

## The use of SAR for monitoring rain forest and agriculture

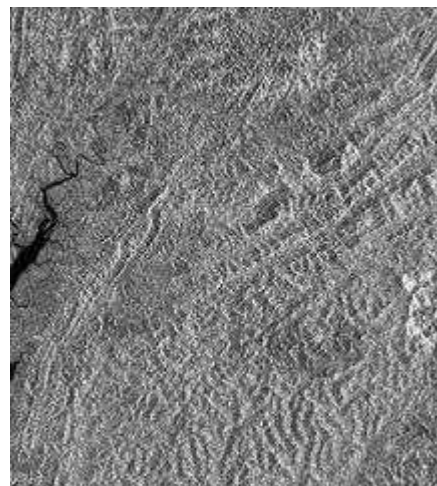
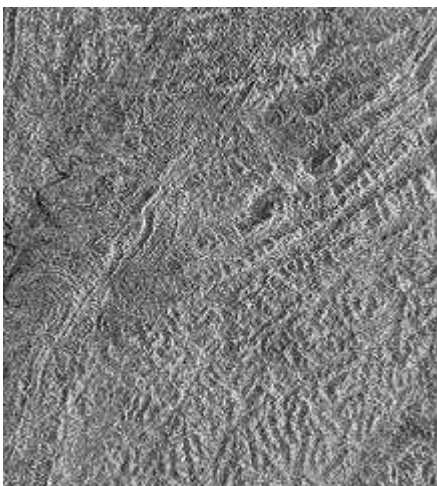
Prof. Chris Oliver, CBE

Change detection based on joint segmentation is an effective technique for monitoring changes in rain forest and agricultural regions. In this example we analyse a sequence of 22 ERS images between 1993 and 2001 of an area of East-Kalimantan in Indonesia.

### Methodology

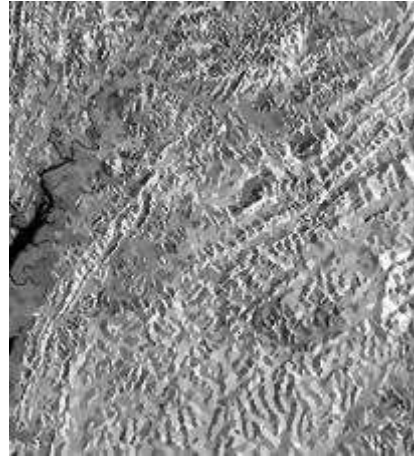
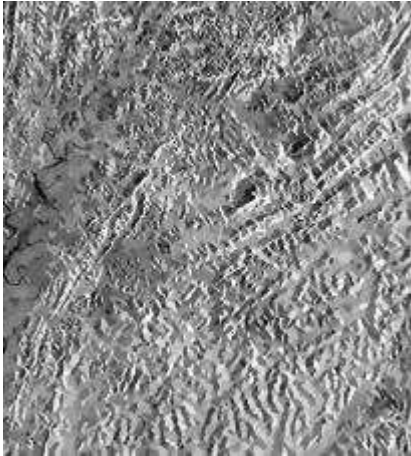
- Individual ERS images are not sufficient to classify forest or crop type because the resolution is low and the image is corrupted by speckle noise.
- Joint segmentation derives a common set of boundaries between homogeneous regions in a complete sequence of images. It is thus much less affected by speckle noise.
- The temporal signature of average intensity can then be used to classify each segment using a Maximum Likelihood classifier. The time sequence provides an additional important source of information about the forest or crop type.

### Typical original images



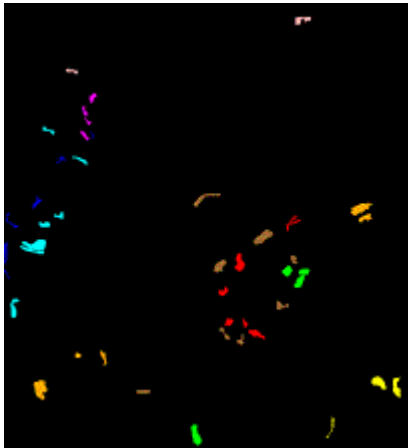
A pair of images from the sequence. Note the effect of speckle and the changes in the appearance of the river.

## Joint segmentation results

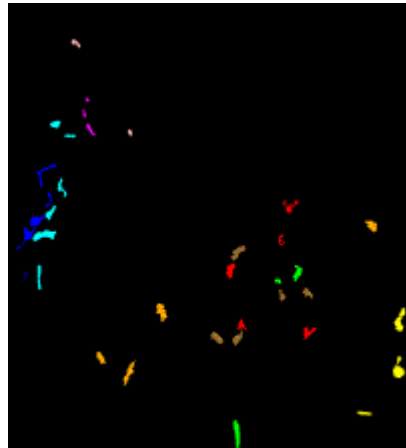


Joint segmentation identifies the common boundaries between homogeneous regions in all 22 images from the sequence. This shows the average intensity from the previous images within those boundaries.

