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PREVIEW

A VEGETATION CANOPY RADIATIVE TRANSFER MODEL AND ITS USE TO
ESTIMATE CANOPY LEAF AREA INDEX AND ABSORBED FRACTION OF
PHOTOSYNTHETICALLY ACTIVE RADIATION

by

Mauro Antonio Homem Antunes

A DISSERTATION

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Doctor of Philosophy

Major: Agronomy (Agricultural Meteorology)

Under the Supervision of Professor Elizabeth Anne Walter-Shea

Lincoln, Nebraska

October, 1997

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DISSERTATION TITLE

A Vegetation Canopy Radiative Transfer Model and its Use to Estimate
Canopy Leaf Area Index and Absorbed Fraction
of Photosynthetically Active Radiation

BY

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GRADUATE COLLEGE
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A VEGETATION CANOPY RADIATIVE TRANSFER MODEL AND ITS USE TO
ESTIMATE CANOPY LEAF AREA INDEX AND ABSORBED FRACTION OF
PHOTOSYNTHETICALLY ACTIVE RADIATION

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University of Nebraska, 1997

Adviser: Elizabeth Anne Walter-Shea

The amount of leaf area and canopy absorbed photosynthetically active radiation (APAR) (often expressed as leaf area index (LAI) and the fraction of APAR (fAPAR)) are important in determining canopy photosynthesis and stomatal conductance rates and, thus, are important for modeling these processes. Inversion of canopy radiative transfer models is a physically-based method of estimating canopy attributes from remotely-sensed bidirectional reflectance factors (BRFs); the need of simple models for this purpose has been suggested in the literature. The objectives of this research are to: 1) develop a simple canopy radiative transfer model, 2) invert the model to retrieve LAI from canopy BRF for various canopies, and 3) estimate fAPAR using the model. A simple model was developed which requires input values of leaf and soil optical properties, leaf angle distribution, leaf spatial distribution parameter, LAI, viewing and illumination geometry and sky diffuse irradiance fraction. Canopy BRFs, fAPAR and input parameters from field experiments in prairie grassland, alfalfa, soybean, and corn under various canopy LAI and illumination and view conditions were used in the analysis. Simulated corn canopy BRFs agreed on average within 0.9% and

1.7% (red and near-infrared (NIR) wavebands, respectively) of observed values. Corn fAPAR values were within ± 0.01 fAPAR units on average. Model output compared well with a detailed model for an alfalfa canopy under a single canopy and illumination condition. Model inversions of observed BRFs from all canopies in the study using NIR BRFs and red and NIR BRFs together yielded LAI estimates within ± 0.1 LAI units. Inversions using red BRFs alone yielded LAI estimates within 1.2 LAI units. fAPAR estimated using inversion-retrieved LAI values were within 0.05 fAPAR units, on average, of observed values. The model has the potential to be used in an operational setting to estimate LAI and fAPAR from remotely-sensed BRF data in the shortwave spectrum. Suggestions for improving canopy attribute inference from remotely-sensed data using the simple model are presented.

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ACKNOWLEDGMENTS

I thank my wife for her love and understanding in the difficult moments during our stay in the United States, and to my parents, brother and sisters for the support and encouragement they always gave me when needed.

I acknowledge my major adviser, Elizabeth Walter-Shea. I thank her very much for the opportunity of pursuing a Ph.D. at the University of Nebraska-Lincoln, and for dedicating the many hours she dedicated in teaching and providing professional guidance. I also thank her for the support, encouragement, and patience and for entrusting me with this difficult task.

The financial support from CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico, Brazil) is acknowledged. I also thank the researchers at INPE (Instituto Nacional de Pesquisas Espaciais) for their support and encouragement, especially Antonio Roberto Formaggio, who encouraged me to pursue the Ph.D. and provided the guidance in applying for the fellowship support and making the contacts outside Brazil.

I thank Tim Arkebauer, Blaine Blad, George Meyer and Shashi Verma, for serving on my Graduate Supervisory Committee, for their time and valuable suggestions and comments throughout the program. Assistance from Mark Mesarch, Brian Lang and Brett Grell in the field experiments is gratefully acknowledged. I thank Jeff Privette for helping to fulfill the research tool requirement.

