HEMISPHERICAL PHOTOGRAPHY AS A TOOL FOR URBAN SUSTAINABILITY EVALUATION AND DESIGN

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Abstract**:** Hemispherical (fisheye) photography is a convenient indirect method for estimating *leaf area index* (LAI) a key indicator of vegetation primary production which offers a useful insight into a range of ecosystem services. Fisheye imagery is frequently used to establish the *sky view factor* or proportion of sky visible from street level, a major determinant of urban microclimate. Analysis of fisheye images also enables calculation of the *fractal dimension* of surrounding urban surfaces and skylines, which is associated with visual diversity and enables comparison of the character of different urban places. In this case study, hemispherical images taken with a digital camera from the centres of a sample of open spaces in a university campus in Sydney, Australia were analysed using public domain software. The resulting LAI, SVF and fractal dimension data were combined to assess the comparative environmental performance and physical ambience of the relevant areas of the campus. This exploratory research suggests that fisheye photography utilising minimal and inexpensive equipment can support a "fast and frugal" comparative environmental evaluation of urban places, and potentially inform the design of more sustainable places. Such an approach may have particular relevance to rapidly urbanising developing countries where resource-intensive methods can be problematic, especially in the context of climate change mitigation and adaptation.

Keywords**:** Fractal dimension, hemispherical photography, leaf area index, sky view factor

I. INTRODUCTION

Over the past few decades it has become clear that anthropogenic environmental impacts are unquestionably global in scope [1-2], climate change being the prime example. Increasing attention devoted to the question of *urban* environmental impact has reflected the intensification of urbanisation itself. The urban population growth rate of 1.8%, nearly twice that of the total global population, is expected to double the number of city dwellers by 2038 compared with 2000 [3]. The majority of these new urban residents will live in developing countries where sustainability is predicated on ensuring the basic human needs of public health, clean water and adequate food, shelter and employment [4-6].

Moreover, as the cities of the "south" catch up economically with the developed "north", so too will their impacts on the environment. According to Canadian environmental planner William Rees, approximately 76% of the world's economic production/consumption and related environmental impacts is currently associated with cities. Buildings alone account for 40% of the materials and about a third of the energy consumed by the world economy [7]

On the other hand, sheer concentration of population and economic activity gives cities enormous leverage in the quest for global sustainability. If the city is the key *problem* in terms of its ecological footprint, it may also provide a *solution* by achieving the necessary critical mass of resources and knowledge to tackle the issue [8-11]. As Levine affirms "… the city is seen as the largest unit capable of addressing the many urban architectural, social, economic, political, natural resource and environmental imbalances besetting the modern world and, at the same time, as the smallest scale at which such problems can be meaningfully resolved in an integrated and holistic fashion" [12: 25].

The need to provide practical solutions to the problems of urban unsustainability has generated a plethora of systems, methods and tools to help understand, manage and design the built environment. Of particular interest are methods which deliver information on more than one aspect, and aspects which can be described by more than one method, enabling correlations and building robustness into the system. A further selection criterion is that to have practical utility, analytical methods should ideally be relatively straightforward to apply.

The present research suggests that hemispherical (fisheye) photography can support a "fast and frugal" multi-purpose comparative evaluation of urban places, and potentially inform the design of more sustainable places. Fisheye photography provides a convenient indirect method for estimating *leaf area index* (LAI), through measurement of the distribution of light penetration through the vegetation canopy. LAI, defined as the leaf area of a vegetation canopy per unit ground area, is a key indicator of vegetation primary production and energy exchange [13]. As such, it offers a useful insight into ecosystem services including carbon sequestration, microclimate amelioration and horticultural amenity. In the urban context, fisheye imagery is frequently used to establish the *sky view factor*, the proportion of sky visible from street level. This is a major determinant of urban microclimate [14] and an important factor in calculating the urban heat island and the lighting, heating and cooling energy requirements of buildings. Analysis of fisheye images also enables calculation of the *fractal dimension* of surrounding urban surfaces and skylines, which is associated with visual diversity and complexity and provides a way to compare the character of different urban places.

Application of fisheye photography allows integrated investigation of the above parameters, involves relatively basic data collection and requires minimal (and inexpensive) equipment. It may thus have particular relevance to rapidly urbanising developing countries where more resource-intensive methods can be problematic, especially in the context of climate change mitigation and adaptation..

II. CONCEPTS AND DEFINITIONS

A. Leaf area index

Canopy leaf area exerts dominant control over photosynthesis, transpiration, energy exchange and other physiological attributes affecting ecosystem processes [15], and its measurement is relevant from site scale to global models of terrestrial primary productivity [16]. Since it is a dynamic variable dependent on species composition and age, site conditions, season and (where present) management regimes [17], there is no unique LAI for a given species, or for plants of a particular height or spread. Values typically range from ≈1 for grasses to ≈10 for rainforest trees. So although it is reasonable to make use of indicative figures based on vegetation structure [18], some form of "ground truth" measurement is obviously desirable.

