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COMPUTATIONAL MODELING OF MULTISPECTRAL REMOTE SENSING SYSTEMS: BACKGROUND INVESTIGATIONS

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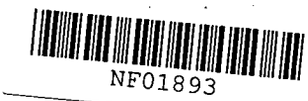

TABLE OF CONTENTS

Page Missing in Original Document

LIST OF TABLES

Page Missing in Original Document

LIST OF FIGURES

1. INTRODUCTION

The following report represents background research for, and technical embellishments of, a comprehensive computational model of a multispectral remote sensing system. This model is being developed as a tool for designing smart sensors which are able to process, edit and classify the data that they acquired. This report provides a forum for details and analyses that have not been suitable for reporting in other formats during the progress of the work. Consequently the reader will be assumed to be familiar with both the computational model and experimental results reported up to this date; (Huck, et al., 1982 and Aherron, et al., 1981). In addition to the two above reports the AIAA (Breckenridge, 1979) and the SPIE (Barbe, 1979) have both published a collection of papers concerning smart sensors and the philosophy behind them.

Accurately predicting the signal produced by a sensor observing a particular target under a specific set of conditions is a very important goal for a model of this nature. Still more important is formulating a model that properly characterizes the stochastic properties of the signal that will likely be encountered. It is the physical nature of the interacting media that is considered to be variable and thus driving the derived quantities such as radiances. A quantity such as path radiance is not considered to have any inherent variability. Accounting for these variabilities introduced a special set of evaluation criteria in choosing a method of dealing with two of the major elements in the remote sensing system model: 1) atmospheric radiative transfer; 2) surface reflectance.

In particular the implementation of the simulation required that the sensor irradiance be calculated for every simulated pixel with its associated random atmospheric conditions, or equivalently the equation of transfer needed to be solved for every pixel simulated. This need of course discriminated heavily against lengthy iterative solutions to the transfer equation, accuracy not withstanding. An analysis of various atmospheric radiative transfer models will be presented.

It is impossible to over emphasize the importance of the spectral reflectance of the targets in remote sensing work. Nevertheless, given the

amount of research about and gathering of spectral reflectances taking place, particularly with respect to vegetation, it is amazing to find there is virtually no data report concerning the variability of spectral reflectances. Theoretical work concerning spectral reflectance has also been rather sparse. Several functional forms for reflectance variability will be examined and a collection of target reflectances will be cataloged.

A goal established early in the development of smart sensor systems was the ability to detect cloud pixels. This ability would allow several options concerning data load reduction or choosing alternate imaging sites. The category of snow/clouds can usually be distinguished in either the visible or near-infrared. To distinguish between snow and clouds alone requires a spectral channel at a wavelength longer than 1.0 μm.

The papers by Huck, et al., (1982) and Aherron, et al., (1981) cover two sets of experiments performed over the period of this contract. The Huck, et al. paper concentrated on classifying pixels into fairly specific classes such as wheat and dark loam. The Aherron, et al. paper concentrated on the task of assigning pixels from any number of different substances into four broad categories which were: bareland, water, vegetation and snow/cloud. An enhancement implementing aerosol attenuation coefficients has produced results updated from those in Aherron, et al. A partial set of updated results for that work are presented. Results for a simple cloud detection algorithm will also be presented.

2. COMPUTATIONAL ATMOSPHERIC RADIATIVE TRANSFER

2.1 Background

The atmosphere is a significant element in the overall remote sensing model. A comprehensive treatment of this element incurs the greatest computational costs of any model element. Numerous assumptions and simplifications are usually made to facilitate "reasonable" limits to the complexity and cost of radiative transfer modeling. Different sets of these assumptions are manifest in the various atmospheric models currently available. Below, a brief discussion is presented of the problem and several computational models in use in remote sensing are highlighted and compared. From these discussions the justification for the chosen model should be apparent. Those not familiar with the equations and terminology of atmospheric radiative transfer should consult Liou (1980) or Wolfe and Zissis (1978) for a background development. The terminology and notation used in this and related papers is almost identical to that used in Chapter 4 of Wolfe and Zissis (1978) which makes it particularly good as an introduction.

The fundamental equation of remote sensing after Slater (1980)

$$L = \frac{1}{\pi} E_o T_o \mu_o \rho T + L_d \rho T + L_p \qquad (2\text{-}1)$$

where $E_o \equiv E_o(\lambda)$ is the solar spectral irradiance at the top of the atmosphere, $T_o \equiv T_o(\lambda,\tau,\mu_o)$ is the atmospheric transmittance along the incident path from the sun to the surface (solar zenith angle = θ_o, $\mu_o = \cos\theta_o$); $L_d \equiv L_d(E_o,\lambda,\tau,\mu_o,\rho)$ is the diffuse sky spectral radiance which results from all radiation scattered downward onto the surface (i.e., integrated at the target over elevation and azimuth); $\rho \equiv \rho(\lambda)$ is the spectral reflectance of the surface (sometimes called "signature"); $T \equiv T(\lambda,\tau,\mu)$ is the atmosphere transmittance along the exitant path from the surface to the sensor (zenith angle = θ, $\mu = \cos\theta$); and $L_p \equiv L_p(E_o,\lambda,\tau,\mu_o,\mu,\phi)$ is the path spectral radiance which results from all radiation scattered upward along the path from the surface to the sensor. The other parameters are wavelength, λ, optical thickness of the atmosphere $\tau \equiv \tau(\lambda)$, and azimuth angle ϕ between the planes of incidence and exitance. The component of the total radiance L which arises

from radiation reflected from the target is referred to as the beam spectral radiance L_b, that is $L_b = L - L_p$, and $L_b \equiv L_b(E_o,\lambda,\tau,\mu_o,\mu,\rho)$.

Now the equation of radiative transfer for a plane parallel atmosphere (Malila, et al., 1971) is given by

$$\mu\frac{dL}{d\tau} = L(\tau,\mu,\phi) - \frac{\omega_o(\tau)}{4\pi} \int_0^{2\pi}\int_{-1}^{1} p(\tau,\mu,\phi,\mu',\phi')L(\tau,\mu',\phi')d\mu'd\phi' - (1-\omega_o(\tau))B(\tau) \tag{2-2}$$

where $\omega_o(\tau)$ is the single scattering albedo which is the ratio of the sum of the scattering coefficients to the sum of the scattering and absorption coefficients. $B(\tau)$ is the Plank radiation function for thermal self-emission. The single-scattering phase function $p(\cdot)$ can be described as a probability density function for the particular direction a photon will scatter relative to the original direction of travel. The function usually has a highly irregular (radially asymmetric) shape. The straight numerical solution of this equation is very time consuming. The first assumption made for even the complex form shown is that the atmosphere is plane-parallel, that is it is an infinite slab bounded below by the ground. For near-nadir looking sensor systems this is not an unreasonable assumption. Several uses of atmospheric radiative transfer models in the remote sensing literature and the methods of a solution for equation will now be examined. First, attention will be focused on the solution of the equation of radiative transfer as implemented in the various methods. Assumptions and approximations concerning the atmosphere will be discussed later.

2.2 Radiative Transfer Models

The models discussed will be limited to those that have received attention in the remote sensing literature. Probably the most widely known model is the one developed by Turner (Malila, et al., 1971 and Turner, 1974) used in early systematic remote sensing studies. Another model receiving more recent attention was developed by Dave (1978) and has been applied to both remote sensing problems, Dave (1979), and solar insolation. O'Neill, et al. (1977, 1978) implemented Liou's (1973) model and compared it to Turner's model and to actual LANDSAT data. Kiang (1980) implemented Hansen's (1969) model for tests concerning atmospheric effects on Thematic Mapper data. The other less general models were encountered, due to Otterman, et al. (1980), and

Lampley and Blattner (1978), upon which discussion will be delayed. Attention will be concentrated on those models that account for all the terms in Eq. 2-1. In dealing with the atmosphere in strictly a transmissive mode, that is accounting for only the first term in Eq. 2-1, LOWTRAN (Selby, et al., 1978) has become the accepted standard model.

The fundamental character of, and difference between most approximate methods of solution for the full equation is in the form and order of approximation of the phase function. This approximation is to allow the elimination of the integration in Eq. 2-2. The phase function determines the directional characteristics of all scattered radiation. Wolfe and Zissis (1978) show plots of some typical phase functions that demonstrate their pronounced asymmetry. Turner used two Dirac delta-functions one forward and one backward to approximate the phase function. Liou (1973) expanded the phase function into a series of N Legendre polynomials in his Discrete Ordinate Method (DOM). References to this model frequently are of the form "2N-stream approximation" where N is an integer. Dave (Dave and Canosa, 1974) used the method of Spherical Harmonics where the phase function and the intensity were expanded into a series of L + 1 Legendre polynomials. Krook (1955) shows that the DOM and Spherical Harmonic methods are equivalent. The accuracy of these equivalent methods can be made arbitrarily high by increasing the number of terms in the expansion (O'Neill, et al., 1977). The typical scattering phase function is a highly "peaked" function and thus rich in harmonics. In essence the Legendre based methods approximated the phase function with some finite set of polynomials (i.e., harmonics) while the Turner method approximated the function with an infinite set of harmonics in the form of the dirac-delta function. All of the above methods can be defined for a single homogeneous layer of any reasonable optical thickness. Hansen (1969) approximated the phase function at 20 discrete directions. The other fundemental difference is the intermediate solutions reached are valid only for an optically thin layer where multiple scattering can be ignored. The properties of an optically thick layer are arrived by aggregating the thin layers. Hansen's model accounts for polarization which is unique for the models discussed.

2.3 Model Comparisons

Ronnholm, et al. (1980) implemented a form closely related to each of the models discussed. The implementation of the radiative transfer models by Ronnholm, et al. assumed several things about the atmosphere. First an analytical form for the "real" phase function was used (Henyey-Greenstein). Second, the atmosphere was assumed to be vertically and horizontally homogeneous. All of the models except Turner's have been implemented with vertical inhomogeneity capabilities but this restriction was necessary for comparison. Each model was run for the same set of atmospheric conditions. (The Ronnholm, et al. literature citations will not be duplicated). Ronnholm, et al. used Twomey's doubling method model as a benchmark or "truth" so to speak, considering it to be more accurate than the other methods compared. Hansen's (1969) and Twomey's models are comparable. A delta-Eddington approximation by Joseph was included which is similar to the Turner model. The Discrete Ordinate Method for 4 streams was implemented using the analytical solution (Liou, 1974). Since the form of the differential equations solved for the DOM and Spherical Harmonics methods are similiar, the DOM's computational times will be considered representative of the Spherical Harmonics Method (when L = N).

One of the major findings of Ronnholm, et al. was the relative computational burden for the three classes of methods. The results are summarized in Table 2.1. The results in Table 2.1 can only be meaningful within the context of the relative accuracy of the various methods. Ronnholm, et al. compare the three methods for various conditions and concludes "... the factor of 20 in computation time saved by the delta-Eddington was judged more valuable than the greater accuracy of the four-stream method." They add "... if optical depths, single scattering albedos or asymmetry factors are either uncertain or known to be flucuating; with relative standard deviations of 10% or greater, then little real benefit is added by the use of computationally precise, but costly, many-stream radiation-transfer algorithms." An important point that should be made here, is that Ronnholm, et al. compare values of reflection, diffuse transmission, and absorption for the atmosphere and thus net fluxes are being compared. For aerosol laden atmospheres, and their highly anisotropic scattering properties, the jump from

TABLE 2.1

Relative computation burden of radiative transfer models used by remote sensing investigators analogy to methods implemented by Ronnholm, et al.

