REMOTE SENSING OF FOREST ENVIRONMENTS
Concepts and Case Studies

Edited by

Michael A. Wulder[1] and Steven E. Franklin[2]
[1] Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, Victoria, British Columbia, V8Z 1M5, Canada
[2] Department of Geography, University of Calgary, Calgary, Alberta, T2N 1N4, Canada

(LAI) are going to be similar, although the formal definition of these attributes, and their estimation in the field, can be quite different. For the purposes of this discussion, we have defined classes of attributes related to: canopy cover, stand structure, stand composition, and disturbance. Each class is defined by the commonality among the attributes themselves, by the aspect of canopy structure that they are related to, and by the way that aspect of canopy structure modifies the quantity and quality of electromagnetic radiation.

4.1 Attributes related to canopy cover

These attributes, which include foliage or canopy cover, F_{APAR}, and leaf area index, have the clearest link with the aspects of the physical organization of the canopy that remote sensing can most easily measure. In conventional optical imagery, such as aerial photos, Landsat ETM+, or SPOT HRV, reflected energy from the canopy and background surfaces mix in a roughly linear fashion, so that if there is 50% canopy cover, then 50% of the signal returned to the sensor will be from foliage, and 50% from the other cover components, such as bare soil, rock, and ground vegetation. Increasing canopy cover will be indicated by decreased reflectance in the visible (especially red) wavelengths (darker tones on aerial photography), due to the high absorptance of foliage in this spectral range. At the same time, foliage is highly reflective in the near-infrared, so that increasing foliage does not affect brightness in this region as much.

Numerous indices ((Normalized Difference Vegetation Index (Tucker 1979), Tasseled Cap Greenness (Crist and Cicone 1983), Simple Ratio (Spanner et al. 1994)) exploit the continuous spectral difference to distinguish between high and low canopy cover (Asner et al., Chapter 8). Any one of these indices can do a reasonable job of predicting a variable like canopy cover or F_{APAR}. One variable that is more difficult to predict, and which has received a lot of attention from the remote sensing community, is LAI. LAI can be considered as the number of layers of leaves that occur above a single point on the forest floor (for details, see Fournier et al., Chapter 4). In forests, LAI can be expected to vary from 0 to 10 and occasionally even higher. Although LAI is a desirable variable for biogeochemical models, the relationship between it and cover is asymptotic; with each additional layer of leaves the amount of additional cover becomes smaller, so that after a leaf area index of 4-6, the additional layers of leaves have little effect on cover. Because changes in reflectance are being driven mostly by the change in cover, the relationship between reflectance (and reflectance derived indices) and LAI is also asymptotic (Sader et al. 1990; Spanner et al. 1990; Chen and Cihlar 1996).

Microwave sensors have also been evaluated for the estimation of cover and LAI, despite their problems with moisture on the leaf surfaces leading to variations in the dielectric constant (Sader 1987). In addition, the horizontal orientation of leaves has been a problem in estimation of LAI in deciduous canopies. However, in needle-leaf coniferous canopies, SAR systems have been able to assess LAI up to values of 4 (Franklin et al. 1994, Ulaby and Dobson 1993).

Estimates of canopy cover have been made using both discrete-return and waveform-sampling lidar sensors. These estimates are made using the fraction of the lidar measurements considered to have been returned from the ground surface (Nelson et al. 1984; Ritchie et al. 1992, 1995, 1996; Means et al. 1999) where the measurements are the number of discrete returns, or the integrated power of a waveform. In most cases, a scaling factor (implicit or explicit) is needed to correct for the relative reflectance of ground and canopy surfaces at the wavelength of the laser (Harding et al. 2001). In these measurements, the definition of the ground surface is a critical aspect of cover determination. If the number or power of the measurements assigned to the ground return are overestimated (i.e., the elevation of the ground surface is overestimated) cover will be underestimated, and vice versa. Lefsky et al. (1999b) reported on a novel technique to estimate LAI in temperate coniferous forests, using measurements of canopy volume from a waveform recording lidar. However, this result has yet to be examined in other ecosystems.

