CHAPTER 1

INTRODUCTION

1.1 Background

Rice (*Oryza sativa* L.) is a main staple crop in Chiang Mai. In crop year 2001/2002, the production areas were 553,237 rai and average yield was 580 kg./rai. (Office of Agricultural Economics, 2002). However, during 1992 – 2001, average grain yield was uncertainly fluctuating (figure 1.1). It shows that risk and uncertainty pervade the environment to rice yield which rice production is practiced in each year.

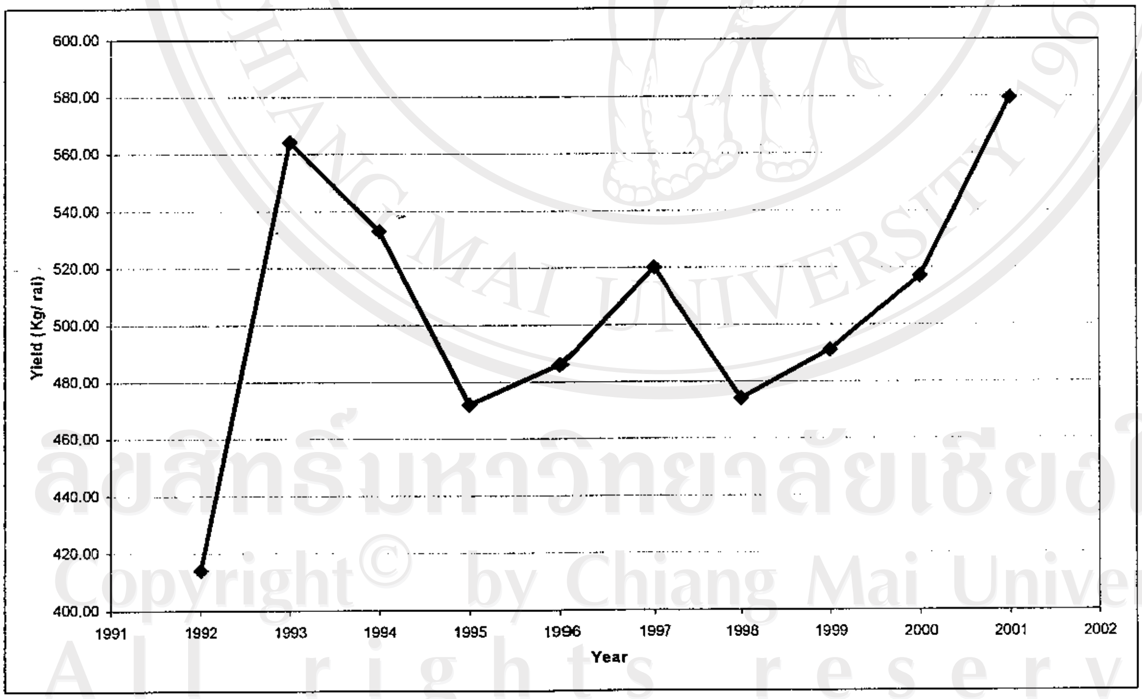

Figure 1.1 Yield of rice production of Chiang Mai province in year 1992-2001

During the coming growing season, the impact of weather, pests, diseases, and other uncontrollable variables are all unknown to varying degrees (Thornton and Wikens, 1998). Of most general relevance and importance are risks associated with the natural environment. Because of its biological nature, agricultural production is directly dependent on nature with all its uncertainties and forwardness including, on the downside, the possible vicissitudes of short-term weather (droughts, floods etc.) and long term climate (such as climatic change including greater variability due to change in the Greenhouse Effect). All these effects from nature impinge on yields and through their effect on market supply and on prices both locally and globally.

Risk associated with the farm system's economic environment relate to uncertainty about (1) market (demand and supply) conditions and prices for inputs and outputs, (2) inflation and interest rates, and (3) productivity through the availability and merit of new technology (McConnell and Dillon, 1997). Farmers, who lack experience of using the new technology and being cautious, are likely to subjectively access it as more risk and less profitable than it possibly is.

