

K&C Science Report – Phase 1

Monitoring Indonesian Forests with ALOS-PALSAR

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Abstract— Deforestation in the Sumatran province of Riau is found to cause an initial marked increase in HH backscatter. Large areas can therefore be rapidly surveyed for evidence of deforestation by measuring temporal variability in a time-series of ScanSAR data. Regions of anomalous change can then be subjected to temporal analysis to find the timing of deforestation events to within 46 days. Algorithms to perform these operations automatically have been implemented and are currently being assessed and refined using field data. Comparable results for annual change are also achievable using Fine Beam Dual (FBD) data, but this involves more substantial data handling and cannot localise the time of deforestation. Though the analysis has been developed only over Riau, it is expected to be generic and transferable, and will be tested in other regions once suitable data are acquired, with the intention of extending it to the whole of Indonesia.

Index Terms— ALOS PALSAR, K&C Initiative, change detection, ScanSAR, tropical deforestation

I. INTRODUCTION

A. Project objectives

The objectives of this project are:

1. To demonstrate that ALOS ScanSAR and FBD data can successfully detect natural forest cover change in Indonesia, where cloud and haze hamper natural forest monitoring based on optical remote sensing data.
2. To assess the ability of ALOS data to detect key natural forest and land cover types in Indonesia.
3. To develop software that permits ALOS-based forest monitoring to be carried out in a scientifically robust manner at technician level.
4. To provide the Indonesian and global community with tools for using ALOS-PALSAR data that allow transparent, accurate and frequent tracking of natural forest cover change independently of cloud and haze and that can be used as a basis for action on biodiversity conservation, forest carbon management, etc.

Up to now, work has been directed primarily toward the first and third objectives, with particular emphasis on the analysis

of ScanSAR time series. The analysis this involves also contributes to meeting the second objective. Our immediate aim is to be able to detect all new deforestation occurring from the start of the ALOS time-series so that it can be reported on at 46 day intervals, and the current drive is focussed on developing the machinery needed to achieve this goal.

Up to now, we have carried out a case study applied to a single time-series of ScanSAR data for the year 2007, in order to develop methods that highlight regions showing evidence of deforestation and track the progress of these events. These methods should be able to analyse a year's ScanSAR images for a single scene within 12 hours. A more rapid but approximate analysis should be achievable within an hour.

B. Scientific findings

Analysis of PALSAR data seems to indicate that multi-temporal ScanSAR data is as capable of measuring deforestation as Fine Beam Dual (FBD) data. This provides major advantages, particularly coverage of wider areas and the ability to locate the timing of deforestation events to within 46 days. Deforestation in Riau (the test area) typically leads to an *increase* in HH backscatter, but at the moment we have no datasets long enough to know how the signal subsequently develops over longer periods. Evidence from Brazil (backed up by physical argument) suggests that the signal will decline with time to values well below that of mature forest. The characteristic signal of a deforestation event indicates that large areas can be rapidly surveyed for evidence of deforestation by measuring temporal variability in a time-series of ScanSAR data. Detected regions of change can then be subjected to temporal analysis to find the actual timing of the event. These operations can be realised by automatic algorithms which have been implemented and are currently being tested. Up to now, the analysis has been developed only over Riau, but we expect it to be generic and transferable, and it will be tested elsewhere once suitable data are acquired, with the intention of extending it to the whole of Indonesia.

II. DESCRIPTION OF THE PROJECT

A. *Relevance to the K&C drivers*

The project was designed to gain better understanding of the land carbon cycle, and in doing so derive information relevant to UNFCCC reporting under Land Use, Land Use Change and Forestry. Its original focus was meant to be temperate forest, but this was modified for three reasons: (1) the greater importance of tropical land use change for the global carbon budget; (2) the proposal for the post-2012 Reduction of Emissions from Deforestation and Degradation mechanism at the Bali COP-12; (3) development of good working links between the University of Sheffield and WWF Indonesia, which gives a means to link technical developments to ground data, provides access to important institutional links in Indonesia, and supports applications on the ground.

The key initial aim of the project was to develop methodology to map changes in forest cover using ALOS PALSAR data. The expectation was that multi-temporal (annual) FBD data would be crucial for this, but investigations at the Riau test site in Sumatra suggest that equivalent, and in fact more powerful, results may be obtained using 46-day repeat ScanSAR data. We also aimed to develop methods to estimate product accuracy, and thence to generate maps of forest cover and maps of forest changes, together with corresponding accuracy assessments. Substantial progress has been made in developing methods to detect deforestation and locating the times of these changes. We are currently planning work in Sumatra to test the performance of the algorithms and optimize the parameters used in them. We then intend, with the help of JAXA, to extend the methods to the whole of Indonesia.

B. *Work approach*

The work has benefited greatly from access to the WWF 2007 land-cover database for Riau & Jambi [1]. This provides detailed information about vegetation types covering the region and is based on remote sensing data nominally for 2007. We also have ALOS ScanSAR and Fine Beam Dual images for much of the same region spanning the same year. With the help of the WWF database we can identify primary forest regions and assess their normal characteristics. It also allows us to reduce the processing task, since for deforestation studies we can ignore areas already known to have other types of land cover. This is very helpful, since a single ScanSAR image typically contains $\sim 19 \times 10^6$ pixels, and a long time-series of images represents a significant amount of data processing. The approach we have developed is to detect anomalous changes in regions labelled as forest; these are likely to indicate deforestation events. Subsequent operations aim to test this hypothesis and determine when the changes occurred. The wider challenge is to extend the methods to regions outside the database where there may be less prior knowledge about forest cover.

Temporal variability within a time-series of images can be charted by recording the temporal standard deviation at each

pixel. Seasonal fluctuations together with slow changes over the period of the time-series may contribute to this, hence to detect deforestation we need a more specific temporal signature. Initial searches used colour-coded combinations of images in conjunction with the WWF land-cover database to survey the type of changes that occur and to identify suspect regions within designated primary forest areas for more detailed study.

