# Assessing Urban Environmental Quality Change of Indianapolis, United States, by the Remote Sensing and GIS Integration

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***Abstract*—Timely and regular information on urban environmental quality (UEQ) is essential for urban planning. This research evaluated the ten-year UEQ changes in Indianapolis, Indiana, U.S.A, based on the synthetic indicators of physical variables extracted from remotely sensed images and socioeconomic variables derived from census data. Physical environmental variables such as land use and land cover data, land surface temperature, normalized difference vegetation index, and other transformed remote sensing variables were derived from the two Landsat images taken in 1991 and 2000. Socioeconomic variables including population density, house characteristics, income, and education level were extracted from US census 1990 and 2000 block group (BG) data. Correlation analysis and factor analysis were performed after the two groups of variables were integrated at the BG level. For each year, four factors were identified and interpreted as greenness, crowdedness, economic status, and scenic amenity. By assigning different weights to each factor, two synthetic UEQ indexes were generated. A comparison of the two synthetic indexes revealed significant changes in UEQ pattern from 1990 to 2000.**

***Index Terms*—Change detection, Landsat images, remote sensing-GIS integration, urban environmental quality.**

## I. Introduction

THE world's cities continue to grow in population size with and without planned development. This urban revolution has triggered a number of environmental problems at multiple scales, including the loss of natural vegetation, open spaces, wetlands, and wildlife habitat, the change of local and regional climates, and the increases in pressure on water, energy, and infrastructure. Timely information on the temporal and spatial patterns of urban environmental quality (UEQ) is the prerequisite for the formation of new policies that endorse sustainable development and smart growth in anticipation of the above-mentioned problems that accompany growth. Therefore, it is essential to assess UEQ at multiple temporal and spatial scales for more effective city planning and management.

The UEQ has long been studied in geographical literature. It has been described using quantitative measures [1]–[17], qualitative descriptions [18]–[20], attitudinal explanations [2], [21], and landscape features [7]–[10], [13]–[15]. However, UEQ is complex in practice and a complete understanding of it is still lacking. It is essentially a multidimensional concept comprising physical, spatial, economic, and social aspects of the urban environment. UEQ can be assessed from a variety of perspectives such as physical urban layout, infrastructure, economic effect, government policy, public opinion, and social consideration. The challenge is that there is no simple way to model and to predict the interaction of all aspects of UEQ. One key issue is how to derive effective UEQ indicators that not only enable people better map the phenomenon but also serve as an effective management tool in urban planning and sustainable development. Like most other geographical phenomena and environmental processes, UEQ is dependent on both spatial and temporal scales. Nevertheless, there are few attempts to have focused on these two properties of UEQ.

Given its unique characteristics, suitable techniques are needed for measuring the spatial variability of UEQ over a whole city at multiple scales. The technology of remote sensing presents advantages over conventional data collection methods and shows great potential in UEQ studies [3], [4], [7]–[10], [13]–[15]. The main attraction of this technology primarily results from the provision of time-synchronized data coverage over a large area with both high spatial detail and high temporal frequency at a low cost and its integration with GIS. Research on UEQ on the basis of remotely sensed data dates back to the 1950s [5]. Among all kinds of digital images collected by different sensors, medium resolution satellite images such as SPOT and Landsat are the primary data sources [3], [4], [7]–[10], [22]. Recently, images having very high spatial and spectral resolutions become available (like IKONOS) and have been applied to conduct UEQ studies at a microscale level [13]–[15]. Information derived from remote sensing data used for UEQ research is mainly concerned with four sorts of environmental variables: vegetation index, land surface temperature, impervious surfaces, and land use and land cover (LULC) types.

Among all the variables used to evaluate UEQ, vegetation is recognized as the key one for many reasons: filtering air, water, and sunlight; cooling urban heat; recycling pollutants; moderating local urban climate; providing shelters to animals and

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recreational areas for people [6], [13], [23]–[26]. This greenness information derived from remotely sensed images to assess UEQ is typically measured by a vegetation index rather than the amount of vegetation cover, for instance, normalized difference vegetation index (NDVI) or vegetation density [13]. These vegetation indexes have been used as the primary indicators of UEQ in different ways. Fung & Siu carried out a dynamic temporal change of UEQ of Hong Kong by applying NDVI data derived from SPOT High Resolution Visible images [3]. In a later study [4], they calculated the mean and entropy of NDVI and found these variables were useful to study the spatial variability of the green space. Based on the vegetation density map produced from the IKONOS image, Nichol & Wong developed a 3-D Virtual Reality model to depict UEQ conditions of Hong Kong at a much detailed level [13].

Temperature is a major concern in urban climate since it relates to the urban heat island phenomenon [27]–[30], and directly affects the thermal comfort and health of urban dwellers [31]. It hence provides a unique perspective of UEQ for a given area. High temperatures are often regarded as undesirable by most people. Several UEQ studies have employed land surface temperature extracted from satellite images as an indicator of urban environment [7]–[10]. These studies used medium resolution data like Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+) imagery. Recently, high resolution images like IKONOS were applied to provide detailed temperature information at a microscale level through data fusion [13], [15].

Impervious surfaces (such as roads, buildings, and parking lots) have been emerging as a key environmental indicator for sustainable urban development in recent years [32], [33]. Impervious surface maps are also helpful for estimating socioeconomic factors like population density and social conditions [34], [35]. Li and Weng incorporated the impervious surface data derived from a Landsat ETM+ image to successfully model the quality of life in Indianapolis, Indiana [7], [8].

For a complete evaluation of UEQ, socioeconomic variables, especially those derived from census data, must be combined with physical variables extracted from remote sensing images through the technique of GIS. However, those physical variables are measured on a per-pixel scale in raster format, while those socioeconomic variables are measured at an areal unit level in vector format. Because of the difference in data format and scale of measurement, methods for integrating the two groups of variables are sought after. Two general approaches have been used in previous UEQ studies: principal component analysis (PCA) [3], [7]–[10] and GIS overlay [10], [13], [15]. These two methods have also been employed as prerequisite to generate a synthetic index to further quantify UEQ. Recently, Nichol and Wong have proposed using multiple-criteria queries for data integration. However, the result is strongly subject to the choice of specific environmental thresholds [13]–[15].

Despite previous research efforts, assessing UEQ through the integration of remote sensing and GIS has not yet been fully explored, especially based on multiple spatial and temporal scales. This research intended to evaluate the UEQ changes from 1990 to 2000 in Indianapolis, Indiana using the integrated techniques of remote sensing and GIS. Specifically, this study intends to 1) derive an UEQ index based on the synthetic indicators of physical variables extracted from Landsat images and socioeconomic variables derived from U.S. census data; and 2) develop a new method for assessing UEQ change over the time.

## II. Study Area

The study area is Indianapolis, located in Marion County, Indiana, USA (Fig. 1). With a consolidated city-county structure [36], the city of Indianapolis and Marion County are often loosely considered the same. As the nation's 12th largest city, Indianapolis is the geographical center of Indiana and the capital of the state. With roads leading out of the city center in all directions, Indianapolis has been famously known as "The Crossroads of America". It is now the most populous city of the state and the second most populous Capital in the US. The metropolitan population was about 1.5 million according to Census 2000. In many aspects, Indianapolis is a typical mid-sized metropolitan area with a decentralized urban/suburban structure [36]. The environmental and socioeconomic characteristics are varied spatially and can affect the environmental quality within the area. By setting down zoning codes, urban planners are in the position of encouraging city variety of all kinds [37]. They hold the potential to design a desirable urban layout (both physical and socioeconomic) to improve the quality of the city. As a result, a better understanding of the city's environmental quality at its current stage and its change across time is valuable for urban planners and environmental managers who target future development.

## III. Methodology

### A. Datasets and Image Pre-Processing

The data sources for this research primarily came from two census data and two Landsat images, with the former used to extract socioeconomic variables and the latter for the environmental variables. The two census data were Census 1990 and 2000. The two Landsat images included one TM collected on June 6, 1991 (TM91) and one ETM+ acquired on June 22, 2000 (ETM+00). Both images were first georectified to a common UTM coordinate system using 1:24,000-scale topographic maps as reference. For each image, 25 ground control points were selected to generate coefficients for a first-order polynomial, and a nearest-neighbor method was applied to resample the image according to their original theoretical spatial resolution. The resultant values of root mean square were all found to be less than 0.4 pixel. Fig. 2 illustrates the procedure of developing two UEQ synthetic indexes and evaluating the ten-year UEQ changes for the study area.

### B. Extraction of Environmental Variables From Image Data

In order to provide a complete representation of the UEQ condition in the physical environmental aspect for the study area, two LULC maps were first derived from the green (G), red (R), and near-infrared (NIR) bands of each Landsat images with different classifiers. The land cover (LC) map was given by performing the unsupervised classification using the Interactive Self-Organizing Data Analysis Technique (ISODATA) clustering method and the maximum likelihood decision rule.

