Landcover Classification using ERS SAR/INSAR Data on Coastal Region of Central Sumatra

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Abstract

In this study, we present a classification method using both optical and SAR data in order to perform landcover classification. We investigate the use of a vector of information, composed of a serie of signatures derived from both SAR and INSAR data. First, different relevant parameters are derived from ERS-SAR data using multitemporal and interferometric analysis. Optical data is then used to define a training set in to order to perform a supervised classification. Our test site is located in a tropical area, in the coastal region of Central Sumatra, Indonesia. This site has a wide variety of landcover types. The region has been undergoing rapid deforestation with the logging of commercially exploitable timber and the conversion of forest to agricultural land. Our results demonstrate that ERS-1/2 tandem data is more suitable than the 35 days repeat pass in discriminating various landcover types. The results of classification using these techniques are compared with existing landuse maps and information derived from SPOT and LANDSAT data.

I. Introduction

The use of spaceborne remote sensing for forest and landuse applications has been widely demonstrated as an important tool, particularly for forest monitoring and landcover identification. More importantly, the easy availability of data on a regular basis from operational satellites such as ERS, JERS, RADARSAT, SPOT and LANDSAT has created the potential for such an analysis to be implemented as a monitoring tool. This is immensely important in areas where extensive logging activities are prevalent. Optical data, like SPOT, remain the best source of information for forest monitoring and landuse classification, with a high resolution and a good discrimination for various lancovers. While optical sensors have been successfully exploited for such studies, their use in tropical areas is severely limited by weather conditions. Indeed, cloud cover poses the greatest restriction to the acquisition of data that may be required at different intervals.

This limitation has been somewhat alleviated by the use of Synthetic Aperture Radars (SARs) which are essentially all-weather systems. Typically such systems provide information of the ground reflectivity, in a manner which is phase preserving. The utility of the phase information was first demonstrated by Graham [1] where he used two vertically separated airborne antennas to receive simultaneously backscattered signals from the terrain. The coherent addition of the signals received by two spatially displaced antennas, which forms the basis of what is now called SAR Interferometry, provides useful information about the topography of the terrain. This technique has also been employed in spaceborne systems where the 'displacement of antennas' is achieved by a single antenna in two separate passes of the satellite [2].

It has been shown that a multiptemporal analysis of SAR data allows to monitor changes in landcover using the backscatter change intensity. Moreover, it has been demontrated in [3,4] for boreal forest and [7] tropical forest that the coherence component derived from an interferometric pair gives additional useful information for landcover classification.

In this paper, we present a supervised classification method using both optical data and radar information derived from SAR and INSAR data. First, we present the different steps to derive a serie of parameters from both amplitude and complex data. In particular, we investigate the usefulness and the limitation of tandem and 35-day repeat-pass interferometry for this application. A description of the supervised classification method is given, where optical data is used to define the training set and control the classification process.

II. Test Site and Data

The test site is located in the coastal region of central Sumatra in the Jambi province, Indonesia. This site has a wide variety of landcover types ranging from mangrove, swamp forest, primary and secondary forests and agricultural land including rice, coconut, rubber and oil palm. The region has been undergoing rapid deforestation with the logging of commercially exploitable timber and the conversion of forest to agricultural land. A landcover map of 1:100 000 scale realised in 1992 is available over this area. A set of optical data composed of two SPOT XS data (1996) and one Landsat TM data (1993) are used for the classification process. These data, in conjunction with the landcover map of 1:100 000 scale realised in 1992, are also used to validate the result of the classification.

Both SAR.SLC and SAR.PRI data are used in this study for multitemporal and interferometric analysis. A set of ERS-PRI data acquired over one year (oct 95 to december 96) are used for multitemporal studies. Interferometric pair acquired during tandem mission (April-June 1996) are used to derive the coherence component.

