MULTITEMPORAL ERS ANALYSIS APPLIED TO FOREST MAPPING

Shaun Quegan(1), Thuy Le Toan(2),
Jiong Jiong Yu(1), Florence Ribbes(2), Nicolas Flourey(2)

1. Sheffield Centre for Earth Observation Science, Hicks Building, University of Sheffield, Sheffield S3 7RH, UK
Tel +44 114 2223778, Fax +44 114 2223809, e-mail: s.quegan@sheffield.ac.uk
2. CESBIO, 18 ave. Edouard Belin, 31401 Toulouse CEDEX 4, France
ABSTRACT

Examination of the physical background underlying the ERS response of forest and analysis of time series of ERS data indicates that the greater temporal stability of forest compared with many other types of land cover presents a means of mapping forest area. The processing chain necessary to make such area estimations involves reconstruction of an optimal estimate of the backscattering coefficient at each pixel, using temporal and spatial filtering, so that classification rules derived from large scale averaging are applicable. The rationale behind the filtering strategy and the level of averaging needed is explained in terms of the observed multitemporal behaviour of forest and non-forest areas. The choice of decision rules is based on the same observations, with the added requirement for robustness. The performance of a classifier based only on change is assessed on a range of testsites in the UK, Finland and Poland. Error sources in this classifier are identified and the possibility of improving performance by including radiometric information in the mapping strategy are discussed. Finally we indicate the changes necessary in the processing chain when other forms of satellite data are available.

ACKNOWLEDGEMENTS

The work was supported by the EU-funded European Forest Observations using Radar (EUFORA) project [ENV4-CT96-030] and JRC/CEO contract Forest Monitoring in Europe with Remote Sensing (FMERS-I, contract No. BI 05-97-07 F1ED ISP SF). The authors wish to thank Mike Taylor of the UK Forestry Commission for help with ground
and meteorological data at Thetford, and the European Space Agency for providing access to ERS data.
1. INTRODUCTION

The past decade has seen the deployment of four satellite-borne Synthetic Aperture Radar (SAR) systems for remote sensing of the Earth's surface: ERS-1 & 2, JERS-1 and RADARSAT. Each of these operates at a single frequency and polarisation. Apart from JERS-1, which provided L-band data until October 1998, they are C band systems which have provided SAR data on a continuous basis since 1991. C band services, with increased flexibility in terms of incidence angle, resolution and polarisation, will continue well into the millennium with Envisat-ASAR (2000) and Radarsat II (2002). A number of other satellite SARs are mooted, but multi-channel systems comparable to the Shuttle or airborne radars are not an immediate prospect. It is therefore important to exploit the full potential of the available, relatively simple C band systems.

A major part of this potential stems from the fact that operational and environmental science users are often interested in dynamic processes. Satellite SARs can reliably provide the multitemporal data needed for observing such processes. Hence attempts to use multitemporal SAR data in various disciplines have grown significantly, with forest studies being one of the most active areas. Numerous research results indicate that SAR can contribute to mapping vegetation cover in regions characterized by frequent cloud cover (e.g. tropical and boreal forests) and monitoring changes in the forest environment, both man-made (deforestation, clear-cutting) and natural (phenology, freeze/thaw status of vegetation, storm, fire damage, etc.). These are essential pieces of information in studies of forest resources and ecosystems and their contribution to the global carbon cycle.
C band SAR has received less attention in this context because most studies have emphasised higher biomass forests, for which C band systems are unsuited. This is because the backscatter saturates when biomass exceeds a certain level, with higher levels occurring for longer wavelengths. Total biomass of up to 150-200 tons/ha can be retrieved from P-band images, whereas at C band, saturation occurs at 30-50 tons/ha [1,2,3]. Since forest biomass can exceed 500 tons/ha, C band displays little sensitivity to spatial or temporal forest variations in many parts of the world. However, low biomass forests are of interest for a variety of reasons:

- European policies will encourage conversion of land to forestry, with an associated monitoring need;
- information on regenerating forests is important in understanding forest dynamics;
- the low density forests of the sub-Arctic zone should be very sensitive to climate warming.

Moreover, changes in forest cover due to clearcutting and burning mark a drastic change in biomass whose mapping on a global scale is important.

