Characterization of Suburban Areas for Land Use Planning Using Landscape Ecological Indicators Derived From Ikonos-2 Multispectral Imagery

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***Abstract*—Very high resolution satellite images are used to derive the spatial distributions of landscape ecological metrics within suburban areas. These indicators are weighted mean patch size and lacunarity computed from thresholded normalized difference vegetation index obtained from multispectral IKONOS-2 imagery. Spatial distributions of the metrics are derived for an extensive suburban area on the southwest edge of London, U.K. Weighted mean patch size and lacunarity values have also been investigated in subimages corresponding to different kinds of suburban land cover and with different box sizes. The results indicate typical ranges of the metrics in environmentally sustainable localities. The spatial distributions of the metrics provide new insight into landscape structure, which can be exploited in land use planning and in the construction of empirical spatial planning heuristics for sustainable urban development.**

***Index Terms*—IKONOS multispectral data, landscape ecology, landscape metrics, suburban land cover, urban development.**

I. Introduction

THERE IS A significant global trend toward the increasing urbanization of the human population with a gradual displacement of work and people toward city areas and away from rural areas. This is not a new phenomenon but the pace of urbanization has been growing with the shift of employment toward high-technology or knowledge-based activities. Most cities in the world are in a state of continual growth facing regional planners with difficult choices over where to permit new housing and industrial development. The southeast of England, and in particular the London area, is a region that currently faces significant future planning challenges. The U.K. Government recently estimated that a further 200 000 homes would be needed in and around London in the next ten years. The government is also committed to the goal of sustainable development, which puts significant constraints on land development policies.

So far remote sensing has not been widely used in land use planning by regional authorities. Several authors have however recognized the potential of remote sensing as a useful tool that can help urban planners [1] and a number of studies have examined the use of remote sensing in understanding urban landscape form and its evolution [2]–[4]. There has been growing interest in the monitoring of urban and suburban environments by remote sensing in recent years as a consequence both of the interest in improving urban environmental quality and of the increase in sensor spatial resolution. There have been a number of studies on the mapping of urban and suburban land cover using classification of multispectral remotely sensed imagery, e.g., [5]. Given the complexity of urban and suburban landscapes, innovative classification methods have been developed using kernel-based spatial reclassification [6], [7], combinations of large numbers of textural features [8], use of Gabor filters [9] and also fuzzy approaches using statistical and neural network methods [10], [11]. In some urban and suburban studies, remotely sensed imagery has been complemented by ancillary geographical data from global information systems [12], [13]. Synthetic aperture radar imagery is also now yielding important new results in urban monitoring [14].

From the perspective of sustainable land use development, the characterization of the environmental quality of urban landscapes becomes especially important. The environmental quality is controlled by many factors such as presence of vegetated areas and of derelict areas, housing density, climate quality, and extent of impervious surfaces. Attempts have been made to monitor and model these factors by use of remote sensing data, e.g., [15]–[21].

II. Scope of This Paper

Most of the previous work on the use of remote sensing for urban or suburban studies has focused on pixel-level or parcel-level land use classification. Whilst mapping of land use in this way makes an important contribution to environmental analysis, a full understanding of the suitability of areas for development must take into account aspects of the surrounding landscape and the overall regional pattern of land use. This can be achieved with remote sensing through the use of approaches derived from “landscape ecology” and in particular through the extraction of landscape metrics [22]. Several different types of landscape metrics can be derived from satellite imagery. These include lacunarity [23], Korcak patchiness exponent, and area-perimeter fractal dimension [24]. Such metrics can provide information about the spatial distributions of vegetated and built-up areas and the relationships between them. In [24], such metrics were

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applied to the analysis of deforestation patterns in the Amazon, and in [25] they were used to analyze rangelands. In this paper, landscape metrics have been derived from suburban imagery on the edge of London, in an area which is undergoing significant land use change as a result of the regional demand for new housing. The aim of this work has been to identify novel approaches for visualizing land use in terms of landscape metrics and in so doing to provide new approaches that can be of use to regional planners. Very high resolution satellite imagery has been chosen for this purpose, as it maximizes the detectability of small-scale features such as roads which separate vegetated areas. From an ecological perspective, a road is a barrier to flora and fauna and needs to be extracted and included in analysis focusing on environmental quality. In addition, the connectivity and spatial cooccurrence of small green islands such as gardens in densely built-up suburban areas can be significant from an environmental point of view.

