Paul Switzer
Department of Statistics
Stanford University
Stanford, CA 94305
William S. Kowalik*
Ronald J. P. Lyon
Department of Applied Earth Sciences
Stanford University
Stanford, CA 94305

Estimation of Atmospheric Path-Radiance by the Covariance Matrix Method

Landsat data from areas of homogeneous reflectance in hilly terrain are used as test areas for estimation of the band-specific atmospheric path-radiances.

Abstract: *A new method has been developed as an extension of Chavez's Regression Technique (Chavez, 1975) to provide estimates of the atmospheric path-radiance in the four Landsat MSS bands. The extension uses the correlation between all four bands of data simultaneously instead of in pairs. The Regression Method and this extension do not require auxiliary data, but operate solely upon the digital numbers recorded on the Landsat tapes. Furthermore, they do not require the presence of sites of low reflectance (basalt flows, clear lakes) or sites of low irradiance (shadows due to topography or clouds) in the Landsat data, or topographic slope data. Instead, we use Landsat data from areas of homogeneous reflectance in hilly terrain as test areas for estimation of the band-specific atmospheric path-radiances.*

The method has been applied to Landsat data from diverse terrain types and atmospheric conditions using three different Landsat images covering semi-arid western Nevada, temperate eastern Pennsylvania, and tropical central New Guinea. The method yields reasonable results from each area.

Introduction

In the application of Landsat data to mineral exploration and rock type discrimination, workers have used ratios of the digital numbers to subdue surface topographic effects and to enhance the difference between the spectral properties of different rock types (e.g., Vincent, 1973; Rowan *et al.*, 1974; Vincent and Rouse, 1977; Raines *et al.*, 1978). It has been noted by several authors (e.g., Krieglar *et al.*, 1969; Rowan *et al.*, 1974; Chavez *et al.*, 1977) that the additive radiance contributed by the atmosphere during imaging results in incomplete removal of the surface topographic effects if not corrected prior to ratioing. Kowalik (1981) has modeled the additive effects of the atmospheric path-radiance and skylight irradiance in ratios of Landsat data, and showed that both effects contribute to falsely large ratio values* on slopes which are well-illuminated and to falsely low

* Now with the U.S. Geological Survey, Box 25046, M.S. 964, Denver Federal Center, Denver, CO 80225.

* Ratio values are considered here with the longer wavelength band in the numerator (5/4, 6/4, 7/4, 6/5, 7/5, 7/6).

0099-1112/81/4710-1469$02.25/0

ratios on poorly-illuminated slopes during imaging by Landsat.

This paper presents the Covariance Matrix Method (CMM) for estimating the additive path-radiance in remote sensing data from the data itself. This method is an extension of Chavez's Regression Technique (Chavez, 1975) which uses the correlation between bands paired individually with Band 7 to estimate the path-radiance. The CMM technique presented here uses the correlation between all bands simultaneously.

The aim of estimating the path-radiance is to obtain appropriate correction values which subdue the residual topographic effects present in raw ratios† of Landsat data so that the ratios are spectrally more descriptive of the actual conditions on the ground.

All Landsat data processing discussed herein was performed in the Stanford Remote Sensing Lab (SRSL) on a PDP11/34 minicomputer with interactive software developed in house.

Atmospheric Correction Model

The radiance measured by a sensor looking vertically through the atmosphere is composed of two primary terms—the brightness contributed by the surface in the field of view of the sensor, and the brightness which did not originate from the surface within the field of view. The former term is information, and is due to direct solar and indirect illumination; the latter term is noise or atmospheric path-radiance.

In model form, the measured radiance y_{ij} for pixel i and spectral band j can be expressed as follows:

$$y_{ij} = c_i x_{ij} + d_j + e_{ij} \tag{1}$$

where $c_i x_{ij}$ is the information due to the direct solar irradiance, d_j is the atmospheric path-radiance, and e_{ij} is the variability unexplained by the model, including the contribution due to pixel-specific indirect irradiance.

The term c_i is an unknown constant multiplier which describes the pixel's topographic surface orientation with respect to the solar position during imaging. c_i equals cos α where α is the angle between the sun vector and the normal to the topographic surface at pixel i.

The x_{ij} term is proportional to the average surface reflectance of pixel i in spectral band j, where the proportionality factor is a product of quantities which are not pixel-specific over suitably small areas of interest. We may write

$$x_{ij} = (S_j T_j H_{dj}) P_{ij} \tag{2}$$

where

S_j = system gain factor in spectral band j;

T_j = atmospheric transmittance from ground to satellite in band j;

H_{dj} = direct solar irradiance in band j upon a surface perpendidicular to the incoming rays at the base of the atmosphere; and

P_{ij} = the reflectance of the pixel i in band j, assumed to be Lambertian.