Social environment related to change in education and lifestyles (McConnell and Dillon, 1997). It could affect the availability and competence of farm labor supply. In the social-policy, there are two dimensions to such policy-risk possibilities: first, uncertainty about what changes may be legislated and, second, uncertainty about the extent to which legislated changes was enforced. Policy risk may affect the farm household's income either through effects on yields, on total output level, or on input and output prices.

The outcome of a management decision under risk can not be sure. In additional, small farmers generally do not have easy access to such formal institutional avenues of risk mitigation as purchased insurance and futures markets (McConnell and Dillon, 1997). Farmers need to make their risky decision of farm management strategies on the basis of their experience, traditional knowledge and whatever other information is available to them. Thus, the evaluation of farm management in their farm is necessary in order to minimize risk in rice production.

1.2 Rationale

Rice production involves making decisions about the dose, form and timing of input applications in relation to expected returns and preferences toward risk. Risk due to uncertainties in weather condition, fluctuation of input and output price and other uncontrollable variables have a large impact on these decisions (Lansigan *et al.*, 1997). Risk arises due to uncertainty regarding future consequences of an action. Farmers are continuously confronting with the challenge of choosing efficient management practices and encountering uncertain outcomes resulting from such choices. In risky situations, a particular choice may appear to be better but not so in others. Given that situations those are likely to eventuate are imperfectly known at the time the choice has to be made. The pertinent question is how to assess the presence of risk in the rice production so that rational choices and strategies of farm management can be made.

Part of managing risk in agriculture consists of coping with production variability between years. It may be critical for the farmer to minimize the fluctuations in household income over time or to maintain or increase a particular wealth level and nutritional status. The crop models can be excellent tools for assessing the production variability associated with weather and related uncertainties for various strategies (Thornton and Wilkens, 1998). The simulation can be replicated using a number of different historical conditions from various previous weather years. This process of replication produces a distribution of yields for that environment. The probability distribution of yield then becomes a proxy for the investigator's expectation of what may likely to happen next season and at what level of probability. It is assumed that next year constitutes a sample drawn at random from the outcome distribution which can be approximated using the model and recently updated weather conditions (Thornton and Wilkens, 1998). This is a general method of deriving an output distribution. Historical weather data may be used in the simulation experiment, or a statistical generator may be used to produce weather records with similar statistical characteristics as those of the historical weather data for the site. The initial conditions of the model are reset at the start of each season. Crop performance is thus replicated over a single growing season, assuming there is no carry-over from one year to the next (Thornton and Wilkens, 1998). In other hands, production in each season is completely independent to one another. Therefore, the generated output distribution can be used to assess risk and crop yield stability in different environments and for various crop management strategies.

The cost of inputs can fluctuate as well as the price of output that depends on demand and supply in the market. It affects farmer's decision making on their farm strategies. Farmer may take risk of using new technologies. For example, fertilizer can increase productivity but if the farmer is lack of knowledge and experience then productivity or net margin can be reduced. The input cost and output prices in recent years were assumed to occur in the next year. The combination of simulated yield with input cost and output prices can be use to generate the simulated net margin.

These output distributions can be used to evaluate risk on the crop management strategies.

Stochastic dominance can be used to rank the farm management strategies. It identifies technologies or strategies that are dominant, those that might be acceptable to risk neutral decision makers and those that could be used by risk-averse individuals. Stochastic efficiency criteria are useful when risk-attitudes can not be measured accurately and do not require precise measurements of risk-preferences (Lansigan *et al.*, 1997). These criterions are particularly suited to the analysis of simulated output and while based on utility theory. The application of stochastic efficiency criteria involves a pair-wise comparison of random variables that relate to financial gains and losses. The outcome of the analysis draw risk-efficient set which contains a subset of treatments that are superior and would be preferred by decision makers whose risk attitudes conform to the assumptions of the analysis (Thornton and Wilkens, 1998).

Therefore, this study evaluated relative risk of alternative management practices and selected the proper one for rice production by combining crop model with stochastic dominance analysis in the light of farmers' perceptions of risk.