Despite this, a variety of reasons hinder effective use of the available C band SAR data in forest observations:

- single SAR images, especially at C band, often show little differentiation between forest and other types of vegetation cover;
- the value of multitemporal data for forest studies has not been widely reported;
- results on forest mapping suffer from a lack of quantitative validation;
suitable analysis methods and computer software are unavailable to potential users of SAR data for forest information.

This study therefore has two main objectives. The first is to explain the role of multitemporal data in mapping forest. This requires investigation of the physical background to the problem coupled with data analysis (Section 2). Our second objective is to define generic methods of dealing with multitemporal ERS SAR data. We will show in Section 3 that the properties of this type of data lead to simple and efficient methods with constraints arising naturally from the data analysis. Section 4 is concerned with validation of the mapping methods, while Section 5 summarises the approach, describes how to generalise it to other SAR data and discusses its relation to mapping based on interferometric coherence.

2. DATA ANALYSIS AND PHYSICAL PRINCIPLES

A. Data description

To provide a context for our approach, we first examine multitemporal data from Thetford, UK, which is a forest site surrounded by a complex pattern of grassland, heath and fields containing various types of crops. Two separate areas of the forest are considered, namely West Harling and King’s Forest, each of which is managed by the UK Forestry Commission (UKFC). The region is flat and has a continental climate with one of the lowest rainfalls in the country. The soil is porous, dry, and contains flints, sand and chalk. Corsican pine is the main timber tree (>50%); the remainder of the forest
consists of deciduous species (i.e. oak and beech), Scots pine and other conifers such as larch, fir, etc. Corsican pine is the preferred species because of its superior timber quality and growth rate compared to Scots pine.

The UKFC provided stock maps for West Harling, last updated in 1996, and for King’s Forest, updated in July 1997. Digitized maps of West Harling and King’s Forest were generated from the two stock maps. These show stand boundaries, species, planting year and compartment areas, but information about biomass and stem volume was not available. However, biomass normally increases with stand age, except where thinning causes an abrupt decrease. Information about woodland areas outside the managed forest was based on the 1 : 10,000 Ordnance Survey maps.

The SAR data available for this test site consists of two full-year coverages by ERS PRI images, with nine ERS-1 images in 1992/3 and eleven ERS-2 images in 1997 (see Table 1). These images were all acquired from the 35-day repeat cycle, so have practically identical geometries.

B. Backscatter behaviour as a function of forest biomass

A plot of average annual backscattering coefficient against age and species for West Harling, using both the 1992/3 and 1997 ERS data sets, is shown as Fig. 1. Each point corresponds to a single stand and stands of Corsican pine (CP), Scots pine (SP), oak (OK) and beech (BE) are included. Note the transition to almost exclusive planting of Corsican pine since 1960; the stands of other species are all at least 37 years old. By
contrast, none of the Corsican pine stands is more than 45 years old. A wider range of ages, from 0 to 65 years, is available for Corsican pine in King’s Forest, as shown in Fig. 2. Similar behaviour occurs for both years and at both sites. Corsican pine displays a characteristic profile, in which the mean backscatter first decreases with age, reaching its lowest level around 15 - 20 years, then increases to a saturation level around -9 to -10 dB. (A similar profile for Corsican pine at Thetford was observed in airborne AIRSAR C band data [4]). Different species saturate at different levels. The deciduous species are about 2 dB brighter than the Corsican pine, with a saturation level around -7.5 dB, while Scots pine lies between the Corsican pine and the deciduous species.

These plots can be understood using results from a Radiative Transfer model constructed for the modelling of pine forest [5, 6, 7]. This shows that, for young stands with low biomass, the backscatter at C band is mainly the sum of direct contributions from the soil, attenuated by the canopy, and the canopy itself. Both the canopy scattering and attenuation come principally from the needles and twigs. The decline in backscatter with age (or biomass or volume) arises from increasing attenuation and is an indication of allometric relations between the total biomass and the biomass of needles and twigs. The backscatter level and the slope of the curves depends strongly on the ground return, which is time and site dependent.

Saturation is readily explained if the canopy is assumed to contain a single category of scatterers with sufficient biomass to reduce the soil contribution to negligible proportions. An elementary calculation then shows the backscattering coefficient to be
independent of the number of scatterers, but dependent on their distribution in size, orientation and dielectric constant [8]. Hence different saturation levels can arise for different species. Amongst the coniferous species, maritime pine gives a higher response than Scot pine, which is in turn above Corsican pine, in accordance with the diameters of their needles. Deciduous species generally have higher backscatter than coniferous, but more work needs to be done to assess the effect of the shape of the scatterers (leaves), as well as the relative importance of attenuation and scattering. Note that stands can vary by about 2 dB for a given stand age. This may arise from the use of age instead of biomass to characterise the younger stands, but could also indicate structural differences in the saturated older stands.

