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# The potential of kernel classification techniques for land use mapping in urban areas using 5m-spatial resolution IRS-1C imagery

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**Abstract.** Two techniques, integrating texture and spatial context properties for the classification of fine spatial resolution imagery from the city of Athens (Hellas) have been tested in terms of accuracy and class specificity. Both techniques were kernel based, using an artificial neural network and the kernel reclassification algorithm. The study demonstrated the high potential of the kernel classifiers to discriminate residential categories on 5 m-spatial resolution imagery. The overall accuracy percentages achieved were 73.44% and 74.22% respectively, considering a seven-class classification scheme. The adopted scheme was subset of the nomenclature referred to as 'Classification for Land Use Statistics Eurostat's Remote Sensing programme' (CLUSTERS) used by the Statistical Office of the European Communities (EUROSTAT) to map urban and rural environment.

## 1. Introduction

Information on land use is very important to support management and planning activities in urban areas. Traditional methods like ground surveys and aerial photography typically provide a lot of the needed information. However, they are costly and difficult to apply in a systematic way. Alternatively, researchers have suggested the use of satellite sensor imagery (Foster 1985, Jensen and Cowen 1999), because it provides regular and up-to-date information in a variety of spectral, spatial and temporal resolutions at lower cost rates.

Most of the studies relating to urban mapping aim to identify interpretation techniques, which account for the urban complexity in relation to the data spatial resolution. This is because these two factors affect the essential use of remotely sensed data in urban studies (Barnsley and Barr 1996). Examples in using Landsat MSS and TM data or Landsat sensor with SPOT HRV data in urban classifications are reported in various studies (Khorram *et al.* 1987, Martin and Howarth 1989). However, their results were not that encouraging regarding class specificity and accuracy and this is attributed to the coarse spatial resolution of the imagery.

The same problems regarding class specificity and accuracy are observed even

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by using finer spatial resolution imagery (5 m or less) from recently developed sensors. This is due to the fact that urban areas are depicted as complex spatial arrangements of different land cover types resulting in a considerable spectral heterogeneity. Therefore class separation becomes a difficult task especially when classification is treated on a per-pixel fashion. For this reason it was decided to experiment with techniques, which incorporate image texture properties and account for the spatial dispersion of individual scene elements within a kernel (Hodgson 1998). Such techniques have been studied in the past on coarser resolution data (Peddle and Franklin 1991, Gahegan and Flack 1996, Ryherd and Woodcock 1996, Paola and Schowengerdt 1997). In the frame of this study the potential of two such kernel based approaches for the classification of 5 m-spatial resolution IRS-1C sensor data has been tested, using as input multi-temporal imagery from the metropolitan area of Athens (Hellas).

## 2. Scope of the study

The study was realised in the frame of a pilot project aiming to identify the extent by which the requirements of EUROSTAT for statistical information over urban areas can be met using fine spatial resolution imagery. Between the main objectives of the study was to examine classification techniques capable to identify settlement patterns of varying residential density, mixtures of built up and vegetative areas, pure vegetation classes, industrial and transportation categories. Table 1 illustrates the classification scheme used. It is a subset of the four levels CLUSTERS nomenclature used by EUROSTAT.

## 3. Input data and pre-processing

Multi-spectral IRS-1C LISS-III and Panchromatic images with spatial resolution of 25 m and 5 m respectively, acquired on 25 November, 1996 as well as on 23 April,

Table 1. Subset of the CLUSTERS nomenclature. Shaded cells describe the seven-class classification scheme used in the study.

| Level I | | Level II | | Level III | | Level IV |
|---|---|---|---|---|---|---|
| All classes | A1 | Residential areas | A11 | Residential areas | A111 | Continuous and dense residential |
| | | | | | A112 | Continuous residential of moderate density |
| | | | | | A113 | Discontinuous residential of moderate density |
| | A2 | Industrial & Commercial | A20 | Industrial & Commercial | | |
| | A3 | Transport | A30 | Transport | | |
| | A4 | Land for recreational purposes | A50 | Land for recreational purposes | A502 | Sport facilities |
| | | | | | A503 | Green or leisure areas |

1997 were used. The images were ortho-rectified and corrected from radiometric and atmospheric distortions. By merging IRS-1C LISS-III with Panchromatic data, enhanced multi-spectral 5 m-spatial resolution images were produced.

