A Four-Component Efficiency Index for Assessing Land Development Using Remote Sensing and GIS

Xia Li

Abstract

A variety of indices have been proposed to facilitate the quantitative analysis in remote sensing applications. The assessment of land development is important for minimizing development impacts and formulating alternative development plans. Much attention has been paid to the quantity of land use changes in general development assessment using remote sensing. However, additional information can be obtained from remote sensing and GIS for revealing land use problems more effectively. This paper presents four indicators, quantity, quality, location, and morphology to characterize land development patterns for fast-growing regions. A four-component efficiency index is further developed for ranking purposes to reflect economic and environmental considerations. The implementation of the method has been demonstrated in a fast-growing region in south China. Efforts have been made to verify the model with independent empirical data.

Introduction

The development of indices is important for many quantitative analyses in remote sensing applications. Various indices have been proposed to enhance the capability of measurement by using remote sensing. For example, the normalized difference vegetation index (NDVI) has been widely applied to the measurement of vegetation biomass (Tucker, 1979). The logarithm index has also been commonly used in estimating the content of suspended sediments in water (Li, 1993). These indices help to extract more accurate and consistent information about natural phenomena and understand the mechanisms by using remote sensing data.

The quantity of land use changes is a common indicator for identifying land use problems. There are many studies devoted to the detection of land use changes from remote sensing (Howarth, 1986; Martin, 1989; Fung and LeDrew, 1987; Carlson and Sanchez-Azofeifa, 1999; Su, 2000; Jusoff and Senthavy, 2003). However, this single indicator cannot reflect all aspects of land development impacts. Other important issues should be considered in the assessment of land development e.g., the quantity of good-quality agricultural land converted into urban land, the distance of developed sites from urban centres, and the pattern of land development. Additional indicators can be developed from remote sensing and GIS for addressing these broader issues. These indicators can provide more information about economic and environmental implications of land development than the single quantity indicator.

Indicators may have problems because of uncertainties in assigning weights and choosing model structures. However, indicators are still important in many fields because they can provide useful information for modeling process. Many indicators have been developed to satisfy different purposes. The development of indicators is application-specific (e.g., the vegetation index NDVI in remote sensing). They provide a means to understand complex geographical phenomena in an easier way.

The objective of the research is to derive a four-component efficiency index to characterize land development patterns for fast-growing areas using remote sensing and GIS. In most situations, the indicator linked to the amount of land consumption has been widely used to provide useful information for development control. However, additional information can be extracted from remote sensing and GIS to reflect broader environmental issues. An integrated approach is required to deal with these factors in a more systematic way which can provide valuable information for policy makers to understand the current situations of land development.

This study is significantly different from the previous study (Yeh and Li, 2001) which uses just the entropy method to measure the spatial patterns of urban development. In this study, an integrated approach will be presented for the assessment of land development using these four components: quantity, quality, location, and morphology which are obtained from remote sensing and GIS. An integrated index will be further formulated from these four components based on the principle of efficiency. It can help to rank cities and towns according to their performance in land development. Empirical data will be used to validate the index by applying it to a fast-growing region in south China.

Methodology

This study will derive the indicators of quantity, quality (suitability), location and morphology from remote sensing and GIS for assessing land development. These four components will be combined together to form a single index for ranking purposes according to the principles of efficiency. The procedure includes two main parts: (1) Derivation of the four indicators using remote sensing data and GIS functions; (2) Formulating a four-component efficiency index based on an integrated approach (Figure 1). The following sections provide the detailed procedure for obtaining these indicators.

School of Geography and Planning, Sun Yat-sen University, Guangzhou 510275, P.R. China (lixia@graduate.hku.hk); also Guangzhou Institute of Geography, Guangzhou 510070, P.R. China (xlib@gis.sti.gd.cn).

Photogrammetric Engineering & Remote Sensing
Vol. 71, No. 1, January 2005, pp. 47–57.

0099-1112/05/7101–0047/$3.00/0

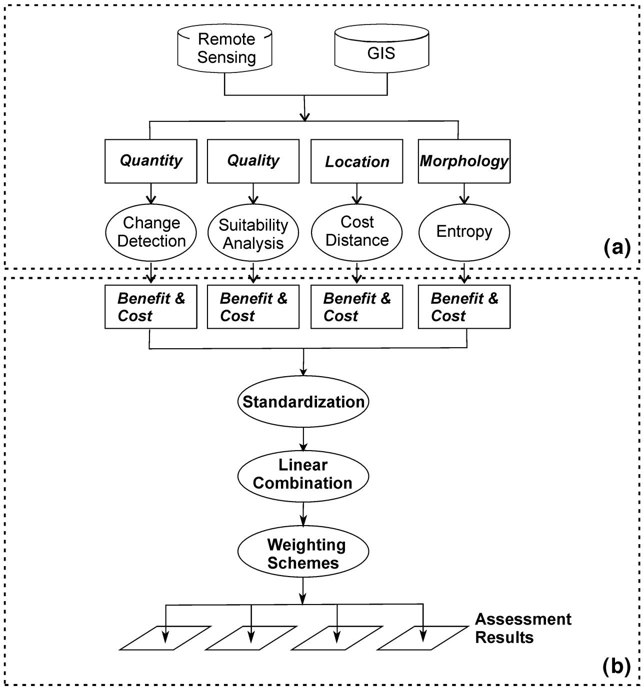

Figure 1. (a) Derivation of the indicators of quantity, quality, location and morphology using remote sensing and GIS; (b) Formulating the four-component efficiency index using a linear combination with various weighting schemes.

The Derivation of Indicators from Remote Sensing and GIS

Quantity

The quantity of land use changes can be obtained by classifying multi-temporal remote sensing images. There are numerous research publications on improving the accuracy of change detection using remote sensing (Eastman and Fulk, 1993; Jensen *et al.*, 1995; Wong *et al.*, 1997; Li and Yeh, 1998; Carlson and Sanchez-Azofeifa, 1999). Usually, supervised classification or unsupervised classification techniques are applied to the classification of land use classes from remote sensing imagery. Then, land use changes are obtained by overlaying the classified images of different dates.

In this study, the change detection is carried out by using the principal components analysis (PCA) method (Li and Yeh, 1998). When two images are used to detect land use changes, the first step of the PCA method is to stack the two images into one single vector consisting of a total of $2n$ bands. PCA is then carried out to compress the original bands into a number of components. As the compressed PCA image contains most of the information of the two original images, it should be possible to use the PCA image for the classification of land use changes. It is found that the first four components contain more than 96 percent of the total variance and the other remaining components have little information about land use changes (Li and Yeh, 1998). Therefore, the first four components are used for change detection.

Training is essential for obtaining the information of land use changes for this PCA method. Interactive supervised classification of land use changes is carried out on the compressed components. The signature of each change class is created by interactive, supervised training. Some field investigation is required to assist the identification of training classes. Land use changes can then be obtained by applying a maximum likelihood classifier to the classification of the PCA image.

