Dynamic simulation of land-use changes in a periurban agricultural system

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Studying the driving forces of land-use change dynamics (LUCD) is important for understanding the change process. A spatially explicit simulation model helps to test hypotheses about landscape evolution under several scenarios. This paper presents a dynamic simulation model of land-use change (LUC) of the Nong Chok area in Central Thailand. Simulation of LUCD has been performed integrating remote sensing, geographic information systems (GIS), and the dynamic simulation toolkit. The model is a cellular automata model that has been developed on the basis of selected spatial and human driving forces. This study was conceived for the simulation of LUC, in particular, from paddy fields to fishponds. The model was run for 19 years from 1981 to 2000. Data describing present and historic land-use patterns were derived from aerial photographs. Transition functions were developed using the ID3 algorithm of the LUC data sets. The model uses as its input a land-use map (1981) and spatial and human variables: distance to canal and age, ownership, religion, education, and family size of the farmers. The results of the simulation showed substantial ability of the model to diffuse fishponds. To validate this spatial simulation model of LUCD, the simulated maps were compared with the reference land-use maps using a set of landscape indices: number of fishpond cells, patch density, mean patch size, edge density, fractal dimension, and mean nearest neighborhood.

Change is a continuous process, but learning is optional. Resources, ecosystem, biophysical environment, and land use/cover on the surface of Earth undergo changes over time. Land cover is the layer of soil and biomass, including natural vegetation, crops, and manmade infrastructure that cover the land surface, whereas land use is the purpose for which humans exploit the land cover. Land-use change is the modification in the purpose of the land, which is not necessarily only the change in land cover but also changes in intensity and management. Land-use and land-cover change are critical issues because of their large influence on agricultural diversification, land quality and productivity, nutrient use, soil/nutrient fluxes, water resources, labor allocation, and impact on human life. Because of their enormous impact and implications, the International Geosphere-Biosphere Program (IGBP) and the International Human Dimension Program (IHDP) started a joint international program of study on land use/cover change (LUCC) (Geoghegan et al 2001). They recognized the need to improve understanding, modeling, and projections of land-use dynamics from the global to regional scale and focusing particularly on the spatial explicitness of the processes and outcomes.

The spatial setting of landscape elements is characterized by the combination of both biophysical and human forces (Fernandez et al 1992). In temporal scales of decades, human activities are basic factors in shaping land-use change. Some of these changes are due to specific management practices and the rest are due to social, political, and economic forces that control land uses (Medley et al 1995). Spatial simulation of land-use change is very important for monitoring and understanding the composition and configuration of the change process, and for observing the behavior of the actors and the interaction between system dynamics and actors and bio-geographical phenomena of the area under investigation. The purpose of LUC simulation modeling is to describe, explain, predict, assess impact, and evaluate hypotheses (Briassoulis 2000). To have a better understanding of landscape evolution, researchers have focused on developing dynamic simulation models (Wang and Zhang 2001, Britaldo et al 2002, Veldkamp and Fresco 1996, Gilruth et al 1995, Wu 1998, Verburg et al 2000, Soepboer 2001). In the arena of simulation modeling, one of the promising approaches to simulate and analyze LUCC is the multi-agent systems (MAS) model of land-use and land-cover change (Parker et al 2003).

During the last few decades, Thailand has undergone rapid urbanization and tremendous economic boom. These changes have rapidly transformed Thailand from a subsistence agrarian economy into a rapidly industrializing country. Most of the economic development activities are concentrated in and around the Bangkok metropolitan area. The growing urbanization in the urban fringe of Bangkok has created pressure for changes in land-use pattern. Nong Chok is on the outskirts of Bangkok. This area has experienced sharp changes in land use during recent years. Farmers have changed their land use from rice production to shrimp and other aquaculture because of the large demand for fish in the market. It is reported that the Department of Fisheries first promoted fish culture in rice fields in the 1950s in the Central Plain of Thailand (Surintaraseree 1988). Infrastructure development (e.g., road networks, electricity) has further enhanced the land-use change process in the area (Ahmad and Isvilanonda 2003). The process of intensification and diversification of agricultural production in irrigated, especially periurban, areas is a very widespread one. And this meets a rapidly growing demand for animal proteins for expanding middle-class urban consumers. This is a generic issue across the cities of developing economies such as Jakarta, Manila, Ho Chi Minh City, and southern China.

Declining profitability from rice production had led to efforts at sector-level agricultural diversification in Thailand. This diversification stimulated the production of high-value-added products such as fisheries, fruits, livestock, etc. During the 1980s and 1990s, Thai agriculture has moved to a more diversified cropping pattern with a variety of cash crops (e.g., aquaculture) (Ahmad and Isvilanonda 2003). Paddy fields are generally physically suitable for building fishponds. In terms of economic returns, fish culture often gives a higher return than rice culture. However, the decision to convert paddy fields to fishponds is often related to food security and social aspects. Moreover, labor availability, market locations, and technology also play an important role in the conversion process.