Satellite	Date	Orbit	Frame	Pass	Type	Baseline (B_p, B_n)
ERS-1	95/10/07	22107	3627+20% SAT	descending	PRI	N/A

ERS-1	96/05/04	25113	3627+20% SAT	descending	SLC	(68, 139)
ERS-2	96/05/05	05440	3627+20% SAT	descending	PRI, SLC	
ERS-2	96/06/09	05941	3627+20% SAT	descending	PRI	N/A
ERS-2	96/09/22	07444	3627+20% SAT	descending	PRI	N/A

Table 1: *List of SAR Data (SAT: Shift Along the Track)*

III. Methodology

First of all, we summarize the processing techniques applied on SAR data for both multitemporal and interferometric studies. Then, we will present the methodology developed to perform the classification using both optical and SAR data.

III.A. Processing techniques
III.A.1. Multitemporal analysis

Amplitude images SAR.PRI are analysed to derive different parameters used in the classification process:

. backscattering coefficient s^{o}

. backscatter intensity change Ds^{0}

. texture

First, an edge-preserving filter (Gamma-MAP, [8]) is performed on each amplitude image in order to significantly reduce the speckle within the image.

Then, backscatter intensity change Ds^{0} could be estimated correctly as follow:

$$\Delta\sigma^0_{dB} = 10 \cdot \log\left(\frac{\bar{I}_2}{\bar{I}_1}\right) \qquad (1)$$

Where $\bar{I}$ is the intensity of the signal after filtering.

Texture parameters (variance and entropy) are derived from the Grey-Level Co-occurrence Matrix using a large window (15x15).

III.A.2. Interferometric processing

Two main components are derived from an interferometric pair. The phase is normally used to derive terrain height. The main application is typically DEM generation, but this component could be also used to estimate the tree height. Nevertheless, the high level of noise over forested areas (especially tropical forest) can not give good estimation of height. Then, for our purpose, only the coherence component derived from the interferometric pair is used.

To generate the interferogram, the two complex images must be first co-registered to within 0.1 pixel accuracy. This step is crucial in order to obtain a good quality of interferogram. A first coarse registration is realised using a serie of ground control points. The lack of bright and clear targets over tropical areas increases the difficulty of finding a good set of GCP's. Fine registration is then perform using correlation both on amplitude and phase.

The degree of coherence g for each pair (s_1, s_2) of co-registered complex values s_1, s_2 is given by:

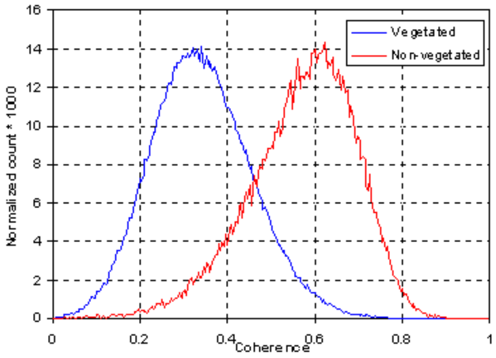
$$\gamma = \frac{\langle s_1 s_2^* \rangle}{\sqrt{\langle s_1 s_1^* \rangle \cdot \langle s_2 s_2^* \rangle}} \qquad (2)$$

Where the bracket <...> represents an ensemble average, which is estimated by the spatial average over a finite-size window.

$$\langle s_1 s_2^* \rangle = \frac{1}{N} \cdot \sum_{i=1}^{N} s_{1,i} \cdot s_{2,i}^* \qquad (3)$$

The value N should be sufficiently large (i.e.: 3x12 or 4x16 pixels window in range and azimuth) to have a good estimation of the degree of coherence within the window.

A first study has been conducted to access the quality of the interferograms that can be generated over tropical areas. Fig. (1).a and (1).b represent the histogram of coherence obtained using tandem and 35-day repeat passes. Low coherence was expected for vegetated areas, as a high coherence value over non-vegetated areas (bare soils, grasslands and deforested areas).



