Aspects of Spatial Autocorrelation of Landsat TM Data for the Inventory of Waste-Disposal Sites in Rural Environments

Abstract

This study concerns the attempt to identify and classify waste-disposal sites by means of Landsat TM data, mainly on the basis of the contrast of their spatial features with the surrounding rural landscape, rather than on their purely spectral responses. In fact, any waste-disposal site may be regarded as a land-cover unit characterized by high spatial variation of its pixel cluster, as compared with the neighboring pixels of the background, which, on the contrary, show an almost uniform pattern. The spatial autocorrelation was analyzed by means of the semivariogram function, which showed different shapes of the land-cover units selected. The potentialities of spatial autocorrelation as a basis for image classification were confirmed. A synthetic descriptor, based on the ratio between sill and range, is proposed as a new tool for waste-disposal-site classification. The experiment was carried out over a portion of the Friuli plain, in northeastern Italy.

Introduction

The problem of inventorying and assessing waste-disposal sites is becoming more urgent than ever. Because controlled landfills are reaching capacity, new ones will have to be approved. At the same time, the number of uncontrolled waste-disposal sites is on the increase, so that central and local government authorities are faced with having to deal with the risk these active and inactive waste sites pose for the environment.

Remote sensing has been used to detect and assess waste-disposal sites with the use of aerial photographs and airborne sensors (Erb *et al.*, 1981; Jones, 1989; Barnaba *et al.*, 1991), with the applications of terrestrial thermography (Zilioli et al., 1992), and with the photointerpretation of digital SPOT HRV imagery (Philipson *et al.*, 1988). Integrated approaches, based mainly on the spectral classification and photointerpretation of Landsat TM imagery, have been conducted by Brivio et al. (1991).

According to a recent inventory conducted in Italy for 275 towns (World Wildlife Foundation, 1988), the dimensions of the smallest waste-disposal sites inventoried range from 50 to 5,000 square metres, and controlled landfills or dump fields are larger, ranging from 10 to 30 hectares. While the former correspond to a few Landsat TM pixels and to some tens of SPOT HRV Panchromatic pixels, the latter accord well with present sensor spatial resolution.

This study attempts to identify and classify waste-disposal sites by means of Landsat TM data, based on the contrast of their spatial properties and structural characteristics with the surrounding rural landscape, rather than on their spectral responses. Indeed, any waste-disposal site, or scene object, can be regarded as a land-cover unit characterized by high spatial variability in its cluster of pixels, as compared with the rural environment, or *background* (Strahler *et al.*, 1986), which, on the contrary, may generally be expected to be uniform and homogeneous.

Because the variations under discussion depend on spatial relationships of pixel distribution, we applied the *spatial autocorrelation* method, which outlines properties whose values, at different places, are related to one another (Webster and Oliver, 1990). Spatial autocorrelation can be measured by setting variance against variable distance: the function so obtained is called the *semivariogram*. This function was recently also found to be valid in the area of remote sensing. We refer here to the application of semivariograms in data analysis (Webster, 1985; Jupp *et al.*, 1989; Wald, 1989), for application in ground-based radiometry (Curran, 1988; Webster *et al.*, 1989), and in image processing (Curran, 1988; Woodcock *et al.* 1988a; 1988b; Ramstein and Raffy, 1989; Cohen *et al.*, 1990; Davis *et al.*, 1991).

Study Area and Data Used

The study area selected was the rural surroundings of Palmanova, Friuli, in northeastern Italy (see map in Plate 1). In the last few decades, this traditionally agricultural region has undergone rapid and continuing urbanization and industrialization, with consequent serious degradation of the land. Geologically, the area is dominated by alluvial plains combined with Pleistocene glacial outwash. Sand and gravel deposits have been intensively exploited, as shown by a number of quarries and mined sites, frequently excavated down to the level of the water-table.

Based on existing thematic maps, ground reconnaissance surveys, and photointerpretation of Landsat TM data (Brivio *et al.*, 1991), a general reference map was drawn on a scale of 1:100,000. This map shows the main land-cover units and waste-disposal-site locations in the Palmanova area. Five main classes of waste-disposal site were recognized: mined lands, quarries, dumps, landfills, and disturbed land. A de-

Photogrammetric Engineering & Remote Sensing,
Vol. 59, No. 9, September 1993, pp. 1377–1382.