While the initial decline and the long term saturation are general properties, the intermediate behaviour may depend on the particular site. This is illustrated by Fig. 3, which plots backscatter against above-ground biomass for the Landes forest, France, using ERS data on 15/12/1996 and Radarsat (at 23° incidence angle) on 25/12/1996. Each data point is the average backscattering coefficient within a stand of 20 to 25 ha. The small difference between ERS and Radarsat may be due to imperfect calibration, the effect of polarisation (ERS operates at VV while Radarsat is an HH system), and changes between between the two dates. Unlike at Thetford, there is no significant dip separating the initial decrease in backscatter from the saturation region (which here occurs when biomass reaches 30-50 tons/ha, corresponding at the Landes to 10-15 years). This is likely to represent a different balance between the roles of attenuation and canopy scattering at the two sites, but quantitative confirmation of this would require detailed
ground measurements from Thetford. Interpretation is complicated by the fact thinning is carried out at Thetford when the stands reach the age of 15-20 years, coinciding with the dip in the response.

Even at Thetford, differences can occur due to particular forestry practices. For example, Figs. 1 and 2 show that the clearcut and very young forest areas in King’s Forest exhibit higher backscatter than at West Harling. This is thought to be due to the practice of piling forest cutting remnants into long ridges at King’s Forest, making the ground surface effectively rougher.

C. Temporal variation of SAR intensity in forest and non-forest areas

Temporal variability also exhibits a characteristic dependence on age or biomass. This is clear in Fig. 4, which displays the annual standard deviation in backscattering coefficient, plotted against age, for 1997 ERS-2 King’s Forest data. An initial sharp decrease is followed by variation of around 0.5 to 1 dB for all stands older than 10 years (with a currently unexplained outlier at 47 years).

Simulations of the C band VV backscattering coefficients at 23° incidence using the model decribed in [6, 7] provide significant insight into this behaviour. Fig. 5 shows calculations for two different soil conditions, wet and rough, and drier and smoother, as biomass is increased in steps of 20 tons/ha. The former conditions correspond to those observed at the Landes forest at the ERS date in Fig. 3, with a volumetric soil moisture content of about 30% and surface rms height of 1.8 cm, while the values in the latter case
are 15% and 1.2 cm, respectively. Fig. 5 also decomposes the total backscatter into a ground contribution, which changes with soil conditions, and a canopy contribution, which remains stable. The shaded area indicates the range of possible temporal change brought about by soil moisture changes. These mainly affect the lowest biomass range, where the behaviour can change from a marked decrease with biomass, when the soil is rough and wet, to a slight decrease under dry conditions.

The temporal behaviour of non-forest areas is usually different, both qualitatively and quantitatively. A given change in soil moisture causes greater variation in clear-cut areas or bare soil surfaces than in forest. Agricultural fields display marked changes due to soil moisture, surface roughness and vegetation growth. Water bodies exhibit large, irregular changes due to the effects of wind. Grasslands and urban areas are stable, but with backscattering coefficients which are lower than forest for grasslands and higher for urban areas.

These differing behaviours are illustrated for a selection of forest and non-forest samples in Fig. 6. For the forest, each plotted point represents a Corsican pine stand of a given age, selected from the data used to form Fig. 2. The non-forest samples are taken randomly from the surrounding agricultural fields, which in this region are likely to contain cereals, sugarbeet, oil-seed rape and grassland (but no detailed information is available). Observations from a given sample are joined by lines to aid interpretation.
The older forest stands, shown in Fig. 6(a), exhibit little variation through the year, but two populations can be distinguished by their backscatter level. The four highest curves are from 47-60 year old stands, so that saturation in the range -10 to -8 dB has occurred (see remark below about the April data). The lowest three curves, lying between -10 and -13 dB, come from 13-15 year old stands which are therefore near the bottom of the dip in Figs. 1 and 2. Young stands are shown in Fig. 6(b) and tend to exhibit higher backscatter and larger variability, as expected from Figs. 2 and 4. Most of the non-forest areas shown in Fig. 6(c) have backscatter values lying well outside the forest range at some times in the year but, at any one time, forest and non-forest may have appear similar. However, the latter exhibit more varied temporal change, corresponding to the variety of vegetation covers in this region. For example, cereals would be expected to have a backscattering coefficient of -5 to -10 dB in winter, falling to -15 to -20 dB in early summer, before increasing again in autumn, whereas oil-seed rape is more stable, with a dip in spring. Sugarbeet has high variability in winter to spring, then stabilises in summer, while grassland is stable throughout the year.

