FOREST INVENTORY USING SATELLITE OPTICAL AND RADAR REMOTE SENSING WITH ANCILLARY DATA

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Abstract

In recent years there has been a marked increase in public awareness of environmental issues particularly the deforestation of the world's rain forest. To this end there is a need for accurate detection, inventory, monitoring and management for forest resources. Optical remote sensing methods have successfully being utilised in the inventory of forest species. The incorporation of ancillary data with remotely sensed data for digital data analysis in determining forest species distribution have further increased the classification accuracy. Ulaby et al. (1982) suggested that, in order to achieve high correct classification rates, it is necessary to have uninterrupted (cloud free) coverage of the area under investigation for successive passes of the satellite.

This paper set out to examine the extent to which satellite imaging radar or synthetic aperture radar (SAR) augment the information content of satellite optical imagery in forest classification and to what extent does the transformation of spectral data and the incorporation of ancillary data improves the classification of forest trees.

Introduction

In the tropics where there is frequent cloud cover, the ability to acquire cloud-free aerial photographs or digital multispectral image from aircraft or satellites are very scarce. One way to rectify this interruption problem is to use an imaging radar, which effectively is immune to the presence of clouds in the atmosphere. If used in conjunction with optical sensors, radar can potentially: 1) improve the forest classification rates under clear sky conditions because it responds to the geometrical and dielectrical properties of vegetation (Ulaby *et. al.*, 1975, 1979) differently than do optical sensors, and 2) serve as a "substitute" for optical sensors during cloud-cover conditions.

The use of radar as remote sensing system is quite recent as compared to aerial photography and digital multispectral scanners from aircraft or satellites. Radar remote sensing first started in 1967 with the large scale topographic mapping project over the Darien province of Panama for project RAMP (Radar Mapping of Panama). The project was flown by Ratheon Autometric with Side-Looking Airborne Radar (SLAR). The Darien province of Panama was not mapped prior to 1967 even though the United States Air Force had previously attempted for nearly 20 years to acquire aerial photography over this area. Persistent cloud cover was the main obstruction in the use of aerial photography for mapping. During the late 1960s and early 1970s large parts of the world were covered by airborne SLAR surveys.

The best known and largest example of these surveys is Project RADAM (RADar AMazonia) where the entire country of Brazil (8.5 million square km) was imaged. The use of SLAR has been superseded by the use of synthetic aperture radar (SAR). This type of radar permits fine resolution radar imagery to be generated at long operating ranges by the use of signal processing techniques.

Radar remote sensing from space began with the launch of Seasat in 1978 and continued with the Shuttle Imaging Radar (SIR) experiment in 1980s. Though there is an extensive archive of radar imagery derived from these programmes, the data are not freely available nor as well understood as other image products due to the complexity of their processing. Nevertheless, their data have attracted considerable attention from researchers.

Despite the potential of radar remote sensing systems, research efforts utilising such systems have been modest. Although not as widely available or as well understood as other remote sensing systems, radar provides a wide array of unique natural resources applications. The combination of microwave and optical remote sensing system would complement each other in their study of natural resources.

Study Area

The study area was Forest of Dean, near Bristol, west of England. The elevation of the study area range from 5 metres to 310 metres above mean sea level (a.m.s.l) with the forest areas above 100 metres (a.m.s.l). The lowland areas consists of grasslands and farm, with orchards at a higher level. Initially, 22 forest tree species were identified from the forest stock map and sub-compartment database. The 22 species are made up of 11 deciduous and 11 coniferous types. After preliminary evaluation of the training sites, it was determined that it was not possible to have each individual species as a class. This was due to the small spatial coverage of some species which would not have allowed enough training samples to be collected and would create difficulty in estimating covariances for training class statistical analysis. Furthermore, species were usually mixed within a sub-compartment boundary. It was extremely difficult to obtain training pixels for mixed classes in a sub-compartment, therefore training samples were confined to classes that are homogenous within a sub-compartment boundary. All of the training sites for each individual group or similar tree species were combined according to their main group; for example; European, Japanese and Hybrid Larch were combined as Larch; Douglas, Noble, Grand and Silver fir were combined as Fir; Scots and Corsican pine were combined as Pine and Norway and Sitka spruce combined as Spruce. In summary, there were three classes for deciduous trees which comprise Oak, Beech and Larch and three classes for coniferous trees consisting of Pine, Fir and Spruce.