The additive term d_j in Equation 1 is the unknown atmospheric path-radiance for spectral band j; d_j is taken to be constant across the small area of interest.

Of course, the path-radiance will not be exactly constant across an image but will vary due to (a) changes in the atmospheric conditions across an image, (b) direction of scan view relative to the sun position, and (c) variation in the average radiance in the area surrounding the pixel being viewed at any instant. Turner *et al.* (1971) and Malila *et al.* (1976) have modeled the significance of the first two effects. Turner (1978) and Otterman *et al.* (1980) present results of modeling which show the significance of the third effect. Dave (1980) has modeled the second and third effects. These three effects would contribute to a slightly different total d_j noise term at each pixel in an image. Ideally, one would want to subtract the appropriate pixel-dependent d_j noise term from each pixel, but no statistically based method could do this.

The term e_{ij} in Equation 1 is the residual unexplained variability which is assumed to be small relative to the variability explained by means of the model. It contains, *inter alia*, the contribution of terrain light and skylight, as well as model departures.

Because areas of geologic interest are commonly hilly, the surface orientation term, c_i, will vary rapidly from pixel to pixel across an image. It is often desirable to remove the brightness effects due to this variation by calculating specific band ratios for each pixel. In the ratio, c_i may effectively cancel if corrections are applied for the additive path-radiance and if the residual term e_{ij} in Equation 1 is relatively small. Fortunately, the skylight term can be small compared to the direct irradiance term, and has a small detrimental effect upon ratio values on high sun angle Landsat data over topographically rough terrain (Kowalik, (1981).

Derivation of Covariance Matrix Method (CMM)

The CMM method presented here cannot provide a pixel-specific atmospheric correction, but it can provide a correction which is locally specific in an average sense to pixels in a given part of an image. The data requirements for the CMM method will now be described, and the derivation of estimates of atmospheric path-radiances, d_j, will be detailed.

If one has a homogeneous test area for which the

† Raw data, i.e., data which has not been corrected for the atmospheric path-radiance or skylight effects.

basic surface reflectance, P_{ij}, is approximately constant over all pixels for each spectral band, then $P_{ij} \doteq P_j$ and $x_{ij} \doteq x_j$ in Equation 2. Therefore, for such a test area, a reduced model is

$$y_{ij} = c_i x_j + d_j + e_{ij}. \tag{3}$$

The unexplained residual variability term, e_{ij}, must now encompass greater model errors because of a more parsimonious model, but it is still taken to be small relative to the variability explained by the model. That is, any and all deviations from the simplified form of Equation 1 which is given in Equation 3 are lumped together into a composite residual term—including effects due to the indirect irradiance, deviations from homogeneity of the "homogeneous" area, and deviations from Lambertianess of the pixels within the "homogeneous" area. The approximations involved and the composite nature of the estimates should be understood.

Suppose, in addition, that the test area has sufficient topographic relief so that the sun angle factor c_i is not the same for all pixels. Then the first two terms of Equation 3 do not collapse together, and it is possible to estimate the atmospheric path-radiances, d_j, for each spectral band, j, up to a linear function. Further, if d_7, say, is exogenously specified, then absolute estimates for the path-radiances in the other spectral bands can be calculated.

The model (Equation 3) as stated is under-specified because there are always alternative parameter values c_i', x_j', d_j' for which $c_i x_j + d_j = c_i' x_j' + d_j'$ for all i and j. However, as will be shown, specifying a value *a priori* for the path radiance on one spectral band will be sufficient to provide unique estimates for the path radiances in all other bands.

The required estimates are obtained by the method of least squares. Specifically we wish to choose parameter values which minimize

$$\sum_i \sum_j (y_{ij} - c_i x_j - d_j)^2. \tag{4}$$

Differentiating with respect to each of the unknowns leads to a set of simultaneous equations when the derivatives are set to zero; i.e.,

$$\frac{\partial}{\partial c_i} : \sum_j y_{ij} x_j - c_i \sum_j x_j^2 - \sum_j x_j d_j = 0 \tag{5}$$

$$\frac{\partial}{\partial x_j} : \sum_i y_{ij} c_i - x_j \sum_i c_i^2 - d_j \sum_i c_i = 0 \tag{6}$$

