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Urban Quality of Life Assessment Using Satellite Image and Socioeconomic Data in GIS

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Abstract : This paper evaluates and maps the quality of life in the Atlanta, Georgia metropolitan area in 2000. Three environmental variables from Landsat TM data, four socioeconomic variables from census data, and a hazard-related variable from toxic release inventory (TRI) database were integrated into a geographic information system (GIS) environment for the quality of life assessment. To solve the incompatibility problem in areal units among different data, the four socioeconomic variables aggregated by zonal units were spatially disaggregated into individual pixels. Principal components analysis (PCA) was employed to integrate and transform environmental, socioeconomic, and hazard-related variables into a resultant quality of life score for each pixel. Results indicate that the highest quality of life score was found around Sandy Springs, Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400 whereas the lowest quality of life score was clustered around Smyrna of Cobb County, the inner city of Atlanta, and Hartsfield-Jackson International Airport. The results also reveals that normalized difference vegetation index (NDVI) and relative risk from TRI facilities are two versatile indicators of environmental and socioeconomic quality of an urban area in the United States.

Key Words : Satellite Image, Socioeconomic Data, GIS, Urban Quality of Life.

1. Introduction

The quality of life of a population is an important concern in social sciences. However, there is no single definition on quality of life and no broadly accepted method to measure it. What is clear from the literature is that some consensual objective indicators including income, housing, and education were widely used to measure quality of life (Wallace, 1971; Smith, 1973; Liu, 1976) and the majority of previous quality of life evaluation studies utilized only socioeconomic indicators from census data as exemplified by the works of Liu (1976) and Bederman and Hartshorn (1984).

In recent years, the integrated use of remotely sensed data and socioeconomic data in geographic information system (GIS) for urban studies has increasingly been made (Martin and Bracken, 1993; Mesev, 2003). One of the major urban applications has focused on quality of life assessment. A handful of previous studies have attempted to assess quality of life indicators in urban areas by integrating

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biophysical variables derived from satellite images and socioeconomic variables extracted from census data. Forster (1983) developed a residential quality index in the city of Sydney, Australia, using spectral reflectance data derived from Landsat MSS images. He employed house size and vegetation content as a positive indicator of quality and roads and nonresidential buildings as a negative indicator. Weber and Hirsch (1992) measured the urban life quality of Strasbourg, France, by combining the high-resolution SPOT XS image data with cartographic and census data. Most recently, Lo and Faber (1997) demonstrated the usefulness of Landsat TM image in conjunction with census data for quality of life assessment in a small city in Georgia with emphasis on normalized difference vegetation index (NDVI) as a desirable quality indicator of urban morphological environment. They argued that satellite image data could complement census data in providing an environmental perspective for the quality of life assessment. Previous studies within the remote sensing research community indicate that urban quality was measured with the use of scales or indices which coupled the socioeconomic with environmental data for a complete evaluation. These studies also show that such an integration provides a more detailed characterization of urban landscape than an approach based solely on socioeconomic data. Despite the benefits from previous studies, the applicability of environmental data as indicators of urban quality of life needs to be tested in a larger city in the United States.

In the past two decades, environmental justice studies in the United States have concerned the link between the spatial distribution of environmental risks and the socioeconomic characteristics of surrounding populations (Liu, 2001). The environmental justice studies have provided a meaningful insight into the use of potential risk from toxic release facilities as a negative indicator in quality of life assessment. The inclusion of industrial hazard-related data in the quality of life assessment has not been attempted in the research community.

In this context, this study aims to evaluate and map the quality of life in the Atlanta, Georgia metropolitan area in 2000 by integrating environmental data from satellite imagery and hazard-related data with socioeconomic data in GIS. After a brief introduction, the methodology is presented and followed by the results with a discussion of them. The last section contains concluding remarks and summary.