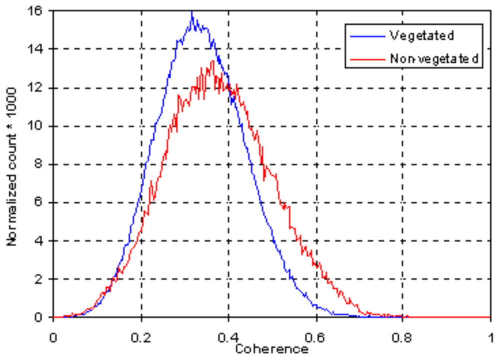


Fig. 1.a: *Histogram of coherence for vegetated* ***Fig. 1.b:*** *Histogram of coherence for vegetated and non-vegetated areas. Tandem Mode and non-vegetated areas. 35-days repeat-pass*

For the tandem mode, there is a marked difference (of about 0.6) in the coherence level between the vegetated areas, where coherence is expected to be low due to the effect of volume scattering, and the non-vegetated areas. The latter, which comprises mainly of bare soil and deforested land, would be expected to give high coherence values. This is, however, not the case for the 35-day repeat-pass where the mean coherence level of the non-vegetated areas has a value of about 0.3, which is also the level for the vegetated areas. Plausibly, this decorrelation could be due to a change in weather conditions or land-use in the 35 days between acquisitions. Thus, while the degree of coherence in a tandem mode serves as a reliable discriminator between vegetation and non-vegetation, it is useless in the case of the 35-day repeat pass.

For forestry, tandem pairs are used to generate the interferometric components in order to reduce the effect of temporal decorrelation of the signal between the two acquisitions.

In addition, value of the baseline also plays an important role on coherence level. It has been demonstrated in [5] that coherence level decreases when the baseline increases. For this reason, we have selected interferometric pairs with baseline less than 300m.

III.B. Classification method

The main idea of our method is to use all available information derived from SAR and INSAR data to perform the classification process.

Using amplitude SAR images, the following parameters can be derived:

. backscattering coefficient s^o

. backscatter intensity change Ds^0 between two images

. texture

Thus, five parameters can be taken into account using two amplitude SAR images (s^o_1, s^o_2, Ds^0_{21}, $texture_1$, $texture_2$). In addition, degree of coherence between two complex SAR images is computed using INSAR data.

On the whole, we can construct a vector of information I of n-order. The number n of discriminators depends on the number of SAR images taken into account for the analysis.

The following vector refers to a set of SAR data using two different dates:

$$I = [s^o_1, s^o_2, Ds^0_{21}, texture_1, texture_2, g_{21}] \quad (4)$$

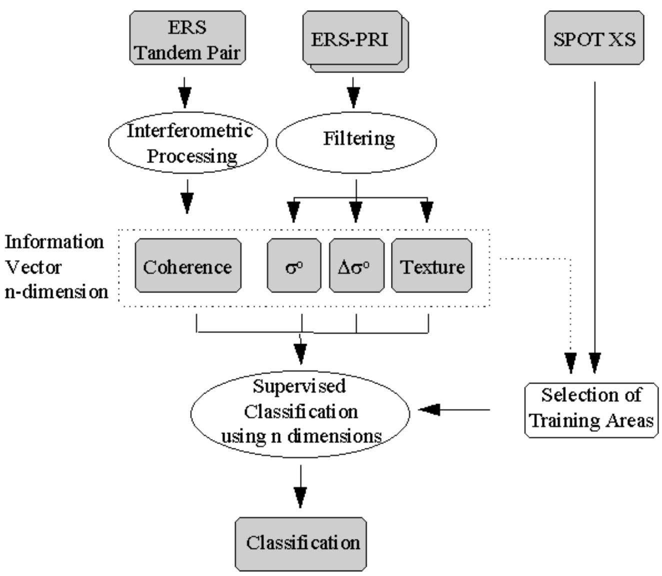


__Fig. 2 :__ Graph of the classification method

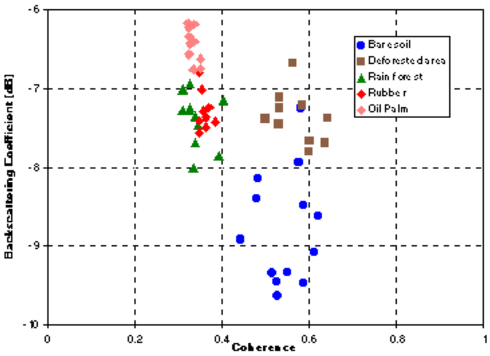
First, a serie of training areas are selected from the SPOT XS image, given a representative set for the different types of landuse found in the image. In this case study, 5 training areas are chosen corresponding to primary forest, rubber, oil palm plantation, rice, bare soil. Then, a supervised classification is performed on the SAR components using the previous training set.

IV. Results

A first analysis was conducted using 3 signatures (coherence, the backscatter intensity (s ^{o}) and backscatter intensity change (D s ^{o})) derived from one tandem pair. The behaviour of the degree of coherence versus the backscattering coefficient is first analysed in order to demonstrate the usefulness of both components.

Fig (3) points out the good discrimination between vegetated (forest, plantation, cultivated areas) and non-vegetated areas (bare soil and deforested areas) using coherence. Nevertheless, different types of landuse could not be separated using only the coherence component. Oil palm plantation and rubber give the same degree of coherence. However, the backscattering coefficient s^{o} can then be used to discriminate these two types of landcovers. Unfortunately, primary forest and rubber could not be separated using both coherence and s^{o}.

The backscatter intensity change between two images acquired at different dates could be used to discriminate various landcover types. Different cultivated areas can then be identified by analysing the growth rate (2-3 months for rice). The change over seasons (dry and wet seasons) can alsso be a discriminator between plantation (small change over the year) and primary forest (very stable).



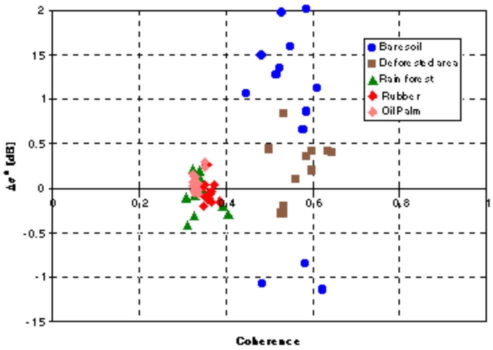


***Fig. 3:** Plot of s ^{o} as a function of coherence* ***Fig. 4:** Plot of D s ^{o} as a function of coherence for different classes of land-use. Tandem mode for different classes of land-use. Tandem mode*

Fig (5).a shows a color composition of three amplitude images (SAR.PRI full scene, R: 96/09, G: 96/05, B: 95/10) covering the entire test site. The bright patch at bottom right corresponds to the town of Jambi. Farming activities take place around the city and along the river Batang Hari. Bright grey areas represent primary and swamp forests. Changes in colour in the middle of the image is related to logging areas, where rapid deforestation takes place. Red patches correspond to new deforested areas, while yellow patches are related to regrowth areas. Coastal zone is composed of various cultivated areas, crops like rice (top right of the image), and different types of plantation (coconut, rubber and oil palm).

Fig (5).b is the coherence image over the same area. As expected, low coherence is found for forest. High coherence is related to bare soil, deforested areas (center of image), or small bushes. A very heterogeneous zone at the top right corresponds to paddy fields, for which various stages of growth could be found at the same time.

Fig. (5).c represents a colour composition (RGB) of coherence / s^{o} / Ds^{o}. Areas with high coherence appear clearly in red, when areas with low coherence (primary and swamp forests) correspond to light blue areas. The discrimination between forest and non-forest appears very clearly, with very sharp edges. This image can be compared with Fig.(5).a.

