Object-oriented classification and Ikonos multispectral imagery for mapping vegetation communities in urban areas

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Presented at SIRC 2005 – The 17th Annual Colloquium of the Spatial Information Research Centre
University of Otago, Dunedin, New Zealand
November 24th-25th 2005

ABSTRACT

The management of vegetated areas by urban planners relies on detailed and updated knowledge of their nature and distribution. Manual photo-interpretation of aerial photographs is efficient, but is time consuming. Image segmentation and object-oriented classifications provide a tool to automatically delineate and label vegetation units. Object-oriented techniques were tested with a very high-resolution multispectral Ikonos image to produce fine scale maps of vegetation communities in Dunedin (New Zealand). The Ikonos image was orthorectified and a first classification produced a map with 4 strata: industrial/commercial (with amenity pastures and tree groups), residential (with amenity pastures and private gardens), vegetation (with other vegetation classes), and water. A hierarchical network of image objects was built to extract vegetation patches of various sizes such as small private gardens and larger exotic plantations. The classification of the image objects was performed using the nearest neighbour (NN) method. Thirteen variables were considered to build the NN feature space, including mean object spectral value and standard deviation for each spectral band, and object compactness. The vegetation map was validated using an independent dataset collected in the field. The original classification scheme included 17 vegetation categories, of which ten were successfully discriminated: forests, exotic plantations, tree groups, exotic scrubs, mixed scrubs, native scrubs, pastures, amenity grasslands, rough grasslands, private gardens. Classes of ecological interest characterized by various canopy densities could not be discriminated (e.g. low and high density gardens, shrublands and scrubs). Vegetation patches smaller than 0.05 ha were efficiently extracted within the city. The overall classification accuracy was 92% and the kappa coefficient was 0.89 (i.e. 89% more accurate than a random classification). Object-oriented techniques and Ikonos imagery proved to be a promising technique to produce GIS-ready vegetation map.

Keywords and phrases: object-oriented classification, Ikonos, vegetation mapping, urban areas

1.0 INTRODUCTION

Vegetation has great value for the provision of ecosystem services in urban areas, e.g. micro-climate regulation, air quality improvement, recreational activities, wildlife habitats (e.g. Bolund and Hunhammar 1999). Management of vegetated areas by urban planners relies on a detailed and updated knowledge of their nature and distribution (PCE 1998, Breuste 2004). In New Zealand urban ecosystems have received little attention compared to rural or protected ecosystems. Urban habitats are largely ignored in New Zealand's Biodiversity Strategy and Resource Management Act, despite the fact that 85% of the population live in towns or cities, with their primary experience of natural habitats being in urban settings (Freeman 1999). Until recently no ecologically based mapping system was available for application to New Zealand cities. An ecological map of Dunedin City was first produced by manually digitising vegetation units from colour aerial photographs (Freeman and Buck 2003). This technique, although efficient for detailed mapping, has proven to be time consuming, thus introducing significant limitations for its future development. Automatic or semi-automatic delineation of vegetation units were recognized as highly desirable.

Very high-resolution multispectral satellites, such as Ikonos or Quickbird, provide a level of detail compatible with urban mapping, i.e. from 4 to 2.5 m spatial resolution. Multispectral sensors also have the advantage, over colour aerial photographs, of recording reflected light in the near infrared domain. Near infrared is the most sensitive spectral domain used to map vegetation canopy properties (Guyot 1990) and may improve the discrimination of vegetation communities. Automatic classification of digital images is traditionally carried out using a per-pixel approach, and thus mainly uses the spectral content of the images. These methods are not well suited for very high-resolution images, especially in urban environments, which consist of a mosaic of small-scale features made up of different materials (e.g. De Jong et al 2000, Hofmann 2001). As many urban or suburban land use types, such as roads, buildings, parking lots, or amenity pasture, grassland, are spectrally similar, spatial information such as texture and context must be exploited to produce more accurate maps (Shackelford and Davis 2003). Object-oriented techniques recognize that important semantic information is not represented in single pixels but in meaningful image objects and their mutual relations, i.e. the context (Blaschke and Strobl 2001, Benz et al 2004). They have a great potential to improve the automatic extraction of information from very high-resolution imagery (Giada et al 2003, Benz et al 2004). This research project aimed to investigate whether multispectral Ikonos images, combined with object-oriented image classification techniques, are suitable for automatic and fine scale mapping of vegetation communities in urban areas.

2.0 STUDY AREA, DATA AND METHODOLOGY

2.1 Study Area

The study site, located in the south-east of the South Island of New Zealand, corresponds to Dunedin City (170°30’ Long E / 45°45’ Lat S). Dunedin City is a medium size city hosting a population of 120,000 people. Despite of being a relatively small area (about 36 km^2), it harbours a wide range of vegetation types, including native remnants, exotic plantations, pasturelands, indigenous tussocks and flax vegetation, regenerating scrubs and bushes. It also includes recreation parks, sport pitches, two cemeteries and a large botanic garden. The Central Business District (CBD) is located in flat terrains along the harbour. Residential areas are located in the surroundings hills located north, west and south-east of the CBD. The topography is gently to moderately rolling with elevations ranging from the sea surface to 400 meters. The mean slope is 10± 9 degrees.

2.2 Data

One multispectral Geo Ortho Kit Ikonos image was acquired on the 20th February of 2005 (mid summer) to map the vegetation communities. The image has a spatial resolution of four meters and includes four spectral bands (blue, green, red, and near infrared). One in-track panchromatic Ikonos stereo pair was acquired on the same day. Both images were supplied by Space Imaging (http://www.spaceimaging.com). A detailed digital vegetation map of Dunedin city (1:3000) was available from a previous project (Freeman and Buck 2003). This map was photo-interpreted from colour aerial photographs taken in 2001 and was used to support the selection of training samples for the classification.

2.3 Methodology

2.3.1 DSM generation and orthorectification

The multispectral Ikonos image was orthorectified to ensure an accurate correction of systematic topographic distortions and the best positional accuracy of the final GIS map. An accurate Digital Surface Model (DSM) was produced using the Ikonos stereo pair and GPS control points (Toutin 2004). The multispectral Ikonos image was then orthorectified using the DSM. An independent validation of the orthorectified product using 16 additional GPS points yielded an average and maximum geolocation error of 1.4 and 3.1 m, respectively. PCI Geomatica OrthoEngine V09 was used to produce the DSM and orthorectify the Ikonos image.

2.3.2 Classification Scheme

The classification scheme used in this study was adapted from the vegetation classification systems developed by Atkinson (1985) and Freeman and Buck (2003) for natural and urban ecosystems (Table 1).

Table 1. Classification scheme (adapted from Freeman and Buck 2003)

Habitat type	***Class***	***Comments***
Build environment	Building	Public, industrial, commercial
	House	Incl. farms (> 0.25 ha)
	Road	
	Sealed surface	Concrete (e.g. parking)
Tree habitats (avg. stem dbh > 0.1 m)	Bush and forest	Structure-rich tree stands, height > 5 m
	Plantation	Exotic tree stands of uniform age, incl. shelterbelts
	Park / Woodland	Scattered trees over grassland or scrub
	Tree group	Isolated group of trees, native and/or exotic, < 1 ha
Scrub habitats (avg. stem dbh < 0.1 m)	Exotic scrub	Closed canopy, non-native species
	Mixed scrub	Closed canopy, mixture of non-native & native species
	Native scrub	Closed canopy, native species
	Exotic shrubland	Open canopy, non-native species
	Mixed shrubland	Open canopy, mixture of non-native & native species
	Native shrubland	Open canopy, native species
	Vineland	Scrub vegetation heavily covered by woody vines
Grassland	Amenity grassland	Intensively managed and regularly mown pasture
	Pasture	Intensively managed and regularly grazed pasture
	Rough grassland	Irregularly managed grassland, including tussocks
	Dune Grassland	Grassland on consolidated dunes
Garden	High density gardens	Rich in trees and shrubs > 50%
	Low density gardens	Poor in trees and shrubs < 50%
Bare ground	Bare ground	Incl. bare soil, gravel, quarry, sand
Water	Coastal water	
	Standing water	
	River and streams	

