# CHAPTER THREE

# Radar remote sensing of regenerating tropical forests

The framework for the research presented in this thesis is the interaction of SAR backscatter, depending on its temporal, spatial, spectral and polarisation characteristics, with regenerating tropical forests. This chapter reviews the use of SAR images to estimate forest properties (such as biomass) and classify forest types (such as regenerating forests) within this framework.

This chapter outlines how SAR backscatter has been related successfully to forest biophysical variables and used for biomass estimation and classification, with emphasis on regenerating tropical forests.

## 3.1. Radar remote sensing of forests

Our current understanding of the interaction of microwave radiation with forest canopies has been obtained primarily from temperate and northern forest ecosystems (e.g. Sader 1987, Le Toan *et al.* 1992). Limited species diversity coupled with spatially and structurally homogeneous stands made the backscatter from these formations easier to understand and model, therefore, a great amount of research has been devoted to them (Leckie and Ranson 1998).

Although there are major differences between temperate, northern and tropical forests, the main findings of radar remote sensing of temperate and northern forests also apply to tropical forests.

Since the 1960s radar systems have been recognised as particularly useful for military applications in tropical regions (such as in Vietnam), where cloud cover is persistent. In the 1970s radar data were declassified and airborne high frequency radar systems were used for mapping natural resources at continental scales. For example, the Brazilian RADAM (Radar Amazon) Project, one of the largest accomplishments in resources surveys by SAR data (Azevedo 1971, Leckie and Ranson 1998). During 1980s and 1990s there was a significant growth in research focused on developing approaches for using SAR in ecosystem studies (Kasischke *et al.* 1997). This was due to the launching of many spaceborne SAR systems (such as the SAR onboard the Japanese Earth Resources Satellite (JERS-1) in 1992) and the increasing need to understand global environmental processes.

To date, the progress made in the study of SAR data from tropical forests has been in the assessment of the potential of radar sensors for the discrimination of land cover types. The ultimate aims being that of (i) monitoring tropical land cover change (Nezry *et al.* 1993, Saatchi *et al.* 1997, Grover *et al.* 1999, van der Sanden and Hoekman 1999) and (ii) mapping forest biomass (Luckman *et al.* 1997a, 1998). These aims are generally included in a broader context intended to assess the contribution of radar to global environmental monitoring and ecosystem modelling (Leckie and Ranson 1998).

### *3.1.3. Forest backscatter*

The main components and scattering mechanisms of the total backscatter from forests comprise backscatter from (1) crown surface and volume, (2) trunks, (3) direct from the ground, (4) crown-ground scattering and (5) double-bounce scattering from trunk and ground (Leckie and Ranson 1998). Figure 3.1 shows these components and the interaction of the main wavelengths used in operational radar remote of forests. Le Toan *et al.* (1992) also included multiple scattering from the branches and canopy attenuated trunk-ground scattering as influencing the total forest backscatter.

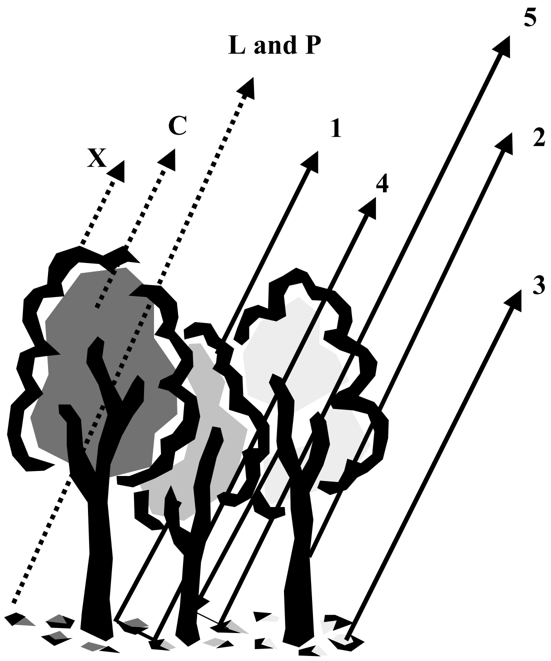


**Figure 3.1**. Main components and scattering mechanisms that influence the total backscatter from forests: (1) backscatter from crown surface and volume, (2) backscatter from trunks, (3) backscatter direct from the ground, (4) crown-ground scattering and (5) double-bounce scattering from trunk and ground (Leckie and Ranson 1998). Also, the interaction of the main wavelengths (bands X, C, L and P) used in SAR remote sensing is shown.