LAI measurement methods may be direct or indirect. The former include destructive sampling and leaf litter collection, with mean leaf area determined by planimetric or gravimetric means and extrapolated across the study area. Indirect methods include spectral analysis of canopy light absorption via aerial or satellite imagery; allometric techniques which utilise relationships between leaf area and other vegetation dimensions such as height or stem diameter; and techniques which infer LAI from measurements of the radiation transmitted through the canopy [17, 19]. Direct methods are accurate but time consuming; indirect methods, being amenable to automation, permit larger sample sizes [17].

Indirect methods based on light transmittance invoke the Beer-Lambert law, which assumes that light is attenuated exponentially as it passes through the canopy [18]. Among such methods, hemispherical (fisheye) photography represents a fast and powerful way of measuring LAI. As summarised by Jonckheere *et al.* [17: 27], fisheye image analysis can "capture the species-, site- and age-related differences in canopy architecture, based on light attenuation and contrast between features within the photo (sky versus canopy)". It relies on determination of the "gap fraction" $P(\theta)$, the amount of sky visible through the canopy:

$$P(\theta) = e^{-G(\theta,\alpha)LAI/\cos(\theta)} \qquad (1)$$

Hence: $\mathrm{LAI} = \ln(P(\theta))\cos(\theta)/G(\theta)$ (2)

where θ = zenith angle of view, α = leaf angle, $G(\theta,\alpha)$ = the "G-function", which corresponds to the fraction of foliage projected on the plane normal to the zenith direction [19].

Bréda points out that fisheye images record *plant* area rather than leaf area, as all radiation-intercepting canopy elements such as branches and stems are included. For this reason, and also as a result of the non-random distribution of foliage elements within the canopy, hemispherical photography tends to underestimate LAI [19]. Moreover, visible light fisheye photography is generally unsuitable for estimating the LAI of urban vegetation, which is typically sparse and difficult to differentiate from surrounding built form in the visible spectrum. But since foliage is highly reflective in the near-infrared (NIR), leaf and non-leaf elements may be segmented in a hemispherical NIR image using readily available image processing software.

Chapman [20] describes a simple method of adapting a conventional digital camera for NIR photography in forest environments, for example to distinguish between branch/bole-view and foliage-view factors. NIR photography can also discriminate between foliage and built form pixels, which may help to overcome the obstructive underestimation problem with visible light hemispherical photography in measuring the LAI of urban vegetation [21]. This is the approach adopted in the present research.

B. Sky view factor

The sky view factor (SVF or Ψ_s), a measure of the degree to which the sky is obscured by the surroundings (trees, buildings etc) at a given point, is another critical environmental variable amenable to measurement through digital fisheye photography [22-23]. Determination of the sky view factor is essential to investigation of urban microclimate [14] and outdoor thermal comfort [24]. Given the impact of built form height and density on solar and long-wave radiation fluxes, Ψ_s is a significant variable in quantifying urban heat island effects [25], and also in evaluating building performance with respect to energy [26] and natural daylighting [27]. Measurement of sky view is equally essential to understanding radiative (light and temperature) phenomena in forest ecology and ecophysiology [19]. Sky view thus represents a multipurpose indicator of environmental performance.

Ψ_s of an urban street canyon is related to the sum of its wall view factors Ψ_w from a reference point in the centre of a hemispherical projection of the urban canyon skyline, where "wall view" refers to the proportion of the image composed of surrounding urban surfaces:

$$\Sigma\Psi_w = 1 - \Psi_s, \tag{3}$$

and:

$$\Psi_w = \frac{1}{2\pi}\left\{(\gamma_2 - \gamma_1) + \cos\beta\left[\tan^{-1}(\cos\beta\tan\gamma_1) - \tan^{-1}(\cos\beta\tan\gamma_2)\right]\right\} \tag{4}$$

where β is the angle of elevation of the wall from a line through the reference point parallel to the wall, γ_1 and γ_2 are the azimuth angles of the wall ends, and subscripts 1 and 2 refer to the closest and furthest wall ends respectively [23, 28].

An alternative approach developed for urban environments [28-29] involves dividing the fisheye image into annuli and calculating the view factor for the azimuthal angular extent αi of each annulus. The projection of the wall W_p is approximated by n annuli on a polar graph, of width $\Delta r = r_0/n$, where r_0 is the radius of the hemisphere; and of angular width αi, $i = 1, \ldots, n$, which enables calculation of Ψ_w over each annulus such that:

$$\Psi_w = \frac{1}{2\pi}\sin\frac{\pi}{2n}\sum_{i=1}^{n}\sin\left[\frac{\pi(2i-1)}{2n}\right]\alpha_i \tag{5}$$

and ψ_s is calculated as per equation (3).

The main limitation of the hemispherical photograph is that it is by definition a snapshot of the urban canyon at a particular time [30], so seasonal changes affecting street trees, for instance, which in turn impact on Ψ_s can only be captured through time series studies.

