An integrated methodology for mapping European forest ecosystems using satellite remote sensing

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ABSTRACT

This paper describes a methodology for mapping European forest ecosystems using satellite remote sensing. The methodology is being developed as part of the FIRS (Forest Information from Remote Sensing) Project, at the Institute for Remote Sensing Applications of the Joint Research Centre, Ispra. The main input data are Landsat Thematic Mapper (TM) images from different stages of the growing season. The multi-seasonal images are first corrected for the geometric and radiometric effects of varying topography, sun position and atmospheric conditions. The imagery is then classified, based on phenological variations in the forests' spectral characteristics. The methodology is implemented as an integrated software system (SILVICS).

1. INTRODUCTION

The main aim of the FIRS (Forest Information from Remote Sensing) Project, which is being coordinated at the Institute for Remote Sensing Applications (IRSA) of the European Commission's Joint Research Centre (JRC), Ispra, is to develop operational GIS and satellite remote sensing methodologies for mapping and monitoring forest ecosystems on a European scale (Kennedy *et al.*, 1994). The information resulting from the FIRS Project will be used as input to the Commission's pan-European forest information system, EFICS (European Forestry Information and Communication System).

Satellite remote sensing has previously been used to map forests on a European scale. In the CORINE Land Cover Project (EEA Task Force, 1992), for example, maps at a scale of 1:100,000 showing 44 land cover types, including three forest classes (broadleaved, coniferous and mixed), were produced for the European Union (EU) countries, including the Mediterranean region, based on computer-assisted visual interpretation of Landsat Thematic Mapper (TM) images. These maps are of limited use from a forester's point of view because they provide no detailed information on forest types, such as species composition, age classes or growth rates.

A map at a scale of 1:6,000,000, showing the distribution of forest (one class) in the European Continent, was produced using computer classification of NOAA-AVHRR (Advanced Very High Resolution Radiometer) satellite imagery (ESA, 1993). Because of the low spatial resolution (1 x 1 kilometres) of the AVHRR sensor, this map only shows areas with continuous forest blocks covering hundreds of hectares. Such areas are limited to the most densely afforested parts of Europe – the Boreal region, for example. Regions where forests are a significant land use but occur in smaller blocks, appear from the map to be relatively devoid of forest cover.

Hill (1993) described a study which was carried out in the Mediterranean region of France, in which Landsat TM images from four different dates were geometrically and radiometrically corrected, and classified into ten land cover types, including vineyards, orchards and three forest classes. For the same study site, spectral mixture analysis of high spectral resolution AVIRIS (Airborne Visible and Infrared Spectrometer) images has been used to map land degradation and soil erosion (Hill *et al.*, 1994).

In this paper, several aspects of using multi-seasonal Landsat TM imagery for forest mapping are illustrated. The examples used are from a forest site in central Ireland. Some essential pre-processing steps – i.e. geometric and radiometric corrections for the effects of topography, sun position and atmospheric conditions – are outlined. A supervised multitemporal classification of the test site into fourteen forest species is described. Finally, an integrated system for mapping European forest ecosystems using multi-seasonal satellite images is presented and discussed.

2. TEST SITE AND DATA

The test site used for this study is the Slieve Bloom Mountains region in central Ireland. Maximum site elevation is just over 500 metres. Forestry is the dominant land use, with the fast-growing conifers Sitka spruce *(Picea sitchensis)* and Lodgepole pine *(Pinus contorta)* being the main species. The entire region is officially classified as a Less Favoured Area within the EU.

In order to examine the seasonal dynamics of a forest canopy's spectral properties, it is necessary to use imagery acquired during the growing season. For the purposes of this study, four Landsat TM images of the test site from mid-spring (18 April 1985), early summer (13 June 1988), late summer (7 August 1988) and mid-autumn (19 September 1986) were selected.

Ancillary data used in the analysis and interpretation of the test site imagery include digitized ground inventory records for all of the forests in the area, and a digital terrain model (DTM) at 20 metres contour intervals.