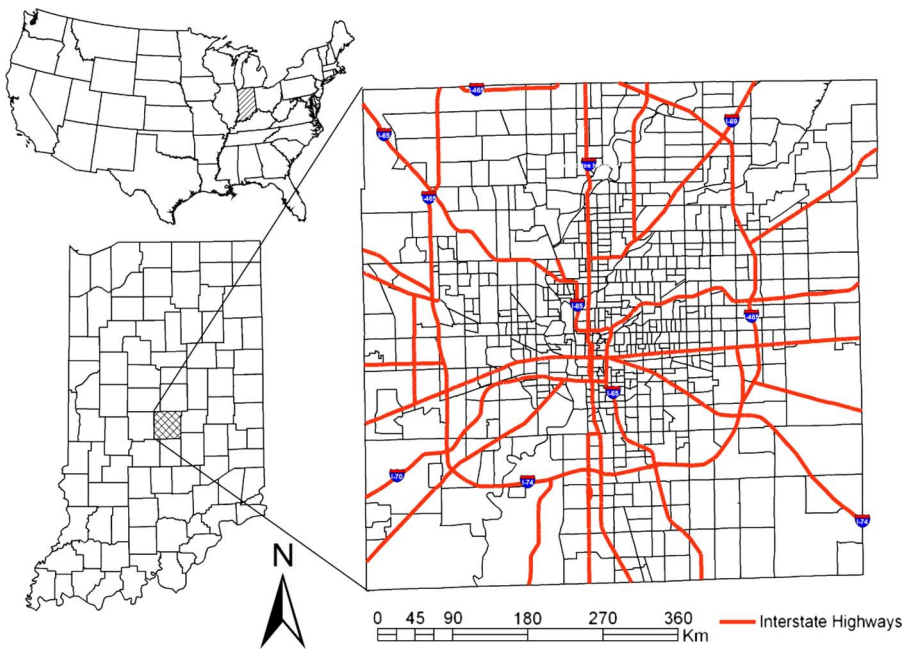


Fig. 1. A map of the study area: Marion County, Indiana, USA, at the census block group level.

The resultant LC categories included cropland and pasture (UCroPas), water (UWater), urban built-up lands (UBuiltup), forest (UForest), grass (UGrass), and barren lands (UBarren). The overall accuracy obtained from these two maps was 88.80% for TM91 and 89.00% for ETM+00. The land use (LU) map was produced using a supervised maximum likelihood classifier. Eight categories were identified: cropland and pasture (SCroPas), water (SWater), commerical and industrial (SComInd), high density residential (SHDR), medium density residential (SMDR), low density residential (SLDR), forest (SForest), and grass (SGrass). The selection of training areas used aerial photographs that were taken around the time of image acquisitions and the results of the unsupervised classification. Zoning data, which is primarily related to land use, was also used in choosing training and test sites for high, medium, and low density residential [17]. The overall accuracy for the two maps was found to be 76.25% for TM91 and 75.50% for ETM+00.

Because temperature is also recognized as an important index of human thermal comfort, it was also derived from the thermal infrared bands of TM91 and ETM+00 using the Weng *et al.* method [27]. Basically, three steps were involved in the procedure: first, converting the digital number (DN) values of the thermal band into spectral radiance; second, converting the spectral radiance to at-satellite brightness temperature, namely, blackbody temperature; and third, adjusting the blackbody temperature to land surface temperature by incorporating emissivity biases due to land cover differences. The last step was accomplished using the LULC maps produced by the unsupervised spectral classification.

Several transformed bands on the basis of reflective channels were additionally created from the two satellite images. They included NDVI and two more indexes that were essentially derived from the Landsat reflective bands (e.g., Normalized Difference Water Index (NDWI), and Normalized Difference Built-up Index (NDBI) [38]. All three variables were computed using the following equations:

$$\begin{aligned}\mathrm{NDVI} &= (\mathrm{Radiance\ Band4} - \mathrm{Radiance\ Band3}) \\ &\quad /(\mathrm{Radiance\ Band4} + \mathrm{Radiance\ Band3}) \quad (1)\\ \mathrm{NDWI} &= (\mathrm{Radiance\ Band4} - \mathrm{Radiance\ Band5}) \\ &\quad /(\mathrm{Radiance\ Band4} + \mathrm{Radiance\ Band5}) \quad (2)\\ \mathrm{NDBI} &= (\mathrm{DN\ Band5} - \mathrm{DN\ Band4}) \\ &\quad /(\mathrm{DN\ Band5} + \mathrm{DN\ Band5}). \quad (3)\end{aligned}$$

The radiance required in the above equations was calculated using the formulas below.

$$\text{For Landsat TM DNs [39]}:$$
$$\mathrm{L}_\lambda = \frac{\mathrm{LMAX} - \mathrm{LMIN}}{\mathrm{QCALMAX}} \times \mathrm{DN} + \mathrm{LMIN} \quad (4)$$

where $\mathrm{L}_\lambda$ is at-sensor spectral radiance $(\mathrm{mWcm^{-2}\ sr^{-1}\ \mu m^{-1}})$, QCALMAX is 255 DN for all TM data, LMIN and LMAX are the spectral radiances $(\mathrm{mW\ cm^{-2}\ sr^{-1}\ \mu m^{-1}})$ for each band at DN equaling to 0 and QCALMAX, respectively.

For Landsat EMT+ DNs [40]:

$$\begin{aligned}&\text{For Landsat EMT + DNs[40]}:\\ &\mathrm{L}_\lambda = \frac{\mathrm{LMAX} - \mathrm{LMIN}}{\mathrm{QCALMAX} - \mathrm{QCALMIN}} \\ &\quad \times (\mathrm{DN} - \mathrm{QCALMIN}) + \mathrm{LMIN} \quad (5)\end{aligned}$$

where $\mathrm{L}_\lambda$ is at-sensor spectral radiance $(\mathrm{mWcm^{-2}\ sr^{-1}\ \mu m^{-1}})$, QCALMIN is 0 or 1 (provided in image headers for ETM+), QCALMAX is 255 DN, LMIN and LMAX are the spectral radiances for each band at DN equaling to 1 and 255, respectively.

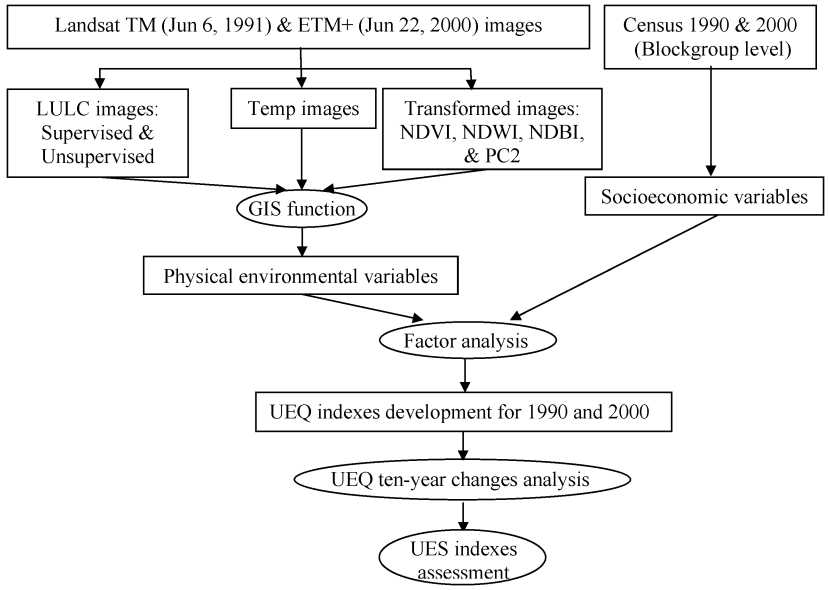


Fig. 2. A flowchart of developing UEQ synthetic index and evaluating the ten-year UEQ changes for the study area.

NDWI is an indicator for water content within vegetation and it is ideal to be combined with NDVI for representing the state of vegetation [38]. By setting suitable threshold values, it is suggested all these indexes can effectively differentiate different LULC types (e.g., vegetation and built-up) [38]. Besides, the second principal components (PC2) extracted from the two images by performing PCA were also produced to serve as an additional vegetation indicator for extracting environmental variables. Although the derived first principal component contains the majority information of all of the original bands, it does not specifically refer to any indicative environmental information and thus was not used in the study.

### C. Extraction of Socioeconomic Variables From Census Data

The social-economic indicators were derived from the census data for 1990 and 2000 at the block group (BG) level. These data together with the related Topologically Integrated Geographic Encoding and Referencing system (TIGER) shape files were downloaded from the U.S. Census Bureau [41]. Since census BG data contained up to hundreds of variables regarding all aspects of socioeconomic condition, a total of 30 variables relating to the variables commonly used in previous UEQ studies (i.e., population density, housing density, and median family income) were initially extracted from the two census datasets, respectively [7]–[10], [22]. After a series of calculation procedure, up to 13 socioeconomic variables were determined for this research: population density (PD), median age population (MedAge), households (HH), house units (HU), vacant house units (VHU), owner-occupied house units(OHU), median house value (HV), medium house income (MHI), median family income (MFI), per capita income (PCI), percentage of families under poverty (POV), unemployment rate (UNEMP), and percentage of college graduates (PCG). All these variables were computed for each BG of census 1990 and 2000. It was noted that the two census datasets do not contain the same number of BGs—census 1990 has 703 BGs and census 2000 has 658—nor do they share a consistent coverage for all areal units. Therefore, the two datasets were preprocessed to remove those "different" BGs to maintain a common 614 analytical units. The modified census data were utilized as the basis for later analysis.

