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Assessment of JERS-1 SAR for monitoring secondary vegetation in Amazonia: I. Spatial and temporal variability in backscatter across a chrono-sequence of secondary vegetation stands in Rondonia

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Abstract. Quantification of the direct impact of land use in the tropics on net biotic carbon flux relies on estimates of rates of deforestation, pre- and post-disturbance biomass, and fate of the cleared land. While existing remote sensing applications are providing estimates of the rates of deforestation and the fate of the cleared land (pasture, croplands, or secondary vegetation), techniques for estimating biomass of natural systems with remote sensing are needed. Synthetic Aperture Radar (SAR) presents a unique opportunity for imaging tropical forests under most cloud conditions and potentially provides information on vegetation biomass. Models for estimating above-ground biomass from SAR data have been developed. In this paper we examine the temporal and spatial variability of mean normalized radar cross-section across a chrono-sequence of secondary vegetation stands and clearings in Rondonia, Brazil. We also assess the impact of the observed temporal and spatial variability in normalized radar cross-section on estimating biomass of secondary vegetation stands. Results indicate that, while quantitative estimates of biomass are not stable due to intrinsic texture, system noise, and environmental effects, JERS-1 data are still useful for categorizing relative differences in development of secondary vegetation stands. Merging Japanese Earth Resources Satellite 1 (JERS-1) SAR data with Landsat Thematic Mapper (TM) derived age information data provide improved characterization of clearings and secondary vegetation in Rondonia.

1. Introduction

1.1. *Land use and inter-annual variability of the global carbon cycle*

While recent estimates of the partitioning of carbon between atmospheric, oceanic, and terrestrial carbon pools point to a temperate terrestrial sink for carbon (Tans *et al.* 1990, Quay *et al.* 1992, Siegenthaler and Sarmiento 1993, Keeling *et al.* 1996,

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Ciais *et al.* 1995a,b), it is still extremely important to quantify the annual net flux of carbon due to tropical land use. Annual, spatially explicit estimates of CO₂ emissions due to tropical land use and land cover change would help resolve some of the issues and discrepancies from the recent carbon model results based on annual atmospheric measurements. Furthermore, the models based on the annual {CO₂}, O₂/CO₂, δ¹³C measurements indicate that the southern tropics was not a strong biotic source or sink of carbon in the early 1990s. Annual measurements of deforestation and regrowth can be used to assess if high rates of abandonment and low rates of deforestation during this time period could explain the dampening of the biogenic source of carbon inferred from the atmospheric measurements (Skole *et al.* 1998).

Conversion of forests to pasture and agriculture results in a net source of biotic CO₂ to the atmosphere, while forest fallow and abandonment into secondary vegetation represent a net sink of biotic CO₂. The magnitude and timing of these fluxes are a function of the extent of the conversion, the fate of the cleared lands, and carbon stocks of the pre- and post-disturbance landscape. While average decadal rates of deforestation on a regional scale are now being quantified more accurately (Skole and Tucker 1993, Townshend *et al.* 1995, INPE 1999), quantitative estimates of the net biotic flux on a decadal average suffer from lack of information on pre- and post-disturbance biomass and the fate of the disturbed lands (e.g. crops land, pasture, or fallow).

1.2. Remote sensing land use and land cover change in tropics

Optical remote sensing has been used extensively to map the extent and rates of deforestation (Tucker *et al.* 1984, Malingreau and Tucker 1988, Skole and Tucker 1993) and the extent and temporal dynamics of secondary vegetation (Mausel *et al.* 1993, Brondizio *et al.* 1994, Skole *et al.* 1994, Adams *et al.* 1995, Alves and Skole 1996, Foody *et al.* 1996, Steininger 1996). Recent results from NASA's Landsat Pathfinder project have revealed that there are extensive areas of secondary vegetation throughout Continental Southeast Asia and Amazonia. Over 30% of the deforested area in the Brazilian Amazon was in some form of secondary vegetation in 1986 and 1992 (Houghton *et al.* 2000), areas of approximately 77 000 km² and 98 000 km² in secondary vegetation in 1986 and 1992, respectively. The impact of these large secondary vegetation pools on the net biotic flux of carbon has yet to be quantified. The dynamics of the secondary vegetation pool and the rate of biomass accumulation needs to be understood in order to assess the impact of secondary vegetation on the global carbon cycle.

Although traditional optical remote sensing techniques can distinguish between cultivated areas, pastures, and secondary vegetation, they are limited in terms of mapping various stages of fallow and secondary forests (Sader 1987). On the other hand, since Synthetic Aperture Radar (SAR) backscatter from a vegetated target is a function of the dielectric properties of the vegetation and soil, surface roughness, and size and orientation of the scatterers (e.g. leaves, branches, and trunks) in relation to the imaging system (Ulaby *et al.* 1981), SAR data have considerable promise in characterizing changes in vegetation structure and biomass of the fallow and secondary vegetation areas (Sader 1987, Dobson *et al.* 1992, Rignot *et al.* 1995). In addition, SAR has a significant advantage over optical systems for monitoring land cover and land cover change due to its ability to image the surface under most cloud conditions.

Multiple frequency, polarimetric SARs can provide estimates of biomass for successional forests up to a certain biomass level, with higher saturation point for

longer wavelengths (summarized in Kasischke *et al.* 1997). Estimates of the saturation point of L-band backscatter from tropical forests vary from 40 t ha^{-1} (Imhoff 1995) to 60 t ha^{-1} (Luckman *et al.* 1997a, Curran and Kuplich 1999). Ranson and Sun (1994) and Rignot *et al.* (1995) have shown that P-band backscatter can be used to estimate biomass for forest stands ranging from 150 t ha^{-1} (temperate forest) to 200 t ha^{-1} (tropical forest), respectively. Yanasse *et al.* (1997) used C-band and L-band SIR-C data to discriminate secondary forest stand ages up to 6 years old. An Amazon wide biomass density retrieval scheme based on JERS data has been developed and tested at a site near the Tapajos River (Luckman *et al.* 1998).

