UNIVERSITY OF ALBERTA

# AGRICULTURAL LAND EVALUATION IN NORTHEAST THAILAND USING CROP MODELING AND REMOTE SENSING, IN A GEOGRAPHIC INFORMATION SYSTEM

by

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## ABSTRACT

The research reported in this dissertation was conducted in Khon Kaen Province, Northeast Thailand. It involved a series of studies designed to investigate the uses of crop modeling and remote sensing, in a geographic information system. Its purpose was to generate information that is useful for the implementation of non-irrigated, dry season peanut cropping. The modeling portion of the research generates land suitability information based on conditions reported in the past. The remote sensing portion adds information on conditions for the time at which the land suitability information would be used.

The crop modeling studies focused on the application of the MACROS model to simulate peanut pod yield data from crop parameters, soil parameters, and historical weather data. These yield data, simulated for ten years, were used as the basis for the land suitability classification. Prior to model application at the regional scale, relevant studies were undertaken to investigate the use of the MACROS crop model for this purpose. These studies included an evaluation for accuracy and usefulness, as well as sensitivity analyses. The MACROS model appeared to be a model of choice for conditions of the study area.

MACROS was then applied at the regional scale to generate a set of maps and accompanying data, showing land suitability under realistic ranges of water table depths and planting dates. Significant reductions in simulated pod yields for later planted peanut crops were investigated using MACROS. Reduced yields were the result of the higher temperature regime during the growing period following later planting.

The remote sensing study was conducted to determine the most appropriate technique, with respect to the minimum number of image spectral bands, and the least complex classification method, that would be required to generate reliable information on the extent of green crop areas just before the dry season. The information on green crop

areas is important because it is usually not necessary, or even possible, to introduce dry season cropping to fields in which other crops already exist. In this study, various statistics including the overall accuracy, producer's accuracy, user's accuracy, KAPPA analysis, and Z statistic, were employed as bases for technique selection. The use of the Minimum Distance method with the LANDSAT -5 TM, band 4 data appeared to be most appropriate when only the areas of non-irrigated agricultural land were considered.

In this dissertation, a geographic information system (GIS) was used effectively to store the information generated using crop modeling and remote sensing, in the form of digital maps and associated attribute data, that can be easily displayed or retrieved. The GIS also provided flexibility for correcting and updating the results, as well as the capability of displaying information from many maps simultaneously.

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# CHAPTER 1

# INTRODUCTION

Northeast Thailand includes approximately one-third of the country in area and population. The majority of the population lives in rural areas and makes their living as small scale farmers. Irrigation is limited to only a small percentage of agricultural land because of the inappropriate topography, which is mainly undulating to rolling. The farming is, therefore, heavily dependent upon rainfed agriculture in which monocropping of rice, kenaf, and cassava is predominant (Polthanee, 1983). Judging from the income per capita and living conditions of the inhabitants, the northeast is the poorest region of the country (Viratphong, 1994).

Various attempts have been carried out to develop the potential of this region and its people. In agriculture, one of the most likely alternatives is to increase the agricultural land use efficiency by introducing multiple cropping systems so that farmers can benefit from more than one crop per year from the same piece of land. Research at experimental stations and selected farmers' fields has shown the potential of several field crops, such as sesame and peanut to grow in the dry season. However, the implementation of dry season crops in the farmers' fields under non-irrigated conditions, frequently failed due to the lack of information on land suitability, especially the suitability in relation to water availability (Limpinuntana, 1985; Vorasoot, 1985).

The only available information is the Land Capability Classification for Field Crop published in the form of 1:100,000 maps and accompanying reports (Soil Survey Division, 1975). This kind of information was generated based on the USDA system of Klingbiel and Montgomery (1961) which was primarily developed for soil conservation and sustainable agricultural production. The information is too generalized for the desired purpose, with no indication of the land suitability level for a specific crop (Landon, 1991; McRae and Burnham, 1981).

The land evaluation procedure suggested in the FAO Framework for Land Evaluation (e.g., FAO, 1976; FAO, 1983) has been widely used to assess land potential for agricultural purposes. This procedure involves the definition of land use requirements to be matched with corresponding land qualities. Since in Northeast Thailand, the most crucial limiting factor for crop production is water, a serious problem occurs as the land quality with respect to water availability is difficult to express in terms of known and accessible land characteristics. This land quality is a complex function of various factors related to soil and its environment, such as rainfall, evaporative demand, and physical properties of soil as expressed by soil water retention and hydraulic conductivity. The commonly used expressions for water availability, as a land quality, derived from soil texture, available water capacity, and rooting depth provide only generalized characterization. This may be useful in studies comparing different land units in a large area, but not in the generation of information necessary for implementation of a specific cropping system on specific fields (Bouma et al., 1993).

