

Effect of Spatial Filtering on Scene Noise and Boundary Detail in Thematic Mapper Imagery

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ABSTRACT: Within-class variation, or scene noise, produces frequent errors in the per-point classification of Thematic Mapper data. To reduce these errors, the imagery is smoothed prior to classification by using various spatial filters. The effect of these filters on the reduction of internal variation within the land cover categories and the preservation of the boundaries between the categories is compared. The variance in each land cover class indicates that the mean filters reduce scene noise to a greater extent than the median filters but analysis of the boundaries under the operation of the mean filters shows them to be more blurred.

The effect on classification is to reduce the spectral class overlap between the more heterogeneous classes while increasing the percentage of unclassified and misclassified pixels near the boundaries. In addition to smoothing scene noise, the median filters preserve boundary detail better. As a result classification accuracies are improved, and there is less misclassification or rejection of boundary pixels.

INTRODUCTION

THE IMPROVED SPATIAL RESOLUTION of Thematic Mapper (TM) of Landsat-4 and Landsat-5, from an Instantaneous Field of View of 79 m to 30 m, has resulted in visually more interpretable images. However, computer interpretations using the standard per-point classifiers have in some cases been less than satisfactory, e.g., Markham and Townshend (1981). Two counteracting effects of increasingly fine spatial resolution on per-point classification have been identified:

- (1) The internal variation (or scene noise) within cover classes is increased (Wiersma and Landgrebe, 1978). For example, scenes of residential areas typically comprise trees, roads, rooftops, and lawns which because of the improved spatial resolution may be incorrectly assigned to their individual component cover types and not to the overall category to which they have been designated. As a result, there will be isolated pixels and groups of pixels whose classification is different from their neighbors.
- (2) The proportion of mixed or boundary pixels is reduced (Townshend, 1980) leading to a corresponding reduction in the number of misclassified or rejected pixels.

The above effects are dependent not only on the spatial resolution of the image but also on the land cover type being classified (Woodcock and Strahler, 1981). Land cover types with a high internal variability will result in additional spectral class overlap or confusion in comparison to classes with low in-

ternal variability. This study is therefore concerned with reducing the scene noise effects within land cover categories where this is necessary, without significantly increasing the proportion of boundary pixels between the categories.

Methods of reducing scene noise previously employed include that of applying an $n \times n$ pixel sized averaging or mean filter to the original imagery prior to per-point classification (Maxwell, 1976; Townshend and Justice, 1981; Dutra and Maschenras, 1984; Toll, 1984). Under this operation, scene detail is smoothed and the gray level range is reduced, but there is an increase in pixels with responses from more than one cover category as the boundaries in the image are blurred (Rosenfeld and Kak, 1982). Silberberg *et al.* (1981) suggest that the image be segmented into regions followed by smoothing within regions. However, the resulting algorithm is computationally complex. An alternative method of preclassification filtering is to smooth the imagery using an $n \times n$ pixel-sized median filter (Atkinson *et al.*, 1985). This type of filter has the advantage of minimizing the loss of boundary detail while still removing scene noise effects (Pratt, 1978).

TM imagery of Reading, U.K., was degraded by using mean and median filters of various sizes and shapes. The operation of each type of filter is outlined, and their effect on the preservation of boundaries and the reduction of scene noise is examined. The ability of the original TM bands to discriminate between the land cover classes is evaluated by using

transformed divergence analysis. The feature combinations selected in this analysis are classified by the maximum likelihood decision rule using both filtered and unfiltered data sets. An assessment is then made of the overall accuracy and class accuracy results.

STUDY AREA

A 512×512 image centered on Reading, U.K. (Plate 1), was selected for its variety of land cover types, the availability of TM data, and the accessibility of ground data to test the results. The TM imagery was acquired on 4 February 1983 from ESRIN, Frascati, and corresponds approximately to the B tapes supplied by the National Aeronautics and Space Administration (NASA) in which no geometric corrections have been applied (Barker *et al.*, 1983). A February scene is not ideal because there is little green vegetation present, and this results in reduced contrast between some classes. However, this scene was the only TM imagery available at this stage of the analysis.

Five classes were selected to represent the major cover types in the area (Table 1) and to correspond to a Level I classification (Anderson *et al.*, 1976). A number of investigations (Campbell, 1981; Craig, 1979; Labovitz and Masuoka, 1984) have shown that Multispectral Scanner data and Thematic Mapper simulation data are highly correlated and suggest that noncontiguous pixels be used to train and test the maximum likelihood classification of Landsat data. Rather than using one large training area per class, several small training sites, each 5×5 pixels square, were randomly located within each cover type to reduce the extent of autocorrelation between pixels (Tubbs, 1979) and to ensure that the variations throughout the scene were represented.

Swain and Davis (1978) suggest a minimum of $10k$ to $100k$ pixels be selected for training a class where k is the number of spectral bands used in the classification. The thermal infrared band was not used because of its much coarser resolution: consequently a maximum of 6 TM bands were used in this analysis, at least 60 pixels per class are required. This is achieved for all the classes except the commercial and industrial area which occupied too small an area to locate randomly sufficient pixels to train the 6 band classifications. The other classifications involved a maximum of 5 bands so the requirement of at least 50 pixels per class is met in all other cases.

SPATIAL FILTERS

Spatial filtering is a context-dependent operation in which the digital value of a pixel is altered according to its relationship with the digital values of the other pixels in the neighborhood or window. Two types of filtering operation are considered in this study.

The averaging or mean filter is a linear operation

in which the central pixel value is replaced by the average digital value of all the pixels within a surrounding window of $n \times n$ size. Under this operation the range of digital values is reduced, and scene noise effects are smoothed, but the boundaries between land cover classes are blurred (Schowengerdt, 1983). The extent of these effects is dependent on the size of the window used in the filtering operation (Rosenfeld and Kak, 1982). A 5×5 pixel sized filter will reduce a greater amount of variance and thus smooth out more scene noise and class boundaries whereas a 3×3 pixel sized filter will result in less blurring of the boundaries but produce less smoothing of scene noise. In these two examples, each of the pixels is given an equal weight of 1 when calculating the average value. By assigning alternative weights to particular pixels within a window, the degree of blurring can be controlled (Rosenfeld and Kak, 1982).