INVESTIGATOR	RONNHOLM'S ANALOG	REL. COMPUTER TIME
TURNER	DELTA-EDDINGTON	1
LIOU	DOM	20
DAVE	DOM	20
KIANG	TWOMEY	10^4

comparing fluxes to comparing intensities with directional dependences is not straight forward. For example, the radiation field incident on a scattering volume has only two components in a two stream approximation and for highly anistropic scattering this is an inadequate approximation for calculating the scattering into the highly specific direction of the sensor. In general, the more anisotropic the scattering phase function, the more accurately it needs to be approximated in order to determine the radiation field within the atmosphere. For the Turner model, the radiation field within the atmosphere is approximated utilizing the double-delta phase function. The actual path radiance contribution of a scattering volume is calculated using that simplified radiation field and interpolated values of the scattering phase function. The hemispherical integration for flux quantities implicit in Ronnholm, et al. tends to mask the inaccuracies. This provides some explanation for the disagreement between Ronnholm, et al., who found little difference between methods for flux quantities, and O'Neill, et al., who found significant differences between the predicted path radiances for the DOM and Turner's model. Even so the remarks by Ronnholm, et al. concerning the uncertainty about atmospheric conditions should not go unheeded, particularly for the case of errors in approximations of the scattering phase function.

It is useful to elaborate on the efforts of O'Neill, et al. concerning calculation of path radiance (O'Neill, et al. 1977, 1978). In O'Neill, et al. (1977) Turner's method and Liou's DOM were implemented assuming vertical homogeneity. The results were fairly comparable for low aerosol optical depths but were divergent as optical depth increased. They attributed this to the crude angular approximations used by Turner and their increasing importance at greater optical depths. In O'Neill, et al. (1978) path radiances computed by the DOM were found to be in good agreement with path radiances determined from LANDSAT data using clear lake reflectors. The DOM performed considerably better than the Turner method for the same set of data. Horvath, et al. (1972) found that the Turner method had systematic errors in predicting atmospheric effects on aircraft multispectral scanner data. The input data used in Horvath, et al. was not of as high a quality as for the O'Neill, et al. work.

The assumption of vertical homogeneity within the atmosphere does not seem plausible considering the distribution of aerosols. Neither Ronnholm, et al. (1980) nor Liou (1975) could demonstrate much difference in modeling results, for flux related quantities, between the lesser and more "accurate" methods of calculation. No test of the assumption's effect, in terms of model results, on radiance values was found. O'Neill, et al. achieved good agreement between LANDSAT determined and model predicted path radiances under the vertical homogeneity assumption.

By far the more important atmospheric constituent in terms of its effect on remote sensing is the aerosols. In certain wavelength regions though, absorption by other constituents becomes important. The major ones being water vapor, ozone, and oxygen in the visible and near infrared regions. Accurately accounting for absorption by the constituents is not a trivial task (Selby, et al., 1978; Dave, 1978). Turner treats the ozone absorption, occuring in the upper atmosphere, as a phenomena separate from the scattering, which takes place in the lower atmosphere. Except for Turner those models that do deal with molecular absorption utilize the Air Force Geophysics Lab's model LOWTRAN (Selby, et al., 1978) or data from that model.

2.4 Special Models

As was mentioned before, two other less general models of transfer were found in the literature. The Otterman, et al. (1980) work was mostly illustrative in nature, dealing only with low optical thickness atmospheres, and is rather unique in its solution. Both Otterman, et al. and Lampley and Blattner (1978) deal only with single scattering. This assumption greatly simplifies the characterization of the radiation field within the atmosphere. For the case of optically thin atmospheres this is not a bad assumption but likely to be encountered only in more arid regions on a regular basis. This assumption, for thin layers, is the basis of the doubling method discussed earlier. Eliminating the effects of multiple scattering is judged to be too large a source of error when dealing with atmospheres optically thick enough to cause significant image degredation.

2.5 Model Selection

One of the evaluation criteria set for evaluation of various atmospheric models was their suitability for use as a computer subroutine for a remote

sensing system simulation. One other approach suggested by O'Neill, et al. (1978) and inferred by Dave (1978) is the use of table-lookup method. For certain problems this could be a very useful technique. But for a general purpose source of radiance data for a stochastic simulation, with many of the input parameters being random variables, it would likely prove excessive in its storage requirements. To define the size of radiance data base needed to satisfy the modeling requirements would require knowledge as to how fine a grid, or subdivision, in each parameter, would be necessary to retain the desired accuracy. This knowledge is not available a priori and would only come from careful and laborious sensitivity analysis for the input parameters. It may be possible to gain increased accuracy, over say the Turner model, by implementing a table lookup scheme for a more accurate model but it would be better to pay the greater price for the subroutine method and get the full benefit of increased accuracy.

From what has been discussed one can see that the Turner model of radiative transfer introduces significant errors to the approximation of sensor incident radiation compared to other more comprehensive models (i.e. DOM). There is though, an estimated twenty fold reduction in computing time realized. Whether or not the error introduced by the Turner model is significant in the light of the uncertainties in the atmospheric parameters has yet to be determined. Ronnholm, et al. showed that, for flux calculations, these errors were not significant. For an initial implementation of a model with multiple scattering capabilities within a comprehensive remote sensing system model, the Turner model is the logical choice. Once greater knowledge of the interrelationships and sensitivities of the various system entities is established, it would probably be best to upgrade to the Dave model.

2.6 Model Implementation

The Turner model was implemented as a subroutine within the computer simulation code. The model is available for purchase from the Environmental Research Institute of Michigan (ERIM) located in Ann Arbor, Michigan. Scattering phase function data files which are distributed with the model were used. Input to the Turner model, as implemented, consists of nine parameters and one function (table form). Those parameters considered to be deterministic

(fixed for a particular run) were E_o - Solar Irradiance, θ_o = Solar Zenith Angle, ϕ = Azimuth angle between incident and exitant vectors, θ = Sensor Zenith Angle, ω_o = Single Scattering Albedo. The scattering phase function was also deterministic. All simulation to date have been performed with phase functions from a continental type aerosol model with a complex index of refraction of m = 1.5 - .01i. The single-scattering albedo was chosen to be .9 and is constant. Simulations have been confined to nadir looking sensors with solar zenith angles in the range of 30° - 50°.

There are four stochastic parameters consisting of ρ_b = background reflectance, ρ_T = target reflectance, τ_R = Rayleigh optical thickness and τ_T = total optical thickness. The background used was a bare land target. Both reflectances are generated according to the functional form discussed earlier. The optical thicknesses are generated by the method discussed in Huck, et al. (1982). It is necessary to separate the Rayleigh component because the phase function used is a weighted mean of the Rayleigh and aerosol phase functions.

The single-scattering albedo used is constant over wavelength which requires a word of warning. The single-scattering albedo defines the relative mix of scattering and absorption in the contribution to attenuation. Therefore in moving from spectral regions characterized by scattering to those with significant absorption the single-scattering albedo changes. A method for varying the single-scattering albedo has not been implemented. The single-scattering albedo chosen (.9) is reasonable for regions of the spectrum without significant absorption. It is therefore necessary to restrict radiative transfer modeling to non-absorbing regions at the present time.

3. SPECTRAL REFLECTANCE MODELS

Ultimately it is the spectral reflectance characteristics of targets, perhaps in concert with spatial distribution characteristics, that provides the information to users of remotely sensed data. It is therefore important that the target reflectance properties introduced to a simulation be as realistic as possible. This is particularly true for optimization studies where optimizing a system for a set of "artificial" targets is of more academic interest than practical use.

There were two major tasks to be addressed in the area of reflectances. One concerned characterizing the deterministic nature of spectral reflectances which consisted of assembling representative spectral reflectance curves for a number of targets of interest. The other task dealt with characterizing the stochastic nature of spectral reflectances by selecting and parameterizing functional forms for describing reflectance variability.

3.1 Reflectance Functions

The quantity utilized in the simulation is the spectral diffuse reflectance defined by Slater (1980).

$$\rho(\lambda) = \frac{\pi L (\lambda)}{E (\lambda)}$$

where the target is assumed to have Lambertian characteristics. The quantity actually measured in the field, depending on the particular measurement program, is more likely the hemispherical-conical reflectance factor which is then normalized to some standard reflector (Smith and Ranson, 1979). Present work has been limited to the Lambertian target assumption though natural targets have been demonstrated to deviate significantly from this assumption (Smith and Ranson, 1979). In general Slater (1980) offers a very good introduction to surface reflectance and its importance in remote sensing and presents a brief introduction to several efforts aimed at modeling plant canopy reflectance. Smith and Ranson (1979) offers a fairly comprehensive review of the literature concerning data and/or models of the directional reflectance characteristics of natural surfaces.

In order to produce spectral reflectances with stochastic characteristics

it was necessary to choose an analytical form for reflectance. The functional form chosen for the reflectance is given by

$$\rho(\lambda) = \rho_o(\lambda)\, e^{-\beta_o(\lambda)X} \tag{3-1}$$

This is the same functional form (Bouguer's Law) as used for atmospheric transmission. The wavelength dependence of reflectance will be omitted in subsequent notation. This form was used because of its analytical tractability and compatibility with the concurrent atmospheric modeling efforts and because the family of curves generated were qualitatively similar to sets of field data (Park, et al., 1980). The parameters of the distribution are $\rho_o(\lambda)$ and $\beta_o(\lambda)$. This is identical to a form for spectral reflectance proposed by Tucker and Maxwell (1976) for vegetation canopies in regions of the spectrum characterized by canopy absorption (i.e., the chlorophyll absorption regions). Within the same spectral region and dependent on the value of X, Tucker (1977) and Tucker and Maxwell (1976) found that

$$\rho = \rho_o + \beta_o X^{-1} \tag{3-2}$$

was also a useful functional relationship.

In Tucker's work X represented any one of several plant canopy characteristics including several biomass measures, leaf water content and chlorophyll content. For the near infrared region from .74 m to 100 m which is characterized by little absorption and relatively high reflectance due to scattering, Tucker (1977) found, again dependent on the value of X, the following two equations to be good approximations of reflectance

$$\rho = \rho_o + \beta_o X \tag{3-3}$$

$$\rho = S\,(1 - e^{\rho_o + \beta_o X}) \tag{3-4}$$

Where S represents the asymptotic reflectance of the vegetative canopy. This is the reflectance that an infinitely thick canopy would display. Park and Deering (1981) developed a set of differential equations (modifications of the Kubelka-Munk model) for describing the interaction of light with

plant canopies that is remeniscent of the Eddington Approximation for atmospheric radiative transfer. If the background reflectance is taken to be zero then the diffuse reflectance formula of Park (retaining previous notation)

$$\rho = \frac{1 - e^{-\beta_o X_o}}{\frac{1}{S} - Se^{-\beta_o X_o}} \qquad (3\text{-}5)$$

Of the above functional forms, only Eqs. 3-2, 3-3, and 3-4 display asymptotic nature. Equation 3-2 asymptotes for large values of X and Eqs. 3-3 and 3-4 asymptote for small and large positive values of X. Ideally if X is some vegetative measure such as biomass per unit area then the reflectance functions should asymptote to the background reflectance for small X and approach the vegetative reflectance asymptote for large X. These three equations were formulated to be driven by inherently positive plant characteristics such as canopy weight. Equation 3-1 is driven by an artificial variable taking positive and negative values. As was previously stated, the resulting curves were qualitatively acceptable.

Target reflectance phenomenon represent a special case of radiative transfer, a subject which has received a great deal of attention over the years. Commenting on the dearth of surface reflectance modeling efforts Smith and Ranson (1979) hypothesize "probably, this is a recognition of the difficulty of specifying the appropriate phase function in both a sufficient and tractable manner and further, performing the necessary measurements to determining the phase functions". They were commenting on the difficulty of specifying and measuring the phase function of such things as twigs and leaves. Smith and Ranson (1979) discuss the formulation development of two major vegetative canopy models, Smith and Oliver (1972) and Suits (1972), taking care to link the "... analytical and physical reasoning of canopy radiation interactions to the broader mainstream of radiative transfer theory". A better understanding and overview can be gained by reading their unified discussion prior to working with the original papers. The radiative transfer methods used in these models can be classed as those that use simplistic approximations to the phase function such as the Eddington approximation.

The following development outlines the parameterization of Eq. 3-1.