3. EFFECTS OF TOPOGRAPHY ON IMAGE GEOMETRY

The effects of topography on image geometry are illustrated in **Figure 1**. As can be seen, point P on the terrain surface has a geodetic (true) position P2, but because of the scanning angle (perspective) of the sensor and the terrain elevation, its position in the image is displaced along the scan line by amount DISP to P1. Perspective displacements are most severe at the edge of a Landsat scene, where the scanning angle is greatest.

The following formula was used to compute the scan-line perspective displacements for the Landsat TM images of the study site:

$$\text{DISP (in metres)} = H_{pix} * (D_{nad} / H_{sat})$$

where DISP is the perspective displacement of each pixel from its true position along the scan-line, H_{pix} is the pixel's elevation (from the DTM) at its geodetic position, D_{nad} is the distance of the pixel from the satellite nadir, and H_{sat} is the orbiting altitude of the satellite (see **Figure 1**).

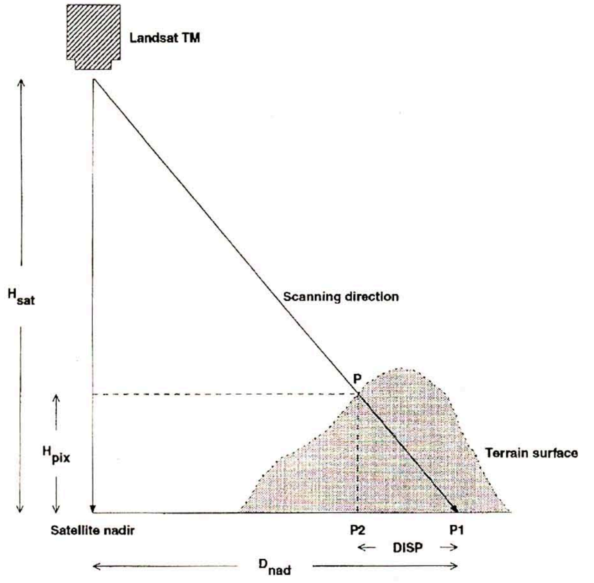

Figure 1 - Scan-line perspective displacements in Landsat TM imagery

In order to correct for the effects of scan-line perspective displacements, the above formula was applied at two stages of the georeferencing procedure – i.e. to each of the ground control points (GCPs), and to each image pixel during image resampling. The x-coordinate of each GCP and image pixel was adjusted by the computed displacement.

4. EFFECTS OF TOPOGRAPHY ON IMAGE RADIOMETRY

The spectral characteristics of a forest canopy, as measured by Landsat TM, vary according to the illumination conditions at the time of imaging. Illumination represents the proportion of direct solar radiation reaching a pixel. It is determined by the sun elevation and sun azimuth angles, and by terrain slope and aspect in mountainous regions.

The effects of topography and sun position on the illumination of multi-seasonal satellite images are illustrated in **Figure 2**. In **Figure 2**, two 5 x 5 kilometre Landsat TM images of the test site from 13 June 1988 (top left) and 19 September 1986 (bottom left) are presented beside the corresponding relief images. The relief images show the relative amounts of light (illumination) received by each pixel, and were computed from the DTM based on the sun elevation and azimuth angles for each imaging date. The Landsat TM images of the test site were all acquired at the same time of day (approximately 11.00am). However, the relief image for September is darker and has more shadow, due to the lower sun elevation angle at this time of year.

