Automated algorithms for extracting urban features from Ikonos satellite data. A case study in New York City.

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Abstract: This paper describes development of feature extraction algorithms using spectral and spatial attributes for detecting specific urban features. Spectral and spatial heterogeneity of urban environment present challenges to their accurate detection and classification from remotely sensed data. Methods include segmenting Ikonos data, computing attributes for creating image objects, and classifying the objects with rules. Low class accuracies were reported for dark and gray roofs. By employing different segmentation scale parameters and a modified approach to feature extraction, we further improved the accuracy. In this approach new rules and attributes were applied selectively to image areas having similar or near-similar spectral and spatial characteristics that could be specified within a threshold. Results showed a remarkable improvement in the accuracy of classes with low spectral separability. We developed different algorithms using a range of spectral and spatial attributes to extract specific urban features from any mss (4m by 4m) Ikonos data.

Key-Words: - Ikonos, Spatial, Spectral, Image, Objects

1 Introduction
Mapping urban features from satellite data is essential for planning, urban development, emergency management and monitoring the environment. The pace of urban development and consequent sprawl demands current spatial and temporal data that can lead to a better understanding of infrastructural needs, land use planning, imperviousness and water pollution. The rapid development of new residential, commercial and industrial areas, reduction in green areas, monitoring of pollution in urban water bodies, flood zone planning, planning emergency evacuation routes, urban housing development, mapping informal settlements are examples of dynamic urban problems. Satellite data provides a unique synoptic view of changing urban landscapes that is critical in spatial analysis and modeling. Different types of satellite systems and sensors have been studied and investigated to provide geospatial solutions to existing and new urban problems [1]. The recent availability of high spatial resolution imagery from satellite sensors such as Ikonos and QuickBird, as well as from digital aerial platforms, provides new opportunities for detailed urban land cover mapping at very fine scales [2]. Several studies have investigated the development and distribution of buildings in a city which is essential for urban environmental investigation, planning [3] and identification of informal settlements [4]. Other studies have demonstrated applications of very high resolution (VHR) satellites for providing spatial details ideally suited for urban mapping [5] [6]. Ikonos, Quickbird images (4m by 4m to 2.5m by 2.5m pixel size) have been used for mapping urban impervious surfaces, roads, and buildings [7] [8].

A vast majority of classifiers for urban mapping were based on spectral analysis which has reported several problems related to either shadows, mixed pixels or low spectral separability between classes [9] [10] [11] [12]. Different digital image processing techniques such as unsupervised classification (ISODATA), supervised classification (MLC, spectral angle mapper) have been used for mapping urban features from Ikonos. Supervised, unsupervised approaches involve use of spectral bands in mss images for mapping urban feature. Many studies have reported limitations of spectral approaches due to the heterogeneity of urban features and spectral confusion of feature classes. Different resolutions of remotely sensed data were used in mapping, of which high-resolution images have been showing very unsatisfactory based on the pixel’s spectral value especially in urban areas [13] [14] [15]. Therefore mapping urban features using spectral approaches alone may not be successful. Apart from the problem of mixed pixel and spectral confusion the spatial heterogeneity (variations in shape, size, area, texture) of urban features may also lead to misclassification of urban pixels. Furthermore these spatial variations are not uniform across the image due to within-field differences. For all the above reasons,
mapping urban features from remotely sensed data has been a challenge for several years.

Feature Extraction uses an object-based approach to classify imagery. An object is a region of interest with spatial, spectral (brightness and color), and/or texture characteristics that define the region. In feature extraction, spectral and spatial attributes are computed for each region to create objects which are then classified with rules based on those attributes. The benefit of an object-based approach is that objects can be depicted with a variety of spatial, spectral, and textural attributes. Feature extraction technique is based on human knowledge and reasoning about specific feature types: e.g. roads may be elongated, some buildings approximate a rectangular shape, vegetation has a high NDVI value, and trees are highly textured compared to grass. Spatial, spectral, or texture properties of a vector object that can be used to classify the object into a known feature type. However, due to lack of automated extraction techniques, the information potential of satellite data has not been fully exploited effectively. The objectives of the study were to map specific urban features using different sets of rules based on the spectral and spatial characteristics. The second major objective was to develop robust feature extraction algorithms for automated retrieval of urban objects from time-series of very high resolution (VHR) satellite data such as Ikonos.

