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Assessment of JERS-1 SAR for monitoring secondary vegetation in Amazonia: II. Spatial, temporal, and radiometric considerations for operational monitoring

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Abstract. While the role of Synthetic Aperture Radar (SAR) in operational tropical forest monitoring has yet to be defined, it is nevertheless a critical technology for improving our understanding of deforestation and secondary vegetation in the tropics. In order to understand the role of this technology in operational monitoring a systematic evaluation, relative to other existing technologies of its performance is required. In this paper we evaluate the spatial, temporal, and noise constraints of JERS SAR data for mapping and monitoring biomass of secondary vegetation in Rondonia, Brazil. Our results indicate that the variability in stand estimates of biomass is high and that the source of the majority of the variability is not from speckle and the intrinsic texture of the secondary vegetation but likely due to differences in environmental conditions resulting in differential background scattering properties. Multitemporal analysis significantly improves biomass estimates to the point where it is possible to map changes in biomass. Slight reductions in the variability in estimates of normalized radar cross-section greatly improve biomass estimation.

1. Introduction

Land use within the tropical rain forest biome has a large impact on the net flux of carbon from the biota and is an important component of the global carbon cycle. 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 the carbon stocks of the pre- and post-disturbance landscape. Understanding the processes of

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deforestation and abandonment will improve estimates of the magnitude of the net biotic flux of carbon from the tropics. Accurate, quantitative estimates of deforestation and secondary vegetation extent, rates of deforestation, land abandonment, and forest regeneration are critical for understanding the global carbon cycle. Remote sensing provides the only approach capable of providing this information accurately and timely, over large areas, at a uniform sampling scheme, and repeatedly over time. Optical remote sensing techniques have proven useful for quantifying deforestation and detecting secondary vegetation, but they have been hampered by persistent cloud cover in some regions and by a lack of sensitivity to biomass. There is a clear need for additional techniques to supplement the role of optical sensors for tropical forest monitoring. One most promising alternative to optical is Synthetic Aperture Radar (SAR) because it is not affected by clouds and offers some sensitivity to biomass. Ultimately, these two remote sensing tools ought to be working in a synergistic fashion to provide the best characterization of deforestation, abandonment and secondary vegetation.

Numerous studies have focused on the use of remote sensing for mapping the extent, temporal dynamics, age, and biomass of secondary vegetation in the tropics (e.g. Lucas *et al.* 1993, Mausel *et al.* 1993, Foody and Curran 1994, Alves and Skole 1996, Steininger 1996, Luckman *et al.* 1997a,b, 1998, Nelson *et al.* 2000). Multitemporal Spot XS and Thematic Mapper (TM) data have been used to create maps of secondary growth age (Lucas *et al.* 1993, Alves and Skole 1996, Steininger 1996, Nelson *et al.* 2000) and persistence (Alves and Skole 1996, Nelson *et al.* 2000). Vegetation indices using red and near-infrared reflectance saturate for separating forest secondary vegetation after a few years (Sant'Anna *et al.* 1995). However, vegetation indices that utilize mid-infrared and near-infrared data (Boyd *et al.* 1996, Steininger 1996, Nelson *et al.* 2000) and texture-based classifiers (Palubinskas *et al.* 1995, Nelson *et al.* 2000) do not saturate as quickly and are better for detecting secondary vegetation in the tropics. Landsat TM spectral properties differ among the successional stages of secondary vegetation in the tropics (e.g. Mausel *et al.* 1993, Moran *et al.* 1994, Steininger 1996, Foody *et al.* 1996, Sohn *et al.* 1999). Over time, reflectance properties of secondary vegetation become indistinguishable from those of mature, undisturbed forest (Mausel *et al.* 1993, Boyd *et al.* 1996, Foody *et al.* 1996). Results from several studies using Landsat TM data indicate that secondary vegetation stands can be spectrally separated into four to six distinct age classes, with the oldest class remaining distinct from mature forest for ≈ 14 –15 years (Boyd *et al.* 1996, Foody *et al.* 1996, Steininger 1996, Sohn *et al.* 1999). Neural net classification techniques have also been used to map secondary vegetation and estimate stand age with single and two-date Spot XS and Landsat TM spectral and textural data (Kimes *et al.* 1999, Nelson *et al.* 2000).