In addition, the non-forest areas tend to have much greater temporal variability. This is clear from Fig. 7, which shows the maximum change throughout the year of the forest stands in Fig. 6(a--b), arranged in order of increasing age, and a larger sample of non-forest areas. Young forest exhibits changes up to 7 dB, but this drops to 2.5 dB or less for the older forest; every non-forest region changes by at least 4 dB. Hence, temporal stability provides a possible characteristic by which forest can be discriminated from non-forest areas.
The effects of weather can be observed in each of Figs. 6(a)-(c), but are more significant for young forest and non-forest areas. Particularly of note is the dip on April 18 in all three plots. This corresponds to the only date when frost occurred. Such conditions can reduce the backscatter and increase the annual variability of older forest. The October increase in backscatter observed for many of the areas in Figs 6(b) and (c) occurred during a rainy period and is probably due to increased soil moisture in the post-harvest period. However, much of the variation during the summer is likely to arise from crop development.

In summary, the C band backscattering coefficient of forest is stable for stands above 30-40 tons/ha, and exhibits higher variability for younger stands mainly due to changes in soil moisture. Without prior knowledge of an area, the temporal variation of C band intensity data can be used to distinguish two general classes:

- vegetation cover exceeding 30 tons/ha, which we interpret as older forest;
- vegetation cover less than 30 tons/ha, which we consider as non-forest, but which on physical grounds must include young and sparse forest.

When we know that the area of interest consists of forest, two forest classes can be discriminated, one with variation of the order of 1-2 dB or less, corresponding to forest of more than 30 tons/ha, and one varying in the range 2-5dB with biomass less than 30 tons/ha. Such prior knowledge may be available, for example, when the scene is dominated by forest and water, clearcut areas or particular crops.
3. FOREST MAPPING ALGORITHM

A processing strategy for forest/non-forest discrimination has been developed based on the above results, as illustrated in Fig. 8. The procedure assumes that \( N \) images from the same 35 day repeat cycle are available and consists of three stages: pre-processing, speckle reduction and classification. The approach can be considered generic to many applications of multitemporal data, but we here wish to stress how the analysis set out in Sections 2 and the particular properties of ERS data provide very strong constraints on how the various steps are carried out.

A. Pre-processing

Pre-processing consists of two steps. The first is calibration, which converts the digital number at each pixel to a \( \sigma^0 \) value following the procedure in [9], and ensures that values of \( \sigma^0 \) from different times and in different parts of the image are comparable. The second step is registration of the images in the multitemporal sequence. For ERS PRI 35-day repeat data, this requires only image translation (here carried out using autocorrelation methods on urban areas within the ERS frame).

B. Speckle filtering

The second, critical stage in the processing chain is to estimate \( \sigma^0 \) in each of the \( N \) images with sufficient accuracy to decide whether the multitemporal behaviour at a given pixel corresponds to forest or non-forest. From Section 2, we see that this requires us to distinguish forest areas changing by less than 2 to 2.5 dB from non-forest regions where
the change exceeds 4 dB. Separation of these two classes by thresholding requires data with an equivalent number of looks (ENL) well in excess of 100, if unacceptably high false alarm rates are to be avoided [10, 11].

A major advantage of multitemporal data is that both temporal and spatial filtering can be employed in order to achieve the required ENL. For a sequence of \( N \) registered multitemporal PRI images, with intensity at position \((x, y)\) denoted by \( I_i(x, y)\), the basic problem in temporal filtering is how to linearly combine them in order to produce \( N \) output images \( J_k(x, y) \) meeting two conditions:

1. \( J_k \) is unbiased, i.e. \( \langle J_k \rangle = \langle I_i \rangle \), where \( \langle \cdot \rangle \) denotes expected value, so that the filtering does not distort the \( \sigma^0 \) values;

2. \( J_k \) has minimum variance, so that speckle is minimised.

