LAND USE CHANGE DYNAMICS: A DYNAMIC SPATIAL SIMULATION

by

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ABSTRACT

It is important to study the driving forces of land use change to understand the change process. Spatially explicit simulation models help to test hypotheses about landscape evolution under several scenarios. This research presents a dynamic simulation model of land use change of Nong Chok area, Central Thailand. Simulation of land use change has been performed integrating remote sensing, Geographical Information Systems (GIS) and dynamic simulation toolkit. The model has been developed based on selected biophysical and human driving forces. It is a cellular automata model that presents vicinity based transitional functions. The study was conceived for the simulation of land use change dynamics, in particular from paddy fields to fishponds. The model was run for 19 years from 1981-2000. Data describing present and historic land use pattern were derived from aerial photographs. Transition functions were developed following entropy calculation by using ID3 algorithm of the land use change datasets. The model uses as its input a land use map (1981), spatial and human variables: distance to canal, age, ownership, religion, education, and family size of the farmers before the simulation starts. The result of the simulation showed considerable performance of the model to diffuse fishponds except few mismatches. To validate this spatial simulation model of land use change dynamics, the simulated maps were compared with the reference land use map (2000) using a set of landscape indices: number of fishpond cells, patch density, mean patch size, edge density, fractal dimension, and mean nearest neighborhood. Further investigation by integrating other variables might allow the model to simulate land use change with greater accuracy.

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CHAPTER ONE
INTRODUCTION

1.1 Background

Change is a continuous process, but learning is optional. Resources, ecosystem, biophysical environment, and land use/cover on the surface of the earth undergo changes over time. Land cover is the layer of soil and biomass, including natural vegetation, crops and man made infrastructures that cover the land surface. Land use is the purpose for which human exploit the land cover (Fresco, 1994, cited in Verburg et al., 2000). 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 (Verburg, 2000, cited in Soepboer, 2001). Land use and land cover change are critical issues due to their great influence in global warming, loss of biodiversity, and impact in human life. Because of their enormous impact and implications, the International Geospehere-Biosphere Program (IGBP) and the International Human Dimension Program (IHDP) initiated a joint international program of study on Land Use /Cover Change (LUCC). They recognized the necessity to improve understanding, modelling, and projections of land dynamics from global to regional scale and focusing particularly on the spatial explicitness of processes and outcomes (Geoghegan et al., 2001).

Change detection is a process of identifying and analyzing the differences of an object or a phenomenon through monitoring at different times (Singh, 1989; Mouat et al., 1993). The detection and analysis of changes in multi-temporal remote-sensing data have assumed an ever-increasing strategic role in several application domains. A wide range of applications can be benefited from the study of change process over a specified area at different times. Recent literature deals with the application of change analysis to different problem domains. Examples of these problems are: *land use/cover change dynamics, global change analysis, monitoring of pressure on the environment, monitoring of agricultural production, assessing drought risk areas, managing coastal zone and assessing damages due to forest fires and deforestation, and monitoring damages due to natural calamities like floods, earthquakes, and volcanic eruption.* Information about land use change is necessary to update land cover maps and for effective management and planning of the resources for sustainable development.

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 them are due to specific management practices and the rest are due to social, political and economical forces that control land uses (Medley et al., 1995). The landscape is dynamic in relation to spatial, structural and functional patterns (Hobbs, 1997). The purpose of land use change simulation modelling is to describe, explain, predict, assess impact, and to evaluate hypothesis (Briassoulis, 2000).

1.2 Statement of the problem

Thailand has undergone rapid urbanization and tremendous economic growth during last few decades. Most of the economic development activities are focused in and around Bangkok Metropolitan. These changes have rapidly transformed Thailand from a subsistence agrarian economy into rapidly industrialized country. The growing urbanization in the outer periphery of Bangkok Metropolitan city has created pressure for the changes in the land use pattern. Nong Chok is a suburb and is located in northeast of Bangkok metropolitan city. Main activity of the area is agriculture, which generates income for the farmers. The area has been experienced sharp changes in the land use pattern during recent years. Farmers have changed their land use from rice production to shrimp and other aquaculture for huge demand of fish in the market. It is reported that the department of fisheries first promoted the fish culture in the rice fields in 1950's 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. It is important to study the driving forces of land use changes to understand the change process. Spatially explicit simulation models help to *test hypotheses about landscape evolution under several scenarios.*

1.3 Objectives of the study

General objective of the study is to develop a methodological framework for a systematic study of dynamic spatial simulation modelling to simulate the land use change over Nong Chok area from 1981 to 2000. Specific objectives of this study are:

- to identify the land use change dynamics over Nong Chok area;
- to assess the underlying factors/decision variables for land use change;
- to simulate the land use change through a dynamic spatial simulation model; and
- to analyze suitable index to measure the landscape fragmentation and validate the model.

1.4 Research questions

The study concerns the following research questions:

- What are the changes in the land use of Nong Chok area?
- How much land use has been turned into other types?
- What is the tendency of the change and what are the driving forces responsible for land use change process?
- Is there any hypothesis for the land use in the neighboring areas of Bangkok?

1.5 Rationale of the study

The study area has undergone a sharp change during recent years. Multi temporal aerial photographs are good sources to detect land use change. It is necessary to investigate the changes in land use pattern to have better understanding of the process. Simulation is considered as an important tool for scientists because it is an excellent way of modelling and understanding social process. Spatial simulation of land use change dynamics is very important to monitor and understand the composition and configuration of the change process, and to observe the behavior of the actors and the interaction between system dynamics and actors and bio-geographical phenomena of the area under investigation. This study allows us to identify the driving factors of the farmers that lead them to change their land use.

1.6 Scope and limitations of the study

This study intended to integrate together remote sensing, GIS and dynamic spatial simulation modelling approach to detect change in land use pattern of Nong Chok area during last 19 years (1981-2000). The expected outcome of the study is a dynamic simulation model based on some biophysical and human driving forces. The model could help to visualize future land use scenarios to test different hypothesis of Nong Chok area as well as other areas around Bangkok. Thus, other bio-geographical features and demographic and socio-economic factors/decision variables could be integrated to study their impacts on decision process of the farmers to change the land use.

The study area has been limited to Moo 1 of Nong Chok district, Bangkok, which is around 10 km^2 in area. Although the area might not be ideal to develop a generic model of land use change dynamics for large-scale land use change process, it was selected due to its sharp land use change from 1981 to 2000 through prior consultation with officials of Agricultural Extension Department of Nong Chok district. Present land use map for this area was prepared from aerial photographs of 2000 and classified into five categories of land use i. e. *paddy field, fish pond, resident and orchard, waterbody,* and *others.* However, this study was concentrated only on land use change from paddy field to fishpond of any variety. This research mainly focused on developing a methodological framework for dynamic spatial simulation of land use change process of Bangkok area.

1.7 Organization of the thesis

This thesis consists of six chapters that describe all the major components of this research including remote sensing change detection, statistical analysis of driving factors, development of transition functions, development of the model in CORMAS toolkit, simulation of land use change, and validation of the model. In Chapter one problem statement was defined with objectives of the study. Chapter two describes the study area with focusing on profile, topography, climate and land use pattern. Chapter three deals with review of literature on remote sensing change detection, land use simulation modelling, and landscape pattern analysis. In Chapter four and five, detailed methodology of this research is presented and discussed with results. This study approached to use multi temporal aerial photographs to detect land use changes over past 19 years (1981-2000). A cellular automata based dynamic simulation model was developed to simulate land-use change using relations between land use and its driving factors in combination with dynamic spatial modelling. The simulated maps were compared with the observed land use maps using landscape pattern indices - number of cells, patch density, mean patch size, edge density, fractal dimension, and mean nearest neighborhood. Chapter six returns to the issues raised in the objectives of the research in Chapter one and adds scientific discussion on results.

CHAPTER TWO

STUDY AREA

2.1 Profile of the study area

Bangkok being the capital city of Thailand differs in administrative and land tenure system from the cities of other provinces. Nong Chok is an amphoe (district) of Bangkok. Moo 1 of Nong Chok has been selected as the study area for this research. It is a suburb of the capital city and is located around 30 kms northeast of Bangkok.

Nong Chok occupies an area of 236.264 km2 and is inhabited by a total population of 80,500 people in 2001 (OAE, 2000). Nong Chok consists of 8 tambons (subdistric) and moo one is situated under Lam Toy Ting tambon. Figure 2.1 and Figure 2.2 show the location map of Nong Chok and map of the study area respectively. The study area is located between latitudes 13°45to 13°50N and longitudes 100°50to 100°55E.

2.2 General topography

The topography of the study area is flat. There is no significant altitudinal difference over the area. The soil characteristics of the study area are homogenous. Thus, there is no effect of soil on the land use pattern in the area. The area is surrounded by canals in all sides, which provide water sources for fishponds and for irrigation to the paddy fields.

2.3 Climate

The study area enjoys a tropical monsoon climate. The mean annual minimum and mean annual maximum temperatures are 23.3° C and 33.1° C respectively with a mean annual temperature of 27.93° C.

According to the general annual rainfall pattern, most areas of the country receive precipitation 1,200 - 1,600 mm a year while the mean annual rainfall of the study area is 409.9 mm and the annual rainy days are 113.

Thailand usually experiences a long period of warm weather due to its location in tropical zone. March to May is the hottest period of the year. The mean relative humidity of the area is 73% (Source: Thailand Meteorological Department).

2.4 Land use pattern

Thailand is a substantial agricultural country. The land use/cover pattern of Nong Chok area is characterized by agricultural lands, orchards, urban areas (residential area), roads, industrial areas, and fallow lands. Main activity of the area is agriculture, which generates income for the farmers. Agricultural activities include: paddy cultivation, fish production, orchard, vegetables, poultry, and so on. However, most of the farmers produce rice while some of them have fishponds, which support their income fully or partly.

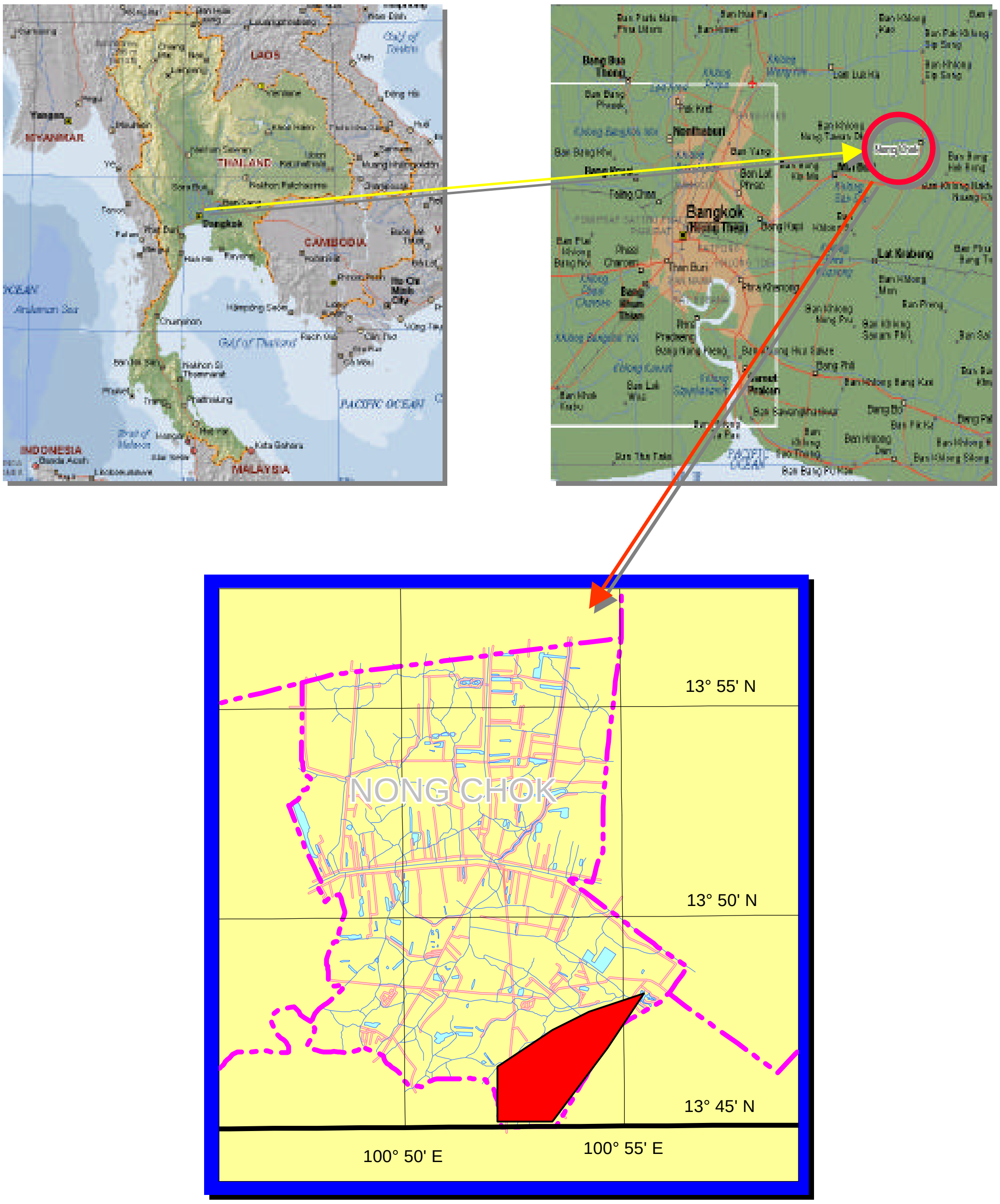


Figure 2.1: Location map of Nong Chok

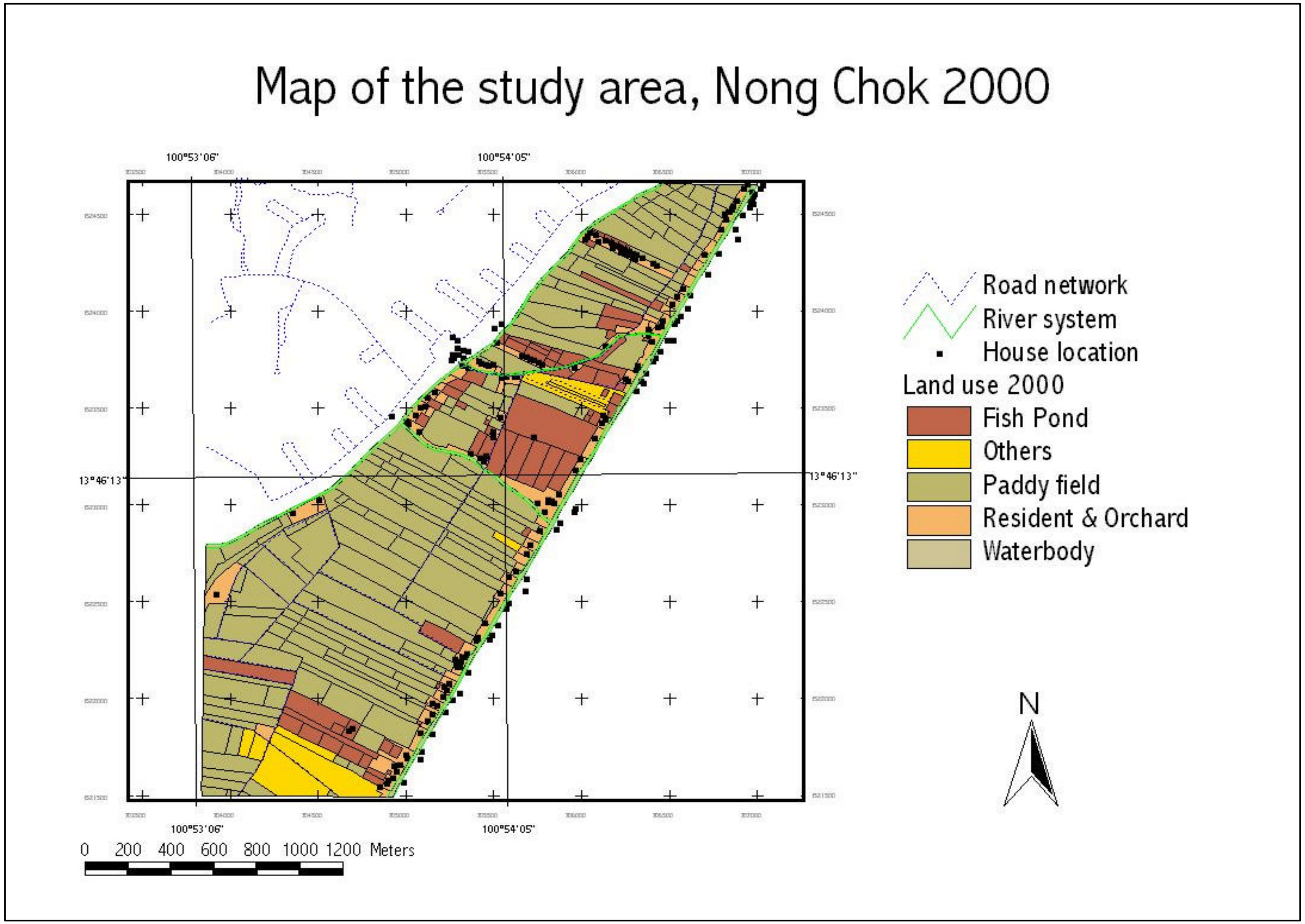


Figure 2.2: Map of the study area, Nong Chok 2000

CHAPTER THREE

LITERATURE REVIEW

This chapter aims in introducing the key issues in land use modelling that are addressed in this thesis. This thesis is composed of three parts: land use change analysis from remote sensing data, simulation of land use change dynamics, and validation of the model. In order of appearance the following issues will be discussed: Preprocessing of remote sensing data; elements of aerial photo interpretation; spatially explicit land use change simulation; cellular automata; ID3 algorithm; landscape pattern analysis.

3.1 Preprocessing of remote sensing data

The principle in using remote sensing data to monitor change is that changes in land cover must be represented in radiance values and these changes should be large enough with respect to radiance changes caused by other factors (Singh, 1989). These other factors include (1) differences in atmospheric conditions, (2) differences in sun angle and (3) differences in soil moisture (Jenson, 1983).

Failure to understand the impact of various environmental characteristics on the remote sensing change detection process can also lead to inaccurate results. When performing change detection, it is desirable to hold environmental variables as constant as possible.

3.1.1 Geometric correction

Raw digital images usually contain both systematic and unsystematic geometric distortions so significant that cannot be used directly as base map without processing. The sources of these distortions range from variations in the altitude and velocity of the sensor platform to factors such as panoramic distortion, earth curvature, atmospheric refraction, relief displacement, and non-linearity in sweep of a sensor's Instantaneous Field of View (IFOV) (Lillesand and Keifer, 2000). The intent of geometric correction is to compensate for the distortions introduced by these factors so that corrected image will have the highest practical geometric integrity.

Accurate geometric fidelity is particularly important for change detection analysis. The geometric correction is normally implemented as a two-step procedure. First, those distortions that are systematic, or predictable, are corrected using data from platform ephemeris and knowledge of internal sensor distortion. Second, those distortions introduced that are essentially random, or unpredictable, are corrected with acceptable accuracy with a sufficient numbers of well-distributed ground control points (GCPs). Earth scientists follow two common procedures to correct random geometric distortions of the remotely sensed data:

i. Image to map rectification
ii. Image to image rectification

3.1.2 Image mosaicing

Image mosaicing overlays two or more images that have overlapping areas (typically geo-referenced) or to put together a variety of non-overlapping images and/or plots for presentation output (typically pixel-based). Individual bands, entire files, and multi-resolution geo-referenced images can be mosaiced. We can use mouse or pixel-pixel or map-based coordinates to place images in mosaics and we can apply a feathering technique to blend image boundaries.

3.2 Elements of aerial photo interpretation

Interpretation of aerial photographs is a difficult task in creating land use map. The interpretation of air photos departs from conventional daily photo interpretation in three important aspects: (1) the portrayal of features from an overhead, often unfamiliar perspective, (2) the frequent use of wavelengths outside the visible range of the spectrum, and (3) the depiction of the earth's surface at unfamiliar scales and resolutions. A systematic study of aerial photo usually involves several basic characteristics of features shown on photograph. Though the exact characteristic useful for any specific task depends on the field of application, most applications consider the basic characteristics are: shape, size, pattern, tone/color, texture, shadows, site, and association (Lillesand and Kiefer, 1994).

3.3 Spatially explicit land use change simulation

The growing awareness of the need for spatially explicit land use change models has approached to the development of a great number of land use change models.

Wang and Zhang (2001) developed a dynamic landscape simulation (DLS) to study the socio-economic effects on landscape change on an area of 5,204 km^2 in Chicago metropolitan region. The model consists of two submodels i.e. urban growth simulation and a land cover simulation submodels. In the study, historical land cover and census data were applied to derive transition thresholds and transition rates of the land cover changes. It adjusts the transition structure of the model dynamically (i.e. transition potentials, threshold and rate), which overcomes the limitations of static and statistical models that use a constant transition probability in simulation modelling. The model also helps selected economic principles to be integrated into landscape simulation.