III. Methodology and Datasets

The test area chosen for this project is situated on the southwest edge of Greater London and stretches from Wimbledon on the east side, to Hampton in the west, and from Richmond on the northern edge to Epsom in the south. Suburban land cover dominates the area. Being on the fringe of the London conurbation, the test area is one in which rapid urban expansion is taking place and in which difficult land use planning decisions will need to be taken in the future. Part of the test area is designated London "green belt." It also contains some historical parks such as that at Hampton Court Palace.

The image data used for this project were acquired on August 21, 2001 by the IKONOS-2 satellite (Space Imaging Corporation). They have been georeferenced using the Universal Transverse Mercator map projection and WGS84 ellipsoid.[1] The complete dataset consists of panchromatic data with a spatial resolution of 1 m and multispectral data, collected in blue, green, red, and near-infrared bands, with 4-m resolution. Fig. 1 shows a color composite of the IKONOS multispectral image for the test area. The sketch map in Fig. 2 shows the locations of the readily identifiable geographical features. The image data of the test area consists of 3832 $\times$ 3714 pixels which covers an area of 15.33 $\times$ 14.86 km. The use of the very high resolution data from IKONOS is to facilitate a strong detection of the linear barriers such as roads. Although not critical to the computation of lacunarity and WMPS, it would be critical in any subsequent analysis in which connectivity of green areas is assessed.

Basic processing and analysis of the satellite imagery were carried out using the ENVI (V3.5) software package. The new algorithms required to compute landscape metrics from the satellite data were developed using IDL (V5.5), incorporating some functions from the ENVI function library.

Most natural landscapes are very complex, and it is difficult to quantify them using a single number. Landscapes are often characterized with metrics that each identify particular types of feature, such as variability of patch size or density of vegetation, which together describe the landscape. Many metrics are available, and the ecologist or the land use planner must select the most appropriate ones from the toolbox to best measure the landscape structure of interest. In order to characterize suburban areas, image metrics have been used in this work that provide information about the relative distributions of the built-up spaces and of vegetated spaces in the test area.

In order to separate vegetated from built-up surfaces in the suburban environment, the normalized difference vegetation index (NDVI) can be used. NDVI has often been applied in land use studies and in mapping primary production, e.g., [26],

[1] http://www.spaceimaging.com/products/ikonos/geo_techspec.htm

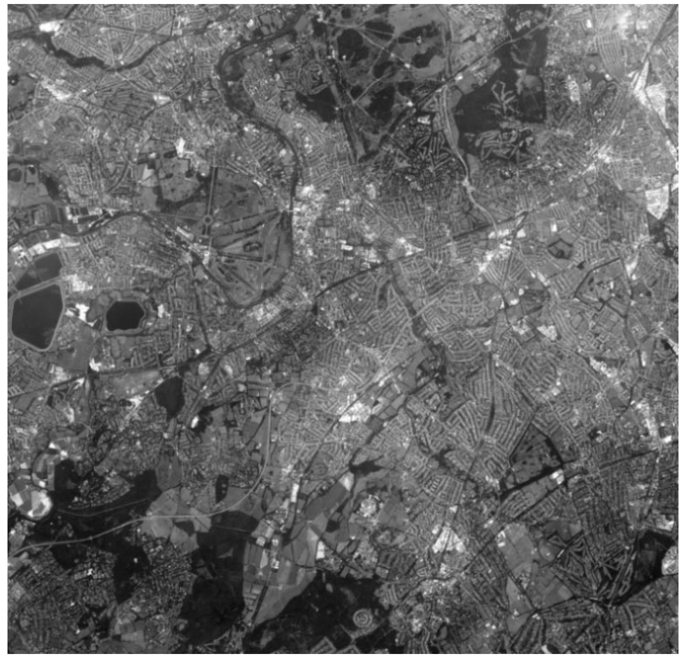


Fig. 1. IKONOS image of suburban test area, southwest London, U.K. Space Imaging LLC © 2002. Supplied by NPA Group www.satmaps.com. Reprinted by permission.

