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THERMAL INFRARED REMOTE SENSING OF VEGETATION CANOPIES

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1 Introduction

Land surface temperature is an important component of the various physical, biological, and chemical processes of the terrestrial ecosystem. It provides a link between the Earth's surface and the atmosphere through its effects on surface energy fluxes. Thermal measurements have been used to estimate surface energy balance and resulting evapotranspiration over agricultural areas [1] and for forests [2]. With the approaching launch of various satellites that are expected to carry instruments suitable for thermal IR remote sensing, the retrieval of land surface temperature has gained more attention [3,4]. The data so acquired at a variety of spatial and temporal scales and their extension to global coverage should facilitate our understanding of local scale processes as they influence regional scale processes and eventually global assessments that are critical to our understanding of the coupling between the terrestrial landscape and the atmosphere.

In general, the thermal infrared spectral region offers significant potential for monitoring global surface conditions or status [5]. This paper reviews thermal infrared remote sensing of vegetation canopies and discusses one approach to implementing model-based correction procedures for directional thermal infrared anisotropy.

2 Basic Energy Balance Formulation

A canopy-soil system can be modeled as an n-layer canopy superimposed upon a simple soil surface layer [6,7]. Within each canopy layer the amount and mixture of components may vary, each possessing different optical, thermal and geometrical properties. The soil surface layer is characterized by a soil bulk density, water content, roughness height and soil composition. The set of energy balance equations of the coupled system in terms of net radiation, R_n, sensible heat, H, latent heat, LE, and ground conduction, G, is given by:

$$R_n = LE + H + G \tag{1}$$

Expanding the net radiation term into up welling and down welling long wave and absorbed short wave radiation components for each system layer, i, yields:

$$\alpha_i \sum_j B_j S_{ij} - 2.0 B_i + A_i - H_i - LE_i - G\delta_{i,s} = 0 \tag{2}$$

where B is the long-wave flux, A is the short-wave energy absorbed, α is the long wave absorption coefficient and $\delta_{i,s}$ is the Dirac delta function indicating that conduction must be included for the ground surface layer. The unknowns in this system of non-linear equations are the canopy layer temperatures and ground temperature. S_{ij} is the fraction of emitted flux from a source layer j that is intercepted by a sink layer, i:

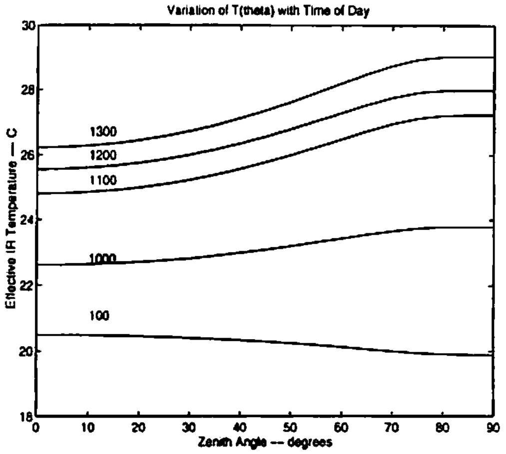

Figure 1: LST Directional Variation

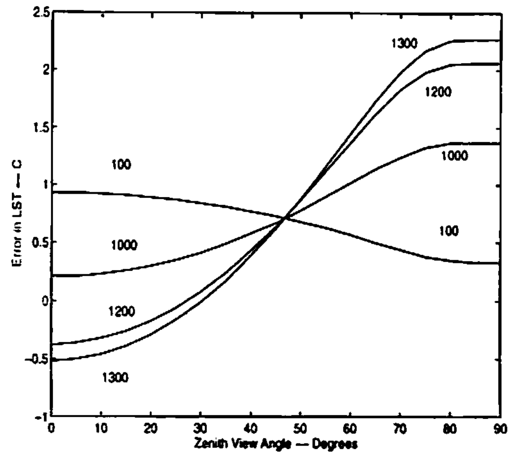

Figure 2: Estimated Error in LST

The overall average emissivity for a scene element containing components of different individual emissivities, ϵ_j, is then given by [8]:

$$< \epsilon >= \sum_j \epsilon_j S_{1j} \tag{3}$$

S_{1j} are the appropriate geometric weighting coefficients for the (horizontal or vertical) subcomponents, j, comprising the resolution cell and describe the contribution of each layer to the atmospheric sink layer (layer 1). The S have often been expressed as simple area proportions, but this is incorrect. In particular, $S_{1j}(\theta, \phi)$ vary with view angle resulting in an effective average emissivity which varies with view angle, and, thus, yielding directionally dependent brightness surface temperatures. This may be true even when the individual ϵ_j, are Lambertian. Thus, in order for surface hemispherical long-wave emittance to be estimated from brightness temperature, corrections for directional variations must be applied. Large-scale sensible and latent heat flux may also then be estimated from satellite or aircraft land surface temperature estimates, if additional surface resistances are included. Figure 1 shows model predictions for land surface temperature as a function of zenith view angle and at varying points in the diurnal cycle (time of day). The canopy modeled was a dense forest canopy. Figure 2 indicates the corresponding errors that would be made in land surface temperature estimation if no view angle corrections were made. The figure also shows the cross-over point recently discussed by Otterman, et al. [9] for sparsely vegetated surfaces. These errors in land surface temperature estimation directly translate into corresponding errors in long wave, and sensible and latent heat estimates for vegetation canopies.