C. Fractal analysis

Fractals are defined as objects of irregular but self-similar form (i.e. the irregularities are repeated across many scales) [31]. Measurement of these self-similar irregularities determines the object's fractal dimension. Strictly speaking, only mathematically defined entities display "true" fractality, i.e. are self-similar across infinite scales such as the well-known Mandelbrot Set [31]. Objects in the real world demonstrate fractal characteristics over a more limited range of scales, so the methods used to identify the fractal dimension must allow for upper and/or lower cut-off points to focus on the scales relevant to the object in question. Fractal dimension is identified by evaluating the increase in measured length of an entity (or surface or volume for higher dimensional objects) when subjected to measurement at incrementally decreasing scales. The resulting data are plotted on a log/log graph of measured values vs. measuring units; the slope of the resulting curve corresponds to the fractal dimension. Formally:

$$N(r) = kr^{-D} \tag{6}$$

where N(r) represents the measured values, r is the length of the measuring unit (scaling factor), D is the fractal dimension and k is a constant. Ignoring k as it does not affect the slope of the curve:

$$\log N(r) = D\log\frac{1}{r} \tag{7}$$

Hence:

$$D = \log N(r) \Big/ \log\frac{1}{r} \tag{8}$$

The method used to determine fractal dimension depends on the type of entity under consideration. The box counting method [described in 32] is commonly used where the fractal dimension of a complex planar image is to be determined, rather than just its boundary. A grid with upper limit mesh size r_u is superimposed on the image, and the number of grid squares ("boxes") N(r) containing some of the image is counted. The process is repeated at increasingly smaller scales until the lower cut-off point r_s is reached. Equation 5.35 is applied for $\{(r_u - r_{u-1}) \ldots (r_{s+1} - r_s)\}$ and the results averaged over the selected range of scales, yielding a constant of proportionality between one and two, equivalent to the fractal dimension.

Batty and Longley's pioneering study of the fractal geometry of cities [33] sparked an upsurge of interest in specifically urban applications of fractal analysis. Their investigations concentrated mainly on city- and regional-scale fractal phenomena, for instance modelling patterns of urban growth and land use, and describing and explaining population density and economic activity in terms of the (fractal) geometric properties of the urban system. Lothian [34] looked to fractal geometry for a key to understanding the visual qualities of landscapes, advocating exploration of the fractal relationships within and between landscape elements. From an urban perspective, such relationships may involve some scaling factor which connects architectural detail (structural elements, ornamentation, materials) at different scales, recalling natural forms such as vegetation, which are inherently more fractal than typical human-made features.

Surprisingly, however, little fractal geometry research has been carried out at the scale between building and city – the urban design scale. The principal reference is the doctoral research conducted by Jon Cooper [35]. Using Oxford as his case study, Cooper determined the fractal dimensions of street patterns, skyline undulations, building elevations, building line indentation and street vistas. Fractal dimensions were compared with morphological features and subjective judgements of photographic images by postgraduate students and staff from Oxford Brookes University. Subsequent studies [36-37] reinforce his initial conclusion that the fractal dimensions of street *skylines* (represented as line tracings from photographs of vistas) provide a composite measure of complexity and character which can inform the quantitative comparison of urban places. His earlier research also supports the proposition that the fractal dimensions of images of street *vistas* offer a robust measure of visual diversity.

III. METHODS

A. Study site

The study site selected for this investigation is the main campus of the University of New South Wales (UNSW), in Sydney, Australia. Established in 1949, UNSW has about 40,000 students and 5000 full- and part-time staff. The main campus occupies 38 hectares and is located six kilometres from the Sydney CBD in the city's eastern suburbs. The campus is delimited by, and morphologically strongly differentiated from, medium density residential areas to the east, south and west. Due to locational constraints such as land values and planning controls, growth in student numbers and expansion of teaching and research activities have been addressed though the intensification of built form – UNSW is a very *urban* space. Its morphological characteristics include:

- High density of built form (overall plot ratio = 1.3);
- General alignment of buildings along an east-west/north-south grid;
- Orthogonal pattern of open space between buildings;
- Dense network of pedestrian and shared vehicular circulation routes;
- Buildings predominantly of four to eight storeys;
- Approximately 72% impervious surfaces;
- Tree canopy cover of 19% (Figure 1).

The campus landscape is characterised by inter-building spaces, with the exception of the expansive "Village Green" sports field to the southwest. These spaces include courtyards (both large and small) and linear pedestrian routes such as the central University Mall. Despite the overall intensity of built form there is a significant element of established vegetation. This includes a number of substantial fig trees (*Ficus* spp.), numerous group and specimen plantings of both native eucalypts and northern hemisphere exotics, and extensive screening vegetation along the campus boundaries.

The building stock predominantly comprises purpose-built educational buildings constructed from the 1950s to the present decade. Also, some 2500 students currently (May 2010) live on campus in dedicated student housing. Public buildings and spaces accessible to the wider community include sports facilities, the library, theatres and auditoria, and a variety of retail services – food outlets, banking and post office facilities, travel agent, news agency, pharmacy etc – are provided on site.

B. Hemispherical photography

A set of fisheye images was originally collected in 2008, as part of a broader research project which included a space syntax analysis of the campus. Space syntax is a method of spatial analysis based on the idea that the architectural structuring of space creates the material preconditions for human patterns of movement, encounter and avoidance [38]. Syntactic analysis begins with the decomposition of the continuous but articulated structure of an urban space into the least set of two-dimensional convex spaces –

street segments, squares, parks etc. A convex space is defined such that any line between any two internal points remains internal to the given space, and no internal angle is greater than 180°, i.e. all points within the space are intervisible. The individual convex spaces identified through the decomposition of the campus open space matrix provided the spatial basis for subsequent hemispherical image analysis.