Training data for classification purposes were selected within irregularly shaped regions. They were sampled systematically within the image to be representative to the complete spectrum of land use classes. The training samples were generated from contiguous groups of pixels belonging to spectrally distinct land cover classes, defining in general multi-modal pixel distributions. The training sites were extracted manually with the help of aerial photography on the false colour composite imagery. These samples were digitised on the screen and they were divided to two groups for training and testing the classification.

## 4. Kernel classifiers

The application of the maximum likelihood (ML) classifier on the two-date multi-spectral and enhanced spatial resolution imagery resulted in severe misclassifications. Indeed, the LEVEL IV residential classes were classified with low accuracy percentages ranging from 8% to 29%. As a parametric classifier the ML algorithm relied on each training sample being represented by a Gaussian probability density function. However, the existing spectral variability of the classes led to the generation of multi-modal statistics, which inevitably resulted in the observed misclassifications. It should be noted that not even classes of LEVEL II were discernible and all residential classes were classified as one mixed class. Figure 1(*a*) illustrates the ML classification results for a subset of the study area.

Unlike the ML pixel based classifier the use of kernel based algorithms resulted in accurate estimates with lower percentage classification errors even for LEVEL IV classes. Two kernel classification techniques have been tested in the frame of the study using a back propagation neural network (NN) and the kernel reclassification algorithm (Barnsley and Barr 1996). The classification map provided by the NN application is shown in figure 1(*b*).

### 4.1. *The artificial neural network approach*

Neural network classifiers offer advantages in cases where insensitivity against noisy and redundant information as well as independence from Gaussian distributions is required. The network configuration permits to handle complex classification tasks when conventional classifiers reach their limits (Benediktsson *et al.* 1990, Paola and Schowengerdt 1995).

With the aim of defining meaningful image combinations for an accurate NN classification and optimum kernel sizes for the extraction of characteristic texture patterns, unsupervised classification experiments were conducted using the topological map network algorithm (Kangas *et al.* 1990). The algorithm was applied for a variety of kernel sizes and input image combinations. These experiments demonstrated that acceptable residential class discrimination was achieved when multi-date multi-spectral and enhanced spatial resolution imagery was classified using kernels of 5 pixels by 5 pixels and larger. This configuration was adopted during supervised back-propagation NN classification.

The architecture of the network was based on former experience. In general a four layer fully interconnected network is sufficient and it is the most common implementation seen in the literature for the classification of multi-spectral imagery (Paola and Schowengerdt 1995, Long Dai and Khorram 1999). The number of