Each pixel of a ScanSAR image covers a region of size $100\text{m} \times 100\text{m}$ and we have made the assumption that under deforestation enough of each pixel is cleared within the 46-day cycle to change significantly the scattering coefficient between successive images in the time-series, thus generating a step in the intensity (more subtle effects due to partial clearance or forest degradation will be studied later). In practice the algorithms use a window to average over squares of 5×5 pixels and we are thus currently working at a spatial resolution of $500\text{m} \times 500\text{m}$ per cycle.

A preliminary routine (*changemap*) distinguishes positive from negative changes that exceed a threshold value. Areas of positive change are picked out as regions of suspected deforestation. This increase is thought to be due to the practice of leaving tree stumps and other detritus behind after felling. The stumps in particular would lead to high backscatter due to the double bounce mechanism. In other areas of the world, alternative management practices may instead lead to a negative change, and partly for this reason it is worth retaining the possibility of studying both types of change.

A more specific routine (*stepmap*) fits a step function to window-averaged data and filters out regions of positive or negative step-size that exceed a given threshold value. This routine picks out many areas in common with *changemap* and some that are different. It also produces extra valuable data on the time of step. However it is relatively slow, taking about $16 \times$ the CPU time of *changemap*. A third routine (*noisemap*) has also been developed to look more generally at regions of anomalous behaviour, particularly with a view to isolating regions that might lead to false detections. This routine is relatively fast and may be used to initially screen large areas for possible regions of interest. Inside the WWF database region it is possible to focus only on known forest areas, but in regions without prior knowledge of land cover a means of locating regions of interest will be needed. Using *noisemap*, pixels that do not include any period of scattering that exceeds the normal standard deviation can be identified and ignored, allowing use of the relatively slow *stepmap* to focus only on the remaining areas.

C. *Satellite and ground data*

In the initial phase of program development we have concentrated on a set of eight ScanSAR images centred on Lat. 1.728 S, Long. 102.332 E that partially overlap the WWF

land-cover database for Riau [1]. This is the complete set of 46-day ScanSAR images for 2007, and they are all acquired with the same geometry. Using such a limited dataset was necessary because data quota limitations prevented more extensive coverage. However, it has been sufficient for developing methods that should have much wider applicability.

In addition, we have nearly full coverage of Riau by FBD data from June to August 2007; a missing strip had to be filled with November data.

Before analysis the eight ScanSAR images were accurately co-referenced using Gamma software. A multi-channel filter [2] was then applied to remove speckle. The IDL code for this procedure has been structured to work automatically with a large number of images and delivers de-speckled files of the same name with modified extensions. The routine also finds the combined intersection areas of all input files and applies to all results. In other words, any regions that are not covered by all input files are removed. Processing takes less than 1 hour for 8 images and intermediate processing files are not currently saved. However, if a significantly longer time base is available it may be worthwhile to implement an iterative procedure to speed the processing of new images [3], which would require the archiving of some intermediate files. The resulting average image is shown in context with the database in Figure 1.

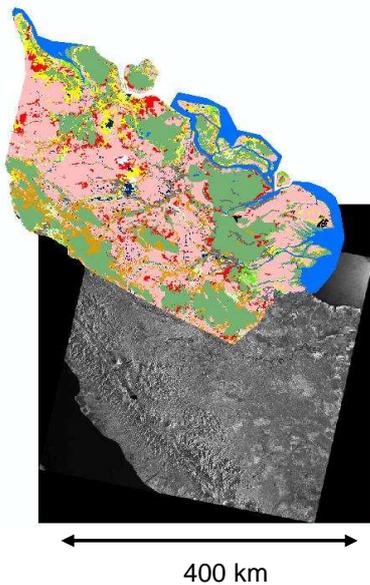


Figure 1. A de-speckled and averaged PALSAR ScanSAR image of the Riau and Jambi regions of Sumatra overlaid by the WWF 2007 land-cover database. Images obtained Jan – Dec 2007, ALOS K&C © JAXA/METI

1) *Regions*

From the preliminary analysis using colour-coded combinations of images in conjunction with the WWF land-cover database, ten regions are discussed here, as detailed in

Table 1. For each of these regions, the intensities of a 5x5 window of pixels are plotted for comparison as a time-series in the Appendix. Two of these (Regions 1 and 3) have all the hallmarks of deforestation events: 1) the intensity changes abruptly over a 46-day period in a region designated as forest; 2) the regions have an angular appearance; 3) they are close to known cleared areas and plantations. In addition, for region 1 the progressive nature of the event is consistent with sequential forest clearance. For comparison, apparently undisturbed regions immediately adjacent to regions 1 and 3 have also been investigated – these have a slow, probably seasonal intensity variation indistinguishable from other regions of primary forest. Regions 5 – 10 have all been chosen because they belong to regions of relatively high temporal standard deviation. These types of region could potentially be wrongly identified as deforestation; it is therefore important to know their characteristics.

Table 1 Regions investigated in detail.

	Latitude South	Longitude East	
Region 1	0° 34' 36.13"	102° 20' 39.63"	Suspected deforestation
Region 2	0° 33' 10.18"	102° 39' 31.80"	Adjacent forest to region 1
Region 3	0° 13' 28.30"	102° 54' 25.47"	Suspected deforestation
Region 4	0° 12' 31.12"	102° 55' 10.97"	Adjacent forest to region 3
Region 5	0° 15' 28.30"	102° 49' 47.49"	A forest region with unusually high s.d.
Region 6	0° 11' 44.51"	102° 40' 48.73"	River and associated forest
Region 7	0° 25' 29.81"	102° 49' 57.83"	An anomalously bright region
Region 8	0° 18' 30.91"	102° 35' 13.05"	Probable flood plain
Region 9	0° 18' 30.94"	102° 33' 39.42"	As above
Region 10	0° 42' 36.26"	102° 58' 44.65"	Paddy fields

The WWF database is very detailed and for the purposes of the current study the regions have been amalgamated into just nine groups as shown in Table 2.