DINAMICA is a spatially explicit simulation model of Amazonian landscape dynamics. It is based on cellular automata model that represents multi-scale vicinity based transitional functions, incorporation of spatial feedback approach to a probabilistic multi-step simulation engine, and the application of logistic regression to calculate the spatial dynamics transition probabilities. The study area is located in the north of Mato Grosso state, Brazil. The model was used to simulate the spatial pattern of land use/cover changes by deforestation, cultivating the land, and eventually abandoning it for vegetation succession. DINAMICA uses as its input a landscape map (e.g. land use/cover map), selected spatial variables which are structured into two subsets according to their static and dynamic nature. It takes soil, vegetation, altitude, slope, distance to rivers, distance to main road, distance to secondary roads, urban attraction factor as static variables before the simulation starts. It generates, as output, simulated maps, the spatial transition probability maps, and the dynamic spatial variable maps for each time step. To validate the simulations, the simulated maps were compared with the observed land use/cover maps using set of landscape pattern indices - fractal dimension, contagion index, and number of patches and multiple resolution fitting procedure (Britaldo et al., 2002).

CLUE, a conceptual model to study the conversion of land use and its effects (Veldkamp and Fresco, 1996) was developed to simulate land-use change using empirically quantified relations between land use and its driving factors in combination with dynamic modelling. CLUE simulates land use conversion involving both biophysical and human drivers. The model changes the land use only if existing land use cannot satisfy biophysical and human demands. Important biophysical driving forces are local biophysical suitability and their fluctuations, land use history, spatial distribution of infrastructure and land use, and the occurrence of pests and diseases. Human driving forces include population size and density, regional and international technology level, level of affluence, target markets for products, economical conditions, attitudes and values, and the applied land use strategy. The model accommodates three basic types of land use changes: land use expansion, intensification, and contraction. The model is applied on national to continental level using course grid size (>1x1 km), which limits its application to regional level.

Gilruth et al., (1995) documented a dynamic spatial model of tropical deforestation and land use change of the Fouta Djallon mountain range in the republic of Guinea, West Africa. They had simulated the pattern of forest clearing for shifting cultivation based on land use/cover, slope, village proximity, site productivity and labor force. These variables were ranked for agricultural preference and a composite agricultural site preference map was generated. To validate the model, the spatial characteristics of the simulated landscape were compared with land use data using size and distribution of agricultural sites, image similarity (kappa test) and physical characteristics (slope and distance from population centers) of the site.

Wu, F., (1998) developed a prototype of a simulation model, SimLand, based on cellular automata (CA), multicriteria evaluation (MCE) and integrated with GIS to simulate land conversion in the urban-rural fringe. In the study, MCE is not used to provide an optional solution to the land allocation problem. Rather, it is used to mimic how land development potential is evaluated via the tradeoff of multiple development factors. A method, analytical hierarchy process (AHP) of MCE, is used to derive behavior-oriented rules of transition in CA. Simulation schemes of the model are projection of land demand, identification of development factors, and preparation of development preference.

A modified version of CLUE model is CLUE-S, Conversion of Land Use and its Effects at Small regional extent (Verburg et al., 2000; Soepboer, W., 2001) integrated a demand module, a module for spatial analysis and decision rules that influence a spatially explicit allocation module. The demand module calculates the demand for a land use over a time frame. The spatial analysis is based on a statistical analysis of driving factors from socio-economic and biophysical dimensions of the land use change. The model was applied to Sibuyan Island, The Philippines and the Klang-Langat watershed, Malaysia. Land conversion was simulated for the island following a linear extrapolation for multiple land use types in the demand module, a spatial analysis based on logistic regression, and decision rules based on expert systems. Driving factors for land use change include population density, geology, erosion vulnerability, altitude, slope, aspect, distance to road, distance to city, distance to port, distance to stream, and distance to coast. The model integrates local conditions to determine the suitability for a land use type and it is reflected in the results of the spatial analysis, regional conditions determine demands and decision rules. It is well interconnected in approaching from local to regional scale and vice versa.

3.4 Cellular automata (CA)

Cellular automata (CA) are simple models for simulation of complex systems. According to Gilbert and Troitzsch (1999) CA model consists of:

- a *euclidean space* divided into a number of identical cells. CA cells might be placed in a long line (one dimension CA), in a rectangular array or even occasionally in a three dimensional cube;
- a cell *neighborhood* of a defined size and shape;
- Each cell can be one of a *discrete cell states* – for example, Fish or Rice, or Tree, Empty or Fire;
- a set of *transition rules*, which determine the state of a cell as a function of the state of the cell and the states of cells in a neighborhood;
- *discrete time steps* with all cell states updated simultaneously. At each time step, the state of each cell may change.

Cellular automata have been used as models in many areas of physical sciences, biology and mathematics, as well as social sciences. One of the simplest examples of cellular automata is Conway's Game of Life.

3.5 ID3 algorithm

ID3 (Quinlan, 1986), stands for inductive decision tree, is a tree where each branch node represents a choice between a number of alternatives, and each leaf node represents a classification or *decision*. Induction decision tree attempts to identify the attributes/variables that best classify the training datasets. The best classifying attribute represents the attribute with *highest information gain.* Then this attribute is used as the root of the decision tree. The process is repeated until it reaches to find the decision i.e. a *Top-Down Greedy* search through the space of possible decision trees. The ID3 algorithm has been widely used in several application domains. There are number of other decision classifiers are also used.

The algorithm is outlined as follows:

- if all the instances belong to a single class, there is nothing to do (except create a leaf node labelled with the name of that class).
- otherwise, for each attribute that has not already been used, calculate the information gain that would be obtained by using that attribute on the particular set of instances classified to this branch node.
- use the attribute with the greatest information gain.

However, ID3 algorithm has been used in this research to characterize the decision variables of the land use change process over Nong Chok area and to derive the decision rules for the model.

3.5.1 Entropy

$$\textbf{E (S)} = \sum_{i=1}^{c} -p_i \log_2 p_i$$

Where

S: training dataset
c: number target classes
p: proportion of examples in *S* belonging to class i

According to information theory, entropy is defined as number of bits required to encode the classification of an arbitrary member of S.

If all instances in S belong to the same class, then E (S) = 0
If S contains same number of instances in each class, then E (S)=1.

3.5.2 Information Gain

The Information Gain is a measure based on Entropy.

$$Gain(S, A) = E(S) - \sum_{v \in Values(A)} \frac{|Sv|}{|S|} E(Sv)$$

Values (A): Set of all possible values of attribute A
S_V: subset of S for which A has value v
|S| : size of S
$|S_V|$: size of S_V

Gain (S, A) is the expected reduction in Entropy caused by knowing the value of the attribute A (Quinlan, 1986)

3.6 Landscape pattern analysis

The structure, function, and change are the three basic landscape characteristics in the study of the landscape ecology. One most important notion is that landscape pattern strongly influences the ecological processes and characteristics (McGarigal and Marks 1995). Landscape structure has a close relationship with abiotic abundance and diversity. Turner (1989) describes the way spatial structure influences most fundamental ecological processes, and how landscape planning and management, conversely, influence landscape structure.

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

3.6.1 Components of pattern

Landscape structure has two basic components: a) *composition,* a non-spatially explicit characteristic, refers to the variety and relative abundance of patch types represented on the landscape. This component of landscape pattern is generally summarized with diversity indices. b) *configuration or structure,* implies the spatial arrangement, position, orientation, or shape complexity of patches on the landscape. There are various indices of landscape structure.

3.6.1.1 Landscape composition

Landscape composition refers to the number and their relative abundance of patch types represented on a landscape. It does not measure or reflect the patch geometry or geographic location. Composition metrics measure landscape characteristics such as proportion, richness, evenness or dominance and diversity. The principal aspects of diversity are richness – simply the number of different patch types and diversity, which incorporates measures of the relative abundance of different patch types.

3.6.1.2 Landscape configuration

There are several aspects of landscape configuration that may be of interest for particular applications. These include:

Size distribution - patch size distribution is relative abundance or frequency of patches in different size categories. These are often illustrated with size classes ordered on a doubling or log scale since the range in sizes can be quite large for many landscapes.

Dispersion - the tendency of the patches to be regularly or contagiously distributed with respect to each other. Usually this is summarized in terms of nearest-neighbor distances among patches of same type.

Contrast - refers to the relative difference among patch types. This can be computed as a contrast-weighted edge distance, where each type of edge (i.e., between each pair of patch types) is assigned a contrast weight.

Shape complexity - various measures of shape complexity are based on the relative amount of edge per unit area. This is indexed in terms of edge-to-area ratios, or as fractal dimension. Shape complexity connotes the geometry of patches: whether they tend to be simple and compact, or irregular and convoluted.

Adjacency (contagion) - refers to the tendency for elements (cells or patches) of a given type to occur next to patches of another type (or in some cases, the same type). This can be expressed as a matrix of pair-wise adjacencies between all patch types, where the elements of the matrix are the proportions of edges in each pair-wise type.

Connectedness - generally refers to functional joining or connections between patches. Functional connection between patches depends on the application or process of interest; patches that are connected for bird dispersal might not be connected for mammal or for hydrologic flow.

There are number of metrics available to describe landscape pattern, but there are still only two major components - composition and structure, and only a few aspects of each of these (Sisk and Moore, 2002).

3.6.2 Landscape pattern indices

Most of the indices highly redundant and dependent among themselves, since only a few primary measurements can be made from patches (patch type, area, edge, and neighbor type), and all metrics are derived from these primary measures. The followings are some important indices selected to study their relative performance with varied parameters in this research.

3.6.2.1 Number of patches (NP)

Number of patches is an indication of the diversity or richness of the landscape. This index can be calculated and interpreted very easily. However, like other richness measures, this interpretation might give misleading results, because 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 way to count the number of patches within a given landscape is:

$$\mathrm{NP} = \sum_{j=1}^{N} Pi$$

Where Pi is the number of patches for land use class i and N is the number of land use classes.

3.6.2.2 Patch density (PD)

A patch represents an area, which is covered by single land cover class. The patch density *(PD)* expresses the number of patches within the entire reference unit on a per area basis. It is calculated as:

$$\mathrm{PD} = \frac{NP}{A}$$

PD = Patch Density
NP = Number of Patches
A = Area

Patch Density depends on the *grain size*, which is the size of the smallest mapping unit of the input data and the number of different categories. The index is a reflection of the extent to which the landscape is fragmented. This index is important for the assessment of landscape structures, enabling comparisons of units with different sizes.

3.6.2.3 Mean patch size (MPS)

Mean patch size is a measure of the composition of the landscape. The formula is:

$$\text{MPS} = \frac{\sum PS}{NP}$$

Where PS is the patch size and NP is the number of patches.

3.6.2.4 Edge density (ED)

An edge is the border between two different classes. Edge density (in m/ha) or ratio of Perimeter/Area equal to the length (in m) of all borders between different patch types (classes) in a reference area divided by the total area of the reference unit. The index is calculated as:

$$\text{ED} = \frac{E}{A}$$

E = total edge (m)
A = total area

In contrast to patch density, edge density considers the shape and the complexity of the patches. Edge density is a measure of the complexity of the shapes of patches and similar to patch density an expression of the spatial heterogeneity of a landscape. Like patch density, edge density is a function of the size of the smallest mapping unit: the smaller the mapping unit the better the spatial delineation is measured, resulting an increase in the edge length (Europa, 2000).

3.6.2.5 Fractal dimension (FD)

Fractal analysis (Mandelbrot, 1983) was introduced as a method to study spatial patterns that are similar when observed at many scales (e.g., self similar). Boundaries or shapes can be quantified using fractals, and the fractal dimension can then be used as a measure of the complexity of spatial patterns. The fractal dimension is a geometric description of an image. Image looks same regardless of the observation scale. It has an integer value for topological sets and a non-integer value for fractal sets. The dimension of a fractal curve is a number that characterizes the way in which the measured length between given points increases as scale decreases.

Fractal geometry is a new language used to describe, model and analyze complex forms of surface. Fractal dimension can measure the texture and complexity from coastline to mountain (Connors, 2002). Fractals have been proposed as a means of characterizing surface irregularities and originally, surface occurring in nature (Mandelbrot, 1983).

Landscape ecology is concerned explicitly with the effect of spatial heterogeneity on ecological processes. This application has been useful in studies of landscape patterns, the spatial patterns resulting from physical, biological, and human forces over geographical area (Turner et al., 1989). Study shows fractal geometry provides a multi-scale quantitative approach to describing landscape patterns.

The following index is the measure of the fractal geometry of landscape (Mandelbrot, 1983). 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 scene, a regression is calculated between log (perimeter/4), the length scale is used in measuring the perimeter and log (size) of each patch (Turner et al., 1989). The fractal dimension is related to the slope of the regression, by the relationship:

D = 2.S

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

3.6.2.6 Mean Nearest Neighborhood (MNN)

Some ecological processes are strongly influenced by the distance separating by 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 Neighbor Distance:

$$MNN = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} hij}{NP}$$

where
h_{ij} = the edge-to-edge (or centroid to centroid) distance from patch ij to the nearest neighboring patch of the same class.

NP = the number of patches in the landscape that have nearest neighbors

This index may be comparable to a species dispersal distances. A landscape with all patches clumped can produce the same *mean* value like a landscape with widely dispersed pairs of patches. Thus, variance should also be considered (Europa, 2000).

CHAPTER FOUR

MATERIALS AND METHODOLOGY

The methodology of this research consists of following three phases (Figure 4.1):

- Land use change analysis,
- Development of the model, and
- Validation of the model.

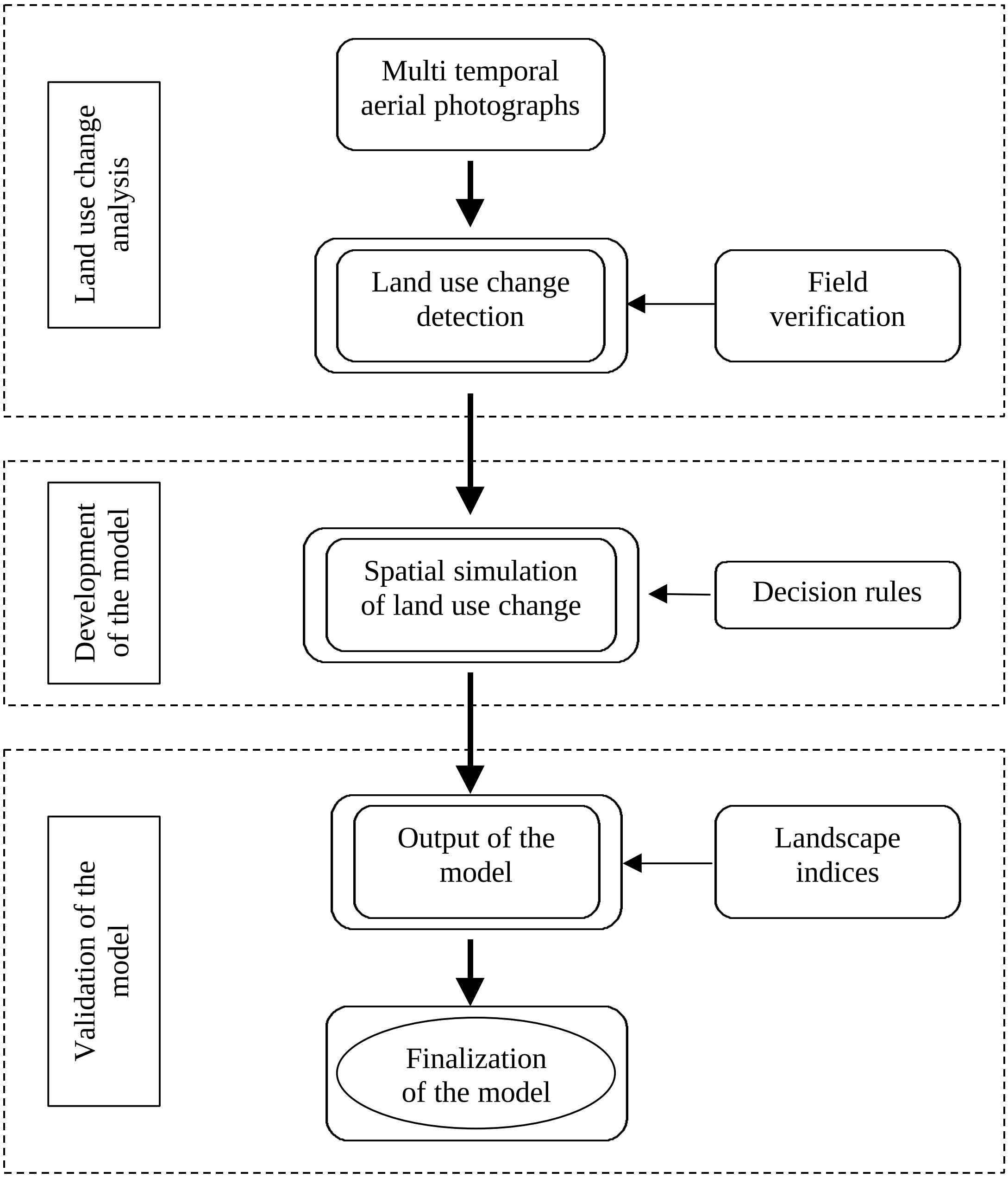


Figure 4.1: Methodological framework of the study

Detailed workflow of the methodology of each phase and its stepwise procedures have been described in the following sections:

4.1 Land use change analysis

4.1.1 Data acquisition and analysis tools

4.1.1.1 Data collection

This study approached the use of a series of aerial photographs to prepare land use map of four dates and land use change map. Due to the shortage of data availability, aerial photographs have been acquired in different scales and different number of paper sheets.

The following aerial photographs (Table 4.1) were collected from Royal Thai Survey Department, Thailand:

Table 4.1: Particulars of multi temporal aerial photographs

Date	Scale	Number of sheets	Roll number
02/11/00	1:15,000	1	002 157
13/11/95	1:20,000	2	0086, 0033
24/02/90	1:15,000	1	363
29/11/81	1:50,000	1	021

Besides, there are other forms of data collected during the study. The following data have been collected for the study:

Paper map:

Topographic map was collected and used as base map for geo-rectification;

Demographic and Socio-economic data:

Demographic and socio-economic data about the farmers were collected by field survey to assess the decision variables/underlying factors of the land use change process. There are many factors involved in the process of land use change. Due to limitation of available data this study attempted to testify the simulation modelling approach with only limited number of variables as a beginning stage. Following data of the farmers have been collected:

- Name of the farmer
- Age
- Education
- Area of land
- Land ownership
- Religion
- Family size
- Area of rice and fish farms
- Annual income

- Other activities of the family
- Comparative income between rice and fish per rai♣/year

4.1.1.2 Software

The following software and tools were used during the study:

✓ Image Processing:
  - ERMapper 6.1
  - ENVI 3.4

✓ GIS data preparation:
  - ArcView 3.2
  - ArcInfo 8.0.2

✓ Statistical analysis:
  - SPSS 11.0
  - MS Excel

✓ Dynamic Spatial Simulation Toolkit:
  - CORMAS 2002

✓ Global Position System (GPS) receiver:
  - Garmin GPS receiver was used during field survey and data collection.

4.1.2 Data processing and analysis

Aerial photographs were scanned and saved as TIFF/Geo-TIFF format. The aerial photographs should be pre-processed before further analysis can be carried on. These were geo-referenced with proper coordinates by image processing software and were used for further analysis. Figure 4.2 describes flowchart of the steps of aerial photo interpretation and processing. In this study, multi-temporal aerial photographs were used to detect land use change dynamics. Global positioning system (GPS) data was collected during field survey as ground control points (GCPs) for geo-referencing of the photographs. GPS receiver was of Garmin brand. The projection system used for GPS reading is UTM, Zone – 47 North, Datum: WGS84. Twelve GCPs were collected throughout the study area (Appendix T1).

