Remote sensing of growth dynamics of Sitka spruce plantation forests in upland Britain

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Abstract:
Monitoring growth patterns over large forest estates using field survey methods is a time-consuming and costly exercise. This study paper evaluates remotely sensed data to help monitor changes in Sitka spruce (Picea sitchensis) plantations in Britain using satellite and airborne laser scanning imagery. The results demonstrate that low-cost satellite image data from the Landsat Enhanced Thematic Mapper (ETM+) sensor can be used to predict and map forest height and basal area characteristics with a good level of accuracy for young crops. Regression analysis of contemporaneous remote sensing data and ground based forest structural measurements is used to predict height and basal area. These models can be applied to any radiometrically normalised image of the same area to give a quantitative description of observed growth in young crops between successive images. This helps to identify and quantify areas of anomalous growth. High resolution airborne laser scanner imagery gives excellent estimation of forest characteristics but is very expensive. These data can, however, be used both to complement field measurements to improve predictions from Landsat data and to assess their quality. We conclude that retrieval of forest structure information is best achieved by the integration of satellite, airborne and ground-based measurements.

Introduction

The ability to monitor change in woodland at regular intervals and in a cost-effective manner is becoming increasingly important for forest planners and environmental managers. Many studies have tried to quantify change in forest area, such as mapping the extent of clear-cutting, a few have tried to identify change on the basis of forest or ecological type, but very few have tried to relate change to a forest structural attribute. We describe a methodology for making rapid and low-cost assessment of Sitka spruce plantations which could be used to assist foresters check that plantations have established successfully and that growers have complied with the levels of stocking required by woodland grant schemes. Quantitative change models could also provide scientists and environmental managers with a wealth of with statistical data on forest structure that would otherwise be expensive and difficult to obtain.

Several scientific publications discuss the problems associated with deriving accurate information from multi-temporal remote sensed data (e.g. Hall et al. 1991, Olsson 1995). Examples of unwanted effects that may impact upon any change analysis include atmospheric effects, differences in illumination and observation angles, and drift in sensor radiometric quality over time. Furthermore, many of the image processing techniques used for change analysis assume that data is acquired by the same sensor, otherwise inter-sensor calibration issues must also be taken into account. Change analysis normally follows one of three paths, (1) data are corrected to physical units and atmospheric effects are removed, (2) data are radiometrically normalised to a relative radiometric scale using reference targets in an image whose reflectance is constant through time, and (3) classification of image into discrete land cover elements (say) which are then compared.

Correction of data to absolute physical units (1) is usually difficult to achieve except with active sensors such as Light Detection And Ranging (LiDAR) and interferometric Synthetic Aperture Radar (SAR) systems. With passive optical sensors it is difficult to collect data on atmospheric scattering and attenuation to allow absolute retrieval of surface reflectance. Image classification uses statistical information unique to each image to segment the data into discrete classes. Apart from problems of cloud or haze obscuring parts of an image, atmospheric or radiometric correction is not required for change analysis using classified images. However, the level of detail that can be extracted from a set of discrete classes is often very limited. Change analysis based or radiometrically normalised imaged (2) appears attractive because it does not require sensor calibration or atmospheric correction. The difficulty with this approach is the subjectivity with which spectrally invariant targets are identified in multi-temporal images of the same area (Du et al. 2004).

While active systems such as LiDAR which make precise physical measurements offer considerable potential for forest change monitoring (Lefsky et al. 1999, Nilsson 1996), these are often impractical in terms of cost for large area survey. Furthermore, even these systems need to be validated against accurate ground based observations of forestry
applications and they are expensive to acquire compared with optical satellite imagery. In this study we try to get the best of both worlds by evaluating radiometrically normalised low-cost satellite image data from the Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) sensors with high-cost (and high quality) airborne LiDAR data and measurements from ground based sample plots.

The objective of this study is to evaluate the quality of quantitative maps of forest change using low-cost satellite image data. The method uses high quality ground based measurements of forest structure to predict height and basal area from the reflectance characteristics of shortwave infrared (SWIR) Landsat image data. Regression models are inverted to give predictions which are independently validated using tree height data derived from airborne LiDAR. A time-series of satellite images are radiometrically normalised using spectrally invariant targets. Statistical models are then applied to each of the radiometrically normalised Landsat images to give a time-series of height predictions on a per-pixel and per-compartment basis.

Study Area
The forest stands used in this study are located in Kielder Forest District, northern England and form part of the forest estate managed by the UK Forestry Commission. In these areas Sitka spruce is the dominant crop and in the Atlantic maritime climate of the UK it is a fast growing tree that is tolerant of acid and waterlogged soils. The topography consists of low undulating hills with an altitude range of 210 to 390 metres. Planting occurs on land with a mean altitude of 290 metres and a mean slope angle of 5.5°. The initial density of the plantation usually exceeds 2,500 trees per hectare (a spacing of 2 x 2 metres between trees and rows). These plantations are almost never thinned and so closure of the forest canopy normally occurs between 14 and 20 years after planting.