2. Data and Methods

1) Study Area and Data

The Atlanta, Georgia metropolitan area serves as a case study area for this research, which comprises the ten-county planning area of the Atlanta Regional Commission (ARC) as is shown in Fig. 1. The city of Atlanta sits in the central part of the greater

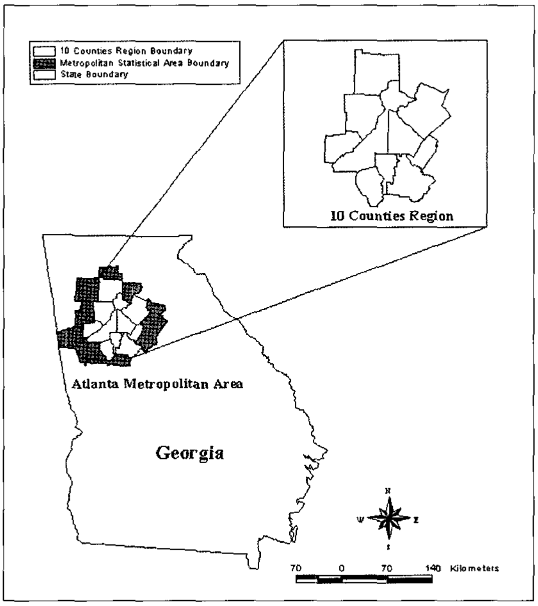


Fig. 1. Location of study area.

metropolitan area. The Atlanta metropolitan area is often known as the major trade, service, and transportation center for the southeastern United States. For the past 30 years, Atlanta has been one of the fastest growing metropolitan areas in the nation. The metropolitan area as a major manufacturing center in the South has also experienced the severe degeneration of urban climate and air quality, particularly with regard to urban warming and the increases in ozone and emission of volatile organic compounds. This study area was selected because of its urban heat island effect detected, degenerated air quality, water quality issues related to urban development downstream of the upper Chattahoochee River, and high levels of urban inequality based on racial segregation.

The quality of life was evaluated on the basis of demographic, economic, educational, housing, environmental, and hazard-related factors. Three environmental variables including land use and land cover, NDVI, and surface temperatures were derived from 2000 Landsat 5 TM imagery over the Atlanta metropolitan area while four socioeconomic variables including population density, per capita income, percent college graduates, and median home value were extracted from 2000 Census. A hazard-related variable, cumulative potential relative exposure to toxic release facilities, was generated from 2000 toxic release inventory (TRI) database. The environmental data were included in the quality of life assessment to provide an environmental perspective as suggested by Lo and Faber (1997). Most of the socioeconomic data were selected on the basis of the commonly agreed set of variables used by social scientists to objectively measure the degree of crowding in an area, the income level, the education level, and the housing condition of the population living in it. A hazard-related variable was adopted in this research since this is an obvious factor of environmental disamenity in urban areas.

2) Extracting Environmental Variables from Satellite Imagery

In Fig. 2, illustrated is an overview of the research methodology implemented for this study. From the Landsat TM image, a land use and land cover map was extracted using a modified version of the Anderson scheme of land use and land cover classification with mixed levels 1 and 2. A hybrid digital image classification was implemented for the information extraction with ERDAS Imagine. From this land use and land cover map, the residential, commercial and industrial (urban use), grassland/pasture/cropland, and forest classes were extracted and water and barren classes were excluded using the reclassification method. The commercial and industrial class called urban use is a negative factor of environmental quality. The overall accuracy of the land use and land cover map was determined to be 87.5 percent. The classification accuracy meets the minimum 85 percent accuracy requirement.