2.3.2 Multi scale image segmentation

The basic processing units of object-oriented image analysis are segments (also called image objects) and not single pixels (Benz et al 2004). The purpose of image segmentation is to first subdivide an image into groups of pixels (segments) corresponding to meaningful objects in the field. These objects are then classified. The size of the image objects is closely related to the scale of the analysis. The splitting/merging process is controlled by similarity or dissimilarity measures, relying on one or several image features, e.g. brightness or colour, texture, shape, or size.

The software used in this research, eCognition V3.0, is the first commercial classification package fully based on object-oriented techniques. It uses a multiresolution segmentation approach which is basically a bottom up region-merging technique starting with one-pixel objects. In numerous iterative steps, smaller image objects are merged into bigger ones (Baatz et al 2004). The outcome of the segmentation algorithm is controlled by the scale and a heterogeneity criterion. The scale is indirectly related to average size of the objects to be detected, and partly depends on the image spatial resolution. The heterogeneity criterion controls the merging decision process, and is computed using spectral layers (e.g. multispectral images) or non-spectral layers (e.g. thematic data such as elevation). The heterogeneity criterion includes two mutually exclusive properties: colour and shape

(Colour = 1 – Shape). Colour refers to the spectral homogeneity whereas shape considers the semantic characteristics of the objects. Shape is divided into two equally exclusive properties: smoothness and compactness (Smoothness = 1 – Compactness) (Baatz et al 2004).

The choice of the segmentation parameters (scale, colour, smoothness and compactness) was determined using a systematic trial/error approach, validated by visual inspection of the quality of the image objects. Once an appropriate scale was identified both the colour and shape criterion were modified to refine the shape of the image objects. Two key scales were identified. A small scale (22) was appropriate to identify small vegetation patches in residential areas (e.g. private gardens, tree groups), and a larger scale (40) was good to extract larger vegetation patches (e.g. plantation, forest, pasture). Most published works found that more meaningful objects were extracted with a higher weight for the colour criterion (Herold et al 2002, Laliberte et al 2004). The colour criterion was assigned a weight of 0.7, whereas the shape received the remaining weight of 0.3 (compactness 0.5 and smoothness 0.5).