### D. Data Integration of Environmental and Socioeconomic Variables

Factor analysis is one of the major approaches to integrate environmental parameters derived from remotely sensed images and socioeconomic variables extracted from census data [7]–[10], [15], [42]. Among all, PCA is used the most for UEQ analysis and was also employed in this study. Before running PCA, all the derived environmental and socioeconomic variables were aggregated to all 614 BGs. Pearson's correlation coefficients (r) were then computed to provide a preliminary analysis of the relationships among the variables. Major principal components representing the majority variance of the original datasets were thus extracted.

### E. UEQ Index Development and Validation

The derived principal components were used to develop a synthetic UEQ index after being weighted by the percentage of variance that each component explained. Accuracy assessment is needed for validating the effectiveness of the developed UEQ synthetic indexes. A few approaches have been proposed by using regression modeling [7], [8] and sociological methods [15]. In this study, the linear regression analysis was performed to assess the robust of the UEQ indexes by using the original variables that showed the strongest correlation with the considered components as predictors. A coefficient of determination ($R^2$) was calculated to examine the effectiveness of the developed regression models.

## IV. Results

### A. Correlation Analysis Results

All the 32 variables extracted from the two year's datasets were first entered to run a Pearson's correlation analysis. Because of the large amount of inputs for the analysis, a complete

TABLE I
CORRELATION MATRIX BETWEEN LULC VARIABLES AND OTHER ENVIRONMENTAL VARIABLES FOR THE 1990 AND 2000 DATA

| | SCroPas | SWater | SComInd | SHDR | SMDR | SLDR | SForest | SGrass | UCroPas | UWater | UBuildup | UForest[b] | UGrass[a] | UBarren |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Temp_{91}$ | -.05 | -.01 | .02 | -.07 | .03 | -.06 | -.05 | -.08 | -.03 | -.01 | -.02 | -.06 | -.06 | -.01 |
| $NDBI_{90}$ | .43 ** | .19 ** | .52 ** | -.12 ** | -.30 ** | -.04 | .27 ** | .43 ** | .37 ** | .20 ** | .54 ** | .25 ** | .44 ** | .32 ** |
| $NDWI_{90}$ | -.19 ** | .09 * | -.32 ** | .34 ** | .09 * | .28 ** | .13 ** | -.05 | -.17 ** | .10 * | -.29 ** | .18 ** | -.08 | -.10 * |
| $NDVI_{90}$ | -.01 | -.04 | -.22 ** | .44 ** | .07 | .39 ** | .18 ** | .13 ** | -.01 | -.02 | -.15 ** | .23 ** | .07 | -.01 |
| $PC2_{90}$ | .24 ** | .03 | .02 | .46 ** | .00 | .44 ** | .32 ** | .39 ** | .20 ** | .06 | .14 ** | .35 ** | .32 ** | .16 ** |
| $Temp_{00}$ | -.30 ** | -.20 ** | -.08 | -.40 ** | .03 | -.36 ** | -.34 ** | -.38 ** | -.22 ** | -.22 ** | -.14 ** | -.44 ** | -.41 ** | -.08 |
| $NDBI_{00}$ | .15 ** | .07 | .44 ** | -.06 | -.23 ** | -.16 ** | .07 | .16 ** | .14 ** | .06 | .38 ** | .04 | .13 ** | .10 * |
| $NDWI_{00}$ | .03 | .09 * | -.25 ** | .24 ** | .11 ** | .30 ** | .17 ** | .07 | -.02 | .11 ** | -.18 ** | .25 ** | .11 ** | -.03 |
| $NDVI_{00}$ | -.06 | -.17 ** | -.26 ** | .12 ** | .07 | .19 ** | -.08 * | -.06 | -.06 | -.17 ** | -.23 ** | .00 | -.04 | -.01 |
| $PC2_{00}$ | .24 ** | -.06 | .05 | .40 ** | .05 | .30 ** | .23 ** | .32 ** | .20 ** | -.05 | .13 ** | .29 ** | .35 ** | .03 |

Note: ** Correlation is significant at the 0.01 level 2-tailed; * Correlation is significant at the 0.05 level 2-tailed.

TABLE II
CORRELATION MATRIX BETWEEN VARIABLES FOR THE 1990 DATA

| | SCroPas | SComInd | SLDR | SGrass | UCroPas | UBuildup | UForest | Temp | NDBI | NDWI | NDVI | PC2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PD | -.22 ** | -.33 ** | -.30 ** | -.35 ** | -.16 ** | -.37 ** | -.29 ** | -.20 ** | -.13 ** | .57 ** | .84 ** | -.34 |
| MedAge | .37 ** | .35 ** | .62 ** | .47 ** | .28 ** | .50 ** | .32 ** | .10 * | -.47 ** | .01 | -.12 ** | -.39 ** |
| HH | .31 ** | .34 ** | .61 ** | .42 ** | .23 ** | .47 ** | .28 ** | -.04 | .12 ** | .04 | .16 ** | .28 ** |
| HU | .28 ** | .34 ** | .57 ** | .39 ** | .21 ** | .46 ** | .26 ** | -.04 | .09 * | .06 | .17 ** | .27 ** |
| OHU | .31 ** | .35 ** | .60 ** | .42 ** | .23 ** | .47 ** | .28 ** | -.03 | .10 * | .04 | .14 ** | .24 ** |
| VHU | .03 | .19 ** | .16 ** | .06 | -.01 | .23 ** | .02 | -.04 | .10 * | .05 | .17 ** | .27 ** |
| MHI | .15 ** | .06 | .41 ** | .27 ** | .12 ** | .12 ** | .33 ** | .04 | .08 * | -.11 ** | -.09 * | -.08 * |
| MFI | .11 ** | .08 | .39 ** | .23 ** | .08 * | .12 ** | .29 ** | -.10 * | -.02 | .36 ** | .42 ** | .41 ** |
| PCI | .05 | .06 | .35 ** | .18 ** | .03 | .09 * | .30 ** | -.10 * | -.02 | .36 ** | .39 ** | .36 ** |
| HV | .13 ** | .09 * | .42 ** | .27 ** | .10 * | .14 ** | .34 ** | -.07 | -.02 | .34 ** | .33 ** | .26 ** |
| PCG | .01 | .08 | .37 ** | .13 ** | -.01 | .10 * | .24 ** | -.11 ** | -.02 | .39 ** | .44 ** | .39 ** |
| POV | -.11 ** | -.15 ** | -.35 ** | -.21 ** | -.07 | -.20 ** | -.19 ** | -.05 | -.05 | .33 ** | .31 ** | .20 ** |
| UNEMP | -.08 | -.10 * | -.24 ** | -.15 ** | -.04 | -.15 ** | -.14 ** | .09 * | .00 | -.28 ** | -.39 ** | -.47 ** |

Note: ** Correlation is significant at the 0.01 level 2-tailed; * Correlation is significant at the 0.05 level 2-tailed; PD—population density; MedAge—median age population; HH-household; HU-house unit; OHU—owner-occupied house unit; VHU—vacant house unit; MHI—median house income; MFI—median family income; PCI—per capita income; HV—house value; PCG—percentage of college graduate; POV—percentage of family under poverty line; UNEMP—unemployment rate.

TABLE III
CORRELATION MATRIX BETWEEN VARIABLES FOR THE 2000 DATA

| | SCroPas | SComInd | SLDR | SGrass | UCroPas | UBuildup | UForest | Temp | NDBI | NDWI | NDVI | PC2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PD | -.22 ** | -.30 ** | -.20 ** | -.30 ** | -.16 ** | -.30 ** | -.29 ** | .50 ** | -.42 ** | .62 ** | .61 ** | -.41 |
| MedAge | .40 ** | .44 ** | .69 ** | .59 ** | .31 ** | .65 ** | .43 ** | -.19 ** | -.32 ** | -.05 | -.05 | -.36 ** |
| HH | .38 ** | .43 ** | .69 ** | .57 ** | .29 ** | .64 ** | .43 ** | -.23 ** | .04 | .085 * | -.03 | .18 ** |
| HU | .37 ** | .42 ** | .66 ** | .55 ** | .28 ** | .63 ** | .41 ** | -.21 ** | .00 | .14 ** | .00 | .21 ** |
| OHU | .48 ** | .46 ** | .84 ** | .70 ** | .39 ** | .68 ** | .57 ** | -.34 ** | .01 | .12 ** | -.01 | .19 ** |
| VHU | .13 ** | .21 ** | .18 ** | .18 ** | .09 * | .30 ** | .10 * | .04 | -.07 | .22 ** | .06 | .32 ** |
| MHI | .22 ** | .09 * | .41 ** | .28 ** | .14 ** | .16 ** | .42 ** | -.55 ** | .07 | -.05 | -.10 * | -.03 |
| MFI | .17 ** | .06 | .38 ** | .23 ** | .10 * | .13 ** | .37 ** | -.51 ** | -.28 ** | .49 ** | .27 ** | .31 ** |
| PCI | .12 ** | .03 | .32 ** | .16 ** | .05 | .07 | .32 ** | -.44 ** | -.26 ** | .47 ** | .25 ** | .24 ** |
| HV | .15 ** | .04 | .32 ** | .19 ** | .08 * | .09 * | .33 ** | -.40 ** | -.21 ** | .42 ** | .19 ** | .13 ** |
| PCG | .08 | .02 | .31 ** | .12 ** | .01 | .07 | .29 ** | -.34 ** | -.18 ** | .38 ** | .23 ** | .17 ** |
| POV | -.16 ** | -.14 ** | -.29 ** | -.23 ** | -.11 ** | -.19 ** | -.24 ** | .43 ** | -.16 ** | .35 ** | .16 ** | .07 |
| UNEMP | -.11 ** | -.08 * | -.21 ** | -.15 ** | -.07 | -.12 ** | -.18 ** | .26 ** | .13 ** | -.32 ** | -.21 ** | -.34 ** |