Scanned aerial photographs were then geo-rectified to remove geometric distortion. Raw digital images or aerial photographs usually contain significant geometric distortions that cannot be used directly as base map without preprocessing. Photographs were geo-referenced with ERMapper and ENVI software. Image to map registration was done with twelve GCPs throughout the study area. Topographic map was used as the base map for image-map geo-referencing. The error root mean square (ERMS) is 0.35 in geo-referencing. Aerial photographs were mosaiced to cover the study area in the case where one photo did not cover the whole study area. Geo-referencing is done with the following projection particulars:

Map projection: UTM
Zone: 47 North
Datum: WGS84

♣ 1 rai = 1,600 m^2

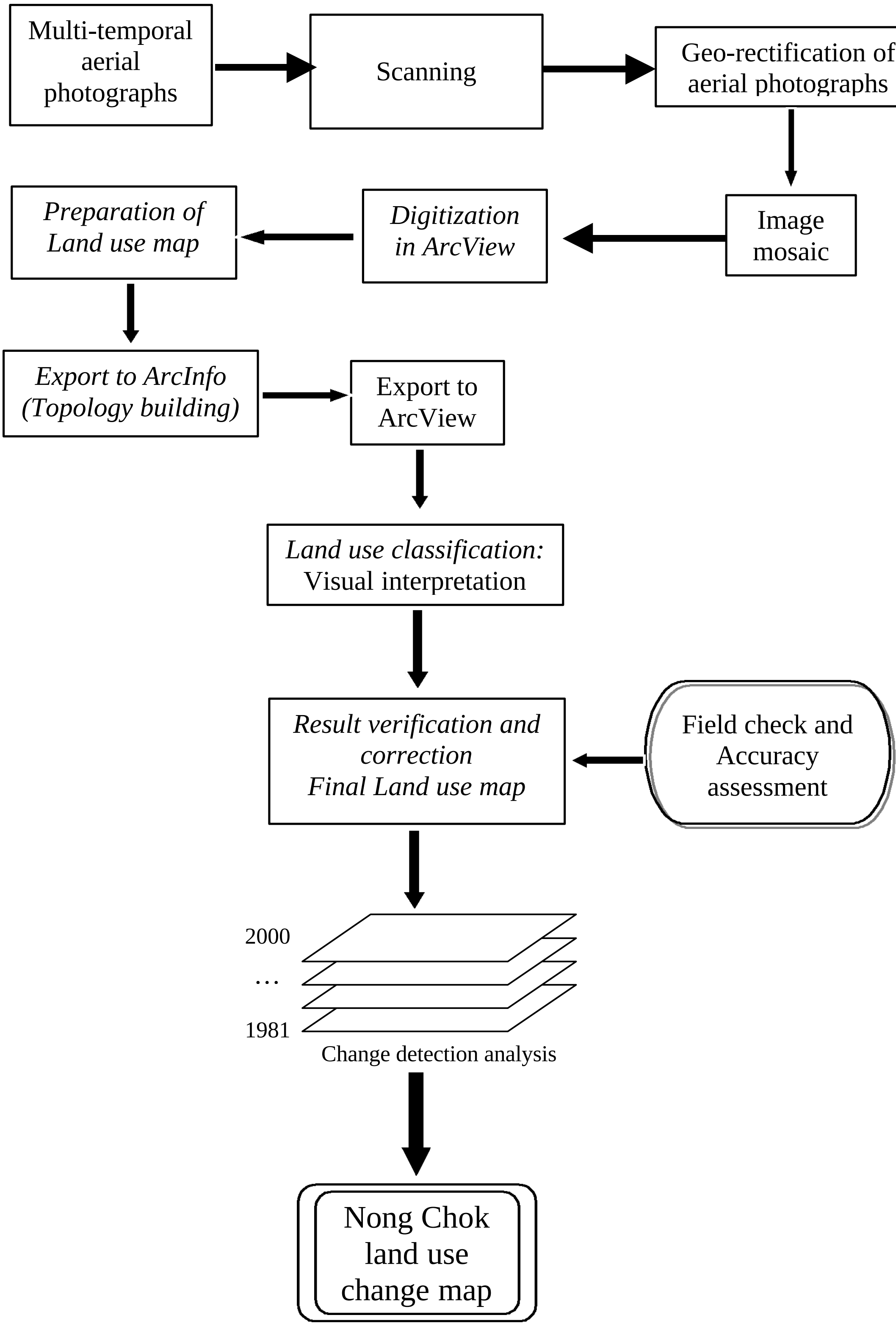


Figure 4.2: Flow diagram shows preparation of land use change map

Central Meridian: 99
Reference Latitude: 0
Scale Factor: 0.9996
False Easting: 500000
False Northing: 0

4.1.3 Land use change map

Geo-rectified aerial photographs were exported as TIFF/GeoTIFF format and opened in ArcView to create land use map. Land use is mapped and classified with the help of aerial photo interpretation elements i.e. *Shape, Size, Pattern, Shadow, Tone/Color, Texture and Association.* Land use was classified into five classes: *paddy field, fishpond, resident & orchard, waterbody,* and *others.* Paddy fields are only paddy producing lands (Figure 4.3a). Fishponds include shrimp and all kind of fishponds (Figure 4.3b). Resident & orchard are homestead area of the farmers with surrounding orchard (Figure 4.3c). Waterbody includes canal only that flows within and around the study area (Figure 4.3d). Others include land, which are currently unused i.e. fallow land (Figure 4.3e).

Land use map, road map, river map, and house location map of 2000, 1995, 1990, and 1981 were developed. Land use, road, and river maps were exported to ArcInfo to build topology. In ArcInfo platform cleaning and building operations were done then maps were exported back to ArcView shape file. Land use maps for four dates were verified by field observation and from interview with farmers for classification validation. Final land use map was developed. In 1981, there was only *paddy field, resident & orchard,* and *waterbody* through out the study area while in 2000, it was observed that a certain amount of land use has been turned to be *fishpond* and *others* types.

4.2 Development of the model

4.2.1 Simulation model of land use change dynamics

To have a comprehensive understanding on the land use changes of the study area, visualization effect with graphical simulation model has been developed. This model is based on the knowledge acquired from historical statistical data of the area. Over 19 years (1981-2000), a series of maps, figures on agricultural production system and changes in socio-economic factors were taken as the input data for the model.

Simulation model is a tool for testing the hypothesis of different scenarios. It gives decision maker a comprehensive look on the land use change mechanism of any area. Spatially explicit simulation models attempt to describe and predict the evolution of ecological attributes with distinct localization and configuration (Baker, 1989). The model is based on cellular automata (CA). Cellular automata models successfully replicate aspects of ecological and bio-geographical phenomena. The model has been developed in CORMAS.

CORMAS stands for Common-pool Resources and Multi-Agents Systems, is an agent based simulation framework based on VisualWorks software, which is a programming environment based on SmallTalk. Cormas provides a set of Smalltalk classes that represents genetic social entities and encodes the behaviors of the actors who are framing the natural resources. This is also equipped with generic spatial entities organized in a

Figure 4.3a: Photograph shows *paddy field* of Nong Chok

Figure 4.3b: Photograph shows *fishpond* of Nong Chok

Figure 4.3c: Photograph shows *resident & orchard* of Nong Chok

Figure 4.3d: Photograph shows *waterbody* of Nong Chok

Figure 4.3e: Photograph shows *others* of Nong Chok

hierarchical way. The architecture of the Cormas interface has been designed to guide the user during model development (Le Page et al., 2001).

The CORMAS window is divided into three parts:

- The definition of the model (‘Model’ pane) where one can describe the entities of simulation (‘Define the entities’ pane), the methods to activate the entities and hence control the simulation (‘Control the evolution’ pane) and the points of view on simulation (‘Define the observation’ pane);
- The various kind of visualisation, essentially the grids, direct communication graph and the chart in the ‘Visualisation’ pane;
- The simulation control itself (‘Simulation’ pane).

Detailed of CORMAS toolkit can be found in the user guide of CORMAS (CORMAS, 2002).

4.2.2 Model structure

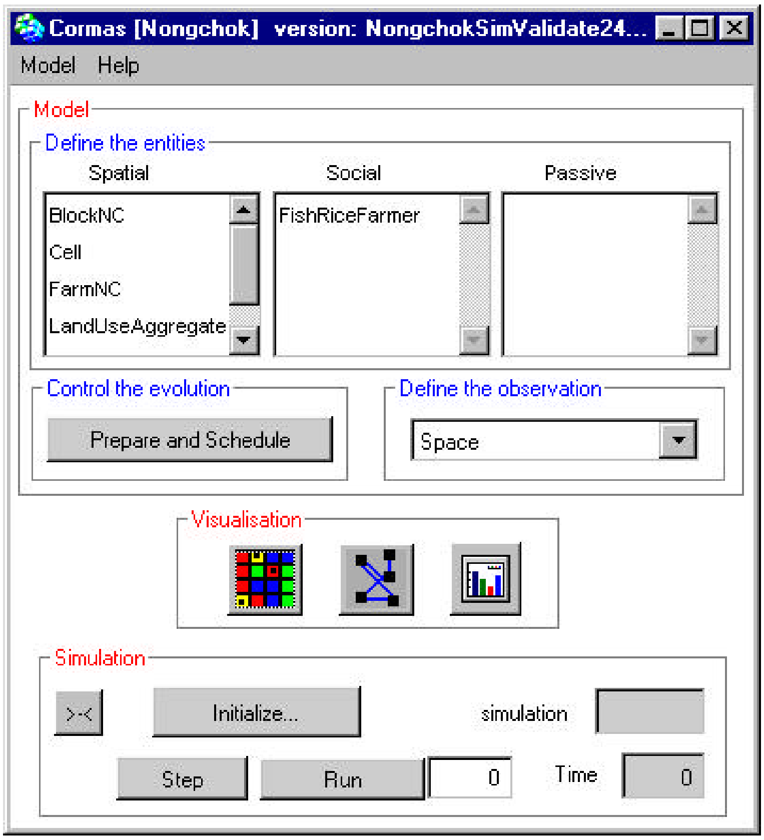
To be compatible with CORMAS land use map of 1981, which was used as initial land use was exported as ASCII format from ArcView. Besides, distance from canal map, ownerId map, parcelId map, blockId map, and farmId map were also exported. These map were imported into CORMAS to build the environment of the model. Grid size of the model is 30 x 30 m.

Figure 4.4 shows the interface of CORMAS and initial state of the Nong Chok model. In the environment there are three types of land use: paddy field, resident & orchard, and waterbody as it was observed in land use map 1981.

The model consists of four levels of spatial units: *farm, block, parcel,* and *cell*. The model functions on cell level which is called *spatial entity element* in CORMAS (Figure 4.5). Cell is the basic spatial unit for development and application of transition rules. Cell has several attributes: FishRiceFarmer, distanceFromCanal, parcel, block, farm and landUse. Parcel is composed of cells, which has same owner and same land use e.g. paddy field. Block is composed of parcels of same owner with same land use. Farm is represented as aggregate of blocks of same owner with different blocks of different land use e.g. paddy field and fishpond. The farmer is denoted as an agent named FishRiceFarmer in the model who has spatial entity farm, block, parcel, and FishRiceCells.

The model works on the environment consists of initial land use, cellular map of distance from canal, ownerId, parcelId, blockId, and farmId. The model starts functioning at the beginning phase with its initial cell state means initial land use. Then for each time step it calculates transition probability of the cells. Among the cells having probability of change, spatial distribution of cells was calculated and the model changes the cells from paddy field to fishpond. This process operates for one time step. The process iterates for 19 steps. It was assumed that each year represents one step. Workflow of the model is shown in Figure 4.6.

Since in 1981 there was no fishpond, the model was initialized with fishpond based on randomization. The rule of initialization is given in Figure 4.7. The rules imply that if the land use of the cell is paddy and neighborhood contains fishpond the model applies



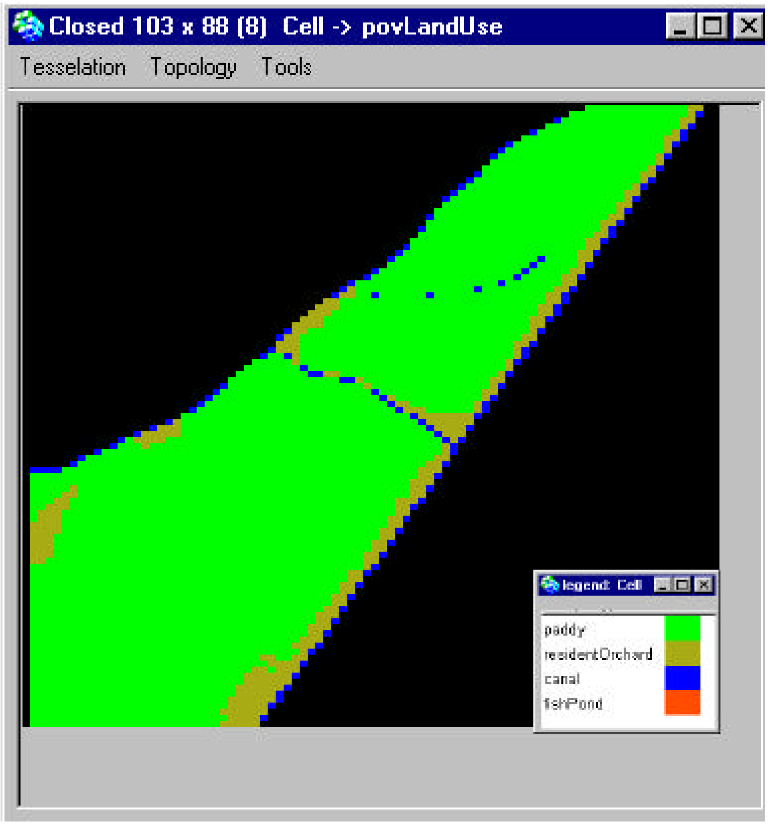


Figure 4.4: Interface of CORMAS (top) and initial state of Nong Chok model (down)

