

URBAN SPATIAL ATTRIBUTES FROM SATELLITE REMOTE SENSING USING END MEMBER ANALYSIS AND VARIABILITY MEASURES.

BRUCE C. FORSTER

CHEN XING

School of Surveying
and Centre for Remote Sensing

University of New South Wales

Sydney
Australia

ABSTRACT:

The radiometric response from urban residential areas is due to a complex mixture of both synthetic and natural surfaces, and is also considered to vary as a function of the spatial distribution of housing units and the spatial resolution of the remote sensing systems. A background is provided to research previously undertaken that has used response variability and methods of end number analysis to monitor and map urban areas using satellite remote sensing data. Current research using SPOT HRV and Landsat TM data collected over the city of Sydney is described, which analyses the relationship between coefficient of variation, over a neighbourhood of pixels, and housing density and house size.

KEY WORDS: Urban, Remote Sensing, Spatial Variability.

1. INTRODUCTION

The effects of increasing urbanisation are being felt throughout the world in both developed and developing countries alike. It is therefore important that the most timely and detailed information is available to aid forward planning in urban areas. Satellite remote sensing can provide some of this information.

However there are a number of difficulties associated with the use of satellite remote scanning data to map and monitor urban areas. These relate particularly to the complexity of the urban landscape which exhibits an extremely heterogeneous surface cover, with considerable interpixel and intrapixel change occurring. This variation severely limits the standard clustering approach to classification where it is assumed that the area of study is comprised of a number of unique and internally homogeneous classes. Further the response recorded by a sensor system is very dependent on the systems ground resolution, and associated point spread function effects.

2. PREVIOUS RESEARCH

The urban complexity and varying sensor resolution have, led a number of researchers to consider the use of textural data, in addition to spectral data, and the use of end-number analysis (ie. the prediction of the proportion of a surface contained within a pixel), for the extraction of urban information from satellite data.

Early research using textural data was undertaken by Todd and Baumgardner (1973) using Landsat MSS data. In this study over Marion County (Indian), a response data was averaged over a number of contiguous picture elements prior to classification. In addition parameters such as mean, range, standard deviation, and correlation coefficients (between spectral bands) were utilised in the classification. They found that the most useful parameters for class separation were the means and standard deviations in the Landsat MSS infrared bands, and it was reported that recognition of urban classes was virtually 100% correct. Swain (1976) also tested a number of auxiliary techniques, for application in land use classification, with less positive results. Various texture measures were used, but Swain reported that virtually no improvement in classification occurred when using combinations of textural and spectral data, compared to the use of spectral data alone. Forster (1983) also incorporated textural data into a study of the Sydney (Australia) urban complex using Landsat MSS data. This study attempted to disaggregate the response from a single pixel into its component parts that derived from the individual surfaces, such as grass, trees, roofs, concrete and bitumen. It was found for most urban surfaces that the prediction of cover percentages were significantly improved by the inclusion of standard deviation over an 8 by 5 pixel array. Forster (1985) further suggested that variance over an array of pixels would increase to a maximum then decrease as housing density increased. He considered that for a homogeneous extended surface that response at a sensor would show little variation. However homogeneity was dependent on both pixel size and the elements being viewed. He indicated that variance of the response over a pixel neighbourhood would increase as the pixel size approached the size of the urban elements and would then reduce as the size of the pixel continued to decrease. He suggested that the resolutions of Landsat TM and SPOT HRV were approaching the optimum for maximum textural discrimination of surface features typically found in medium to low - density cities. It necessarily followed, he said, that for a constant pixel size variance would pass through a maximum as building density varied from high to low. This concept is illustrated in figure 1.

Woodcock and Strahler (1987) considered this concept in some detail for a number of different classes of land use and followed on from earlier work, Strahler et al (1986) and Woodcock and Strahler (1985), primarily related to forest classes. They went onto say that if the

spatial resolution was considerably finer than the objects in the scene, most of the measurements in the image would be highly correlated with their neighbours and a measure of local variance would be low. If the objects approximated the size of the resolution cells, then the likelihood of neighbours being similar decreases, and the local variance rises, and as the size of the resolution cells increased and many objects were found in a single resolution cell, the local variance would decrease. This was essentially the same concept Forster (1985) proposed for urban areas. For a real urban situation Woodcock and Strahler (1987) estimated a peak variance occurring at 10 and 15 metres, for a residential development in California. The concept was further elaborated by Forster and Jones (1988) and Takeuchi and Tomita (1988) for urban areas.