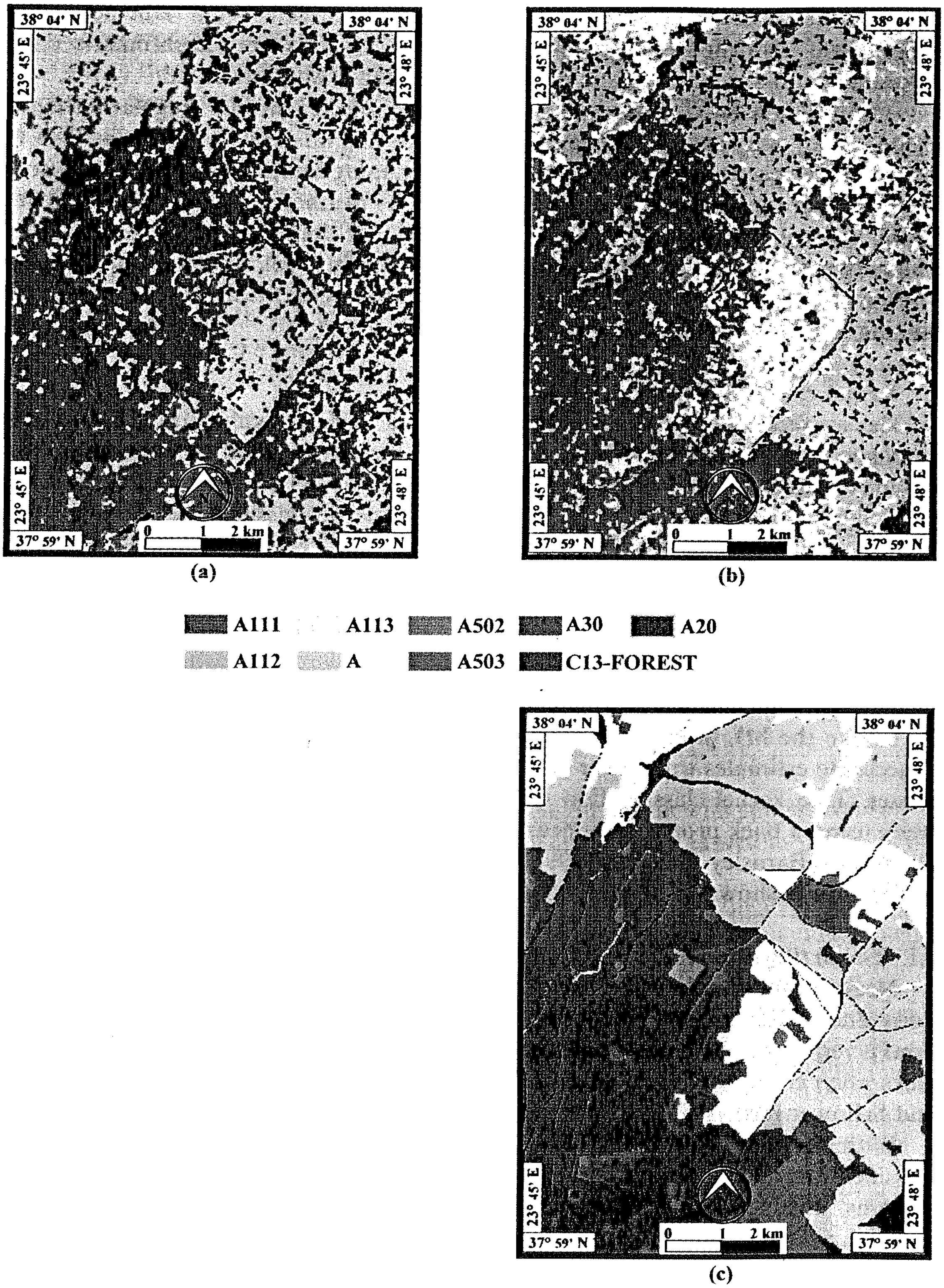


Figure 1. Classification maps resulted from the application of the (*a*) ML, and (*b*) NN algorithms. The resulted land use map appropriately refined with the help of ground data and ancillary information is illustrated in figure 1(*c*). The pixel-based approach did not succeed to classify residential density categories and most of them were returned as one mixed class (grey areas). In contrast kernel based classifications returned single residential classes (figure 1(*b*)). The illustrated area is approximately 75 km$^2$ and it is located at the north east of the Athens centre.

hidden nodes was determined by iterative trails during the training procedure. This resulted in the 6-14-26-7-layer configuration, since it guaranteed the best network learning capability. Various classifications with different kernel sizes (3 by 3, 5 by 5, 7 by 7, etc) were conducted and the output maps were compared against the ground data. These experiments showed that a kernel 7 by 7 was best suited, since higher level classification accuracy percentages were obtained for the LEVEL IV-classes and at the same time elongated structures and class boundaries were kept undistorted. Moreover the computational demands retained at a reasonable level. Table 2(*a*) summarises the classification results for each class, as well as the overall classification accuracy achieved for the seven LEVEL IV-classes (73.40%).

### 4.2. *The kernel reclassification algorithm*

The kernel reclassification algorithm derives information on urban land use in two stages. The first involves labelling of the image pixels into single land cover classes using a pixel based clustering algorithm. In a second stage, the pixel labels are grouped into discrete land use categories on the basis of their frequency of occurrence and spatial arrangement within a kernel. The basic assumption underlying this approach is that individual categories of land use classes are characteristic

Table 2. Confusion matrices resulted from the application of the NN and kernel reclassification algorithms.

