J. F. POTTER Lockheed Engineering and Management Services Company, Inc. Las Vegas, NV 89109

The Channel Correlation Method for Estimating Aerosol Levels from Multispectral Scanner Data*

The errors in this method are small enough to make it useful for such applications as monitoring smoke plumes.

INTRODUCTION

IN THIS PAPER we discuss the estimation of atmospheric aerosol levels from airborne multispectral scanners. It is assumed that the aerosols are uniform in composition and size distribution. The "aerosol level" can be defined in terms of any measurable quantity that varies linearly with the total number of particles in a column below the aircraft. This would include the total mass loading and the in what follows, could in most cases be replaced with "aerosol optical depth."

It is of interest to be able to determine aerosol levels in the atmosphere from multispectral scanner (MSS) data for two reasons. First, aerosols can have a significant effect on the MSS data and, if one is interested primarily in targets on the ground, it is desirable to remove this effect. Much effort has been expended in developing algorithms to do this (Minter, 1978; Lambeck and Potter, 1978). Some of

ABSTRACT: A method for estimating aerosol levels from multispectral scanner data is investigated. It is based on the idea that, when certain channels are regressed against certain other channels, the slope and intercept of the regression line depends on the aerosol level. Further, it is assumed that the distance between such regression lines is proportional to differences in the aerosol level and that the deviations of the data points from the fitted lines are proportional to the inherent errors in estimating aerosol levels for individual pixels. Estimates of the accuracy attainable were made for data obtained near Los Angeles with a Daedalus multispectral scanner. It is estimated that the average error in optical depth, when applying the method to individual pixels that are members of the training data, is 0.09. When the estimaates are for cells of size 10 pixels by 10 pixels, the corresponding error is 0.05. When the cells are not members of the training data, the error is 0.06. These errors are small enough to make the method useful for certain applications.

total optical depth. Because the optical depth is usually the easiest way to measure the aerosol level, the term "aerosol level," which is used extensively

* Although the research reported upon in this article has been funded wholly or in part by the United States Environmental Protection Agency through contract 68-03-3049 to Lockheed Engineering and Management Services Company, Inc., it has not been subjected to Agency Review and, therefore, does not necessarily reflect the views of the Agency and no official endorsement should be inferred.

PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING, Vol. 50, No. 1, January 1984, pp. 43-52. these algorithms depend on an explicit knowledge of the aerosol level. Second, there are many applications, such as pollution studies and visibility monitoring, in which it is desirable to monitor aerosol levels remotely.

There are, of course, instruments such as LIDAR systems and solar radiometers which are better suited to measuring aerosol levels than multispectral scanners, but these instruments can give only limited coverage (at least until airborne scanning LIDAR systems are readily available). The MSS gives wide coverage over extended areas and therefore would be most useful if suitable algorithms could be developed. Several approaches to estimating aerosol levels from MSS data or photography have been tried. These include:

- Methods based on knowledge (or assumptions) about the reflectance of certain targets in the scene, especially low reflectance targets whose apparent brightness is strongly dependent on the aerosol level (Potter, 1977; Potter and Mendlowitz, 1975; Potter, 1984).
- Methods based on the selection of linear combinations of channels which are particularly sensitive to aerosols (Lambeck, 1977; Lambeck and Potter, 1978).
- The Piech Walker method. This method (which is patented by its authors) involves the study of targets which are partly in direct sunlight and partly in the shade (Piech and Walker, 1971, 1972).
- Methods which depend on correlations between channels (Switzer *et al.*, 1981; Potter and Mendlowitz, 1975).

In most of these methods, the average aerosol level over a segment consisting of many pixels is estimated. In this paper we investigate the possibility of using correlations between channels to estimate the aerosol level for each pixel or for small groups of pixels which we shall call "cells." Our objective is to estimate the accuracy with which this can be done and to determine the best combination of channels for doing it.

METHOD

The channel correlation method is based on the findings that (1) the data from certain MSS channels are highly correlated with the data from certain other channels and (2) aerosols have a different effect on different MSS channels. Generally, the lower the channel (i.e., the shorter the wavelength) the more sensitive are the data to changes in the aerosol level. This is because aerosols usually scatter more light at shorter wavelengths.

When one regresses the data from a given channel against the data from some higher channel, one typically obtains the results shown schematically in Figure 1. Here it is assumed that the data are for some relatively large segment. In this study we shall be dealing with segments of 7200 pixels. Lines 1 and 2 represent regressions for low and high aerosol levels, respectively.

In order to understand Figure 1, we first show that if there is a linear relationship between the data for two channels the addition of a uniform aerosol layer across the segment will result in a different but still linear relationship between these channels. If the atmosphere is horizontally homogeneous, then for any channel of MSS data, say channel *i*, there is a linear relationship between the MSS data, X_i , and the reflectance, R_i , of the pixels. This is well known and is described in detail by Potter (1977).



FIG. 1. Schematic representation of regression lines for high and low aerosol levels.

Let this relationship be described by

$$X_i = A_i R_i + B_i$$

where A_i and B_i are constants depending on the incident solar radiation, the aerosol level, the background reflectance of the scene, and the characteristics of the sensor. For some other channel, j, we have

$$X_i = A_i R_i + B_j.$$

If the R_i and R_j are linearly related, then the X_i and X_j also will be linearly related. If the optical depth is changed (uniformly) over the segment, then these same relations will hold except that the values of the constants A_i , A_j , B_i , and B_j will change. Thus, there will still be a linear relationship between X_i and X_i but a different one.

