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A DATA MINING APPROACH TO SIMULATING LAND USE DECISIONS: MODELING FARMER'S CROP CHOICE FROM FARM LEVEL DATA FOR INTEGRATED WATER RESOURCE MANAGEMENT

Benchaphun Shinawatra Ekasingh and Kamol Ngamsomsuke

Department of Agricultural Economics,
Faculty of Agriculture,
Chiang Mai University,
Chiang Mai, Thailand 50200

Rebecca A. Letcher

Integrated Catchment Assessment and Management Centre,
Building 48a, The Australian National University,
Canberra, ACT, Australia

Jessica Marjorie Spate

Department of Mathematics,
The Australian National University,
Canberra, ACT, Australia

ABSTRACT

Water and land resources in Thailand are increasingly under pressure from development. In particular, there are many resource conflicts associated with agricultural production in northern Thailand. Communities in these areas are significantly constrained in the land and water management decisions they are able to make. This paper describes the application of a data mining approach to describing and simulating farmers' decision rules in a catchment in northern Thailand. This approach is being applied to simulate social, economic and biophysical constraints on farmers' decisions in these areas as part of an integrated water management model.

1 INTRODUCTION

Resource management in Northern Thailand is largely focused on the sustainability of water and forest resources. In the highlands, forest lands are declining while agricultural lands are increasing. Soil erosion and soil fertility are important resource problems in the middle and higher slopes. Water use is also increasing with increased conflicts between the uplanders and lowlanders. Water scarcity is evident both in the uplands and the lowlands. This is often attributed to increasing use and storage in the uplands. Declining forest cover is causing concerns among policy makers and farmers in the lowlands. Declining water quality is caused by increased soil erosion and sedimentation from the slopes, attributed in part to decreases in forest cover in upland areas.

Another management concern is the conversion of farmlands to non-agricultural uses, especially in the lowlands. Rapid urban and industrial growth has resulted in increasing demand for farmlands. Good agricultural land is being converted to housing projects, golf courses, resorts, hotels, commercial areas and industrial uses. These developments trigger increases in land prices, which in turn trigger increased conversion of forests to farmland in the upper slopes, calling into question the sustainability of agricultural land use.

This paper describes a model of farmer decision-making in Northern Thailand that has been developed as part of an Integrated Water Resources Management Project being undertaken as a collaboration between Thai Universities, Government agencies and The Australian National University, under the coordination of the Royal Project Foundation. A brief outline of the project is given before details of the socioeconomic analysis are provided.

2 THE IWRAM PROJECT AND DSS COMPONENTS

The Integrated Water Resource Assessment and Management (IWRAM) project has been developing integrative methodologies and associated software toolboxes to assess these natural resource management issues by exploring the economic, environmental and sociocultural implications of different levels and patterns of cultivation and other water use in several representative catchments. This project is currently in its second phase, incorporating an extended collaboration between Thai agencies including the Department of Land Development, the Royal Forestry Department and the Royal Irrigation Department, Chiang Mai University and the Australian National University. The project is coordinated by the Royal Project Foundation.

Phase II of this project has been focused on the development of IWRAM-XL, a Decision Support System for integrated water resource assessment and management that incorporates key biophysical and socioeconomic components. There are four main components of IWRAM II:

1) Hydrological modeling, including modeling the impact of deforestation and other major land use changes on catchment yields;

2) Crop modeling, including collection and analysis of field data to calibrate and test a crop model for the study area;

3) Erosion modeling, based on a version of the USLE which has been modifed for use in Northern Thailand; and,

4) Socioeconomic analysis, including the development of farmer decision-making models and simulation of the impacts of different land use and management options on household income and other key indicators of socioeconomic performance.

Phase II of the IWRAM project has been focused more heavily on adoption, validation and testing of the decision support tools than Phase I, which was focused primarily on prototyping the integrated modeling capacity required. During Phase II, the decision support tools have been redeveloped for new catchment areas to enable roll-out of these tools to a broader range of extension officers. Phase II has also simplifying the model platforms to make them more accessible to a wider range of on-ground users in Thailand, as well as redeveloping some model components to better enable application of the DSS in the field. This has included developing an IWRAM application written in Excel and VB, a more accessible platform for the majority of model users.