Note: ** Correlation is significant at the 0.01 level 2-tailed; * Correlation is significant at the 0.05 level 2-tailed; PD—population density; MedAge—median age population; HH-household; HU-house unit; OHU—owner-occupied house unit; VHU—vacant house unit; MHI—median house income; MFI—median family income; PCI—per capita income; HV—house value; PCG—percentage of college graduate; POV—percentage of family under poverty line; UNEMP—unemployment rate.

report of their results is not offered here. Tables I, II, and III only list the r(s) computed by variables later proved to be important for the research. Among the environmental variables, the qualities of temperature, NDVI, NDBI, NDWI, and PC2 were not assessed during the data creation procedure. To shed some light on their qualification on the study, Table I summarizes their correlation with all the LULC variables that have been evaluated by classification accuracy assessment. In general, the correlation coefficients tended to be relatively low for most the tested data. Clearly, while the $\mathrm{Temp}_{91}$ was poorly correlated with all the LULC variables, the one derived from the 00 image $(\mathrm{Temp}_{00})$ maintained a much better negative correlation with all the vegetation classes (SForest, SGrass, UForest, and UGrass: $\mathrm{r} = -0.34 - -0.44$). This difference may be explained from the contrast of the spatial detail provided by the two original thermal bands. With the coarse 120 m resolution,

TABLE IV
SUMMARY OF COMMUNALITY FOR 33 VARIABLES AND 31 VARIABLES

| | 1990 Communality | | 2000 Communality | |
|---|---|---|---|---|
| | 32 variables | 28 variables | 32 variables | 29 variables |
| SCroPas | .95 | .95 | .95 | .95 |
| SWater | .92 | .92 | .94 | .94 |
| SComInd | .78 | .78 | .92 | .92 |
| SHDR | .47 | | .47 | |
| SMDR | .48 | | .40 | |
| SLDR | .78 | .78 | .75 | .75 |
| SForest | .86 | .86 | .81 | .81 |
| SGrass | .98 | .98 | .97 | .97 |
| UCroPas | .93 | .93 | .91 | .91 |
| UWater | .94 | .94 | .93 | .93 |
| UBuiltup | .85 | .85 | .91 | .91 |
| UForest | .88 | .88 | .90 | .90 |
| UGrass | .99 | .99 | .98 | .98 |
| UBarren | .67 | .67 | .85 | .85 |
| Temperature | .41 | | .86 | .86 |
| NDBI | .84 | .84 | .84 | .84 |
| NDWI | .90 | .90 | .94 | .94 |
| NDVI | .95 | .95 | .75 | .75 |
| PC2 | .88 | .88 | .85 | .85 |
| Population density | .70 | .70 | .72 | .72 |
| Median age population | .93 | .93 | .95 | .95 |
| Households | .97 | .97 | .96 | .96 |
| House unit | .98 | .98 | .96 | .96 |
| Occupied house unit | .97 | .97 | .89 | .89 |
| Vacant house unit | .72 | .72 | .62 | .62 |
| Median house income | .88 | .88 | .83 | .83 |
| Median family income | .92 | .92 | .88 | .88 |
| Per capital income | .93 | .93 | .89 | .89 |
| Median house value | .77 | .77 | .74 | .74 |
| Percentage of college graduates | .78 | .78 | .77 | .77 |
| Percentage of families under poverty | .55 | .55 | .57 | .57 |
| Unemployment rate | .47 | | .41 | |

the $\mathrm{Temp}_{91}$ was less useful than the 30 m $\mathrm{Temp}_{00}$ for the current study. $\mathrm{Temp}_{00}$ was also strongly associated with the four transformed index bands (NDVI, NDWI, NDVI, and PC2), with a positive r reported for the first one $(\mathrm{r} = .427)$ and three negative rs for the rest three ($\mathrm{r} = -0.60$–$-0.80$). This further demonstrates $\mathrm{Temp}_{00}$ could be a valuable variable for the study. The correlation coefficients reported for other tested variables, however, were quite consistent between the two datasets for the two years. Overall, the NDBI had a strong positive relationship with SComInd ($\mathrm{r} = 0.52$ for 90; $\mathrm{r} = 0.44$ for 00) and UBuildup ($\mathrm{r} = .54$ for 90; $\mathrm{r} = 0.38$ for 00) classes, suggesting its potential in mapping the city's building layout. The NDWI illustrated similar relationships as NDVI with SComInd ($\mathrm{r} = -0.32/-0.22$ for 90; $\mathrm{r} = -0.25/-0.26$ for 00) and UBuildup ($\mathrm{r} = -0.29/-0.15$ for 90, $\mathrm{r} = -0.18/-0.23$ for 00). The two PC2s were found to be more efficient than the two NDVIs in indicating the city's vegetation environment, as they consistently showed a gentle positive correlation with the vegetation classes (SForest, SGrass, UForest, and UGrass: $\mathrm{r} = 0.320.39$ for 90; $\mathrm{r} = 0.230.35$ for 00).

Tables II and III list the correlation coefficients for the selected environmental and socioeconomic variables for the two years. For the image classified variables, the urban LULC classes (SComInd and UBuildup) were relatively strongly associated with all house density indexes such as HU and OHU ($\mathrm{r} = 0.34$–$0.47$ for 1990; $\mathrm{r} = 0.42$–$0.68$ for 2000) and population characteristics like HH and MedAge ($\mathrm{r} = 0.35$–$0.50$ for 1990; $\mathrm{r} = 0.44$–$0.65$ for 2000). The two green vegetation LULC classes (SGrass and UForest) showed higher positive correlations than the urban LULC categories (SComInd and UBuildup) with most income variables (MHI, MFI, and PCI: $\mathrm{r} = 0.21$–$0.33$ for 1990; $\mathrm{r} = 0.23$–$0.42$ for 2000). This implies high-income residents tend to cluster around the green physical landscapes. For the temperature variable, the $\mathrm{Temp}_{00}$ appeared to hold strong negative correlations with all income variables (MHI, MFI, and PCI: $\mathrm{r} = -0.44$–$-0.55$) and HV $(\mathrm{r} = -0.40)$, but a great positive correlation with POV $(\mathrm{r} = .43)$, suggesting the hot environment fails to attract the high-income groups and it is often the home to poor residents.

The results concerned the several transformed images (NDBI, NDWI, NDVI, and PC2) indicated the two vegetation indexes—NDVI and PC2—had gentle positive correlations with most income variables (MHI, MFI, and PCI: $\mathrm{r} = 0.26$–$0.42$ for 1990; $\mathrm{r} = 0.13$–$0.31$ for 2000) and the HV ($\mathrm{r} = 0.26$–$0.33$ for 1990; $\mathrm{r} = 0.17$–$0.23$ for 2000), but they were all negatively associated with POV ($\mathrm{r} = -0.20$–$-0.31$ for 1990; $\mathrm{r} = -0.21$–$-0.34$ for 2000) and UNEMP ($\mathrm{r} = -0.39$–$-0.47$ for 1990; $\mathrm{r} = -0.15$–$-0.21$ for 2000). Hence, it is generally expensive to afford a green living environment.

TABLE V
ROTATED FACTOR LOADING MATRIX FOR THE 1990 AND 2000 DATA (LOADING LARGER THAN 0.750 ARE HIGHLIGHTED)

