A Modeled-Based Sub-Pixel Scale Mountain Terrain Normalization Algorithm for Improved LAI Estimation from Airborne CASI Imagery

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Abstract

The effects of terrain and forest structure on the radiometric properties of multispectral CASI imagery were examined for predicting ground based optical estimates of leaf area index (LAI) and effective leaf area index (eLAI). Terrain influences the position of trees within the canopy relative to the sensor, thus changing the contribution of canopy, background and shadow to the overall pixel signal recorded. To account for these variations, a modified approach using the Li and Strahler Geometric Optical Mutual Shadowing (GOMS) model in 'multiple forward mode' (MFM) has been used. Using the MFM approach, a series of look-up tables were produced relating forest structural variables defining tree shape and canopy density as well as derived terrain variables of slope and aspect with their corresponding spatial abundance of scene components. These tables were then used to normalize terrain effects at the sub-pixel scale, accounting for the variation in scene component fractions. This new approach was evaluated against NDVI and scene fractions from spectral mixture analysis of imagery for which four radiometric corrections were applied to account for slope and aspect at the pixel scale. The ability to predict ground based estimates of LAI from a Tracing Radiation and Architecture of Canopies (TRAC) system as well as eLAI from a LAI-2000 instrument was assessed. The radiometric corrections used for comparison were the cosine, statistical-empirical, Minnaert and C-corrections. The results show that the simple cosine correction was not appropriate in mountainous terrain as it over corrected the image preventing accurate estimation of LAI. The statistical-empirical, Minnaert and C-corrections each yielded an improvement in the prediction of leaf area using spectral mixture analysis, however, the MFM approach showed the best overall improvements in LAI and eLAI predictions.

1.0 Introduction

Remote sensing of forest leaf area in mountainous terrain is important to a wide range of forest management and research fields (NRC, 1998). Accurate estimates of leaf area index (LAI) are required in studies of ecophysiology, atmosphere-biosphere interactions and global change. LAI is defined as one half the total leaf area per unit ground area (Chen, 1996). LAI is one of the primary forest structural measures used in remote sensing and processed-based models to characterize forest canopies because of the importance of green leaves in many biological and physical processes in forest canopies (Sellers, 1987; Running and Coughlan, 1988; Bonan, 1993). LAI was identified by Running et al., (1986) as the single most important variable that can be derived from remote sensing that is of most importance to ecologists. This research builds on earlier successes using spectral mixture analysis (SMA) in making accurate estimates of forest biophysical parameters in low relief environments (Hall et al, 1995, 1996; Peddle et al, 1999). Spectral mixture analysis (Adams et al., 1993) separates individual pixels into the main scene components that contribute to the overall signal recorded by the sensor. In highly structured conifer canopies, the main components that contribute to pixel level brightness include sunlit canopy, sunlit background and shadow. The fundamental concept of spectral mixture analysis is that the spectral properties of each of these components combine and contribute to the overall pixel value based on their spatial abundance on the ground as viewed by the sensor. The abundance of each component is highly related to forest structure, which is the basis for the strong predictive capability of spectral mixture analysis. As forest structure changes so does the relative amount of each scene component visible to the sensor. This methodology has been shown to provide better predictions over traditional methods such as vegetation indices (Peddle et al., 1999, 2000a). For example, the Normalized Difference Vegetation Index (NDVI) does not account explicitly
for the influence of background vegetation and shadow on pixel level reflectance (Hall et al, 1995), thereby reducing the ability to make accurate estimations of forest biophysical parameters.

In a high relief, forested environment, terrain variations further influence the abundance of these scene components visible to the sensor. Terrain affects the position of trees within the canopy relative to the sensor, thus changing the contribution of sunlit canopy, sunlit background, and shadow to the overall pixel signal recorded by the sensor. Therefore, the thrust of this research is the development of new image processing techniques which account for variations in sub-pixel scale scene fractions induced by terrain. The main hypothesis presented in this research is that a terrain normalization method that explicitly accounts for forest structure will provide improved estimates of leaf area index in mountainous terrain. In addressing the influence of terrain, a new way of using geometric optical reflectance models in a multiple forward mode (MFM) was adapted for mountainous terrain applications. A controlled experiment was designed to test the ability of spectral mixture analysis and multiple forward mode reflectance modeling for predicting ground based optical estimates of leaf area index. Unique aspects of this research include a co-registered multi-scale Compact Airborne Spectrographic Imager (CASI) image data set, detailed forest structural measurements collected for input to forest reflectance models and for validation purposes, and the use of a variety of ground-based optical instruments to estimate leaf area index in the field.

