

*Full Research Paper*

## **Object-Based Classification of Ikonos Imagery for Mapping Large-Scale Vegetation Communities in Urban Areas**

**Renaud Mathieu**<sup>1,2,\*</sup> **Jagannath Aryal**<sup>3</sup> and **Albert K. Chong**<sup>1</sup>

1 Spatial Ecology Research Facility, School of Surveying, University of Otago, PO Box 56, Dunedin, New Zealand; E-mail: renaud.mathieu@stonebow.otago.ac.nz

2 Earth Observation Research Group, Natural Resources & Environment, CSIR, PO Box 395, Pretoria 0001, South Africa; E-mail: rmathieu@csir.co.za

3 Centre for Advanced Computational Solutions, Lincoln University, PO Box 84, Lincoln, New Zealand; E-mail: aryalj@lincoln.ac.nz

\* Author to whom correspondence should be addressed.

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**Abstract:** Effective assessment of biodiversity in cities requires detailed vegetation maps. To date, most remote sensing of urban vegetation has focused on thematically coarse land cover products. Detailed habitat maps are created by manual interpretation of aerial photographs, but this is time consuming and costly at large scale. To address this issue, we tested the effectiveness of object-based classifications that use automated image segmentation to extract meaningful ground features from imagery. We applied these techniques to very high resolution multispectral Ikonos images to produce vegetation community maps in Dunedin City, New Zealand. An Ikonos image was orthorectified and a multi-scale segmentation algorithm used to produce a hierarchical network of image objects. The upper level included four coarse strata: industrial/commercial (commercial buildings), residential (houses and backyard private gardens), vegetation (vegetation patches larger than 0.8/1ha), and water. We focused on the vegetation stratum that was segmented at more detailed level to extract and classify fifteen classes of vegetation communities. The first classification yielded a moderate overall classification accuracy (64%,  $\kappa = 0.52$ ), which led us to consider a simplified classification with ten vegetation classes. The overall classification accuracy from the simplified classification was 77% with a  $\kappa$  value close to the excellent range ( $\kappa = 0.74$ ). These results compared favourably with similar studies in other environments. We conclude that this approach does not provide maps as detailed as

those produced by manually interpreting aerial photographs, but it can still extract ecologically significant classes. It is an efficient way to generate accurate and detailed maps in significantly shorter time. The final map accuracy could be improved by integrating segmentation, automated and manual classification in the mapping process, especially when considering important vegetation classes with limited spectral contrast.

**Keywords:** object-based classification; remote sensing; cities; New Zealand; biodiversity; habitat.

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## 1. Introduction

Green space plays a major role in providing satisfactory environmental conditions for urban dwellers. Vegetation is a vital component as it affects key environmental processes: e.g. air filtering, micro climate regulation, and rainwater drainage (Bolund and Hunhammar 1999). In recent years there has been an increasing awareness both in the importance of urban ecosystems as a source of biodiversity (Cornelis and Hermy 2004; Sandstrom et al. 2006; Smith et al. 2006), and in the need to inventory, restore, or enhance biodiversity in cities (Savard et al. 2000). Changes of species arrangement may alter the capability of vegetated areas to provide ecosystem services (Andersson 2006). Further, it is suggested that the future of global nature conservation may rely increasingly on conservation of biodiversity in cities. As more and more humans become city dwellers, their willingness to protect biodiversity may depend on their day to day experience of nature in cities (Savard et al. 2000; Dunn et al. 2006).

The conservation and enhancement of vegetation communities by urban planners and ecologists requires a detailed and updated knowledge of their nature and distribution (Millington and Alexander 2000; Breuste 2004). Aerial photographs are primary data sources for detailed mapping of urban vegetation (Seidling 1998; Freeman and Buck 2003). The mapping process is generally based on photo-interpretation and manual digitizing of thematic units using a combination of spatial image properties (size, shape, texture, pattern) and spectral properties (tone, colour). Heavy reliance on the interpreter's expertise is both the strength and weakness of this approach; such maps are richly detailed but the process is time consuming (Freeman and Buck 2003). Automatic or semi-automatic delineation of vegetation units may provide an important time saving technique.

Earlier satellite sensors (Landsat MSS, TM), having a spectral band in the near infrared part of the spectrum, had good spectral resolution however, they had too coarse a spatial resolution to produce detailed maps in urban areas. Today very high resolution (VHR) satellites are capable of providing spatial details compatible with urban mapping (Thomas et al. 2003; Nichol and Lee 2005). Ikonos or Quickbird images (4 to 2.5 meter pixel size) have been used for mapping urban impervious surfaces, roads, and buildings (Sawaya et al. 2003; Péteri et al. 2004). With regards to vegetation, some researchers have dealt with vegetation density and abundance (Small 2003; Nichol and Lee 2005), and others with vegetation condition (Stow et al. 2003). Still others focused on the production of land use/land cover maps, but these generally include only two or three vegetation classes (Herold et al. 2003; Jain and Jain 2006; Carleer and Wolff 2006). Such data is very useful for understanding a wide

range of environmental and socio-economic issues such as urban micro-climate and heat island effects, air quality and human health, and housing values. However, the thematic precision of past studies is generally insufficient for studying urban ecological processes and assessing biodiversity resources. Habitat studies, for example, often require more detailed inventories due to the fact that differences in vegetative structure and species composition (e.g. native versus exotic), are often critical for wildlife (Hostetler 1999; Cunningham 2006; Johnson et al. 2007).

Conventional classification methods use per pixel approaches (Bayesian theory or artificial neural networks) that rely only on the spectral information or colours contained in the image. As the spatial resolution increases, between-class spectral confusion and within-class spectral variation increases. This is especially true in urban environments that typically consist of mosaics of small features made up of different materials. Consequently, spatial information such as texture and context must receive greater attention in the classification process to produce more accurate maps (Blaschke and Strobl 2001; Shackelford and Davis 2003).