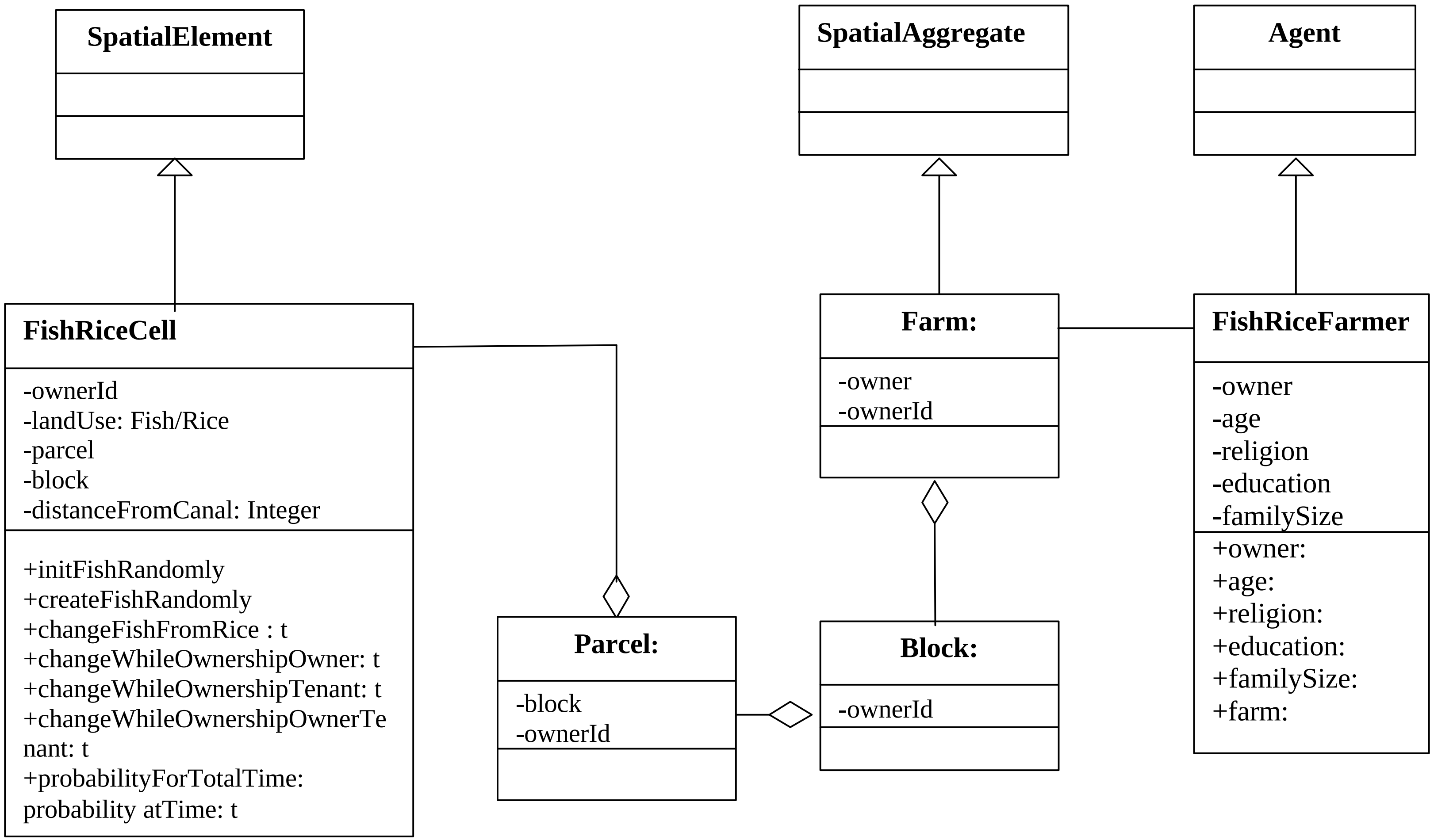


Figure 4.5: Spatial entity elements of Nong Chok model

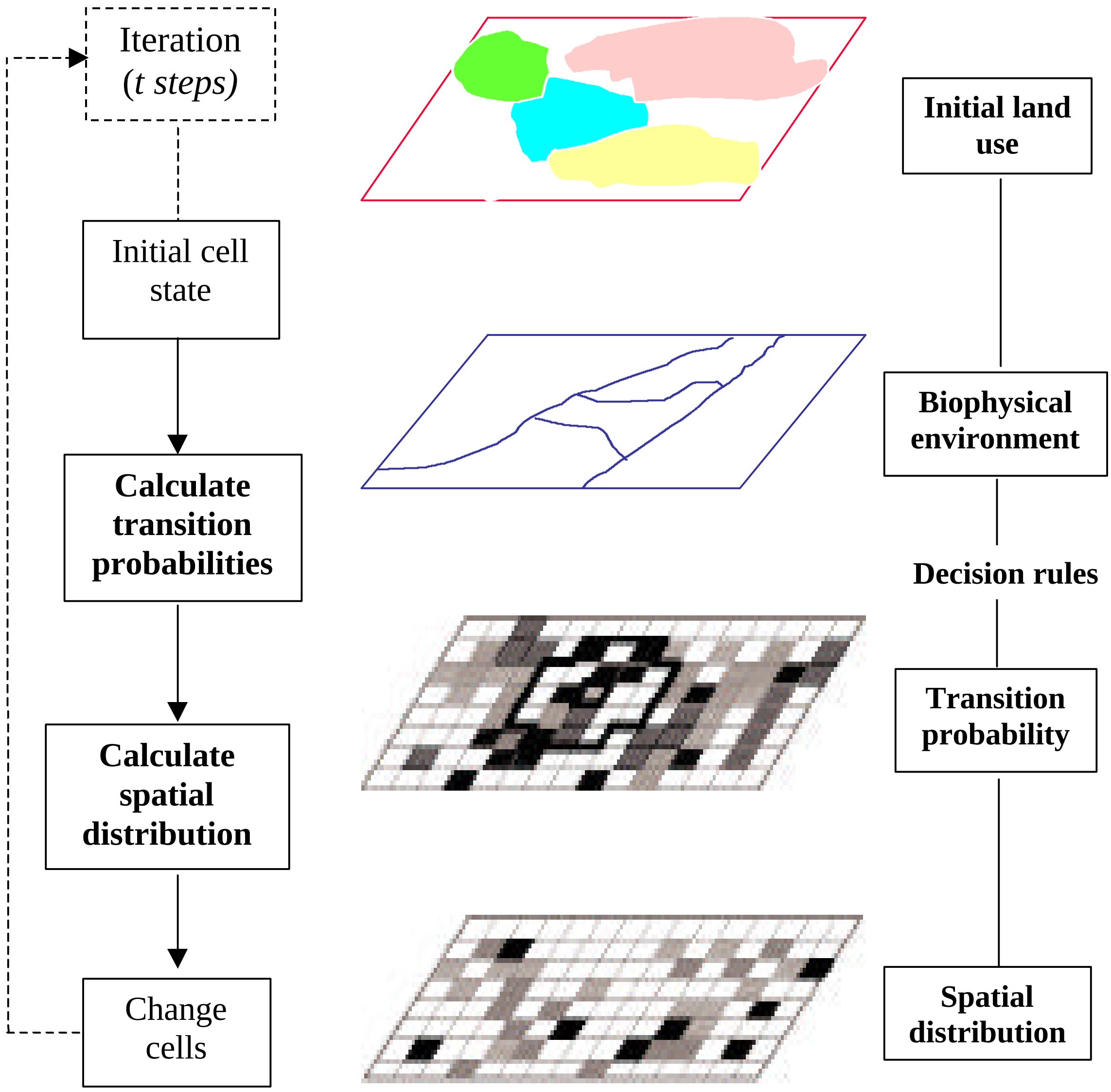


Figure 4.6: Dynamic spatial simulation modelling diagram

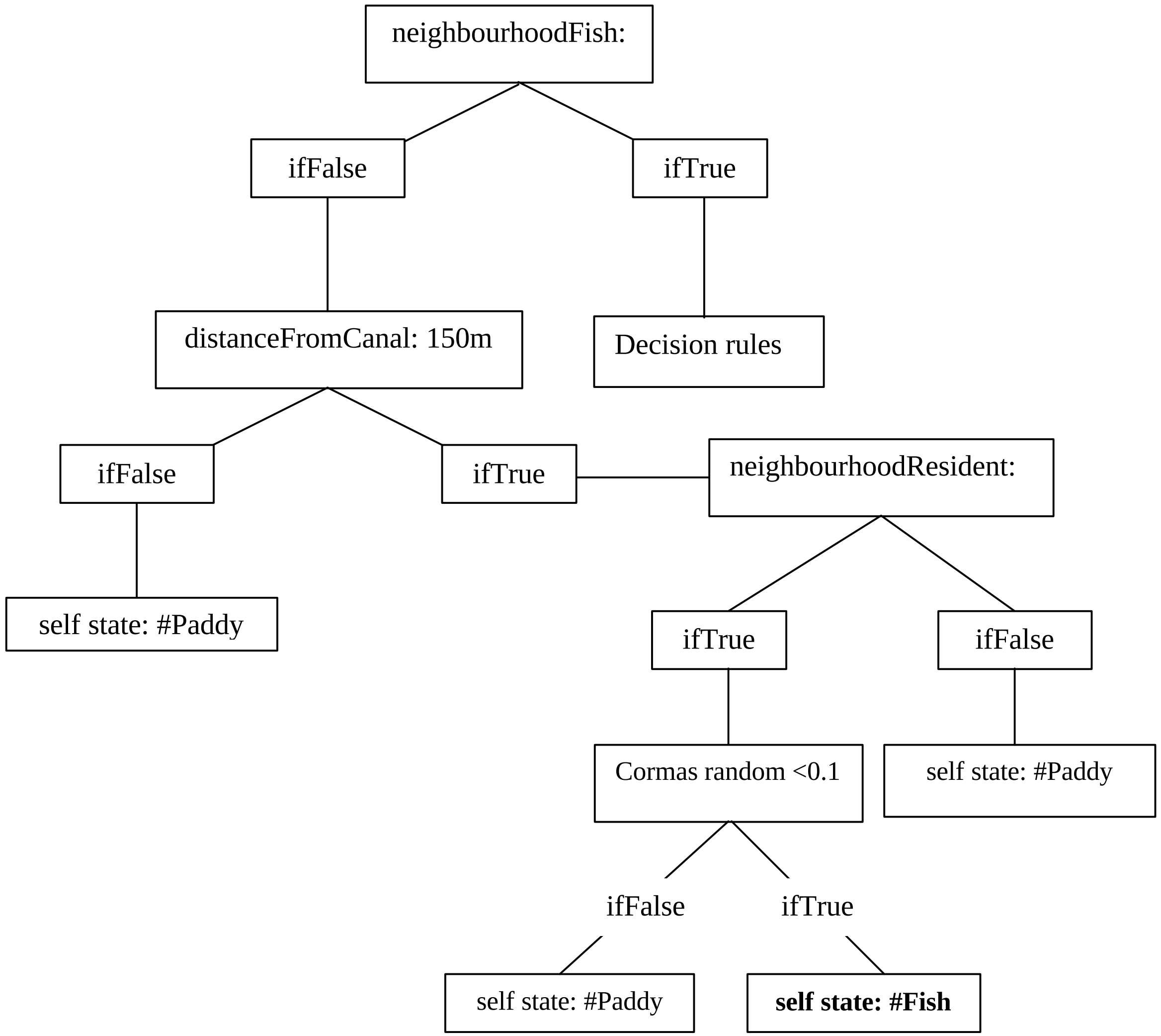


Figure 4.7: Rules of initialization of random fishponds into the model

decision rules else if neighborhood contains no fishpond and if the cell is within 150 meters of canal and neighborhood contains residentOrchard then CORMAS draws a random number and if the number is below 0.1 then the land use of the cell is changed to fishpond. If the random number is above 0.1 then land use state is kept same. The fishpond is created stochastically. Experience of farmers was taken into account to initialize the fishpond.

Water is needed to develop and maintain fishpond. Thus, distance from canal is important and it was also observed that farmers used to keep their fishpond close to their resident to take care of the fishponds. In the light of the above information, fishpond was initialized in the model.

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

4.2.3 Development of decision rules

4.2.3.1 Decision tree construction using ID3 algorithm

Transition function of the model was developed based on ID3 algorithm. Among the collected demographic and socio-economic factors of the farmer only five factors were used in this study as decision variables. These are *age, ownership, religion, education,* and *family size* of the FishRiceFarmer. Each variable was categorized into three classes based on statistical analysis between percentage of land use change and decision variables (Appendix T2).

From cross tabulation of each decision variable and change index (changed parcel was assigned value 1 and parcel without change was assigned 0). The variables were ranked into 1, 2, and 3 based on relative weight (Table 4.2) i.e. class 1 has least percentage of change while class 3 has highest percentage of change (Appendix T2). This ranking was done based on trail and error method to find correlation between land use change and different class rank.

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

Table 4.2 Decision variables with class ranking

Variables	**Value**	**Class Ranking**
Ownership	Owner + Tenant	1
	Tenant	2
	Owner	3
Age	<36	1
	36 - 55	2
	>55	3
Education	<4	1
	(4-10)	3
	>10	2
Family size	<4	2
	(4-6)	3
	>6	1
Religion	Christian	1
	Islam	2
	Buddist	3

4.2.4 Conversion of decision tree into equivalent set of rules

Decision tree for changing land use from paddy field to fishpond shows the relationship among all the decision variables and change attributes. The decision tree was converted into an equivalent set of decision rules. Decision rule is based on *IF … AND … THEN …… ELSE* statement. This decision rules were applied into CORMAS to develop the simulation model. For example:

If myOwner ownership = “owner + tenant” and: myOwner familySize = <4 then landUse = #paddy (no change).

Else If myOwner ownership = “owner + tenant” and: myOwner familySize = (4 - 6) and: myOwner age = (36-55) then landUse = #fishpond $_{p0.813}$ (change probability 0.813)

4.3 Measuring landscape fragmentation and validation of the model

Quantitative methods are necessary to compare spatial patterns and evaluate the performance of spatial simulation models (Turner, 1989). One of the important questions in simulation modelling is how to compare model outputs and validate the model. There are numerous indices used in landscape pattern analysis to measure the landscape fragmentation and validation of spatially dynamic model. From search in the available literatures the following indices are summarized:

- Number of classes (NC) and number of patches (NP)
- Patch density (PD)
- Mean patch size (MPS)
- Edge density (ED)
- Fractal dimension (FD)

- Mean nearest neighbor distance index (MNN)
- Dominance index
- Diversity index
- Contagion index
- Interspersion and juxtaposition index (IJI)

Since the study area is very small only covering an area of 10 km^2 and this research considered only land use change from paddy field to fishpond, all the above indices are not applicable in this study. However, after screening all the indices, *number of cells, patch density, mean patch size, edge density, fractal dimension,* and *mean nearest neighborhood* were found to be useful for this study.

The indices were applied to simulation outputs and the value of the index was calculated. Simultaneously the indices were also applied to reference map (land use map 2000). The workflow is shown in the Figure 4.8.

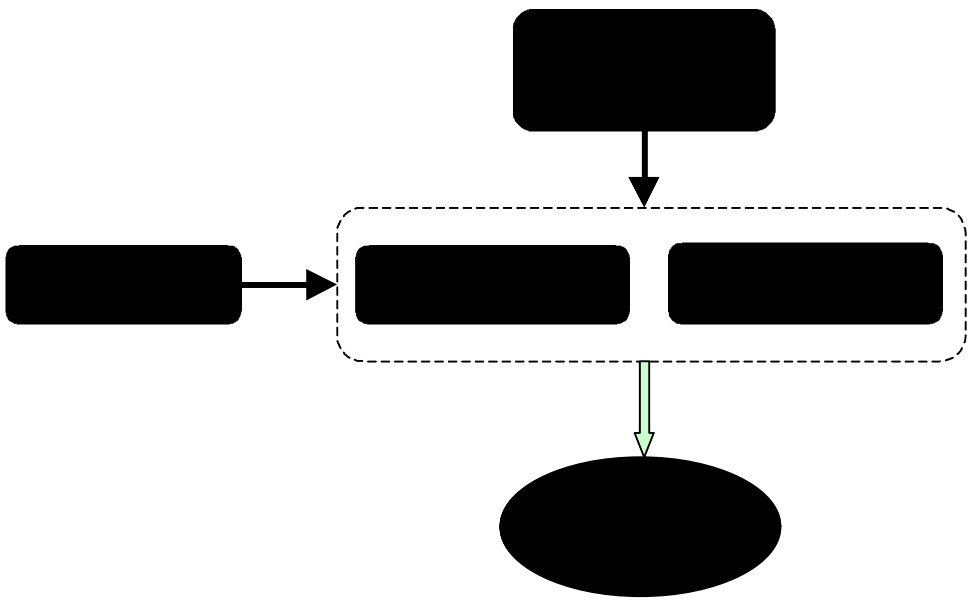


Figure 4.8: Flow diagram of measuring landscape fragmentation and validation of the model

CHAPTER FIVE
RESULTS AND DISCUSSION

5.1 Data collection and preparation

A series of aerial photographs were used in this research to prepare land use map and land use change map. The study area is around 10 km^2 in size. The research focused on land use change from paddy field to fishpond. Therefore, satellite data from Landsat, IRS or even SPOT was considered not useful for the study. However, high-resolution satellite data from IKONOS could be useful. But the cost involved to acquire IKONOS data is very high, which limits its application and moreover for multi-temporal satellite data from IKONOS is not available for the study. In the above circumstances, aerial photographs were used in this research.

The photographs were taken by airplane on different dates. The quality of each photograph is different due to the changes in photographic technology. Therefore, it is impossible to evaluate the accuracy of these images. Aerial photograph of 1981 has course resolution but other dates are of better resolution. There have also been observed variation in the radiometry of two photos of the same date but those were taken at different times. Remote sensing data collection and processing of the data for this research were enough to identify the land use change.

5.2 Geo-rectification

Aerial photographs were geo-rectified to remove geometric distortions. In usual case, aerial photographs are orthorectified to remove geometric distortions and distortions due to relief and shade in mountainous terrain. But Nong Chok has flat topography without any altitudinal effects on land. Considering the situation of Nong Chok, only geo-rectification was done to remove geometric distortions with ERMS 0.35.

5.3 Demographic and socio-economic variables

Different driving forces at different scales play a key role in the land use and land use patterns. There is no systemic study carried out on spatial simulation of land use change dynamics in Thailand. Thus, it was difficult to identify driving factors of the land use change mechanism for this study. However, literature on dynamic spatial simulation of land use change concerns simulation on different pattern of land use changes in other parts. Perhaps the most intensively studied phenomenon is the deforestation process, which can serve as an example of the complexity of land use changes. More recent efforts also address other form of land use conversions including urban expansion i.e. land cover change on urban and rural fringe, and agricultural intensification. DINAMICA (Britaldo et al., 2002), SALU (Stephenne and Lambin, 2001), CLUE (Veldkamp and Fresco, 1996), DLS (Wang and Zhang, 2001), CLUE-S (Verburg et al., 2002; Soepboer, 2001) and SimLand (Wu, 1998) models are examples of the land use/cover change simulation. However, most of the applications were carried on regional scale, in some cases mountainous terrain, or on highly urbanized areas. Most study approaches involving number of driving forces including demographic, biophysical, climatic, political, economic, and social types. These driving factors include population dynamics, proximity to forest, proximity to road network, urban attraction factors, employment ratio, topography, elevation, slope, aspect, erosion, soil type (Wu, 1998; Verburg et al., 2002; Soepboer, 2001), land tenure, farm size, income, and distance to market (Table 5.1).

Table 5.1: Driving forces of spatially explicit land use change in Central America (summarized by Kok, K., 2001).

Land use change driver	Type	Source
Population density	Demographic	Rudel and Roper (1997), Angelsen (1999), Pfaff (1999), Veldkamp and Fresco (1997)
Distance to city		Southgate *et al.* (1991)
Distance to road		Sader and Joyce (1988), Parayil and Tong (1998)
Topography	Biophysical	Hall *et al.* (1995), Rudel and Roper (1997)
Elevation		Veldkamp and Fresco (1997), Pontius *et al.* (2001)
Slope		Sader and Joyce (1988), Kammerbauer and Ardon (1999)
Soil type		Ludeke *et al.* (1990), De Koning *et al.* (1998)
Climate variability	Climatic	Chomitz and Gray (1995), De Koning *et al.* (1998)
Life zone		Sader and Joyce (1988), Ludeke *et al.* (1990)
Land redistribution programs	Political	Brockett, (1988), Jones (1989)
Park protection		Chomitz and Gray (1995), De Koning *et al.* (1998)
Subsidy system		Quiros *et al.* (1987), Hansen-Kuhn (1993)
Land tenure	Economic	Becker *et al.* (1998), Humphries (1998)
Farm size		Thorpe (1997)
Income		Stonich (1993), Rudel and Roper (1997)
Distance to market		Chomitz and Gray (1995), Godoy *et al.* (1997)
Tradition	Social	Joly (1989), Edelman (1992)
Status		Schelhas (1996)
Education level		Godoy *et al.* (1997), De Koning *et al.* (1998)
Diseases	Miscellaneous	Jones (1989)
Civil war		Diaz-Bonilla (1990)

This research concentrated only land use change from paddy field to fishpond and applied on only a small landscape. Consequently, the following driving factors of the FishRiceFarmers have been collected:

- ✓ Name of the farmer
- ✓ Age
- ✓ Education
- ✓ Area of land
- ✓ Land ownership
- ✓ Religion
- ✓ Family size
- ✓ Area of rice and fish farms
- ✓ Annual income
- ✓ Other activities of the family
- ✓ Comparative income between rice and fish per rai[✧]/year

During field survey it was intended to identify all the above-mentioned factors of the farmers but in reality it was difficult to get data about *annual income*, *comparative income*

✧ 1 rai = 1,600 m^2

between rice and fish per rai/year from farmers, which were assumed to have immense importance in modelling the land use change dynamics. In most cases, the farmers were either reluctant to give information on income or provided vague data which was unsuitable to be used in this research. Then a screening was done and the research aimed to focus only on **age, education, religion, ownership,** and **family size** of the farmers as decision variables. The decision rules for change mechanism were subsequently developed based on these factors.

5.4 Land use change map

The land use maps of four years (1981, 1990, 1995, and 2000) were developed from aerial photographs. These maps were checked and verified by ground truthing and by farmers interview about previous land use. It was difficult to differentiate between fishponds and waterlogged paddy fields from aerial photographs. However, fishponds were found to have smooth surface and finer texture than water logged paddy fields and subsequently the land use map was developed.

This research focused only on land use conversion from paddy field to fishpond and aimed to develop a dynamic simulation model based on observed phenomena. For each patch of land whether it has been changed from 1981 to 2000 was identified and a change map was created (Figure 5.1), which has only change and no change attributes. The land use change was considered when farmers change its land use from one type to another e.g. paddy field to fishpond during 1981-2000. Each patch was assigned an *ownerId* so that it can be integrated with decision variables data from field survey on farmers of the area.

In 1981, there were only three types of land uses: *paddy field, resident & orchard,* and *waterbody.* Total areas covered by each land use type were - paddy field (2,787,931.952 m^2), resident & orchard (290,331.182 m^2), and waterbody (112,197.494 m^2). While in 2000, there were five categories of land use: *paddy field, fishpond, resident & orchard, waterbody*, and *others*. Total areas covered by each land use type were - paddy field (2,154,530.044 m^2), fishpond (440,618.351 m^2), resident & orchard (300,316.281 m^2), waterbody (112,181.692 m^2), and others (181,903.298 m^2). Fishponds include both shrimp and other types of fishponds (Table 5.2). Figure 5.2 shows increase of fishpond areas and decrease of paddy field areas from 1981-2000.

In the early years of the period 1981 to 2000, the rate of land use change was slower than later years. Average rate of transition for 19 years (1981-2000) is 23,190 m^2/year. The years could be divided into two phases (1981-1990, and 1990-2000). Rate of land use change between 1981-1990 is 17,705 m^2/year and 1990-2000 is 28,126 m^2/year.

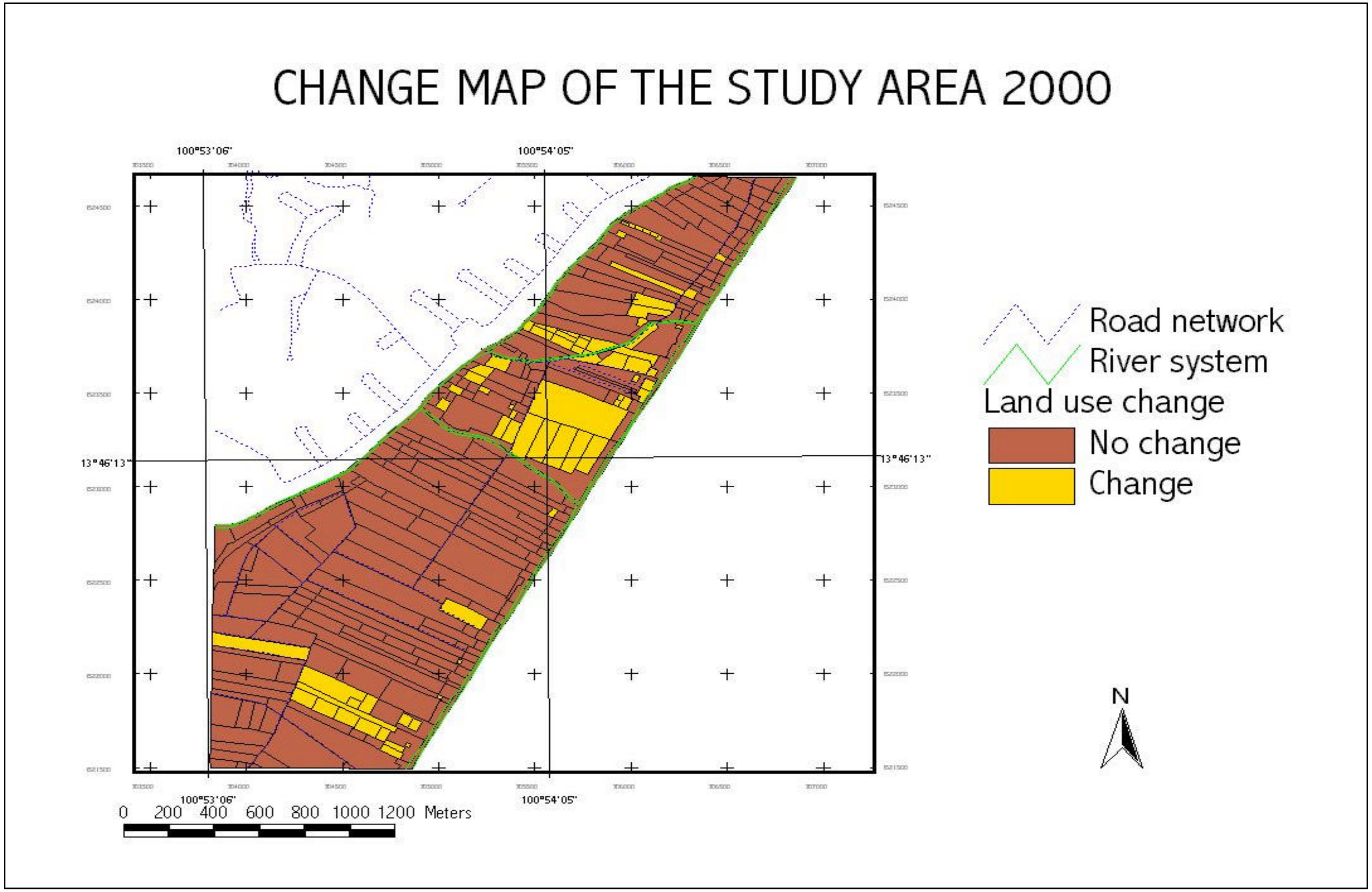


Figure 5.1: Land use change map of the study area

Table 5.2: Areas of different land use types from 1981-2000

Land use type[⌖]	Land use 2000 areas (m^2)	Land use 1995 areas (m^2)	Land use 1990 areas (m^2)	Land use 1981 areas (m^2)
Paddy field	2,154,530.044	2,265,443.373	2,629,284.389	2,787,931.952
Fish Pond	440,618.351	359,337.697	159,351.000	-
Resident & Orchard	300,316.281	324,462.412	264,018.900	290,331.182
Waterbody	112,181.692	112,133.339	112,163.958	112,197.494
Others	181,903.298	128,188.198	25,443.715	-

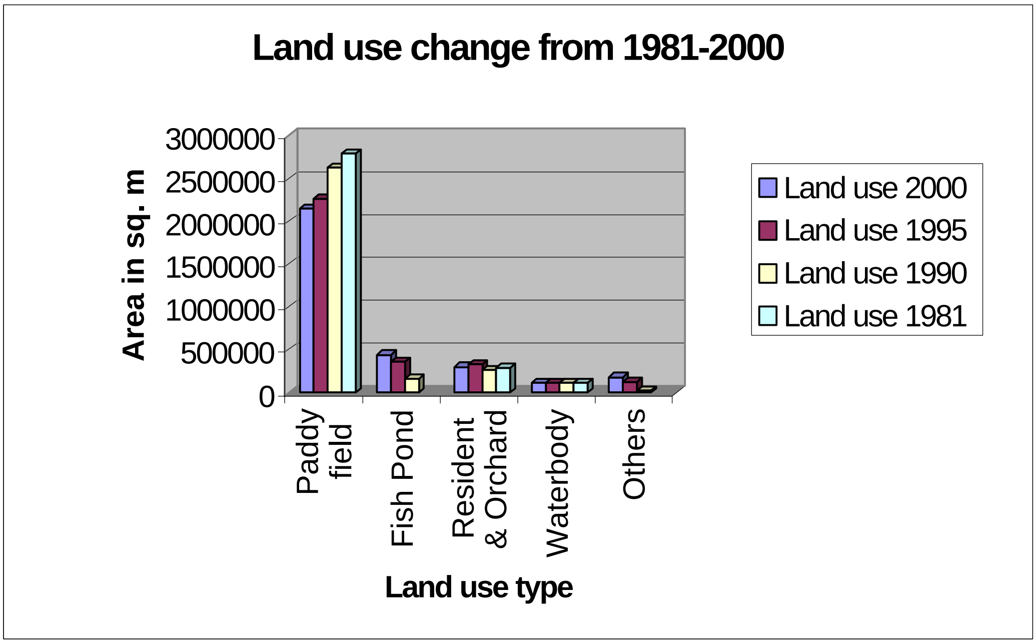


Figure 5.2: Graph shows land use conversion from 1981-2000

5.5 Development of decision rules

5.5.1 Entropy calculation of Nong Chok dataset

In the land use change dataset, there is two target classes: Change and No change. Total case in this study is 298 composed of change instances 72 and No change instances 226. Thus, the entropy for the change dataset is 0.798 bit.