The median filter is a nonlinear operation in which the pixel values within a given window are ranked in ascending order. The central pixel value is then replaced by the median value of all the pixels in the neighborhood. It has been shown that abrupt and gradual changes in discrete signal output are preserved following the use of a one-dimensional median filter of 5 pixel length while isolated noise is eliminated and oscillations are suppressed (Pratt, 1978; Tukey, 1977; Rosenfeld and Kak, 1982). The median filtering technique can be extended to two dimensions by using a filter window of $n \times n$ pixel size. Pratt (1978) has demonstrated that using a 3×3 pixel-sized filter, thin vertical, horizontal, and diagonal lines are destroyed along with isolated noise and the corners of square features. An even greater amount of variance and therefore scene noise is reduced using the larger 5×5 median filter (Narendra, 1981).

A cross-shaped median filter 5 pixels long and wide, in which the value at the center of the cross is replaced by the fifth largest value, may reduce the adverse effects outlined, but the extent of noise suppression is also reduced (Rosenfeld and Kak, 1982; Schowengerdt, 1983). Alternatively, a separable median filter can be used (Narendra, 1981), in which the imagery is filtered using a one-dimensional filter 5 pixels long along the rows, followed by one-dimensional filtering of 5 pixels length along the columns. The output is not identical to the 5×5 square filter because the median of each of the 5 pixels is first found along the rows. The median of these row medians then becomes the final output value. Under this filtering operation the corners of square features with edges parallel to the edges of the image are preserved. The corners of square features orientated at 45 degrees to the image edge will be removed. This is an improvement over the 5×5 square median filter which removed all corners.

To illustrate some of the effects of the mean and

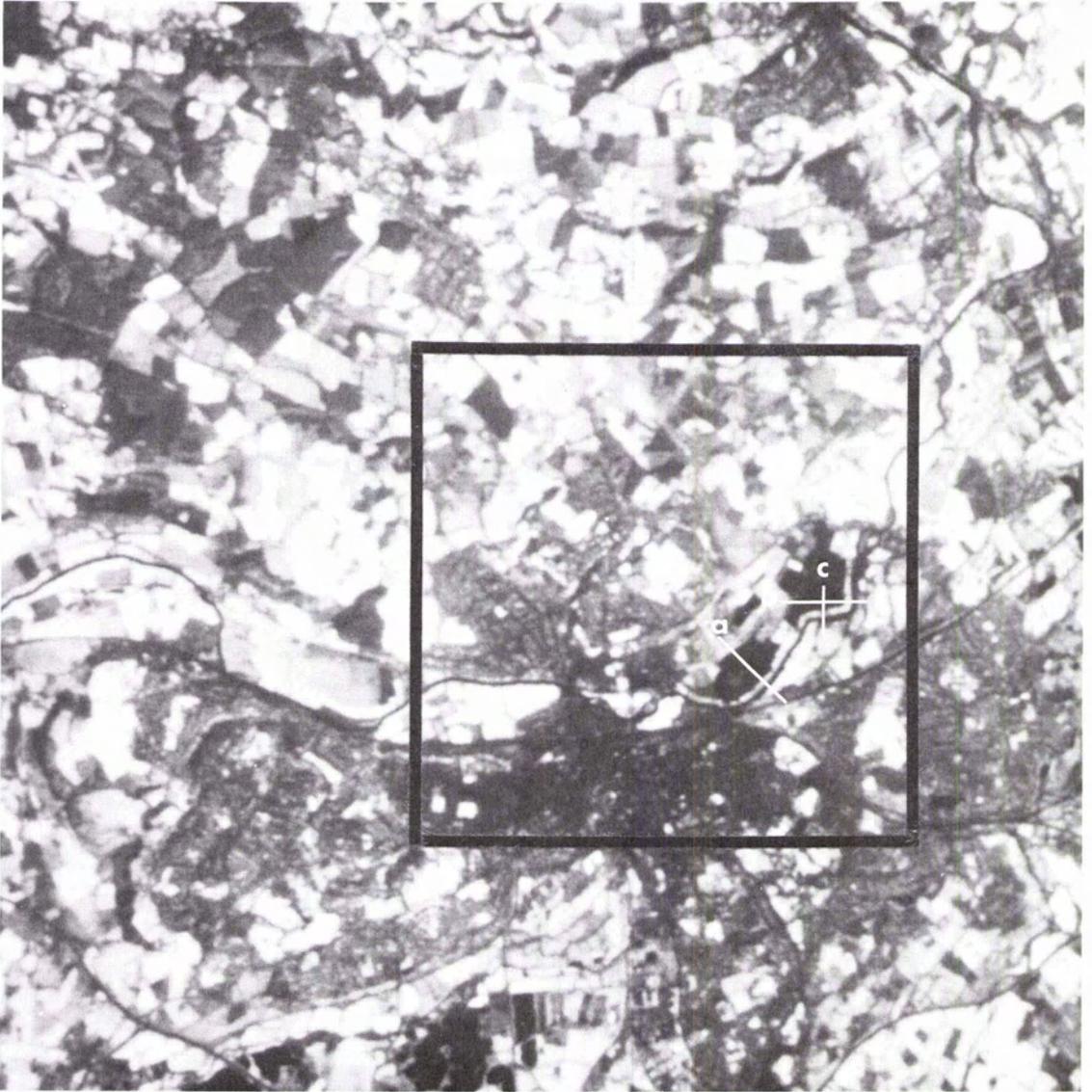


PLATE 1. The Study Area, Thematic Mapper Band 4, Reading, U.K., (512 × 512 scene).

median filters on edges, three dummy images were derived showing a diagonal boundary, a horizontal boundary, and a vertical boundary. Figure 1 illustrates the diagonal boundary. A 5×5 square median filter and a 5×5 square mean filter were each passed over the images. The abrupt gray level change is preserved by the median filter in all three directions. The mean filter, however, has completely blurred the edges. In both cases information of two pixels width is lost around the border of the image. The role of the filtered bands was then assessed using a real data set. Each of the six original Thematic Mapper bands of the Reading scene were smoothed using five separate filter operators. The

filters selected for analysis were the 5×5 square mean filter; the 3×3 square mean filter; the 5×5 square median filter; the 3×3 square median filter; and the separable median filter comprising a one-dimensional filter of 5-pixel length, applied first to the rows and then to the columns.