417 convex spaces > 5m^2 were defined on a CAD plan of the campus (Figure 2). A sample of 79 spaces was selected to achieve representative site coverage, excluding inaccessible areas such as campus construction sites and spaces belonging to private residential colleges. The centroid of each space was taken as the origin point for the fisheye image.

The first set of photographs was taken in January 2008, using a standard Nikon Coolpix 990 digital camera fitted with an FC-E8 fisheye lens to record a 2048 x 1536 pixel image from each convex space centroid at 1.5 metre height. A second set of photos was taken from the same origin points in January 2009, using a Coolpix camera NIR-adapted by removal of its IR filter and attachment of a “cold mirror” filter to block visible wavelengths [20]. The same FC-E8 fisheye lens was used as for the earlier fieldwork. All photos were taken during overcast conditions to ensure relative uniformity of sky luminance with respect to the zenith angle, and were overexposed approximately one stop to maximise the contrast between sky and foliage.

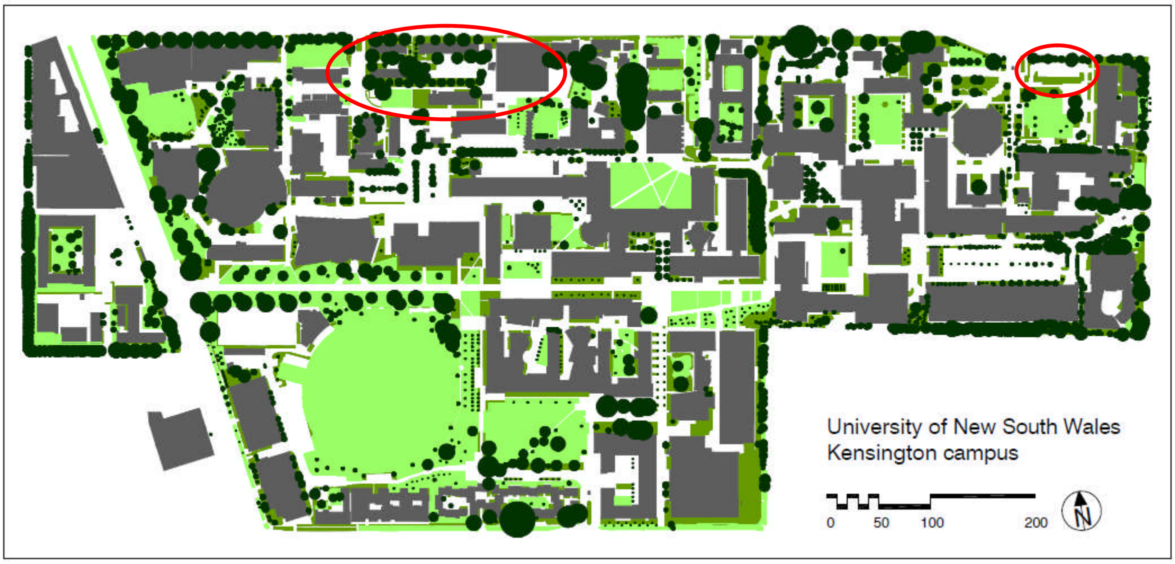

Fig. 1 Kensington campus plan, current at September 2007. Grey = buildings; white = paved surfaces; light green = lawn; mid green = shrubs; dark green = trees. The circled area to the left was redeveloped in 2008-9 as an 1100 bed student housing complex; the circled area to the right as of 2009 houses a new medical research facility.

The reason for obtaining two photo datasets was to enable statistical comparison of the two photographic methods for estimating LAI (visible light and NIR) with a third approach, based on vegetation structural characteristics, to identify which of the two photographic methods gave the more accurate result. This research is reported in detail elsewhere [21]; in summary, statistical analysis showed that LAI estimated through NIR image analysis correlates more closely with LAI estimated through allometry. This acknowledges the fact that foreground foliage is more easily differentiated from background built form in the near infrared than in visible wavelengths.

The combined dataset used in the present research, derived from the sample of 79 convex spaces, comprised:

- LAI data obtained from NIR fisheye images taken in January 2009;
- SVF data obtained from visible light fisheye images taken in January 2008;
- Fractal dimension data (skylines and surfaces) obtained from visible light fisheye images taken in January 2008.

It should be noted that NIR photography is equally suitable for obtaining SVF and fractal data as visible light photography, and as discussed above, it is the preferred option for LAI estimation. The wavelengths used (visible or NIR) do not affect the information content of the resulting images in relation to sky view factor or fractal dimension, hence a single NIR-adapted Nikon Coolpix camera with FC-E8 lens is entirely suitable to obtain all three types of data.

The data analysis was carried out as follows:

Leaf area index.