The rate of carbon accumulation during secondary succession is a function of many factors, including type of disturbance (e.g. method of clearing, temperature and frequency of burning), agricultural practices (intensity), size and shape of disturbance, and climate (Bazzaz and Pickett 1980, Ewel 1983, Uhl *et al.* 1988, Nepstad *et al.* 1991, Fearnside and Guimarães 1996). There have been numerous studies measuring rates of accumulation in above ground and/or below ground biomass in tropical secondary forests following anthropogenic disturbance (e.g. Fittkau and Klinge 1973, Edwards and Grubb 1977, Sabhasri 1978, Uhl and Jordan 1984, Andriesse and Schelhas 1987, Uhl 1987, Saldarriaga *et al.* 1988, Uhl *et al.* 1988, Nepstad *et al.* 1991, Kauffman *et al.* 1995). Rates of above-ground biomass accumulation in abandoned pastures and agricultural areas can vary dramatically from less than $1 \text{ t ha}^{-1} \text{ y}^{-1}$ for areas under long-term intensive pasture use (Nepstad *et al.* 1991) to over $12 \text{ t ha}^{-1} \text{ y}^{-1}$ for light to moderate use areas (Alves *et al.* 1997, Nepstad *et al.* 1991, Uhl *et al.* 1988). Since the role of land use, climate, and edaphic controls on rates of forest aggradation is not well understood, estimation of changes in above-ground biomass and structure of secondary vegetation with remote sensing would be extremely useful for augmenting field-based studies.

In this paper we examine the potential of using multitemporal JERS-1 SAR data for quantifying differences in rates of recovery of secondary vegetation for a site in central Rondonia. First, we characterize the temporal and spatial variability of JERS-1 normalized radar cross-section, herein called sigma naught, across a chronosequence of secondary vegetation stands. Then, we test the biomass density, herein called biomass, retrieval scheme presented by Luckman *et al.* (1998) for mapping biomass at the landscape scale, and evaluate the impact of using multitemporal JERS-1 SAR data for estimation of biomass. A quantitative understanding of sensitivity of estimating biomass changes with JERS data will highlight the effectiveness of this sensor for monitoring rates of regeneration in Amazonia. In an effort to estimate the impact of residual slash on the overall radar backscatter from secondary vegetation stands, we also examine the temporal changes in mean sigma naught with age of clearings. While Luckman *et al.* (1998) asserted that the biomass retrieval scheme is generalizable for sites across the Amazon provided sigma naught estimates are cross-calibrated to fit their model, our hypotheses concern the use of a model of similar shape with an asymptotic relationship between sigma naught and biomass. Our conclusions provided in this paper are intended to be relative, and would not change despite the use of directly fit values of model parameters specific to our site in Rondonia. In a companion paper (Salas *et al.* 2001) we develop a series of statistical models to evaluate, in an operational context, what level of changes in biomass one might be able to identify with JERS-1 SAR data for a given confidence level. These models assess both the impact of number of JERS images on coefficient of variation of mean biomass estimates and how size of the secondary vegetation stands influence the confidence interval of the biomass estimates.

2. Methods

2.1. Multi-temporal Thematic Mapper (TM) classifications

Annual Landsat TM from 1989 to 1998 (see table 1) were obtained through the NASA's Landsat Pathfinder project (Townshend *et al.* 1995). The first image in the time series was used as a base image and registered to north-up UTM projection using the coordinate estimates from the spacecraft ephemeris. TM data from subsequent years were co-registered to the base image using a first order transformation, based on between 30 and 35 manual ground control points, with rms errors less than 0.6 pixels.

The co-registered TM data were classified using an unsupervised (ISODATA) clustering technique, followed by a manual, knowledge-based assignment of the 45 clusters into seven thematic classes (forest, cleared, natural non-forest, water, cloud, cloud shadow, and secondary vegetation). Mixed clusters were masked out and re-clustered to enhance class separability. Areas of water, cloud, cloud shadow, and natural non-forest were masked out of the classifications.

2.2. Mapping the age of individual secondary vegetation stands and clearings

Land cover changes were quantified using post-classification change detection, resulting in a transition sequence for each pixel. For example, a pixel that was deforested in 1990, abandoned to secondary vegetation in 1993, and then remained as secondary vegetation through 1996 would have a transition sequence from 1989 to 1996 of 'FDDSSSS', where F, D, and S represent forest, non-forest, and secondary vegetation classes, respectively. The histograms of all possible transition sequences were analysed to quantify the land cover change dynamics. Initial analysis of the magnitude of the number of land cover change transitions between 1989 and 1996 and their spatial patterns revealed a highly dynamic landscape (Salas *et al.*, in preparation). Likely some of this dynamic is the result of edge effects due to sub-pixel mixing, artefacts from mis-registration, and classification errors, but based on the size of many of these changes this is also highly dynamic landscape where land use patterns result in rapid changes in land cover (Skole *et al.* 1994, Alves and Skole 1996).

For this study, we segmented clearings and stands of secondary vegetation into two sets of age classes based on whether or not we knew when the areas were

Table 1. Landsat TM data used for multitemporal classifications. While optical data suffer less from seasonality effects (excluding clouds), the images acquired at the end of and during the wet season tend to have a slightly higher proportion of secondary vegetation due to rapid growth of herbaceous vegetation.