Table 2 WWF database amalgamated regions

Landcover	Fill
Primary Forest (all types)	
Shrub, Grass & Fern	
Regrowth (All types including Forest, Shrubs, Semak, Belukar Muda)	
Plantation (Rubber, Oil Palm, Acacia, Coconut)	
Paddy fields	
Water	
Agricultural (mixed agriculture, mixed garden)	
Cleared, cleared post acacia harvested, etc.	
Burnt	
Built	

All the regions given in Table 1 lie within the database. Here, in Figure 2 we show the context of the two regions of main interest. The land-cover maps are superimposed on composite ScanSAR images colour-coded to reference the beginning, middle and end of the cycle. In these images the regions of interest lie at the image centres. Region 1 changed relatively late in the year (see Appendix) and appears as a bluish patch in Figure 2(a), region 3 changed closer to mid-cycle and appears

as a greenish patch in Figure 2(b).

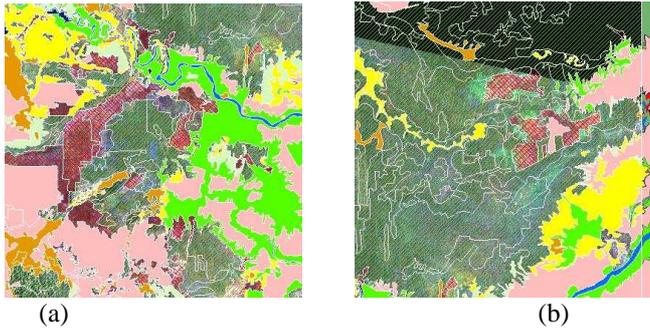


Figure 2 (a) A small section of a time-averaged de-speckled PALSAR ScanSAR image surrounding region 3 showing texture probably associated with plantation drainage. (b) A high resolution FBD image of the same area where the colour derives from polarisation channels shown as: HH-red, HV-green, HH/HV-blue. Images obtained Jan – Dec 2007, ALOS K&C © JAXA/METI

2) Normalisation

An initial view of the areas that are subject to change can easily be obtained from the temporal standard deviation for each pixel. However, over a whole year, it is evident that the average backscatter of the forest regions changes significantly. Most of our work has therefore been carried out with images corrected for this (probably) seasonal variation by normalising intensities relative to the forest background. Deviations relative to this background that lie within areas designated as primary forest then highlight regions of interest. By masking out non-forest regions these can easily be isolated and identified, as shown in figure 3.

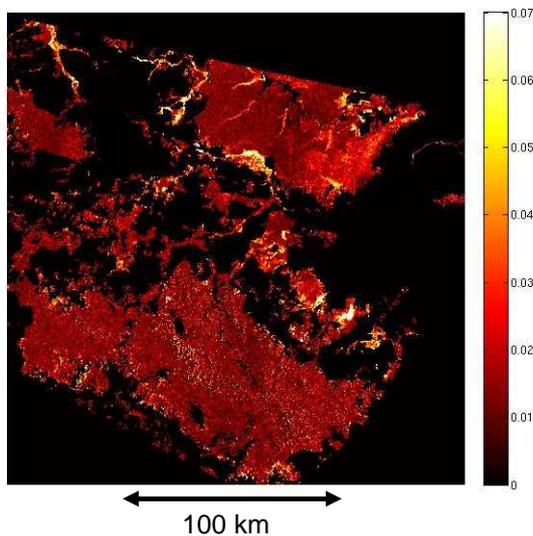


Figure 3. Temporal standard deviation map of areas labelled as forest in the WWF database that overlap with the image region. Areas outside the forest or image are shown in black and the standard deviation of other regions is indicated by the colour-bar, with regions of highest standard deviation shown in white. Images obtained Jan – Dec 2007, ALOS K&C © JAXA/METI

3) Tools

Three MATLAB routines have been developed and are described briefly below. The routine *noisemap* was originally designed to seek anomalous areas that might confuse the step fitting routine. In particular, if steps are found in data with overall high or low average values compared to forest they are unlikely to be part of the forest. Strongly fluctuating data might also lead to an erroneous fit. All of these routines incorporate user-defined window-averaging and a detection threshold value, T_d , expressed in units of the forest temporal standard deviation SD_F :

$$T_d = T_h / SD_F \quad (1)$$

where T_h is the threshold expressed as an intensity and the standard deviation is obtained from the fluctuations over the full extent of forest available in the image according to the WWF database.

Table 3a noisemap

Inputs	Meaning
a	The set of N images, i.e. time-series data
Tnorm	Forest intensity normalization data
mask_stat	Forest intensity statistics
T_d	A detection threshold; see Eq. (1)
nwin	A window size for spatial averaging

Outputs	Output pixels are set = 0 unless the following criteria are met:
hav	Pixels with average intensity $> \text{mean} + T_h$
lav	Pixels with average intensity $< \text{mean} - T_h$
nz	Pixels with a noise metric $nz > \text{mean} + T_h$
sdev	Pixels with temporal standard deviation $> \text{mean} + T_h$
nzmin	Pixels with a temporal minimum value $< \text{mean} - T_h$
nzmax	Pixels with a temporal maximum value $> \text{mean} + T_h$

The noise metric was designed to discriminate between a step function response and strong temporal fluctuations. It can be represented as

$$nz_{ij} = \frac{1}{N} \sum_{k=1}^{N-1} |\Delta\sigma_{ijk}|, \quad (2)$$

where σ_{ijk} is the (i, j) 'th pixel of the k 'th image and $\Delta\sigma_{ijk} = \sigma_{ijk} - \sigma_{ijk-1}$ is the change in intensity between images. It is strongly correlated with other noise measures such as the standard deviation, but it may have a specific use in avoiding false positives, as we show later.

