Using multispectral satellite imagery to estimate leaf area and response to silvicultural treatments in loblolly pine stands

Francisco J. Flores, H. Lee Allen, Heather M. Cheshire, Jerry M. Davis, Montserrat Fuentes, and Daniel Kelting

Abstract: The relationship between leaf area index (LAI) of loblolly pine plantations and the broadband simple ratio (SR) vegetation index calculated from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data was examined. An equation was derived to estimate LAI from readily available Landsat 7 ETM+ data. The equation developed to predict LAI with Landsat 7 ETM+ data was tested with ground LAI measurements taken in 12 plots. The root mean square error of prediction was 0.29, an error of approximately 14% in prediction. The ability of Landsat 7 ETM+ data to consistently estimate SR over time was tested using two scenes acquired on different dates during the winter (December to early March). Comparison between the two images on a pixel-by-pixel basis showed that approximately 96% of the pixels had a difference of <0.5 units of SR (approximately 0.3 units of LAI). When the comparison was made on a stand-by-stand basis (average stand SR), a maximum difference of 0.2 units of SR (approximately 0.12 units of LAI) was found. These results suggest that stand LAI of loblolly pine plantations can be accurately estimated from readily available remote sensing data and provide an opportunity to apply the findings from ecophysiological studies in field plots to forest management decisions at an operational scale.

Introduction

Much of the variation in forest production can be accounted for by variation in canopy light absorption. Stand factors that determine light absorption include amount of leaf area, crown and canopy structure, phenology, and leaf optical properties (Jarvis and Leverenz 1983; Cannell 1989). The amount of leaf area, measured through the leaf area index (LAI), is the most important factor in canopy light absorption (Jarvis and Leverenz 1983; Asner and Wessman 1997). In addition to its connection with forest production, LAI is related to other important ecological processes, such
as evapotranspiration and nutrient cycling. Because of the importance of LAI in several ecological processes, considerable research has focused on developing tools to estimate it. Remote sensing has been successfully used to estimate LAI (Running et al. 1986; Curran et al. 1992; Chen and Cihlar 1996; White et al. 1997; Flores 2003), making it possible to monitor ecological processes at the landscape level.

Studies of several species have found strong responses in LAI and forest production to increases in water and (or) nutrient availability (Linder 1987; Vose and Allen 1988; Colbert et al. 1990; Dalla-Tea and Jokela 1991; Albaugh et al. 1998; Carlyle 1998; Smethurst et al. 2003), indicating that leaf area and production are below their biological potential. In the case of intensively managed forest plantations, a large difference between current and potential production levels means that there are real opportunities to increase financial returns.

The development of improved management systems to achieve higher production levels requires the use of technology that is cost effective while providing for environmentally sustainable forest production. As addressed by Allen (2001), achieving and maintaining higher levels of forest production requires effective manipulation of site resources (e.g., water and nutrients) and should be based on an understanding of (i) what resources limit forest production; and (ii) how those resources are affected by silvicultural treatments. Forest managers responsible for broad, usually heterogeneous, land-base management need to address two more questions: (iii) where in the land base does a given resource limitation occur; and (iii) when in the life of the stand does a given resource limitation occur. Those two questions are critical for implementing improved management practices based on sound ecophysiological principles.

The use of remote sensing to estimate LAI is based on the selective absorption of radiation by vegetation canopies, which results in distinctive patterns for the reflectance of shortwave radiation. The reflectance spectrum for green vegetation is characterized by low reflectance in the red (R) region (0.6–0.7 μm), associated with chlorophyll absorption; and substantially larger near infrared (NIR) reflectance (0.7–1.2 μm), related to internal leaf structure (Myneni et al. 1995; Jensen 2000). Several vegetation indices (VIs) using these two regions of the reflectance spectrum, R and NIR, have been empirically related to LAI, foliar biomass, and light absorption (Running et al. 1986; Goward et al. 1994; Wu and Strahler 1994; Flores 2003). In addition to the empirical evidence, there is strong theoretical evidence showing the connection between VIs, chlorophyll abundance, and light interception (Myneni et al. 1995; Sellers 1985, 1987; Sellers et al. 1992).