This problem has the solution [12, 13]

\[
J_k = \sum_{i=1}^{N} A_{ik} I_i \quad 1 \leq k \leq N \tag{1}
\]

where the weighting coefficients \( A_{ik} \) are defined by

\[
A_{ik}' = \sigma_i \frac{C_i^{-1}\sigma}{\sigma_i C_i^{-1}\sigma} \tag{2}
\]

Here \( A_k = (A_{k1}, \ldots, A_{kN}) \) is the coefficient vector appropriate for output image \( k \), \( ' \) denotes transpose, \( \sigma' = (\langle I_1 \rangle, \ldots, \langle I_M \rangle) \), \( C_i = \langle I_i I_i \rangle - \langle I_i \rangle \langle I_i \rangle \) is the covariance matrix of the intensity data and \( J, I, C \) and \( \sigma \) are all calculated at the position \((x, y)\). The explicit formula (2) for calculating \( A_k \) is derived in implicit form in [12].
This general treatment (2) needs estimates of the correlations between the temporal images. However, over the 35 day repeat period, the C band correlation would be expected to fall to very low values in the type of temperate region considered here, except for areas of undisturbed bare soil and urban areas. Examination of the ERS data and sampling statistics indicates that measured correlations can depart significantly from zero as a result of sampling error and significant bias when edges occur in the sampling window. The measured correlations therefore introduce spurious effects into the filtering and it is more correct to set them to zero. This leads to a much simplified form of the filter, given by

\[ J_k(x, y) = \frac{\sigma_k}{N} \sum_{i=1}^{N} \frac{I_i(x, y)}{\sigma_i}, \quad 1 \leq k \leq N \quad (3) \]

Two remarks on the performance of this filter are relevant. Firstly, in principle the temporal filter should not degrade the spatial resolution. In fact, the estimate of the \( \sigma_i \) needed in (3) requires spatial averaging within a window in each image of the temporal sequence. This leads to some loss of resolution, which is minimised by using an adaptive processing window, as described in [14]. Secondly, if there are \( N \) uncorrelated multitemporal images each consisting of \( L \)-look data, then the filtered data will ideally have \( N \times L \) looks. In practice, errors in the estimates of the \( \sigma_i \) reduce this value. For example, temporal filtering of the 11 ERS-2 PRI images from 1997, each of which is 3-look, leads to data with approximately 25 looks.
Even with large numbers of images available, the gain in radiometric resolution from temporal filtering alone clearly cannot meet the requirements discussed in Section 2. Further gains can only come from spatial filtering, using a strategy which again follows from the properties of the ERS data. In particular, there is little or no detectable texture at the scale of typical processing windows at the resolution and incidence angle of ERS. Hence the appropriate model for the data is the multi-look gamma distribution [11]. For spatially uncorrelated pixels, this would imply that the maximum likelihood estimate (MLE) of \( \sigma_i \) for each image is simply the average of the (intensity) pixels in the window. However, both the sampling of the PRI data and the temporal filtering lead to spatial correlation. While the local average is then no longer the MLE, it still provides an unbiased estimate which we adopt in our processing, again using spatially adaptive methods to preserve resolution. A more sophisticated approach would require estimates of the local spatial correlation, at the expense of greatly increased processing time and estimation error, for little probable gain in performance.

Unlike temporal filtering, the maximum possible gain in ENL using spatial filtering is not well-defined, being limited only by the number of pixels available within a typical uniform region in the scene. Hence the processing window can be as large as a typical uniform target. However, larger windows place greater reliance on the effectiveness of the spatial adaptivity and it is safer to choose window sizes defined by the necessary ENL. The analysis in this paper uses windows of size 11x11 pixels. For uniform targets, after allowance for spatial correlation, the temporal and spatial filtering would then together yield an ENL of around 500. Estimation error, spatial adaptivity and image
structure all cause significant reductions in this value, and make the ENL spatially variable within the final images. However, the filtering strategy has sufficient safety margin to ensure that the ENL needed for our problem is achieved.

Note that other multitemporal studies have used spatial filtering based on maximum a posteriori (MAP) filtering [14, 15], assuming gamma distributed texture. Because this is not the appropriate model for ERS data at the scales of interest, the filter tends to leave noise in the output, especially near edges. The images hence appear sharper but need further filtering to reduce classification error [15].