The routine *changemap* fits a straight line to the window-averaged intensity time-series. The input arguments are similar to those for *noisemap*, but include an additional mask, represented here as M , that limits the area over which the calculations are performed. This may be a mask obtained from regions of the WWF database (particularly forest) or it may be

obtained from regions identified by *noisemap* as having, e.g., a significantly high standard or other deviation from the norm. Note that the criterion for detecting positive change (“*cpos*”) in Table 3b could equally be expressed as “pixels with a fitted final image intensity $> T_{sd}$,” and similarly for *cneg*.

Table 3b changemap

Inputs	Meaning
a	The set of N images, i.e. time-series data
Tnorm	Forest intensity normalization data
mask_stat	Forest intensity statistics
Tsd	A threshold relative to forest standard deviation
nwin	A window size for spatial averaging
M	A mask determining a region to be analysed

Outputs	Output pixels are set = 0 unless the following criteria are met:
cpos	Pixels with positive change gradient $> T_h / N$
cneg	Pixels with negative change gradient $< - T_h / N$
C1pos	Pixels with fitted 1 st image intensity $> \text{mean} + T_h$
C1neg	Pixels with fitted 1 st image intensity $< \text{mean} - T_h$

The routine *stepmap* fits a step function to the window-averaged intensity time-series using the matlab routine *fminsearch*; this in turn uses a Nelder-Mead simplex algorithm to optimise the fit. The routine is initialised by finding the time of maximum change, the initial value and the final value. The fit is relatively slow compared to *changemap* and overall timings for this routine are roughly $16 \times$ those for *changemap*. Like *changemap*, the input arguments include a mask, *M*, that limits the area over which the calculations are performed. In the absence of any prior knowledge of forest cover, it currently seems as though this mask can best be chosen using values of *nzmax* from *noisemap* with a suitable threshold. This quantity simply identifies the maximum value for a window-averaged pixel in the time series; clearly, unless some values in the time-series are above a given threshold, there is no point in applying a step fit.

For a set of 8 images of size 400x400 pixels in the absence of any masks, timings obtained for Region 1 on our high-performance computing system (<http://www.shef.ac.uk/wrgrid/iceberg>) were: *noisemap* ~ 19.3 s, *changemap* 85.3 s and *stepmap* 1375.6 s. These would scale to roughly 39 min, 2.85 hr & 45.85 hrs respectively for the full image size. With masking provided by *noisemap* the values recorded for Region 1 were *changemap* 18.3 s and *stepmap* 302 s, which scale to a more manageable 37 min and 10.1 hrs respectively for full images.

Example fits using a line and a step function are shown in figure 4 for the data of Region 1.

Table 3c stepmap

Inputs	Meaning
a	The set of N images, i.e. time series data
Tnorm	Forest intensity normalization data
mask_stat	Forest intensity statistics
Tsd	A threshold relative to forest standard deviation
nwin	A window size for spatial averaging
M	A mask determining a region to be analysed

Outputs	Output pixels are set = 0 unless the following criteria are met:
spos	Pixels with positive step change $> \text{mean} + T_h$
sneg	Pixels with negative step change $< \text{mean} + T_h$
bpos	Pixels with baseline $> \text{mean} + T_h$
bneg	Pixels with baseline $< \text{mean} - T_h$
tpos	Returns the image number for the time of greatest change if spos >0
tneg	Returns the image number for the time of greatest change if spos <0

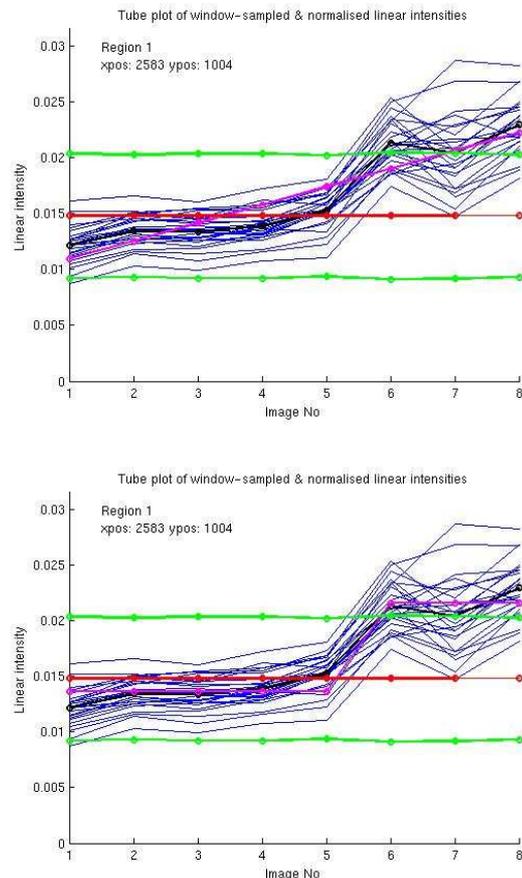


Figure 4. Fitting of normalized intensity time series for a region suspected of being subject to deforestation: (a) by a simple line (b) by a step function. Each fit is shown as a magenta line. Blue lines represent the normalized intensity over the whole series for 25 individual pixels centred at 0.576703 S, 102.677675 E; the average of these is shown as a black line. The red line shows the forest mean intensity and the green lines represent 1 standard deviation either side.

III. RESULTS AND SUMMARY

1) Results

The results of the stepfitting exercise are illustrated in Figure 5 for two different threshold levels. In Table 4 the numbers of pixels for each category are recorded. It can be seen that, of the 4481 pixels assigned, 2491 lie within the known forest, leaving 1990 outside. This means that, in the absence of any prior land-cover knowledge, the false-positive ratio is at least 44.4%. For a higher threshold level the total number of hits decreases to 1353 of which 641 lie outside the known forest so that the false-positive ratio has increased to 47.3%. An associated map of the step timings is shown for Figure 6 for the higher threshold. A comparison with figure 5 shows that the areas chosen outside the forest return an early step time & this may be a way of distinguishing some false from true positives.