This paper attempts to develop a methodological framework on the dynamic simulation of land-use changes and a characterization of the spatial setting of the landscape through landscape indices. Simulation is considered to be an important tool for scientists because it is an excellent way to model and understand the social process. This paper first describes land-use changes over the Nong Chok area. Then it discusses the development of multi-agent systems modeling, the decision rules derived from the ID3 algorithm for the model, and the simulations. The most important issue is to validate the simulation model. This paper outlines some state-of-the-art landscape indices as an approach to characterizing the simulated maps and to validating the model. The simulated maps were compared with the observed land-use maps using the landscape pattern indices.

Profile of the study area

Nong Chok is an *amphoe* (district) of Bangkok Province and is situated around 30 km northeast of the Bangkok metropolitan area (Fig. 1). The study area comprises around 3.2 km^2 under Lam Toy Ting *tambon* (subdistrict) and is geographically distributed between latitudes 13°45′ to 13°50′ N and longitudes 100°50′ to 100°55′ E. Nong Chok enjoys a tropical monsoon climate. The mean annual temperature is 27.9 °C, the mean annual rainfall is 409.9 mm, and the mean relative humidity is 73% (TMD 2002).

Fig. 1. Location map of the study area (polygon), Nong Chok, Thailand.

The topography of the study area is flat, without any significant variation in elevation. The soil characteristics are homogeneous (as expressed by farmers during the interview). Thus, soil does not affect the land-use pattern in the area. There are canals on all sides of the study area, which provide a water source for fishponds and irrigation for paddy fields.

The landscape of Nong Chok is characterized by agricultural lands, orchards, urban areas (residential areas), roads, industrial areas, and fallow lands. The main activity of the area is agriculture, which produces income for the farmers. Agricultural activities include paddy cultivation, fish production, orchards, vegetables, poultry, and others. However, most of the farmers produce rice while some of them have fishponds, which support their income fully or partially.

Excellent harmony exists among the villagers, who follow different religions. Most of the people practice Buddhism, which is followed by Islam. There is a golf course in the northwestern part of the study area. A lot of people had moved into the study area during the establishment of the golf course.

Landscape pattern indices

The most effective manner for landscape planners to understand, plan, and manage change is by developing a basic understanding of the dynamic interactions of the structure and function of the landscape. Landscape ecology deals with the patterning of ecosystems in space. The importance of spatial effects for ecological processes has led to the development of state-of-the-art landscape indices for quantifying landscape pattern.

Landscape structure has two basic components: (1) *composition*, a nonlocation-explicit characteristic that refers to the variety and relative abundance of patch types represented on the landscape; (2) *configuration or structure*, which implies the spatial arrangement, position, orientation, or shape complexity of patches on the landscape.

Quantitative methods are necessary to compare spatial patterns and to evaluate the performance of spatial simulation models (Turner 1989). One of the important questions in simulation modeling is how to compare model outputs and validate the model. Several indices are used in landscape pattern analysis to measure landscape fragmentation (Wu et al 2000) and in the validation of spatially dynamic models (Britaldo et al 2002, Gilruth et al 1995).

Since the study area is very small (covering around 3.2 km^2) and this research considered only land-use change from paddy field to fishpond, all the widely used indices are not applicable in this study. However, after screening, *number of patches, patch density, mean patch size, edge density, fractal dimension*, and *mean nearest neighborhood* indices were found to have good potential for this study. Landscape pattern indices are discussed in detail in the section on indicators for validation of the model.

Materials and methodology

Simulation of land-use change has been performed integrating remote sensing, geographic information systems (GIS), and a dynamic simulation toolkit. The study has the following three main components (Fig. 2): (1) land-use change analysis, (2) development of the model, and (3) validation of the model. This paper focuses on only the simulation of land-use change dynamics and validation of the model.

Data set used for the study

A series of aerial photographs was used to prepare a land-use change map of different dates (1981, 1990, 1995, and 2000) for the study. The aerial photographs are of different scales (i.e., 1981: 1:50,000; 1990: 1:15,000; 1995: 1:20,000; 2000: 1:15,000). The resolution of the aerial photographs used for the photo interpretation is 65 cm. Different thematic layers, such as a house map, road map, and canal map, were developed using these aerial photographs. A topographic map was used for georectification purposes. Demographic and socioeconomic data about the farmers were collected by a field survey to assess the decision variables/underlying factors of