$$\frac{\partial}{\partial d_j} : \sum_i y_{ij} - x_j \sum_i c_i - n d_j = 0, \tag{7}$$

where n is the number of pixels. Combining Equations 6 and 7 to eliminate d_j gives

$$x_j = \sum_i y_{ij}(c_i - \bar{c}) / \sum_i (c_i - \bar{c})^2 \tag{8}$$

where $\bar{c}$ is the average of the c_i Solving Equation 7 for d_j gives

$$d_j = \bar{y}_j - \bar{c} x_j. \tag{9}$$

Now substitute the above for d_j in Equation 5 and solve for $(c_i - \bar{c})$, i.e.,

$$(c_i - \bar{c}) = \sum_j x_j (y_{ij} - \bar{y}_j) / \sum_j x_j^2, \tag{10}$$

where $\bar{y}_j$ is the observable average over all pixels of the measured radiance in band j. Substituting Equation 10 into Equation 8 gives

$$x_j = q \cdot \sum_k x_k S_{jk} \tag{11}$$

where

$$q = \sum_k x_k^2 / \sum_j \sum_k x_j x_k S_{jk}$$

and

$$S_{jk} = \frac{1}{n} \sum_i (y_{ij} - \bar{y}_j)(y_{ik} - \bar{y}_k).$$

S_{jk} is the calculated covariance between the measured radiance in bands j and k, from which the name of our method is derived. Since the S_{jk} involve only the observed data, i.e., the y's, they may be calculated directly. Equation 11 may now be used to solve for the unknown x_j's iteratively in terms of the measured radiances. The x_j's for all bands are then estimated simultaneously.

It is useful to recast Equation 11 in matrix form; i.e.,

$$\mathbf{x} = q\mathbf{S}\mathbf{x}, \tag{12}$$

which indicates that the parameter vector $\mathbf{x}$ is an eigenvector of the covariance matrix $\mathbf{S}$.

The vector $\mathbf{x}$ is taken to have all positive components in the construction of the model since x_j is the direct solar irradiance for band j. Now, no two eigenvectors can have all positive components because they are orthogonal. Therefore, there will be a unique all-positive eigen vector of S, up to a constant multiplier. This all-positive eigenvector will be the required solution for Equation 11 or Equations 11 or 12.

If one of the path-radiance values, d_j, is specified *a priori*, then the others can now be estimated. For example, suppose we take $d_7 = 0$, then Equation 9 gives $\bar{c} = \bar{y}_7 / x_7$, and

$$d_j = \bar{y}_j - (\bar{y}_7 / x_7) x_j. \tag{13}$$

Since the x_j/x_7 do not depend on the unknown constant multiplier, they can be derived absolutely from the proportional solution obtained to Equations 11 or 12.

To test the fit of the underlying model to the data requires auxiliary data, but comparisons with path-radiances calculated by other methods in ratio applications are useful. Computing the required eigenvector of the covariance matrix **S** could be tried by the iterative method suggested by Equation 8 or by some other method, but care is needed to check convergence and senstivity to starting values. For the data we have so far analyzed this has not been a problem. The method will not work, for example, if all spectral bands are uncorrelated.

Regression and Histogram Minimum Methods

The Regression Method for estimating the d_j noise term (Chavez, 1975) uses a regression of the brightness data in each band against Band 7. The Y-intercept of the regression equations provide an estimate of the d_j noise in the other bands because the information content of the Landsat bands tends to be highly correlated. The Regression Method provides composite estimates of the additive terms just as the CMM method does, and estimates from each method are commonly similar. The CMM method applied to two spectral bands is equivalent to the Regression Method.

The most common technique for estimating the d_j noise term, the Histogram Minimum Method (HMM) (Chavez, 1975; Taranik, 1977), assumes that a pixel of very low reflectant (basalt flows, clear water) or low irradiance (shadowed due to topography or clouds) occurs somewhere in the entire Landsat image. For such a pixel, the d_j information term is assumed to be negligible and the satellite measurement is therefore an estimate of d_j noise. In practice a suitable pixel may not be present, especially in highly reflectant desert terrain on imagery recorded under sun elevation angles higher than the angle of repose (about 33 degrees).

