MONITORING LANDSCAPE CHANGES OF COASTAL ZONE USING MULTI-TEMPORAL REMOTE SENSING IMAGES

Jihn-Fa JAN (Taiwan)
Associate Professor, Department of Land Economics
National Chengchi University
64, Sec. 2, ZhiNan Road, Taipei 116, Taiwan
Telephone: +886-2-29393091 ext. 51647 Facsimile: +886-2-29390251
E-mail: jfjan@nccu.edu.tw
Yu-Ching HSU (Taiwan)
M.S., Department of Land Economics
National Chengchi University
64, Sec. 2, ZhiNan Road, Taipei 116, Taiwan
Telephone: +886-2-29393091 ext. 50621 Facsimile: +886-2-29390251
E-mail: 97257022@nccu.edu.tw
Chih-Da WU (Taiwan)
Postdoctoral Fellow, Research Center for Environmental Changes
Academia Sinica
128 Academia Road, Section 2, Nankang, Taipei, 115, Taiwan
Telephone: +886-2- 26539885 ext.860 Facsimile: +886-2-27833584
E-mail: chidawu@gate.sinica.edu.tw

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ABSTRACT: The coastal zone environment is easily affected by many natural and man-made factors, especially improper land use that result in rapid disappearance of coastal sand dunes. In this paper, by using three SPOT images acquired between 2003 and 2009, the change detection analysis of sand dunes and land use show temporal and spatial variability in the costal zone of I-Lan Plain, Taiwan. Based on the results of image classification, the land use/land cover changes and spatial variability was analyzed by using Fragstats, a software for landscape ecological studies. The objectives of this research include: (1) assessment of classification accuracy of two image classification methods; (2) analyzing spatial variability of land-use and sand dunes area; (3) developing a statistical model for illustrating the relationship between land use and changes of ecological environment of coastal zone. It is expected that the results of this study will provide the administration authority with solid scientific basis for strategic decision making on sustainable management of the coastal zones.

1. INTRODUCTIONS

Environmental changes are often resulted from land-use changes due to human activities. Therefore, it is necessary to investigate the status of land-use in order to understand possible factors that may influence the environment. Several landscape models have been developed to describe, explain, or predict landscape dynamics. For landscape studies, by measuring spatial configurations of patches on a landscape such as their density, size, shape, edge, diversity, interspersion, and juxtaposition, a variety of indices are often used to describe or assess the structural condition of a landscape (McGarigal and Marks, 1994). Moreover, these indices can be used to compare landscape patterns on different scale statistically (Hulshoff, 1995).

In recent years, due to rapid advancement of remote sensing technology, the availability and spatial/spectral resolution of remote sensing data had been greatly improved. As a result, remote sensing technology has become a very cost effective tool for large scale land use / land cover investigation as compared to traditional field investigation approach. The objective of this study was to investigate land use changes by using landscape indices derived from multi-temporal SPOT images.

2. MATERIALS AND METHODS

2.1 Study site

The study area selected for this research was part of I-Lan plain and costal zone located in north-eastern Taiwan, with a total of about 7,571 ha (Fig.1). Affected by human activities, topographic and climatic conditions, the main land use patterns of I-Lan plain are crop lands and aquiculture, and there are coastal forest and sand dunes in coastal zones.

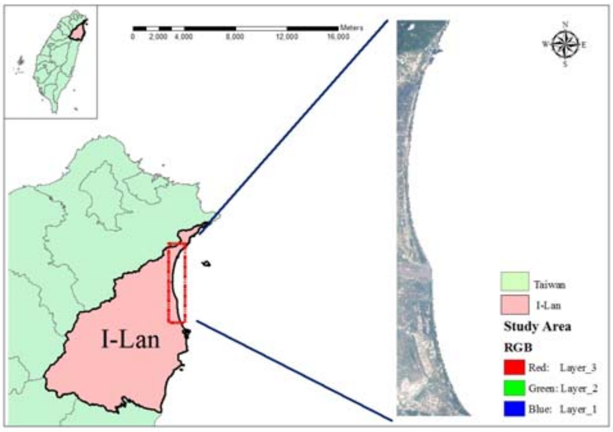

Fig.1. Location of the study area

2.2 Data

The remote sensing data used for this study included 3 SPOT 5 images acquired on 6/1/2003, 4/11/2006, and 5/29/2009, respectively (Fig. 2). The images were level 3 orthophotos with TWD97 (Taiwan Datum 1997) coordinate system, and atmospheric and spectral corrections were done by the provider. In addition, various ancillary data was used in the study, including DEM (digital elevation model), weather data, and vector data of land use, streams, roads, and administrative boundaries.