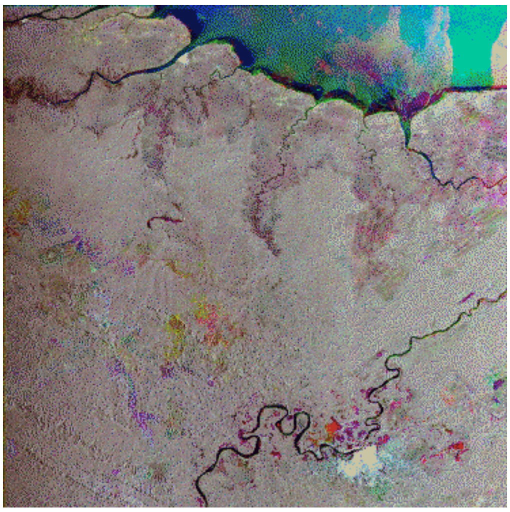


Fig. 5.a

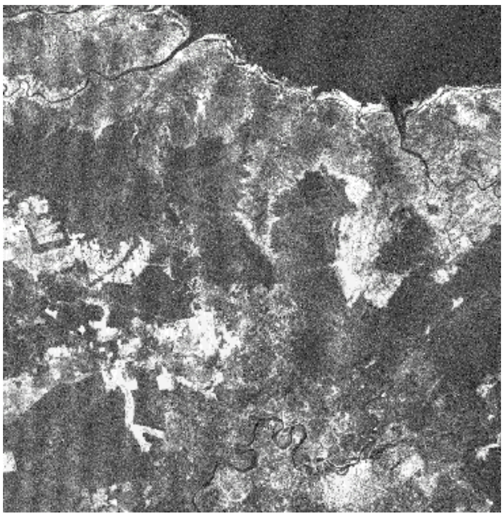
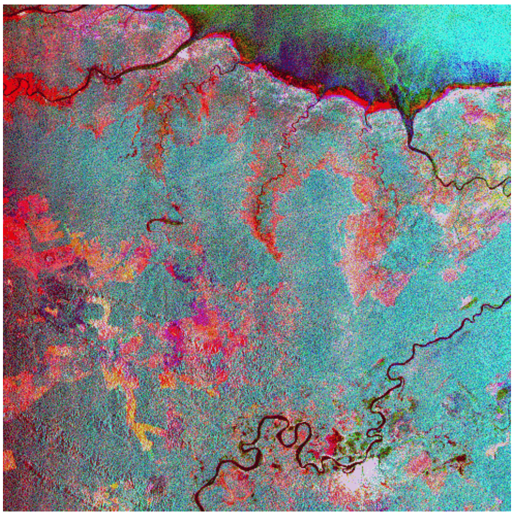


Fig. 5.b

Figure (5)a,b,c:



SAR PRI and SLC data over Jambi province, Sumatra, Indonesia

Scene center Lat. / Long. (deg.): -1.216 / 104.503

Frame: 2637 + 20% Shift Along Track

Orbit: 22107, 25113, 05440, 07444

a.: Colour composition of 3 amplitude images

R: 96/09/22, G: 96/05/04, B: 95/10/07)

b.: Coherence image (tandem pair 96/05/04-05)

c.: Colour composition

R: coherence, G: Amplitude 96/09,

B: Amplitude 96/05

Fig. 5.c

Two test sites have been selected from Fig (5).a.

The first one corresponds to a forested area where intensive logging takes place, covering 25x20km.

Fig (6).a shows a colour composition of the three dates as described before. The difference between forested areas and plantation is not clear. Changes in colour can be related to change in moisture content and landuse (regrowth). For this raison, it is difficult to discriminate very clearly forest from non-forest areas.

Fig. (6).b represents the coherence. Very strong contrast between forested and non-forested areas is found. In addition, this information is recovered also in mountainous areas. In this case, fig. (6).a gives less information, when relief distortion is dominant. Notice that change index could not give a good discrimination between forest and plantation which are almost stable in time. In this case, only coherence can discriminate the two.