The magnitude of the scattering mechanisms and the importance of the different components are dependent on geometric factors (e.g., structural attributes of trees, canopy and soil surface roughness) and dielectric properties of vegetation and underlying surface (e.g., moisture content of vegetation and soil) (Dobson *et al.* 1995). Wavelength, polarisation and incidence angle of radiation control these scattering mechanisms (Leckie and Ranson 1998) and the final backscatter as a result of surface and/or volume scattering.

At X band, which is a short wavelength, the backscatter results mainly from the upper part of the canopy (Le Toan *et al.* 1992) and the leaves, twigs and small branches (Leckie and Ranson 1998). There is little penetration of the radiation into the canopy, therefore, volumetric scattering and soil contribution to the final backscatter are weak.

At C band, which is a intermediate wavelength, greater penetration of the radiation into the canopy enables further sources of scattering to be active and so there is some volumetric scattering. Typical sources of scattering at C band are secondary branches and leaves (Ranson and Sun 1994, Leckie and Ranson 1998). The penetration of crown thickness by the radiation is normally not exceeded (Le Toan *et al.* 1992).

At longer L and P band wavelengths, the penetration of the radiation into the canopy is deeper and components from the lower parts of the canopy are included in the scattering (Le Toan *et al.* 1992), as well as the major woody biomass components (trunks and branches) (Dobson *et al.* 1992). Trunk-ground and crown-ground interactions are important at these wavelengths (Leckie and Ranson 1998) and are mainly dependent on the canopy structure and openness. Foliage and small branches act as attenuators of the radiation at these wavelengths (Kasischke *et al.* 1997).

The incidence angle of the SAR sensor determines the amount of vegetation illuminated by the radar beam. The angular dependence is stronger for surface scattering mechanisms, when higher scattering is observed for small incidence angles (Leckie and Ranson 1998). Volumetric scattering mechanisms in the canopy will dominate for high incidence angles, as a large amount of the canopy is illuminated. For incidence angles close to nadir, depending on the wavelength and forest type, the ground will contribute to the scattering mechanisms.

The polarisation of the radiation determines the type of interaction with the forest components. Co-(or like) polarised radiation interact with structures with a similar orientation, so vertical stalks will interact strongly with VV (Vertical transmit and receive) polarisation. Horizontal branches or the soil surface interact strongly with HH (Horizontal transmit and receive) polarisation. HH can also be a result of trunk-ground scattering interactions (Dobson *et al.* 1992) and VV is more sensitive to canopy attributes (Dobson *et al.* 1995). Cross-polarised backscatter (HV - horizontal transmit and vertical receive and/or VH) is related to volumetric scattering, as the canopy is a medium capable of depolarisation (Saatchi and Rignot 1997). In general, double bounce trunk-ground, when not as a result of a perfect corner reflector situation (Leckie and Ranson 1998), is more likely to produce backscatter in a distinct polarisation than the received one (Waring *et al.* 1995).

### 3.2. Modelling forest backscatter

Interpretation of radar imagery relies on knowledge about backscatter process and the relative importance of various scattering mechanisms that contribute to the final backscatter (Richards 1990). When trying to establish links between backscatter, scattering mechanisms and vegetation components, energy-matter interaction models have been used. Many types of models are available to predict the backscatter for a given target and SAR parameters. Comparison with real SAR data allows various mechanisms and the contribution of each vegetation component in the final backscatter to be understood. For backscatter modelling purposes, the forest canopy has two main characteristics: the gross structure of the scattering medium and the geometry and electromagnetic properties of the individual vegetation components (Saatchi and McDonald 1997).

There are several types of backscatter models. When based on electromagnetic theory and known expressions for backscatter coefficients, these models are called radiative transfer (RT) models, and their 'order' is determined by the complexity of scattering taken place at the target (Richards 1990). First order RT models take into account only volume, surface and double-bounce (from trunk and ground and foliage or branches and ground) scattering mechanisms. Backscatter involving two or more scattering events is thought to be attenuated inside the canopy and is considered in the second order RT models (Richards 1990). There are several examples of first order radiative transfer in the literature, but by far the most utilised is the Michigan microwave canopy scattering model (MIMICS) (Ulaby *et al.* 1990). This model considers the canopy as two distinct homogeneous layers over a ground surface. The first order solution consists of a sum of the scattering mechanisms occurring between these three layers (McDonald *et al.* 1991).

Other types of backscatter models are the index or regression models, which are based on preconceived mathematical expressions and the model parameters are found by regressions (Richards 1990). The disadvantages of these models are the dependence of model parameters (where a change would preclude application on other situation) and little information provided on the physics of the scattering events involved (Richards 1990). A third type of model is called functional or conceptual, but could be called phenomenological because of their ability to explain phenomena rather than energy-matter interactions (Richards 1990).