Different approaches have been developed to deal with the complexity of urban environments. These include: kernel based reclassification (Zhang and Wang 2003), texture analysis and expert systems (Stefanov et al. 2001; Herold et al. 2003), and lacunarity and fractal approaches (Myint and Lam 2005). Object-based classification techniques provide another alternative that have already demonstrated the potential for improving the automatic extraction of information from VHR imagery (Giada et al. 2003; Benz et al. 2004). Object-based techniques recognize that important semantic information is not always represented in single pixels but in meaningful image objects and in their contextual relations. For example, it is more likely that a pixel adjacent to a private garden should be classified house, road or private garden rather than forest. Object-based classification comprises two steps: image segmentation and object classification. Image segmentation subdivides the image into groups of contiguous pixels called objects or segments that correspond to meaningful features or targets in the field (Blaschke and Strobl 2001). These objects might be roads, houses, water bodies, pine plantation, native forest, and so on. The images are segmented into homogeneous objects based on the spectral information and local patterns or textural information that are included in groups of neighbouring pixels. Object-based classifications can consider a wide range of variables, e.g. reflectance, texture, shape, size of objects, and can potentially produce more accurate and detailed maps than conventional classification strategies.

Urban ecosystems have received little attention in New Zealand compared to rural or protected ecosystems (Freeman 1999). The first detailed ecological map of a New Zealand city, Dunedin, was produced by manually digitizing and interpreting vegetation units from colour aerial photographs and field based ecological surveys (Freeman and Buck 2003). In their study, Freeman and Buck proposed an original habitat classification hierarchy applicable to New Zealand cities. The technique, useful for detailed mapping, has proven to be time consuming, thus introducing significant limitations for its future extension and development. In this paper we undertook to assess the suitability of an alternative method. This method combined very high resolution multispectral Ikonos images and object-based classifications in the automated production of large-scale maps of vegetation communities in urban environments.

## 2. Study Area

The study area includes the core urban sector of Dunedin City and the immediate surrounding rural areas. Dunedin is located on the south-east coast of the South Island of New Zealand. It is a medium-sized city by New Zealand standards with a population of approximately 114,000 people (Statistics New Zealand 2005). The Central Business District (CBD) is located on flat terrain near the harbour while the residential areas are distributed in the surrounding hills located north, west and south-east of the CBD. Situated at 170°30' East and 45°52' South, Dunedin has a cool temperate, sub-humid maritime climate. It harbours a wide range of vegetation types, including native remnants, exotic plantations, pasture lands, indigenous tussock, flax vegetation, and regenerating scrubs and bushes. It also includes recreation parks, sports pitches, three cemeteries, and a large Botanic Garden (Freeman and Buck 2003). The topography is gentle to moderately rolling (slopes between 8 and 25 degrees) with elevations ranging from sea level to approximately 400 metres.

## 3. Data and Methods

### 3.1. Ikonos images and preprocessing

One in-track panchromatic Ikonos stereo pair (one meter spatial resolution) was acquired on the 20th of February 2005 and used to generate an accurate Digital Surface Model (DSM). One multispectral Ikonos image (100 km<sup>2</sup>) was programmed on the same mid-summer day to map the vegetation communities. The multispectral image had a spatial resolution of four metres and included four spectral bands (blue, green, red, and near infra-red). The images were provided with rational polynomial coefficients to enable users to orthorectify the imagery (Dial et al. 2003). PCI Geomatica Orthoengine V9.0 was used with the DSM for orthorectifying the multispectral Ikonos image. The validation of the orthorectified product with sixteen independent and well distributed control points yielded an average and maximum geolocation error of 1.4 and 3.1 metres, respectively.

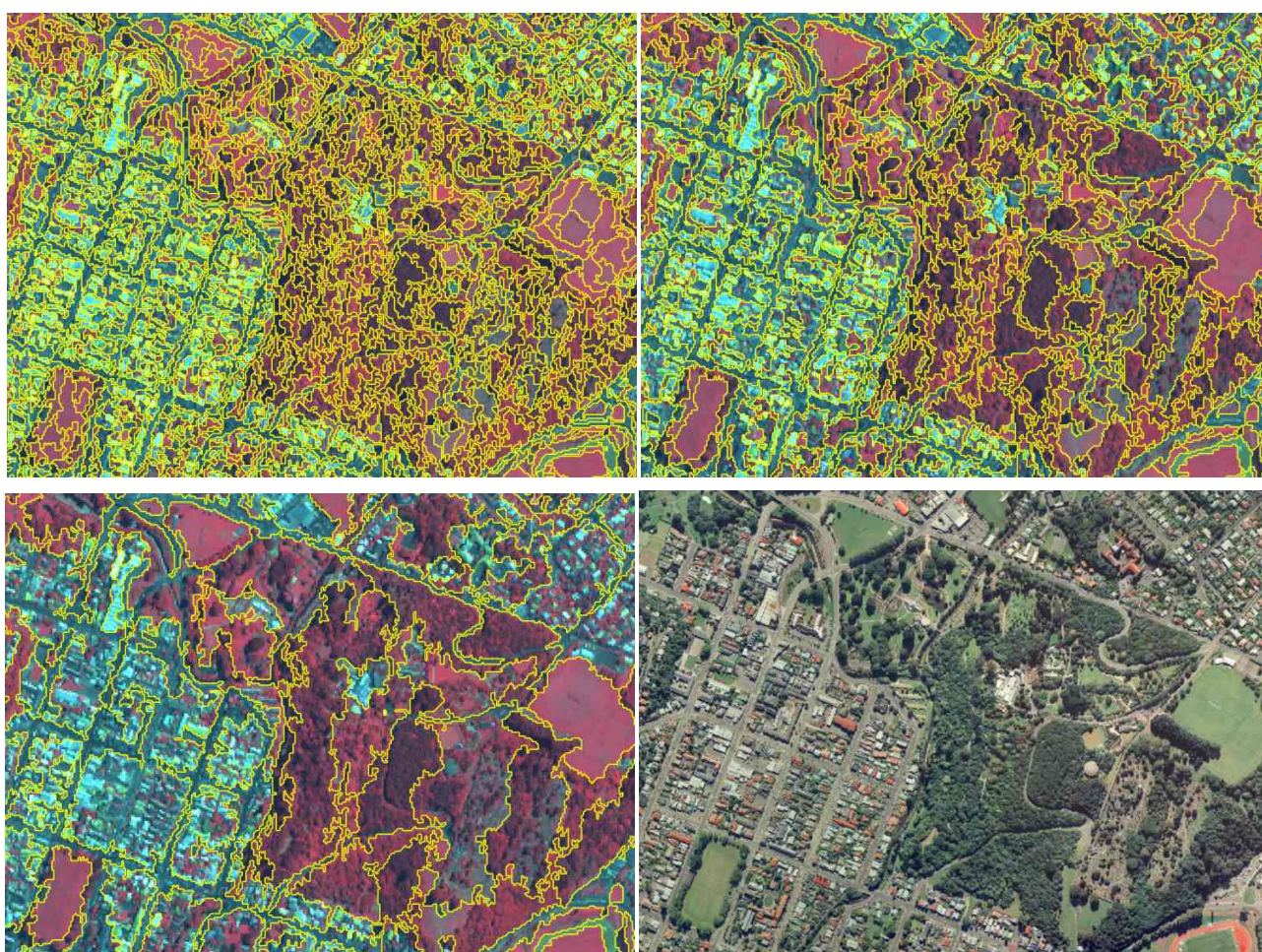
### 3.2. Multi-scale image segmentation and classification

