MONITORING FOREST GROWTH USING LONG TIME SERIES OF SATELLITE DATA

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ABSTRACT

Forest managers and policy makers require timely information about the current state of forest resources over large areas. One important factor is forest growth and compositional change, which currently can only be approximately modeled in the time between field surveys. This study investigates whether a sequence of satellite images from Landsat-5 TM can be used to monitor forest growth, and specifically compare growth rates between different forested plots from the Swedish National Forest Inventory. Seven Landsat Thematic Mapper scenes were acquired over a 12-year period during the vegetation season. An image-based relative calibration procedure was applied to normalize the images for differences in atmospheric clarity and other specific conditions of image acquisition, and pixel values were extracted at sample plot locations for each scene. Plots were then selected from the inventory data for comparison of their spectral profiles over the 12-year period. Longitudinal regression models were fit to the datasets to test the significance of site index as an explanatory variable. It was found that once the effect of age was removed, the recorded site index could not explain the residual variance in individual plot trajectories. This is probably due to problems with precise positioning of the plots in the image, but also the fact that the site index is a rather coarse predictor of actual growth.

1 INTRODUCTION

1.1 Background

Effective forest management requires detailed information about the current state of the resource as well as tables or models for forecasting future conditions. With this information, forest managers are able to select appropriate management treatments to optimize economic output as well as achieve certain preservation and diversity goals. In Sweden, and typical in other countries, new management inventories start with delineation of homogeneous stands in aerial photographs followed by measurement of forest parameters at a number of sample plots within each stand. Inventory parameters, stored in a database, are updated in subsequent years following the inventory using growth models, from recorded harvesting activities, and from periodic re-measurement. After some time, it is typical for uncertainty to accumulate in the inventory data, either from errors in the initial estimates, from departures from predicted behavior in the models, from unexpected damages, and from inaccurate updating of management treatments. After some years of continuous update, it is typical for errors to be so large, that the entire inventory must be re-done from scratch. There is considerable economic benefit if the information in the inventories can be improved, or if the useful life can be extended by even a few years.

On a larger scale, the National Forest Inventory (NFI) in Sweden collects information about the forest land for the entire country using a network of permanent and temporary sample plots. There are roughly 18000 sample plots distributed throughout the country with a higher sampling density in the south. Temporary plots are allocated and measured only once, while permanent plots are revisited on roughly a 5-year cycle. Information from the NFI is used to identify long-term trends in wood-supply, forest composition, and health, and is an important input for environmental monitoring and setting national forest policy. While the purely plot-based design does provide objective estimates of forest state, it is not particularly efficient for sampling certain attributes, such as annual cutting intensity or rare forest types.

In both of these inventory applications, there is a need to monitor forest growth and changes in the years between field samples, and to generalize measurements taken on sample plots to areal units. Satellite remote sensing, from moderate resolution sensors such as SPOT or Landsat-TM, has always offered much promise in this field, since it can provide an independent view of large forest holdings for relatively low cost per hectare. In theory, a new image over the same area during the vegetation season every 1-3 years could be used to detect unexpected changes, as well as identify departures from expected forest growth predicted by the models. Such information, at the very least, could be used to direct field inventory activities in a more efficient way. Ideally, satellite image sequences could be fully integrated into a spatially and temporally explicit estimation scheme to improve estimates of the current state of the forest.

Yet despite considerable research effort in satellite remote sensing for forestry, it has not been widely used operationally. We could speculate on the historical reasons for this as (1) a lack of facilities for handling spatially referenced digital data at the end-user level, (2) lack of precise position information for sample plots, (3) the cost and complexity of ordering data, and (4) a lack of suitable methods for handling images together with sample plots to extract useful information in the forest inventory context. At least points 1-3 above have changed recently with widespread use of GIS and relational databases for storing inventory information, GPS for positioning plots in the field, and efficient web-based tools for ordering low-cost data such as from Landsat-7 ETM+. This project addresses the 4^{th} point, and specifically methods for extracting information about growth from temporal image sequences.