However, Fig (6).c represents the colour composition with coherence/s^{o}/Ds^{o}. Clear and sharp limits between forest (yellow patches) and non-forest areas (blue) are very prominent.

The result can be visually compared with the SPOT XS image. New deforested areas can be seen in Fig (6).c at the center bottom (circle). This area is still forested on the SPOT XS image acquired 2 months before the tandem pair.

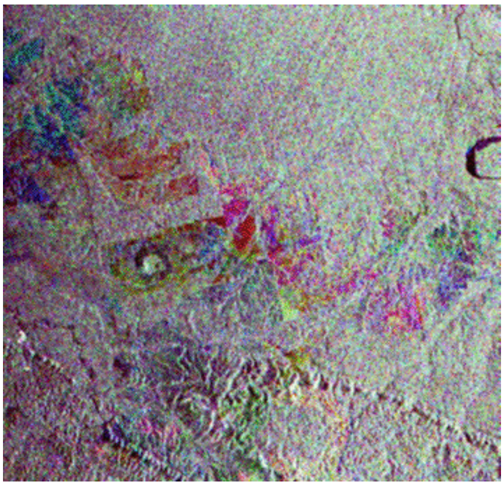


Fig. 6.a

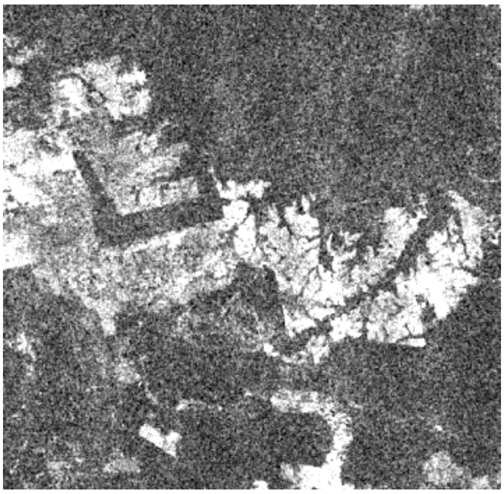


Fig. 6.b

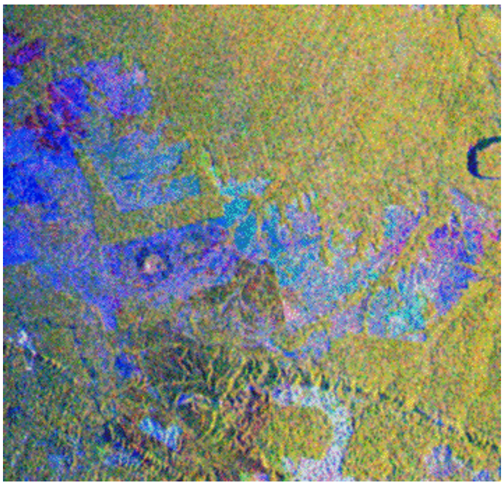


Fig. 6.c

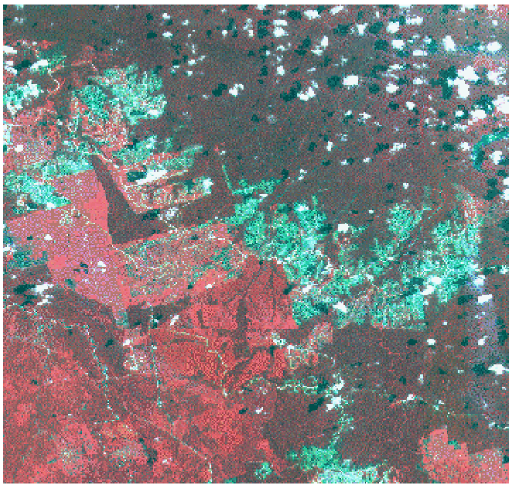


Fig. 6.d

The following example show result of the classification process over the coastal region, composed of swamp forest in the bottom of the image and cultivated areas along the coast (rice, rubber and oil palm plantation, coconut).