#### 3.2.1. Image segmentation

The object-based classification software used in this research was eCognition Professional 4.0 (Definiens). eCognition uses a multi-resolution segmentation approach which is 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 a scale factor and a heterogeneity criterion. The scale factor is indirectly related to the average size of the objects to be detected (see example Figure 1). 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 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 (Baatz et al. 2004).



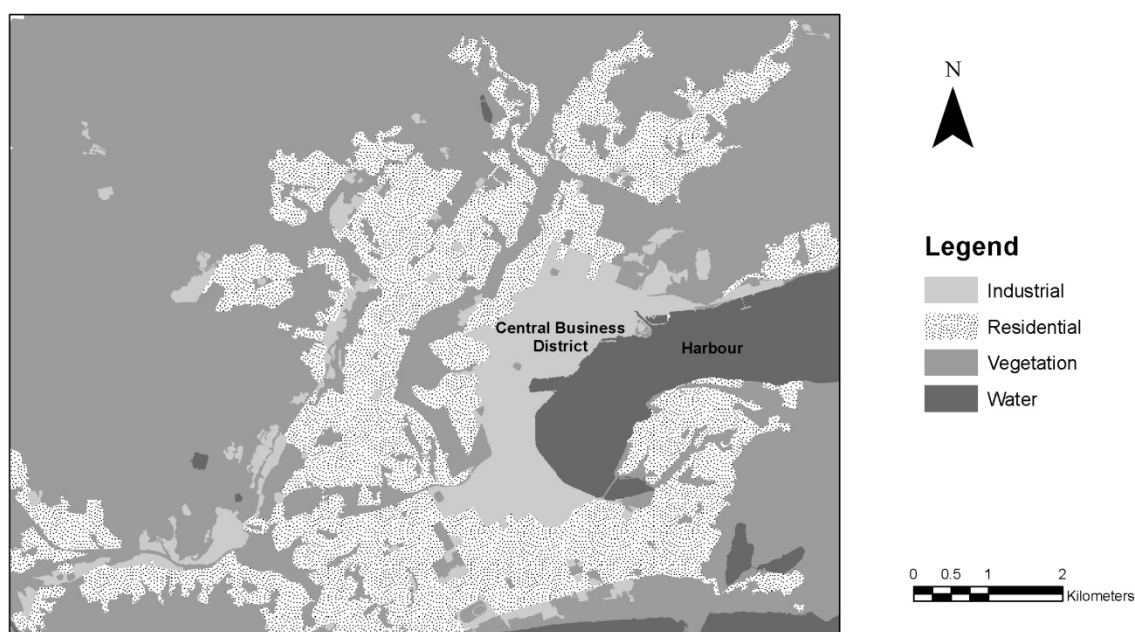
The optimum segmentation parameters depend on the scale and nature of the features to be detected. These were determined using a systematic trial and error approach validated by the visual inspection of the quality of the output image objects, i.e. how well the image objects matched feature boundaries in the image. Once an appropriate scale factor was identified, the colour and shape criterion were modified to refine the shape of the image objects. Most published works have found that more meaningful objects are extracted with a higher weight for the colour criterion (Herold et al. 2002; Laliberte et al. 2004). In this application 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). Two key hierarchical scale levels were identified. A first level was used to stratify the urban areas and a second, more detailed level, was created to map vegetation communities within the vegetation-dominated strata.



**Figure 1.** Segmentation of the Ikonos image at the scale of 22 (upper left), 40 (upper right), 125 (lower left), and colour aerial photograph (lower right). Yellow lines delineate the image objects. The Ikonos image is displayed as a false colour composite, red channel = near infrared, green channel = red, blue channel = green. The vegetated area shown in the image is the Dunedin Botanical Garden, one of the significant ecological entities located within the city.

### 3.2.2. Stratification of urban areas

A 125-scale segmentation layer was created to stratify the study area according to four broad classes or strata: industrial / commercial (low vegetation density), residential (intermediate vegetation density), vegetation (high vegetation density), and water (Figure 2). The four classes were classified with the nearest neighbour (NN) classifier. The NN classifier allows quick and straightforward classification and can use a variety of variables related to spectral, textural, shape and/or contextual properties of the image objects (Baatz et al. 2004). At this level we used the mean features of the four spectral bands, as these (especially the NIR) are good representations of the variation of vegetation density between classes. A few wrongly-classified image objects were reassigned manually to the correct classes based on local knowledge and the Ikonos image. A similar technique was used to refine some boundaries between strata. The industrial / commercial stratum consisted of the CBD and other significant peripheral industrial / commercial sectors. These included mainly commercial and industrial buildings with only few small vegetation patches such as amenity pastures and tree groups. Residential blocks consisted essentially of well structured patterns intermixing roads, single or double storey individual houses, and private backyard gardens of various size and density. The extraction of private gardens from the residential strata is detailed in Mathieu et al. (2007). Any vegetation communities or patches larger than 0.8/1 ha (e.g. plantation, native scrub, forest, dune grassland) were automatically classified into the vegetation stratum. In this paper, we focus on the vegetation stratum where the vegetation patches are believed to be of sufficient size to have functional ecological processes and to host some self-sustainable plant and animal populations.



**Figure 2.** Vegetation, industrial / commercial, residential, and water strata of Dunedin City, New Zealand, extracted from the multispectral Ikonos image.