1.2 Spectral Development of Forests Over Time

The spectral reflectance of tree crowns and forest canopies have been measured and modeled to try to understand the relationship between spectral signatures and forest parameters. Through normal growth and compositional change, the spectral signature will change over time in response to changes in the conditions on the ground. This relationship is complex and difficult to model accurately, and unfortunately the traditionally most important inventory parameters (stem number, height, volume, basal area, etc) may not be the most important factors for determining the temporal course of spectral reflectance (Nilson and Peterson, 1994). During the early stages of stand growth, the satellite signal is dominated by the reflectance characteristics of the field-layer vegetation and exposed soil or rocks. As trees grow and the canopies close over, the background vegetation becomes less important and the species composition and total leaf area of the canopy becomes dominant. Height growth comes into effect mostly through the amount of internal shadowing, especially in the shortwave infrared wavelengths because of good atmospheric penetration. In a mature forest with a fully closed canopy and stable leaf area, increases in basal area, and thus volume, have minimal effect on spectral reflectance. The spectral development of a forest stands, as a function of age, are well approximated by a decaying exponential function of time within each spectral band. Of course disturbances will introduce discontinuities into this otherwise smooth profile.

It has been proposed that the spectral behavior of forests over time, or its spectral-temporal trajectory, could be used to monitor forest development. Häme (1991) refers to the “spectral life cycle” of a forest stand as its spectral trajectory over a full rotation. He constructed descriptive models for life cycles that included discontinuities caused by periodic stand thinning. Jupp and Walker (1996), outline the potential in this area and suggest using geometric-optical models to construct *expected* profiles, to which observed data can be compared. Nilson and Peterson (1994) propose that a set of tables or curves could be produced that represent expected spectral development for a number of site conditions, as a direct analogy to growth curves used widely in forestry. Here the geometric-optical canopy reflectance model provides a link between the forest inventory data and remotely sensed data. These developments with canopy reflectance modeling are certainly encouraging, but to be used effectively, image data must be calibrated to physical units of surface reflectance factors to be compared to model outputs. The alternative is to use methods based on statistical relationships rather than physical considerations. This is the approach taken in this study- we are interested in picking out the general spectral trends over time and comparing these profiles in a relative manner.

1.3 Objectives

In this study we explore the possibility to compare forest growth rates on sample plots from a sequence of Landsat TM imagery. The emphasis is using a realistic, rather than ideal, image dataset and using a random sample of forest plots from the Swedish NFI that reflects the full variability of forest conditions in the area. The main question is whether a spectral-temporal profile derived from a normalized image data sequence can explain differences in forest productivity. We focus on the parameter *site index*, since it is an important predictor of forest growth, and it is widely used in growth modeling.

2 STUDY AREA AND TEST DATA

2.1 Study area

The study area is in the coastal area of Västerbotten in northern Sweden near the city of Umeå. This area is predominantly forested with stands of pure and mixed Norway spruce (*Picea Abies*), Scots Pine *(Pinus Sylvestris*) and birch (B*etula Pendula*). Land ownership is split between large companies and private owners, but almost all forest land is intensively managed for timber and pulpwood production. The predominant harvesting and management activities in the area are clearcutting in blocks of 2-10 ha, possible site preparation by soil scarification, planting, removal of deciduous shrubs in young stands, and several commercial thinnings during a stand's approximate 100 yr rotation period. The study area is shown together with the satellite scene extents in figure 1.

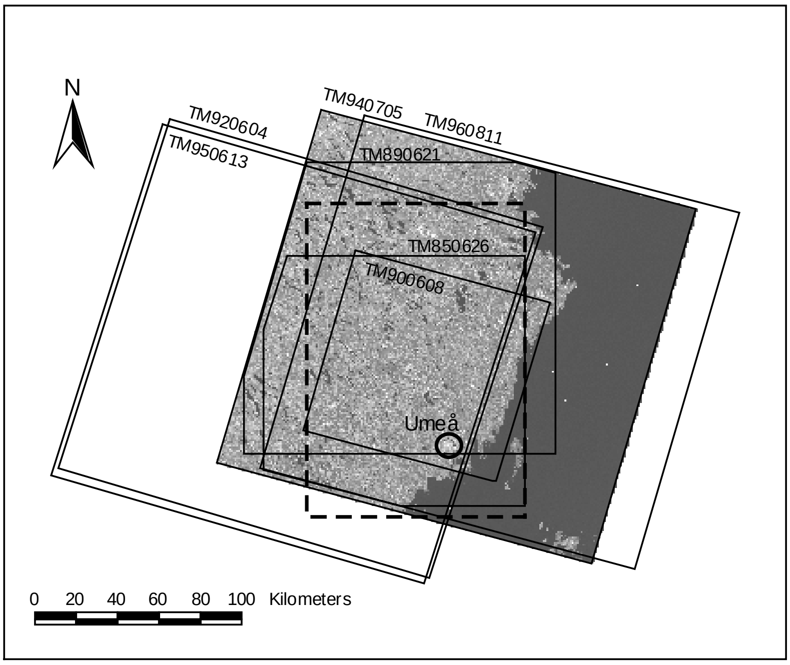

Figure 1. Satellite scene extents showing the study area (dashed line). The scene from 1994 is shown for reference, other scene extents are outlined with a solid line.

2.2 Satellite Imagery

Year	Date	Path/Row
1985	June 26	193/15
1989	June 21	193/15
1990	June 8	193/15
1992	June 6	194/15
1994	July 5	193/15
1995	June 13	194/15
1996	August 11	193/15

Table 1. Satellite scenes

There were 7 different Landsat scenes over 11 years used for this investigation (table 1.). All images are from the Thematic Mapper sensor aboard Landsat-5 and were precision corrected to the Swedish National Grid and resampled to 25m by the SSC Satellitbild (now Satellus AB). The scenes were selected to be relatively cloud-free in the area of interest and as close as possible to the peak of the vegetation season. No suitable scenes were available in the missing years. Not all images are full-scenes as is apparent by their extents in figure 1. In practice for the purpose of this investigation, the study area was reduced to the intersection of these scenes, so there are no missing values to deal with in the regression models.

2.3 Field Data

Field data were collected as a part of the normal operations of the Swedish National Forest Inventory. Sample plots of 7m (temporary) or 10m(permanent) radius are arranged in clusters on a regular grid. Variables are recorded by field teams on the sample plots according to an established protocol. Observations are made about the soil and hydrology conditions, ground vegetation, tree size and species composition. Several variables are derived or calculated for the plot level, based on sample trees. The database was queried for all plots measured within the study area during 1985 to 1996. Due to the cyclic nature of the inventory, and the large proportion of temporary plots, very few in this set were actually re-measured during the period. In total 1545 plots were available in the study area after screening for clouds.

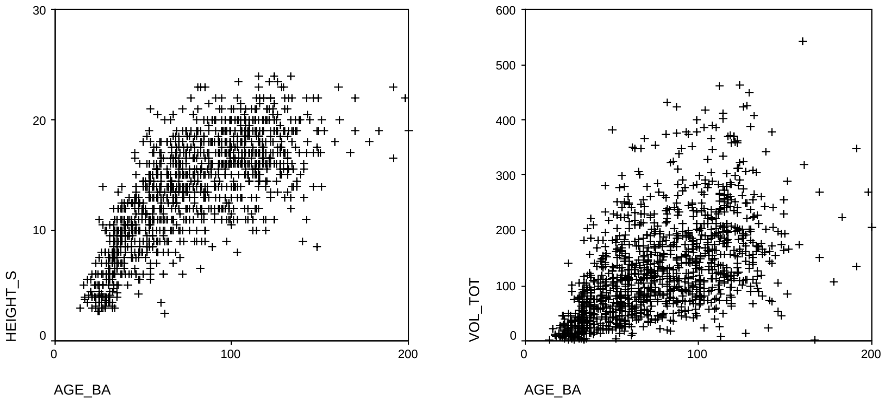

Figure 2a) Stand height v.s. age shows significant variation due to site productivity. b) Stem volume (per hectare) as a function of age

Unfortunately the position information for the plots is rather variable. Plots have nominal coordinates according to the inventory design. They may have digitized coordinates from 1:10000 scale maps, and the most recently surveyed plots are positioned with differential GPS. In all cases the best positional information available was used to extract pixel values from the image for comparison with the field data.

3 METHODS

3.1 Image Normalization

Differences in atmospheric clarity during the different dates of image acquisition mean pixel values are not directly comparable between images in the temporal sequence. In general the atmosphere affects the recorded radiance through attenuation (a wavelength-dependent multiplicative effect) and path radiance (a wavelength-dependent additive effect). One approach to calibrating for these differences is to first convert the recorded digital counts to radiance through published calibration factors, then model the atmospheric radiative transfer to convert to surface reflectance factors with can be compared. This however requires *in situ* measurements of atmospheric parameters during the time of image acquisition. For a recent discussion of procedures, see Ouaidrari and Vermote, 1999. In the absence of in situ measurements, the atmospheric parameters may be inferred from radiance over dark targets such as clear lakes (Teillet and Fedosejevs, 1995). This approach to calibration has the advantage of being based on physical considerations, and results could be compared to model outputs. However with Landsat-5 at least, the main difficulty may be retrieving realistic radiance values from the recorded digital counts. After several years of operation, the on-board calibration of Landsat-5 was essentially unknown, and different receiving stations applied different calibration factors at different times for producing data. For a discussion of the issues, see the appendix in Teillet and Fedosejevs (1995). Without sensible starting values for radiance, the atmospheric correction procedures have almost no chance of producing realistic surface reflectances. This situation may improve with future sensors, but there are still advantages to using purely image-based statistical methods for relative image calibration in this context.

In response to the difficulties with absolute calibration and atmospheric correction, several image-based statistical techniques have been used. These usually make use of the observation that for a narrow field-of-view sensor such as Landsat TM, recorded digital counts are a near-linear function of surface reflectance within each spectral band. Even the physics-based calibration procedures arrive at this result after simplifying assumptions are made. Thus rather than estimating linear calibration factors to convert to surface reflectance, you can estimate linear calibration factors to compensate for the relative scale difference from one scene to another. These procedures normally make use of a set of stable reflectance targets or so-called pseudoinvariant features (Schott and Salvaggio, 1988, Heo and FitzHugh, 2000), or bright and dark control sets derived from image scattergrams (Hall et. al, 1991). However, for forest monitoring, slightly better results can be achieved by using a selection of forest pixels for the 'stable' reference (Olsson, 1993). This has the effect of also neutralizing other effects such as vegetation phenology and sun-angle effects, at least to the best linear approximation.

Here we use a method that was described in Joyce and Olsson (1999). It consists of deriving a band-specific linear correction factors between each pair of adjacent images, and propagating this correction through the sequence to match a specified reference. We used the 1994 image as a reference. This method achieves good results because the correction factors are derived from image pairs that are close together in time, and it doesn't rely on having complete overlap of all images for all dates. It does not however compensate for the expected drift in the mean value over time.

3.2 Temporal data analysis

The methods for detecting unexpected changes between *two* dates of imagery are well developed and tested (see Coppin and Bauer, 1996 for a review) but there have been few attempts to use longer time series of images to monitor gradual trends such as those associated with forest growth or decline. Since these are clearly time-dependent data, the first thought may be to apply some of the well-developed theory of analysis of time series to model individual plot spectral trajectories. The problem is that these time series are too short to derive estimates of autocorrelation, the time points may not be equally spaced, and there may be frequent missing values. One could also fit individual regression models to each short sequence without regard to the serial correlation and use the coefficients of the regression models to make inferences. Lawrence and Ripple (1999) use this technique for monitoring vegetation recovery based on temporally modeled crown closure estimates.

There are techniques applied in the social sciences in the field of longitudinal data analysis (see Diggle, 1994) that may be useful in this application. A longitudinal data set consists of time sequences of measurements taken from several experimental units (called *Subjects* from the social science heritage). The subjects can be regarded as a sample from some underlying population, and often have covariate information attached to them. The focus of longitudinal studies is to compare the differences in *temporal* behavior between subjects or groups. In this context, our subjects are sample plots and the covariate information may be site index or species composition. The observed response variable over time is the spectral values from a normalized image time sequence.

Longitudinal analysis is in contrast to cross-sectional analysis where temporal behavior is inferred by comparing experimental units with *different* ages at a *common* time. We start the data exploration by looking at the relationship between spectral values and age. This gives an idea of the expected time profile of an individual plot, however there are potentially large differences between conditions on plots that aren't controlled for. The advantage of longitudinal analysis is that the between-plot differences are separated from the temporal behavior of individual plots.

Statistical analysis was performed with the Oswald extension to Splus (Smith et al, 1996), which is available for free from the University of Lancaster. Oswald extends SPlus data types to include a *longitudinal data frame*, or collection of time series indexed by subject. Additional covariates can be added to the data frame for use in regression models. These covariates can be subject-specific (different values for each subject, but constant over time), or time-specific (different value for each time, but constant over subjects).

4 RESULTS

4.1 Cross-sectional data exploration

We start by a cross-sectional data exploration of the 1994 image. Since the field data are collected on different dates, the age is updated to the year 1994. Age is actually basal-area weighted age on the plot, except in the very young stands where the stand age is used. Scatterplots of spectral values in band 4 and 5 v.s. age are shown in figures 3a and 3b.

The lines are local Loess regressions for pine-dominated and spruce-dominated plots. The purpose is to get an idea of the general spectral development profile over the long term. The interpolated lines are shown on a scatterplot of band 4 and 5 (fig 3c) to illustrate the changing spectral signature with age. A monotonic decrease is apparent in both bands, with a plausible exponential decay form. There is large variance around the mean trend, which may reflect differences in site conditions and growth rate.

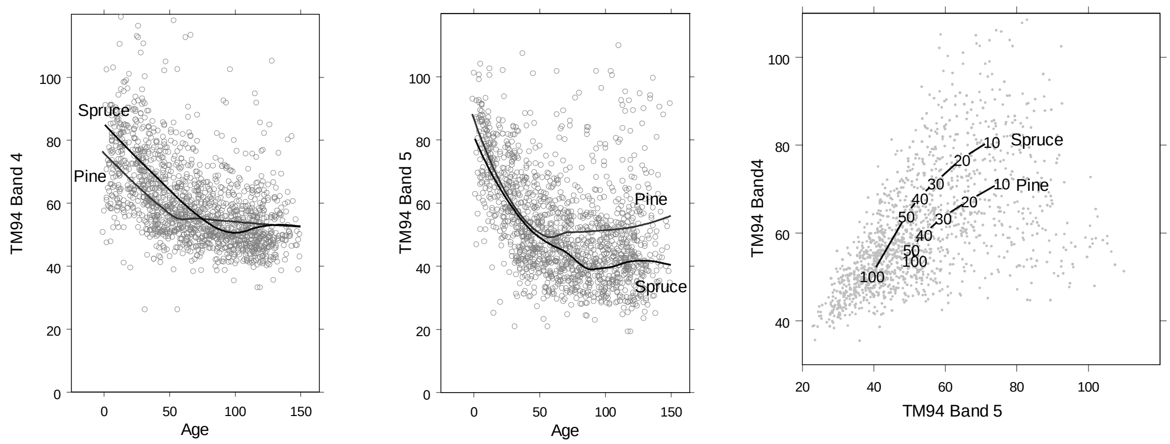

Figure 3. a) Scatterplot of TM band 4 (1994) vs age with Loess interpolation for pine- and spruce-dominated sample plots. b) same with TM band 5. c) Band 4-5 spectral space with the Loess interpolations from a) and b) plotted against all pixel values in background.

4.2 Longitudinal comparison between plots

Now we focus on comparing the temporal behavior of individual plots over the 12-year period. From the cross-sectional view above, we would expect that time trajectories for individual plots would be generally decreasing over the period, with a rate or slope that is influenced by the age of the forest on the plot. Over this short period, we can just examine the linear component of the trend as a simplification. If the rate of decrease is a function of age, then we could theorize that for a given age, differences in the slope would be an indication of the productivity of the site.

Figure 4. Subset of pine dominated plot profiles in TM5 (normalized)

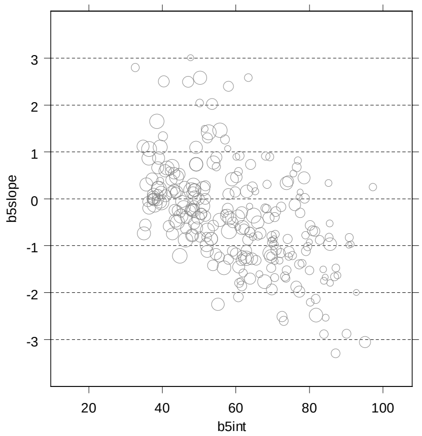

Figure 5. Plot of fitted linear coefficients for Pine-dominated plots in TM5.

For this investigation, we selected first plots that were pine- dominated and between 5 and 50 yrs of age in order to reduce the variance from species differences. There were 251 plots in this subset, and it is rather difficult to display all of the temporal profiles graphically, so a subset of 20 are shown in figure 4 to give an idea of the variance around individual lines.

In longitudinal analysis it is often useful to first ignore serial correlation and fit functions using ordinary least squares to all profiles or groups. The model for this written in longitudinal form would be

$$y_{ij} = \alpha_i + \beta_i t_{ij} + \varepsilon_{ij} \quad (1)$$

where y is the response for plot i at time j, α and β are plot-specific intercepts and slopes of individual linear regressions. A scatterplot of the fitted coefficients is shown in figure 5. The size of the data points varies with the plot age. The fact that some slopes are positive is an artifact of the mean-value trend being removed during image normalization.

