PALSAR wide-area mapping and annual monitoring methodology for Borneo

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Abstract. This paper describes the operational radar mapping processing chain developed and steps taken to produce a provisional wide-area PALSAR forest and land cover map of Borneo for the year 2007, compliant with emerging international standards (CEOS guidelines, FAO LCCS). The methodology is based on the classification of FBS and FBD image pairs. To cover Borneo the equivalent of 554 standard images is required. The final overall accuracy assessment result shows this demonstration map product is in 85.5% full agreement with the independent reference dataset and in 7.8% 'partial agreement'.
Monitoring land cover change on an annual basis requires consistent year-to-year mapping. This implies that the localised and temporal effects of environmental factors on the backscatter level (such as inundation or El Niño drought) and variation due to differing observation dates/cycles (related to change of season) have to be accounted for strip by strip. New concepts for (a) automated intercalibration of radar data, (b) time-consistency and (c) automated adaptation of radar signatures to changing environmental conditions have been evaluated for its usefulness to improve the classification and the consistency of annual monitoring.

I. INTRODUCTION

Worldwide concern about global climate change driven by increasing greenhouse gas (GHG) emissions is growing. Land cover change, including deforestation, plays a significant role as it was estimated to represent 20% of global annual CO2 emissions in the 90's [1, 2], while recent studies show a decrease to 12.5% in the last decade [2]. Consequently, measures are taken to reduce emissions from land cover change. For example, the EC and several countries (such as The Netherlands, the UK, Belgium and Germany) require compliance with sustainability criteria for the production of biofuels and bioliquids [3]. Specific references are made to land cover in such schemes. For example, the EU Renewable Energy Directive [4] excludes areas with high carbon stocks, including forests and wetlands, for the production of biofuels and bioliquids. In addition, agreements are being negotiated under the UN Framework Convention on Climate Change (UNFCCC) to compensate tropical forest countries for Reduced Emissions from Deforestation and forest Degradation [5].

The availability of credible and regularly updated spatial information on forest and land use/cover (change) at the local to national levels will be a precondition for successful implementation of the abovementioned initiatives. Such information is currently not readily and consistently available in most tropical forest regions. Satellite observations will play a key role to help objectively measure forest, land cover, and biomass changes.

Persistent cloud cover in tropical rain forest areas severely limits the practical use of optical satellite observation [6, 7]. This is especially true when systematic annual wall-to-wall coverage or fast response over 'hot spot' areas is pursued. Radar (or SAR) does not have this limitation. Besides looking through clouds, smoke and haze, radar is capable to look inside

and below the forest canopy, revealing unique information related to wetland ecosystem features, hydrology and biomass.
The classification of (L-band) radar images is hard in comparison to optical images. The radar return signal not only depends on the upper canopy or bare soil characteristics (like in optical systems) but is also sensitive to bio-physical characteristics such as biomass, flooding under a closed canopy, and soil moisture. The sensitivity to a larger number of terrain parameters gives rise to more ambiguities in the interpretation of radar images. This problem can be mitigated by using time series of radar observation or by using additional (historical) optical data.

The Kyoto & Carbon (K&C) Initiative was initiated by the Japanese Space Exploration Agency (JAXA) Earth Observation Research and Applications Centre (EORC) in 2000, to support environmental conventions, carbon cycle science and natural conservation, with information that cannot be obtained in a feasible manner by any other means [8, 9]. Relevant to the establishment of the K&C Initiative is the unique suitability of ALOS PALSAR to support acquisition of the type of regional-scale information needed, given the L-band SAR sensitivity to vegetation structure and inundation, and the microwave cloud-penetrating capacity to ensure global observations. The K&C Initiative aims to provide (1) systematic global observations and consistent data archives, and (2) derived and verified thematic products. The PALSAR observation strategy has been designed to provide consistent wall-to-wall observations at fine resolution of almost all land areas on Earth on a repetitive basis, in a manner which has earlier been conceived only for coarse- and medium-resolution instruments [8, 9].

The prototype area for demonstrating the PALSAR wide-area forest and land cover mapping methodology is the island of Borneo in South East Asia. Borneo is the third largest island in the world and covers approximately 750,000 km^2. Almost three quarters of the island is part of Indonesia (Kalimantan), with the remainder covered by Malaysia (Sarawak and Sabah) and Brunei Darussalam. Borneo was almost entirely covered by tropical evergreen broadleaved forest until the 1950s. Intensive logging of predominant commercial Dipterocarp species and conversion to cropland, oil palm and timber plantations has reduced forest cover significantly. Other major natural vegetation types include [10, 11]: peat swamp forests, which are found in the coastal and sub-coastal lowlands, freshwater swamps along rivers inland, and mangrove forests in the coastal plains.

The main objective of this paper is to summarise progress made during the second phase of the K&C Initiative with a focus on the methodologies for wide-area mapping (section 2) and wide-area monitoring (section 3) and the prototype area Borneo. Some results for consistent time series mapping are discussed in section 4. Ad hoc results for other areas, including Sumatra, Papua and the Amazon, and other product types, such as inundation or biomass maps, will not be addressed here. An outlook for further development is presented in section 5. The wide-area mapping methodology and the validation of the 2007 Borneo map has been published already [12]. For completeness of understanding this methodology will be summarised (section 2) and extended (section 3) to a framework methodology for handling annual and consistent wide-area time-series.

II. WIDE AREA MAPPING

A. Summary of wide area mapping methodology

Input data

PALSAR is operated in one mode only during a cycle of 46 days [8]. The default mode changes for ascending passes, while descending passes are always acquired in ScanSAR mode (Table 1). Path images (or strip data) constitute the basic input data for all products to be generated within the K&C Initiative. Path images are extended images, which may extend to several thousands of km in length (Table 1). For Borneo, for 2007, Fine-Beam data are acquired in cycle 9 (FBS) and cycle 13 (FBD), coinciding with the wet and dry season, respectively. The methodology presented in [13, 12] is based on the classification of FBS-FBD image pairs.

Table 1. PALSAR radar default observation modes and K&C path product characteristics.

Mode	FBS	FBD	ScanSAR
Polarization	HH	HH+HV	HH
Incidence angle range	36.6°~40.9°	36.6°~40.9°	18.1°~43.0°
Swath width	70 km	70 km	360 km
Resolution (4 looks)	10 m	20 m	~100 m
Pass designation	Ascending	Ascending	Descending
Coverage	Global	Global	Regional /Global
K&C slant range path images:			
Nominal pixel spacing	52x35 m	52x70 m	40x70 m
Number of looks	64	64	12~20

A wall-to-wall coverage of Borneo in Fine-Beam mode requires 277 standard images (or 22 strip images) collected in 22 passes. Ideally, to reach the optimum spatio-temporal homogeneity, all data should be collected within one cycle. In practice, because of technical reasons not discussed here, only 70-80% of the desired radar images actually become available. In many instances missing data can be replaced by data from an adjacent cycle. Since replacement data reduce the spatio-temporal homogeneity this should be done with care. The time structure within one cycle is such that the time elapsed between observations of adjacent strips is 17 days or 29 days. The time laps are an inherent feature of any mosaic and these have to be dealt with carefully within classification procedures.

Processing chain

The processing chain consists of three blocks sub-divided in eleven steps, as illustrated in Fig.1. It starts with the selection of radar data, geometric and radiometric pre-processing steps, and further preparations for the thematic classification process (the pre-processing block). Next, radar path images are classified, labeled and the resulting maps are validated (the classification block). Finally, the classified path images are mosaicked by processing the areas of overlap and tiled into the final map sheets (the mosaicking block).

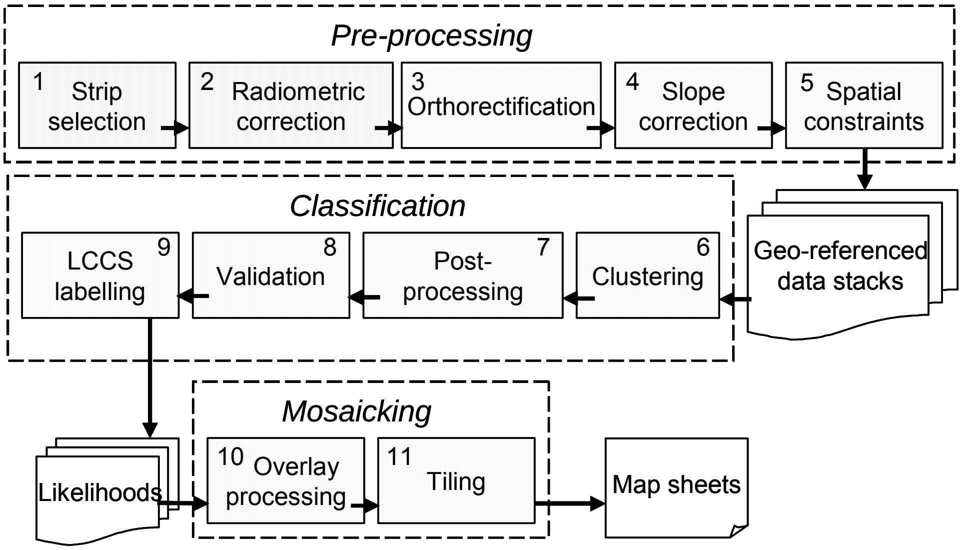


Figure 1. Basic elements of the processing chain for wide-area radar mapping.