### 3.2.3. Fine scale vegetation mapping

A smaller scale factor (40) was found appropriate to extract the vegetation communities from the vegetation stratum. We used a classification scheme adapted from the habitat classification systems developed by Freeman and Buck (2003) and adapted to the New Zealand urban environment (Table 1). This is a hierarchical system based on physiognomic vegetation units and derived from previous classification systems (Atkinson 1985). The first level starts with broad structural categories such as tree habitats or shrubland; the second level introduces finer categories where species arrangement and canopy cover are included. The third level (not shown) generally concerns more detailed species-based class differentiation, and is used especially for woody habitats. Native shrublands, for example, are classified as broadleaf shrublands, tea-tree shrublands, grey shrublands or mixed native shrublands. We restricted our classification to the first two levels of Freeman and Buck's classification system. Some marginal classes (small and/or localized in the city or at close proximity) were not considered in our classification as it would have been impossible to collect appropriate samples to train the classifier and to assess the final map accuracy (e.g. saline wetland, indigenous fernland).

**Table 1.** Classification scheme for the vegetation community classes and other habitats in Dunedin City, New Zealand (adapted and modified from Freeman and Buck, 2003).

Level I - habitat type	Level II - class	Description
Tree habitats (avg. stem dbh > 0.1 m)	Bush and forest	Structure-rich tree stands, height > five meters
	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, < one 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
	Vineland	Scrub vegetation heavily covered by woody vines
Shrubland (avg. stem dbh < 0.1 m)	Exotic shrub	Open canopy, non-native species
	Mixed shrub	Open canopy, mixture of non-native & native species
	Native shrub	Open canopy, native species
Grassland	Amenity grassland	Intensively managed and regularly mown pasture
	Pasture grassland	Intensively managed and regularly grazed pasture
	Rough grassland	Irregularly managed grassland, including tussocks
	Dune grassland	Grassland on consolidated dunes
Non vegetation	House	Including farms (> 0.25 ha)
	Bare ground	Inclusive bare soil, gravel, quarry, sand
	Road, sealed surface	Concrete (e.g. parking)
	Coastal water	
	Standing water	

A total of 280 image objects were selected and surveyed in the field to serve as training samples for the classification. The study area was divided into four quadrants of equal size. The number of training samples selected for each class was proportional to its importance in terms of area covered, with a minimum of one sample per quadrant for the smallest classes. The samples were originally selected using the earlier habitat map produced by Freeman and Buck (2003) and were checked in the field during the autumn 2005. A series of data was collected to assist the classification: site dimension, habitat type, land use type, slope, aspect, elevation, dominant species, and vegetation density and structure (tree, shrub, and grass). The habitat and land use classes of the surrounding image objects were also recorded when possible. The classification of the vegetation stratum was also performed using the nearest neighbour (NN) algorithm. Thirteen variables were considered to build the NN feature space:

- Mean spectral value of image objects,
- Standard deviation of spectral values of image objects,
- Ratio of mean spectral value to sum of all spectral layer mean values of image objects,
- Compactness of image objects (length x width / number of pixels).

The three first above-mentioned variables were computed for each of the four spectral bands of the Ikonos image. An optimised feature space was finally selected by observing the best separation distance between vegetation communities. The classification output was refined by implementing simple expert rules. The rules were implemented by assigning crisp membership functions. The membership function receives a value 1 (*yes*) if the rule is observed (e.g. plantation larger than one ha) or a value 0 (*no*) if the rule is not observed (e.g. plantation smaller than one ha). If the rule is observed an action is undertaken. The following rules were applied:

- If *plantation* smaller than one hectare then reclassify as *tree group*.
- If *forest* smaller than one hectare then reclassify as *tree group*.
- If *tree group* larger than one hectare then reclassify as second best class.

### 3.3. Accuracy assessment

The accuracy assessment focused on the vegetation communities within, or at close proximity, to the city. A total of 370 validation polygons were surveyed in the field to define their membership to one of the categories of vegetation communities. Sixteen validation polygons were discarded as they could not be accessed or were found to include two or more vegetation classes on the ground. The total sample consisted of 1.3% of the vegetation strata which is above the one percent generally recommended (Congalton 1991). Typical confusion matrices were built to assess the accuracy of the vegetation classifications (Congalton 1991). Classes predicted by the NN classifier were compared to classes observed in the field. The confusion matrices were built using the polygons as validation units. These are the basic spatial units of the vegetation maps, and thus are believed to be more appropriate to assess the classification than individual pixels. Although the polygons have various size (including many pixels) each of these is assumed to correspond to a single and coherent vegetation patch. In our



opinion, individual pixels cannot be considered as independent objects (because of autocorrelation effects) and could potentially bias the classification assessment.

Descriptive statistics (user's accuracy, producer's accuracy, overall accuracy) as well as kappa statistics ( $\kappa$ ) were computed and analyzed (Congalton 1991). The  $\kappa$  statistic measures the accuracy of the whole confusion matrix considering the actual agreement in relation with chance agreement. It provides an indicator showing whether the classification is better than a random classification. Test statistic values (Z-statistic) were compared with the critical value 2.57 ( $Z_{\alpha/2}$ ) to determine the significance of the classification accuracies at 99% confidence interval (Congalton and Green 1999). We also used the categories proposed by Landis and Koch (1977) to assess the performance of the statistics: poor ( $< 0.41$ ), moderate (0.41 to 0.61), good (0.61 to 0.81), and excellent ( $> 0.81$ ). Although these categories are arbitrary they provide useful qualitative benchmarks.