| | 1990 | | | | 2000 | | | |
|---|---|---|---|---|---|---|---|---|
| | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
| SCroPas | **.96** | .15 | .02 | -.05 | .18 | **.95** | .07 | .00 |
| SWater | .14 | .11 | .12 | -.04 | .24 | .12 | .11 | -.06 |
| SComInd | .31 | .28 | -.01 | -.25 | .34 | .39 | .00 | -.27 |
| SLDR | .14 | .51 | .29 | .38 | .67 | .10 | .25 | .22 |
| SForest | .63 | .07 | .14 | .15 | .10 | .67 | .16 | .05 |
| SGrass | **.88** | .22 | .11 | .10 | .38 | **.83** | .08 | .03 |
| UCroPas | **.96** | .08 | .02 | -.05 | .11 | **.95** | .01 | -.02 |
| UWater | .18 | .15 | .13 | -.03 | .25 | .13 | .13 | -.05 |
| UBuildup | .36 | .39 | .02 | -.16 | .57 | .40 | .02 | -.22 |
| UForest | .61 | .08 | .20 | .19 | .19 | .70 | .24 | .11 |
| UGras | **.87** | .20 | .09 | .04 | .39 | **.81** | .11 | .06 |
| UBarren | .61 | .11 | .04 | -.04 | .01 | .16 | .01 | .04 |
| Temp | | | | | -.09 | -.24 | -.31 | **-.72** |
| NDBI | .38 | .02 | .00 | -.58 | .01 | .14 | -.17 | **-.83** |
| NDWI | -.14 | -.01 | .28 | **.83** | .04 | .01 | .33 | **.89** |
| NDVI | .04 | .07 | .28 | **.93** | -.02 | -.08 | .13 | **.86** |
| PC2 | .25 | .11 | .20 | **.83** | .14 | .24 | .01 | **.76** |
| PD | -.14 | .15 | -.32 | -.13 | .07 | -.16 | -.19 | .00 |
| MedAge | .24 | **.92** | .08 | .10 | **.94** | .22 | .08 | .01 |
| HH | .16 | **.95** | .12 | .10 | **.95** | .20 | .12 | .04 |
| HU | .14 | **.97** | .09 | .06 | **.96** | .19 | .10 | .03 |
| OHU | .16 | **.95** | .11 | .09 | **.78** | .32 | .17 | .14 |
| VHU | -.06 | **.79** | -.11 | -.19 | .70 | .03 | -.12 | -.07 |
| MHI | .13 | -.04 | **.90** | .20 | .06 | .15 | **.84** | .25 |
| MFI | .08 | .00 | **.94** | .16 | .07 | .10 | **.90** | .20 |
| PCI | .03 | .04 | **.95** | .07 | .05 | .04 | **.93** | .10 |
| HV | .10 | .15 | **.82** | .19 | .07 | .09 | **.85** | .12 |
| PCG | -.03 | .15 | **.87** | .04 | .10 | .00 | **.86** | .04 |
| POV | -.04 | -.04 | -.55 | -.35 | -.11 | -.06 | -.49 | -.20 |
| Initial eigenvalue | 9.63 | 5.15 | 3.66 | 2.27 | 10.28 | 5.28 | 2.81 | 2.48 |
| % of variance | 34.38 | 18.40 | 13.08 | 8.11 | 32.44 | 18.21 | 9.68 | 8.53 |
| Cumulative % | 34.38 | 52.78 | 65.85 | 73.96 | 35.44 | 53.64 | 63.32 | 71.86 |

Note: PD—population density; MedAge—median age population; HH-household; HU-house unit; OHU—owner-occupied house unit; VHU—vacant house unit; MHI—median house income; MFI—median family income; PCI—per capita income; HV—house value; PCG—percentage of college graduate; POV—percentage of family under poverty line.

Obviously, the results in Tables II and III show the correlations between environmental and socioeconomic variables were inclined to be low. The examination of the original table listing the correlation coefficients of all input variables (not provide in the paper) indicates much stronger correlations existed between those variables belong to be either environmental or socioeconomic. This was due to the high redundant information contained in different variables within each of the two datasets. It is thus necessary to reduce the data dimension by using factor analysis.

### *B. Factor Analysis Results*

Factor analysis is mainly utilized in two ways: data reduction and structure detection. In the current study, factor analysis was mainly used to reduce the initial 32 UEQ variables. The principal component method of extraction aims at identifying uncorrelated components that account for variation in the original variables and ordering them based on their variation. Since only a few components will account for most of the variation, they are identified as the key factors to represent the original variables. In this way, the number of variables can be reduced.

For all input variables depicting the condition of the UEQ in 1990 and 2000 for the study area, the initial results of factor analysis concerned that of Kaiser–Meyer–Olkin (KMO) and Bartlett's test values. These two indexes are often used to examine the suitability of data for factor analysis [7]. The data are acceptable for factor analysis only when their KMO is larger than 0.50 and the significant levels of Barlett's test is less than 0.10 [7]. With the significant levels of Barlett's test all equaled to 0.000, the KMOs of the two datasets were 0.78 and 0.50, respectively, implying their suitability for factor analysis. All the 32 variables were then checked by their communalities in order to further validate their capabilities in factor analysis (Table IV). Communality serves as an indicator of the amount of variance that is accounted by each variable with the consideration of the factors in the factor solution. Generally speaking, small communalities correspond to variables which do not fit well with the factor solution and hence should be removed from the analysis. Table IV indicates that three variables, SHDR, SMDR, and UNEMP, detected small communalities (less than 0.50) for both datasets. Temperature also observed a small communality for the 1990 dataset. All these variables were

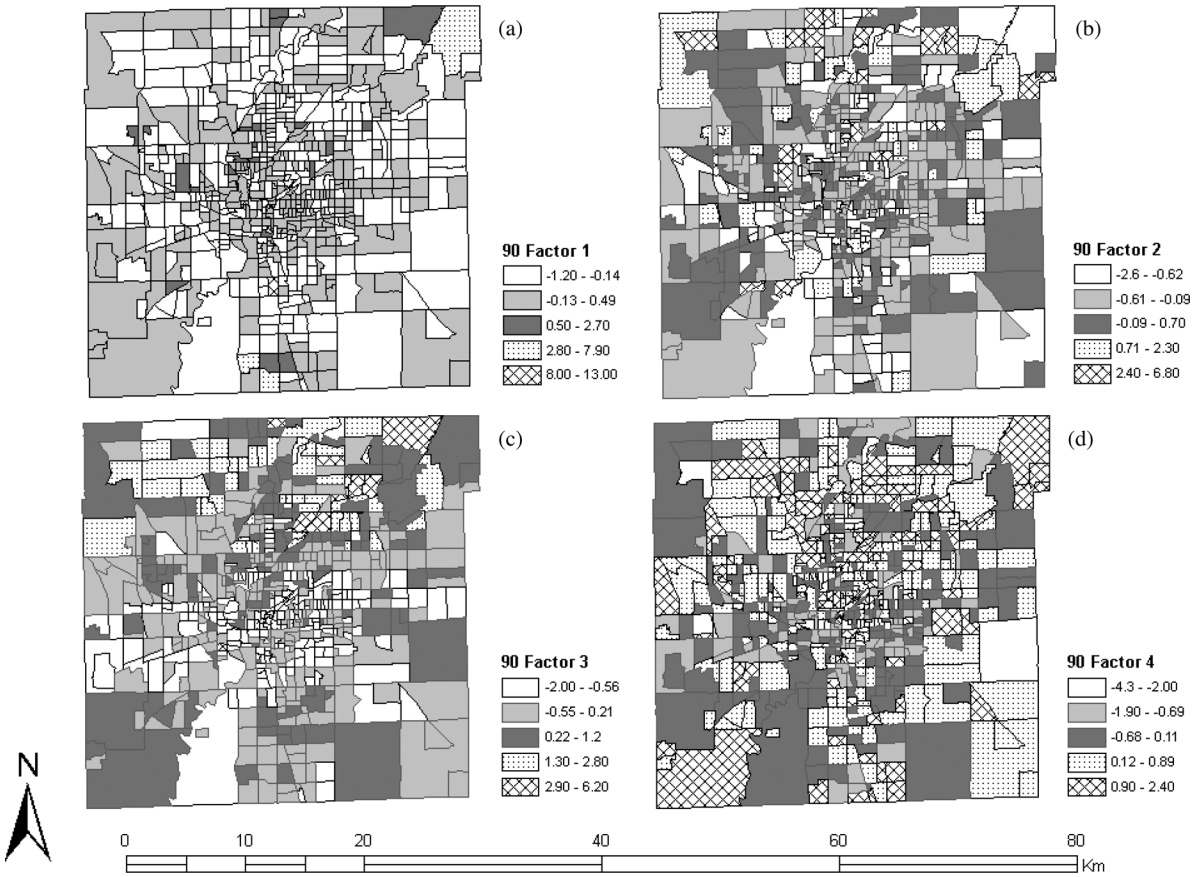


Fig. 3. The four 1990 factor scores: greenness indicator (a), crowdedness indicator (b), economic indicator (c), and scenic amenity indicator (d).

thus dropped in the subsequent analysis. At the end, only 28 variables of the 1990 dataset but 29 for the 2000 dataset were used for the factor analysis.

Using the rule of minimum eigenvalue should be larger than 1.00 [14], four factors were extracted from each dataset (Table V). To assist the interpretation of resultant factors, factor solution was rotated using the varimax approach. Overall, for the 1990 dataset, the first factor accounted about 34.38% of the total variance; the second factor 18.40%, the third factor 13.08%, and the fourth factor 8.11%. Together, the first four factors explained approximately 74% of the variance. For the 2000 dataset, the first factor accounted about 35.44% of the total variance; the second factor 18.21%, the third factor 9.68%, and the fourth factor 8.53%. Together 72.86% of the total variance was accounted for by the first four factors.