0099-1112/93/5909–1377$03.00/0

Pietro A. Brivio
Ilaria Doria
Eugenio Zilioli
Remote Sensing, Institute for the Geophysics of the Lithosphere, CNR, 56 Via Ampère, 20131 Milano, Italy

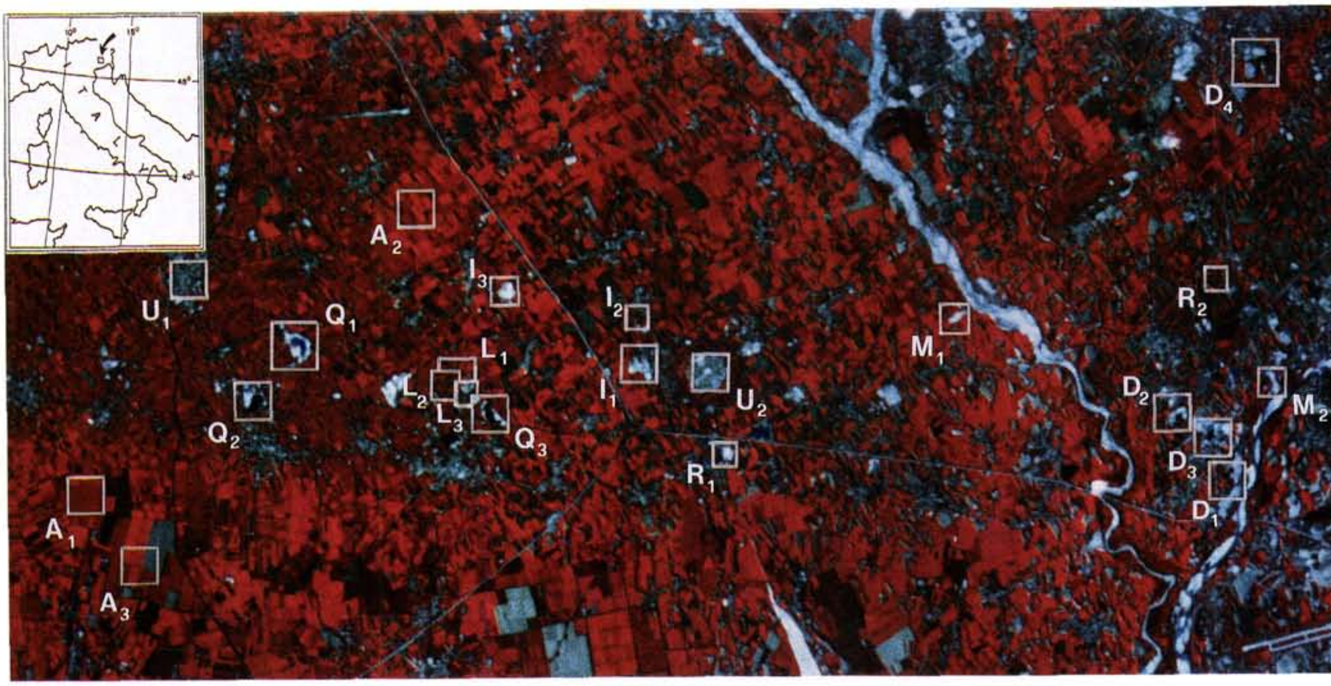

Plate 1. Sub-scene of Palmanova, Friuli, Italy. Landsat TM, standard False Color Composite (RGB : 432). Frame: 191-28, Quadrant 3. Acquisition date: 25 July 1989. Dimensions: 1,000 columns by 500 lines. UTM center coordinates: 5087000, 363950 (Zone 32). Location of waste-disposal sites and other land-cover units are outlined and labeled: M = Mined land; Q = Quarry; D = Dump; L = Landfill; R = Disturbed land; I = Industrial area; U = Urban site; A = Agricultural areas.

TABLE 1. CLASSIFICATION OF WASTE-DISPOSAL SITES OCCURRING IN THE AREA AROUND PALMANOVA, FRIULI, ITALY.