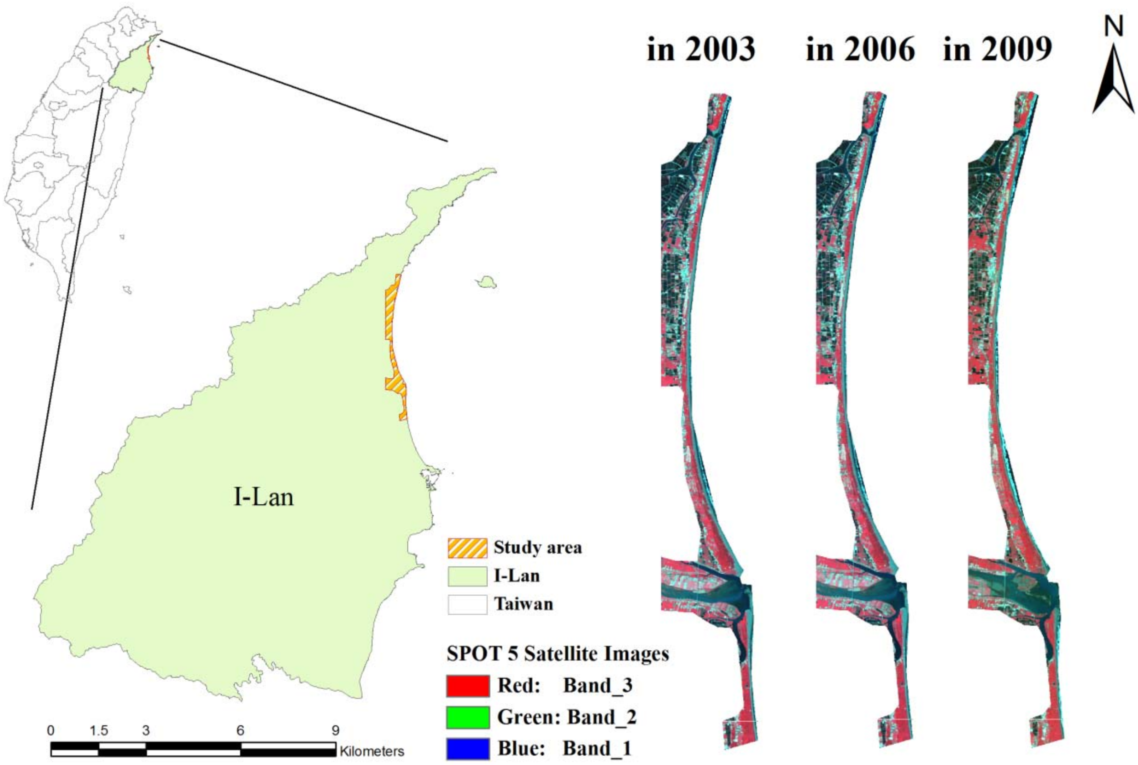

Fig. 2. SPOT images of the study area.

2.3 Methods

2.3.1 Land use/cover classification using stratified classification method

A post-classification comparison method was applied to understand the spatial patterns of land cover types in different time periods. Hierarchical classification approach was used to classify the image data (Jensen, 2004). First, supervised classification approach with maximum likelihood algorithm was used to classify the 2006 image data into five land use categories, which included water body, built-up area, cropland, sandy area, and forest land. The training areas and validation areas were selected by comparing the images with land use vector maps produced in 2006. Secondly, unsupervised classification approach was used to separate the costal forests from crop lands due to similar spectral signatures between these two land cover types. The same procedure was applied to classify the 2003 and 2009 image data. Figure 3 shows the classification results.