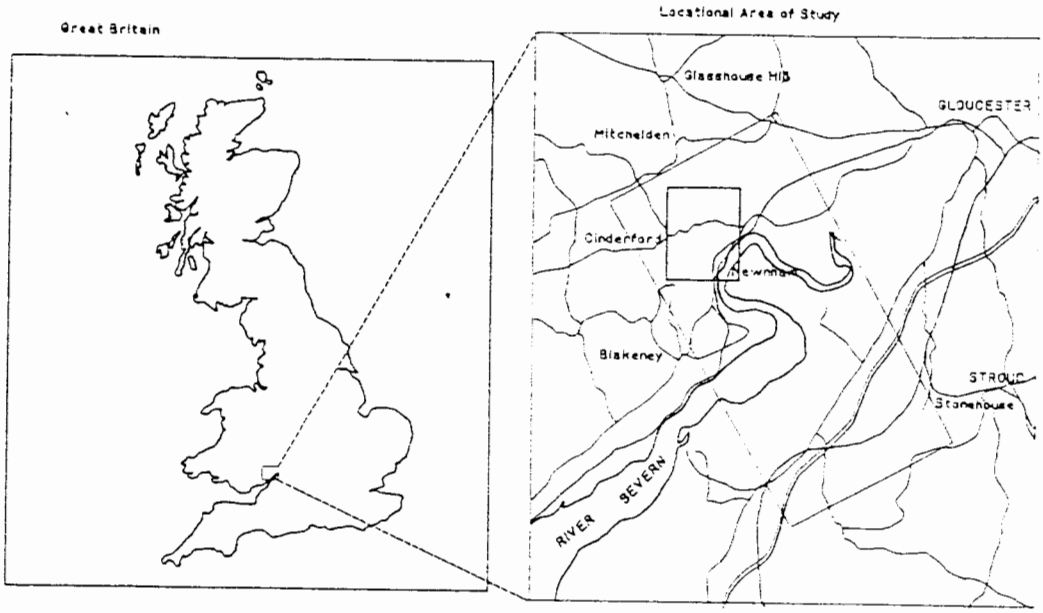

Figure 1. Locational map of Study Area. The larger rectangular area indicates the Seasat SAR coverage. The smaller rectangular area shows the study area incorporating Seasat SAR, Landsat TM and Terrain data.