(*a*) Back-propagation NN classification results

| | A111 | A112 | A113 | A20 | A30 | A502 | A503 | Classified totals | Producer's accuracy (%) | User's accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| A111 | 2291 | 420 | 24 | 402 | 1 | 9 | 0 | 3147 | 91.02 | 72.80 |
| A112 | 224 | 2389 | 389 | 70 | 323 | 26 | 0 | 3421 | 77.14 | 69.83 |
| A113 | 0 | 288 | 1754 | 18 | 90 | 23 | 396 | 2569 | 64.91 | 68.28 |
| A20 | 1 | 0 | 0 | 330 | 0 | 0 | 0 | 331 | 39.19 | 99.70 |
| A30 | 1 | 0 | 0 | 0 | 495 | 0 | 0 | 496 | 49.55 | 99.79 |
| A502 | 0 | 0 | 18 | 0 | 0 | 351 | 0 | 369 | 75.32 | 95.12 |
| A503 | 0 | 0 | 517 | 22 | 90 | 57 | 1796 | 2482 | 81.93 | 72.36 |
| Reference totals | 2517 | 3097 | 2702 | 842 | 999 | 466 | 2192 | 12815 | Overall Classification Accuracy = 73.40% | |

(*b*) Kernel reclassification algorithm results

| | A111 | A112 | A113 | A20 | A30 | A502 | A503 | Classified totals | Producer's accuracy (%) | User's accuracy (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| A111 | 2365 | 408 | 5 | 373 | 70 | 8 | 0 | 3229 | 93.96 | 73.24 |
| A112 | 145 | 2511 | 371 | 48 | 322 | 17 | 0 | 3414 | 81.08 | 73.55 |
| A113 | 0 | 176 | 1889 | 73 | 216 | 30 | 378 | 2762 | 69.91 | 68.39 |
| A20 | 2 | 1 | 0 | 303 | 3 | 0 | 0 | 309 | 35.99 | 98.06 |
| A30 | 5 | 1 | 0 | 0 | 295 | 0 | 0 | 301 | 29.53 | 98.01 |
| A502 | 0 | 0 | 12 | 0 | 0 | 389 | 55 | 456 | 83.48 | 85.30 |
| A503 | 0 | 0 | 425 | 45 | 93 | 22 | 1759 | 2344 | 80.24 | 75.04 |
| Reference totals | 2517 | 3097 | 2702 | 842 | 999 | 466 | 2192 | 12815 | Overall Classification Accuracy = 74.22% | |

spatial mixtures of spectrally distinct land cover classes. An overview of this technique is given in Barnsley and Barr (1996).

The first segmentation into discrete land cover labels was generated by the application of a standard ISODATA unsupervised clustering on the two-date multi-spectral and enhanced spatial resolution imagery. In the following the pixel labels were related to land cover classes by photo-interpretation. This rendered a classification in five broad land cover classes: 'active vegetation', 'open field', 'street', 'building', and 'bare soil'. The fact that training data were not representing single land cover classes but entire areas of specific land uses prevented the application of a parametric supervised classification for land cover map generation. Unsupervised clustering for the initial low-level image segmentation has been employed in similar studies as well (Wharton 1982).

The kernel reclassification algorithm, focuses on the calculation of the so called 'adjacency event' matrix. The value of each '*ij*' element of this matrix denotes the frequency with which pixels belonging to land cover classes '*i*' and '*j*' occur one adjacent to other in the area defined by a kernel, that scans the image. Similarly during training the kernel is passed over the representative sampled areas, which are of the same size as the scanning kernel, and the corresponding 'training or template' matrices are calculated. During classification the adjacency-event matrix which is calculated for each new position of the kernel is compared with each of the template matrices and the land use category defined by the template matrix which best match the current adjacency-event matrix is assigned to the central pixel of the kernel.

During training effort was placed to determine kernel sizes suitable for texture discrimination and define representative template matrices for each land use. This procedure demonstrated that residential class separation was possible by using kernels of 9 pixels by 9 pixels wide and larger. However with the aim to retain linear features undistorted, an 11 pixels by 11 pixels kernel was finally selected for the classification. Additionally, in order to estimate the algorithm's computational demands as a function of the kernel size, a much larger kernel of 25 pixels by 25 pixels was also used. These experiments demonstrated that the selection of the 11 by 11 pixels kernel was better by far regarding classification accuracy and computational requirements. The overall classification accuracy estimated over the seven LEVEL IV-classes was 74.22%. A detailed presentation of the relevant classification results is given in table 2 (*b*).