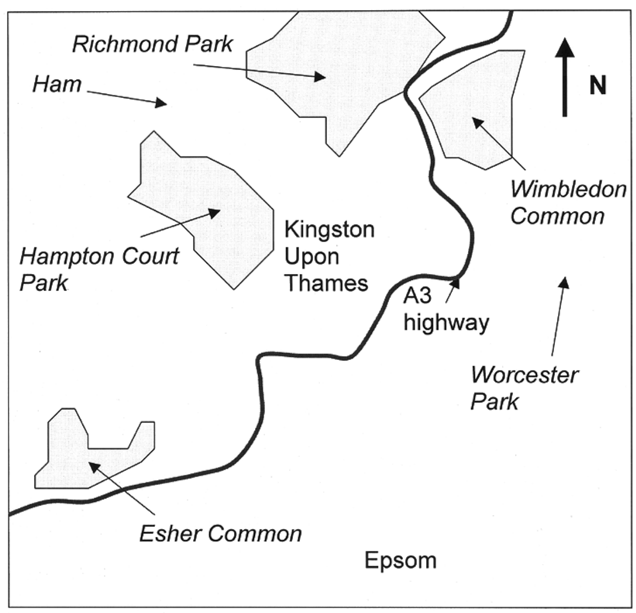


Fig. 2. Sketch map of image area showing location of principal geographical features.

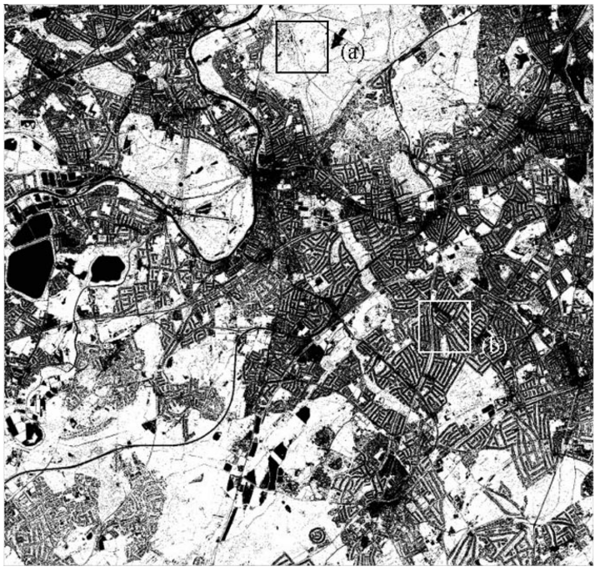


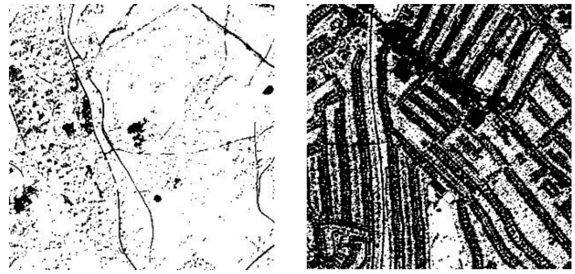
Fig. 3. NDVI image thresholded at a value of 0.3.

though its use with IKONOS imagery has not been extensive. NDVI is given by

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}}$$

where NIR is the reflectivity in the near-infrared part of the spectrum and VIS is the reflectivity in the red part. IKONOS provides four bands of multispectral data as follows: Band 1: blue- 0.45–0.52 μm; Band 2: green- 0.52–0.60 μm; Band 3: red- 0.63–0.69 μm; Band 4: near-infrared: 0.76–0.90 μm. The red and near-infrared bands (bands 3 and 4) are used in the calculation of NDVI (as the VIS and NIR parameters, respectively). To extract useful information from the NDVI image it is thresholded. Pixels above the threshold are likely to be found at areas of significant vegetation. Several vegetation pixels group together to form vegetation patches. The size and distribution of the areas of these vegetation patches are important in characterizing the ecological nature of urbanized or semiurbanized areas. Fig. 3 shows a binary image with values -1 (in black) denoting nonvegetation land cover and $+1$ (in white) indicating vegetated land cover. This was derived from the test image in Fig. 1 by thresholding NDVI at a value of 0.3, which was found by trying different thresholds until a good classification was found. Misclassifications result if the threshold is not chosen carefully.