Class	Description and Identifying Features
Mined Land (M)	Clearly recognizable exposed high reflecting surfaces, caused by exploitation and mining of alluvial sands and/or gravel.
Quarry (Q)	Sites where mining of alluvial deposits has cut the ground water-table, leaving small ponds surrounded by ground with washed alluvials or bare soils, often destined for use as uncontrolled dump.
Dump (D)	Open heaps of solid wastes, often illegal, in unordered and uncontrolled accumulation, with no evidence of maintenance.
Landfill (L)	Deposits of solid waste compacted and controlled, usually by means of heavy machinery, and partially covered by soil.
Disturbed Land (R)	Abandoned waste-disposal sites that may appear in two forms: simply disturbed, bare land or, more often, stabilized areas, sometimes with vegetation. Such areas are often too small and their features too masked to be always clearly detectable.

scription of the five classes is given in Table 1, according to the definitions of Philipson *et al.* (1988) and Barnaba *et al.* (1991).

A Landsat TM image, centered at 191-28, third quadrant, was acquired on 25 July 1989, thus ensuring the maximum reflectance contrast between the main landscape features, in particular, between soil and water and between water and vegetation.

A sub-scene of 1,000 columns by 500 lines, equivalent to about 450 km^2, in which the scene objects taken into account (either waste-disposal or land-cover units) are outlined and labeled (Plate 1), was extracted from the original scene.

Specifically, 14 waste-disposal sites, plus a further eight scene objects – three Industrial Areas (I), two Urban Sites (U), and three Agricultural Areas (A) – were identified. Industrial and urban areas were selected and expected to show a structural complexity similar in some ways to the waste-disposal sites, while the agricultural sites were taken as representing the scene samples of homogeneous background. Figure 1 shows four examples of representative waste-disposal sites. For a more complete understanding of the different situations, the four image subsets are accompanied by photographs taken on the ground.

Waste-disposal sites differed greatly in shape and size, depending on type and utilization. Table 2 summarizes each class geometrical characteristics, showing mean areas in hectares and mean linear dimensions in pixels, assuming the model for the scene objects to be square. Mean linear size computed over the entire sample population of waste-disposal sites was ten TM pixels.

The Semivariogram Function

Digital images can be considered the realization of a stochastic process $Z(x)$, in which $\mathbf{x}$ is a two-dimensional position vector. Assuming that the weak stationarity conditions are fulfilled, i.e., mean and variance are independent of the position $\mathbf{x}$ and covariance is only a function of the distance between locations, the process $Z(x)$ can be studied by the "regionalized variable" theory (Matheron, 1965). Within this mathematical context, the spatial information, inherent in

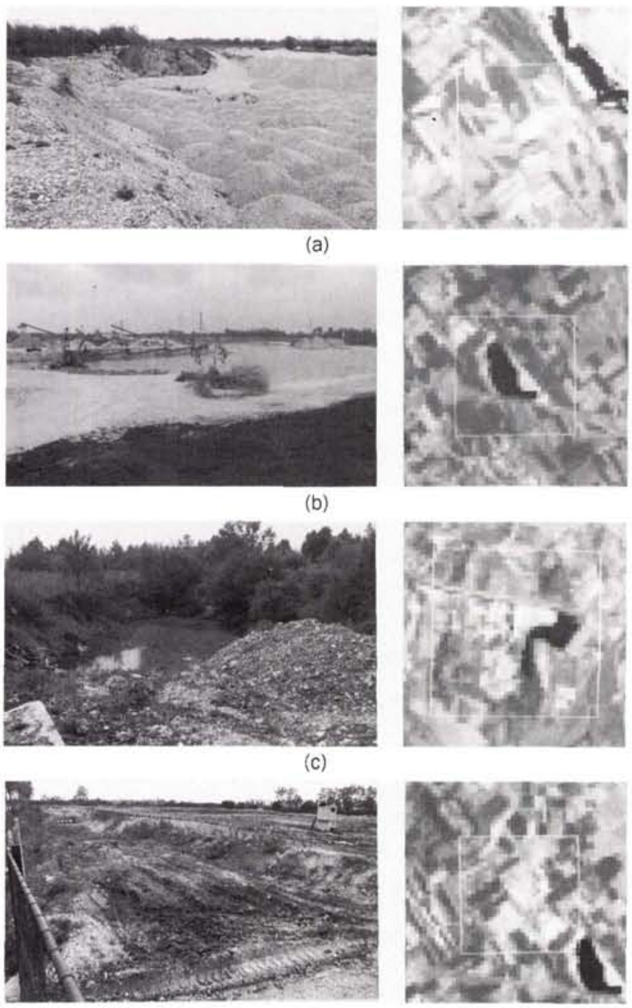

Figure 1. Enlargements from sub-scene of Plate 1 representative of some class sample sites selected for their spatial characteristics: (a) Mined Land M_1, (b) Quarry Q_3, (c) Dump D_4, and (d) Landfill L_1. Photographs on the ground are included for a more complete understanding of different situations.