Table V reports the factor loadings for each variable on the four selected factors after rotation. In this study, the analysis of factor loadings only considers variables with loadings larger than 0.71, which is suggested as excellent [43]. For the 1990 dataset, Factor 1 had large positive loadings with four LULC variables: SCroPas (0.96), SGrass (0.88), UCroPas (0.96), and UGrass (0.87). Clearly, this factor was strongly linked to the greenness of the environment. The higher the score in Factor 1 is, the better the UEQ in the greenness aspect is. Factor 2 had high positive loadings with two population characteristics (HH—0.95 and MedAge—0.92) and three house density properties (HU—0.97, OHU—0.95, and VHU—0.79). Consequently, this factor indicated the degree of crowdedness of the study area. The higher the score of Factor 2 is, the less the space for people to resides is available, thus leading to a poor living environment. Apparently, Factor 3 exhibited a strong positive correlation with all three income variables (MHI—0.90, MFI—0.94, and PCI—0.95), the education variable (PCG—0.87), and the house value variable (HV—0.82). This was the factor related to material welfare. The higher the score in Factor 3 is, the better the city in its economic status is. Only three variables were found to have loadings larger than 0.71 in Factor 4 and they were all derived from the images' transformed index bands: NDWI (0.83), NDVI (0.93), and PC2 (0.83). Factor 4 was obviously associated to the scenic amenity of the region. The larger the score of Factor 4 is, the better the physical environmental quality is. Fig. 3 shows the geographic distribution of the four factors. Overall, their distribution is subject to the spatial pattern possessed by the original variable that had the highest loadings with them. In 1990, the four factors had the highest loadings with cropland and pasture (SCroPas and UCroPas), HU, PCI, and NDVI, respectively, and they hence displayed a similar pattern to the ones relative to these variables.

The examination of the factor loadings reported by the 2000 dataset demonstrated similar results. The only exception was the corresponding information represented by different factors was rearranged in the 2000 data. In this case, the first factor was directed to crowdedness aspect of the city since it had strong pos-

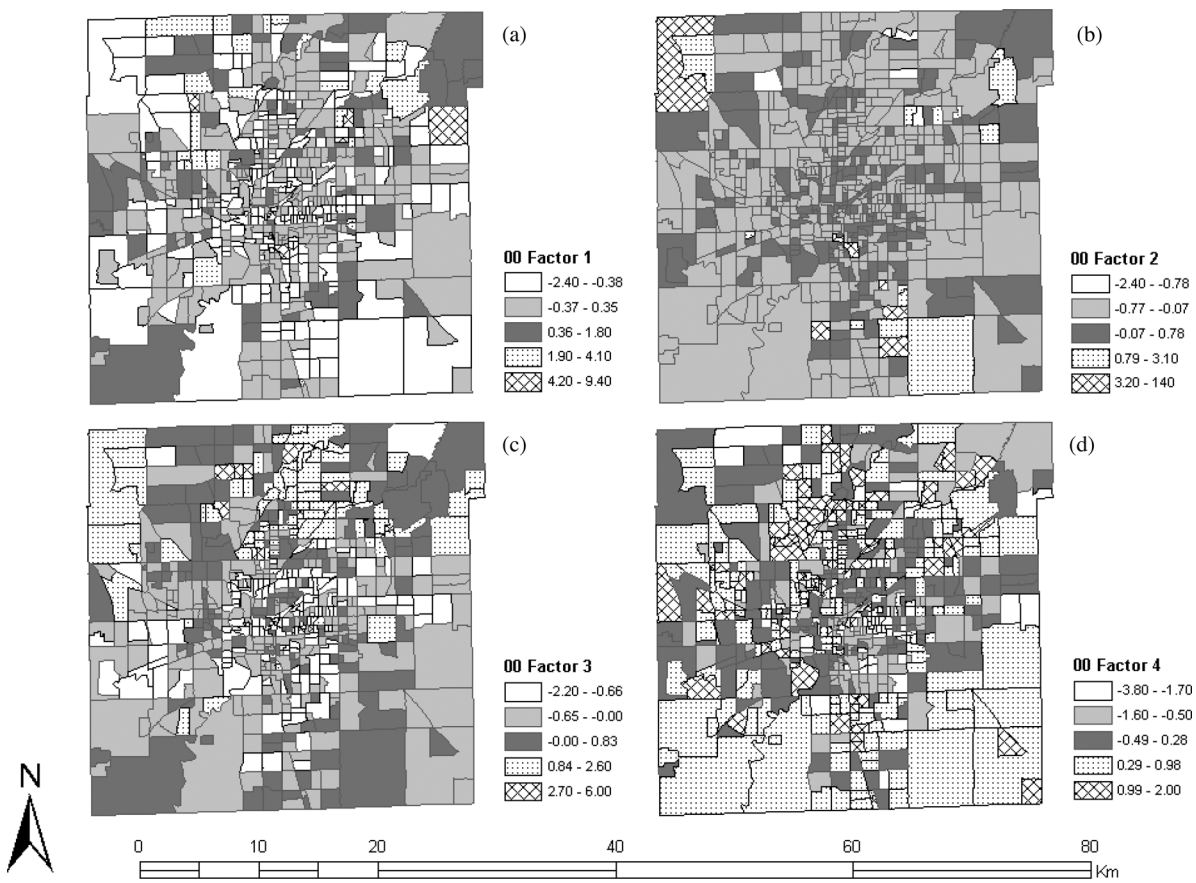


Fig. 4. The four 2000 factor scores: crowdedness indicator (a), greenness indicator (b), economic indicator (c), and scenic amenity indicator (d).

itive loadings with HH (0.95), MedAge (0.94), HU (0.96), and OHU (0.78). Factor 2 could be viewed as the greenness indicator since its higher loadings were all provided by LULC types of SCroPas (0.96), UCroPas (0.65), SGrass (0.88), and UGrass (0.87). The interpretation of Factors 3 and 4 revealed comparable results that have been observed from the 1990 data. With high loadings of all income variables (MHI—0.84, MFI—0.90, and PCI—0.93), the education variable (PCG—0.86), and HV (0.85), Factor 3 was also an indicator of depicting the economic image of the region. Finally, Factor 4 had significant positive loadings with NDWI (0.89), NDVI (0.86), and PC2 (0.76), but strong negative loadings with temperature (−0.72) and NDBI (−0.83). Consequently, this factor was the best in illustrating the overall scenic amenity status of the study area. The higher the score in Factor 4 is, the better the UEQ in its physical environment aspect is. Fig. 4 shows the geographic distribution of the four factors. Just like what have revealed from the 1990 data, the distribution of the four factors was comparable to those of the HU, cropland and pasture (SCroPas and UCroPas), PCI, and NDWI, since they had the largest loadings with these variables.

Generally speaking, the extracted factors were all suitable to be used as the indicators of the environmental quality of the study area in different dimensions in the two years: greenness, crowdedness, economic status, and scenic amenity. The difference of the weight of individual indicators in describing the general UEQ of the study area of that period demonstrated a significant change over the ten years. In the 1990 when the city was less developed, the overall UEQ was primarily depicted by green vegetation. However, after ten years of construction and development, the environmental quality of the study area was mainly accounted by house units, which indicated the environment had been significantly affected by socioeconomic factors.

### C. UEQ Synthetic Index and UEQ Change Analysis

Since different factors represented UEQ in various aspects, it is necessary to combine all them into a synthetic index. Two UEQ models were thus developed and utilized in this work. Because the greenness, economic, and scenic amenity indicators were contributing positively to UEQ, they were assigned a positive sign. The crowdedness indicator, however, was treated as a negative contributor to UEQ and a negative sign was hence attached to it. The percentage of variance that each factor explained was used as weight to create the following two equations:

$$\mathrm{UEQ1990} = (34.38 \times \mathrm{Factor\ 1} - 18.40 \times \mathrm{Factor\ 2} + 13.08 \times \mathrm{Factor\ 3} + 8.11 \times \mathrm{Factor\ 4})/100 \quad (6)$$

$$\mathrm{UEQ2000} = (-35.44 \times \mathrm{Factor\ 1} + 18.21 \times \mathrm{Factor\ 2} + 9.68 \times \mathrm{Factor\ 3} + 8.54 \times \mathrm{Factor\ 4})/100. \quad (7)$$

The UEQ score for each BG was then calculated and the results are illustrated in Fig. 5. In general, the UEQ score of 1990 ranged from −1.64 to 4.02 with a standard deviation of 0.42. This data were then normalized between 0 and 1 (Fig. 5(a)).

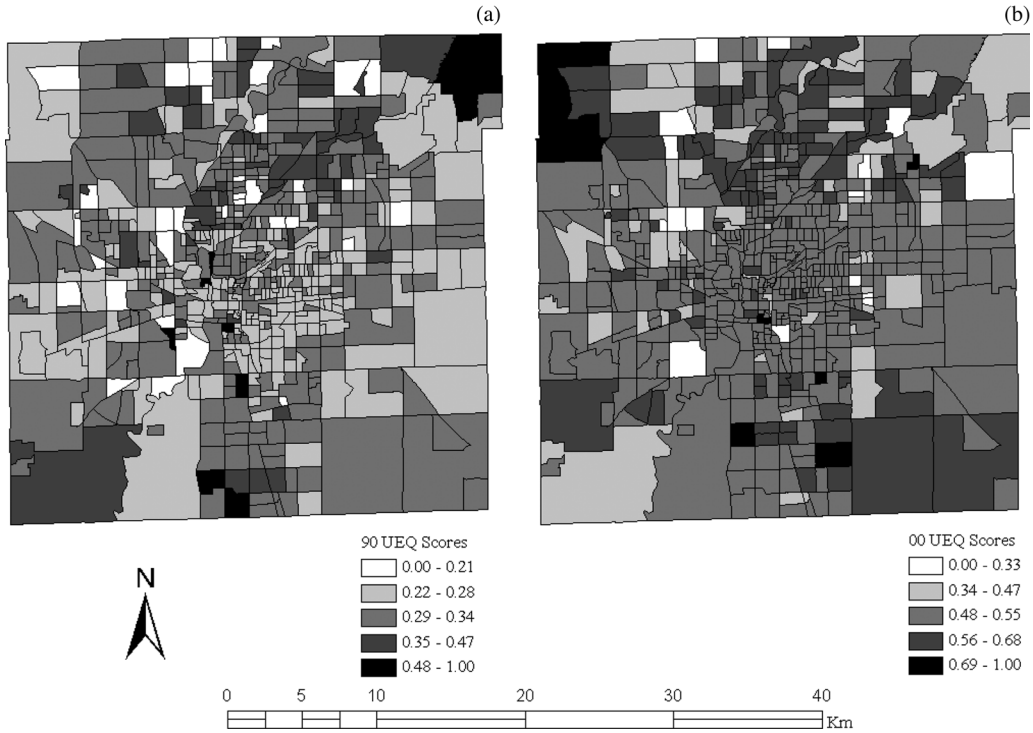


Fig. 5. The 1990 (a) and 2000 (b) synthetic environmental quality indexes.