From bands 3 and 4 of the Landsat TM data, NDVI was computed for each pixel. The NDVI as a greenness measure is universally perceived to be a highly desirable quality of the morphological environment. For Landsat TM data, the NDVI is computed from TM band 4 (0.76 - 0.90μm) and TM

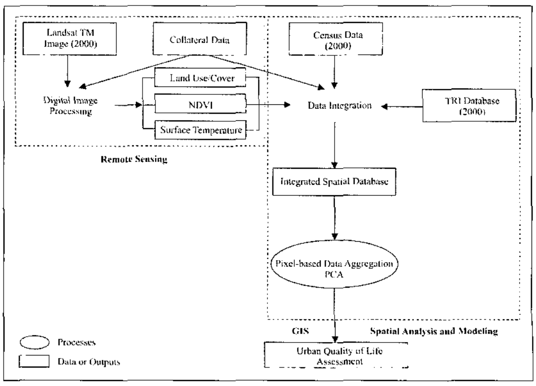


Fig. 2. Research methodology.

band 3 (0.63μm - 0.69μm), using the following formula:

$$\mathrm{NDVI} = \frac{TM_4 - TM_3}{TM_4 + TM_3}$$

where TM_3 is band 3 of Landsat TM image, and TM_4 is band 4 of the image. The value varies from -1 to +1 as greenness increases. This ratio was quantified by using the ERDAS Imagine.

From band 6 of the Landsat TM data, the thermal infrared band, surface temperature was also computed for each pixel. It is an important physical variable in the sense that it can affect human comfort. Surface temperatures in a city are affected by the land use and land cover types and are an important measurement to consider for the urban heat island phenomenon (Lo *et al.*, 1997). Extraction of surface temperatures from the Landsat 5 TM band 6 data required conversion of the spectral radiances (L) into at-satellite temperatures T(K) using the following equation suggested by Wukelic *et al.* (1989):

$$T(K) = \frac{K2}{\ln(\frac{K1}{L}+1)}$$

where $T(K)$ is at-satellite temperature in Kelvin, $K2$ is calibration constant 2 (=1260.56) in Kelvin, $K1$ is calibration constant 1 (=607.76) in w.m^{-2}.ster^{-1}.mm^{-1}, and L is spectral radiance in w.m^{-2}.ster^{-1}.mm^{-1}. This formula was implemented with the help of the Spatial Modeler functionality in the ERDAS Imagine. The correction for emissivity (ε) was also conducted according to the nature of land cover. In general, vegetated areas are given a value of 0.95 and non-vegetated areas 0.92 as suggested by Nichol (1994). This differentiation is based on the NDVI image calculated as described above. The emissivity corrected surface temperature (T_s) is computed as follows (Nichol, 1994):

$$\mathrm{Ts} = \frac{T(K)}{1 + (\lambda T(K)/\alpha) \ln \varepsilon}$$

where λ is the wavelength of emitted radiance (= 11.5 μm), a is hc/K (1.438 * 10^{-2} mK), K is Stefan-Bolzmann's Constant (1.38 * 10^{-23} J/K), h is Planck's constant (6.26 * 10^{-34} J-sec), c is velocity of light (2.998 * 10^{8} m/sec), and ε is surface emissivity. These absolute temperatures were then converted into Celsius (C) by subtracting from them the temperature of the ice point (273.15 K).

3) Extracting Socioeconomic and Hazard-related Variables

From the census data, the following variables were extracted at the census block group level: population density, per capita income, median home value, and percent of college graduates. The block group represents the smallest enumeration unit for which socioeconomic information is available. The boundary file for census block group level was extracted from 2000 Census TIGER/Line file.

The TRI database is a national database of industrial facilities that release toxic and hazardous chemicals, and contains a complete inventory of toxic release sites in all major U.S. cities. This database serves as one of the more reliable approximations of chronic toxic release currently available. From the TRI database, the industrial facilities released airborne emissions were extracted to relax the analytical complexity and then a risk surface was generated using the following equation proposed by Cutter *et al.* (2001):

$$CPE_i = \sum_{j=1}^{n} (1.0 - \frac{d_{ij}^{\,p}}{T_j^{\,p}})$$

where CPE_i is cumulative proximal exposure to population in census unit i from distance to facility j at locations 1 through n (total number of facilities), d_{ij} is distance from population i to facility j, T_j is distance at which exposure is negligible for facility j, and p is rate of reduction of exposure at increasing distance from j. The CPE was then weighted by the relative potential risk score (RPRS) for each TRI facility in order to utilize the magnitude and the relative toxicity of release from TRI facilities.