C-band radar data are less useful than L-band data for mapping biomass of re-growing forest (Rignot *et al.* 1997, Saatchi *et al.* 1997, Yanasse *et al.* 1997). Single polarization (HH) L-band radar data have been used successfully to map deforestation and secondary vegetation and estimate ranges of biomass accumulation from radar backscatter (Luckman *et al.* 1997b, 1998) and phase coherence (Luckman *et al.* 2000). There appears to be a general agreement that radar backscatter increases with increasing biomass and saturates at some biomass level. Estimates of the saturation point of L-band data from tropical forests vary from 40 t ha^{-1} (Imhoff 1995) to 60 t ha^{-1} (Luckman *et al.* 1997a). Ranson and Sun (1997) and Rignot *et al.* (1995) have shown that P-band backscatter can estimate biomass for forest stands up to 150 t ha^{-1} (temperate forest) to 200 t ha^{-1} (tropical forest), respectively.

The baseline for an operational forest monitoring system necessitates complete forest inventories as frequently as every 5 years (Ahern *et al.* 1998). Analysis of Landsat cloud cover metadata indicates that persistent cloud cover in the tropics would severely limit the ability to map annual changes using Landsat data. For example, from 1990 to 1994 less than 50% of the 228 Landsat World Reference System II footprints covering the Brazilian Amazon was covered by a low cloud cover (<20%) Landsat TM image. Clearly, due to persistent cloud coverage, complete optical coverage is difficult, therefore, attempts at measuring rates of deforestation and secondary vegetation would benefit from SAR imagery, thereby ensuring complete coverage. Numerous studies have demonstrated that SAR data can be used to detect deforestation (e.g. Rignot *et al.* 1997, Saatchi *et al.* 1997). A systematic evaluation of errors in estimating deforestation and secondary vegetation relative to estimates derived from optical remote sensing platforms is needed to understand the role of radar in the context of operational forest monitoring. This evaluation should focus on the performance of multistate SAR data for operational forest monitoring. While it is clear that SAR must play an important role in an operational tropical forest monitoring systems (cf. GOFCS Strategy Document), the role has yet to be defined. Knowing the level of performance of SAR for mapping land cover change is critical, especially for regions shrouded by persistent cloud cover where SAR may be the only viable alternative to optical sensors. While several studies have indicated that both optical (e.g. Skole *et al.* 1994, Foody *et al.* 1996, Steininger 1996) and SAR (Luckman *et al.* 1997a,b, Curran and Kuplich 1999) data can be used to characterize differences in secondary vegetation, new research needs to focus on how differences in the rates of forest aggradation can be quantified to improve our understanding of the controls on carbon sequestration across the landscape.

In Salas *et al.* (2001, this issue) we examined the spatial and temporal variability of mean normalized radar cross-section, called sigma naught (or σ^0), across a chronosequence of secondary vegetation stands and clearings. In order to evaluate the potential of using multitemporal JERS-1 SAR data for quantifying differences in rates of recovery of secondary vegetation, we applied the biomass density retrieval scheme presented by Luckman *et al.* (1998) and evaluated the sensitivity of using multitemporal JERS-1 SAR data for biomass density estimation. The temporal and spatial stability of the mean stand σ^0 estimates were highly variable due to differential effects of changes in environmental conditions and variability of intrinsic heterogeneity (texture) of the stands. In this paper we develop a series of statistical models to evaluate, in an operational context, what level of changes in biomass density, herein called biomass, one might be able to identify with JERS-1 SAR data for a given confidence level. These models assess the impact of multiple JERS data takes and size of the vegetation secondary vegetation stands on the coefficient of variation of our biomass estimates. Performance of estimating biomass is evaluated based on the ability to quantify the presence and magnitude of biomass change over time.

