Inverse BRDF Modelling of BOREAS Conifer Stands

H. Peter White, John R. Miller
Department of Physics and Astronomy, York University
4700 Keele St., North York, Ontario, M3J 1P3, Canada
Phone: 416-736-2100 ext. 33854 / Fax: 416-736-5626
email: redbeard@yorku.ca / URL: http://eol.crestech.ca

Jing M. Chen
Canadian Centre for Remote Sensing
588 Booth Street, Ottawa, Ontario, K1A 0Y7, Canada
Phone: 613-947-1266 / Fax: 613-947-1406
email: jing.chen@ccrs.nrcan.gc.ca / URL: http://www.ccrs.nrcan.gc.ca

Abstract - BRF's of boreal forest conifer canopies were observed and modelled using the MODIS BRDF/Albedo algorithms which included a recently derived Inverse 4-Scale Model. Derived BRDF functions show reasonable agreement with observed BRF. As many inverse models are limited to handling specific situations (such as high or low LAI), the Inverse 4-Scale Model was derived to allow one model use for investigation of a wider variety of canopy conditions.

INTRODUCTION

Multiangle, hyperspectral measurements of the reflectance of boreal forest conifer stands have been acquired with the Compact Airborne Spectrographic Imager (CASI) as part of the BOREAS project. This includes observations performed during winter (Feb. 1994) and late summer (Sept. 1994) field campaigns. The datasets were obtained at an altitude of 1600 meters above ground level. Upwelling radiance was measured in the principal illumination plane, perpendicular to this plane, and at a 45^0 angle to this plane, at view zenith angles (VZA) ranging between -45^0 to 45^0. Measurements were performed near local solar noon, maximizing the illumination zenith angle (IZA) for each campaign. IZA's were $\sim 70^0$ during Feb., and $\sim 50^0$ during the Sept.

Datasets were investigated using the MODIS BRDF/Albedo algorithm (V2.4) developed at Boston Univ. [2] This algorithm, designed to test several combinations of kernels, provides a best fit linear kernel combination to observed BRF [3]. Kernels include two volume scattering derivations based on the formulas of Ross (one thick, one thin), as well as three geometric kernels, two derived from the modelling approach of Li and Strahler for sparse and dense canopies, and one based on the random placement model of Roujean. This algorithm was previously successfully used to accurately model measured BRF of an artificial canopy and to produce BRDF functions that capture observed variations with IZA [4]. This method however demonstrated how variations in factors such as illumination angle or understorey coverage would alter the best fit kernel combination. As each BOREAS site was observed at various IZA, with highly reflective (snow) and moderately reflective (vegetation) understories, one model or kernel combination capable of providing reasonable BRDF surfaces over a wide range of conditions would provide a better direct comparison.

INVERSE 4-SCALE MODEL DERIVATION

The 4-scale model developed by Chen and Leblanc [1] considers four levels of canopy architecture, incorporating the influence of tree, branch, shoot, and needle distributions. Radiative transfer through the canopy is derived using probability determinations of sunlit and shaded portions of the canopy. Four surface proportions are computed: tree crown illuminated (P_T), tree crown shaded (Z_T), and ground illuminated (P_G) and shaded (Z_G). Each is then multiplied by its reflectivity factor (wavelength dependant) to compute BRF's for a given view and illumination geometry:

$$R = P_T \cdot R_T + Z_T \cdot R_{ZT} + P_G \cdot R_G + Z_G \cdot R_{ZG} \quad (1)$$

Derivation of this model into its inverse kernel form requires isolating angular from non-angular components.

The tree crown illuminated proportion defines the overall probability of observing sunlit foliage, and shall be used here to demonstrate how the inversion into kernel form was done. This function is expressed in terms of the probability of viewing illuminated foliage within a crown (P_{Tf}), the canopy gap fraction through a crown (P_{ig}: probability of illuminated ground), and a within canopy hot spot function (F_s) :

$$P_T = \left[\left(1 - P_{ig}\right) - P_{Tf}\right] \cdot F + P_{Tf} \quad (2)$$

As with traditionally defined hot spot functions, F_s is unity at the hot spot and zero when the illumination and view angles are far apart. Thus the crown illuminated proportion is equal to the probability of illuminated tree ($1-P_{ig}$) at the hot spot and to P_{Tf} at large scattering angles. The derived function of Chen and Leblanc incorporated deriving this as a

0-7803-4403-0/98/$10.00

function of scattering angle ($\Delta\theta$) and the distribution of gap sizes within and between the tree crowns. Separation of the angular and non-angular components of this proved to be complex. Instead, the shape of the hot spot function was considered for a variety of IZA. In all cases, $F_S \rightarrow 0$ as $\Delta\theta \rightarrow 90^0$ or as VZA$\rightarrow 90^0$ (for backscatter). The maximum scatter angle ($\Delta\theta_{Fmax}$) where $F_S \neq 0$ was defined as 90^0 in the forescatter direction and VZA-IZA in the backscatter direction (along the illumination plane). An elliptical function around the hot spot was used to define $\Delta\theta_{Fmax}$ at any azimuth angle using these parameters. As the hot spot decreases exponentially from 1, a purely angular hot spot function was derived:

$$F_s = \exp\left(\frac{-2\pi \cdot VZA}{\Delta\theta_{F\max}}\right) \quad (3)$$