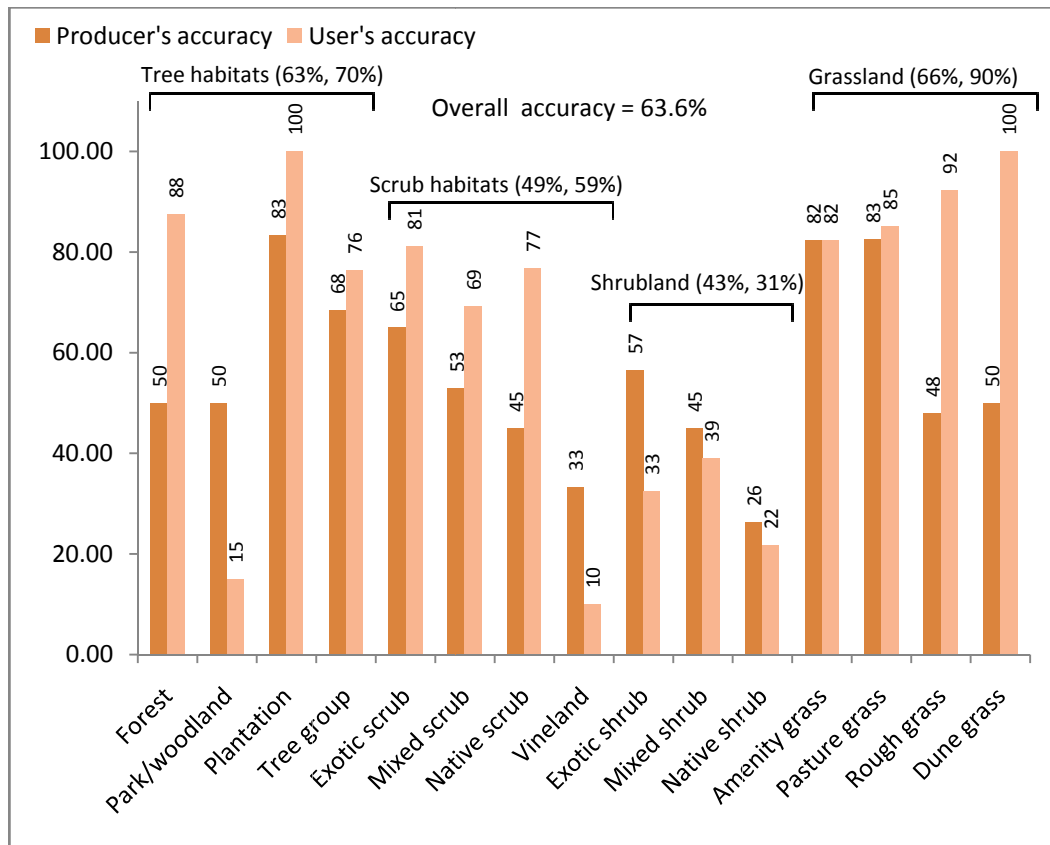
#### 4. Results

Table 2 presents the confusion matrix of the vegetation community map with fifteen classes. Confusion occurred between amenity grass (14%) and pasture grass (13%). Rough grass was confused mainly with exotic shrub (16%) and with mixed shrub (12%). Dune grass was confused with native shrub (33%) and rough grass (17%). Forest was mainly confused with vineland (14%) whereas park/woodland was confused with forest (33%) and tree group (17%). Tree group was confused with park/woodland (27%). Strong confusion occurred between the scrub and shrub vegetation communities, and also with vineland and park/woodland. The overall accuracy of the classification was a moderate 63.6% (Figure 3). Dune grass and plantation had 100% user's accuracy. Pasture grass, rough grass, forest, and exotic scrub user's accuracy were higher than 80%. Poor user's accuracy was obtained for vineland (10%), park/woodland (15%), native shrub (21.7%), exotic shrub (32.5%), and mixed shrub (39.1%). Most vegetation community classes had higher user's accuracy than producer's accuracy.

**Table 2.** Confusion matrix of the classification of vegetation communities using fifteen classes, Dunedin City, New Zealand (total number of validation objects = 354).

Ground references Classification		Tree habitats				Scrub habitats				Shrubland			Grassland				R
		For	Par	Pla	Tre	Exo	Mix	Nat	Vin	Exo	Mix	Nat	Am	Past	Rou	Du	
Tree Habitats	Forest	14 (50)	2 (33)														16
	Park/woodland	2 (7)	3 (50)	2 (7)	5 (27)	1 (5)	1 (6)		1 (17)		2 (10)	1 (5)			2 (8)		20
	Plantation			25 (83)													25
	Tree group	3 (11)	1 (17)		13 (68)												17
Scrub habitats	Exotic scrub					13 (65)				2 (9)	1 (5)						16
	Mixed scrub						9 (53)				4 (20)						13
	Native scrub						2 (12)	10 (45)	1 (17)								13
	Vineland	4 (14)				2 (10)	2 (12)	7 (33)	2 (33)	1 (4)	1 (5)	1 (5)					20
Shrubland	Exotic shrub	1 (4)		2 (7)		3 (15)	1 (6)		1 (17)	13 (57)	2 (10)	10 (52)	1 (2)	2 (3)	4 (16)		40
	Mixed shrub	3 (10)		1 (3)		1 (5)		1 (5)		2 (9)	9 (45)	2 (10)	1 (2)		3 (12)		23
	Native shrub	1 (4)					2 (12)	3 (14)	1 (17)	5 (21)	1 (5)	5 (26)		1 (2)	2 (8)	2 (33)	23
Grassland	Amenity grass				1 (6)								42 (82)	8 (13)			51
	Pasture grass												7 (14)	52 (83)	2 (8)		61
	Rough grass														12 (48)	1 (17)	13
	Dune grass															3 (50)	3
	Column Total	28	6	30	19	20	17	21	6	23	20	19	51	63	25	6	354

Values are given in number of image objects, values in parenthesis are percentages given in relation to the column total.