Table 4 Pixel counts for detections with *changemap* and *stepmap* and the number of overlaps with each other and the forest class.

(a) with thresholds set low at 0.5, 0.35, 0.65

Count	Forest	<i>cpos</i>	<i>spos</i>
Forest	57009	5552	2491
<i>cpos</i>	5552	9279	3529
<i>spos</i>	2491	3529	4481

(b) with thresholds set high at 1.0, 0.75, 0.75

Count	Forest	<i>cpos</i>	<i>spos</i>
Forest	57009	1353	712
<i>cpos</i>	1353	1917	960
<i>spos</i>	712	960	1353

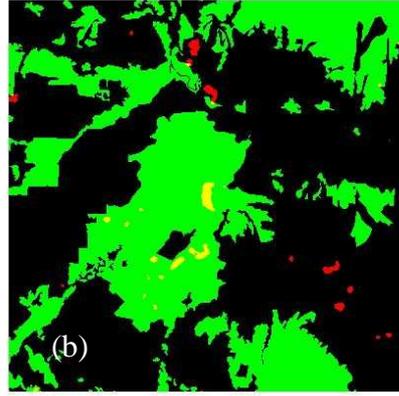
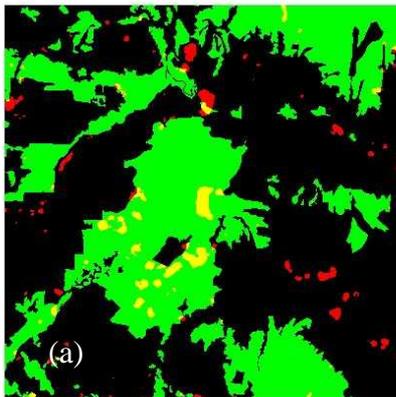


Figure 5. An image centred on region 1 using the routine *stepmap* overlaid on the primary forest regions (shown green). Non-zero values of *spos* are shown red or yellow where they overlay forest regions: (a) with threshold set at 0.65 standard deviations (b) with threshold set at 1.0 standard deviations.

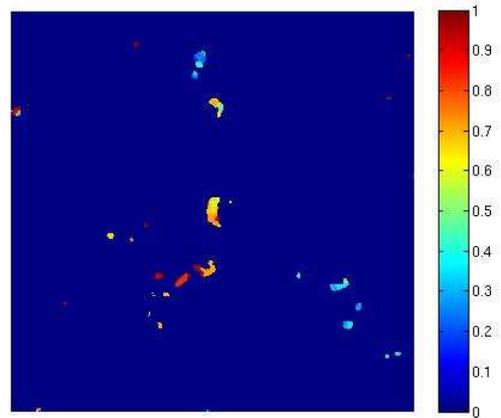


Figure 6. An image associated with 4(b) showing the time of step for the regions highlighted. The colour-bar represents a continuous advancing time scale with 0 meaning no image and images 8 mapped on to 1. It thus represents advancing time with are mapped on to the scale 0-1.

In figure 7 the low threshold map of Figure 5(a) is overlaid by the primary forest regions and the noise metric, n_z (Eq. (1)), which takes the blue channel. Where the noise metric overlays the high-step regions outside the forest the colour becomes pink, and it can be seen that many of these likely false-positive areas have been picked out in this colour. These areas appear to be associated with paddy fields (compare with Figure 2(a)). The intensity plot shown as region 10 in the Appendix demonstrates that paddy fields can show very strong fluctuations, which suggests that n_z may indeed be a useful tool for reducing this particular source of false positives.

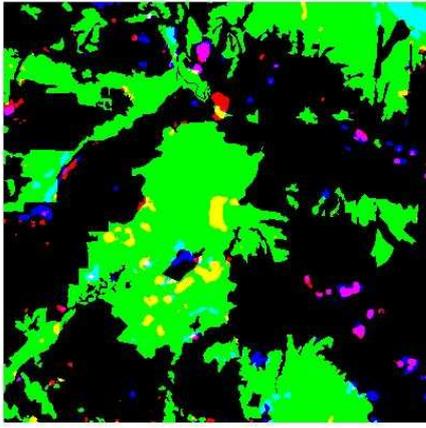


Figure 7 An image centred on region 1 using the routine *stepmap* overlaid on the primary forest regions (shown green). Non-zero values of *spos* are shown red or yellow where they overlay forest regions. Overlaid in blue are pixels with high values of *nz*; where coincident with the step-fitted regions these show as pink. Virtually none of the regions identified as suspect in the forest are overlaid by this metric (where they would appear white in this image). The *stepmap* and *noisemap* thresholds were set at 0.65 and 1.0 standard deviations respectively.

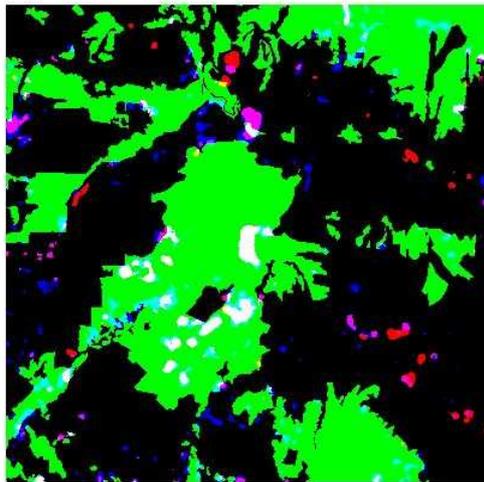


Figure 8 An image centred on region 1 using the routine *stepmap* overlaid on the primary forest regions (shown green). Non zero values of *spos* are shown red or yellow where they overlay forest regions. Overlaid in blue are pixels with high values of *cpos*; where coincident with the stepfitted regions these show as pink. Most of the regions identified as suspect in the forest are overlaid by this metric (where they appear white in this image). The *stepmap* and *noisemap* thresholds were set at 0.65 and 1.0 standard deviations respectively.