To summarise, the properties of ERS data mean that for this application only the simplest filtering operations are needed. The complicated part of the filtering strategy is embedded in the spatial adaptivity. Temporal filtering provides an initial improvement in ENL possible for any registered image sequence. Further increases in ENL come from spatial filtering of each image, using window sizes dictated by the problem. Similar conclusions are likely in many other land applications of ERS PRI data, such as hydrology or agriculture.

C. Classification based on change

The filtering provides $N$ images in which each pixel is an unbiased estimate of $\sigma'$ and the ENL has been increased sufficiently to allow reliable decisions to be made on the temporal sequence at each pixel. Forest/non-forest classifications can then be obtained by applying different thresholds to a pixel-based change measure. Three ways of
measuring change were considered: annual standard deviation of backscatter, maximum dB difference between any two dates over the year and mean annual variation (mva). For $N$ images, this latter measure is defined by [15]:

$$\text{mva} = 10 \log \left[ \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} R_{ij} \right]$$

where $R_{ij} = \max(1, \frac{I_i}{I_j}, \frac{I_j}{I_i})$ is the normalised ratio of intensities in image $i$ and image $j$. This index is equivalent to a weighted geometric average, with greater weights attached to bigger changes.

Scatterplots and regression lines of one measure against another are shown in Fig. 9, using forest and non-forest 1997 data from King’s Forest. The high correlation coefficients imply that at this site all three measures give equivalent outputs. In general, however, mva and maximum difference measures are to be preferred since they rely on intensity ratios, hence are resistant to radiometric distortions caused by topography and systematic calibration errors.

Fig. 10(a-b) shows mva images based on ERS-1 1992/3 and ERS-2 1997 data for West Harling and the results of applying thresholds of 2 and 2.5 dB to these images are shown as Figs. 10(c-d) and (e-f) respectively. The stock maps are used to indicate the compartment boundaries and pixels exhibiting change below the threshold are classified as forest. Combining Fig. 7 with Fig. 9(b) suggests a threshold on mva of 2.5 dB to classify the 1997 data (accepting the errors for young forest), but this produces significant misclassification of the non-forest area in 1992/3. Comparisons of the 1992/3 and 1997 data for a sample of non-forest areas in fact indicated much lower values of
mva at the earlier date. The reason for this is unknown (for example, rainfall patterns in
the two years are not significantly different). Lowering the threshold to 2 dB reduces the
misclassified area outside the forest in 1992 but leads to increased misclassification of
young forest in 1997. If an unsupervised common threshold is desired, 2 dB seems the
better choice, as long as we accept that physically the young forest class has not
developed the characteristics of the forest class.

With this threshold, the majority of the managed forest is correctly picked out in both
data sets. The thin belt of woodland running east-west to the south of West Harling is
also correctly identified, as was confirmed using the Ordnance Survey map of this area.
Inside West Harling, the small misclassified patches of forest all lie within young stands.
In addition, changes in the forest from 1992/3 to 1997 are apparent, with several clearcut
areas and young plantations in 1997 which were forest in 1992/3.

From the basic concept of the algorithm, it is clear that classification errors will occur for
two types of region:

1. non-forest areas whose average variation is less than the selected threshold;
2. forest regions whose average variation exceeds the threshold.

Types of target giving rise to the first type of error include urban areas or buildings (e.g.
farm buildings to the north of the forest area) and grassland (such as occurs along the
river valley which cuts into the north-west of the forest). Some correction for this type of
error should be possible by using absolute values of the backscattering coefficient. As
shown in Fig. 6, for older forest areas, \(-13 \text{ dB} < \sigma' < -8 \text{ dB}\). Urban areas tend to contain
bright targets whose RCS lies above this range, while grassland often appears darker than forest. In fact, tests at West Harling indicated little gain from this refinement, although more extensive evaluation is needed.

The second type of error occurs for young forest, whose response is essentially that of the underlying soil, until the canopy is sufficiently dense to cause significant attenuation of the soil return. In terms of the physical content of the radar backscatter, young forests are therefore comparable to certain agricultural crops or low bushland and cannot be detected correctly by the ERS SAR. Hence correction of this type of error may require information not available from the radar data.