We assume X_o is a (standard) normal random variable with mean $\mu_\rho = 0$ and variance $\sigma_\rho = 1$. Repeating the formula for reflectance. The assumption of normality for X will be discussed more completely in a later section. When X is assumed to be a normal variate the reflectance, given by Eq. 3-1, has a log-normal distribution.

$$\rho = \rho_o e^{-\beta_o X} \tag{3-6}$$

then

$$\mu_\rho = \rho_o e^{-\frac{1}{2}\beta_o^2} \tag{3-7}$$

$$\sigma_\rho = \mu_\rho^2 \left(e^{\beta_o^2} - 1\right) \tag{3-8}$$

If we have estimates for μ_ρ and σ_ρ denoted $\hat{\mu}_\rho$ and $\hat{\sigma}_\rho$, respectively, then by substituting the estimates into the above formulas yields estimates of the parameters.

$$\beta_o = \sqrt{LN\left(1 + \frac{\hat{\sigma}_\rho^2}{\hat{\mu}_\rho^2}\right)} \tag{3-9}$$

$$\rho_o = \frac{\hat{\mu}_\rho}{\sqrt{1 + \frac{\hat{\sigma}_\rho^2}{\hat{\mu}_\rho^2}}} \tag{3-10}$$

Finding data to define the variability of spectral reflectances (i.e., σ_ρ) has not been very fruitful. As of yet, no data has been found on the covariance (between wavelengths) of spectral reflectance for various targets. Values for the variance (i.e., the diagonal terms of the covariance matrix) can be estimated from data, for wheat, reported by Collins (1978) through the following reasoning as shown below.

A simple expression for the remote sensing equation for vertical sun and sensor can be defined as

$$L = \frac{1}{\pi} E_o T^2 \rho + Lp$$

(With notation as before in atmospheric section). Over small geographical areas it can be assumed that all the terms are constant except ρ. Allowing the calculation of

$$\sigma_L = \frac{1}{\pi} E_o T^2 \sigma_\rho$$

$$L = \frac{1}{\pi} E_o T^2 \bar{\rho} + \bar{L}p$$

Collins reports data for medium altitude aircraft in a fairly dry area (Imperial Valley) thus Lp is ignored and thus dividing Eq. 3-12 by Eq. 3-3 gives

$$\frac{\sigma_L}{\bar{L}} = \frac{\sigma_\rho}{\bar{\rho}} = \text{Coefficient of variation (CV)}$$

Collins reports CV as percent standard deviation of measure radiance which determines $\frac{\sigma_\rho}{\rho}$ necessary for formulas 9 and 10. Since Collins was working with radiances an estimate of $\bar{\rho}$ necessary for Eq. 3-10 is not available.

Rao, et al. (1978) similarly reported reflectance CV's for grain crops and soil. The data was for variation over several months and encompassed atmospheric corrections of unknown nature making it unsuitable for present efforts. A CV of .1 was chosen for all agricultrual crops after reviewing Collins data.

As a note of explanation, Smith and Oliver (1972) developed a stochastic vegetation canopy model but more appropriately should be termed a Monte Carlo model in that the photon interaction with various canopy constituents (canopy orientation and distribution) was treated as a random process but then the canopy composition was constant and thus is fundamentally different than the model being discussed.

So far discussions of reflectance have centered on vegetation. The same function was also used for the other targets. For soil Condit (1970) was a valuable source of spectral reflectances. The nature of the curves presented allowed an estimate of reflectance variability to be made. Each soil was characterized by two spectral reflectance curves: one for dry

soil and one for wet soil. The mean and variance for that soil was determined by the following

$$\hat{\mu}_\rho = \frac{\rho_{dry} + \rho_{wet}}{2}$$

$$\hat{\sigma}_\rho = \frac{\rho_{dry} - \rho_{wet}}{2}$$

In general, variances were chosen for other targets in order to achieve "Reasonable families" of curves in a stochastic simulation. One significant modification of the parameters was made for vegetation. The reflectance variability σ_ρ was made proportional to reflectance. That is CV was constant (.1) and multiplied by $\bar{\rho}$ to yield σ_ρ for estimating β_o and ρ_o. The effect of this modification can be seen in the difference in variability behaviour between vegetation and sand in Fig. 4 of Huck, et al. (1982). As one can see this introduces variations in σ_ρ over wavelength. It should be noted that the ± sigma plots of Fig. 4 (Huck, et al., 1982) are for $\pm\sigma_x$ and not $\pm\sigma_\rho$ such that they enclose ≃67% of the simulated reflectance values even though ρ is not normally distributed. This should become clear in the section on statistical characteristics.

The reflectance covariance matrix Σ_ρ for targets in general is defined as

$$\Sigma_\rho = \sigma_\rho^2 \, I_n$$

for

$$\lambda_i \qquad i = 1, 2, 3, \ldots, n$$

and where I_n = n x n identity matrix and σ_ρ is constant, but defining

$$\bar{\rho}^2 = \begin{bmatrix} \bar{\rho}^2_{\lambda_1} & & & & 0 \\ & \bar{\rho}^2_{\lambda_2} & & & \\ & & \bar{\rho}^2_{\lambda_3} & & \\ & & & \ddots & \\ 0 & & & & \bar{\rho}^2_{\lambda_n} \end{bmatrix}$$

and $CV = \frac{\sigma_\rho}{\bar{\rho}}$

the covariance matrix for vegetation is

$$\Sigma_\rho = CV^2 \, I_n \, \bar{\rho}^2$$

where CV is taken to be constant.

It is particularly important that the off-diagonal terms of the reflectance covariance matrix be approximated in future work and especially for investigation concerning the optimum choice of spectral channels. It has frequently been observed, or bemoaned if you will, that several of the LANDSAT channels are redundant. This is due in part to the high correlation of reflectance in the different channels. For example both LANDSAT channel 6 (.7 - .8) and channel 7 (.8 - .11) fall in the spectral region for vegetation characterized by the same reflectance phenomenon. Thus changes in the nature of the plant that affect reflectance in channel 6 affect channel 7 in almost the same way. This spectral reflectance correlation for channel 6 and channel 7 is true for most targets and therefore one of the channels is fairly redundant.

Wiersma and Landgrebe (1979) make an important contribution to remote sensing where they "develop an analytical procedure for the design of the spectral channels for multispectral remote sensor systems". Though never explicitly stated, it appears their analysis is based on spectral radiance data. The important point to this discussion is that they chose an optimal (mean-square) set of spectral channels where the analysis was based on the spectral radiance covariance matrix and is aimed at reducing channel redundancy. By reducing correlation between the channels they increase the information available from a fixed number of channels. This is shown by the techniques of Information Theory. Their radiance data does not allow the estimation of the spectral reflectance covariance necessary for the present modeling efforts.

3.1 Target Reflectance Curves

As was indicated, the target reflectances represent an important element in the remote sensing simulation. A collection of target reflectances

was gathered and subsequently used in simulations reported to date. Data collected was limited to in situ reflectances for single or collections of whole plants. Only data available in the open literature was utilized. There exists a large body of reflectance data produced for NASA, in raw form, that has yet to be utilized.

Examination of remote sensing literature from the early 60's to present shows the tendency to report reflectances to longer wavelengths in the infrared. Even with this tendency, very little reflectance data is published for wavelengths longer than 1.1 μm which happens to correspond to the limit of LANDSAT spectral coverage. Some data utilized in the cloud detection tests, which required data out to 1.60 μm, was of rather crude spectral resolution especially in the .50 μm to .80 μm range that is so important for the BAM categorization discussed in Aherron, et al. (1981). The sources of reflectance data are listed in Table 3.1 along with the figure number(s) for the plot(s) of that data.

TABLE 3.1

REFLECTANCE DATA

FIGURE NUMBERS	SOURCE OF DATA
FIG. 3.1 - 3.4	Lansing, 1970
FIG. 3.5 - 3.6	Condit, 1970
FIG. 3.7	Vlcek, 1974
FIG. 3.8	Suits and Safir, 1972
FIG. 3.9 (Silt Loam)	Bowers and Hanks, 1965
FIG. 3.9	Orr, et al., 1963
FIG. 3.10	O'Brien and Munis, 1975
FIG. 3.11	Hansen, 1969
FIG. 3.12	Novosel'tsev, 1965
FIG. 3.13	Leeman, et al., 1971