Entropy $$E(S) = \sum_{i=1}^{c} -p_i \log_2 p_i$$

Where
S: training dataset
c: number target classes, i.e. change, nochange
p: proportion of examples in *S* belonging to class i

[⌖] Explanation of different land use types is given in section 4.1.3

$$P_{Change} = -\left(\frac{72}{298}\right)\log_2\left(\frac{72}{298}\right) = 0.303$$

$$P_{Nochange} = -\left(\frac{228}{298}\right)\log_2\left(\frac{228}{298}\right) = 0.495$$

$$E(S) = P_{Change} + P_{Nochange} = 0.303 + 0.495 = 0.798\,\text{bit}$$

5.5.2 Information gain of Nong Chok dataset

This calculation leads to find out the highest information gain from the entire decision variables (detailed calculation has been given in Appendix T3). The decision tree was developed through the top down search of the entire decision space (Figure 5.3).

Information Gain

$$Gain(S, A) = E(S) - \sum_{v \in Values(A)} \frac{|Sv|}{|S|} E(Sv)$$

Values (A): Set of all possible values of attribute A
S_V: subset of S for which A has value v
|S| : size of S
$|S_V|$: size of S_V

Gain (S, Education)

$$E(S) - \frac{|S_{<4}|}{|S|} E(S_{<4}) - \frac{|S_{(4-10)}|}{|S|} E(S_{(4-10)}) - \frac{|S_{>10}|}{|S|} E(S_{>10})$$

$$= 0.798 - (13/298)0.890 - (25/298)0.855 - (260/298)0.786$$

= 0.001 bit

2) Gain (S, Ownership)

$$= E(S) - \frac{|S_{owner+tenant}|}{|S|} E(S_{owner+tenant}) - \frac{|S_{tenant}|}{|S|} E(S_{tenant}) - \frac{|S_{owner}|}{|S|} E(S_{owner})$$

$$= 0.798 - (32/298)0.974 - (216/298)0.489 - (50/298)0.971$$

= **0.176 bit**

3) Gain (S, Age)

$$= E(S) - \frac{|S_{<36}|}{|S|} E(S_{<36}) - \frac{|S_{(36-55)}|}{|S|} E(S_{(36-55)}) - \frac{|S_{>55}|}{|S|} E(S_{>55})$$

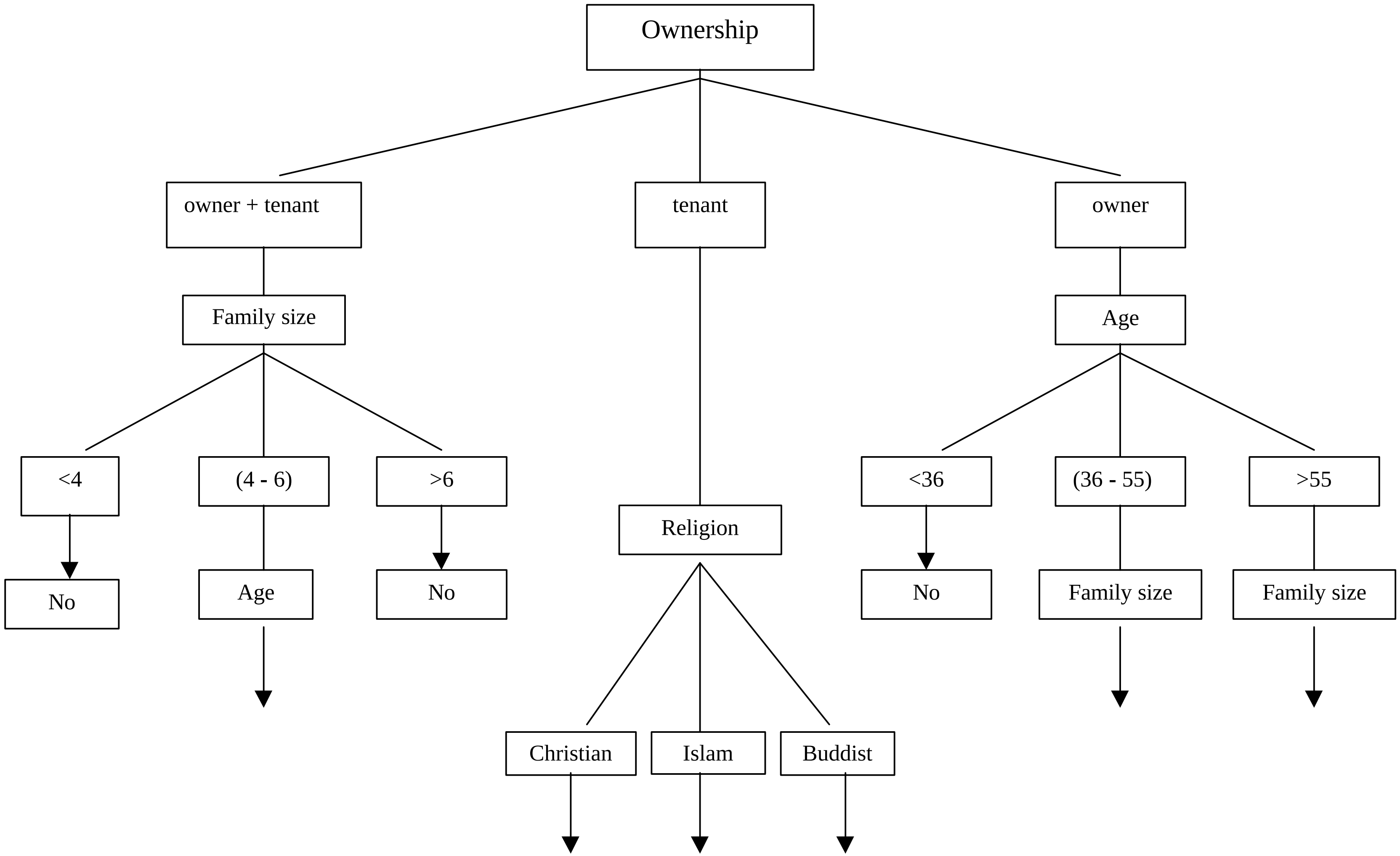


Figure 5.3: Decision tree structure

$= 0.798 - (47/298)0 - (116/298)0.837 - (145/298)0.886$

$= 0.07\,\text{bit}$

4) Gain (S, Religion)

$$E(S) - \frac{|S_{Christian}|}{|S|}E(S_{Christian}) - \frac{|S_{Islam}|}{|S|}E(S_{Islam}) - \frac{|S_{Buddist}|}{|S|}E(S_{Buddist})$$

$= 0.798 - (5/298)0.971 - (45/298)0.956 - (248/298)0.742$

$= \ 0.02\,\text{bit}$

5) Gain (S, Family size)

$$= \ E(S) - \frac{|S_{<4}|}{|S|}E(S_{<4}) - \frac{|S_{(4-6)}|}{|S|}E(S_{(4-6)}) - \frac{|S_{>6}|}{|S|}E(S_{>6})$$

$= 0.798 - (33/298)0.330 - (102/298)0.874 - (163/298)0.804$

$= \ 0.022\,\text{bit}$

Information gains of all the change variables are shown in Table 5.3.

Table 5.3: Information gain against each decision variables

Decision Variables	**Information Gain (bits)**
Education	0.001
Ownership	**0.176**
Age	0.07
Religion	0.02
Family size	0.022

From the above table the highest information gain is the *ownership*. Thus, *ownership* has turned to be the root of the decision tree. Now in *ownership* there are three land entitlement i.e. instances: o*wner+tenant*, *tenant*, and *owner*. Here *owner+tenant* means farmer has their own land, moreover, they have taken rent of land from other people. These people are mostly living in Bangkok. *Tenant* means they do not have their own land but have taken land rent from other people for cultivation and *owner* means they have their own land for cultivation. Owner of the land can take decision to change land use from one type to other while tenant farmer cannot follow the same. So, in most cases, they follow the existing land use pattern of the land.

At each instance, for example, *owner+tenant* there are 32 cases (Appendix T3), the process is continued to identify highest information gain for this instance. In this case, the highest information gain is the *family size*. Now in *family size* there are three instances: <4, (4-6), and >6. For instances family size <4 and >6, the tree stops branching since there is no cases in instance <4 and only two cases in instance >6 but they have only no change index. While in instance (4-6), there are 30 cases, where they have both change and no change attributes. Thus, the process was continued and the highest information gain in *family size*

(4-6) is *age*. The tree cannot move further at this stage since after *age* there is no effect of *education* and *religion.* All 30 cases in age have same *education* level and *religion* background e. g. *education* class is <4 and *religion* is buddist. Here, in case of *age,* there are again three instances: <36, (36-55) and >55. For *age* group <36 there is no case. In *age* group (36-55) there are 16 cases and *age* >55 there are 14 cases. As the tree stops here due to lack of data, the decision for change was probabilistic. Since in *age* group (36-55) there are 16 change cases and 3 no change cases. While in *age* group >55 there are 6 change cases and 8 no change cases. The probability for land use change is estimated 0.813 and 0.429 for *age* group (36-55) and >55 respectively (Figure 5.4a). The process is continued for other ownership instances i.e. *tenant,* and *owner*.

The second instance of *ownership* variable is *tenant*. In this instance there are 216 cases (Appendix T3), out of 216 cases 193 are no change and 23 are change cases. In this instance highest information gain is *religion*. In case of *religion* there are three instances: *christian*, *islam*, and *buddist*. In instance of *christian* there is no case. In instance of *islam* highest information gain is *family size.* In *family size* there are three instances: <4, (4-6) and >6. In *family size* <4 although both *age* and *educatio*n has highest information gain emphasis is given to *education*. There are total 8 cases in *education*. For education level <4, transition probability is estimated 0.286 since in this instance only 2 cases out of 7 have changed. For *education* level >4 there is only 1 case but with no change attribute. In *family size* (4-6) highest information gain is *education*. There are total 24 cases in *education*. For *education* level <4, transition probability is estimated 0.5 since in this instance there is 1 case in both change and no change attribute. For *education* level >10 there is no change case. For *education* level (4-10) transition probability is estimated 0.318 since in this instance only 7 cases out of 22 have changed. In *family size* >6, there is no change case. In instance of *buddist* highest information gain is *age*. In *age* there are three instances: <36, (36-55) and >55. In *age* group <36 there are 40 cases but all with no change attributes. In *age* group (36-55) highest information gain is *family size*. In *family size* <4 transition probability for change is estimated 0.05 since there is 1 out of 20 cases is change. In *family size* (4-6) transition probability for change is estimated 0.109 since there are 5 out of 46 cases are change. In *family size* >6 there are 4 cases with no change attribute. In *age* group >55 highest information gain is *family size*. In *family size* <4 there are 16 cases but all with no change attribute. In *family size* (4-6) transition probability for change is estimated 0.135 since there are 5 out of 37 cases are change. In *family size* >6, transition probability for change is estimated 0.111 since there are 2 out of 18 cases are change (Figure 5.4b).

The third instance of *ownership* variable is *owner*. In this instance there are 50 cases (Appendix T3) of which 20 cases are of no change and 30 are change attributes. In this instance highest information gain is *age*. In case of *age* there are three instances: *<36, (36-55),* and *>55*. In instance age <36, there are 5 cases but all with no change attribute. In instance of (36-55) highest information gain is *family size*. In *family size* there are three instances: <4, (4-6) and >6. In *family size* <4 there are 9 cases. In all these cases they have similar *education* background. Thus, the tree cannot move further. The transition probability is thus estimated 0.75 since there are 6 cases out of 8 are change. For *family size* (4-6), and >6 they have all no change attribute. In instance age >55, highest information gain is *family size*. In *family size* there are three instances: <4, (4-6) and >6. For *family size* <4, highest information gain is *religion*. There are three instances in *religion*: *christian, islam,* and *buddist*. For *christian* transition probability is estimated 0.60