EFFECT OF THE MEAN AND MEDIAN FILTERS ON THE BOUNDARIES

The digital values in band 4 of the original and filtered TM images were extracted along the cross-sections located on Plate 1, and the resulting histograms are shown in Figure 2. The water-filled gravel

TABLE 1. THE NUMBER OF PIXELS USED TO TRAIN AND TEST THE CLASSIFICATION OF THE LAND COVER CATEGORIES IN THE AREA

| Land cover class | Number of pixels | |
|------------------------------------|------------------|---------|
| | training | testing |
| Suburban: low density residential | 125 | 270 |
| Commercial/Industrial | 50 | 45 |
| Water: lakes and rivers | 125 | 9 |
| Woodland: deciduous and coniferous | 125 | 90 |
| Agriculture: cropland and pasture | 250 | 258 |
| Total | 675 | 702 |

pits and the River Thames were chosen because the variety of boundary types and orientations present are clearly defined in cross-section due to the very different spectral response of the water in comparison to the surrounding land cover. Plates 2a and 2b illustrate the visual effects of filtering the imagery using the 5×5 mean and the 5×5 median filter respectively. Several conclusions can be drawn from the results in cross-section (Figure 2):

- both gradual and abrupt boundaries in the diagonal, horizontal, and vertical directions are better preserved in the median filtered images in comparison to the mean filtered data in which all the edges are blurred.
- The 3×3 median filter preserves both gradual and abrupt boundaries in all three directions to a greater extent than the 5×5 median filter. The 3×3 mean filter only retains the diagonal boundaries better than the 5×5 mean filter.
- The separable median filter preserves only the diagonal boundaries. The horizontal and vertical boundaries are smoothed out. The gradual change in cross-section B (Plate 1 and Figure 2) is also preserved, but this is also orientated at a diagonal.

THE EFFECT OF THE MEAN AND MEDIAN FILTERS ON THE REDUCTION OF SCENE NOISE

The covariance matrices of the digital values in the training areas of each of the classes were used to evaluate the extent to which each of the filters reduced within-class variance. Three examples are given in Table 2 in order to illustrate the varying degrees and scales of internal heterogeneity in the land cover types of the area.

In order to reduce some of the subjectivity of the supervised classification procedure, the training areas had been randomly located within the classes. Consequently, some of the training areas were located near boundaries and this affected the variance results following the filtering operation. This was particularly evident in the water class which comprised gravel pits (Plate 1). In this example mean filtering of bands 4 and 5 using a 5×5 kernel actually increased variance, since the boundaries were blurred and the training areas located near to the boundaries were affected. The 5×5 median filter

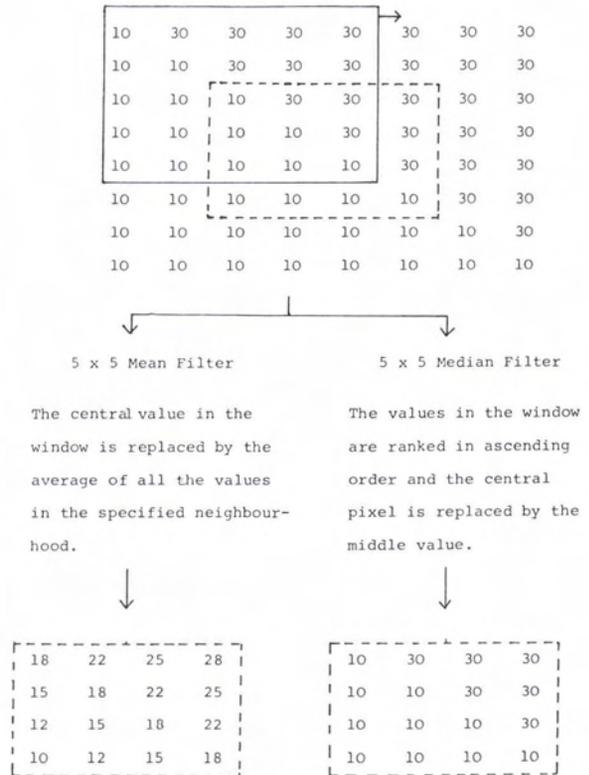


FIG. 1. Diagonal Boundary in Simulated Data. Similar images were also derived to simulate a horizontal and a vertical boundary.

and the 3×3 sized filters did not produce these adverse effects. The other bands were not affected in this way because they do not show the effect of the water-induced variations to such a great extent.

The within-class variance of the residential area was smoothed out to a greater extent following mean filtering in comparison with median filtering. The 5×5 sized filters were also more effective than either the 3×3 sized filters or the separable filter in reducing variance.

The variance of the agricultural class is on a different spatial scale from that in the residential area. Training areas were located within large internally homogeneous fields which comprised several component cover types such as pasture, winter wheat, and bare soil. The variance therefore appears to arise from differences between fields rather than differences within fields.

In all cases, however, the variation has been reduced by spatial filtering. The mean filters normally perform better than the median filters in reducing variance, as do the 5×5 filters when compared to the 3×3 filters or the separable filter. Similar results were found for the commercial and woodland classes. The results for all the classes also indicated the low variability within the February scene.