2 Study site and spatial characteristics of urban features

Study site consists of Queens, Brooklyn (New York City boroughs), Paterson (New Jersey) and parts of Jersey City. Five Ikonos images are used in this study (see Fig 1). On all these images, the land use varies from dense built up to low-density built up, recreational sites, open spaces, trees and water bodies (East River and Hudson River). The majority of the land use in the September 2003 image are industrial buildings (60% of the study site) covering an average area of 11,056 m². Of these buildings approximately 80% are gray roofs, 15% dark roofs and 5% white roofs. Gray roofs and white roofs were characterized by two distinct shapes - rectangular and circular (white roofs only), whereas their shapes varied across the image. Dark roofs were limited to square and rectangular shapes while their area ranged from 5800m² to 1700m². The second major land use category is commercial (99% gray roofs) which covers approximately (20% of the study site). The commercial gray roofs were more or less uniform in shape (rectangular) and area (3500m²).

Similar spatial patterns were also observed on the September 2001 image with the exception of industrial roofs which were much larger in size (gray roofs, dark roofs and white roofs ranging from 22,000m² to 5000m²). Additionally circular white roofs that were observed on the September 2003 image were not found in this region. In the August 2004 image the general land use consist of residential (50%), recreational (20%), commercial and industrial (30%) approximately. The residential buildings (small gray roofs) have similar shape, pattern and size. Most of the residential buildings were found in close proximity to independent trees. Recreational areas consist of clusters of trees with similar pattern, texture and shape. Majority of the roofs consisted of large, medium and small gray roofs with varying roof shapes. Similar spatial properties were also observed in the January 2008 image with the exception of having larger proportion of the land use belonging to industrial/commercial classes. The majority of the land in the image May 2008, is covered by residential buildings (60%), Industrial 20% and recreational 15%. The residential buildings consist of high-rise buildings...
that are found in clusters. There are shadows cast by these buildings that are found to the western side of the buildings. The above spatial characteristics of an urban area is important to understand for classification.

### 3 Imagery acquisition

Cloud-free and orthorectified Ikonos satellite images were used in the analysis. Time-series of images (Sep 2001, Sep 2003, Aug 2004, Jan 2008 and May 2008) were acquired in geotiff formats. The Ikonos imagery consists of a single (1m by 1m) panchromatic and four multispectral bands (4m by 4m). The images have a radiometric resolution of 11 bits per pixel and were projected to the Universal Transverse Mercator (UTM), zone 18, WGS84 datum. The data specifications and resolution characteristics of Ikonos are shown in Table 1.

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#### Table 1: Ikonos data characteristics

### 4 Methodology

Figure 2a and 2b shows the methodology used in this study. The preliminary research focused on a fully processed and orthorectified Ikonos multispectral imagery acquired on 10th September, 2003 over Queens and Brooklyn boroughs of New York City. After detailed visual examination of the study area seven class classification format was defined based on the criteria as laid out by [16]. Classification scheme was modified to center on specific urban features. The image was then segmented by using different scale level parameters and weights for each class. Image segmentation was followed by developing rules for feature extraction. Each set of rules were assigned appropriate spectral and spatial attributes based on their specific band reflectivity and absorption features. Average band ratio, minimum maximum band ratios, shape, size, roundness, elongation, rect-fit, and area features were employed to design the rules and assign attributes. The final set of rules and attributes were developed by using a combination of both spectral and spatial attributes. The accuracy of the classification results was estimated by using both primary (ground truth data and secondary data that were acquired either from other merged image data or from existing databases such as the Open Accessible Space Information System Cooperative (OASIS) that is created and hosted by the Center for Urban research, City University of New York (CUNY). OASIS website accesses GIS maps and planning data sets from different agencies. We used both raster and vector data (aerial photo images, street and road networks, buildings) from the OASIS website to visually compare the results from rule based classification.