Acquisition date	Season
7 July 1989	dry
2 December 1990	early wet
12 June 1991	early dry
22 June 1992	dry
7 October 1993	late dry
4 June 1994	early dry
25 July 1995	dry
25 June 1996	dry
28 June 1997	dry
17 July 1998	dry

initially cleared from forest and, for the secondary vegetation classes, how long the area remained as non-forest. Table 2 contains the class transitions we used for this analysis. To insure that the land cover of the secondary vegetation and the clearings did not change between the 1996 TM acquisition and the JERS acquisitions later in 1996, the 1997 TM classification was used to remove those areas that changed land cover between the 1996 and 1997 TM inventories. All other transition combinations not listed in table 2 were masked out. Individual fields or stands were identified and labelled in a GIS by running an eight-neighbour clump algorithm. A 3×3 low-pass filter was used to identify boundary pixels for each clump. These boundary pixels were then removed to minimize the impact of single or sub-pixel mis-registration between the multitemporal SAR data and the TM-based land cover database, and to remove boundary effects at the edge of intact forest and clearings/secondary vegetation stands that cause increased backscatter at the near boundary and radar shadows at the far boundary (Leckie and Ranson 1998). All stands or fields smaller than 0.75 ha were subsequently removed from the analysis to minimize the variance of the mean stand sigma naught due to speckle. Our resulting map of secondary vegetation contained 182 stands, ranging from 1 to at least 8 years old.

2.3. Accuracy assessment of secondary vegetation and clearing age

An accuracy assessment on the 1998 classification was performed with 166 field reference points collected in October 1998. The overall classification accuracy was 98.2% with producer's/user's accuracies of 100%/97.97% and 83.3%/100.0% for the non-forest and secondary vegetation classes, respectively. However, to estimate the overall classification accuracy of the land cover change statistics, estimates of accuracy from additional time periods are needed. This study area is also a field validation site for NASA's Landsat Pathfinder Humid Tropical Forest project. The Landsat Pathfinder accuracy assessment for this area for the 1993 TM scene used 103 reference points with an overall accuracy of 84%, a user's accuracy over 96% and a producer's

Table 2. Class transitions for estimating age and land-use history for the secondary vegetation stands and clearings. Each entry for the transitions was derived from a single TM classification.

Secondary vegetation classes			Clearing classes		
Transition from 1989 to 1996	Age in 1996 (years)	Code	Transition from 1989 to 1996	Age in 1996 (years)	Code
FFFFFFDS	1	1	FFFFFFFD	1	1
FFFFFFDSS	2	2	FFFFFFDD	2	2
FFFFDSSS	3	3	FFFFFDDD	3	3
FFFDSSSS	4	4	FFFFDDDD	4	4
FFDSSSSS	5	5	FFFDDDDD	5	5
FDSSSSSS	6	6	FFDDDDDD	6	6
FSSSSSSS	7	7	FDDDDDDD	7	7
DDDDDDDS	1	11	DDDDDDDD	8+	8
DDDDDDSS	2	12	SSSSSSSD	1	11
DDDDDDSSS	3	13	SSSSSSDD	2	12
DDDDSSSS	4	14	SSSSSDDD	3	13
DDDSSSSS	5	15	SSSSDDDD	4	14
DDSSSSSS	6	16	SSSDDDDD	5	15
DSSSSSSS	7	17	SSDDDDDD	6	16
SSSSSSSS	8+	18	SDDDDDDD	7	17

accuracy over 90% for the non-forest class. Areas that were cleared previously and not classified as deforested must, therefore, be secondary vegetation, hence the accuracy of the deforested class controls the accuracy of the transitions. Although we have not performed an annual accuracy assessment for each classification, we estimate the overall accuracy of the 8 year (1989–1996) post-classification change detection to range between 72% (based on 1993 Pathfinder accuracy results) to 85% (based on the 1998 results). The objective of our TM image classification was to create the most accurate possible maps of deforestation and vegetation regrowth. Therefore, we performed rigorous manual editing by heads up digitizing on the full resolution TM data. While the methods used for the Landsat Pathfinder analysis were similar in using multiple clustering, the manual editing step was performed at 1:250 000 scale with hardcopy overlay for the Pathfinder analysis to facilitate timely completion of the over 2000 images for the Landsat Pathfinder Humid Tropical Forest project (see Chomentowski *et al.* 1994 for more details on Pathfinder processing). As a result of these slight differences in processing detail, the overall accuracy should be closer to the 85% estimate derived from the 1998 assessment.

2.4. JERS-1 SAR data pre-processing

The Japanese Earth Resources Satellite 1 (JERS-1) was launched and operated by National Space Development Agency of Japan (NASDA) from February 1992 until October 1998. Onboard the JERS-1 satellite was an L-band (1.275 GHz) SAR with horizontal co-polarization (HH). The JERS-1 SAR imaged with a 35° look angle and a ground resolution of 18 m in both range and azimuth with a 44 day revisit cycle. Table 3 lists the eight level 2.1 products (three-looks with 12.5 m pixels) used for this study. Figure 1 contains a subset of the 1996 TM image and a three-date RGB composite of the 1996 JERS images from October, August, and July, respectively. These data were obtained through our participation in NASDA's Global Rain Forest Mapping Project (see Rosenqvist *et al.* 2000 for details on GRFM). JERS-1 SAR data were used for our analysis of secondary vegetation because the lower frequency of L-band is more sensitive to above-ground biomass than C-band data available from ERS or Radarsat, the only other satellite-based SARs.

All eight images were co-registered automatically using image cross-correlation. To convert from 16-bit digital numbers (DN) to normalized radar cross-section,

Table 3. JERS-1 SAR level 2.1 data used. Image 4 was processed by JPL, the remaining seven images were processed by NASDA. Cross-calibration differences were less than 0.5 dB. The range ramp correct was derived using an empirical line model.