All faculty and staff of the former Department of Agricultural Meteorology (now the School of Natural Resource Sciences) have helped one way or another and I thank all of them for this. I thank Jay Ham and Dale Bramer (Kansas State University) for allowing me to

conduct my research in their research field in 1995 and Al Weiss and Alex Moreno (UNL) for allowing me to use an area of their research field in 1996. A special thanks to Sharon Kelly for her assistance.

I thank all my colleagues and friends for their encouragement and for sharing the good and difficult moments during this program.

Others who have helped along the way are Marv Anderson, Kevin Leapley, and Sheldon Sharpe (from UNL) and Dave Bigelow from Colorado State University.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations:

ARDC	University of Nebraska Agricultural Research and Development Center
BRF	Bidirectional reflectance factor
DOY	Day of the year
fAPAR	Fraction of absorbed photosynthetically active radiation
FIFE	First ISLSCP Field Experiment
fRPAR	Fraction of reflected PAR from the canopy/soil medium
fSAPAR	Fraction of soil absorbed PAR
ILF _s	Illuminated leaf fraction
ISF _s	Illuminated soil fraction
ISF _v	Illuminated soil fraction in the viewing direction
ILF _v	Illuminated leaf fraction in the viewing direction
ISLSCP	International Satellite Land Surface Climatology Project
LAD	Leaf angle distribution
LAI	Leaf area index
LEF _s	Effective leaf area index in the solar direction
LEF _v	Effective leaf area index in the viewing direction
MBE	Mean bias error
MFRSR	Multi-Filter Rotating Shadow-Band Radiometer
MMR	Barnes Modular Multiband Radiometer
MRE	Mean relative error
NDVI	Normalized difference vegetation index
NIR	Near infrared
NIST	National Institute of Standards and Technology
NMLR	Nebraska Multiband Leaf Radiometer
PAR	Photosynthetically active radiation
ILF _v	Illuminated leaves in the viewing direction
ISF _v	Illuminated soil in the viewing direction
RMSE	Root mean square error
SRVI	Simple ratio vegetation index
SSF _v	Shaded soil fraction in the viewing direction
SLF _v	Shaded leaf fraction in the viewing direction
SZA	Solar zenith angle
TLF _v	Total leaf fraction in the viewing direction
TM	Thematic Mapper
TSF _v	Total soil fraction in the viewing direction
VI _s	Vegetation indices
VZA	View zenith angle

Symbols:

ρ_s	Soil reflectance
ρ_l	Leaf directional hemispherical reflectance factor
τ_l	Leaf directional hemispherical transmittance factor
α_l	Leaf absorptance
δ	Angle between leaf normal and the sun
θ_l	Leaf normal angle (from the vertical)
$\bar{\theta}_l$	Mean leaf tilt angle
θ_i	Solar zenith angle (from the vertical)
θ_r	View zenith angle (from the vertical)
φ_l	Leaf azimuth in relation to the solar azimuth
φ_i	Solar azimuth (from the north)
φ_r	View azimuth (from the north)
φ_{rel}	Relative azimuth between solar and viewing directions
φ_l	Leaf azimuth in relation to the solar azimuth
Φ_i	Incoming flux
Φ_r	Reflected flux
λ_0	Leaf spatial distribution parameter
$\chi(\theta_i, \varphi_i; \theta_r, \varphi_r)$	Illumination-view joint probability coefficient
ω_i	Solid angle of the incoming beam
Ω_i	Projected solid angle of the incoming beam
ω_r	Solid angle of the reflected beam
Ω_r	Projected solid angle of the reflected beam
AB_B	Fraction of leaf abaxial side projected towards the sensor and illuminated on the abaxial side in the backscatter direction
AD_B	Fraction of leaf abaxial side projected towards the sensor and illuminated on the adaxial side in the backscatter direction
AD_F	Fraction of leaf abaxial side projected towards the sensor and illuminated on the adaxial side in the forward scatter direction
$f_r(\theta_i, \varphi_i; \theta_r, \varphi_r)$	Bidirectional reflectance distribution function
I_d	Sky diffuse flux intensity
I_0	Total incoming flux intensity (direct plus diffuse)
I_{D0}	Direct beam flux intensity at the top of the canopy
K	Interception coefficient
w_j	weight given to each viewing-illumination condition in the inversions

“Everything should be made as simple as possible, but not simpler”

(Albert Einstein)

