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Original article

Predicting Land Use Change Affected by Population Growth by Integrating Logistic Regression, Markov Chain and Cellular Automata Models

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Abstract

Demographic change was considered to be the most major driver of land use change although there were several interacting factors involved, especially in the developing countries. This paper presents an approach to predict the future land use change using a hybrid model. A hybrid model consisting of logistic regression model, Markov chain (MC), and cellular automata (CA) was designed to improve the performance of the standard logistic regression model. Experiment was conducted in Giao Thuy district, Nam Dinh Province, Vietnam. Demography and socio-economic variables dealing with urban sprawl were used to create a probability surface of spatio-temporal states of built-up land use for the years 2009, 2019, and 2029. The predicted land use maps for the years 2019 and 2029 show substantial urban development in the area, much of which are located in areas sensitive to source protections. It also showed that aquacultural land changes substantially in areas where are in the vicinity of estuary or near the sea dike. There was considerable variation between the communes; notably, communes with higher household density and higher proportion of people in working age have larger increases in aquacultural areas. The results of the analysis can provide valuable information for local planners and policy makers, assisting their efforts in constructing alternative sustainable urban development schemes and environmental management strategies.

Keywords: Land Use Change, Population Growth, Logistic Regression, Markov Chain, Cellular Automata, Giao Thuy District

1. Introduction

The intensity of land use change in response to world population growth and its consequences for the environment warrant in-depth studies of these transformations (Wu *et al*., 2006). Land is an important and finite resource for most human activities such as settlement, agriculture, forestry, animal husbandry, industry, transportation and recreation. It has been tightly coupled with economic growth (Richards, 1990). One of the six possible forces driving land-use and land-cover changes is population increase and its level of affluence, technology, political economy, political structure, and attitudes and values (Meyer and Turner, 1992). An increase in population arises a sequence of immediate life sustaining needs such as residence space, food and fiber. However, due to the finite amount of available land, fast economic development and population growth lead to deforestation and loss of arable land and biodiversity, and reduction of environmental services (Lambin *et al*., 2001).

In recent years, the Land use/Land cover (LULC) change community has produced a large set of operational models that can be used to predict or explore possible land use change trajectories (Verburg *et al*., 2006). The models can be useful tools to understand the exploration of future land use

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dynamic under different scenario conditions. Furthermore, scenario analysis with land use models can also support land use planning and policy. Logistic regression (McCullagh and Nelder, 1989) analysis has been one of the most frequently utilised approaches during the past two decades for predictive land use modelling by means of variation of inductive modelling. Thereby, it is crucial to consider spatial effects, namely spatial autocorrelation and spatial heterogeneity, to challenge regression assumptions (Anselin, 1988; Fotheringham *et al*., 2000). However, the logistic regression model suffers from the quantification of change and temporal analysis (Hu and Lo, 2007). Thus, empirical estimation and dynamic simulation models have been used to simulate land use change. Various types of rule-based modelling, for instance cellular automata (CA), are most appropriate for incorporating spatial interaction effects and the treatment of temporal dynamics. CA models focus on the simulation of spatial patterning rather than on the interpretation of spatiotemporal processes of urban sprawl, there is a deficiency of incorporation among dynamic simulation models and socio-economic and demographic variables (Hu and Lo, 2007). Due to limitations of each individual modelling technique (Poelmans and Van Rompaey, 2009) proposed a hybrid approach based on logistic regression coupled with CA transition rules, which results in an improved model quality, nevertheless, their model was not able to quantify the amount of land use change.