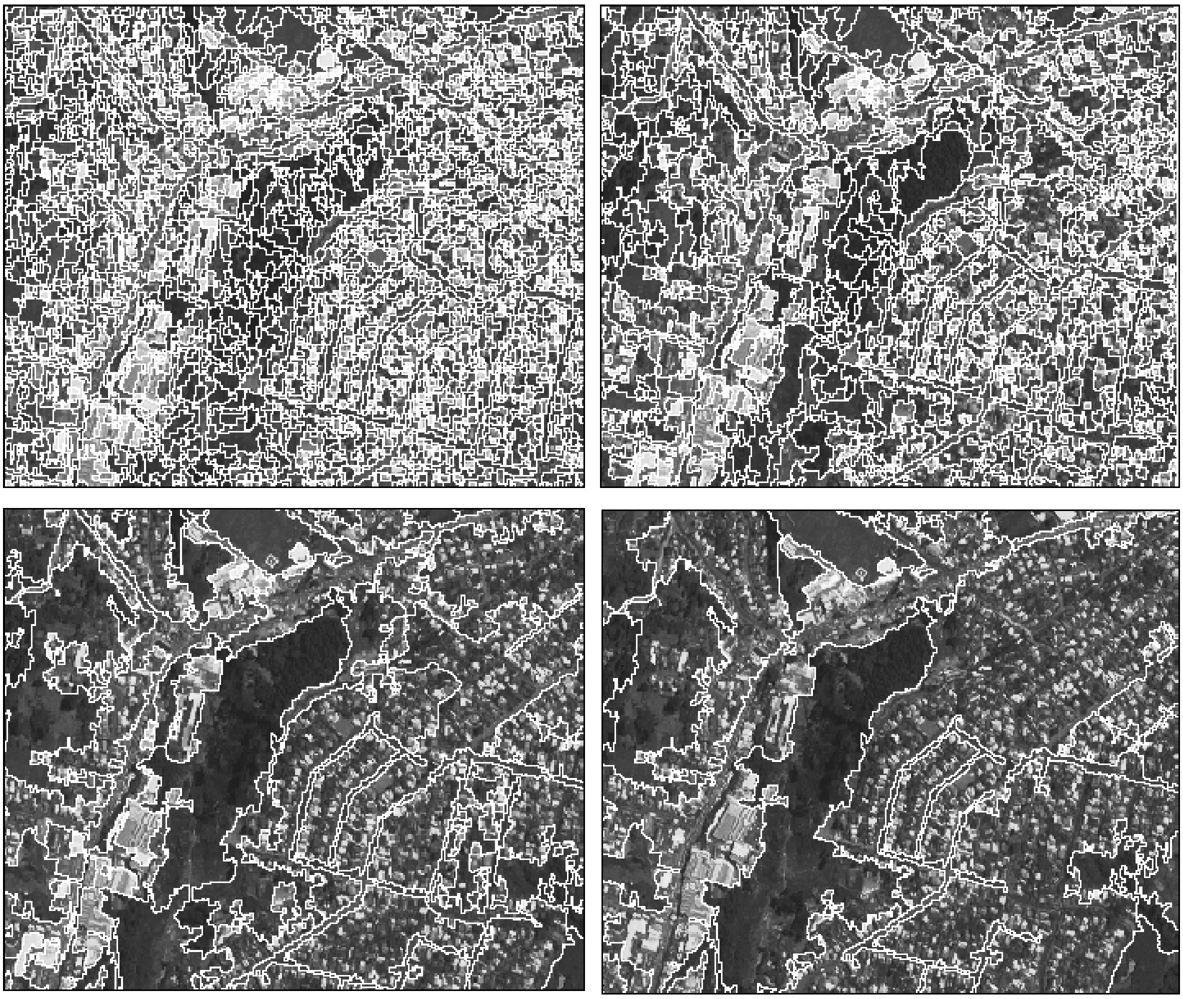

Figure 1. Segmentation of the Ikonos image at the scale of 22 (upper left), 40 (upper right), 125 (lower left), and 250 (lower right)

2.3.4 Training samples and validation data set

For the collection of training and validation samples the main focus was set on the vegetation classes. For the training samples the study area was divided into four quadrants of equal size. The number of training samples selected for each class depended on its significance in term of areas covered, but a minimum of one sample per quadrant was selected for the smallest classes. The samples were selected using the vegetation map produced by Freeman and Buck (2003) and were checked in the field during the autumn 2005. A number of attributes were collected: site size, habitat type, land use type, slope, aspect, elevation, dominant species, vegetation density, vegetation structure. When possible the habitat and land use classes of surrounding polygons were recorded. For classes easily interpretable from the Ikonos images or the aerial photographs (e.g. garden, road, and house) training sample were selected without field support. In total 280 training samples were collected. Vegetation communities within or at close proximity with the city where targeted for the validation exercise. A coarse classification was produced to map vegetation and non vegetation image objects. The approximate boundaries of the city were photo-interpreted from the Ikonos images to separate the urban and suburban areas from the rural areas. A total of 90 vegetation image objects were randomly selected outside the city (rural areas) while another set of 360 vegetation image objects was randomly selected within the city. All 450 validation polygons were surveyed in the field (about 1.2 % of the vegetation of the study area).