	OAK		BEECH		LARCH		SPRUCE		FIR		PINE	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
TM1	27.6	1.7	26.2	1.8	24.2	1.8	21.7	1.7	23.2	2.1	23.3	2.9
TM2	9.5	1.3	9.1	1.0	7.8	1.4	5.6	1.7	6.1	1.7	6.4	2.3
TM3	11.6	2.3	11.1	2.2	7.0	1.9	4.2	1.9	4.7	2.4	6.4	4.2
TM4	41.5	6.5	41.3	3.9	38.6	5.5	37.4	8.9	46.7	11.8	36.9	4.3
TM5	66.9	8.5	58.4	6.9	46.2	6.6	31.8	7.2	40.1	8.4	42.3	12.8
TM7	28.2	3.8	24.2	3.2	18.4	3.0	11.3	2.9	13.7	3.8	16.2	6.5
PCA1	111.3	17.9	93.5	18.4	57.8	18.9	18.8	17.9	35.4	23.5	43.0	32.2
PCA2	85.8	11.8	79.5	7.9	69.2	9.5	58.4	13.8	75.0	16.6	64.6	11.3
PCA3	164.3	9.5	153.1	6.8	140.5	7.5	122.4	9.8	120.9	16.0	137.8	14.3
S123	99.1	21.0	88.8	20.0	54.1	21.7	20.4	20.3	30.3	25.9	38.2	34.4
S57	120.8	14.3	104.5	14.4	77.7	14.1	45.4	14.7	61.4	17.5	67.6	25.3
1/4	85.2	11.6	80.6	9.5	80.3	10.9	76.9	16.5	66.7	18.2	80.3	10.3
1/5	52.5	6.0	57.1	5.8	66.8	7.7	89.9	17.3	75.2	12.4	72.5	12.6
3/2	149.4	14.8	148.7	17.6	112.1	20.8	93.3	25.5	95.9	27.5	117.7	29.2
4/5	78.6	9.9	90.1	9.5	106.6	13.4	145.8	18.8	142.9	27.8	115.6	22.2
7/4	86.7	12.6	74.0	7.1	60.8	11.3	39.1	10.3	39.4	15.7	54.7	17.7
2S3	114.6	8.5	114.8	10.0	135.0	11.6	147.8	17.9	146.1	17.8	132.4	17.4
3S1	74.2	9.2	74.5	9.8	55.8	9.4	39.4	13.9	41.1	14.3	50.8	17.7
3S5	36.9	4.8	39.9	5.5	32.6	5.2	28.1	7.9	25.5	8.3	31.1	9.3
4S1	151.5	8.3	154.7	6.7	155.2	8.1	158.3	12.4	167.0	14.7	155.1	7.5
4S5	96.7	7.1	104.9	6.4	115.2	8.1	136.6	10.5	135.2	16.0	119.7	13.2
7S4	102.4	9.3	93.2	5.7	81.5	9.7	59.2	11.6	58.6	16.8	74.9	15.6
TAS1	76.6	11.7	68.8	9.1	53.6	9.8	37.9	12.7	51.9	14.3	48.1	15.9
TAS2	99.7	12.4	91.6	8.5	80.6	9.6	68.2	13.4	85.4	15.9	76.2	12.1
TAS3	134.5	13.4	151.6	11.1	171.2	10.3	197.5	9.7	189.8	14.9	177.1	21.7
TAS4	148.0	15.0	156.8	11.2	175.4	11.9	195.3	15.7	83.3	33.9	182.4	19.7
SLOPE	62.7	30.8	61.4	19.8	41.9	29.0	65.4	32.2	83.3	33.9	24.4	19.7
ASPECT	116.1	69.3	193.1	54.6	12.7	1.4	145.3	76.7	116.3	63.6	126.9	62.8
ELEV	125.1	26.9 1	75.5	26.7	218.7	25.6	150.7	40.5	136.2	32.8	227.7	32.6
SAR	61.7	27.9	52.3	18.0	49.1	1.9	57.5	22.8	60.7	25.1	54.4	20.0

Table 1 The mean and standard deviation of forest tree species for all sets of bands.

Methodology

Digital satellite imagery from Landsat Thematic Mapper (scene path 203 row 24 date of imaging 24 April 1984), Seasat Synthetic Aperture Radar (SAR) (ascending orbit 1307 and date of imaging 26 September 1978), forestry stock maps and database and Ordnance Survey 1:10,000 topographic maps were used for the analysis.

The processing of the 8-bit TM image and 16-bit Seasat SAR image was carried out using programs written in FORTRAN 77 on a DIGITAL VAX 11/750 computer; all the programs were created in the Remote Sensing Centre University of Nottingham, England. The Landsat TM and Seasat SAR have to be spatially and spectrally integrated. Experience to date indicates that processed satellite image have excellent internal geometry. Consequently image data can be rectified/registered to map coordinates using polynomials of the first or second degree. The TM image have a spatial resolution of 30m and Seasat radar image have a resolution of 25m. As the rectification/registration process usually requires the resampling of data, therefore it is required to bring the pixels of the two data set to a common dimension of 20 metres.