For dark pixels, line 2 in Figure 1 is above line 1 because the effect of increasing the aerosol level is to increase the brightness of dark pixels and the effect is greater in the lower channel than in the higher channel. For bright pixels line 2 is below line 1 because the effect of increasing the aerosol level is to decrease the brightness of bright pixels and, again, the effect is larger for the lower channel. The point where the lines cross is a function of the aerosol levels and the light scattering characteristics of the aerosols. In many cases it is outside the range of the data.

Studies on Landsat data have shown that there often is, in fact, a correlation between the slopes and intercepts of such lines and measured haze levels (Potter and Mendlowitz, 1975).

Regression lines such as those depicted in Figure 1 are computed for a whole segment of data, and the corresponding aerosol level is an average over the segment. If one had a family of such lines corresponding to different (uniform) aerosol levels, one

could presumably use them to determine aerosol levels for that segment. However, in doing this one would have to be careful to allow for variations in sun angle and sensor calibration that can change these lines.

The question we wish to investigate is the following: Assuming one has such a family of lines for a segment, each corresponding to some known, uniform aerosol level, how accurately could one use them to estimate the aerosol level for individual pixels in the segment or for small cells of pixels?

The question of how to obtain such a family of lines will not be dealt with extensively here. Obviously, one would wish to obtain data on a very clear day to calculate the line for a minimal aerosol level. Associated ground measurements of the aerosol level would be very desirable. The lines for higher aerosol levels could be obtained from theory, using an atmospheric model, or from data taken at higher aerosol levels. These approaches could be combined, with one or two sets of observations at higher aerosol levels being used to "calibrate" the theoretical models. Also, if it is found that the regression lines for different segments on clear days are nearly identical, then lines obtained for one segment could be used for others. This was done in the current study.

The data used in this study were obtained using the EPA Daedalus DS-1260 scanner on a flight at an altitude of 20,000 feet above mean sea level in the Los Angeles area on 9 October 1980. Characteristics of the scanner are described in Appendix A. On one of the flight lines near Baldwin Park, two areas were found that appeared suitable for this study. One area had a relatively thick and uniform aerosol layer over it. This was obvious from the imagery. The other area, separated from the first by a range of mountains, was relatively clear. Three segments, labeled A, C, and D, were selected in the thick aerosol area (called the hazy area in what follows) and two segments labeled F and G were selected in the clear area. Each segment was 120 pixels long (i.e., in the direction of the flight line) and 60 pixels wide. They were all directly beneath the aircraft so that the look angle was almost the same for all pixels. This was desirable because the effect of an aerosol depends on the look angle. Furthermore, the segments were chosen to have similar ground cover, which was that of a well-developed urban area. For this reason other segments, which contained large parks and gravel pits, were not used.

Pairs of segments were selected, each pair consisting of one hazy segment and one clear segment. For each pair a number of pairs of channels were selected. For a given pair of segments and a given pair of channels, two regression lines were computed, one for each segment. It was assumed that, for an aerosol level of zero, both segments of the pair would produce the same regression line. This is equivalent to assuming that the regression line, $L_{\rm C}$, obtained from the clear segment also applies to the hazy segment and that the regression line, L_{H} , obtained from the hazy segment also applies to the clear segment. Further, it was assumed that the aerosol level of an individual pixel from either segment could be estimated by linear interpolation of its position in the scatter plot (Figure 1) relative to the two regression lines; i.e., if the coordinates of the pixel in the scatter plot are (X_i, Y_{ij}) , where Y_{ij} is the Y value for the j^{th} pixel with the X value X_i , then an estimate of its aerosol level is given by

where

$$Z_{ii}^{H} = (Y_{ii} - Y_{iH})/(Y_{iH} - Y_{iC}).$$

 $\tau_{ii} = \tau_H + Z_{ii}^H (\tau_H - \tau_C)$

Here Y_{iH} and Y_{iC} are the ordinates of the lines L_H and L_C at $X = X_i$, and τ_H and τ_C are the aerosol levels for the hazy and clear segments, respectively. An equivalent expression for τ_{ii} is given by

$$\tau_{ij} = \tau_C + Z^C_{ij} (\tau_H - \tau_C) \tag{1B}$$

where

$$Z_{ii}^{C} = (Y_{ij} - Y_{iC})/(Y_{iH} - Y_{iC})$$

It should be noted that use of Equations 1A and 1B is a rather simplified method of estimating τ_{ii} . The actual paths followed by pixels in a plot like Figure 1 when the haze level is changed are quite complex. This question is currently under investigation. However, use of Equations 1A and 1B should provide results sufficiently accurate for the purposes of this paper.

Consider the hazy segment. The average of the estimated haze levels for the pixels in the segment is given by

$$\overline{\tau}_{H} = \frac{1}{N} \sum_{ij} \tau_{ij} \qquad (2)$$

where *N* is the total number of pixels in the segment and the sum is over all of these pixels. Using Equation 1A, we obtain

$$\overline{\tau_H} = \tau_H + \overline{Z^H} \left(\tau_H - \tau_C \right) \tag{3}$$

where

$$\overline{Z^H} = \frac{1}{N} \sum_{ij} Z^H_{ij}.$$
 (4)

One might think that $\overline{\tau}_H$ should be equal to τ_H . In general, this is not true. However, we shall see that in many cases the difference is extremely small.