This paper focuses on work undertaken by the socioeconomic team in developing a model of farmer decision making in the study catchments. Overall the socioeconomic component of IWRAM II has three main objectives:

1. To ascertain farmers' land and water use together with their economic returns in agricultural production;

2. To model farmers' decision making and crop choice in the watersheds under study; and,

3. To integrate these analyses and models with biophysical component models in the overall decision support system for integrated water resource assessment and management.

Household level farm decision models based on a linear programming formulation were developed as part of IWRAM Phase I (Letcher et al., under review; Merritt et al., 2002; Merritt et al., in press; Merritt et al., under review). Development of these models was an important part of developing the conceptual framework for integration and treatment of decision making in the IWRAM DSS. However, experience within the team leading into Phase II of the project suggested that a simpler, easier to understand method, which was capable of simulating grid-based land use decisions would be preferable for several reasons. Firstly, the linear programming (LP) method used to simulate decisions in Phase I meant that a spatial map of land use decisions was not able to be produced by the model. Planning processes in Thai agencies tend to be based on GIS analysis of planning outcomes. As such there was a strong message from these agencies that for the DSS to be adopted models would need to provide results on a grid basis. Secondly, the LP method was not well understood by many of the agency staff involved in the project. This was a significant barrier to adoption of results from the DSS. Finally, the LP method was also based on assumptions of profit maximisation. This is a controversial assumption in the case of subsistence production systems that are a significant component of the agricultural systems of the study area.

3 STUDY SITE

Three catchments of the Ping river basin were chosen for the study: Mae Rim catchment, Mae Kuang catchment and Mae Ping Part II catchment (see Figure 1). These catchments are in the Chiang Mai and Lamphun provinces of Thailand. The Ping river is one of four main rivers in Northern Thailand. The other three rivers are the Wang, Yom, and Nan rivers, which together with the Ping river run into the Chao Phraya River, the most important river in Thailand, cutting through the Central Plains through Bangkok, the capital of Thailand. As such, the Ping Basin is an important watershed in Thailand.

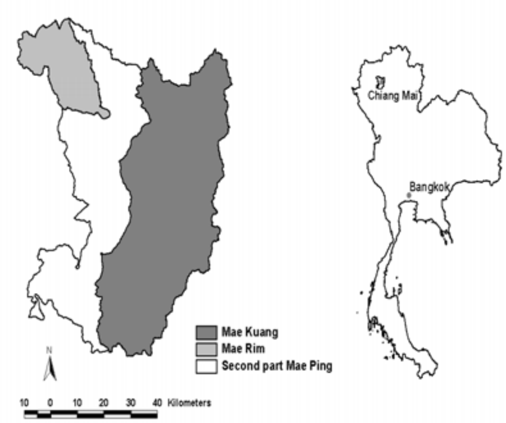

Figure 1: Study area

In the Chiang Mai – Lamphun areas, elevation is around 400 metres above sea level (msl) along the river beds and rising to 600-700 msl in the upper slopes and 1000-1300 msl in the higher slopes of the watershed. Rainfall is around 1200 mm per year.

The study area is rich in irrigation systems. Local and traditional weirs are abundant, with approximately 2,000 weirs in the area. There are also government irrigation projects e.g. reservoirs and surface water irrigation projects. Irrigation water is sourced from both surface and ground water systems.

The main cropping patterns are rice in the wet season, with some dry season crops, such as soybean, garlic, shallot, tomatoes, potatoes and onion. Land is increasingly being converted to fruit tree production, including longan, lychee, mango and oranges, because of good profitability. Markets for these fruit trees are sometimes volatile. Their capital needs are also high.

In the middle and upper slopes of the study area, farm land is not usually irrigated and water is scarce. Farmers are also much poorer than those in the lowlands. Many of them are from ethnic minorities, including Karen, Hmong, Akha and Lisu. These people have largely migrated from Laos, Myanmar and China over the last century.

The entire study area has also been classified into a series of Land Units by the Department of Land Development. This approach defines the given yield of a crop for a particular land unit (or land suitability class) based on the FAO land evaluation procedures (FAO, 1976). A single land unit reflects a combination of soil class and topography. This biophysical classification concept has been incorporated in the socioeconomic analysis to simplify integration between the socioeconomic and biophysical components of the IWRAM project.