4.2 Attributes related to canopy height

The next group of variables are related to the mean and variability of canopy height. These include tree volume, aboveground biomass, basal area, mean diameter-at-breast-height (DBH), stem density and stand age. Again, the formal definition of these attributes, and their estimation in the field, are quite variable. One variable, age, does not seem to belong at all. However, since age itself cannot be directly sensed, it is most often predicted from variables that are related to height and its variability.

Change in these attributes during the early stages of stand development can be estimated using the same cover-related spectral patterns described above, during the period in which change in vegetation cover is rising with vegetation biomass. However, with the exception of very low productivity stands, canopy closure occurs early on in most stands, while height and other attributes continue to change. Trees continue to grow in height for much of their individual lifetimes without dramatic spectral changes at the leaf level. However the spatial organization of the forest does change, as the size of the average dominant or co-dominant crown increases. Furthermore, the development of patch-scale dynamics, as the initial cohort of trees dies and younger trees take their place, means that the canopy's structure keeps changing long after the oldest trees die. This increasing variability is a sign of older stands in many forest types and can be seen in optical imagery as the presence of increasing shadow.

Accurate estimation of height-related variables is one of the most difficult tasks in the remote sensing of forests, especially in moderate to high biomass forests. Passive optical and active microwave sensors can predict these variable well in the first stages of stand development, but at moderate and high levels of biomass or volume they have poor discrimination or none at all. In a summary of research on SAR systems, Waring et al. (1995) stated that single-band systems with a single polarity had a detection limit of 150 Mg ha^{-1} for biomass and that even a combination of bands and polarizations would reach their limit at 250 Mg ha^{-1}. Similar results pertain for optical remote sensing (Sader et al. 1989; Hyppa et al. 1998; Lefsky et al. 2001). Nevertheless, for monitoring the first stages of forest development, managed stands with a short rotation age, or forests with naturally low biomass, microwave and optical systems can be effective. In some conifer forests (in particular Douglas-Fir / western hemlock) the observable aspects of canopy structure continue to change throughout stand development, and prediction of height, and its relative variables (such as aboveground biomass and in some cases, age) are more successful. These aspects of canopy structure can include trees of large stature, deep shadow, snags and dead wood in the canopy, and extensive colonization of the canopy by lichens.

It is becoming widely accepted that lidar sensors have a capacity for measuring height related attributes, including volume and aboveground biomass, to a greater degree than any other sensor type. Studies involving both discrete-return and waveform-record sensors have had success measuring height (Nelson et al. 1988), volume (Maclean and Krabill 1986), biomass (Lefsky et al. 1999a; Lefsky et al. 1999b; Drake et al. 2002), and basal area (Lefsky et al. 1999a, 1999b). These studies have involved deciduous (Lefsky et al. 1999a; Drake et al. 2002), coniferous (Nelson et al. 1988; Nilsson 1996; Naesset 1997; Lefsky et al. 1999b) and mixed (Maclean and Krabill 1986) stands in boreal (Naesset 1997; Nilsson 1996), temperate (Maclean and Krabill 1986; Nelson et al. 1988; Lefsky et al. 1999a, 1999b) and tropical sites (Nelson et al. 1997; Drake et al. 2002). While lidar currently remains one of the more expensive remote sensing datasets to obtain, the increasing use of this technology for land surveying may bring down costs. In addition, analyses pairing lidar with either optical (Hudak et al. 2002) or interferometric SAR (Rodriguez et al. 2002) may result in a lower cost alternative to comprehensive lidar coverage.

4.3 Composition attributes

Attributes related to composition are the most difficult set of attributes to summarize, due to the diversity of attributes themselves and the variety of spectral or other features used to predict them. Compositional attributes include physiognomy, phenological types (deciduous vs. evergreen), species level composition, and a variety of cover type classifications. Composition can be related to the spectral qualities of the vegetation itself, vegetation cover and its pattern, and even the spectral qualities of the background that the vegetation partially obscures. This presents an inherently complicated picture, however in many forested landscapes the tasseled cap transformation can simplify the spectral qualities of a scene, by contrasting the vegetation against soil, shadow and other scene components. Although the coefficients of the tasseled cap were derived from examination of multiple MSS (Kauth and Thomas 1976), and later TM (Crist and Cicone 1983), scenes, an empirical analysis of images from forested scenes usually produces three bands that are similar to it. Therefore, it is justifiable to use this ordering of the spectral variance of a scene as a tool to understand composition.