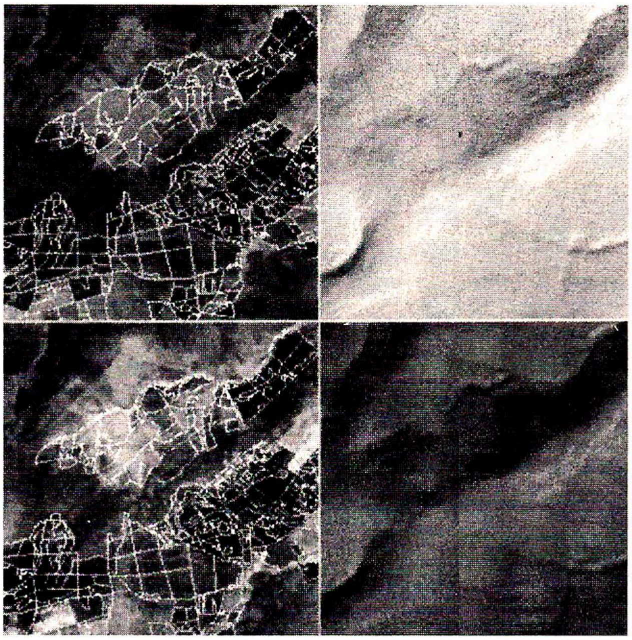

Figure 2 - Left: Landsat TM images with ground inventory boundaries. Right: relief images

Many methods exist for correcting (or normalizing) satellite imagery for the radiometric effects of topography. Four methods of slope-aspect correction are evaluated by Itten *et al.* (1992). All require computation of the sun incident angle for each pixel, and differ according to whether or not actual image statistics are used for calibration, whether or not surfaces are regarded as lambertian, and whether or not account is taken of diffuse (scattered) light.

The method of topographic normalization which was used in this study is based on the following formula (from Itten *et al.*, 1992):

$$L_H = L_S * (\text{cosine (SZ)} / \text{cosine (I)})^{K}$$

where L_H and L_S are the radiance observed for horizontal and sloped surfaces, respectively, SZ is the solar zenith angle, I is the sun's angle of incidence relative to the normal of a sloped pixel, and K is the Minnaert Constant, which can be approximated as:

$$K = \log (\text{cosine (SZ)} / \text{cosine (I)})$$

In order to evaluate this method of topographic normalization, eight forest stands were selected from the most topographically variable areas of the test site. The effects of the topographic normalization of the September 1986 Landsat TM image on the spectral signatures of these stands are presented in **Table 1**. In **Table 1**, a decrease in signature variance following topographic normalization is indicated by a relative efficiency value less than one. Decreased signature variance should improve the results of subsequent image classifications.

From **Table 1** it can be seen that, in all except the visible blue channel (TM 1), there has been a general decrease in signature variance following topographic normalization (although in some cases the decrease is slight or nonexistent).

Table I - Effects of topographic normalization on spectral signatures of forest stands

			Ratios of signature variance after topographic normalization to that before, for Landsat TM channels					
Forest stand	**Area (hectares**	**1st species / planting year**	**TM 1**	**TM 2**	**TM 3**	**TM 4**	**TM 5**	**TM 7**
1	8.9	Sitka spruce / 1968	**9.09**	**1.37**	**1.14**	**0.75**	**0.88**	**0.96**
2	28.5	Sitka spruce / 1974	**1.33**	**0.96**	**0.99**	**0.83**	**1.00**	**1.01**
3	13.6	Sitka spruce / 1964	**3.57**	**0.79**	**1.11**	**0.85**	**1.00**	**1.03**
4	6.1	Sitka spruce / 1968	**4.55**	**0.79**	**0.81**	**0.73**	**0.82**	**0.96**
5	11.2	Sitka spruce / 1964	**1.08**	**0.97**	**1.00**	**1.00**	**1.00**	**1.00**
6	7.7	Sitka spruce / 1964	**2.86**	**0.89**	**0.93**	**0.74**	**0.92**	**1.02**
7	7.2	Sitka spruce / 1971	**4.76**	**0.90**	**1.00**	**0.64**	**0.83**	**0.94**
8	16.4	Sitka spruce / 1973	**1.37**	**0.92**	**0.97**	**0.85**	**0.94**	**1.00**

It is also clear from Table 1 that there has been a significant increase in signature variance in the visible blue channel. This is because of the high proportion of diffuse radiation, caused by scattering, in this channel. Since the normalization algorithm which was used assumes that all radiation is direct, the result has been a massive over-correction of the radiation signal in the visible blue channel, as evidenced by the increased variance.