The image processing software ImageJ v1.33 [39] and vegetation canopy analysis program Gap Light Analyzer v2 [40] were used to differentiate foliage from non-foliage pixels through adjustment of histogram values prior to calculation of LAI for all locations. Gap Light Analyzer (GLA) allows the user to mask unwanted areas of an image such as buildings, which are then disregarded in the LAI calculation. The original colour fisheye photos were imported into the software as 2048 x 1536 pixel bitmaps. Digital "masks" were drawn on the images to exclude elements of built form intruding on the sky, which the software would otherwise interpret as dense foliage. The images were then converted to binary for analysis by the GLA software. Figure 3 illustrates a typical NIR image pre- and post-processing.

Sky view factor.

The "RayMan" program [41] utilises morphological input data obtained from either 3D digital models or fisheye photographs of real spaces to calculate Ψ_s and Ψ_w. As noted in the introduction, Ψ_s is the key factor derived from the 3D geometry of a place needed to calculate its microclimatic and biometeorological properties. These include mean radiant temperature T_{mrt}, the area-weighted average temperature of the objects surrounding a person, and predicted mean vote (PMV), a measure of satisfaction with one's thermal environment. RayMan uses Ψ_s in combination with data on albedo and emissivity of surfaces, air temperature, humidity, wind speed, cloud cover and the observer's activity level and clothing cover (which are separately entered into the program) to calculate T_{mrt}, PMV and related properties. The present objective is to explore the particular value of hemispherical photography as one source of input data to RayMan and other models, so these other inputs to (and outputs from) RayMan are noted by way of describing the methodology, but are not addressed further here.

Fractal analysis.

Cooper's research cited above [35-37] involved analysis of images of street-level vistas, with a camera viewing angle corresponding to the human field of view (≈50°). The proposition argued here is that a full 180° image captured at a given point though fisheye photography contains more visual information than a 50° "slice". Two fractal dimension (D) values were calculated for each image: D_{sky} representing skyline traces, and D_{surf} representing surrounding surfaces. ImageJ was used to pre-process the fisheye images to extract the skyline traces (Figure 3). Pre-processing comprised gamma-correction to compensate for the initial overexposure required for determination of LAI, thresholding to convert to a binary image (with the sky represented by white pixels) and edge detection. The resulting skyline edge traces were saved as 1486 x 1486 bitmap images and analysed in Fractal 3e [42], which includes an algorithm for thinning lines to single pixel width, to determine D_{sky} through the box counting method. The software

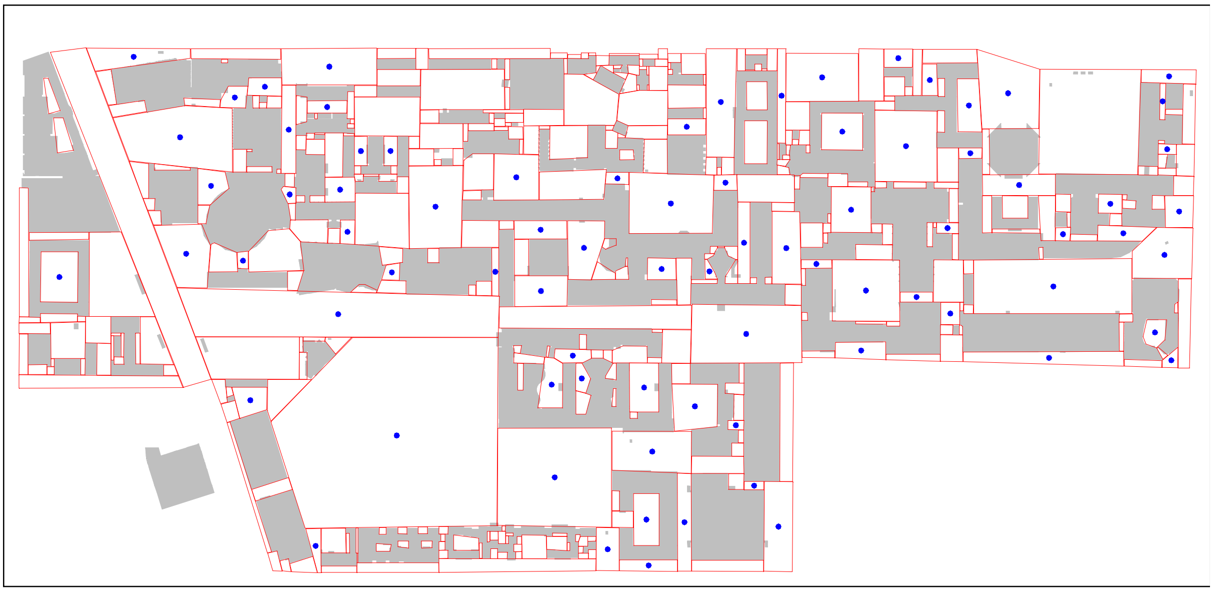

Fig. 2 Decomposition of the campus into its constituent convex spaces, delineated in red; the centroids of the sample set are shown in blue, and buildings are shaded grey.

automatically optimises the number of boxes to fit the scale of the image being analysed. The original gamma-corrected images were separately analysed in Fractop, a java-based public domain program originally developed for biological image analysis [43-44]. Fractop was selected in preference to Fractal 3e to calculate D_{surf} because it allows manual adjustment of box size to maximise the difference between low and high D_{surf} values.