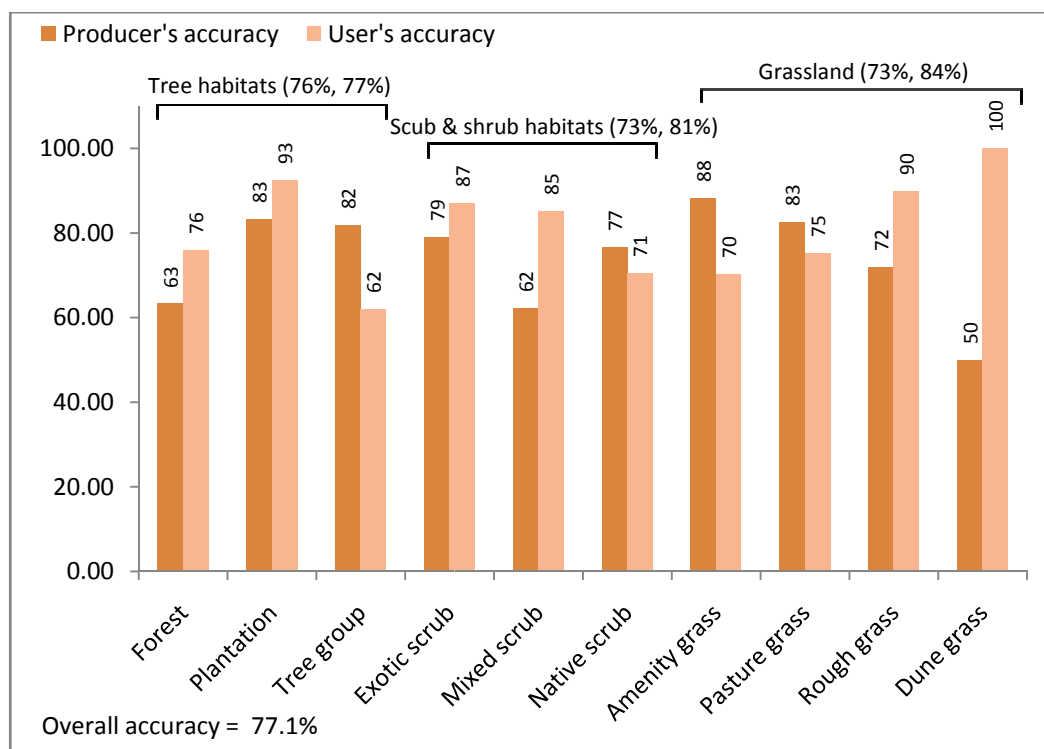
**Figure 3.** Producer's accuracies, user's accuracies, and overall accuracy of the classification of vegetation communities using fifteen classes, Dunedin City, New Zealand. Mean producer's and user's accuracy (in parenthesis) are given for level 1 habitat types (see Table 1).

The confusion in classification noted above led to a regrouping of classes and the creation of a simplified classification scheme. The highest levels of confusion were found in the following classes: vineland, park/woodland, scrub, and shrub communities. Vineland and park/woodland only cover a small percentage of the total land area in Dunedin City, 0.1% and 2.4% of the vegetated areas respectively (Freeman and Buck 2003), and were discarded. The six scrub and shrub classes were merged to create three classes: exotic scrub, mixed scrub, and native scrub. The simplified classification scheme consisted of four grass classes (amenity grass, pasture grass, rough grass, and dune grass), three tree classes (forest, plantation, and tree group), and three scrub classes (exotic scrub, mixed scrub, and native scrub). Table 3 presents the confusion matrix of the vegetation community map with ten rather than fifteen classes. Some confusion persisted, although generally to a much lesser extent. Dune grass was confused with amenity grass (17%), rough grass (17%), and native scrub (17%). Forest was mainly confused with tree group (17%) and native scrub (13%). Tree group was confused mainly with amenity grass (14%). The main confusion of mixed scrub was that with amenity grass (8%), forest (8%), and native scrub (8%). Native scrub was also confused with pasture grass (9%). The overall accuracy of the simplified classification was good at 77.1% (Figure 4). All classes had more than 60% user's accuracy. Out of ten classes five had more than 85% user's accuracy and three had between 75% and 85% user's accuracy.

**Table 3.** Confusion matrix of the classification of vegetation communities using ten classes, Dunedin City, New Zealand (total number of validation objects = 354).

Ground references Classification		Tree habitats			Scrub & shrub habitats			Grassland				Row Total
		Forest	Plantation	Tree group	Exotic scrub	Mixed scrub	Native scrub	Amenity grass	Pasture grass	Rough grass	Dune grass	
Tree habitats	Forest	19 (63)		1 (4)	1 (2)	3 (8)	1 (2)					25
	Plantation		25 (83)		2 (5)							27
	Tree group	5 (17)		18 (82)	1 (2)	1 (3)	2 (4)			2 (8)		29
Scrub & shrub habitats	Exotic scrub		1 (3)		34 (79)	1 (3)	2 (4)		1 (2)			39
	Mixed scrub	2 (7)	1 (3)			23 (62)	1 (2)					27
	Native scrub	4 (13)	2 (7)		3 (7)	3 (8)	36 (77)			2 (8)	1 (17)	51
Grassland	Amenity grass			3 (14)		3 (8)	1 (2)	45 (88)	10 (16)	1 (4)	1 (17)	64
	Pasture grass		1 (3)		2 (5)	2 (5)	4 (9)	6 (12)	52 (83)	2 (8)		69
	Rough grass					1 (3)				18 (72)	1 (17)	20
	Dune grass										3 (50)	3
Column Total		30	30	22	43	37	47	51	63	25	6	354

Values are given in number of image objects, values in parenthesis are percentages given in relation to the column total.



**Figure 4.** Producer's accuracies, user's accuracies, and overall accuracy of the classification of vegetation communities using ten classes, Dunedin City, New Zealand. Mean producer's and user's accuracy (in parenthesis) are given for level 1 habitat types (see Table 1).

Both classifications were found to be statistically significant and better than random classifications:

- Classification fifteen classes:  $\kappa = 0.52$ , Z-statistic = 17.5
- Classification ten classes:  $\kappa = 0.74$ , Z-statistics = 25.2

The  $\kappa$  value of the original classification (15 classes) was in the mid section of the “moderate” range while the  $\kappa$  value of the simplified classification (10 classes) was close to the “excellent” range. Conditional  $\kappa$  values were also computed for each vegetation class of the simplified classification (Congalton and Green 1999). Excellent agreement or good agreement was found for five and four classes respectively. Only the tree group class had a moderate agreement, although very close to the good range (Table 4). The classification results were considered satisfactory for the classes having a good or excellent agreement to their reference category.

**Table 4.** Conditional kappa value ( $\kappa$ ) for the ten vegetation communities classes of the simplified classification (computed after Congalton and Green 1999).

Level I – habitat type	Level II - class	Conditional $\kappa$ value	Range *
Tree habitats	Forest	0.74	good
	Plantation	0.92	excellent
	Tree group	0.6	moderate
Scrub & shrub habitats	Exotic scrub	0.85	excellent
	Mixed scrub	0.83	excellent
	Native scrub	0.66	good
Grassland	Amenity grass	0.65	good
	Pasture grass	0.70	good
	Rough grass	0.89	excellent
	Dune grass	1	excellent

\* Classification after Landis & Koch (1977)

The areas of the vegetation communities and other habitat types (built-up areas, bare ground, water, and sand) were computed for the whole city (Table 5). The urban area was delineated by creating a buffer of 200 meters outside the main settlements (including the residential stratum and the industrial / commercial stratum). The city included 1884 ha (57.8%) of vegetation communities (excluding the private gardens within the residential area), while 1385 ha (42.2%) consisted of non-vegetated habitat types. The most represented vegetation class was amenity grass with 502 ha (15.4%) and the least represented class was dune grass at 7 ha (0.2%).