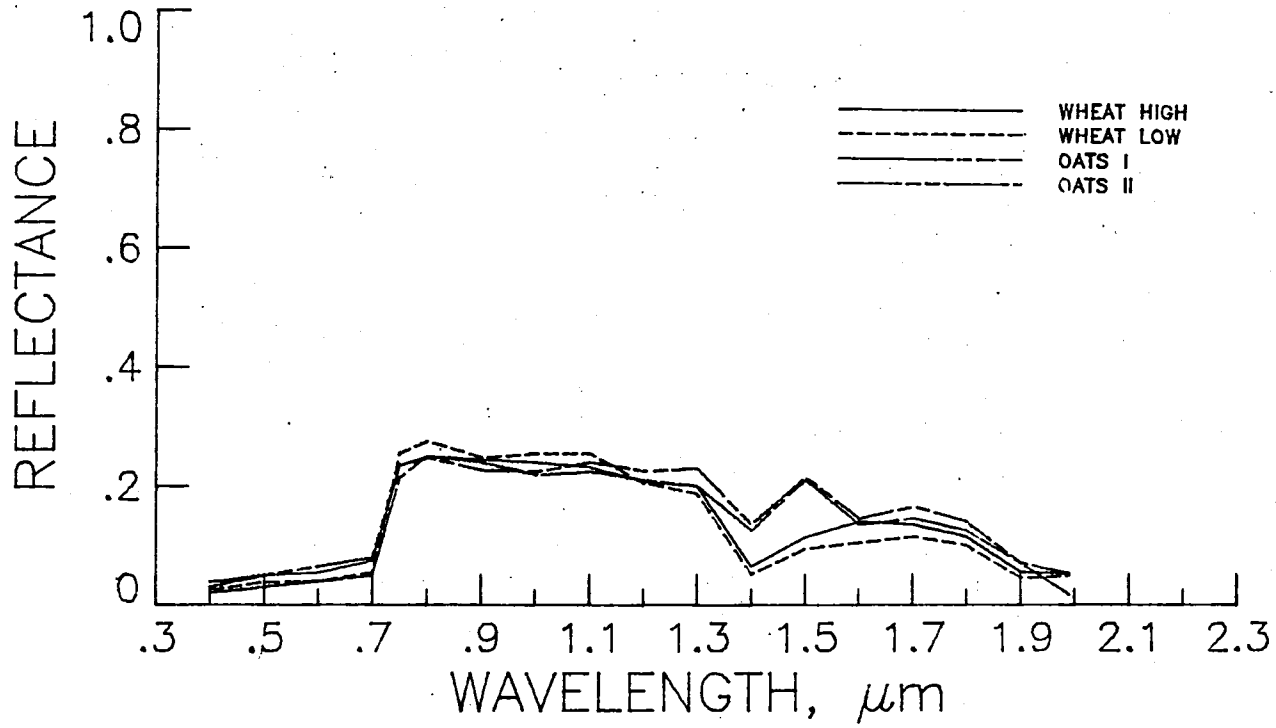

FIGURE 3.1 SPECTRAL REFLECTANCES

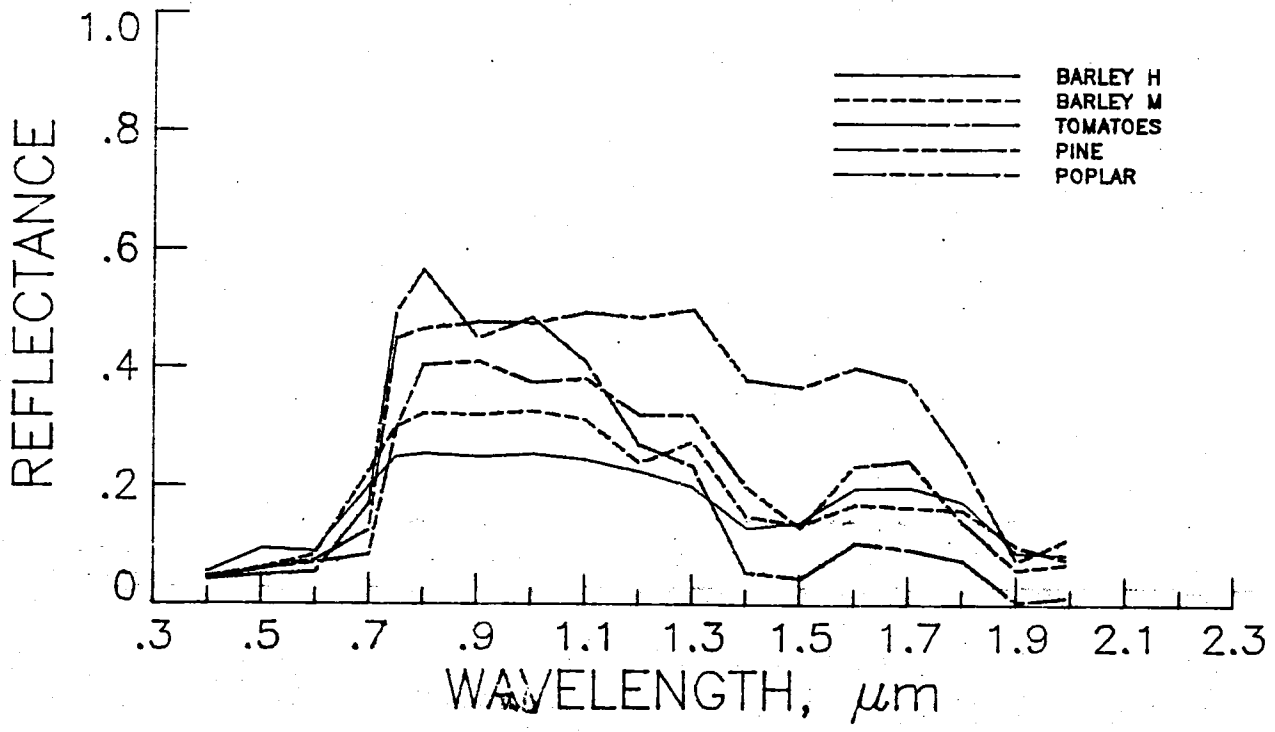

FIGURE 3.2 SPECTRAL REFLECTANCES

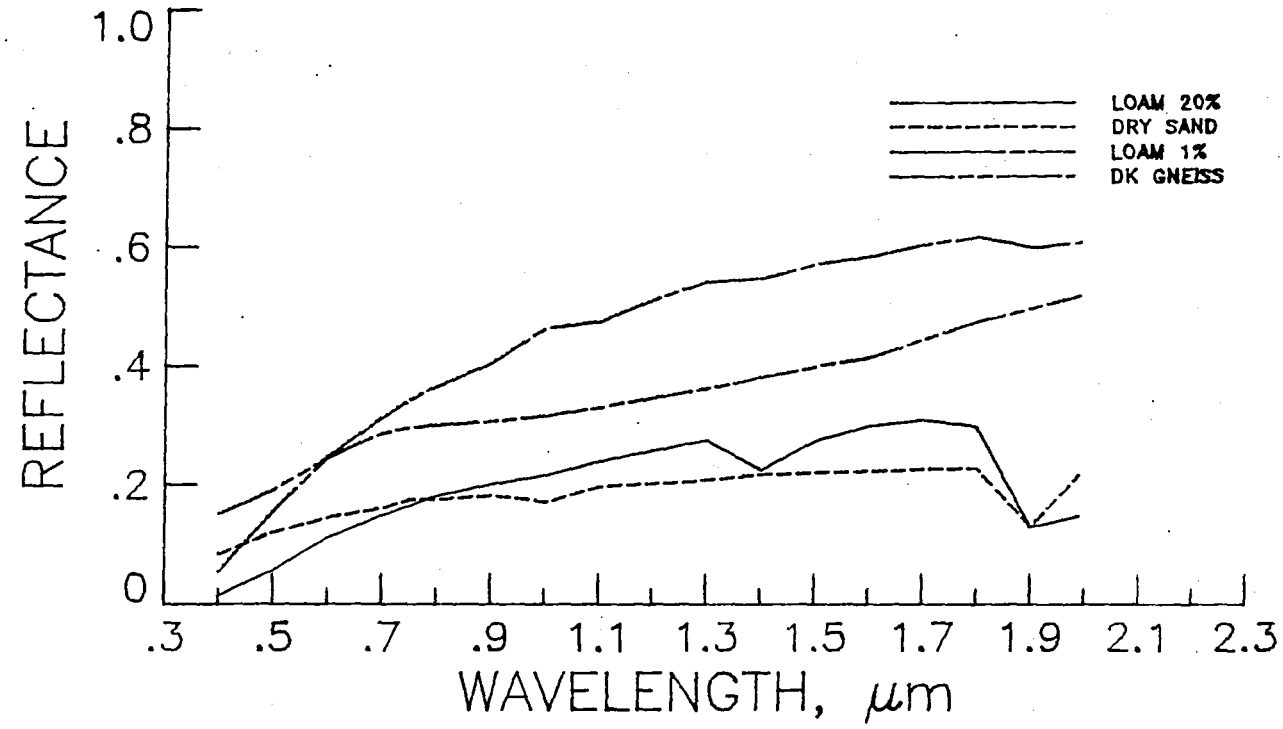

FIGURE 3.3 SPECTRAL REFLECTANCES

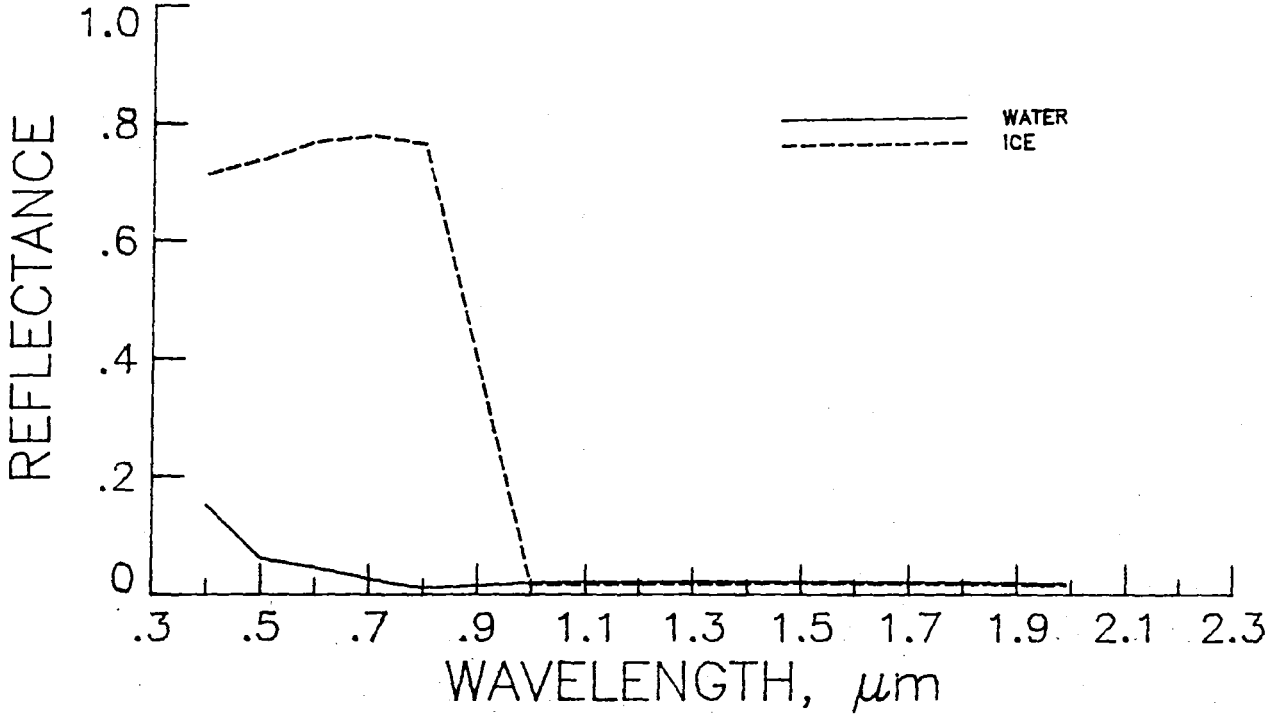

FIGURE 3.4 SPECTRAL REFLECTANCES

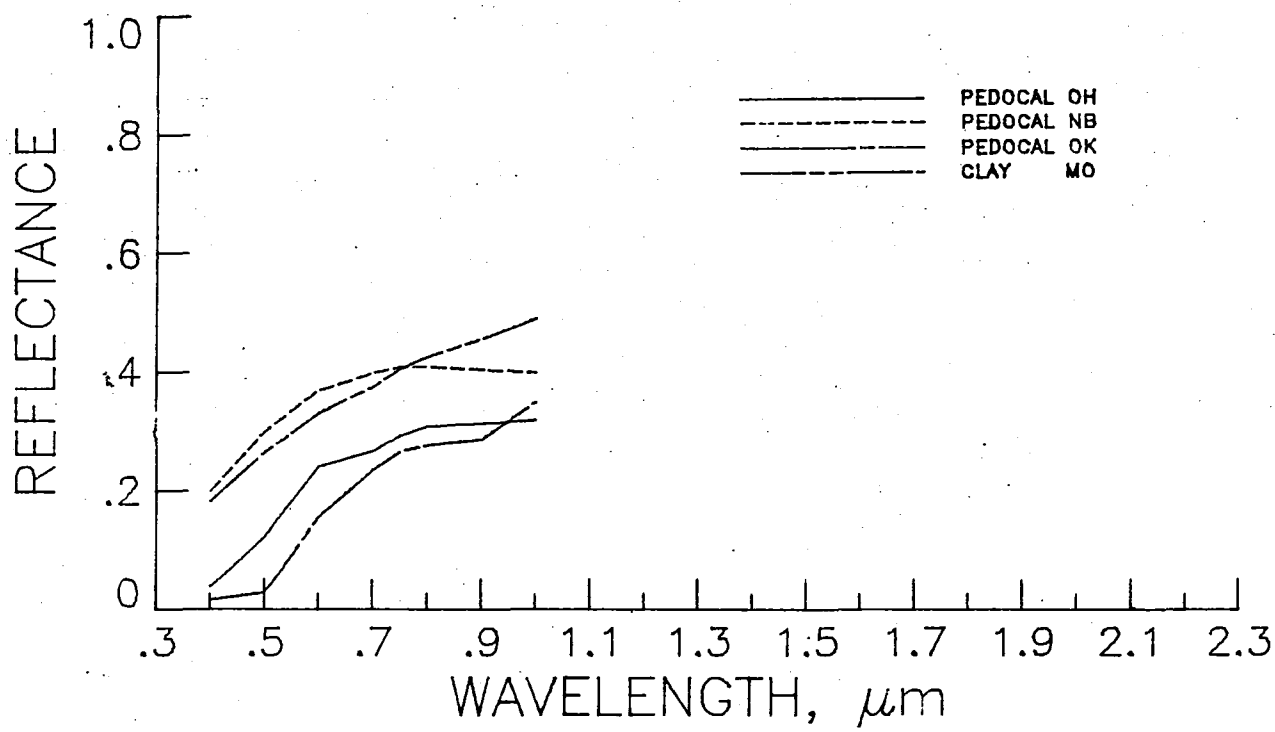

FIGURE 3.5 SPECTRAL REFLECTANCES

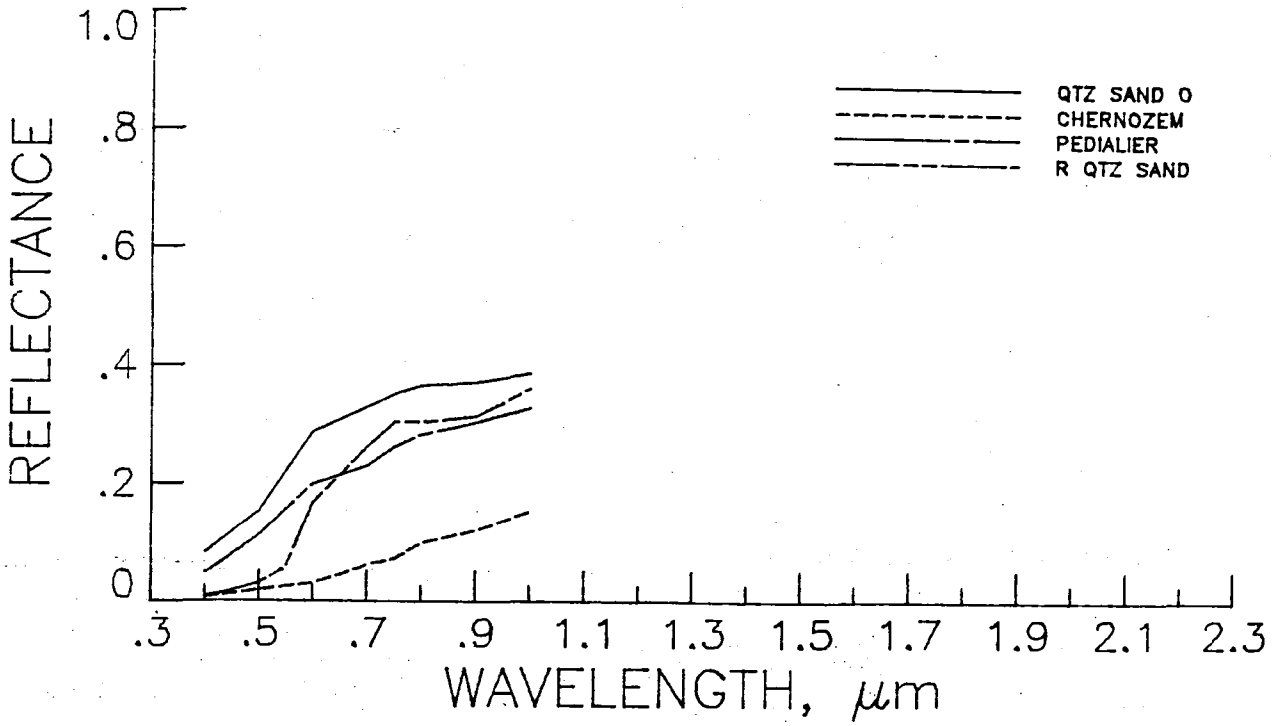

FIGURE 3.6 SPECTRAL REFLECTANCES

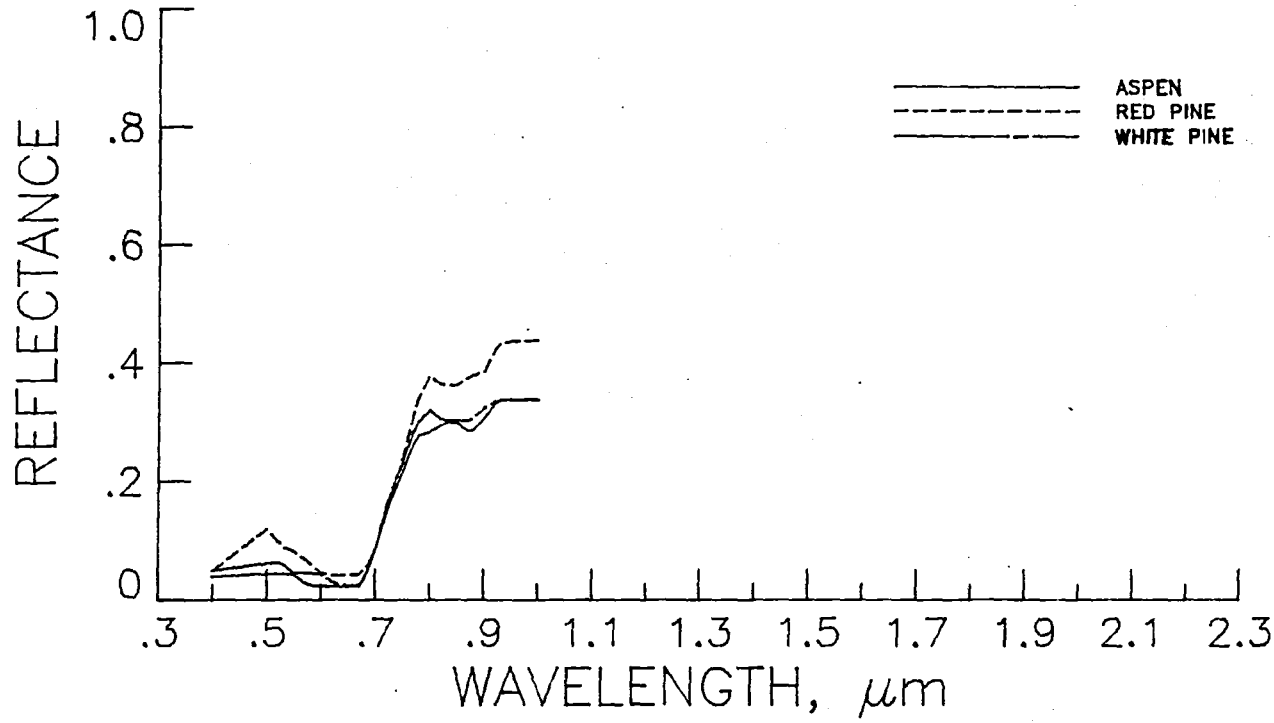

FIGURE 3.7 SPECTRAL REFLECTANCES

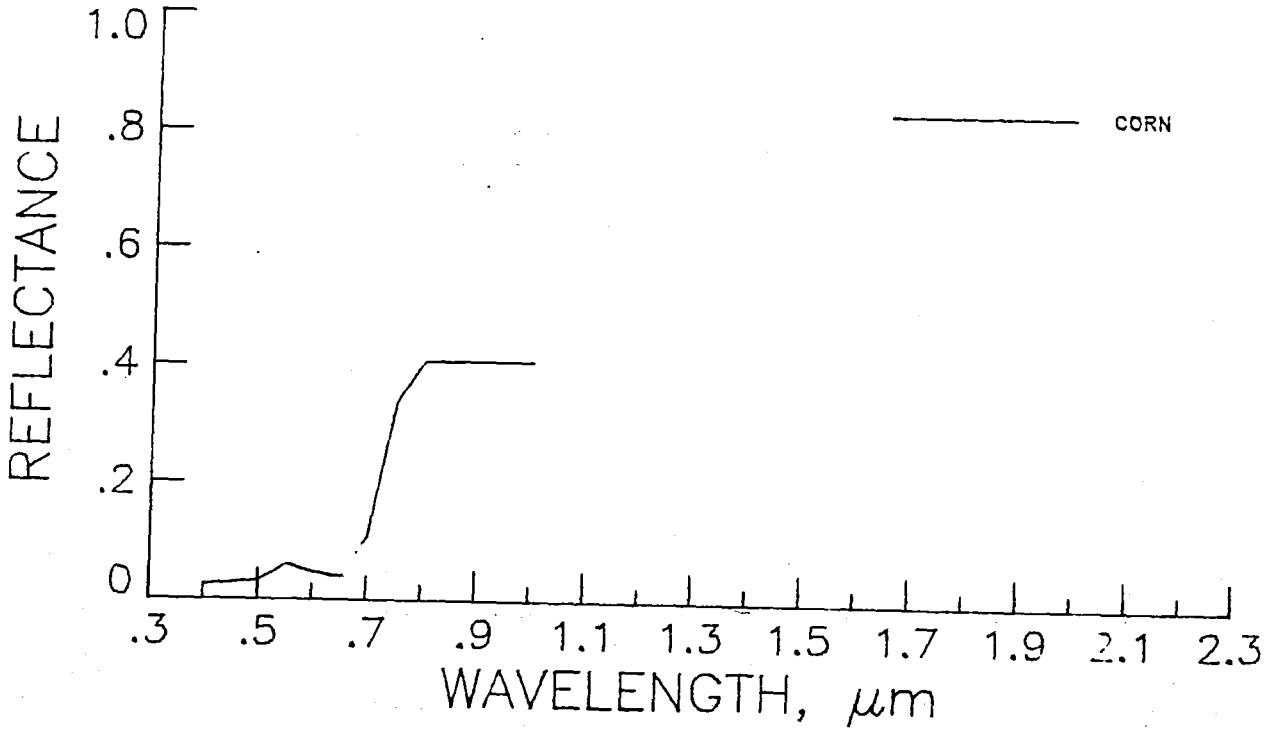