Image no.	Date	Season	Range ramp (dB)	Cross-calibration (dB)	NES0 (dB)
1	27 Feb 1993	wet	1.058	0.11	−16.35
2	21 Apr 1993	wet	1.182	−0.35	−16.37
3	22 Sep 1994	late dry	1.538	−0.44	−16.29
4	23 Oct 1995	late dry	0.374	−0.37	−14.88
5	13 Jul 1996	dry	1.516	−0.33	−17.16
6	26 Aug 1996	dry	0.954	−0.09	−15.04
7	9 Oct 1996	late dry	1.340	−0.14	−15.75
8	22 Nov 1996	early wet	0.948	0.09	−14.93

Figure 1. (a) Three-date RGB composite of JERS SAR images from 9 October, 26 August, and 13 July from 1996, respectively. (b) TM image from 25 June 1996 in 4, 3, 2, RGB. The following areas are labelled: A, recently cleared land (after 25 June and before 13 July); B, older clearing; C, secondary growth (red colour in TM image); D, undisturbed forest (cross-calibration site); and E, dirty pasture. Note that in (a) the recent clearings have higher intensity with less heterogeneity than intact forest.

sigma naught (σ°) values in dB the following formula was applied:

$$\sigma^\circ = 20 \log_{10}(\text{DN}) + F \quad (1)$$

where F is the NASDA provided correction factor (-68.5 dB for the images nos

1–7 and –68.3 dB for image no. 8). Equation (1) and the correction factors are taken from Shimada (1998). While it is possible to use the noise vector to improve the noise floor for JERS data (Chapman *et al.* 1999), it was not applied for this application. An estimate of noise equivalent σ° was derived from average DN values from a region of open water.

A range ramp in σ° values from mature forest stands was observed. While these data have been calibrated, there are still some residual artefacts due to significant antenna pattern variations, random gains in range, and slight incidence angle effect across the JERS footprint. The antenna pattern variations and random gain deviations have been observed before in data processed at NASDA (Rosenqvist *et al.* 2000). An empirical linear correction was derived from a 60 km transect in range covering primary forest to normalize the impact of these combined range effects (Leckie 1990, Ranson and Sun 1994). The range ramp across this transect varied from less than 0.4 dB to over 1.5 dB (see table 3). The 23 October 1995 image was processed at the Alaska SAR Facility (ASF). ASF used a different antenna pattern correction algorithm that has been shown to perform a better correction (Chapman *et al.* 1999). The slight range ramp observed is attributed to the variations in incidence angle from near range to far range (34° to 43°) (Chapman *et al.* 1999). It is assumed that, while this linear empirical correction may not properly model incidence angle effect for non-forested areas across the landscape, the impact will be a second-order effect due to the small range in incidence angles and, hence, is ignored. This noise due antenna pattern artefacts may be a result of the older SAR processor used at NASDA for these data.

To apply the biomass density retrieval scheme proposed by Luckman *et al.* (1998), we applied a cross-calibration correction procedure to normalize the gain of these eight JERS images relative to the reference image used to derive the biomass model parameters. Mean and coefficient of variation statistics of σ° for a 228 hectare ($\approx 14\,600\,12.5$ m pixels) area of mature forest was extracted from all eight images. The cross-calibration gains were relatively small (<0.5 dB) and are listed in table 3.

2.5. Extraction of stand and clearing σ° statistics and confidence limits

Radar imagery contains many sources of variability which contribute to the spatial and temporal variability in estimating mean σ° from a target. Our data pre-processing attempted to remove variability due to changes in calibration gains and antenna pattern corrections for different incidence angles. However, to estimate the mean σ° from distributed target (stand of secondary vegetation or an individual clearing) other sources of variability must be considered, including speckle and the intrinsic spatial heterogeneity of the target (Rignot and Kwok 1993). Canopy structure of secondary vegetation in the Amazon varies dramatically with and across age classes due to differences in species composition and growth rates. This type of spatial heterogeneity can be seen as mesoscale roughness in radar imagery, which is often expressed as image texture.

Physical scattering models predict that the σ° from randomly distributed scatters (including leaves, branches, and boles of the trees) will have a negative-exponential distribution whose mean value represents the true σ° of the target (Oliver 1991). Rignot and Kwok (1993) modelled the power (P) of a radar return at a given pixel location (i, j) for a region l would be:

$$P_{i,j,l} = \{\langle I \rangle_l T_{i,j,l} + \langle n_i \rangle\} S_{i,j} \quad (2)$$

where $\langle I \rangle$ is the expected backscattered power, $T_{i,j,l}$ is a random texture variable, n_i is system noise due to a mixture of noise sources (assumed to be additive and a function of slant range), and $S_{i,j}$ is an image speckle random variable. Since speckle and system noise can strongly modulated spatial statistics from space-borne SAR systems where the signal-to-noise ratio can be low, removal or estimation of speckle and system noise is necessary (Rignot and Kwok 1993). Noise equivalent σ° (NES0) was estimated from regions of open water within the images. For the eight images used in this study, NES0 ranged from -14.88 to -17.16 dB (see table 3). Estimates of the lower limit of σ° from secondary forests suggest that σ° values will exceed -11.0 dB. Therefore, since NES0 estimates are at least 2.88 dB less than the lowest σ° values for secondary forests, system noise was assumed to be negligible. Therefore equation (1) above can now be expressed as follows:

$$P_{i,j,l} = \langle I \rangle_l T_{i,j,l} S_{i,j} \quad (3)$$

The variance-to-mean square ratio of speckle can be estimated by $1/N$ where N is the equivalent number of looks (ENL) which is only a function of the imaging and processing system characteristics and not on the distribution of radar cross-section of the target (Rignot and Kwok 1993). Vieira (1996) estimated N for the NASDA level 2.1 product to be 2.8. For this study we analysed only those stands and clearings that were at least 0.75 ha. Given that the resolution of JERS is 18 m, at least 23 independent samples were used to estimate mean σ° . Therefore, our maximum variance-to-mean square ratio due to speckle is $0.0155 (23 \times \text{ENL})^{-1}$. The influence of speckle on our mean σ° estimates will be small.