CHAPTER 1

INTRODUCTION

1.1. REMOTE SENSING OVERVIEW

Remote sensing has been used to evaluate vegetative canopy processes (i.e., radiation absorption, photosynthesis and stomatal conductance), for vegetation type screening and mapping and as an ancillary tool for yield forecasts. In the beginning of satellite remote sensing, research was mainly devoted to understanding how to use the data either by visual or digital interpretation of images. At that time knowledge regarding the radiative transfer in vegetation was limited; most of the studies were adapted from plant physiology studies in which the physical and physiological basis for the signals measured by remote sensors were studied (e.g., Gates et al., 1965; Knipling, 1970). Application of remotely-sensed data (in this case signals in the shortwave region of the spectrum, the object of this research) was limited to the use of simple relations between canopy attributes (canopy processes and characteristics such as leaf area index (LAI), leaf angle distribution (LAD) and ground cover) and single spectral bands or vegetation indices (VIs), which employ transformations of radiances or reflectances of two or more bands. LAI, ground cover, fraction of photosynthetically active radiation absorbed by the canopy (fAPAR) and intercepted PAR were the canopy attributes commonly related to VIs. The use of empirical relationships (curve fitting) between remotely-sensed data or its transforms, like VIs, to extract quantitative information about the vegetation is referred to as the empirical approach to canopy attribute inference from remotely-sensed data (Hall et al., 1995).

Elimination of background effects (soil and leaf litter) was attempted through the use of the simple ratio vegetation index (SRVI) (Pearson and Miller, 1972) (red band radiance/near-infrared band radiance or reflectance) and the normalized difference vegetation index (NDVI) (Rouse et al., 1973). However the SRVI and NDVI do not totally eliminate background effects so that other indices have been introduced over the years, e.g., the tasseled cap by Kauth and Thomas (1976), the PVI by Richardson and Wiegand (1977), the SAVI by Huete (1988); the TSAVI by Baret et al. (1989) and the ARVI by Kaufman and Tanré (1992) among others (Tucker, 1979; Jackson, 1983).

Initially, canopy radiative transfer modeling (e.g., Suits, 1972; Verhoef, 1984) and optical property measurement efforts were devoted to understanding radiative processes. Later a numerical approach of inferring canopy attributes using canopy radiative transfer models (i.e., the inversion approach, the object of Chapter 3) was introduced (Goel and Strebel, 1983). The numerical inversion consists of using a model to simulate canopy bidirectional reflectances factors (BRFs, see Appendix A for further explanation of reflectance terms) under various viewing (or illumination) conditions while varying the unknown model variables (which represent the desired canopy attributes). The simulated BRFs are then compared with the observed BRFs. The inversion retrieved canopy attributes are those variable values that give the lowest differences between observed and simulated BRFs.

The use of canopy radiative transfer models for inversions is referred to as a physically-based approach because it is based on mathematical formulations which relate vegetation attributes, soil spectral characteristics and illumination and view conditions to

canopy radiative transfer (Hall et al., 1995). To use models to retrieve surface features, the models can be inverted either numerically or analytically to calculate canopy attributes. These canopy attributes in turn may be used to calculate canopy state attributes (i.e., albedo, fraction of absorbed photosynthetically active radiation, and photosynthetic capacity) using the same radiative transfer model. To date much of the effort related to inversions of canopy reflectance models has been directed toward the study of the technique itself (Goel and Strebel, 1983; Goel et al., 1984; Privette et al., 1994) as well as toward identifying the parameters and conditions under which inversions should work (Goel and Thompson, 1984a, 1984b, 1984c; Schluessel et al. 1994; Privette et al., 1995; Privette et al., 1996).

Inversions of canopy radiative transfer models are expected to give more reliable results than empirical approaches; however no direct comparison between these two approaches has been performed. Two problems regarding remote sensing requirements for the use of currently available models for inversions were identified by Hall et al. (1995): 1) the dimensionality of the remote sensing measurement space (the number of illumination and viewing geometries used in the inversions) must equal or exceed the number of attributes being estimated; 2) in the more detailed models (models based on the solution of the radiative transfer equation for vegetation canopy conditions), the number of attributes that must be estimated is large, and the dimensionality requirements for their estimation often exceed the intrinsic dimensionality of the remotely-sensed data. In addition, complex radiative transfer interactions as represented in current models need to be simplified to enhance computational speed while at the same time producing a reliable model.