Within the context of western Oregon, Cohen et al. (2001) found that brightness (essentially the average of the six non-thermal TM bands) is associated with soil and litter cover (soil is commonly brighter), varying proportions of vegetation cover (high cover is darker), and with the distinction between conifer and deciduous cover (conifer is darker). Greenness (the contrast between visible and infrared bands) is associated with changes in vegetation cover (similar to NDVI) and with the proportion of conifer versus hardwood. Wetness, which is a contrast between the visible and near-infrared channels and the mid-infrared bands, is associated with increasing age and crown size in conifer stands, with lower wetness in more developed stands. In western Oregon, these three simple transformed bands have been shown to explain much of the variation in vegetation cover, conifer cover, conifer crown diameter and age (Cohen et al. 2001).

Any sensor that approximates the selection of bands that Landsat offers (e.g., the HRVIR sensor on SPOT 4) should be able to duplicate these results. However, sensors that do not include the middle-infrared band may not be able to adequately represent the wetness component of the tasseled cap, which may set a lower bound on the number and kind of bands that a sensor for forestry applications should have. Setting an upper bound on the spectral information that is needed for such a sensor is more difficult. Hyperspectral sensors have been advanced as one way to get better composition information, and some results support this (Gong and Yu 1997; Martin et al. 1998). However, as pointed out earlier, most plants have very similar spectral responses, and sunlit foliage (from which the spectra will be most clear) occurs in mixture with other components of a canopy image: shadow, shadowed foliage, and background. Therefore it is unclear whether the hyperspectral approach will yield widespread advances in predicting forest composition.

4.4 Change / disturbance monitoring

Change detection involves the comparison of images from a given location at two or more points in time. One can simply compare summaries of classifications for a given area at different points in time, or can conduct a spatially explicit analysis involving direct comparisons on a pixel-by-pixel basis (Gong and Xu, Chapter 11). In the latter, and more usual case, accurate spatial registration of two or more images in required.

Optical images are the dominant type of remote sensing for change detection, and have proven to be useful for the detection of both dramatic (stand replacement disturbances, Hall et al. 1989; Cohen et al. 2001) and subtle disturbances (insect, low intensity fire, thinning (Franklin et al. 1995; Jakubauskas et al. 1990; Franklin et al. 2000). Image processing approaches developed for optical images have also been applied to SAR images (Banner and Ahern 1995), despite difficulties with the high variability in backscatter due to moisture and seasonality (Cihlar et al. 1992), and the dependence of backscatter on topography and incidence angles (Drieman 1994; Edwards and Rioux 1995). However, the development of interferometric SAR systems, especially those on space borne platforms may soon begin to supplement optical images as a source of data for change detection. The coherence measurement appears to be more stable (Baltzer 2001) than backscatter as variable for change detection analysis. No work on change detection from lidar has yet been published, but numerous groups are looking at doing change detection in height over relatively short time increments (3-10) years. It is believed that such data may provide an estimate of net primary productivity or mean annual increment of volume.

5. CONCLUSION – SELECTING A SOURCE OF IMAGERY

Selecting a source of imagery can be a complicated process, but the first priority must be to select a data source that has a record, preferably in the peer reviewed literature, of being able to predict the attributes you are interested in, and the resolution of the dependent variables you will need.

Resolution in this case refers to the number of levels you need, from a binary presence/absence (as in forest/non-forest determinations) to continuous estimates of a variable like age or aboveground biomass. Increasing resolution in the dependent variable requires a higher level of correlation between the imagery and the dependent variable. For example, accurately distinguishing, with a given confidence, three classes of an attribute requires a lower level of correlation between the attribute and the data source than does distinguishing ten classes or estimating that attribute continuously.

We have reviewed four classes of forest attributes and their ability to be predicted from various imagery types. Variables related to canopy cover will, in the absence of overwhelming cloud cover problems, usually be predicted from optical imagery; the option of using microwave data in this instance will require more complex processing, but is capable of making some of the same measurements, particularly in coniferous canopies. Optical sensors of any spatial resolution are appropriate for cover-like measurements, and hyperspectral data may offer some benefits by being able to use only those narrow spectral regions with the highest contrast, but multispectral data should do an adequate job.