The two most common VIs are the simple ratio (SR), NIR/R, and the normalized difference vegetation index, (NIR – R)/(NIR + R). These indices, calculated from broadband multispectral remote sensing, have been successfully used to characterize the LAI of forest stands. Running et al. (1986) showed a strong linear relationship between LAI and SR for coniferous forest in Oregon. Working in the same area, Law and Waring (1994) found a linear relationship between LAI and SR for understory vegetation. White et al. (1997) found a linear relationship between SR and LAI for coniferous and hardwood stands in montane ecosystems, and Chen and Cihlar (1996) found similar results for boreal forests. In the case of southern pines, Curran et al. (1992) demonstrated the potential for using Landsat Thematic Mapper data to characterize the seasonal dynamics of LAI. Flores (2003), using the SR calculated from narrowband hyperspectral data, developed an empirical model to estimate LAI in loblolly pine (Pinus taeda L.) stands. The relationship between LAI and SR was not affected by site, stand structure, or time of year. SR can also be calculated from readily available multispectral satellite data (e.g., from Landsat and Sentinel pour l’observation de la Terre (SPOT)), providing managers with an excellent opportunity to acquire spatially explicit LAI estimates for operational forest management.

In the United States, intensive plantation management is concentrated in the southeast. This region contains about 23% of the softwood growing stock in the United States, supplies most of the US domestic wood supply, and includes almost 50% of the world’s industrial forest plantations (Cubbage and Abt 1999). Loblolly pine is the dominant species planted.

The objectives of this study were (i) to establish a relationship between LAI and broadband SR; and (ii) to investigate whether SR can be consistently estimated over time by using cloud-free Landsat 7 ETM+ data.

Methodology

Relationship between leaf area index and broadband simple ratio

The relationship between LAI and broadband SR was examined by using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data, as well as two HyMap hyperspectral images from Flores (2003). Landsat 7 ETM+ was selected because of its temporal frequency (every 16 days), spatial resolution (30 m × 30 m pixels), radiometric calibration, and availability. The recent malfunction of Landsat 7 ETM+ in May 2003 makes it more difficult to use for monitoring in many cases now. However, other satellites share these sensor characteristics, including SPOT and Landsat 5, and the results found with Landsat 7 ETM+ can be extended to their sensors (cross-calibration may be needed).

The relationship between LAI and SR from Landsat 7 ETM+ (referred to as SR(band 7)) was first examined using ground measurements of LAI collected in October 2000 from Southeast Tree Research and Education Site 2 (SETRES2). The site was located in the Sandhills of Scotland County, NC; details about the site and study design can be found in Retzlaff et al. (2001). Briefly, SETRES2 was installed in 1994 with five loblolly pine open-pollinated half-sib families (trees with one parent in common) from two provenances: the Atlantic Coastal Plain (ACP) and Lost Pine, Texas (LPT). The experimental design includes whole plots of fertilized and nonfertilized treatments. Split plots within each whole plot correspond to two provenances (ACP and LPT), and split plots within the provenance plot correspond to 5 half-sib families (10 fertilized and nonfertilized plots in each block). Eight blocks, from a total of 10 available in the study, were used for LAI measurement. The fertilized plots received annual fertilization, with elements and rates applied
on the basis of foliar analysis of nutrient concentrations. All plots received competing vegetation control; for that reason, at the time of LAI measurement there was either no understory or a small amount of senescent grass present (not included in the LAI measurements). Average tree height ranged from 3 to 6 m (control and fertilized plots, respectively).

On the ground, LAI was measured with the LAI-2000 Plant Canopy Analyzer (PCA) (LI-COR 1991) for all 10 plots available per fertilizer treatment in each of eight blocks. In each plot, we sampled and averaged 20 points to estimate plot LAI (details in Flores 2003). The data were averaged by fertilizer treatment plot; the size of the resulting plot was 140 m × 60 m. Where the fertilized (or nonfertilized) plots of two different blocks were adjacent, the data were aggregated on a larger plot (140 m × 120 m) to increase the number of pixels located completely within the same treatment. Twelve plots were available for establishing the relationship between SRHM and LAI. From a Landsat 7 ETM+ image acquired on 9 October 2000, one or more pixels falling entirely within the plot boundary were selected and related to ground LAI measurements.

