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A STOCHASTIC ATMOSPHERIC MODEL FOR
REMOTE SENSING APPLICATIONS

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1.0 INTRODUCTION

In remote sensing applications there is a need for an atmospheric model to simulate the response of a satellite sensor for realistic, variable atmospheric conditions. In addition, there is a need for an atmospheric model to "correct" the sensor response for expected or anticipated atmospheric conditions which exist for a particular region of interest.

The remote sensing of the Earth's surface and the interpretation of various surface elements is a complex problem for many reasons. First, there is the variability of the surface itself; the reflectance and emissivity of surface features are dependent upon factors which are either difficult to model or predict. Thus, the intrinsic radiance of a species of vegetation will depend upon the growing season, soil moisture, time of day, wind speed, precipitation history, and perhaps other factors which are difficult to analyze. Second, atmospheric effects can play a role in varying the radiance of the surface material at the surface and also in the radiance along the path which connects the sensor and the target element. Thus, one can have a variable atmosphere as a result of the spatially and temporally varying aerosol or the variable gaseous components such as water vapor, ozone, and carbon dioxide. In addition, there is the presence of clouds and, therefore, cloud shadows which must be accounted for in the analysis of remote sensor data.

Remote sensing means different things to different groups. One may be interested in estimating the proportion of crops or materials in a given region. Another may be interested in the identification of various features based upon spectral properties. In early work in remote sensing, investigators attempted to create signatures of various materials based upon their actual spectral characteristics in a known area. Then the sensor was transported to another area and each pixel of data was then tested to determine how it compared spectrally with the known signatures. By designating a specific area for investigation one could then classify the pixels according to their spectral classes. Another method can be used however; one which is based upon models of various materials. The models can be general so that they are characteristic of many of the variables which are used to represent actual data. Thus, a particular crop model might have the capability of predicting spectral reflectance in terms of the period during the growing season, the time of day, soil moisture, and wind speed. This is then an attempt to remove some of the variability associated with various material classes.

A similar problem exists with the atmosphere. In the extension of spectral signatures from one area to another the atmosphere will be different and, therefore, errors will be introduced into the processing of images for classification analysis. A deterministic atmospheric radiation model would certainly be desirable. Unfortunately, it is impossible to predict the optical state of the atmosphere throughout the time span and spatial region over which remote sensing takes place. In lieu of such models, we shall investigate the statistics of basic atmospheric optical properties so that we can determine a measure of the variability of the atmosphere for particular times and areas of concern. We base our stochastic model on actual data for optical thickness as measured by sensors throughout the world.

2.0 MODEL PARAMETERS

In remote sensing technology there are many parameters which are used in the description of surface features and the atmosphere. Because we are considering the atmosphere in this investigation rather than the details of the surface, we will consider the atmospheric parameters in some detail. The primary parameters on which the radiation at the sensor depends are those listed in Table 1.

Table 1. List of Primary Parameters for Remote Sensing

Target Bidirectional Reflectance	$\rho(\hat{\Omega},\hat{\Omega}')$
Background Albedo	ρ_B
Spectral Optical Thickness	τ_o
Target Directional Emissivity	$\varepsilon(\hat{\Omega})$
Background Emissivity	ε_B
Single Scattering Albedo	ω_o
Scattering Phase Function	$p(\cos\chi)$
Density of Each of i-th Gas Component	n_i
Extraterrestrial Solar Irradiance	E_o
Geometry	$\hat{\Omega},\hat{\Omega}_o$

Many of these primary parameters are, in turn, related to more basic quantities such as those listed in Table 2. These quantities are used in models for the specification of the primary parameters and should be considered for the detailed modeling of the inherent features of surface and atmospheric quantities. It should be noted that we have not included the functional dependence of each parameter in the tables. It will be assumed that the physical (radiometric) and optical quantities are spectral and depend upon the wavelength of the radiation.

Table 2. List of Basic Quantities for Primary Parameters	
Barometric Pressure	P
Aerosol Index of Refraction	m
Aerosol Size Distribution	n(r)
Aerosol Shape Factor	s
Particulate Number Density	N
Atmospheric Temperature	T_a
Cloud Temperature	T_c
Target Temperature	T_t
Background Temperature	T_b
Water Vapor Pressure	e
Spectroscopic Parameters	Λ_i

We now describe briefly the radiometric quantities which are used in the deterministic and stochastic atmospheric radiation models. The surface radiance, that is, the upward-directed radiance at a surface element is given by the following equation:

$$L_o\,(\hat{\Omega}) = \int_{2\pi} \hat{n}_s \cdot \hat{\Omega}' \rho(\hat{\Omega},\hat{\Omega}') L_{in}(\hat{\Omega}') d\hat{\Omega}', \tag{1}$$

where n_s is the unit normal surface vector, $\rho(\hat{\Omega},\hat{\Omega}')$ is the bidirectional surface reflectance which is dependent upon the directional unit vector for the incoming radiation $\hat{\Omega}'$ and the vector for the outgoing radiation $\hat{\Omega}$. The incoming radiance L_{in} $(\hat{\Omega})$, in turn, depends upon the atmosphere and the background surface albedo. It is the task of agronomists, hydrologists, geologists, and others to present specific models of the bidirectional reflectance for their respective disciplines. Once this is done the atmospheric scientist can use his models of the atmosphere to generate the downwelling radiation field so that one can calculate the surface radiance

$L_0(\hat{\Omega})$. For many examples one can use the assumption of a diffuse surface in which case the bidirectional reflectance is constant with respect to direction and we have for the surface radiance

$$L_0 = \frac{\rho}{\pi} E_{TOT}, \tag{2}$$

where ρ is the surface albedo and E_{TOT} is the total (solar plus diffuse sky) downward irradiance on the target.

The radiance at a sensor aperture can be expressed as

$$L = L_0 T + L_p,$$

where T is the transmittance along the path between the target and the sensor and L_p is the path radiance. These two quantities are dependent upon the scattering and absorptive properties of the atmosphere, the geometry, and in the case of path radiance, the surface albedo. Many models exist which can be used to calculate the transmittance and path radiance, some of which are summarized by Turner [1]. Because of the relatively simple closed-form expressions used in a modified two-stream model, we will use the model of Turner [2,3,4] in our analysis.