![Figure 2 Methodology](image-url)

**Figure 2 Methodology**

Due to the heterogeneity of urban features and variations in their spatial characteristics such as shape, size, area the accuracy of class features particularly gray and dark roofs were low. Therefore, we attempted a modified per-field approach to improve the low accuracy of class features which is discussed under section ‘modified approach’. In this approach we used multiple...
5 Modified approach (per-field)
Spatial and spectral attributes are useful in extracting urban features as mentioned above but due to the within scene variations (shape, area, spectral values) of different urban features it is difficult to apply rule sets with any consistency across the image. Therefore, we segmented the image based on the characteristics of the spatial configuration of urban features. We extracted image objects using different segmentation parameters related to the homogeneity criterion of the multi-resolution segmentation algorithm, and measured how homogenous or heterogeneous an image object is within itself. The homogeneity criterion is calculated as a combination of color and shape properties of both the initial and the resulting image objects of intended merging [25] [26].

From the above it is clear that classification of urban features from high resolution images have to base on a thorough knowledge about the characteristic of the spatial configuration of urban objects. Therefore, we adopted a modified approach in which we segmented each image into regions that were homogenous in their spatial configuration characteristics i.e. shape, size and area. Rules and thresholds were applied by using a new set of spatial and spectral attributes to detect urban features.

6 Development of algorithms to extract urban features
We divided the study site into various segments to correspond the classes to the real world objects. The scale level was used to delineate the boundaries of all feature classes. Small segments were merged with larger ones from the same feature class using different merging scale thresholds. Initially, the September 2003 image was classified using a combination of different spatial, spectral, customized (combination of different rule-sets) and texture rule-sets. We then applied the same rule sets to a series of multi-temporal Ikonos images (Fig 1) in a modified approach (per-pixel) that is discussed in detail in the following paragraphs. The segments, spectral and spatial attributes to extract specific urban feature objects from multi-temporal Ikonos images are summarized. The classified features were then exported to a vector–GIS format for further spatial analysis and modeling. Accuracy assessment revealed higher class accuracies for all classes in the modified approach as compared to the initial results. In the following paragraphs we discussed the different algorithms that may be used to retrieve specific urban objects from any Ikonos multispectral imagery. The discussion also includes the appropriate choice of combinations of spectral/spatial attributes.

7 Results
7.1 Rule based classification and distribution of urban features
We developed rules and algorithms for an Ikonos image that was acquired on September 2003. We then tested the robustness of these rules and algorithms for feature extraction by applying them on multi-temporal Ikonos images (September 2001, August 2004, January 2008, and May 2008).

7.1.1 Gray roofs
Large gray roofs (area ranging from 800m² to 1800m²) were delineated by a process of visual examination. The minimum segmentation scale level was 33.4 and maximum was 43.1. Residential gray roofs were delineated using a smaller segmentation scale level of 21.6 for the September 2003 image only. We found that the green band was useful for extracting urban features that have generally low reflectance values. Vegetation, gray roofs, parking lots and roads were broadly classified and extracted by using the spectral attribute ‘Avg_band_Green’ (average pixel value of green band). We separated vegetation from other impervious surfaces by using the spectral attribute ‘Avg_band_NIR’. The NIR band isolated vegetation from impervious surfaces. We used the same algorithm for extracting vegetation from impervious surfaces for the September, 2001 image but also used the red bands in addition to the NIR. The image area is characterized by features that were spectrally similar to gray roofs such as parking lots, play grounds, tennis courts basketball courts. Therefore in this case the spectral attribute were not adequate to delineate gray roofs. As discussed before, gray roofs also exhibited some generic shape features such as rectangles and squares (Fig 3). We applied spatial attributes such as such as ‘elongation’, ‘compactness’ and ‘form factor’ to separate and extract gray roofs from other impervious and irregularly shaped features such as parking lots and roads. ‘Elongation’ is a shape measure that gives a measure of the ratio of the major axis of the polygon to the minor axis of the polygon. Elongation attributes were used to separate gray roofs from roads.