Stand structure can be successfully estimated from optical and microwave sensors, up to relatively low levels of plant biomass. Therefore, if one's study area is predominately low biomass forest, or you only need a few classes of structure, they can be useful. If detailed estimates of forest structure are required in a high biomass study area, lidar will provide the best results. However, for study areas greater than a few tens of km^2 lidar, it is currently too expensive (~US$ 500 / km^2) for many studies.

For general land and forest cover classification, the same caveat used above still holds; unless you have overwhelming cloud cover problems you will probably want to use optical remote sensing. Again, data of many spatial resolutions can be used for these applications, and there is also a good case for hyperspectral data for these applications. One caveat for *hyperspatial* data that bears repeating is that, if individual trees fall in multiple pixels, each pixel may be in one of several classes (shadow or sunlit, young foliage or old), requiring a detailed analysis to retrieve common land-use classes.

For change detection, hyperspectral data does not offer any obvious improvements over multispectral data – the types of change commonly being mapped are related to differences in canopy cover, which is well within a multispectral sensor's ability to describe. High spatial resolution data could have some interesting applications for change detection – but precisely matching images from two dates becomes more difficult as pixel sizes decrease. Low spatial resolution devices will almost always contain changed and unchanged area in a large pixels, although the MODIS device will produce a 250 m change detection product for global monitoring of land cover change hotspots. The 250 m resolution probably represents an upper limit for accurate change detection and, for most studies, one of the moderate resolution optical sensors would be preferable.

Finally, we believe that our review of sensors for forestry applications strongly suggests that the "best" sensor is often more than one sensor. Whether the combination is high-resolution and lower-resolution (as in Cohen et al. 2001; or Zhu and Evans 1992), multi- and hyper-spectral (Ranchin and Wald 2000), or conventional optical and lidar (Hudak et al. 2002), the motivation is the same – combining the strengths of two or more sensors to create a solution that is tailored for the application being considered. Recognizing the individual strengths and weaknesses of each type of sensor is the first step towards applications that properly use them.

REFERENCES

Abrams, M. J., Kahle, A. B., Palluconi, F. D., & Schieldge, J. P. (1984). Geologic mapping using thermal images. *Remote Sensing of Environment,* 16, 13-33.

Asner, G. P., Braswell, B. H. Schimel, D. S., & Wessman, C. (1998). Ecological research needs from multiangle remote sensing data. *Remote Sensing of Environment,* 63, 155-165.

Bachman, C. G. (1979). *Laser Radar Systems and Techniques*. Artech House, MA.

Baltsavias, E. P. (1999). Airborne laser scanning: existing systems and firms and other resources. *ISPRS Journal of Photogrammetry & Remote Sensing,* 54, 164-198.

Baltzer, H. (2001) Forest mapping and monitoring with interferometric synthetic aperture radar (InSAR). *Progress in Physical Geography,* 25, 159-177.

Banner, A. V., & Ahern, F. J. (1995). Incidence angle effects on the interpretability of forest clearcuts using airborne C-HH SAR imagery. *Canadian Journal of Remote Sensing,* 21, 64-66.

Brock, J. C., & Wright, C. W. (2000). Preliminary results from a NASA Experimental Advanced Airborne Research LIDAR (EAARL) survey of Pacific Reef in Biscayne National Park, Florida. *Proc. 9th International Coral Reef Symposium,* 233. USGS Center For Coastal Geology, Florida.

Chauhan, N. S. (1997). Soil Moisture Estimation Under a Vegetation Cover: Combined Active Passive Microwave Remote Sensing Approach. *International Journal of Remote Sensing,* 18, 1079-1097.

Chen, J. M., & Cihlar, J. (1996). Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment*, 55, 153-162.

Cihlar, J., Pultz, T. J., & Gray, A. L. (1992). Change detection with synthetic aperture radar. *International Journal of Remote Sensing,* 13, 401-414.

Cohen, W., Harmon, M.,Wallin, D., & Fiorella, M. (1996). Two decades of carbon flux from forests of the Pacific Northwest. *Bioscience,* 46, 836-844.

Cohen, W., Spies, T. A., & Fiorella, M. (1995). Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, U.S.A. *International Journal of Remote Sensing,* 16, 721-746.