TABLE 2. MEAN AREAS IN HECTARES OF THE FIVE WASTE-DISPOSAL CLASSES AND MEAN LINEAR DIMENSIONS IN PIXELS, ASSUMING THE MODEL FOR THE SCENE OBJECTS TO BE SQUARE

Class	N° of Objects Mapped	Mean Class Area (ha)	Mean Linear Size (pixel)
Mined Land (M)	2	7.9	9.3
Quarry (Q)	3	12.9	10.8
Dump (D)	4	18.5	14.4
Landfill (L)	3	10.0	10.5
Disturbed Land (R)	2	2.5	5.1
Total	14	10.4	10.0

the digital image, is analyzed by using the properties of the semivariogram function $\gamma(h)$ defined by the relationship:

$$\gamma(h) = 1/2(n-h) \sum_{i=1...n-h} [Z(x_i) - Z(x_i + h)]^2 \qquad (1)$$

in which $Z(x)$ is the radiance value measured at pixel x, h is the lag or distance in the image, expressed as a number of pixels, defining the different locations $(x + h)$ at which the regionalized variable Z is observed, and n is the number of observations required to estimate $\gamma(h)$. Characteristic semivariogram features are sill, range, nugget effect, derivative at the origin, and anisotropy (Jupp *et al.*, 1989). Hereafter, some definitions are recalled:

- The *sill C*, indicating the semivariogram value in which the function remains constant as separation distances increase and equals the general data variance. Often, in the remotely sensed data a lack of the sill can be observed; in these cases semivariograms are defined unbounded since no finite *a priori* variance is expected (Oliver *et al.*, 1989).
- The *range a* of influence, definable only for the bounded semivariograms, indicating the lag value at which the semivariogram reaches the sill. The range is the critical h at which the correlation structure ceases to exist and data vary randomly.
- The *nugget* C_o, indicating the variance contribution by the noise of the sensor system. It can be defined as the limit of the semivariogram function when the lag h tends to be zero.

Because the waste-disposal sites are land-cover units characterized by a vegetation, water, bare-soil, and solid-waste mix, we expect a high radiometric variability in their pixel clusters. Thus, waste-disposal sites should show higher sills than the rural environment of the background.

Although a certain anisotropy can be observed in the image (Plate 1 and Figure 1), we assume the spatial structure to be isotropic, because directional organization of ground features is absent. In addition, two-dimensional semivariograms are more difficult to interpret in terms of shape, range of influence, and height of the sill (Woodcock *et al.*, 1988b).

The $\gamma(h)$ function was calculated by the matrix method. This method evaluates, first, the semivariogram for all rows and the semivariogram for all columns, and then takes the average of these two semivariograms at each lag h.

Application of the Semivariogram to Object Classification

Spatial and Geometric Considerations

Spatial structure in digital images, and related statistics, depend very much on the relationship between the spatial resolutions of satellite sensors, *i.e.*, ground pixel dimensions, and the size of objects in the scene. In addition, the estimate of the semivariogram depends on the number n of observations, its reliability decreasing with the increase in h: the maximum value of h should be between one-fifth and one-third of the number of rows and columns of the digital image (Webster, 1985). On the other hand, if the window size is too large, the spatial characteristics of objects may be obscured and eventually lost. Indeed, for large windows, the characteristic structure of the objects may be masked by the voluminous presence of the background.

Bearing in mind the mean values of the geometric dimensions shown in Table 2, which are 10.4 hectares and 10 pixels, the ratio of 3:1 as between the window and sample size was adopted in the subsequent step of the analysis.

Analysis of the Semivariogram Shapes

Semivariograms were computed for all 22 land-cover units presented in Plate 1 and for each spectral band. Figure 2 gives results for one object per class. The following relevant points may be made:

- Band TM3 (red) seems to be the most discriminating band of classes considered, followed by band TM1 (blue).