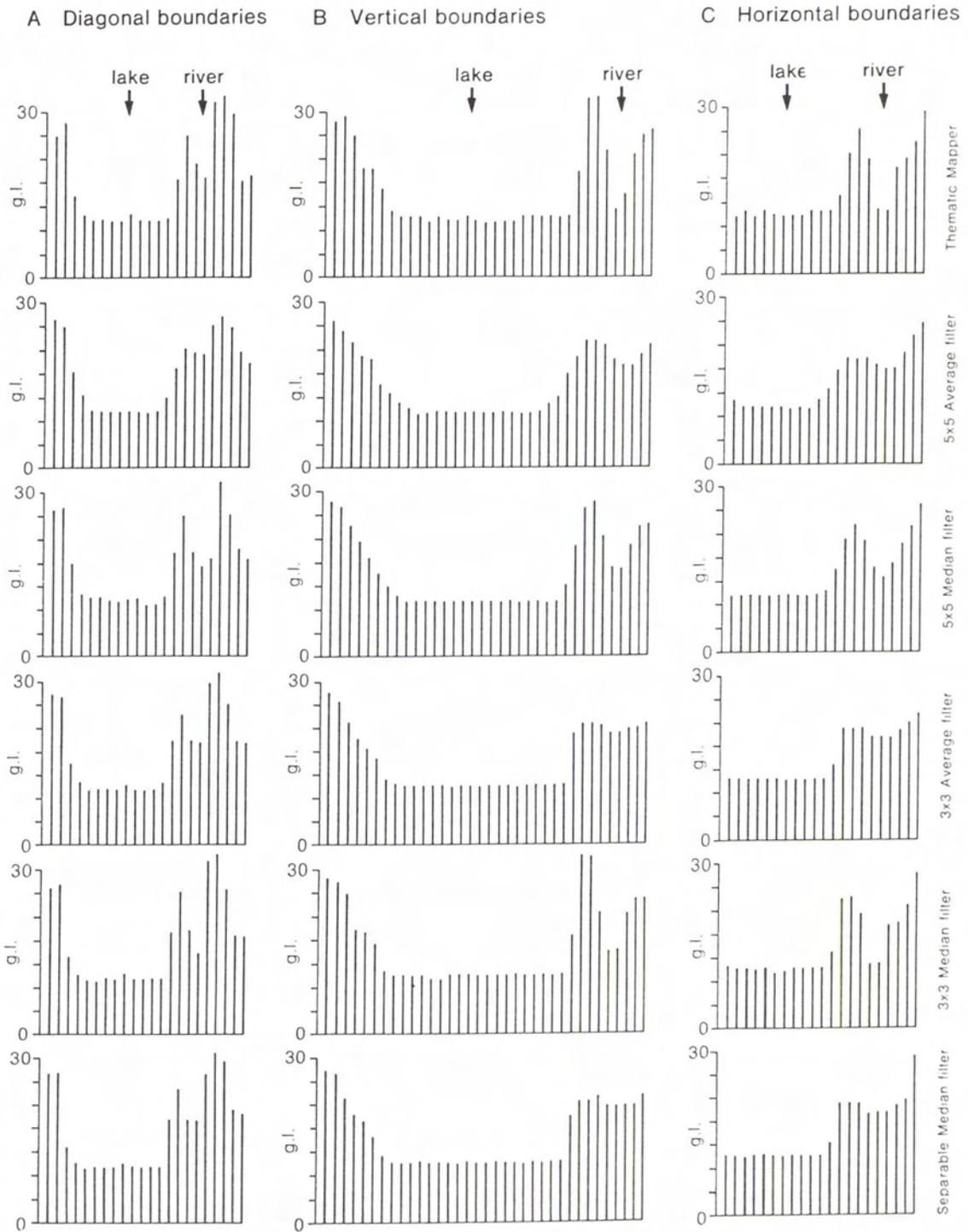


FIG. 2. Digital Values in Band 4 of the Original TM Data and the Filtered Data Sets across the Sections Illustrated in Figure 1.

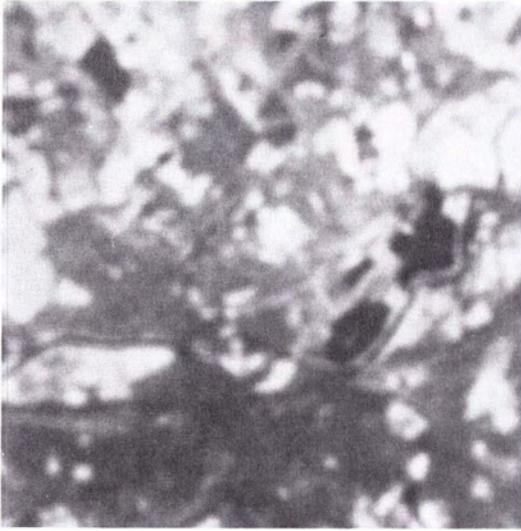


PLATE 2a. 5 × 5 Mean Filtered Band 4 (subscene)



PLATE 2b. 5 × 5 Median Filtered Band 4 (subscene)

MAXIMUM LIKELIHOOD CLASSIFICATION

Combinations of the 2, 3, 4, 5, and 6 bands best able to separate the land cover classes were selected using transformed divergence analysis of the original Thematic Mapper data set. The objective of such a feature selection procedure was to minimize the overall probability of misclassification. Pairwise divergence is a measure of the distance between the probability density distributions of two classes (Swain and Davis, 1978; Singh, 1984). The best feature set to discriminate between the classes is found

by maximizing this distance. Where the number of classes is greater than two, the average pairwise divergence is used to evaluate all possible feature combinations. Transformed pairwise divergence allows for the saturation of the probability of correct classification at 100 percent and has been found to be a superior distance measure when compared with divergence when the average pairwise distance measure is used as a criterion for feature selection (Swain *et al.*, 1971; Kailath, 1967). The results for the transformed divergence analysis of the TM data are given in Table 3.