Few situations, such as the specular reflection from a water surface, can be modelled exactly. The complexity of a forest ecosystem may require a combination of different models (Richards 1990). Also, the straightforward inversion of the models to obtain the required output is unlikely and connecting models are often needed (Kasischke and Christensen 1990).

Backscatter models are evolving to be more complex and realistic (Leckie and Ranson 1998). Recently, Castel *et al*. (2001) presented the Architectural Plant Model (AMAP), which relies on both qualitative and quantitative architectural plant growth descriptions. The AMAP model provides a more realistic 3-D view of trees and allows differentiating vertical profiles of ageing canopies. A RT model was modified, fed by canopy parameters derived by using AMAP model and successfully tested using data from pine stands in Southern France (Castel *et al.* 2001).

For tropical forest environments, the available current backscatter models would require adaptations to take into account a large number of vegetation variables. The difficulties in obtaining data required as input for the available models also hamper their application for such environments. However, some authors have used existing models such as MIMICS (Grover *et al.* 1999) and a model based on the one devised by Attema and Ulaby (1978) (Luckman *et al.* 1998) to try to understand scattering mechanisms over tropical forests.

To date, few attempts have been made to construct backscatter models that are applicable exclusively to tropical ecosystem variables (Leysen, pers. comm. 1998).

### 3.3. Biomass estimation and mapping

The study of radar remote sensing of forests has been aided by theoretical models, which have helped researchers to understand the causative factors for the backscatter coming from forests (Dobson *et al.* 1995). The dependency of backscatter on above ground biomass was observed and related to the penetration of the radiation into the canopy and interaction with the trunk, where most of the volume, therefore, biomass of the vegetation is concentrated (Sader 1987, Le Toan *et al.* 1992, Dobson *et al.* 1992).

HV polarisation in longer wavelengths (L or P band) is the most sensitive to biomass (Sader 1987, Le Toan *et al.* 1992, Ranson *et al.* 1997a) because it originates mainly from canopy volume scattering (Wang *et al.* 1995), trunk scattering (Le Toan *et al.* 1992) and is less affected by the ground surface (Ranson and Sun 1994). The sensitivity of backscatter to biomass is, however, limited by an asymptotic response of backscatter beyond certain levels of biomass, a phenomenon which is wavelength dependent (Dobson *et al.* 1995, Kasischke *et al.*1997). This 'saturation' of the backscatter is considered the limit for an accurate estimation of biomass from SAR data (Imhoff 1995a) and normally corresponds to backscatter coming from biomass of mature forest or dense forest vegetation (table 3.1).

**Table 3.1. Saturation levels for backscatter/biomass relationship**

| Author | Type of forest | Band | Biomass (T ha$^{-1}$) |
|---|---|---|---|
| Sader (1987) | Temperate broadleaf and pine | L | 100 |
| Dobson *et al.* (1992) | Two species of pine | P<br>L | 100-200 |
| Rauste *et al.* (1994) | Temperate coniferous | L | 100 |
| Imhoff (1995a) | Combined data from conifer and broadleaf evergreen | C<br>L<br>P | 20<br>40<br>100 |
| Rignot *et al.* (1997) | Tropical | L | Likely close to 100 |
| Luckman *et al.* (1997a) | Tropical | L | 60 |
| Araújo *et al.* (1999) | Tropical | L | 100 |

The lack of a backscatter/biomass relationship does not necessarily indicate the lack of sensitivity of backscatter to vegetation. For example, a structural descriptor described as a ratio between vegetation surface area and volume (SA/V) was found by Imhoff (1995b) to have an influence on backscatter

Some approaches have been proposed to minimise the influence of the asymptote or extend the range of estimated biomass from SAR data. Most of these relate to polarisation and bands ratios, meant to isolate the contribution of biomass to the backscatter and reduce the effect of forest structure (Ranson and Sun 1994, Foody *et al.* 1997). As forest backscatter in different wavelengths and polarisations originate from separate layers of a canopy, the use of multiple channels or multistep approaches (e.g., Dobson *et al.* 1995) could be used to estimate total above-ground biomass (Kasischke *et al.* 1997). For example, the ratio $P_{HV}$ and $C_{HV}$ was used successfully by Ranson and Sun (1994) to estimate biomass up to 250 T $ha^{-1}$ in a mixed conifer/deciduous temperate forest.

Dobson *et al.* (1995) consider these band ratios too simplistic, although effective in extending the range of estimable biomass. Their argument is that the biomass estimate can hide a variety of structural factors, as same biomass values can represent few tall trees or many short trees. The corresponding backscatter will be much higher for the few tall trees than for the many short ones (Dobson *et al.* 1995). In spite of this, a combination of bands and polarisations in a multistep approach made possible the mapping of biomass in a mixed temperate forest up to 250 T $ha^{-1}$ (Dobson *et al.* 1995). Saatchi *et al.* (1997) found an early asymptote on the backscatter in regenerating tropical forest and attributed it to the lack of the contribution of fresh biomass components (like lianas and leafy vegetation understory and overstory) in the calculation of (woody) biomass.