2. Methods

In this section we provide a summary of the methods used in our analysis. Section 2.1 contains a brief description of how the individual secondary vegetation stands were mapped and how their ages were calculated. Sections 2.2–2.5 provide the details of the JERS data pre-processing, extraction of secondary vegetation stand level σ^0 statistics, and the biomass density model used, respectively. Section 2.5 describes the statistical methods and models used. The text provided in these four

sections is paraphrased from our companion paper in this special issue, where more details on the image processing methods can be found. Our analysis is based on using multitemporal TM data for mapping age and size of secondary vegetation stands and multitemporal JERS data for generation of σ° statistics for a site in Rondonia, Brazil (figure 1).

2.1. TM analysis of secondary vegetation stand age and size

Annual co-registered Landsat TM from 1989 to 1998 were classified using an unsupervised (ISODATA) clustering technique, followed by a manual, knowledge-based assignment of the 45 clusters into forest, cleared, natural non-forest, water, cloud, cloud shadow, and secondary vegetation classes. Areas of water, cloud, cloud shadow, and natural non-forest were removed. These 10 classifications were then combined to create land cover changes map using post-classification change detection. 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. For this study, we segmented the stands of secondary vegetation into two sets of age classes based on whether or not we knew when the areas were initially cleared from forest and how long the area remained as non-forest prior to secondary growth formation. Contiguous areas with the same land cover transition sequence over the 10-year period were identified and labelled using an eight-neighbour clump algorithm. A 3×3 low-pass filter was then used to identify edge pixels, which were removed to minimize the impact of mis-registration between the multitemporal SAR data and the TM-based secondary vegetation stand map. All stands smaller than 0.75 ha were subsequently removed from the analysis to minimize the variance of the mean stand σ° due to speckle (see discussion below). We estimate the overall accuracy of the stand age maps to range between 72% and 85% (Salas *et al.* 2001, this issue). The location of the study area and an example of the stand age map are provided in figure 1. Areas that have not been deforested appear tan in the age map in figure 1, with the remaining colours representing various ages, as of 1998, of clearings and secondary vegetation stands.

2.2. JERS-1 SAR data pre-processing

We analysed eight L-band (1.275 GHz), HH polarized, SAR from the Japanese Earth Resources Satellite 1 (JERS-1). Table 1 lists the eight level 2.1 products (three-looks with 12.5 m pixels) used for this study. These data were obtained through our participation in NASDA's Global Rain Forest Mapping Project (see Rosenqvist *et al.* 2000 for details on GRFM). These images were co-registered automatically using image cross-correlation and converted to normalized radar cross-section (σ°) values in dB with the following formula:

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

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). We applied an empirical linear correction, derived from a transect of primary forest, to account a ramp in σ° with range (Leckie 1990, Ranson and Sun 1994). The range ramp across this transect varied from 0.4 to 1.5 dB (see table 1). While, theoretically, this linear empirical correction may not properly model incidence angle effects for non-forested areas across the landscape or correct for non-linear effects of system noise with slant range, we assume that the residual noise correlated with range would be a second order effect due to the small range in

Figure 1. Location maps of the Rondonia site, and subsets of the secondary vegetation and clearing stand age map, 25 June 1996 TM image, RGB composite of 9 October, 26 August, and 13 July 1996 JERS images.

incidence angles across our study area. We then cross-calibrated these data to normalize their gain differences. The cross-calibration offsets (table 1) were derived from mean and coefficient of variation statistics of σ° from 228ha of mature forest.

Table 1. JERS-1 SAR level 2.1 data used. Image 4 was processed by JPL, the remaining seven images were processed by NASDA.

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

NES0, Noise equivalent σ° .

2.3. Extraction of stand σ° statistics and confidence limits

Speckle and the intrinsic spatial heterogeneity (texture) of vegetation impacts our ability to accurately estimate the mean σ° from stands of secondary vegetation (Rignot and Kwok 1993). The estimate of coefficient of variation caused by speckle and intrinsic texture can be estimated by:

$$CV = \sqrt{\frac{V_t}{N} + V_t} + \frac{1}{N} \quad (2)$$

where N is effective number of looks (ENL) and V_t is the variance due to texture (from Luckman *et al.* 1998), following Oliver (1991), and is calculated as

$$V_t = \frac{\left(\frac{SD}{\mu}\right)^2 - \frac{1}{N}}{1 + \frac{1}{N}} \quad (3)$$