A need for spatial models of land use change was therefore identified (Mertens and Lambin, 1997). Arsanjani *et al.* (2013) integrated CA, logistic regression, and Markov chain (MC) models in order to produce temporal outputs from the logistic regression model in Tehran, Iran. Various environmental and socio-economic variables were taken into account to create a probability surface of spatiotemporal states of built-up land use for the years 2006, 2016, and 2026. However, the set of specific factors could be different in other areas due to the differences in environmental and socioeconomic conditions. For instance, Tehran, the capital of Iran, is the most populous city in Iran and Western Asia with 8.8 million in the city and 15 million in its larger metropolitan area (CityMayors, 2006). While, Giao Thuy is a rural district located in coastal of Vietnam, a developing country, where population has grown exponentially in the past decades. About 85% of the population lives in rural areas and depends on subsistence agriculture for their livelihoods. The average population density in the region is 814 persons per square km in long period. According to statistical data reported by Nam Dinh statistical Office, the main factors leading to land use change in Giao Thuy district, Nam Dinh province, Vietnam could include households density, the proportion of people in working age, and distance to the sea dike. Those factors were different from those of (Arsanjani *et al*., 2013). Therefore, this study attempted to apply the integration of CA, logistic regression, and MC models to simulate the landuse change in Giao Thuy district through the relationship with the variables related to population and socioeconomic conditions.

2. Study Site and Data

Giao Thuy is a rural district (belong to Balat estuary) (see Fig. 1) located in Nam Dinh Province in the Red River Delta in Vietnam. In 2003, population of the district was 207,273. The district covers an area of 166 km² and has a central town named Ngo Dong. Besides, this district included 20 communes and a small town. Giao Thuy district has the Xuan Thuy Natural Wetland Reserve, which is the only Ramsar site in Vietnam (Halls, 1997). In 1988, 120 km² of mangroves were designated for inclusion for a reserve.

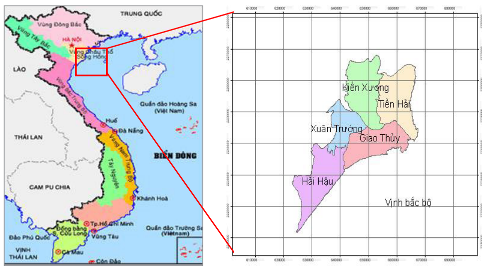

Fig. 1. Red River Delta and the Giao Thuy study area, Vietnam

3. Material, Data Sources and Methodology

3.1 Materials and data sources

The satellite images and demographical data are necessary for this research. In this study, the satellite images used for extracting land use maps includes: Landsat 5 Thematic

Mapper (TM) images of 1989, 1999, and 2009 provided by United States Geological Survey (USGS). The following Table 1 shows the details of satellite images with acquired time and resolution. The demographical data reported in 2000 and 2011 was provided by Nam Dinh statistical Office (see Table 2). Additionally, a topographic map (scale of 1:25,000) established by the Vietnamese Ministry of Natural Resources and Environment (MONRE) in 2015 was used.

Table 1. List of Landsat data with acquired time and resolution (Source: USGS)

Sensor	Path/Row	Acquired Date	Local time	Resolution (m)
TM	126/046	23 November 1989	9h41'	30
TM	126/046	18 October1999	9h54'	30
TM	126/046	27 September 2009	10h07'	30

Table 2. Demographical data (Source: the report of Nam Dinh statistical Office)

Year	Population (persons)	Number of households	The proportion of people in working age (%)
1989	164,107	38,160	52.2
1999	194,635	47,471	54.4
2009	188,903	56,164	67.7

3.2 Methodology

3.2.1 LULC classification

Land use maps of Giao Thuy in 1989, 1999, and 2009 were generated from LANDSAT 5 TM images acquired in the aforementioned years. Image pre-processing removed distortions, precision and corrected terrain data (Level 1T) using the Universal Transverse Mercator (UTM) projection and WGS 84 datum (Zone 48, North). The 1989, and 1999 images were geo-referenced to the 2009 one. Prior to segmentation in eCognition Developer software, the quality of the images was improved using spectral enhancement.

