Image Quality, Statistical and Textural Properties of SAREX data from the Tapajos test site

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ABSTRACT

The image quality of the SAREX data set from the Tapajos test site is examined in the light of the available CCRS calibration data. Noise removal and its effects on the statistical properties of the data is addressed. Mathematical modeling is used to predict HH/VV differences, incidence angle effects and general trends; these are compared to the SAREX data. Model results are close to observations up to near grazing angles of incidence. Observed large HH/VV differences seen at near grazing angles may be due to surface scattering from the top of the forest canopy allied with Brewster angle effects. Textural discrimination of surface cover types is investigated; preliminary results are presented.

THE SAREX DATA SET

The data examined was from the SAREX-92 (South American Radar Experiment) campaign. The area of interest for this study is in the Tapajos National Park, in Amazonia. This test site was denoted BRA1; data was collected using the Canadian Centre for Remote Sensing (CCRS) C-band airborne SAR operating in HH and VV polarisations.

In this study BRA1.1 and BRA1.2 are examined. BRA1.1 was imaged with the radar in wide swath mode. This has angles of incidence of 45° at near range and 85° at far range, giving a swath width of approximately 65 km. The slant range resolution is 20 m and the azimuth resolution is 10 m. BRA1.2 was imaged in narrow swath mode. This has angles of incidence of 45° at near range and 76° at far range, giving a swath width of approximately 18 km. The resolution is 6 m in both range and azimuth.

DATA CALIBRATION

The calibration data (Ulander, 1991) consists of a noise power, calibration factor, absolute range (in metres) and angle of incidence against each pixel in range. The noise power is found by using an onboard noise generator as a reference source. The calibration factor takes into account the $R^2$ range dependence, antenna pattern, atmospheric attenuation etc. The backscatter $\sigma_0$ is found by subtraction of the noise floor from the data and multiplication by the calibration factor. Images were calibrated to $\sigma_0$ using this method, enabling comparison with results from modeling and data from other sources.

Noise effects

The SAREX data is nominally the result of taking 7 looks in amplitude, but practically (by examination of the mean squared uniformity of homogeneous areas) it appears closer to 6-look (Hawkins, 1992). An analytical form for the probability density function for multi-looking in amplitude is not available, and here it is approximated by the square root of multi-look intensity data, i.e. the square root of a 6-look gamma distribution. In the calibration method outlined in the previous section the noise intensity at pixel $j$ is subtracted from the image intensity at that point. If the image intensity yields a value less than the noise floor then the output is set to zero. The proportion of pixels set to zero by this process is:

$$\int_0^{\beta} \frac{\Gamma(\nu)}{\Gamma(\nu/\beta)} \frac{x^{\nu-1}}{\Gamma(\nu)} e^{-\frac{x^{\nu}}{\beta}} dx$$

where $\beta = \mu_\nu/\nu$, $\mu_\nu = \text{mean of underlying gamma distribution}$, $\nu = \text{order parameter (number of looks)}$, and $N$ is the intensity noise floor below which all pixels are set to zero ($\sqrt{N}$ is the amplitude noise floor). It is found that 1% of pixels are set to zero when the noise floor is 0.2976 $\times \sqrt{\mu_\nu}$, and 5% when the noise floor is 0.4758 $\times \sqrt{\mu_\nu}$ (the mean of the square root of a 6-look gamma distribution is 0.9392 $\times \sqrt{\mu_\nu}$).

A plot of observed amplitude divided by the noise amplitude for the wide swath data is shown in figure 1(a). Also shown are the noise levels at which 1% and 5% of the original pixels are removed. It is clear that the noise will cause problems at far range. These limitations must be taken into account when examining calibrated data. In the narrow swath case the noise intensity stays well below observed data values; the results are not shown.

COMPARISON OF OBSERVATIONS WITH THEORY AND MODELLING

Figure 1(b) shows how averaged backscatter varies with increasing range pixel number (and incidence angle) for a section of the wide swath HH data. The river Tapajos is seen at far range where the backscatter falls into the noise. Another distinctive feature is seen around range pixel number 3300; the sharp fall in backscatter is due to an escarpment between the higher level 'Terra Firme' forest and the forest at the river level. Due to the look direction, part of this escarpment is in radar shadow. It can be seen that the escarpment and the river Tapajos lie in a small range of very high incidence angles. However this is a very significant proportion of the swath in terms of pixels, of the order of a quarter.

Model calculations were performed using the Michigan Microwave Canopy Scattering (MIMICS) model (Ulaby, 1990); the results for both HH and VV polarisation are shown in figure 1(c). The model was run on a 10 metre thick, wet canopy consisting of uniformly distributed leaves and branches. The absolute value for backscatter, $\sigma_0$, and the downward trend as range increases are similar to those seen in the data. The data was also in good agreement with results for backscatter from trees at C-band at an incidence angle of 55° (Ulaby, 1989).