Data
Landsat 5 TM and Landsat 7 ETM+ sensor data were used in this study because these sensors have short wave infrared (SWIR) spectral bands that correlate well with forest structural variables. The satellite data used is summarised in Table 1. The LiDAR data used in this study was acquired by the UK Environment Agency using an Optech ALTM sensor with a 1047 - 1210 nm laser pulse. Part of Kielder forest was flown on 28th March 2003 at a resolution of approximately 2 points per m². Ground survey plots were selected from an analysis of the Forest Commission’s sub-compartment database that contains information on species, planting date, soil type and expected yield among other variables. All data have been geo-referenced and integrated into a GIS (Geographic Information System). Ground survey plot and individual tree locations were determined using a Leica Series 300 differential GPS.

Methodology
The LiDAR imagery is geometrically corrected as part of the post-processing procedure using differential GPS data. The geometric correction of the Landsat used 59 ground control points to project the image to the British National Grid using an affine transformation. The Root Mean Square Error was 0.86 pixels (approx. 24 m) for the Landsat ETM+. Previous studies using satellite imagery have shown that the Landsat TM and ETM+ sensor data acquired under good atmospheric conditions is of sufficiently high quality to differentiate forest stands of varying species, volume or health characteristics (Ardo 1992; Danson and Curran 1993; Dewulf et al. 1990; Puhr and Donoghue 2000). The raw digital image data used were Landsat TM level 1B and Landsat ETM+ Level 1R. This means that each channel in the multi-spectral imagery is calibrated into the same relative radiance units. However, the data has not been reduced to actual ground leaving radiance and no attempt has been made to correct for atmospheric attenuation of signal. However, analysis and interpretation of spectral change through time does require that the data are radiometrically normalised.

Comparison of spectral response can be achieved by applying a linear radiometric normalisation function to a set of multi-temporal images. Using this technique, imagery acquired under different illumination conditions are normalised to a baseline image and quantitative data are converted into the same relative reflectance/radiance units (Hall et al. 1991, Heo and FitzHugh 2000). Factors that should be held constant (or quantified) between image data sets include sensor radiometry, topography, and interaction of radiation with ground surface (non-Lambertian reflectance). Factors that are corrected by the transformation are radiation differences due to small changes in solar zenith and azimuth angles and multiplicative atmospheric attenuation.

The Landsat data were normalised using the method described by Hall et al. (1991). This technique uses relative rather than absolute radiometric adjustment by making the assumption that pixels with the same reflectance properties should have the same DN values. This implies that the only change in the spectral signature of these pixels between two
different image dates is due to linear differences in atmospheric, solar irradiance and radiometric conditions. Normalising the images will account for these differences using parameters determined empirically from bright and dark target pixels that are assumed to be spectrally invariant over time. The transformed data appear as if they have been imaged under the same atmospheric and irradiance conditions. Figure 1 shows the radiometric relationship between the 3 Landsat scenes studied. The 2002 scene is used as the reference for normalisation and the graph shows that the regression based on the spectrally invariant targets for the 2000 and 2003 scenes match well to the ideal of a \( y = x \) relationship. In theory, this technique is not absolutely robust since atmospheric scattering can have additive as well as multiplicative effects. However, the results show that atmospheric attenuation through additive (offset from \( y = x \)) or multiplicative (change in gradient) effects do not significantly affect these data. This normalisation method can be applied to any data set in an image time series where spectral bands overlap and so SPOT 4/5 or IRS LISS 3 data could be used in any future change analysis using the same procedure.

The second stage involved locating and recording forest structure information from field sample plots and relating these data to corresponding reflectance values from the Landsat images. The Forestry Commission’s database was used to identify suitable forest compartments. The compartments selected were regular in shape, contained a minimum of 80 Landsat pixels, and appeared homogenous on the aerial photographs and satellite imagery. Thirteen compartments were selected for quantitative measurement. In each of the selected compartments a minimum of two 200m² sample plots were established. A summary of the ground reference data measurements is presented in Table 2. The mean DN number of a 3x3 window around the plot location was recorded for each stand in each reflective TM band following the methodology of Puhr and Donoghue (2000) to reduce potential errors associated with identifying the exact location of the pixel on the image. As well as recording structural forest parameters, the type and proportion of understorey vegetation present in the sample plot was also noted. This information was used as a measure of the degree of forest canopy closure. Tree height was determined from the LiDAR data by subtracting the elevation information from the first and last laser pulses. Using TerraScan software laser pulses are classified into above ground and ground surface points. Tree height is determined by subtracting points classified as canopy-top from the derived ground surface model.