An object-based approach was used to produce LULC map with 8 classes: Agricultural land, Water, Aquacultural land, Mangrove, Sedge-land, Open land, Built-up land, and Salt-land. As LULC spatial data became more widely available (either for sale or for free), such data (e.g. LANDSAT satellite images) could be more extensively used in developing countries (Yagoub and Bizreh, 2014). This study followed the following steps to achieve the object based image classification: 1. Segmentation; 2. Classification; 3. Accuracy assessment.

Firstly, the multi-resolution (MR) segmentation algorithm available in eCognition Developer 8.7 software (Trimble, 2011) was carried out. Parameters for the segmentation include scale, shape ratio, and compactness/smoothness ratio was examined at different values. “Scale” is one of the important criteria in segmentation process. Scale value directly affects the size of the segmentation objects. Shape ratio value refers to the form and the structure of individual objects. The change in the shape ratio optimizes the spectral or spatial homogeneity of the resulting segmentation. While, “smoothness” is defined as the ratio of an object’s perimeter to the perimeter of this object’s boundaries that run parallel to the image borders; “compactness” is the ratio of an object’s perimeter to the square root of the number of pixels within that image object. We hereby chose this segmentation as the most appropriate for the purpose of our work. In segmenting these images, the spatial and spectral characteristics of the image pixels were considered. The segmentations of this study were conducted at a scale of 10, color/shape ratio (0.8/0.2), and compactness/smoothness ratio (0.5/0.5).

The second step in the object-oriented method was to classify image objects. The classification stage was done using the segmented image in association with the training data (class signatures) to achieve a good classification of the land cover pattern of the study area. The water in these categories is the most different in spectral with others, especially in near infrared channel. Therefore, water was extracted based on band #3 and #5 of Landsat TM. After that, the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) were used to establish a high quality rule-set for mangrove and built up land. Information on image bands, image reflectance, and the relationships between neighbouring objects is required to develop a highly accurate rule-set. To improve the accuracy of the classification, manual editing was carried out.

Finally, to assess the accuracy of the classified maps, the ground truth data was used. The classification accuracy is achieved by comparing the ground truth data points with the classified images, points were sampled along roads, focusing on typical land-cover types in the region. The degree of agreement of the classified image position and the ground truth data points provides the classification accuracy of the image classification process. The accuracy of the resulting maps is based on 98 ground control points taken from high-resolution Google Earth images and fieldwork. The Kappa coefficient, which is calculated according to the Congalton formula (Congalton, 1991), deals with the experiment between the remote sensing data and the in-situ observation.

3.2.2 LULC change prediction

The overall method used for change prediction in this study was illustrated in Fig. 2. The method integrated CA, logistic regression, and MC models to predict changes. The details of the processing phases were as follows:

Logistic regression model is a regression model which covers the case of binary dependent variables (i.e. it can only take value of "0" and "1") (McCullagh and Nelder, 1989). Logistic regression model was used to associate the urban growth with demographic, econometric and biophysical driving forces and to generate an urban expansion probability map. In a raster GIS modelling environment, the data layers are tessellated to form a grid of cells. The nature of the LULC of a cell is dichotomous: either the presence of urban growth or absence of urban growth. The dependent variable predicted by a logistic regression model is a function of the probability that a particular theme will be in one of the categories (Huang *et al*., 2009).

Markov chain model: The MC model is a stochastic process that satisfies the Markov property (Rozanov, 1982), this can predict how likely one state is to change to another state. Its key-descriptive tool is the transition probability matrix (Jamal, 2012). A *transition probability matrix* (P) of LULC during interested period indicates the transition probability (p_{ij}) that each pixel of LULC transformed from class i to j. The transition probability then is used for projecting LULC in the future: the distribution of each LULC class at time $t + 1$ was projected forward using the LULC distribution at the beginning time t and the transition probability matrix P, as follows:

$$p_{ij} = \frac{n_{ij}}{n_i} \tag{1}$$

$$\sum_{j=1}^{k} p_{ij}=1 \tag{2}$$

$$P \times M_i = M_{i+1} \tag{3}$$

where n_i is the total number of pixels of class i transformed during interested period; n_{ij} is the number of pixels transformed from class i to j; k is the number of LULC classes; P is transition probability matrix; M_t is the distribution of each LULC class at time t.