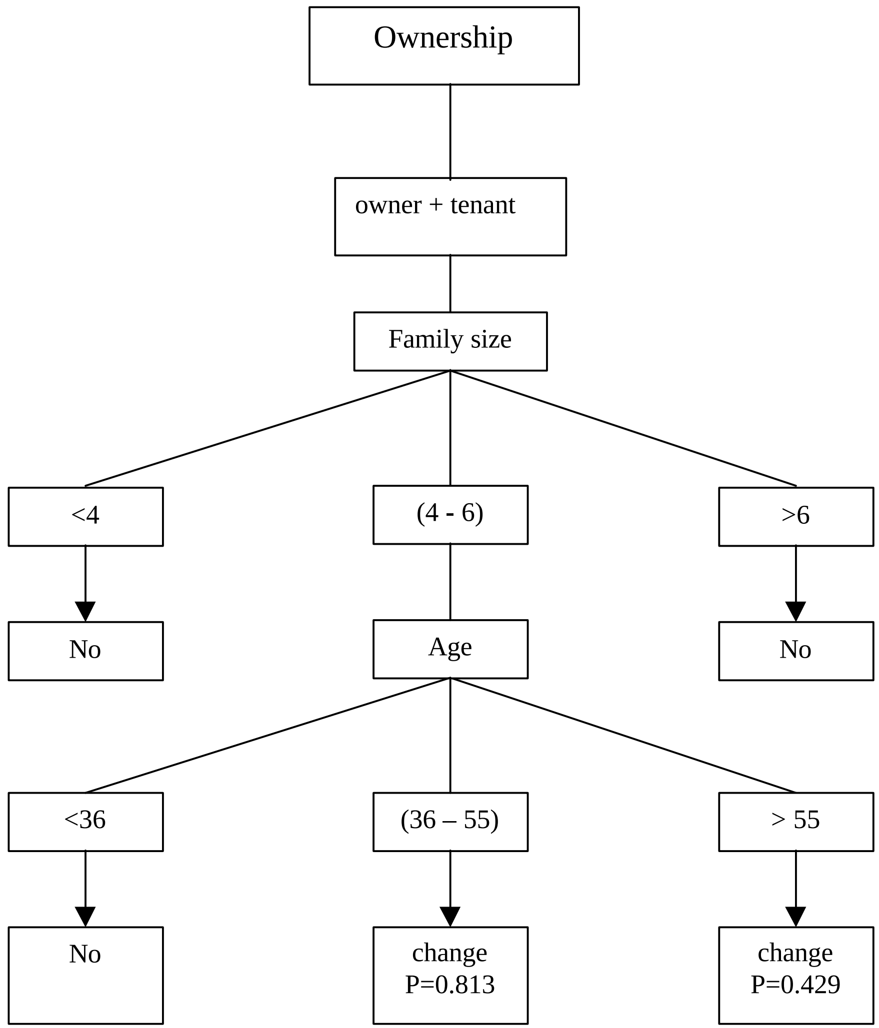


Figure 5.4a: Decision tree structure

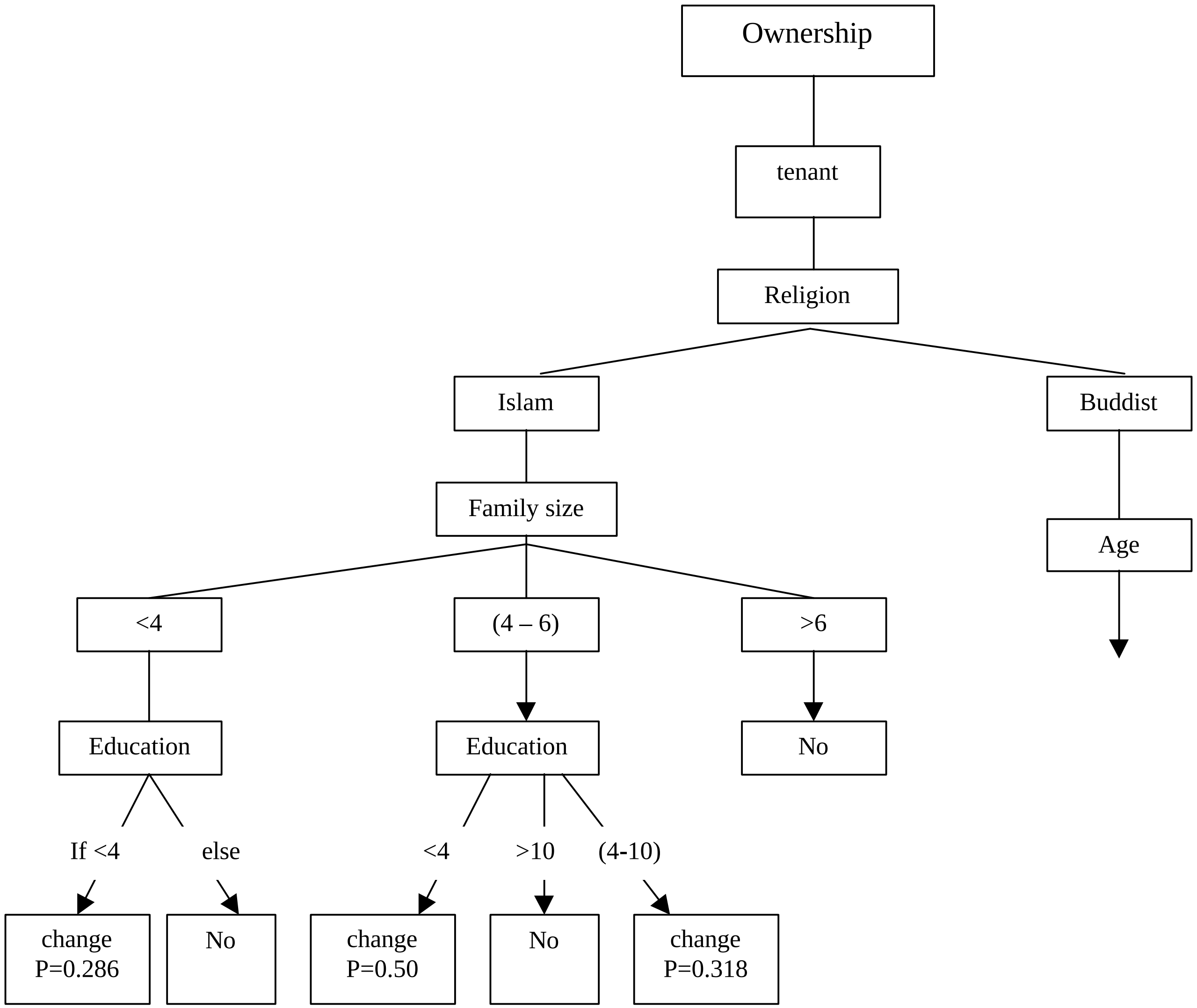


Figure 5.4b: Decision tree structure

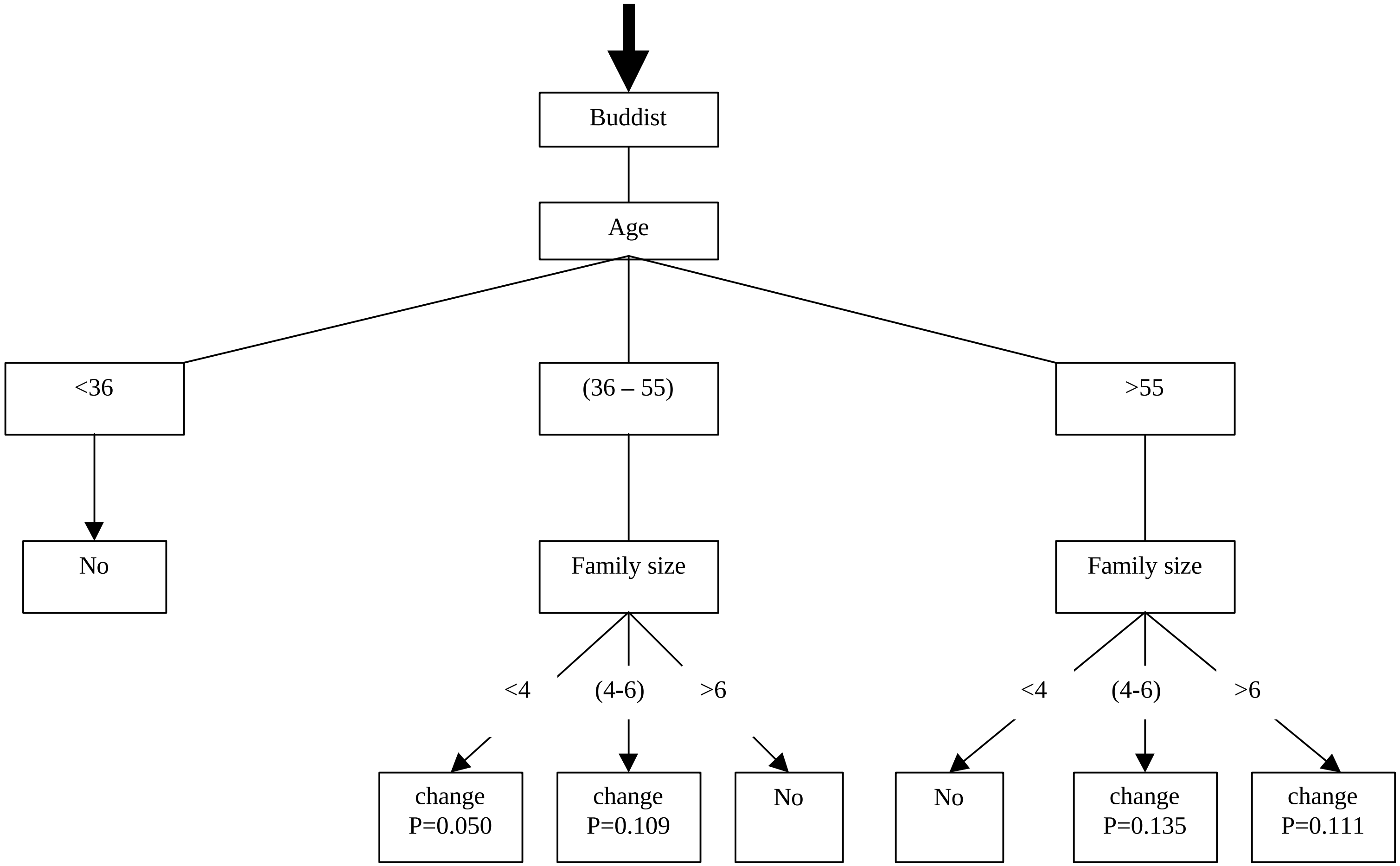


Figure 5.4b: Decision tree structure

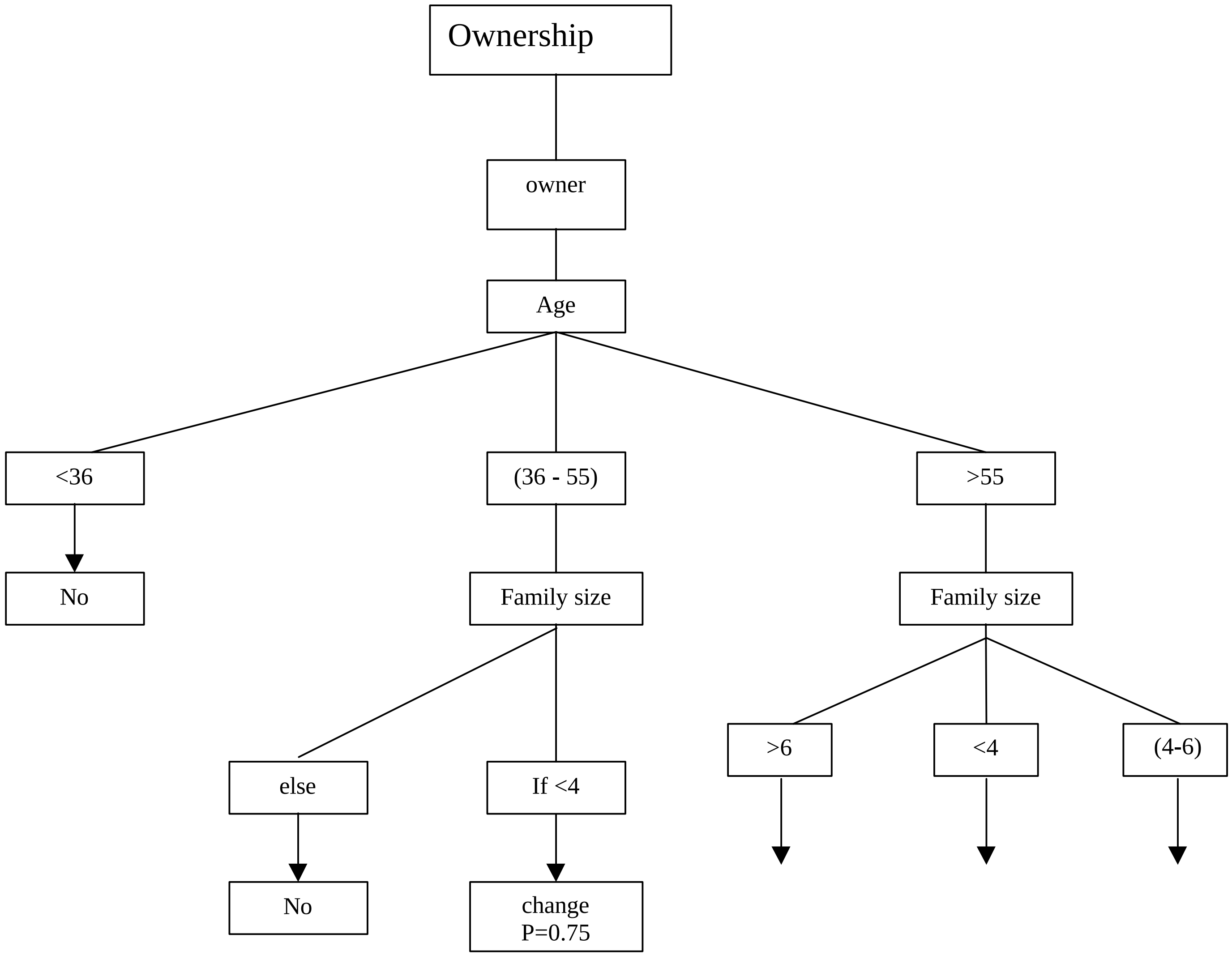


Figure 5.4c: Decision tree structure

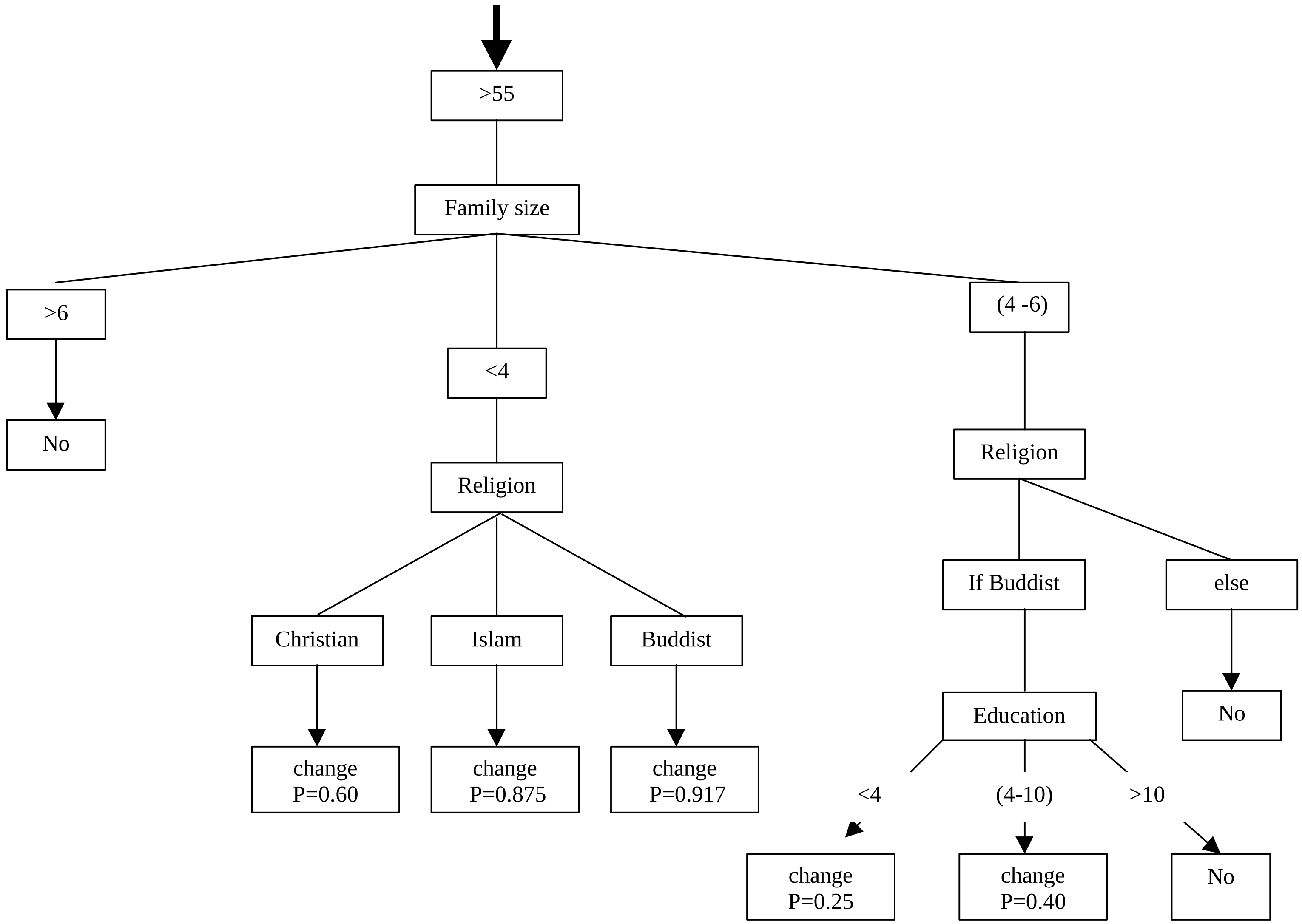


Figure 5.4c: Decision tree structure

since there are 3 cases out of 5 cases are change but all cases have similar *education* level. For *islam* transition probability is estimated 0.875 since there are 7 cases out of 8 cases are change but all cases have similar *education* level. For *buddist* transition probability is estimated 0.917 since there are 11 cases out of 12 cases are change but all cases have similar *education* level. For *family size* (4-6), highest information gain is *religion*. There are three instances in *religion*: *christian*, *islam*, and *buddist*. For *buddist* highest information gain is *education*. *Education* has three levels: <4, (4-10), and >10. For *education* level <4 transition probability is estimated 0.25 since there is 1 case out of 4 cases are change. For *education* level (4-10) transition probability is estimated 0.40 since there are 2 cases out of 7 cases are change. For *education* level >10 there is no case. For *christian*, and *islam* there is no case with change attribute. Thus, the tree cannot grow further (Figure 5.4c).

Rate of transition from 1981-2000 is not linear. Rate of transition from 1981, 1990, 1995 and 2000 shows that rate from 1981-1990 is slower than 1990-2000. Thus, transition probability for simulation was calculated (Figure 5.5) for each time step according to the equation 4.1.

$$y = 4ax^2 \qquad \textit{Equation 4.1}$$

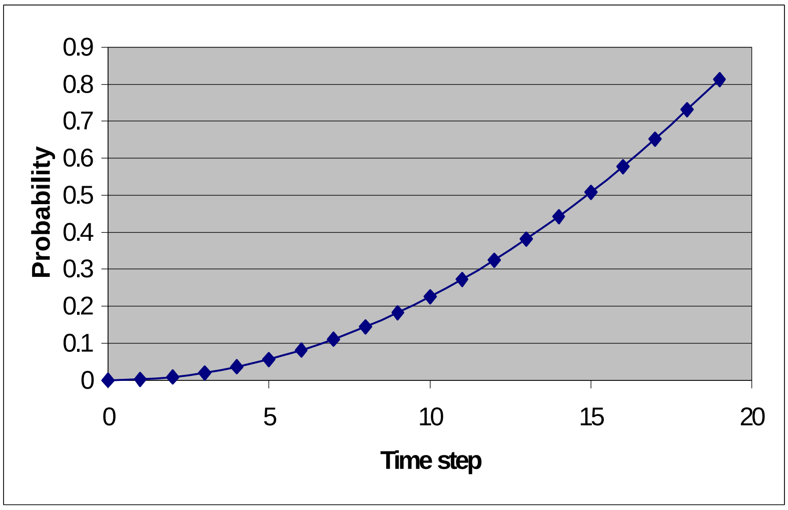


Figure 5.5: Transition probability for each time step

5.6 Simulation of land use change

The study area for this research is very small. Moreover change in land use was not significant enough to develop a generic model of the land use change.

Since in 1981 there were only paddy fields but no fishpond, the model was initialized with fishponds based on randomization (Figure 5.6). The model has been run for 19 time steps. Simulation results have been shown in Figure 5.7. In the simulation result most of the fishponds were distributed into four clusters, which is similar to land use change map (Figure 5.1). There was no fishpond in the western part of the area near golf course due to insufficient water flow into the nearby canal. Moreover, water in the canal gets polluted

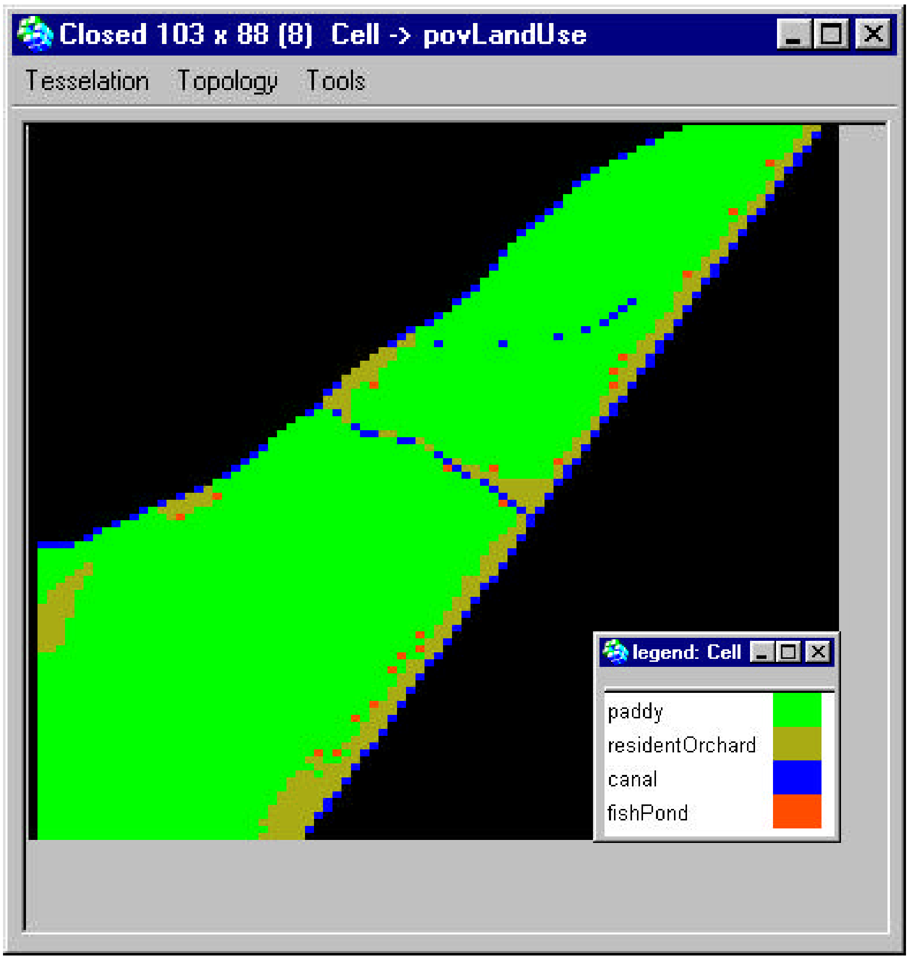


Figure 5.6: Initialization of the model with random fishponds

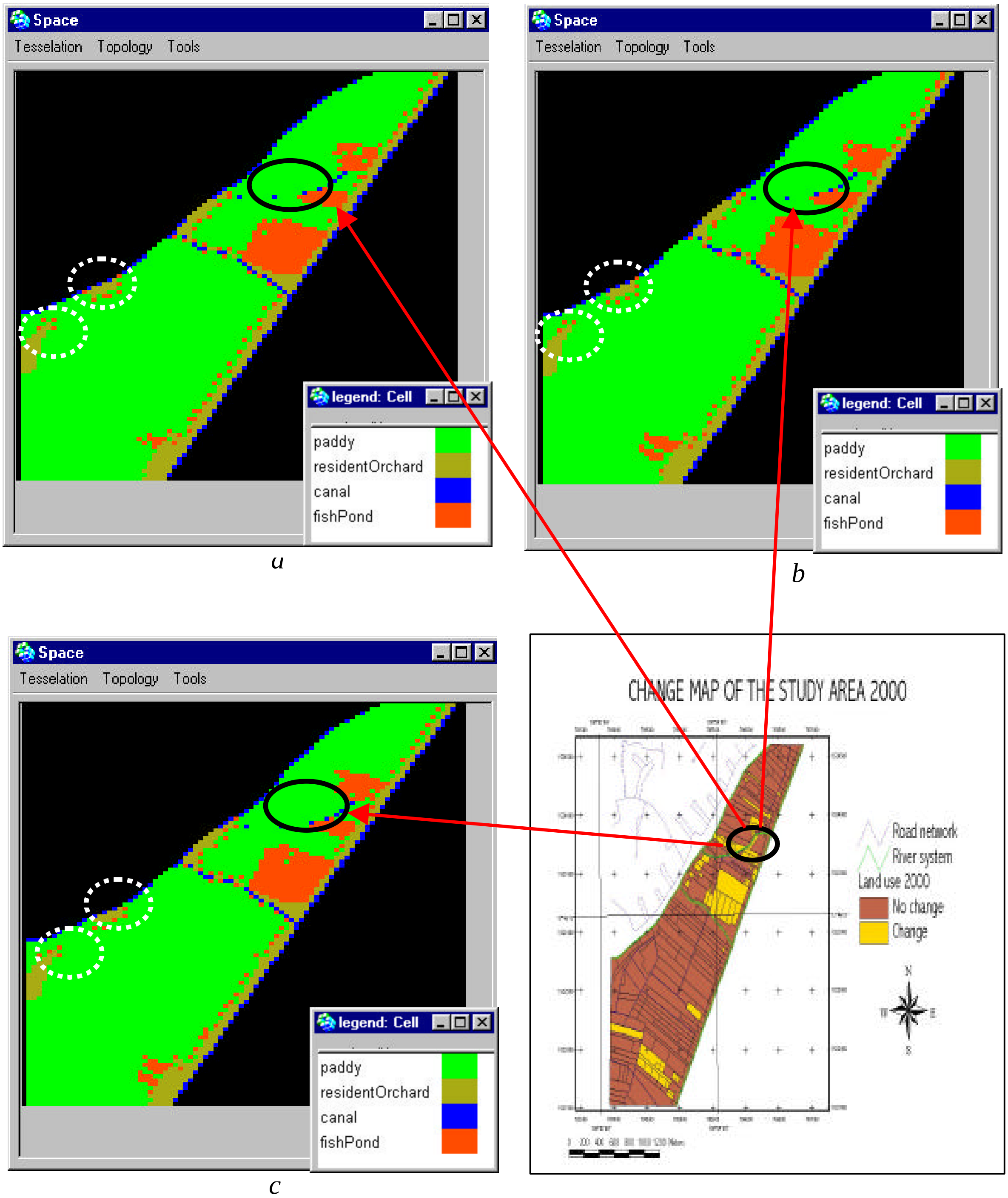


Figure 5.7: Different maps produced by simulation

from pesticides of the agricultural fields. Although the simulation created small fishpond (one pixel) both in the western part and along the resident & orchard, the reference map does not show any fishpond in that part. This happened due to the stochastic distribution of fishpond of the model at each time step.