2.0 Study Area and Data Set

The study site is centered at 115°4'20"W, 51°1'13''N on the eastern slopes of the Rocky Mountains straddling Barrier Lake in Kananaskis Country, Alberta, Canada. This region covers approximately 77km² and includes a full range of terrain aspects, and slopes ranging from 3° to 30°. The site is within the montane/sub-alpine forest region M.5, and is dominated by stands of Lodgepole Pine (Pinus contorta var. latifolia Dougl ex. Loud.), Engelmann Spruce (Picea engelmannii Parry ex Engelm.), White Spruce (Picea glauca (Moench) Voss), trembling aspen (Populus tremuloides Michx), balsam poplar (Populus balsamifera L.) on lower, more moist slopes, and some scattered Douglas fir (Pseudotsuga menziesii (Mirb.) Franco) (Rowe, 1972). The site encompasses a range of forest structure and LAI values.

A CASI image data set was acquired over Kananaskis from 9:30 to 13:00 hrs on July 18, 1998. The imagery was acquired at three nominal spatial resolutions of 60cm, 1m, and 2m, and co-registered to a digital elevation model. The weather during image acquisition was judged to be ideal throughout the mission, with clear skies and only light winds. For this analysis, the CASI was used in a modified spatial mode configuration, with 8 matching spectral bands were collected at all three spatial resolutions. The limited number of bands collected was a function of the finite rate at which the CASI sensor can record data. At the flying elevation required to capture 60cm data, the aircraft speed was too great to collect more spectral bands, therefore, a compromise between spectral and spatial information was made. Several geometric and illumination issues had to be considered during mission planning because of the terrain within the study area. The terrain prevented the aircraft from maintaining a constant elevation above the ground surface during image acquisitions; therefore, the across track pixel resolution varied along all flight lines. This was accounted for by identifying a nominal flying datum (1550m ASL), which distributed the amount of variation more evenly throughout the study site. Image acquisition was also planned to increase canopy shadowing obscuring the background vegetation, reduce shadows from terrain and to take advantage of clear morning skies.

One requirement of data collection in this study was to capture variability in both forest structure and terrain. Plots were located to capture a full range of slopes and aspects as well as to provide a wide variety of forest structures. A total of 31 plots were used in this study. Each plot was 10m x 10m, to ensure an adequate number of pixels at each spatial resolution would be within the plot. The plots consisted of pure and mixed softwood species (Lodgepole pine, white spruce and Douglas fir). Due to the limited sample size, separating the plots by species was not feasible, therefore the analysis was undertaken using all the conifer plots together.

Various in situ ground data sets were collected in the study area, including field spectral data, LAI estimates, forest structural data, and positional information, as described in the following sections.

2.1 Field Spectral Data

There were two requirements for spectral data collected on the ground. First, field measurements were needed of ground radiometric calibration targets visible in the imagery to correct for atmospheric effects. These targets were located in the imagery and used as pseudo-invariant targets to perform empirical radiometric normalization of the images to reflectance (Jensen, 1996, Johnson, 2000). Second, spectral measurements were collected of individual scene components (sunlit canopy, sunlit background and shadow) to act as reference endmembers in both the spectral mixture analysis and the forest reflectance model. All spectral
measurements were collected using an ASD-FR portable field spectroradiometer, covering a 350-2500nm range at 1nm spectral resolution, using field procedures as outlined in Johnson (2000).