A source of variation in our mean σ° estimates comes from the intrinsic spatial heterogeneity of the targets (secondary vegetation stands and clearings). Luckman *et al.* (1998) following Oliver (1991), indicated that intrinsic texture (heterogeneity) variance (V_t) can be estimated by

$$V_t = \frac{\left(\frac{\text{SD}}{\mu}\right)^2 - \frac{1}{N}}{1 + \frac{1}{N}} \quad (4)$$

where (SD/μ) is the coefficient of variation (CV) within the stand and N is ENL (NB in Luckman *et al.* (1998) the equation for V_t had an error in that the square of SD/μ was missing). From equation (4) the expected CV value due to both speckle and texture was then calculated using

$$\text{CV} = \sqrt{\frac{V_t}{N} + V_t + \frac{1}{N}} \quad (5)$$

from which approximate 95% confidence limits in dB of two times the standard error of the mean were calculated using

$$10 \log \left(1 \pm 2 \text{CV} \frac{1}{\sqrt{n}} \right) \quad (6)$$

where n is the number of pixels in the stand. Note that this method of calculating confidence limits does not account spatial correlation in σ° between neighbouring pixels resulting from the pixel size being smaller than the resolution of the sensor. Including correlation between pixels in the calculation would increase the width of

the confidence limits, but would not alter the pattern of relative values of confidence limits between even sized stands. To account for pixel-to-pixel correlation, we increased the confidence intervals based on the number of pixels within each stand.

Using equations (1), (4), (5) and (6) we calculated mean σ° and 95% confidence limits for each of the 182 stands of secondary vegetation and σ° for each of the 152 clearings.

2.6. Biomass density model

Luckman *et al.* (1998) developed a semi-empirical model for estimating biomass density of regenerating forests across the entire Brazilian Amazon using JERS-1 L-HH $^\circ$ data. The model coefficients were derived from field and radar observations for a site near the Tapajos River and then validated using independent field and JERS-1 data from Manaus. They concluded that noise due to speckle and image texture limits the utility of the above-ground biomass estimates to distinguishing four broad classes of regeneration state. We decided to use their model to quantify differences in broad biomass levels across the landscape and to track changes in biomass levels with time. Their model relates field estimates of biomass (B) to σ° by

$$\sigma^\circ = a - e^{-(bB + c)} \quad (7)$$

where a , b , c are constants that were empirically derived from field-based estimates of biomass for 18 forested stands near the Tapajos River in the State of Para. Inverting this model to estimate biomass (B) from σ° yields the following equation

$$B = \frac{-\ln(a - \sigma^\circ) - c}{b} \quad (8)$$

Using equation (8) with our mean stand values and our confidence ranges, biomass for all 182 stands of secondary vegetation for each of the JERS images was estimated. We used the following values $a=0.170$, $b=0.053$, and $c=2.146$ (taken directly from Luckman *et al.* 1998) for our calculations. While the biomass model saturates with respect to σ° at a biomass level around 60 t ha^{-1} , equation (8) will provide biomass estimates beyond the σ° model saturation point. Therefore, for graphical purposes, we arbitrarily set maximum biomass estimates levels at 100 t ha^{-1} .

3. Results and discussion

3.1. Landscape variability in σ° across a chrono-sequence of secondary vegetation and clearings

Precipitation in this region of the Amazon is highly seasonal. There is a pronounced dry season from June through August during with less than 4% of the annual 2250 mm of precipitation. Monthly mean precipitation derived from station measurements from 1978 through 1993 is provided in figure 2. Unfortunately, daily precipitation for this region of Rondonia was not available for the time period of our JERS SAR data, therefore we examined image statistics to estimate relative variability due to surface moisture. Radar backscatter increases as soil moisture increases, often leading to decreased image contrast for landscapes in the Amazon with pastures and forest (Grover *et al.* 1999). Examination of our four JERS images from 1996 revealed that the 13 July image had the largest contrast between cleared areas and intact forest ($> 2 \text{ dB}$ difference) and that the 9 October and 22 November images had the smallest contrast (figure 3). The 13 July image was assumed to have the least amount of soil moisture effects and, hence, was used to characterize the

Figure 2. Mean monthly precipitation. Data are averages from station data acquired from 1978 to 1993 (source: Division National Agua Energy Electric, Brazil). This region of the Amazon has a very pronounced dry season, running from June through August, with less than 3% of the total annual precipitation.

mean σ° of our three broad land cover classes (forest, secondary vegetation, and cleared lands) across the landscape.

General trends at the landscape scale indicated that σ° increases with age of the secondary vegetation stands and decrease with age of clearings (see figure 4). Across a 3 year chrono-sequence of regrowth from 1 to 4 years the mean σ° derived from all stands ranged by 1.4 dB (–10.4 to –9.0 dB). The range between the mean values from all the 4- to 8-year-old stands was less than 0.3 dB. This increase in σ° with stand age was expected as secondary vegetation stands tend to accumulate above-ground biomass with age. Rates of biomass accumulation for areas following light use in the region recover at an average annual rate ranging from 6.6 to 8.7 t ha⁻¹ (Alves *et al.* 1997). On average 1-year-old clearings had mean σ° of –8.8 dB, higher than the 1- to 4-year-old stands of regrowth. Mean σ° for the 3- and 8-year-old clearings were over 3 dB and 5 dB lower than the 1-year-old, respectively, possibly reflecting a loss of residual biomass with age. Following forest clearing, slash is often left on site to dry out for up to 2 months after felling of the trees prior to burning. In Rondonia, clearing typically takes place in June and July, followed by burning in August and September. Estimates of burning efficiencies (amount of biomass consumed by the burn) range from 39% (Houghton 1991) to 51% (Kauffman *et al.* 1995). The σ° data in figure 4 are from 13 July 1996, which was likely acquired before burning had begun for the 1996 dry season. All 1-year-old clearings had been cleared by the 24 June 1996 TM scene used to map these new clearings. The large difference (2.5 dB) in 1-year- and 2-year-old clearings is most likely due to the first burn. After the first burn, the biomass of slash declines more slowly due to decay processes with occasional repeated burning to establish and maintain pasture.