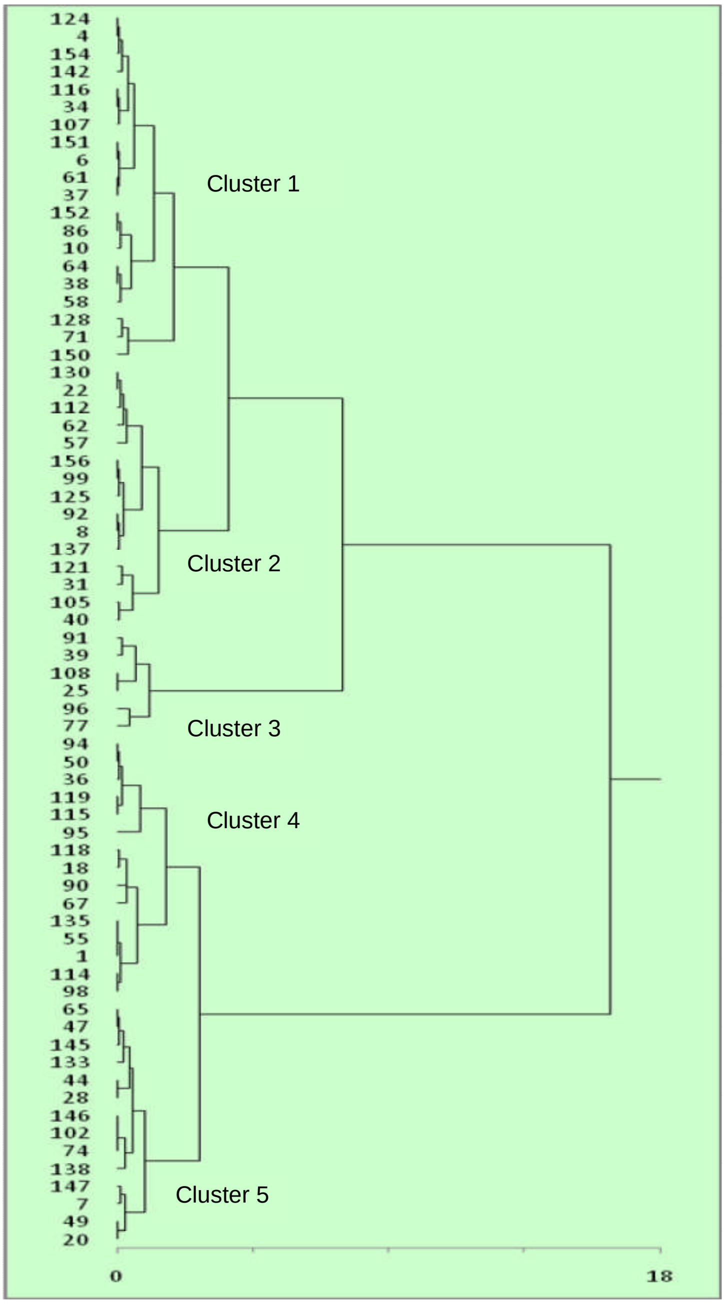

Fig. 4 Dendrogram showing the five main clusters obtained through a hierarchical cluster analysis of the convex space dataset.

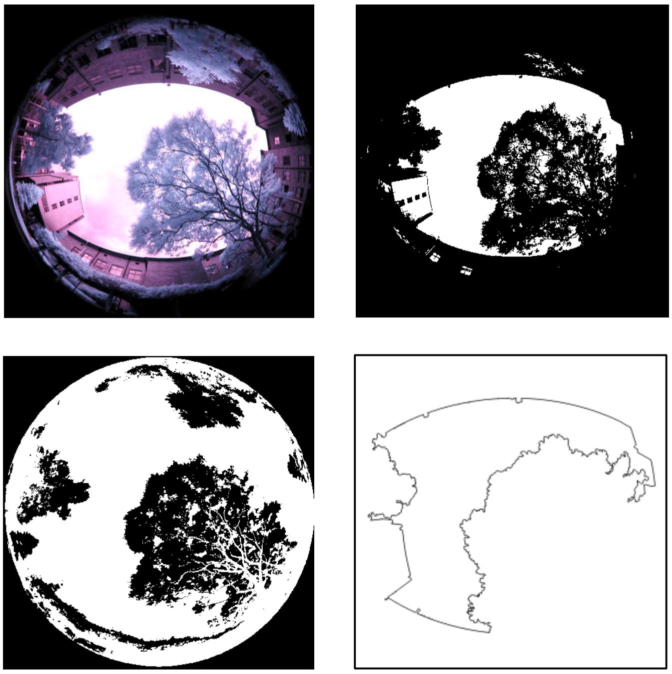

Fig. 3 Top left: hemispherical NIR image from the centroid of a typical convex space; top right: binary segmented image; bottom left: binary segmented image following application of suitable thresholds to separate foliage from built form pixels; bottom right: skyline trace of the same image.