2.2 Ground Based LAI Estimation

Two optical instruments were used to estimate canopy leaf area in the test plots. The first instrument was the LAI-2000 Plant Canopy Analyzer, which provided an estimate of effective LAI (Welles and Norman 1991). The LAI-2000 assumes a random leaf distribution and does not account for canopy architecture and therefore provides an estimate of effective leaf area index (eLAI). However, the LAI-2000 does resolve the leaf angle orientation to avoid biasing the eLAI values. The LAI-2000 uses a fish-eye optical sensor sampled at five concentric angles (0-13, 16-28, 32-43, 47-58, 61-74 degrees) to measure the amount of foliage in the vegetation canopy as a function of the change in attenuation of radiation through the canopy. To quantify the change in radiation as it passes through the canopy, two measurements are needed: a measure of diffuse light outside the canopy, and a second measure of diffuse light taken below the canopy. For each plot, five measurements were collected under the canopy and compared to measurements of diffuse light taken outside the canopy. These measures were then averaged to produce a single estimate of eLAI for each plot.

The second optical instrument was the Tracing Radiation and Architecture of Canopies (TRAC) which provided an estimate of the clumping index and LAI (Chen and Kwong, 1997). This instrument consists of three quantum sensors. Two of these sensors are pointed upwards to measure the down-welling total diffuse PAR, with the third sensor pointed downward to measure the reflected PAR from the ground. In addition, the TRAC measures sunfleck width, which is related to gaps in the overhead canopy. Based on the assumption that foliage is rarely distributed randomly in canopies, the resulting gap fraction and gap size distribution are used to calculate a foliage-clumping index in the TRAC software to produce the final LAI value. The TRAC collects continuous measurements while the operator walks a transect perpendicular to the principal plane of the sun and, if possible, parallel to the slope. For each plot in the study, five transects were made and a single LAI value was calculated.

2.3 Forest Structural Data

Stand structural data were collected for input to the canopy geometric optical reflectance model. These variables were used to define the shape and spatial distribution of trees within a stand. These included tree species, stand density, crown closure, horizontal crown radius, vertical crown radius, tree height, and height distribution, each of which were measured using standard forest field techniques. Other forest structure measurements collected included ground-based estimates of slope and aspect, diameter at breast height (DBH), ground cover vegetation composition, and plot maps detailing the location of each tree.

2.4 Field and Image Position

A key component of this analysis was the ability to accurately locate field measurements in the image data. To facilitate this, a differential global positioning system (DGPS) was used to obtain field positions with +/- 1m accuracy. GPS positions were collected for each plot and used to locate the plots on the imagery. Several ground control points were also collected and used to control and correct field and image position. These points were demarcated in the field with a highly visible, high contrast target, which was readily visible in the CASI imagery. Careful examination of the geometric correction showed less than a single pixel variation between the 60 cm and 2 m resolutions (less than 2m absolute variation in alignment), which was acceptable for our analysis.

3.0 Methods

3.1 Spectral Mixture Analysis

To test the ability of SMA to predict forest leaf area in mountainous terrain, a series of tests was designed. As a basis for comparison, a SMA trial was first performed using the reference endmembers collected in the field without any attempt to account for the variations induced by terrain. Subsequent SMA trials were performed after applying various terrain normalizations to the imagery. Four terrain normalization equations (Cosine, Statistical-Empirical, Minnaert, and C-corrections) were applied to the CASI imagery, prior to the spectral mixture analysis. The scene fractions obtained from the various terrain-normalized images were then tested in terms of the ability to predict the ground-based estimates of LAI. In each case the SMA algorithm was parameterized with the set of endmembers that represented the species in the given plot.

The SMA algorithm produced a set of scene fraction values and an estimate of RMS error for each pixel. The fractions produced by the algorithm represent the physical abundance of sunlit canopy, sunlit background, and shadow on the ground. To match the scale of the LAI information collected on the ground, the output of the SMA needed to be aggregated.
to the plot scale. The fractions produced for each plot were summed and averaged over the plot area, thus avoiding the difficulties of resampling the spectral values to the plot level.

Once the scene fractions were scaled to the plot level, they were validated to ensure they accurately represented the spatial abundance of sunlit canopy, sunlit background, and shadow. A quantitative validation of sub-pixel scale fractions at 1m and 2m resolution was performed using a maximum likelihood (ML) supervised classification of sunlit canopy, sunlit background and shadow classes at the 60cm resolution. For example, a 10 x 10 m test plot contained approximately 25 pixels at 2m resolution for which a set of scene fractions was produced and aggregated. These scene fractions were compared to the ML classification of 280 pixels at the 60cm resolution that comprised the same plot area. This provided a first-order validation of the fractions produced at the 1m and 2m image resolutions. Potential error can be introduced into this analysis due to the mixtures of materials that occur within a 60cm pixel as well as from errors in classification. However, this method of validation provided a meaningful way of evaluating SMA fractions prior to biophysical analysis, based on previous successful scene fraction validations using this approach applied to a different airborne image data set (Peddle and Johnson, 2000).