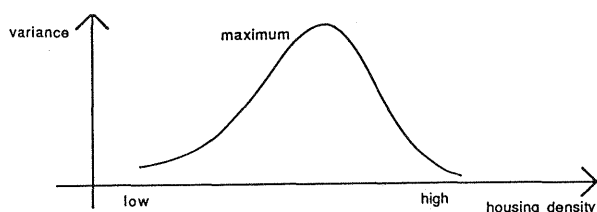


Figure 1. Schematic relationship between response variance and increasing housing density.

In the latter papers pseudo-satellite data was generated from airborne multispectral scanner data to give data of resolutions 5, 10, 20, 30, 50 and 80 metres. Classification of urban structures (low-rise versus high rise, and low-density versus high density) was undertaken using a local density average and a local density variation of the multispectral images. The correlation of these two variables was shown to have the highest classification performance at ground resolutions of 20 and 30 metres.

Research by Ng (1990) was directed at modelled urban environments of three housing densities and three house size categories, a total of nine housing classes. He simulated the response of a 3 x 3 array moved across these modelled environments for pixel sizes of 5, 10, 20, and 30 metres, and examined the standard deviations resulting for each pixel size and for visible and near infrared modelled responses. He showed that six of the housing classes could be separated on the basis of mean and standard deviation using the equivalent of a 10 metre resolution near infrared sensor system. He further showed that a combination of the 10, 20 and 30 metre pixel sizes would allow discrimination of all nine classes. Other researchers have approached the problem of urban heterogeneity by attempting to unmix mixed pixels into their component parts. Forster (1983) used a method of inverse regression to separate urban cover types. A number of approaches to unmixing or end member analysis have been suggested by Settle, Craig, Smith et al, Bierwith, and Makin et al (all 1990) for a number of non-urban applications. Shimabukoro et al (1988) used a constrained least squares method to derive the proportion of shade in forested areas.

Many of these approaches are not as suitable in their application to urban areas because of the large number of cover classes involved and the limited number of spectral bands available from current satellite remote sensing systems. Research currently being undertaken at the University of New South Wales is examining the initial reduction of cover classes using near-infrared to visible response ratios, which essentially provide constant ratios for vegetated surfaces and for synthetic

surfaces, in the two dimensional spectral space, and allows the estimation of proportions for mixed pixels. An alternative linear programming approach that constrains the proportion values to be non - negative, and for the proportions to add to one, is also being researched.

Current research at the University of New South Wales is also examining the use of response variance as an input to the prediction of residential housing density and residential house size. This research will be now described in more detail.

3. HOUSING DENSITY AND HOUSE SIZE

This section provides preliminary results from an analysis of thirty residential sites over the Sydney (Australia) metropolitan area, using both Landsat Thematic Mapper (TM) and SPOT HRV panchromatic (P) and multispectral (XS) mode data, that show that both house size and housing density are determinants of radiometric variability. It is recognised that sensor spatial resolution and pixel size are not the same, due to sensor point spread function effects, however, to simplify the analysis a pixel is considered equivalent to a ground resolution element in the following discussion.

Thirty sites of dimension 180 metres by 180 metres, were selected over the Sydney Metropolitan area, to represent a range of single dwelling densities and house sizes. Using aerial photographs a sampling procedure was designed to allow the collection of

- (a) housing density
- (b) percentage of cover types
- (c) house size and
- (d) radiometric response and response coefficient of variation over a 60 metre by 60 metre neighbourhood, for data from SPOT HRV P and XS modes, and Landsat TM (excluding TM Band 6, thermal infrared). SPOT HRV data were acquired in October 1986 and Landsat TM data in September 1985.

The sampling framework for an individual site is illustrated in figure 2.

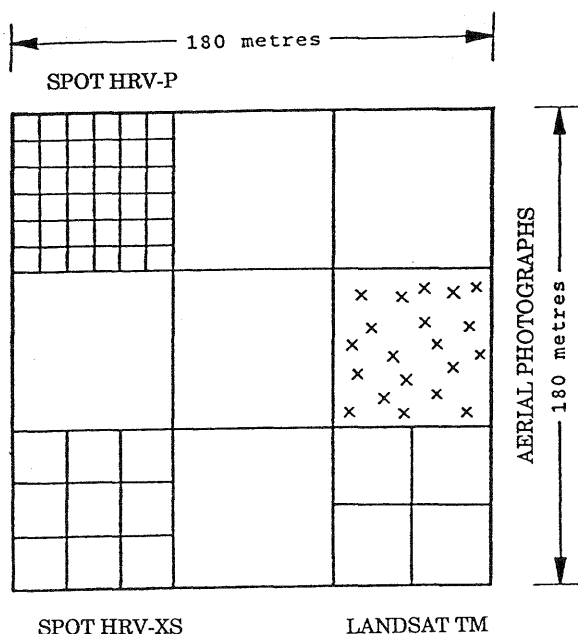


Figure 2. Illustration of the sampling procedure, showing the primary 180 metre x 180 metre sampling unit, the size of the pixels for the various sensing systems and the random samples from aerial photography.