The calibrated VV backscatter is similar in terms of general trends and fluctuations to the HH, although there are differences which are examined further in the following section.

Comparison of HH and VV backscatter

Figure 1(d) shows the difference between the HH and VV backscatter as we cross the wide swath (BRA1.1), plotted against range pixel number. Across approximately half of the swath (in terms of range pixels) the observed HH polarised backscatter is approximately 1-1.5 dB higher than VV. However, at far range (where
the angle of incidence is between 80° and 85°) this difference increases to approximately 4–6 dB.

The HH-VV backscatter difference calculated using the MIMICS model is between 0.3 and 0.9 dB across the whole swath. Intuitively we might expect no difference in HH and VV volume scattering from a homogeneous medium; leaves and branches in the crown are uniformly distributed. However, the uniform distribution in solid angle used in the model results in an angular distribution in the look direction of the sensor more favourable to horizontally polarised than to vertically polarised scattering. For the wet, thick canopy layer used in the calculations the main contribution to the return comes from volume scatter from the tree crown layer, as at C-band there is little penetration into the canopy (i.e. the radar cannot `see' the trunk or ground layers). The large HH-VV differences observed at far range require a different mechanism than volume scattering.

A possible explanation is that, at large incidence angles, the air-canopy interface begins to behave like a surface. If so, in the specular direction at near grazing angles, Brewster angle effects will occur (the dielectric values for leaves indicate a Brewster angle near 80°). This will tend to decrease the forward scattered vertically polarised reflection with respect to horizontally polarised reflection (Born, 1975). The radiation is then returned to the sensor via a near normal reflection from leaf or branch. This double scattering mechanism is possible because of the highly irregular topography of the forest canopy. This effect cannot be reproduced by MIMICS since the model assumes no surface scattering at the top of the canopy and is only a first-order model (i.e. only a single scattering event within the crown layer is allowed).

TEXTURAL PROPERTIES

Examination of the SAREX data indicates that texture provides clearer forest/non-forest discrimination than mean backscatter. Here we discuss the use of two single point statistics as texture estimators, the coefficient of variation and the order parameter estimate, although other work has been carried out using Poisson point processes, power spectra and autocorrelation function measurements to characterise texture in the imagery.

The coefficient of variation (CV) of n-look amplitude data for a uniform, distributed target is given by

\[ CV = \frac{1}{n} \left( \frac{4}{n} - 1 \right) \]  

(2)

The bias and variance of an estimate of the CV depend on the size of the estimation window. Approximations are given in (Caves, 1993). Significant variations from the value given in (2) can be interpreted as evidence for texture.

Image texture can be modelled as a varying Radar Cross Section (RCS) multiplied by speckle. When the RCS is gamma distributed, texture is described by an order parameter. This can be conveniently estimated by forming the difference between the average log intensity and the log of the average intensity. This estimate is to be preferred to more widely known moment-based methods (Oliver, 1995). The CV is basically such a moment measure.

Classification by texture

Forest/Non-forest classification

A 512 by 512 pixel test image was extracted from the SAREX narrow swath (BRA1.2) data showing a distinct boundary between forested and agricultural areas (figure 1(e)). The coefficient of variation and order parameter estimate were calculated within windows stepped across the image. A range of window sizes was examined. Figure 1(f) is an image showing the coefficient of variation calculated within an 8 by 8 pixel window; a threshold applied to the CV values gives good discrimination between forested and agricultural areas. Similar results were obtained using the order parameter estimate. A point by point comparison between the coefficient of variation and the order parameter estimate over the test image showed that they were highly correlated. The results discussed below therefore use only the coefficient of variation.

Different forest textures

Four areas were extracted from the BRA1.2 narrow swath data within the Tapajos national forest. Comparing histograms of the underlying pixel values of 5 and 6 look simulated amplitude speckle distributions and of the four extracted areas show that the forested areas exhibit texture (i.e. they are different from the speckle distributions); there are also clearly visible differences between the histograms from the different forested areas. The fundamental question is whether these differences can be related to physical differences on the ground. To test this, the distributions of CV values calculated within square windows of side 4, 8, 16 and 32 pixels were compared for the different forest areas. Results show that, for all window sizes investigated, these CV distributions overlap considerably. Thus it would not be possible to separate these textures reliably on a pixel basis in the CV image. Area based measures may possibly be useful as discriminators, since the mean values of the CV of textures from ‘Terra Firme’ forest are above those from lower lying ground, except at the smallest window size. Confirmation of this needs more investigation into the optimum window sizes to use based on the spatial scales of the texture within the data.

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FIGURE 1