From the above it is clear that classification of urban features from high resolution images have to base on a thorough knowledge about the characteristic of the spatial configuration of urban objects. Therefore, we adopted a modified approach in which we segmented each image into regions that were homogenous in their spatial configuration characteristics i.e. shape, size and area. Rules and thresholds were applied by using a new set of spatial and spectral attributes to detect urban features.
and air port runways (e.g. on the January 2008 image). Compactness is a shape measure that indicates the compactness of the polygon. Compactness calculated using following formula: Compactness = \sqrt{(4 * \text{area})/\pi} / \text{outer contour length}. ‘Form factor’ is a shape measure that compares the area of the polygon to the square of the total perimeter. ‘Formfactor’ is computed using following formula: Formfactor = 4 * \pi * (\text{area}) / (\text{total perimeter})^2. ENVI-Zoom user manual, 2007). We used ‘compactness’ and ‘form’ factor spatial attributes to isolate gray roofs from other impervious surfaces such as parking lots specifically for 2001, 2004 and 2008 images. However, even the spatial attributes had limitations that contributed to lower accuracies for gray roofs. For example, the sides of some high-rise buildings were detected as roofs.

The spectral attributes employed to extract dark roofs were similar to that of the gray roofs. Dark roofs were extracted using Avg_band_green from the September 2001, 2003 and May 2008 images. For the August 2004 and May 2008 images we used ‘Avg_band_red’ spectral attribute. However, ‘Avg_band_red’ also extracted feature class water, shadows and vegetation along with dark roofs. These classes were separated from dark roofs by using spectral attribute ‘Avg_band_NIR/band ratio’ (color space and band ratio). Band ratio attribute computes the normalized band ratio between two bands, using the following equation: \((B2 - B1) / (B2 + B1 + \text{eps})\) where B1 is the green band and B2 is NIR band and eps is a small number to avoid division by 0 (ENVI Zoom user manual 2007). By applying the above attributes we found that inland water from East River on the August 2003 image, water reservoirs found on the May 2008 image, bridges and roads (on all images) were also classified as dark roofs due to near-spectral similarities to water. Therefore, we employed spatial features such as area, rectangular fit, compactness, roundness and elongation to separate dark roofs from roads, bridges and water. ‘Area’ attribute measures the total area of the polygon, minus the area of the holes (values are in map units). The ‘Rectangular fit’ is a shape measure that indicates how well the shape is described by a rectangle. This attribute compares the area of the polygon to the area of the oriented bounding box enclosing the polygon. ‘Roundness’ is a spatial attribute that compares the area of the polygon to the square of the maximum diameter of the polygon. All the images were acquired exposed off-nadir exhibited elongated shadows. To separate shadows from dark roofs we used elongation and compactness attributes. For the images that were acquired at noon, which exhibited less shadows, we used roundness and rectangular fit spatial attributes to extract dark roofs. Inland water bodies, roads that were also extracted as dark roofs separated using combination of elongation and area spatial attributes. The road networks of the northern parts of the image were separated from dark roofs using elongation spatial attributes.

**Figure 3 Variations in spatial attributes (shape) of gray roofs.**

### 7.1.2 Dark roofs

Dark roofs in the image were categorized in two sizes – large sized dark roofs consisting of an area approx. 7,094 m² or medium sized (areas ranging from 1000-5000 m²). Most of the large dark roofs were found to the north-eastern parts of the series of images. However, for the May 2008 image, we used a lower segmentation scale level ranging from 15-28.8 to delineate smaller dark roofs whilst a higher segmentation scale level of 44.2 was used to delineate the larger dark roofs located to the north eastern parts of the image.

### 7.1.3 White roofs

White roofs were scattered across the entire Ikonos images. Most of the white roofs ranged from 1800m² to 1400m² in area and were uniform in their shapes (square/elongated). Exceptions for the shapes of white roofs were aircrafts, tanks/reservoirs (Sep 2003 and Jan 2008) images. The segmentation scale that delineated white roofs ranged from 33.4 to 55.9. We used the spectral attribute, ‘Avg_band_red’ ranging from (98-230
pixel values) to delineate white roofs from Aug 2004, Jan 2008, and May 2008 images. We found that the ‘Max_band_red’ (maximum value of pixels in red band ranged from 252-1567 pixel values was equally effective in extracting white roofs (applied on Sep 2001, and 2003 images). However, when this spectral attribute was applied another spectral attribute ‘Avg_band_NIR’ (pixel values ranging from 146-647) was required to delineate the white roofs from other light grey roofs (applied on the Sep 2001 and 2003 images).