The contours from the OS 1:10,000 map and the Forestry maps were manually digitised using the Laser-Scan System at the Geographic Information System Laboratory, University of Nottingham. Elevation, slope and aspect map of the study area were created using the Laser-Scan DTM software. The attributes of each digitised forest compartment were obtained from the sub-compartment database. These attributes were land use, crop type, species, planting year and soil type. These attributes were subsequently used as parameters in the maximum likelihood classification of the satellite images.

The TM data were enhanced and transformed through principal components analysis, simple ratio, normalised difference ratio and Kauth-Thomas (tasselled cap) transformation. The SAR data were filtered to reduce speckle. The digitisation of contours created a DEM from which slope, aspect and elevation images formed. All the above transformations created a number of variables (images or features) which will be used in the classification of forest species.

Seasat SAR Image and Speckle Noise Removal

SAR images are well-known for the salt-and-pepper appearance or the speckle effect. Speckle or the peculiar granular pattern is due to the random fluctuations in the return signal observed from an area-extensive target represented by one pixel. The presence of speckle in an image reduces the ability of a human observer to resolve fine detail. If analysis is to be by the use of digital analysis equipment, including interactive viewing system, then this speckle presents a problem. Numerous ways have been proposed to suppress speckle. Basically SAR speckle suppression techniques fall into two categories (Lee, 1983, Muller and Hoffer, 1989). Firstly the reduction of speckle before image formation and secondly the application of a smoothing filter after images have been formed. Most techniques operate on

the image after its formation and the speckle reduced using digital spatial filtering techniques. In this study the speckle were filtered using the sigma filter of Lee (1983).

Feature Selection

Classification cost increases nonlinearly with the number of features used to describe pixel vectors in multispectral space - i.e. with the number of spectral bands associated with a pixel. With the use of maximum likelihood classification, the cost increase is quadratic. Therefore it is sensible economically to ensure that no more features than necessary are utilised when performing a classification. Features which do not aid discrimination, by contributing little to the separability of spectral classes, should be discarded since they will represent a cost burden. Removal of least effective features is referred to as feature selection, this being one form of feature reduction.

Feature selection is normally carried out by determining the statistical *separability* of classes; in particular, feature reduction is performed by checking how separable various spectral classes remain when reduced sets of features are used. Divergence (D) is a commonly used form of separability measure designed to predict best channel combinations for multispectral classification of earth features. The use of the Divergence measure requires that the measurements on the members of the k classes (or land use categories) are distributed in multivariate normal form. The divergence measure (D) based on a subset of m of the p features is computed for classes i and j following Singh (1984) with a zero value indicating that the classes are identical. The greater the value of D(i,j) the greater is the class separability based on the m selected features.

$$D(i,j) = 0.5\ Tr[\ (S_i - S_j)\ (S^{-1}_j - S^{-1}_i)] + 0.5\ Tr[(S^{-1}_i - S^{-1}_j)(M_i - M_j)\ (M_i - M_j)^T\ ] \qquad (1)$$

where S is the class covariance matrix.
M is the mean vector.
T is the transpose of the matrix.

The distribution of D(i,j) is not well known so a measure called the transformed divergence is used instead. This has the effect of reducing the range of the statistics, the effect increasing with the magnitude of the divergence. Thus when average are taken, the influence of one or more pairs of widely-separated classes will be reduced. The transformed divergence is calculated as;

$$TD(i,j) = c[1 - \exp(\ - D(i,j) / 8\ )\ ] \qquad (2)$$

with c being constant used to scale the values of TD onto a desired range. 100 is used as a scaling factor, which gives the value of TD to be interpreted in the same way as percentages. A value of TD of 80 or more indicates good separability of the corresponding classes i and j.