Because of the ease with which we could obtain data and because there is a reasonably good understanding of atmospheric particulates, we will concentrate on the stochastic nature of the atmospheric aerosol in this investigation. In a previous study, Turner considered the representation of the spectral optical thickness of the atmosphere in terms of a random variable. It should be recalled that the aerosol optical thickness of Earth's atmosphere can be expressed as the following:

$$\tau_{0,A}(\lambda) = \int_0^\infty \kappa_A(\lambda,z)dz, \tag{4}$$

where $\kappa_A\ (\lambda,z)$ is the volume extinction coefficient at altitude z. Because the particulates are so variable we can consider $\tau_{o,A}(\lambda)$ as the most variable part of the optical thickness, at least in the spectral regions where gaseous absorption is weak. Thus, the aerosol optical thickness can have any positive value, i.e.,

$$0 \leqslant \tau_{o,A}(\lambda) < \infty \tag{5}$$

Another quantity of considerable importance in radiative-transfer theory is the single-scattering albedo $\omega_o(\lambda)$. It is the ratio of the volume scattering coefficient to the volume extinction coefficient and is a measure of the amount of scattering. It has the following range:

$$0 \leqslant \omega_o(\lambda) < 1 \tag{6}$$

3.0 STOCHASTIC MODEL

In this section we consider the formalism for the statistical properties of the highly variable atmospheric components.

3.1 Sensor Response

A typical sensor has detectors the output of which is usually in volts. In any case, we can write the sensor output

$$s_k = \int_0^\infty L(\lambda)\ S_k(\lambda) d\lambda, \tag{7}$$

where $S_k(\lambda)$ is the spectral response function of the sensor for the k-th channel. If the radiance $L(\lambda)$ is known then the integration can be performed and the response s_k can be determined.

The response s_k and the radiance $L(\lambda)$ are considered to be stochastic quantities i.e., they have properties which are associated with random variables. As stated earlier, the randomness arises from two factors; 1) the unknown or statistical nature of the surface properties, and; 2) the statistical nature of the atmosphere. Thus, we consider the mean and covariance of the sensor response for channels k and k' i.e.,

$$R_k = E\left\{s_k\right\} \tag{8}$$

$$C_{kk'} = E\left\{(s_k - R_k)(s_{k'} - R_{k'})\right\}, \tag{9}$$

where E denotes the expectation.

3.2 The Covariance Matrix

For multispectral remote sensing applications one can use the maximum likelihood decision rule for classification. Let us designate the logarithm of the radiance by a vector X_k, i.e.,

$$X_k = \ln L_k. \tag{10}$$

One can then use the n-dimensional normal distribution function i.e.,

$$f(x_1, x_2, \ldots, X_n) = \frac{1}{(2\pi)^{n/2}\sqrt{C}} \exp\left\{-\tfrac{1}{2}\sum_{k,k'=1}^{n} C^{-1}_{kk'}(X_k - \bar{X}_k)(X_{k'} - \bar{X}_{k'})\right\} \tag{11}$$

when C is the determinant of the covariance matrix $C_{kk'}$. We will now develop an expression for the covariance matrix for the spectral radiance in terms of the variances, means, and covariances of the known quantities. Let us consider the stochastic parameters to be optical thickness τ, single-scattering albedo ω, and the background albedo ρ_B. The spectral radiance for the i-th pixel and the k-th channel can be represented approximately by

$$L_{ik}(\tau, \omega, \rho_B) = \rho_{ik}\, F_k(\tau, \omega, \rho_B) + G_k(\tau, \omega, \rho_B), \tag{12}$$

where F_k is a radiometric factor related to the atmospheric transmittance between the target and observer and the total (direct plus diffuse) downwelling irradiance at the target. G_k is a radiometric factor related to the path radiance and ρ_{ik} is the spectral reflectance of the i-th pixel for the k-th channel. Averaging over all pixels in a training set or for a model of a particular class we get

$$\bar{L}_k(\tau, \omega, \rho_B) = \bar{\rho}_k F_k(\tau, \omega, \rho_B) + G_k(\tau, \omega, \rho_B). \tag{13}$$

It should be noted that the terms in Equation 13 depend upon the atmospheric parameters τ and ω and the background reflectance ρ_B. If we now denote $f(\tau)$, $g(\omega)$, and $h(\rho_B)$ as probability density distribution functions for the parameters τ, ω, and ρ_B respectively, we can then integrate each of these parameters over all atmospheric states for which the distribution functions are valid, and obtain their mean values. In a later section we will perform these averages for a specific region and time of year. Thus, the complete average is given by

$$\bar{L}_k = \bar{\rho}_k \bar{F}_k + \bar{G}_k. \tag{14}$$

The radiance covariance matrix is then written as

$$C(L_k, L_{k'}) = \sum_{i=1}^{n} \sum_{j=1}^{n} (L_{ik} - \bar{L}_k)(L_{jk'} - \bar{L}_{k'}). \tag{15}$$

Substituting expressions 12 and 14 into Equation 15 and carrying out the algebra gives us the final expression for the radiance covariance matrix,

$$\begin{aligned} C(L_k, L_{k'}) = {} & C(\rho_k, \rho_{k'})\, C(F_k, F_{k'}) + \bar{\rho}_k \bar{\rho}_{k'} C(F_k, F_{k'}) + \\ & \bar{F}_k \bar{F}_{k'} C(\rho_k, \rho_{k'}) + \bar{\rho}_k C(F_k, G_{k'}) + \\ & \bar{\rho}_{k'} C(F_{k'}, G_k) + C(G_k, G_{k'}). \end{aligned} \tag{16}$$