## 5. Conclusions

Kernel classification techniques proved to be useful for the classification of residential density classes on 5 m-spatial resolution imagery. In contrast the pixel based ML classifier returned most of these classes as one mixed class. Kernel based classifiers closed this gap and classified directly residential classes with high level accuracy. The classification accuracy was linked to the kernel size and for this reason further research is currently conducted to identify optimum functional relations between classification accuracy, land use class specificity, kernel sizes and image spatial resolutions.

In respect to the different image combinations it was concluded that multi-temporal sets of enhanced spatial resolution images was by far the best input for kernel classifications as they provide significant spectral and texture information. However, new approaches accounting for image structural properties should be envisaged especially nowadays that new generation satellite sensor imagery of 1 m-spatial resolution is available (e.g. IKONOS-2).

## References


BARNSLEY, M. J., and BARR, S. L., 1996, Inferring urban land use from satellite sensor using kernel-based spatial reclassification,. *Photogrammetric Engineering and Remote Sensing*, **62**, 949–958.

BENEDIKTSSON, J. A, SWAIN, P. H., and ERSOY, O. K., 1990, Neural network approaches versus statistical methods in classification of multi-source remote sensing data. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, 540–552.

FOSTER, B. C., 1985, An examination of some problems and solutions in monitoring urban areas from satellite platforms. *International Journal of Remote Sensing*, **6**, 139–151.

GAHEGAN, M., and FLACK, J., 1996, A model to support the integration of image understanding techniques within a GIS. *Photogrammetric Engineering and Remote Sensing*, **62**, 483–490.

HODGSON, M. E., 1998, What size window for image classification? A cognitive perspective. *Photogrammetric Engineering and Remote Sensing*, **64**, 797–807.

JENSEN, J. R., and COWEN, D. C., 1999, Remote Sensing of urban/suburban infrastructure and socio-economic attributes. *Photogrammetric Engineering and Remote Sensing*, **65**, 611–622.

KANGAS, J. A., KOHONEN, T. K., and LAAKSONEN, J. T., 1990, Variants of self organizing maps. *IEEE Transactions Neural Networks*, **1**, 93–99.

KHORRAM, S., BROCKHAUS, J. A., and CHESHIRE, H. M., 1987, Comparison of Landsat MSS and TM data for urban land use classification. *IEEE Transactions on Geoscience and Remote Sensing*, **GE-25**, 238–243.

LONG DAI, X., and KHORRAM, S., 1999, Remotely sensed change detection based on artificial neural networks. *Photogrammetric Engineering and Remote Sensing*, **65**, 1187–1194.

MARTIN, L. R. G., and HOWARTH, P. J., 1989, Change detection accuracy assessment using SPOT multispectral imagery of the rural-urban fringe. *Remote Sensing of Environment*, **30**, 55–56.

PAOLA, J. D., and SCHOWENGERDT, R. A., 1995, A review and analysis of back-propagation neural networks for classification of remotely sensed multi-spectral images. *International Journal of Remote Sensing*, **16**, 3033–3058.

PAOLA, J. D., and SCHOWENGERDT, R. A., 1997, The effect of neural network structure on a multispectral land use/land cover classification. *Photogrammetric Engineering and Remote Sensing*, **63**, 535–544.

PEDDLE, D. R., and FRANKLIN, S. E., 1991, Image texture processing and data integration for surface pattern discrimination. *Photogrammetric Engineering and Remote Sensing*, **57**, 413–420.

RYHERD, S., and WOODCOCK, C., 1996, Combining spectral and texture data in the segmentation of remotely sensed images. *Photogrammetric Engineering and Remote Sensing*, **62**, 181–194.

WHARTON, S. W., 1982, A contextual classification method for recognising land use patterns in high resolution remotely-sensed data. *Pattern Recognition*, **15**, 317–324.