We also used a second approach to examine the relationship between LAI and SR_L7. Instead of directly modeling ground LAI measurements using SR_L7, we established a relationship between SR from narrowband HyMap data (referred to as SR_HM) and SR_L7. The strong relationship between LAI and SR_HM (Flores 2003) was then used to establish a relationship between LAI and SR_L7. Two methods were also used to examine the relationship between SR_HM and SR_L7. First, HyMap hyperspectral data were convolved to broadband reflectance in bands 3 and 4 from Landsat 7 ETM+ and used to calculate SR_L7. More than 6000 pixels from the HyMap image acquired in October 2000 were used to determine the relationship measured narrowband and simulated broadband SR (referred to as the theoretical relationship). The second method used both HyMap and Landsat 7 ETM+ data (referred to as the empirical relationship) to account for differences in sensor altitude (705 km for Landsat 7 ETM+ and approximately 5 km for HyMap), atmospheric and illumination conditions, and pixel size, as these may affect the relationship between SR_HM and SR_L7.

The spatial domain used to make the comparison was a regular grid of 20 cells × 50 cells, and the dimension of each cell was 100 m × 100 m, for a total area of 2 km × 5 km. For each cell, the average SR from Landsat 7 ETM+ and HyMap was calculated and used to develop the model. Given the extent of the area (10 km²), several land uses were represented, including loblolly pine and longleaf pine (Pinus palustris Mill.) stands, annual field crops, and areas dominated by deciduous broadleaf vegetation. For modeling the relationship between SR_HM and SR_L7, we used spatial statistics to test for autocorrelation in the data and to fit a spatial regression model that takes spatial autocorrelation into account. A detailed description of the method and the results from this spatial statistical analysis can be found in Flores (2003). In this paper, only the final spatial regression model is presented. The statistical analyses were performed using SAS System version 8.02 (SAS Institute Inc. 2001), S-Plus 2000 release 2 (MathSoft 1999), and S+ Spatial Stats (Kaluzny et al. 1998).

### Landsat 7 ETM+ data and preprocessing

The Landsat 7 ETM+ data were acquired on 9 October 2000 (path 16, row 36). A subset of this scene, including SETRES2, was coregistered to the HyMap image.

Using gains and offset values from the image header files, we converted the digital numbers from the Landsat 7 ETM+ scene to radiance (L_i). After that, the radiance values were converted to exoatmospheric reflectance (reflectance at the top of the atmosphere) with the following formula (Markam and Barker 1986):

\[ R_i = \frac{\pi L_i d^2}{E_s \cos \theta} \]

where \( L_i \) is the spectral radiance at the sensor for band \( i \) (W/(m²·sr·µm)); \( d \) is the Earth–sun distance (astronomical units); \( E_s \) is the mean solar exoatmospheric irradiance for band \( i \) (W/(m²·sr·µm)); and \( \theta \) is the solar zenith angle (°).

The values for Earth–sun distance and mean solar exoatmospheric irradiance were found in Tables 11.3 and 11.4 in the *Landsat 7 ETM+ Science Data Users Handbook* (Irish 1999).

Finally, the broadband SR was calculated with the following equation:

\[ SR_L7 = \frac{R_{B4}}{R_{B3}} \]

where \( R_{B4} \) is the exoatmospheric reflectance in band 4 (0.76–0.9 µm); and \( R_{B3} \) is the exoatmospheric reflectance in band 3 (0.63–0.69 µm).

