An Urban Environmental Quality index for Salford, Greater Manchester: A disaggregated approach

Oliver Gunawan, Richard P. Armitage, and Philip James

School of Environment and Life Sciences, University of Salford, Salford, M5 4WT, UK
Tel. (0161 295 3261)
o.t.gunawan@edu.salford.ac.uk; r.p.armitage@salford.ac.uk, p.james@salford.ac.uk

Summary: This research investigates the Urban Environmental Quality (UEQ) of Salford, Greater Manchester using an integrated Geographic Information System and remote sensing approach. Five variables have been chosen representing different characteristics of the urban landscape (Normalised Difference Vegetation Index, Normalised Difference Building Index, building height, surface temperature, and proximity to water). Principal Component Analysis was used to create a pixel-based UEQ index. This index was positively related to a previously created area-based index. Ranges of pixel values were larger in lower quality areas, reducing as UEQ increased. This reflects the broad range of land uses present across the urban landscape.

KEYWORDS: Urban Environmental Quality, GIS, Urban Modelling

1. Introduction

Urban environmental management is becoming of central importance due to increasing residential accommodation demands and maintaining access to quality urban green space. Defining environmental quality is problematic. One approach, adopted by socio-economic methods like the UK's Index of Multiple Deprivations (McLennan *et al.* 2011), is to create an index that compares the relative rather than absolute quality of locations. Urban environmental quality (UEQ) provides a quantitative measure of quality by assessing physical characteristics and composition of urban landscapes, rather than social compositions (van Kamp *et al*. 2003). This paper follows Nichol and Wong's (2005, pp 49-50) definition of UEQ as "A complex and spatially variable parameter which is a function of interrelated factors including the urban heat island, the distribution of greenery, building density and geometry, and air quality". Assessing UEQ is challenging and previous studies have focussed on using secondary variables as proxy measures (Nichols and Wong, 2005; Li and Weng, 2007).

The approach presented in this paper is based on a series of remotely sensed data sets. Remote sensing was used due to its ability to capture data over a large area, allowing the whole city landscape to be analysed (van Delm and Dulinck, 2009). In addition to spatial coverage, remote sensing sensors can also capture heat patterns over cities (Nichols and Wong, 2005) and, using LiDAR sensors, characterise the morphology of the city in the form of Digital Surface Models (Liu, 2008). Consequently, Geographic Information Systems (GIS) offer an ideal platform for collection and integration of datasets for UEQ analysis (Aubrecht *et al*. 2009; Martinez, 2009).

Building on previous work (Gunawan and Armitage, 2011), in which a quantitative UEQ index was created using Lower Super Output Areas (LSOA) as the spatial framework, this paper presents a pilot study, which seeks to create a finer resolution index using 30 m pixels, which will be compared against the LSOA index. It is anticipated that this will characterise UEQ variation within LSOAs. This disaggregated information could offer better information to urban planners regarding identification of areas for management or improvement (Carsjens and Ligtenberg, 2007).

2. UEQ Variables

A number of secondary variables have been selected to reflect components of the physical landscape. Pacione (2003) and Barbosa *et al*. (2007) highlight vegetation as having a positive influence on both the physical and social health of city dwellers. Popular surrogate measures for vegetation are indices, such as the Normalised Difference Vegetation Index (NDVI) (Lo and Faber, 1997), derived from remotely sensed data. A major feature of any urban area is the built environment and this has been characterised from remotely sensed data using measures such as the Urban Heat Island effect (Rizwan *et al*. 2008), and indices such as the Normalised Difference Built-Up Index (NDBI) (Zha *et al*. 2005). The urban environment is 3 dimensional and there are clear variations in the heights of buildings between city centre locations and more suburban areas (Gunawan and Armitage, 2011). Hui *et al.* (2007) also found that proximity to water was linked to attractiveness in residential areas. All these variables were derived for use in this study (Table 1).

Table 1. UEQ variables

Measure of urban quality	Variable
Urban Vegetation	Normalised Difference Vegetation Index
Built Environment	Normalised Difference Built-up Index
	Building Height
Land Surface Temperature	Surface Temperature
Proximity to Water	Distance from Water Bodies

3. Method

NDVI, NDBI and surface temperature variables were created from a June 2006 Landsat Thematic Mapper scene. NDVI derived from bands 3 and 4, NDBI from bands 4 and 5, and temperature from band 6. Distance to water was derived from a land cover map created from a supervised classification of the Landsat scene. Building height measurements were derived from airborne Lidar data and an average height per pixel was calculated. The five variables were then normalised using z-scores.