**Modelling**

The sample plots were used to determine the relationship between forest structural variables and reflectance. Two observations were excluded from the dataset as they contained high levels of natural regeneration and appeared as outliers that weaken the predictive ability of the model. Single and multiple band regression models were tested, with simpler single band models preferred over the more complex models for two reasons. First, the amount of variation explained by the addition of other bands did not improve the fit of the models to the ground survey data as summarised by the \( R^2 \) values. Secondly, a simple model based on a single SWIR band yields a simple model that can be understood in a physical sense and can easily be transferred to other locations. Inspection of the scatter plots for Landsat TM and ETM+ SWIR data suggests that the relationship between reflectance and forest variables is non-linear. A number of non-linear regression models were applied to the data, and a model of the type selected below best describing the relationship:

\[
y = ax^b
\]

Where \( y \) is mean tree height, \( x \) is the Landsat band 7 normalised DN value and \( a \) and \( b \) are empirically derived constants.

\[
\text{Mean height} = 15709 \times \text{ETM7}^{-2.57} \tag{2}
\]

The relationship between mean sample plot height and the LiDAR is linear (equation 3) and so a conventional least squares linear regression model is appropriate.

\[
\text{Mean height} = 0.93 \times \text{LiDAR} + 0.95 \tag{3}
\]

**Results**

The regressions between ground reference data, Landsat and airborne LiDAR data are summarised in Table 3. Height is strongly related to radiance in all Landsat 7 ETM+ bands with the exception of the near infrared band. The relationship between stand diameter and radiance is negative and relatively weak. Landsat ETM+ band 3 (\( R^2 = 0.57 \)) gave the highest \( R^2 \) values. These \( R^2 \) values indicate that stand diameter cannot be predicted with any certainty using models constructed from Landsat data. The relationship between basal area and radiance is strong. The band with the highest \( R^2 \)
value is Landsat ETM+ band 3 ($R^2 = 0.76$). The sharpest decrease in radiance level occurs with basal areas of 20 m$^2$/ha or more. There is no observed relationship between tree density and the Landsat data. Height shows the strongest relationship with satellite radiance data in the shortwave infrared ($R^2 = 0.80$), see Figure 2. This band will also be affected less by additive atmospheric scattering than the other Landsat bands and so it was used to predict tree height. Since historical Landsat data have been radiometrically normalised it is possible to apply the prediction retroactively and so produce a height change image.

The LiDAR height model is very strongly related ($R^2 = 0.98$) to mean height within the sample plot, and not surprisingly, is also correlated with diameter, basal area and age. Figure 3 shows the LiDAR height plotted against mean sample plot height values. Having derived a prediction of height from Landsat data it is interesting to compare this with the LiDAR height model data since we know that the LiDAR agrees very well with ground measurements. The $y = x$ relationship between these data is strong ($R^2 = 0.68$, see Figure 4), but as expected a little weaker that the $y = ax^3$ power function relationship with the ground sample data ($R^2 = 0.80$).

The results appear to suggest that satellite data can provide robust mechanism for estimating and monitoring the height of Sitka spruce stands especially during the phase of growth leading up to canopy closure. Figure 5 shows an example forest change image produced by combining height prediction data from three separate Landsat images 2000-2003. The dark shades represent areas of low height prediction that in this picture is non-forested land. The brighter grey shades represent areas that have reached canopy closure in 2000 and canopy reflectance has changed very little over that period. On the other hand, strongly coloured areas, such as the red and yellow shaded stands have seen significant change from one period of image acquisition to the next. While a qualitative image of change could be produced from the raw Landsat data, the advantage of using height prediction models to generate the composite is that it can be queried directly to obtain quantitative predictions meaningful to foresters. Despite the relatively low spatial resolution of the Landsat imagery the level of detail is sufficient to identify areas of anomalous behaviour quite easily. Obvious examples of applications include the monitoring of wind damage following severe storm events where it may be difficult and expensive to assess the degree of damage over very wide areas using airborne survey. Another obvious application areas is the monitoring of compliance with the conditions attached to woodland grant schemes where funding is given to plant crops to agreed areas and levels of stocking density. The use of satellite data would allow a regulator to make a preliminary assessment of every grant scheme area by overlaying the digital boundary data on a height change image. At present such schemes are only monitored by field visits to a random sample. The use of image data would allow field survey to be targeted primarily at sites that appeared anomalous. Where forest management data are held in a GIS, the satellite predictions of variables such as average stand height can be compared with expected growth rates by overlaying the satellite predictions with GIS or web mapping software.

From a forest management perspective a rapid method of identifying anomalous growth in newly established plantations is useful for targeting limited field resources. By combining LiDAR survey with satellite observation it is clear that the need for accurate ground measurements, which are expensive to obtain, could be substantially reduced and it would be possible to generate an empirical prediction of height based largely on carefully targeted LiDAR survey.