4) Data Integration by Pixel-based Disaggregation

Three environmental variables such as land use and land cover, NDVI, and surface temperature, and the hazard-related variable, the risk surface, are per-pixel data while four socioeconomic variables such as population density, per capita income, median home value, and education level are zonal data. Previous studies (Weber and Hirsch, 1992; Lo and Faber, 1997) aggregated pixel-based data to zonal units to tackle the incompatibility problem in areal units among different data. However, this zone-based approach can not reveal subunit variation in zonal units. This approach also has analytical pitfalls such as the modifiable areal unit problem (MAUP) and the incompatibility problem with environmental data. In this research, a pixel-based approach was alternatively used to spatially disaggregate four socioeconomic variables within census block groups into individual pixels.

Two demographic variables, population density and percent of college graduates, were transformed for each pixel using a spatial microsimulation model. To spatially disaggregate population data from census block groups into individual pixels by the principle of three-class dasymetric mapping, the following equation proposed by Mennis (2003) was implemented in ArcView:

$$P_{ubc} = \frac{F_{ubc} * P_b}{N_{ub}}$$

where P_{ubc} is population assigned to one grid cell of land use/land cover class u in block group b and in county c, F_{ubc} is total fraction for land use/land cover class u in block group b and in county c, P_b is population of block group b, and N_{ub} is the number of grid cells of land use/land cover class u in block group b. The total fraction (F_{ubc}) is calculated as follows:

$$F_{ubc} = \frac{D_{uc} * A_{ub}}{[(D_{hc} * A_{hb}) + (D_{lc} * A_{lb}) + (D_{nc} * A_{nb})]}$$

where F_{ubc} is total fraction of land use/land cover class u in block group b and in county c, D_{uc} is population density fraction of land use/land cover class u in county c, A_{ub} is area ratio of land use/land cover class u in block group b, D_{hc} is population density fraction of land use/land cover class h in county c, D_{lc} is population density fraction of land use/land cover class l in county c, D_{nc} is population density fraction of land use/land cover class n in county c, A_{hb} is areal ratio of land use/land cover class h in block group b, A_{lb} is area ratio of land use/land cover class l in block group b, and A_{nb} is area ratio of land use/land cover class n in block group b. The three classes of land use and land cover used in the dasymetric mapping process include the residential, commercial and industrial, and other (grassland/pasture/cropland and forest) classes.

Two economic variables, per capita income and median home value, were interpolated for each pixel using a geostatistical modeling method known as inverse distance weighting (IDW). Unlike spatially extensive data such as population, these variables are spatially intensive data which are expected to have the same value in each part of a zone (Goodchild and Lam, 1980).

5) Development of Quality of Life Scores

Principal components analysis (PCA) was used to integrate and transform the eight variables into a resultant quality of life score for each pixel. The PCA has proved to be valuable in the analysis of multispectral remotely sensed data (Jensen, 1996) by serving as a data transformation technique. It can convert a large number of correlated data into a smaller number of uncorrelated components whose axes in attribute space are rotated with respect to the original attribute space. Before the analysis, each variable was standardized through a linear scale transformation method based on the minimum and maximum values as expressed in the following equation:

$$y_i = \frac{(x_i - X_{min})}{(X_{max} - X_{min})}$$

where y_i is the standardized score, x_i is the raw value, X_{max} is the maximum value, and X_{min} is the minimum value. The value of standardized scores ranges from 0 to 1. Then, all eight variables described above were stacked up and an image of eight layers was generated in the ERDAS Imagine. Finally, the PCA analogous to the analysis of multispectral remotely sensed data was applied to the eight layers of image data using the ERDAS Imagine.