IV. RESULTS AND DISCUSSION

There was a clear association between D_{sky} and the amount of vegetation visible, the diversity of heights and rooflines of surrounding built form, and also the *dominance* of built form (a function of both the height and the distance of built elements to the image origin, i.e. the convex space centroid). As well as reflecting the presence of vegetation, high D_{surf} values were associated with the level and complexity of contrast between elements (structures and surfaces) in the surrounding built form. Spaces with low D_{sky} typically featured surrounding buildings of regular height with flat roofs and few if any trees or shrubs. Low D_{surf} was again associated with the absence of vegetation, and also with absence of architectural detailing and ornamentation on surrounding building façades.

Sky view factor by definition is proportional to the degree of openness or enclosure of a given convex space with respect to the ratio of its area to the height of surrounding surfaces (buildings and vegetation). The convex space with the highest Ψ_s value for the UNSW study site is not surprisingly the campus sports field (#95 in Figure 5).

LAI is, of course, proportional to the amount and type of vegetation visible in the fisheye image. Typically, this includes convex spaces at the periphery of the campus which have been planted with screening trees. It should be noted that fisheye photography cannot account for the LAI of grasses and groundcover species or in the urban context, any vegetation which cannot be clearly differentiated from surrounding built form even in near infrared wavelengths. Thus urban fisheye photography will inevitably underestimate total LAI, and should be read instead as a measure of the LAI of larger shrubs and trees. Previous work by the author relating to the UNSW campus [21] suggests that low-growing species contribute about 9% of the total LAI of the convex spaces selected for this case study.

Table 1 sets out the descriptive statistics for the dataset. D_{sky} could not be obtained for eight convex spaces due to extensive vegetation cover, and both D_{sky} and Ψ_s were unobtainable for one space due to the presence of an overhead awning.

TABLE 1

DESCRIPTIVE STATISTICS FOR
HEMISPHERICAL IMAGE ANALYSIS DATA

	D_{sky}	D_{surf}	SVF	LAI
Mean	1.110	1.730	0.294	0.623
Std Error	0.009	0.005	0.019	0.059
Std Dev.	0.072	0.046	0.168	0.527
Minimum	1.000	1.567	0.031	0.000
Maximum	1.246	1.849	0.824	2.090
Count	70.000	79.000	78.000	79.000

Each convex space can be individually characterised by its particular combination of skyline and surface fractal dimensions, sky view factor and leaf area index values. Spaces can also be grouped based on their similarities and differences with respect to these values. *Cluster analysis* is a multivariate statistical method used to group objects based on their characteristics. It is fundamentally a heuristic approach; explanation and interpretation of the outcomes are matters for the researcher. *Hierarchical* cluster analysis assembles the identified groups hierarchically, starting with separate clusters of elements sharing similar properties which are aggregated stepwise until only a single cluster is left, or vice versa.

Figure 4 shows the output of a hierarchical cluster analysis of the data to identify convex spaces with similar characteristics, and Figure 5 maps the core clusters onto the campus plan. Ward's method was used to maximise cluster homogeneity by minimising the sum of squared deviations of observations from their cluster means at each step of the analysis [45]. Squared Euclidean distance was selected as the interval measure to give greater weight to significant differences between clusters.

Clusters 1-5 are separated out at the third step of the analysis; although differences are identified between convex spaces at the fourth and subsequent steps, the similarities are greater than the differences beyond step three, as indicated by the distance scale at the bottom of Figure 4.

The major differentiation occurs between clusters 1-3 and clusters 4 and 5. Convex spaces belonging to clusters 1-3 on average have higher LAI, D_{sky} and D_{surf} values than the dataset mean, all of which suggest a greater amount of vegetation. Cluster 3 in particular has a mean LAI about 2.5 times the mean for the full dataset; spaces belonging to this cluster are typically heavily treed.

Cluster 1 contains a number of larger spaces with significant vegetation, as well as a range of buildings of varying heights, rooflines and architectural detailing, as indicated by higher than average D_{sky} and D_{surf} values. The convex spaces in Cluster 2 have similar characteristics to those in Cluster 1, but tend to be smaller and have lower Ψ_s and LAI, reflecting a greater intensity of built form and less vegetation.

Cluster 4 is characterised by a high mean sky view factor, and although LAI is also higher than the dataset mean, both fractal dimension metrics are lower. Spaces belonging to this cluster are typically extensive and bounded by buildings of similar height, extensive width and little façade detail.

Cluster 5 is distinguished by a mean LAI less than one-sixth of the dataset average, and also a low Ψ_s value; these spaces are predominantly small "urban canyons" surrounded by relatively tall buildings.

V. CONCLUSIONS

The main purpose of this paper is to describe and explain a streamlined methodology for the initial comparative evaluation of urban places with reference to: potential ecosystem services (LAI); microclimate (Ψ_s, when combined with readily available weather and building materials data); and visual variety and character (D_{sky} and D_{surf}). The campus case study is provided to illustrate how this methodology may be applied in practice – it is not intended as a conclusive "proof of concept". Further research is obviously required to test the methods in different