The probability of viewing illuminated foliage within a tree crown (P_{Tf}) considers the contributions of the sunlit foliage within the sunlit part of the crown (Q_1) and the sunlit foliage within the self-shaded part of the crown (Q_2). Here, shaded and sunlit portions of the crown are determined as the portions of a solid surfaced crown.

$$Q_1 = \Gamma(\Delta\theta) \cdot \left(1 - e^{(-L_H(C_i + C_v))}\right)\left(\frac{C_i C_v}{C_i + C_v}\right) \quad (4)$$

$$Q_2 = \Gamma(\Delta\theta) \cdot \left(e^{(-L_H C_i)} - e^{(-L_H C_v)}\right)\left(\frac{C_i C_v}{C_v - C_i}\right) \quad (5)$$

Where, given a clumping index (Ω_E), a needle to shoot area ratio (γ_E), and a random foliage angle distribution $G(\theta)$:

$$C_{i,v} = \frac{\Omega_E \cdot G(\theta)}{\gamma_E \cdot \sin(\theta_{i,v})} \quad (6)$$

For this function, the sunlit foliage components were examined and found to be approximately equal ($Q_1 \cong Q_2$). This is to be expected as the foliage exists in such a way as to maximize their sunlight gathering efficiency. Leaves on the north side of the tree must be able to be exposed to sunlight at some level. Using this approximation, the traditional portions of shaded and sunlit crown surface need not be known. Thus the function P_{Tf} can be expressed as:

$$P_{Tf} = \frac{\Omega_E \cdot G(\theta)}{\gamma_E} \Gamma(\Delta\theta)\left[\frac{1}{\sin(\theta_i) + \sin(\theta_v)}\right] \quad (7)$$

The probability of having illuminated understorey (P_{ig}) or viewed understorey (P_{vg}) are determined using the same geometry. This includes a canopy gap fraction (P_{gap}), with stand density (m/A) trees per area, to determine the contribution of the underlying surface reflectance. It also includes a Neyman type-A non-random distribution ($P_N(i)$). Observations of tree distribution during the BOREAS 1994 campaigns demonstrated that trees are grouped together in clumps, with the clumps being distributed randomly. Using this distribution, the probability of j trees intercepting the view (or illumination) path (P_{tj}) more accurately describes the non random spatial variations caused by environmental conditions such as topography, soil, and other processes.

$$P_{vg} = \sum_{j=0}^{\kappa} P_{tj}(V_g) \cdot (P_{gap}(\theta_v))^j \quad (8)$$

The probability is maximum at nadir where the crown cross section relative to the canopy site area (V_g/A) is minimized and the probability of viewing between trees is highest. The probability approaches zero at 90^0 as $P_{gap} \rightarrow 0$, and falls off linearly from the nadir value.

$$P_{gap}(\theta) = e^{\left(\frac{-G(\theta)\Omega_E}{V_g \cdot \gamma_E} \frac{A}{m}\right)} \quad (9)$$

$$P_{tj}(V_g) = \sum_{i=j}^{\kappa} P_N(i) \cdot \left[\frac{(i+j-1)!}{(i-1)! \cdot j!}\right]\left[1 - \frac{V_g}{A}\right]^i \left[\frac{V_g}{A}\right]^j \quad (10)$$

The near linear nature of this function leads to a linear approximation. As VZA$\rightarrow 90^0$, $P_{vg} \rightarrow 0$. As VZA$\rightarrow 0^0$, P_{vg} can be approximated by the largest terms at j=0 and j=1.

$$P_{vg} = \left(\sum_{i=0}^{\kappa} P_N(i)\left[1 - \frac{V_g}{A}\right]^i\right) + P_{gap}\left(\sum_{i=1}^{\kappa} P_N(i) \cdot i \cdot \left[1 - \frac{V_g}{A}\right]^i \left[\frac{V_g}{A}\right]\right) \quad (11)$$

Approximating the tree distribution with the more traditional Poisson function, and as the function $P_N(i) \rightarrow 0$ for large values of κ, this equation can be simplified for small values of V_g:

$$P_{vg}(0^o) = e^{-\left(\frac{mV_g(0^o)}{A}\right)} + \frac{mV_g(0^o)}{A} P_{gap} e^{-\left(\frac{mV_g(0^o)}{A}\right)} \quad (12)$$

$$P_{vg}(0^o) = \left(e^{-\frac{m}{A}V_g(0^o)}\right) \cdot \left(1 + \frac{m}{A}\pi r^2 \cdot P_{gap}(0^o)\right) \quad (13)$$

Given these two endpoints, the linear relation between VZA and P_{vg} can be expressed as:

$$P_{vg}(\theta_v)=\left(e^{-\frac{m}{A}\pi r^2}\right)\left(1+\frac{m}{A}\pi r^2\cdot P_{gap}(0^0)\right)\left(1-\frac{2\theta_v}{\pi}\right) \quad (14)$$