Data preparation (steps 1-5)
K&C strip images may suffer from substantial radiometric deformation. For some strips the values fall-off in the near range, for other strips in the far range. Very often the brightness varies in azimuth direction. To allow classification of the Borneo 2007 strips these errors have been estimated and corrected strip by strip using ad-hoc procedures. Handling multi-annual data series requires a more systematic approach which will be discussed in section 3.

For radar orthorectification the software package of Gamma Remote Sensing [14] is used together with the SRTM-4 DEM. Slope steepness and slope orientation maps are created as auxiliary output layers. Using the WGS84 datum, the strips are projected as an unprotected map with latitude and longitude (or Equiangular map projection), which is convenient for near equator latitudes. The geo-location accuracy of the final product depends on the quality of the DEM. For flat areas and Fine-Beam mode this accuracy is 9.3 m, with a standard deviation of 5 m [15, 16].

Auxiliary spatial information layers can be used as *a priori* information to constrain the classification process. The ocean mask, for example, is used to limit classification to the land surface. The lowland mask (experimentally selected as < 50m amsl) indicates the area where wetland classes are likely to occur. The mangrove mask is made by visual inspection of the FBS-FBD radar mosaic. These areas have typical drainage patterns and backscatter levels and are easily recognized. This mask is helpful to avoid confusion created by the similarity of radar backscatter levels for *nipah* and recently deforested areas. When handling multi-annual data series the possibilities to handle such ambiguities are much better (see section 3).

Slope correction (step 4)
Backscatter of terrain is modulated by the surface geometry of hills and mountains. This modulation is a function of slope steepness, slope orientation and the scattering mechanism of the terrain. Several approaches for radiometric slope corrections can be found in literature. These approaches differ in the physical description of the backscatter mechanism. In our approach the terrain is assumed to behave as an opaque isotropic volume scatterer. This assumption seems appropriate for Borneo, where most slopes are covered by (dense) forest. Test results for an area almost completely covered by dense forest confirm this assumption as demonstrated in [12].

Classification steps (steps 6-9)

Several approaches for continental scale mapping (and monitoring) have been tested. A literature review and comparison of techniques is presented in [13]. It was found that the most promising and most accurate approach is a Bayesian approach based on (supervised and/or unsupervised) mixture modeling followed by Markov Random Field (MRF) classification. This approach has been validated successfully on agricultural areas in Europe [13]. The unsupervised approach is ideal for the complex and heterogeneous landscapes encountered in the tropics, where ground truth is often very limited or missing, and where a rigid overview of the bio-physical characteristics and dynamics of the terrain is often lacking. The basic principles are simple. The feature space of the radar data set is analyzed and divided (or segmented) in statistical clusters following certain criteria. In case the complexity of the terrain is not well-known the optimum number of clusters can be computed from the so-called Bayesian Information Criterion or BIC. One or more clusters can be assigned to a single thematic class on the basis of field data and/or physical considerations. Additional ground data collection may be needed in case clusters can not be identified.

The challenges for wide area mapping of heterogeneous landscapes are substantially larger than for localized areas. The (wide) area is covered by images of many different dates, which are constrained within 46-days cycles as much as possible. However, even within this short time span backscatter differences between adjacent strips may occur (caused by factors such as flooding, logging or fire). Moreover, local differences, for example run-off differences between watersheds, may result in additional complexity. This means that clusters found in different radar images may have different statistics, even though they belong to the same thematic class. Radiometric error increases this problem. Another complication is the large variation in landscapes, the various degrees of forest disturbance and degradation, and the wide spread of crop cultivation (such as oil palm, and rice paddy) and presence of severely degraded wastelands. Hence, within our methodology, an overall legend should be constructed from an analysis of clusters of local mixture models created for many characteristic zones in Borneo. The resulting legend is mainly based on the radar data, i.e. on what the radar can differentiate. A validation study using a fully independent set of reference data should confirm the appropriateness of this radar legend, and provide a means to translate (or aggregate) the classification results into a map compliant with FAO Land Cover Classification System (LCCS) standards.

The adapted approach consists of the following four steps: (1) Stratification of the area in a number of landscape types, each comprising a number of typical land cover types; (2) Selection of representative sub-areas within each landscape for a fair number of radar strips; (3) Selection and provisional labeling of representative clusters; (4) Analysis of selected clusters. The selected clusters are evaluated for statistical consistency (i.e. similarly labeled clusters should be close in feature space), *completeness* (the clusters should give a description of feature space, i.e. without leaving large areas unidentified) and physical consistency (relative position of clusters in feature space should have a physical meaning).

Because of the aggregation of clusters from different strips (i.e. observations at different times and additional radiometric unbalance as compared to a single strip) the aggregate is larger than it would be for clusters from a single strip. Consequently, wide area mapping results in a certain decrease of thematic detail. For multi-annual data sets this problem can be mitigated (see section 3). It should be noted that the cluster aggregate not necessarily should have to contain unsupervised clusters only. When good ground truth is (or becomes) available many clusters equally well could be obtained (or replaced) from supervised delineation of training areas. Cluster aggregates are the basis of the thematic classification. After evaluation of the thematic map individual clusters could be removed, added or re-labeled. This procedure is iterative: validation or additional/better ground truth may lead to improved tuning and a revision of the map.

For multi-annual data sets the above-mentioned procedure for legend development, notably step 3, i.e. the selection and provisional labeling of representative clusters, can be improved significantly by analysis of the temporal change of the statistics of the clusters of representative areas and incorporating knowledge on the dynamics of land cover change and dynamics of environmental factors such as inundation and drought (see section 3).

Mosaicking approach (steps 10-11)
Mosaicking takes place after classification. The classification of pixels in the overlap regions may differ because of small differences in observation date(s) and residual radiometric error. Within the Bayesian approach applied, the posterior likelihood for all classes are available and a single classification can be constructed according certain (Bayesian) criteria, resulting in a seamless map for those areas where real changes (like flooding, cutting, or fire) did not take place.

B. Borneo 2007 map and validation procedure

The provisional PALSAR map of Borneo for the year 2007 (Fig.2) has an LCCS-compatible legend with 18 land cover classes including seven forest types, two woodland types, two shrubland types, two grassland types and three anthropogenic vegetation types (Table 2). A more elaborate description of this legend as well as qualitative validation results (from comparison with other maps, with other legends) and quantitative validation results (from Landsat, Quickbird and IKONOS images, acquired in the same year 2007) are reported in [12]. It should be noted that many classes form continua along a biomass and/or wetness gradient. These ranges are arbitrarily split in a number of classes. In this context, *partial agreement* is defined as confusion with an adjacent class along a continuum, with a fairly similar biophysical characterization. The final overall accuracy assessment result showed that this demonstration map product is in 85.5% full agreement with an independent reference dataset and in 7.8% 'partial agreement'. The accuracy achieved is widely considered adequate, a very promising result for a sub-continental high resolution map based on just single-year radar data.

Lowland forest
Riverine forest
Swamp forest
Mangrove forest
Nipah mangrove forest
Peat swamp pole forest
Peat swamp / Riverine shrub
Forest mosaics
High shrub
Medium shrub
Ferns / grass
Grasslands
Cropland (upland)
Cropland (irrigated)
Plantations
Tree cover, burnt
Water bodies
Layover /Shadow
No strip coverage
Mountain forest

Table 2. Legend for PALSAR map of Borneo.