The standard deviation of the estimated aerosol levels τ_{ii} about $\overline{\tau}_H$ is given by

$$s_\tau \, = \, \left[\frac{1}{N \, - \, 1} \sum_{ij} \, (\tau_{ij} \, - \, \overline{\tau}_H)^2 \, \right]^{1_2}.$$

Using Equation 1A, one finds

$$s_{\tau} = s_z \left(\tau_H - \tau_C \right) \tag{5}$$

where

(1A)

$$s_{z} = \left[\frac{1}{N-1}\sum_{ij} (Z^{H}_{ij} - \overline{Z^{H}})^{2}\right]^{1/2}.$$
 (6)

In computing both $\overline{Z^{H}}$ and s_z , pixels were eliminated if they corresponded to a value of X such that $Y_{iH} - Y_{iC}$ was less than a given threshold value. This is because Equation 1A gives anomalously large values for τ_{ij} when $Y_{iH} - Y_{iC}$ is too small. In what follows it will be said that such pixels have been "thresholded."

Similar equations can be derived for the clear segment.

If one assumes a uniform aerosol level for each segment, then the means and standard deviations given by Equations 3 and 5 provide a measure of the accuracy in estimating the aerosol levels for individual pixels when the technique is applied to the training data. The calculated standard deviation, s_z , would in this case be due to the imperfect correlation between the pixel reflectances. However, because we can be sure that the aerosol levels in the segments were not perfectly uniform, a contribution to s_z surely came from variation in the aerosol level across the segments. In this sense s_z is an upper limit on the inherent error in this method.

RESULTS FOR SINGLE PIXELS

Table 1 shows the results for segments A and G for all possible pairs of channels. The threshold level was 1.0 counts. Because the values of τ_H and τ_C were not precisely known, the table contains values of \overline{Z} and s_z rather than $\overline{\tau}$ and s_{τ} . From these one can immediately obtain values for $\overline{\tau}$ and s_{τ} for any estimate of τ_H and τ_C by using Equations 3 and 5. Also given in Table 1 are the correlation coefficient, R, for the regression and the number, N_T , of pixels thresholded in each case.

Each line in Table 1 corresponds to a different combination of channels. The channels used for the abscissa and ordinate are given in the first and second columns, respectively. Columns 3 through 6 give the results for segment A; columns 7 through 10 give the results for segment G. For both segments the number of thresholded pixels is quite small compared to the total number of pixels in each segment (7200). Also, for both segments the bias term \overline{Z} is negligible for almost all of the channel combinations, and where it is not negligible the standard deviation is also very large.

The two best channel combinations are 6-2 and 6-3. Both have relatively small values of \overline{Z} and s_z . Notice that the results for channel combinations involving channel 1 are poorer than those involving channels 2 and 3. This is unfortunate because channel 1 is the most sensitive to haze effects and, therefore, is potentially the most useful channel. It is not known whether this problem is due to a genuine lack of correlation between channel 1 and the other channels or if there is some problem with channel 1 in the MSS. There is some evidence to support the latter possibility. In particular, there is in much of the channel 1 data an apparent nonlinearity near 130 counts, which appears as a bright stripe near the edge of the image.

The correlation decreases dramatically when the channel difference is 3 or more and one of the channels is 8, 9, or 10. It is interesting to note that in some of these cases, such as 9-2, one still achieves a relatively small value for the standard deviation even though the correlation is essentially zero. In this case all the information is contained in Channel 2. The variation in the data for Channel 2, caused by the difference in aerosol level between the segments, was significantly larger than the variance in the data due to the different reflectances of the pixels. Thus, the brightness of Channel 2 alone is in this case a fairly good indicator of aerosol level. Obviously, results obtained using these channelsor just Channel 2 alone-will be better for segments having small variances in the reflectances. The ideal case would be for a uniform target where all the pixels had the same (preferably low) reflectance. On the other hand, for pairs of channels where there is a high correlation between the channels, it is not a disadvantage to have a large variance in pixel reflectance. Indeed, the method works better with a large variance. Thus, the channel pairs that will give the best results are determined by the correlation between the reflectances and the variance in the reflectances. A high correlation will not necessarily give the best results. However, in this paper we are mainly concerned with studying the high correlation case, and for the segments used in this study the best results were obtained for pairs of channels with relatively high correlations.

The results for segments D and F are shown in Table 2. Here no pixels were thresholded except for channel combination 3-2 where all of the pixels were thresholded and channel combination 4-2 where 289 pixels were thresholded in segment D and 36 in segment F. In all cases \overline{Z} was less than 0.005. Otherwise, the pattern of the results is similar to those obtained for segments A and G. Note, however, that here the correlations are generally higher. One might expect that this would lead to smaller standard deviations, but it did not. As before, the best channel combinations are 6-2 and 6-3.

The quantity that one would really like to have is not s_z but s_τ . In order to estimate s_τ , an estimate of $\tau_H - \tau_C$ is required. Unfortunately, no ground measurements of optical depth were available for these data. It should be noted that, even if such measurements were available, a large number of them distributed over the area in question would be required if one were to have much confidence in the results. Qualitatively, it was obvious from the imagery that there was a relatively thick and uniform haze layer over the hazy segments and a relatively thin and uniform layer over the clear segments.