Let us now examine Equation 16 carefully in order to understand its significance. The matrices involving F_k and G_k are known if we know the joint probability density distribution functions for the optical thicknesses. For example, the covariance matrix elements for $C(F_k, F_{k'})$ are given by

$$C(F_k, F_{k'}) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(F_k, F_{k'})(F_k - \bar{F}_k)(F_{k'} - \bar{F}_{k'})\, dF_k\, dF_{k'}, \tag{17}$$

where $f(F_k, F_{k'})$ is the joint probability density function. This, in turn, is known in terms of the distribution function g for the optical thicknesses i.e.,

$$f(F_k, F_{k'}) = g(\tau_k, \tau_{k'})/J, \tag{18}$$

when J is the Jacobian of the transformation between the variables. From reflectance models we can determine the means and covariance for the reflectances in Equation 16 and, therefore, the complete covariance matrix for multispectral radiances is determined. The diagonal value of the matrix is the variance. It is given by

$$\sigma^2(L_k) = \sigma^2(\rho_k)\sigma^2(F_k) + \bar{\rho}_k^2\,\sigma^2(F_k) + \bar{F}_k^2\sigma^2(\rho_k)$$

$$+ 2\bar{\rho}_k C(F_k, G_k) + \sigma^2(G_k) \tag{19}$$

We can now treat special cases of Equation 19. If the atmosphere is constant, that is, if there is no variation in the optical properties of the atmosphere then we have for the variance

$$\sigma^2(L_k) = \bar{F}_k^2\sigma^2(\rho_k), \tag{20}$$

which indicates that as the atmospheric turbidity increases from one stable condition to another the variance decreases. This fact is reasonable; indeed, the variance will be zero if the turbidity or the atmospheric optical thickness is very large because F_k decreases as turbidity increases and there will then be no variation at all. This is illustrated in Figure 1 for dark and bright surfaces for various atmospheres. As the visibility decreases the dark surfaces will brighten and the bright surfaces will darken and all surfaces will approach the limit point which is the path radiance.

For the special case of a constant surface Equation 19 gives us

$$\sigma^2(L_k) = \bar{\rho}_k^2\sigma^2(F_k) + 2\bar{\rho}_k C(F_k, G_k) + \sigma^2(G_k). \tag{21}$$

Equation 21 is quite interesting; it indicates that if we know the statistics for the atmosphere throughout a uniform spatial area then the reflectance can be determined by solving for $\bar{\rho}_k$. Thus, the atmospheric statistics are found by examining a data base on optical thicknesses and the complete variance $\sigma^2(L_k)$ is determined experimentally by remote sensing. A direct experiment using, say, the Landsat multispectral sensor should confirm the validity of Equation 21.

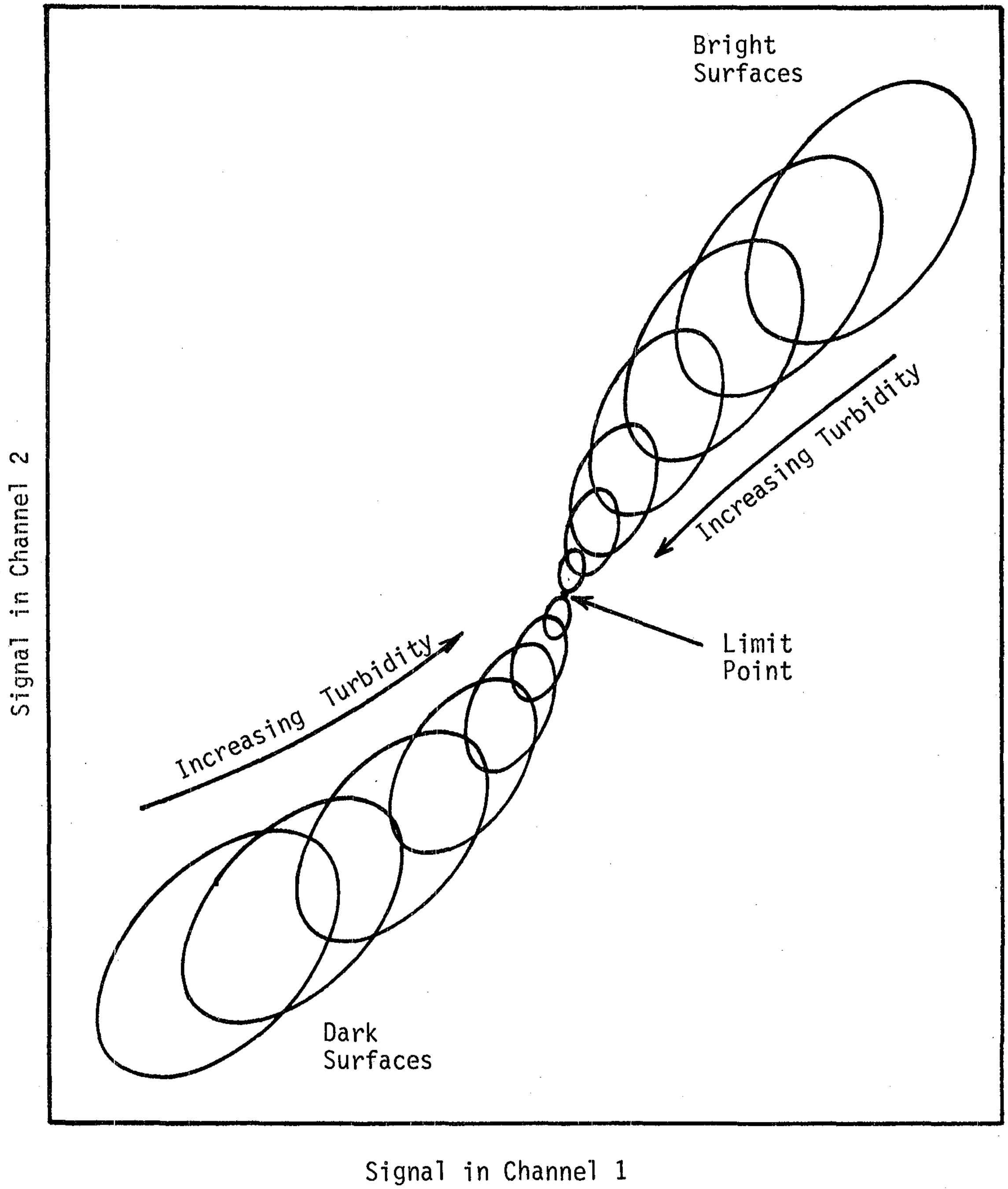

Figure 1. Two-dimensional Representation of Spectral Signatures as a Function of Atmospheric Turbidity