In the middle part of the study area there was no fishpond in the simulated map (Figure 5.7 black circle). Since the neighborhood of resident of the cell was taken into account during initialization of the simulation and there was no resident around that area in 1981 so that the model could not initialize and diffuse the fishpond over that area.

5.7 Validation of the model

Landscape pattern has four basic elements: number, size, shape and dispersion of patches. These elements are important to interpret ecological processes. It is imperative to validate the simulation model of any kind to be acceptable as a tool to test different hypotheses. Various researchers used landscape pattern indices to validate their simulation model 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 simulated map and compared with reference map to validate the methodological framework of the Nong Chok model.

5.7.1 Areas of fishpond

Simulated fishponds have shown an area of 288,000 m^2 (Figure 5.8) whereas in reference map the areas of fishpond were 415,800 m^2. Thus, the overall agreement of the simulated fishpond is 69% of the reference map (Table 5.4). This index only considers total area of fishponds not their spatial distribution.

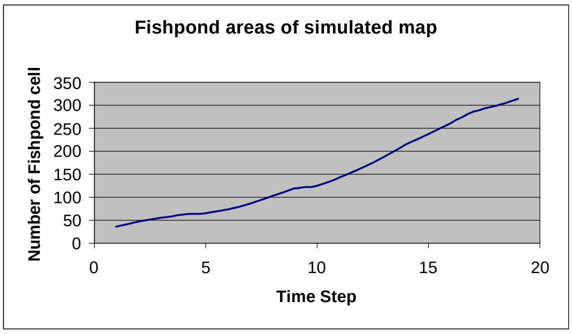


Figure 5.8: Fishpond areas of simulated map

5.7.2 Patch density (PD)

Patch density of the simulated map was calculated based on entire study area i.e. number of patches on entire area. Patch density of the simulated map and the reference map are 0.0177265 (Figure 5.9) and 0.00393922 respectively.

Since the landscape is very small and the model simulates random fishponds based on createRandomFishpond method in the model and diffuses new fishponds simultaneously based on decision rules for each time step. Consequently, there are a number of small fishponds (one pixel) along the resident in the simulated map. Thus, the number of patch of fishponds is more in the simulated map than in the reference change map, which gives higher patch density value in simulated map. Several researchers used patch density index to validate simulated map for regional scale landscape. This index is not suitable for small-scale study.

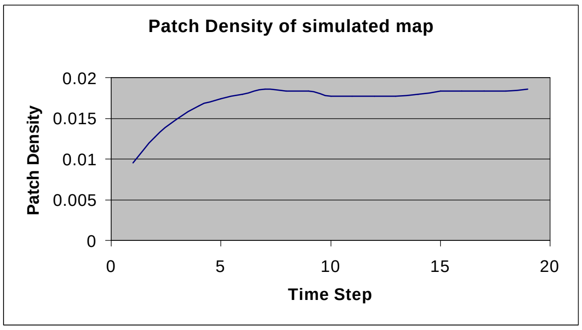


Figure 5.9: Patch density of simulated map

5.7.3 Mean patch size (MPS)

Mean patch size is mean area of the patches in the landscape. Mean patch size of the simulated map is 5.06349, which indicates the area is 5 x 900 = 4,500 m^2 (Figure 5.10). Whereas mean patch size of the reference map is 33, which indicates the area is 33 x 900 = 29,700 m^2. Mean patch size value of the patches increased during the simulation from 1 to 5. This index gives information on fragmentation of the landscape.

Mean patch size index is also suffering from the same drawbacks as mentioned in patch density.

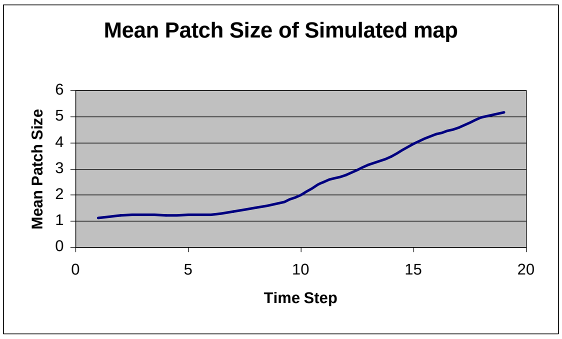


Figure 5.10: Mean patch size of simulated map

5.7.4 Edge density (ED)

Edge density of the simulated map is 0.112549 (Figure 5.11). Following the same procedure of patch density, edge desnity of the simulated map was calculated based on the entire study area. While edge density of the reference change map is 0.122116.

This index reveals very good agreement between simulated and reference change map. Edge density counts on the total edge of patches in the landscape. Although the simulation could not simulate properly in the middle part of the landscape, this index showed good agreement. The reason is that the index counts all tiny foshponds along the resident, which were not found in the reference map.

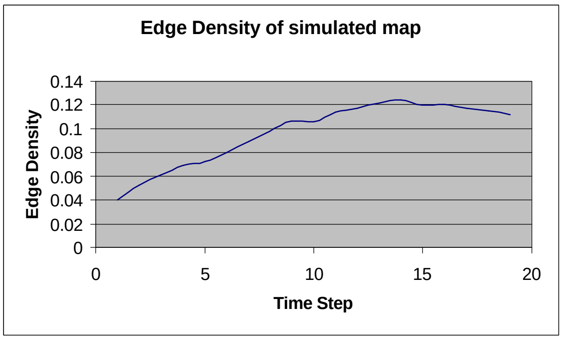


Figure 5.11: Edge density of simulated map

5.7.5 Fractal dimension (FD)

Fractal dimension is a measure of the complexity of the patches of different land use classes in a landscape and is widely used in landscape pattern analysis. The higher the fractal dimension the more complex the landscape is. Fractal dimension of the simulated map is 1.17994 (Figure 5.12). In the first half of the simulation, fractal dimension was increasing but in the last half it decreased. For validation of the simulated landscape researchers try to find correlation of the complexity of the patches between simulated and reference landscape (Britaldo et al., 2002). Fractal dimension of the reference change map is found to be 1.33807. This index characterizes the complexity of the landscape.

Fractal dimension between simulated and reference map shows very close tie.

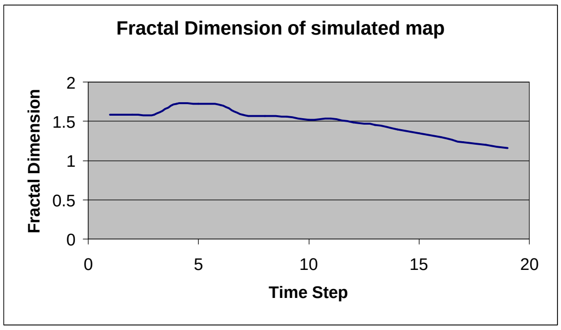


Figure 5.12: Fractal dimension of simulated map

5.7.5 Mean nearest neighborhood (MNN)

Mean nearest neighborhood of the simulated map is 5.83 (Figure 5.13). While Mean nearest neighborhood of the reference change map is 9.43. This reveals that simulated map is less fragmented than reference map. At the initial stage of the simulation MNN was decreasing but at the later stage it was stable at 5.83. This index indicates the isolation and distribution of patches.

Although this index did not reveal very good agreement between simulated and reference map, this could be useful for validation of spatial simulation. This index considers the configuration or structure of the patches in the landscape, which is important for dynamic spatial simulation of land use change.

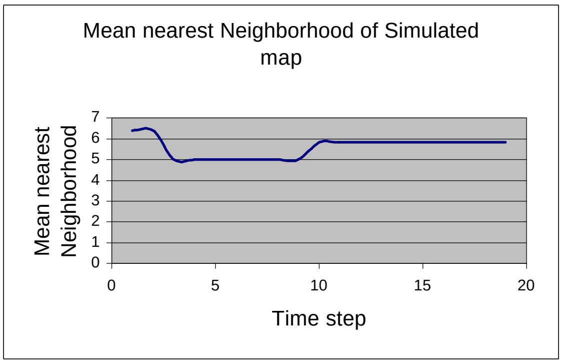


Figure 5.13: Mean nearest neighborhood of simulated map

Table 5.4 : Analysis of landscape indices of the simulated and reference change map

	Landscape indices					
	NFC	**PD**	**ED**	**FD**	**MPS**	**MNN**
Simulated map	320	0.0177265	0.112549	1.17994	4,500 m^2	5.83
Reference map	462	0.0039392	0.122116	1.33807	29,700 m^2	9.43
% deviation	4%	-	1%	7.9%	-	-
Overall agreement	69%	-	-	-	-	-

NFC : number of fishpond cells, PD : patch density, ED : edge density, MPS : mean patch size, MNN : mean nearest neighborhood.

Fishpond areas, patch density, mean patch size, edge density, and fractal dimension indices only consider composition of the patches in the landscape. Conversely mean nearest neighborhood considers configuration of the patches. Most of the landscape pattern indices have redundancy among them and consider diversity or composition of the landscape only. To validate spatial simulation model of land use change dynamics consideration should be given on spatial distribution or configuration of the patches in the landscape.

CHAPTER SIX

CONCLUSIONS

A simulation model with an aim to simulate land use change dynamics of Nong Chok area was developed based on selected biophysical and human driving forces. The simulations were performed using land use data extracted from multi temporal aerial photographs. The result of the simulation showed considerable performance of the model to diffuse fishponds from paddy field. Following conclusions could be derived from this study:

In 1981, the land use pattern of the study area was simply paddy field, resident & orchard and waterbody but in 2000 land use had been changed to fishpond and others type. The rate of change is not linear in temporal scale. In later years rate of change (29,707 m^2 per year) was faster than earlier years (17,705 m^2 per year).

The biophysical and human driving factors used in this research are distance from canal, ownership, age, education, religion, and family size. Ownership of the land was found to be the most sensitive among all driving factors. Education and religion could not significantly influence the transition function. The topography and soil characteristics of the study area are uniform. One of the important factors affecting the land use change process is comparative economic benefit from alternative crops. But during the interview about the price or profit from rice or fish the farmers could not provide accurate information. Thus, the study focused on the available data collected from the farmers as decision variables.

- During developing the spatial simulation model, the driving factors have been determined based on statistical analysis. Spatial simulation methodology of land use change has been developed integrating remote sensing, Geographical Information Systems (GIS) and dynamic simulation toolkit. Transition functions of the spatial simulation were developed by using ID3 algorithm. The model was able to simulate the diffusion of fishponds following the transition functions.

- Only six landscape pattern indices were calculated for both simulated and reference maps. Among them number of fishpond cells, edge density, fractal dimension were found very effective for small scale landscape analysis. Patch density and mean patch size indices are not very effective in this study due to random effects. The number of fishponds between simulated and reference maps showed 69% overall agreement. Deviation of fractal dimension and edge density between simulated and reference maps were very little. Even though mean nearest neighborhood did not show close tie it could be important index in validation of simulation of land use change dynamics.

Remote sensing data for this research was enough to identify land use change. But, socio-economic data was not enough to develop concrete decision rules. Further investigation may concentrate on other demographic and socio-economic data collection and analysis.

However, this research has developed the transition function to simulate land use change dynamics in Nong Chok area. The model worked well except few mismatches, which indicates that the decision variables for that area were not enough to simulate the change. Detailed study on that particular area is needed to modify the rules. The study could not validate the model by applying the transition functions to other areas due to unavailability of data. If the model could be applied to other dataset then the transition functions could be tuned to modify the model. The sensitivity of all driving forces could be measured. Further investigation may lead other factors to test their sensitivity.

All variables in this study were static. The model starts working on certain conditions and in each step it only calculates the transition probability based on fixed parameters of the variables. Further study may focus dynamic variables for each time step.

The model considered only land use change from 1981 to 2000. Transition functions of the cellular automata were subsequently developed based on this change datasets. Due to the lack of time the model could not focus on land use change between 1981-1990, 1990-1995, and 1995-2000 separately. Further investigation could focus on this issue and simulation results could be compared dynamically with different simulations and reference maps (1990, 1995 and 2000).

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Appendix T1: Ground control point (GCPs) with RMS

GCP	Easting	Northing	RMS
1	704520.70	1522660.11	0.3280
2	704864.70	1522459.99	0.5360
3	705288.87	1523164.09	0.2157
4	705462.26	1523641.95	0.3037
5	706057.35	1523994.00	0.2857
6	705630.66	1524393.29	0.2325
7	705306.64	1523954.20	0.2471
8	704842.13	1523418.84	0.4400
9	704484.10	1523105.54	0.6532
10	704326.46	1523663.76	0.3077
11	704401.85	1524392.78	0.4851
12	705080.01	1524467.84	0.2801

Appendix T2: Cross tabulation between decision variables and Change index

Cross tabulation between Education and Change index

			Change Index	
			No change	**Change**
			0	**1**
Education	**2**	Count	8	3
		Percentage within change index	3.5%	4.2%
	3	Count	0	1
		Percentage within change index	0%	1.4%
	4	Count	161	58
		Percentage within change index	71.2%	80.6%
	6	Count	34	3
		Percentage within change index	15.0%	4.2%
	9	Count	5	0
		Percentage within change index	2.2%	0%
	11	Count	4	0
		Percentage within change index	1.8%	0%
	12	Count	7	1
		Percentage within change index	3.1%	1.4%
	16	Count	7	6
		Percentage within change index	3.1%	8.3%
Total		Count	226	72
		Percentage within change index	75.80%	24.20%

Cross tabulation between Ownership and Change index

			Change Index	
			No change 0	**Change 1**
Ownership	**owner+ tenant**	Count	13	19
		Percentage within change index	5.80%	26.40%
	tenant	Count	193	23
		Percentage within change index	85.40%	31.90%
	owner	Count	20	30
		Percentage within change index	8.80%	41.70%
Total		Count	226	72
		Percentage within change index	75.80%	24.20%

Cross tabulation between Age and Change index

			Change Index	
			No change 0	**Change 1**
Age	**<36**	Count	47	0
		Percentage within change index	20.8%	0%
	(36-55)	Count	85	31
		Percentage within change index	37.6%	43.1%
	>55	Count	94	41
		Percentage within change index	41.6%	56.9%
Total		Count	226	72
		Percentage within change index	75.80%	24.20%

Cross tabulation between Religion and Change index

			Change Index	
			No change 0	**Change 1**
Religion	**Christian**	Count	2	3
		Percentage within change index	0.9%	4.1%
	Islam	Count	28	17
		Percentage within change index	12.40%	23.26%
	Buddist	Count	196	52
		Percentage within change index	86.7%	72.2%
Total		Count	226	72
		Percentage within change index	75.80%	24.20%

Cross tabulation between family size and change index

			Change Index	
			No change	**Change**
			0	**1**
Family size	**1**	Count	10	10
		Percentage within change index	4.4%	13.9%
	2	Count	13	6
		Percentage within change index	5.8%	8.3%
	3	Count	59	14
		Percentage within change index	26.1%	19.4%
	4	Count	56	17
		Percentage within change index	24.8%	23.6%
	5	Count	46	20
		Percentage within change index	20.4%	27.8%
	6	Count	11	3
		Percentage within change index	4.9%	4.2%
	7	Count	13	2
		Percentage within change index	5.8%	2.8%
	8	Count	18	0
		Percentage within change index	8.0%	0%
Total		Count	226	72
		Percentage within change index	75.80%	24.20%

Appendix T3: Calculation of entropy and information gain of Nong Chok change datasets

	Total case	**No change**	**Change**	**Information (bit)**		
	298	226	72	0.798	bit	
Variables	**Total case**	**No change**	**Change**	**Information (bit)**		
Education						
1	13	9	4			
2	25	18	7			
3	260	199	61	0.796	Gain	0.001
Age						
1	47	47	0			
2	116	85	31			
3	135	94	41	0.727	Gain	0.070
Ownership						
1	32	13	19			
2	216	193	23			
3	50	20	30	0.622	Gain	0.176
Religion						
1	5	2	3			
2	45	28	17			
3	248	196	52	0.777	Gain	0.020

Family size

1	33	31	2			
2	102	72	30			
3	163	123	40	0.775	Gain	0.022

Ownership (owner + tenant)

	Total case	**No change**	**Change**	**Information (bit)**		
	32	13	19	0.974	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	0	0	32	0.974	0.974	0.000
Age	0	18	14	0.911	0.974	0.064
Religion	0	0	32	0.974	0.974	0.000
Family size	2	0	30	0.889	0.974	0.086

Ownership (tenant)

	Total case	**No change**	**Change**	**Information (bit)**		
	216	193	23	0.489	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	9	12	195	0.477	0.489	0.012
Age	42	89	85	0.454	0.489	0.035
Religion	0	35	181	0.452	0.489	0.037
Family size	31	64	121	0.470	0.489	0.019

Ownership (owner)

	Total case	**No change**	**Change**	**Information (bit)**		
	50	20	30	0.971	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	4	13	33	0.908	0.971	0.063
Age	5	9	36	0.826	0.971	0.144
Religion	5	10	35	0.963	0.971	0.008
Family size	0	38	12	0.854	0.971	0.117

Ownership (owner + tenant) >Family size

	Total case	**No change**	**Change**	**Information (bit)**		
(4 - 6)	30	11	19	0.948	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Age	0	16	14	0.831	0.948	0.117
Education	0	0	30	0.948	0.948	0.000
Religion	0	0	30	0.948	0.948	0.000

Age[1]	Total case	No change	Change	Probability
1	0	0	0	0.000
2	16	3	13	0.813
3	14	8	6	0.429

Ownership (owner + tenant)>Family size

	Total case	No change	Change	Information (bit)	
>6	2	2	0	0.000	bit

Ownership (tenant)>Religion

	Total case	No change	Change	Information (bit)		
Islam	35	25	10	0.863	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Age	2	19	4	0.834	0.863	0.029
Education	9	0	26	O.860	0.863	0.003
Family size	3	8	24	0.815	0.863	0.048

Ownership (tenant)>Religion (Islam)>Family size

	Total case	No change	Change	
>6	3	3	0	0.000

Ownership (tenant)> Religion (Islam)>Family size

	Total case	No change	Change	Information (bit)		
<4	8	6	2	0.811	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Age	7	0	1	0.755	0.811	0.056
Education	7	0	1	0.755	0.811	0.056

Education[2]	Total case	No change	Change	Probability
1	7	5	2	0.286
3	1	1	0	

Ownership (tenant)> Religion (Islam)>Family size

	Total case	No change	Change	Information (bit)	
(4-6)	24	16	8	0.918	bit

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[1] After age there is no effect of *education* and *religion*. All cases have same *education (4-10)* and *religion (buddist)* background.

[2] Correlation between Education and Family size is 1. Thus, Education is taken here as the next branch of the decision tree.

