	*	***	**	**
abandoned pasture	*	**	*	**
forest undulating relief	**	***	****	****
forest flat relief	**	****	***	***
regeneration	*	***	**	***
roads	**	****	***	***
water bodies	****	****	****	****

Table 6. Increasing numbers of stars correspond to increasing suitability.

It was noted that, in TM data, regeneration areas are brighter and show a different texture to primary forest. In the radar data, differences in texture between regenerating areas and other classes are visible only in the SAREX narrow swath data as a result of its higher resolution. Drainage and water bodies are well defined in both optical and radar imagery. Also, the roads sometimes disappear in ERS-1 images, possibly due to the road direction. This qualitative treatment implies that optical images, in general, give more information to discriminate land cover.

However, the ability of ERS-1 to enhance TM data for the purpose of determining the extension, location and stage of the regeneration of areas of secondary forest in the Tapajos region was investigated. Multi-spectral Landsat TM images from 1986 to 1992 were co-registered, segmented and used to delineate several classes of land cover for each date available and an associated age map. The segmentation process used was a region growing type procedure for multi-spectral data [30]. Regions were labelled using a clustering algorithm based on gray level, region size and historical knowledge gathered from prior field work and other sources. Thematic images were then formed with the following classes: bare soil, mixed pasture and bare soil, new secondary vegetation (juquira), secondary vegetation, primary forest, river, and shadows and clouds.

The 1992 image classification was evaluated [6] by comparing it with visual interpretation. The results are shown in the confusion matrix below:

	Prim. Forest	Sec. Veget.	Juquira	Pasture	BSoil	Total
Primary Forest	10	3	0	0	0	13
Secondary Vegetation	1	26	2	2	0	31
Juquira	0	4	1	8	0	13
Pasture	0	2	1	14	6	23
Bare Soil	0	0	0	2	51	53
TOTAL	11	35	4	26	57	133

Table 7. Confusion matrix between visual classification and classification based on image segmentation

The percentage of agreement was 77%: the Kappa coefficient of agreement was 67.76, with a variance of 0.0023. The classification of the juquira proved the most problematic, possibly due to it occurring on several different types of abandoned area (pasture, agricultural, bare soil, etc.).

The thematic images were superposed in a GIS and an age map was generated using a simple logical inference scheme, with age classes defined as areas with recent activities, areas with different

stages of secondary vegetation (varying from one to six years of regeneration), old secondary forest (more than six years old), and primary forest. This inferential approach to generating age classes could readily be modified to include ERS-1 data. It was observed that there is a functional relationship between the stages of the classified secondary vegetation and the normalized difference vegetation index (NDVI) using bands 3 and 4 of 1992 Landsat TM (see Figure 27; the error bars correspond to one standard error in the estimator).

The average gray level for the ERS-1 image, as a function of the regeneration age, was also calculated (see Figure 28). In agreement with the modelling results, it seems that ERS-1 data is sensitive to regeneration stages. It has an approximately constant response up to four years old regrowth, but it is different from areas with recent activities. There is an increasing tendency from four years old to older regenerations, but for primary forest there is a decrease in backscatter, perhaps due to higher texture.

The aforementioned results show that the mean values of ERS-1 data may be different for different regeneration stages (for instance, the mean difference between 0-2 and more-than-six year old regeneration is statistically significant). However, the associated change in backscatter is only 1.1 dB; this suggests that it may not always be possible to detect these differences since the sample size required to detect this difference would be very large.

This sensitivity to regeneration age for C-band SAR will be further investigated using multi-temporal ERS data, and the study will be extended to include :

- Mixture models to improve the age classification;
- Mathematical morphology methods to extract connected segments belonging to the same class and analyze their feature time evolution;
- SIR-C multi-polarised and multi-frequency data.

6 CONCLUSIONS AND FUTURE WORK

Forest/non-forest discrimination is possible using two images acquired under different soil moisture conditions, as long as the soil surface is not too rough; rough soil appears to give similar response to primary forest under all reasonable soil moisture conditions. Note that the important condition needed is a change in soil moisture; this is **not** a seasonal effect (in our data the **dry** conditions occurred during the rainy season, but the **wet** conditions occurred during the **dry** season). Even a small amount of regrowth makes discrimination difficult since it gives similar backscatter to primary forest at the angle of incidence of ERS-1.

An inferential structure for age mapping based on simple Boolean logic using Landsat TM has been developed, which can be adapted to utilise ERS-1 data. This has been used to demonstrate a weak trend associated with age in both observations and model results.

Change detection by thresholding difference images can automatically detect non-forest areas. Pre-processing using simulated annealing or segmentation to reduce speckle greatly improves results but is computationally expensive, although the updated version of simulated annealing gives a large improvement in this respect. Annealing and segmentation both detect small areas of change in primary forest areas. Structure in the histogram of the differenced annealed image also corresponds to particular sections of the image. Both of these observations deserve further investigation. Averaging blocks of pixels to reduce speckle produces results comparable to the more sophisticated methods as the window size increases, but cannot be used for small area detection.