After the change detection procedure is completed, the layer of land use changes is overlaid with the polygons of administrative boundaries. The overlay is useful for obtaining the aggregated information of land use changes in each administrative unit (e.g., a town). It is not difficult to find out which towns have large amounts of land development.

Quality (Land Suitability)

The quality indicator reveals the degree of urban encroachment on the best agricultural land. Land quality can be calculated mainly according to the physical attributes of land (Mcrae and Burnham, 1981). In this study, land quality is calculated by using a geographic information system (GIS). The quality is determined mainly by the factors of soil types and topographic conditions. The maps of soil types and topography of the study area are digitized into GIS before the derivation of the quality indicator. Then, the ratings are carried out for these two factors according to local experiences. The criteria for the ratings are to grade the land according to its likely yield (McRae and Burnham, 1981). These rating factors are finally combined to form the quality indicator (suitability) by using an additive formula:

$$S(i) = 0.5\, Soil(i) + 0.5\, Slope(i) \qquad (1)$$

where $S(i)$ is the score of land quality, $Soil(i)$ is the score related to soil types, and $Slope(i)$ is the score related to the slope factor.

Location (Distance)

The location indicator measures the cost-distance between development sites and the closest centre or sub-centre. Development sites with closer distances to urban centres or sub-centres are preferable because there is a less transportation cost. Distance-based variables can be used to indicate the spatial attractiveness of centres. There are various parameters and options in specifying the forms of distance that affect the decision of land development (Batty *et al.*, 1999; Xie, 1996). In this study, the distance variable is calculated by using the cost-distance function of GIS. The main centre (the City Proper) and sub-centres (town centres) of the study area are first digitized into GIS to create a point layer. The point layer is then used to calculate the shortest cost-distance between each location and the main centre or sub-centres.

Morphology

Morphology is an important measurement in many fields, such as geography, ecology, transportation, and urban systems (Ewing, 1997; Banister *et al.*, 1997; Burchell *et al.*, 1998). The integration of remote sensing and GIS provides a convenient tool to measure the sprawl degree of land development. This study uses entropy to represent the concentration or dispersion of land development (Yeh and Li, 2001). The relative entropy, which is scaled down to between 0 and 1, is described as follows (Thomas, 1981):

$$H_n = \sum_i^n p_i \log(1/p_i)/\log(n) \qquad (2)$$

where p_i is the probability or proportion of a phenomenon (variable) occurring in the ith zone ($p_i = x_i / \sum_i^n x_i$), x_i is the observed value of the phenomenon in the ith zone, and n is the total number of zones.

Urban development can be concentrated around existing urban areas (centres) or along roads. Two independent variables, the distance to town centres and the distance to roads, are used to calculate the average entropy. These two independent variables, which were retrieved from GIS, are useful for the identification of configuration and orientation of morphology. Two buffer images are created respectively based on the proximity to town centres and roads. The town-based entropy (H_t) and the road-based entropy (H_r) can then be obtained by using Equation 2. The average entropy (H_{av}) is then calculated from H_t and H_r:

$$H_{av} = \frac{H_t + H_r}{2}. \tag{3}$$

The entropy can be used to measure the compactness of land development and the diffusion of urban areas. If the distribution is maximally concentrated at a location, the lowest value, zero, will be obtained for the average entropy. An evenly dispersed distribution will lead to the maximum value of one.

A Four-Component Efficiency Index Using the Integrated Approach

A single index can be derived to represent the combined effect of these four components: quantity, quality, location, and morphology. The index is useful for ranking the cities and towns according to their economic and environmental performances for planning purposes. The formulation of the integrated index is based on the concept of efficiency. Efficiency can be achieved if an allocation of resources produces the maximum amount of benefit with a fixed amount of cost, or generates the minimum amount of cost with a fixed amount of benefits (Zhou, 2001; Tietenberg, 2003). The efficiency index is given as follows:

$$EI = B - C \tag{4}$$

where B is benefits, and C is costs.

The estimation of the benefits and costs is based on these four variables: *quantity, quality* (land suitability), *location*, and *morphology*. A four-component efficiency index is proposed to accommodate these four variables based on Equation (4):

$$EI = \sum_k w_k(B_k - C_k) \tag{5}$$

where w_k is the weight for the kth variable.

Quantity is the first indicator to estimate the related benefits and costs in consuming agricultural land resources. It is assumed that the demand curve (marginal benefit curve) for a depletable resource is linear and stable over time (Tietenberg, 2003). Thus, the inverse marginal benefit curve in consuming an amount of agricultural land Q can be written as follows (Yeh and Li, 1998):

$$MB = a - bQ_p \tag{6}$$

where MB is the marginal benefit, Q_p is per-capita land consumption ($Q_p = Q/P$), P is population, and a and b are parameters ($a > 0$ and $b > 0$).

Then, the total benefit (B_{quan}) from extracting the amount Q is the integral of this function:

$$B_{quan} = \iint (a - bQ_p)dQ_p dP = aQ_pP - bQ_p{}^2P/2 \tag{7}$$

where B_{quan} is the total benefit related to the quantity indicator (*quan*).

The marginal cost of extracting that resource is further assumed to be a constant c. The total cost (C_{quan}) of extracting the amount Q is:

$$C_{quan} = cQ_pP \tag{8}$$

where c is a parameter ($a > c$).

Then, the net benefit (NB_{quan}) becomes:

$$\begin{aligned} NB_{quan} &= B_{quan} - C_{quan} = (aQ_p - bQ_p{}^2/2 - cQ_p)P \\ &= -mQ_p^2 + lQ_p \end{aligned} \tag{9}$$

where NB_{quan} is the net benefit estimated from the quantity indicator (*quan*), and $m = \frac{b}{2}P > 0$ and $l = (a - c)p > 0$.

Quality is the second indicator to address the issues related to urban encroachment on good-quality land. The cost with regard to the quality can be estimated by suitability analysis. A piece of agricultural land has the suitability for a certain type of agricultural activities in terms of its productivity. After agricultural land has been converted into urban land, the suitability for agricultural production will be removed forever. The cost in terms of quality (agricultural suitability) can be calculated by using the following formula:

$$C_{qual} = \gamma \sum_{i \in \Omega} S(i)/A_\Omega \tag{10}$$

where C_{qual} is the average suitability cost for the quality indicator (*qual*), γ is a parameter, $S(i)$ is the suitability (potential) for agricultural production at cell i, Ω is the set of development sites, and A_Ω is the total area of development sites. C_{qual} can be conveniently calculated by using GIS functions.

Location is the third indicator that represents the transportation cost (C_{locat}) incurred by moving goods from development sites to urban centres. The distance between a development site and urban centres is a proxy for the cost. Cost-distance, instead of Euclidean distance, is used to describe the influences of transportation conditions. Different land use types are associated with different amounts of transportation cost. For example, railways have lower cost than highways for moving goods. Each site (cell) will have a value proportional to the relative transportation cost according to its land use type. The cost-distance $c(i)$ between a cell (i) and the closest centre can be conveniently calculated using GIS functions. Then, the average distance cost of development sites is calculated as follows:

$$C_{locat} = \lambda \sum_{i \in \Omega} c(i)/A_\Omega \tag{11}$$

where C_{locat} is the average distance cost related to the location indicator (*locat*), λ is a parameter, $c(i)$ is the cost-distance at site i, Ω is the set of development sites, and A_Ω is the total area of development sites. The larger the average distance-cost is, the less the efficiency of land development.

M*orphology* is the fourth indicator to address the aggregated effects of spatial patterns. Development cost will be incurred by providing facilities (e.g., roads, pipelines, schools, and hospitals) to new development sites. Fragmented land use patterns will obviously increase this type of development cost. Fragmentation degree can be represented by the average entropy (H_{av}). The fragmentation cost (C_{morph}) is therefore proportional to the fragmentation degree:

$$C_{morph} = \mu H_{av} \tag{12}$$

where C_{morph} is the fragmentation cost for the morphology indicator (*morph*), and μ is a parameter.

By taking these four variables into account simultaneously, the EI indicator in Equation 5 can be revised as follows:

$$\begin{aligned} EI &= w_1NB_{quan} - w_2C_{qual} - w_3C_{locat} - w_4C_{morph} \\ &= w_1NB_{quan} - w_2\gamma \sum_{i \in \Omega} S(i)/A_\Omega - w_3\lambda \sum_{i \in \Omega} c(i)/A_\Omega - w_4\mu H_{av}. \end{aligned} \tag{13}$$

These four terms, NB_{quan}, $\sum_{i \in \Omega} S(i)/A_{\Omega}$, $\sum_{i \in \Omega} c(i)/A_{\Omega}$, and H_{av} are measured at different scales. It is inappropriate to sum them up directly. They should be standardized by scaling down the values within the range from 0 to 1 for comparison. The standardization can be carried out according to the following linear formula:

$$Y' = (Y - \text{minimum})/(\text{maximum} - \text{minimum}) \quad (14)$$

where Y is the original score of the four variables and Y' is the standardized score.

The new standardized variables are: NB'_{quan}, $\left(\sum_{i \in \Omega} S(i)/A_{\Omega}\right)'$, $\left(\sum_{i \in \Omega} c(i)/A_{\Omega}\right)'$, and H'_{av}. Then, Equation 13 becomes:

$$EI = w_1' NB'_{quan} - w_2' \left(\sum_{i \in \Omega} S(i)/A_{\Omega}\right)' - w_3' \left(\sum_{i \in \Omega} c(i)/A_{\Omega}\right)' - w_4' H'_{av} \quad (15)$$

where $w_1' = w_1$, $w_2' = w_2\gamma$, $w_3' = w_3\lambda$, and $w_4' = w_4\mu$.

The parameters of w_1', w_2', w_3', and w_4' are the final weights to be determined for calculating the index. Since the four terms have been standardized, these weights can be heuristically defined according to their importance in the assessment. A common method to determine the weights is to use Saaty's pairwise comparison procedure (Wu and Webster, 1998; Eastman, 1999). The comparison is mainly based on experts' knowledge and preferences. A higher value of the weight means that the variable will be treated more importantly. If these variables are treated equally, all the weights can be assigned with equal values.

Implementation and Analysis Results

Study Area and Data

The study area covers the whole city of *Dongguan* which is situated in the eastern part of the Pearl River Delta. It includes the City Proper and 29 towns with an area of 2,465 km^2. The region witnessed fast economic development with the GDP (gross domestic product) growth rate as high as 27 percent in the early 1990s. The fast economic growth was accompanied by a rapid urbanization process with huge amounts of land use conversion in the region.

Landsat TM images (10 December 1988, 13 October 1990, and 22 November 1993) were used to obtain land use types and reveal the quantity of land consumption in the fast-growing period. GIS was used to derive additional information for the analysis. The spatial layers of soil types, roads, rivers, administrative boundaries, and topography were created by digitizing the 1:50000 survey maps into GIS. These data were stored as vector layers using ArcInfo® GIS. Some economic data were also collected from statistical yearbooks.

The Derivation of the Four Variables

The proposed method is tested by assessing land development in the period of 1988–1993 in the study area. The assumption of the efficiency calculation is based on the conversion from agricultural land to urban land. A large amount of land development was witnessed in the region in the early 1990s. The quantity of land development in 1988–1993 was obtained by using the two Landsat TM images taken 10 December 1988 and 22 November 1993. The change detection was carried out according to the PCA method. The training samples for supervised classification were identified on the compressed PCA image.

First, the two original images were displayed as standard false-color composites on the monitor. The PCA image was also displayed and live linked to these two original images using the ERDAS Imagine© software. Then, training sites were picked up conveniently on the PCA image using a cursor when these images were live linked. The two original images were used just to assist the identification of training samples in the PCA image. Actually, the training only needs to pick up *from-to* change classes which are present in the PCA image by comparing these three linked images. Maximum likelihood classification was performed on the PCA image, producing a thematic image with the information of land use change. Decomposing was later carried out to obtain land use classes in 1988 and 1993. The quantity of land development for each town was summed by overlaying the layer of land use changes with the layer of town boundaries.

The accuracy assessment was carried out according to land use maps and field investigation. A total of 1,132 pixels were collected to estimate the classification accuracy. GPS was used to aid the identification of field data on images. The Kappa coefficient is 0.85, and the total accuracy is 0.86 according to the accuracy assessment.

The quality issue is also important for the assessment of land development. Land was ranked according to the quality for agricultural production. Two factors, soil types and topographical features, were used for the ranking purposes. The 1: 50000 soil maps were digitized and polygons were built to represent soil types in vector format. The 1: 50000 topographical maps were also digitized for building a digital terrain model (DTM). The TIN function of ArcInfo® was used to create the slope maps. These two layers were finally converted into raster format for the derivation of the quality indicator. A lookup table was created to provide the scores for rating each factor according to agriculture productivity (Table 1). Some local knowledge (e.g., the average yield for each soil type) were required for creating the lookup table. The final score of land quality (suitability) was calculated according to Equation 1.

The location indicator was obtained according to the calculation of the closest cost-distance between the development

Table 1. The Lookup Table for Calculating the Scores of the Quality Indicator

	Soil Types	Slope (Degree)	Score
1. Paddy Soil Types	1) No. 23, 27, 25, 26, 21 (Yield > 9,000 kg/ha)	0–2.5	150–120
	2) No. 29, 17, 15, 42, 11, 22, 19, 2, 41, 4, 8, 10, 24, 20 (Yield = 7,500–9,000 kg/ha)	2.5–5	120–100
	3) No. 13, 30, 7, 18, 37, 40, 33, 28, 38, 31, 12, 9, 3, 35, 36, 14 (Yield = 6,000–7,500 kg/ha)	5–7.5	100–70
	4) No. 32, 34, 6, 1, 39, 5, 16 (Yield = 4,500–6,000kg/ha)	7.5–10	70–60
2. Dry Cultivated Soil Types	1) No. 45, 46, 47, 48, 49, 52, 55, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64	10–15	60–25
3. Mountain Soil Types	1) No. 44, 50, 51	15–30	25–15
	2) No. 43, 65	>30	15–0

sites and the centre or sub-centres. The study area has poly-centres including a major centre (the City Proper) and 29 town centres. Table 2 lists the cost values for various land use types according to the transportation cost. Normal cells are assigned with the value of one. Other land use types, such as roads, railways, expressways and water, are assigned with various values which are proportional to the travel time. For example, the use of railway systems will make the travel time much shorter and a small cost value will be assigned to this land use type. Finally, the shortest cost-distance *c(i)* can be conveniently calculated using the *COSTDISTANCE* command in ArcInfo® GRID.

The morphology indicator was calculated according to the average entropy. The calculation of the average entropy requires the creation of buffer zones according to the distances to urban centres and roads. Each buffer zone has a width of 1 km. The amount of urban land in each buffer zone is summed as the spatial variable (x_i) in Equation 2.

The Calculation of the Four-Component Efficiency Index

There are a number of parameter values to be determined for the above equations. Actually, the parameters of *a, b* and *c* have been substituted by *m* and *l* in Equation 9. The parameter of *m* and *l* can be estimated from local experiences. The parameters of γ, λ, μ, w_1, w_2, w_3, and w_4 are also substituted by w'_1, w'_2, w'_3, and w'_4 in Equation 15. Therefore, this proposed method only requires determining a total of six parameter values $-m$, l, w'_1, w'_2, w'_3, and w'_4.

These two parameter values, *m* and *l*, should be estimated before the calculation. In Figure 2, the net benefit (NB_{quan}) increases as the *per capita* land consumption increases from the beginning according to Equation 9. It reaches the maximum value when the *per capita* land consumption is at the optimal point. Then, the net benefit decreases because the increasing amount of land consumption results in a large amount of cost, which overrides the benefit.

It is assumed that the optimal per-capita land consumption (Q_p^0) can be known from local knowledge. In this study, the optimal is set to 150 m^2 per capital according to the national standard. The maximum net benefit is set to 1 (unit). According to these assumptions, it is not difficult to obtain the parameter values as follows:

$$m = \frac{1}{(Q_p^0)^2} = \frac{1}{150^2}, \text{ and } l = \frac{2}{Q_p^0} = \frac{2}{150}.$$

These four variables $\left(NB_{quan}, \sum_{i\in\Omega} S(i)/A_\Omega, \sum_{i\in\Omega} c(i)/A_\Omega, \text{ and } H_{av}\right)$ were standardized by scaling them down into the same range from 0 to 1 according to Equation 14. The weights of w'_1, w'_2, w'_3, and w'_4 in Equation 15 were determined before the calculation of the efficiency index. The determination of these weights is influenced by expert's perception and knowledge. The simplest way is to treat these weights equally for each term if there are no special preferences. However, sometimes it is useful to use different weights to reflect the importance of each variable for a special objective.

Saaty's pairwise comparison can be used to incorporate expert's perception and knowledge in deciding the weights (Wu and Webster, 1998; Eastman, 1999). The comparison considers the relative importance of the two factors (variables). The techniques can be applied to creating a series of matrices based on various preferences (objectives). This study uses five weighting schemes: equal weights, quantity-emphasized, quality-emphasized, location-emphasized, and morphology-emphasized. A 9-point reciprocal scale was used to rate each factor over every other factors and a 4×4 matrix of ratings was produced for each rating scheme (Figure 3).

Saaty (1990) proposes a consistency ratio to examine the consistency of the matrix. He suggests that the matrix should be re-evaluated if the ratio value is greater than 0.10.

Table 2. Cost Values Used for Various Types of Cells

Cell Types	Cost Values
Normal Cells	1.0
Water	3.0
Railways and Expressways	0.1
Main Roads	0.2
Other Roads	0.3

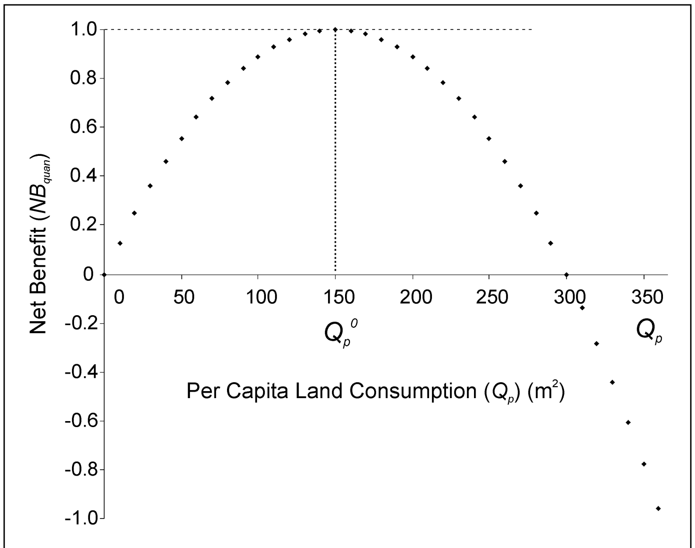

Figure 2. The relationship between net benefit and per capita land consumption.

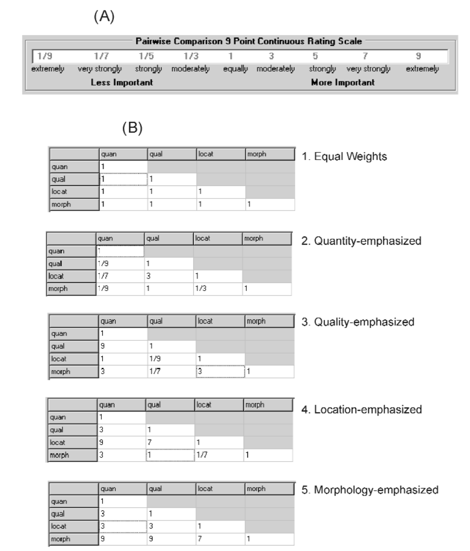

Figure 3. (a) 9-point rating scale for Saaty's pairwise comparison; (b) The matrices from five weighting schemes to incorporate experts' knowledge and preferences for the four indicators.

Table 3 is the results of the weights derived from the five weighting schemes using IDRISI® software.

The values of *EI* can be calculated for each weighting scheme. Finally, the *EI* index was scaled down into the range from 0 to 1 by using the following equation:

$$EI' = \frac{EI - EI_{\max}}{EI_{\max} - EI_{\min}}. \tag{16}$$

The Analysis Results

The monitoring reveals that the quantity of land development in 1988–1993 is very large in the study area. The area of urban land rapidly increased from 16,234.6 ha to 41,087.9 ha in the period. A total of 10.4 percent of the land area was converted into urban land just within this short period. The land consumption was far beyond the necessity of its population. The average land consumption *per capita* rapidly increased from 128.4 m^2 to 295.8 m^2 in the period of 1988–1993. In many towns, the amount of land consumption was unacceptable by the nation's standard (100–150 m^2 per capita). Plate 1 is the TM satellite images of the City Proper in 1988, 1990, and 1993. It provides the evidence of the faster expansion of the City Proper in the early 1990s. The rapid urban expansion mainly took place in the period of 1990–1993.