2.3.5 Urban and suburban stratification

Prior to the classification the study area was stratified according to 4 broad classes: industrial / commercial (low vegetation density), residential (intermediate vegetation density), vegetation (high vegetation density), and water (Figure 2).

A 125 scale segmentation layer was created and classified into the four classes using the nearest neighbour (NN) approach (4 spectral bands, mean features). At this scale residential blocks including gardens, roads and houses are identified as single image objects (see Figure 1). Wrongly classified image objects were reassigned manually to the correct classes, based on local knowledge and information provided by the Ikonos image and aerial photographs. These data were also used to systematically refine approximate boundaries between strata.

Any vegetation patches larger than 0.8/1 ha was automatically assigned to the vegetation stratum. Consequently, the industrial / commercial stratum and the residential stratum only included small vegetation patches potentially classified as amenity pastures or tree groups, and as amenity pastures, tree groups, or gardens, respectively. As all other vegetation classes were included in the vegetation stratum this reduced significantly the risks of confusion between vegetation classes. For instance forest or mixed shrubs were not present in residential areas and could not be confused with dense private gardens.

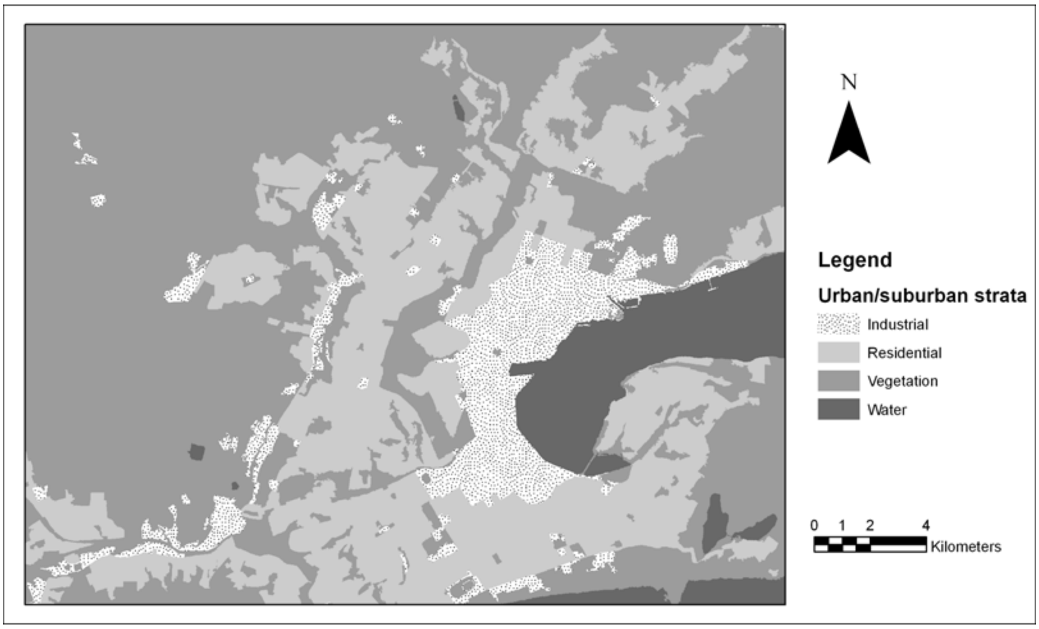

Figure 2. Industrial, residential and vegetation strata in Dunedin City

2.3.6 Object-oriented classification

The classification was performed using the nearest neighbour (NN) method which assigns classes to image objects based on minimum distance measurements. The NN classifier can potentially use a variety of variables related to spectral, textural, shape and/or contextual properties of image objects. Thirteen variables were considered to build the NN feature space: mean object spectral value, standard deviation, ratio (mean spectral value / sum of all spectral layer mean values), and object compactness (length x width / number of pixels). The first three variables were computed for the four spectral bands of Ikonos. For each stratum an optimized feature space was finally selected by observing the best separation distance between classes.