The extent of spatial clustering among pixels with respect to quality of life scores was measured by Moran's I as a spatial autocorrelation index. The Moran's I ranges from -1 to +1 as the similarity of adjacent cells increases. The significance of the normality assumption and the randomization assumption was also tested. The form of Moran's I is formally given as follows:

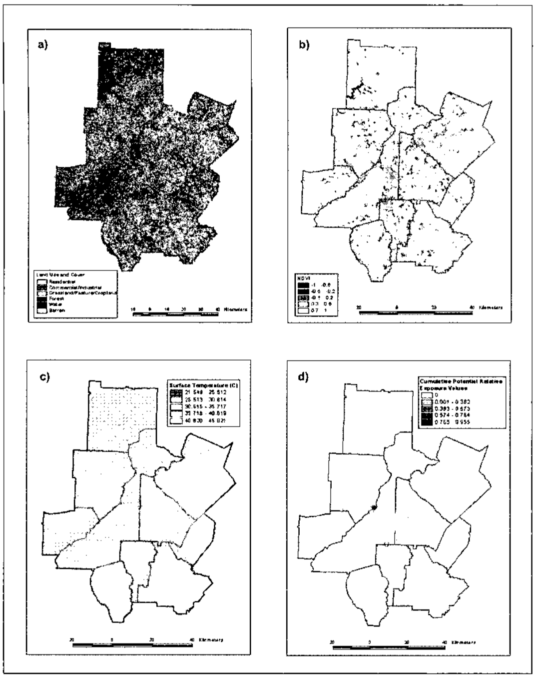
$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (z_i - z_m)(z_j - z_m)}{\sum_i w_{ij} (z_i - z_m)^2}$$

where n is the total number of cells in an image, z_i is the value of the attribute of cell i, i = 1 to n, z_j is the value of the attribute of cell j, j = 1 to n, z_m is the mean cell value for the image, and w_{ij} is the similarity of i's location and j's location, w_{ij} = 1 if cells i and j are directly adjacent (4-adjacent) and 0 otherwise.

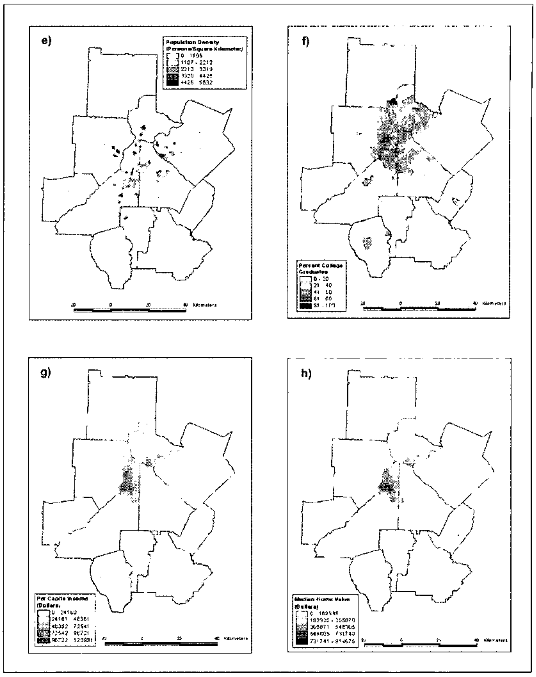
3. Results and Discussion

This research employed eight factors as being relevant to determinant of the quality of life in the Atlanta metropolitan area in 2000. The eight factors are illustrated in Figs. 3 and 4. For the quality of life assessment, the eight factors are divided into two major groups such as positive factor and negative factor. The negative factor with the higher values being less desirable to the quality of life includes urban use, surface temperature, population density, and cumulative potential relative exposure to TRI facilities. Unlike other negative factors, the value of the urban use variable was assigned to one of 10 rank scores, with 2 being the commercial and industrial class and 10 being the residential class before standardization in order to reflect the undesirability to the quality of life. The positive factor with the higher values being more desirable to the quality of life contains NDVI, percentage of college graduates, per capita income, and median home value.