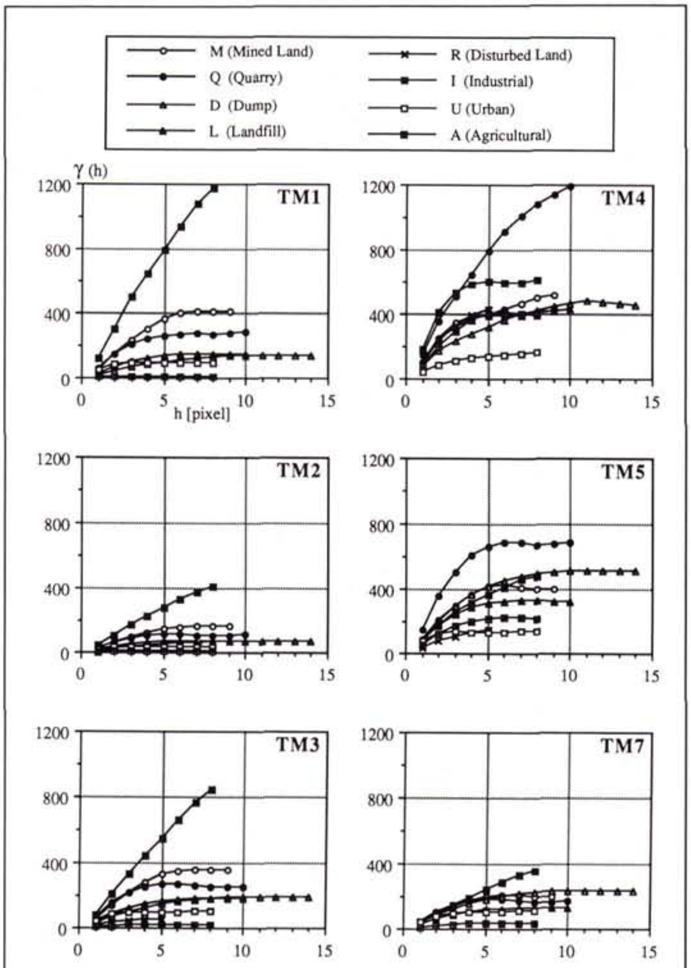

Figure 2. Experimental semivariograms of the eight selected class samples, at the different reflective TM wavelengths.

- Industrial site I3 shows the steepest semivariogram slope, almost in the visible bands.
- The illegal waste site or dump D_4 and landfill L_1 look very similar to one another in the visible bands, while in the infrared bands they show sufficient contrast for separation, particularly in band TM5.
- Pinpointing and distinguishing between classes of interest appears difficult in band TM4, where waste-disposal samples can easily be confused with agricultural site A_2. However, quarry Q_3 is strikingly differentiated from the other classes.

The class separation observable in the infrared bands is mainly due to the strong spatial reflectance contrasts inferred by water and bare or vegetated land surfaces.

Parameterization by Sill and Range

In order to standardize the results, the measured semivariograms were fitted to some of the *authorized* models (Clark, 1979; Webster, 1985; Davis, 1986), although these models should actually be applied only to *punctual* semivariograms, or semivariograms as derived from point measurements (Woodcock *et al.*, 1988a). The experimental semivariograms concerning land-cover units of major interest (Figure 2) called for the consideration of the exponential and spherical models.

The exponential model is defined as

$$\gamma(h) = C[1 - \exp(-h/a)] \qquad (2)$$

while the spherical model is formulated as

$$\gamma(h) = C[3/2(h/a) - 1/2(h/a)^3] \quad \text{for } h \le a$$
$$\gamma(h) = C \quad \text{for } h > a \qquad (3)$$

The semivariogram models were computed in the most suitable spectral band (TM3), for considering the quarry Q_3 waste-disposal site, whose geometric dimensions are nearer to the mean population values given in Table 2.

The accuracy of the fitting was estimated through the relative standard deviation S between the semivariogram values observed and the mathematical model (Ramstein and Raffy, 1989). The analytical expression of S is

$$S = \sum_i [(\gamma_{obs}(h_i) - \gamma(h_i))/(\gamma_{obs}(h_i))]^2 \qquad (4)$$

The S values for the exponential model averaged 58 percent while, for the spherical model, the figure was 18 percent. Therefore, the spherical model was computed, for each of the semivariograms measured, and their principal parameters, sill C and range a, were obtained.