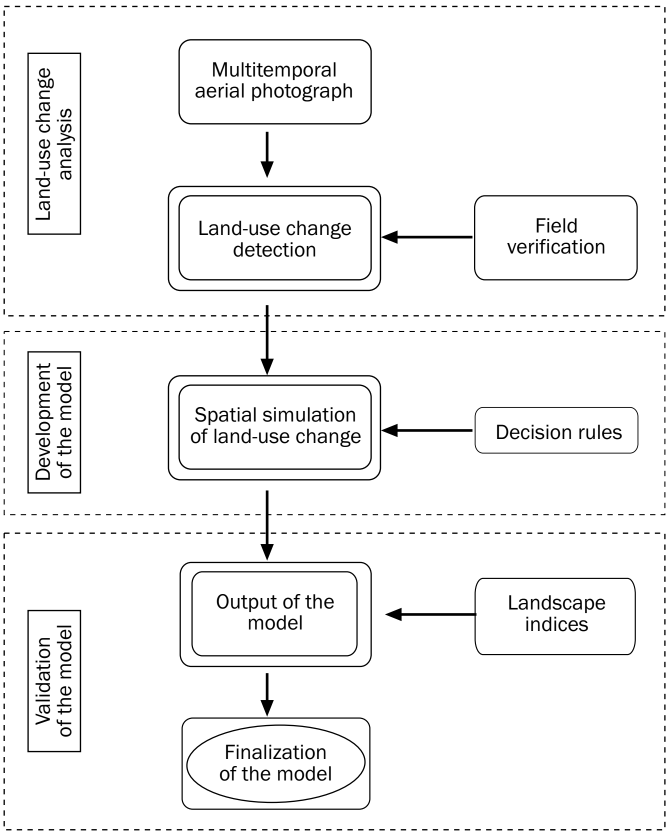

Fig. 2. Methodological framework of the study.

the land-use change process. Because of the limitation of available data, this study attempted to develop the model with a limited number of variables. Land ownership, education, age, religion, and number of family members of the farmers were used as decision variables. A spatial factor, distance to canal, was calculated from the land-use and canal maps.

Land-use change analysis

The photographs were georectified using image-processing software following standard procedures (Anwar 2002). Land-use maps and other associated thematic layers of 1981, 1990, 1995, and 2000 were extracted from aerial photographs using GIS software (Anwar 2002). Land use was classified into five categories: paddy field, fishpond, resident and orchard, waterbody, and others. Paddy fields are only paddy-producing lands. Fishponds include shrimp and all kinds of fishponds. Resident and orchard are homestead areas of the farmers with surrounding orchard. Waterbody refers to only a canal that flows within and around the study area. Others includes land that is currently unused, such as fallow land. In 1981, only paddy field (2.78 km^2), resident and orchard (0.29 km^2), and waterbody (0.11 km^2) were represented throughout the study area, whereas, in 2000, it was observed that a certain amount of land use has been turned into fishpond (0.46 km^2) and others (0.16 km^2) (Table 1).

Multi-agent modeling

Multi-agent systems (MAS), often denoted as agent-based (computational) modeling (Epstein and Axtell 1996), consist of a number of interacting autonomous agents (Gilbert and Troitzsch 1999, Weiss 1999, Ferber 1999). MAS has generated substantial attention in recent years as an important tool, technique, and metaphor for conceptualizing, designing, implementing, analyzing, and exploring the understanding of complex adaptive systems and can be modeled as bottom-up. MAS can be used to set up spatial models that integrate social and ecological dimensions (Janssen et al 2000). A detailed overview on MAS and land-use and land-cover change can be found in Parker et al (2003).

The conceptual model. The model is a cellular automata (CA) model that presents vicinity-based transitional functions such as DINAMICA (Britaldo et al 2002). CA are simple models for the simulation of complex systems, which successfully replicate aspects of ecological and biogeographical phenomena (Parker et al 2003). The model

Table 1. Areas of different land-use types from 1981 to 2000.

Land-use type[a]	Land use, 2000 area (km^2)	Land use, 1995 area (km^2)	Land use, 1990 area (km^2)	Land use, 1981 area (km^2)
Paddy field	2.15	2.26	2.62	2.78
Fishpond	0.46	0.35	0.15	–
Resident and orchard	0.30	0.32	0.26	0.29
Waterbody	0.11	0.11	0.11	0.11
Others	0.16	0.12	0.02	–

[a]Explanation of different land-use types is given in the section on land-use change analysis.

on the biophysical environment consists of initial land use (1981) and a canal map. It is a two-dimensional space. For each time-step, it calculates the transition probability of the cells based on decision rules. Among the cells having a probability of change, the spatial distribution of changed cells was calculated and the model changed the cells from paddy field to fishpond. The study was conceived for the simulation of land-use dynamics, in particular, from paddy fields to fishponds. This process operates for one time-step. The simulation iterates for 19 steps. It is assumed that each year represents one step. Figure 3 shows the workflow of the simulation of the model.

Decision tree using ID3 algorithm. Transition function of the model was developed based on the ID3 algorithm (Quinlan 1986), which has been widely used in several application domains. Selected demographic and socioeconomic factors of the farmer (i.e., age, ownership, religion, education, and family size) were categorized into three classes based on statistical analysis between percentage of land-use change and decision variables (Anwar 2002).

A decision tree is developed following the ID3 algorithm with change index[1] data sets. This ID3 algorithm was used to characterize the decision variables of the land-use change process over the Nong Chok area. The ID3 algorithm tries to find out the root of the decision tree based on the highest information gain using entropy calculation (Anwar 2002). The process continued through the decision space to find out change and no-change decisions.