FIGURE 3.8 SPECTRAL REFLECTANCES

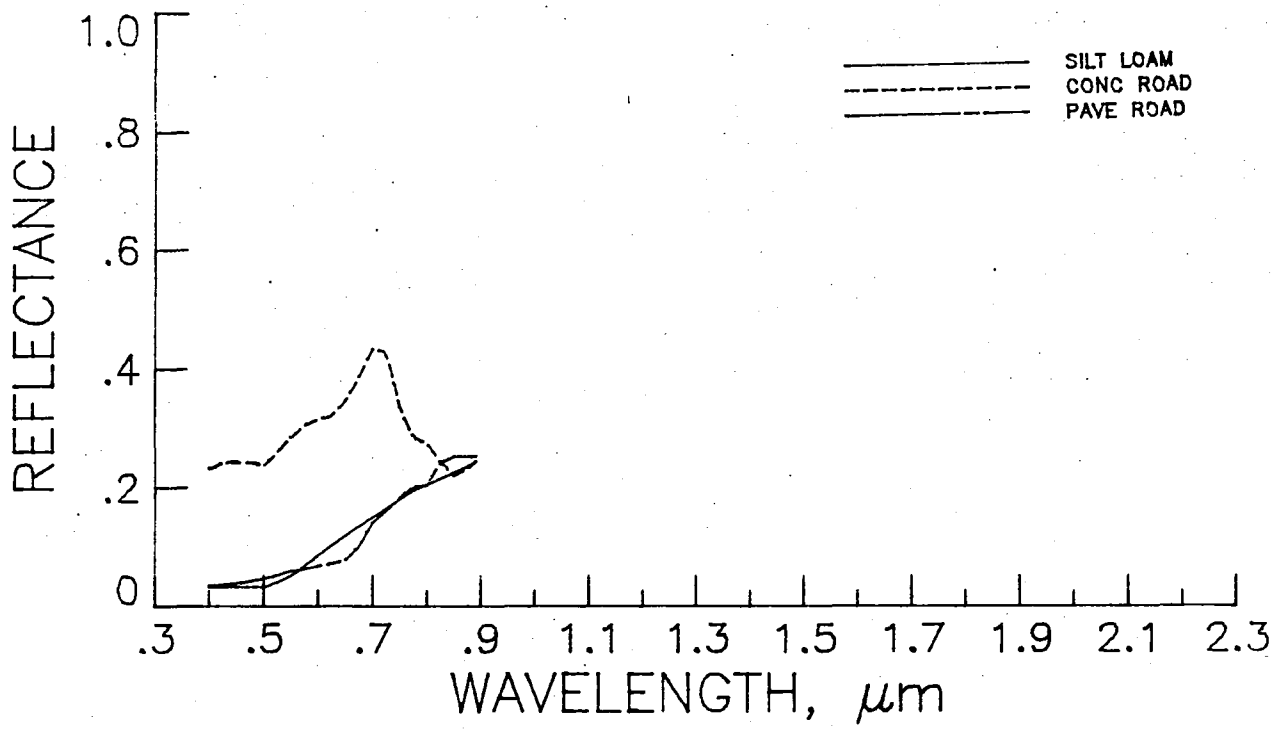

FIGURE 3.9 SPECTRAL REFLECTANCES

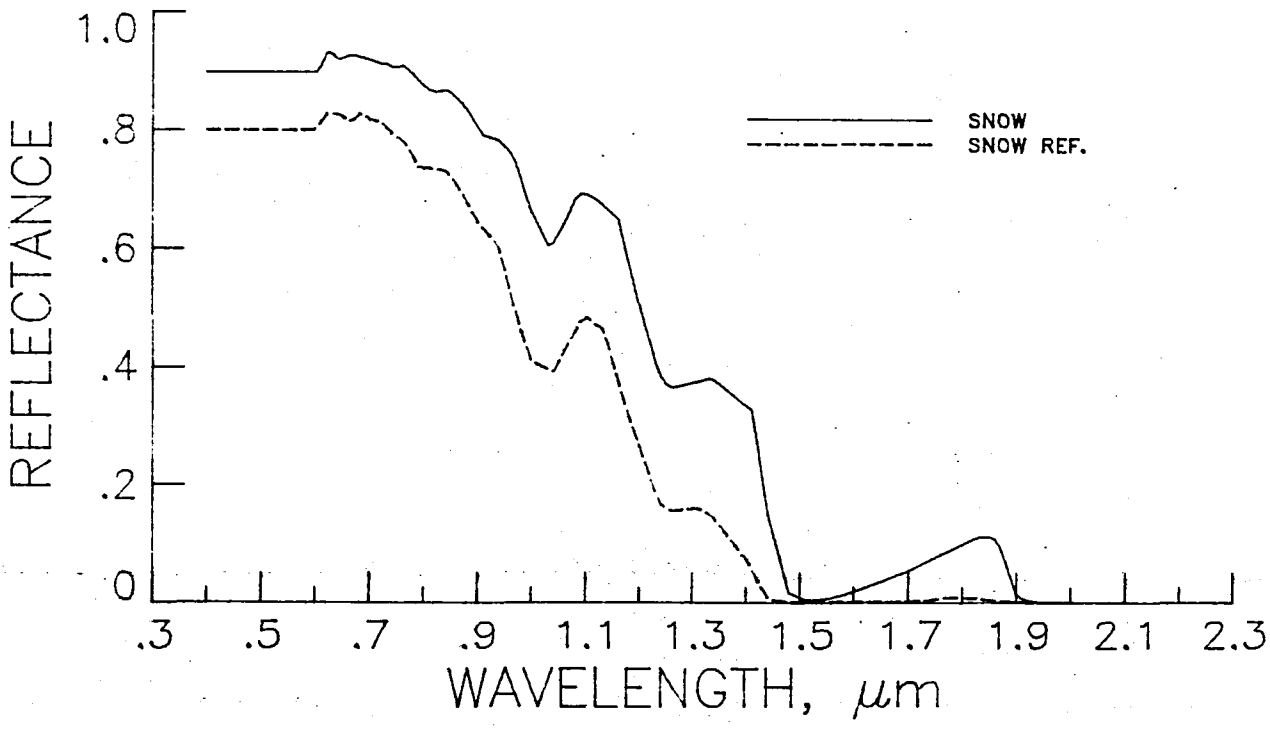

FIGURE 3.10 SPECTRAL REFLECTANCES

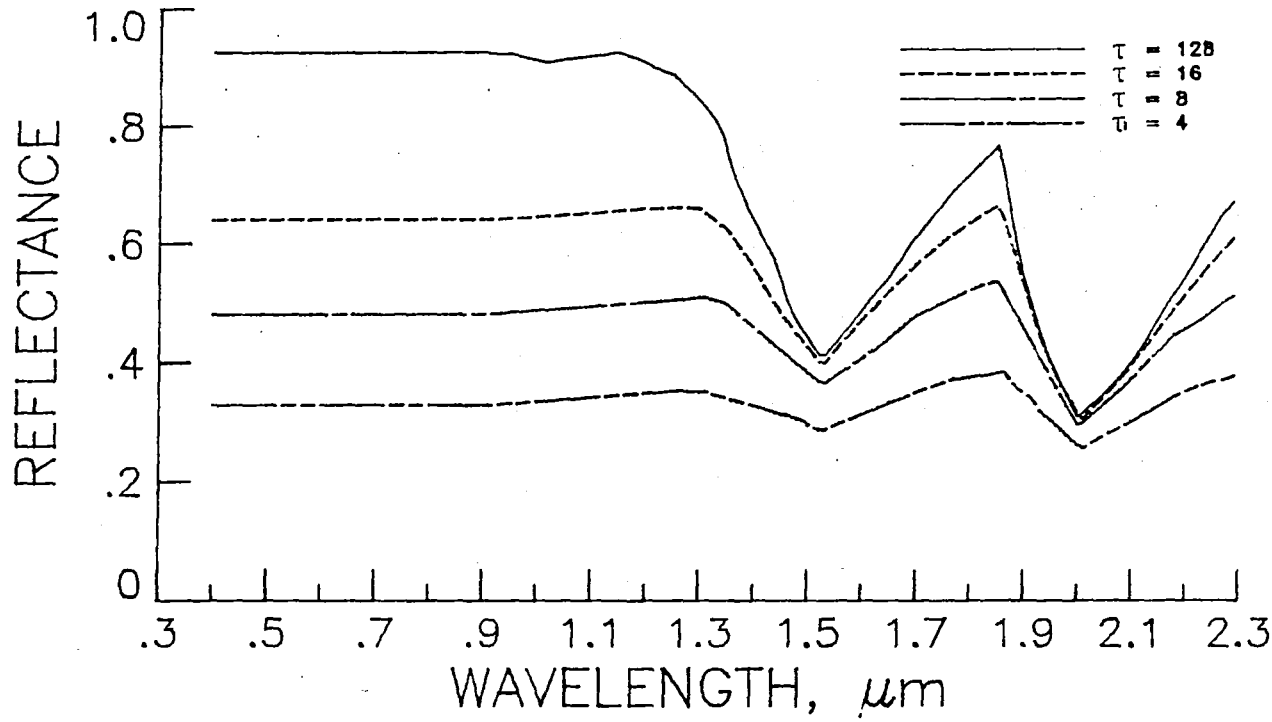

FIGURE 3.11 SPECTRAL REFLECTANCES (τ = OPTICAL THICKNESS)

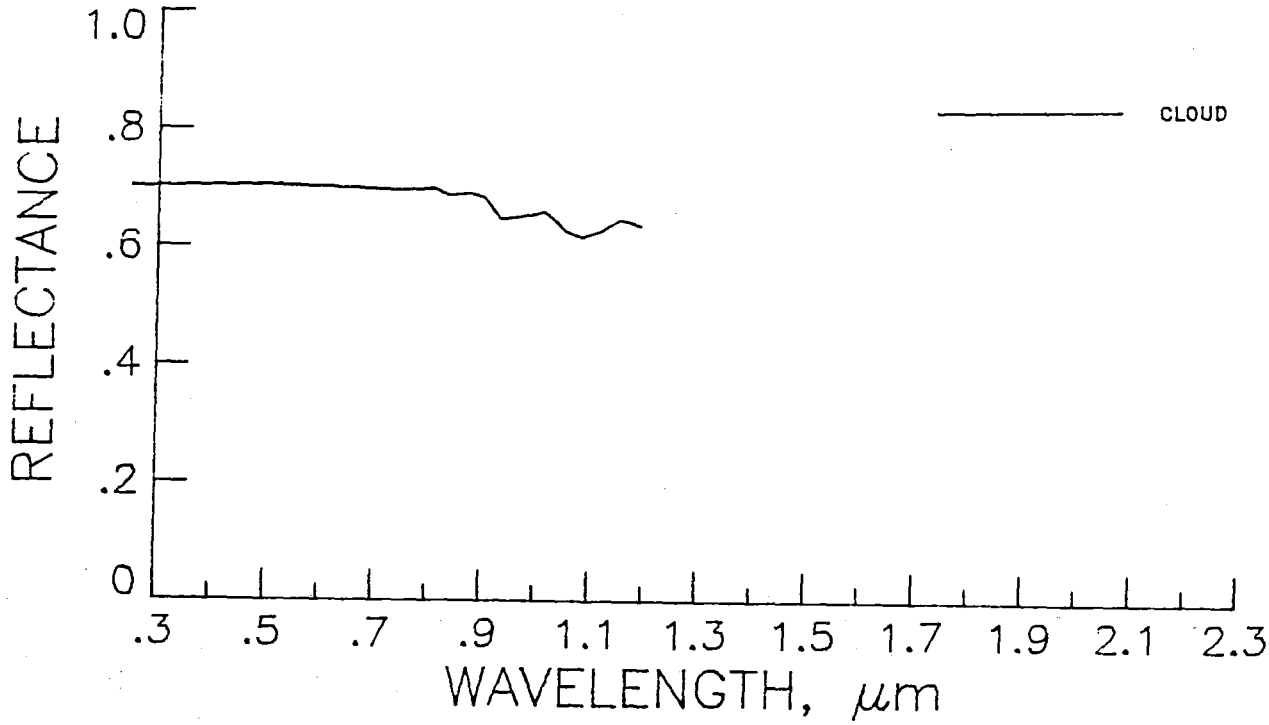

FIGURE 3.12 SPECTRAL REFLECTANCE

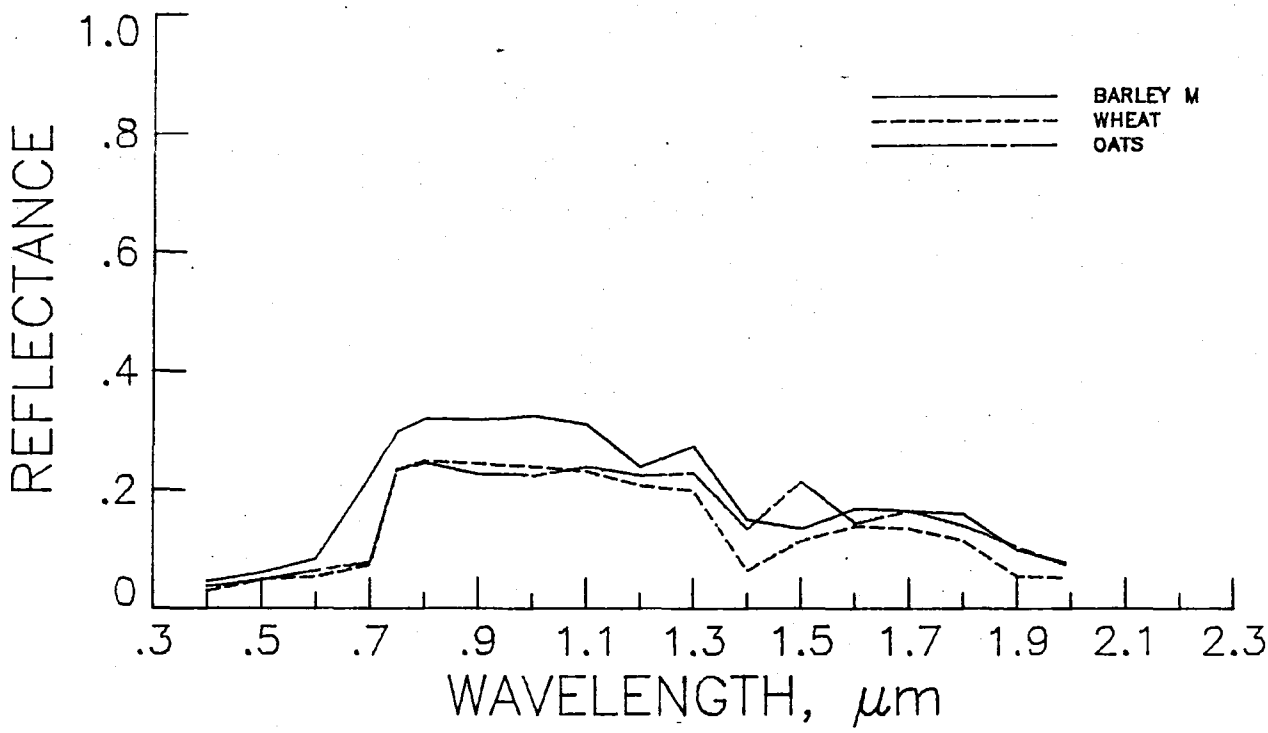

FIGURE 3.13 SPECTRAL REFLECTANCES

4. CLOUD DETECTION

4.1 Background

For an Earth resource observation system clouds present a major limitation to the collection of data. Worldwide cloud cover is approximately 45% (Barnes et al., 1968), which represents a very significant potential for obscuration of ground targets. The ability to indentify clouds reliably would allow several options for smart sensor systems including the ability to avoid imaging of cloudy areas and to eliminate cloud pixels from the data to be transmitted to ground stations. An even more sophisticated task for a sensor system with reliable cloud detection capability would be the selection of alternate imaging areas in the event that the primary target is cloud covered.