3.3 Radiative Transfer

Using an atmospheric radiation model we will now develop expressions for the means and variance of the path radiance. For simplicity, we will use a single-scattering approximation for the path radiance, i.e.,

$$L_p(\tau,\mu,\phi) = L_A\left[1-e^{-(\tau_R + \tau)(\frac{1}{\mu} + \frac{1}{\mu_o})}\right] \tag{22}$$

where τ_R is the Rayleigh optical thickness and τ is the aerosol optical thickness. It is assumed that the Rayleigh value for a gaseous atmosphere is always known. It is given by

$$\tau_R(h) = \tau_R(h_o)\,\frac{P}{P_o}\,, \tag{23}$$

where $\tau_R(h_o)$ is the value at some standard altitude (sealevel), P is the barometric pressure at altitude h, and P_o is the pressure at sealevel. The cosine of the nadir view angle is μ and the cosine of the solar zenith angle is μ_o. The factor L_o is the asymptotic radiance, given by

$$L_A = \frac{\omega_o\mu_o E_o p(\mu,\phi,-\mu_o,\phi_o)}{4\pi(\mu+\mu_o)}\,, \tag{24}$$

where E_o is the known extraterrestrial solar irradiance at the top of the atmosphere and $p(\mu,\phi,-\mu_o,\phi_o)$ is the single-scattering phase function. The asymptotic value for path radiance is reached for infinite optical depth, i.e., for a very turbid atmosphere. A representation of the path radiance is given in Figure 2. We can write L_p

as

$$L_p(\tau) = L_A(1-ae^{-b\tau})\,, \tag{25}$$

where

$$a = e^{-b\tau_R} \quad \text{and} \quad b = \frac{1}{\mu} + \frac{1}{\mu_0} . \tag{26}$$

We now use a log-normal distribution function for the representation of the aerosol optical thickness i.e.,

$$f(\tau) = \frac{1}{\sqrt{2\pi}\,\sigma\tau} \exp\left[-\frac{1}{2\sigma^2}(\ln \tau - m)^2\right] , \tag{27}$$

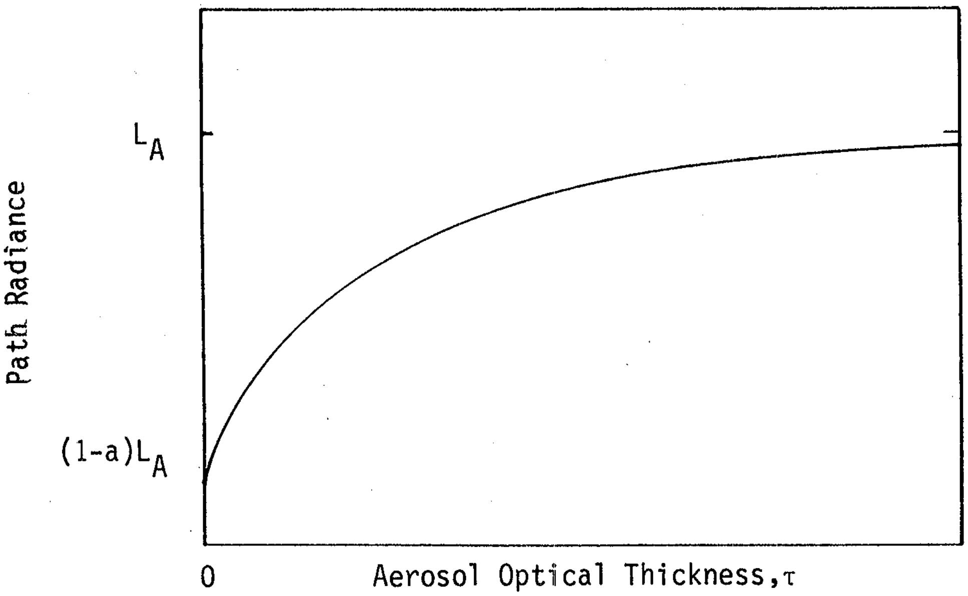

Figure 2. Path Radiance vs Aerosol Optical Thickness

where σ^2 is the variance and m is the mean value. The mean value for L_p is then

$$\bar{L}_p = L_A - L_A a \int_0^\infty e^{-b\tau} f(\tau) d\tau \tag{28}$$

$$= L_A(1-I). \tag{29}$$

Likewise, we can determine the variance in the path radiance i.e.,

$$V(L_p) = \overline{L_p^2} - \bar{L}_p^2, \tag{30}$$

where

$$\overline{L_p^2} = L_A^2(K-I^2), \tag{31}$$

where the I and K integrals are

$$I = \frac{a}{\sqrt{\pi}} \int_{-\infty}^{\infty} \exp\left[-(t^2+e^{\alpha+\beta t})\right] dt \tag{32}$$

and,

$$K = \frac{a}{\sqrt{\pi}} \int_{-\infty}^{\infty} \exp\left[-(t^2+e^{2\alpha+\beta t})\right] dt, \tag{33}$$

where

$$\alpha = -be^{m} \text{ and } \beta = \sqrt{2}\,\sigma. \tag{34}$$

The integrals must be done numerically and in a later section we will evaluate them to find the mean and variance in the path variance for a specific geographical area.

3.4 Atmospheric Data

The author made many contacts with atmospheric scientists and experimentalists in meteorological data analysis to acquire a comprehensive data base for the atmospheric optical parameters such as single-scattering albedo and optical thickness. Virtually nothing exists on ω_0, so we will have to assume values which are generally characteristic of a particular region of investigation.

Although it is not difficult to measure the optical thickness, it does require spectral filters and a clock-drive to orient a sensor toward the sun. Usually the devices used require special handling by trained personnel and uniformity of devices and methods of deployment. As a result, good values of $\tau_0(\lambda)$ are available only for particular sites and for limited times. The most comprehensive set of turbidity values is that of the turbidity network or the Background Air Pollution Monitoring Network (BAPMON) data [5] for 1978 which can be obtained from the National Climatic Center in Asheville, NC. Using a two-band sensor, the data included turbidity measurements for selected sites on an hourly basis for the following locations.

Ireland
Spain
Federal Republic of Germany
Hungary
Bulgaria
Italy
Turkey
Afghanistan
India
Canada
United States
El Salvador
Antarctica
Pacific Islands
Australia

Data tapes are available from the National Climatic Center from which one can obtain daily and monthly mean values, variances, and covariances for the two spectral bands.

Associated with the turbidity, one can also obtain the usual weather data from the National Climatic Center. Therefore, one can correlate the turbidity or optical thickness with various parameters such as visibility, pressure, temperature, and relative humidity. Likewise, one can generate the multivariate probability distribution functions for all the variables.