Channel			Seg	ment A			Se	gment G	
х	Y	N_T	R	Z	s_z	N _T	R	Z	s _z
2	1	2	0.66	0.00	0.92	13	0.84	0.00	0.76
3	2	102	0.93	-0.01	0.65	70	0.97	0.00	0.54
4	3	3	0.97	0.00	0.61	29	0.99	0.00	0.62
5	4	0	0.98	0.00	0.37	0	0.99	0.00	0.45
6	5	3	0.99	0.00	0.45	25	0.99	-0.01	0.51
7	6	221	0.95	0.00	2.30	147	0.98	-0.01	2.02
8	7	234	0.42	0.13	2.03	129	0.62	-0.02	2.44
9	8	0	0.98	0.00	0.63	0	0.97	0.00	0.93
10	9	0	0.99	0.00	1.20	0	0.99	0.00	1.64
3	1	0	0.67	0.00	0.64	0	0.84	0.00	0.58
4	2	2	0.91	0.00	0.43	16	0.95	0.00	0.46
5	3	0	0.96	0.00	0.31	0	0.97	0.00	0.42
6	4	0	0.96	0.00	0.34	2	0.97	0.00	0.44
7	5	0	0.95	0.00	0.62	3	0.97	0.01	0.77
8	6	706	0.14	0.20	1.94	68	0.47	-0.02	2.15
9	7	67	0.28	0.10	1.39	31	0.46	-0.02	2.51
10	8	0	0.97	0.00	0.59	0	0.95	0.00	0.89
4	1	0	0.67	0.00	0.51	0	0.83	0.00	0.50
5	2	0	0.90	0.00	0.31	0	0.93	0.00	0.39
6	3	0	0.94	0.00	0.27	0	0.95	0.00	0.40
7	4	0	0.93	0.00	0.37	0	0.94	0.00	0.52
8	5	69	0.21	0.16	1.24	27	0.48	-0.03	1.93
9	6	65	0.00	0.10	1.30	23	0.30	0.00	2.20
10	7	70	0.27	0.11	1.35	20	0.44	0.01	2.70
5	1	0	0.65	0.00	0.42	0	0.81	0.00	0.43
6	2	0	0.87	0.00	0.28	0	0.91	0.00	0.38
7	3	0	0.86	0.00	0.36	0	0.90	0.00	0.49
8	4	115	0.24	0.00	0.74	31	0.46	-0.02	1.20
9	5	52	0.07	-0.02	1.02	20	0.30	0.02	1.81
10	6	80	0.01	0.10	1.17	19	0.27	0.01	2.35
6	1	0	0.62	0.00	0.37	0	0.78	0.00	0.40
7	2	0	0.80	0.00	0.30	0	0.85	0.00	0.43
8	3	4	0.08	-0.03	0.74	7	0.36	-0.01	1.24
9	4	0	0.09	-0.07	0.54	0	0.28	0.00	0.94
10	5	16	0.05	-0.03	0.82	10	0.27	0.00	1.46
7	1	0	0.59	0.00	0.36	0	0.73	0.01	0.42
8	2	0	0.10	-0.01	0.42	3	0.34	0.00	0.69
9	3	0	-0.07	0.00	0.42	0	0.17	0.00	0.71
10	4	0	0.07	-0.01	0.50	0	0.24	0.00	0.82
8	1	0	0.14	0.00	0.36	0	0.29	0.00	0.49
9	2	0	-0.03	0.00	0.33	0	0.15	0.00	0.55
10	3	0	-0.09	0.00	0.40	0	0.12	0.00	0.66
9	1	0	0.05	0.00	0.33	0	0.13	0.00	0.46
10	2	0	-0.05	0.00	0.32	0	0.10	0.00	0.53
10	1	0	0.03	0.00	0.32	0	0.09	0.00	0.45

 $T_{ABLE} \ 1. \quad SINGLE \ PIXEL \ Results \ for \ Segments \ A \ and \ G$

A rough quantitative estimate of τ_H and τ_C was obtained from a somewhat different analysis of these data. In this case the aerosol level was measured by the optical depth. The analysis was based on an algorithm called ATCOR II, designed to make atmospheric corrections to MSS data (Potter, 1984). An earlier version of this algorithm, ATCOR, was used to make atmospheric corrections to Landsat data (Potter, 1977). Both of these algorithms are based on a particular atmospheric model described in Potter (1977). The inputs to the ATCOR II algorithm are the mean value of the data for a given segment in a given channel and the data value for the darkest pixel in that segment. The program then determines the relationship between the following three parameters: (1) the average reflectance, \overline{R} , of the pixels in the segment, (2) the reflectance R of the darkest pixel, and (3) the optical depth, τ . For each possible value of \overline{R} , it determines the corresponding values of R and τ which are consistent with the two inputs to the program. Also, it determines minimum and maximum values of \overline{R} consistent with these inputs.

For a given channel, the procedure for estimating the optical depths was as follows. It was assumed