### HyMap data and preprocessing

The low-altitude hyperspectral image used in this study was collected using the HyMap sensor from an aircraft in October 2000. The pixel size was 4.5 m × 4.5 m, and the spectral coverage included the range 0.47–2.5 µm. The sensor collected 126 bands with bandwidths of approximately 0.015 µm. Science Applications International Corporation (SAIC) provided the imagery; Analytical Imaging and Geophysics collected and calibrated the data to apparent reflectance and georectified the image. The radiative transfer model ATREM was used for the atmospheric correction and for conversion of the data to reflectance (Gao et al. 1996). The model is based on water vapor removal on a pixel-by-pixel basis from the 0.94 and 1.14 water vapor absorption bands. The model also takes into account the effect of six gases (CO₂, O₃, N₂O, CO, CH₄, and O₂), assuming a uniform amount of gases across the scene (Gao et al. 1996). After the data were transformed to reflectance, spectral smoothing was performed with the EFFORT algorithm (Boardman 1998).

Narrowband SR was calculated with the following equation (based on Flores 2003):

\[ SR_{HM} = \frac{R_{803}}{R_{666}} \]

where \( R_{803} \) is the reflectance at wavelength 0.803 µm; and \( R_{666} \) is the reflectance at wavelength 0.666 µm.

The known spectral responses of Landsat 7 ETM+ bands 3 and 4 (Irish 1999) were used to convolve the HyMap
hyperspectral data to those broadbands, using the following equation:

\[ R_S = \frac{\int R(\lambda) S_q(\lambda) d\lambda}{\int S_q(\lambda) d\lambda} \]

where \( R(\lambda) \) is the HyMap reflectance at wavelength \( \lambda \); \( q \) is the Landsat 7 ETM+ band (3 or 4 in this case); and \( S \) is the Landsat 7 ETM+ relative spectral response at wavelength \( \lambda \) (Irish 1999).

The processing of HyMap and Landsat 7 ETM+ data was performed with the image processing software ENVI 3.4 (Research Systems 2000).

**Comparison of SR estimates over time**

The goal of this particular analysis was to test whether SR can be consistently measured over time using cloud-free Landsat 7 ETM+ images. \( SRL_7 \), calculated as explained for the analysis at SETRES2, was compared between images acquired at different dates during the winter (January–March 2000). The assumption for this analysis was that winter LAI for most forest types, and especially for pine stands, should be fairly stable. On average we would expect the same SR from both images. Two areas of approximately 12 km \( \times \) 12 km were selected on available Landsat 7 ETM+ scenes for the coastal plain of North Carolina. Loblolly pine plantations dominated the selected areas, but other land uses were also present, including stands of deciduous broadleaf species and field crops. The first image from the first area (area A1), acquired on 5 February 2000, was selected from the Landsat 7 ETM+ scene in path 15, row 35. A second image of the same area, acquired on 1 March 2000, was selected from an overlapping scene in path 14, row 36. The first image from the second area (area A2), acquired on 29 January 2000, was selected from the Landsat 7 ETM+ scene in path 14, row 35. A second image of the same area, acquired on 5 February 2000, was selected from an overlapping scene in path 15, row 35. The two winter images from areas A1 and A2 were registered to Universal Transverse Mercator zone 18, with the first scene used as a reference. Between 30 and 40 ground control points were used to register the images within 1-pixel accuracy (based on root mean square error).

For area A1, a comparison of SR on a pixel-by-pixel basis was made after a wavelet filter was applied to remove short-range variation. The multiresolution property of wavelet approximation was used to remove some of the short-range variation in SR. We used a discrete wavelet transform (Bruce and Gao 1996) of each Landsat 7 ETM+ SR image from area A1 to compute a multiresolution decomposition of the images with six levels. Level 1 contained the finest scale components; level 6, the coarsest. The wavelet used for the discrete wavelet transform was a symmlet (s6 in S+ WAVELET software). After the multiresolution decomposition was computed, level 1 was removed, and the image was reconstructed using the other five levels. The result was a smoothed image, making more evident the longer range variations in SR.

For many applications, it may only be necessary to have an estimate of LAI at the stand level; consequently, we evaluated the ability of Landsat 7 ETM+ to consistently estimate stand SR. We identified 41 pine stands in area A1 and 42 in area A2. Average SR values were calculated and compared.