In addition to the above data, a gridded data base [6] is available for Europe containing cloud coverage, cloud type, cloud base and cloud top heights, as well as temperature, pressure, and relative humidity at eighteen layers from the surface up to 18.23 km (60,000 ft.) altitude. One could use this data base to generate the probability density distribution functions for clouds in the same way that we can do for aerosols. A multivariate probability distribution function would give us the number of clouds within some selected area for any season as a function of cloud coverage, cloud type, base height, etc. Having these distributions, one could then calculate the expected values for the line-of-sight transmittance for the cloud-free-line-of-sight. Because we have data for various levels in the atmosphere, we can also generate the distribution functions in four-dimensions, i.e. the three space dimensions and time. Although we have not analyzed the cloud data, one can generate the probability distributions for an arbitrary line-of-sight for space-to-ground transmittances and radiances. In the present investigation we have used the turbidity climatology data for two channels for one month as an example of the technique.

The example which we shall take is for Cerro Verde in El Salvador as given by the BAPMON data. This station was chosen because a fairly large sample of observations was available, in comparison to some of the sample sizes for other months and other stations. Table 3 illustrates the aerosol optical thickness for the month of July, 1978 for the spectral bands 500nm and 880nm. The mean, variances, and standard deviations for both bands are calculated. Also, we determined the covariance and the correlation. It should be noted that the correlation coefficient of 0.979 is high which implies a physical connection between the two bands - certainly not a surprising result. In Figure 3 we present a histogram of the El Salvador data. As can be seen, most of the values lie near an optical thickness of 0.1. In Figure 4 we have plotted the results simultaneously for both spectral bands. The high correlation is clearly seen.

Table 3 AEROSOL OPTICAL THICKNESS

LOCATION: Cerro Verde, El Salvador

Month (1978)	Day	N	τ_A(500 nm)	τ_A(800 nm)
7	1	5	0.19342	0.18881
7	2	1	0.18190	0.25559
7	4	4	0.07368	0.07368
7	5	1	0.08980	0.08059
7	6	6	0.11513	0.11513
7	7	8	0.09210	0.09901
7	8	6	0.08059	0.07599
7	10	1	0.07368	0.09441
7	11	3	0.11973	0.08980
7	12	1	0.08980	0.09441
7	13	4	0.08750	0.07368
7	14	4	0.05987	0.07599
7	18	2	0.06908	0.07829
7	19	1	0.07138	0.06447

Table 3 AEROSOL OPTICAL THICKNESS (cont.)

LOCATION: Cerro Verde, El Salvador

Month (1978)	Day	N	τ_A(500 nm)	τ_A(800 nm)
7	21	2	0.06908	0.08289
7	23	3	0.14967	0.16348
7	24	2	0.38683	0.52269
7	25	4	0.25559	0.35920
7	26	6	0.32466	0.37993
7	27	3	0.09210	0.08059
7	29	2	0.14046	0.11973
Mean			0.134	0.151
Variance			0.00759	0.01486
S.D.			0.08709	0.12191
Covariance			0.01039	
Correlation			0.97900	

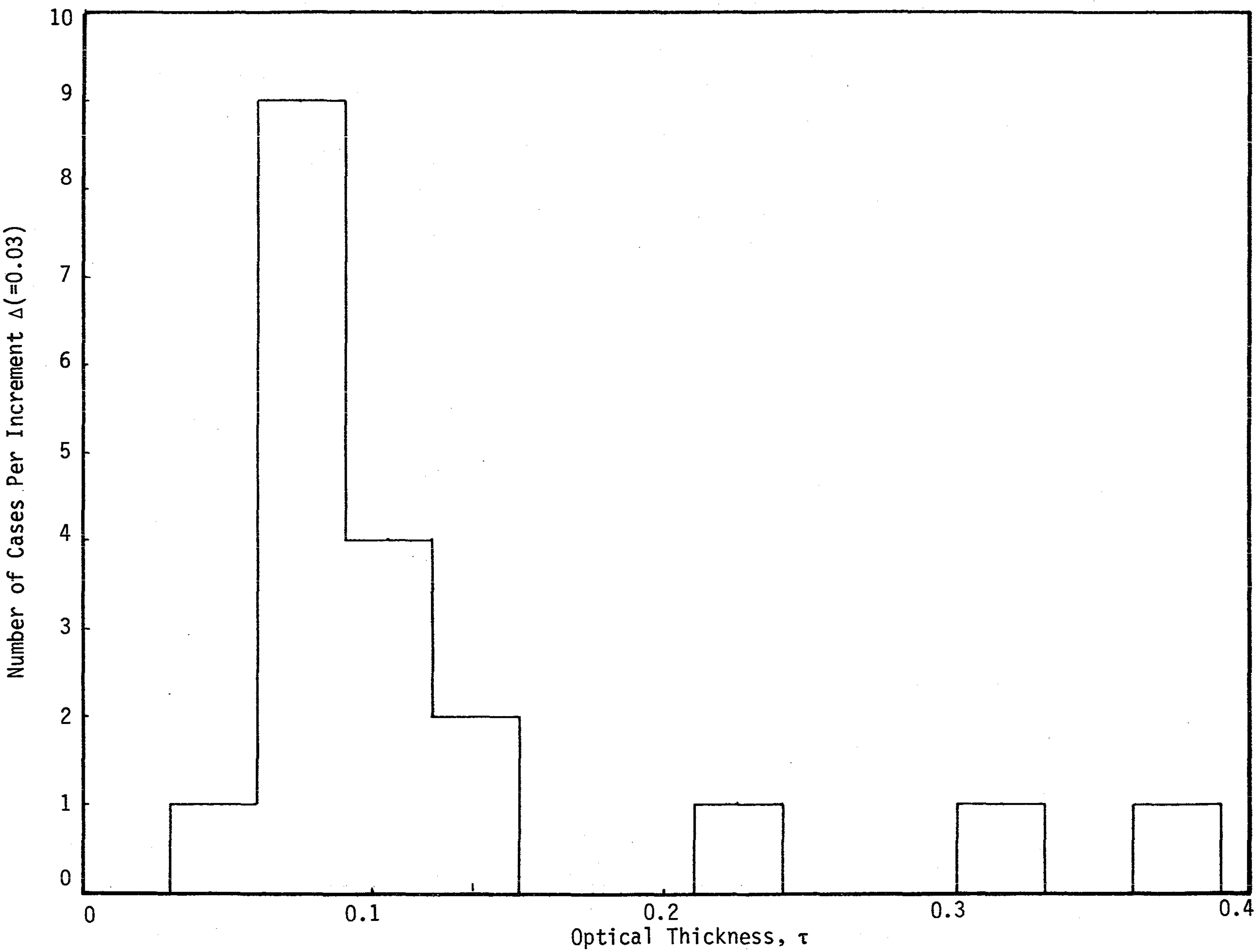

Figure 3. Histogram of El Salvador Optical Thickness Data (July, 1978)