1.3 Literature Review

1.3.1 Risk and Uncertainty

Uncertainty and risk go hand in hand with farming. They are a pervasive feature of the farm environment. Uncertainty is a pervasive feature of life. It may sometimes exist in the past and may be relevant to the future. Uncertainty is defined as imperfect knowledge (McConnell and Dillon, 1997). In the context of farm management, risk is relevant to managerial decision making about the planning and running of the farm system. Decisions do not have a single sure outcome are known because of the influence of forces beyond the farm manager's control. Such decisions have an array of possible outcomes which can be specified by the effective decision maker in the form of a subjective probability distribution corresponding directly to their personal degrees of belief in the occurrence of the possible outcomes.

While uncertainty is always present but risk may not be. Risk is only present when the uncertain outcomes of a decision are regarded by the decision maker (McConnell and Dillon, 1997). For a decision problem under uncertainty whose outcomes are regarded as significant, the present of risk is specified by the entire set of subjective probability distributions for the choice-contingent outcomes that may occur. The complete probability distribution set for the possible outcomes of a particular choice can fully depict the risk which that particular choice entails for the decision maker. Other measures of risk such as the range or mean and variance or coefficient of variation of the distribution of outcomes are only partial measures of risk (McConnell and Dillon, 1997).

1.3.2 Cropping Simulation Model

Simulation models, in general, are a mathematical representation of a real-world system (Hoogenboom, 2000). In reality, it is impossible to include all the real world interactions into the modeled system. Therefore, the model might include many assumptions, especially when information that describes the interactions of the system is inadequate or does not exist. Depending on the scientific discipline, there are different types of models, ranging from very simple models that are based on one equation to extremely advanced models that include thousands of equations.

Agriculture involves biological factors for which, in many cases, the interactions with the environment are unknown. The science of plants and crops represents an integration of the disciplines of biology, physics, and chemistry. Plant and crop simulation models are a mathematical representation of this system.

Crop models, in general, integrate current knowledge from various disciplines, including agro-meteorology, soil physics, soil chemistry, crop physiology, plant breeding, and agronomy, into a set of mathematical equations to predict growth, development and yield (Hoogenboom, 2000). Crop growth models are physiologically based, in that they calculate the causal relationships between the various plant functions and the environment. The opposite would be a statistical approach, using correlative relatives between all processes. Crop models can also be identified as being deterministic, in that they make an exact calculation or prediction. In this case, the opposite would be stochastic or probabilistic models, which provide a different answer for each calculation. Crop models are simulation models, in that they use one or more sets of differential equations, and calculate both rate and state variables over time, normally from planting until harvest maturity or final harvest. Some of the earliest crop simulation models simulated only photosynthesis and a simple carbon balance over time. Other processes, such as vegetative and reproductive development and the plant water balance were added at a later date (Hoogenboom, 2000).

Crop simulation models can play an important role at different levels of applications, ranging from decision support for crop management at a farm level to advancing understanding of sciences at a research level (Hoogenboom, 2000). Weather data are the most important input for all these applications of the simulation models. The main goal of most applications is to predict final yield in the form of grain yield, fruit yield, root or tuber yield, biomass yield for fodder, or any other harvestable product. In some cases, associated variables, such as resource use or the impact of pollution on the environment, might also be of interest. Certain application link the price of the harvestable product with the cost of inputs and production to determine economic returns. In some cases, crop simulation models are used for policy management (Hoogenboom, 2000).

In general, the management applications of crop simulation models can be defined as strategic, tactical, and forecasting applications. In strategic applications of crop simulation models and decision support systems, the models are mainly run to compare alternative crop management scenarios. This allows for the evaluation of various options that are available with respect to one or more management decisions (Tsuji *et al*., 1998). To account for the interactions of these management scenarios with weather conditions and the risk associated with unpredictable weather, simulations are conducted for at least 20-30 different weather seasons or weather years (Hoogenboom, 2000). In tactical applications, the crop models are run before planting or during the actual growing season so that immediate measures can be made to improve crop performance. Both strategic and tactical applications provide information for decision making by either farmer, consultant, policy maker, or other person involved directly with agricultural management and production. Forecasting applications can be conducted either prior to planting of a crop or during the growing season. The main objective is to predict yield; this information can be used at farm-level for marketing decisions or at national level for policy issues and food security decisions.