After the scene fractions were validated, the fractions produced from each set of normalized imagery were evaluated in terms of their ability to predict ground-based estimates of leaf area index acquired using the LAI-2000 and TRAC. Separate linear regression analyses to predict LAI values were performed using the shadow, sunlit canopy and sunlit background fractions produced at each image resolution and from each set of terrain normalized imagery. The ability to predict LAI was based on the magnitude of the regression coefficient of determination ($r^2$). NDVI was also computed from each set of terrain normalized imagery at all spatial resolutions, and used to predict LAI for comparison with the SMA results.

### 3.2 Geometric Optical Reflectance Modeling

For the modeling analysis, the Li and Strahler (1992) Geometric Optical Mutual Shadowing (GOMS) model was selected because of several advantages over other geometric optical reflectance models. Firstly, the GOMS model represents tree crowns as spheroids that have been shown to be superior to other crown geometric forms such as cylinders and cones (Peddle et al., 1999). Secondly, the GOMS model provides capabilities to deal with complex crown mutual shadowing influenced by solar zenith angles and stand structure. Mutual shadowing is more likely at higher latitudes and in mountainous terrain where shadows are often longer. Thirdly, the GOMS model is relatively easy to parameterize from fieldwork or baseline inventory data. Fourthly, the GOMS model uses slope and aspect in model calculations and is therefore more appropriate for mountainous terrain compared to other models which do not have this capability.

The model can be used in either forward or inverse mode. In forward mode, the model produces as output an average pixel level reflectance value in each spectral band, as well as scene component fraction values based on inputs of tree dimension, illumination geometry, stand density, and the spectral component reflectances. In inverse mode, the model provides as output the physical descriptions of forest structure (tree height, stand density, and tree height distribution, and horizontal and vertical crown radius), based on inputs of pixel level reflectance, the spectral properties of each individual stand component, and illumination geometry. In this research a new approach to using the GOMS model is adapted for use in mountainous terrain, in which an inverse modeling capability is realized based on forward mode runs which account for changes in pixel level reflectance as a function of stand structure and terrain.

### 3.3 Multiple Forward Mode Approach

Typically, any study focused on providing quantitative forest structural information is set in the context of model inversion since that mode provides physical descriptors of stand structure based on spectral input data. In this study, an approach that provided a basis for quantifying forest reflectance as a function of varying stand structure and terrain was needed. Not only would such a method provide a means of characterizing forest reflectance as a function of terrain, but it will also provide an inherent ability to normalize these effects.

To account for these variations, a modified approach using the GOMS model in "multiple forward mode" (MFM) was adapted for mountainous terrain from previous MFM work in a flat, mixed forest environment in eastern Canada in which the multiple forward mode idea was first developed (Peddle, 1999; Peddle et al., 2000b). The MFM approach is outlined briefly here; a more complete description of this method is contained in Peddle et al. (2000c), in which MFM was coupled with the 5-scale reflectance model and used for unsupervised cluster labeling and independent classification of boreal forest terrain.

Multiple forward mode is an extension of standard forward mode usage, with greater user flexibility incorporated both on input and output. In standard forward mode, the user must provide input...
data for each model trial. The model then computes a single pixel value corresponding to the set of physical inputs and spectral component measurements. A key advantage of MFM is that it permits a range of input values to be specified, thereby relaxing the requirement for exact inputs, which may be inaccurate, difficult to obtain, and not representative over larger areas. For example, instead of specifying a single stand specific value for horizontal crown radius, the user may provide a range of values and a model increment. This method allows the user to explicitly address the variability in the stand. The model then runs multiple times in forward mode for each possible combination of physical canopy descriptors, view geometries, and illumination angles, over the full range specified for each parameter. For a given set of physical inputs, all values are considered throughout the range with respect to the increment steps specified by the user. As output, the model produces a large look-up-table of values that relates pixel level reflectance, scene component fractions, and input structure and illumination geometry values. These MFM look-up tables were computed over the full range of forest structural and terrain variability in the study area. These tables can then be searched and sorted to retrieve quantitative information relating scene reflectance or scene component fractions to any model input.