As reported in Table 1, the cross correlation among the eight variables indicates that NDVI is negatively correlated with urban use (r = -0.8899), surface temperature (r = -0.9762), population density (r = -0.9682), and relative risk from TRI facilities(r = -0.9724). This implies that NDVI is a versatile environmental quality variable. However, it is clear that NDVI is positively correlated with per capita income (r = 0.8480), median home value (r = 0.7542), and percentage of college graduates (r = 0.4729). The implication is that NDVI also appears to be a good indicator of socioeconomic characteristics of an urban area. These results are consistent with those found in the previous study by Lo and Faber (1997). It is also worthy to note that relative risk from TRI facilities is negatively correlated with NDVI (r = -0.9724), percentage of college graduates (r = -0.5040), per capita income (r = -0.8655), and median home value (r = -0.7731), but positively correlated with urban use (r = 0.8774), surface temperature (r = 0.9509), and population density (r = 0.9856). This suggests that relative risk from TRI facilities is also another versatile indicator of environmental and socioeconomic quality of an urban area. In other words, this gives a new insight into



Figs. 3. Environmental and hazard-related variables.
a) land use and land cover, b) NDVI, c) surface temperature, and d) cumulative potential relative exposure values to TRI facilities.



Figs. 4. Socioeconomic variables.
e) population density, f) percent college graduates, g) per capita income, and h) median home value.

Table 1. Correlation matrix of variables.

	LULC	NDVI	TEMP	POPD	EDU	PINCO	HOME	RISK
LULC	1							
NDVI	-0.8899	1						
TEMP	0.8694	-0.9762	1					
POPD	0.8515	-0.9682	0.9549	1				
EDU	-0.5123	0.4729	-0.4436	-0.4510	1			
PINCO	-0.7789	0.8480	-0.8350	-0.8517	0.6822	1		
HOME	-0.6976	0.7542	-0.7436	-0.7517	0.7057	0.9183	1	
RISK	0.8774	-0.9724	0.9509	0.9856	-0.5040	-0.8655	-0.7731	1

LULC-Urban use; NDVI-NDVI; TEMP-Surface temperatures; POPD-Population density;
EDU-Percent college graduates; PINCO-Per capita income; HOME-Median home value;
RISK-Cumulative potential relative exposure.

urban environmental justice analysis.

The main reasons to transform the data in PCA are to compress data by eliminating redundancy, to emphasize the variance within the original data, and to make the data more interpretable. Generally, the first two or three components explain a high proportion of the variance in the original data whereas the remaining components describe progressively less of the variance and can be dropped. As shown in Table 2, the PCA identified two principal components which describe over 95 percent of total variance of the original data. The first principal component explained

Table 2. Principal component loadings.

Variables	Component Loadings		Communality
	PC1	PC2	
LULC	-0.9147	0.3846	0.98
NDVI	0.9879	-0.0316	0.98
TEMP	-0.9730	0.0534	0.95
POPD	-0.9851	0.1375	0.99
EDU	0.5072	-0.3658	0.39
PINCO	0.8738	-0.0551	0.77
HOME	0.7801	-0.0945	0.62
RISK	-0.9911	0.0684	0.99
Eigen Value	0.8416	0.0299	
Variance (%)	92.6	3.30	

LULC-Urban use; NDVI-NDVI; TEMP-Surface temperatures; POPD-Population density; EDU-Percent college graduates; PINCO-Per capita income; HOME-Median home value; RISK-Cumulative potential relative exposure; PC1-Principal component 1; PC2-Principal component 2.