The backscatter/biomass issue must be treated with care, as a lot of variation exists not only on the ecosystems themselves, but also in the way their biomass are estimated.

Establishing a strong link between backscatter and forest variables is an important part of the successful estimation of forest biomass from backscatter. As already mentioned, models are often used to explain the relationship between forest variables, scattering mechanisms and SAR configuration parameters (Richards 1990, Kasischke and Christensen 1990). Another approach is the use of statistical analysis, where forest variables are related to SAR backscatter by regression models (Sader 1987, Le Toan *et al.* 1992, Rauste *et al.* 1994). Some authors used the combination of the two approaches, in most cases to assess the results of the predicted biomass or backscatter via regression (Ranson and Sun 1994, Ferrazzoli *et al.* 1997, Franson and Israelson 1999). Statistical procedures such as stepwise regression were also used to determine the best set of bands and polarisations to discriminate biomass levels (Ranson *et al.* 1997a).

The mapping of biomass in Northern Michigan forest was achieved successfully by Dobson *et al.* (1995) using a three-step process: (1) forest classification into structural categories, (2) estimation of structural variables (basal area, height and crown biomass) from polarimetric SAR data and (3) estimation of total biomass based on a simple biophysical model. Accuracy assessment was performed based on available land cover maps and was accurate up to a biomass of at least 250 T $ha^{-1}$. Modelled backscatter and ratio images of multitemporal polarimetric SAR data were also used successfully to map biomass in a Northern forest of Maine (Ranson and Sun 1994). PHV data were used for estimating stem volume of forests in Finland (Rauste *et al.* 1994), as were pine forests biomass estimated and mapped (Beaudoin *et al.* 1994). A procedure devised by Ranson *et al.* (1997a) combined simulated variables of a forest growth model to AIRSAR data based backscatter model and the result was a third model relating all variables. The final map underestimated biomass and the backscatter asymptote was at biomass levels of 150 T $ha^{-1}$ (Ranson *et al.* 1997a). For boreal forests, however, another procedure based on combined SAR and Landsat Thematic Mapper (TM) data allowed the estimation of biomass up to 150 T $ha^{-1}$, with RMS (root mean square) errors around 37 T $ha^{-1}$ (Ranson *et al.*1997b).

The mapping of biomass for a large area in Brazilian Amazonia used JERS-1 SAR mosaic data (Luckman *et al.* 1998) and the biomass categories mapped were from 6 T $ha^{-1}$ to 13 T $ha^{-1}$, 14 T $ha^{-1}$ to 31 T $ha^{-1}$ and above 31 T $ha^{-1}$. The limitation of the rôle of SAR data on biomass estimation was attributed to the asymptote in the backscatter/biomass relationship (Imhoff 1995a, Luckman *et al.* 1998), although no alternatives were considered.

### 3.4. Forest classification

Classification of a remote sensing image is a process that recognises one or several categories of real-world objects in pixels (Mather 1999). Normally spectral patterns present within the images are used as a numerical basis for categorisation, due to objects inherent reflectance, emittance or scattering properties (Lillesand and Kiefer 2000).

Classification can use also spatial and temporal information as a basis for categorisation. Spatial classifiers categorise image pixels based on their spatial relationships with the surrounding pixels and texture is a commonly used measure of these relationships (Lillesand and Kiefer 2000). The temporal domain can be used as an aid to the categorisation of spectral and spatial features present in remote sensing images. Some features can be identified only when, for instance, a particular season or phenological stage is reached. The classification process will then use combined information from the spectral and spatial domains in a temporal series of data (Lillesand and Kiefer 2000).

The study of forest ecosystems usually requires their differentiation from the remaining land covers and the classification of specific vegetation communities (Kasischke *et al.* 1997). Regenerating tropical forests, for instance, are normally found close to mature forest but also close to agricultural crops, pastures and urban settlements, making their differentiation from the remaining land cover very useful.

Two main approaches used to classify SAR data have been (1) maximum likelihood classification (MLE) including supervised and unsupervised cluster analysis and (2) knowledge-based hierarchical decision trees (Kasischke *et al.* 1997). The extendibility of MLE classification results to global scales is usually impaired by the need for localised training (Kasischke *et al.* 1997). Knowledge-based approaches have been proposed to overcome this limitation by using explicit relationships between backscatter and vegetation structure and then reclassification based on these links and floristic community (Dobson *et al.* 1995, Kasischke *et al.* 1997, Bergen *et al.* 1998).