**Results**

**Relationship between leaf area index and broadband simple ratio**

At SETRES2, LAI ranged from 0.9 to 3.2 (Table 1). LAI was significantly related to \( SRL_7 \), with an \( R^2 \) of 0.98 (Fig. 1, Table 2). This regression, although highly significant, does not account for errors in both LAI and SR measurements. A detailed treatment of regression analysis for empirical relationships between LAI and VIs, accounting for measurement errors, can be found in Fernandes and Leblanc (2005).

We found a strong linear relationship between \( SRL_7 \) and \( SRL_7 \) calculated from HyMap using the prelaunch spectral response (Fig. 2, Table 2). Furthermore, when actual Landsat 7 ETM+ and HyMap images were used, the spatial regression model used to fit the data also showed a strong linear relationship between \( SRL_7 \) and \( SRL_7 \) (Table 2). The slope of the spatial regression model was almost the same as the slope of the theoretical relationship between \( SRL_7 \) and \( SRL_7 \) that we calculated from HyMap using the prelaunch spectral...

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response (Table 2), whereas the intercept was only slightly different. These results indicate good agreement between the two approaches used to relate SR from Landsat and HyMap sources (Fig. 2).

On basis of the theoretical relationship between SR_{L7} and SR_{HM} (Table 2) and the model estimating LAI from HyMap SR (Flores 2003), the following equation can be used to estimate LAI with SR_{L7}:

\[ \text{LAI} = 0.56 \text{SR}_{L7} - 0.83 \]

LAI for SETRES2 was then predicted with eq. 5, and the resulting values were highly correlated with the observed LAI values (Table 2). The predicted values, however, slightly underestimated the observed LAI values (Fig. 3). The root mean square error of prediction was 0.29, an error of approximately 14% in prediction.

Comparison of simple ratio estimates over time

The SR image showed a much smoother pattern than the original image after the short-range variation was removed by wavelet decomposition (Fig. 4). Pixel-by-pixel comparison of the SR from the smoothed winter images of area A1 showed that most pixels were close to the 1:1 line (Fig. 5). Some clusters of points were evident above and below the 1:1 line, suggesting increases and decreases in LAI for those pixels on image 2, respectively. Almost 96% of the pixels had a difference of <0.5 units of SR from image 1 to image 2. Further examination of the spatial location of areas with differences of >0.5 units of SR showed that a high percentage of those pixels were located in a clear-cut stand (labeled H in Figs. 6 and 7), a thinned stand (labeled T in Figs. 6 and 7), and some winter crops (labeled C in Figs. 6 and 7). Most of the remaining areas with differences of >0.5 units of SR were located at the edges of forest stands (Fig. 7).

Mean SR was also calculated in polygons corresponding to pine stands within the two study areas, using the original resolution data (30 m × 30 m). The relationship between mean SR values for those stands calculated from both winter images showed a very strong linear relationship. For area A1, the coefficient of determination was very high ($R^2 = 0.98$), and the points were aligned on a 1:1 line (Fig. 8, Table 3). The maximum difference in mean stand SR between the two images was 0.2 units of SR (approximately 0.12 units of LAI). For area A2, there was also a strong relationship ($R^2 = 0.94$) between mean SR from both winter images.

### Table 2.

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Lower</th>
<th>Upper</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAI = $a + b$SR_{L7}</td>
<td>0.98</td>
<td>Intercept</td>
<td>-0.88</td>
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<td></td>
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<td>0.97</td>
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<td>SR_{HM} = $a + b$SR_{L7th}</td>
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<td>Intercept</td>
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<td>0.27</td>
<td>0.29</td>
<td>&lt;0.0001</td>
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<tr>
<td></td>
<td></td>
<td>Slope</td>
<td>0.95</td>
<td>0.95</td>
<td>0.95</td>
<td>&lt;0.0001</td>
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<tr>
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<td>0.7233</td>
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<tr>
<td></td>
<td></td>
<td>Slope</td>
<td>0.95</td>
<td>0.93</td>
<td>0.97</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

Note: LAI_{pred} is LAI predicted with eq. 5; LAI_{obs} is LAI measured at SETRES2 with LAI-2000 PCA; SR_{L7th} is Landsat 7 ETM+ SR calculated from HyMap using the known spectral response for bands 3 and 4. All models were significant ($p < 0.0001$).
Fig. 4. Simple ratio estimated from Landsat 7 ETM+ (SR$_{L7}$) for area A1 before (a) and after (b) the application of a wavelet smoothing.