where $(SD\mu^{-1})$ is the actual coefficient of variation (CV) within the stand. Vieira (1996) estimated N for a single JERS-1 three-look pixel to be 2.8. Using the estimated CV we can estimate the 95% confidence limits in dB by

$$10 \log \left(1 \pm 2CV \frac{1}{\sqrt{n}} \right) \quad (4)$$

where n is the number of uncorrelated pixels in the stand. Note that (4) ignores all sources of variation except texture and speckle. An improved confidence limit, but still accounting only for texture and speckle, would be

$$10 \log \left(1 \pm t_{0.05, n-1} CV \frac{1}{\sqrt{n}} \right) \quad (4a)$$

We used level 2.1 data with a spatial resolution of 12.5 m. However, since JERS resolution is 18 m, there is a significant amount of correlation between neighbouring pixels that must be accounted for in calculating our confidence intervals. Using these equations we calculated mean σ° with the 95% confidence limits for each of the 182 stands of secondary vegetation.

Shimada (1996) estimated N for the NASDA level 2.1 three-look product to be 2.1. The discrepancy with the Vieira estimate could be due to differences in the SAR processor used to create the products. If N is closer to 2.1 then our overall confidence limits would be wider than reported here by a factor inversely proportional to the size of the secondary vegetation stand.

2.4. Biomass density model

Luckman *et al.* (1998) developed a semi-empirical model for estimating biomass density of regenerating forests with JERS-1 radar σ° data and asserted that the model is generalizable to other regions in the Amazon. We tested their model for quantifying broad differences in biomass of our secondary vegetation stands. Inverting their model to estimate biomass (B) from σ° , expressed in linear units, yields

$$B = \frac{-\ln(a - \sigma^\circ) - c}{b} \quad (5)$$

where a, b, c are constants that were empirically derived from field data from Tapajos region in Para State in the Amazon. 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. Unfortunately, when $\sigma^\circ \geq a$, the estimate produced by (5), or equivalently by (4), is undefined, since the model saturates with respect to σ° , not biomass density. This situation occurred frequently in all the scenes examined. Unfortunately, the model does not provide a natural or saturated biomass density level, but some value must be specified. To provide estimates in these cases, we used

$$B = \frac{-\ln(0.00005) - c}{b} = 146.4 \quad (5a)$$

which is slightly larger than the largest estimate calculated using (5), or 143.1 t ha^{-1} . Using these equations we then calculated the biomass for all 182 stands of secondary vegetation for each of the JERS images listed in table 1.

2.5. Statistical methods and models

Given the availability of multiple, contemporaneous images, confidence limits can be calculated for σ° (in linear units), σ° (in dB), and biomass in two different ways. First, the full-width (upper minus lower limit) of the 95% confidence limits for σ° (in linear units) may be calculated as

$$2E = 2t_{0.05,n} \frac{SD}{\sqrt{n}} \quad (6)$$

with the corresponding width for σ° in dB calculated using (4a). The full-width for biomass may be calculated by substituting $\sigma^\circ + E$ and $\sigma^\circ - E$ into (5) or (5a) as appropriate, and taking the difference. Note that this procedure specifically assumes that the all contributions to the variability in σ° and biomass, other than those from speckle and texture, are negligible.

Alternately, given J scenes, we might consider calculating the full-width of the 95% confidence limits for σ° in linear units as $2t_{0.05,J-1}$ times the standard deviation of the J estimates of σ° about their arithmetic mean. Confidence limit widths for σ° in dB and biomass may then be calculated as before. This procedure has the advantage that all sources of variation between scenes are accounted for, not just speckle

and texture. Substantial differences between confidence limits calculated using (6), (4a), and (5a) in turn, and those calculated from the observed temporal variability in the estimates, must be regarded as evidence that speckle and texture are not the major controlling factors in the variability of the estimates. Confidence limits were calculated for both methods using only those 139 stands which were present in all four of the 1996 scenes, since confidence limits based on only two or three scenes would be more variable.