Maximum-a-posteriori (MAP) Bayesian classifier was developed for the classification of multifrequency polarimetric SAR data and differed to the MLE approach because of the revisions on the decision rules about the classes nature (Saatchi and Rignot 1997).

Recent research has shown promising results using segmentation methods (Oliver 1998, Frery *et al.* 1999, Grover *et al.* 1999). These methods consist of aggregation of pixels with similar properties and limits defined by the borders of the segments (Yanasse *et al.* 1997). The segment labelling is performed afterwards in a classification procedure.

Artificial Neural Network (ANN) based classifiers are also a promising approach. Among ANN advantages are facilitated incorporation of different types of data which do not have to fit any particular statistical distribution (Atkinson and Tatnall 1997).

The advantages of each approach depend on the suitability of the classification estimator to the available data set, which will determine a high accuracy on the classification process. Good field knowledge, field data and adequate maps make far easier algorithm training (when needed) and accuracy assessment of the final classification.

Temperate and boreal forest types have been classified with radar data (Saatchi and Rignot 1997, Bergen *et al.* 1998, Williams *et al.* 1999). For management inventory purposes, however, radar data does not provide detailed enough information (Leckie and Ranson 1998). Nevertheless, radar data can provide complementary information to aerial photographs (Leckie and Ranson 1998) and forest biophysical parameters have been estimated (Ranson and Sun 1994, Dobson *et al.* 1995, Ranson *et al.* 1997b). When radar data are combined with optical data, forest mapping capabilities are usually increased.

Manual interpretation of radar images played an important rôle on the mapping of tropical forest types in Brazil and Colombia (RADAM Project) (Kasischke *et al.* 1997) and today is still considered an important technique for discriminating forest types (Leckie and Ranson 1998, Kuntz and Siegert 1999).

Accurate automatic classification of radar data for tropical forest is still under development and some of the achievements are showed in table 3.2. Merging classification techniques (Rignot *et al.* 1997), the use of estimators adapted to radar data (Nezry *et al.* 1993, Saatchi *et al.* 1997, Saatchi *et al.* 2000) and the use of texture measures derived from SAR images (Oliver 1998, Saatchi *et al*. 2000) seem to be the trends for the high classification accuracy of the vegetation on the tropics. Some authors, however, found the use of a minimum of two SAR C, L and/or P channels essential to discriminate between regenerating forest and selectively logged forest (van der Sanden and Hoekman 1999). Similarly to temperate forests, SAR for tropical forests has promising but yet complementary capabilities (van der Sanden and Hoekman 1999).

Optical sensor data are commonly combined with SAR images when studying tropical forests (Nezry *et al.* 1993, Rignot *et al.* 1997, Araújo *et al.* 1999). Time series of optical images have been used as a reference in the field or prior to field work to establish the age of clearings and land cover history (Foody *et al.* 1997, Luckman *et al.* 1997a, Yanasse *et al.* 1997, Salas and Skole 1998). Thematic maps reflecting age-related areas were created from classified TM images in a pixel-to-pixel Boolean basis (Sant'Anna *et al.* 1995). This procedure, however, is still not possible with SAR images, due to the much poorer classification performances in tropical forest classes.

### *3.4.1. Spatial characteristics of backscatter - texture*

Texture can be defined as the variation of the grey level of a single pixel (tone) within a neighbourhood (Mather 1999). This variability can be structured and reflects the spatial relationships among grey levels of pixels (Mather 1999). Texture is dependent on (i) the scale of the variation to be defined and (ii) on the scale of observation, limited by the spatial resolution of remotely sensed data (Mather 1999). For backscatter, textural attributes quantify the pattern of spatial variations in the strength of backscatter (van der Sanden and Hoekman 1999). An optimised texture measure depends on the statistical properties of the backscatter (Oliver and Quegan 1998) and is based on the statistical dependence between pixels within a region (Kurvonen and Hallikainen 1999).

Many texture measures in remotely sensed data are referenced as important tools in vegetation and land cover classification. Local statistics texture measures are statistical moments (such as mean, skewness, kurtosis and coefficient of variation (CV)), of the window from which the texture of the image is extracted (Kurvonen and Hallikainen 1999). Second-order texture measures (such as entropy, energy, contrast, etc.) relate to statistical dependence between pixels in a given distance and direction and are calculated from the grey-level co-occurrence matrix (GLCM) (Kurvonen and Hallikainen 1999, Mather 1999). Another approach for texture analysis includes the variogram that provides a concise description of the scale and pattern of spatial variability in remotely sensed data (Curran *et al.* 1998). These texture measures will be discussed in detail in chapter 6.