Figure 3. Landscape statistics. The dynamic range, defined as difference between mean backscatter of forest and clearings, is provided. The image from 960 713 has the largest contrast (dynamic range) between mean forest backscatter and mean clearing backscatter. The two images acquired late in the dry season and early in the wet season have the lowest contrast. From this it appears that the 13 July image is driest.

3.2. JERS σ° statistics for individual clearings and stands of secondary vegetation

Temporal variability in stand level σ° estimates can result from change in JERS-1 calibration, system noise, speckle, image texture, topographic effects influencing per-pixel scattering area estimates, and environmental conditions (Luckman *et al.* 1998). These first three potential sources of variability in σ° are unlikely to have much of an impact given our cross-calibration procedure and stand size limitations imposed for this analysis. This region of Rondonia is relatively flat, so topographic effect will likely be small. The influence of intrinsic image texture was characterized by equation (4). Variations in soil and plant dielectric properties and their relative contributions to stand level σ° will vary depending on the environmental conditions and the overall stand structure.

The mean and variance of σ° estimates for each clearing and secondary vegetation stand were spatially and temporally highly variable. While the clearing exhibited the same general trend that we observed on the landscape scale, namely a decrease in σ° with age, the variability within the same age classes was comparable to the temporal changes resulting from loss of residual slash following initial clearing (see figure 5). First year clearings had mean σ° values ranging from approximately -6.5 to -12.0 dB. Some clearings had higher σ° than the surrounding forest, most likely due to enhanced double bounce caused by the ground and slash interactions (Rignot *et al.* 1997, Saatchi *et al.* 1997). High response ($\sigma^\circ > -8.0$ dB) was observed from the 1- and 2-year-old clearings in all four 1996 images. In the 13 July image, 12 of

Figure 4. Mean backscatter across the landscape by age, calculated by averaging intensity means of all secondary vegetations stands or cleared areas. Error bars represent the 95% confidence levels (± 1.96 standard error). Statistics derived from the 13 July 1996 image. Backscatter is higher for younger clearings and rapidly decreases with age. Backscatter is lower for young stands of secondary vegetation and increases with age.

the 39 (31%) 1-year-old clearings had σ° values greater than -8.3 dB, the threshold for old regeneration and primary forest class in Luckman *et al.* (1998) biomass density retrieval scheme. These 12 clearings represented 36% of the total area for all 1-year-old clearings. Of the 2-year-old clearings, 20% (12% of the area) had mean σ° greater than -8.3 dB, a lower percentage than the 1-year-old population. On an area weighted basis more than 96% of the older clearings had mean σ° less than -8.3 dB in all four 1996 images. The new clearings did not exhibit an appreciable decrease in σ° from the early dry season data to the later dry season images as would be expected once the slash for the clearing had been burned, indicating that environmental conditions may mask land use impacts on mean σ° . Normalization of soil moisture and micro-scale surface roughness effects would lead to better information on differences in clearing process. Further quantification of these differences would be useful for quantifying variability in clearing practice (amount of slash removed off site), burning efficiencies, and rates of decay of residual biomass.

While there is a general trend of increasing σ° with secondary vegetation stand age, there are significant temporal and spatial differences within age classes of secondary vegetation (figure 6). The temporal differences in σ° from 13 July to 22 November are apparent with higher σ° in the late dry season/early wet season images. The observed across-stand variability within age classes was expected to a certain extent due to variability in amounts of residual slash, rates of biomass accumulation and differences in species composition. The temporal variability is

Figure 5. Mean backscatter by age of clearing. (a) 13 July 1996, (b) 26 August 1996, (c) 9 October 1996, and (d) 22 November 1996. While there is a general trend of decreasing backscatter with age, there is also considerable range of mean backscatter within a single age cohort, as well as temporal differences. The October and November images tend to have higher mean values, likely because of higher dielectric properties of the target due to increased moisture content of soils and vegetation. Magnitude of the soil moisture effect depends on the soil texture and the surface roughness of the clearings.

likely due to changes in environmental conditions (e.g. moisture content of soil and vegetation) resulting in large variations in mean σ° .

We converted mean σ° to biomass using equation (8) to look at trends in biomass estimates with age of the secondary vegetation stands (figure 6). Biomass estimates were extremely variable and tended to increase with age of the stands. The biomass model from Luckman *et al.* (1998) was derived by fitting a sigmoid curve to field-based estimates of biomass using a least squares fit. It is important to note that this sigmoid function reaches an asymptote at the biomass saturation point (Luckman *et al.* 1997a). Estimates of the saturation point for JERS L-HH biomass retrievals range from 40 t ha^{-1} (Imhoff 1995) to 60 t ha^{-1} (Luckman *et al.* 1997a, Curran and Kuplich 1999). Therefore, biomass estimates above the $40\text{--}60 \text{ t ha}^{-1}$ range may be artefacts of the sigmoid function and not a reflection of differences in the actual above-ground biomass. Nevertheless, there are important trends in these results. The percentages of secondary vegetation stands at or above the saturation point increased with age. From the 13 July image, we see only one 1-year-old stand above the saturation point, where more than 60% of the 8-year-old stands were above the saturation point. Estimates from the October and November images had a larger percentage of the biomass estimates saturate. While the secondary vegetation stands may have accumulated some biomass between June and November, the large increase of saturated estimates is likely due to higher mean σ° , likely resulting from wetter