Spatial attributes such as ‘convexity’, ‘rectangular fit’ were applied for Sep 2003, Jan 2008 and May 2008 images. The spatial attribute ‘convexity’ measures the convexity of the image objects. ‘Convexity’ was applied to delineate white roofs from other open impervious spaces (Sep 2003, May 2008). The spatial attribute ‘rectangular fit’, indicates how well the shape is described by a rectangle. Rectangular fit, was used to prevent round tanks/ reservoirs as well as the aircrafts, from being extracted as white roof (Jan 2008).

### 7.1.4 Vegetation

The feature class vegetation consisted of trees, grass, and recreational areas. Most of the vegetation was located in the north-eastern parts of the image (Queens and Brooklyn) and ranged from 140,640 m² to 863,984 m² in area. The segmentation scale level for delineating vegetation was 10.8 to 43.1. We used two spectral attributes (‘Avg_band_NIR’ and band ratio) methods for classifying vegetation. The initial method was to use the spectral attribute ‘Avg_band_NIR’ which broadly classified vegetation along with dark roofs and gray roofs. We used the ‘Max_band_green’ to isolate vegetation from dark and gray roofs. The spectral attribute band ratio, is a measure of normalized difference vegetation index (NDVI) formulized using red and green bands, capable of extracting vegetation without using any spatial attributes (Aug 2004, May 2008). In some instances, the extraction of vegetation by using this attribute was challenging due to the low separability and spectral confusion particularly between vegetation and bare ground (Jan 2008 image). We therefore used spatial attribute – ‘roundness’ to separate bare ground from vegetation. In the Sep 2003 image, some of the grey roofs were also classified as vegetation due to low spectral seperability between (grey roofs and grass due to their overlapping locations. To separate the grey roofs from grass we applied the ‘texture’ spatial attribute which is the average variance of the pixels comprising the region inside the kernel.

### 7.1.5 Trees

Trees were mostly located in residential neighborhoods and in parks. In this study three types of categories - tree cluster, row and independent trees made up the class tree. A segmentation scale level ranging from 3.1 to 25.2 was used to delineate the trees from the images.

Separating trees from vegetation was challenging since trees are spectrally similar to other types of vegetation. Our initial approach was to use the ‘average band NIR’ and ‘max_band_red’ to isolate trees, gray roofs and other impervious surfaces. We used spectral attributes ‘band ratio’, ‘min_band_NIR’ and max_band_green to separate gray roofs and other impervious surfaces from trees. ‘Max_band_green’ was only used when gray roofs were extracted as trees as was the case in the Sep 2001 and Sep 2003 images. In another instance, inland water distributaries of East River, Hudson River and Willow Lake (Jan 2008) were also classified as trees possibly due to the presence of vegetation in the river. Therefore we used spectral attribute ‘min_band_NIR’ on the Jan and May 2008 images for separating rivers from trees. We used spectral attribute band ratio to isolate trees from dark roofs (Aug 2004). Although spectral rules extracted most of the trees, some row and independent trees were not extracted from the image. We used spatial attributes of ‘roundness’ to extract tree clusters and individual trees that were otherwise difficult to classify by using spectral rules only (Sep 2003).

### 7.1.6 Water

Majority of the feature class water consist of lakes, reservoirs, East River, Hudson River, and Inland distributaries of East and Hudson rivers. A segmentation scale level ranging from 8.3 to 50.3 was used to delineate water. We used spectral attribute ‘avg_band_NIR’ to extract the feature class water. In some instances, dark roofs were also extracted as water. On the Jan 2008 image we used spectral attribute of ‘avg_band_red’ to separate water from dark roofs. However on the Aug 2004 image we used spatial rule ‘area’ to delineate dark roofs from water, since roofs were smaller comparatively to the river. One of the difficulties faced in classifying water was that some inland distributaries of East and Hudson Rivers were not extracted as water (less than 5% of the total area). Since the water was not deep it had mixed pixels which posed challenges in its extraction.

### 7.1.7 Shadow

The feature shadow was challenging to classify due to the differences in objects that casts shadows. For instance the shadows cast by a building over water body are spectrally different from shadows cast over land. Shadows encountered in land can also be from man-
made or natural objects. These were variations of type shapes and sizes of shadows observed within study site are responsible for low accuracy observed in accuracy assessment. The segmentation scale level used to delineate shadows ranged from 6.8 to 39.8.