The MFM model was parameterized using ranges of physical input that were assessed based on direct measurements taken in the field. Each range of input values was expanded beyond the variability seen in the field to ensure that the model captured all the variability in the stand. The view angle was held constant as nadir and the illumination geometry was assigned based on the solar positions during the CASI airborne image acquisition. The terrain inputs were assigned based on the variation in slope and aspect derived from the DEM. Reference endmember values used in the SMA trails were used as spectral inputs to the model. The modeling intervals for each parameter were selected based on two criteria. First, an interval was selected which allowed sufficient variation in stand structure to be characterized. Secondly, since a smaller interval size resulted in more model runs, a balance between model intervals and numbers of trials was also considered.

The first step in the analysis was the validation of the scene component fractions produced by the MFM approach. To facilitate this, the MFM model was parameterized with the stand structure and terrain variables of each plot, from which scene component fractions were produced from the model runs. Both SMA and the GOMS MFM require endmember spectral inputs, and both approaches produced sub-pixel scale fractions as output. This permits SMA and GOMS MFM fraction output to be directly compared. Initial observation of these results showed that the SMA fractions and those produced using the MFM approach consistently indicated acceptable agreement.

The next step was to quantify the influence of terrain on scene fraction values given the same stand structure. Terrain has no influence over the sun-crown geometry because trees are considered geotropic (perpendicular to the geoid) (Gu and Gillespie, 1998). Terrain roughness and slope/aspect position, however, influence the position of trees within the canopy relative to the sensor, thus changing the contribution of sunlit canopy, sunlit background, and shadow to the overall pixel radiance recorded by the sensor. The influence of terrain was quantified using the MFM approach. Input stand structural values for a given stand were held constant and only the slope and aspect values were input as ranges. The output was a look-up table that quantified the influence of terrain on forest reflectance and scene fraction values.

Using this look-up table approach, the reflectance and scene fraction values for any forest stand can be normalized to flat terrain. To accomplish this, several steps were followed. First, the MFM model was parameterized with the range of forest structure measured on the ground for a given plot. The illumination and terrain inputs were kept constant for the time of image acquisition and the position of the plots, respectively. The scene fraction outputs from the GOMS MFM analysis were compared to scene fractions produced for the plot using SMA. Once a match was found, the structural inputs which produced these values were recorded from the look-up table. This set of forest structure variables represents the best physical characterization of the stand from the look-up table. Next the MFM model was re-parameterized using these structural values and the slope and aspect values were adjusted to flat terrain. The output from this trial was a set of terrain normalized scene fraction values that this stand structure would produce on flat terrain. The normalized scene fraction values were then used to predict LAI using linear regression analysis, as in the SMA.

4.0 Results and Discussion

4.1 Spectral Mixture Analysis

The first set of results was the validation of the scene fractions produced using SMA. The scene fractions and RMS error produced using each normalization method were evaluated separately to ensure that the fractions produced were correct in a physical scene prior to any attempt to predict LAI. During the initial testing of the algorithms, it was obvious that the cosine correction was unusable in most of the study area. The
correction factors produced using the cosine correction method could not account properly for moderate or steep slopes, or aspects facing away from the sun. The cosine correction adjusted the digital values of the pixels to such an extent that the endmembers no longer properly characterized the scene, therefore it was not appropriate to perform any further analysis involving the cosine correction.

For the remaining normalization methods, as a first test the RMS error produced from each endmember set and normalization method was used as an initial indicator of the endmembers ability to represent the scene. The RMS error was low in all trials, (maximum of only 0.02%), which suggested that the endmembers used in each case were representative of spectral values in the scene.