Variables	Class 1	Class 2	Class 3	Attribute info	Total info	Gain
Age	0	17	7	0.915	0.918	0.003
Education	2	0	22	0.911	0.918	0.008

Education	Total case	No change	Change	Probability
1	2	1	1	0.5
2	0			
3	22	15	7	0.318

Ownership (tenant)>Religion

	Total case	No change	Change	Information (bit)		
Buddist	181	168	13	0.373	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Age				0.345	0.373	0.027
Education				0.366	0.373	0.007
Family size				0.354	0.373	0.019

Ownership (tenant)>Religion (Buddist)>Age

	Total case	No change	Change	
<36	40	40	0	0.000

Ownership (tenant)>Religion (Buddist)>Age

	Total case	No change	Change	Information (bit)		
(36-55)	70	64	6	0.422	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Family size	4	20	46	0.408	0.422	0.014
Education	0	5	65	0.415	0.422	0.007

Family size	Total case	No change	Change	Probability
1	4	4	0	
2	20	19	1	0.05
3	46	41	5	0.109

Ownership (tenant)>Religion (Buddist)>Age

	Total case	No change	Change	Information (bit)		
>55	71	64	7	0.465	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	Total info	**Gain**
Family size	18	16	37	0.298	0.465	0.167
Education	0	0	71	0.465	0.465	0.000

Family size	Total case	No change	Change	Probability
1	18	16	2	0.111
2	16	16	0	
3	37	32	5	0.135

Ownership (owner)>Age

	Total case	No change	Change	Information (bit)	
<36	5	5	0	0.000	bit

Ownership (owner)>Age

	Total case	No change	Change	Information (bit)		
(36 - 55)	9	3	6	0.918	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	0	9	0	0.918	0.918	0.000
Religion	0	9	0	0.918	0.918	0.000
Family size	0	8	1	0.721	0.918	0.197

Family size	Total case	No change	Change	Probability
1	0	0	0	
2	8	2	6	0.750
3	1	1	0	

Ownership (owner)>Age

	Total case	No change	Change	Information (bit)		
> 55	36	12	24	0.918	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	4	0	32	0.852	0.918	0.066
Religion	5	10	21	0.915	0.918	0.003
Family size	0	25	11	0.699	0.918	0.220

Ownership (owner)>Age (>55)>Family size

	Total case	No change	Change	Information (bit)		
<4	25	4	21	0.634	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	0	0	25	0.634	0.634	0.000
Religion	5	18	12	0.567	0.634	0.068

Religion[3]	Total case	No change	Change	Probability
1	5	2	3	0.600
2	8	1	7	0.875
3	12	1	11	0.917

Ownership (owner)>Age (>55)>Family size

	Total case	No change	Change	Information (bit)		
(4-6)	11	8	3	0.845	bit	
Variables	**Class 1**	**Class 2**	**Class 3**	**Attribute info**	**Total info**	**Gain**
Education	4	0	7	0.844	0.845	0.001
Religion	0	2	9	0.751	0.845	0.094

Religion	Total case	No change	Change
1	0	0	0
2	2	2	0
3	9	6	3

Education	Total case	No change	Change	Probability
1	4	3	1	0.250
2	0	0	0	
3	7	5	2	0.400

[3] No effect of Education on change after Religion

Appendix T4:

Nong Chok land use change datasets

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
192	146	1	0	1	19	3	4	2	tenant	3	Buddist	3	5
199	146	1	0	1	19	3	4	2	tenant	3	Buddist	3	5
212	146	1	0	1	19	3	4	2	tenant	3	Buddist	3	5
310	146	3	0	1	19	3	4	2	tenant	3	Buddist	3	5
149	139	1	0	1	30	3	6	2	tenant	3	Buddist	2	1
151	139	1	0	1	30	3	6	2	tenant	3	Buddist	2	1
156	139	1	0	1	30	3	6	2	tenant	3	Buddist	2	1
168	139	1	0	1	30	3	6	2	tenant	3	Buddist	2	1
180	139	5	0	1	30	3	6	2	tenant	3	Buddist	2	1
302	139	3	0	1	30	3	6	2	tenant	3	Buddist	2	1
303	139	3	0	1	30	3	6	2	tenant	3	Buddist	2	1
209	156	1	0	1	30	3	6	2	tenant	3	Buddist	2	3
213	156	1	0	1	30	3	6	2	tenant	3	Buddist	2	3
221	156	1	0	1	30	3	6	2	tenant	3	Buddist	2	3
223	156	1	0	1	30	3	6	2	tenant	3	Buddist	2	3
232	156	1	0	1	30	3	6	2	tenant	3	Buddist	2	3
321	156	3	0	1	30	3	6	2	tenant	3	Buddist	2	3
323	156	3	0	1	30	3	6	2	tenant	3	Buddist	2	3
44	113	1	0	1	32	2	12	2	tenant	3	Buddist	3	4
48	113	1	0	1	32	2	12	2	tenant	3	Buddist	3	4
49	113	1	0	1	32	2	12	2	tenant	3	Buddist	3	4
55	113	1	0	1	32	2	12	2	tenant	3	Buddist	3	4
59	113	1	0	1	32	2	12	2	tenant	3	Buddist	3	4
61	113	3	0	1	32	2	12	2	tenant	3	Buddist	3	4
295	113	3	0	1	32	2	12	2	tenant	3	Buddist	3	4
121	129	1	0	1	32	3	6	2	tenant	2	Islam	1	8
279	129	3	0	1	32	3	6	2	tenant	2	Islam	1	8
15	105	1	0	1	34	3	6	2	tenant	3	Buddist	2	3
18	105	1	0	1	34	3	6	2	tenant	3	Buddist	2	3
28	105	1	0	1	34	3	6	2	tenant	3	Buddist	2	3

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
287	105	3	0	1	34	3	6	2	tenant	3	Buddist	2	3
12	105	1	0	1	34	3	6	2	tenant	3	Buddist	2	3
14	105	1	0	1	34	3	6	2	tenant	3	Buddist	2	3
31	109	1	0	1	35	3	6	2	tenant	3	Buddist	3	5
33	109	1	0	1	35	3	6	2	tenant	3	Buddist	3	5
38	109	1	0	1	35	3	6	2	tenant	3	Buddist	3	5
193	168	3	0	1	35	3	6	2	tenant	3	Buddist	1	8
194	168	1	0	1	35	3	6	2	tenant	3	Buddist	1	8
195	168	1	0	1	35	3	6	2	tenant	3	Buddist	1	8
202	168	1	0	1	35	3	6	2	tenant	3	Buddist	1	8
203	168	1	0	1	35	3	6	2	tenant	3	Buddist	1	8
207	168	1	0	1	35	3	6	2	tenant	3	Buddist	1	8
178	166	1	0	2	36	3	4	2	tenant	3	Buddist	3	5
41	110	1	0	2	37	3	4	2	tenant	3	Buddist	3	4
50	110	1	0	2	37	3	4	2	tenant	3	Buddist	3	4
292	110	3	0	2	37	3	4	2	tenant	3	Buddist	3	4
135	131	2	1	2	37	3	6	2	tenant	2	Islam	3	5
60	112	1	0	2	38	3	4	2	tenant	3	Buddist	3	4
67	112	2	1	2	38	3	4	2	tenant	3	Buddist	3	4
66	112	3	0	2	38	3	4	2	tenant	3	Buddist	3	4
65	116	1	0	2	38	3	6	2	tenant	3	Buddist	3	5
72	116	1	0	2	38	3	6	2	tenant	3	Buddist	3	5
73	116	2	1	2	38	3	6	2	tenant	3	Buddist	3	5
75	116	2	1	2	38	3	6	2	tenant	3	Buddist	3	5
283	116	3	0	2	38	3	6	2	tenant	3	Buddist	3	5
22	104	1	0	2	39	3	4	2	tenant	3	Buddist	3	4
286	104	3	0	2	39	3	4	2	tenant	3	Buddist	3	4
326	104	1	0	2	39	3	4	2	tenant	3	Buddist	3	4
327	104	1	0	2	39	3	4	2	tenant	3	Buddist	3	4
98	123	2	1	2	41	3	4	2	tenant	2	Islam	3	5

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
102	123	1	0	2	41	3	4	2	tenant	2	Islam	3	5
112	123	1	0	2	41	3	4	2	tenant	2	Islam	3	5
276	123	3	0	2	41	3	4	2	tenant	2	Islam	3	5
96	121	1	0	2	42	3	4	2	tenant	2	Islam	1	7
201	150	1	0	2	43	3	4	2	tenant	3	Buddist	2	3
205	150	1	0	2	43	3	4	2	tenant	3	Buddist	2	3
315	150	3	0	2	43	3	4	2	tenant	3	Buddist	2	3
170	169	1	0	2	45	3	4	2	tenant	3	Buddist	2	3
172	169	1	0	2	45	3	4	2	tenant	3	Buddist	2	3
184	169	1	0	2	45	3	4	2	tenant	3	Buddist	2	3
189	169	1	0	2	45	3	4	2	tenant	3	Buddist	2	3
228	160	1	0	2	45	2	11	2	tenant	3	Buddist	2	3
233	160	1	0	2	45	2	11	2	tenant	3	Buddist	2	3
239	160	1	0	2	45	2	11	2	tenant	3	Buddist	2	3
318	160	3	0	2	45	2	11	2	tenant	3	Buddist	2	3
244	162	2	1	2	45	2	12	2	tenant	3	Buddist	2	3
19	107	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
21	107	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
39	107	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
42	107	2	1	2	45	3	4	2	tenant	3	Buddist	3	4
289	107	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
290	107	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
23	106	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
35	106	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
36	106	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
46	106	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
288	106	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
291	106	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
196	147	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
210	147	2	1	2	45	3	4	2	tenant	3	Buddist	3	4

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
220	147	1	0	2	45	3	4	2	tenant	3	Buddist	3	4
311	147	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
312	147	3	0	2	45	3	4	2	tenant	3	Buddist	3	4
131	135	1	0	2	45	3	9	2	tenant	3	Buddist	3	6
145	135	1	0	2	45	3	9	2	tenant	3	Buddist	3	6
147	135	1	0	2	45	3	9	2	tenant	3	Buddist	3	6
154	135	1	0	2	45	3	9	2	tenant	3	Buddist	3	6
171	135	3	0	2	45	3	9	2	tenant	3	Buddist	3	6
97	170	3	0	2	47	3	4	2	tenant	2	Islam	2	2
155	141	1	0	2	48	3	4	2	tenant	3	Buddist	3	4
128	155	1	0	2	48	3	4	2	tenant	2	Islam	3	6
132	155	2	1	2	48	3	4	2	tenant	2	Islam	3	6
133	155	3	0	2	48	3	4	2	tenant	2	Islam	3	6
185	145	1	0	2	49	3	4	2	tenant	3	Buddist	3	4
197	145	1	0	2	49	3	4	2	tenant	3	Buddist	3	4
309	145	3	0	2	49	3	4	2	tenant	3	Buddist	3	4
186	167	1	0	2	50	3	4	2	tenant	3	Buddist	2	3
188	167	1	0	2	50	3	4	2	tenant	3	Buddist	2	3
160	143	1	0	2	51	3	4	2	tenant	3	Buddist	2	3
163	143	1	0	2	51	3	4	2	tenant	3	Buddist	2	3
167	143	1	0	2	51	3	4	2	tenant	3	Buddist	2	3
177	143	1	0	2	51	3	4	2	tenant	3	Buddist	2	3
187	143	1	0	2	51	3	4	2	tenant	3	Buddist	2	3
307	143	3	0	2	51	3	4	2	tenant	3	Buddist	2	3
119	128	3	0	2	52	3	4	2	tenant	2	Islam	3	4
125	128	2	1	2	52	3	4	2	tenant	2	Islam	3	4
114	128	3	0	2	52	3	4	2	tenant	2	Islam	3	4
104	124	2	1	2	53	3	4	2	tenant	2	Islam	3	5
108	124	1	0	2	53	3	4	2	tenant	2	Islam	3	5
275	124	3	0	2	53	3	4	2	tenant	2	Islam	3	5

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
206	152	1	0	2	55	3	4	2	tenant	3	Buddist	3	5
230	152	1	0	2	55	3	4	2	tenant	3	Buddist	3	5
317	152	3	0	2	55	3	4	2	tenant	3	Buddist	3	5
113	127	2	1	2	55	3	4	2	tenant	2	Islam	3	4
117	127	1	0	2	55	3	4	2	tenant	2	Islam	3	4
105	127	3	0	2	55	3	4	2	tenant	2	Islam	3	4
211	154	1	0	2	55	3	4	2	tenant	3	Buddist	3	6
153	140	1	0	2	55	3	4	2	tenant	3	Buddist	1	8
157	140	1	0	2	55	3	4	2	tenant	3	Buddist	1	8
175	140	1	0	2	55	3	4	2	tenant	3	Buddist	1	8
304	140	3	0	2	55	3	4	2	tenant	3	Buddist	1	8
137	132	2	1	3	56	3	4	2	tenant	2	Islam	3	6
198	149	1	0	3	58	3	4	2	tenant	3	Buddist	2	2
222	149	1	0	3	58	3	4	2	tenant	3	Buddist	2	2
227	149	1	0	3	58	3	4	2	tenant	3	Buddist	2	2
314	149	3	0	3	58	3	4	2	tenant	3	Buddist	2	2
204	151	1	0	3	58	3	4	2	tenant	3	Buddist	3	4
208	151	1	0	3	58	3	4	2	tenant	3	Buddist	3	4
234	151	2	1	3	58	3	4	2	tenant	3	Buddist	3	4
316	151	3	0	3	58	3	4	2	tenant	3	Buddist	3	4
158	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
165	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
174	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
182	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
190	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
200	144	1	0	3	58	3	4	2	tenant	3	Buddist	3	5
308	144	3	0	3	58	3	4	2	tenant	3	Buddist	3	5
4	102	1	0	3	60	3	4	2	tenant	3	Buddist	2	3
5	102	1	0	3	60	3	4	2	tenant	3	Buddist	2	3
6	102	1	0	3	60	3	4	2	tenant	3	Buddist	2	3

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
13	102	1	0	3	60	3	4	2	tenant	3	Buddist	2	3
16	102	1	0	3	60	3	4	2	tenant	3	Buddist	2	3
297	102	3	0	3	60	3	4	2	tenant	3	Buddist	2	3
284	102	3	0	3	60	3	4	2	tenant	3	Buddist	2	3
161	165	3	0	3	60	3	4	2	tenant	3	Buddist	3	4
166	165	1	0	3	60	3	4	2	tenant	3	Buddist	3	4
169	165	1	0	3	60	3	4	2	tenant	3	Buddist	3	4
173	165	1	0	3	60	3	4	2	tenant	3	Buddist	3	4
84	119	1	0	3	60	3	4	2	tenant	2	Islam	3	4
85	119	3	0	3	60	3	4	2	tenant	2	Islam	3	4
92	119	3	0	3	60	3	4	2	tenant	2	Islam	3	4
143	138	1	0	3	61	3	4	2	tenant	3	Buddist	2	2
150	138	1	0	3	61	3	4	2	tenant	3	Buddist	2	2
152	138	1	0	3	61	3	4	2	tenant	3	Buddist	2	2
164	138	1	0	3	61	3	4	2	tenant	3	Buddist	2	2
301	138	3	0	3	61	3	4	2	tenant	3	Buddist	2	2
217	148	1	0	3	61	3	4	2	tenant	3	Buddist	3	6
313	148	3	0	3	61	3	4	2	tenant	3	Buddist	3	6
179	142	1	0	3	61	3	4	2	tenant	3	Buddist	1	8
181	142	1	0	3	61	3	4	2	tenant	3	Buddist	1	8
183	142	1	0	3	61	3	4	2	tenant	3	Buddist	1	8
191	142	1	0	3	61	3	4	2	tenant	3	Buddist	1	8
305	142	3	0	3	61	3	4	2	tenant	3	Buddist	1	8
306	142	3	0	3	61	3	4	2	tenant	3	Buddist	1	8
141	137	1	0	3	64	3	4	2	tenant	3	Buddist	3	5
146	137	1	0	3	64	3	4	2	tenant	3	Buddist	3	5
162	137	1	0	3	64	3	4	2	tenant	3	Buddist	3	5
176	137	2	1	3	64	3	4	2	tenant	3	Buddist	3	5
300	137	3	0	3	64	3	4	2	tenant	3	Buddist	3	5
99	133	1	0	3	65	3	4	2	tenant	3	Buddist	3	4

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
120	133	1	0	3	65	3	4	2	tenant	3	Buddist	3	4
122	133	2	1	3	65	3	4	2	tenant	3	Buddist	3	4
124	133	2	1	3	65	3	4	2	tenant	3	Buddist	3	4
127	133	2	1	3	65	3	4	2	tenant	3	Buddist	3	4
298	133	3	0	3	65	3	4	2	tenant	3	Buddist	3	4
37	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
40	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
43	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
45	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
47	111	2	1	3	65	3	4	2	tenant	3	Buddist	1	7
52	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
53	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
54	111	1	0	3	65	3	4	2	tenant	3	Buddist	1	7
56	111	2	1	3	65	3	4	2	tenant	3	Buddist	1	7
293	111	3	0	3	65	3	4	2	tenant	3	Buddist	1	7
294	111	3	0	3	65	3	4	2	tenant	3	Buddist	1	7
296	111	3	0	3	65	3	4	2	tenant	3	Buddist	1	7
7	101	1	0	3	65	3	4	2	tenant	3	Buddist	3	5
8	101	1	0	3	65	3	4	2	tenant	3	Buddist	3	5
9	101	3	0	3	65	3	4	2	tenant	3	Buddist	3	5
94	120	2	1	3	66	1	2	2	tenant	2	Islam	3	4
90	120	3	0	3	66	1	2	2	tenant	2	Islam	3	4
219	153	1	0	3	67	3	4	2	tenant	3	Buddist	3	4
225	153	1	0	3	67	3	4	2	tenant	3	Buddist	3	4
139	136	1	0	3	67	3	4	2	tenant	3	Buddist	3	5
144	136	1	0	3	67	3	4	2	tenant	3	Buddist	3	5
159	136	1	0	3	67	3	4	2	tenant	3	Buddist	3	5
299	136	3	0	3	67	3	4	2	tenant	3	Buddist	3	5
278	130	3	0	3	68	3	4	2	tenant	2	Islam	3	4
107	126	3	0	3	70	1	2	2	tenant	2	Islam	2	3

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
111	126	1	0	3	70	1	2	2	tenant	2	Islam	2	3
115	126	2	1	3	70	1	2	2	tenant	2	Islam	2	3
118	126	1	0	3	70	1	2	2	tenant	2	Islam	2	3
126	126	3	0	3	70	1	2	2	tenant	2	Islam	2	3
129	126	2	1	3	70	1	2	2	tenant	2	Islam	2	3
277	126	3	0	3	70	1	2	2	tenant	2	Islam	2	3
87	118	2	1	2	45	3	4	1	owner + tenant	3	Buddist	3	4
89	118	3	0	2	45	3	4	1	owner + tenant	3	Buddist	3	4
91	118	2	1	2	45	3	4	1	owner + tenant	3	Buddist	3	4
93	118	2	1	2	45	3	4	1	owner + tenant	3	Buddist	3	4
95	118	2	1	2	45	3	4	1	owner + tenant	3	Buddist	3	4
101	118	2	1	2	45	3	4	1	owner + tenant	3	Buddist	3	4
282	118	3	0	2	45	3	4	1	owner + tenant	3	Buddist	3	4
241	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
247	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
255	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
258	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
261	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
265	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
266	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
267	164	2	1	2	50	3	4	1	owner + tenant	3	Buddist	3	5
324	164	3	0	2	50	3	4	1	owner + tenant	3	Buddist	3	5
215	159	1	0	2	53	3	4	1	owner + tenant	3	Buddist	1	7
218	159	1	0	2	53	3	4	1	owner + tenant	3	Buddist	1	7
236	161	2	1	3	56	3	4	1	owner + tenant	3	Buddist	3	5
246	161	2	1	3	56	3	4	1	owner + tenant	3	Buddist	3	5
249	161	1	0	3	56	3	4	1	owner + tenant	3	Buddist	3	5
256	161	2	1	3	56	3	4	1	owner + tenant	3	Buddist	3	5
259	161	2	1	3	56	3	4	1	owner + tenant	3	Buddist	3	5
325	161	3	0	3	56	3	4	1	owner + tenant	3	Buddist	3	5

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
51	114	1	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
57	114	1	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
58	114	2	1	3	72	3	4	1	owner + tenant	3	Buddist	3	5
62	114	2	1	3	72	3	4	1	owner + tenant	3	Buddist	3	5
63	114	3	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
64	114	3	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
328	114	3	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
329	114	3	0	3	72	3	4	1	owner + tenant	3	Buddist	3	5
3	103	1	0	1	35	2	16	3	owner	3	Buddist	2	3
11	103	1	0	1	35	2	16	3	owner	3	Buddist	2	3
17	103	1	0	1	35	2	16	3	owner	3	Buddist	2	3
20	103	1	0	1	35	2	16	3	owner	3	Buddist	2	3
285	103	3	0	1	35	2	16	3	owner	3	Buddist	2	3
123	125	3	0	2	37	3	4	3	owner	3	Buddist	3	6
109	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
134	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
136	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
138	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
140	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
142	134	2	1	2	48	2	16	3	owner	3	Buddist	2	2
148	134	3	0	2	48	2	16	3	owner	3	Buddist	2	2
71	134	3	0	2	48	2	16	3	owner	3	Buddist	2	2
224	158	2	1	3	57	3	4	3	owner	3	Buddist	3	4
226	158	1	0	3	57	3	4	3	owner	3	Buddist	3	4
245	158	2	1	3	57	3	4	3	owner	3	Buddist	3	4
319	158	3	0	3	57	3	4	3	owner	3	Buddist	3	4
68	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
70	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
74	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
76	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3

ParcelId	OwnerId	Lu_Index	Change_Index	Age_rank	Age	Edu_rank	Edu	Ownership	L_tenure	Rel_rank	Religion	Fam_rank	Fam_size
77	117	3	0	3	58	3	4	3	owner	3	Buddist	2	3
78	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
80	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
81	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
82	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
83	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
86	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
88	117	2	1	3	58	3	4	3	owner	3	Buddist	2	3
103	122	1	0	3	59	1	2	3	owner	2	Islam	3	4
280	122	3	0	3	59	1	2	3	owner	2	Islam	3	4
24	108	3	0	3	65	3	4	3	owner	2	Islam	2	1
25	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
26	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
27	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
29	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
30	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
32	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
34	108	2	1	3	65	3	4	3	owner	2	Islam	2	1
79	173	1	0	3	68	1	2	3	owner	3	Buddist	3	6
100	115	5	0	3	70	3	4	3	owner	1	Christian	2	1
106	115	2	1	3	70	3	4	3	owner	1	Christian	2	1
110	115	2	1	3	70	3	4	3	owner	1	Christian	2	1
116	115	2	1	3	70	3	4	3	owner	1	Christian	2	1
281	115	5	0	3	70	3	4	3	owner	1	Christian	2	1
214	157	1	0	3	76	3	4	3	owner	3	Buddist	3	5
216	157	1	0	3	76	3	4	3	owner	3	Buddist	3	5
320	157	3	0	3	76	3	4	3	owner	3	Buddist	3	5
240	163	2	1	3	76	1	3	3	owner	3	Buddist	3	6