TABLE 2. THE VARIANCE IN EACH OF THE DATA SETS FOR THE AGRICULTURAL, RESIDENTIAL, AND WATER CLASSES

| Class | Band | Thematic Mapper | 5 × 5 mean filtered | 5 × 5 median filtered | 3 × 3 mean filtered | 3 × 3 median filtered | Separable median filtered |
|-------------|------|-----------------|---------------------|-----------------------|---------------------|-----------------------|---------------------------|
| Agriculture | 1 | 3.79 | 1.87 | 2.24 | 2.13 | 2.55 | 2.28 |
| | 2 | 1.10 | 0.63 | 0.73 | 0.80 | 0.80 | 0.71 |
| | 3 | 2.44 | 1.68 | 1.76 | 1.85 | 1.83 | 1.77 |
| | 4 | 33.16 | 30.99 | 30.71 | 32.01 | 30.91 | 30.74 |
| | 5 | 7.80 | 6.36 | 6.52 | 6.44 | 6.51 | 6.42 |
| | 6 | 5.08 | 3.42 | 3.80 | 3.35 | 3.76 | 3.83 |
| Residential | 1 | 3.09 | 1.18 | 1.36 | 1.32 | 1.50 | 1.62 |
| | 2 | 0.96 | 0.33 | 0.55 | 0.41 | 0.62 | 0.53 |
| | 3 | 1.70 | 0.80 | 0.98 | 0.95 | 1.03 | 1.02 |
| | 4 | 12.98 | 6.84 | 7.41 | 8.64 | 9.17 | 7.63 |
| | 5 | 8.62 | 3.38 | 3.47 | 4.65 | 4.91 | 3.86 |
| | 6 | 3.49 | 0.73 | 0.89 | 0.95 | 0.95 | 1.00 |
| Water | 1 | 3.07 | 0.79 | 0.51 | 0.94 | 0.87 | 0.66 |
| | 2 | 1.64 | 1.16 | 1.29 | 1.62 | 1.33 | 1.31 |
| | 3 | 1.58 | 1.23 | 0.99 | 1.17 | 1.24 | 1.09 |
| | 4 | 0.23 | 1.18 | 0.20 | 0.28 | 0.12 | 0.11 |
| | 5 | 0.73 | 0.95 | 0.32 | 0.36 | 0.33 | 0.43 |
| | 6 | 1.19 | 0.33 | 0.20 | 0.18 | 0.22 | 0.19 |

TABLE 3. THE BANDS SELECTED BY TRANSFORMED DIVERGENCE ANALYSIS AS BEING BEST ABLE TO DISCRIMINATE BETWEEN THE LAND COVER CATEGORIES. THESE BANDS WERE USED IN THE CLASSIFICATION OF THE ORIGINAL TM BANDS AND EACH OF THE FILTERED DATA SETS

| Number of bands to be used in the classification | TM bands selected by transformed divergence analysis | | | | | |
|--|--|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| 2 | | | X | X | | |
| 3 | | | X | X | X | |
| 4 | X | | X | X | X | |
| 5 | X | X | X | X | X | |
| 6 | X | X | X | X | X | X |

- 3 × 3 mean filtered TM channels
- 5 × 5 median filtered TM channels
- 3 × 3 median filtered TM channels
- separable median filtered TM channels

The classes were given equal a priori probabilities of 1.0. A rejection threshold of 0.1 percent was also applied to each class.

ACCURACY ASSESSMENT

Several test areas each 3 pixels square were located randomly within each cover class ensuring no overlap with the training areas. Areas of 3 × 3 pixel size were chosen to test the cover types in the study area more comprehensively than if 5 × 5 pixel-sized areas were used. The number of pixels used to test the accuracy in each class (Table 1) is proportional to the area covered by the class. Thus, although the minimum number of 50 samples per class (Hay, 1979) is not achieved in every category, the errors of omission and commission can be reasonably inferred between the classes. It can also be assumed that the overall accuracy assessments are correct to within ±5 percent at the 95 percent confidence level because the total number of pixels tested (702) exceeds the specified minimum sample size of 400 (Cochran, 1963). The overall accuracy results and the individual class results are plotted in Figures 3 and 5. Figure 4 shows the number of pixels rejected in each of the classifications.

Accuracies of classification using data involving a combination of filtered and original TM data have been shown to be better than when the unfiltered TM data are used alone (Cushnie, 1984; Atkinson *et al.*, 1985). In this analysis the classification of the TM bands is directly compared with the classification of each of the filtered data sets.

Six maximum likelihood classifications involving the five band combinations in Table 3 from each of the following data sets were compared:

- Thematic Mapper (TM) channels
- 5 × 5 mean filtered TM channels

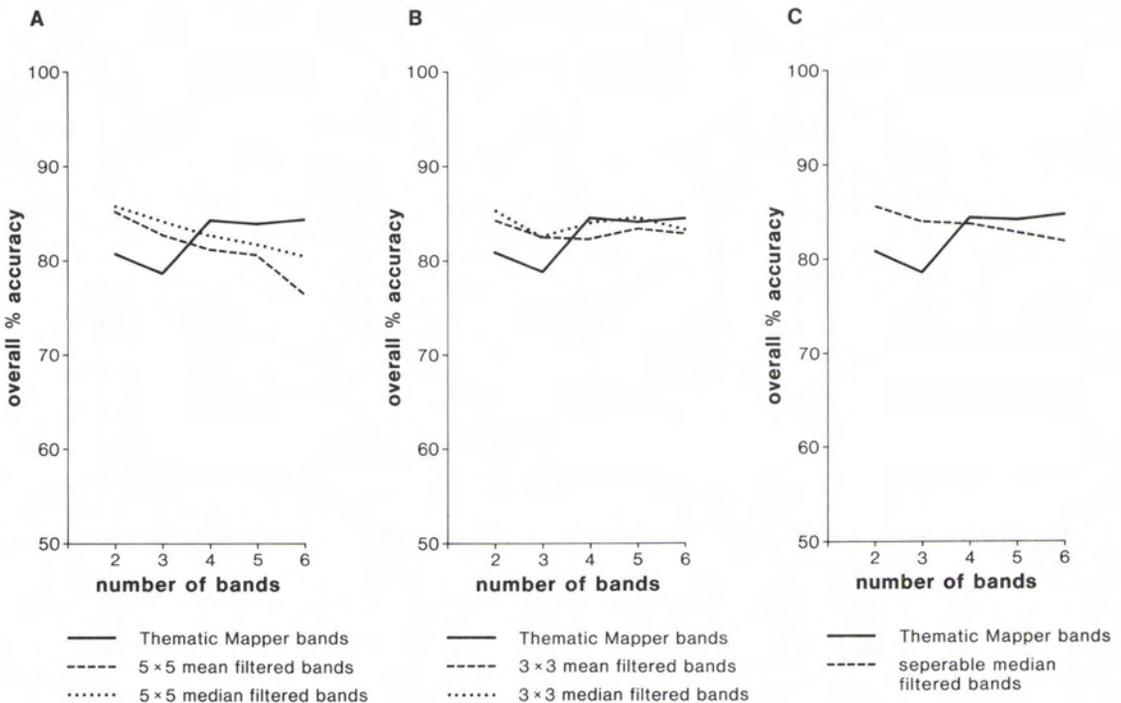


FIG. 3. Overall Percentage Accuracy of Each of the Classifications. Results are within ±5 percent of the true accuracies at the 95 percent confidence levels. The bands used in the classifications are indicated in Table 2.

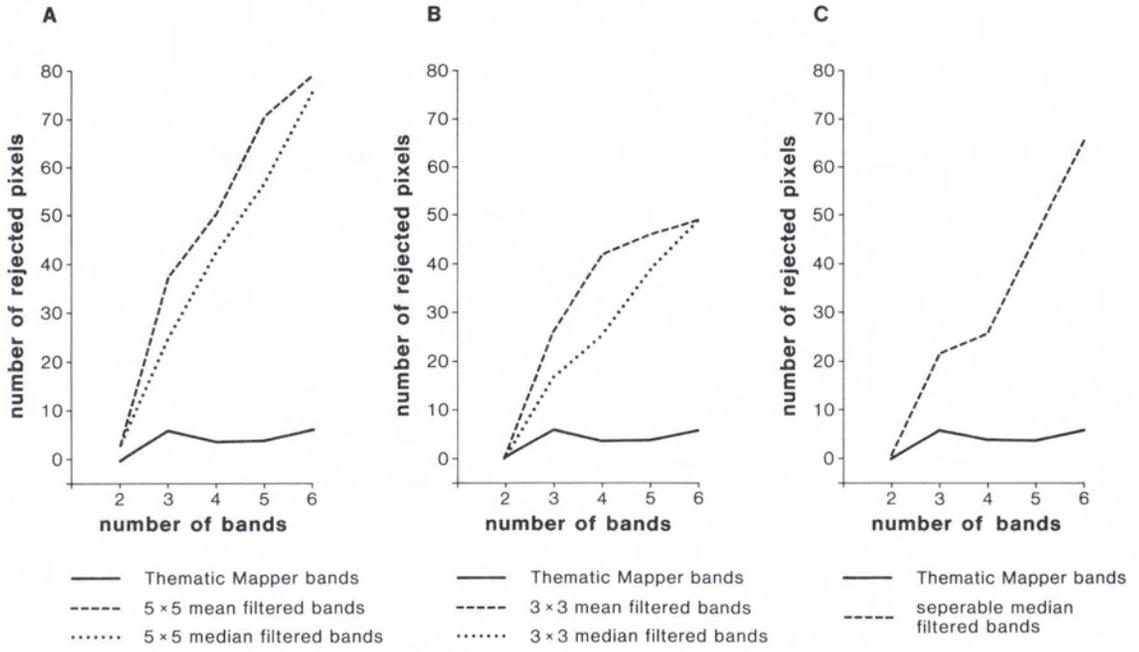


FIG. 4. The Number of Rejected Pixels in Each of the Test Areas.

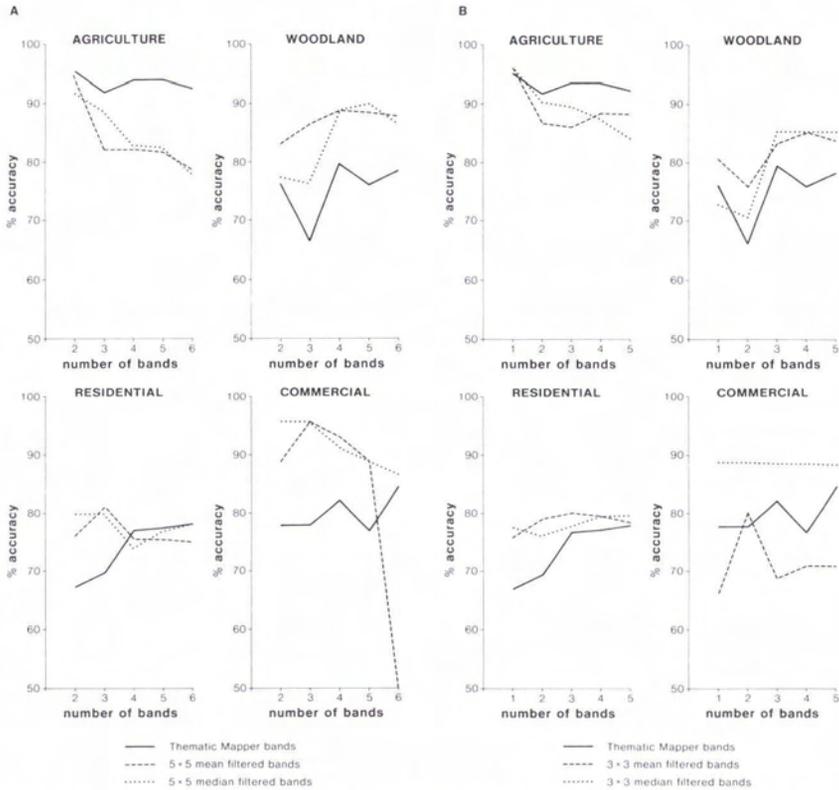


FIG. 5. Percentage Accuracy within Each Land Cover Category. Note that no water was misclassified within the test areas.