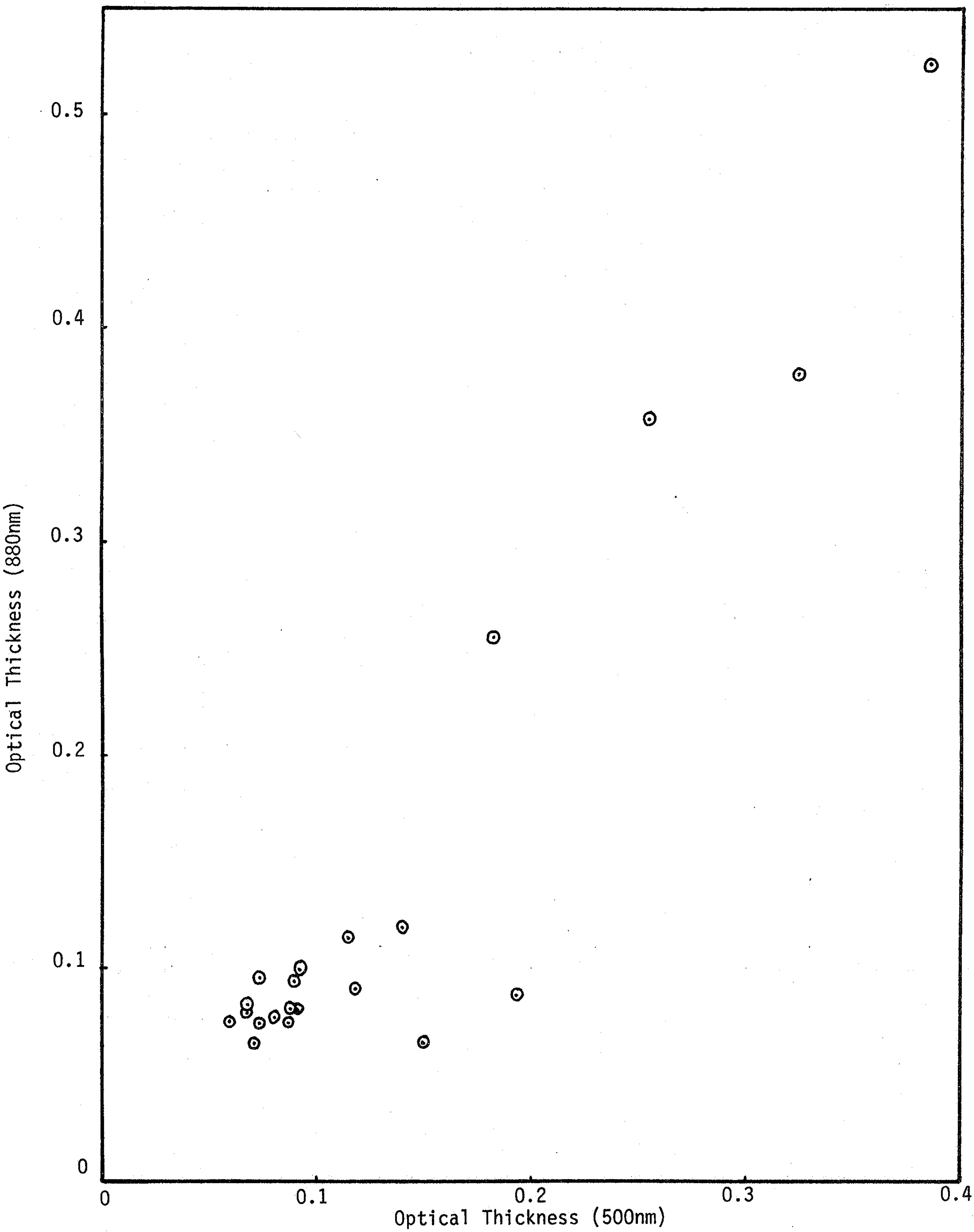

Figure 4. El Salvador Optical Thickness Data (July, 1978)

Similar data for the variable gaseous components such as ozone, water vapor and carbon dioxide are difficult to obtain. Suitable data bases probably exist, but to extract the effective absorber amounts and correlate the results with time of year and location is a large task. In the case of clouds, the problem is two-fold; first, one must develop probability distribution functions for clouds in terms of geographic location and time, and, second, one must then correlate the cloud type with effective reflectance and emissivity. A possible solution is to use spectral bands as in the Thematic Mapper to discriminate large, distinct clouds from snow.

3.5 Results of Calculations

Using the El Salvador data as an example, we considered the following scenario:

Solar zenith angle $\theta_0 = 0^0$
Nadir view angle $\theta = 0^0$
τ_R (Rayleigh optical thickness) = 0.1241
Wavelength λ = 500nm

From these data we can determine the path radiance distribution function by the following:

$$g(L/L_A) = \frac{f[\tau(L)]}{\left|\frac{dL}{d\tau}\right|}, \tag{35}$$

when $f[\tau(L)]$ is the probability distribution function for the optical thickness. The corresponding function $g(L/L_A)$ or $g(X)$, where $X = L/L_A$ is given in Figure 5. Evaluating the integrals in Equations 32 and 33 we obtain

$I = 0.40016$
$K = 0.32837$

so that the mean path radiance is

$$\bar{L}_P = 0.6L_A, \tag{36}$$

and the variance in the path radiance is

$$V(L_P) = 0.16824\ L_A^2. \tag{37}$$

Similar results can be generated for the covariance between bands and for any region and time for which optical thickness data are available.