Some classes can only be found in a specific stratum (e.g. private gardens in residential areas). Thus, the multi scale segmentation was constrained by the boundaries of the strata. This ensured that no individual image object could belong to two strata. Two hierarchical segmentation levels were produced. Level 1 was produced at a scale of 22 and level 2 at a scale of 40. Level 1 was used to classify small features such as individual private gardens and houses in the residential strata. Similarly, meaningful image objects were extracted from the level 2 for both the industrial / commercial and vegetation strata. The two hierarchical classified levels were then integrated into a single level and exported to ArcGIS

A confusion matrix (predicted classes versus observed classes) was built to assess the accuracy of the final vegetation map. User's accuracy, producer's accuracy, overall accuracy, and Kappa coefficient were computed and analyzed (Congalton 1991).

3.0 RESULTS

During the classification process some classes presented in Table 1 could no be easily discriminated (e.g. high and low density gardens). The confusion matrix given in Table 2 is simplified and results from the merging of poorly discriminated classes. Additionally, only the results of the vegetation classes are presented. The confusion matrix indicates a very accurate classification (>0.9) for amenity grasses, gardens, exotic plantations, mixed scrubs, and pastures (Table 2). Good results (>0.7) are obtained for forests, mainly confused with native scrubs, and for native scrubs, that are mixed with amenity grasses and forests. The poorest accuracies are found for exotic scrubs, that are confused with amenity grasses. However, the poorest accuracies (user's accuracy and producer's accuracy) remained higher than 0.75. The overall classification accuracy (0.92) was relatively high with 0.92 and the kappa coefficient was 0.89. This indicates the classification was 89% more accurate than what would have been generated by a completely random classification.

Table 2. Confusion matrix of the urban vegetation communities mapped from a multispectral Ikonos image

	Amenity grass	Garden	Tree grp	Plant	Forest	Exotic	Mixed	Native	Rough grass	Pasture grass	***Row Total***	**User acc (%)**
Amenity grass	96	4	3	1		2		1		4	111	0.86
Garden	3	56									59	0.95
Tree group	1		24		1						26	0.92
Plantation				27						1	28	0.96
Forest			1		14			1			16	0.87
Exotic	1				1	7					9	0.78
Mixed							3				3	1.00
Native			1		2			12			15	0.80
Rough grass									4		4	1.00
Pasture grass	5		1						1	158	165	0.96
Column total	107	60	31	28	18	9	3	14	5	163	436	
Prod acc (%)	0.90	0.93	0.77	0.96	0.78	0.78	1.00	0.86	0.80	0.97		

4.0 DISCUSSION AND CONCLUSION

The original classification scheme included 17 vegetation categories. Ten of these categories were successfully discriminated: forests, exotic plantations, tree groups, exotic scrubs, mixed scrubs, native scrubs, pastures, amenity grasslands, rough grasslands, private gardens. Significant confusions occurred between classes of ecological interest. Low density gardens (including less than 50% of trees or shrubs, the remaining being grasses) could not be discriminated from high density gardens (including less than 50% of trees or shrubs) in residential areas. Vineland were also confused with scrubs, but this class was very scarce in the area with only 2 ha (Freeman and Buck 2003). Scrub (close canopy) and shrublands (open canopy) were difficult to discriminate. The selection of appropriate training samples was complicated by the fact that the definition of these classes lacks of consensus amongst ecologists. They ultimately belong to a unique continuum of vegetation density.

eCognition V3.0 was efficient to automatically extract patches of vegetation as small as 0.05 ha. In particular, small patches of private gardens were mapped with a high degree of accuracy in the residential areas. This is an interesting point as the manual digitizing of individual private gardens is usually considered unpractical and too resource consuming (Freeman and Buck 2003). The Figure 3 illustrates the distribution of private gardens in the residential strata. Variations of garden density across the area are evident. In Mornington (north-east) gardens tend to be large and abundant while in the St Kilda area (south) gardens tend to be small and less abundant. These data can be extracted over large areas and could provide interesting insights in environmental or ecological studies (e.g. association between environment, health, and socio-economic status, distribution and movements of urban wildlife).