In figure 8 the low threshold map of Figure 5(a) is overlaid by the primary forest regions and high values of *cpos*, which indicates a high level of change over the time-series (see Table 3b). Where this overlays *spos* (the high-change step-fit metric Table 3c) within the primary forest region the result is white, and where it overlays *spos* outside the forest region the result

is pink. The white areas suggest that *changemap* matches the results of *stepmap* within the forest regions and supports its use as a quick but possibly rough tool for locating suspect areas. Note that the pink areas in figure 8 tend to complement those in figure 7. A number of red areas remain and thus *changemap* may also be useful in combination with *stepmap* to cut down the false positive ratio.

In figure 9, the results of step fitting are again combined with the noise function *nz* and the primary forest mask for Region 3 and its surroundings. In this figure the angular areas shown black are designated “cleared post acacia harvested” in the WWF database (see figure 2b) and are picked out well by plotting the *hav* metric of *noisemap*. Red areas identified by *stepmap* overlap some of these regions and also extend into the forest, where they show as yellow. Region 3 itself shows yellow in the centre of figure 9(a). The noise metric *nz* has again been successful in picking out some erroneously identified regions outside the forest area (where blue and red combine to give pink) but has not picked out the mottled region inside the forest boundary in the lower-right quadrant (a typical locality has the position: 0° 16' 59.61" S, 102° 57' 26.41 E"). This is labelled in the WWF database as “swamp forest very open canopy”. This region is also picked out by *changemap* and so it is a probable false positive area that we cannot currently reject by using alternative metrics. An associated map of the step timings is shown in Figure 9(b), where it is clear that this mottled region stands out in red (meaning the step was fitted at the end of the sequence) while the more likely suspects for deforestation changed around mid-sequence and are coloured blue or yellow. Time-series plots for this region show a steady increase in intensity over the year, suggesting that *stepmap* has erroneously fitted a region of change with a step at the sequence end. This is a problem that may be remedied by using a longer time-sequence but alternative means of identifying these difficult areas are also being sought.

We have already made some comparisons with Fine Beam Dual (FBD) images, and expect to extend this, particularly with a view to developing the second objective of the project. A large region to the north-west of region 3 has clearly been affected by plantation work, as evidenced by linear features that are probably due to drainage channels. These have not been picked out by our analysis so far because the forest region was probably cleared after the images used to compile the WWF database, but before 2007. These are shown more clearly in figure 10(a) and compared with a higher resolution FBD image in Figure 10(b). These features could probably be picked out on a ScanSAR images by using a texture filter, and this will be investigated during the next phase of the work.

Although the exact location of Region 3 is seen to be within the WWF-designated primary forest area in Figure 9(a) in the FBD image (acquired 27/07/2007), in Figure 10(b) it is clearly seen to be part of the plantation, but also coloured blue. The intensity plot for this region (shown in the Appendix) shows

that the event occurred between images 3 and 4, which were acquired in May (03/05/2007) and June (18/06/2007) respectively – i.e. before the FBD image. The evidence could suggest that primary deforestation occurred in June and the ground was quickly turned to plantation by July, or more likely (since much of the plantation seems established) that Region 3 is actually a plantation management event in a pre-existing plantation rather than deforestation. If this is true the WWF database is in error; currently planned fieldwork will establish this. This clearly highlights the importance of FBD images to support or refute the results of temporal ScanSAR analysis.

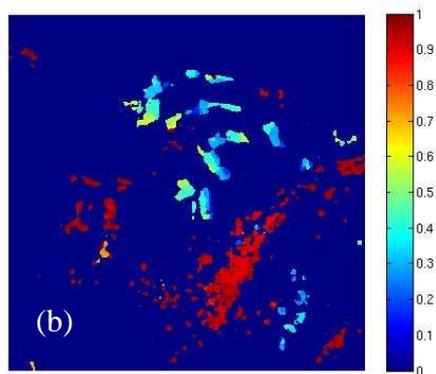
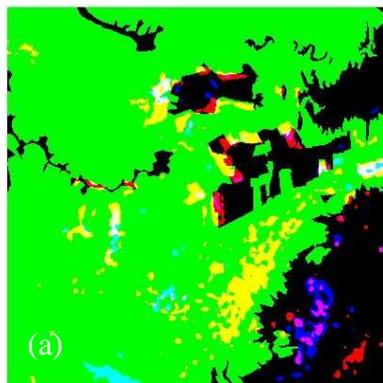


Figure 9(a) An image centred on region 3 using the routine *stepmap* overlaid on the primary forest regions (shown green). Non-zero values of *spos* are shown red or yellow where they overlay forest regions. Overlaid in blue are pixels with high values of *nz*; where coincident with the stepfitted regions these show as pink. Here, some regions show white where forest regions are overlaid by both metrics. A mottled region (lower centre right) shows yellow, but seems unlikely to be due to deforestation. The *stepmap* and *noisemap* thresholds were set at 0.65 and 0.5 standard deviations respectively. (b) The same image showing the time of step for the regions highlighted. The colour bar represents a continuous advancing time scale with 0 meaning no image and image 8 mapped on to 1. It thus represents advancing time mapped onto the scale 0 -1. The mottled region shown as red in this figure indicates that a step has been fitted right at the end of the time-series.