5. EFFECTS OF ATMOSPHERE ON IMAGE RADIOMETRY

Solar radiation is strongly affected by the atmosphere as it travels from the sun to target (i.e. the land surface) and, following reflection, from target to satellite sensor. By the time it reaches the sensor, the radiation has been attenuated (weakened) by (a) scattering, whereby radiation is deflected by molecules and haze particles in the atmosphere, and (b) absorption, whereby radiation energy is absorbed by the atmosphere's constituent gases. The level of atmospheric interference depends largely on the degree of scattering of the signal, which is determined by the amount of haze (aerosol) present.

By correcting for atmospheric interference, changes in the measured spectral reflectance of cover types between imaging dates will represent real changes, rather than resulting from the different amospheric conditions. Knowledge of the actual atmospheric conditions at the time of imaging is usually difficult or impossible to acquire, and so the atmospherc parameters must be estimated empirically by atmospheric modelling.

The ATCOR model (Richter, 1991) was used for atmospherically correcting the Landsat TM images of the test site. The main atmospheric parameter determined by ATCOR is aerosol optical depth, which can be related to ground visibility. Once the ground visibility has been estimated, the raw (uncorrected) satellite image is converted to a reflectance image, in which pixel values represent actual ground reflectances without atmospheric effects.

The effects of atmospheric correction on the spectral-phenological profiles (SPPs) of three forest species in the test site are illustrated in **Figure 3**. An SPP is a temporal profile in which major spectral indicators, such as Normalized Difference Vegetation Index (NDVI) and the Tasseled Cap transforms – Brightness (TCB), Greenness (TCG) and Wetness (TCW) – are plotted against phenophase. In **Figure 3**, solid lines indicate raw data (i.e. SPPs before atmospheric correction) and dashed lines indicate reflectance data (i.e. SPPs after atmospheric correction).

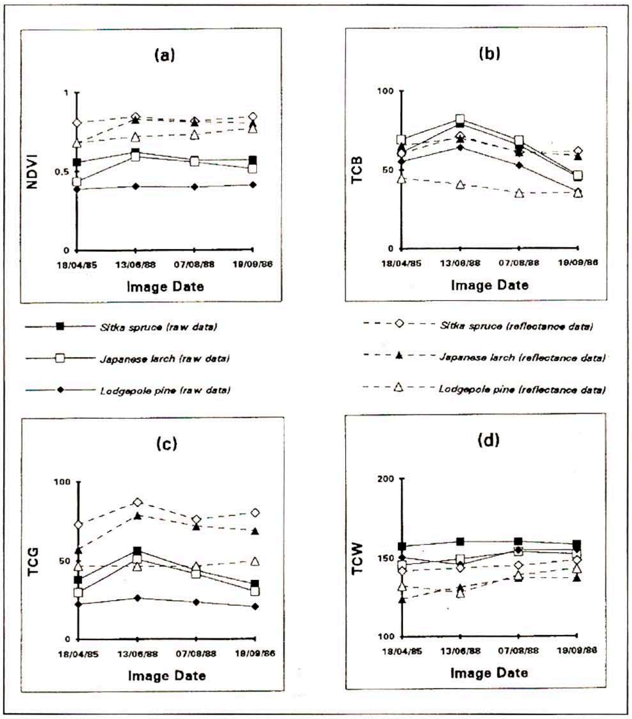

Figure 3 - Effects of atmospheric correction on spectral-phenological profiles of forest species

The major impact of atmospheric correction on the SPP data is to be expected for the three Tasseled Cap transforms, but is worthy of comment in the case of NDVI, a widely used spectral indicator for vegetation biomass and productivity. It is often suggested that because sums and differences are used in computing NDVI, rather than absolute values, this index is relatively unaffected by atmospheric interference. In reality, however, NDVI reflects the contrast between near-infrared and visible red radiation, and the latter is more affected by atmospheric interference (and therefore by atmospheric correction) than the former, as indicated by **Figure 3(a)**.