2.3.2 Logistic regression analysis on spatial distribution of sandy areas

In this research, we used binary logistic regression method to analyze possible factors that may contribute to land cover changes. Logistic regression is a form of regression that allows one to predict discrete outcome from a set of independent variables of any type, including continuous, discrete, dichotomous, or a mixture of any of these. Because logistic regression can be used to solve nonlinear problems, it has been applied in many different fields such as behavioral science, social science, educational science, landscape ecology, and epidemiology (Backer, 1989; Cheng et al., 2005).

A binary logistic regression (also called logistic model, or logit model) is denoted as:

$$\log it(p) = \log\left[\frac{p}{1-p}\right] = B_0 + B_1 X_1 + B_2 X_2 + \ldots B_n X_n \tag{1}$$

where B_0 is the intercept, B_n are the regression coefficients, X_n are the predictor variables, p is the probability of binomial response variable. The model is equivalent to the following:

$$p = \frac{e^{B_0 + B_1 X_1 + B_2 X_2 + \ldots B_n X_n}}{1 + e^{B_0 + B_1 X_1 + B_2 X_2 + \ldots B_n X_n}} \tag{2}$$

To estimate the probabilities of various land cover types changing to sandy area in I-Lan coastal zone, the response variable was the status of whether a land cover type was changed to sandy area by comparing the images of 2003 and 2006. In considering the topographic, environmental, and climatic factors, a total of 15 predictor variables were selected for this model, including elevation, slope, distance to roads, distance to stream, distance to embankment, distance to protection forest, precipitation, wind speeds of all four seasons, and wind directions of all four seasons. A stratified random sampling method was applied to select sample points for the analysis. Based on the classification results of 2003 image, 1% of each land cover type was chosen as sample pools. Then we selected 800 points from those changed from the other cover types to sandy area, and 800 points from those did not change to sandy area. Totally there were 1600 valid sample points. The binary logit model was used estimate the probability model of land cover changes in coastal zone.

3. RESULTS

3.1 Land-cover maps

The images were classified to five land cover types, including water body, built-up area, cropland, sandy area and forest land. Water body consists of river, aquaculture farms; built-up areas represent roads, transportation lands, buildings, grave land and barren land; and cropland are farmlands, either harvested or not. The land cover classification results are shown in Fig. 3. Table 1 shows the classification accuracy of various land cover types in the 2006 image. The overall classification accuracy was 93.6%, with a kappa statistics of 91.75%. The percentage of all five land cover types is depicted in Table 2. Based on the classification results, we observed that there is a tendency of increase in built-up areas, and decrease in cropland and sandy areas.

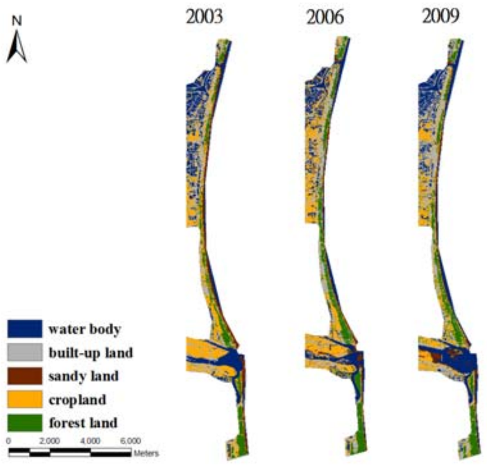

Fig. 3. Classification results of the study area.

Table 1. The confusion matrix of the classification result of 2006 image

	Water body	Built-up area	Sandy area	Cropland	Forest land	Total	Consumer's accuracy
Water body	533	5	0	0	0	538	99.07%
Built-up area	0	519	0	30	0	549	94.54%
Sandy area	13	26	181	0	0	220	82.27%
Cropland	0	50	0	530	11	591	89.68%
Forest land	0	1	0	6	314	321	97.82%
Total	546	601	181	566	325	2219	
Producer's accuracy	97.62%	86.36%	100%	93.64%	96.62%		
Overall accuracy		93.60%		**Kappa**	91.75%		

Table 2. Percentage of land cover types

Land cover type	2003	2006	2009
Water body	27.46%	24.01%	29.17%
Built-up area	24.34%	25.59%	28.29%
Sandy area	8.15%	7.23%	6.64%
Cropland	27.40%	26.76%	23.41%
Forest land	12.65%	16.41%	15.22%
Total	100%	100%	100%