93 percent of total variance of the original variables while the second principal component accounted for only 3 percent. The first principal component showed strong positive loadings on four variables such as NDVI, per capita income, median home value, and percentage of college graduates whereas very strong negative loadings on four variables such as urban use, surface temperature, population density, and relative risk. The second principal component exhibited very weak positive loading on urban use, surface temperature, population density, and relative risk. On the other hand, the second component represented very weak negative loadings on NDVI, percentage of college graduates, per capita income, and median home value. In Table 2, the communality for each variable revealed that the two principal components together accounted for the following: an extremely high proportion of the variance of urban use, NDVI, surface temperature, population density, and relative risk; a moderately high proportion of the variance of per capita income and median home value; and a low

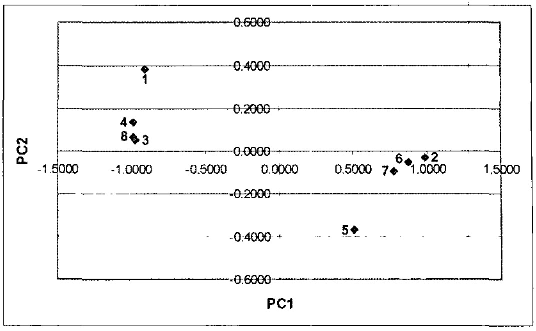


Fig. 5. A scatter plot of principal components 1 and 2.

1-Urban use; 2-NDVI; 3-Surface temperatures; 4-Population density; 5-Percent college graduates; 6-Per capita income; 7-Median home value; 8- Cumulative potential relative exposure; PC1-Principal component 1; PC2-Principal component 2.

proportion of the variance of percentage of college graduates. In other words, the two principal components reflected very strongly the environmental and hazard-related characteristics and strongly the socioeconomic characteristics of the Atlanta metropolitan area.

Fig. 5 illustrates the relative positions of the eight variables plotted in a graph according to their component loadings in component 1 (X axis) and component 2 (Y axis). The resulting component pattern indicates two dichotomous relationships between the cluster of environmental variables and the cluster of socioeconomic variables, and between the cluster of desirable indicators and the cluster of undesirable indicators. The cluster of the socioeconomic or desirable variables includes NDVI, per capita income, median home value, and percentage of college graduates whereas the cluster of the environmental or undesirable variables consists of urban use, surface temperature, population density, and relative risk. It is interesting to note that NDVI is much closer to the socioeconomic cluster than the environmental one. In contrast, population density is much closer to the environmental cluster than the socioeconomic one.

Because the first principal component explained 93 percent (above the 90% cut-off level) of the total variance of the eight variables and reflected very strongly both environmental and socioeconomic variables, this first component was used to create a quality of life score map. Fig. 6 shows the quality of life score map based on the first principal component scores. The resultant quality of life score ranges from 0.01 to 2.46. A higher level of quality of life is associated with a higher principal component score. The map exhibits higher quality of life areas around Sandy Springs, Roswell, Alphretta, the northern parts of Fulton County along Georgia 400, the southwestern and northeastern parts of Fayetteville, the southern parts of Conyers, and the northwestern parts of East Point. On the map, lower quality of life areas are clustered around Smyrna, the inner city of Atlanta, and Hartsfield-Jackson International Airport. A sectoral pattern of spatial variation in quality of life was also detected along major roads. This suggests that it is necessary to control transportation, urban land use, vegetation cover, and location of industrial facilities for sustainable urban development in the Atlanta metropolitan area. The extent of spatial clustering among pixels with respect to quality of life scores was quantified by Moran's I. The result showed that the spatial autocorrelation coefficient was 0.99 for only pixels covering metropolitan Atlanta. This indicates that the quality of life scores are strongly spatially polarized in the Atlanta metropolitan area.