CLASSIFICATION RESULTS AND DISCUSSION

CLASSIFICATION USING THE TM BANDS

Overall accuracy in the per-point classification of the original feature vectors improves as the number of bands used in the classification increases. Significant spectral class overlap occurs between the land cover categories characterized by a heterogeneous assemblage of component cover types. For example up to 20 percent of the residential area is misclassified as the woodland category and vice versa. This can be directly attributed to the scene noise effects outlined in the Introduction. Other errors arise with the misclassification of the agricultural areas into the residential class. This could be due to the similarity in spectral response between the bare fields present in this February scene and the bare road and rooftops of the residential area. The hedgerows between the fields will also have a similar spectral response as the hedges and other vegetative areas contribute to portions of the residential category.

CLASSIFICATION USING MEAN FILTERED TM BANDS

By spatially filtering the Thematic Mapper bands prior to classification, scene noise effects are reduced. As a result the confusion between the woodland and residential classes is reduced from 20 percent to 12 percent. The resulting increase in overall

accuracy is counteracted to some extent by the decrease in accuracy of the agricultural class. This can possibly be explained by the fact that with spatial filtering, the boundaries between the agricultural fields (i.e., the hedgerows) are blurred, producing more pixels with a spectral response similar to that of the residential class. These adverse boundary effects increase as more bands are classified with the consequence that overall accuracy decreases. Filtering the data may also result in additional autocorrelation between neighboring pixels in the training areas, contributing to the decline in accuracy as more bands are used in the classification procedure. Smoothing with the 3 x 3 mean filter produced better classification results than using the 5 x 5 filter both in the overall percentage accuracy and in the number of pixels remaining unclassified.

The results for individual classes show that the 3 x 3 filter decreases the mixed pixel effects experienced in the agricultural class following filtering using the 5 x 5 window. Modest improvements of 1 to 5 percent are achieved in the residential class using the 3 x 3 filter compared with the 5 x 5 filter. These 3 x 3 filter results are in turn up to 10 percent higher than those achieved using the unfiltered TM bands. In the woodland category the converse is true. The 5 x 5 filter results are 3 to 10 percent higher than the 3 x 3 filter results. This may be attributed to the varying scales of internal heterogeneity within the woodland and residential classes which are affected differently depending on the size of the filter.

The erratic behavior in the accuracy of classification of the commercial area as more mean filtered bands are used can possibly be explained by the increased dimensionality for the reasons outlined by Landgrebe (1978). Only 50 pixels were used to train the commercial class, and as an increasing amount of information is being derived from this fixed number of samples, the accuracy is adversely affected.

CLASSIFICATION USING THE MEDIAN FILTERED BANDS

Generally the trends observed under the classification of the bands smoothed using the mean filters, were also present in the classification result of the median filtered bands. However, the overall accuracy results are 1 to 4 percent higher using the median filtered bands when compared with the results using the mean filtered bands. This can be attributed to the fact that fewer pixels remain unclassified particularly under the operation of the 3 x 3 median filter. There does not appear to be a significant difference between the effect of the square mean and median filters on the individual class results except in the agricultural class where fewer misclassifications into the residential class occur under the operation of the median filters.

The separable median filter produces an improvement of up to 5 percent over the equivalent classi-

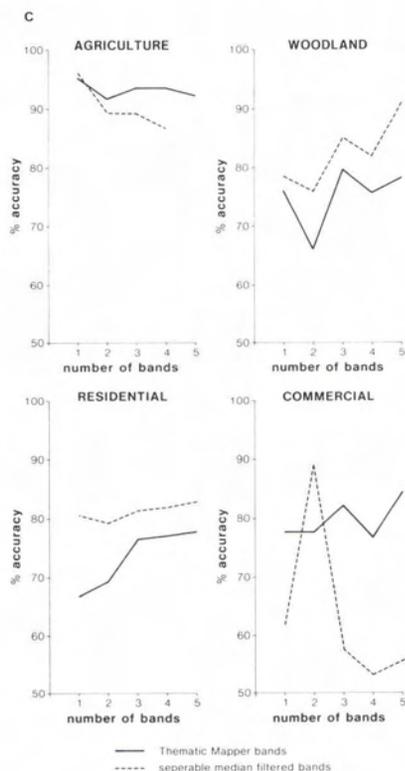


FIG. 5. Continued

fications using the 3×3 mean and median filters and up to 10 percent improvement over the classifications using the 5×5 mean and median filters in the residential category. This suggests that the spectral class overlap between the residential and the woodland classes is best reduced using the separable median filter.

CONCLUSIONS

It can be concluded that spatial filtering of TM data improves the separability of Level I land cover classes particularly those characterized by a heterogeneous assemblage of component cover types as their internal scene noise effects are reduced. As a result there is an overall improvement in the classification accuracy of filtered data when compared with the classification accuracy of TM data.

It is less evident from the results which shape or type of filter is the best to employ in the spatial filtering procedure. The results for overall accuracy and the number of rejected pixels indicate that the proportion of mixed pixels increases when TM data are smoothed using the mean filters since the boundaries between the land cover classes are blurred. These mixed pixels are usually either rejected or misclassified. The square median filters have better boundary-preserving properties, so by using these filters to smooth the TM data the proportion of pixels being misclassified or rejected can be reduced.

The use of the smaller window size in the filtering operation reduces the adverse effects at the boundaries while still smoothing out some scene noise effects. The classification results following the use of the separable filter suggest that the effect of alternative filter shapes both between land cover classes and within land cover classes, needs to be examined further.

Smoothing may introduce additional autocorrelation effects between neighboring pixels. This may explain some of the decrease in accuracy experienced as more filtered bands are classified. In order to establish if this is the case, the classification could be carried out using noncontiguous training pixels.

The individual class results suggest that the effect of spatial filtering is dependent on the extent and nature of the internal variability of a category in relation to the size and shape of the filter used. Further research will involve increased sample sizes both for training and testing in order to establish which is the best filter to employ and for which categories. Initial indications are that spatial filtering is beneficial to a Level I classification of TM data and that some form of median filtering is a slight improvement over mean filtering due to the better boundary-preserving properties of the median filter.