In running the strategic application of crop simulation model, two approaches were usually applied. They are seasonal and sequential analysis approaches.

Seasonal analysis

In the seasonal analysis applications, a management decision is evaluated for a single season. The decision variables may include: crop and cultivar selection; plant density and spacing; planting date; timing and amount of irrigation applications; timing, amount and type of fertilizer applications; and other options that a particular model might have. Applications can also include investment decisions, such as those related to the purchase of irrigation systems. Thornton and Hoogenboom (1994) describe a special software program of the DSSAT crop simulation models that was developed for seasonal analysis applications. This software can also be applied to the outputs produced by other software.

Sequence analysis

In the sequence or crop rotation analysis, one or more crop rotations can be analyzed. In this model, different cropping sequences are simulated across multiple years. It is critical that, in a crop rotation analysis, the water, nitrogen, carbon and other soil balances are simulated as a continuum by incorporating the effect of the proceeding crop cultivation and practices to the proceeding one. The main goal of a cropping sequence application is to determine the long-term change of soil variables as a function of different crop rotation. Thornton and Wikens (1998) present a general sequence analysis tool for crop simulation models. His procedure has been implemented in the DSSAT suite. Weather again plays a key role as input for these long-term crop rotation and crop sequencing simulations. One can use a sequence of observed historical weather data to simulate a particular long-term crop rotation. This was applicable for evaluating the performance of a modeling system with data from long-term crop rotation trials. In this case, the weather conditions observed during these long-term crop rotation trials as well as the crop management scenarios were used as inputs for the crop rotation modeling study.

1.3.3 Stochastic Dominance Analysis

One of the most widely applied models for studying decision making under uncertainty is the expected utility model (Lansigan *et al.*, 1997). Implementation of the model requires that both the probability distribution of outcomes (which measures risk) and the utility function (which measures risk-attitudes) of decision makers be precisely known. Measurement of risk-preferences which is directly the elicitation of utility function, or indirectly by imputation, is subject to large errors. Stochastic efficiency criteria are useful when risk-attitudes can not be measured accurately. These criterions satisfy the axioms of the expected utility model but do not require precise measurements of risk-preferences. As opposed to complete ordering achieved when risk-preferences are precisely known, stochastic efficiency rules provide only a partial ordering (Lansigan *et al.*, 1997).

Stochastic efficiency rules are implemented by pairwise comparisons of cumative distribution functions (CDFs) of outcomes (e.g., yields, net incomes) resulting from different actions. If the only restriction that can be placed on the nature of the utility function is that 'more' is preferred to 'less'. The first degree stochastic dominance (FSD) rule can be applied where no assumptions are made about the risk-attitudes of the decision maker. If decision makers are assumed to be risk-averse then the second degree stochastic dominance (SSD) rule is applicable. The rule selects distributions that are preferred by all risk-averse decision makers as being risk-efficient (Lansigan *et al.*, 1997).

The attractive features of stochastic dominance analysis are (1) that it does not require knowledge of the decision maker's utility function and (2) that it is based on direct comparisons between full probability distributions of outcomes (McConnell and Dillon, 1997). However, its disadvantages are (1) that it requires knowledge of the decision maker's subjective probability distributions for the possible outcomes of all the relevant alternative decisions; (2) that it necessitates pair-wise comparison of risky alternatives where the potential number of comparisons rising exponentially with the number of alternatives, thereby quickly making the assessment burdensome; and (3) that it generally does not lead to the one best alternative but rather to some set of undominated alternatives (McConnell and Dillon, 1997).