## Ground truth for classification



Training set

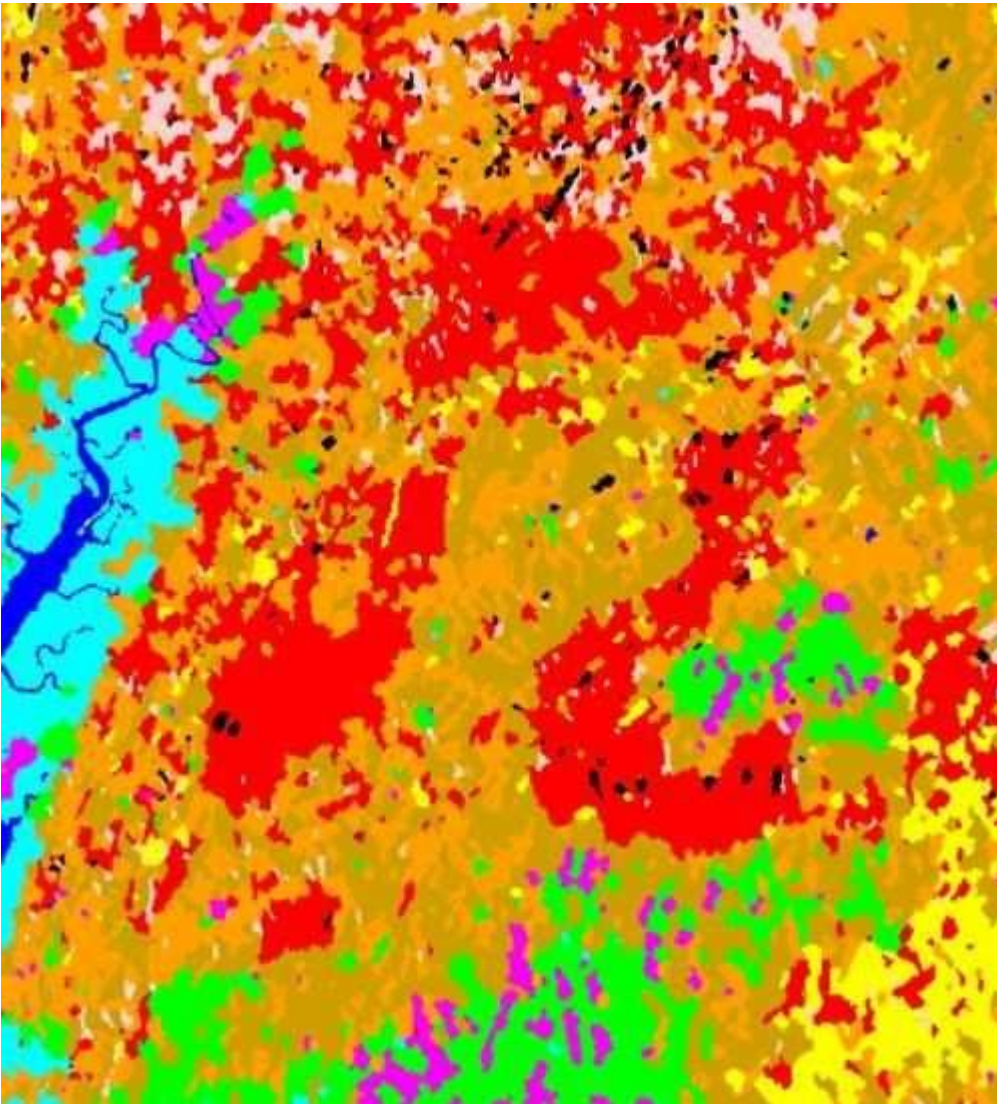


Test set

Classes:

- |                            |                    |
|----------------------------|--------------------|
| 0. Shadow (black)          | 5. F.E.P. (orange) |
| 1. Mangrove (cyan)         | 6. Rubber (red)    |
| 2. Unburnt nipah (magenta) | 7. Kebun (yellow)  |
| 3. Unburnt forest (green)  | 8. Rice (pink)     |
| 4. Burnt forest (brown)    | 9. Water (blue)    |

## Classified image



Note the regions of burnt (brown) and unburnt (green) forest.

Black regions denote shadowing in mountain regions.

## Validation against test set

		Assigned class							
True class	0	1	2	3	4	5	6	7	8
0	0.895	0.064	0.005	0.021	0.014	0	0	0	0.002
1	0	0.552	0.212	0.368	0.033	0	0	0	0
2	0.019	0.110	0.789	0.003	0.080	0	0	0	0
3	0	0.002	0.008	0.772	0.200	0.016	0.002	0	0
4	0	0	0	0.260	0.457	0.283	0	0	0
5	0	0	0	0.038	0	0.893	0.055	0.013	0.001
6	0	0	0	0.036	0	0.171	0.793	0	0
7	0	0	0	0	0.317	0.142	0	0.541	0
8	0.012	0.003	0	0	0	0	0	0.002	0.980*

\* 0.003 from class 8 is assigned to mountain shadow

Confusion matrix for validation against the test set. Average probability of correct classification is 0.741 compared with 0.871 for the training set.

**These preliminary results are part of a collaboration between Prof. Chris Oliver and Ruandha Sugardiman, Martin Vissers and Dirk Hoekman of Wageningen Agricultural University, the Netherlands. A complete publication is in preparation.**