The Markov transition matrix is used to determine the relevant years for the assessment process (in this study they are 2019 and 2029). The LULC map of existing land use in 2009 was produced by calculating data recorded between 1989 and 1999. The predicted land use map for 2019 and 2029 are based on measured data of the 1989, 1999 to 2009 period. However, MC is not a spatially explicit model; therefore, it is not an appropriate model to estimate the location of change, which needs to be integrated with other spatial models.

Cellular Automata uses proximity concept to triggers LULC dynamics: a cell closers to present land cover of the same class have a higher probability to change to a different class. Four CA components are cell, states, neighborhoods, and rules (Verburg *et al*., 2004). Rules define cell states in the future step. The transition of a cell from a land cover to another depends on the neighborhood cell states.

In this study, the Logistic-Markov–CA model was performed using IDRISI Selva® software, version 17.0. This software allows simulating suitability maps for the predicted land use and requires land use maps and transition probability matrices (Schneider and Pontius, 2001). We used cross tabulation of two images of different time to produce transition probability matrix. IDIRISI CA-Markov module then operates 5x5 contiguity filter to estimate the neighborhood pixels predicting LULCC from time period two to a later time period (Fig. 2). Variables of the logistic regression-Markov-CA model were shown in Table 3.

A suite of six potential explanatory variables denoted by X_i (i = 1, 2, ···, 6) (see Table 3) were selected a priori based on existing theories of land use causes, fieldwork experience, data availability and literature review on relationship between land use change and natural and anthropogenic factors (Ivan and Kabrda, 2007; Lambin *et al*., 2001; Geist and Lambin, 2002; Huang and Hsiech, 2012). The binary output values (i.e. value of "0" and "1") represent the state of no change (0) or change (1) of the LULC for three period 1989-1999, 1999-2009 and 1989-2009 were denoted by Y_i (i = 1, 2, 3).