4 DATA COLLECTION

Two surveys of households in these three catchment areas were conducted as part of the socioeconomic component of the IWRAM project. In the first stage, a farmers' survey was conducted by the Department of Land Development covering 23 Land Units (312 households, 212 being from Mae Ping Part II Watershed and 100 being from Mae Kuang). This survey was conducted in the year 2000. In the second stage, another farmers' survey was conducted (in 2001) by a team from Chiang Mai University covering 23 Land Units and 284 households (50 being from Mae Rim Watershed, 109 from Mae Kuang and 125 from Mae Ping Part II Watersheds). After major land units together with their administrative boundaries were identified, sample households were selected based on these land units. These households were chosen to supplement the survey previously done by DLD, so that land units surveyed did not overlap with those previously surveyed. Global positioning system (GPS) equipment together with detailed administrative maps were used to pinpoint the exact location and farmers in these land units were selected for interviews. Approximately 4-8 households having the same cropping pattern were selected at each location.

Together, the two surveys covered 37 Land Units and 596 households. There were about 8 farm households interviewed in each Land Unit. In addition, informal interviews and sociological studies were also conducted to supplement understanding of farming systems in the area. Questions asked related to cropping patterns, problems of farming, use and management of irrigation systems and environmental problems.

Table 1 summarises the main information requested from households during the survey conducted by Chiang Mai University. The final data set collected represents a comprehensive database of crop activities and household characteristics suitable for classifying decision-making behaviour in the study area. Data mining techniques were then used to derive from this data set a set of decision rules, describing wet and dry season cropping decisions using these household attributes.

Table 1: Survey information collected by Chiang Mai University team

Information requested	
Part 1	General: household characteristics: farm and household size
Part 2	Land type, tenure and land utilization, crop year 2001
Part 3	Production costs for annual crops and perennial crops including fertilizers, materials, machinery and labour use
Part 4	Output, product sold and income for annual or perennial crops
Part 5	Income for other sources and capital availability
Part 6	Environmental problems
Part 7	Past use of land, competition of annual crops, farmers' attitude
Part 8	Use and management of irrigation water

5 DATA MINING TECHNIQUES

The data collected in this survey represents a system that is well suited to representation by a decision tree classification scheme (Whitten and Frank, 1991). Decision tree algorithms output a graphical 'tree' where each branch represents a decision (for example, rainfall greater than or less than NNmm/year) and each leaf or node a classifier value (for example crop = rice). By branching, the data is split into successively smaller blocks until each block can be assigned a classifier with little or no mis-classifications. Below is a very simple example taken from (Spate, in prep.), a decision tree representing the system used to decide whether or not a given year is a leap year.

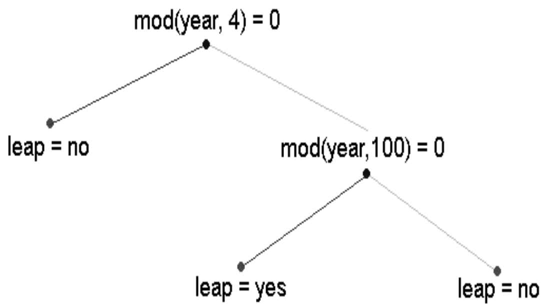

Figure 2: Example decision tree

Here, the first decision is Is the year zero modulo four? which is equivalent to Is the year exactly divisible by four? in plain language. If the answer is no, be proceed down the red branch and arrive at the classifier No, this year is not a leap year. If the answer is yes, we proceed down the left branch and encounter the split Is the year zero modulo 100? (Is the year exactly divisible by 100?). If this condition is true, proceed down the green branch to the No leaf, and if it fails, the classifier is Yes. From this, a given year is a leap year if and only if the year is exactly divisible by four but not by 100. Of course, the system in this paper is much more complex than the simple leap year/not leap year classification, and the trees representing it will reflect this.

Once the tree has been built with a complete training dataset, it can then be used to generate classifier values for data where this information is not given. Using the leap year example, the training set would be a record containing two variables- year and a yes/no indicator denoting whether the corresponding year is a leap year or not. Then, a year can be input into the complete tree to obtain a yes or no answer for the year in question. In this paper, the training set consists of the described in Table 3, with the classifier taking a value from the set of possible crops, summarised in Table 2.