The 180 metre by 180 metre primary sampling cell was divided into 9 secondary cells. Colour aerial photography was used to sample the percentage of cover type and the number of houses in each secondary cell. Average house size was then determined by dividing the percentage house cover by the number of houses in each cell. These values were averaged to give mean values over the primary site for house size in square metres and housing density in housing units per hectare. Housing densities and house sizes ranged from 5 to 25 units per ha (mean 11.2) and 150 to 400 m² (mean 258), respectively, over the thirty sites.

The remotely sensed data were registered and resampled to the ground so that each secondary cell contained 4 Landsat TM pixels, 9 SPOT HRV XS-mode pixels and 36 SPOT HRV P-mode pixels. For each the mean and coefficient of variation were determined. These values were then averaged over the 180 metre by 180 metre primary cells.

An examination of the relationship between house size, housing densities and coefficient of variation for different pixel sizes was undertaken using SPOT HRV P-mode, SPOT HRV XS Band 1 and Landsat TM Band 2 data. It was considered that these data sets represented approximately the same spectral range so that any change in the coefficient of variation would be solely due to the spatial distribution of the urban elements, rather than due to varying spectral response. To allow the data to be compared it was considered that more appropriate measures of housing characteristics were house size as a proportion of a pixel and house numbers per pixel, rather than in square metres and units per hectare. That is the average house size as a proportion of the area of a pixel and the number of house units per pixel with respect to the 100, 400 and 900 m² pixel area of the three satellite sensors. Practically these data provide the equivalent of a much greater range of densities and house sizes for a unit pixel area. Regression analysis was used to relate these transformed house sizes and house numbers to the coefficients of variation.

4. RESULTS OF ANALYSIS

Because of the wide range of values of house size and density, it was considered appropriate to use logarithmic values of these variable to give regression equations of the following form.

$$\text{Log}_{10} S = a_0 + a_1 C + a_2 C^2$$

$$\text{and } \text{Log}_{10} N = b_0 + b_1 C + b_2 C^2$$

where S = House size as a proportion of pixel size
 N = House numbers per pixel
 C = Coefficient of variation for SPOT HRV P, SPOT HRV XS Band 1 and Landsat TM Band 2 data
 and a_i and b_i are regression coefficients.

Ninety values were used in the regression (30 sites and 3 sensors) to give the following regression equations and multiple correlations (r)

$$\text{Log}_{10} N = 1.01 - 22.23C + 56.45C^2 \quad \dots(1)$$

$$r = 0.75 \text{ with an F-value of } 56 \text{ and}$$

$$\text{Log}_{10} S = -1.57 + 21.67C - 52.35C^2 \quad \dots(2)$$

$$r = 0.79 \text{ with an F-value of } 72$$

Both these equations show significant relationships and a plot of the curves are shown in figure 3 and figure 4.

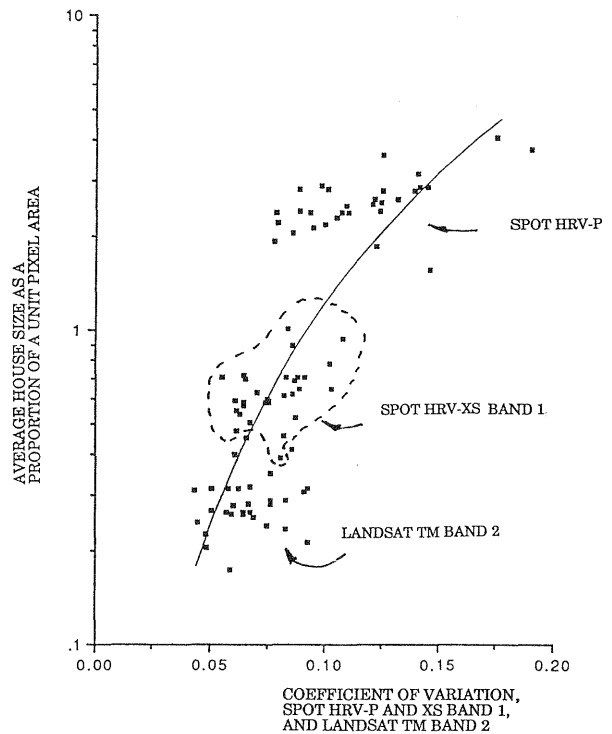


Figure 3. House size per pixel (log₁₀ scale) as a function of coefficient of variation of SPOT HRV-P and XS band 1, and Landsat TM band 2.