4. ASSESSMENT OF THE METHODOLOGY

Quantitative assessment of the performance of this approach is difficult because the only information about areas outside the managed forest is provided by the Ordnance Survey map. We therefore have little information on the non-forest class and limited information on other woodland. Even within the forest, a field visit indicated the difficulty of knowing how to interpret the data provided by the forestry map. However, an attempt to assess the above approach and compare it with forest estimates using other sensors was carried out within the EU Forest Monitoring in Europe using Remote Sensing (FMERS) project [16]. The major emphasis of this study was on classification using a range of optical satellite data, but it included a SAR component based on ERS data.
The testsites for this project were selected to cover a range of forest types (coniferous, broad-leaved deciduous, broad-leaved evergreen and mixed forest). A two-class separation into forest and non-forest was carried out using the ERS data by the method discussed in Section 3. In some cases the optical data considered just these two classes, while in other cases separation into three or more classes was attempted. Geocoding issues meant that SAR/optical comparisons were only carried out at sites in the UK (Thetford), Finland and Poland. Ground data for the performance assessment was based on transect information provided by independent investigators familiar with the local areas.

Table 2 shows SAR results for the UK, Finnish and Polish testsites. For the UK site, over 90% of the pixels along the transects were correctly classified, but this value needs to be qualified. The selected ground data transects ran only through the forest areas, so that the non-forest class was not properly represented. The correct way to interpret the value is that 10% of the forest pixels along the transects were misclassified (principally in the young plantation areas). However, the best optical result gave only 74% correct pixels in a three-class discrimination.

At the Finnish testsite, the principal cover types were boreal forest and water, with some agricultural areas and villages. Since water shows large dynamic range variations, depending on wind conditions, good classification performance (over 94%) is possible on this testsite. The best two class separation using optical data also gave 94% classification accuracy. It is noteworthy that while the best performance from the SAR uses all 15
available dates, over 90% correct classification is achieved when just two summer SAR images are used. At this time of the year, farming activity causes significant change in the agricultural areas while the forest is stable. By contrast, classification accuracy drops to 84.6% when a winter-summer pair of images is used, because the presence of snow causes significant changes in $\sigma^0$ for both the forest and non-forest classes. The result at the Polish testsite, although not as good as at the two other sites, is comparable to the result obtained with TM.

Note that the presence of relief prevented detailed geometric matching and hence evaluation by the transect method in the FMERS study. Relief also causes radiometric distortion, but the method developed for the SAR analysis should be resistant to such effects in moderate relief because it relies on image ratios. However, it will have limitations in steep terrain because of layover, foreshortening and the need for very precise registration.

5. DISCUSSION AND CONCLUSIONS

The only type of current satellite SAR data available for operational applications is C band intensity data from ERS and Radarsat. This state of affairs will continue into the Envisat and Radarsat-2 era, which makes it important to exploit fully the potential of this data type. This requires both understanding of where the relevant information is to be found in the data and appropriate methods to access it. Multitemporal signatures are particularly important in many applications. This paper has discussed a generic approach
to multitemporal analysis and indicated how the approach can be matched to the problem of forest area measurement with ERS PRI data.

Observations and modelling suggest that the most telling discriminator of forest cover is temporal stability, as long as its biomass exceeds 30-40 tons/ha. This leads to a physically-based classification scheme with several attractive features:

- the methodology is physically-based and unsupervised;
- it is resistant to moderate relief and to systematic calibration errors;
- it appears robust, being applicable without modification at a range of testsites (although improved performance is possible if the change threshold is optimised to local conditions);
- it uses simple algorithms which have been optimised to the properties of ERS, but can be readily adapted to Radarsat (and other) data.

In addition, since the methodology is rule-based, its error sources (stable non-forest targets, forest regions exhibiting significant variability) are easy to identify but may not be easy to correct; further work is needed on this issue.

Although not described in detail here, the approach here has been compared with results using coherence data from a single ERS Tandem pair acquired during March 1997 [17]. It has been demonstrated elsewhere that thresholds on coherence can be used to discriminate forest and other cover types [18]. For the West Harling site, the coherence added no extra information on forest area and suffered from some confusion in the non-forest areas, probably due to working of agricultural fields in the day separating between the Tandem pair of images. For King’s Forest, the higher coherence of grassland
allowed it to be much better discriminated from forest and removed the confusion in the temporal signature. However, coherence has similar problems to multitemporal analysis in detecting young forest, because coherence is significantly larger for young than for older forest (mainly because of the lack of attenuation of the high coherence signal from the ground). In addition, interferometric data is not currently available from the ERS pair of satellites.