Discussion

As in previous studies, a linear relationship was observed between LAI and SR$_{L7}$ (Running et al. 1986; Chen and Cihlar 1996; White et al. 1997).

The strong empirical relationship between SR$_{L7}$ and SR$_{HM}$ (see Fig. 2 and Table 2) and the similarity between that relationship and the theoretical relationship between the two sensors provide clear evidence that SR$_{L7}$ can be used to estimate SR$_{HM}$.

The LAI values predicted from SR$_{L7}$ observations applied to the relationship between LAI and SR$_{HM}$ (Flores 2003) were significantly related to the LAI values estimated by the LAI-2000 PCA. However, it was evident that the predicted values underestimated the observed LAI (see Fig. 3). The reason for this bias could be explained in part by the overestimation of LAI by the LAI-2000 PCA in October, which was associated with the presence of dead foliage (Flores 2003). It was also evident (Fig. 3, Table 2) that the bias was higher for higher LAI values. This higher bias at higher LAI could be related to an underestimation of SR$_{L7}$. Because the pixel size (30 m × 30 m) was large relative to the plot size (140 m × 60 m or 140 m × 120 m), some reflectance contribution from areas outside the plots, which have low LAI, is likely. The effect should be higher on fertilized plots, as the difference in SR between a plot and its surroundings is likely to be larger. Despite this bias, the mean square prediction error was low (0.3 LAI units), which is encouraging for operational application of this technology. We recommend the use of eq. 5 to estimate LAI from SR$_{L7}$, instead of the model fitted using empirical data from the 12 plots in SETRES2. The latter could be influenced by the large pixel size in relation to plot size.

It is important to note that the SR from Landsat 7 ETM+ needs to be calculated using reflectance values from bands 3 and 4. In this study, exoatmospheric reflectance values were used to estimate SR, and we found close agreement with estimates using the prelaunch spectral response for Landsat 7 ETM+ and HyMap data (see Fig. 2). The use of atmospherically corrected reflectance from bands 3 and 4 will likely improve the robustness of this model over time, especially when applied to scenes with significant amounts of atmospheric water vapor.

Pixel-by-pixel comparison of SR during winter showed that SR$_{L7}$ can be consistently estimated over time using exoatmospheric reflectance values and cloud-free scenes. Close to 96% of the pixels presented a difference in SR$_{L7}$ of <0.5 units, which, according to eq. 5, represents a difference in LAI of <0.3 units. Most pixels with changes in SR of >0.5 units (representing 4% of the total area) were in areas with real changes in LAI in the period between image acquisitions. Winter and snow-free images are recommended for LAI monitoring in most loblolly pine stands. Butson and Fernandes (2004) found somewhat larger differences when retrieving LAI from overlapping clear-sky Landsat 7 ETM+ imagery. They found an average absolute difference in LAI of 0.5 units and a maximum absolute difference of 0.7 units. In their analysis, they used summer images, which may be
one reason for the larger differences in LAI: phenological differences are more pronounced during the summer.

During winter, phenological differences are minimized, which results in a wider window of opportunity for cloud-free images. In the particular case of loblolly pine, which carries the foliage for 2 years, during the winter there is only one cohort of foliage (the one produced during the last growing season). For that reason, winter LAI can be used to estimate foliage production during the last growing season (as well as litterfall the following fall), and that information could be valuable for nutrient-use assessment and productivity estimates. Furthermore, there are models of foliage accretion and senescence (Dougherty et al. 1995; Sampson et al. 2003) that can be used to estimate LAI during the growing season and then to estimate light interception and productivity using process-based models such as 3-PG (Landsberg and Waring 1997). An alternative approach would be the use of readily available (coarser spatial resolution) MODIS data to retrieve the seasonal display of LAI. The enhanced vegetation index derived from MODIS has been shown to be highly related to LAI and also resistant to atmospheric and soil background conditions (Huete et al. 2002). Further testing and refining of a multiscale approach to estimating LAI display during the growing season can prove to be valuable, especially for process-based productivity estimates at the stand level.