Conclusions

Landsat TM and ETM+ imagery can be used to generate accurate predictions of stand height during the period of up to canopy closure (approx age 14-20 years) of Sitka spruce in the UK. The results suggest that LiDAR may be used in place of field measurements to help drive stock assessment models over very large areas of forest at a very low cost. We conclude that retrieval of forest structure information is best achieved by the integration of satellite, airborne and ground-based measurements. Through such integration of data into a GIS, foresters have a powerful tool which is capable of providing a rapid overview of a large forest estate. The satellite data provides both a pictorial view of the forest and quantitative information that can be easily compared with conventional stand level forest inventory data using web based mapping tools.

Acknowledgements

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Project website: http://www.geography.dur.ac.uk/ForestSAFE

References


Heo, J. and FitzHugh, T.W., 2000, A Standardized Radiometric Normalization Method for Change Detection Using Remotely Sensed Imagery, Photogrammetric Engineering and Remote Sensing,


Table 1. Summary of imagery used

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Date</th>
<th>Resolution (m)</th>
<th>Quality</th>
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<tr>
<td>Landsat TM</td>
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<td>30</td>
<td>Cloud-free</td>
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<tr>
<td>Landsat ETM+</td>
<td>02/9/2002</td>
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<td>Cloud-free</td>
</tr>
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<td>Landsat ETM+</td>
<td>01/3/2003</td>
<td>30</td>
<td>Cloud</td>
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<tr>
<td>LiDAR</td>
<td>28/03/2003</td>
<td>Density 2 hits/m²</td>
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</table>

Table 2. Summary of plot reference data

<table>
<thead>
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<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
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<tr>
<td>Age (years)</td>
<td>33</td>
<td>18.8</td>
<td>8</td>
<td>59</td>
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<td>Density (trees ha⁻¹)</td>
<td>2,732</td>
<td>2,614</td>
<td>1,150</td>
<td>12,300</td>
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<td>Basal area (m² ha⁻¹)</td>
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<td>17.4</td>
<td>4.5</td>
<td>69.4</td>
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<td>Height (m)</td>
<td>11.1</td>
<td>6.7</td>
<td>1.5</td>
<td>22.3</td>
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<tr>
<td>Diameter (cm)</td>
<td>17.1</td>
<td>5.1</td>
<td>4.3</td>
<td>23.8</td>
</tr>
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</table>

SD* = Standard deviation

Table 3. Summary of models used to estimate forest parameters from satellite and LiDAR

<table>
<thead>
<tr>
<th>Sensor/ band</th>
<th>Height</th>
<th>Diameter</th>
<th>Basal Area</th>
<th>Age</th>
<th>Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>LANDSAT ETM+ (02/09/2002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Band 1 Blue</td>
<td>0.67</td>
<td>0.15</td>
<td>0.28</td>
<td>0.79</td>
<td>0.16</td>
</tr>
<tr>
<td>Band 2 Green</td>
<td>0.84</td>
<td>0.49</td>
<td>0.64</td>
<td>0.87</td>
<td>0.26</td>
</tr>
<tr>
<td>Band 3 Red</td>
<td>0.86</td>
<td>0.57</td>
<td>0.76</td>
<td>0.89</td>
<td>0.25</td>
</tr>
<tr>
<td>Band 4 NIR</td>
<td>0.60</td>
<td>0.18</td>
<td>0.23</td>
<td>0.78</td>
<td>0.24</td>
</tr>
<tr>
<td>Band 5 SWIR</td>
<td>0.80</td>
<td>0.39</td>
<td>0.52</td>
<td>0.83</td>
<td>0.28</td>
</tr>
<tr>
<td>Band 7 SWIR</td>
<td>0.80</td>
<td>0.49</td>
<td>0.57</td>
<td>0.83</td>
<td>0.31</td>
</tr>
<tr>
<td>LiDAR (28/03/2003)</td>
<td>0.98</td>
<td>0.53</td>
<td>0.60</td>
<td>0.80</td>
<td>0.49</td>
</tr>
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</table>

Coefficient of determination ($R^2$)

$R^2$ values in italics denote $P$ values (>0.05) all remaining $P$ values (<0.05)
Figure 1: Radiometric relationship for Landsat Band 7 (dashed line represents y=x)

Figure 2: Mean height predicted from Landsat Band 7 showing presence (+) or absence (-) of understorey vegetation.

Figure 3: Mean height predicted from LiDAR data

R² = 0.983
RMSE = 0.833 m

Figure 4: Comparison of LiDAR and Landsat height models

R² = 0.797
RMSE = 0.323 m
Figure 5. Composite image using Landsat height model for 2000 (blue), 2002 (green), 2003 (red).