In order to identify clouds they must be adequately characterized spectrally. As one can imagine, determining the spectral reflectance of a cloud is no easy task. The reflectance data available for clouds has generally been the product of radiative transfer modeling (Hansen 1969, Novoseltsev, 1965). In the visible and near-infrared region of the spectrum both snow and clouds form a single category of what might be called bright white targets. Within this spectral region the two classes have such closely similar spectral characteristics as to make the identification of clouds as a class unreliable. Only in the longer infrared wavelengths do the two classes show significant differences.

Valovcin (1978) made a important comprehensive study of the snow/cloud discrimination problem specifically aimed at potential on-board methods. Valovcin utilized, for his analysis, spectral radiance data from cummulus and cirrus clouds and snow obtained from a high flying aircraft. He analyzed several different discrimination tasks including identifying different cloud types. For the simple cloud versus snow discrimination he found that a radiance threshold for a .11 μm bandwidth spectral channel centered at 1.56 μm achieved an 85% + accuracy. Though no test results were reported for such, he suggests that moving the channel center to 1.525 μm might improve results.

4.2 Test

Based on results and data reported by Valovcin (1978) a new channel was

added to the basic set of two channels used in the target categorization tests reported in Aherron, et al. (1981). Those channels consisted of one centered at .65 μm and one centered at .85 μm with a bandwidth of .02 μm. The new channel for cloud detection was centered at 1.55 μm with a .1 μm bandwidth.

As was indicated above the reflectance data utilized in the modeling was the result of theoretical investigations. Hansen (1969) used the doubling method solution to the radiative transfer equations, discussed in the section concerning atmospheric radiative transfer, to determine the diffuse spectral reflectance of ice clouds of various optical thickness. Novolsel'tsev calculated the spectral reflectance of a cloud composed of water droplets. Zander (1966) measured the reflectance of laboratory generated ice clouds and his data compares favorably with that report by Hansen (1969). Stochastically clouds are treated the same as non-vegetated surfaces.

A cloud detection algorithm was formulated based on the 3 above channels. The algorithm is basically a two level decision tree. First, the snow/cloud category is seperated from the other categories based on a threshold radiance in the .65 μm channel. This is the method previously used in simple categorization (Aherron, et al. 1981). The second level decision of snow versus cloud is based on a threshold in the 1.55 channel. Figure 4.1 shows the covariance elipse plots for a collection of targets similar to those used in Aherron, et al. (1981) simulated for 23 km visual range. The first level categorization boundaries are indicated by dotted lines. Included in the snow/cloud category are a snow target, an optically thick water droplet cloud, and four ice clouds of various optical thicknesses. The ice clouds are indicated on the ellipse plot according to optical thickness.

The ill-placed clouds are a manifestation of two problems in dealing with clouds. First is the problem of thin clouds. It is an arbitrary decision as to what constitutes a cloud and what is merely haze in terms of the magnitude of their effect on the received signal. Secondly, the method by which clouds are simulated assumes a perfectly absorbing background (immediately behind the target as opposed to that outside the field of view). Thus clouds of low optical thickness, with a corresponding significant transmissive contribution to radiance will be simulated as having too low a radiance, by a magnitude

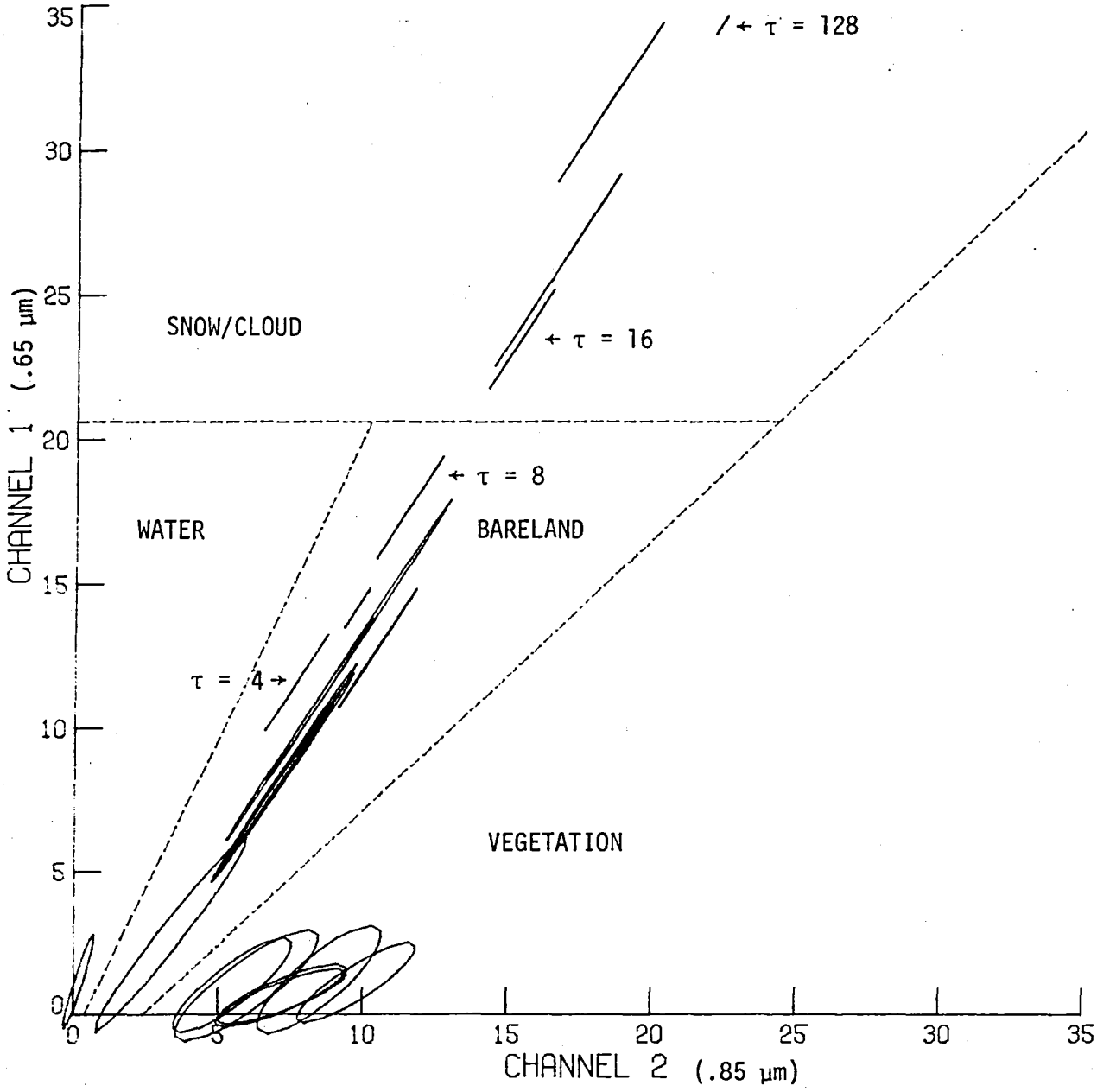

FIGURE 4.1 COVARIANCE ELLIPSE PLOT FOR 23 km VISUAL RANGE AND 30% SOLAR ZENITH ANGLE WITH ICE CLOUDS ANNOTATED WITH OPTICAL THICKNESS.

dependent on the intended background. The cloud set used to test the algorithm was limited to those with optical thickness of 16 or greater in order to make the results of snow versus cloud more meaningful. This limits the test of the ability to distinguish snow versus clouds to those pixels that can be reliably categorized as snow/clouds.

Figure 4.2 shows the .65 μm versus 1.55 μm ellipse plots for a similar but smaller set of data as used for Figure 4.1. The cloud and snow classes have been indicated. A threshold value in the 1.55 μm channel can be seen to seperate snow and clouds fairly well. This algorithm was implemented and tested for the three atmospheric conditions (as qualified by visual range), and used two solar zenith angles for testing in Aherron, et al. (1981).

Overall the snow versus cloud discrimination accuracy was very good. The worst case was for a visual range of 5 km but the difference between 5 km, 10 km, and 23 km results was insignificant. Table 4.1 shows the snow and cloud confusion matrix for the 5 km case.

The above test has served to show that given perfect snow/cloud versus other categorization the snow versus cloud discrimination is simple and accurate. In practical applications the snow/cloud versus other categorization can be rather unreliable. It will be the major source of error in dealing with clouds.

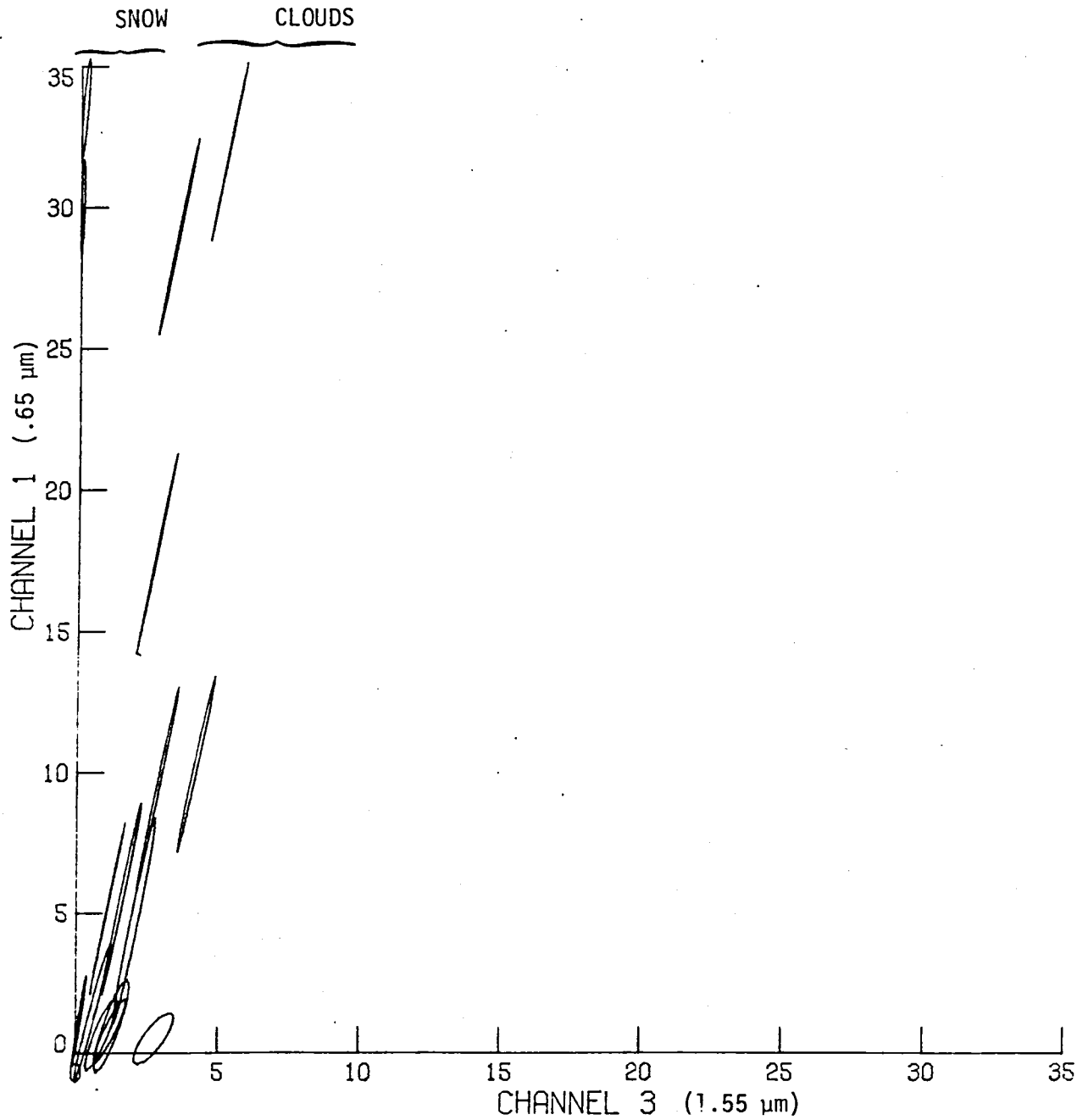

FIGURE 4.2 COVARIANCE ELLIPSE PLOT FOR 23 km VISUAL RANGE AND 30° SOLAR ZENITH ANGLE WITH SNOW AND CLOUDS INDICATED

TABLE 4.1

Snow versus Cloud confusion matrix for 5 km visual range and 30° solar zenith angle.