The value of TD(i,j) are average for all possible mutually-exclusive pairs of classes i and j and the average (the average pairwise divergence) is denoted by TD_{av}

$$TD_{av} = 2/k(k-1)TD(i,j) \qquad (3)$$

The aim of feature selection or class separability is to produce the subset of m features that best combines classification accuracy and computational economy. The number of subsets of size m that can be drawn from a set with p elements is;

$$\binom{p}{m} = \frac{p!}{m!(p-m)!} \qquad (4)$$

the symbol ! indicates factorial.

In the study area 30 channels of spectral data (see Table 1) were derived from the original 6 TM bands, its transformation (principal component analysis, simple ratio, normalised difference ratio and tasselled cap), DEM and SAR, all the channels to be used for the classification. Using equation 4, and determining a sub-set of 4 from 30 would give 27405 subsets. The computation of such a large number of the average pairwise divergence is to be avoided. The problem of selection of more likely subsets is similar to the problem of determining the best subset of independent variables in multiple linear regression. Inter class (pairwise all classes) transformed divergence value for each band or set of bands were computed from the scale of 0 to 100. The choice of best four channels for each set of bands were computed by divergence and the results are shown in Table 2 to Table 6.

Number of variables	Av.Tr. Divergence	Band numbers .....
1	12.22	1
2	66.40	1 E
3	77.39	1 E 6
4	84.60	1 E 6 4
5	89.74	1 E 6 4 A
6	91.46	1 E 6 4 A S
7	92.91	1 E 6 4 A S 2
8	93.96	1 E 6 4 A S 2 3
9	94.83	1 E 6 4 A S 2 3 5
10	95.41	1 E 6 4 A S 2 3 5 R

1 = TM1 2 = TM2 3 = TM3 4 = TM4 5 = TM5 6 = TM7

Table 2. Summary of Feature Selection for TM Bands with DEM and SAR.

Number of variables	Av. Tr. Divergence	Band numbers ...
1	5.32	3
2	71.49	3 E
3	81.86	3 E 5
4	87.97	3 E 5 A
5	90.81	3 E 5 A 2
6	94.48	3 E 5 A 2 4
7	96.96	3 E 5 A 2 4 1
8	97.52	3 E 5 A 2 4 1 S
9	97.78	3 E 5 A 2 4 1 S R

1 = PCA1 of TM 1-5 & 7.
2 = PCA2 of TM 1-5 & 7.
3 = PCA3 of TM 1-5 &7.
4 = PCA1 of TM 1,2&3. 5 = PCA1 of TM 5&7.

Table 3. Summary of feature selection for Principal Component Analysis with DEM and SAR

Number of variables	Av. Tr. Divergence	Band numbers .....
1	10.71	2
2	67.76	2 E
3	81.12	2 E 4
4	87.41	2 E 4 A
5	90.70	2 E 4 A 1
6	92.41	2 E 4 A 1 S
7	93.36	2 E 4 A 1 S 5
8	94.18	2 E 4 A 1 S 5 3
9	94.86	2 E 4 A 1 S 5 3 R

1 = TM1/TM4. 2 = TM1/TM5.
3 = TM3/TM2 4 = TM4/TM5.
5 = TM7/TM4.

S = Slope A = Aspect E = Elevation R = SAR

Table 4. Summary of feature selection for simple ratio with DEM and SAR.

Number of variables	Av.Tr. Divergence	Band numbers .....
1	9.67	1
2	63.68	1 E
3	75.72	1 E 6
4	82.82	1 E 6 A
5	87.16	1 E 6 A 4
6	89.92	1 E 6 A 4 3
7	91.76	1 E 6 A 4 3 S
8	93.10	1 E 6 A 4 3 S 5
9	95.65	1 E 6 A 4 3 S 5 2
10	96.15	1 E 6 A 4 3 S 5 2 R

1 = (TM2-TM3)/TM2+TM3) 2 = (TM3-TM1)/TM3+TM1)
3 = (TM3-TM5)/(TM3+TM5)
4 = (TM4-TM1)/(TM4+TM1) 5 = (TM4-TM5)/(TM4+TM5)

Table 5. Summary of feature selection for selection normalized difference ratio with DEM and SAR.