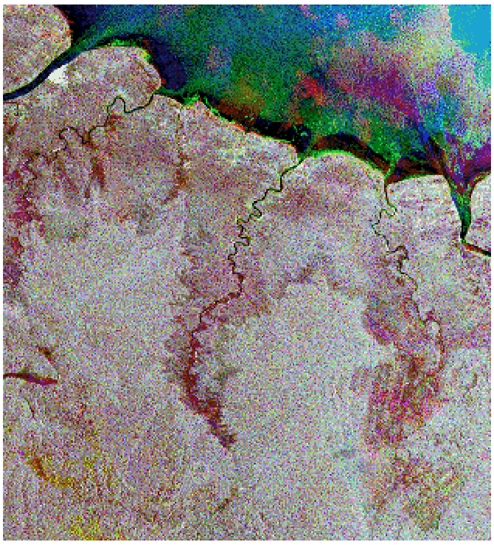


Fig. 7.a Color composition of 3 PRI

R: 96/09/22, G: 9605/04, B: 95/10/07

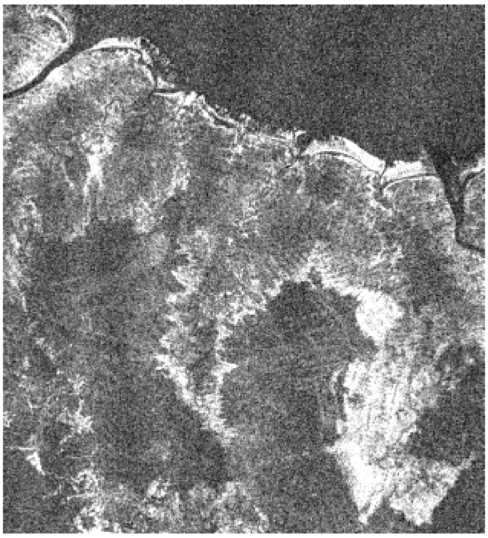


Fig. 7.b Coherence image (tandem pair, May 96)

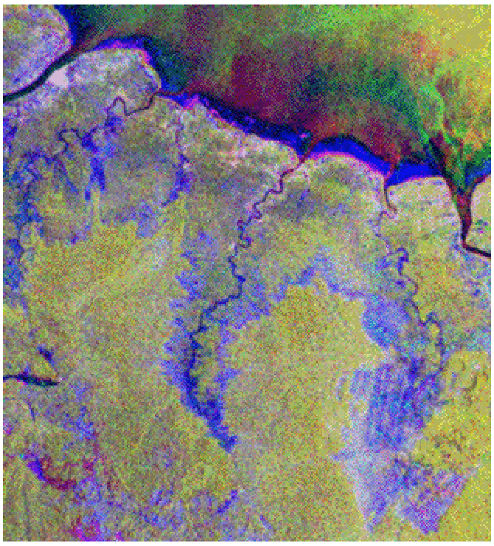


Fig. 7.c Colour composition

R: coherence, G: Amplitude 96/09, Amplitude 96/05

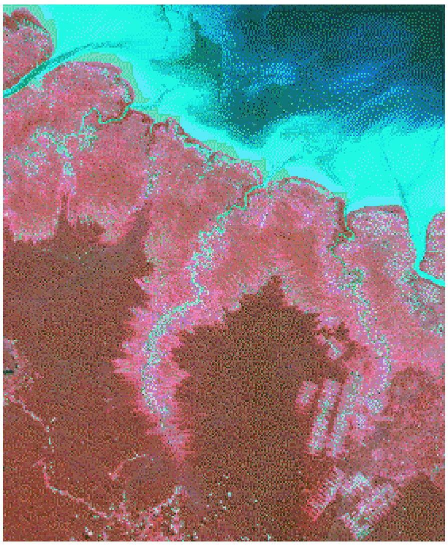
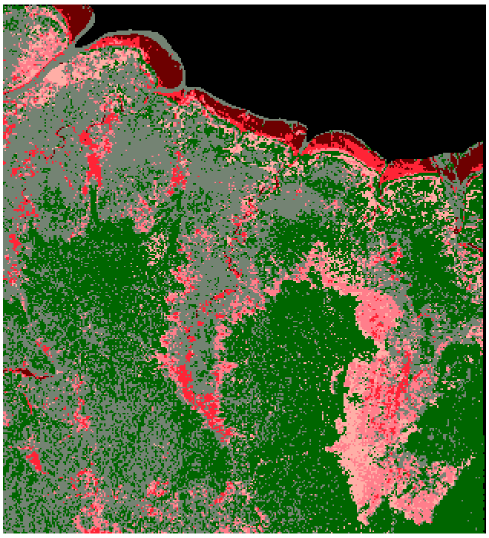