Table 2: Crop groupings used for analysis

Crop type	**Category (Label)**	**Crops included in category**
Rice	rice_wet, rice_dry	glutinuous rice, non glutinuous rice
Non-rice field crops	maize_wet, maize_dry	corn, maize, baby corn and sweet corn
Non-rice field crops	bean_wet, bean_dry	green soybean, ground nut, sweet bean,soybean and yard longbean
Vegetables	leafveg_wet, leafveg_dry	head lettuce, bakchoi cabbage, chinese cabbage, spinach, kale, green cabbage, cabbage, cauliflower, michilli
Vegetables	rootveg_wet, rootveg_dry	carrot, chinese raddish, potato, gobo, garlic and shallot
	othveg_wet, othveg_dry	bitter guord, chilli, bunching onion, tomato, sweet basil and basil
Other annual crops	flower_dry	marigold and curcuma
Other annual crops	tobacco_dry	tobacco
Tree crops	banana	banana
Tree crops	longan	longan
Tree crops	lychee	lychee
Tree crops	mango	mango
Tree crops	tea_coffee	tea, coffee
Tree crops	ornamental	ornamental trees

Table 3: Data Mining variables.

Variable	**Description**	**Values used for analysis**
Watershed	There are 3 watersheds or catchments: Mae Ping II, Mae Rim and Mae Kuang catchments.	Not used in analysis as unable to extrapolate to other catchments.
LU	Land unit as defined by the Department of Land Development	Values as defined by DLD.
Profitgrp	This is calculated from gross margin level. Profit aspiration is divided into 5 groups. Certainly a farmer wants more profit rather than	<=3000 baht: profitgrp=1 >3000 to <=6000 baht: profitgrp=2 >9000<=12000 baht: profitgrp

Variable	Description	Values used for analysis
	less, but usually more profit means more risk, skills and management. One can think of these as a variable indicating risk and skill levels. Level one of profitgrp is low risk, low return and easy skills. Level two and three being medium risk, return and medium level of skills. Level four and five being high risk, return and high skills level.	=3 >12000 to <=15000 baht: profitgrp 4 >15000: profitgrp=5
Costrd	This is redefined from the actual cost of production. This variable indicates the level of investment farmers want to make in a particular crop.	cost 2 <=2000 baht: costrd=2000 >2000 to <=4000 baht: costrd=4000 >4000 to <=6000 baht: costrd =6000 >6000 to <=8000 baht: costrd 8000 >8000 to <=10000: costrd=10000 >10000 to <=12000 baht: costrd= 12000 >12000 to <=15000: costrd=15000 <15000: costrd=20000
Landlabor	This is farm size divided by the units of household labour. Low values indicate land scarcity in relation to labour. High values indicate relative land abundance in relation to labour.	
Farmsize	This is farm size in rai (6.25 rai = 1 hectare). This variable is a bit different from landlabor ratio as it indicates the absolute size of the farm and may have bearing in crop choice.	
Labor	The number of units of household labour.	
Hhmem	The number of household members.	
Altercrop	This is an indication from farmers whether there is in their thinking availability of an alternative crop.	1=yes, 2=no
Offfarm	This variable summarised farmers' ideas about availability of off farm employment. This may be important as to plant a particular crop may release or prevent farmers to participate in these off farm occupation.	1=yes, 2=no
Livestock	Are there livestock in the farm? Generally, this variable is not important to farmers' decision making.	1=yes, 2=no
Tenure	This variable indicates land tenure status for farmers.	1=owned land, 2=rented land, 3 = part own and part rent.
Flood	This is not actual flooding but rather waterlogging incidence. Farmers were asked to respond to the question "Do you experience waterlogging/flooding in your fields in some years?"	1=yes, 2=no
Drought	In the same way, farmers were asked "Do you experience dry spells/droughts in your land in some years?"	1=yes, 2= no.
Wateruse	This variable indicates water availability and use. Note that land unit may be correlated with this variable.	1= surface water irrigation, 2= no irrigation, 3= availability of pump water for irrigation
Waterorg	This indicates farmers' status in a water users' association. This variable is generally not	0=no, 1=yes