3 Model-Based Regression and ANN Estimation Procedure

One approach to estimating the S_{1j} geometric view factors necessary to correct for land surface temperature anisotropy effects is indicated in Figure 3. The basic strategy is to use the optical reflective channels for, e.g. MODIS [3], to retrieve the scene view factor matrices which can then be applied to estimate the directionally dependent emissivity factors for vegetation/soil

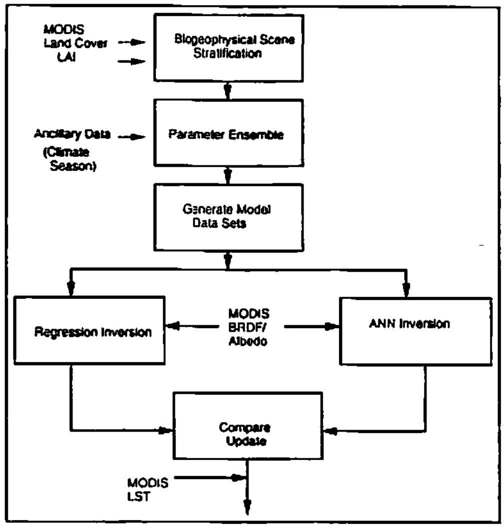

Figure 3: Estimation Strategy

mixtures. Two iterative techniques are proposed–model based regression and artificial neural networks (ANN). Both techniques create initial training or sample data using physically based radiative transfer and energy budget models for the canopy / soil system. The estimates derived from each technique are compared until convergence is achieved and/or to yield error bounds on the techniques. An initial *a priori* estimate of $S_{1j}(\theta, \phi)$ is formulated based on the MODIS Land Cover Classification, Leaf Area Index and other ancillary information. MODIS inferred bidirectional reflectance distribution functions or albedo measurements are used as inputs into the regression and ANN estimators.

In the regression method, we can model the radiance of a "standard reference scene, here the *a priori* case. That is, we know

$$L_o = f(X, p_o) \tag{4}$$

where p_o is the unknown parameter and X is the stratification index or pointer. Expanding L in a Taylor series about the reference state vector, p_0,

$$L(\lambda) = f_o(\lambda) + \sum_{k=1}^{n_p} \frac{\partial f}{\partial p_k}(p_k - p_{k_o}) + ... \tag{5}$$

rewriting in terms of a reduced observation vector

$$\begin{aligned} L_e &= L - f_o \\ P_e^o &= p - p_o \\ A_o &= (\frac{\partial f}{\partial p_k})_o \\ L_e &= A_o P_e^o + E \end{aligned} \tag{6}$$

where A_o represents a matrix of partial derivatives of dimension number of observations, e.g. wavelength, by number of parameters and E is an error term with covariance matrix, S_E. The least squares best estimate for P_e^o is given by:

$$P_e^o = (A_o^T A_o)^{-1}(A_o^T S_E^{-1})L_e \tag{7}$$

In the ANN approach to estimating $S_{1j}(\theta, \phi)$ we can use standard feed-forward, multilayer neural networks, but trained using sets of $\{input, output\}$ data pairs provided by physical model simulation runs. There are two general steps in the training of a backpropagation ANN. These consist first of a feed-forward iteration to calculate the output of the network, as a function of the interconnection weights, based on training input values presented to the input layer. This is then followed by a backpropagation learning rule designed to minimize the mean squared error between network predicted outputs and training set values. The learned network weights are then applied to calibrated and atmospherically corrected satellite observations.

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References

1. R. C. Vining and B. L. Blad, Estimation of sensible heat flux from remote sensed canopy temperature, J. Geophys. Res., 1992, vol. 97, pp. 18951-18654.

2. L. L. Pierce and R. G. Congalton, A methodology for mapping forest latent heat flux densities using remote sensing, Remote Sens. Environment, vol. 24, pp. 405-418, 1988.

3. V. V. Salomonson, W. L. Barnes, P. W. Maymon, H. Montgomery, and H. Ostrow, MODIS: Advanced facility instrument for studies of the earth as a system, IEEE Trans. Geosci. Remote Sensing, 1989, vol. 29, pp. 1-16.

4. H. Fujisada, Design and performance of ASTER instrument, Proc. SPIE, 1995, vol. 2583, 16-25.

5. A. J. Prata, V. Caselles, C. Coll, J. A. Sobrino, and C. Ottle, Thermal remote sensing of land surface temperature from satellites: current status and future prospects, Remote Sensing Reviews, 1995, vol. 12, pp. 175-224.

6. T. Yamazaki, J. Dondo, T. Watanbe, and T. Sato, A heat balance model with a canopy of one or two layers and its application to field experiments, J. Appl. Meteorology, 1992, vol. 31, pp. 86-103.

7. J. A. Smith and S. M. Goltz, A thermal exitance and energy balance model for forest canopies, IEEE Trans. Geosci. Remote Sens., 1994, vol. 32, pp. 1060-1066.

8. Francois Becker and Zhao-Liang Li, Surface temperature and emissivity at various scales: definition, measurement and related problems, Remote Sensing Reviews, 1995, vol 12. pp. 225-253.

9. J. Otterman, J. Susskind, T. Brakke, D. Kimes, R. Pielke and T. J. Lee, Inferring the thermal-infrared hemispheric emission from a sparsely vegetated surface by directional measurements, 1995, Boundary-Layer Meteorology, vol 74, pp. 163-180.