The terrain normalized fractions were produced by first applying each terrain normalization method (c-correction, statistical-empirical, Minnaert) to the original CASI imagery. Then, SMA was applied to each normalized image, and the resulting fractions compared to the ML classification of the normalized image. There was good agreement between the fractions produced at the 1m and 2m resolutions with the ML supervised classification at 60cm resolution. The difference, expressed as a percentage, was determined for each of the three scene components sunlit canopy, sunlit background and shadow with respect to the ML classification. The highest agreement was found between the SMA fractions produced without any normalization applied to the images. Differences ranged between 3% and 6% for each scene component, with the maximum variation observed for the shadow component. Image scale seemed to have little effect on the results obtained from the 1m and 2m CASI data. These results suggest that the SMA trials were in fact producing representative scene fractions prior to terrain normalization. When the terrain normalizations were applied prior to SMA the percent difference increased using each of the C-correction, Statistical-Empirical and Minnaert approaches. The best overall correspondence between the scene fractions and ML classification was found using the C-correction. Differences ranged between 2% and 5% for the sunlit canopy component providing a small improvement over that obtained without terrain normalization. The difference increased for the sunlit background and the shadow component from 7% to 10% and 3% to 11%.

These results were important as they suggest that terrain normalizations based on pixel level illumination differences did not properly account for the variations induced by changes in slope, aspect and forest structure at the sub-pixel scale. However, as will be shown later, they still provided an improved estimate of LAI compared to use of the original, uncorrected scene fractions.

Each scene component fraction and NDVI were used as independent variables in predicting both LAI and eLAI obtained from the two optical instruments. The results of the trials are summarized in Tables 1 and 2. The results show that the use of terrain normalization algorithms improved the estimation of LAI and eLAI using both SMA and NDVI. The best predictor of TRAC LAI was using SMA with the statistical-empirical correction. The best predictor of eLAI from the LAI-2000 was using SMA with either the C-correction or the statistical-empirical corrections. NDVI showed the greatest improvement in the prediction of LAI and eLAI using the Minnaert correction.

<table>
<thead>
<tr>
<th>Normalization Method</th>
<th>SMA (1m/2m)</th>
<th>NDVI (1m/2m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0.69(b)/0.65(b)</td>
<td>0.33/0.34</td>
</tr>
<tr>
<td>Minnaert</td>
<td>0.72(c)/0.70(s)</td>
<td>0.51/0.50</td>
</tr>
<tr>
<td>C-correction</td>
<td>0.76(c)/0.75(c)</td>
<td>0.41/0.41</td>
</tr>
<tr>
<td>Statistical-Empirical</td>
<td>0.77(c)/0.75(s)</td>
<td>0.46/0.48</td>
</tr>
</tbody>
</table>

Table 1. Magnitude of the coefficient of determination ($r^2$) using SMA and NDVI applied to terrain normalized images to predict TRAC LAI. The best scene fraction for each SMA trial is shown in brackets for sunlit canopy (c), sunlit background (b) and shadow (s).

<table>
<thead>
<tr>
<th>Normalization Method</th>
<th>SMA (1m/2m)</th>
<th>NDVI (1m/2m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0.62(b)/0.62(b)</td>
<td>0.45/0.44</td>
</tr>
<tr>
<td>Minnaert</td>
<td>0.70(c)/0.70(s)</td>
<td>0.54/0.55</td>
</tr>
<tr>
<td>C-correction</td>
<td>0.71(c)/0.69(c)</td>
<td>0.48/0.48</td>
</tr>
<tr>
<td>Statistical-Empirical</td>
<td>0.68(c)/0.68(s)</td>
<td>0.50/0.50</td>
</tr>
</tbody>
</table>

Table 2. Magnitude of the coefficient of determination ($r^2$) using SMA and NDVI applied to terrain normalized images to predict LAI-2000 eLAI. The best scene fraction for each SMA trial is shown in brackets for sunlit canopy (c), sunlit background (b) and shadow (s).