		DECISION	
		SNOW	CLOUD
TRUTH	SNOW	198	2
	CLOUD	0	346

5. MODEL ENHANCEMENT TESTS

Subsequent to the publication of Aherron, et al. (1981) an enhancement was made to the aerosol and Rayleigh attenuation coefficients ($\alpha i(\lambda)$) which altered the spectral radiance signatures produced by the simulation. Figure 4.1 represents signatures produced utilizing the new coefficients. Two of the three experiments in Aherron, et al. were repeated with enhanced coefficients and are summarized in Table 5.1.

Table 5.1(A), which corresponds to Figure 8(B) of Aherron, et al., shows results for the 7 class set. There are two major conclusions that can be drawn from this figure. One is that the MLH (Maximum Likelihood) aggregation method is fairly sensitive to changes in solar zenith angle. Second, recalling that the BAM (Boundary Approximation Method) is substantially cheaper computationally, the BAM is the best method of the three for the task of categorization for this set of classes.

Figure 5.1(B), which corresponds to Figure 8(C) of Aherron, et al., shows results for a larger set of 20 classes. Again the MLH method proves susceptable to changes in solar zenith angle. The MSD (mean square distance) aggregation method gave the highest accuracy but with the increased cost over the BAM. These new results show even more dramatically the importance of the mix of classes (i.e task assignment) in determining sensor system performance. Ultimately the mix of classes on which sensor systems are tested should be based on realistic probability of occurrence data. This final point will be elaborated on in Section 6.

TABLE 5.1 (A)

CATEGORIZATION ACCURACIES FOR 3 VISUAL RANGES AND TWO SOLAR ZENITH ANGLES FOR 17 CLASSES.

	SOLAR ZENITH ANGLE					
VISUAL RANGE	30°			40°		
	MLH	MSD	BAM	MLH	MSD	BAM
23 km	1.	.96	.99	.91	.96	.98
10	1.	.96	.99	.91	.95	.98
5	1.	.96	.99	.91	.96	.98

TABLE 5.1 (B)

CATEGORIZATION ACCURACIES FOR 3 VISUAL RANGES AND TWO SOLAR ZENITH ANGLES FOR 20 CLASSES.

	SOLAR ZENITH ANGLE					
VISUAL RANGE	30°			40°		
	MLH	MSD	BAM	MLH	MSD	BAM
23 km	.96	.93	.86	.85	.90	.86
10	.95	.91	.86	.85	.90	.86
5	.96	.92	.87	.85	.91	.86

ALL TRAINING SETS GENERATED FOR 23 km VISUAL RANGE AND 30° SOLAR ZENITH ANGLE.

6. STOCHASTIC MODELING

6.1 Introduction

This section deals with the stochastic nature of the remote sensing system simulation. The analytical details of the stochstic properties of the model have been discussed in other sections or in other papers (Huck, et al., 1982). Included in this section are observations and discussions concerning the limitations encountered and the implications of various assumptions made in the treatment of stochastic model properties.

The general philosophy in addressing the statistical properties of the remote sensing system has been to statistically characterize the fundamental values or processes within each model element. For instance, during the discussion of atmospheric radiative transfer models, it was stated that it was the amount and characteristics of the atmospheric constituents that was "driving" variation in radiance quantities. The limit of resolution to which this fundamental characterization is carried is defined by practical realization, as opposed to availability considerations. For plants it is realistic to collect statistical data on biomass for good size data sets. It is unrealistic to expect statistical data on the number of leaves and their orientation, twig volume, and number of flowers or fruits for anything but a small collection of cases. Due to the scarcity of good statistical data on target characteristics (i.e., biomass, water content) reflectance variability was driven by an artifical variable. Statistical data at the process resolution desired was not always available or complete and estimates were used where necessary. For targets, statistical data was not available for the fundamental characteristics or for the reflectances.

6.2 Statistical Distribution Characteristics

The assumption of the normality of statistical distriubtions in remote sensing work is almost universal. For those quantities, such as sensor irradiance, which are a function of many independently (perhaps) distributed quantities, the central limit theory of statistics would provide some justification for that assumption.

Strictly speaking, the normal distribution is not valid for quantities such as path radiance because of the exclusion of negative radiances. The normal distriubtion was chosen for the distribution of the atmospheric constituent amounts and reflectance artificial variables. For atmospheric constituent amounts this assumption is intuitively pleasing. The case of reflectance variables does not offer such appeal. One problem concerns the rather arbitrary nature by which targets are identified. For instance, one may ask at what point does thin vegetation become bare land or what is the difference between a thin cloud and thick haze. If for example, the reflectance variable for vegetation were biomass, there seems no intuitive justification for assuming that it is normally distributed. A more likely case would be an asymmetrical distribution that peaked at the biomass deemed to be the necessary minimum to be classified vegetation. The second major limitation with regards to reflectance artificial variables is the restriction of reflectance to the range of 0 to 1. For a particular portion of the spectral reflectance curve for a target characterized by low or high mean reflectance, the range of possible reflectances is truncated. If the normal assumption is used for the artificial variable in this situation, the allowable size of the reflectance variability is unduly restricted.

The failure of the normal assumption for radiance data has been demonstarted both in field and computational experiments. Valovcin (1978) plotted mean radiance and ±1 sigma radiance curves for snow and cirrus clouds. Both of the minus sigma curves showed radiances below zero which are physically impossible. Presenting ± sigma curves (or bars) suggests things about the statistical distribution that may or may not be true. Sigma curves, which are symmetric about the mean, lead the reader to believe that the probability density function (PDF) is symmetrical. The plots presented by Valovcin clearly preclude the assumption of a symmetrical PDF and therefore rule out the normal assumption. Similarily the 1 sigma ellipses for several simulated classes in Fig. 4.1 enclose negative radiances in the same manner as Valovcin's data.

6.3 Distribution Parameters

It was mentioned briefly in the section on reflectance there is a correspondence on covariance between channels and their redundancy. The exact redundancy is a function of the probability density functions of the channels.

For a multivariate normal distribution the channel redundancy is specified exactly by the covariance matrix (see for example a text on Information Theory) and this is the distribution that will be assumed for illustrative purposes. Using the same normality assumption, Wiersma and Landgrebe (1979) attributed all the covariance for a set of spectral radiance data to covarying reflectances, with one exception. The atmospheric water vapor absorption bands were eliminated from the analysis. The sophistication and rigor of their analysis is almost unparalled in the remote sensing literature, and should be reviewed to understand the importance of covariance "structure" in determining optimal spectral channels. One of the shortcomings of Wiersma and Landgrebe's analysis is the lack of consideration given to the contribution of the atmospheric variability to the spectral radiance covariance structure. This shortcoming is almost certainly due to the lack of data to quantify and statistically characterize the atmospheric effects present in the data.

The simulation that has been discussed herein has the capability to combine the effects of the reflectance and the atmosphere on the spectral radiance covariance structure. The reflectance covariance structure was discussed in the surface reflectance section. Defining the atmospheric contribution to radiance covariance has been no more fruitful than for the reflectance. The model utilized for atmospheric radiative transfer variability requires that the covariance of atmospheric constituent amounts be defined. For example, it would be necessary to define the correlation between atmospheric water vapor content and aerosol burden. So far no such data has been found. Simulations run to date have assumed all constituents to be uncorrelated with the exception of aerosols and water vapor which are assumed to have perfect positive correlation. Fraser (1975) reports covariance data for optical depths determined from solar attenuation data. By assuming some model for the various atmospheric constituents contributions to optical depth, it might be possible to invert the covariance data for the constituent amounts but so far efforts in this area have not been successful.

6.4 Decision Theory Considerations

It became apparent during the work represented in Aherron, et al. (1981) and cloud detection algorithm performance reported herein that classification

or categorization accuracies where highly dependent on the probability of encountering various targets. This is a familiar subject to those with knowledge of Bayesian decision theory. The two statistical values necessary for Bayesian decision calculations are the conditional probability of a signal given that it was produced by a certain class and the a priori probability of encountering that class (Duda and Hart, 1973). The statistical characterizations and models discussed to date have been concerned with defining the conditional probability function for a class. The algorithm performance evaluation model utilized thus far has been a simple overall classification or categorization accuracy. These figures have been based on equal a priori probabilities for classes. When classes are aggregated into categories the a priori probabilities are not necessary equal. This point must be kept in mind when comparing the reported overall decision accuracies.

Discussion of the Boundary Approximation Method (BAM) decision algorithm in Aherron, et al. (1981) points out the need for class a priori probabilities in balancing the type I and type II errors of categorization when formulating the exact algorithm parameters. As the overall remote sensing model becomes more realistic and accurate in future work, it will be necessary to include realistic a priori probabilities of occurence for both classes and categories. At least two potential methods for channel bandwidth and location selection will require such knowledge. One of these, an information theory based method, was used by Kondratyev (1975) for choosing spectral channels. Kondratyev's analysis was fairly crude and the method he used is still relatively unexplored. Secondly, Bayesian Decision Theory, as was discussed before, requires the same class probability data.

7. SUMMARY & CONCLUDING REMARKS

This report has presented supporting research and data for a previously reported comprehensive remote sensing system simulation (Huck, et al. 1982). A review of various models of atmospheric radiative transfer was presented. The qualitative accuracy and the quantitive computational complexity of the various models was compared. Using those comparisons and evaluation criteria that included recognition of the uncertainties about atmospheric parameters, the Turner (1974) model was chosen for use in the remote sensing system simulations. A detailed discussion of the stochastic implementation of the Turner model was given. Various functional forms for spectral diffuse reflectance that allow introduction of variability were given and discussion was made of certain properties of reflectance variability that are desirable in dealing with realistic targets. A compilation of various spectral reflectance curves utilized in simulations was presented.

The special problem of detecting clouds reliably has been examined. For optically thick clouds a test of a preliminary detection algorithm has shown very high accuracy. Thin clouds pose a problem in detection that needs to be examined more closely. The detection algorithm tested requires a spectral channel at .65 μm and 1.55 μm. As was pointed out in Huck, et al., (1982), the remote sensing system simulation being developed is unique in its treatment of the stochastic elements of the remote sensing system. The lack of good data for parameterizing the statistical nature of the atmosphere and target reflectances was discussed especially as it pertained to defining the wavelength covariance matrix for radiances. The need for a priori probability of occurence data for targets was discussed. Finally, a partially updated set of categorization results for the experiment reported in Aherron, et al. (1981) was presented which showed the simplest method of categorization performing even better relative to the other methods than previously reported.

Hopefully modeling efforts such as described provide insight to the overall sensor systems design effort as well as those people involved in basic research concerning fundamental processes.

One role that remote sensing system modeling plays in research is to encourage a more insightful look at available data and more careful definition of needs for future data collection. Specifically the statistical nature

of the various system elements becomes more important as the modeling becomes more refined and generalized. And finally, modeling should help to make informed decisions as to the importance of various effects and error sources within remote sensing systems.

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16. Abstract

A computational model of the deterministic and stochastic process of remote sensing has been developed based upon the results of the investigations presented. The model is used in studying concepts for improving worldwide environment and resource monitoring. A review of various atmospheric radiative transfer models is presented as well as details of the selected model. Functional forms for spectral diffuse reflectance with variability introduced are also presented. A cloud detection algorithm and the stochastic nature of remote sensing data with its implications are considered.

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