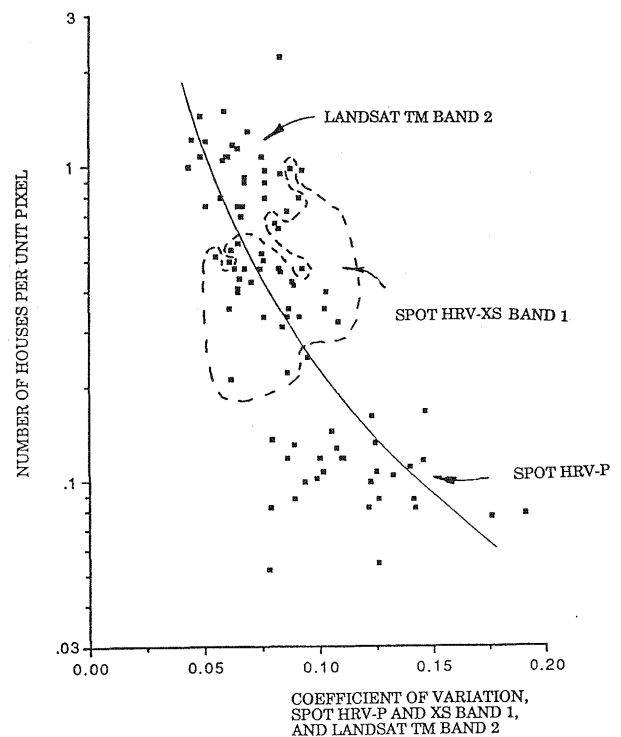


Figure 4. House number per pixel (log₁₀ scale) as a function of coefficient of variation of SPOT HRV-P and XS band 1, and Landsat TM band 2.

It is apparent that CV (coefficient of variation) from figure 3 increase with house size, which is expected from a theoretical consideration, but does not show the expected decrease as house size increases to a saturating level. Analysis of percentage cover and

house size data showed a positive correlation ($r = 0.45$) between house size and percentage tree cover, which may obscure the theoretical decline expected as house size increases. Equally apparent, from figure 4, is the decline in CV as house numbers per pixel increase, resulting in a greater interpixel homogeneity. Nevertheless the theoretical drop in CV as house numbers reduce is not found.

From the results of equations 1 and 2, it is apparent that both housing density and house size are factors determining CV. It was therefore considered appropriate to examine this relationship in more detail, for only one of the satellite data sets. SPOT HRV XS band 2 (visible red) was chosen for this purpose.

It was considered from the previous results that the relationship between house size and coefficient of variation may vary depending upon the density of the housing. To test this is a regression analysis of size versus CV, stratified on the basis of housing density, was undertaken.

Dummy variables were introduced into the regression to effect the stratification, which allowed three separate equations for each density strata to be determined as follows

$$S_1 = 0.13 + 2747.79CX_2 \quad \dots(3)$$

$$S_2 = 232.15 + 247.42CX_2 \quad \dots(4)$$

$$S_3 = 321.16 - 1038.97CX_2 \quad \dots(5)$$

where S_1 is house size, in m^2 , for $N < 8.5$ houses per ha,

S_2 is house size, in m^2 , for $8.5 < N < 12.5$ houses per ha, and

S_3 is house size, in m^2 , for $N > 12.5$ houses per ha, and

CX_2 is CV of SPOT HRV XS band 2.

(Note that $r = 0.83$ and $F = 10$ for the overall regression containing the dummy variables).

Equation 3 and 4 show a strong positive relationship between house size and CV for low density areas and a strong negative relationship for high density areas. A plot of these relationships are shown in figure 5. Areas of medium density tend to have similar house sizes and a wide range of coefficients of variation. These results, however, should be treated with some caution because of the limited number of values in each housing strata, and the possible interacting effect of tree cover.

5. SUMMARY AND CONCLUSIONS

A consideration of past research showed that textural measures in addition to spectral values, could also be used to advantage in the analysis and classification of urban areas from satellite remotely sensed data. An analysis of thirty residential sites over the city of Sydney has shown that the relationship of house size and housing density to coefficient of variation is quite strong and shows a strong interrelationship between all three variables. It is considered that the relationship, however, may be confused by variations in tree cover, and this effect should be examined in future research.