The results show that the use of terrain normalization algorithms improved the prediction of LAI using either SMA or NDVI. The ability of SMA to predict LAI increased from an $r^2$ of 0.69 using the background fraction before terrain normalization, to 0.72, 0.76 and 0.77 using the Minnaert, C-correction and Statistical-empirical methods using the sunlit canopy fraction, respectively. The ability of NDVI to
predict LAI increased from an $r^2$ of 0.33 to 0.51 using the Minnaert correction at the 1m resolution. The ability to predict eLAI from the LAI-2000 also increased from an $r^2$ of 0.62 using the background fraction before terrain normalization, to 0.70, 0.71 and 0.68 using the Minnaert, C-correction and Statistical-empirical methods using the sunlit canopy fraction, respectively. NDVI predictions of eLAI also increased from an $r^2$ of 0.45 to 0.54 using the Minnaert correction. In these results, we did not observe any pattern in which a particular fraction provided consistently better results.

4.2 Multiple Forward Mode Results

The output from the MFM approach was evaluated in a similar manner as the SMA results. The first step was to validate the scene fractions produced from the reflectance model. The same ML supervised classifications produced at the 60cm resolution to test the SMA results were used here to test the output of the MFM approach. The difference between the classification and the MFM scene fraction ranged from 3% to 17%, with the largest difference found in the shadow fraction. Image resolution had no effect on the difference in scene fractions as the fractions produced were only a function of the model-inputs measured on the ground. Examination of the structural input data for each trial showed that the maximum errors occurred near the extremes of the structural range provided to the model for each plot. The results suggest that, as expected, these extremes did not accurately characterize the plot and that the mean structural data provided the best representation of stand structure based on the magnitude of difference between the ML classification and scene fractions produced from the MFM.

The MFM lookup table containing the full set of modeled fractions was then searched to find modeled fractions which matched those produced by SMA. Once a match had been found, the structural input data associated with that set of modeled fractions were recorded. This structural information was then used to re-parameterize the model prior to terrain normalization. This first step ensured that the forest structure inputs to the MFM model accurately characterized each stand. After the match had been established the model was re-parameterized with this structural data and the terrain variables were adjusted to flat terrain. The output from this trial was the normalized scene fractions used to predict LAI.

The results of the linear regression analyses to predict the two sets of leaf area index estimates from the TRAC and LAI-2000 are summarized in Table 3 for the 1m and 2m resolutions. Each scene component fraction was used in a separate regression analysis to test the ability to predict leaf area index. The highest magnitudes of $r^2$ were found using shadow fraction to predict LAI from the TRAC, with $r^2$ values of 0.83 and 0.80 for the 1m and 2m data, respectively. The results for the LAI-2000 were similar, with $r^2$ values of 0.79 and 0.75 obtained using shadow fraction for the 1m and 2m data, respectively. The best regression results were found using the shadow fraction as the independent predictor of either estimate of leaf area. This result is consistent with previous research where shadow fraction was the best predictor of forest biophysical parameters (Hall et al, 1995; Peddle et al, 1999; Peddle and Johnson, 2000). Therefore, the results obtained here suggest that this normalization method is accounting for forest structure at the sub-pixel scale.

<table>
<thead>
<tr>
<th>Image Resolution</th>
<th>TRAC LAI</th>
<th>LAI-2000 eLAI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1m</td>
<td>0.83</td>
<td>0.79</td>
</tr>
<tr>
<td>2m</td>
<td>0.80</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Table 3 Magnitude of the regression coefficient of determination ($r^2$) using the MFM approach to predict TRAC LAI and LAI-2000 eLAI at the 1m and 2m image resolutions. Shadow fraction was best in each trial.

The greatest improvements in predicting LAI were provided using the MFM approach to account for the effects of terrain, and forest structure as compared to each normalization method. The highest $r^2$ values for predicting TRAC LAI were 0.83 and 0.80 at the 1m and 2m resolutions (Table 3). Increases in $r^2$ values of 0.14 and 0.15 were obtained in predicting TRAC LAI values at the 1m and 2m resolutions respectively, compared to SMA without normalization. The MFM also provided improvements in $r^2$ of 0.32 and 0.30 compared to the best normalized NDVI results. Prediction of LAI-2000 eLAI increased by a magnitude of 0.17 and 0.13 at the 1m and 2m image resolutions, compared to SMA without normalization. Improvements over the best normalized fractions were 0.08 and 0.05 for the 1m and 2m images, respectively. The MFM approach also provided improvements in estimating eLAI over terrain normalized NDVI with increases in $r^2$ of 0.25 and 0.20 for the 1m and 2m data, respectively. These improvements can be attributed to accounting for the internal stand structure during terrain normalization using the MFM approach.