Potential difficulties

We have seen that the high level of false positives recovered in Region 1 can be significantly reduced by using other metrics. The mottled (assumed) false-positive area in Region 3 currently can only be recognised from its very late time-of-step. This is quite possibly the result of the step fitting routine attempting to fit something which is not a step, and investigating this will be a priority. We are surer of the results that give a clear step signal in mid time-series, when there are data either side of the step to inform the routine. However, the hope would be to identify regions that are being deforested during the most recent cycle, rather than those that have already been deforested, say 6 months ago. A single step at the end of a sequence may therefore be insufficient for an unambiguous identification of deforestation. Regions that fluctuate wildly in scattering intensity or have an annual spiky variation (like paddy fields) can be discounted, but regions that have shown low variation in the past and suddenly change are clearly of interest. An ability to recognise and map primary forest regions without prior knowledge forms part of the second objective of this project and clearly is important to the wider application of the approach described above.

Further investigation is needed into how the analysis is affected by use of the known forest variation to normalise data and detect changes relative this background. It is well known that rainfall varies markedly over Sumatra and so it may be expected that the annual variation of backscatter from forest may vary from place to place. In the absence of this knowledge we may be forced to normalise with respect to some local average or even with respect to the whole temporal image variation. To this end it may be worth studying the annual variation of other land-cover categories for comparison.

3) Summary

The characteristic sharp increase in backscatter caused by tropical deforestation allows large areas to be surveyed rapidly for evidence of deforestation by first measuring temporal variability in a time-series of ScanSAR data to detect regions of interest, then temporal analysis in these regions to locate the time of the event to within 46 days. This process has been implemented as an automatic algorithm, which is currently being assessed in a case study using ground data from Riau.

Data have already been obtained to extend the time-series for the current ScanSAR scene. These will be processed with an updated algorithm, together with the images used here, to assess the findings in this report; this is expected to show that an extended series gives better confidence in the results. We then aim to analyse the whole scene and, depending on data availability, extend the analysis to the whole of the area covered by the WWF database.

Up to this point, our analysis has been developed only over Riau, but we expect it to be generic and transferable, and we

will test it in other regions once suitable data are acquired, with the intention of extending it to the whole of Indonesia. This will require methods to define a prior approximate map of primary forest, which can be based on optical or radar data. This will be investigated in the next phase of the work.

The work described in this report has its most important application in understanding the tropical carbon balance and in its contribution to the proposed UNFCCC Reduced Emissions from Deforestation and Degradation mechanism. The PALSAR sensor appears to be an extremely powerful tool for tracking tropical deforestation, but it is critical for its general acceptance that well-founded methods to use the data are developed, tested, demonstrated and made available in a form that can readily be applied by the tropical forest nations themselves. This work aims to make progress towards supplying both the necessary tools and confidence in their ability to deliver the required information.

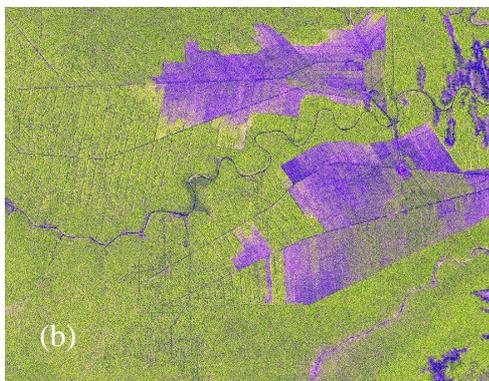
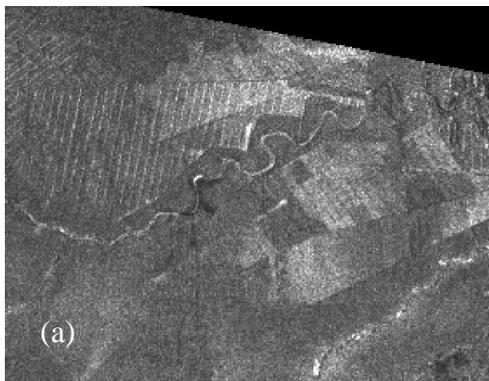
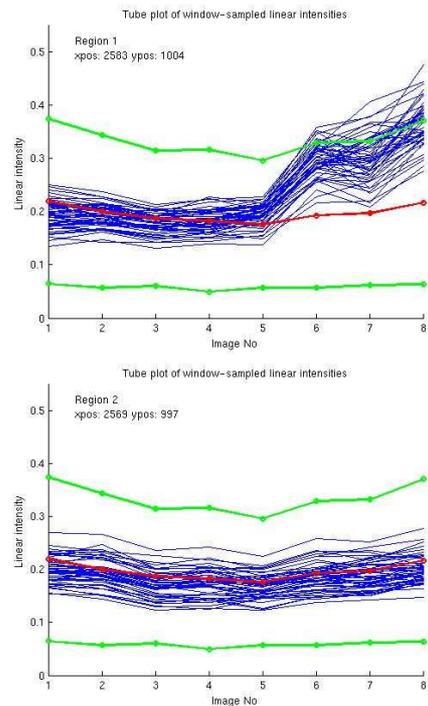