3.2 Logit model of the spatial distribution of sandy areas in the coastal zone

The logit model derived from the sample data is as follows:

$$\log it\,(p) = 11.1725 - 0.4305 \times \mathrm{B}_1 + 0.0009 \times B_2 - 0.0049 \times B_3 + 0.0018 \times B_4 + 55.0056 \times B_5 - 25.2362 \times B_6 - 9.0171 \times B_7 + 0.2379 \times B_8 \quad (3)$$

The predictor variables included elevation, distance to embankment, distance to stream, distance to protection forest, wind speed in fall, wind speed in winter, wind direction in winter, and slope. The logit model of sandy areas distribution between 2003 and 006 is shown in Table 3. The Waldχ^2 and p-value show that these factors have significant effects on the spatial distribution of sandy areas in the coastal zone.

Table 3. The logit model of sandy areas distribution between 2003 and 006

Predictor variables	Regression coefficients	Wald χ^2	Pr.$>\chi^2$
Iintercept	11.1725	45.1913	0.0001
Elevation	-0.4305	97.2758	0.0001
Distance to embankment	0.0009	52.8008	0.0001
Distance to stream	-0.0049	70.0173	0.0001
Distance to protection forest	0.0018	6.1519	0.0001
Wind speed in fall	55.0056	79.8379	0.0001
Wind speed in winter	-25.2362	65.9785	0.0001
Wind direction in winter	-9.0171	88.2118	0.0001
Slope	0.2379	52.5402	0.0001

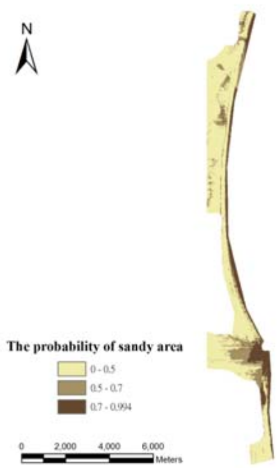

Fig. 4. Probability distribution of sandy area

The Spatial Analyst of ArcGIS was used to derive the probability distribution map of the coastal zone, which is shown in Fig. 4. The cell values are between 0 and 1, which represent the probability of being sandy area. The map shows that the areas with high probability (higher than 0.5) coincide with the sandy areas in the coastal zone. Furthermore, by comparing the classification results of 2006 and 2009 images, we can evaluate the prediction accuracy of the logit model. Figure 5 shows the predicted probability distribution map using data of 2006. Table 4 shows the validation results. By examining the 2006 and 2009 maps, the prediction accuracy is above 80% if we choose 0.5 as the probability threshold of changing to sandy area. In the distribution map of 2009, there was more than 75% of sandy area fell in the area with predicted probability higher than 0.5. Overall, the estimation accuracy was acceptable.

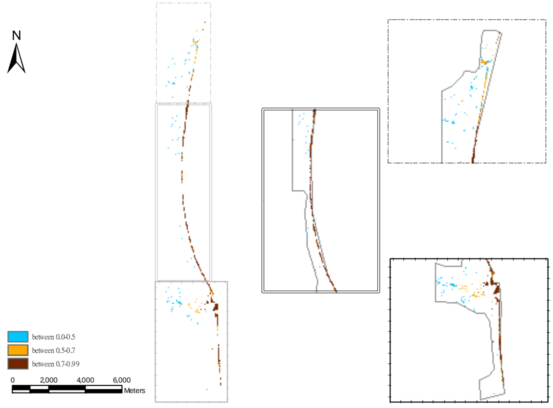

Table 4. The validation results

Predicted probability	**0.0-0.5**	**0.5-0.994**
Percentage of sandy area in 2006	19.9%	80.1%
Percentage of sandy area in 2009	25.1%	74.9%

Fig. 5. Predicted distribution using 2006 data

4. CONCLUSIONS

The results of this study show that the image classification process yielded quite acceptable classification accuracy, and the logit model was able to predict land cover changes in costal zone with accuracy over 80%. In this study we selected 15 predictor variables, which represent topographic, environmental, and climatic factors. However, land cover changes may also be affected by some other factors such as population distribution, the amount of tourists, and development of industrial areas. Further study will incorporate more predictor variables in order to improve the accuracy of prediction.

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6. LITERATURE CITED

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