An important operational issue not addressed here is the number of images needed for the mapping. For cost reasons, a trade-off between the minimum number and the classification performance should be determined for a given site. Based on the temporal behaviour of forest and non-forest classes, the best dates will be those which correspond to maximum changes in the non-forest classes, in order to obtain the best contrast with the temporally stable forest classes. At Thetford, it has not proved easy to isolate a small number of images carrying all the essential change information, because of the complexity of the region. However, this is still being investigated, as a generally applicable methodological approach is needed. Certainly, one constraint on the use of temporal change for forest mapping in more northern regions is that times of freezing or snow need to be excluded, as these conditions cause marked changes in the forest backscatter.

The analysis above used the properties of the ERS data to derive a simplified filtering approach, but this can easily be modified to other datatypes. For JERS data, the much longer coherence times mean that the temporal filter would need to take account of
correlation between images. This would also be true if the data sequence contained one or several Tandem pairs. However, the explicit form of the temporal filter given by (2) makes it easy to cater correctly for such cases. Note, in fact, that the filter (2) does not even require the datatypes to be the same, and could be applied, for example, to combined ERS and JERS data, as long as they were accurately registered. The spatial filtering for such lower resolution data would still be simple because of the lack of texture. By contrast, the simple temporal filtering scheme is appropriate for fine mode Radarsat data but the spatial filtering must take account of image texture.

Note that the FMERS study, in attempting to quantify classification performance, raised serious questions about the appropriate methodology for doing this. Access to area-extensive validated ground data on regions containing both forest and non-forest is not easily available, but is crucial in any comprehensive assessment. Means to provide such data should form part of any attempt to apply these methods to large-scale problems.

Although the data handling approach described in this paper has been developed in the context of forestry using ERS data, it is relevant to other data types and in applications where the spatial structure of the scene remains essentially unchanged and the information is contained in the multitemporal behaviour of $\sigma^0$; agriculture and hydrology provide two such examples. However, the details of the processing chain summarised in Fig. 8 need modification both for datatype differences and the particular application.
REFERENCES:


Fig. 1 Backscatter vs age for forest stands in West Harling.

Fig. 2 Backscatter vs age for forest stands in King’s Forest.

Figure 3: Variations of the ERS and RADARSAT backscattering coefficient with total biomass, Landes forest.
Fig. 4 Annual standard deviation of backscatter vs age for King’s Forest.

Figure 5: Simulated backscatter as a function of total biomass for different soil conditions, Landes forest.
Fig. 6 Temporal curves for King’s Forest area: (a) older forest (b) young forest and (c) surrounding non-forest areas.
Fig. 7 Maximum intra-annual backscatter change of forest and non-forest samples. Forest samples 1 - 4 are young forest of less than 6 years old.

Processing Strategy

Fig. 8 Processing strategy for forest/non-forest mapping using multitemporal ERS PRI 35-day repeat data
Fig. 9 (a) max. dB difference vs std; (b) mva vs max. dB difference.
Fig. 10 mva images of West Harling ERS-1 1992/3 and ERS-2 1997 and classification results using different thresholds.

<table>
<thead>
<tr>
<th></th>
<th>JAN</th>
<th>FEB</th>
<th>MAR</th>
<th>APR</th>
<th>MAY</th>
<th>JUN</th>
<th>JUL</th>
<th>AUG</th>
<th>SEP</th>
<th>OCT</th>
<th>NOV</th>
<th>DEC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERS-1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1992-</td>
<td></td>
<td></td>
<td></td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1993</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERS-2</td>
<td></td>
<td></td>
<td></td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td>●</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1 Available multitemporal ERS data for Thetford, UK
<table>
<thead>
<tr>
<th>Site</th>
<th>No. of images</th>
<th>Season</th>
<th>Spr</th>
<th>Sum</th>
<th>Aut</th>
<th>Win</th>
<th>% correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>UK</td>
<td>11</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>90.7</td>
</tr>
<tr>
<td>Finland</td>
<td>15</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>94.1</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>✓✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>90.4</td>
</tr>
<tr>
<td>Poland</td>
<td>2</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>77.4</td>
</tr>
</tbody>
</table>

Table 2  ERS SAR classification results for the FMERS testsites.