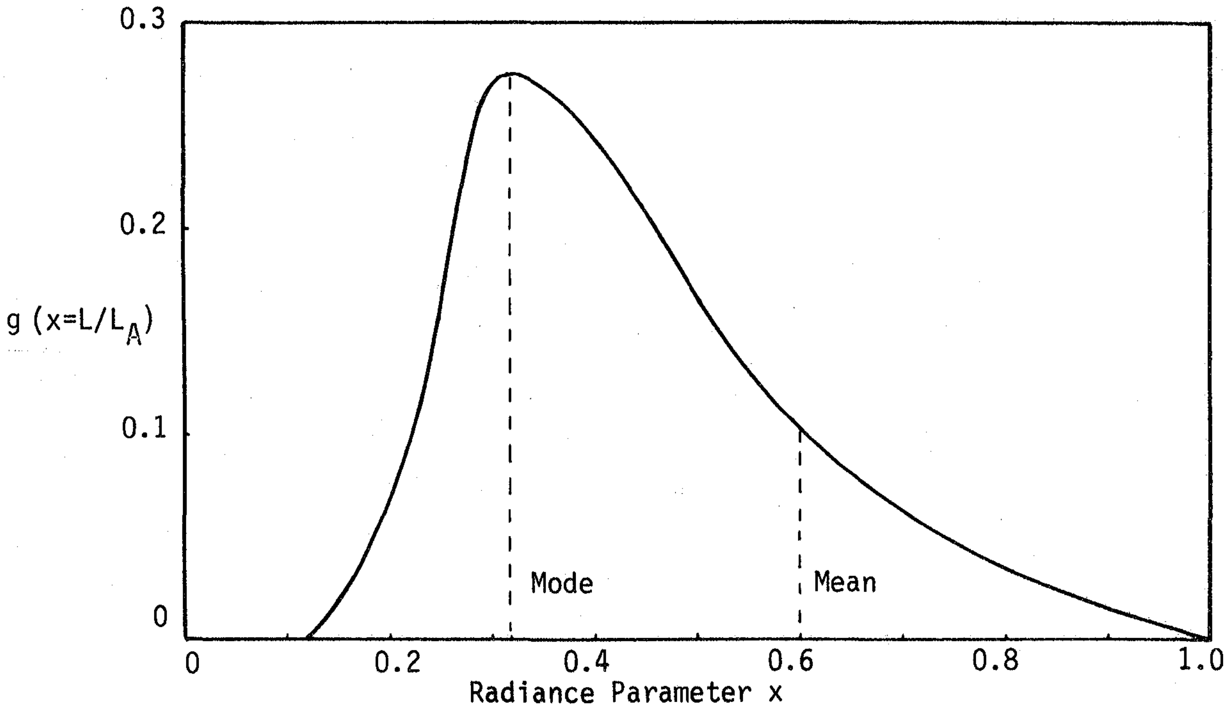

Figure 5. Probability Distribution Function for Path Radiance, for Cerro Verde, El Salvador (July, 1978)

4.0 CORRECTION ALGORITHMS

Having determined the radiance covariance matrix and the mean radiance vector one can then process multispectral data for a particular condition. There are several methods available for processing.

Method 1: The philosophy here is to obtain atmospheric data for large areas of the world for various times of day for different times of year. From this data base, one can then generate the statistics for the atmospheric parameters and, therefore, the corresponding probability distribution functions. Then, using radiative-transfer models one can determine the covariance matrices and the mean values of the radiometric parameters. Using actual field reflectances or models of reflectance one can determine the means and covariance of the surface reflectances for various classes of materials. Finally, all of this information is combined as in Equation 16 to determine the actual radiance covariance matrix and the mean radiances for use in the decision algorithm. The resulting classification accuracy should be better than previous methods which rely on a "universal" mean and covariance. The general pattern is illustrated in Figure 6. It is obvious that as more atmospheric data become available the more complete will be our representation of atmospheric states and the more accurate will be our classification.

Method 2: A variation of the above method is to consider a limited number of data sets. Let our reference radiometric factors be denoted by $\bar{F}$ and $\bar{G}$, that is, these are averages for some training set. Let the corresponding averages for the unknown area be primed i.e., $\bar{F}'$ and $\bar{G}'$. The bar indicates that we have averaged over all atmospheric states. Then, one can operate on the measured radiance L_i' to obtain a corrected radiance i.e.,

$$L_i^c = \left(\frac{L_i' - \bar{G}'}{\bar{F}'}\right)\bar{F} + \bar{G}. \qquad (38)$$

Let us consider a simple example. From our atmospheric and material class data bases we determine $\bar{F}$ and $\bar{G}$ for the middle of Kansas in June. We now