For each class, mean sill and range values were analyzed in the a-C space. As an example, Figure 3 shows the scattergrams for bands TM1, TM3, and TM5. For any spectral band, plots indicate clear separation between the two populations of scene objects: waste-disposal sites and the other land-cover units, particularly agricultural sites A. If disturbed land class R is excluded, because of the practical problem of recognizing it as a specific landscape unit, the four main classes of waste-disposal site show a specific concentration in the a-C space. To further differentiate between waste-disposal classes, a new synthetic parameter was defined by ratioing the two parameters C and a in the six TM bands. Resulting values are summarized in Table 3, in which the variability ranges between the minimum and maximum values, for each spectral band are also presented. The ratio C/a in band TM5 shows the highest variability, and offers the cle-

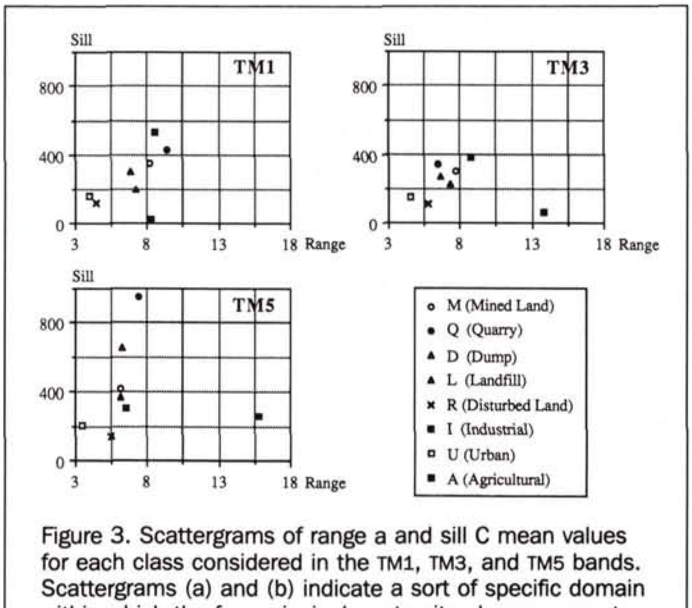

Figure 3. Scattergrams of range a and sill C mean values for each class considered in the TM1, TM3, and TM5 bands. Scattergrams (a) and (b) indicate a sort of specific domain within which the four principal waste-site classes seem to fall.

TABLE 3. SILL/RANGE RATIO FOR THE EIGHT SCENE OBJECT CLASSES IN THE SIX REFLECTIVE TM SPECTRAL BANDS. VARIABILITY RANGE EXPRESSED AS A PERCENTAGE, TAKING BAND TM5 AS A REFERENCE, IS ALSO INDICATED.

Class	TM1	TM2	TM3	TM4	TM5	TM7
Mined Land	43.5	17.1	39.8	69.9	68.5	31.6
Quarry	45.8	20.4	53.6	87.6	128.8	36.3
Dump	44.4	17.9	41.9	83.3	104.8	43.3
Landfill	27.9	13.0	31.9	70.3	59.5	21.1
Disturbed Land	26.1	7.8	18.5	74.0	25.9	16.7
Industrial Area	62.8	21.4	44.1	85.2	47.4	24.9
Urban Site	39.9	14.0	32.6	30.6	59.3	32.1
Agricultural Fields	3.0	1.4	4.7	31.0	16.2	4.4
Variability Range (%)	53	18	43	50	100	34

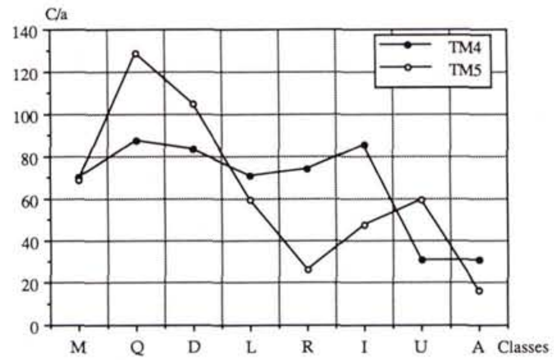

Figure 4. Diagrams of sill/range ratios from mean values of each class, in bands TM4 and TM5. Maximum separations between classes occur in band TM5 ($\Delta\lambda$ = 1.55 to 1.75 μm). Resemblances, as they occur between urban sites U and landfills L, are solved with the help of spectral band TM4.