Nearly 3% of BGs had UEQ scores higher than 0.50 at the new scale. These BGs scattered around the study area from the inner city to the city edge with some located in the northeast side and some centered in the middle south. They correspond to the rich UEQ zones characterized with stronger greenness, larger living space, and higher income status. As approaching the city's downtown, the UEQ conditions became poorer. BGs having the lowest UEQ scores were randomly found throughout the county. These poor UEQ zones were primarily linked to low capital income together with either predominant little greenness or high population density or the mixture of both. With a range of $-3.06$ to 2.89, the original UEQ score of 2000 also resulted in a moderate standard deviation (0.42) across the region. After being standardized to the new scale of 0–1 range, approximately 3% of BGs had UEQ scores greater than 0.6 (but over 75% were higher than 0.5) and most of them were found in the city's suburban area with some centered the midnorth and northwest corner and some located in the midsouth and southeast corner [Fig. 5(b)]. Just like those good UEQ zones identified in 1990, these BGs were characterized with lower population density, more abundant greenness, and better economic status. Most BGs with poorer UEQ scores (less than 0.3) were presented in the northern part of the county outside the downtown fringe mainly due to the cluster of houses.

Significant environmental quality changes were uncovered when the two maps were compared. It is found that the best UEQ zones in 1990 were all transformed to less favorable zones in 2000. The environmental quality of most BGs in the south and the southeast was generally improved during the ten years of development. In 1990, the city center was recognized as the mixture of all kinds of UEQ conditions with tendency to poor environment. In 2000, most BGs in this area were classified as medium level UEQ zones. Spatially, the whole city suffered from more poor UEQ zones in 1990 than in the year of 2000. Most of the BGs identified as poor in 1990 have been classified as medium level UEQ in the 2000 map. Most of the medium level UEQ zones in the 1990 map, however, were identified as poor zones in the 2000 map. It should be noted that the determination of UEQ zones in the two maps was somewhat different, subject to the UEQ models that were applied. Although UEQ synthetic indexes were developed using the same indicators (greenness, crowdedness, economic, and scenic amenity) and the same modeling procedure, each indicator was weighted differently. This difference in weight further suggests the temporal change of UEQ's connotation. As the urban environment changed over the time, the components previously recognized as important in constituting the synthetic UEQ index may now become less important. In this study, greenness was recognized as the most crucial factor in 1990. Nevertheless, it became less crucial in 2000, and the most critical factor for 2000 was crowdedness.

### D. UEQ Validation Results

For the sake of evaluating the effectiveness of the developed UEQ models, regression analyses were performed with the original variables that had the highest loadings with the corresponding factors as the independent variable and the synthetic indexes as the dependent variables and the results are reported in Table VI. The $\mathrm{R}^2$ values showed that the two constructed UEQ models could account for more than 94% of the variance in the UEQ at the BG level in the two years. Overall, all four predictors did well in explaining UEQ variances in the two models, since the significance values of $F$ were all as small as 0.00 (smaller than 0.05, the confidence level chosen in this

TABLE VI
SUMMARY OF THE TWO UEQ REGRESSION MODELS

| Models | $R^2$ | Constant | Predictors | Coefficients |
|---|---|---|---|---|
| 90 synthetic UEQ | .94 | -.50 | UCroPas | .85 |
| | | | House unit | -.53 |
| | | | Per capital income | .28 |
| | | | NDVI | .25 |
| 00 synthetic UEQ | .95 | -2.24 | House unit | -.98 |
| | | | SCroPas | .61 |
| | | | Per capital income | .24 |
| | | | NDWI | .21 |

study). All these results demonstrated the strength of the linear regression relationships between the predictor and outcome variables and thus the validity of the two UEQ models.

## V. DISCUSSIONS AND CONCLUSIONS

This research explored the potential of the integration of satellite images and census data in assessing UEQ within a GIS framework base on a case study in Indianapolis, Indiana, USA. For each year, four major factors were identified: greenness, crowdedness, economic status, and scenic amenity. By assigning different weights to each factor, the synthetic UEQ indexes were created in 1990 and 2000. The investigation of the two synthetic indexes revealed great changes of UEQ in the study area between 1990 and 2000.

In this study, since the UEQ input variables were mainly in two formats: raster images and vector GIS data, one critical issue centered on the integration of remote sensing and GIS. Ideally, a total integration is expected. Yet the accomplishment of this task requires the understanding of two technical impediments: the raster-vector data model dichotomy and the problem of data uniformity. Remote sensing is raster oriented data collection while GIS is vector-based. Both raster and vector data models represent two distinct approaches to geospatial data processing and analysis with their own pros and cons. To blur the raster-vector dichotomy, possible solutions often involve the conversion of both types of data into a common format either in raster's or in vector's. However, the conversion between the two formats can introduce significant errors [44]. In practice, the conversion of vector data into individual pixels seems to be less realistic, since technically disaggregating vector data to pixels is more difficult to obtain. Besides, GIS is increasingly applied in decision making, planning, and environmental management. Hence, a vector format is more preferred in data integration for urban planning and environmental applications. The second technical obstacle for the data integration regards the problem of data uniformity. Remote sensing images are primarily used to depict gradients of continuous spectral information over space by changes in DNs recorded at each pixel. The census GIS data, however, are collected at an administrative unit level (e.g., census blocks, BGs, and tracts) where the spatial continuity property of recorded data is no longer kept throughout space. In other words, two kinds of data are acquired at different scales. Yet there is no single answer as to what levels (scales) the two data types can be best integrated. The current research took the census BGs as the basic aggregation unit with a raster to vector conversion performed. The application of aggregation data then introduces the notable modifiable areal unit problem that has been addressed in many previous literatures [31], [45], [46].

Since UEQ is the result of all factors (physical, ecological, and socioeconomic, etc.) that are spatially interacted with each other and this relationship changes with scales, the phenomenon is scale-dependent in nature. Based on the scale of observation and measurement, its report may suggest promising at one scale but undesirable at another. Obviously, there remains difficult to identify the "optimal" scale for UEQ analysis. Further research efforts are needed to establish a commonly accepted UEQ definition, which would help to develop methods for repeatedly modeling the spatial context of UEQ and scale dependency of the phenomenon.

In general, the results of this study could impact policy assessment instruments and assist local governments and environmental agencies in monitoring UEQ. The two UEQ models established in the research can be applied to assist urban planners not only to evaluate the city's current UEQ condition, but also to devise efficient development polices to construct a more desirable future UEQ environment at the census BG level. Land use planners and policy makers can thus make policy adjustments to encourage effective urban landscape and economic development for building a "green" and "prosperous" city (and hence a better UEQ environment) rather than a "crowded" city (and thus a poor UEQ environment). This then helps making essential progress towards achieving greater urban sustainability that emphasizes the long-term integration of environmental protection, economic development, and social health. Many studies have suggested a more sustainable city is featured by green space [47], economic growth [48], and continuity of open spaces [49], which correspond well with the key factors in determining a city's UEQ condition according to the current study. Evidently, cities with favorable UEQ environment hold the possibility of delivering a more sustainable future. Besides, the methodology developed in the research can be easily adopted to conduct cross-case and cross-time comparisons at a meaningful level. This leads to a better understanding of the relationship between UEQ and urban physical and socioeconomic condition at a larger scale. It hence lays the groundwork for expediting the realization of the long-term and holistic decision-making process of urban sustainability.

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## REFERENCES


[1] S. H. Bederman and T. A. Hartshorn, "Quality of life in Georgia: The 1980 experience," *Southeastern Geographer*, vol. 24, pp. 78–98, 1984.

[2] M. Bonaiuto, F. Fornara, and M. Bonnes, "Indexes of perceived residential environment quality and neighbourhood attachment in urban environments: A confirmation study on the city of Rome," *Landscape and Urban Planning*, vol. 65, pp. 41–52, 2003.

[3] T. Fung and W. Siu, "Environmental quality and its changes, an analysis using NDVI," *Int. J. Remote Sens.*, vol. 21, pp. 1011–1024, 2000.