6. FOREST CLASSIFICATION USING MULTI-SEASONAL LANDSAT TM IMAGES

The level of discrimination between forest types which can be achieved using single-date multispectral satellite data, such as Landsat TM imagery, is generally quite low. As a result, many land cover surveys using satellite remote sensing limit themselves to a small number of forest classes – three, for example, in the case of the CORINE Land Cover Project, as described earlier. This low level of discrimination is due to a combination of the limited spectral resolution of current satellite sensors, and the intrinsically small variations that exist between different forest types' spectral characteristics.

Multitemporal classification of satellite image data has been widely and successfully used to map important changes in land cover, including forests, between imaging dates. Multitemporal classification can also be used to improve the level of discrimination between forest types. The reason for this is that classification of multitemporal images exploits the varying seasonal dynamics (phenology) of different forest canopies.

SPPs such as those in **Figure 3** can be used by image classifiers to maximize discrimination between spectrally similar species which are difficult to separate at any one phenophase. It can be seen from **Figure 3(a)**, for example, that whereas Japanese larch (a deciduous conifer) and Sitka spruce are virtually indistinguishable from each other for most of the growing season, their NDVIs are very different in mid-spring (18-04-1985), when the larch foliage is new.

The results of the supervised (maximum likelihood) multitemporal classification of the Landsat TM images of the test site, following geometric and radiometric correction, are presented in **Table 2**. In **Table 2**, fourteen forest stands as defined in the ground inventory records are listed across the top, while the corresponding forest types as predicted by the image classifier are listed vertically on the left hand side. (Note that the column percentages in Table 2 do not necessarily sum to 100, because some pixels were assigned to a null class).

It can be seen from **Table 2** that 92.9 % of the Lodgepole pine stand, for example, was correctly classified, while 2.1 % was erroneously classified as an intimate mixture of Lodgepole pine and Sitka spruce. As can be seen, the overall classification accuracy (i.e. the average accuacy as weighted by the number of pixels in each of the fourteen forest stands) was 78.5 %.

Table 2 - Results of the supervised multitemporal classification of Landsat TM imagery

GROUND INVENTORY DATA

MULTITEMPORAL IMAGE CLASSIFICATION

	S spruce	L pine	N spruce	D fir	J larch	S pine	L pine / S spruce	N spruce / S pine	Beech	Oak / Beech	Oak / Ash	N spruce / Oak	E larch / Beech	N spruce / Beech
S spruce	78.9	0.4	12.4	1.0	0.0	5.8	0.9	0.0	6.1	0.0	0.0	1.4	0.0	7.8
L pine	4.4	92.9	0.0	0.0	0.0	0.0	4.3	0.0	0.0	0.0	0.0	0.3	0.0	0.0
N spruce	3.8	0.0	67.5	2.1	0.0	2.9	0.0	0.0	0.0	0.0	0.0	5.8	0.0	19.8
D fir	0.0	0.0	0.0	67.0	0.0	0.0	0.9	8.0	2.0	0.0	0.0	0.0	0.0	0.9
J larch	0.3	0.0	0.0	0.0	97.4	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0
S pine	1.3	0.4	0.0	2.1	0.0	85.5	11.3	4.0	0.0	0.0	0.0	1.0	0.0	0.0
L pine / S spruce	1.9	2.1	1.3	0.0	0.0	2.9	78.3	1.5	0.0	0.0	0.0	0.0	0.0	0.0
N spruce / S pine	0.9	0.4	1.3	22.7	1.3	0.0	0.0	74.9	0.0	1.5	0.0	1.0	3.5	6.0
Beech	3.8	0.4	1.7	1.0	1.3	1.4	2.6	0.0	77.6	0.0	0.0	6.5	7.0	0.9
Oak / Beech	0.0	0.4	0.0	1.0	0.0	0.0	0.0	5.0	0.0	88.1	2.7	3.1	3.5	0.0
Oak / Ash	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	2.0	3.0	96.4	0.0	0.0	0.0
N spruce / Oak	0.3	0.4	4.7	1.0	0.0	0.0	0.0	0.0	2.0	1.5	0.0	76.4	0.0	20.7
E larch / Beech	0.0	0.4	0.0	1.0	0.0	0.0	0.0	4.0	2.0	2.2	0.0	0.7	84.9	0.0
N spruce / Beech	4.4	0.0	11.1	1.0	0.0	1.4	0.0	0.0	6.1	0.0	0.0	3.8	0.0	41.4