(Using adaptive techniques to classify the NDVI image has also been attempted, to obtain a more local threshold for different parts of the image.) It can be seen that the vegetated areas are highly distinct in white, and nonvegetated such as buildings, roads, rivers, and water bodies (reservoirs) are shown in black. Striped areas corresponding to rows of residential houses separated by gardens are very clear at this resolution. The misclassification of pixels is estimated at $\sim$10%. Overall, the NDVI image thresholded at 0.3 appears from local knowledge to give an accurate and usable separation of the vegetated and nonvegetated land cover in this area. This area also has excellent transportation networks into central London as well as amenities. It is, therefore, one of the areas in which the demand for new housing is most acute and where part of the government strategy for housing development is being realized, thus leading to a rapid trend of urbanization.



(a) (b)

Fig. 4. NDVI images for two test regions. (a) Suburban parkland area (Richmond Park). (b) High-density residential area (Worcester Park).

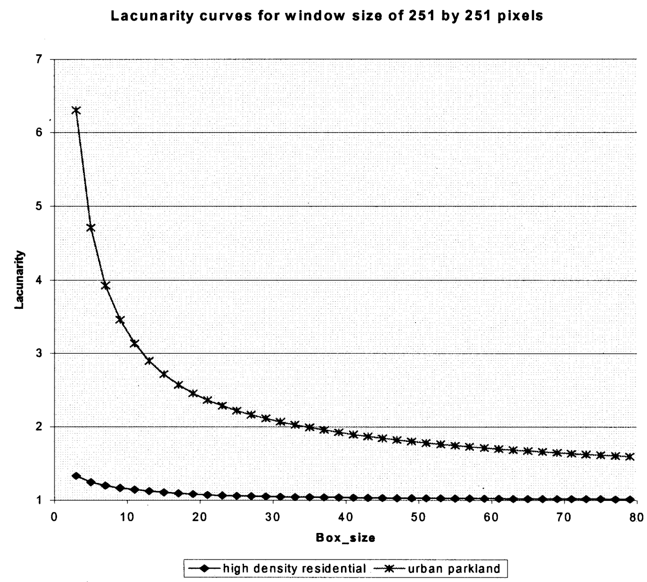


Fig. 5. Vegetation lacunarity curves for two test subareas from the image of Fig. 1, representing “suburban parkland” and “high-density residential” areas. A fixed window of size 251 $\times$ 251 pixels was used with varying box size.

IV. Landscape Metrics

We have used two landscape metrics in this work to characterize the distribution of vegetation patches within suburban areas. The “weighted mean patch size” (WMPS) [27] and “lacunarity.” WMPS provides information about the size distribution of vegetation patches in a region, and lacunarity provides an indicator of the spatial clustering of such patches.

The mean patch size and weighted mean patch size are measures for quantifying landscape structure. The mean patch size is the average size (area) of vegetative patches within a window. The weighted mean patch size is intended to better quantify landscape structure by including information on both patch size and number [27]. It is similar to the mean patch size, except that it is biased toward the size of large patches.

Lacunarity can be used as a measure of the distribution of patches of pixels in a scene [23]. The lacunarity value helps to compare two regions with identical patch sizes: the one with the highest “clumpiness” of patches rather than an even spatial scattering will have the highest lacunarity. Essentially, lacunarity is high when there is a range of patch sizes of a par-