Lansigan *et al.* (1997) combined crop modeling with economic risk analysis for the evaluation of crop management strategies. An agro-ecological approach is presented for the evaluation of alternative management options for rice production in the light of farmers' attitudes towards risk. The approach combined eco-physiological crop growth modeling with stochastic dominance theory and is illustrated for a case study of rainfed lowland rice in Victoria, Tarlac Province in Philippines. The eco-physiological rice growth model of ORYZA_W simulated possible outcomes for the estimation of probability distributions of rice yields under different management scenarios. Relatively simple management options were considered for soils with different water storage capacities, plant density, seedling age at transplanting, bund height and puddle soil depth. Stochastic dominance analysis was applied to identify risk-efficient management option. A critical appraisal of the proposed agro-ecological method for risk-analysis is given and suggestions are made for refinement and further research.

Hien *et al.* (1997) used stochastic dominance determine the risk characteristics of phosphate fertilization of millet, sorghum and maize with commercial NPK fertilizer, rock phosphate and partially acidulated rock phosphate in Burkina Faso. On farm-trial data from 1989, 1990 and 1991 in three rainfall zones was used. Stochastic dominance permitted a timely and detailed analysis of risk inherent in phosphate fertilizer alternatives. Because on farm-trails involve a modest number of alternative, pairwise stochastic dominance comparisons are feasible. The stochastic dominance analysis permits researchers to communicate to extension staff and policymakers not only the degree of risk but also something about the characteristics of the crop response that contribute to risk.

1.4 Objectives of the Study

The objectives of this study are as follows.

1. To simulate rice yield and gross margin for the alternative management option for rice production.
2. To study levels of risk in each rice production management strategy in Chiang Mai province.
3. To formulate rice production management strategies in Chiang Mai province.

1.5 Scope of the Study

This study covered the following issues.

1) It focused on irrigated rice production areas of San Sai district, Chiang Mai province. A crop model was used to simulate the effects of erratic weather conditions using the past 30 year data with varying management practices on different rice varieties, levels and patterns of fertilizer application, soil series, and planting seasons in the study areas. Crop model was used as seasonal analysis of strategic applications.

2) Based on rice cultural practices and biophysical conditions facing rice farmers in irrigated areas of Chiang Mai province, this study covered 4 rice varieties (Niew San Pa Thong (NSPT), RD6, Khaow Dawk Mali 105 (KDML105) and San Pa Thong 1 (SPT1)), three soil series (Hang Dong, San Sai and San Pa Thong series), two planting seasons (Rainy and dry seasons) and three different fertilizer management level (see Table 1.1).

Table 1.1 Fertilizer management level of photo period-sensitive variety (KDML105, NSPT, RD6) and photo period-insensitive variety (SPT1)

Fertilizer management Level	Photo period-sensitive variety	Photo period-insensitive variety
Low Level	- first day planting using 16-20-0 fertilizer at the rate of 10 kg./rai - after 45 day using 46-0-0 fertilizer at the rate of 3 kg./rai	- first day planting using 16-20-0 fertilizer at the rate of13 kg./rai - after 40 day using 46-0-0 fertilizer at the rate of 4 kg./rai
High Level	- first day planting using 16-20-0 fertilizer at the rate of 20 kg./rai - after 45 day using 46-0-0 fertilizer at the rate of 6 kg./rai	- first day planting using 16-20-0 fertilizer at the rate of 25 kg./rai - after 40 day using 46-0-0 fertilizer at the rate of 10 kg./rai
Intensive Level	- using urea fertilizer application at dose rate of 7, 7, 15 and 7 kg./rai after plant at 20, 50, 60 and 80 days	- using urea fertilizer application at dose rate of 9, 9, 19 and 9 kg./rai after plant at 20, 50, 60 and 80 days

3) A common criticism is that most farmers have different objectives but the weighted placed on each objective in unknown (Hien *et al.*, 1997). This study assumed rice farmers to have two distinctive objectives, the rice self sufficiency and optimize their rice farm income. The proper farm management strategies were derived by mean of stochastic dominance analysis on simulated rice yield and net margin for these different groups of farmer respectively.