TABLE 2. SINGLE PIXEL RESULTS FOR SEGMENTS D AND F

Chan	inel	Segme	nt D	Segme	nent F	
х	Y	R	s _z	R	s _z	
2	1	0.80	1.41	0.78	1.43	
3	2	*		*		
4	3	0.98	1.04	0.98	1.05	
5	4	0.99	0.59	0.99	0.68	
6	5	0.99	0.61	0.99	0.67	
7	6	0.97	1.62	0.97	1.55	
8	7	0.56	1.51	0.56	1.42	
9	8	0.98	0.78	0.98	0.77	
10	9	0.99	1.07	0.99	1.29	
3	1	0.81	1.09	0.79	1.05	
4	2	0.87*	1.24	0.95*	0.65	
5	3	0.97	0.58	0.96	0.62	
6	4	0.73	1.00	0.70	1.05	
7	5	0.96	0.77	0.95	0.77	
8	6	0.36	1.26	0.37	1.18	
9	7	0.40	1.31	0.42	1.22	
10	8	0.97	0.70	0.95	0.77	
4	1	0.80	0.89	0.78	0.87	
5	2	0.93	0.58	0.93	0.57	
6	3	0.94	0.50	0.93	0.52	
7	4	0.93	0.57	0.92	0.59	
8	5	0.38	0.99	0.39	0.92	
9	6	0.19	1.16	0.21	1.09	
10	7	0.40	1.23	0.40	1.15	
5	1	0.78	0.71	0.76	0.70	
6	2	0.90	0.50	0.89	0.51	
7	3	0.88	0.58	0.86	0.58	
8	4	0.36	0.80	0.37	0.74	
9	5	0.21	0.94	0.22	0.87	
10	6	0.18	1.13	0.19	1.06	
6	1	0.76	0.60	0.73	0.62	
7	2	0.84	0.54	0.81	0.54	
8	3	0.24	0.71	0.23	0.66	
9	4	0.19	0.77	0.19	0.71	
10	5	0.19	0.92	0.19	0.86	
7	1	0.70	0.59	0.68	0.59	
8	2	0.23	0.63	0.23	0.59	
9	3	0.06	0.70	0.06	0.64	
10	4	0.17	0.76	0.15	0.71	
8	1	0.19	0.60	0.23	0.58	
9	2	0.06	0.62	0.06	0.58	
10	3	0.04	0.70	0.02	0.64	
10	1	0.04	0.50	0.09	0.57	
10	2	0.04	0.62	0.01	0.56	
10	1	0.03	0.56	0.05	0.50	

that \overline{R} was the same for all the segments. A minimum value, \overline{R}_{MIN} for \overline{R} , was estimated by selecting the largest of the minimum values calculated for the five segments; a maximum value, \overline{R}_{MAX} for \overline{R} , was estimated by selecting the smallest of the maximum values calculated for the five segments. Then, for each of the segments, the optical depths corresponding to \overline{R}_{MIN} and \overline{R}_{MAX} were calculated. The median value between these two extremes was then taken as the estimate. These are given in Table 3. The figures in parentheses after the estimates are the differences between the median values and the extreme values and are, therefore, a kind of upper limit on the error involved. A separate estimate of the optical depth was derived from each of the channels 1 to 5. Because the values determined from different channels are for different wavelengths, they were all converted to estimates for the optical depth at wavelength $0.5 \ \mu m$ by assuming that the optical depth varied with wavelength in accordance with the aerosol model used in the ATCOR II program. Note the substantial variations between the estimates from different channels. These differences could be due to inaccuracies in calibration of the instrument, absorption effects (which are not included in these estimates), or inaccuracies in the way the aerosol model represented the wavelength variation of the aerosol parameters.

It will be seen that the errors in parentheses in Table 3 are quite large. However, the quantity required to compute s, is not the aerosol level itself but the difference in aerosol level between the hazy and clear segments. This can be obtained by subtracting the values given in Table 3. However, it was computed a slightly different way. For each pair of segments shown in Table 4, we calculated the difference $\tau_H - \tau_C$ for range of values of \overline{R} between $\overline{R}_{\text{MIN}}$ and $\overline{R}_{\text{MAX}}$. These were then averaged to get the values given in Table 4. The errors shown in parentheses are one half the difference between the values of $\tau_H - \tau_C$ corresponding to \overline{R}_{MIN} and \overline{R}_{MAX} . It will be seen that these error estimates are much smaller than the error estimates given in Table 3. The reason is that the calculated value of $\tau_H - \tau_C$ is not a sensitive function of \overline{R} (assuming, as we do, that the value of \overline{R} is the same for both segments).

* Pixels thresholded.

TABLE 3. AEROSOL LEVELS DETERMINED BY FIVE DIFFERENT CHANNELS

Channel	Α	С	D	F	G
1	0.44 (0.12)	0.46 (0.12)	0.42 (0.12)	0.28 (0.14)	0.22 (0.15)
2	0.36(0.14)	0.39 (0.13)	0.36(0.14)	0.24(0.15)	0.20(0.16)
3	0.45(0.15)	0.50(0.14)	0.45(0.15)	0.30(0.17)	0.25(0.19)
4	0.49(0.13)	0.57(0.12)	0.51(0.13)	0.31(0.16)	0.25(0.18)
5	0.42 (0.11)	0.53 (0.09)	0.46 (0.10)	0.24 (0.14)	0.15 (0.14)
Mean	0.43	0.49	0.44	0.27	0.21
S.D.	0.05	0.07	0.06	0.03	0.04

Channel	A-F	A-G	C-F	C-G	D-F	D-G
1	0.15 (0.02)	0.21 (0.03)	0.18 (0.02)	0.24 (0.03)	0.14 (0.02)	0.20 (0.03)
2	0.12(0.02)	0.16(0.03)	0.15(0.02)	0.19(0.03)	0.12(0.02)	0.16(0.03)
3	0.15(0.02)	0.20(0.04)	0.20 (0.03)	0.25(0.03)	0.16(0.03)	0.21(0.04)
4	0.18(0.03)	0.25(0.05)	0.26(0.04)	0.32(0.05)	0.20(0.03)	0.27(0.05)
5	0.18 (0.03)	0.27 (0.03)	0.29 (0.04)	0.37 (0.05)	0.22 (0.04)	0.31 (0.04)
Mean	0.16	0.22	0.22	0.27	0.17	0.23
S.D.	0.03	0.04	0.06	0.07	0.04	0.06