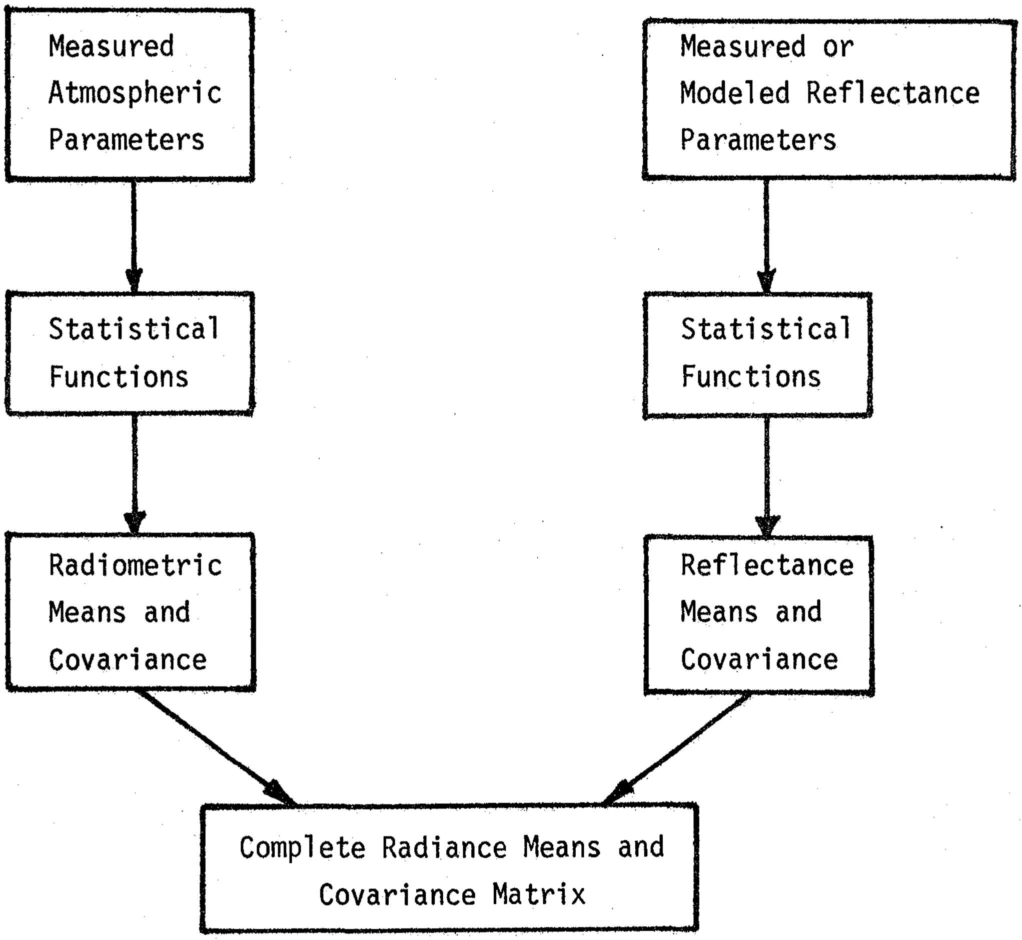

Figure 6. Method for Atmospheric Correction of Multispectral Data

want to classsify materials in Texas in August so we use the corresponding values $\bar{F}'$ and $\bar{G}'$ for that time and location. The L_i are then the actual radiances appropriate to the Texas location for each pixel i. L_i^c is then the new or corrected radiance. If it turns out that the atmospheric conditions and the material classes in Kansas are the same as those in Texas, then $\bar{F}'=\bar{F}$ and $\bar{G}'=\bar{G}$ and

$$L_i^c = L_i, \tag{39}$$

a result which indicates that we can do no better than the training set or model data base. In any case, this is a method which allows us to extend the spectral signatures.

<u>Method 3:</u> Another method we can use is based upon the assumption that one knows or can identify a particular class of objects in a multispectral data set or frame. We then have the following:

$$\sigma^2(L) = F^2\sigma^2(\rho), \tag{40}$$

where it is assumed that we know the variance $\sigma^2(\rho)$ for a particular class of materials. From the measured radiance data we know $\sigma^2(L)$. Hence we know the atmospheric parameter F. Likewise, in taking the average over the known data we have

$$\bar{L} = \bar{\rho}F + G, \tag{41}$$

where $\bar{L}$ is measured and $\bar{\rho}$ is known. Therefore, both factors F and G are determined and one can process <u>all</u> data in the region. A corrected radiance is

$$L_i^c = \left(\frac{L_i - G}{F}\right)\bar{F} + \bar{G}, \tag{42}$$

where $\bar{F}$ and $\bar{G}$ are the known factors from a reference area.

5.0 CONCLUSIONS AND RECOMMENDATIONS

In this investigation we have analyzed measured optical thickness data for one station in a simple two-band sensor network. The statistics were gathered for one month from the National Climatic Center in Asheville, North Carolina. The measurement stations are located in fourteen areas of the world and represent, as best as we can determine, a complete and comprehensive optical thickness data set. As described in this report, if all the data were analyzed we could generate the statistics and probability density distribution functions for optical thickness in terms of time of day, month, and geographic location. Even if this were done, it would represent data only for two bands in the visible part of the spectrum. Nevertheless, the use of the data set would be better than not using it as has been done in the past.

In this work we have assumed diffuse reflectances for the targets. Although this is not a serious restriction, for completeness one should develop a corresponding formalism for non-Lambertian surfaces. This could have been done here, but it would have led to an unnecessarily complex formalism. The key development in this investigation is the expression for the general covariance matrix of radiances in terms of basic atmospheric and reflectance data. Given reflectance data and atmospheric data we can generate a more realistic radiance covariance matrix for particular spatial and temporal regions. This should lead to more accurate probabilities of classification than before because we are using data which more nearly represent the region under consideration. It should be noted that this is a statistical argument in that there may be occasions when one obtains a high classification probability because the unknown data just happen to possess values which are close to the reference data set. For example, if the reference set is Kansas in June and the unknown set is Texas in August, it is possible that the same atmospheric state could prevail in both places for the times considered. In general, however, this is unlikely, so that a statistical method based upon actual atmospheric data should provide the user with a <u>consistently</u> higher classification probability for a large number of data sets.

We recommend further development in this area. A complete stochastic atmospheric radiative-transfer model can now be developed i.e., one which includes the variation in the single-scattering albedo and the gaseous components. If data are lacking one could at least develop the mathematical formalism and use whatever theoretical models exist in atmospheric physics to establish some stochastic parameters. For actual remote sensing users we suggest the further analysis of optical thickness data and the implementation of the algorithms in this report to multispectral classification problems.

REFERENCES

1. "Multiple Scattering Atmospheric Radiation Models", Robert E. Turner, Proceedings of the Society of Photo-Optical Instrumentation Engineers, Vol. 277, 1981.

2. "Remote Sensing in Hazy Atmospheres", R.E. Turner, Proceedings of ACSM/ASP Meeting in Washington, D.C., March 1972.

3. "Atmospheric Effects in Remote Sensing", R.E. Turner, Remote Sensing of Earth Resources, Volume II, F. Shahrokhi, Ed., 1973.

4. "Contaminated Atmospheres and Remote Sensing", R.E. Turner, Remote Sensing of Earth Resources, Volume III, F. Shahrokhi, Ed., 1974.

5. "Global Atmospheric Background Monitoring for Selected Environmental Parameters. BAPMON Data for 1978", Environmental Data and Information Service, National Climatic Center, Federal Building, Asheville, N.C. 28801, May 1981.

6. "Cross-Correlation Analysis to Determine the Environmental Parameters Correlated with Electro-Optical System Performance", AFWAL-TR-81-1099, SAI for AFWAL/AAWA, Dayton, Ohio, November 1982.

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16. Abstract

There are many factors which reduce the accuracy of classification of objects in the satellite remote sensing of Earth's surface. One important factor is the variability in the scattering and absorptive properties of the atmospheric components such as particulates and the variable gases. For multispectral remote sensing of the Earth's surface in the visible and infrared parts of the spectrum the atmospheric particulates are a major source of variability in the received signal. It is difficult to design a sensor which will determine the unknown atmospheric components by remote sensing methods, at least to the accuracy needed for multispectral classification. In this report we examine the problem of spatial and temporal variations in the atmospheric quantities which can affect the measured radiances. We develop a method based upon the stochastic nature of the atmospheric components, and, using actual data we generate the statistical parameters needed for inclusion into a radiometric model. Methods are then described for an improved correction of radiances. These algorithms will then result in a more accurate and consistent classification procedure.

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