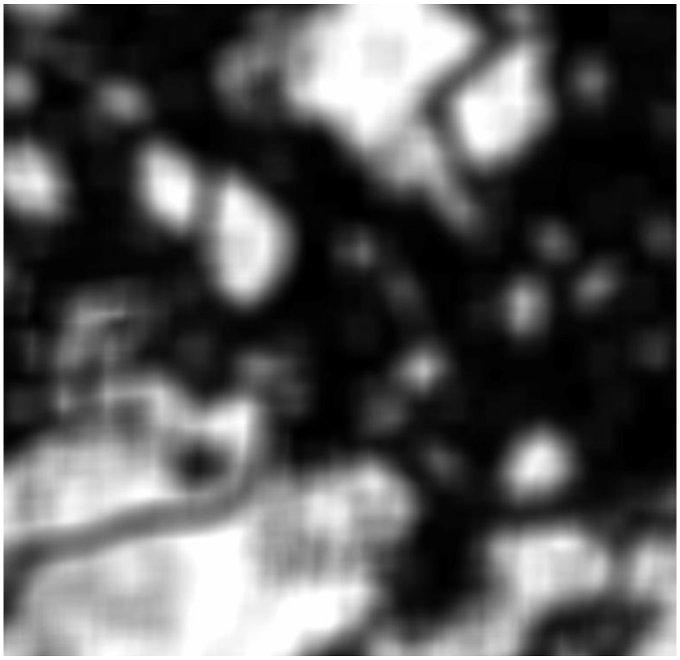


Fig. 6. WMPS image calculated from Fig. 1 with a moving window of size 251 × 251 pixels.

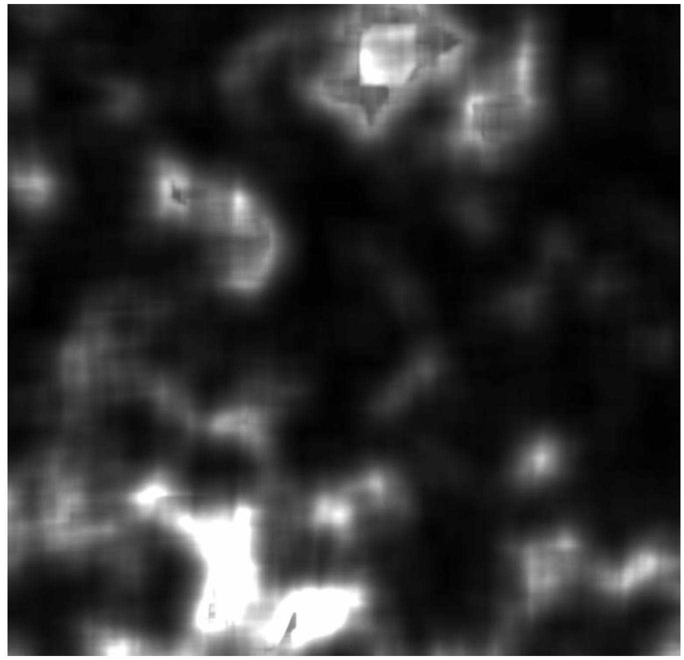


Fig. 7. Lacunarity image calculated from Fig. 1 with a moving window of size 251 × 251 pixels and a fixed box size of 7 × 7 pixels.

ticular type (vegetated, nonvegetated, etc.). To calculate lacunarity, a square box with a set width is moved across the image in a raster-scan fashion within a fixed image window, which is normally smaller than the full image size. In order to calculate vegetation lacunarity, at each position in the window a count is made of the number of interpatch pixels (nonvegetated pixels) within the square box in the thresholded NDVI image. These counts are summarized in a histogram. The mean and variance of the counts are calculated. The lacunarity L is then given by

$$L = \left(\frac{\text{variance}}{\text{mean}^2}\right) + 1.$$

We have calculated the lacunarity (Fig. 5) in two different subareas of the image, shown in Fig. 4. The first area (suburban parkland) contains significant vegetation and was measured within Richmond Park. The second area is high-density residential and was measured near Worcester Park. The computation is performed using the interpatch pixels which are not of the type "vegetation" (i.e., coded -1 in the thresholded NDVI image).

V. Obtaining WMPS and Vegetation Lacunarity Images

Within urban or suburban environments that are subject to necessary development (i.e., where housing development must take place because of population pressure), an appropriate urban land use planning strategy for "sustainability" will be to choose to develop the landscape in such a way as to ideally conserve, or at least reduce by the minimum amount, both WMPS and vegetation lacunarity in the region. Since both quantities only provide a characterization of a locality centred on a given pixel, regional planning decisions need to take into account the regional variations of these quantities.