TABLE 4. AEROSOL LEVEL DIFFERENCES

Table 5 shows results similar to those in Tables 1 and 2 for the channel combination 6-2 for all six combinations of one hazy and one clear segment. There were no pixels thresholded in any of these cases, so N_T is not given. Also, because in all cases Z was less than 0.002, that quantity was not given. Here the mean values of the differences given in Table 4 were used to estimate the standard deviation in the aerosol level, s_{τ} , from Equation 5. Also, the quantity P, which is the standard deviation of the aerosol level expressed as a percentage of the aerosol level, was estimated using the mean values given in Tables 3 and 4. However, the estimates for \tilde{P} are very rough because of the large errors indicated in Table 3. The standard deviations, s_z and s_{τ} , and the relative error, P, are smaller for the hazy segment in each pair than they are for the clear segment. This is probably a reflection of the well known fact that the variance in the data is smaller for higher aerosol levels. The average values of s₋ for the three hazy segments and the two clear segments are 0.08 and 0.092, respectively. This represents a fairly large error. Also, the average relative error for the clear segments is quite large (38 percent). However, the relative error for the hazy segments is much smaller (18 percent).

A slightly different way of estimating these errors is to assume that the aerosol level was the same for the three hazy segments and for the two clear segments. This results in an average aerosol level of 0.45 for the hazy segments and 0.24 for the clear segments. These values were used to compute s_{τ} and *P* from the average values for s_z in Table 5. We obtained 0.080 and 0.092 for s_z for the hazy and clear segments, respectively, and 18 percent and 39 percent for the corresponding values of *P*. These are essentially identical to the results obtained above.

These errors may be acceptable for certain applications, particularly ones that involve larger aerosol levels and therefore have smaller relative errors.

Averaging over Cells, and Application to Data other than Training Data

In the last section we saw that there was a substantial error associated with estimating the aerosol level of individual pixels when using the channel correlation technique. One might hope to reduce this by averaging over many pixels. In this section we divide each segment into cells of size 10 pixels by 10 pixels and study the errors when one estimates the average aerosol level for each cell. In doing this, we selected pairs of segments as before and computed the corresponding hazy and clear regression lines for each pair. The lines from each pair were used to estimate the aerosol levels for the cells of all the five segments. Thus, we were able to study the application of the method to the training data and also other data not used in training. All these calculations were for the channel pair 6-2

Consider one of the hazy segments. Let τ_k be the result of averaging the values of τ_{ij} over the 100 pixels in cell k. The mean of the τ_k is $\overline{\tau_H}$ and is given

Pair	Seg	R	s_z	S_{τ}	Р	Seg	R	S_z	S_{τ}	Р
A F	А	0.87	0.30	0.048	11	F	0.89	0.38	0.061	25
A G	A	0.87	0.28	0.062	14	G	0.91	0.38	0.084	35
CF	С	0.95	0.37	0.081	18	F	0.89	0.44	0.097	40
CG	C	0.95	0.36	0.097	22	G	0.91	0.42	0.11	47
DF	D	0.90	0.50	0.085	19	F	0.89	0.51	0.087	36
DG	D	0.90	0.48	0.11	25	G	0.91	0.49	0.11	47
Mean			0.38	0.081	18			0.44	0.092	38
S.D.			0.09	0.023	5			0.05	0.020	8

TABLE 5. RESULTS FOR CHANNELS 6 AND 2

by Equation 3. The standard deviation of the τ_k relative to $\overline{\tau_H}$ is given by

$$S_{\tau} = S_z \left(\tau_H - \tau_C \right) \tag{7}$$

where

$$S_z \; = \; \left[\frac{1}{71} \sum_k \, (Z_k^H \; - \; \overline{Z^H})^2 \; \right]^{1/2} \, . \eqno(8)$$

Here $\overline{Z^{H}}$ is given by Equation 4 and

$$Z_{k}^{H} = \frac{1}{100} \sum_{ij} Z_{ij}^{H}$$
(9)

where the sum is over the 100 pixels in cell k.

We can also define a root mean square error of the τ_k relative to τ_H . This is given by

$$E_{\tau} = E_z \left(\tau_H - \tau_C \right) \tag{10}$$

where

$$E_z = \left[\frac{1}{72} \sum_k \left(Z_k^H\right)^2\right]^{1_{2}}.$$
 (11)

A similar set of quantities can be defined for a clear segment.

Table 6 shows the results. Each segment pair was used to compute the quantities \overline{Z} , S_z , and E_z for each of the five segments. Consider first the two segments in each line that are members of the segment pair for that line. The data for these segments describes what happens when the method is applied to the training data. For these segments the bias is 0.00 as expected. When one averages the six values for S_z where the segment is the hazy segment, one