Principal Component Analysis (PCA) was used to investigate the variability present in the set of variables. PCA combines highly correlated variables, enhancing dimensions of variability (Rogerson, 2006). Using a method proposed by Li and Weng (2007) a UEQ index was created. The methods involves using the eigenvalues from the first four PCA components to weight the PCA score for each pixel, these are then summed. Equation 1 shows this process.

$$UEQ\_index = \sum_{1}^{n} ((1.934 * a) + (1.017 * b) + (0.857 * c) + (0.813 * d) \quad (1)$$

Where n is sample number (the number of pixels in each dataset) and a, b, c and d are the first four PCA axes scores for each pixel. Resulting pixel values were normalised so a value of 1 had the highest quality and -1, the lowest. The grid was then compared against a LSOA-based analysis from Gunawan and Armitage (2011).

4. Results

The results of the PCA are shown in Table 1. The first PCA axis appears to relate to a gradient between pixels dominated by vegetation and those dominated by the built environment (buildings, roads etc.). The second axis appears to relate negatively to distance to water, but positively to building height. The third axis principally relates to temperature and building height, suggesting it characterises the Urban Heat Island effect (Rizwan *et al.* 2008). Finally, PCA axis four is related to water proximity and building height.

Table 2. Component Coefficients for PC Axes

PC components	1	2	3	4
Eigenvalues	1.93	1.02	0.86	0.81
NDVI	0.60	0.13	0.32	0.05
NDBI	-0.58	-0.33	-0.27	-0.00
Dist from Water	0.24	-0.76	0.17	-0.55
Temperature	-0.29	-0.27	0.75	0.50
Building Height	-0.37	0.45	0.46	-0.66

In Figure 1, the dark green areas indicate higher UEQ values across Salford and are generally situated to the west and north. The east, where Salford joins Manchester's urbanised city centre, is characterised by lower values shown in pale green. The more urbanised areas, with impermeable land cover and taller buildings, coincide with the lower UEQ values.

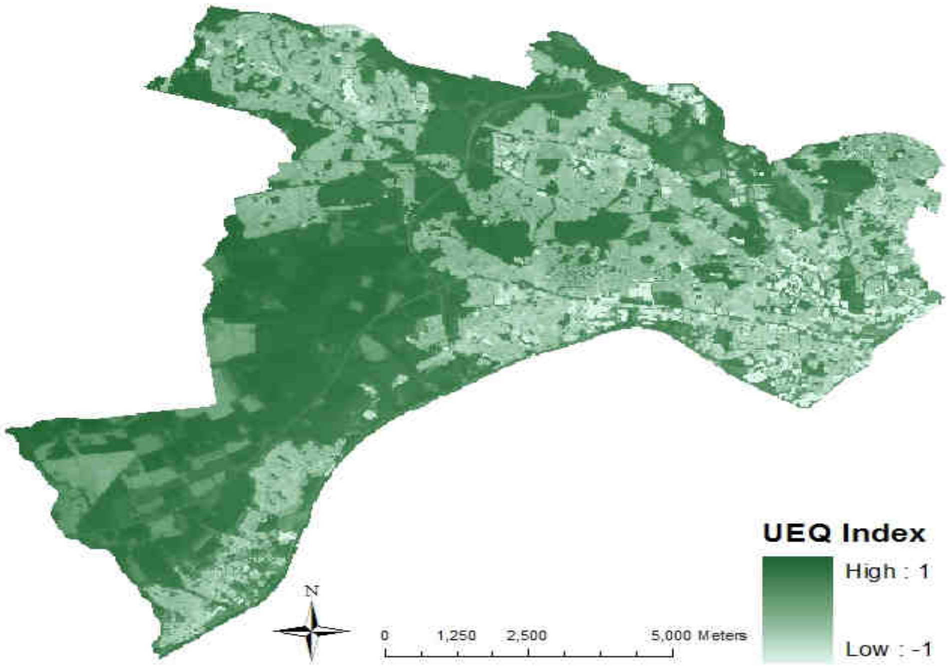

Figure 1. Pixel-based UEQ index. This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown.

Figure 2 displays the mean per-pixel UEQ values within each LSOA. The different colours correspond to four "urban types" (City Centre, High Density Suburbs, Low Density Suburbs and 'Urban Green') derived at the LSOA level in work by Gunawan and Armitage (2011). As expected, there is a strong correlation between the LOSA-based and mean pixel-based UEQ indices (R^2 = 0.8923. The four LOSA level urban types occupy their own specific regions of Figure 2. City Centre and High Density Suburbs, with lower UEQ scores, are predominately towards the left, while Low Density Suburbs and Urban Green are towards the right of Figure 2. Figure 3 displays the range of pixel-based PCA values in each LSOA. The range is generally lower in LSOAs classified as Low Density Suburbs and Urban Green, than it is in LSOAs classified as City Centres and High Density. City Centre LSOAs tend to display largest ranges, potentially indicating the greatest degree of variability in composition.