arest differentiation between the objects studied. This band gave a mean ratio difference for each class of about 15 percent of total amplitude. However, there remains a possibility of confusion between urban sites U and landfills L. This problem can be easily overcome in the light of the information supplied by band TM4. The diagrams in Figure 4 effectively illustrate these observations and confirm the capabilities of "multispectral spatial analysis" based on autocorrelation concepts for waste-disposal-site classification.

Conclusions

The application of spatial-textural analysis to outline scene objects, whose structure contrasts with background homogeneity, definitely seems to be an effective tool for producing an inventory and assessment of waste-disposal sites. The experiment presented suffers from the limitation of being only a case study concerning rural features typical of northern Italy.

Regarding the results, the following points should be made:

- Qualitative analysis of the experimental semivariogram shapes led to the conclusion that the spectral bands TM1, TM3, and TM5 are the most suitable for scene object identification.
- Of the various *authorized* models of the function $\gamma(h)$, the spherical model was adopted.
- The distribution of the 22 scene samples in the *a-C* space yields significant results through representation of the class barycenters. In fact, in the scattergrams the waste-disposal classes occupy a specific area, clearly separate from the rest of the land-cover unit.
- The use of ratios combining sill and range from semivariograms offers promising conclusions. The proposed ratio *C/a* already draws clear distinctions between the eight classes studied, especially in band TM5. The only uncertainty concerns the classes landfills L and urban centers U, which, however, is solved in band TM4.

These initial results hold out good prospects and justify spatial analysis as an effective tool for achieving reliable automatic waste-disposal-site classification.

Acknowledgments

The authors are grateful to Miss F. Pagnoni for information she supplied on the characteristics of waste-disposal sites and to Mr. H. Bloemer for kindly reviewing the text. They also wish to acknowledge the valuable suggestions of anonymous reviewers. Financial support was provided, within the framework of an associated CNR-TEI-ENEA research project on the subject, by the Italian Ministry of the Environment (Law 441/87), and partially by ASI-Italian Space Agency (Contract N. RS-7/91).

References

Barnaba, E. M., W. R. Philipson, A. W. Ingram, and J. Pim, 1991. The use of aerial photographs in county inventories of waste-disposal sites. *Photogrammetric Engineering & Remote Sensing,* 57(10):1289–1296.

Brivio, P. A., I. Doria , M. A. Gomarasca, S. Moriondo, F. Pagnoni, R. Tomasoni, and E. Zilioli, 1991. *Potenzialità del telerilevamento da satellite e da aereo nella ricerca di aree soggette ad inquinamento e degrado, anche finalizzata alla individuazione di discariche abusive, tramite analisi di stress ambientale e alterazione delle caratteristiche pedologiche di zone campione.* Second and Third Progress Reports, Ministry for the Environment of Italy, Research Project L. 441/87 CNR-TEI-ENEA, Rome.

Clark, I., 1979. *Practical Geostatistics.* Applied Science Publishers, London.

Cohen, W. B., T. A. Spies, and G. A. Bradshaw, 1990. Semivariograms of digital imagery for analysis of conifer canopy structure. *Remote Sensing of Environment,* 34(3):167–178.

Curran, P. J., 1988. The semi-variogram in remote sensing: an introduction. *Remote Sensing of Environment,* 24(3):493–507.

Davis, F. W., D. A. Quattrochi, M. K Ridd, N. S. Lam, S. J. Walsh, J. C. Michaelsen, J. Franklin, D. A. Stow, C. J. Johannsen, and C. A. Johnston, 1991. Environmental analysis using integrated GIS and remotely sensed data: some research needs and priorities. *Photogrammetric Engineering & Remote Sensing,* 57(6):689–697.

Davis, J. C., 1986. Statistics and Data Analysis in Geology. John Wiley & Sons, New York.

Erb, T. L., W. R. Philipson, W. L. Teng, and T. Liang, 1981. Analysis of landfills with historic airphotos. *Photogrammetric Engineering & Remote Sensing,* 47(9):1361–1369.