Estimates from the CMM, Regression, and HMM Techniques

Landsat data from rectangular blocks of pixels (N = 100 to 420) were taken from five different homogeneous-appearing areas in western Nevada on a Landsat-1 image from 16 September 1972 (sun elevation = 46°, Scene ID = 1055-18053). The five areas are from the Sand Mtn. dune, Desert Mtns., Sand Springs Range, Cocoon Mtns., and Stillwater Range (Figure 1). The specific blocks of pixels within these areas were chosen visually

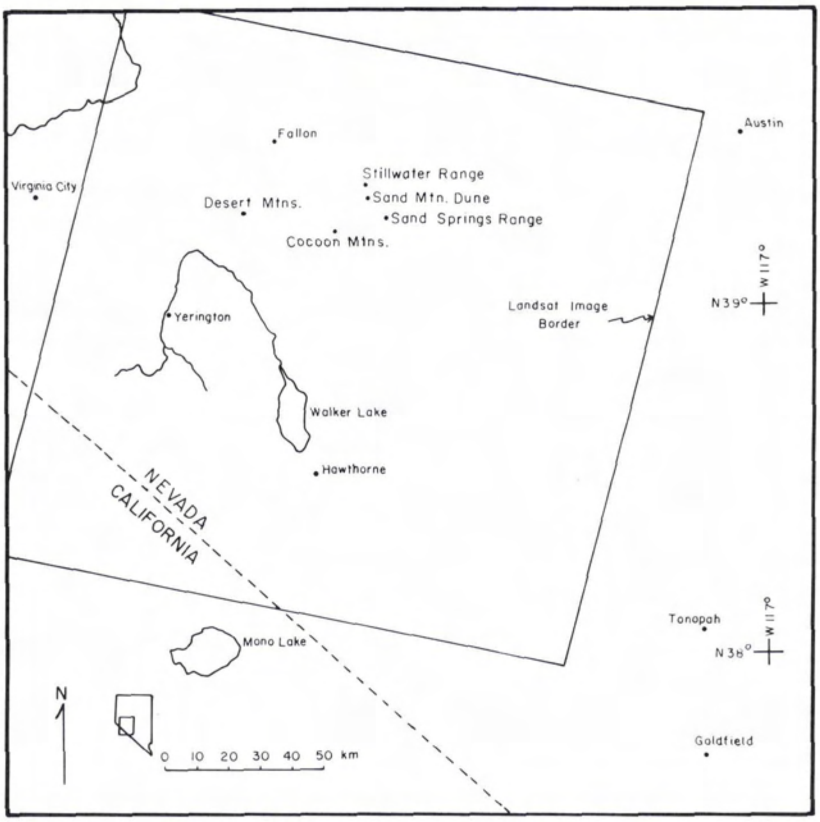

FIG. 1. Location map of the western Nevada area studied showing the Landsat image frame border of the Walker Lake scene. The small map in the legend shows the area in Nevada covered by Figure 1.

from a color television display of a false color representation of the Landsat data.

The Sand Mtn. dune is composed of aeolian grains, predominantly quartz with abundant volcanic lithic fragments. Dark-colored Tertiary andesite and basalt units outcrop in the Desert Mtns., Cocoon Mtns., and Stillwater Range in the areas from which the Landsat data were extracted. Cretaceous granitic rocks outcrop in the Sand Springs Range sample area. All of these areas except the Sand Mtn. dune have a sparse cover of low bushes (mean about 14 percent cover), predominantly of the *Atriplex confertifolia* vegetation province (Daubenmire, 1978). The Sand Mtn. dune has no vegetation cover where sampled.

d_j noise estimates for the five data blocks were obtained by both the CMM and Regression algorithms. The path-radiance in Band 7 was assumed to be 0.0 DN in each case. Histogram minimum values were obtained from the immediate surroundings (within 15 km) and from the whole Landsat scene. The Histogram Minimum Method (HMM) was not intended by Chavez (1975) to operate locally. We apply it to local areas here to demonstrate that estimates from the CMM and Regression Methods are noticeably different from the local HMM estimates. The whole scene HMM estimates are from Walker Lake, a large, 200 ft deep terminal pluvial lake (Koch *et al.*, 1979) which lies near the center of the Landsat frame (Figure 1). These four sets estimates are given in Table 1.

The noise estimates obtained by the CMM and Regression Methods are similar. Except for the Sand Mtn. dune estimate, they are also smaller than the whole scene HMM estimates. The local HMM estimates are largest.

The CMM and Regression estimates describe the local composite additive effect more accurately than the HMM estimates. This can be demonstrated by study of the effect of each correction upon ratio values.