An appropriate mechanism for achieving this is to compute WMPS and lacunarity "images" covering a geographical area,

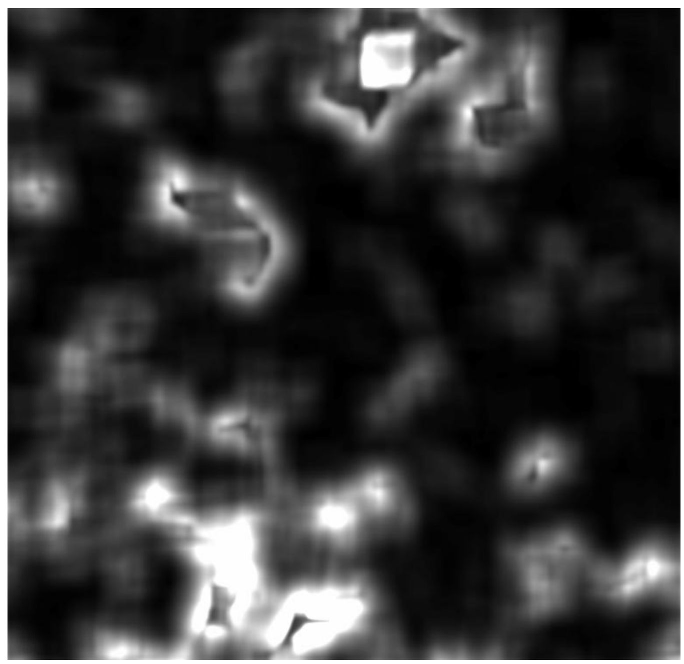


Fig. 8. Lacunarity image calculated from Fig. 1 with a moving window of size 251 × 251 pixels and a fixed box size of 51 × 51 pixels.

i.e., by moving the window within which these quantities are calculated over the entire input satellite image and calculating an array of WMPS and lacunarity values at the successive locations of the center of each window position. The measurement is assumed to be valid for the pixel location at the center of the window. The window has to be moved over every pixel in the image in order to generate an image illustrating the variability of the chosen metrics. The values of WMPS and lacunarity obtained can be mapped to grayscale values that can then be color

TABLE I
AVERAGE VALUES OF WEIGHTED MEAN PATCH SIZE AND LACUNARITY OF DIFFERENT TYPES OF SUBURBAN LAND COVER DERIVED FROM THE TEST IMAGE OF SOUTH WEST LONDON SUBURBS

	Entire sub-urban test area	**Sub-urban parkland (Richmond Park)**	**Low density residential area (Ham)**	**High density residential (Worcester Park)**
Weight Mean Patch Size (pixels)	100 - 62000	~ 50000	~ 10000	~ 500
Vegetation Patch Lacunarity (box size 7 x 7 pixels)	1.01 – 21	~ 4	~ 2	~ 1.2
Vegetation Patch Lacunarity (box size 51 x 51 pixels)	1.01 - 6	~ 1.8	~ 1.4	~ 1.05

coded using a smoothly changing color map for visualization purposes.

VI. EXAMPLE RESULTS OF REGIONAL WMPS AND VEGETATION LACUNARITY IMAGES

Figs. 6–8 show color-coded WMPS and lacunarity images derived from the IKONOS-2 scene for the test area of Fig. 1.

Fig. 6 shows the weighted mean patch size for the image, calculated with a window size of 251 $\times$ 251 pixels. The spatial pattern of WMPS clearly indicates the main areas of vegetation, but also highlights localities in which some large vegetation patches exist among extensive built up areas. The dark areas have the lowest WMPS values and represent those parts of the landscape in which ecologically significant vegetation patches are not present. It is suggested that these could be targeted for urban development in the first instance. The WMPS ranged from 100 to 62 000 pixels corresponding to areas of 0.0016–0.992 km^2.

Fig. 7 is the lacunarity image, calculated with a window size of 251 $\times$ 251 pixels and a box size of 7 $\times$ 7 pixels. The lacunarity range was from 1.01 to 20.9. Whilst the spatial pattern of lacunarity is broadly similar to the WMPS image, there are some significant differences. In particular, road features have less effect, and high lacunarity values are confined to smaller areas where there is good vegetation patch “clumpiness.” From an ecological perspective, the lacunarity image can be interpreted as indicative of the priority areas for preservation of existing natural vegetated land cover and of areas in which urban development should not take place. Fig. 8 is a lacunarity image calculated with a window size of 251 $\times$ 251 pixels and a box size of 51 $\times$ 51 pixels. This image is indicative of spatial clustering of vegetation patches at a larger scale. The lacunarity range was from 1.01 to 5.98.