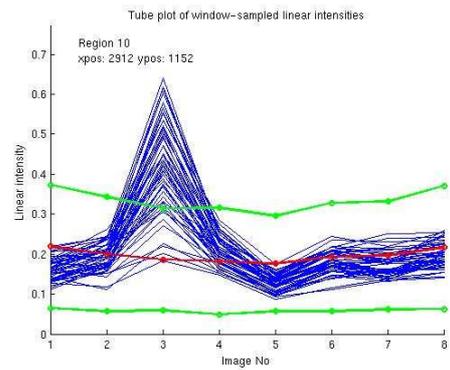
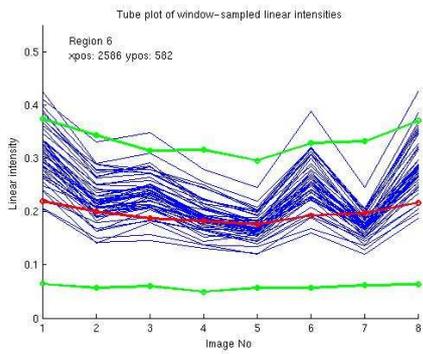
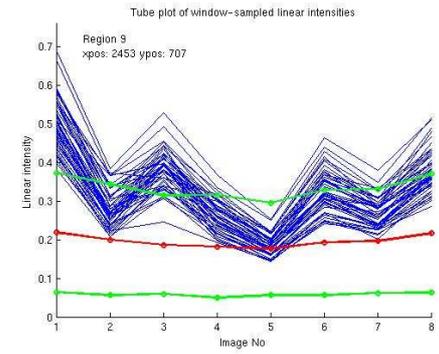
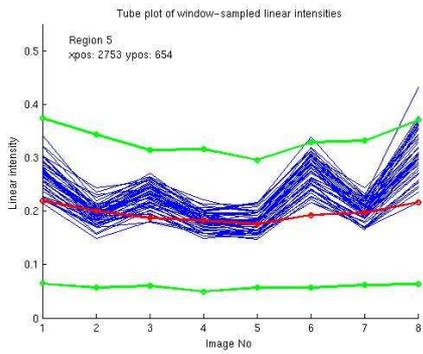
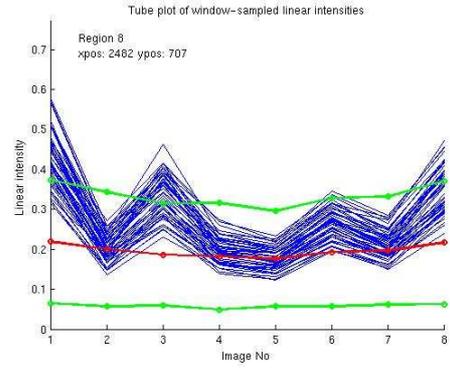
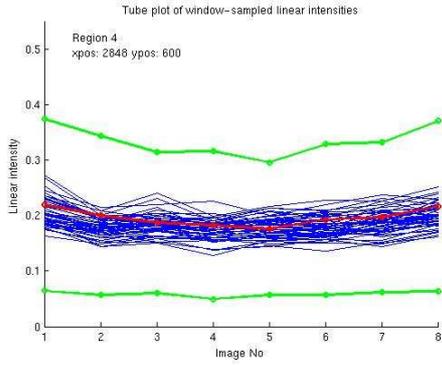
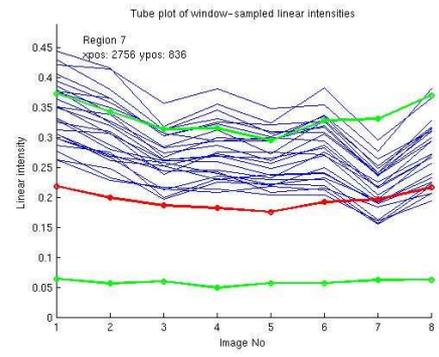
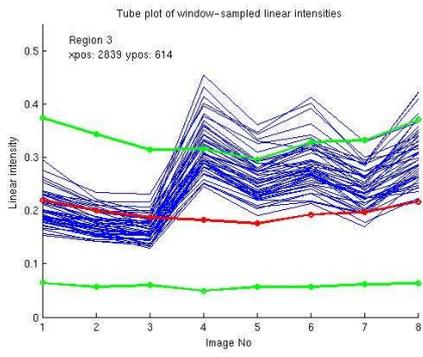
Figure 10 (a) A small region of a time-averaged de-speckled ScanSAR image surrounding region 3 showing texture probably associated with plantation drainage. PALSAR in ScanSAR mode acquired Jan-Dec 2007 © JAXA/METI (b) A high resolution FBD image of the same area where the colour derives from polarisation channels shown as: HH-red, HV-green, HH/HV-blue. PALSAR in FBD mode acquired July 2007 © JAXA/MET

IV. MISCELLANEOUS

1) Appendix

This Appendix displays time-series plots for the ten regions detailed in Table 1. The 25 lines shown in each plot correspond to the individual pixels in a 5x5 window centred on the central pixel of each region. The red and green lines show the mean and one standard deviation values for the whole image (excluding pixels with value zero).





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Biographies



Shaun Quegan received the B.A. (1970) and M.Sc. (1972) degrees in mathematics from the University of Warwick. His Ph.D., awarded by the University of Sheffield in 1982, was concerned with atmospheric modelling. Between 1982 and 1986 he was a Research Scientist at Marconi Research Centre, and led the Remote Sensing Applications Group from 1984-86. He established the SAR Research Group at the University of Sheffield in 1986, whose success led to his Professorship awarded in 1993. In the same year he

helped to inaugurate the Sheffield Centre for Earth Observation Science, of which he remains the Director. In 2001 he became the Director of the UK National Environmental Research Council Centre for Terrestrial Carbon Dynamics, which is concerned with assimilating Earth Observation and other data into process models of the land component of the carbon cycle. In addition, since 2008 he has led the Carbon Cycle Theme of the UK National Centre for Earth Observation. He has served on many national and international committees, including the JAXA Kyoto and Carbon Initiative, the ESA Earth Science Advisory Committee (2003-2007) and as Chairman of the Terrestrial Carbon Observations Panel (2002-2007). He was also a co-proposer and member of the Mission Assessment Group for the BIOMASS mission, currently under Phase-A study with ESA. His earlier interests in the physics, systems and data analysis aspects of radar remote sensing are now subsumed in the more general aim of exploiting general EO technology to study the Earth's carbon cycle.



Martin Whittle received a B.Sc. in Chemistry in 1974 and a Ph.D. in 1979 awarded by University of Manchester. He is a researcher with a background in laser light scattering, infra-red photo-ionisation, computer simulation of liquids, gels, emulsions and slurries including electrorheological systems. He has also worked in data mining of web-search databases and virtual screening with a variety of techniques including data fusion in a drug-discover context.