The difference between the 1m and 2m image resolutions had little influence on the ability to predict leaf area index using any of the methods tested. Generally, a decrease in the spatial resolution in the
remote sensing imagery will cause a decrease in the variance among pixels, reducing the ability to extract biophysical information using traditional methods. However, neither spectral mixture analysis nor the geometric optical reflectance model were considerably affected by this resolution change, since the pixel resolution in both cases was still smaller than individual tree crowns. If the pixel size was larger than an individual tree crown, the effects may have been more pronounced.

Based on the results obtained, the ability to predict TRAC LAI was greater than the ability to predict eLAI from the LAI-2000. There are two possible reasons for this. First, the orientation of the optics on the TRAC instrument constrain the FOV to only the canopy above the sensor, which was inside the plot boundaries, whereas, the large FOV of the LAI-2000 may have included an area of canopy outside the plot. This is significant since image analysis was performed only on pixels within the boundaries of the plot. Therefore, it is possible that the LAI-2000 captured information from outside the plot, which was not accounted for in the image analysis. Second the TRAC accounts for the non-random nature of forest canopies by measuring sunfleck width, which is related to gaps in the overhead canopies. These sunfleck values are strongly related to canopy structure and geometry. Both SMA and the GOMS MFM account for forest structure as part of their predictive ability. SMA estimates the abundance of sunlit canopy, sunlit background and shadow visible to the sensor, which is related to forest structure. The GOMS MFM approach directly accounts for forest structure through the structural model inputs provided by the user.

Accurate forest information is particularly important if the results are to be used in process based ecophysiological models where LAI is one of the primary variables used to characterize the forest canopy. The MFM approach provided the best results in all cases, in terms of the ability to predict LAI. With respect to practicality and ease of use, the MFM modeling approach requires several additional inputs compared to SMA, however, only ranges of physical values are required, and these are easily obtained and possibly more representative of stand spatial variability. For example, these input data can be acquired through base line vegetation inventories such as the Alberta Vegetation Inventory (AVI), with the relaxed requirement for detailed forest measurements using the MFM approach resulting in it being a suitable approach in many circumstances.

5.0 CONCLUSION

The ability to provide accurate estimates of forest biophysical information over mountainous terrain provides improved parameterization for regional and global scale process-based ecological models. This research has shown the utility of geometric optical reflectance models, and in particular the use of a new 'multiple forward mode' (MFM) approach in mountainous terrain which provided a means to account for the influence of terrain at the sub-pixel scale, improving the estimation of ground-based LAI. Compared to NDVI and SMA, the best overall remote sensing estimates of ground-based LAI from the TRAC instrument was found using the MFM approach, with $r^2$ values of 0.83 and 0.82 for the 1m and 2m image resolutions, respectively. The best estimates of eLAI from the LAI-2000 were found using the MFM approach with $r^2$ values of 0.79 and 0.75 for the 1m and 2m image resolutions, respectively.

In terms of forest image analysis and reflectance modeling, the MFM approach provides several advantages. The first advantage is that the MFM approach allows a wide range of structural and illumination inputs to be tested in a single set of model runs. The model runs can also be conducted to vary one single input variable only, while several other parameters are held constant. For example, varying only the slope and aspect values (holding all other values constant) allows the model to test the effects of changing terrain on modeled spectral response. Another advantage of the MFM approach is it does not require specific or exact physical parameters. Instead, only a range is required which can more easily be discerned from baseline inventory data or field data. If this information is unknown, MFM can still be used by specifying the full range of possible model inputs. Lastly, unlike typical modeling which produces a single set of output results (e.g. inversion models), the MFM produces a range of output values related to variations in forest structure and illumination, thereby providing a basis to study and further understand the influence of stand structure and terrain on scene reflectance.

Future research will include testing the ability of the MFM approach to predict other forest biophysical parameters such as biomass and NPP. There is also the potential to integrate the MFM approach with other radiative transfer models and other approaches such as tree delineation algorithms, to possibly provide further improvements over that obtained using MFM alone. Other work will include the use of MFM in change detection studies.
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References


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