Figure 2 shows Landsat-1 5/4 ratio values from ten pixels along a scan line in the hilly terrain of the southern Stillwater Range on 16 September 1972. The area traversed by the scan line is fairly homogeneous in reflectance and was not within the same area sampled to obtain the CMM and Regression estimates. If the additive d_j noise effect is properly removed, the ratio values should be quite similar all along the traverse because the surface orientation effect will be subdued.

The raw ratio values from well-illuminated southeast facing slopes are larger than those from the northwest facing slopes along the traverse. This effect is a predictable result of the additive d_j noise effect (Kowalik, 1981). The two sets of HMM estimates each cause the opposite effect—the poorly-illuminated northwest-facing pixels are assigned abnormally large ratio values because those estimates were too large. d_j noise estimates which are too large can yield falsely large ratio values over poorly-illuminated sites, as this exam-

TABLE 1. ESTIMATES OF d_j FROM LANDSAT-1 DATA (16 SEP 72, SUN ELEVATION = 46°) FOR FIVE DIFFERENT AREAS IN WESTERN NEVADA. THE CMM, REGRESSION, LOCAL HISTOGRAM AND SCENE HISTOGRAM ESTIMATES ARE PRESENTED. THE SAME DATA SETS WERE USED FOR THE CMM AND REGRESSION ALGORITHMS FOR EACH AREA. VALUES ARE IN DIGITAL NUMBERS (DN), 0-127 SCALE

		CMM	Regression	Hist Min Local	Hist Min Scene
Desert Mtns.	C4	12.7	13.8	23	17
(N = 400 pixels)	C5	5.2	6.7	19	7
	C6	3.3	4.7	15	3
	C7	0.0	0.0	12	0
Cocoon Mtns.	C4	12.5	13.6	21	17
(N = 400 pixels)	C5	4.8	6.3	17	7
	C6	3.1	4.5	14	3
	C7	0.0	0.0	12	0
Stillwater Range	C4	13.5	14.6	21	17
(N = 100 pixels)	C5	5.5	7.1	17	7
	C6	3.5	4.9	14	3
	C7	0.0	0.0	12	0
Sand Mtn.	C4	21.5	22.3	21	17
(N = 144 pixels)	C5	10.2	11.5	17	7
	C6	8.3	9.2	14	3
	C7	0.0	0.0	12	0
Sand Springs Range	C4	12.7	15.0	21	17
(N = 200 pixels)	C5	5.3	7.5	17	7
	C6	3.1	4.6	14	3
	C7	0.0	0.0	12	0

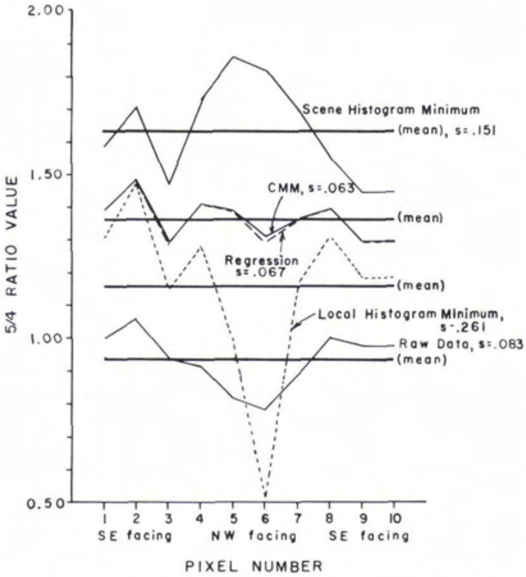

FIG. 2. The 5/4 ratio values from a traverse of hilly terrain in the Stillwater Range, Nevada. The ratio values are shown in raw mode and after corrections four different path radiance estimation methods were applied.

ple shows. This problem partly explains why some researchers have preferred to use ratio data in mineral exploration which has not been corrected for the d_j noise effect (e.g., Rowan *et al.*, 1974; Krohn *et al.*, 1978). Abnormally large ratio values are easily generated locally by a correction which is slightly too large.

When the CMM estimates from the Stillwater Range are applied, there is no longer a preference for well- or poorly-illuminated pixels to be high or low in ratio values in agreement with the homogeneity of reflectance along the traverse. It is not known how much of the variability remaining in the ratios corrected by the CMM estimates is due to slight spectral inhomogeneity along the pixels or to noise in the Landsat data and to an imperfect correction.

The Regression estimates provide corrected ratio values which are similar to those from the CMM method, but with a slightly larger standard deviation (Figure 2).

This example of the usefulness of estimates from the CMM and Regression methods is not restricted to these ten pixels and is repeated consistently in other areas.