Figure 6. Mean stand backscatter by age of secondary vegetation. (a) 13 July 1996, (b) 26 August 1996, (c) 9 October 1996, and (d) 22 November 1996. While there is a general trend of increasing backscatter with stand age, there are significant temporal and spatial differences within age classes of secondary vegetation. The temporal differences in backscatter from 13 July to 22 November are apparent with higher backscatter in the late dry season/early wet season images. The spatial variability within the same age classes is due to surface roughness, and land use effects, sensitivity of the backscatter characteristics with small changes in biomass, as well as variability in rates of biomass accumulation. The temporal variability is due to changes in environmental conditions (e.g. moisture content of soil and vegetation) resulting in large variations in mean stand backscatter.

environmental conditions and higher soil and vegetation moisture content (Curran and Kuplich 1999).

We examined the temporal stability of estimating biomass by comparing, on a stand-by-stand basis, biomass estimates for all >8-year-old stands from our 13 July 1996 image with the three other 1996 estimates (figure 7). In this figure we have drawn a line at 31 t ha^{-1} to represent the maximum biomass of secondary vegetation that Luckman *et al.* (1998) estimate can be separated from mature regrowth with a 95% confidence level. Once again the estimates vary dramatically across these four images and hence are not temporally stable. As stands age, the variance in mean σ° due to environmental conditions should decrease due to enhanced scattering from higher above-ground biomass. For example, Hashimoto *et al.* (1997) documented different seasonal variation in JERS-1 σ° for dirty pastures and two biomass classes of secondary vegetation in Rondonia, with ranges decreasing from over 2 dB to 1 dB. However, at the same time, as the stands develop there should be increased canopy heterogeneity as the overstorey develops resulting in greater variance due to texture effects (Luckman *et al.* 1997b). A large percentage of the 13 July estimates that are below the saturation point exceed the saturation point for the other dates

Figure 7. Relative biomass estimates for 8-year-old stands of vegetation regrowth. The dashed lines represent a saturation point of approximately 31 t ha^{-1} . Four quadrants are labelled. Quadrant I: stands with no saturation in at least two periods. Quadrant II: saturation in 13 July but not for all three later estimates. Quadrant III: no saturation in 13 July but saturated at later date. Quadrant IV: saturation in both inventories.

(figure 7, quad 3). Secondly, there are many stands that exceeded the saturation point in the 13 July image (assumed to have the least soil moisture effects) and did not saturate for the later estimates (figure 7, quad 2). A majority of the stand estimates were above the saturation biomass levels (quad 4). Based on the Alves *et al.* (1997) biomass accumulation rates of between 6.6 and $8.7 \text{ t ha}^{-1} \text{ y}^{-1}$, we would expect all the stands to have biomass levels exceeding the 31 t ha^{-1} saturation point. Of the 135 >8-year stands in our analysis, only two had biomass estimates below the saturation point for all four estimates, but if we only look at the 13 July data then 21 stands were below saturation point. The presence of some stands below this point indicate that either: (a) the rate of biomass accumulation is well below the Alves *et al.* rates of 6.6 – 8.7 t ha^{-1} , (b) the JERS estimates significantly underestimate the actual biomass, or (c) the TM classifications of vegetation regrowth areas are wrong. While dirty (not well maintained) pastures often have similar TM spectral properties to young secondary vegetation, especially for early dry season TM acquisitions, the probability is quite low that a dirty pasture would be classified as secondary vegetation in all eight TM classifications because the farmers would need to maintain the pastures at some point in this period to still be able to use the land as pasture. Once the farmer maintained the field by burning the herbaceous vegetation the TM classification would have mapped the area as cleared.

Figure 8 illustrates the range in biomass estimates for all the 1-year-old stands

Figure 8. Relative biomass estimates for 1-year-old secondary vegetation. The dashed lines represent a saturation point of approximately 31 t ha^{-1} . Four quadrants are labelled. Quadrant I: stands with no saturation in at least two periods. Quadrant II: saturation in 13 July but not for all three later estimates. Quadrant III: no saturation in 13 July but saturated at later date. Quadrant IV: saturation in both inventories.

in 1996. While the percentage of regrowth stands above the saturation point in all four images is much lower (16%), 86% of the stands had at least one estimate above the saturation biomass level of 31 t ha^{-1} . From the 13 July image alone, 16% of the stands were above the saturation point. All of these 1-year-old stands had been cleared from forest in 1994, were used for 1-year (1995) prior to secondary vegetation formation and therefore there could still have a large portion of residual slash remaining on site from the original clearing event in 1994.

3.3. Analysis of variance of spatial and temporal variability in stand σ°

We performed an analysis of variance (ANOVA) derived from mean stand σ° measurements from all four 1996 images to quantify the relative contributions of stand and temporal variability to the overall variance of the stand σ° . All 179 secondary-growth stands for which data were available from more than one scene were included in the analysis, yielding 685 observations. We assumed that the change in above-ground biomass between the 13 July and 22 November would have a negligible effect on the mean σ° for any given stand. For this analysis we modelled the measured σ° in linear units (σ_{ij}°) for a particular stand (i) at any given time (j) as

$$\sigma_{ij}^\circ = \mu + S_i + T_j + \varepsilon_{ij} \quad (9)$$

where μ is the average σ° across all stands and time periods, S_i is the expected difference of stand i from the average, T_j is the expected difference of a stand observed at time j from the average, and ε_{ij} is uncorrelated error due to noise. In performing the ANOVA, observations were weighted inversely proportional to their variance (calculated as $CV_{ij}^2 \sigma^\circ_{ij}$).