Jones, H. K., and T. R. E. Chidley, 1989. The application of low cost aerial video and photographic data to assess environmental impact caused by the migration of gas away from landfill sites. *Proceedings IGARSS '89 and 12th Canadian Symposium on Remote Sensing,* Vancouver, pp. 1674–1676.

Jupp, D. L. B., A. H. Strahler, and C. E. Woodcock, 1989. Autocorrelation and regularization in digital images. II: Simple image models. *IEEE Transaction on Geoscience and Remote Sensing,* 27(3):247–258.

Matheron, G., 1965. *Les variables régionalisées et leur estimation.* Masson, Paris.

Oliver, M., R. Webster, and J. Gerrard, 1989. Geostatistics in physical geography. Part I: theory. *Trans. Inst Br. Geogr.* 14(3):259–269.

Philipson, W. R., E. M. Barnaba, A. Ingram, and V. L. Williams, 1988. Landcover monitoring with SPOT for landfill investigations. *Photogrammetric Engineering & Remote Sensing,* 54(2):223–228.

Ramstein, G., and M. Raffy, 1989. Analysis of the structure of radiometric remotely-sensed images. *International Journal of Remote Sensing,* 10(6):1049–1073.

Strahler, A. H., C. E. Woodcock, and J. A. Smith, 1986. On the nature of models in remote sensing. *Remote Sensing of Environment,* 20(2):121–139.

Wald, L., 1989. Some examples of the use of structure functions in the analysis of satellite images of the ocean. *Photogrammetric Engineering & Remote Sensing,* 55(10):1487–1490.

Webster, R., 1985. *Quantitative Spatial Analysis of Soil in the Field.* Springer-Verlag, New York.

Webster, R., P. J. Curran, and J. W. Munden, 1989. Spatial correlation in reflected radiation from the ground and its implications for sampling and mapping by ground-based radiometry. *Remote Sensing of Environment,* 29(1):67–78.

Webster, R., and M.A. Oliver, 1990. *Statistical Methods in Soil Resource Survey.* Oxford University Press, Oxford.

Woodcock, C. E., and A. H. Strahler, 1987. The factor of scale in remote sensing. *Remote Sensing of Environment,* 21(3):311–332.

Woodcock, C. E., A. H. Strahler, and L. B. Jupp, 1988a. The use of variograms in remote sensing: I. Scene Models and Simulated Images. *Remote Sensing of Environment,* 25(3):323–48.

———, 1988b. The use of variograms in remote sensing: II. Real digital images. *Remote Sensing of Environment,* 25(3):349–379.

World Wildlife Foundation, 1988. *Censimento delle discariche sul territorio italiano.* WWF Open Report, Rome.

Zilioli, E., M. A. Gomarasca, and R. Tomasoni, 1992. Application of terrestrial thermography to the detection of waste-disposal sites. *Remote Sensing of Environment,* 40(2):153–160.

(Received 10 February 1992; revised and accepted 8 December 1992; revised 22 December 1992)

Call for Nominations ASPRS Vice President

ASPRS is seeking nominations for 1994 Vice President from industry. Nominations must be made by a nominating letter signed by not less than 155 voting members and must contain a biographical sketch of the nominee.

Submit nominations to the Executive Director, 5410 Grosvenor Lane, Suite 210, Bethesda, Maryland, 20814-2160 by Wednesday, December 8, 1993 (20 weeks prior to the day of the 1994 Annual Meeting).

If you have any questions or need additional information, please contact Stanley A. Morain, chair, ASPRS Nominating Committee (505-277-4000).

Call for Nominations ASPRS Fellow and Honorary Member Awards

ASPRS would like to encourage members to submit nominations for its Fellow and Honorary Member awards.

The Fellow Award is relatively new. It is conferred on active Society members who have performed exceptional service in advancing the science and use of the mapping sciences and for service to the Society. Nominees must have been active members of the Society for at least ten years at the time of their nomination.

The Honorary Member Award is ASPRS's highest honor. It recognizes an individual who has rendered distinguished service to the Society and/or who has attained distinction in advancing the science and use of the mapping sciences. It is awarded for professional excellence and service to the Society. Nominees must have been active members of the Society for at least fifteen years at the time of their nomination.

For more information, or to obtain a nomination form for these very special awards, please call Mindy Saslaw at 301-493-0290.