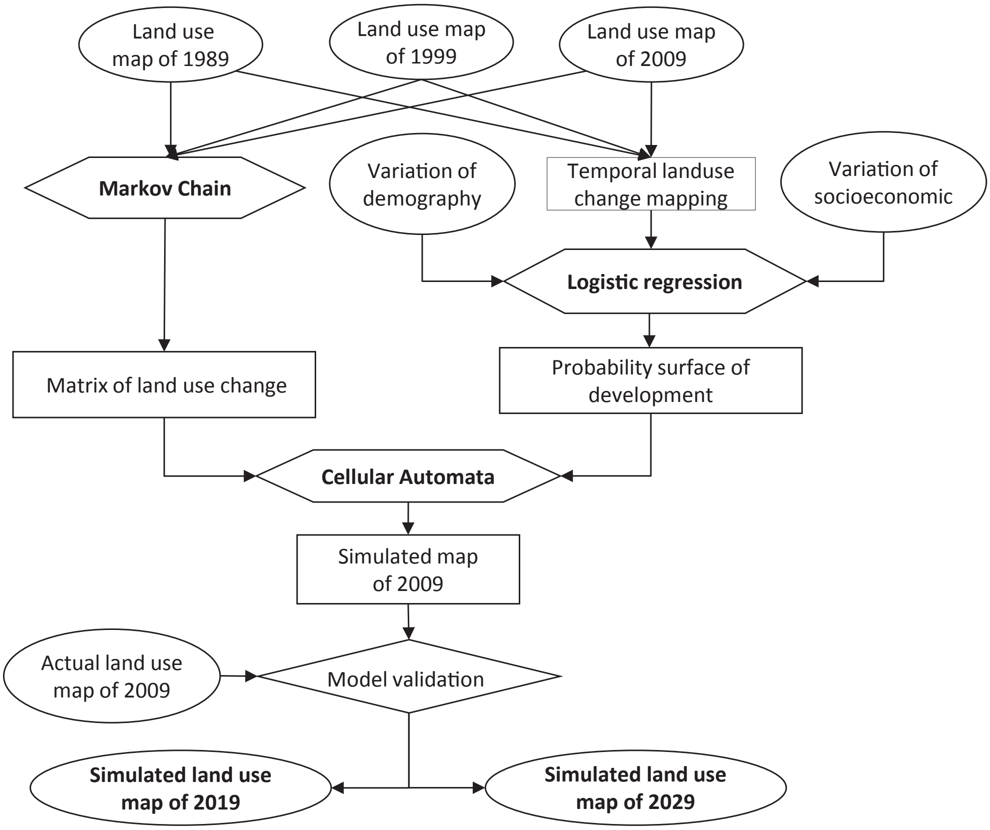

Fig. 2. Flowchart of the experimental method

Table 3. List of variables included in the Logistic regression-Markov-CA model

Variable	Meaning	Nature of variable
Dependent Y_1 (1989-1999) Y_2 (1999-2009) Y_3 (1989-2009)	0 – no change; 1 – change	Dichotomous
Independent		
X_1	Population density (person/km^2)	Continuous
X_2	Households density (Number of households /km^2)	Continuous
X_3	The proportion of people in working age (% person/km^2)	Continuous
X_4	Distance to active economic centers (km)	Continuous
X_5	Distance to the nearest major road (km)	Continuous
X_6	Distance to the sea dike (km)	Continuous

4. Results

4.1 Land use/ Land cover change

Using the method described in Section *3.2.1 LULC classification*, the LULC maps were obtained as shown in Fig. 3. The Kappa coefficient for quality assessment of LULC classification for the years 1989, 1999, and 2009 are 71,88%, 78,54% and 80%, respectively, these show a high accuracy in LULC classification. The LULC maps can provide further insights about land use change trends and rates. The results revealed land use change history and quantity of change in each LULC class. The main land use in the area (represented in the 1989, 1999, and 2009 maps) was agriculture followed by water, and built-up areas with total 86,6%. Areas of land used for agriculture decreased more than 3% and water decreased more than 7% of its original level at the first stage.

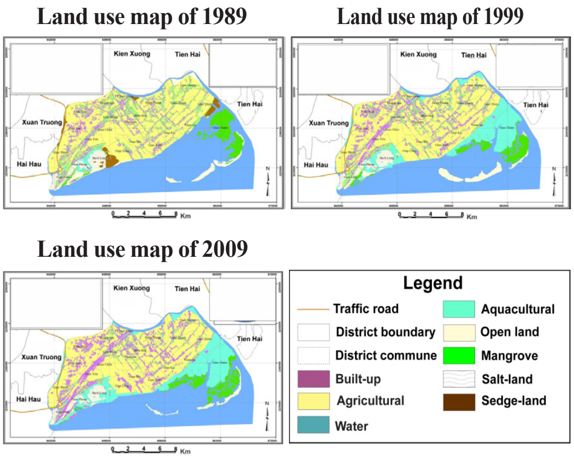

Fig. 3. Extracted land use maps of 1989 (upper left), 1999 (upper right), and 2009 (lower)

Meanwhile, built-up areas increased about 2.5% from 1989 to 2009.

According to the Table 4, aquacultural land increased dramatically from 0.95% in 1989 to 12.6% in 2009. The built-up area also rose significantly. The reason could be due to the booming of tourism and recreation business in the area due to acceleration in the rate of summer resort establishment at the coast provided more job opportunities for the local inhabitants. The sources of income from new jobs enhanced the standards of living of the local communities.

4.2 Quantification of future changes

Fig. 4 showed the output product of the logistic regression model, which is a probability surface maps indicating development of aquacultural and urban area. The probability surface shows level of development of a cell by a particular amount of probability (1 = high probability, 0 = low probability). In fact, there were total of 32 probability maps obtained from the logistic regression model for period 1989-1999 and 1999-2009. Fig. 4 only illustrated some examples, which show high probability of change from some classes to built-up or aquacultural land.

The results (i.e. transition probability surface maps, matrices) were used for further change analysis and determining the estimated quantity of change that is assumed to be an input for the CA model. In this investigation, logistic regression and CA models were chosen to spatialize the estimated change quantity. The final simulated land use map for 2019 and 2029 was demonstrated in Table 5 and Fig. 5. The area differences between the simulated land use map of

Table 4. Quantity of land use change over time in terms of hectare and percentage of each category

Year / Category	1989		1999		2009		1989-1999	1999-2009	1989-2009
	Ha	%	Ha	%	Ha	%	Ha	Ha	Ha
Built-up	4525	16.2	4792	17.1	5239	18.7	+267	+447	+714
Agricultural	9415	33.7	9200	32.9	8578	30.6	-215	-622	-837
Water	10256	36.7	8188	29.3	8491	30.4	-2048	+303	-1745
Mangrove	1304	4.7	1039	3.7	1174	4.2	-265	+135	-130
Aquacultural	248	0.9	3208	11.6	3528	12.6	+2960	+320	+3280
Salt-land	728	2.6	682	2.4	648	2.3	-46	-34	-80
Open land	884	3.2	764	2.7	314	1.2	-120	-450	-570
Sedge-land	600	2.1	87	0.3	8	0.0	-513	+79	-434

2019 and 2029 by classes were computed and illustrated in Fig. 6. According to Fig. 6, from 2019 to 2029, build-up and aquacultural land will increase significantly, whereas area of water and agriculture will reduce. This is suitable to the development planning of the local government.

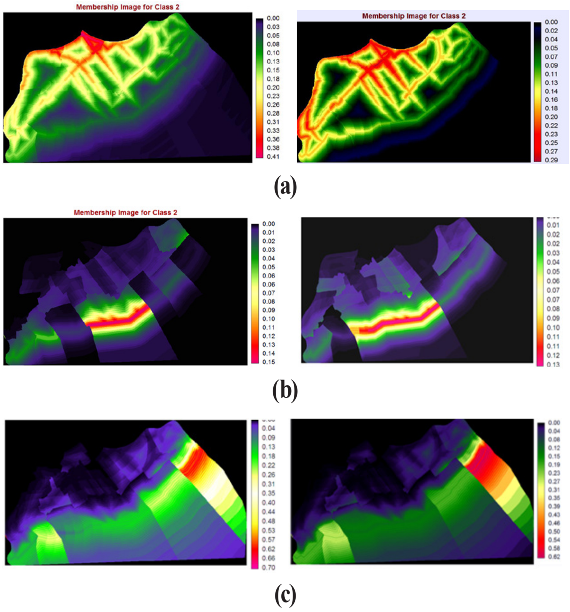

Fig. 4. Predicted transition probability of change for period 1989-1999 (left) and 1999-2009 (right): (a) from agricultural land to built-up land, (b) from agricultural land to aquacultural land, (c) from mangrove land to aquacultural land

Table 5. Quantity of land use through the Markov chain model for 2019 and 2029 in hectare

Category Year	Built-up (ha)	Agricultural (ha)	Water (ha)	Mangrove (ha)	Aquacultural (ha)	Salt-land (ha)	Open land (ha)	Sedge-land (ha)
2019	6105	7731	7930	1207	4508	302	177	0
2029	6834	7146	6118	1301	5843	211	107	0

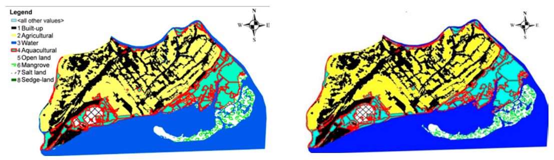

Fig. 5. Simulated land use maps of 2019 (left) and 2029 (right) through the Logistic-Markov-CA approach