To quantify the contribution of factors other than speckle and texture to the variability in observed σ° , we performed a series of χ^2 tests on the σ° from the four 1996 scenes. Since σ° (in linear units) for a polygon is estimated as the mean σ° for all pixels in the polygon, and since the number of pixels in a polygon is generally large, it follows directly from the Central Limit Theorem that the estimated σ° is approximately normally distributed about the true value. The quantity

$$SE_{\sigma^\circ}^2 = \frac{SD^2}{n} \quad (7)$$

provides an unbiased estimate of the variance of σ° , under the null hypothesis that the variance of σ° arises from texture and speckle only. Recalling that a sum of squared, normally distributed variables is distributed as chi-squared, we may test the null hypothesis by comparing

$$\chi^2 = \sum_{ij} \frac{(\sigma_{ij}^\circ - \hat{\sigma}_i^\circ)^2}{SE_{\sigma_{ij}}^2} \quad (8)$$

to the critical values of χ^2 for $IJ - I$ degrees of freedom. In (8), i indexes I stands or polygons, and j indexes J scenes. Equation (7) is calculated separately for each polygon and scene. Stand area affects the value of chi-squared through the relationship between stand area and n , which affects $SE_{\sigma^\circ}^2$. In equation (8), each stand is treated as an equally weighted observation. The quantity $\hat{\sigma}_i^\circ$, is the least-squares mean of the σ_{ij}° values, which minimizes χ^2 . We calculated χ^2 for all 179 stands that were represented in more than one of the 1996 images combined, and for each stand separately. The combined χ^2 provides a powerful overall test of whether the observed variation between images could have arisen from texture and speckle alone. The χ^2 values for each stand individually provide a direct measure of the magnitude of the observed temporal variation relative to the expected temporal variation under the null hypothesis.

Following the results of the χ^2 tests, we further examined the behaviour of the coefficient of variation of the biomass predictions, based on the observed inter-temporal variability in predicted biomass. We further examined the implications of the magnitude of observed coefficients of variation for biomass predictions, for the coefficient of variation of estimates of change.

3. Results and discussion

3.1. Effects of factors other than speckle and texture

Confidence limits based on speckle and texture only, and confidence limits based on observed inter-temporal variation, are shown for σ° (in linear units), σ° (in dB), and biomass in figure 2. First, considering the confidence limits based on speckle and texture alone, it is notable that many stands exceeded the 'worst-case' scenario presented by Luckman *et al.* (1998, p. 135) of full-widths of 1.18 dB. In part, this is because 22% of the stands considered are less than the 1 ha size used by Luckman

Figure 2. The 95% confidence limits for σ^0 (linear units), σ^0 (dB), and biomass calculated based on speckle and texture alone (left column) and based on actual inter-temporal variation among images (right column).

et al. (1998) in their assessment. The spatial scale of land-clearing and conversion activities is small in this region of Rondonia. Analysis of the distribution of secondary vegetation stands indicates that over 60% of the stands were smaller than 5 ha (figure 3). On an area-weighted basis, over 45% of the area in secondary vegetation was in stands smaller than 5 ha. Only one stand had estimates of textures variance, calculated using equation (3), higher than the maximum value of 0.2826 reported by Luckman *et al.* (1998). Regardless of the inter-temporal variability that may or may not be reduced by better signal-to-noise ratio (SNR), texture and speckle impact on confidence limits will be high for a majority of the secondary vegetation stands in this region.

Turning to the confidence limits based on observed inter-temporal variability, the difference in magnitude of the two sets of confidence limits is striking, regardless what variable is considered. Although the effect is somewhat exaggerated by the degrees of freedom used for t in (4a) and when evaluating the variability directly, most of the effect arises from the sheer variability in the images. As shown by Salas *et al.* (2001, this issue), this inter-temporal variability does not arise from consistent variation from one scene to the next, which could be reduced by a different cross-calibration method. Indeed, despite careful cross-calibration, 125 of 139 stands show

Figure 3. Size class distribution of secondary vegetation stands, ranging from 0 to 1 ha to larger than 11 ha. Percentage of each class with respect to total area in secondary vegetation is also plotted. Note that there are many more stands in the smaller range (1–4 ha) than above 8 ha. Approximately 50% of the area in secondary vegetation are in stands less than 5 ha. Stand sizes were calculated from multitemporal TM analysis (see Salas *et al.* 2001, this issue).

variability exceeding the 1.18 dB threshold identified by Luckman *et al.* (1998) when all sources of variation are considered. In practice, this translates into confidence limits for biomass that approach the range of biomasses calculated using (5) and (5a), or 0–146 t ha⁻¹. Confidence limits of such a great magnitude do indicate quite clearly that for many stands the biomass is almost completely undetermined by a single image.