Average accuracy: 79.1 % Overal accuracy: 78.5 %

7. CONCLUSIONS

In this paper the geometric and radiometric correction of multi-seasonal Landsat TM images for the effects of varying sun position, topography and atmospheric conditions has been described. The use of multitemporal image classification to increase the level of discrimination between forest types has been illustrated.

A methodology for mapping European forest ecosystems using multi-seasonal satellite images is being developed at IRSA, as part of the FIRS Project. The methodology is implemented as SILVICS (Satellite Image Land Vegetation Integrated Classification System), an integrated, in-house software system at IRSA. Included in SILVICS are routines for pre-processing and classifying multi-seasonal satellite imagery, using the methods illustrated earlier.

Input into SILVICS, which is currently at a developmental stage, are multi-seasonal Landsat TM images. The images are corrected geometrically and radiometrically. Tasseled Cap, NDVI and other transforms are applied. Classification schemes appropriate for the forest ecosystem regions are used. Forest types of interest are selected using a European forest nomenclature system. Two related studies which have been carried out as part of the FIRS Project concern: (a) the regionalization and stratification of European forest ecosystems; (b) the design of a European system of forest nomenclature suitable for use in satellite remote sensing surveys.

Finally, a methodology such as that outlined in this paper would be suitable for mapping European forest ecosystems at regional scales. The examples used here were from an Irish test site. Prior to its extension to other areas, the methodology should be adapted for a wider range of European forest environments. In Mediterranean areas, for example, classification of images using spectral mixture analysis techniques may be appropriate, because of the extremely heterogeneous landscapes which are typical of this region.

REFERENCES

EEA Task Force, 1992, CORINE Land Cover. Brochure prepared as contribution to European Conference of International Space Year. Munich (30 March – 4 April 1992). 22 p.

ESA, 1993, Remote Sensing Forest Map of Europe. Brochure accompanying map, prepared as ESA contribution to World Forest Watch (WFW) Project of International Space Year 1992. 18 p.

Hill J., 1993, High Precision Land Cover Mapping and Inventory with Multitemporal Earth Observation Satellite Data: the Ardeche Experiment. PhD dissertation. University of Trier, Germany. 114 p.

Hill J., Mehl W. & Altherr M., 1994, Land degradation and soil erosion mapping in a Mediterranean ecosystem. In: Imaging Spectrometry – a Tool for Environmental Observations. J. Hill and J. Megier (editors). Kluwer Academic Publishers. Eurocourses: Remote Sensing (Volume 4), pp. 237-260.

Itten K.I., Meyer P., Kellenberger T., Leu R., Sandmeier St., Bitter P. & Seidel K., 1992, Correction of the impact of topography and atmosphere on Landsat TM forest mapping of Alpine regions. Remote Sensing Series, 18. Department of Geography, University of Zurich, Switzerland. 50 p.

Kennedy P., McCormick N. & Folving S., 1994, European forest ecosystems mapping and forest statistics: the FIRS Project. In: Proceedings of International Workshop on Designing a System of Nomenclature for European Forest Mapping. Joensuu, Finland (13-15 June 1994). European Commission, Report EUR 16113 EN, pp. 33-48.

Richter R., 1991, Atmospheric Correction of Landsat TM, MSS and SPOT Images: ATCOR User Manual. DLR, German Aerospace Research Establishment, Institute for Optoelectronics, Wessling, Germany. 35 p.