Variable	Description	Values used for analysis
	important in crop choice as wateruse is a more important variable.	
Adjcap	This variable indicates household owned capital availability but adjusted for farm size and number of crops grown.	
Adjcapgrp	This is regrouped from adjcap. It indicates whether (owned) capital is low, medium and more for the household. Farmers can borrow more but the amount of borrowed capital is not available in the data set.	adjcap<=5000 baht: adjcapgrp =1 adjcap>5000 to <=10000 baht: adjcapgrp=2 adjcap>10000 baht: adjcapgrp =3

Most useful decision trees will not classify all input instances correctly. Nor should they, as almost all training data contains noise, and to fit every instance would result in a large and overfitted tree. A measure of classification performance must be defined and applied on the training set of a held-back validation dataset where the correct classification is known. The simplest such measure is the percentage of correctly classified instances, but this one number provides no information on the breakdown of mis-classifications by class. For example, we would like to know how good the classification is for rice, and how many instances of vegetables are incorrectly assigned to another class. A confusion matrix is used to summarise this information. The example confusion matrix below is the output from a two-class classification. The positions A1 and B2 are filled by the number of instances correctly assigned to classes A and B respectively. Position A2 shows the number of instances of class A incorrectly assigned to class B, and similarly position B1 denotes the number of B instances assigned to class A.

The confusion matrix concept is easily generalisable to multi-class problems such that the land use classification problem in this paper, keeping in mind that the matrix row denotes the correct class and the matrix column the assigned class. Also note that a perfect confusion matrix is wholly diagonal. To obtain representative confusion matrices the common practice of 10-fold cross validation is followed, where errors are estimated by independently generating 10 separate decision trees each built from 90% of the data with 10% held back for validation.

There are many algorithms available for constructing decision trees. The algorithm used in this paper is the C4.5 model (Quinlan, 1993) as implemented in the WEKA software package (see for example Whitten and Frank, 1991). C4.5 is a well-used standard algorithm, often used to benchmark new methods (see for example Buntine, 1993; Quinlan, 1996). The WEKA project is also well known in the data mining community.

6 DATA MINING RESULTS

In order to perform data mining on the survey results, the crops were grouped into several categories. These were based not only on economic characteristics of the crops, but also on advice from agronomists in the project team. The labels used to identify crop categories are given in Table 2, with a suffix used to indicate whether the crop is grown in the wet or the dry season.

The variables considered from the survey by the data mining analysis as possible descriptors of crop choice are summarised in Table 3. In some cases these variables were groups into discrete classes to aid with the analysis. A description of the groups used is also given in the table. Labels used in this table are consistent with the labels used for variables in the final decision trees.

Wet and dry season crop choices were analysed separately using the data mining algorithm. In both seasons the data was able to be classified accurately using only four attributes: land unit, estimated cost of production, the land-labour ratio, and estimated profit level.

Given these decision trees, each land unit can be divided into many wet and dry season crops depending on the farmers' profit expectations and their resources e.g. capital (estimated cost of production, land and labour availability). The decision tree can be used predict what crops a representative farmer will grow in the study areas, given different assumptions about resource availability.

A brief summary of the fit of the decision trees to the survey data is given below. The full decision trees for wet and dry season crops are given in Figures 3 and 4 respectively.

6.1 Wet season decision tree

The percentage of correctly classified instances was 95.8% out of a total of 2416 instances. The final wet season decision tree consisted of 32 leaves (see Figure3). Table 4 contains the confusion matrix for wet season crops. This matrix illustrates for each crop class the number of wrongly and rightly classified instances. Where instances are incorrectly classified, the column heading shows the number of instances wrongly classified under each crop type. For example, five instances of wet season leafy vegetables (leafveg_wet) were wrongly classified as wet season beans (bean_wet).

6.2 Dy season decision tree

The model for dry season crop choice is very similar to the wet season model. The minimum number of instances used was 3. Other settings were: no reduced error pruning (false); subtree raising (true); and, binary splitting (true). The predictability of the dry season tree was lower. This was because there were fewer farmers in the dry season data set. The dry season decision tree consists of 29 leaves (see Figure 4).