TABLE 6. RESULTS FOR CELLS. CHANNELS 6 AND 2

Pair	Statistic	А	С	D	F	G
	Z	0.00	-0.09	-0.25	0.00	-0.20
A F	S.	0.13	0.17	0.20	0.17	0.25
	$\tilde{E_z}$	0.13	0.19	0.32	0.17	0.31
	Z	0.00	-0.07	-0.23	0.14	0.00
A G	S.	0.12	0.18	0.20	0.15	0.20
	E_z	0.12	0.19	0.30	0.20	0.20
	Z	0.14	0.00	-0.16	0.00	-0.24
CF	S.	0.14	0.17	0.22	0.19	0.30
	$\tilde{E_z}$	0.20	0.17	0.26	0.19	0.38
	Z	0.12	0.00	-0.15	0.16	0.00
CG	S.	0.13	0.17	0.21	0.17	0.22
	$\tilde{E_z}$	0.17	0.17	0.25	0.23	0.22
	Z	0.33	0.20	0.00	0.00	-0.27
DF	S.	0.17	0.21	0.26	0.22	0.34
	$\tilde{E_z}$	0.37	0.29	0.26	0.22	0.43
	Z	0.29	0.20	0.00	0.18	0.00
DG	S.	0.15	0.24	0.26	0.19	0.25
	$\tilde{E_z}$	0.32	0.31	0.26	0.26	0.25

obtains a value of 0.18 with a standard deviation of 0.062. This value is a factor of 2.1 smaller than the corresponding value (0.38) when there is no averaging over pixels. Similarly, when the segment is the clear segment of the segment pair, one obtains an average value of 0.21 with a standard deviation of 0.028. This is also a factor 2.1 smaller than the corresponding value without averaging over pixels (0.44). One might have expected a larger factor because we are averaging over 100 pixels and would expect a factor of 10 if they were randomly chosen. The smaller factor implies that there are substantial correlations between the pixels in a cell. Nevertheless, the factor of 2.1 represents a considerable improvement.

In order to estimate the errors in aerosol level, we shall use the second method discussed in the previous section, i.e., we shall assume that the three hazy segments all have the same aerosol level and that the two clear segments both have the same aerosol level. Taking the difference between these two levels to be 0.21, as before, we find that we should be able to estimate the aerosol levels of cells of 100 pixels with an average error of 0.04 to 0.05 in optical depth.

Let us now consider the segments which are not members of the segment pair. The average of the absolute value of the bias term, \overline{Z} , over the 18 such cases in Table 6 is 0.19. We shall assume that this is entirely due to the fact that the regression lines used were for other segments, i.e., we shall assume that none of the bias was due to a real difference in aerosol levels between the segment in question and the corresponding (i.e., hazy or clear) segment in the segment pair being used. Thus, the error $E_{,}$ in Table 6 should be somewhat of an upper limit. The average of E, over the 18 values, where the segment is not a member of the segment pair, is 0.28. Multiplying this by the assumed difference of 0.21 between the hazy and clear segments, one obtains a value of 0.06 for the estimated error when one uses regression lines from one segment pair to estimate aerosol levels of cells of 100 pixels in another segment. This result applies only to segments such as those considered here where the targets on the ground are quite similar.

DISCUSSION AND CONCLUSIONS

For this data set we have estimated that the average error involved in determining aerosol levels for individual pixels that are members of the training data is an error in optical depth of about 0.09. When the estimates are for cells of size 10 pixels by 10 pixels, the corresponding number is 0.05. When the cells are in segments other than the training segments, the error is 0.06.

A number of approximations were made to arrive at these error estimates. First, it was assumed that linear interpolation between the regression lines was adequate. It is clear that linear interpolation is only approximately correct because the radiance reflected by an aerosol layer does not vary linearly with the aerosol level and neither does extinction. However, for small optical depths such as those indicated here, it is expected that the effect would be approximately linear. A quantitative investigation of this question can be performed by using the methods described in Potter (1977) and Potter (1984). We have performed such calculations for a few simple cases and found that the errors involved are generally less than 10 percent. However, it is recommended that this question be investigated carefully by anyone wishing to use this method for actual applications.

Second, it was assumed that the aerosol levels were uniform over each segment. Any non-uniformity in the actual aerosol levels would have increased the variance and therefore increased our error estimates. In the case of a clear segment, it is unlikely that the contribution was very large. One way to investigate this question would be to obtain some data under extremely clear conditions where this source of variance would be negligible. Such data would also be valuable for investigating the error in applying training data from one area to make estimates in other areas. Another way to eliminate the variance due to the atmosphere would be to make flights close to the ground beneath most of the atmospheric variation. However, one would then have to simulate the corresponding high altitude results by averaging the low altitude data to reduce the spatial resolution. In any case, to the extent that there were variations in the aerosol level across the segments, our error estimates are upper limits.

A third assumption was that the average reflectance of all the segments was the same. This was the key assumption in determining the difference in optical depths using the ATCOR II algorithm. Differences in the average reflectance were probably largely responsible for the differences between the six columns in Table 4, although some contribution was surely made by actual differences in the aerosol levels. In any case, an estimate of the combined effect of reflectance and aerosol variations can be obtained from the standard deviation of the six means in Table 4. The average of these means is 0.21 and the corresponding standard deviation is 0.037. Therefore, these effects may contribute an error of the order of 18 percent to our error estimates.

Finally, our estimates are based on the aerosol model used in the ATCOR II algorithm. It was designed to represent a typical continental haze and is described in detail in Potter (1977). Obviously, in applying a method such as this, it would be advantageous to know all relevant parameters for the aerosol, i.e., the scattering diagram and the profiles of the volume scattering and absorption coefficients. However, in situations where one is attempting to determine aerosol levels from aircraft data, complete information of this kind will rarely be available and many assumptions will have to be made. In the present case we do not have any ground measurements of the aerosol characteristics. Because the ATCOR II algorithm and the algorithm used in this paper to measure aerosol levels both depend primarily on the increase in brightness caused by the aerosol layer, the error estimates given at the beginning of this section are approximately those that would be obtained in a situation where the aerosol was described by our model. Probably the most significant variation from our model is that the actual aerosol present had some absorption. In this case our estimates of optical depth differences would be lower than the actual differences. This does not mean that our estimates are wrong. It simply means that our estimates are for the case where there is no absorption. If we had used a model with some absorption, we could have derived estimates relevant to that case. An alternative to the procedure followed above would be to use the differences for channel 2 in Table 4 rather than the means over the channels. The rationale for this is that our results are mainly dependent on channel 2 because they were derived from channels 2 and 6 and the aerosol is expected to have the largest effect in channel 2. If this is done, it reduces the error estimates given at the beginning of this section by a factor of 1.4.