The difference in magnitude between the variability arising from speckle and texture alone, and the actual variability, is most clearly described by the overall χ^2 test for all stands using the 1996 data ($\chi^2 = 1897.1$, d.f. = 506, $p < 0.001$). The ratio of χ^2 to d.f. indicates that the observed variance among scenes is, on average, 375% of that expected from speckle and texture alone. Clearly, other factors are contributing to the differences between scenes for many stands. Accounting for additive temporal effects that are consistent across scenes reduces χ^2 somewhat, but not to a practically significant degree ($\chi^2 = 1807.7$, d.f. = 503, $p < 0.001$). Such temporal effects include any environmental or sensing variations which affect all stands across a scene in a consistent, additive fashion. Given the relative unimportance of a consistent temporal effect, we must consider that this extraneous variability arises from some temporally variable factor, such as environmental conditions or sensor calibration, differentially interacting with the characteristics of the stands of interest. Seasonal differences in

surface conditions can influence σ° values differently for pastures, secondary forests, and primary forest, with pasture exhibiting a large (>2 dB) seasonal variability, secondary vegetation exhibiting a smaller (~ 1 dB) variability, and no effect on primary forests (Hashimoto *et al.* 1997).

Examining the χ^2 values for individual stands (figure 4) allows us to gauge the consistency of the extraneous variability, relative to the variability introduced by speckle and texture. It is noteworthy that 76 of 179 stands showed χ^2 values less than the expected value (equal to the number of scenes in 1996 in which the stand was present, minus one), clearly indicating that the extraneous variability impacts some stands and not others. The lack of clear association between individual-stand χ^2 values and the least-squares σ° value might suggest, at first, that the extraneous variability is not associated with mean σ° , and therefore unrelated to biomass. However, recall that χ^2 measures variability relative to the variability imposed by speckle and texture, which is correlated with mean σ° and biomass. A more careful consideration suggests that the absolute magnitude of the extraneous variability, when it does come into play, is associated with the same factors that govern texture. There is clearly a relationship between texture and stand biomass due to changes in canopy structure during development (Luckman *et al.* 1997b). Since mean σ° from stands with higher biomass will be less susceptible to variations in environmental

Figure 4. Individual-stand χ^2 values. The expected value of χ^2 is shown as a dashed line; dotted lines show the upper and lower critical values for a one-tailed error rate of 0.05. If texture and speckle were the dominant sources of variability, the points would cluster around the expected value, with 5% of the points outside each of the two dotted lines.

condition, such as soil moisture and dielectric properties of sub-canopy vegetation, the magnitude of the extraneous variability may be related to biomass.

3.2. Coefficient of variation of biomass predictions

The parameters used in the biomass model were developed using field data from Tapajos, and tested with data from Manaus. Likely, the model would have different parameters if it were calibrated for our site in Rondonia because of differences in site conditions, soil properties, and species composition. Nevertheless, our results and conclusions would not change because of the non-linear relationship between σ° and biomass and, therefore, are intended to be relative.

A useful measure of the variability in predictions of biomass is the coefficient of variation of the predictions, calculated in a straightforward fashion as the standard deviation of the estimates from each scene, rescaled by their mean. The CV is plotted against the mean predicted biomass for each stand in figure 5. A nuisance feature in developing this relationship between biomass and its CV was the presence of σ° values for which $\hat{\sigma}_i^\circ \geq a$. All stands that had at least one estimate where $\sigma^\circ \geq a$ were omitted from this analysis. Fortunately, most of the stands omitted from this analysis were in the biomass range above which JERS-1 data are regarded as unsuitable for biomass estimation (Imhoff 1995, Luckman *et al.* 1997b, Curran and Kuplich 1999). The stands for which (5a) was unnecessary all lie within this range. For these stands,