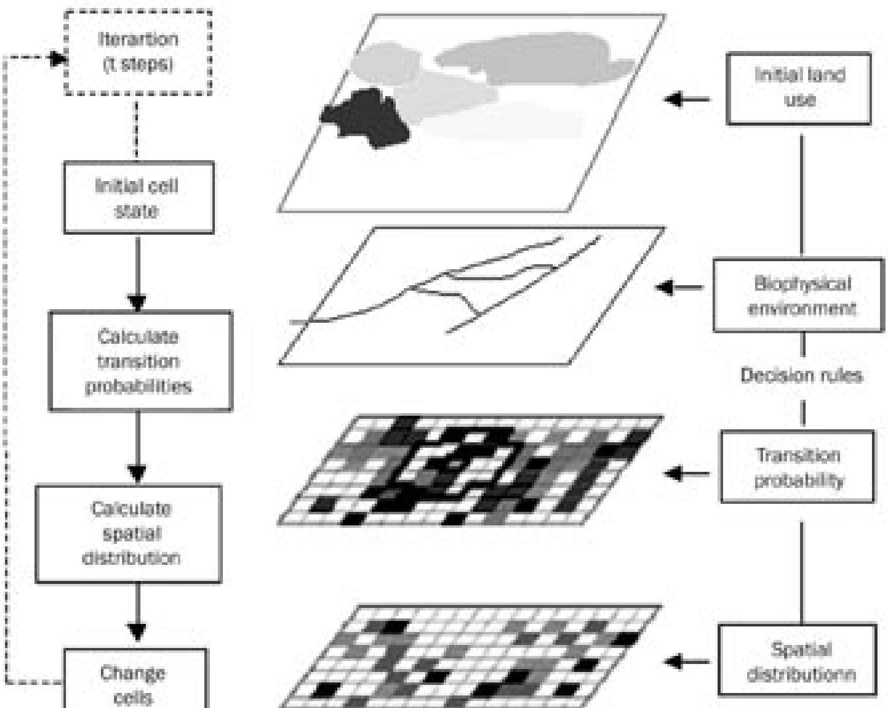

Fig. 3. Dynamic spatial simulation modeling diagram.

[1]A changed parcel was assigned a value of 1 and a parcel without change was assigned 0.

The heuristic decision-making methodology for changing land use from paddy field to fishpond shows the relationship among all the decision variables and change attributes (parcel whether changed or not changed). The decision tree was converted into an equivalent set of decision rules. The decision rules are based on an "if … and … , then … else…" statement. These decision rules were applied in CORMAS (common-pool resources and multi-agent systems) to develop the simulation model. For example,

If myOwner ownership = "owner + tenant" and myOwner familySize = <4, then land use = #paddy (no change).

Else If myOwner ownership = "owner + tenant" and myOwner familySize = (4–6) and myOwner age = (36–55), then land use = #fishpond$_{P0.813}$ (change probability = 0.813, calculated from statistical analysis).

The structure of the model. The unified modeling language (UML) (see Le Page and Bommel, this volume) class diagram of the model consisting of spatial entity, spatial aggregate, and agents is shown in Figure 4. The spatial entity is composed of four levels of spatial units: farm, block, parcel, and cell. "Cell" is the basic spatial unit for the development and application of transition rules. Cell has several attributes: OwnerID, landUse, parcel, and distanceFromCanal. "Parcel" is composed of cells, which have the same owner and same land use (e.g., paddy field). "Block" is composed of parcels of the same owner with the same land use. "Farm" is represented as an aggregate of blocks of the same owner with different blocks with different land use (e.g., paddy field and fishpond). The farmer is denoted as an agent named FishRice-Farmer in the model, who has a spatial entity farm composed of block, parcel, and FishRiceCells. FishRiceFarmer has attributes such as owner, age, religion, education, and familySize.

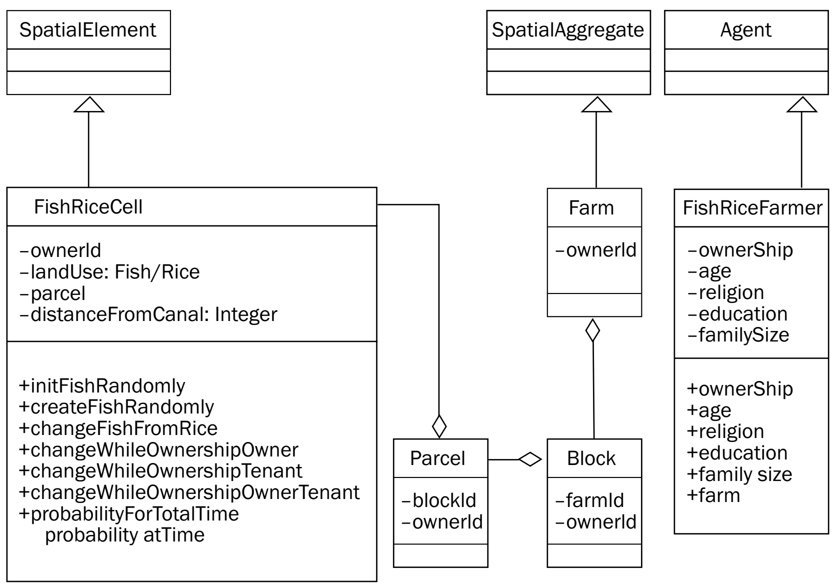

Fig. 4. UML (unified modeling language) class diagram of the Nong Chok model.

The model was implemented in CORMAS, an agent-based simulation toolkit (Le Page and Bommel, this volume). To be compatible with CORMAS, a land-use map of 1981, which represents initial land use, was exported in ASCII format from ArcView. The maps (distance to canal map, ownerId map, parcelId map, blockId map, and farmId map) were also exported. Before doing so, the survey database of farmers with ownerId was integrated with the maps through GIS. These maps were imported into CORMAS to build the environment of the model. Grid size of the model is 30 × 30 m, which means that the GIS data sets for 1981, 1990, 1995, and 2000 were resampled into 30-m resolution and exported to CORMAS. All simulations and subsequent analysis (calculation of the landscape pattern indices value) are accomplished on 30 × 30-m cell resolution. Figure 5 shows the initial state of the Nong Chok model in CORMAS. The environment has three types of land use: paddy field, resident and orchard, and waterbody, as was observed in the 1981 land-use map.

Simulation. There were no fishponds in the study area in 1981 (Table 1). So, the model was initialized with fishpond based on randomization. The rules imply that, if the land use of the cell is paddy and the neighborhood contains a fishpond, the model applies decision rules; otherwise, if the neighborhood contains no fishpond, if the cell is within 150 m of a canal, and if the neighborhood contains residentOrchard, then CORMAS draws a random number and, if the number is below 0.1, the land use of the cell is changed to fishpond. If the random number is above 0.1, the land-use state is kept the same. The fishpond is created stochastically. Water is needed to develop and maintain the fishpond. Thus, distance from the canal is important and it was observed that farmers used to keep their fishponds close to their residence to take care of them. In the light of the above information, fishponds were initialized in the model.

Fig. 5. Initial state of the Nong Chok model (1981 data) in CORMAS.

The model simulates for 19 time-steps. For each time-step, it creates new fishponds randomly and simultaneously extends the fishponds following decision rules. Thus, the extension of fishponds is stochastic in this model.

Indicators for validation of the model

Validation deals with comparing the model outputs with the real-world observation. The process answers how well the model outcomes represent the real-world system (Parker et al 2003). Several criteria exist to evaluate the model: correctness, consistency, universality, simplicity, and novelty (Manson 2002). The model in this study is validated using the following landscape pattern indices in terms of quantitative correspondence between the model's behavior and the reference map. Thus, it is more a model assessment than a rigorous validation that is proposed in this paper.

Description of the indices. The following landscape pattern indices were scrutinized from the literature. These indices are used only for fishpond class diffusion over the landscape. Thus, the indices calculated values for fishpond class of the simulated maps such as $\mathrm{NP}_{\mathrm{fishpond}}$, $\mathrm{PD}_{\mathrm{fishpond}}$, $\mathrm{MPS}_{\mathrm{fishpond}}$, $\mathrm{ED}_{\mathrm{fishpond}}$, $\mathrm{FD}_{\mathrm{fishpond}}$, and $\mathrm{MNN}_{\mathrm{fishpond}}$. Simultaneously, the indices were applied to a reference map (1981, 1990, 1995, and 2000). They were programmed into the CORMAS toolkit. The implementation of these indicators is facilitated by the existence of CORMAS primitives that allow the creation of spatial composite objects and allow the primitives to calculate the edge of composite objects or distance between composite objects.

Number of patches (NP). A patch represents an area that is covered by a single land-cover class. This is an indication of the diversity or richness of the landscape. This index can be calculated and interpreted easily. However, like other richness measures, this interpretation might give misleading results because the size of the area covered by each class is not considered here. Even if a certain class covers only the smallest possible area, it is counted. The index is calculated as $\mathrm{NP} \sum_{j=1}^{N} = Pi$, where Pi is the number of patches for land-use class i and N is the number of land-use classes.

Patch density (PD). The patch density expresses the number of patches within the entire reference unit on a per area basis. It is calculated as $\mathrm{PD} = \frac{NP}{A}$, where NP and A represent the number of patches and area, respectively.

Mean patch size (MPS). Mean patch size is a measure of the composition of the landscape. The formula is $\mathrm{MPS} = \frac{\sum PS}{NP}$, where PS and NP denote patch size and number of patches, respectively.

Edge density (ED). An edge is the border between two different classes. In contrast to patch density, edge density considers the shape and complexity of the patches. The index is calculated as $\mathrm{ED} = \frac{E}{A}$, where E and A denote total edge (in m) and total area, respectively.

Fractal dimension (FD). A perimeter to area relationship can be used to calculate the fractal dimension of patch perimeters using grid data. Using all patches of a single cover type (or all cover types) in a landscape, a regression is calculated between log (perimeter/4), the length scale used in measuring the perimeter, and log (size) of each patch (Turner et al 1989). Fractal dimension is related to the slope of the regression, by the relationship D = 2*S*, where *S* is the slope.

The dimension can range between 1.0 and 2.0. If the landscape is composed of simple geometric shapes such as squares and rectangles, the FD will be small. If the landscape contains many patches with complex and convoluted shapes, the FD will be large (Krummel et al 1987).

Mean nearest neighborhood (MNN). Some ecological processes are strongly influenced by the distance separating patches of the same class. Various nearest neighborhood metrics attempt to encapsulate in a single number the characteristic of the degree of separation. One of the more common is the mean nearest neighborhood distance, $MNN = \frac{\sum_{i=1}^{m} \sum_{i=1}^{m} h_{ij}}{NP}$, where h_{ij} is the edge-to-edge (or centroid-to-centroid) distance from patch *ij* to the nearest neighboring patch of the same class and *NP* is the number of patches in the landscape having nearest neighbors.

Results

Simulation of land-use change

Dynamic simulation with stochastic components produces one of the possible scenarios of the model. This helps us to understand the underlying process of the system. Simulation outputs of three different runs are presented in Figure 6. On the simulated maps, most of the fishponds were distributed into four clusters, which is similar to the land-use change map (Fig. 6). There was no fishpond in the western part of the area near the golf course because of insufficient water flow into the nearby canal. Moreover, water in the canal becomes polluted from pesticides from the agricultural fields. Although the simulation created a small fishpond (one pixel) in both the western part (Fig. 6, white circles) and along the "resident and orchard," the reference map does not show any fishpond in that part. This happened because of the stochastic distribution of the fishpond of the model at each time-step.

The middle part of the study area had no fishpond on the simulated map (Fig. 6, black circle). Since the neighborhood of the resident of the cell was taken into account during initialization of the simulation and there was no resident around that area in 1981, the model could not initialize and diffuse the fishpond over that area.

Spatial characteristics of model output

Various researchers used landscape pattern indices to validate their simulation models (e.g., fractal dimension, contagion index, and number of patches, Britaldo et al 2002). Number of fishpond cells, mean patch size, edge density, patch density, fractal dimension, and mean nearest neighborhood indices were calculated from the simulated map and compared with the reference maps to validate the Nong Chok model.

Area of fishpond. Simulated fishponds have shown an area of 0.29 km^2, whereas, on the reference map (land-use map 2000), the fishpond area was 0.46 km^2 (Fig. 7A). Thus, the overall agreement of the simulated fishpond is 62% of the reference map.

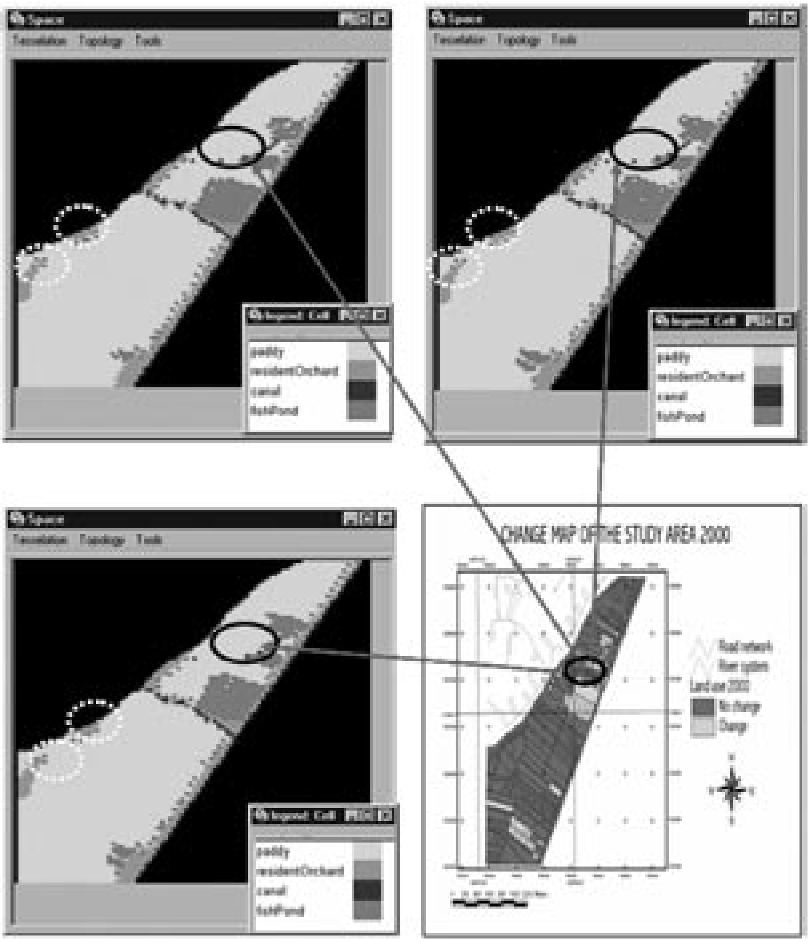

Fig. 6. Outputs of three different runs of the simulation (final map).

As the study area is around 3.2 km^2, the model produced a fishpond in simulation that was 9%, while the actual fishpond on the reference map was 14%. This index considers only total area of fishponds, not their spatial composition. Both the simulated and reference maps show a similar pattern of fishpond diffusion over the years.

Patch density (PD). PD of the simulated map was calculated based on the entire study area (i.e., number of patches in the entire area). The PDs of the simulated map and the reference map (2000) are 0.017 and 0.0017 (Fig. 7B), respectively. In the simulation, the density increases very fast and a plateau is reached earlier.

The landscape is very small and the model simulates random fishponds based on the createRandomFishpond method and diffuses new fishponds simultaneously, following decision rules for each time-step. Consequently, there are several small fishponds (one pixel) along the resident on the simulated map. Several researchers used the patch density index to validate a simulated map for regional-scale landscape.

This index may not be suitable for a small-scale study area because of its initial randomization effect.

Mean patch size (MPS). MPS is the mean area of the patches in the landscape. MPS of the simulated map is 5, whereas MPS of the reference map (2000) is 32 (Fig. 7C). The MPS value of the patches increased during the simulation from 1 to 5. This index gives information on fragmentation of the landscape. The mean patch size index also suffers from the same drawbacks as mentioned with patch density.

Edge density (ED). ED of the simulated map is 0.112 (Fig. 7D, left). Following the same procedure for patch density, ED of the simulated map was calculated based on the entire study area. Edge density of the reference change map (2000) is 0.059 (Fig. 7D, right). Edge density measures the total edge of patches in the landscape. Although the simulation could not simulate properly in the middle part of the landscape, it showed a high value in the simulation because it counts all tiny fishponds along the resident, which were not found on the reference map.

Fractal dimension (FD). FD of the simulated map is 1.17 (Fig. 7E, left). In the first half of the simulation, FD increases, but in the last half it decreases. To validate the simulated landscape, researchers try to find correlation of the complexity of the patches between the simulated and reference landscape (Britaldo et al 2002). FD of the reference change map (2000) is found to be 1.31 (Fig. 7E, right). This index characterizes the complexity of the landscape. Interestingly, FD of the simulation showed a decreasing trend because of the tiny fish cells, whereas, on the reference map, FD is increasing.

Mean nearest neighborhood (MNN). MNN of the simulated map is 5.83, while MNN of the reference change map (2000) is 23.32 (Fig. 7F). This reveals that the simulated map is less fragmented than the reference map. MNN decreases on the reference map because of the rapid diffusion of fishponds (Fig. 7F, right). This index indicates the isolation and distribution of patches.

Fishpond areas, patch density, mean patch size, edge density, and fractal dimension indices consider only the composition of the patches in the landscape. Conversely, mean nearest neighborhood considers the configuration of the patches. Most of the landscape pattern indices have redundancy among them and consider diversity or composition of the landscape only.

Discussion and conclusions

This is a preliminary model of diffusion from paddy field to fishpond based on selected spatial and human driving forces. The model uses as its input a land-use map (1981) and spatial and human variables: distance to canal, age, ownership, religion, education, and family size of the farmers. Land ownership was found to be the most sensitive among all the driving factors. Education and religion could not significantly influence the transition function. Young farmers are more courageous in adopting new land use despite the risk factor. The topography and soil characteristics of the study area are uniform and thus do not influence the land-use change process. Other important driving forces affecting land-use change are comparative economic return from alternative crops from the same land, market dynamics, various policies, and wage levels, etc., that are operating at a higher level and are modeled as factors exogenous