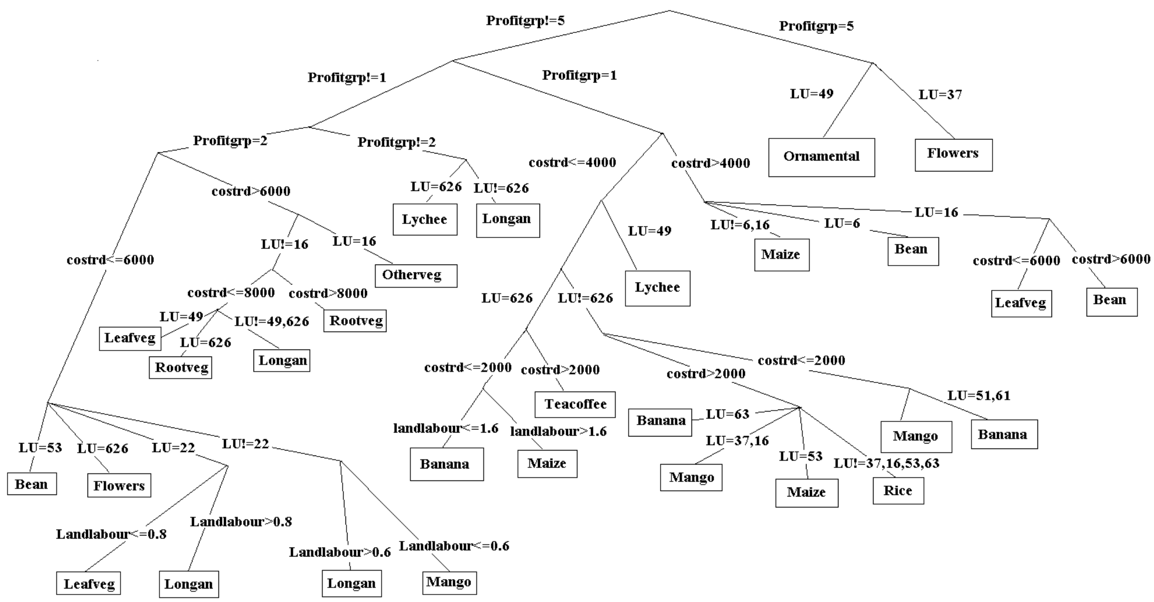

Figure 3: Wet-season decision tree

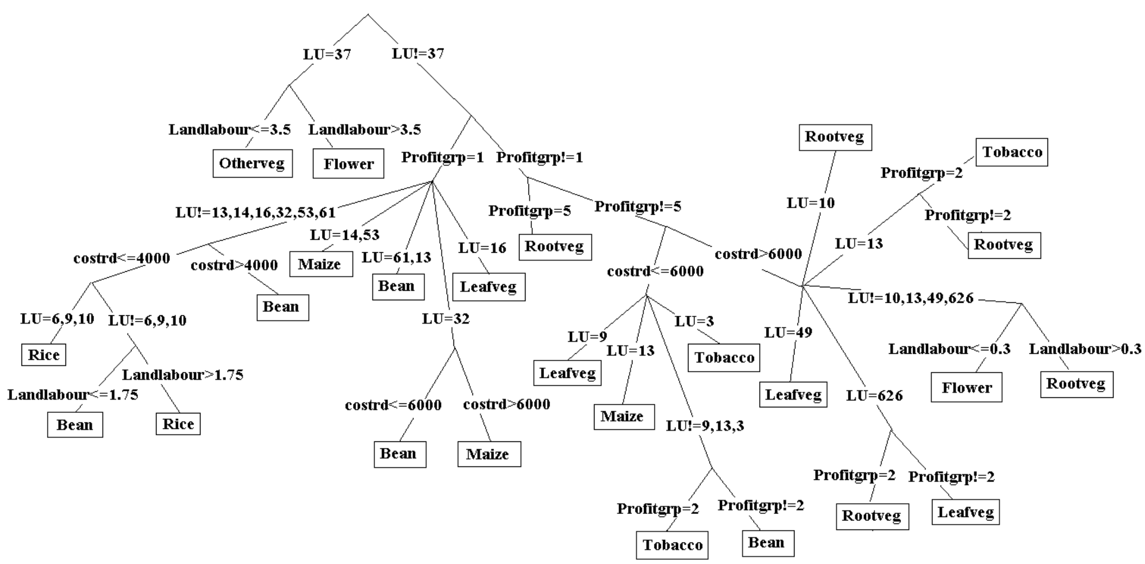

Figure 4: Dry-season decision tree

Flower crops will be grown in certain land units. Root crops are grown when expectations of profit are high. Overall 86% of instances were correctly classified by the dry season decision tree. The confusion matrix for dry season crops is given in Table 5. This confusion matrix shows that the most frequent errors are for crops wrongly classified as rice (beans and maize).