From this analysis we again see that the 13 July and 26 August images had lower mean σ° and the October ninth image had higher mean σ° values than the 22 November images (table 4), which is consistent with our expectations based on the mean landscape statistics (figure 3).

A decomposition of the components of the variance in σ° is shown in table 5. This decomposition is based on the unweighted contributions of the different parameters to estimated σ°_{ij} values, and the corresponding residuals. Variation between stands that is consistent from image to image is indicated by the variability of the S_i values, and represents the majority of the variance. Variance between images that is consistent from stand to stand is indicated by the variability of the T_j values. The relatively small magnitude of this variation, and its minor contribution to the overall variance, suggest the careful cross-calibration procedures employed here were successful in minimizing scene-wide impacts of calibration and environmental effects. In addition, changes in environmental conditions between images had a differential effect on the stands. However, the contribution of noise (ε_{ij} values) is large. The expected magnitude (in a root mean square sense) of the uncorrelated noise term is 74% of the expected magnitude of the difference of a stand from the mean. Because the error term is uncorrelated across a scene, it cannot be reduced through cross-calibration or the inclusion of a range of ground-truthed reference stands in the imaged area. Contributions to the overall error term include image texture, speckle, relative calibration, random system noise (Rignot and Kwok 1993), and within scene variability in environmental conditions (e.g. soil and vegetation moisture content). However in this case, the contribution of the error term is several times the contribution that would be expected from texture and speckle alone ($\chi^2 = 1807.7$, d.f. = 503,

Table 4. Estimated departure from average σ° for each of the four scenes in 1996, in linear units. The two dry-season scenes show lowest average σ° , consistent with expectation. The difference among images is statistically significant ($F = 0.23$, d.f. = 3, $p < 0.0001$).

Date	T_j
13 July	-0.0030
26 August	-0.0031
9 October	0.0054
22 November	0.0007

Table 5. Magnitude of effects in the ANOVA, and variance components as a percent of the total. While temporal variability (consistent within a scene) is small, noise from stand to stand is large, and similar in order of magnitude to the variability between stands within a scene.

Source	Root mean square value	Percent of variance
Stand variability (S_i)	0.0238	63.4%
Temporal variability (T_j)	0.0035	1.4%
Noise (ε_{ij})	0.0177	35.2%

$p < 0.001$). Therefore, given the fairly high system signal-to-noise characteristics of these images, a large source of the noise term is likely due to the relative calibration and environmental conditions. There may also be a slight slant-range dependence that impacts the relative contribution of system noise across a single image. Since the relative calibration of JERS is approximately 1.0 dB and the range in expected σ° is less than 2.5 dB across a biomass range from 6 t ha^{-1} to the saturation point of 31 t ha^{-1} , calibration and differential effects on changing environmental conditions control the total noise contribution.

Soil moisture impact on mean stand σ° will be a function of soil moisture, soil roughness and amount of above-ground biomass. Stands with high biomass will likely be less sensitive to differences in soil moisture beneath the canopy in the absence of standing water. Based on a threshold of $p < 0.05$, we estimate that, for 45% of secondary vegetation area, the variance in linear σ° within a stand estimate was within the expected range due to texture and speckle effects and, therefore, less sensitive to changes in environmental conditions. Looking at the temporal impact of background effects on stand σ° provides useful information on the overall scattering properties of the target. σ° from a vegetated target is a function of the vegetation dielectric properties and structure, and sub-canopy surface conditions. Since within a given dry season the structure of secondary vegetation canopy will not change much and vegetation in this region do not experience water stress, differences in σ° are a function of sub-canopy conditions and water on vegetation surfaces (not withstanding variability due to system noise and relative calibration errors). The amount of temporal variability in mean σ° can be used to separate qualitative differences in stand scattering properties.

4. Conclusion

This study evaluated the spatial and temporal variability in L-HH σ° from secondary vegetation stands and clearings across a chrono-sequence of ages using JERS-1 SAR data. At the broad landscape scale, mean radar σ° increased with age of secondary vegetation, likely a result of higher above-ground biomass levels with age, and decreased with age of clearings, likely due to decreases in residual slash over time by burning and decay processes. However, at the stand level these σ° trends are more difficult to quantify. The temporal variability in mean stand σ° due to system noise, relative calibration errors, environmental and site conditions is comparable to the expected dynamic range of σ° across the biomass values expected for secondary vegetation stands younger than 6 years old. The range in σ° within age classes was greater than the range across age classes. The source of this variability is likely due to a combination of differences in rates of regeneration, intrinsic stand texture, amount of residual slash, and soil and vegetation moisture conditions. Furthermore, differences in σ° signal between two stands at the same time, or between two observations of a single stand, is likely to include a sizeable noise contribution.

While quantitative retrievals of biomass with JERS need to be evaluated on a case-by-case basis, multitemporal JERS data can be used to estimate qualitative differences in stand characteristics. An assessment of statistical variability in σ° with multirate JERS relative to expected variance from texture, speckle, and system noise provides information on stability of the stand scattering properties for upland forest. While these differences may not relate directly to biomass, inferences about signal saturation can be made.

JERS-1 SAR data acquired during the dry season data provided better contrast

in general than the wet season data, but the best images cannot be selected based solely on acquisition date due to precipitation events during dry months. In addition to better characterization of secondary vegetation stand scattering properties, multi-date images improves the classification of clearings, secondary vegetation and forest by resolving some ambiguities due to the clearing process. Synergy of Landsat-derived age information with JERS derived scattering properties provide a better characterization of the overall structure of clearings and secondary vegetation stands in Amazonia. Further work is needed to quantify the implications of using JERS derived biomass estimates of secondary vegetation for mapping differences in rates of regeneration. The relationship between stand structure and radar texture needs to be researched further as a potential source of complementary information to mean stand σ° .

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