**Table 5.** Areas of vegetation communities and other habitat types Dunedin City, New Zealand.

<b>Level I – habitat type</b>	<b>Level II - class</b>	<b>Area (ha)</b>	<b>Percent (%)</b>
Tree habitats	Forest	77.5	2.4
	Plantation	40.0	1.2
	Tree group	281.1	8.6
Scrub & shrub habitats	Exotic scrub	57.8	1.8
	Mixed scrub	112.6	3.5
	Native scrub	385.2	11.8
Grassland	Amenity grass	502.2	15.4
	Pasture grass	390.4	11.9
	Rough grass	31.2	1.0
	Dune grass	6.6	0.2
Total area vegetation (a)		1884.6	57.6
Non vegetation	Built	1,204.8	36.8
	Bare ground (Bare soil)	3.6	0.1
	Bare ground (Quarry, Gravel)	43.7	1.3
	Water	131.8	4.0
	Sand	1.1	0.0
Total area other habitats (b)		1385.0	42.4
<b>TOTAL AREA (a) + (b)</b>		<b>3269.6</b>	<b>100.0</b>

## 5. Discussion

### 5.1. Classification accuracy

Vegetation communities found in urban areas share many similarities with the communities of more natural or agricultural environments, but they also present some substantial differences. Vegetation fragmentation is high in cities, and can be extreme, with patches of various sizes, generally fairly small, isolated within a harsh matrix of mostly impervious materials. In this highly modified and landscaped environment vegetation associations tend to be complex and heterogeneous, from a point of view of structure (e.g. mixes of trees, shrubs, and lawn patches in recreational parks) or of species association (e.g. various mixes of indigenous and exotic vegetation). Finally, some communities are more typically associated with the built environments and are essential components of urban ecology (Meurk and Hall 2000), for instance amenity pastures (e.g. sports fields), recreational parks (e.g. botanical gardens), or private gardens. The high heterogeneity and small patch size of urban vegetation has limited the earlier use of satellite imagery for detailed ecological mapping in cities. This has become technically feasible in the recent years with the availability of very high resolution satellite imagery (Nichol al. 2007), although the data processing is not fundamentally different from what would be implemented in a more natural setting. The availability of appropriate datasets has matched



an increase of interest in urban ecology as well as an increase of attention given to the quality of life in cities. Emerging techniques such as object-based classification techniques are also well suited to urban mapping in their capacity of handling higher level of data heterogeneity and more complex spatial patterns. While examples of thematically detailed vegetation mapping using satellite imagery are numerous at medium and fine scales in natural environments (Rutchev and Vilcheck 1994; Mickelson et al. 1998; Thenkabail et al. 2004; Bock et al. 2005; Yu et al. 2006), few examples have been reported in urban areas. This research intended to contribute to fill this gap.

The two classifications of urban vegetation presented in this research have overall accuracies ranging from 63.6% to 77.1% ( $\kappa$  value from 0.52 to 0.74) for fifteen and ten classes, respectively. Classification accuracy is largely dependent on the number of classes considered, i.e. the accuracy generally increases when the number of classes decreases. However, the spectral contrast between classes, class heterogeneity, and the purity of collected samples (both for training and validation), play a vital role in increasing or decreasing the overall accuracy. Similar accuracy results were reported in fine-scale habitat mapping with very high resolution satellite imagery. Keramitsoglou et al. (2005), for example, used a kernel based re-classification method for mapping five habitat classes (Lake Kerkini, Greece) and obtained 71% overall accuracy. Bock et al. (2005) using an object-based classification system extracted eight vegetation classes with 81% overall accuracy from a Quickbird image (Wye Downs, UK). Thenkabail et al. (2004) reported an overall accuracy of 48% for nine vegetation classes in tropical rainforests (Akok, Cameroon). Yu et al. (2006) implemented an ambitious species-based vegetation classification of very high resolution airborne imagery. They obtained an average accuracy of 48.2% for 43 vegetation classes with a large variation between classes (from 4 to 100%, standard deviation = 21.2%). Most of these projects dealt with protected or rural environments. In urban areas Zhang and Feng (2005) achieved 97% overall accuracy, but only considered two vegetation classes, i.e. tree and grass.

The accuracy assessment of the original classification (fifteen classes) showed that classes such as vineland; park/woodland; scrub communities, and shrub communities yielded low user's and producer's accuracies. The discrimination of urban vegetation communities at such a detailed level produced a map with limited reliability. Difficulty arises from similarities in spectral reflectance and hence in spectral signatures among some classes. Vineland is a scrubby habitat heavily covered by woody vines and was confused with other scrub and shrub classes. Although ecologically significant, vineland is also one of the least represented habitats in the city. Similarly, it was difficult to automatically classify park/woodland as this class appears to lack a unique character. Park/woodland is an anthropogenic habitat characterized by clumped trees/shrubs scattered over exotic grassland. The heterogeneous nature of park/woodland makes it often difficult for the segmentation process to identify the boundaries of this vegetation community. A high level of confusion also occurred between native, exotic, and mixed shrublands and scrub habitats. This confusion occurred for several reasons. Shrublands differ from scrubs by having a lower density of woody materials and generally being more open vegetation communities. The change from scrub to shrubland is a natural continuum, thus a subjective decision is required to establish the boundary. The decision whether an object is in one class or another can be based on small density differences. Further, mixtures of native and/or exotic plant species often produce canopies with very close structure and colour. However, scrub habitats dominated by a single species were an exception in the sense that they tended to be easier to detect; for

example, gorse-dominated (*Ulex europaeus*) vegetation communities exhibit typical canopies with yellow flowers. For similar reasons complex arrangements of native and exotic species were also not easily recognizable from detailed colour aerial photographs in Freeman and Buck's project (Claire Freeman, Pers. Comm.). A high accuracy in the classification of these complex habitats was found to require intensive field checks. This relied upon experienced field ecologists capable of identifying a large number of plant species. Moreover, boundaries between natural (e.g. native habitat) and semi-natural plant communities (e.g. mixed habitats) are typically gradual and diffuse as compared to the sharp boundaries of anthropogenic habitats such as pine plantation or amenity grass. This creates subjectivity or uncertainty in boundary detection, which in turn generates classification inaccuracies.