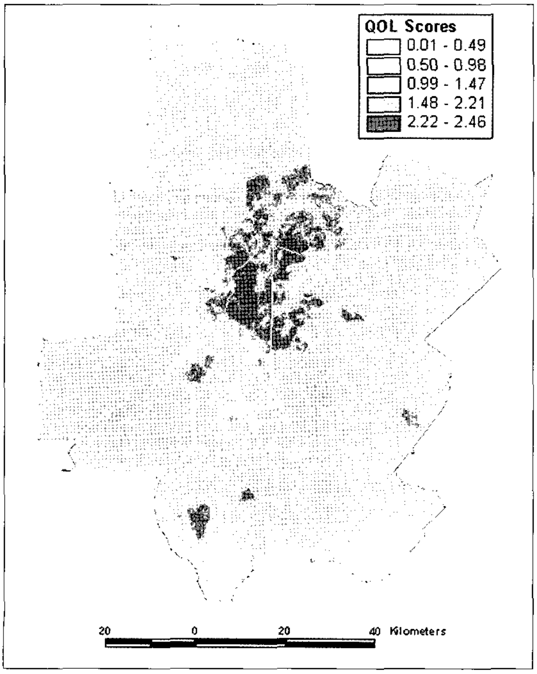


Fig. 6. Urban quality of life scores.

The findings from this research provide technical, theoretical, and policy implications. First, this research demonstrated the potential of the integrated use of remotely sensed data and socioeconomic data in GIS for urban quality of life assessment. Particularly, this study has demonstrated how biophysical measurements can be reliably extracted from satellite imagery, and how these spatially extensive measurements can then be analyzed with socioeconomic data in GIS for quality of life assessment. In the integrated approach, GIS was used to integrate, analyze, and visualize hazard-related, socioeconomic, and environmental data, and to assist in satellite image processing. This integrated approach facilitated developing new database and thus performing a new form of analysis in urban quality of life assessment.

Second, this research employed relative risk from TRI facilities as a hazard-related variable in the quality of life assessment. Results indicate that this hazard-related variable is a new versatile indicator of environmental and socioeconomic quality of an urban area in the United States. Therefore, this study provides the possibility to frame the quality of life assessment within the environmental justice context.

Third, this study may provide a benchmark for detailed analysis of quality of life. The findings from this research can be used by urban planners and decision makers to find out any problem areas in the allocation of human services in the Atlanta metropolitan area. This may help make a contribution towards building sustainable communities in the problem areas.

4. Conclusions

Until now, this research assessed and mapped the quality of life in the Atlanta metropolitan area in 2000. For the quality of life assessment, this study integrated three environmental factors including land use and land cover, NDVI, and surface temperatures from the Landsat TM image and four socioeconomic factors such as population density, per capita income, percent college graduates, and median home value from the census data with a hazard-related factor from the TRI database. The environmental factors and a hazard-related factor as an obvious indicator of environmental disamenity were adopted in the quality of life assessment to provide an environmental perspective and to reflect the context of urban environmental justice. Unlike most previous studies using the zone-based approach, this study employed the pixel-based approach to solve the incompatibility problem in areal units among environmental, hazard-related, and socioeconomic data. The four socioeconomic variables aggregated by census block groups were spatially disaggregated into individual pixels using the methodological framework developed in this research. The pixel-based approach allowed for revealing the sub-unit variation in zonal units.

The PCA-based approach analogous to the analysis of multispectral remotely sensed data was used to integrate and transform environmental, hazard-related, and socioeconomic variables into a resultant quality of life score for each pixel. The PCA of the eight variables confirmed that NDVI was a versatile indicator of environmental and socioeconomic quality of an urban area in the United States. The PCA also revealed that relative risk from TRI facilities was a new versatile indicator of environmental and socioeconomic quality in the Atlanta metropolitan area. This sheds light on urban environmental justice studies in the United States. The findings from this study showed that the highest quality of life score was found around Sandy Springs, Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400 whereas the lowest quality of life score was clustered around Smyrna of Cobb County, the inner city of Atlanta, and Hartsfield-Jackson International Airport.

This research unlocked the spatial pattern of the quality of life in the Atlanta metropolitan area. The conceptual and technical frameworks developed in the present study may be applicable to other metropolitan areas in order to improve our understanding of the spatial pattern of quality of life and to examine the role of environmental risks in the spatial patterning.

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