Similar derivations can be performed with the other terms of the model, providing an inverse model in kernel form for the MODIS BRDF algorithm approach. This results in 4 kernels for a set IZA, or 6 kernels for multiple IZA data sets. The 4 kernel model is considered here, and is expressed as:

$$R = f_{iso} + f_{hot}k_{hot} + f_{vol}k_{vol} + f_{geo}k_{geo} \quad (15)$$

Where:

$$\begin{aligned} f_{iso} &= R_{ZT} \\ f_{hot} &= (R_T - R_{ZT})(1-P_{ig}) + (R_G - R_{ZG}) \\ f_{vol} &= (R_T - R_{ZT})(1-P_{ig})\frac{\Omega_E}{\gamma_E} \\ f_{geo} &= \left(R_{ZT}R_{ZT} + (R_G - R_{ZG})P_{ig}\right) \\ &\cdot e^{\left(-\frac{m}{A}\pi r^2\right)}\left(1+\frac{m}{A}\pi r^2\cdot P_{gap}(0^0)\right) \end{aligned} \quad (16)$$

$$\begin{aligned} k_{hot} &= e^{\left(\frac{-2\pi}{\Delta\theta_{max}}\Delta\theta\right)} \\ k_{vol} &= \left(1-e^{\left(\frac{-2\pi}{\Delta\theta_{max}}\Delta\theta\right)}\right)\cdot\frac{G(\theta)\cdot\Gamma(\Delta\theta)}{\sin(\theta_i)+\sin(\theta_v)} \\ k_{geo} &= \left(1-\frac{2\theta_v}{\pi}\right) \end{aligned} \quad (17)$$

SOUTH OLD JACK PINE RESULTS

Reflectance data at 665nm and 800nm from the Southern Old Jack Pine (SOJP) BOREAS site was used to test the 4-Scale Inverse Model, and to compare it with the other kernels. Two areas were used, one of high tree density (dense canopy, 1082 tree/ha) and one with a relatively lower tree density (sparse canopy, 482 tree/ha). In both cases, the MODIS BRDF algorithm provided the best fit (RMSE=0.01) for the Ross-Thin/Li-Sparse kernel combination. The Inverse 4-Scale kernels also provided an excellent fit (RMSE=0.01), as shown in Fig.1 for the dense canopy cover.

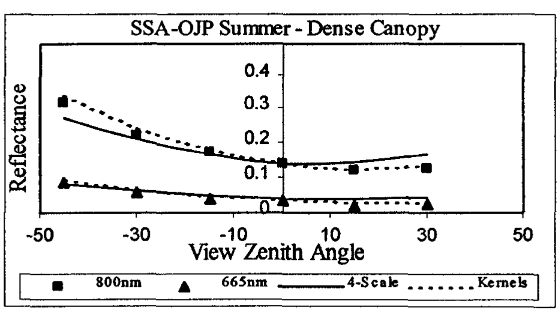

Figure 1 : Inverse 4-Scale and Thin/Sparse Model Fits

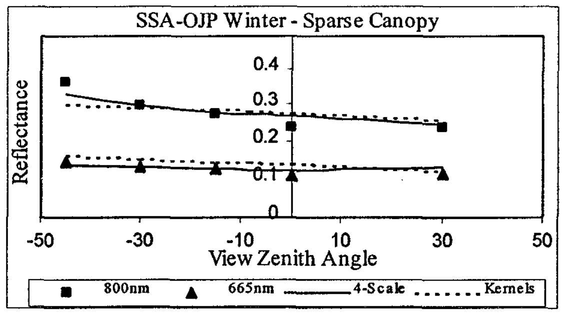

Figure 2 : Inverse 4-Scale and Thick/Sparse Model Fits

When tested for the winter data, the MODIS BRDF algorithm provided the best fit for the sparse canopy site using the Ross Thick, Li Dense kernels. The dense canopy cover site was best modelled with the Ross Thick, Li Sparse kernel combination. In both cases the Inverse 4-Scale model provided a fit with an error of the same order of magnitude.

CONCLUSIONS

The Inverse 4-Scale Model provides a method of comparing canopy BRDF's under different environmental conditions without having to alter model approximations to provide better surface fitting. This model does not have to rely on a priori conditions, but is limited at present to unique IZA per surface fitting.

REFERENCES

[1] Jing M. Chen and S. G. Leblanc, "A Four-Scale Bidirectional Reflectance Model Based on Canopy Architecture", IEEE Trans. GéoSci. Remote Sens., 1996.

[2] Alan H. Strahler, and J. Muller, "MODIS BRDF/Albedo Product: Algorithm Theoretical Basis Document", version 3.2, NASA EOS MODIS, 1995.

[3] Wolfgang Wanner, X. Li, & A. H. Strahler, "On the Derivation of Kernels for Kernel-Driven Models of Bidirectional Reflectance", J. Geo. Res., 1995.

[4] H. Peter White, J. R. Miller, R. Soffer, and W. Wanner, "Semiempirical Modelling of Bidirectional Reflectance Utilizing the MODIS BRDF/Albedo Algorithm Models", IGARSS'96 proceedings.