In general, there is an unclear utilisation of the spatial domain in the analysis of remotely sensed data (Curran *et al.* 1998). While recent forest discrimination research has shown interest on the textural approach, results are difficult to extrapolate because of the variety of physical environments and techniques used.

For temperate forests in Finland, texture measures (CV and four measures derived from GLCM) from a multitemporal set of SAR images were found to increase the accuracy of classification results, even though the final accuracy was around 65% (Kurvonen and Hallikainen 1999).

Table 3.3 shows some recent results using SAR textural information for tropical forest discrimination. Low discrimination accuracy results and absence of a texture measure that works with all or certain forest types are the main conclusions that can be draw from table 3.3. Also, the use of a simple texture measure (such as the mean) can result in accurate discrimination between forest types (Yanasse *et al.* 1997, Podest and Saatchi 1999).

Despite low accuracy in the discrimination of forest types, some authors report encouraging representation of classes with distinctive texture signatures (Miranda *et al.* 1996, 1998, van der Sanden and Hoekman 1999). Perhaps the gap in texture modelling (Oliver and Quegan 1998) will be resolved with a better understanding of the physics that governs backscatter and associated texture, given that texture is still a promising approach.

### *3.4.2. Temporal characteristics of backscatter*

The dielectric characteristics of vegetation and soils have a strong effect on backscatter and are important sources of variation in $\sigma^{\circ}$. Varying weather conditions are related to changes in water content of vegetation and soils, therefore, impact directly on backscatter (Gates 1991). In addition to rainfall, air temperature and wind speed can induce physiological and/or geometric changes in the vegetation components and influence backscatter (Leckie and Ranson 1998). The monitoring of seasonal phenological development is a substantial part of forest ecosystem studies and justifies the study of temporal backscatter.

**Table 3.2.** Examples of classification approaches using radar imagery in tropical ecosystems (adapted from Kasischke *et al.* 1997).

| Ecosystem | Purpose | Classifier[a] | Data source | No of classes and types[b] | Accuracy[c] | Radar band/ polarisation | Reference |
|---|---|---|---|---|---|---|---|
| Tropical forest and adjacent areas | Vegetation mapping | Supervised MLE adapted to radar | SIR-B SPOT-HRV | 6 and 8 W,B,A,F,U,Aru plus rF, C | Medium on SIR-B High on SIR-B +HRV (8 classes) | $L_{HH}$ | Nezry *et al.* 1993 |
| Subtropical forest and wetlands | Ecosystem mapping | MLE cluster | AIRSAR | 7 W,B,A,H,S, F(2) | Medium | P,L,C, all polarisations | Pope *et al.* 1994 |
| Tropical floodplain forest | Map forest flooding | Decision tree | SIR-C | 5 W,fH,H,F,fF | High | $L_{HH}$,$L_{HV}$, $C_{HH}$ | Hess *et al.* 1995 |
| Tropical forest and adjacent areas | Map deforestation and regeneration | Supervised on TM, after MAP on SIR-C | SIR-C Landsat TM | 6 and 7 W,F,fdF,yrF,B, Ct | High on SIR-C Higher on SIR-C +TM (7 classes) | $L_{HH}$, $L_{HV}$, $C_{HH}$,$C_{HV}$ | Rignot *et al.* 1997 |
| Tropical forest and adjacent areas | Map deforestation and land use | MAP supervised | SIR-C | 5 F,rF,A,Ct,dF | Medium | $L_{HH}$, $L_{HV}$, $C_{HH}$,$C_{HV}$ | Saatchi *et al.* 1997 |
| Tropical forest and adjacent areas | Map forest and non forest | Annealed segmentation | CCRS airborne SAR | 2 F, nF | High with texture (from parameters of K-distribution) | $C_{HH}$ | Oliver 1998 |
| Amazon Basin | Map land cover types in the Amazon Basin | MAP and hierarchical decision based on texture measures | JERS-1 SAR 100 m resolution image mosaic | 14 W, r, F, nF and 10 vegetation types | Medium with first order texture measures | $L_{HH}$ | Saatchi *et al.* 2000 |

[a]Classification approaches: Maximum likelihood estimator (MLE), Maximum-a-posteriori Bayesian (MAP).

[b]Agriculture (A), water (W), bare soil (B), clearings (c), urban (U), forest (F), flooded (f), young (y), regenerating (r), trunks (t), rubber (ru), disturbed (d), non(n), dead (d).

[c]High indicates >90% classification accuracy, medium indicates 70-90% classification accuracy.