When stand SR in area A2 was estimated, a significant bias was detected (Table 3). The reason for this bias can be found in the strong change in reflectance background from one image to the other. Although the images were collected close in time (i.e., 8 days apart), the first image was collected right after a snowstorm, whereas the second image was collected after most of the snow had melted. The strong difference in reflectance in the R and NIR from the back-
ground (snow) is most likely responsible for the bias on SR estimation in area A2. Huete et al. (1985) also found a decrease in SR associated with brighter backgrounds. Snow is an extreme case of bright background, and in areas where snow is not frequent, winter scenes with snow cover should be avoided.

Remote sensing has been successfully used to estimate the leaf area of loblolly pine stands (Flores 2003), as well as that of other forest types (Running et al. 1986; Curran et al. 1992; Chen and Cihlar 1996; White et al. 1997), and this can be a key link between the development of improved silvicultural practices and the application of those practices to broad land areas. Field trials have provided an understanding of which factors are controlling current levels of leaf area and forest production in different soil–climate conditions. These trials have also provided estimates of levels of leaf area and forest production that could be achieved with intensive management, and then a difference between current versus potential stand LAI could be used as a diagnostic tool to identify stands likely to respond to intensive management (Allen 2001). Using this concept, researchers have proposed stand LAI estimates to identify stands that will potentially respond to fertilization (Vose and Allen 1988; Allen 2001). Remote sensing estimates of LAI can be a key element in the application of this concept. Furthermore, the response after fertilization can be efficiently monitored for quality control and for determination of whether and when refertilization is required.

The ability to detect changes in LAI will be important for several other applications. For example, young stands with high non-pine vegetation can be identified. Glover and Zutter (1993) found a strong relationship between the number of hardwoods at age 3 and the 27-year basal area yield of pine and emphasized the need to quantify the abundance of competing hardwoods in those early years of the stand. Remote sensing can clearly be used for that purpose if advantage is taken of the strong phenological differences between pine and hardwoods and the ability of Landsat 7 ETM+ to detect changes in LAI. For instance, large differences in remotely sensed LAI between winter (dormant season) and early spring are expected only in areas dominated by deciduous hardwoods, because they have no foliage during the winter and have a much faster foliage accretion in spring than pine (for hardwoods, see Porter (1997) and Kuers and Steinbeck (1998); for pine, see Kinerson et al. (1974), Mudano et al. (1992), and Dougherty et al. (1995)).

Despite the strong empirical and theoretical evidence supporting the use of remote sensing to estimate LAI and the

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**Table 3. Summary statistics for models fitted in the comparison of simple ratio (SR) estimates over time.**

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Lower</th>
<th>Upper</th>
<th>$p$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Area 1</strong></td>
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<td></td>
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</tr>
<tr>
<td>$SR_{i1} = a + bSR_{i2}$</td>
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<td>Intercept</td>
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<td>-0.10</td>
<td>0.3</td>
<td>0.3039</td>
</tr>
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<td></td>
<td></td>
<td>Slope</td>
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<td><strong>Area 2</strong></td>
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<td>Intercept</td>
<td>-0.91</td>
<td>-1.27</td>
<td>-0.55</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Slope</td>
<td>1.04</td>
<td>0.96</td>
<td>1.12</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

**Note:** $SR_{i1}$ and $SR_{i2}$ are SR calculated from image 1 and 2, respectively. All models were significant ($p < 0.0001$).
opportunities to improve forest productivity by using LAI information, there is no broad-scale operational use of remote sensing to estimate LAI as an aid for silvicultural decision-making. This is particularly striking in the case of intensively managed plantation forests, where high investments provide a strong incentive to use better information for decision-making. Furthermore, in intensively managed forest plantations, many of the potentially confounding effects in remote-sensing determination of LAI are reduced. Stands have a single dominant species, are of the same age, are planted at a known spacing, and have known boundaries.

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References