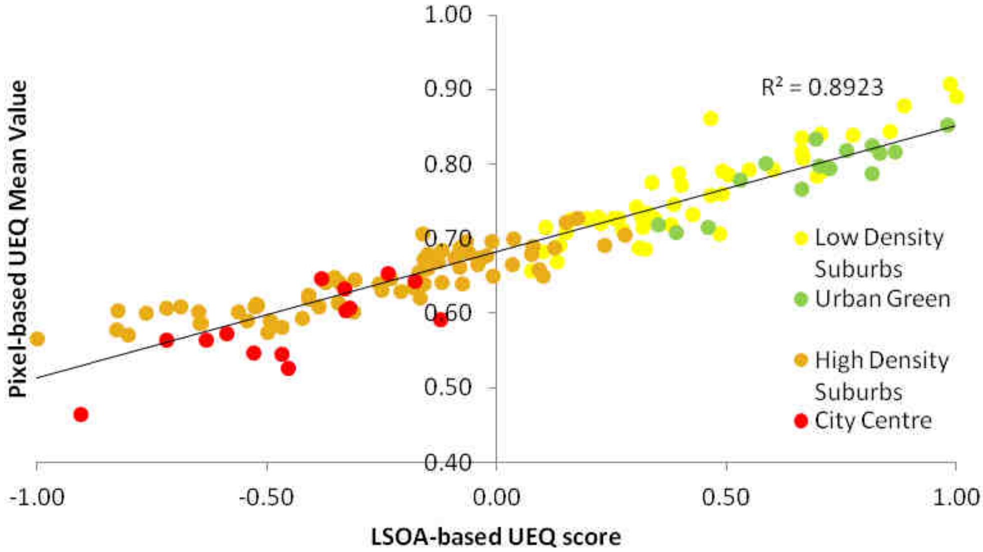

Figure 2. Mean pixel-based UEQ scores within each LSOA

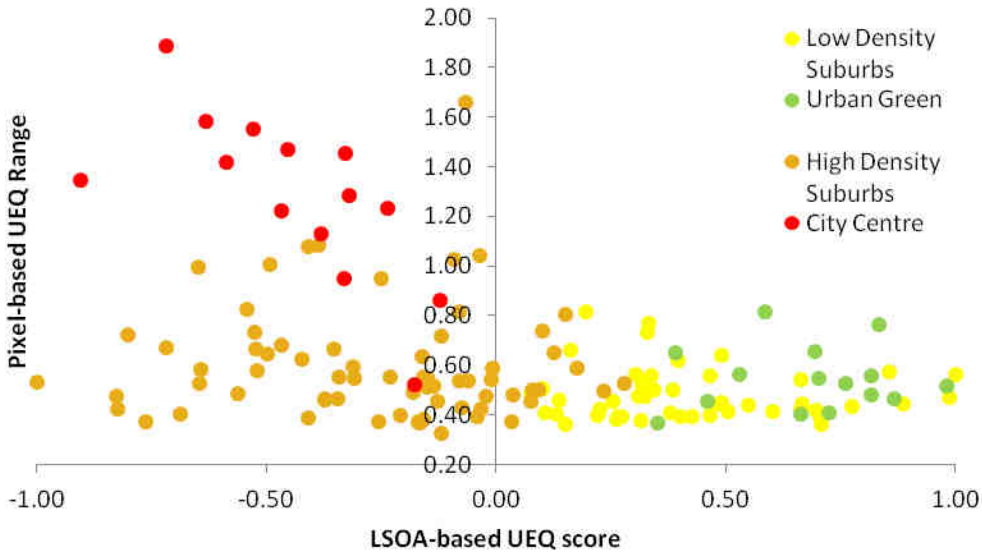

Figure 3. Pixel-based UEQ score ranges within each LSOA

5. Discussion

This study found general correspondence between negative UEQ scores in dense inner-city areas and positive scores in greener suburban areas for Salford. These findings are similar to those in other studies using similar approaches (i.e. Lo and Faber, 1997; Nichols and Wong, 2005; Li and Weng, 2007). The per-pixel UEQ analysis reinforces the earlier LSOA-based finding of Gunawan and Armitage (2011), but adds to it by highlighting differences in UEQ variability within LSOAs. For example, the pixels in the LSOAs characterised as City Centre demonstrated the highest range of UEQ indices values, while the lowest range was found in LSOAs labelled as Low Density Suburban or Urban Green. Wu *et al.* (2006) suggest this is partly explained by the complex mosaic of small land cover patches that characterise more urbanised areas.