Fig. 7.d Landsat image . Date: June 9th 1989



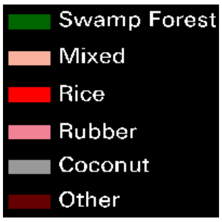


Fig. 7.e Classification map obtained from SAR/INSAR data and using supervised classification method.

Fig (7).a shows a colour composition of 3 PRI images. Canals, used to irrigate paddy-fields, appears in yellow at the top left of the image. Grey patches correspond to swamp forest. Linear features at the middle right correspond to intensive cultivated areas. Dark red patches along the river (top left) are related to rice.

Coherence image (Fig (7).b) shows a good contrast between plantation and forest. Logging areas located in hilly terrain (bottom left) appear clearly at the bottom left of the image. Logging routes and deforested areas then appear with a high coherence value in fig (7).b. These areas are not clearly visible in fig (7).a due to relief distortions which affect the amplitude of the radar signal.

Fig (7).c represents the colour composition with coherence/s^o/Ds^o. This image can be compared with the Landsat TM image (Fig. (7).d) acquired in 1989. Nevertheless, some changes in lancover occured since 1989, especially along the boundary between swamp forest and cultivated areas.

Supervised classification is then performed on SAR/INSAR data set, using training areas selected in the TM image. 4 classes was used over this site: forest, rice, coconut, rubber. Swamp forest is correctly classified (green), and a good contrast is obtained with rubber plantation (pink). Grey patches are related to coconuts. Moreover, a mixing between rubber and swamp forest is visible at the bottom left of the image. Rice appears in red (growing stage), and is located along the river. Nevertheless, some misclassifications appear, especially on heterogeneous areas (mixing between coconut and rice).

V. Discussion / Conclusion

Multitemporal analysis is not sufficient for landcover classification over tropical areas. Some landcover types can not be discriminated, due to similar s^o and Ds^o (e.g.: forest and rubber).

However, it has been demonstrated that multitemporal study in combination with interferometric analysis can give useful information for landcover classification. The coherence component appears as a new discriminator. We have based our method on the use of a vector of information of n-order, composed of a serie of parameters derived from both SAR and INSAR data: coherence , s^o, Ds^o, texture. Optical data is then used to define a training set in order to control the supervised classification. Further analysis will be conducted to improve the classification process, in order to reduce the percentage of misclassification.

Tandem pair is more appropriate for this kind of study, in order to reduce the temporal decorrelation of the signal. Moreover, small baselines are required to avoid a degradation of the level of the coherence due to baseline decorrelation.

Nevertheless, sensitivity to biomass remains low with C-band. Moreover, L-band appears to be more suitable for this type of application. To significantly improve the methodology, combination of both ERS and JERS-1 data should be used for this application. Backscattering coefficient and backscatter change intensity could then be derived from JERS-1 Data, and combined with coherence component extracted from ERS interferometric pair.

Examples presented in this paper show that the combination of coherence, s^o and Ds^o allows to discriminate various landcover types, and also to distinguish very fine features. For this reason, as an analogy with SPOT, this colour composite (coherence, s^o, Ds^o) could be useful for visual interpretation in order to supplement the lack of optical data.

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