**Table 3.3.** Examples of the use of texture measures in SAR imagery of tropical forests (adapted from Kasischke *et al.* 1997).

| Ecosystem | Purpose | Texture measure. Result assessment | Data source | No of classes and types[b] | Discrimination accuracy[c] | Band/ polarisation | Reference |
|---|---|---|---|---|---|---|---|
| Tropical forest and adjacent areas | Vegetation mapping | Semivariogram texture classifier. Confusion matrix. | JERS-1 | 4 W,F, oF, fF | Low | $L_{HH}$ | Miranda *et al.* 1996 |
| Tropical forest and adjacent areas | Discriminate regenerating stages | Tonal mean, CV (Coefficient of Variation). BD and ED. | SIR-C, Landsat TM age map | 7 RA, (0,2], (2,4], (4,6], (6,8], >=9 years old, F | Good for the mean in L band ($L_{HV}$ better) Poor with CV, better with L band | L,C, all polari-sations | Yanasse *et al.* 1997 |
| Tropical forest and adjacent areas | Discriminate regenerating stages | K-distribution $\alpha$ parameter, CV, GLCM contrast. CV. | CCRS airborne SAR, Landsat TM age map | 5 B, 1-3, 4-6, >6 years old, F | Low and only between F and other classes Better with CV | $C_{HH}$,$C_{VV}$, | Luckman *et al.* 1997b |
| Tropical forest and adjacent areas | Map major land cover types | CV,mean,variance, entropy,energy, skewness,kurtosis, contrast. MLE and BD. | JERS-1 SAR 100 m spatial resolution | 8 W, F, rF, nF, fF, fnF, wS, nwS | Medium with mean, variance and entropy. Mean best for overall separability | $L_{HH}$ | Podest and Saatchi 1999 |
| Tropical forest and adjacent areas | Map detailed land cover types | GLCM derived texture measures. $TD_{ij}$, MLE, Kappa statistics. | CCRS airborne SAR | 8 F (5 types), lF, rF, nF | Low, better measures contrast and correlation | X,C all polari-sations | van der Sanden and Hoekman 1999 |

[a]Result assessment approaches: Maximum likelihood estimator (MLE), Bhattacharyya distance (BD), Euclidean distance (ED), transformed divergence ($TD_{ij}$).

[b]Agriculture (A), water (W), bare soil (B), clearings (C), forest (F), recent activities (RA), savanna (S), flooded (f), logged (l), regenerating (r), open (o), woody (w), disturbed (d), non(n).

[c]High indicates >90% classification accuracy, medium indicates 70-90% classification accuracy, low indicates <70% classification accuracy..

Results from studies on the seasonal forest backscatter indicated that soil frost and snow can reduce relative backscatter values and be detected at L and C bands (Pulliainen *et al.* 1999). Also, the absence of leaves in deciduous forest trees lowered the backscatter at C band, raising the assumption of leaves as highly forward scatterers (Ahern *et al.* 1993). Other authors, however, found a very weak correlation between ERS-1 SAR C band backscatter and seasonal changing variables, as foliage dynamics (Mougin *et al.* 1998). Weather related variables (rainfall, wind speed and air temperature) were reported as not being clearly related to backscatter from a deciduous-coniferous forest (Mougin *et al.* 1998).

Seasonal effects were observed in a walnut orchard backscatter at X and L bands. Changes at X band backscatter were attributed to changing water content of branches and leaves, while at L band to both soil and vegetation water content variation (McDonald *et al.* 1991).

For tropical environments, seasonal L band backscatter was detected by Rosenqvist (1996a) from oil palm stands. The seasonal behaviour corresponded to high backscatter coinciding with the two annual dry seasons in the area and was attributed to changing water content of leaves and fronds. For rubber tree plantations, however, even after shedding their leaves, little variation of backscatter with time was detected (Rosenqvist 1996a). In Brazilian Amazonia, a backscatter seasonal cycle, corresponding roughly with low backscatter for dry season and high backscatter for wet season, was detected in low biomass regenerating forest plots and attributed to the changing water content of vegetation and soils (Kuplich and Curran 1999).

A general consensus among researchers is that data from the dry season in the tropics are the most useful when differentiating vegetation classes (Rignot *et al.* 1997, Luckman *et al.* 1998, Grover *et al.* 1999, Kuntz and Siegert 1999). In addition, backscatter/biomass relationships are stronger during the dry season, because the influence of water and consequent increase on backscatter are minimised (Luckman *et al.* 1998, Kuplich and Curran 1999).

For Amazonian forest, the influence of the season on the backscatter is not restricted to the effect of water, but also to land cover dynamics, which determines, in addition to the increased soil moisture in wet seasons, the availability of some temporary crops (Saatchi *et al.* 1997). Moreover, the dry season is the preferable time for logging, forest clearing and pasture burning, thus care must be taken when analysing dynamic tropical environments (Saatchi *et al.* 1997).