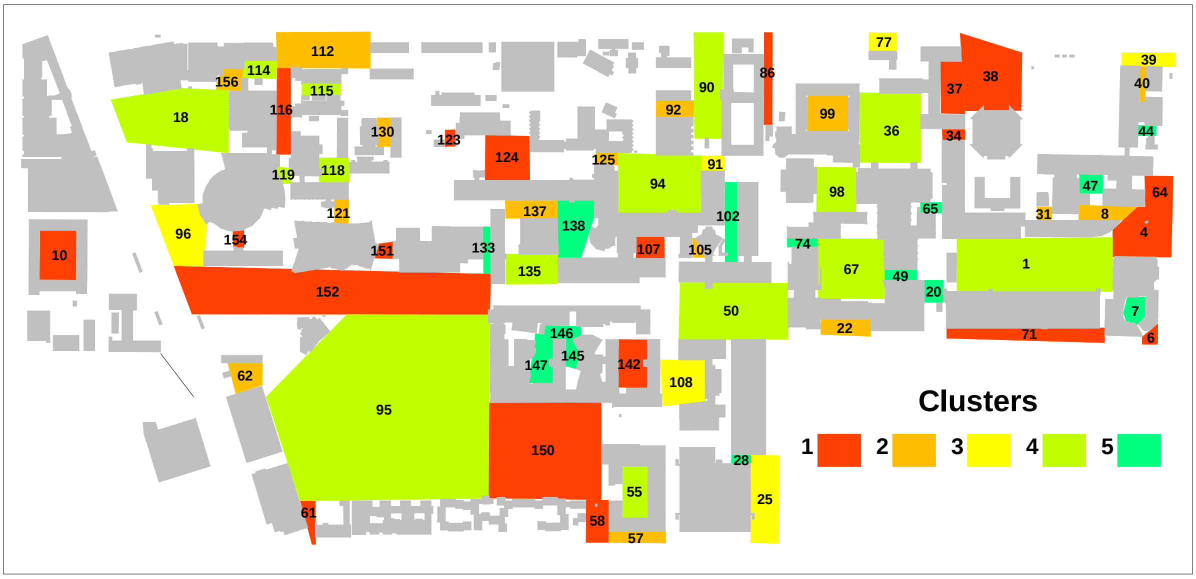

Fig. 5 The core clusters of convex spaces with similar characteristics mapped onto the campus open space plan. Buildings are shaded grey.

urban contexts and to validate the findings through triangulation using different methods, involving for example the direct measurement of LAI, and survey of occupants to explore perceptions and preferences for spaces with diverse fractal properties.

The proposed methodology would therefore seem particularly relevant (especially in the context of climate change mitigation and adaptation) for application in rapidly urbanising developing countries where resource-intensive methods can be problematic. On the other hand, the necessary *approximations* (and indeed inaccuracies) associated with low cost, rapid assessment must also be acknowledged. It should also be reiterated that the perceived potential for this methodology here is in the *comparative* assessment of places; the results must not be taken as absolutes.

For example the D value of a digital photograph is not an absolute property of the hemispherical view thus represented, given the range of choices involved in image processing and analysis. The application of fractal analysis to quantify the quality defined as "visual diversity" is relative – the numerical values obtained are meaningful only within the frame of reference provided by the hardware and software used in the investigation. In addition, where deciduous vegetation is a significant factor, skyline fractal dimension D_{sky} (and sky view factor Ψ_s) are subject to seasonal change.

Jonckheere *et al*. note a variety of potential sources of error in determining LAI from hemispherical pho-

The resources required for this type of investigation are inexpensive and easily obtained: an NIR-adapted Nikon Coolpix camera and several public domain software programs.

tography, including camera exposure, unevenness of sky lighting, reflections from foliage and image editing [17]. In general, fisheye photography tends to underestimate LAI; Jonckheere *et al*. suggest a figure of about 15% compared with direct sampling of leaves, although they still conclude that it offers a convenient and powerful indirect method for measuring a range of forest canopy parameters. However, inspection of pre-and post-GLA processed images suggests the underestimation of LAI within an urban space such as the UNSW campus may be at least twice that, particularly as grasses/groundcovers are excluded. Again, if inter-site comparison is the desired outcome rather than a high degree of accuracy of individual results, NIR hemispherical photography may provide the required information within acceptable limits.

The mathematics involved in fractal analysis is straightforward and the software used to calculate D is relatively simple. The programs employed to estimate LAI and Ψ_s are more sophisticated, but have been tested extensively in practice and are deemed fit for purpose. Gap Light Analyzer is widely used in forestry and land management research and can also calculate a variety of measures not utilised here, such as the amount of above- and below-canopy direct, diffuse and total radiation. RayMan outputs agree well with results obtained from experimental studies in temperate climates [41], although the authors add that further validation, especially in tropical regions, is required.

This essentially exploratory research suggests that NIR hemispherical photography offers a rapid and convenient way:

- To estimate LAI between urban sites, as an indicator of vegetation primary production and hence the ecosystem services provided by urban vegetation;
- To measure the sky view factor, a major determinant of urban microclimate; and
- To determine the fractal dimensions of urban surfaces and skylines, which are associated with visual diversity, complexity and urban character.

In summary, fisheye photography presents a way to capture significant attributes of the *overall* space from the perspective of the observer immersed in it, with potential application in urban landscape planning and design. It also reinforces the present focus on conducting a variety of measurements from the one spatial vantage point – a many-to-one mapping of observations to locations – which facilitates data collection, correlation and comparability between places.

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