Spectral attributes employed to delineate shadows varied from one image to the other. Most of the shadows encountered on land were classified using spectral attribute ‘avg_band green’ (Sep 2001, Sep 2004, Aug 2004 and Jan 2008). When shadows were cast by the cloud cover on the land, we used spectral attribute ‘avg_band green’. However, in some cases ‘avg_band_green’ extracted shadows along with trees. Thus spectral attribute band ratio was applied to eliminate trees from being classified (Aug 2004). When shadows extracted by ‘max_band_green’ included dark roofs and inland distributaries of water we employed ‘avg_band_red’ to delineate water and dark roofs from shadow (Jan 2008). To classify shadows cast by man-made objects we used spectral attribute ‘min_band_red’, which classified all urban shadows, dark roofs and water. The ‘avg_band_green’ was then used to eliminate all dark roofs from the classification. The Max_band_red prevented water from classifying as shadows (May 2008). Spectral attributes often misclassified dark roofs and inland distributaries of rivers as shadows. Thus we employed spatial attributes such as intensity, which measure the brightness of an object in combination with rectangular fit attribute isolate shadow from water (Sep 2001). Spatial attributes of rectangular fit, area and elongation were also used to isolate shadows from the inland distributaries of East River (Sep 2003). The area attribute is the total area of the polygon, minus the area of the holes measured in map units. However these rule-sets were not able to classify about 5% of the East River particularly the inland distributaries of East river and the shadows of the bridges on the East river. In addition the ‘area’ attribute was also applied to prevent some dark roofs from being classified as shadows (Aug 2004, May 2008). By a combination of spectral and spatial attributes and pixel-based approach we were able to successfully extract several urban features from the Ikonos image. Since these algorithms were developed for one image and then tested on time series of multi-temporal Ikonos datasets these algorithms may be used to extract urban features that may fall into similar spatial and spectral characteristics. Fig 4 shows the different urban features that were extracted by using this method.

8 Accuracy Assessment
The classification accuracy was measured by using a standard error matrix. The matrix was compared by using a pair-wise z-score significance test. We compared the classification results with ground truth image data to assess the overall accuracy. An error matrix was computed to obtain the user’s and producer’s accuracy. The producer’s accuracy represents the measure of omission errors that correspond to those pixels belonging to a class of interest that the classifier has failed to recognize. The user’s accuracy, on the other hand, refers to the measure of commission errors that correspond to those pixels from other classes that the classifier has labeled as belonging to the class of interest. We have considered minimum of 458 pixels in evaluating the accuracy as recommended by [27]. An independent validation of the extracted polygons was also performed by exporting vector layers on to high resolution 1m by 1m fused image (multiplicative technique merged pan band with multispectral bands).

9 Conclusions
Very high resolution satellite data has limited spectral resolution. It is important to develop spatial, textural contextual or relational attributes for extracting feature classes from VHR satellite data such as Ikonos. Feature extraction technique is a useful approach for extracting specific urban features from VHR satellite data. We have demonstrated that by using a combination of both spectral and spatial attributes such as band ratio, min-max band, average band etc as well as spatial attributes of elongation, area, size, area, rect-fit specific urban features may be extracted in an automated manner from VHR data.

We have also demonstrated a methodology to improve classification of urban features. By segmenting a section of the image which had similar spatial characteristics, we were able to extract urban features with low spectral resolution such as gray roofs, white roofs and dark roofs that have been traditionally difficult to delineate from urban regions. We tested the various combinations of spectral and spatial attributes and applied different sets of algorithms on a time series of multispectral and multi temporal Ikonos images covering various urban regions of New York City.

By using different combinations of spectral and spatial attributes, we have developed a methodology to extract and map urban features from VHR data and tested the robustness of the algorithms by extrapolating the algorithms on other images having the same resolution (4m by 4m; mss) characteristics. However, there are some limitations to this approach also. For example, the classified area must be urban and be near similar if not similar to geographic regions like New York. Although all cities do not have the same spatial characteristics, there is promise in the approach to analyze series of
VHR data for developing a suite of algorithms to map urban features.

**Feature Extraction of Urban Objects.**

![Feature Extraction of Urban Objects](image)

**Figure 4: Urban features extracted by the automated algorithms**
10 Acknowledgements
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References:


