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Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling

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Rapid land use change has taken place in many coastal regions of China such as the Zhujiang Delta over the past two decades due to accelerated industrialization and urbanization. In this paper, land use change dynamics were investigated by the combined use of satellite remote sensing, geographic information systems (GIS), and stochastic modelling technologies. The results indicated that there has been a notable and uneven urban growth and a tremendous loss in cropland between 1989 and 1997. The land use change process has shown no sign of becoming stable. The study demonstrates that the integration of satellite remote sensing and GIS was an effective approach for analyzing the direction, rate, and spatial pattern of land use change. The further integration of these two technologies with Markov modelling was found to be beneficial in describing and analyzing land use change process.

Keywords: Land use management, satellite remote sensing, GIS, Markov modelling, South China.

Introduction

Since 1978, when China initiated economic reform and an open-door policy, rapid land use and land cover change has taken place in most of its territory. Rapid industrialization and urbanization has resulted in the loss of a significant amount of agricultural land. This is especially true in many coastal regions and cities, such as the Zhujiang Delta, where maximizing economic efficiency is the top priority of development. Because of the lack of appropriate land use planning and the measures for sustainable development, rampant urban growth and massive disappearance of agricultural land have had severe environmental consequences. Moreover, the dike-pond system, an environmentally conserving agriculture-aquaculture technology, specially developed for utilizing the low-lying flood-prone environment in the delta, has also undergone changes. All these changes have the potential to undermine the long-term harmonious people–environment relationship. There is an urgent need for evaluating the magnitude, pattern, and type of land use and land cover changes and for projecting future land development.

Satellite remote sensing, in conjunction with geographic information systems (GIS), has been widely applied and been recognized as a powerful and effective tool in detecting land use and land cover change (Ehlers *et al*., 1990; Meaille and Wald, 1990; Treitz *et al*., 1992; Westmoreland and Stow, 1992; Harris and Ventura, 1995; Yeh and Li, 1996, 1997, 1999; Weng, 2001). Satellite remote sensing provides cost-effective multi-spectral and multi-temporal data, and turns them into information valuable for understanding and monitoring land development patterns and processes and for building land use and land cover data sets. GIS technology provides a flexible environment for storing, analyzing, and displaying digital data necessary for change detection and database development. Satellite imagery has been used to monitor discrete land cover types by spectral classification or to estimate

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biophysical characteristics of land surfaces via linear relationships with spectral reflectances or indices (Steininger, 1996). Post-classification comparison and multi-date composite image change detection are the two most commonly used methods in the change detection (Jensen, 1996). In recent years, the techniques of satellite remote sensing and GIS have been increasingly used to examine the spatial and temporal patterns of land use and land cover change in China, especially related to urban growth (Dai *et al*., 1996; Yeh and Li, 1996, 1997, 1999; Chen *et al*., 2000). Scale-dependent relationships between Chinese land uses and driving forces have also been examined using correlation and regression analyses (Verburg and Chen, 2000).

Remote sensing and GIS based change detection studies have predominantly focused on providing the knowledge of how much, where, what type of land use and land cover change has occurred. Only a few models have been developed to address how and why the changes occurred. The models of land use and land cover change process fall into two groups: regression-based and spatial transition-based models (For good summaries of these models, please refer to review articles by Baker (1989), Lambin (1997), and Theobald and Hobbs (1998)). The majority of research utilizes regression-based approach, which relates the locations of land use and land cover change to a set of spatially explicit variables, and uses models such as logistic (Landis, 1994; Turner *et al*., 1996; Wear *et al*., 1998), and hedonic price models (Geohegan *et al*., 1997). Spatial transition-based models often refer to cellular automaton simulation models, which allow for predicting future land development based on probabilistic estimates with Monte Carlo or other methods (Clarke *et al*., 1997; Clarke and Gaydos, 1998). One crucial limit to the development of the process models is, however, the deficiency of explicit modelling tools for change processes in the current generation of remote sensing and GIS systems. Equally important is the issue of data availability (Baker, 1989). Moreover, few studies have attempted to link satellite remote sensing and GIS to stochastic modelling methods in land use and land cover change studies, in spite of the fact that the techniques for such linkages have become mature in recent years due to advances in the technology of GIS and its integration with remote sensing. This missing linkage has hindered modelling and assessing the dynamics of land use and land cover change, and significantly impeded progress towards understanding of earth–atmosphere interactions, biodiversity loss, and global environmental change.

This paper presents a method that combines satellite remote sensing, GIS, and Markov modelling to analyze and predict land use and land cover changes in the Zhujiang Delta of southern China between 1989 and 1997. The techniques of satellite remote sensing and GIS are integrated to quantify and analyze land use and land cover changes using Landsat TM data and field surveyed *in situ* data. Markovian modelling is then used to examine the stochastic nature of the land use and land cover change data and to project the stability of future land development in the region.

Markov modelling of land use and land cover changes

Markov chains have been used to model changes in land use and land cover at a variety of spatial scales. Changes in land use were often separated from changes in land cover/vegetation type, in spite of similarities in method and approach. Markov analysis of vegetation types tends to focus on a small area of less than a few hectares or on a single small plot. When a few hundred hectares of land are involved, data sampling is usually applied to limit the workload to scattered plots or transects (Baker, 1989). On the other hand, land use studies using Markov chain models tend to focus on a much larger spatial scale, and involve both urban and non-urban covers (Drewett, 1969; Bourne, 1971; Bell, 1974; Bell and Hinojosa, 1977; Robinson, 1978; Jahan, 1986; Muller and Middleton, 1994). All of these studies use the first-order Markov chain models. The order of the Markov chains has only been formally tested in a few studies (Bell, 1974; Robinson, 1978). Stationarity has usually been assumed, except in a few instances where it has been tested (Bourne, 1971; Bell, 1974; Bell and Hinojosa, 1977). Brown *et al*. (2000) recently presented an approach to estimating transition probabilities between two binary images in a study of land use and land cover relationship in the Upper Midwest, USA. This approach, according to Huber (2001), needs to be improved and generalized in order to estimate properly Markov transitions from a pair of images.

Markov chain models have several assumptions (Parzen, 1962; Haan, 1977; Wang, 1986; Stewart, 1994). One basic assumption is to regard land use and land cover change as a stochastic process, and different categories are the states of a chain. A chain is defined as a stochastic process having the property that the value of the process at time t, X_t, depends only on its value at time $t-1$, X_{t-1}, and not on the sequence of values $X_{t-2}, X_{t-3}, \ldots, X_0$ that the process passed through in arriving at X_{t-1}. It can be expressed as:

$$P\{X_t = a_j | X_0 = a_0, X_1 = a_1, \ldots, X_{t-1} = a_i\} = P\{X_t = a_j | X_{t-1} = a_i\} \quad (1)$$

Moreover, it is convenient to regard the change process as one which is discrete in time ($t = 0, 1, 2, \ldots$).

The P $\{X_t = a_j | X_{t-1} = a_i\}$, known as the one-step transitional probability, gives the probability that the process makes the transition from state a_i to state a_j in one time period. When ℓ steps are needed to implement this transition, the P $\{X_t = a_j | X_{t-1} = a_i\}$ is then called the ℓ-step transition probability, $P_{ij}^{(\ell)}$. If the $P_{ij}^{(\ell)}$ is independent of times and dependent only upon states a_i, a_j, and ℓ, then the Markov chain is said to be homogeneous. The treatment of Markov chains in this study will be limited to first order homogeneous Markov chains. In this event:

$$P\{X_t = a_j | X_{t-1} = a_i\} = P_{ij} \quad (2)$$

where P_{ij} can be estimated from observed data by tabulating the number of times the observed data went from state i to j, n_{ij}, and by summing the number of times that state a_i occurred, n_i. Then

$$P_{ij} = n_{ij}/n_i \quad (3)$$

As the Markov chain advances in time, the probability of being in state j after a sufficiently large number of steps becomes independent of the initial state of the chain. When this situation occurs, the chain is said to have reached a steady state. Then the limit probability, P_j, is used to determine the value of $P_{ij}^{(\ell)}$:

$$\lim_{n} P_{ij}^{(n)} = P_j \quad (4)$$

where:

$$P_j = P_i P_{ij}^{(n)} \quad j = 1, 2, \ldots, m \text{ (state)}$$

$$P_i = 1 \quad P_j > 0$$

As land use and cover change reflects the dynamics and interplay of economic, social, and biophysical factors over time, it would be implausible to expect stationarity in land use/cover data. However, it might be practical to regard land use/cover change to be reasonably stationary if the time span is not too great.

Markov modelling of land use and land cover changes have not been substantial by the use of satellite imagery and digital image processing technique. Previous studies mostly utilize data sampled from field surveys, existing maps, or aerial photography (Drewett, 1969; Bourne, 1971; Bell, 1974; Bell and Hinojosa, 1977; Robinson, 1978; Jahan, 1986; Muller and Middleton, 1994). Data uncertainty in these studies remains relatively high, because only a certain amount of sites was sampled. The use of satellite imagery would create an opportunity for improved analysis. Moreover, the Markov models have been mostly employed for studies around a city or a slightly larger area, with a regional concentration in North America. The application of stochastic models to simulate dynamic systems such as land use and land cover changes in a developing nation is rare. Clearly, much work needs to be done in order to develop an operational procedure that integrates the techniques of satellite remote sensing, GIS, and Markov modelling for monitoring and modelling land use and land cover changes.

Study area

The Zhujiang (literally 'the Pearl River') Delta, located between latitudes 21°40′N and 23°00′N, and longitudes 112°00′E and 113°20′E, is the third biggest river delta in China. This study focuses on the core area of the delta, which has an area of 15 112 sq. km (Figure 1). Geomorphologically, the delta consists of three sub-deltas formed by sediments, namely, the Xijiang, Beijiang, and Dongjiang Deltas. The process of sedimentation still continues today, and the delta is extending seaward at a rate of 40 m per year (Gong and Chen, 1964). The climate of the delta is basically tropical with an average annual temperature between 21°C and 23°C, and an average precipitation from 1600 to 2600 mm. Natural vegetation is predominantly evergreen.

Economically, the Zhujiang Delta is the largest area of economic concentration in South China. Since 1978, it has had a dramatic economic expansion under China's economic reform policies, and therefore has been regarded as a model for Chinese regional development. The establishment of Special Economic Zones and the Economic Open Zone has encouraged foreign firms to locate their factories there as village-township enterprises.

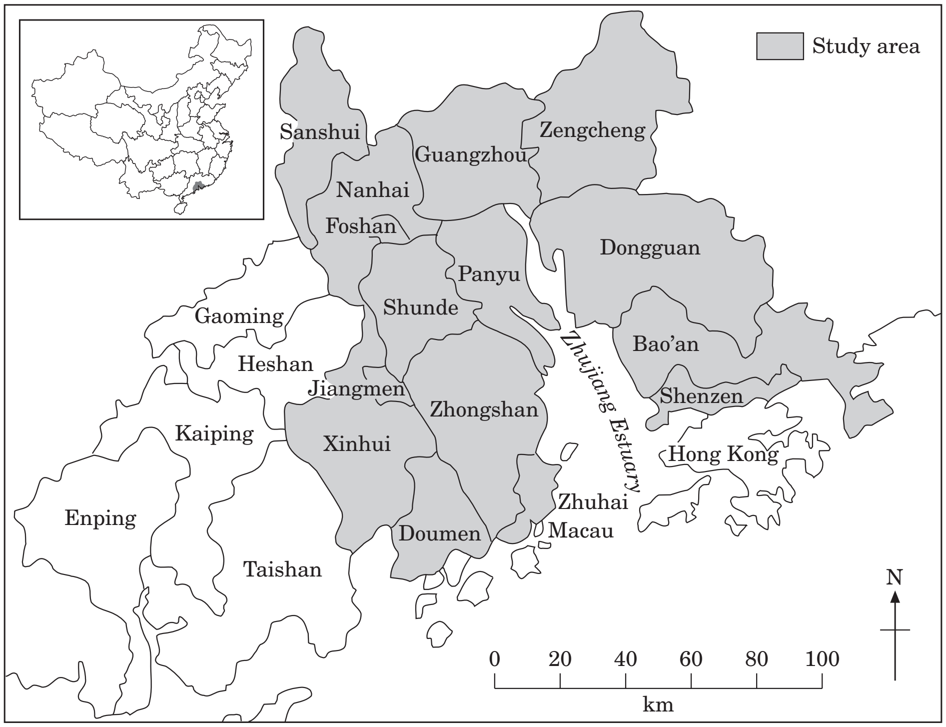

Figure 1. A map of the study area.

The labor-intensive industries, in association with cash crop production, have transformed the spatial economy of the delta (Lo, 1989; Weng, 1998). The rapid economic development has brought about fundamental changes in land use and land cover patterns. The study aims to understand the land use and land cover dynamics using the techniques of remote sensing, GIS, and stochastic modelling.

Methods

Land use and land cover change detection

Land use and land cover patterns for 1989, 1994, and 1997 were mapped by the use of Landsat Thematic Mapper data (December 13, 1989, January 25, 1994, and August 29, 1997), which have a 30-m ground resolution (except for the thermal IR band (band 6), which has a 120-m resolution) and 7 spectral bands. A modified version of the Anderson scheme of land use/cover classification was adopted (Anderson *et al.*, 1976). The categories include: (1) urban or built-up land, (2) barren land, (3) cropland (rice), (4) horticulture farms (primarily fruit trees), (5) dike-pond land, (6) forest, and (7) water.

Each Landsat image was enhanced using linear contrast stretching and histogram equalization to improve the image to help identify ground control points in rectification. The two dates of images were rectified to a common UTM coordinate system based on 1:50 000 scale topographic maps. These data were resampled using the nearest Neighbor algorithm, so that the original brightness values of pixels were kept unchanged. The resultant root mean squared error was found to be 0·73 pixel (or 21·9 m on the ground) for the 1989 scene, 0·62 pixel (18·6 m) for the 1994 scene, and 0·58 pixel (17·4 m) for the 1997 scene.

Since this study requires the detection of fine changes in surface reflectances, radiometric correction became necessary. However, no ancillary data on the atmospheric conditions during the satellite overpasses were available to account for atmospheric differences between the two dates. A relative radiometric correction method using image regression (Jensen *et al.*, 1995; Jensen, 1996) was therefore employed, by which the brightness value of each pixel of the subject scene (the 1989 scene) was related to that of the reference image (the 1997 scene) band by band to produce a linear regression equation. This image normalization method can minimize or eliminate the effects caused by using historical remotely sensed images of nonanniversary dates with varying sun angle, atmospheric, and soil moisture conditions (Jensen, 1996, pp. 116–119).

A supervised signature extraction with the maximum likelihood algorithm was employed to classify the Landsat images. Both statistical and graphical analyses of feature selection were conducted, and bands 2 (green), 3 (red), and 4 (near infrared) were found to be most effective in discriminating each class and thus used for classification. The feature selection process reduced the number of bands to be processed in the database, but should not affect the classification accuracy (Jensen, 1996). Training site data were collected by means of on-screen selection of polygonal training data method. A total of 140 training sites was chosen for each image to ensure that all spectral classes constituting each land use and land cover category were adequately represented in the training statistics. The accuracy of the three classified maps was checked with a stratified random sampling method, by which 50 samples were selected for each land use and land cover category. The reference data was collected from field survey or from existing land use and cover maps that have been field-checked. Large-scale aerial photos were also employed as reference data in accuracy assessment when necessary.

In performing land use and land cover change detection, a cross-tabulation detection method was employed. A change matrix was produced. Quantitative areal data of the overall land use and land cover changes as well as gains and losses in each category between 1989 and 1997 can be compiled. The change matrix gives the knowledge of the main types of changes (directions) in the study area. In order to analyze the nature, rate, and location of land use and land cover changes, a set of 'gains' and 'losses' images for each category was also produced. These 'change' images was overlaid with an image of the county/city boundary, which was constructed in a vector GIS environment and converted into a raster format with the resolution of 30 meters. This GIS overlay intended to find land use and land cover change information within each county or city.

Markovian analysis of the land use/cover change process

Using land use and cover change data derived from satellite images, this study also establishes the validity of the Markov process for describing and projecting land use and cover changes in the delta, by examining statistical independence, Markovian compatibility, and stationarity of the data.

The testing of statistical independence hypothesis involves a procedure for comparing the expected numbers under the hypothesis with the actual data. If the number of land use and land cover categories is M, then the statistic to be computed is Karl Pearson's χ^2 with $(M-1)^2$ degrees of freedom. This statistic may be called K^2 to differentiate it from its distribution (χ^2). Letting N_{ik} stands for the number of cells having category i in 1989 and k in 1997, and $\mathbf{N_{ik}}$ for the expected number under the Markov hypothesis, the statistic is then

$$K^2=\sum_{i}\sum_{k}(N_{ik}-\mathbf{N_{ik}})^2/\mathbf{N_{ik}} \tag{5}$$

The 0·05 critical region for $M=7$ is thus any value of K^2 greater than 55·8. Any computed value of less than this critical number will lead to a conclusion that the data are compatible with the hypothesis of independence.

The computation of expected number $\mathbf{N_{ik}}$ requires a direct application of the Chapman–Kolmogorov equation (Parzen, 1962; Stewart, 1994). According to the Markov hypothesis, the transition probability matrix governing the period 1989–1997 can be obtained by multiplying the 1989–1994 and 1994–1997 matrices. These transition probabilities can be computed with the aid of the GIS analysis function, and used in the following formula to calculate the expected numbers:

$$\mathbf{N_{ik}}=\sum_{j}(N_{ij.})(N_{.jk})/N_{.j.} \tag{6}$$

where:

$N_{ij.}$ is the number of transitions from category i to j during the period 1989 to 1994;

$N_{.jk}$ is the number of transitions from category j to k during the period 1994 to 1997; and

$N_{.j.}$ is the number of hectares cells in category j in 1994.

To test for first-order Markovian dependence, a chi-square goodness-of-fit test is used. This statistical test judges whether or not a particular distribution adequately describes a set of observations by making a comparison between the actual number of observations and the expected number of observations. The statistic is calculated from the relationship:

$$\chi_c^2=\sum_{i}\sum_{k}(O_{ik}-E_{ik})^2/E_{ik} \tag{7}$$

where O_{ik} is the observed and E_{ik} the expected number of transition probability from 1989 to 1997. The distribution of E_{ik} is a Markovian distribution, however, the distribution of χ_c^2 is a chi-square distribution with $(m-p-1)^2$ degrees of freedom where m is the dimension of the matrices, and p is the number of parameters estimated from the data. The hypothesis that the data are from the Markovian distribution is rejected if

$$\chi_c^2 > \chi^2_{1-a,(m-p-1)2} \tag{8}$$

Finally, the hypothesis of stationarity is tested. The significance of stationarity of a Markovian process is that one can project future land development based on the current transition probabilities. According to the stationarity assumption, the changes recorded over the 5-year period from 1989 to 1994 and the 3-year period from the 1994 to 1997 result from the same transition mechanism. If so, then the 1989–1994 matrix can be used to predict the distribution of land use/cover categories in 1999, 2004, and so on, and the 1994–1997 matrix can be used to predict it to the year 2000, 2003, and so on. Indeed, they can both be used to project the distribution indefinitely into the future. The resulting equilibrium, or steady state distributions, may provide an indication of the ultimate trend of the land development process.

Results

Land use and land cover change in the Zhujiang Delta

The land use and land cover maps for 1989, 1994, and 1997 were produced from Landsat TM images and displayed in Figures 2–4 respectively. The overall accuracy of the land use/cover maps for 1989, 1994, and 1997 was determined to be 90·57 percent, 88·43 percent, and 85·43 percent respectively. The KAPPA indices for the 1989, 1994, and 1997 maps were 0·89, 0·86, and 0·83 respectively. Clearly, these data met the minimum standard of 85 percent stipulated by the USGS classification scheme (Anderson *et al.*, 1976). Overall, the user's and producer's accuracies were high. The accuracy is therefore sufficient for evaluation of land use and land cover changes.

Table 1 shows the land use and land cover change matrix from 1989 to 1997. From the table, it is clear that there has been a considerable change (12·82% of the total area) during the 8-year period. Urban or built-up land and horticulture farms have increased in area (by 47·68% and 88·66% respectively), and cropland has decreased in area (by 48·37%).

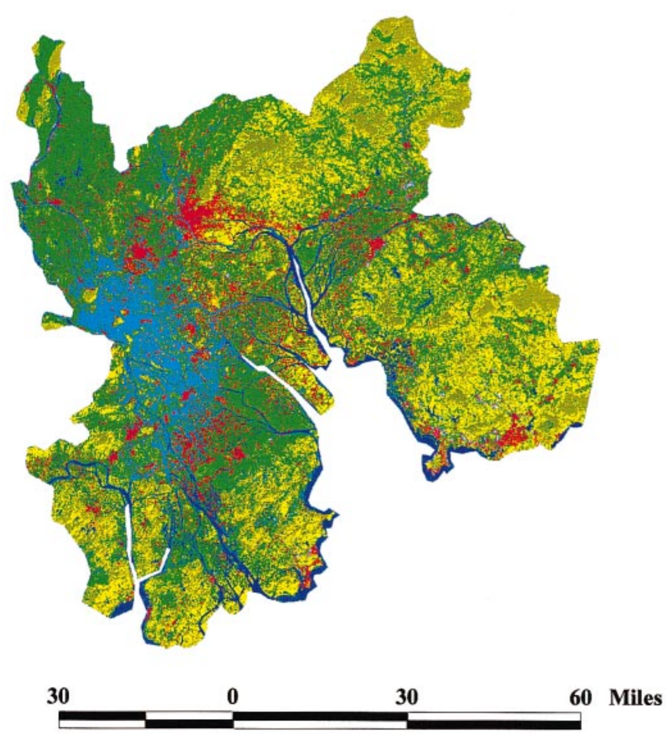

Figure 2. Land use and cover in the Zhujiang Delta, 1989.

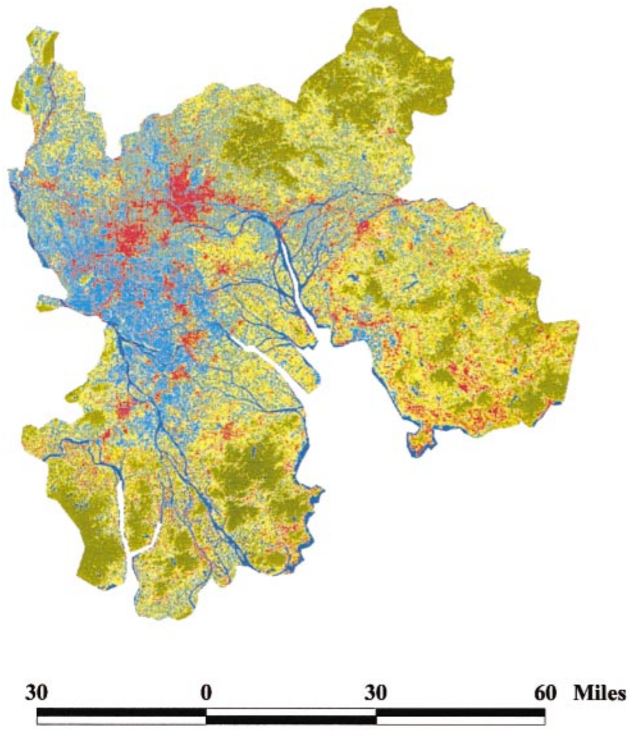

Figure 3. Land use and cover in the Zhujiang Delta, 1994.

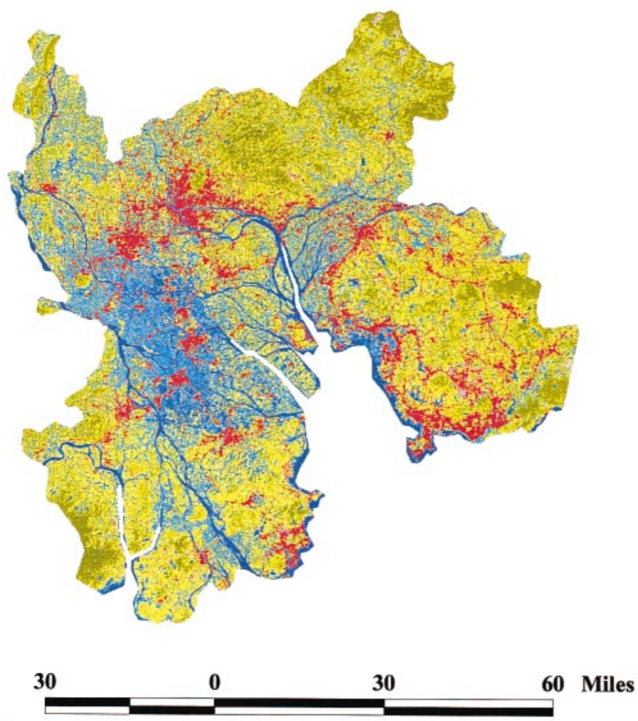

Figure 4. Land use and cover in the Zhujiang Delta, 1997.

The remote sensing-GIS analysis further indicates that of the 47·68 percent (65 690 hectares) increase in urban or built-up land, 37·92% results from cropland and 16·05% from horticulture farms. Barren land contributes 5·70% to the increase, totaling 11 603·4 hectares. The overlay

Table 1. Land use/cover change matrix, 1989–1997 (in hectares)

1989	1997							1989 Total
	Urban or built-up	Barren land	Cropland	Horticulture farms	Dike-pond land	Forest	Water	
Urban or built-up	54 189	493·38	20 890·8	35 816·8	15 887·4	3082·77	7407·36	137 768
Barren land	11 603·4	661·77	4156·02	8690·4	1285·47	1414·53	1293·75	29 105
Cropland	77 151·5	4651·11	152 400	215 536	55 272·7	44 497·1	29 258·4	578 767
Horticulture farms	32 660·8	3775·23	44 972·9	132 372	12 850·2	43 752·3	8222·22	278 605
Dike-pond land	14 902·8	321·03	33 931·4	20 238·6	42 489·7	2640·96	31 327·4	145 852
Forest	8378·64	3028·59	26 294·7	102 589	3906·72	128 048	5436·81	277 683
Water	4571·37	472·95	16 156·6	10 366·1	11 179·7	1845·09	64 414·3	109 006
1997 total	203 458	13 404	298 803	525 609	142 872	225 281	147 360	1 556 787
Change (ha)	65 690	−15 701	−279 964	247 004	−2980	−52 402	38 354	702 095
Change (%)	+47·68	−53·93	−48·37	+88·66	−0·02	−18·87	+3·19	12·82

of the urban expansion map with a city/county mask reveals the spatial occurrence of urban expansion within administrative regions. Table 2 shows that in absolute term the greatest urban expansion occurred in Dongguan (+23 478·90 ha), Bao'an (+14 941·08 ha), Nanhai (8004·1 ha), and Zhuhai (+5869·71 ha). However, in percentage term, the largest increase in urban or built-up land occurred in Zhuhai (1100·00%), followed by Shenzhen (306·65%), Bao'an (233·33%), and Dongguan (125·71%). Massive urban sprawl in these areas can be ascribed to rural urbanization, which is a common phenomenon in post-reform China. Rapid urban development in the form of small towns in the east side of the delta is highly influenced by the investment from Hong Kong (Yeh and Li, 1996). In contrast, old cities such as Guangzhou and Foshan, do not show a rapid increase in urban or built-up land because they have no land on which to expand further (as they have already expanded fully in the past) and the concentration of urban enterprises is in the city proper. Shenzhen and Zhuhai were designated as Special Economic Zones at the same time, but the pace of urbanization in the two cities has been quite different. Urban development in Shenzhen had largely been completed in the 1980s, while Zhuhai's urban expansion appears primarily during the period 1989–1997 (+5869·71 ha).

During the same period, cropland has decreased by 48·37% in the study area. The cross-tabulation of the 1989 and 1997 land use/cover maps reveals that most of the losses were converted to horticulture farms (215 536 ha) and to urban or built-up land (77 151·5 ha). The vast conversion of cropland to horticulture farms has much to do with a recent shift in agricultural production policy, in which

Table 2. Satellite-detected urban expansion and cropland loss in the Zhujiang Delta, 1989–1997

City/county	Urban change (ha)	Urban change (%)	Cropland change (ha)	Cropland change (%)
Baoan	14 941·08	233·33	−4268·90	−16·33
Dongguan	23 478·90	125·71	−62 965·90	−64·13
Doumen	1600·83	75·00	−6403·30	−28·57
Foshan	533·61	8·33	−3201·66	−85·71
Guangzhou	4802·50	20·45	−21 344·40	−47·62
Jiangmen	2134·44	133·33	−2134·44	−50·00
Nanhai	8004·10	60·00	−28 281·30	−50·96
Panyu	1067·22	14·29	−18 676·40	−52·24
Sanshui	0·00	0·00	−37 886·30	−54·62
Shenzhen	3219·12	306·65	−3201·66	−75·00
Shunde	3735·28	58·33	−2134·40	−13·33
Xinhui	1601·44	27·27	−22 411·60	−42·86
Zengcheng	0·00	0·00	−24 546·10	−47·92
Zhongshan	3201·60	24·00	−43 222·40	−58·27
Zhuhai	5869·71	1100·00	−4268·88	−61·54

cash crops such as fruit, vegetables, and flowers are highly advocated. A query regarding the location and dimension of the land use/cover change indicates that cropland loss occurred largely in three areas. A major cluster emerged in Sanshui and Nanhai, where the Beijiang River and Xijiang River converge to produce a vast area of fertile alluvial deposits. A second cluster appeared in the central part of Zhongshan. Field surveys indicate that sandy fields (*Sha Tian*) occupy this area, a major type of paddy soil that intensive agricultural activities have modified into a high yielding cropland. A third cluster of cropland loss was observed in the estuary of the East River, which had been the only major paddy cultivation region in the east side of the delta. These observations suggest that most of the cropland loss occurred in good-quality agricultural land. Therefore, the sustainability of agriculture is questionable given that this trend of land use and land cover change continues. The overlay of cropland loss map with a city mask makes it possible for generating the statistics of cropland loss found in each city/county (Table 2). These figures are useful for examining the relationship between cropland loss and socio-economic drivers of land use and land cover change.

Stability of the land use/cover change process

The transition probabilities governing the periods 1989–1994, 1994–1997, and 1989–1997 are calculated. Table 3 shows transitional probabilities (TPs) between 1989 and 1997. For instance, the TP from barren land to urban/built-up was 0·267; from cropland 0·1132; from horticultural farms 0·0897, and so forth. This computation is based on the actual number of observations in land use and land cover change during the same period regardless of the way that the change process occurred.

The expected TPs between 1989 and 1997 under the Markov hypothesis are also calculated and displayed in Table 4. They were obtained by multiplying the periods 1989–1994 and 1994–1997 matrices using Chapman–Kolmogorov. From Table 4, it is noted that the TP to urban/built-up from barren land would be 0·1735; from cropland 0·1225; and from horticultural farms 0·0972, if the land use and land cover change process was Markovian.

The computed value of the statistic K^2 is $1{\cdot}6425^{*}10^5$, much greater than 55·8. The hypothesis of statistical independence is therefore rejected. The land use and land cover change data are statistically dependent, but the question is whether this dependence can be characterized by first-order Markov dependence, or by a higher order dependence.

The computed value of χ^2_c is 0·5731. The degree of freedom is 36 since two parameters (μ_x and δ^2_x) are estimated from the normal distribution. For $\alpha = 0\cdot05$, the value of $\chi^2_{0\cdot9536}$ is 29·1. The hypothesis is thus accepted. In other words, it can be hypothesized that the data are generated by a Markov process at a risk of 5%.

Whether the land use and land cover change process in the delta has been stabilized is a more critical issue relating to land development policies. To answer this question, steady state probabilities in the three different periods are computed and compared (Table 5). These numbers show the probabilities that a land cell will be in the different categories at a sufficiently distant point in time. A short inspection of this table indicates

Table 3. Land use transitional probabilities, 1989–1997

1989	1997						
	Urban or built-up	Barren land	Cropland	Horticulture farms	Dike-pond land	Forest	Water
Urban or built-up	0·3454	0·0042	0·1607	0·2899	0·1101	0·0353	0·0545
Barren land	0·267	0·0195	0·183	0·3651	0·0505	0·0669	0·0481
Cropland	0·1132	0·0082	0·2579	0·3923	0·0864	0·0915	0·0505
Horticulture farms	0·0897	0·0126	0·157	0·479	0·0395	0·1894	0·0328
Dike-pond land	0·0982	0·0024	0·2335	0·1485	0·2754	0·0324	0·2096
Forest	0·0219	0·0078	0·0962	0·3674	0·0141	0·4695	0·023
Water	0·0077	0·001	0·027	0·0196	0·0198	0·0041	0·9206

Table 4. Expected values of land use/cover transitional probabilities under Markov hypothesis, 1989–1997

1989	1997						
	Urban or built-up	Barren land	Cropland	Horticulture farms	Dike-pond land	Forest	Water
Urban or built-up	0·2122	0·0120	0·1842	0·3334	0·0939	0·0851	0·0792
Barren land	0·1735	0·0121	0·1862	0·3817	0·0759	0·0983	0·0723
Cropland	0·1225	0·0089	0·2114	0·3723	0·0904	0·1134	0·0811
Horticulture farms	0·0972	0·0085	0·1761	0·3858	0·0602	0·2090	0·0633
Dike-pond land	0·1049	0·0062	0·2306	0·2475	0·1558	0·0709	0·1841
Forest	0·0441	0·0063	0·1357	0·3803	0·0328	0·3526	0·0484
Water	0·0145	0·0013	0·0339	0·0445	0·0207	0·0156	0·8696

Table 5. A comparison of steady state probabilities

	Urban or built-up	Barren land	Cropland	Horticulture farms	Dike-pond land	Forest	Water
1989–1997	0·0714	0·0058	0·1137	0·2419	0·0510	0·1176	0·3939
1989–1994	0·0817	0·0082	0·1327	0·2303	0·1055	0·3126	0·1317
1994–1997	0·0431	0·0032	0·0688	0·1226	0·0308	0·0446	0·6870

that the three distributions are distinctly different, implying the differences in transition mechanism. The 1994–1997 distribution is particularly different from the other two. As a result, the idea that the process is stationary may be rejected although this assumption has not been thoroughly tested as a hypothesis. However, if the three transition matrices are to continue in a stationary manner, the distribution of land use/cover categories can be projected for a remote future: 7·14% of the land will be urban or built-up, 0·58% will be barren land, 11·37% will be cropland, 24·19% will be horticulture farms, 5·1% will be dike-pond land, 11·76% will be forest, and 39·39% will be water.

Discussion and conclusions

This paper describes how the technologies of satellite remote sensing, GIS and stochastic modelling are combined to address land use and land cover changes in the Zhujiang Delta, China, during the period 1989–1997. It was found that urban or built-up land and horticulture farms have notably increased in area, while cropland has decreased. Urban land development was uneven in different parts of the delta, and was closely related to the loss of cropland. The land use development has not been stabilized, and the two study periods of time (1989–1994 and 1994–1997) had different transition mechanisms.

The use of Landsat TM data to detect land use and land cover changes has been generally a success. The digital image classification coupled with GIS has demonstrated its ability to provide comprehensive information on the direction, nature, rate, and location of land use and land cover changes as a result of rapid industrialization and urbanization. However, the issue of class uncertainties in image classification has not been examined in this paper. Although the land use and land cover maps have a reasonably high overall accuracy, the accuracy of different classes varies. The horticulture farms class was confused with several other classes due to their diversity. This confusion has hindered the obtainment of accurate TPs. Moreover. the image classification method used in this study was not spatially implicit. The method thus has a limitation in improving image classification accuracy for individual classes.

The Markov chain models have shown the capabilities of descriptive power and simple trend projection for land use and land cover change, regardless of whether or not the trend actually persists. The analysis can serve as an indicator of the direction and magnitude of change in the future as well as a quantitative description of change in the past. There are several limitations in land use and land cover change applications, however. First, these models are difficult to accommodate high-order effects. Baker (1989) suggests that these effects can be modeled by redefining the state space, so that new states are defined by both present and preceding states. A second-order model, for instance, would include m^2 states instead of m states in a first-order model. Second, the influence of exogenous and endogenous variables to the transitions, i.e. non-stationary transitions, cannot be incorporated into the models so that land use and land cover change processes can be understood. This limitation can be addressed by using one of the two approaches: setting TPs as a function of these variables (which can vary in both time and space), or switching between different stationary transition matrices (Baker, 1989). Finally, spatial dependence of transitions is not accounted for in simple constant-transition models. Turner (1987) shows a method to conditioning changes to the initial states in adjacent sites, in addition to conditioning changes in the initial states, and therefore introduces spatial dependence into Markov modelling.

The issue of obtaining observed TPs is crucial. Early Markov models were parameterized using data observed and measured from field surveys and air photography. These data tended to be biased and costly. The use of satellite remote sensing enables us to calculate less biased TPs from the full extent of the landscape (Hall *et al*., 1991; Paster and Johnson, 1992). In addition, remotely sensed data are cost-effective, multiple-date, and ready to input into GIS.

The ability of GIS to integrate spatial data from different sources, with different formats, structures, projections, or levels of resolution is especially useful in land use and land cover studies. Quantifying temporal change often involves using such sources as historical maps, air photos, and satellite images. Changes in the spatial distribution of land classes can be summarized by overlaying maps of different dates and analyzing their spatial coincidence. Changes from one land class to another can be mathematically described as probabilities that a given pixel will remain in the same state or be converted to another state (Johnson, 1993). The use of GIS with digitized maps provides more precision in determining TPs over different portions of the landscape at different times, removing many of the difficulties in early works of parameterizing Markov matrices (Johnson *et al*., 1996).

The integration of satellite remote sensing, GIS, and Markov modelling provides a means of moving the emphasis of land use and land cover change studies from patterns to processes. Data and computational limits are becoming less significant due to advances in remotes sensing for change detection and in the incorporation of remotely sensed data and auxiliary data into GIS (Baker, 1989). The most compelling research issues may be a lack of appreciation of the power of the integration and understanding of how to incorporate existing knowledge in useful models of land use and land cover change.

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