### 5.2. Object-based approach and urban ecological mapping

Classifications produced with object-based techniques are readily available in vector format and can be directly imported and analyzed in a vector-based GIS package (e.g. ArcGIS). This is a significant advantage over traditional per-pixel classification techniques which produce raster-based maps. No post processing operation is required to clean up individual misclassified pixels, i.e. salt and pepper effect. Object-based classifications use a segmentation process to identify and delineate meaningful targets in digital images. An important point is that the segmentation process can be seen as an automated digitizing of target boundaries. Figure 1 shows that the scale 40 delineates vegetation units such as amenity grass, tree groups, park/woodland, bush and forest quite well in the Botanical Garden of Dunedin. This automated extraction of objects is by itself very cost-effective as it reduces the necessity for laborious on-screen digitizing, which is by far the most time-consuming task of the standard photo-interpretation process (Freeman and Buck 2003). More research is required to assess or validate the quality or geometric accuracy of the objects generated by the segmentation. For instance, Moller et al. (2007) proposed a comparison index to support the selection of an optimal segmentation scale. However, Baatz et al. (2004) suggested that beyond quantitative evaluation of segmentation procedures, no segmentation result is fully convincing if it does not satisfy the human eye.

In contrast to pixel-based classification, the manual reclassification of wrongly classified objects or polygons is technically feasible, although it may be time consuming, thus cancelling the relative advantages of the exercise. In this research, manual reclassification was successfully used to correct some obvious confusion, such as the confusion of plantation or amenity grass with other classes. The decision to reclassify an object was only based on the photo-interpretation of the Ikonos image which is the main source of decision support for the classification. Further, we believe that a combination of strategies, including automated segmentation and classification, as well as manual classification, could be the most appropriate approach when a large amount of thematic and geometric details are required to map vegetation communities or habitats in urban environment.

The manual digitising and photo-interpretation of vegetation units from colour aerial photographs produced semantically more detailed vegetation maps than those we produced (Freeman and Buck 2003). However, in Freeman and Buck's study a significant fieldwork component was still required to ensure the most accurate distinction between some vegetation communities (e.g. mixes of native and exotic habitats). Manual digitising of vegetation units is a valid option in the case of small- and medium-sized cities, although cost issues may limit the mapping exercise to large vegetation patches

such as remnants and indigenous habitats. For a city the size of Dunedin, a vegetation community map took a single researcher approximately a year to complete (Claire Freeman, Pers. Comm.). The manual approach becomes more difficult in large cities, especially if smaller vegetation patches have to be extracted. In this case, automated segmentation and object-based classification with Ikonos imagery is more cost effective, but has the semantic limitations shown in this research. To cater for these deficiencies a third option would be to make greater use of manual classification and to undertake more systematic field checks, both for the most difficult classes (e.g. scrub and shrublands), and also in areas where there is a high diversity of habitats. The discrimination of certain vegetation communities, e.g. dense vs. more open habitats, may be improved by applying object-based techniques to higher multi-resolution image products such as fused panchromatic and multispectral images. Fusion techniques are available, which merge into one unique dataset the high spectral quality of multispectral images and the high spatial quality of their panchromatic counterparts, e.g. Ikonos, multispectral 4 meters and panchromatic 1 meter (Ranchin et al., 2000). A third level of scale could be investigated by applying object-based classification techniques to digital aerial photographs. This could include the near infrared band which is the most sensitive part of the spectrum to vegetation types and density (Guyot, 1990). With a potential ground pixel size anywhere between 5 and 50 centimetres, micro-scale vegetation or biodiversity features, such as individual trees in the streets or small shrubs and ponds in private gardens, could be correctly identified and inventoried using these methods.

Dunedin City is a medium-sized city by New Zealand standards (fifth city in term of population after Auckland, Wellington, Christchurch, and Hamilton), and a small city by international standards; similar cities are ranked around 200 in the USA and above 500 in Europe (City Mayors Statistics, 2007). The replication of this work in larger cities of New Zealand would most likely require minor adaptation as vegetation communities and city structure (CBD, residential areas) are quite similar to Dunedin, although the size of the city may induce some limitations such as those discussed above. However, the mapping of vegetation community in other world cities would require at least the modification of the classification scheme as to reflect the local topo-climatic conditions and urban eco-history. Although the highest hierarchical levels are likely to be quite similar to the one found in New Zealand, many local differences and specificities may be required at the lowest hierarchical levels (e.g. species associations). Further, the stratification process may need to be adapted in areas where urban development is less planned and formal (e.g. developing countries) and / or where the boundaries between built-up and vegetated areas are less defined.

## 6. Conclusion

Detailed urban habitat maps are usually created by manual interpretation of aerial photographs, but this is time-consuming at large scales. To address this issue, we applied object-based classification techniques to very high resolution multispectral Ikonos images to produce a map of vegetation communities in Dunedin City, New Zealand. A vegetation stratum (including vegetation patches larger than 0.8/1ha) was segmented at a detailed scale to extract and classify fifteen classes of vegetation community. The first classification yielded a moderate overall classification accuracy (64%,  $\kappa = 0.52$ ), mainly because of confusion between scrub habitats, shrublands, vineland and park/woodland. This led us to consider a simplified classification with ten vegetation classes. The overall classification was

77% with a  $\kappa$  value close to the excellent range ( $\kappa=0.74$ ). This approach did not provide maps at the same level of semantic detail as those produced by manually interpreting aerial photographs, but it was still possible to extract a number of ecologically significant vegetation classes. Object-based classification of Ikonos imagery was found to be an efficient way to generate accurate and detailed vegetation maps in significantly shorter time than with previous methods. The final map accuracy could be improved by integrating segmentation, automated and manual classification in the mapping process, especially when considering important vegetation classes with limited spectral contrast. Ultimately the application of either of these techniques, manual photo-interpretation vs. object-based classification, or a combination of both, to other cities will provide enhanced biodiversity understanding in the urban environment. However, the final choice of mapping technique will depend on the objectives (e.g. identifying minimum patch size, thematic accuracy) and the resources available.

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