Thus, there are a number of uncertainties in our error estimates. Most of them appear to make our estimates conservative, i.e., upper limits. The results indicate that the errors involved in this method are not small but they are probably small enough for certain applications. In particular, this method might be suitable for monitoring smoke plumes.

Obviously, it is desirable to obtain more accurate results. There are several ways to do this. One way would be to make sure that the scanner data are of the highest possible quality. It was mentioned above that the poor performance of channel 1 in this experiment may have been due to problems with the scanner. Other ways to improve the results have to do with improved algorithms. This study considered only two channels at a time and therefore did not fully exploit the information available in all the channels. Multiple regression and other multivariate techniques should be investigated.

If it is desired to use data with look angles that are substantially different from the vertical, then methods must be developed to account for the dependence of the aerosol effect on look angle.

ACKNOWLEDGMENTS

The author wishes to acknowledge the assistance of Mr. Ridgeway Weerackoon, who wrote most of the computer programs used in this work, and to

PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING, 1984

thank Dr. Thomas Mace for many helpful discussions.

References

- Lambeck, P. F., 1977. Signature Extension Preprocessing for Landsat MSS Data. ERIM 122700-32-F, ERIM, Ann Arbor, Mich.
- Lambeck, P. F., and J. F. Potter, 1978. Compensation for Atmospheric Effects in Landsat Data. *Proceedings of* the LACIE Symposium, NASA Lyndon B. Johnson Space Center, Houston, TX 77058, pp. 723-738.
- Minter, T. C., 1978. Methods of Extending Crop Signatures from One Area to Another. Proceedings of the LACIE Symposium, NASA Lyndon B. Johnson Space Center, Houston, TX 77058, pp. 757-800.
- Piech, K. R., and J. E. Walker, 1971. Aerial Color Analysis of Water Quality. *Journal of the Surveying and Mapping Division*, ASCE, Vol. 97, pp. 185-197.
- Piech, K. R., and J. E. Walker, 1972. Thematic Mapping of Flooded Acreage. *Photogrammetric Engineering*, Vol. 38, pp. 1081-1090.
- Potter, J., 1977. The Correction of Landsat Data for the Effects of Haze, Sun Angle, and Background Reflectance. *Proceedings of the 4th Symposium on Machine Processing of Remotely Sensed Data*, LARS, Perdue University, West Lafayette, Indiana.
 - —, 1984. Modeling the effects of Aerosols on Multispectral Scanners. To Be Published.
- Potter, J. F., and M. Mendolowitz, 1975. On the Determination of the Haze Levels From Landsat Data. Proceedings of the Tenth International Symposium on Remote Sensing of Environment, ERIM, Ann Arbor, Mich., pp. 695-703.

Switzer, P., W. S. Kowalik, and R. J. P. Lyon, 1981. Estimation of Atmospheric Path-Radiance by the Covariance Matrix Method. *Photogrammetric Engineering and Remote Sensing*, Vol. 47, No. 10, pp. 1469-1476.

(Received 13 May 1982; revised and accepted 11 September 1983)

APPENDIX A MSS CALIBRATION

Table A.1 shows the calibration for the 10 channels. Each channel has a range of 256 digital levels or "counts." In the column headed X(0) is given the number of counts that correspond to an input radiance of zero. In the column headed dX/dN is given the number of counts per unit radiance. Unit radiance is 1 μ W/cm² - nm - str.

TABLE A.1. MSS CALIBRATION

Channel	$\mathbf{X}(0)$	dX/dN
1	15	18.33
2	8	14.88
3	12	17.59
4	9	13.20
5	18	23.16
6	18	18.09
7	20	23.41
8	10	15.73
9	24	24.64
10	20	21.93

Forthcoming Articles

- H. Ebner and P. Reiss, Experience with Height Interpolation by Finite Elements.
- A. H. A. El-Beik and R. Babaei-Mahani, The Quadrustational Close-Range Photogrammetric System.
- M. T. Erez and E. Dorrer, Photogrammetric Data Acquisition Using an Interactive Computer Graphics System.
- A. H. Gerbermann, J. A. Cuellar, and H. W. Gausman, Relationship of Sorghum Canopy Variables to Reflected Infrared Radiation for Two Wavelengths and Two Wavebands.
- *Y. Jim Lee* and *R. W. McKelvey*, Digitized Small Format Aerial Photography as a Tool for Measuring Food Consumption by Trumpeter Swans.
- James R. Lucas, Photogrammetric Densification of Control in Ada County, Idaho: Data Processing and Results.
- Atsushi Okamoto, Orientation Problem of Two-Media Photographs with Curved Boundary Surfaces.

J. Funso Olorunfemi, Land Use and Population: A Linking Model.

A. Peled and B. Shmutter, Analytical Generation of Orthophotos from Panoramic Photographs.

Leslie H. Perry, Photogrammetric Summary of the Ada County Project.

Craig H. Tom and *Lee D. Miller*, An Automated Land-Use Mapping Comparison of the Bayesian Maximum Likelihood and Linear Discriminate Analysis Algorithms.

52