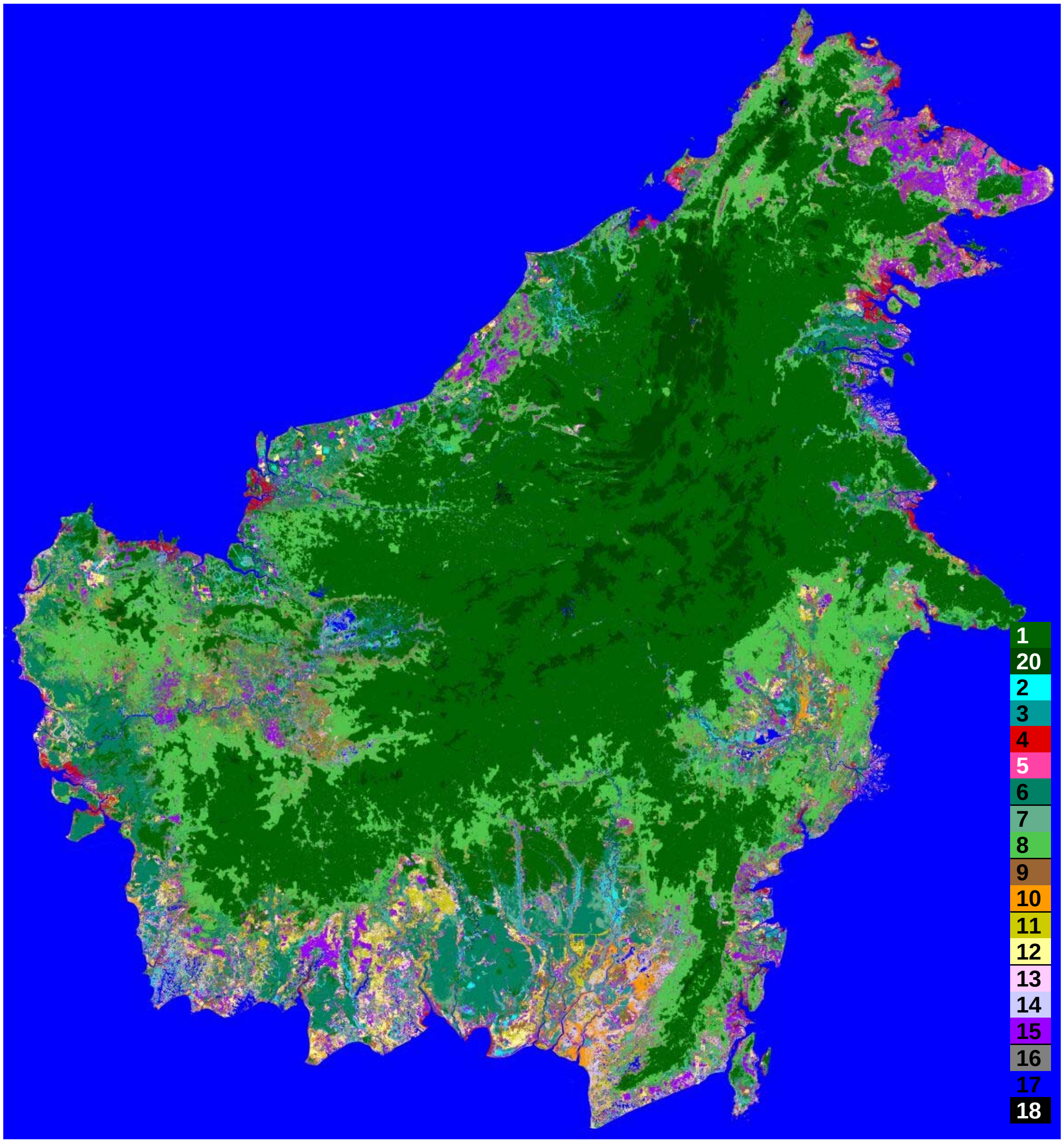
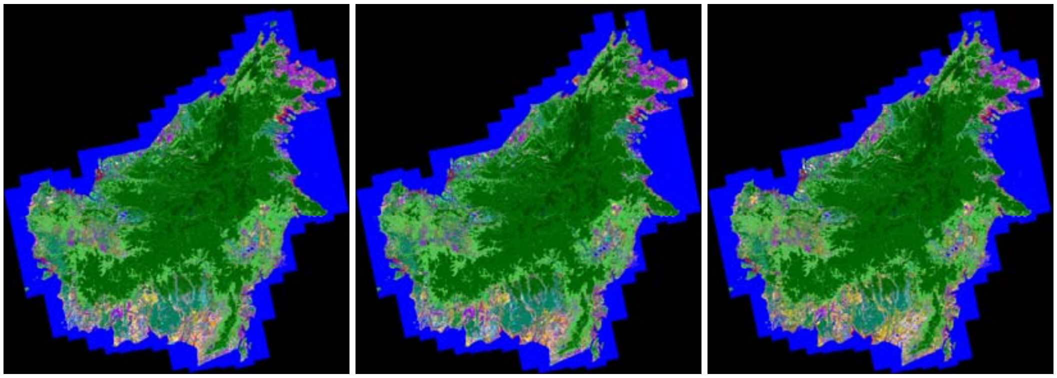


Figure 2. Overview thematic map of Borneo, 2007, derived from FBS and FBD PALSAR strip data (Legend: Table 2). Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

C. Single year classifications of 2007, 2008 and 2009

The legend developed for the Borneo 2007 map and its associated class statistics, in principle, can be applied in a straightforward manner to the 2008 and 2009 radar data sets. After careful calibration and intercalibration (to be discussed in section 3) the map series shown in Figure 3 emerges. Although gross features are identical and processes of deforestation are captured fairly well, careful inspection reveals inconsistencies which apparently result from local changes in class statistics, notably in the El Niño year 2009. These changes can be caused by environmental factors such as drought and inundation and will be discussed in the next section.



2007 2008 2009

Figure 3. After careful calibration and intercalibration of the 2007, 2008 and 2009 data sets and straightforward application of the statistics associated with the legend developed for the Borneo 2007 map, corresponding 50 m resolution maps for the years 2008 and 2009 have been produced. Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

III. CONSISTENT TIME SERIES

Structure of section 3
In this section (A) the general approach to handling time series, (B) physical background, (C) details of the processing steps and (D) modelling results are discussed.

A. General approach

Monitoring land cover change on an annual basis requires consistent year-to-year mapping. This implies that the localised and temporal effects of environmental factors on the backscatter level (such as inundation or El Niño drought) and variation due to differing observation dates/cycles (related to change of season) have to be accounted for strip by strip. The approach is based on the availability of sufficiently long radar time-series for a wide area. Such a series ideally should provide sufficient information to detect '*within-class'* variation of backscatter levels and to deduce its physical cause.
In Borneo the weather conditions in the years 2007 and 2008 have been "average" and relatively wet. The year 2009 has been "dry" because of a moderate El Niño event, which is usually more pronounced in the Provinces Central and East Kalimantan.. As such, these three years form a good basis to explore the possibilities for a system capable of handling within-class backscatter variation.

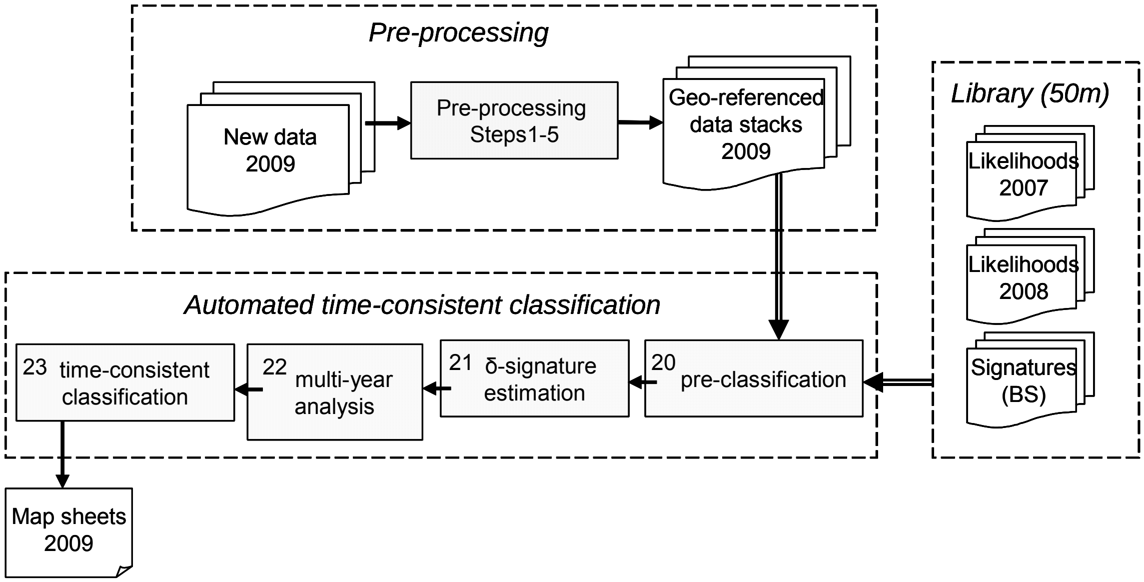


Figure 4. Simplified flow chart showing additional steps for automated time-consistent classification in relation to the steps already shown for single-year wide area mapping in Fig.1.

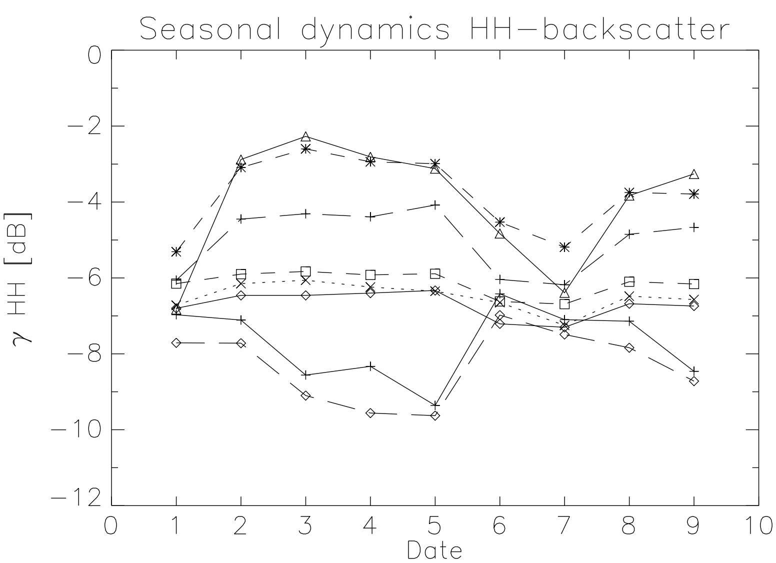
Flow chart

Fig.4 shows a simplified flow chart with the additional steps needed for automated time-consistent classification. The chart is divided in three basic blocks. The first block, the pre-processing block, has a lot in common with the flow presented in Fig.1 for a single year wide area classification. The main difference is that the radiometric calibration should result in radar strips not only being of the same level between strips but also between years. This is not done anymore in the ad-hoc manner as discussed earlier in section 2, but in an automated way to be discussed in more detail hereafter (in paragraph C). The second block is a library. This library contains several types of data of which the maps of class likelihoods of earlier years and a legend with associated features in the form of *'base signatures'* are the most important elements. The new concept of base signatures will be elucidated later (in paragraph C). The third block is entitled automated time-consistent classification. It entails several new approaches to classification such as a 'pre-classification' (step 20), an automated estimation of (localised in space and time) signature correction or 'δ-signature' estimation (step 21), a process which simultaneously functions as a temporal filter as well as a change / no-change detector (step 22), and the final classification (step 23). These latter steps are also elucidated later (in paragraph C),

B. Physical background

The classification of the wide area map is based on the HH and HV radar backscatter level of the 'dry' season and the HH radar backscatter level of the 'wet' season. The underlying assumption is that for the whole island of Borneo, and during the entire periods for acquisition of FBS and the FBD radar data, these levels are class specific, and only depend on the season (i.e. dry or wet). This assumption may be violated regionally, in parts of strips, notably under more extreme conditions such as El Niño periods (which are more severe in Central Kalimantan as compared to Sarawak), or when replacement data are used from adjacent cycles with dates which may already fall into the dry-wet period transitions. This is illustrated in Fig.5. It shows the averaged backscatter for a number of classes over an entire Wide Beam scene located in Central Kalimantan for the period November 2006 until December 2007.

These nine scenes are acquired consecutively with the omission of the July 2007 acquisition. The dates with sequence number 5, 6 and 7 are located in the dry season (April-October) and the remaining in the wet season (November-March). The upper three curves show land cover classes with increased backscatter in the wet season due to increased soil moisture and flooding under the canopy. The two lower curves show decreased backscatter in the wet season because of partial inundation. The remaining three are fairly stable over the year. The characteristics of the first date (which is in the wet season) resemble those of the dry period. This is caused by the extension of the dry period in the El Niño year 2006 into November. Similarly, the characteristics at the fifth date resemble those of the wet season and indicate a prolonged flooding period. Since the FBS and FBD acquisitions are taken in the middle of the dry and wet periods they usually have the characteristic levels corresponding to this seasons. It can be noticed that the backscatter levels in November 2006 (date 1) correspond well with the levels at the end of the next dry period September 2007 (date 7) and that the December 2006 and 2007 levels (dates 2 and 9, respectively) are fairly similar. During the transition period between seasons backscatter levels increase and decrease at class dependent rates. These changes are correlated between classes and may be modelled empirically (as will be discussed later on).



Curve type	*Land cover type*	*Dates*	
		1	20061111
Solid - triangle	Degraded forest	2	20061227
Dashed - asterisk	Burnt forest	3	20070211
Long dash - plus	Swamp forest and woodland	4	20070329
Dashed - square	Mixed forest	5	20070514
Dots - cross	Mangrove forest	6	20070814
Solid - diamond	Peat swamp pole forest	7	20070929
Solid - plus	Rice paddy fields	8	20071114
Long dash - diamond	Regularly flooded shrub	9	20071230

Figure 5. Central Kalimantan, PALSAR Wide Beam time series acquired in nine consecutive passes (the dates are shown in the legend; only July 2007 is missing). The three curves in the middle show a relatively small temporal backscatter variation for HH-polarisation for the classes mixed forest, mangrove forest and peat swamp pole forest. The upper three curves show classes with increased backscatter and the lower two curves show classes with decreased backscatter in the dry season. Note that 2006 was a very dry year with prolonged dry season. Consequently on 11 November 2006 (Date 1) the terrain is still very dry, while on 14 November 2007 the terrain is already wet and more inundated (Date 8).

C. Details of processing steps

Calibration and intercalibration

The absolute calibration accuracy of PALSAR standard data is < 0.64 dB [15, 16]. This means that data of subsequent years could have a difference in radar backscatter level up to 0.64 dB (which is fairly large), even though there is no change in land cover or environmental conditions. This shift could result in classification error and the subsequent erroneous interpretation as land cover change.

Wide area classification and monitoring requires far more precise calibration. This can be achieved by using stable objects as a reference. In our approach this is done by matching the radar backscatter level of (closed canopy) forest between strips and between years (this is called ‘intercalibration’). It is expected that radar backscatter variation through intercalibration, can be limited to a few tenths of a dB, which probably is sufficiently small to allow for accurate classification and land cover change detection.

This process is illustrated in Figures 6 and 7. It uses range profiles averaged over land pixels and forest pixels (iteratively, from previous classification results). These shapes are analysed and processed by cutting of parts in the near and far range, and by flattening the central parts. For the flattening, in general, a first order polynomial is sufficient. Subsequently the levels are corrected using the stable (Bornean Dipterocarp) forests areas as reference. Small ‘hubs’ at the near and far ends of the reduced range window usually fall into overlap regions and are removed later in the classification process. In rare cases these areas are needed (when strips have poor overlap) and these ‘hubs’ should be corrected in addition. This type of automation allows fast processing of large data sets with little (< 0.2 dB) remaining variability between strips and years.

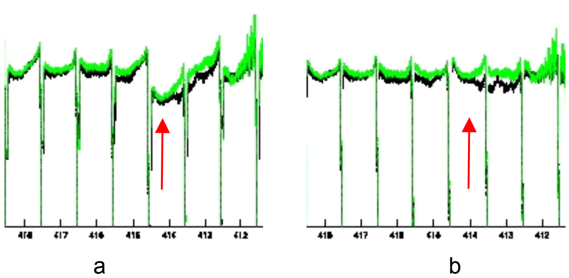


Figure 6. Range profiles of backscatter averaged over entire strips. A selection of strips from Borneo FBS 2009 data are shown ranging from strip RSP412 (left and East) until strip RSP 418 (right and West) with the near range at the left side of each strip. These figures are indicative for the presence of (visual) striping patterns. (a) Original data with black curve indicating the mean backscatter values over azimuth lines for all land pixels and green showing the mean values for all forest pixels. (b) Idem, after calibration and intercalibration, showing a flattening of these black and green curves, notably the green curve. The red arrow corresponds to strip RSP416.

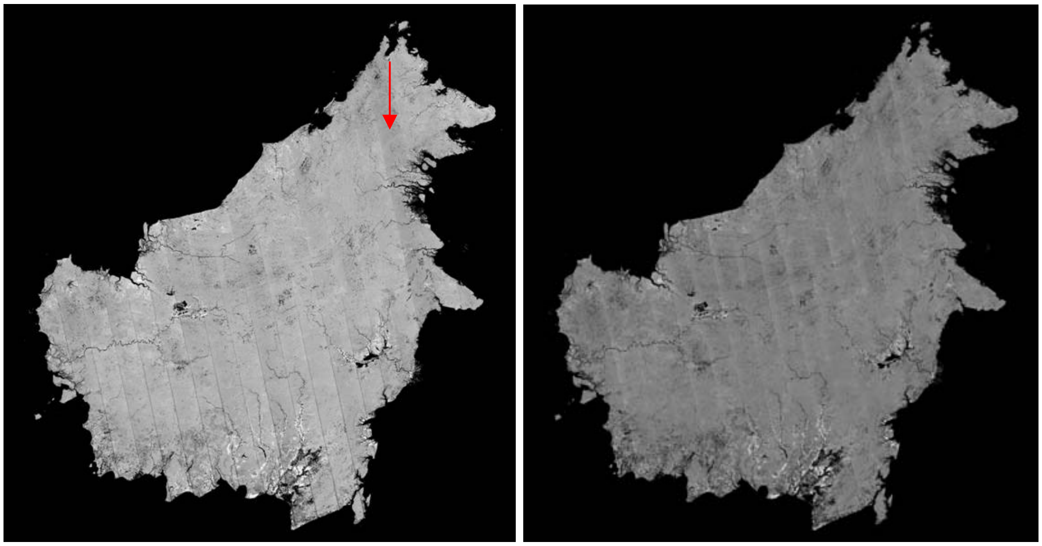


Figure 7. Borneo FBS 2009 mosaics before (left) and after (right) calibration and intercalibration. The red arrow corresponds to the darker strip RSP416 (as shown in Fig.6). The mosaics are created by warping near range over far range. The white striping pattern which remains after (fully automated) correction are near range pixels in the overlap zone which are usually not selected for mapping purposes. Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

Concept of differential signatures (step 21)

For each class a radar signature (S) can be thought of as having a fixed part, the base signature (S_B) depending on the characteristic 'average' structure of a class, and a variable part, the differential signature (S_δ). The variable part S_δ is a function of within-class structural differences (f_S) and environmental factors (f_E) such as soil moisture level (m_s) or inundation. The structural differences are local and refer to objects or parts of objects, such as even-aged sections of an oil palm plantation area. The environmental factors are global, i.e. they are manifest in an entire image or part of a strip, and affect multiple classes simultaneously. This model for the radar signature of a class can be expressed as follow:

$$S = S_B + S_\delta\,(f_S\,;f_E), \qquad [1]$$

With:

S	= signature in terms of mean backscatter vector μ and covariance matrix Σ (for specific band combinations, e.g. FBS-HH, FBD-HH and FBD-HV)
S_B	= base signature related to characteristic 'average' class structure
S_δ	= differential signature in terms of mean backscatter shift and as function of f_S and f_E
f_S	= local (within-class) structural variation
f_E	= global (scene averaged) variation due to environmental factors

Techniques are in development to (automatically) estimate the influence of f_E on S_δ and apply these corrections on the class signatures S_B of a whole scene. Accounting for the influence of environmental factors in the (multi-temporal) classification process should allow for more consistent mapping and monitoring. Several examples will be shown in paragraphs D and E.

Consistent time-series theory (or temporal filter) (step 22)

In case the Borneo 2007 map is based on 2007 data exclusively and the Borneo 2008 map is based on 2008 data exclusively, then errors in the 2007 map and errors in the 2008 map, both may result in the erroneous mapping of change. This huge error propagation may be mitigated by techniques which do not treat 2007 data and 2008 data as being fully independent. An approach with three components is proposed with the following elements which are tentatively referred to as: (i) probabilistic normalisation, (ii) land cover change modelling and (iii) incorporating spatial extent of change. Mathematically such a process can be described by two 17-dimensional vectors (we use 17 primary classes during the classification processing; some more classes result from the post-processing steps) and a 17x17 matrix (which relates to all possible class changes between the 2007 and 2008 map).

(i) The first component is probabilistic normalisation. For example, when the 2007 posterior probability vector (or likelihood vector) for a pixel x_i, has the highest value for the vector entry associated with class *a*, then this pixel gets label *a* in 2007. However, when in 2008 class *b* is the most likely one, then a state change to label *b* should be considered. In this case the posterior probabilities of class *b* in 2007 and class *a* in 2008 should also be taken into account. There are three possibilities for the 2007-2008 state, namely $a \rightarrow b$ (as suggested by the individual ML classifications), or $a \rightarrow a$ (no change), or $b \rightarrow b$ (backward change). An estimator for the normalization has been developed.

(ii) The estimation of changes can be additionally constrained by including the likelihood of land cover changes following from locally developed land cover change models.

(iii) A final additional constraint follows from spatial filtering of change conform a Markov Random Field process, i.e. a certain change is more likely when many neighbouring pixels befall a similar change.

The first two components have global validity (i.e. they are identical for all pixels) and the third component has local significance only (i.e. in the pixel neighbourhood). As a result the computation gets very demanding when the third component is included. For the preliminary results given in the next paragraph the second component is applied in a very conservative way and the third component is not yet included at all. Further increase of computational complexity follows from adding additional years.

D. Modelling results

Following the empirical result of Figure 5, the theoretical concept of differential signatures and the application of new techniques to estimate the fraction of signature change caused by environmental variability, the correlation of such changes can be derived empirically. Figure 8 shows results for data of Sarawak for a limited number of strips (RSP423-425) and years (2007-2009). For example Figure 8a shows the strong correlation with r^2=0.90 for FBS-HH data between environmentally induced radar signature changes of the classes 2 (riverine forest) and 7 (peat swamp *padang* forest). Also class 6 (peat swamp pole forest) and 9 (high shrub) are highly correlated at r^2=0.88 (Figure 8b). However, classes 6 and 7 are negatively correlated with r^2=-0.71 (Figure 8c). Evaluation of all results reveals a correlation structure of two groups with high within-group correlation and negative between group correlation. This result is in accordance with the empirical finding shown in Figure 5. The group members are shown in Table 3. For FBD-HH and for FBD-HV the grouping is different as illustrated by the positive correlation r^2=0.91 for classes 6 and 7 in FBD-HH (Figure 8d).

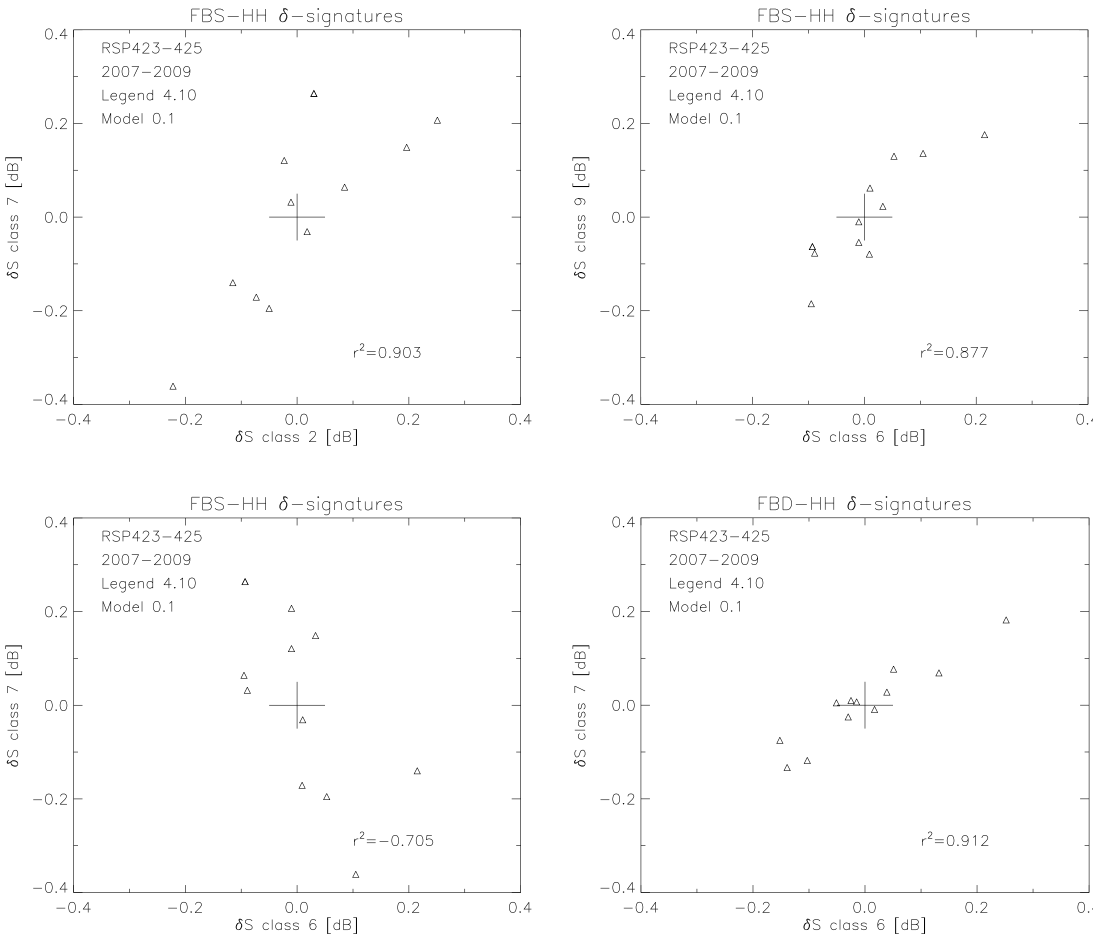


Figure 8abcd. Correlations of differential signatures for several class pairs.

Table 3. Differential signature correlation structure for FBS-HH data.

	Group 1		**Group 2**
2	*Riverine Forest*	1	*Forest*
3	Swamp Forest	6	Peat Swamp Pole Forest
7	*Peat Swamp Padang Forest*	8	*Secondary Forest*
16	*Burnt Peat Swamp Forest*	9	High Shrub
		10	Medium Shrub
		11	Ferns / Grass
		12	Alang-Alang
		13	Dryland Agriculture
		14	Wetland Agriculture
		15	Tree Plantation

Another example of the influence of environmental factors is shown in Figure 9. Though all data are from the same strip (RSP422) and carefully calibrated and intercalibrated (between the years 2007, 2008 and 2009) and, as a result, the forest levels seem to be near identical everywhere, the backscatter level of young oil palm plantation areas seems to vary strongly, and particularly in the southern part of the strip (in East Kalimantan). The excessive drought caused by the 2009 El Niño Central Kalimantan is believed to be the main cause of a significant backscatter level decrease.

The example shown in Figure 10 shows that the effects of drought can occur within a short time span. A section in Sarawak near along the border of strips RSP424 and RSP425 is shown for the years 2007 (Fig.10a) and 2009 (Fig.10b). Again the border is invisible within the forest areas. In 2007 the border is prominent in the mangrove area (near centre) while in 2009 the border is prominent in the young oil palm plantation (near top) and the older oil palm plantation (near bottom). The 2007 mangrove example is a special case. This mangrove complex is surrounded by peat swamp forests and is located more than 100 km from open sea. This may cause specific hydrological conditions which makes this mangrove complex the only complex in Borneo frequently showing noticeable backscatter level increases. The sharp contrast in the 2009 image is caused by the difference between slightly dry conditions for the strip RSP 425 observation (at 19 July) and the very wet condition for the strip RSP 424 observation (at 17 August). From a simple model describing S_δ (see eq.1) with $f_E = f_E\ (m)$, where m is a terrain wetness indicator, the results in Table 3 follow. According to this model, the FBD observation of RSP424 at 17 August 2009 is taken under very wet terrain conditions (m=+3.5) which causes the light brown hues in the young oil palm plantation area. For the other observations shown in Table 3 the value of m ranges between +1 and -1.2, which is considered to be a typical range of terrain wetness variation.

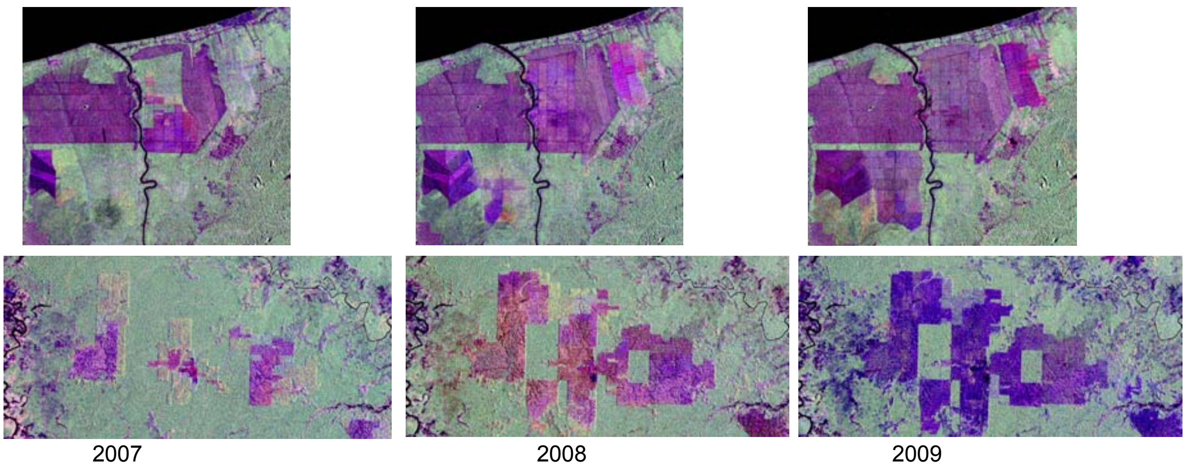


Figure 9. Oil palm development area in Sarawak (top, 25 x 22 km) and in Central Kalimantan (bottom, 36 x 17 km). Colour scheme: FBS-HH, FBD-HH, FBD-HV. Though all data originate from the same strip (RSP 422) the plantations in Sarawak maintain fairly stable backscatter levels, while in Central Kalimantan they seem to vary from year to year. The latter is partly related to the 2009 El Niño drought. Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

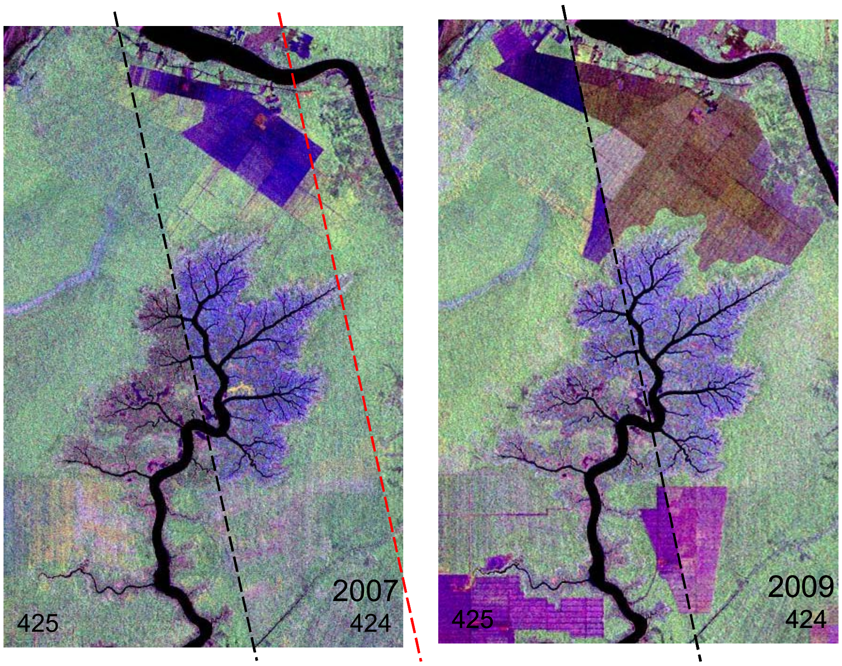


Figure 10ab. A 33km x 52 km section at the border of strips RSP424-425 in Sarawak for the years 2007 (left) and 2008 (right). In 2007 the contrast is noticeable in the mangrove area (centre image) and in 2009 in the young oil palm plantation (top) and older oil palm plantation (bottom). The seam between the RSP424 and RSP425 FBD 2007 strips had to be shifted to the right (red dashed line) because of a slightly different (approx. 10 km more eastwards) coverage.

Table 3. Results of differential signatures modelling *) using the parameter *m* as wetness indicator.

	RSP425	*m*	RSP424	*m*
2007-FBS	26Feb (cycle 9)	0.1	9Feb (cycle 9)	-0.2
2007-FBD	29Aug (cycle 13)	-0.4	12Aug (cycle 13)	-1.2
2009-FBS	3Mar (cycle 25)	+0.3	14Feb (cycle 25)	-0.1
2009-FBD	19Jul (cycle 28)	+1.0	17Aug (cycle 29)	**+3.5**

*) version B2D2-A2.2 420-426

IV. TIME SERIES CLASSIFICATION EXAMPLES

A. Examples at two test sites

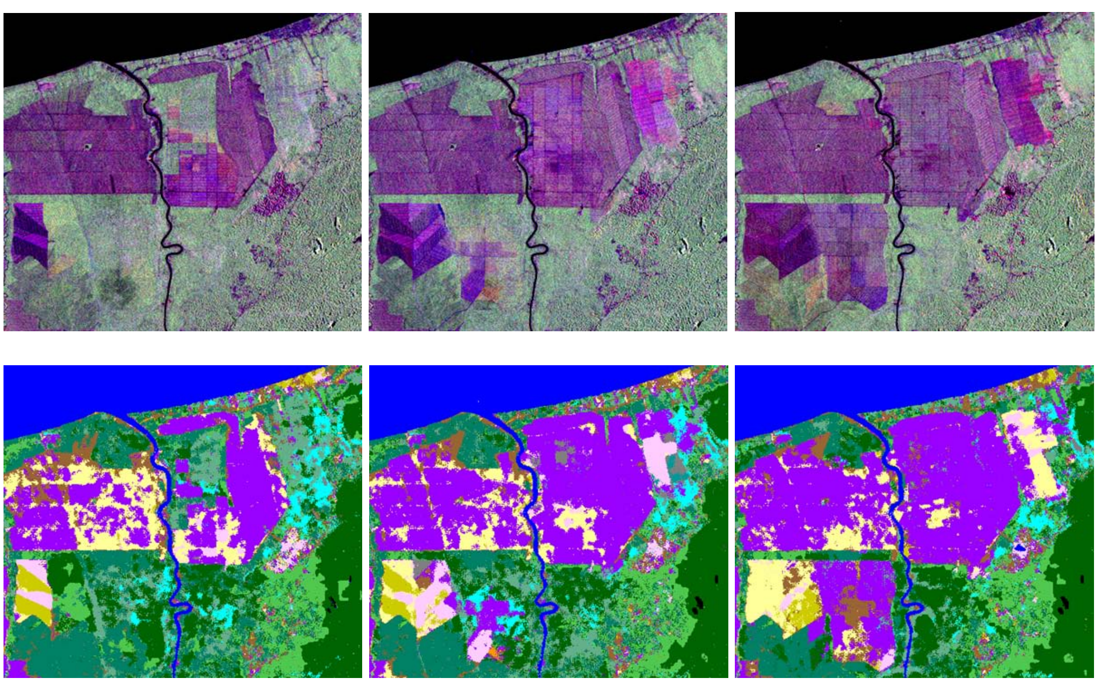
ALOS PALSAR is well suited to provide accurate and up-to-date information in a consistent and repetitive way. In the example shown in Figure 11 radar images of a 25 km wide oil palm plantation development area in Sarawak, Insular Malaysia, are shown. The radar images of the years 2007, 2008 and 2009 and the associated land cover classification maps show the fast conversion of forest and grasslands into new oil palm plantations.

Indonesia and Malaysia are the world's largest producers of palm oil and both countries have promoted rapid expansion of the plantation acreage in the past decade(s). Existing land use plans designate large tracts of land as so-called "forestlands" (in Indonesia: "*kawasan hutan*" and in Malaysia: "Permanent Forest Estate"). These forestlands are largely reserved for forestry, biodiversity conservation and environmental functions and exclude its use for forest plantation. In Borneo, forestlands also comprise vast areas of peat land. Nevertheless, local NGO and national government reports indicate that there are numerous cases where oil palm concession areas overlap with forest areas and wetlands (such as peat swamp forests) in legally protected forestlands. The actual extent of plantation development and associated risks, however, are not sufficiently known. This is a major barrier to the implementation of sustainable palm oil production and its certification.

The ecological, social and economic impacts of (illicit) forestland conversion are of concern to many stakeholders. Palm oil from illicit sources can undermine the credibility of certification schemes (such as Roundtable on Sustainable Palm Oil, RSPO) and government policies and schemes (such as the Reduced Emissions from Deforestation and Degradation, REDD).

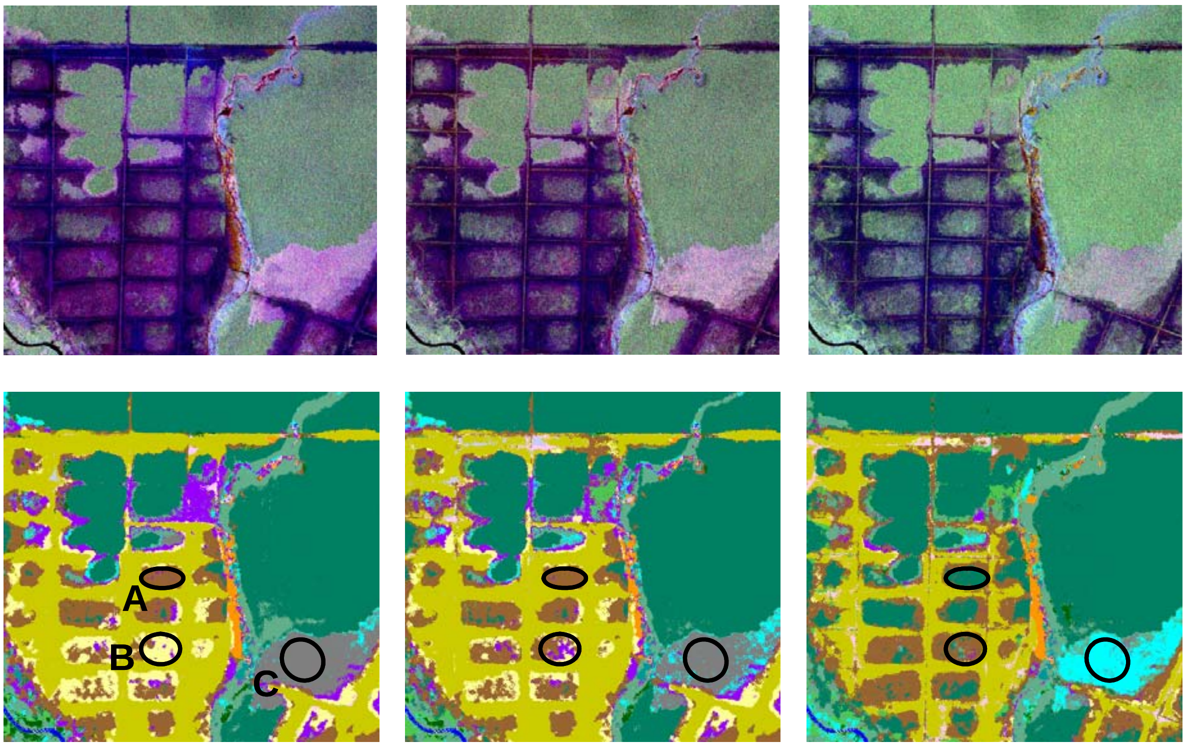
A second example is given in Figure 12. This area in Central Kalimantan is covered with regenerating peat swamp forest. The peat swamp forests in this area were heavily drained by canals which were constructed for the mega-rice project in the period 1996-1997. During the severe El Nino drought of 1997 the area was damaged severely by forest fires and (below) ground fires. In recent years efforts have been made to restore the ecosystem by blocking canals. As a result the forest is regenerating in wet and ‘normal’ years, while in dry years, such as in 2006 and 2009, the regeneration is slower or new damage occurs. Since 2006 this process can be monitored with PALSAR and since 2009 this area is a GEO-FCT validation site (BOR-3) where a REDD project is being implemented.

Several cases of consistent succession stages can be observed in Fig.12a. Overall, the area of ferns reduces; grass is replaced by high shrubs; high shrubs by peat swamp forest and a (seasonally flooded) area of burnt peat swamp forest changes into riverine shrubs. In Figure 12b FBD-HV backscatter levels in dB for three areas of change are indicated. These values are indicative to the phenomenon that in consistent time series mapping (1) land cover type can change even though backscatter levels do not change and (2) backscatter can change even though land cover type does not change. In both cases this can be the correct interpretation which follows from the change in radar signatures due to local and temporal environmental factors



2007 2008 2009

Figure 11. Consistent time-series result (RSP422). ALOS PALSAR is very useful for the detection of changes in forest and land cover. The systematic data acquisition strategy implemented by JAXA allows annual updates of land cover maps over wide areas, such as Borneo island. The purple colour shows the development of oil palm plantations in an approximately 25 km wide area in the state of Sarawak, Malaysia. (Top row) radar data with same colour coding as in all previous figures; (bottom row) maps in colours according the legend shown in Table 2.



2007 2008 2009

Figure 12a. Consistent time-series result for the GEO FCT validation site BOR-3, located in strips RSP421-422. This area is covered with regenerating peat swamp forest. Several cases of consistent succession stages can be observed. Overall, the area of ferns (olive green) reduces; grass (B; yellow) is replaced by high shrubs (brown) and high shrubs (A) by peat swamp forest (blue green). In the bottom left (C) a (seasonally flooded) area of burnt peat swamp forest (grey) changes into riverine shrubs (cyan). (Top row) radar data with same colour coding as in all previous figures; (bottom row) maps in colours according the legend shown in Table 2.

	2007	**2008**	**2009**
A	-19.1	-18.7	-17.4
B	-20.5	-19.1	-17.6
C	-16.9	-16.2	-16.1

Figure 12b. FBD-HV backscatter levels in dB for the 3 areas indicated in Fig.12a. These values are indicative to the phenomenon that in consistent time series mapping (1) land cover

type can change even though backscatter levels do not change and (2) backscatter can change even though land cover type does not change. This is a result of the effect of correcting for changing environmental conditions in time series analysis.

B. Example of wide-area products

Though the techniques for consistent time series classification are still under development it was possible to generate prototype wide area map products for Sarawak.

Figure 13 shows a forest cover change map for the years 2005, 2007 and 2009. This map is based on the combination of a land cover map derived from Landsat 2005 images, the land cover maps derived from PALSAR FBS and FBD data of the years 2007, 2008 and 2009 data, supporting MODIS data and the map of peatland distribution [ref]. The map shows forest and non-forest areas and differentiates between deforestation on peat and deforestation elsewhere. The deforestation is shown for the 2005-2007 interval and the 2007-2009 interval. Validation is still ongoing.

Figure 14 shows a biomass stratification map based on the PALSAR 2009 land cover map and proxy above-ground dry biomass values measured in Sarawak as found in the literature.

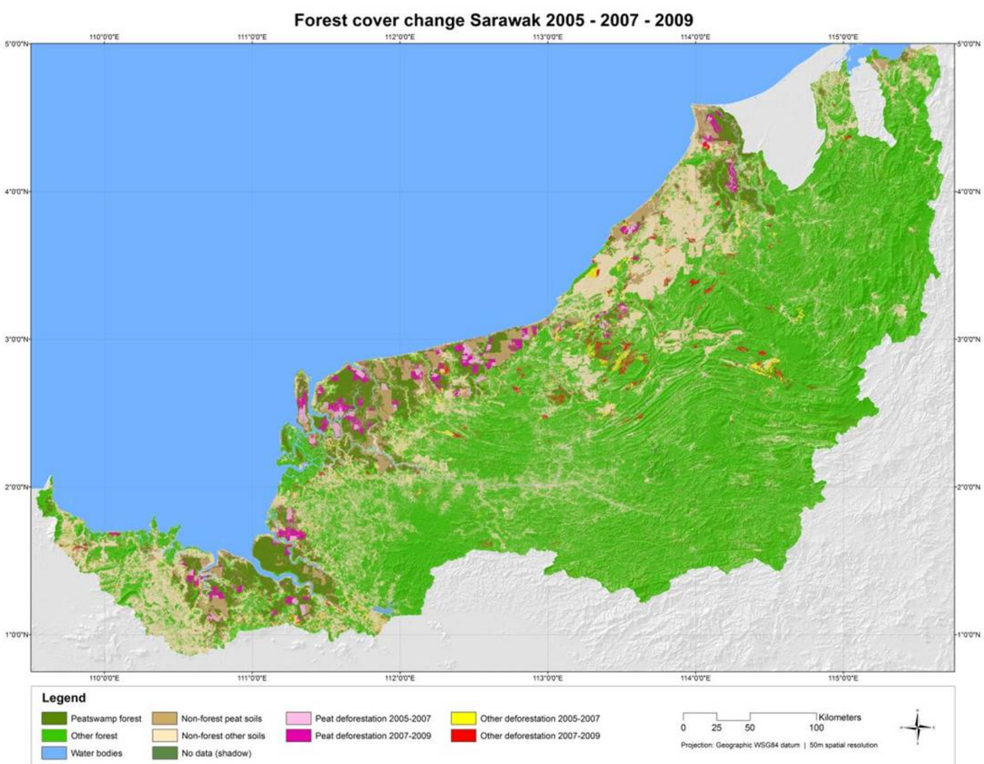


Figure 13. Forest cover change map of Sarawak for the years 2005, 2007 and 2009. The map shows deforestation on peat soil and deforestation elsewhere (both for 2005-2007 and 2007-2009). Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

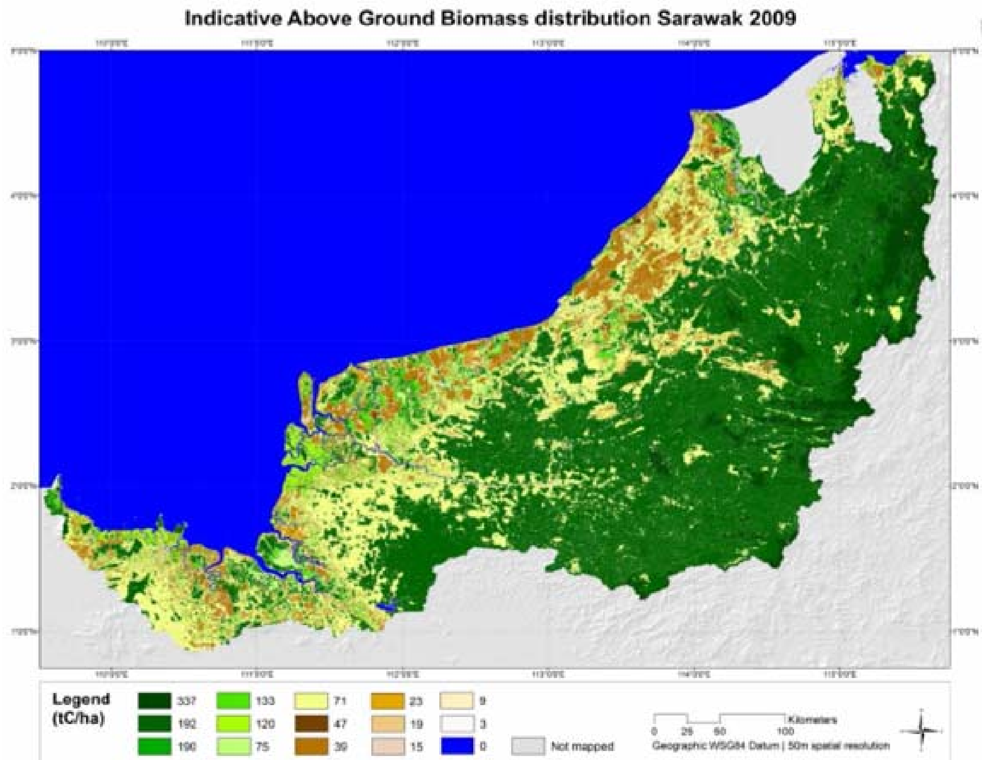


Figure 14. Biomass stratification for Sarawak based on the 2009 PALSAR land cover map. The map shows 15 biomass levels, which are the typical averaged values found in literature for the land cover classes mapped. Input PALSAR data courtesy: ALOS K&C © JAXA/METI.

V. CONCLUSIONS AND OUTLOOK

A. Results and conclusions

Wide-area mapping

Wide-area radar mapping in complex tropical rain forest areas faces two main challenges. The first is to assess probabilistic descriptions of classes in a sufficiently robust manner to handle the variability caused by radiometric error (within and between strips) and variability caused by the range of observation dates. The second challenge is the need to cope with a situation where ground truth is sparse, often outdated or erroneous.

A Bayesian approach based on (unsupervised) mixture modeling followed by Markov Random Field (MRF) classification has been selected for its suitability and flexibility to deal with these circumstances. Slope corrections are necessary. In our approach the terrain is assumed to behave as an opaque isotropic volume scatterer. This assumption seems appropriate for Borneo, where most slopes are covered by (dense) forest.

With two observations in Fine-Beam mode (per year) only, it is not possible to capture the complex dynamics in certain areas well. This limits the possibility to map agricultural areas and wetlands accurately and may be a source of confusion between wetlands, agricultural areas and dryland forests. Since many low biomass classes are very dynamic and wetland forest classes show seasonal behavior as well as differences due to local variation in watershed run-off regime, the additional use of ScanSAR data is highly recommended to improve results further. The use of long (multi-year) time-series of ScanSAR data (approx. 100 m resolution) is expected to yield a more detailed mapping of the various types of peat swamp forest. Optical data may provide relevant additional information to improve differentiation between primary and secondary forest, which is difficult with the current 2007 FBS-FBD PALSAR data set.

The official map of the Ministry of Forestry (MoF) of Kalimantan based on Landsat data (acquired until 2005) and the Globcover map of Borneo based on MERIS data have been used as reference land cover maps for qualitative comparison. A reference data set was created by stratified random sampling of IKONOS and Quickbird images, using Landsat data and available local maps as supporting data.

The overall classification result for the single year 2007 is that 85.5% is in full agreement and 7.8% in 'partial agreement'. Only 4.1% is in clear disagreement. Minor confusions add up to the remaining 2.6%. For a wide-area map with a relatively large number of 18 thematic classes, using only two radar observations, and considering the time-lags between adjacent strips, this result is very promising. For more details see [12].

Consistent time series

New concepts for (a) automated intercalibration of radar data, (b) time-consistency and (c) automated adaptation of radar signatures to changing environmental conditions have been evaluated for its usefulness to improve the classification and the consistency of annual monitoring.

(a) For automated intercalibration range profiles averaged over land pixels and forest pixels are made. These shapes are analysed and processed by cutting of poor data parts in the near and far range, and by flattening the central parts. This type of automation allows fast processing of large data sets with little (< 0.2 dB) remaining variability between strips and years.

(b) Huge error propagation may be mitigated by techniques which do not treat 2007 data and 2008 data as being fully independent. An approach with three components has been discussed with the following elements which are tentatively referred to as: (i) probabilistic normalisation, (ii) land cover change modelling and (iii) spatial extent of change.

(c) An approach has been introduced to describe radar signatures as consisting of a fixed part depending on the characteristic 'average' structure of a class, and a variable part depending on environmental factors such as soil moisture level or inundation. Since environmental factors affect many classes simultaneously within a large region within a strip, the strength of such factors can be estimated and adaptations to the radar signatures can be made. Several examples of the impact of environmental factors have been presented. Accounting for the influence of environmental factors in the (multi-temporal) classification process should allow for more consistent mapping and monitoring. Several time series examples in peat swamp and oil palm plantation development areas have been shown.

B. Outlook to K&C phase 3

The validation of the 2007 Borneo map revealed some weaknesses. It is believed these may be mitigated with the development of a more appropriate legend either in terms of class description, associated statistics and/or completeness (i.e. by adding missing classes). To this aim new field work campaigns have been executed in 2010 in East Kalimantan and in West Kalimantan, with a focus on complex and dynamic areas. Another campaign was executed in Harapan forest in Sumatra, one of the new Indonesian GEO-FCT validation sites. More campaigns in Borneo are foreseen in the coming two years (2011-2012). The developed mapping and monitoring methodologies and future legend development for Borneo may benefit similar work in Sumatra and Malaysia equally well because of ecological similarities.

In an effort to develop generic methodologies, parallel efforts are ongoing in totally different eco-regions such as the Guiana Shield, Gabon and New Guinea. An example for Surinam, where work commenced in 2010 is shown in Figure 15.

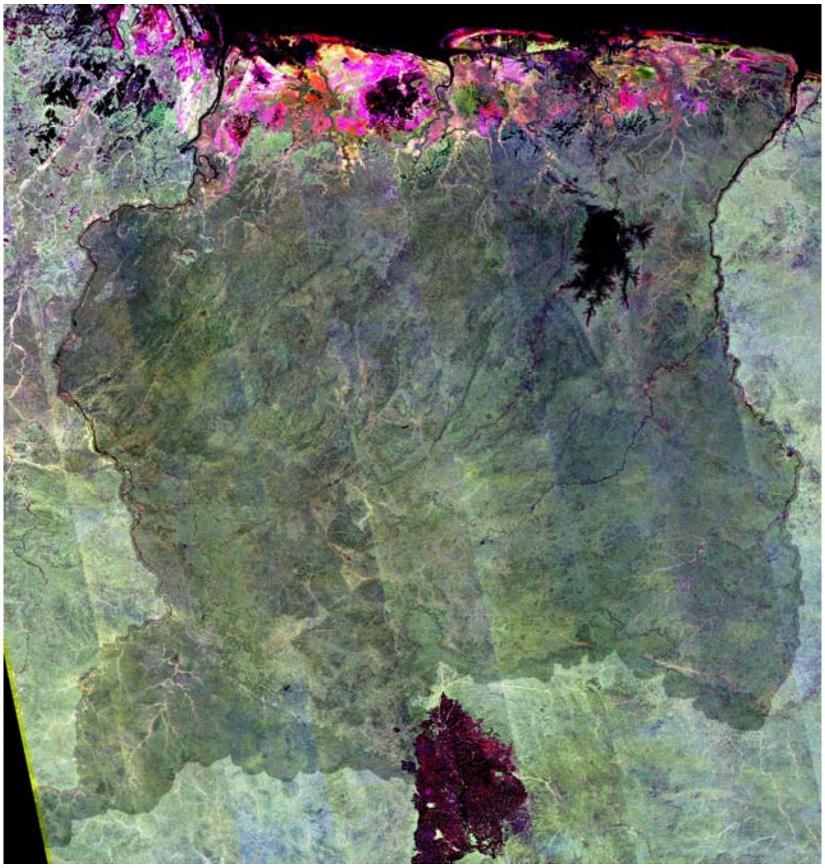


Figure 15. PALSAR FBS-FBD 2009-2010 mosaic of Suriname. The mosaic is stretched to enhance features of the forest in the interior. As compared to Borneo forest biomass levels are substantially lower and, consequently, seasonal variation caused by wetness is more pronounced. The coastal region is characterised by the presence of mangroves, swamps, marshes and savannas. PALSAR data courtesy: ALOS K&C © JAXA/METI.

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