Figure 5. Coefficient of variation for biomass estimates (in percent), as a function of predicted biomass. This figure and curve are derived from only those stands with no instances of $\sigma^\circ > a$. Most of the stands had at least one instance when $\sigma^\circ > a$.

it is clear that the CV increases with increasing biomass. The solid curve fit to these coefficients of variation is described by

$$CV(\%) = 6.4983 \sqrt{\text{biomass}} \quad (9)$$

For example, if the estimated biomass of a stand were 10 t ha^{-1} , based on a single scene, we would expect that estimate to have a CV of 20.5%. This implies approximate 95% confidence limits of $6\text{--}14 \text{ t ha}^{-1}$. By contrast, for a stand with an estimated biomass of 25 t ha^{-1} , we would expect a CV of 32.5%, implying 95% confidence limits of approximately $9\text{--}41 \text{ t ha}^{-1}$. Clearly, stands with small biomass are much better resolved—both in absolute and relative terms—than stands with large biomass.

3.3. Single versus multitemporal JERS observations for estimating changes in biomass

To the degree that the variability indicated by figure 5 reflects operational success in quantifying biomass, to what degree of accuracy can we quantify biomass differences (either from stand to stand within a scene, or within a stand over time)? If a stand imaged at one time has biomass B_1 , estimated with coefficient of variation CV_1 , and at a second time has biomass B_2 , estimated with coefficient of variation CV_2 , the standard error of the estimate of the difference will be

$$SE_{B_2 - B_1} = \sqrt{B_1^2 CV_1^2 + B_2^2 CV_2^2} \quad (10)$$

and the coefficient of variation of the estimated difference will be

$$CV_{B_2 - B_1} = \frac{SE_{B_2 - B_1}}{|B_2 - B_1|} \quad (11)$$

The situation when estimating the difference between different stands at the same time is directly analogous. Using (11), and the relationship between biomass and its CV from a single scene as given in (9), we can plot the CV we would expect to obtain for the change in biomass of a stand, as a function of its initial biomass and percent growth (figure 6). Several aspects are immediately apparent. First, if a single scene is used at each time of observation, changes in biomass as large as 30% between the two periods cannot be resolved reliably regardless of the initial biomass of the stand. Second, even considering a 100% change or doubling of biomass, a single scene at each time period provides insufficient information for a reliable resolution unless the initial biomass of the stand is $< 10 \text{ t ha}^{-1}$. For example, if $B_1 = 10 \text{ t ha}^{-1}$ and $B_2 = 20 \text{ t ha}^{-1}$, the CV of the change is 62%, or 6.2 t ha^{-1} . The approximate 95% confidence limits on the change would be $10 \pm 12.4 \text{ t ha}^{-1}$. In other words, using a single scene at each time period, changes in biomass are unlikely to be well-resolved unless the change is very large, or the stand is nearly bare at one of the two time periods.

Fortunately, it is possible to improve on the resolution by using multitemporal images. If J images are available at each time period, then

$$SE_{B_2 - B_1} = \sqrt{\frac{B_1^2 CV_1^2 + B_2^2 CV_2^2}{J}} \quad (12)$$

If we can suggest a target value of $CV_{B_2 - B_1}$ for a given change, then we may estimate

Figure 6. Coefficient of variation (%) for estimates of change in biomass, using a single scene at each time period, as a function of initial biomass and percent change.

the required number of scenes as

$$J = \frac{B_1^2 CV_1^2 + B_2^2 CV_2^2}{(B_2 - B_1)^2 CV_{B_2 - B_1}^2} \quad (13)$$

Using (9) as the relationship between biomass and the CV of its estimate, a solution to (13) is shown in figure 7. The target value of $CV_{B_2 - B_1}$ is taken as 50%, which is not an overly restrictive value. It implies approximate 95% confidence limits equal to plus or minus the actual change, or a 39 in 40 chance of obtaining the correct sign on the change. With this rather loose definition of acceptable accuracy, we see that moderate numbers of additional contemporaneous scenes at each time period do improve accuracy considerably. For example, with a 44-day repeat cycle, it is possible to obtain eight or nine images in a year. That additional information at each time period would allow identification of changes as small as 30% of initial biomass in stands with as little as 17 t ha^{-1} , and identification of a doubling in biomass up to the saturation point.