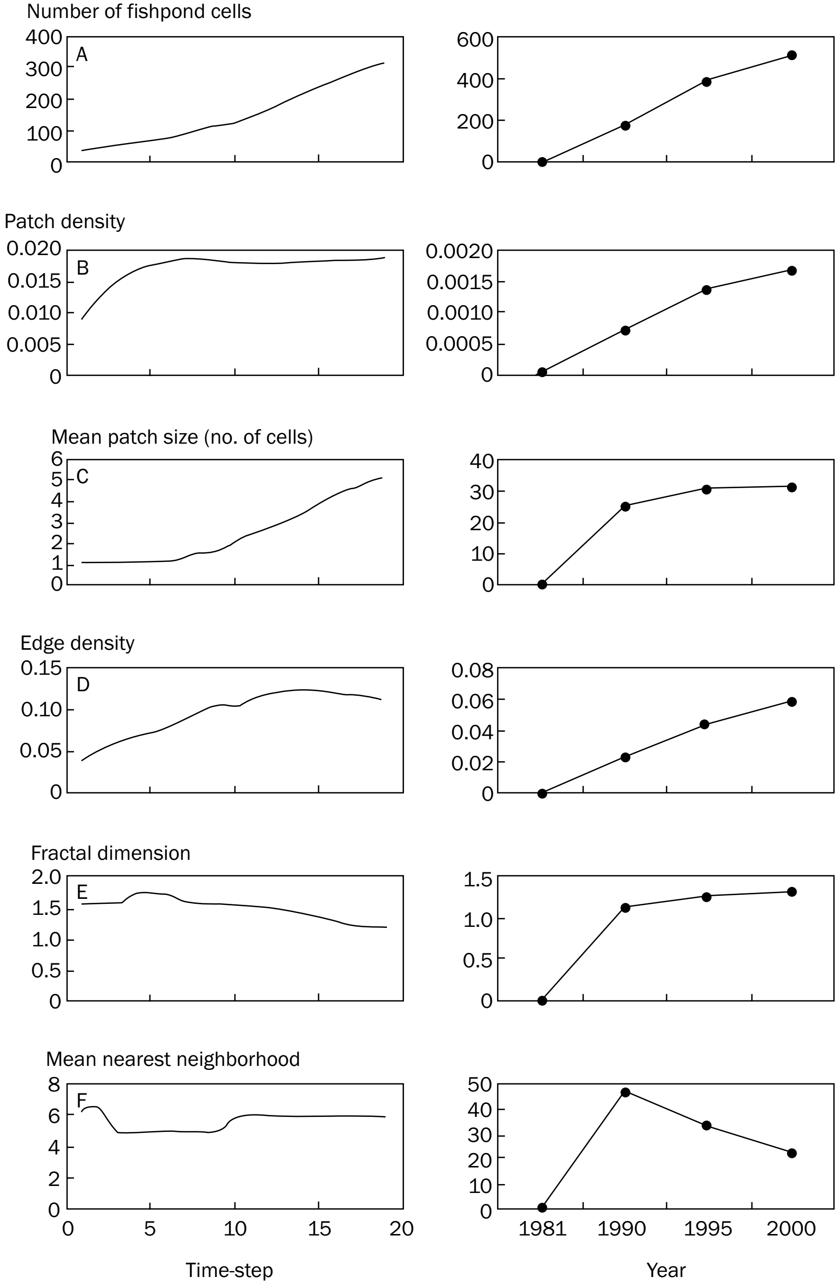

Fig. 7. (A) Fishpond areas, (B) patch density, (C) mean patch size, (D) edge density, (E) fractal dimension, and (F) mean nearest neighborhood of the simulated map (left side) and reference map (right side).

to the system. The model, however, focused on the available data collected from the farmers as decision variables. More work in the field should be done.

The model was able to diffuse the fishpond substantially from 1981 to 2000. To validate this spatial simulation model of land-use change dynamics, the simulated maps were compared with the reference land-use maps using a set of landscape indices: number of fishpond cells, patch density, mean patch size, edge density, fractal dimension, and mean nearest neighborhood. The indices do not exhibit a similar pattern on the reference and simulated maps because of two factors. First, the indices suffered considerably from the random effects. The randomized creation of fishponds during the initialization process generated a number of fishpond cells (single pixel), which raised the index value to 0.017 for PD and 0.112 for ED on the simulated maps vis-à-vis the reference map (Table 2). Future research should carefully focus on this aspect. The number of fishponds between the simulated and reference maps showed 62% overall agreement. Farmers who are early adopters of the new land use got information about fishponds from fishery extension workers. Once one farmer converts land use from paddy to fishpond, this diffuses among his neighboring farmers if fish cultivation produces a higher profit. So, the diffusion is spatially clustered as it is seen on both the simulated and reference maps. An index such as the mean nearest neighborhood measures this spatial clustering. Even though MNN did not show a close agreement, it could be an important index for validating the simulation of land-use change dynamics. Second, the dynamics of the model should rest more with agents' decisions. In this version of the model, a diffusion dynamics is simulated based on rules applied to the spatial entities. In reality, the land-use change decision is made by agents.

Comparing the results of simulation with an existing land-use map is always risky. The issue of validation raises here a crucial question whether a good fit of index validates the model or a bad fit does not, as some indices revealed in this study. A system is modeled with a certain number of variables as essential to represent the process of investigation. These variables might not be the most appropriate ones. Moreover, the model could show some possible scenarios of land-use change instead of many others. The two scenarios produced by the reference map and the model might both be different and both be true in terms of what could happen in the study area. Thus, the focus of the simulation should be to study the overall dynamics of the systems and understand what drives the process and leads to understanding the process and creation of the spatial pattern of land-use change, not a direct pixel-by-pixel comparison between the simulated and real map.

Table 2. Analysis of landscape indices of the simulated and reference change map.

Item	Landscape indices[a]					
	NFC	PD	MPS	ED	FD	MNN
Simulated map	320	0.017	5	0.112	1.17	5.83
Reference map (2000)	513	0.0017	32	0.059	1.31	23.32

[a]NFC = number of fishpond cells, PD = patch density, ED = edge density, MPS = mean patch size (number of cells), FD = fractal dimension, MNN = mean nearest neighborhood.

The model, however, fails to incorporate some aspects of the dynamic behavior of the variables. All variables in this study were static. The model starts working on certain hypotheses and in each time-step it calculates the transition probability based on fixed parameters of the variables. The sensitivity of driving forces operating at a higher scale should be measured. Further investigation may lead to other factors to test their sensitivity. The model could also simulate fishpond diffusion on the 1990 data set as initial land use to see the behavior of the model. Farmers were sometimes found to stop fish cultivation during the study period (1981-2000), but the model did not integrate that behavior.

Another important feature of the model is its cellular automata cell size, which was 30 × 30 m. This cell size was chosen to boost the simulation. However, the model could be tested with a different cell size to observe its impact on the diffusion process.

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Notes

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