Table 4: Wet-season crop confusion matrix

a	b	c	d	e	f	g	h	i	j	k	l	m	classified
184	0	0	0	0	0	0	0	0	0	0	0	0	a= banana
0	189	0	0	0	0	0	0	0	0	0	0	0	b=bean_wet
0	0	188	0	0	0	0	0	0	0	0	0	0	c=flower_wet
0	5	0	154	10	0	0	0	0	0	0	15	0	d=leafveg_wet
0	0	0	20	162	4	0	2	0	0	0	1	0	e=longan
0	0	0	0	0	192	0	0	0	0	0	0	0	f=lychee
0	0	0	0	0	0	183	0	0	0	4	0	0	g=maize_wet
0	0	0	0	0	0	0	179	0	0	3	0	0	h=mango
0	0	0	0	0	0	0	0	182	0	0	0	0	I=ornamental
0	0	0	0	0	0	0	0	0	180	0	0	0	j=othveg_wet
1	0	0	0	2	0	13	21	0	0	151	0	1	k=rice_wet
0	0	0	0	0	0	0	0	0	0	0	188	0	l=rootveg_wet
0	0	0	0	0	0	0	0	0	0	0	0	188	m=tea_coffee

Table 5: Dry season crop confusion matrix

a	b	c	d	e	f	g	h	<--	classified as
29	1	3	0	0	17	0	0		a=bean_dry
0	48	0	0	0	0	0	0		b=flower_dry
0	0	50	0	0	0	0	0		c=leafveg_dry
4	1	0	18	0	19	0	3		d=maize_dry
0	0	0	0	50	0	0	0		e=othveg_dry
5	0	0	0	0	49	0	0		f=rice_dry
0	0	0	0	0	0	50	2		g=rootveg_dry
0	0	0	0	0	0	0	48		h=tobacco_dry

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AUTHOR BIOGRAPHIES

BENCHAPHUN SHINAWATRA EKASINGH is an Associate Professor in Agricultural Economics, Chiang Mai University, Thailand. She received a Ph. D. from Michigan State University in agricultural and natural resource economics in 1985. She has extensive experiences in highland and natural resource development in Southeast Asia. She is active in international agricultural development and currently the Chair of Board of Trustees of the International Plant Genetic Resource Institute, one in 15 international research centers under the Consultative Group of International Agricultural Research. Her email address is <bench.ek@chiangmai.ac.th>

KAMOL NGAMSOMSUKE is a lecturer in the Department of Agricultural Economics, Faculty of Agriculture, Chiang Mai University. He received a Ph.D. in agricultural economics from University of the Philippines Los Banos in 1995. He has extensive experiences in socio-economic study in highland and lowland agriculture of the nortern Thailand. He has special interest in mathematical programming and economic model and simulation. His email address is <agikngms@chiangmai.ac.th>.

REBECCA A. LETCHER is an economist in Integrated Catchment and Management Centre (ICAM), The Australian National University, Australia. She has background in hydrology but did her Ph.D in economics from Australia National University. She has authored and coauthored many publications in decision support in integrated natural resource management. In ICAM, she is active in bringing in economics into interdisciplinary work of integrated natural resource management. Her email address is <rebecca.letcher@anu.edu.au>

JESSICA MARJORIE SPATE graduated from the Australian National University with first class Honours in 2002, after majoring in mathematics and computational science. Automated data analysis, machine learning, and data mining methods from these disciplines are currently being combined with a strong interest in environmental and hydrological modeling to explore novel ways useful knowledge can be extracted from raw data. Error and uncertainty quantification with these techniques are also under consideration, and with the above will form the basis a of PhD thesis to be submitted in early 2006. Contact email: <jessica.spate@anu.edu.au>