3.4. Impact of noise on estimating biomass

The variability in our mean σ° for our stands was higher than could be accounted for due to texture and speckle alone. Potential sources of this variability include system noise, relative calibration errors, and environmental conditions (primarily surface moisture on vegetation and soil moisture). While estimating contributions of

Figure 7. Number of contemporaneous scenes at each time period required to achieve a 50% coefficient of variation on biomass change estimates, as a function of initial biomass and percent change.

environmental conditions is unlikely with a single polarization instrument like JERS, better estimates of the scattering from vegetation alone may be possible with multi-polarization sensors. Therefore, in an attempt to quantify impact of improved SNR (in this sense we consider noise all sources variability not due directly to biomass, including environmental conditions, system noise, calibration offsets, etc.), we modelled the relative bias, coefficient of variation, and relative RMSE of estimating biomass with a 1.0 dB versus 0.5 dB normally distributed errors of mean stand σ° estimates. The model first assumes an actual biomass value and calculates the 'true' σ° by inverting equation (5), which was then converted to dB. Based on the 'true' estimate of σ° we calculated the probability density from our assumed distribution of σ° based on our errors (0.5 or 1.0 dB) and then recalculated biomass from the distribution. Numerical integration was used to estimate the expected value of bias (observed—'true' biomass), variance (observed biomass—average biomass)², and mean squared error (observed biomass—'true' biomass)². From these we calculated the relative bias, CV, and relative RMSE as percentages. These steps were repeated across a range of biomass values to create figure 8. The results highlight the interplay between stand biomass and potential errors in estimating biomass. The observed positive bias can be explained by the non-linear (sigmoidal) relationship between σ° and biomass. A decrease in overall SNR of 0.5 dB would extend the range of biomass where there is little (<10%) bias, lower CV and lower RMSE. Clearly, any

Figure 8. Differences in relative bias, coefficient of variation, and relative RMSE (expressed as percentages) for 'observed' biomass from JERS due to normally distributed noise of 0.5 dB (dashed line) and 1.0 dB (solid line). The non-linear relationship between backscatter and biomass is readily apparent.

improvement in SNR will have a large impact on improving the success of estimating stand biomass given the sensitivity of these estimates confidence limits over the small dynamic range of σ° expected for biomass levels below the saturation point.

4. Conclusion

A statistical analysis of σ° statistics from a series of secondary vegetation stands was presented. These statistics were used to model and assess the impact of spatial and temporal variability in estimating stand biomass and changes in stand biomass with single and multistate JERS SAR data. Many of the secondary vegetation stands in this study had confidence limits due to speckle and texture alone that exceeded the 'worst-case' estimate provided by Luckman *et al.* (1998). While these differences are likely due to the smaller stands in this study, the size class distribution of stands across the landscape in Rondonia indicates that much of the secondary vegetation is contained in these smaller stands (<5 ha). Nevertheless, speckle and texture are not the largest controlling factors on the variability of mean stand σ° estimates. Extraneous factors, such as natural noise due to changes in environmental conditions, have the largest impact on the variance of biomass estimates. However, this variability due to these extraneous factors does not impact all stands of secondary vegetation, likely due to the presence of a biomass saturation point. The coefficient of variation

of biomass estimates increases with stand biomass. With single data JERS imagery biomass cannot be estimated for most of the stands in this region of Rondonia. Multitemporal observations improve the accuracy of biomass estimates sufficiently to enable identification of changes in biomass. Given the non-linear relationship between backscatter and above-ground biomass, a 0.5 dB reduction in extraneous variability would significantly improve biomass estimation, especially for levels below 40–50 t ha⁻¹.

While it is clear that estimation of biomass from natural systems, like secondary vegetation in the Amazon, with a single polarization L-band SAR is extremely difficult, it appears feasible to provide the carbon cycle community information useful for improving our understanding of carbon sequestration in secondary vegetation in Amazonia. Improved techniques for estimating contributions of noise will further enhance this application because we then will be able to quantify stand to stand variability due to environmental conditions.

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