The use of a per-pixel method has also removed some of the subjectivity and assumption of homogeneity associated with arbitrary spatial units such as LOSAs (Li and Weng, 2007). LSOAs reflect population density; therefore they are irregularly sized, with smaller LSOAs clustered around urban centres and larger LSOAs towards urban fringes. The uniform pixels used here are not shaped by administrative boundaries and are therefore more objective spatial units.

6. Conclusions

This research has demonstrated the calculation of a per-pixel quantitative measure of UEQ, building on previous research that employed census units. The initial results correspond to earlier studies. It is hoped that this research will provide a useful basis for a more in-depth study of UEQ, combining both physical and socio-economic characteristics of the urban landscape. Further work will focus on validation and verification of the UEQ indices and further testing on other urban landscapes.

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8. References

Aubrecht, C., Steinnocher, K., Hollaus, M. and Wagner, W. (2009). Integrating earth observation and GIScience for high resolution spatial and functional modelling of urban land use. *Computers Environment and Urban Systems 33 (1)***,** 15-25.

Barbosa, O., Tratalos, J.A., Armsworth, P.R., Davies, R.G., Fuller, R.A., Johnson, P. and Gaston, K.J. (2007). Who benefits from access to green space? A case study from Sheffield, UK. *Landscape and Urban Planning 83 (2-3),* 187-195.

Carsjens, G.J. and Ligtenberg, A. (2007). A GIS-based support tool for sustainable spatial planning in metropolitan areas. *Landscape and Urban Planning 80 (1-2)* 72–83.

Gunawan, O. and Armitage, R.P. (2011). Measuring Urban Environmental Quality across Salford using an integrated Geographic Information Systems and Remote Sensing approach. *Proceedings of GISRUK*, 27-29 April 2011, Portsmouth, UK.

Hui, E.C.M., Chau, C.K., Pun, L. and Law, M.Y. (2007). Measuring the neighbouring and environmental effects on residential property value: Using spatial weighting matrix. *Building and Environment 42 (6),* 2333-2343.

Li, G. and Weng, Q. (2007). Measuring the quality of life in city of Indianapolis by integration of remote sensing and census data. *International Journal of remote Sensing 28 (2),* 249-267.

Liu, X. (2008). Airborne LiDAR for DEM generation: some critical issues. *Progress in Physical Geography 32 (1),* 31-49.

Lo, C.P. and Faber, B.J. (1997). Integration of Landsat Thematic Mapper and Census Data for Quality of Life Assessment. *Remote Sensing of Environment 62 (2),* 143-157.

McLennan, D., Barnes, H., Noble, M., Davies, J., Garratt, E. and Dibben, C. (2011). *The English*

Indices of Deprivation 2010, London: Department for Communities and Local Government.

Martinez, J. (2009). The use of GIS and indicators to monitor intra-urban inequalities. A case study in Rosario, Argentina. *Habitat International 33 (4),* 387–396.

Nichol, J. and Wong, M.S. (2005). Modeling urban environmental quality in a tropical city. *Landscape and Urban Planning 73 (1),* 49-58.

Pacione, M. (2003). Urban environmental quality and human wellbeing - a social geographical perspective. *Landscape and Urban Planning 65 (1-2),* 19-30.

Rizwan, A.M., Dennis, Y.C.L. and Liu, C. (2008). A review on the generation, determination and mitigation of Urban Heat Island. *Journal of Environmental Sciences 20 (1),* 120-128.

Rogerson, P.A. (2006). *Statistical Methods for Geography: A Students Guide, 2nd Edition,* London, Sage Publications.

van Delm, A. and Dulinck, H. (2009). Classification and quantification of green in the expanding urban and semi-urban complex: Application of detailed field data and IKONOS-imagery. *Ecological Indicators 11 (1),* 52-60.

van Kamp, I., Leidelmeijer, K., Marsman, G. and de Hollander, A. (2003). Urban environmental quality and human well-being towards a conceptual framework and demarcation of concepts; a literature study. *Landscape and Urban Planning 65 (1-2),* 5-18.

Wu, Q., Hu, D., Wang, R., Li, H., He, Y., Wang, M. and Wang, B. (2006). A GIS-based moving window analysis of landscape pattern in the Beijing metropolitan area, China. *International Journal of Sustainable Development and World Ecology 13 (5),* 419-434.

Zha, Y., Gao, J. and Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing 24 (3),* 583-594.

9. Biography

Oliver Gunawan is a first year PhD Student from the University of Salford. Research interests span urban GIS and remote sensing, in particular spatial analysis of the relationships between ecosystem services and the urban landscape.

Dr. Richard Armitage is a Senior Lecturer with research interests in mapping and characterising natural and semi natural environments.

Prof. Philip James is Professor of Ecology whose research interests include Ecosystem Services in relation to urban environments.