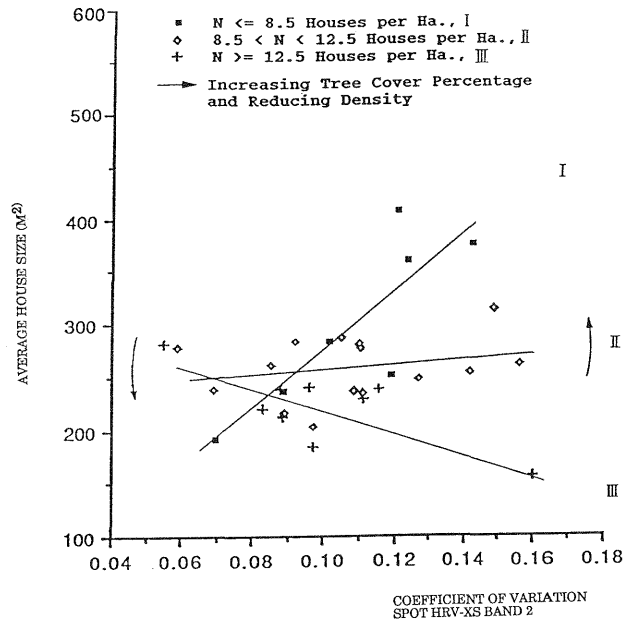


Figure 5. House size in square metres, stratified by housing density (N houses per hectare, for stratas I, II and III) as a function of coefficient of variation in SPOT HRV-XS band 2.

REFERENCES

- Bierwith, P.N. Mineral and vegetation mapping over Mound Spring deposits near Lake Eyre: An application of data - calibrated pixel unmixing using Landsat TM data In: Proc. Fifth Australasian Rem. Sens. Conf., Perth Australia, Vol. 1, pp 341-351.
- Craig, M., 1990. Unsupervised unmixing of remotely sensed images. In: Proc. Fifth Australasian Rem. Sens. Conf., Perth, Australia, Vol. 1, pp 324-330.
- Forster, B.C., 1983. Some urban measures from Landsat. Photo. Eng. and Rem. Sens., 49, 1693-1707.
- Forster, B.C., 1985. An examination of some problems and solutions in monitoring urban areas from satellite platforms. Int. J. of Rem. Sens., 6, 139-151.
- Forster, B.C. and Jones, C., 1988. Urban density monitoring using high resolution space borne systems. In: Int. Arch. Photogramm. Rem. Sens., Kyoto, Japan, Vol. 27, Part B9, pp VII 189-VII 195.
- Ng, T.K., 1990. Predicting residential housing density and housing size with satellite imagery using simplified models. Research Project Report, Master of Engineering Science, Univ. of New South Wales, Sydney, Australia.
- Settle, J.J., 1990. Contextual models and the use of Dirichlet priors for mixing problems. In: Proc. Fifth Australasian Rem. Sens. Conf., Perth, Australia, Vol. 1, pp 314-323
- Shimabukuro, Y.E., Haertel, V.F.A., Smith, J.A., 1988. Landsat derived shade images of forested areas. In: Int. Arch. Photogramm. Rem. Sens., Kyoto, Japan, Vol. 27, Part B7, pp 534-543.
- Smith, M.O., Adams J.B. and Gillespie A.R. Reference endmembers for spectral mixing analysis. In: Proc. Fifth Australasian Rem. Sens. Conf., Perth, Australia, Vol. 1, pp 331-340.

Strahler, A.H., Woodcock, C.E., and Smith, J.A., 1986. On the nature of models in remote sensing. *Rem. Sens. of Environment*, 20, 121-139.

Swain, P.H., 1976. Land use classification and mapping by machine-assisted analysis of Landsat multispectral scanner data. LARS Information Note, 111276, Purdue, U.S.A.

Takeuchi, S and Tomita, T, 1988. Evaluation of some spectral and spatial features of satellite images using airborne MSS data for the analysis of urban areas. In: *Int. Arch. Photogramm. Rem. Sens.*, Kyoto, Japan, Vol. 27, Part B7, pp 599-606.

Todd, W., and Baumgardner, M.F., 1973. Land use classification of Marion County, Indiana, by spectral analysis of digitized satellite data. LARS Information Note, 101673, Purdue, U.S.A.

Woodcock, C.E., and Strahler, A.H., 1985. Relating ground scenes to spatial variation in images. In: *Proc. Third NASA Conf. on Mathematical Pattern Recognition and Image Analysis*, Texas A and M University, pp 393-449.

Woodcock, C.E., and Strahler, A.H., 1987. The factor of scale in remote sensing. *Rem. Sens. of Environment*, 21, 311-332.