There is severe problem when good quality agricultural land has been converted into urban land in the region. In Figure 4, agricultural land was classified into classes 1–7 according to agricultural productivity; class 7 is the best land, and class 1 is the poorest land for agricultural production. GIS overlay analysis reveals that some towns in the region have consumed large amounts of good agricultural land for urban development. A total of 41.7 percent of urban development took place at the most fertile land (classes 6–7).

The location factor in influencing land development can be easily identified as agricultural land near urban centres and roads which is more likely to be converted for urban development. It is very common that development sites are located beside roads. Although the transportation cost may be lower for such development patterns, they are not in a compact urban form.

There is a substantial variation in the development patterns among these towns according to the calculation of entropy. Some towns appear more dispersed than others. The region witnessed dispersed development patterns on the whole. This can be confirmed by calculating the average entropy (H_{av}) from the 1988, 1990 and 1993 satellite images. The average entropy increases as urban areas diffuse into agricultural areas. The increase of the average entropy was 2.7 percent in 1988–1990 and 8.9 percent in 1990–1993, respectively.

The four-component efficiency index was used to assess land development for each town in the study area. Five weighting schemes were used to determine the weights for the assessment. Each weighting scheme represents different concerns or preferences. Figure 5 is the assessment results using equal weights, the four indicators are treated equally in this assessment scheme. The towns of Liaobu, Chashan, Hengli, Zhongtang, Dalang, and Dongkeng have the index values above 0.85. These towns can be regarded as better examples of using land resources for urban development according to these four criteria (variables) of equal weights. At the same time, the towns of Fenggang, Shilong, Hongmei, Shatian, and Tangsha have low values of the index which indicate poor performance in using land resources. It is straightforward to determine the type of land use problems that may exist for a specific town according to these four indicators.

Figure 6 shows the assessment results for the other four weighting schemes with various preferences: quantity-emphasized, quality-emphasized, location-emphasized, and morphology-emphasized. In Figure 6a, the major concern is the quantity of land development. The assessment results are sensitive to this indicator since more importance is given to it. The towns near the City Proper have better performance according to the assessment. This means that the quantity of land consumption is more reasonable in these towns than in others. In contrast, the towns of Fenggan and Tangsha have used too much agricultural land. For example, Fenggang has the land consumption as high as 1,075 m^2 *per capita*. The consumption of a large amount of land resources will generate a significant amount of environmental cost; therefore, these towns will have worse performance under this objective.

More importance can be given to the quality indicator for the assessment. The towns which perform well mainly at this aspect can be identified in Figure 6b. The towns near the City Proper also have good performance in the assessment. The result of this assessment is very similar to that of the quantity-emphasized assessment.

When the location factor is associated with a more important weight, these towns far away from the major transport networks tend to be ranked lower in the assessment (Figure 6c). For example, the towns in the western part of the region have poor accessibility, and usually have low values of the index. However, the influence from the location factor is not absolute because the other three factors also play a role in the assessment.

The assessment can be obtained by putting more importance in the morphological factor. It can be seen that the remote towns also have poor performance under this objective (Figure 6d). These towns include Hongmei, Shatian, Machon, and Dalingshan. Therefore, land development in these towns tends to be more dispersed.

It is apparent that the assessment results are sensitive to the parameter values (weights), and different results may be obtained based on different weighting schemes. However, some general patterns can still be observed from the above assessment results, and some clusters can be found from the mapping of the efficiency. The towns near the City Proper generally appear more efficient in using land resources according to the assessment for these weighting schemes. This is quite understandable since the City Proper and the nearby towns have better development control. The analysis indicates that the proposed index can generate the similar macro-patterns, although the results are sensitive to the weights. Different sets of weights will lead to the variations in micro-patterns.

TABLE 3. THE WEIGHTS DERIVED FROM THE PAIRWISE COMPARISON FOR VARIOUS PREFERENCES

Preferences	Quantity	Quality	Location	Morphology	Consistency Ratio
Equal weights	0.2500	0.2500	0.2500	0.2500	*0.00 (acceptable)*
Quantity-emphasized	0.7186	0.0630	0.1554	0.0630	*0.03 (acceptable)*
Quality-emphasized	0.0630	0.7186	0.0630	0.1554	*0.03 (acceptable)*
Location-emphasized	0.0517	0.1222	0.7039	0.1222	*0.03 (acceptable)*
Morphology-emphasized	0.0491	0.0856	0.1558	0.7095	*0.09 (acceptable)*

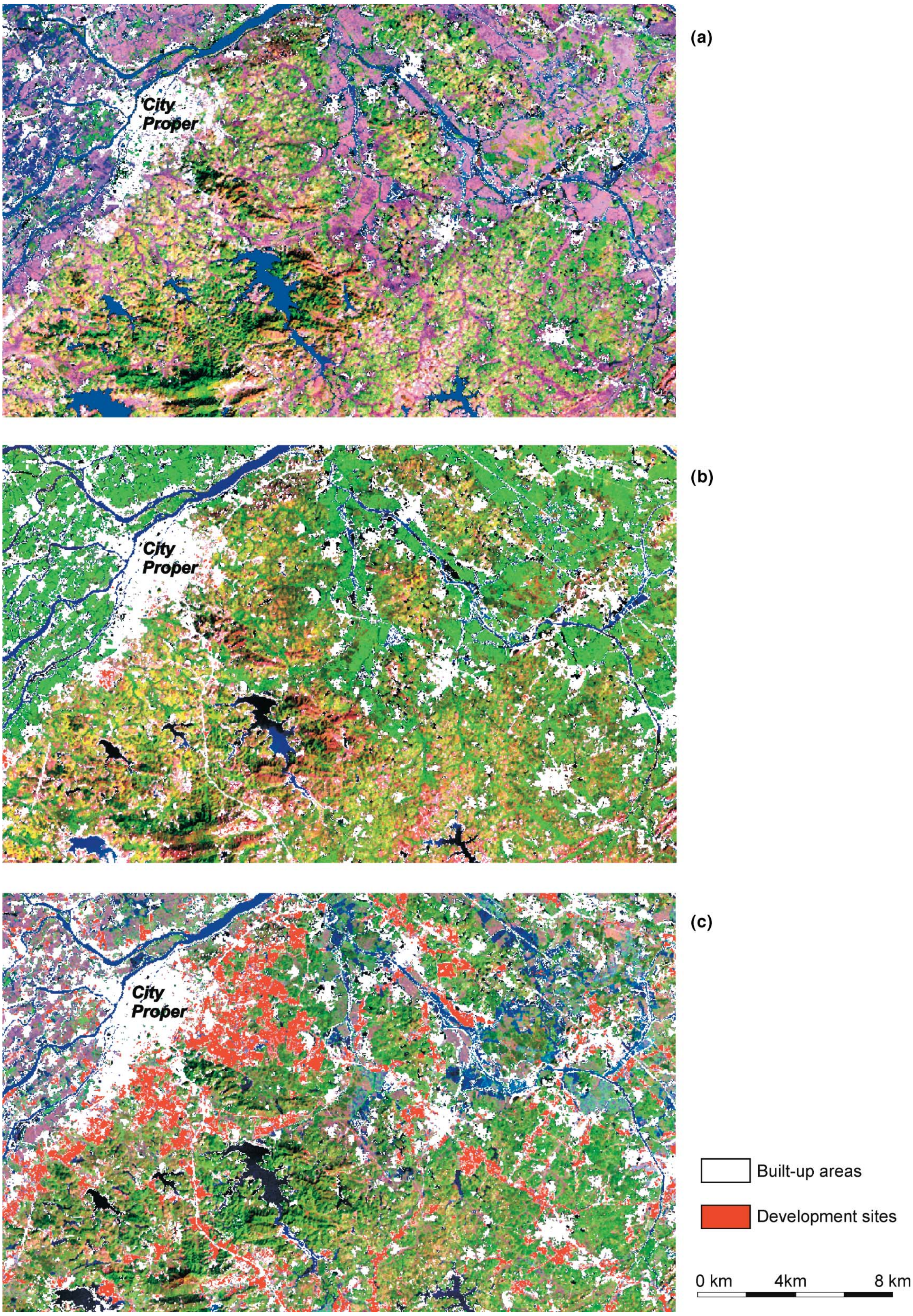

Plate 1. Rapid expansion of urban land (built-up areas and development sites) in the city proper of Dongguan in (a) 1988, (b) 1990, and (c) 1993. The image was produced by overlaying the original false color composites (R: TM 5, G: TM 4, B: TM 3) of 1988, 1990 and 1993 with the detected built-up areas (white color) and development sites (red color), respectively.

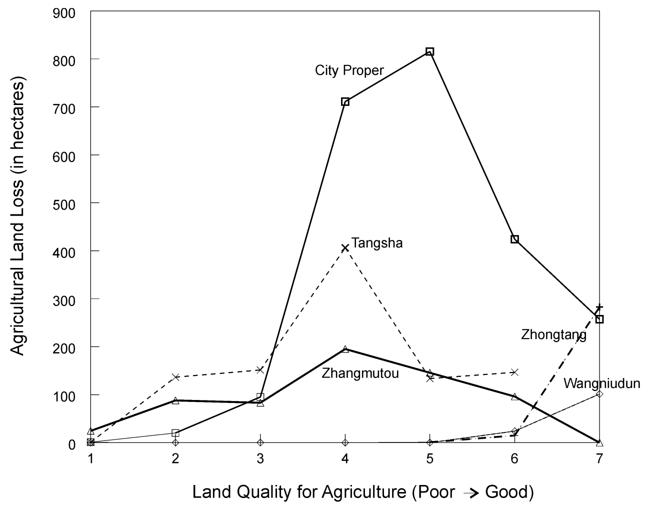

Figure 4. Incidence of agricultural land loss on land class by selected towns in Dongguan in 1988–1993. The figure was produced by overlaying the layer of agricultural land loss with the layer of land quality. Land quality was based on soil types and slope.

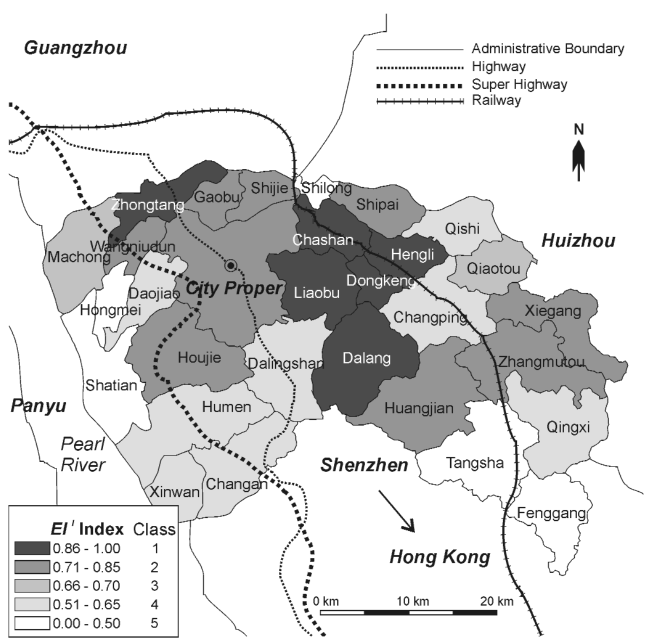

Figure 5. Assessment of land development using the efficiency index with equal weights.

The above analysis has demonstrated that remote sensing and GIS are able to provide additional information about land use conversion. The four indicators (quantity, quality, location, and morphology) can reflect different economic and environmental aspects of land development. The analysis results will be more reasonable by taking the combined effects of these factors during development assessment. The proposed four-component efficiency index is useful for ranking the cities or towns according to their performance in land development. These indicators can provide detailed spatial information for planning purposes. They can assist in the implementation of some recent development theories, such as *compact development* (Jenks *et al.*, 1996) or *smart growth* (Johnson, 2001). A *better* or *worse* development plan can be conveniently identified according to the assessment. This can help urban planners to plan and manage land development more efficiently.

In 1994, China has to implement the *Ordinance for the Protection of Primary Agricultural Land* (State Council, 1994) to control the aggressive land development. The direction and magnitude of land use changes have been affected by this new land policy. However, there is a general lack of proper tools to measure its impacts and effectiveness. The proposed method can provide a convenient and operational framework for the assessment of land development by using remote sensing and GIS.

Validation of the Model

There is a question about the validity of the model, i.e., knowing the calculated efficiency values are able to reflect the actual situation. A common problem of using indicators is that the results are usually sensitive to parameter values. Some calibration procedures are usually required to minimize the uncertainties. In this study, the parameters for estimating NB_{quan} have been calibrated by using the national standard data. There is still a need to validate the final index (*EI*). Some independent data can be used to verify the model, although it is very difficult to obtain such data. Ideal data are always unavailable for Chinese cities. However, some proxy data can be used for this purpose. In the statistical yearbooks of Chinese cities, there is some limited data about the economic efficiency for each administrative unit (e.g., towns). The efficiency data are about the benefit (income) versus cost for specific types of economic activities, and they are expressed in a monetary term. The economic efficiency can be linked to the efficiency of using land resources. It is assumed that the towns (cities) with good efficiency in using land resources will help to achieve good economic efficiency. Thus, the model will be valid if the proposed indicators have a good relationship with the data of the economic efficiency from the statistical yearbooks.

We will examine if there is relationship between the ratio (income/cost) and the four spatial indicators. Figure 7 shows the correlation between the ratio and each of these four indicators. Table 4 lists the regression results. The analysis indicates a strong relationship between the ratio and NB'_{quan}; its coefficient is positive. This means that a higher value of NB'_{quan} can indicate better economic efficiency. The regression verifies that NB'_{quan} is a good indicator of efficiency. The positive coefficient of regression coincides with the positive coefficient of NB'_{quan} in Equation 15. The relationships between the ratio and the other three indicators are not so significant. However, the total correlation coefficient (R^2) is still as high as 0.92. The high value of R^2 is mainly due to the strong relationship between the ratio and NB'_{quan}.

Conclusion

It is convenient to obtain the information about the quantity of land use changes from remote sensing. Land use changes have profound impacts on the environment. Urban development encroaching on a large amount of agricultural land is not preferable for sustainable development. The measurement of such impacts should consider other aspects besides the quantity indicator. Additional indicators should be developed to facilitate the assessment of development impacts by the integration of remote sensing and GIS.

This study demonstrates that the measurement of land development can be improved by using additional information

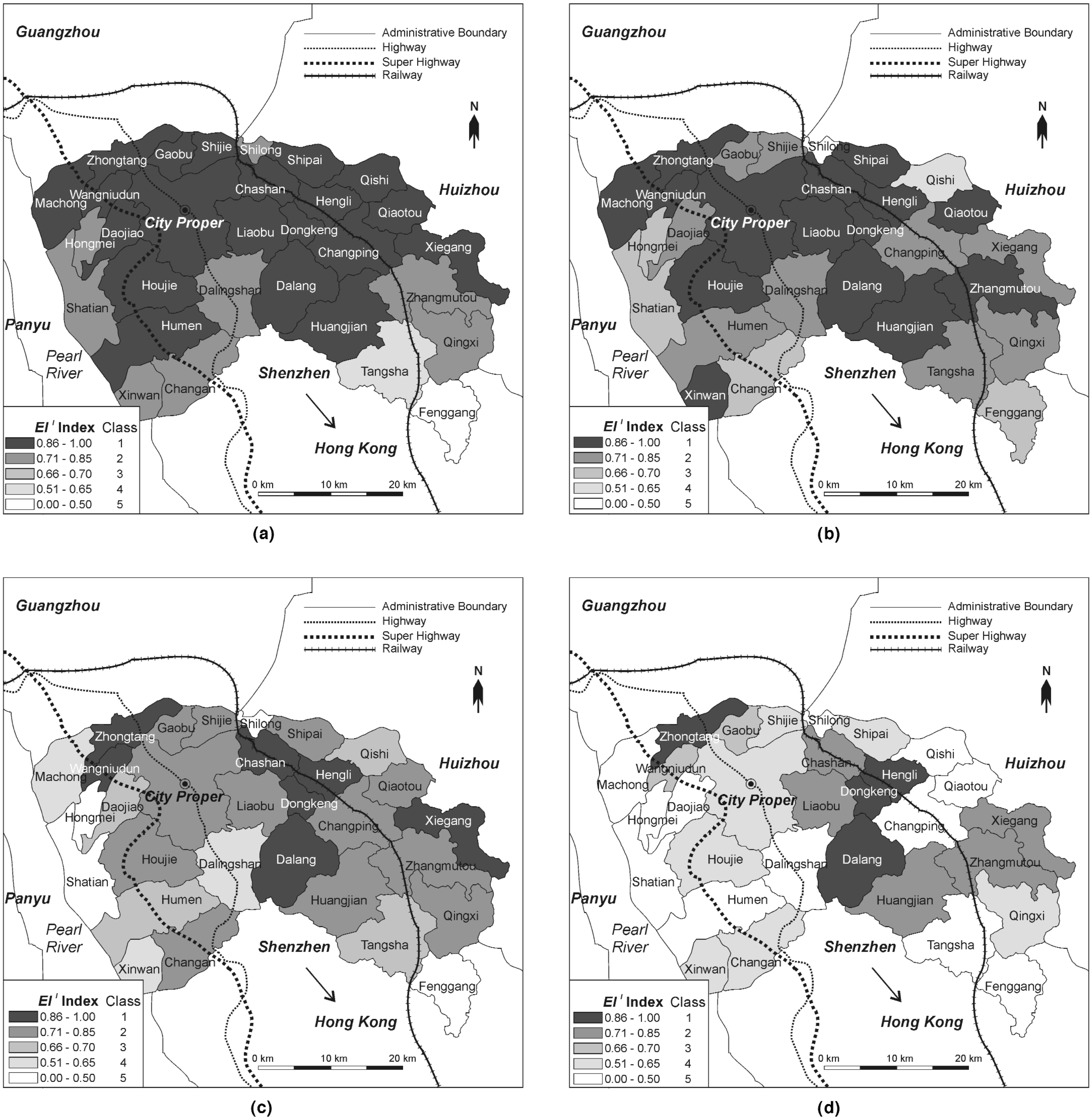

Figure 6. Assessment of land development using the efficiency index with different weights: (a) Quantity-emphasized weights, (b) Quality-emphasized weights, (c) Location-emphasized weights, and (d) Morphology-emphasized weights.

from remote sensing and GIS. The indicators of quantity, quality, location, and morphology can provide useful information about the impacts of land use changes. They are able to address broader economic and environmental issues related to land development. A four-component efficiency index is further proposed for ranking cities and towns by dealing with the combined effects of these four factors. This provides an operational framework for urban planners to measure and evaluate land development more efficiently and accurately.

This method allows the experts' knowledge and preferences to be incorporated in the assessment. Different weights can be applied to each indicator in the assessment for a specific objective. Saaty's pairwise comparison techniques are useful for determining the weights in the calculation of the four-component index under this situation. Different weighting schemes can be used subject to the objectives of assessment. These weighting schemes may have influences on the assessment results. However, the analysis indicates that the proposed method can produce similar macro-patterns of

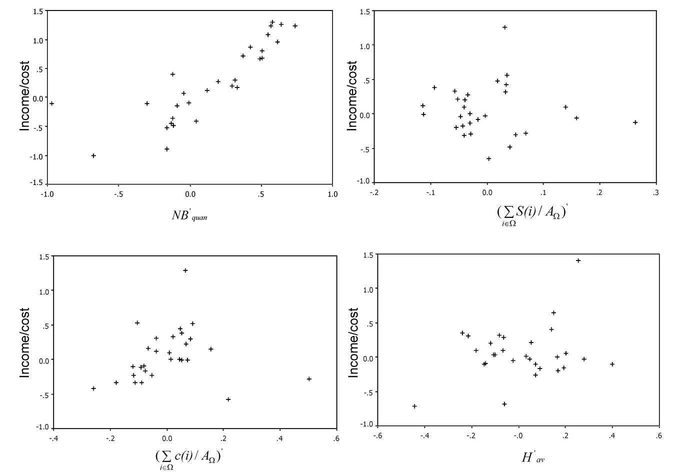

Figure 7. Scattergram showing the relationship between economic data (income/cost) and the four spatial indicators.

assessment for various weighting schemes. The determination of the weights is transparent as a result of using the pairwise comparison method. This can lead urban planners to understand the implications of the assessment results more easily. They can explore different assessment results under various planning objectives and environmental concerns.

The proposed indicators are useful for revealing land use problems in the study area. It is found that some towns perform badly with regard to the use of land resources. Usually, land development does not take place at the right location and time. Not much attention has been paid to the formulation of compact urban forms in the region, and this has created additional cost because of resource and energy consumption. Such development patterns have posed significant impacts on local agricultural production.

In this study, some experiments have been carried out to test the validity of the proposed model. Empirical data are also used to determine some of the parameters in deriving the quantity indicators which can reflect some economic characteristics. Further studies are still required to verify the model by using more empirical data. Importantly, this study uses a linear transformation to standardize the data which may have limitations when non-linear transformation is more suitable. More training data may be required to study the proper forms of transformation for data standardization. The difficulty is that many environmental problems cannot be easily measured and represented by mathematical equations. A further elaborated assessment may require the consideration of other factors, such as irrigation systems, development infrastructure, social and economic centres, and economic scales. However, this study primarily provides an operational method to use remote sensing and GIS for the assessment of land development for fast growing areas.

Acknowledgments

This study is supported by the funding from the National Natural Science Foundation of China (NSFC) (Project No. 40471105 and Project No. 40071060). It is also supported by the '985 Project' of GIS and Remote Sensing for Geosciences from the Chinese Education Department. The author is grateful to the three anonymous referrers whose comments are very useful for improving this paper.

References

Banister, D., S. Watson, and C. Wood, 1997. Sustainable cities: transport, energy, and urban form, *Environment and Planning B*, 24:125–143.

Batty, M., Y.C. Xie, and Z.L. Sun, 1999. Modelling urban dynamics through GIS-based cellular automata, *Computer, Environment and Urban Systems*, 23:205–233.

Burchell, R.W., N.A. Shad, D. Listokin, H. Phillips, A. Downs, S. Seskin, J. S. Davis, T. Moore, D. Helton, and M. Gall, 1998. *The costs of sprawl – revisited*, National Academy Press, Washington, D.C., 268 p.

Carlson, T.N., and G.A. Sanchez-Azofeifa, 1999. Satellite remote sensing of land use changes in and around San Jose, Costa Rica, *Remote Sensing of Environment*, 70(3):247–256.

Eastman, J.R., and M. Fulk, 1993. Long sequence time series evaluation using standardized principle components, *Photogrammetric Engineering & Remote Sensing*, 59(6):991–996.

Eastman, J.R., 1999. Multi-criteria evaluation and GIS, *Geographical Information Systems* (P.A. Longley, M.F. Goodchild, D.J. Maguire, and D.W. Rhind, editors), John Wiley and Sons, New York, pp. 493–502.

Ewing, R., 1997. Is Los Angeles-style sprawl desirable?, *Journal of the American Planning Association*, 63(1):107–126.

Fung, T., and E. LeDrew, 1987. Application of principal components analysis change detection, *Photogrammetric Engineering & Remote Sensing*, 53(12):1649–1658.

Howarth, P.J., 1986. Landsat digital enhancements for change detection in urban environment, *Remote Sensing of Environment*, 13:149–160.

Jenks, M., E. Burton, and K. Williams, 1996. Compact cities and sustainability: an introduction, *The Compact City: A Sustainable Urban Form?* (M. Jenks, E. Burton, and K. Williams, editors), E&FN SPON, London, pp. 11–12.

Jensen, J.R., K. Rutchey, M.S. Koch, and S. Narumalani, 1995. Inland wetland change detection in the Everglades Water Conservation Area 2A using a time series of normalized remotely sensed data, *Photogrammetric Engineering & Remote Sensing*, 61(2):199–209.

Table 4. Regression Analysis Between the Statistical Data and the Proposed Indicators

Spatial Variables	Unstandardized Coefficients *B*	Standard Error	Standardized Coefficients *Beta*	*t*	*Sigma*
NB'_{quan}	1.408	.173	.782	8.149	.000
$\left(\sum_{i\in\Omega} S(i)/A_\Omega\right)'$	−.245	.929	−.021	−.264	.794
$\left(\sum_{i\in\Omega} c(i)/A_\Omega\right)'$	.374	.537	.075	.696	.493
H'_{av}	.548	.413	.179	1.327	.196

a Dependent variable: Income/Cost.
b Linear regression through the origin.

Johnson, M., 2001. Environmental impacts of urban sprawl: a survey of the literature and proposed research agenda, *Environment and Planning A*, 33:717–735.

Jusoff, K., and S. Senthavy, 2003. Land use change detection using remote sensing and geographical information system (GIS) in Gua Musang district, Kelantan, Malaysia, *Journal of Tropical Forest Science*, 15 (2):303–312.

Li, X., 1993. A united model for quantitative remote sensing of suspended sediment concentration, *International Journal of Remote Sensing*, 14(14):2665–2676.

Li, X., and A.G.O. Yeh, 1998. Principal component analysis of stacked multi-temporal images for monitoring of rapid urban expansion in the Pearl River Delta, *International Journal of Remote Sensing*, 19(8):1501–1518.

Mcrae, S.G., and C.P. Burnham, 1981. *Land Evaluation*, Clarendon Press, Oxford, 239 p.

Martin, L.R.G., 1989. An evaluation of Landsat-based change detection methods applied to the rural-urban fringe, *Remote Sensing and Methodologies of Land Use Change Analysis* (C. R. Bryant, E. F. LeDrew, C. Marois, and F. Cavayas, editors), University of Waterloo, Waterloo, pp. 101–116.

Saaty, T.L., 1990. *The analytic hierarchy process: planning, priority setting, resource allocation*, University of Pittsburgh, Pittsburgh, 287 p.

State Council, 1994. *Ordinance for the protection of primary agricultural land*, State Council, Beijing, China, 12 p. (in Chinese).

Su, Z., 2000. Remote sensing of land use and vegetation for mesoscale hydrological studies, *International Journal of Remote Sensing*, 21 (2):213–233.

Thomas, R.W., 1981. *Information Statistics in Geography*, Geo Abstracts, University of East Anglia, Norwich, United Kingdom, 42 p.

Tietenberg, T., 2003. *Environmental and natural resource economics*, Addison Wesley, Boston, 646 p.

Tucker, C.J., 1979. Red and photographic infrared linear combination for monitoring vegetation, *Remote Sensing of Environment*, 8:127–150.

Wong, R.K, T. Fung, K.S. Leung, and Y. Leung, 1997. The compression of a sequence of satellite images based on change detection, *International Journal of Remote Sensing*, 18(11):2427–2436.

Wu, F., and C.J. Webster, 1998. Simulation of land development through the integration of cellular automata and multicriteria evaluation, *Environment and Planning B*, 25:103–126.

Xie, Y., 1996. A generalized model for cellular urban dynamics, *Geographical Analysis*, 28:350–373.

Yeh, A.G.O., and X. Li, 1998. Sustainable land development model for rapid growth areas using GIS, *International Journal of Geographical Information Science*, 12(2):169–189.

———, 2001. The measurement and monitoring of urban sprawl in a rapid growing region using the entropy method, *Photogrammetric Engineering & Remote Sensing*, 67(1):83–90.

Zhou, J.M., 2001. *Sustainable development in Asia, America and Europe with global applications: a new approach to land ownership*, Edward Elgar Publishing Ltd., Cheltenham, UK, 518 p.

(Received 13 May 2003; accepted 10 October 2003; revised 11 November 2003)