[4] T. Fung and W. Siu, "A study of green space and its changes in Hong Kong using NDVI," *Geographical and Environmental Modelling*, vol. 5, pp. 111–122, 2001.

[5] N. E. Green, "Aerial photographic interpretation and the social structure of the city," *Photogrammetric Engineering*, vol. 23, pp. 89–96, 1957.

[6] N. Heynen, "Green urban political ecologies: Toward a better understanding of inner-city environmental change," *Environment and Planning A*, vol. 38, pp. 499–516, 2006.

[7] G. Li and Q. Weng, "Measuring the quality of life in city of Indianapolis by integration of remote sensing and census data," *Int. J. Remote Sens.*, vol. 28, pp. 249–267, 2007.

[8] G. Li and Q. Weng, "Integration of remote sensing and census data for assessing urban quality of life: Model development and validation," in *Urban Remote Sensing*, Q. Weng and D. A. Quattrochi, Eds. Boca Raton, FL: Taylor and Francis Group, LLC, CRC Press, 2007, pp. 311–336.

[9] C. P. Lo, "Application of Landsat TM data for quality of life assessment in an urban environment," *Computer, Environment, and Urban Systems*, vol. 21, pp. 259–276, 1997.

[10] C. P. Lo and B. J. Faber, "Integration of Landsat Thematic Mapper and census data for quality of life assessment," *Remote Sens. Environ.*, vol. 62, pp. 143–157, 1997.

[11] E. D. Metivier and R. M. McCoy, "Mapping urban poverty housing from aerial photographs," in *Proc. 7th Int. Symp. Remote Sens. Environ*, 1971, pp. 1563–1569.

[12] N. Munier, "Economic growth and sustainable development: Could multicriteria analysis be used to solve this dichotomy?," *Environment, Development and Sustainability*, vol. 8, pp. 425–443, 2006.

[13] J. E. Nichol and M. S. Wong, "Modeling urban environmental quality in a tropical city," *Landscape and Urban Planning*, vol. 73, pp. 49–58, 2005.

[14] J. E. Nichol and M. S. Wong, "Assessment of urban environmental quality in a subtropical city using multispectral satellite images," *Environment and Planning B Planning and Design*, vol. 33, pp. 39–58, 2006.

[15] J. E. Nichol and M. S. Wong, "Assessing urban environmental quality with multiple parameters," in *Urban Remote Sensing*, Q. Weng and D. A. Quattrochi, Eds. Boca Raton, FL: Taylor and Francis Group, LLC, CRC Press, 2007, pp. 311–336.

[16] M. Pacione, "Urban environmental quality and human wellbeing—A social geographical perspective," *Landscape and Urban Planning*, vol. 65, pp. 19–30, 2003.

[17] J. S. Wilson, M. Clay, E. Martin, D. Stuckey, and K. Vedder-Risch, "Evaluating environmental influences of zoning in urban ecosystems with remote sensing," *Remote Sens. Environ.*, vol. 86, pp. 303–321, 2003.

[18] K. Abolina and A. Zilans, "Evaluation of urban sustainability in specific sectors in Latvia," *Environment, Development and Sustainability*, vol. 4, pp. 299–314, 2002.

[19] D. M. Smith, *The Geography of Social Well-Being in the United States*. New York: McGraw-Hill, 1973.

[20] M. Wackernagel and J. D. Yount, "Footprints for sustainability: The next steps," *Environment, Development and Sustainability*, vol. 2, pp. 21–42, 2000.

[21] M. Keiner, "Re-emphasizing sustainable development—The concept of 'evolutionability'," *Environment, Development and Sustainability*, vol. 6, pp. 379–392, 2004.

[22] C. Weber and J. Hirsch, "Some urban measurements from SPOT data: Urban life quality indices," *Int. J. Remote Sens.*, vol. 13, pp. 3251–3261, 1992.

[23] H. Akbari, A. H. Rosenfeld, and H. Taha, "Summer heat islands, urban trees and white surfaces," *ASHRAE Trans.*, vol. 96, pp. 1381–1388, 1990.

[24] H. Akbari, L. S. Rose, and T. Haider, "Analyzing the land cover of an urban environment using high resolution orthophotos," *Landscape and Urban Planning*, vol. 63, pp. 1–14, 2003.

[25] E. G. McPherson, "Cooling urban heat islands with sustainable landscapes," in *The Ecological City: Reserving and Restoring Urban Biodiversity*, R. H. Platt, R. A. Rowntree, and P. C. Muick, Eds. Amherst, MA: The University of Massachusetts Press, 1994, pp. 151–171.

[26] S. Vries, R. A. Verheiy, P. P. Groenewegen, and P. S. Spreeuwenberg, "Natural environments—Healthy environments? An exploratory analysis of relationship between green space and Health," *Environment and Planning A*, vol. 35, pp. 1717–1731, 2003.

[27] Q. Weng, D. Lu, and J. Schubring, "Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies," *Remote Sens. Environ.*, vol. 89, pp. 467–483, 2004.

[28] Q. Weng and S. Yang, "Managing the adverse thermal effects of urban development in a densely populated Chinese city," *J. Environ. Management*, vol. 70, pp. 145–156, 2004.

[29] Q. Weng, H. Liu, B. Liang, and D. Lu, "The spatial variations of urban land surface temperatures: Pertinent factors, zoning effect, and seasonal variability," *IEEE J. Selected Topics in Applied Earth Observations and Remote Sens.*, vol. 1, pp. 154–166, 2008.

[30] U. Rajasekar and Q. Weng, "Spatio-temporal modeling and analysis of urban heat islands by using Landsat TM and ETM+ imagery," *Int. J. Remote Sens.*, vol. 30, pp. 3531–3548, 2009.

[31] B. Liang and Q. Weng, "Multiscale analysis of census-based land surface temperature variations and determinants in Indianapolis, United States," *J. Urban Planning and Development*, vol. 134, pp. 129–139, 2008.

[32] M. Ji and J. R. Jensen, "Effectiveness of subpixel analysis in detecting and quantifying urban imperviousness from Landsat Thematic Mapper imagery," *Geocarto International*, vol. 14, pp. 33–41, 1999.

[33] C. L. Arnold and C. J. Gibbons, "Impervious surface coverage: The emergence of a key environmental indicator," *J. Amer. Planning Assoc.*, vol. 62, pp. 243–258, 1996.

[34] D. Lu, Q. Weng, and G. Li, "Residential population estimation using a remote sensing derived impervious surface approach," *Int. J. Remote Sens.*, vol. 27, pp. 3553–3570, 2006.

[35] C. Wu and A. T. Murray, "Estimating impervious surface distribution by spectral mixture analysis," *Remote Sens. Environ.*, vol. 84, pp. 493–515, 2003.

[36] S. Nunn, "Role of local infrastructure policies and economic development incentives in metropolitan interjurisdictional cooperation," *J. Urban Planning and Development*, vol. 121, pp. 41–56, 1995.

[37] E. Talen, "Land use and human diversity: Exploring the connection," *J. Urban Planning and Development*, vol. 131, pp. 214–232, 2005.

[38] X. L. Chen, H. M. Zhao, P. X. Li, and Z. Y. Yin, "Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes," *Remote Sens. Environ.*, vol. 104, pp. 133–146, 2006.

[39] B. L. Markham and J. L. Barker, "Landsat MSS and TM Post-Calibration Dynamic Ranges, Exoatmospheric Reflectances and At-Satellite Temperatures," EOSAT Technical Notes, Aug. 1986.

[40] G. Chander and B. Markham, "Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges," *IEEE Trans. Geosci. Remote Sens.*, vol. 41, pp. 2674–2677, 2003.

[41] United States Census Bureau. [Online]. Available: http://www.census.gov/

[42] J. R. Jensen, *Remote Sensing of the Environment: An Earth Resource Perspective*. New York: Pearson Education, 2000.

[43] A. L. Comrey and H. B. Lee, *A First Course in Factor Analysis*, 2nd ed. Hillsdale, New JerseyNJ: Erlbuum, 1992.

[44] R. S. Lunetta, R. G. Congalton, L. K. Fenstermaker, J. R. Jensen, and L. R. Tinney, "Remote sensing and geographic information system data integration: Errors sources and research issues," *Photogrammetric Engineering and Remote Sensing*, vol. 57, pp. 677–687, 1991.

[45] S. Openshaw, *The Modifiable Areal Unit Problem*, ser. CATMOG Series, 38. London, UK: Inst. British Geographers, 1983.

[46] A. S. Fotheringham and D. W. S. Wong, "The modifiable areal unit problem in multivariate statistical analysis," *Environment and Planning A*, vol. 23, pp. 1025–1044, 1991.

[47] K. N. Irvine, P. Devine-Wright, S. R. Payne, R. A. Fuller, B. Painter, and K. J. Gaston, "Green space, soundscape and urban sustainability: An interdisciplinary, empirical study," *Local Environ.*, vol. 14, pp. 155–172, 2009.

[48] C. Landorf, G. Brewer, and L. A. Sheppard, "The urban environment and sustainable ageing: Critical issues and assessment indicators," *Local Environ.*, vol. 13, pp. 497–514, 2008.

[49] A. Ozdemir, "Urban sustainability and open space networks," *J. Applied Sciences*, vol. 7, pp. 3713–3720, 2007.

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