### 3.5. Summary

The study of backscatter of regenerating tropical forests is a relatively new topic (Foody *et al.* 1997, Luckman *et al.* 1997a, 1998, Yanasse *et al.* 1997, Salas and Skole 1998). When describing tropical land cover types the diversity of logging and agricultural practices in areas surrounding tropical forest is revealed. Potential sources of forest regeneration are added to the ones following slash and burn cycles. Disturbed forests as a result of selective logging (by hand or machine) are also common land cover types described for the tropics (Saatchi *et al.* 1997, van der Sanden and Hoekman 1999, Kuntz and Siegert 1999, Kuplich *et al.* 2000b). Different practices trigger forest regeneration and most of the works concerning backscatter of tropical had at least one land cover type or class labelled either as regrowth forest (Nezry *et al.* 1993, Pope *et al.* 1994, Rignot *et al.* 1997), secondary forest (Kuntz and Siegert 1999, van der Sanden and Hoekman 1999) or regenerating forest (Foody *et al.* 1997, Yanasse *et al.* 1997, Luckman *et al.* 1997a,b, 1998, Grover *et al.* 1999).

As part of the regenerating forest process, deforested areas are usually present in tropical environments and its discrimination from mature forest assessed. Discrimination between these areas is a function of the contrast offered by the backscatter of the deforested areas (Ribbes *et al.* 1997). The type of logging seems to determine the intensity of radar backscatter, as woody debris can be removed or not. If removed and the soil is left bare, the radar response will be of the soils, therefore, the rules about roughness and soil moisture apply, with stronger backscatter for rougher and wetter soils (Ulaby *et al.* 1974).

The presence of residual biomass after logging produces high horizontally polarised returns, as this polarisation interacted strongly with the remaining trunks (Rignot *et al.* 1997). When some trees are left standing, double-bounce scattering occurs between trees and clear forest floor and LHH returns are higher than others bands in SIR-C configuration (Saatchi *et al.* 1997). If the wavelength penetrates the forest canopy, horizontal co-polarised radiation will also give information about the underlying soil and canopy- and trunk-ground interactions (Hess *et al.* 1995).

Some recent studies have suggested limitations on the use of C band in tropical forest area discrimination (Pope *et al.* 1994, Luckman *et al.* 1997b, Rignot *et al.* 1997, Saatchi *et al.* 1997, Yanasse *et al.* 1997, Grover *et al.* 1999). The reason for that is the backscatter asymptote at low levels of biomass and consequent C band insensitivity to even young regenerating forest areas (Saatchi *et al.* 1997). The shallow penetration of the C band into forest canopies restricts its use for the differentiation between deforested areas and forest when the soil is dry and the influence of water is minimised (Luckman *et al.* 1997a, Grover *et al.* 1999). Kuntz and Siegert (1999), however, found some discrimination power on the texture extracted from ERS-1 SAR images (CVV band) for Indonesian forests.

L band has proved some success in tropical vegetation studies, owing to its deeper penetration and volumetric interactions into the canopy (Grover *et al.* 1999). When configured as LHV its sensitivity to forest biomass and structure allowed some discrimination between regenerating stages (Yanasse *et al.* 1997) and between regenerating and mature forest (Saatchi *et al.* 1997). The backscatter asymptote was found to be the reason for the low separability between regenerating areas and L band with at least two different polarisations was suggested to perform this task (Rignot *et al.* 1997).

Regenerating forest backscatter will approach that of the surrounding mature forest as the forest grows, so the differentiation between regenerating and mature forest can become difficult (Leckie and Ranson 1998, Salas and Skole 1998).

Reliable assessment of various forest types including regenerating, selectively-logged and mature tropical forest required SAR data on C, L and/or P bands (van der Sanden and Hoekman 1999). Four biophysical indices derived from fully-polarimetric SAR data were used successfully to discriminate vegetation types (called landscape units) in the tropics (Pope *et al.* 1994).

The great variety of tropical forest ecosystems still did not allow the finding of an ideal radar configuration capable of identification and discrimination at the desired level. A multitemporal approach along with texture analysis (Saatchi *et al.* 1997) can help clarify backscatter/tropical forest relationships.

The influence of regenerating tropical forest characteristics (e.g. species composition, their structures and canopy properties) on the backscatter is still not fully understood. An initial attempt to group regenerating forests by their dominant species (therefore, reducing structural variability) was made and some encouraging results obtained (Foody *et al.* 1997). Variation in biomass was secondary to canopy spatial variability (canopy closure and homogeneity) in the backscatter of tropical forest in Belize (Pope *et al.* 1994). These highlight the limitations of approaches used to study tropical regenerating forests until now and the amount of work still to do.