Number of variables	Av.Tr. Divergence	Band numbers .....
1	47.17	E
2	72.97	E 3
3	81.22	E 3 A
4	87.16	E 3 A 2
5	90.69	E 3 A 2 1
6	92.37	E 3 A 2 1 S
7	93.20	E 3 A 2 1 S R
8	93.93	E 3 A 2 1 S R 4

1 = Brightness 2 = Greenness
3 = Wetness 4 = Nonesuch

Table 6. Summary of feature for Tasselled Cap bands with DEM and SAR.

Maximum likelihood classification

The classification algorithm used was the supervised Gaussian maximum likelihood classifier. This classifier has been demonstrated to be extremely powerful and efficient in a great number of investigations for land cover classification from multispectral imagery (Tom and Miller 1984, Maselli *et al.* 1990). However, it is well recognized that there are drawbacks to the use of this algorithm, most notably the assumption that each cover class is modelled by unimodal probability distributions. When applied to highly heterogeneous surface, the extent of some cover classes tends to be overestimated with respect to that of other classes, so that the general utility of the entire process can be seriously decreased. In the use of this algorithm care was taken to ensure that classes with distinct multimodal probability distributions are subdivided into unimodal Gaussian spectral classes.

Results

From Table 1, the mean and standard deviation of each forest tree for every channel were tabulated and it can be concluded emprically that forest tree species that gave a high standard deviation value would not gave a good separation between forest clases. If these channels were used in the clIf these channels were used in the classification process would result in a lower classification accuracy. It is quite difficult to choose the best four channel for classification based on empricall formula and this task could be overcome by the divergence measure.

The forest class separability for the five sets of channels were analysed statistically through divergence measure and the results are shown in Table 2 to Table 6. From these tables it could be shown firstly a single band or channel would give an average transformed divergence measure of less than 10. As we increase the channel to two and above the average transformed divergence measure increased significantly to above 60. This indicates that more information could be obtained with two or more channels. Up to a point as one increases the number of channels, the average transformed divergence measure increases very slowly and this could be observed when more than five channels were used. Thus in this study the best four channels were used for classification which gave a transformed divergence measure of over 80.

The addition of SAR data in the five sets of channels as indicated in Table 2 to 6, all gave SAR a very low level of important. The irrelevant of filtered SAR data may be attributed firstly by the data quality, which was rescaled from 16-bit to an 8-bit dynamic range. Secondly the filtered process of speckle reduction, blurs the image which finds it difficult to select good training areas. The third factor may be due to the character of Seasat SAR wavelength of 23.5 cm which register the return signal from forest species during September when the data were recorded. In September most of the deciduous and coniferous trees begin to shed their leaves, thus the return signal from deciduous and coniferous trees were quite difficult to differentiate which creates a spectral overlap.

Terrain data (Elevation) plays an important part in the improvement of separability and

overall accuracy of forest tree species. Elevation data seems ion channel (after spectral data), selected by divergence criteria. This was due dominantly by the spatial distribution of forest classes on higher elevation above 100 metres.

Conclusion

On the basis of source data and the classifier used it is concluded that Seasat SAR do not make any significant contribution to the separability of forest trees, but terrain data improves the classification accuracy. The refinements in training and class selection would certainly have further boasted the accuracy of forest tree classification.

This study has establish a routine operational use of remote sensing, imaging radar and other ancillary data integration for the classification of forest trees and the results could be incorporated in a GIS. It recommends the used of new improved classifier and new generation of improved radar satellite data sources such as the European Earth Resources Satellite (ERS-1) or the Japanese Earth Resources Satellite (JERS-1).

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