Note that the absolute value of the ratios in Figure 2 are directly related to the d_j noise estimates which were subtracted. In all cases, a larger d_j estimate was subtracted from the denominator than from the numerator. Therefore, the ratios are larger after a correction.

The CMM and Regression estimates of d_j for the Sand Mtn. dune are much larger than the estimates from the other four areas. This effect has been observed on other Landsat data sets from the Sand Mtn. area, and similarly large estimates have also been obtained from Landsat data over the Kelso dunes in the Mojave Desert of southern California. We attribute the larger estimates from the Sand Mtn. dune and Kelso dune areas to a much larger indirect irradiance term, and to a larger local path-radiance term (see Otterman, 1978) for these unvegetated and highly reflectant areas. The adjacent volcanic and granitic ranges are somewhat vegetated and have a less reflectant rock/soil cover. The local path-radiance and indirect illumination terms should therefore be smaller for those areas.

We conclude that the Histogram Minimum Method can provide d_j noise estimates which are too large or too small and which are not locally applicable for proper removal of the topographic effect by ratioing. The CMM and Regression estimates take the local conditions into account and can provide appropriate estimates of the additive terms.

The CMM and Regression Methods thus have the potential for providing spatially varying estimates of the path-radiance. It should be realized that because part of the estimate is due to the indirect irradiance *signal*, subtraction of different estimates from different parts of a scene may result in lower classification accuracy when numerical classification schemes based on the band variables are used. On the other hand, when ratio variables are used, subtraction of spatially varying estimates should subdue the variability of the ratio values due to topographic effects better than subtraction of a constant value verywhere in the scene.

To test the CMM and Regression methods in non-desert terrain, we applied those two methods to blocks of Landsat data from hardwood forested hills on the Pocono Plateau in eastern Pennsylvania and to the mountainous rainforests of New Guinea. Those d_j noise estimates and the HMM values are given in Table 2. The path-radiance in Band 7 was assumed to be 5 DN (0-127 scale) for these heavily vegetated terrains. The value of 5 DN was estimated from a table of modeled path-radiance values for Landsat imaging under various atmospheric, illumination, and background reflectance conditions in Malila *et al.* (1976). The CMM and Regression estimates are very similar within each data set, and they correspond in size to the respective HMM estimates.

The CMM and Regression methods cannot be applied indiscriminantly to any block of Landsat data. The methods assume that the variability in raw DN's of the test area is due to the surface orientation effect, not to variation of reflectance within the data block. The algorithms will always

TABLE 2. ESTIMATE OF d_j NOISE FROM EASTERN PENNSYLVANIA AND NEW GUINEA (DN UNITS)

		CMM	Regression	Hist Min Local	Hist Min Scene
Eastern Pennsylvania	C4	25.4	25.6	25	21
(ID = 1403-15120)	C5	15.3	15.6	14	9
Sun elevation = 49°	C6	14.0	15.1	12	11
	C7	5.0	5.0	4	4
New Guinea	C4	16.5	16.7	16	12
(ID = 1028-00140)	C5	9.6	9.7	8	6
Sun elevation = 49°	C6	7.2	8.5	10	6
	C7	5.0	5.0	6	4

calculate correction values which tend to subdue the variability of the ratios in the input data block. If reflectance inhomogeneity and/or no topography are present in an input data block, the calculated estimates will not be appropriate estimates of the d_j noise term.

An important caveat to the assumption of terrain reflectance homogeneity of the test area is that the reflectance be homogeneous as the satellite sees it. This constraint is far less stringent than if the surface had to be homogeneous upon the ground. The spectral and spatial resolution of Landsat are such that many areas in our experience appear "homogeneous" in reflectance, especially at low-sun elevation angles because shadowing due to surface roughness elements and a lower signal-to-noise ratio tend to homogenize the surface spectral character. At very low sun angles (~25 degrees), however, topographic shadowing may be present, and not enough signal is available from the totally shadowed pixels to yield "homogeneous" areas. At low sun angle, the HMM method might provide useful estimates of the path-radiance.

CONCLUSIONS

The CMM and Regression Methods can provide similar and appropriate estimates of corrections for the additive terms to enable removal of topographic effects by ratio variables. These two methods have the potential for providing spatially varying estimates of the path-radiance from the remotely-sensed digital data. However, because part of the estimate obtained from these methods is due to the indirect irradiance signal, the estimates are more directly related to the ground reflectance than are the actual atmospheric path-radiance values.

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(Received 5 August 1980, revised and accepted 29 March 1981)

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