The use of Ikonos images and object-oriented classification techniques was encouraging to map vegetation communities in urban areas. Compared to the more traditional per-pixel classification techniques object-oriented techniques produce vector maps ready to be integrated and analysed in a GIS database. The multiscale segmentation of real world features and their integration into a single level is a powerful approach as it is analogous to the human perception of its environment (cognition).

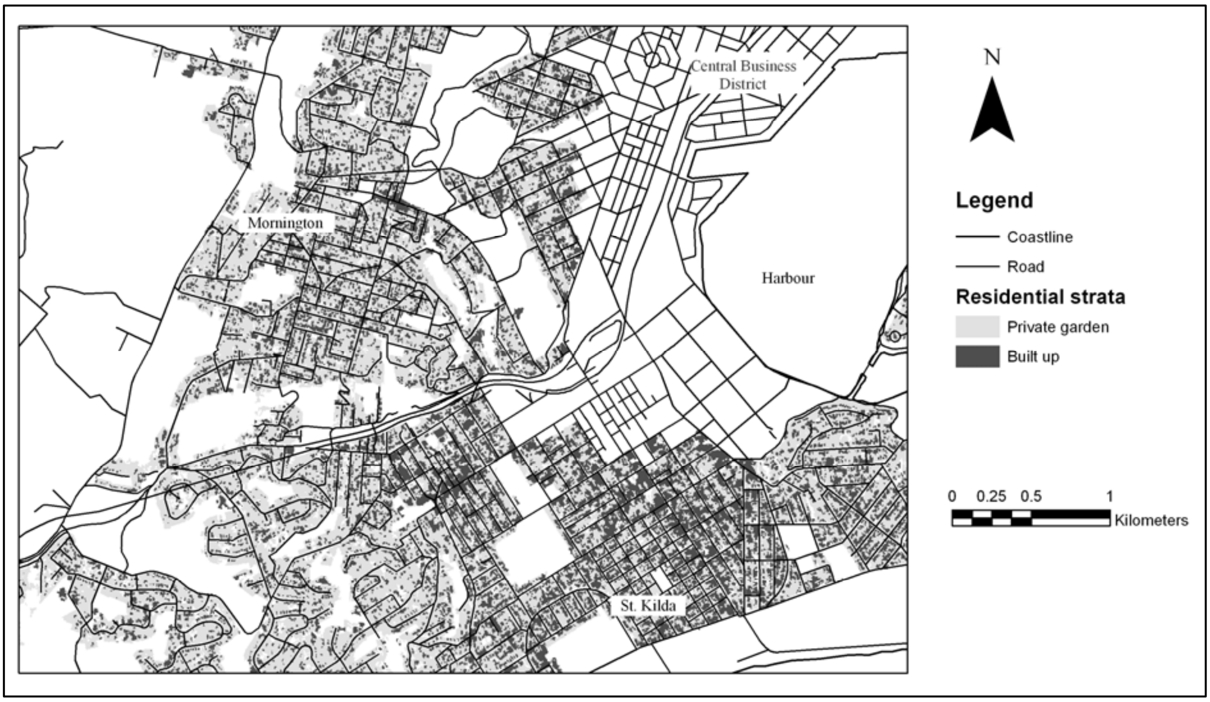

Figure 3. Automatic mapping of private gardens in residential areas

ACKNOWLEDGEMENTS

The authors wish to acknowledge Dr Claire Freeman for providing the ecological map of Dunedin.

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