If we are interested in inferring something about the growth rate from these profiles, the effect of age must somehow be removed, either by selecting *cohorts* in blocks or including the factor of age in the longitudinal regression. A random effects longitudinal regression model was fit to these data treating the slopes and intercepts as random variables. As expected, the factor of age turns out to be highly significant. Unfortunately when the factor Site Index was added to the regression, it turned out to not significant. This means the opportunity for estimating site index from these profiles, after the factor of age is removed, is rather limited.

5 DISCUSSION AND CONCLUSIONS

Examining the plots shown in figure 3, it is clear that forest reflectance generally decreases with age in wavelengths for both TM4 and TM5. This is in agreement with results of Nilson and Peterson (1994). The curve for pine seems to reach a flat asymptotic value at a younger age than spruce. The apparently abrupt change at near 50yrs for pine could be an effect of management treatments, where in this area pine stands are typically thinned. When interpreting the profiles in figure 3c, one must keep in mind that these are averaged across many different site conditions and the data are not balanced. Individual profiles could differ considerably from this mean.

This exploration of temporal image data analysis for forest monitoring is meant to illustrate the concept and highlight both the potential and the difficulties. The results were somewhat disappointing in that individual trajectories were unable to explain differences in site index from these data. Some contributing factors are certainly the uncertainties in plot positioning, but also the fact that site index itself is a rather coarse predictor of growth. Future work will address other variables that are recorded on the plots to examine what explains differences in temporal trajectories. The multivariate extension using several TM bands is also of interest.

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REFERENCES

Coppin, P. R., and Bauer, M. E., 1996, Digital change detection in forest ecosystems with remote sensing imagery, Remote Sensing Reviews, 13:207-234.

Diggle, P.J., Liang, K. Y., and Zeger, S. L. (1994), Analysis of Longitudinal Data, Oxford University Press.

Hall, F. G., Strebel, D. E., Nickelson, J. E., and Goetz, S. J., 1991, Radiometric Rectification: Toward a common radiometric response among multidate, multisensor images, Remote Sensing of Environment, 35:11-27.

Heo, J., and FitzHugh, T.W., 2000, A Standardized radiometric normalization method for change detection using remotely sensed imagery, Photogrammetric Engineering and Remote Sensing, 66(2):173-181.

Häme, T., 1991, Spectral interpretation of changes in forest using satellite scanner images. Ph.D. Thesis, Faculty of Agriculture and Forestry, University of Helsinki, Acta Forestalia Fennica 222.111 p.

Joyce, S., and Olson, H., 1999, Long-term forest monitoring with temporal-spectral trajectories from Landsat TM data. Proceedings: IUFRO conference on Remote Sensing and Forest Monitoring, Rogow Poland.

Jupp, D. L. B., and Walker, J., 1996, Detecting structural and growth changes in woodlands and forests: The challenge for remote sensing and the role of geometric-optical modeling.- In: Gholz, H.L., Nakane, K., and Shimoda, H. (eds). The Use of Remote Sensing in the Modeling of Forest Productivity. Kluwer Acad. Publ., Dordrecht, The Netherlands, pp. 75-108.

Lawrence, R. L. and Ripple, W. J., 1999, Calculating change curves for multitemporal satellite imagery: Mount St. Helens 1980-1995, Remote Sensing of Environment, 67:309-319.

Nilson, T., and Peterson, U., 1994, Age dependence of forest reflectance: analysis of the main driving factors, Remote Sensing of Environment, 48:319-331.

Olsson, H., 1993, Regression functions for multitemporal relative calibration of Thematic Mapper data over boreal forest, Remote Sensing of Environment, 46:89-102.

Ouaidrari, H., and Vermote, E., 1999, Operational atmospheric correction of Landsat TM Data, Remote Sensing of Environment, 70:4-15.

Schott, J. R., Salvaggio, C., and Volchok, W. J., 1988, Radiometric scene normalization using pseudoinvariant features, Remote Sensing of Environment, 26:1-16.

Smith, D.M., Robertson, W.H. and Diggle, P.J. (1996) Oswald: Object-Oriented Software for the Analysis of Longitudinal Data in S, Technical Report MA 96/192, Department of Mathematics and Statistics, University of Lancaster, LA1 4YF, United Kingdom. http://www.maths.lancs.ac.uk/Software/Oswald (Apr. 2000).

Teillet, P.M., and Fedosejevs, G., 1995, On the Dark Target Approach to Atmospheric Correction of Remotely Sensed Data, Canadian Journal of Remote Sensing. 21(4):374-387