Table I gives a summary of the values of the WMPS and lacunarity in the test area as a whole and in the subimages of Fig. 4 representing different types of suburban land cover. The low-density residential areas and suburban parkland areas have lacunarity values (at box size of 7 $\times$ 7 pixels) in the range 2–4, whereas the high-density residential area has a lacunarity value of the order of 1.2. At a box size of 51 $\times$ 51 pixels, the low-density residential areas and suburban parkland areas have lacunarity values in the range 1.4–1.8, whereas the high-density residential area has a lacunarity value of the order of 1.05.

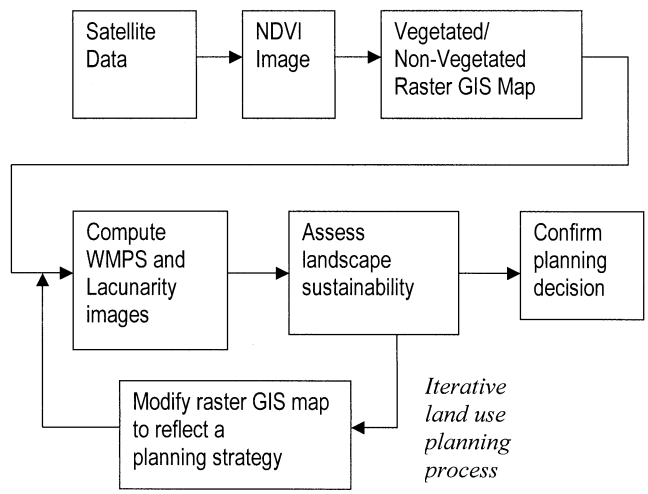


Fig. 9. Iterative land use planning scheme based on modeling process using WMPS and lacunarity images.

VII. DISCUSSION

In this work, we have demonstrated how WMPS and lacunarity images, which provide a visual representation of the ecologically meaningful spatial structure of suburban areas, can be derived from very high resolution satellite imagery. By computing WMPS and lacunarity images, planners can visualize the current spatial distribution of WMPS and lacunarity in a geographical region. Whilst the visualization of such images by itself provides new insight into suburban landscapes, by making artificial changes to the greenness spatial distribution and recomputing WMPS and lacunarity, it would be possible to understand the local impacts of different land use planning strategies and modify those strategies accordingly (Fig. 9). WMPS and lacunarity images could, thus, become important tools in regional development planning in the suburban context. Whilst it is still too early to predict the full benefit of this approach, it is possible to see a significant role for WMPS, lacunarity, and other landscape ecological metrics, computed from very high resolution imagery as two-dimensional (2-D) image products, within suburban planning decision support systems. However, before this can become feasible, more work is needed to understand optimum strategies for employing such quantities. All landscape metrics require the selection of window sizes and, in some cases such as lacunarity, also a box size. By utilizing a variety of window and box sizes, a vast spectrum of 2-D image products can be derived. A key issue is to determine which ecological metric images from such a vast spectrum are the most meaningful and useful in the context of land use planning. The results from this work appear to show that for environmentally sustainable land use in suburban areas local WMPS should be maintained at values in excess of 10 000 pixels (equivalent to 0.16 km^2) and lacunarity at values exceeding 2.0 at box size 7×7 (28×28 m) and exceeding 1.4 at box size 51×51 pixels (204×204 m). This corresponds to maintaining a relatively low density of housing and a good clustering of local green areas, which would be supportive of recreation and diversification of flora and fauna. However, more work is needed "calibrate" the land use planning and development process in terms of such metrics. From such an approach, it is possible to envisage the derivation of empirical development laws such as conservation of lacunarity, maximization of WMPS, or maintenance of minimum values of these and other quantities in particular urban or suburban contexts. High-resolution satellite imagery was motivated by the need to detect small-scale features. However, as the NDVI can only distinguish between vegetative and nonvegetative pixels, the classification is fairly unsophisticated.

The NDVI is a relatively simple way of assessing the spatial texture of ecological quality, as it only categorises into two classes. Consequently we are considering the recently proposed normalized difference built-up index (NDBI) [28].

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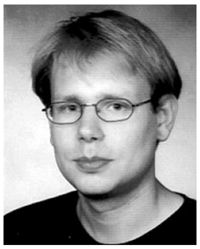

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