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REFERENCES

- Anderson, J. R., Hardy, E. E., Roach, J. T., and Witmer, R. E., 1976. A land use and land cover classification system for use with remote sensor data: U.S. Geological Survey, Professional Paper 964.
- Atkinson, P., Cushnie, J. L., Townshend, J. R. G., and Wilson, A., 1985. Improving Thematic Mapper land cover classification using filtered data: *International Journal of Remote Sensing* (in press).
- Barker, J., Gunther, F. J., Abrams, R. B., and Ball, D., 1983. TM digital image products for applications, in: *Landsat-4 Science Investigations Summary, Feb. 83 and Dec. 83*: NASA Conference Publication 2326, Vol. I, pp. 116-126. National Aeronautics and Space Administration, Goddard Space Flight Center, Greenbelt, MD.
- Campbell, J. B., 1981. Spatial correlation effects upon accuracy of supervised classification of land cover: *Photogrammetric Engineering & Remote Sensing*, v. 47, p. 553.
- Cochran, W. G., 1963. *Sampling Techniques*: John Wiley & Sons, New York.
- Craig, R. G., 1979. Autocorrelation in Landsat data: *Proceedings of the 13th International Symposium on Remote Sensing of the Environment*, Ann Arbor, Michigan, pp. 1517-1524.
- Cushnie, J. L., 1984. Improving the accuracy of computer classification of Thematic Mapper data: *Proceedings of the 10th Anniversary Conference on Satellite Remote Sensing: Reviews and Previews*, Reading, UK, 18-21 Sept. 1984, pp. 329-338.
- Dutra, V. L., and Mascarenhas, N. D. A., 1984. Some experiments with spatial feature extraction methods in multispectral classification: *International Journal of Remote Sensing*, v. 5, pp. 303-313.
- Hay, A. M., 1979. Sampling designs to test land use mapping accuracy: *Photogrammetric Engineering & Remote Sensing*, v. 45, pp. 529-533.
- Kailath, T., 1967. The divergence and Battacharyya distance measures in signal selection: *IEEE Transactions on Communication Theory*, v. COM-15, pp. 52-60.
- Labovitz, M. L., and Masuoka, E. J., 1984. The influence of autocorrelation in signature extraction: *International Journal of Remote Sensing*, v. 5, pp. 315-332.
- Landgrebe, D. A., 1978. Useful information from multispectral image data: Another look: in *Remote Sensing: The Quantitative Approach*, (eds. P. H. Swain and S. M. Davis), McGraw-Hill Inc., New York, pp. 343-347.
- Markham, B. L., and Townshend, J. R. G., 1981. Land cover classification accuracy as a function of sensor spatial resolution: *Proceedings of the 15th International Symposium on Remote Sensing of the Environment*, Vol. III, Ann Arbor, Michigan, pp. 1075-1090.
- Maxwell, E. L., 1976. Multivariate systems analysis of

- multispectral imagery: *Photogrammetric Engineering & Remote Sensing*, v. 42, pp. 1173-1186.
- Narendra, P. M., 1981. A separable median filter for image noise smoothing: *IEEE Transactions on Pattern Analysis and Machine Intelligence*, v. PAMI-3, no. 1, pp. 20-29.
- Pratt, W. K., 1978. *Digital Image Processing*: John Wiley & Sons, New York, pp. 330-333.
- Rosenfeld, A., and Kak, A. C., 1982. *Digital Picture Processing*, Vol. 1: Academic Press Inc., London, pp. 261-267.
- Schowengerdt, R. A., 1983. *Techniques for Image Processing and Classification in Remote Sensing*: Academic Press Inc., London, pp. 187-190.
- Silberberg, T., Peleg, S., and Rosenfeld, A., 1981. Multi-resolution pixel linking for image smoothing and segmentation: in *Techniques and Applications of Image Understanding*, (ed. J. J. Pearson), The International Society for Optical Engineering, Washington SPIE Vol. 281, pp. 625-627.
- Singh, A., 1984. Some clarifications about pairwise divergence measure in remote sensing: *International Journal of Remote Sensing*, v. 5, pp. 625-627.
- Swain, P. H., 1978. Fundamentals of pattern recognition in remote sensing: in *Remote Sensing: The Quantitative Approach*, (eds. P. H. Swain and S. M. Davis), McGraw-Hill Inc., New York, pp. 148-152 and 166-167.
- Swain, P. H., Robertson, T. V., and Wacker, A. G., 1971. Comparison of divergence and B-distance in feature selection: *LARS Information Note 020871*, Laboratory for Applications of Remote Sensing, West Lafayette, IN, 12 pp.
- Toll, D. L., 1984. Landsat-4 Thematic Mapper scene characteristics for a suburban and regional test site: *Landsat-4 Science Investigations Summary, Feb. 83 and Dec. 83*, NASA Conference Publication 2326, Vol. II, National Aeronautics and Space Administration, Goddard Space Flight Center, pp. 153-159.
- Townshend, J. R. G., 1980. The spatial resolving power of the Earth Resources Satellites: A review: National Aeronautics and Space Administration, *NASA Technical Memorandum 82020*.
- Townshend, J. R. G., and Justice, C., 1981. Information extraction from remotely sensed data: A user view: *International Journal of Remote Sensing*, v. 2, pp. 313-329.
- Tubbs, J. D., 1979. Classification results using spatially correlated Landsat data: in *Proceedings of the 13th International Symposium on Remote Sensing of the Environment*, Ann Arbor, Michigan, pp. 1499-1505.
- Tukey, J. W., 1977. *Exploratory Data Analysis*. Addison-Wesley Publishing Company, Reading, Massachusetts, pp. 205-214.
- Wiersma, D. J., and Landgrebe, D. A., 1978. The analytical design of spectral measurements for multispectral remote sensor systems: West Lafayette, Indiana, Laboratory for Applications of Remote Sensing, *LARS Technical Report 122678*.
- Woodcock, C. E., and Strahler, A. H., 1983. Characterising spatial patterns in remotely sensed data: in *Proceedings of the 17th International Symposium on Remote Sensing of the Environment*, Ann Arbor, Michigan. Vol. II, pp. 839-851.

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