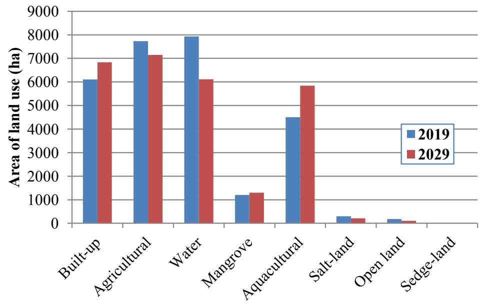

Fig. 6. The area difference between simulated land use classes of 2019 and 2029

4.3 Model validation

In order to validate the obtained model, the probability map of change for 1999 was utilised to allocate the attained quantity of change through the customised CA function. Then the land use map of 2009 was simulated and compared with the actual map of 2009. Comparison of the 2009 LULC map to the predicted one obtained from Logistic-Markov-CA method (Table 6) revealed a good agreement between the two maps with an overall accuracy above 79% and overall kappa exceeding 0.78. The results indicated that the Logistic-Markov-CA model was successful in predicting the LULC in 2009. This indicates that the model can be reliably used to predict future land use change in the area given the assumption of stable rates of change.

Table 6. Assessment of the agreement between predicted and actual LULC in 2009 (BU = Built-up, AGR = Agricultural, WT = Water, AQ = Aquacultural, OP = Open land, MAG = Mangrove, SA = Salt land, SEG = Sedge land)

	BU	AGR	WT	AQ	OP	MAG	SA	SEG
Producer's accuracy	0.69	0.89	0.82	0.80	0.73	0.74	0.87	1.00
User's accuracy	0.78	0.81	0.85	0.86	0.76	0.77	0.84	0.65
Overall Kappa	0.7812							
Overall accuracy	0.7915							

5. Discussion and conclusions

As shown in Table 4 and 5, after 2009, the land use change trend is agricultural, open land, sedge-land and water land area decreased significantly. The maximum rate of reduction is still sedge-land, it is nearly 0% in 2009. However, aquacultural, and built-up land are increasing year by year. The growth of built-up land and aquacultural area is the biggest with 714 and 3280 ha, respectively. This change will persist for long time, until it reaches a relatively steady state.

During the period 1989 and 2009 the most stable LULC class was the salt-land with around 2.5% of total area. The most dynamic LULC class with the lowest transition persistence was the mangrove area. Due to, there was a conflict between two classes mangrove and aquaculture in Giao Thuy. In recent years, mangroves are subjected to various changes of management, resulting in large-scale shrimp farming and illegal logging. The human impact on mangroves threatens not only the natural protection of the coast, but also deprives the area of a natural habitat of birds and other wild life species. The environmental consequences are felt in the rapid decline of the mangrove forests in Nam Dinh: of the estimated 8,400 ha mangrove area only 50 percent is still covered by various species of plants (Kleinen, 2003).

The prediction of potential distribution of the LULC classes in 2019, and 2029 (see Figs. 5 and 6) shows expansion in aquaculture, and mangrove. It also shows increases in quarries and growth in the residential centers in the area, especially in Quat Lam town as well as an increase in the resorts area on the coastal dunes. The consequence of the current trend of land use change due to developmental activities was likely the deterioration of natural landcover. Thus, the pressure on these areas will grow on agricultural land, salt-land and the open-land near human settlements are likely to become prime targets for change in the future.

In this study, the three techniques were combined for the following purposes: firstly, the logistic regression model was utilised to create a probability surface and to determine the most probable sites for development; secondly, the MC model was used to retrieve the quantity of change. Because land development policy has been inconsistent in recent years population growth and land development rates are impossible to synchronise. Thirdly, the CA model is a significant tool to allocate probable changes under predefined conditional rules. This CA model allocated the amount of change, beginning with the cells of highest probability. Therefore, the approach is capable of predicting the most probable sites for development, estimating the likely amount of change as well as allocating the estimated quantity within the study area.

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