An automatic monitoring system to detect changes in forest boundaries would therefore need to acquire images soon after deforestation and before significant regrowth could occur. Since images under wet and dry conditions are also required it seems likely that images need to be acquired on a monthly basis. This approximate figure needs proper analysis based on RCS saturation time for regrowth, rainfall probability as a function of season and seasonal likelihood of forest clearing. Changes can be absorbed into an existing logical structure to keep track of regeneration age.

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Figure 3: Pre-processing by smoothing over a 7×7 window

Figure 4: Pre-processing by smoothing over a 18×18 window

Figure 5: Pre-processing by smoothing over a 30×30 window

Figure 2(a) Multi-temporal ERS-1 image of test area
Red(22/05/92), Green(31/07/92),Blue(22/05/92)

(b) Landsat Thematic Mapper image of test area (29/07/92)
Red(Band 3), Green(Band 4), Blue(Band 5)

Figure.1 ERS-1 Multi-temporal image.
Red(18/12/92), Green(31/07/92), Blue(22/05/92)

Figure 6: Pre-processing using GMAP over a 9×9 window (pre-averaged data)

Figure 7: Pre-processing using GMAP over a 15×15 window (pre-averaged data)

Figure 8: Pre-processing using simulated annealing of 1 iteration (pre-averaged data)

Figure 9: Pre-processing using simulated annealing of 2 iterations (pre-averaged data)

Figure 10: Pre-processing using simulated annealing run to convergence (pre-averaged data)

Figure 11: Pre-processing image segmentation ($pe = 10^{-4}$, pre-averaged data)

Figure 12: Pre-processing image segmentation ($pe = 10^{-3}$, pre-averaged data)

Figure 13: Thresholded TM images from 29/07/92, band 3 and band 5

Figure 14: Comparison of thresholded TM image (band 5) and thresholded radar difference images

Figure 15: No of pixels falling above a threshold in radar difference images

22/05/92

31/07/92

18/12/92

Figure 16: Daily rainfall for ten days preceeding each ERS-1.SAR.PRI image acquisition

Incidence angle = 23 degrees, RMS roughness = 2.0 cm.

Figure 17: Modelled radar backscatter from bare soil of varying soil moisture content

Figure 18: Modelled backscatter from bare soil, using Michigan empirical soil model

Figure 19: Modelled forest canopy backscatter using MIMICS

Figure 20: Comparison of Backscatter calculated using MIMICS model and calibrated data

(a) Comparison of model output with SAREX wide swath data

(b) Comparison of model output with SAREX narrow swath data

(c) Comparison of model output with SAREX nadir swath data

Figure 21: Comparison of Backscatter calculated using MIMICS model and calibrated SAREX data

Figure 22: Sensitivity of Backscatter calculated using MIMICS model to leaf thickness

Figure 23: Proportion of total backscatter from 10m crown layer

Figure 24: Backscatter from vegetation layer (leaves only) over bare soil

(a) Comparison of model output with SAREX wide swath data

(b) Comparison of model output with SAREX narrow swath data

(c) Comparison of model output with SAREX nadir swath data

Figure 25: Backscatter difference (HH - VV) calculated using MIMICS model and calibrated SAREX data

Figure 26: Comparison of ERS-1 and SAREX wide swath data

Figure 27:

Figure 28:

Year	1992		
Month	May	July	December
Day	Rainfall mm.		
1	5.0	0.0	0.0
2	0.0	0.0	0.0
3	0.7	0.2	0.0
4	0.0	0.0	0.0
5	0.0	0.0	1.6
6	0.0	0.0	0.0
7	0.6	0.2	0.0
8	2.7	0.6	0.0
9	0.6	3.3	0.0
10	0.0	3.8	0.0
11	0.0	0.2	0.0
12	0.0	3.0	0.0
13	0.0	2.0	0.0
14	0.0	0.2	0.0
15	0.0	3.2	18.6
16	25.8	2.0	0.0
17	0.1	0.0	0.0
18	3.2	4.8	0.0
19	0.0	0.0	0.0
20	0.0	0.0	0.0
21	0.0	0.0	0.0
22	1.0	0.2	2.4
23	0.0	0.0	0.0
24	8.4	0.0	0.0
25	0.0	0.0	0.0
26	4.6	10.6	0.0
27	3.6	13.0	0.0
28	2.4	0.4	0.0
29	0.0	0.0	0.0
30	0.0	4.8	0.0
31	0.0	0.0	0.0
TOTAL	58.7	52.5	22.6
AVERAGE	1.9	1.7	0.7
MAX	25.8	13.0	18.6
MIN	0.0	0.0	0.0

Meteorological Station: 82246 BELTERRA
 Latitude : 02:38 S
 Longitude : 54:57 W
 Altitude : 176 m.

Table.8 Rainfall data from Tapajos Region.