The use of computerized crop simulation modeling is a promising alternative to the above. Since a crop model is capable of handling large volumes of data simultaneously, it can simulate crop growth and yield for each land unit in relation to water availability, as reflected by various environmental factors mentioned earlier. Data on crop yield can, in turn, be used directly to effectively classify the suitability of land for a specific cropping system (Dumanski and Onofrei, 1989).

For a particular dry season, the information on the extent of green crops just before the dry season should also be considered, in addition to the information on land suitability evaluated from crop yields simulated for a number of years in the past. It is usually not necessary, or even possible to introduce cropping to fields in which other crops already exist. Satellite remote sensing is an effective means of generating information on the area covered by green crops at a particular time of the year. This is a relatively simple land use / cover to identify. However, since this information must be generated within a very limited time at the beginning of the dry season, the appropriate technique in terms of computing time, space in computer, and reliability of results, has to be carefully determined.

Hence, this dissertation entitled "Agricultural Land Evaluation in Northeast Thailand using Crop Modeling and Remote Sensing, in a Geographic Information System" was conducted with two major objectives:

*(i) To study the feasibility of using crop modeling to generate information on land suitability for non-irrigated, dry season peanut cropping.*

*(ii) To determine the most appropriate remote sensing technique to generate information on the extent of green crops just before the dry season.*

A geographic information system (GIS) was used to facilitate the collection, storage, and manipulation of the information generated, using crop modeling and remote sensing techniques. In addition to the major objectives, this dissertation was also intended to provide information about procedures for land evaluation, using crop modeling, remote sensing, and GIS under conditions in the northeast region. Therefore, where appropriate, more details about the procedures for selection, collection, and use of the available data and information specific for this area are presented.

This dissertation focused on non-irrigated, dry season peanut cropping because peanut (*Arachis hypogaea*) is considered one of the most promising crops to grow in the dry season without irrigation. The agronomy and socio-economics of peanut cropping have been studied over many years in many locations (e.g., Chantorn, 1983; Jintrawet et al., 1983; Jintrawet et al., 1985; Jintrawet et al., 1986; Kerdsuk, 1986; Kerdsuk and Patanothai, 1990). Therefore, relatively large amounts of information for land evaluation is available. Khon Kaen Province was selected as the study area because it has all of the major landscapes, soils, and agricultural land uses of the region. Also, field data required in the process of land evaluation are available for the province.

It is expected that the findings from this dissertation will help improve procedures for land suitability evaluation for circumstances in Northeast Thailand. As a consequence, more accurate results, for the implementation of dry season cropping, will be generated. This should support agricultural extension in the region. Since effective use of these results may require knowledgeable users familiar with the rationale and scientific background for this approach, some effort will be needed to train potential users. For instance, potential users such as extension specialists may gain experience through a co-operative project, similar to those reported by Jintrawet et al. (1985), and Jintrawet et al. (1986). In these projects, the extension specialists and the researchers, who generated the information on land suitability, worked together as an inter-disciplinary team. This should be of mutual benefit to both sides. Extension specialists will have an opportunity to better their scientific knowledge and experiences in such technologies as crop modeling, remote sensing, and GIS, and be able to use the land evaluation results effectively. On the other hand, the researchers will have an opportunity to learn about the weaknesses of the evaluation procedure, when applied under field conditions. This information is necessary for the future improvement of the procedures.

The dissertation is written in a "paper format" of 8 chapters, each of which describes a separate, but integrated part of the research. Chapter 2 presents general information of the study area in terms of location, climate, landscape, soil, and land use/cover. Chapters 3 to 6 are devoted to studies on the use of the MACROS crop model to generate information on land suitability for non-irrigated, dry season cropping. The crop modeling studies proceeded in a stepwise fashion, with the result from one step providing necessary information for the next. In Chapter 3, the model evaluation for its accuracy and usefulness is discussed. This evaluation consisted of two phases: calibration and validation. For the model calibration, a number of input parameters were calibrated to obtain agreement between the experimental and simulated results. In the validation phase, the calibrated model was validated to assess its accuracy and usefulness. Satisfactory agreement between the observed and the corresponding simulated values in terms of pod yield and shoot dry weight, indicated that the model was valid and could be applied at the regional scale.

Prior to the model application, the sensitivity analyses of the suitability class to changes in the weather stations used to supply the rainfall data, and to changes in the classification criterion, are reported in Chapter 4. These analyses were conducted with two objectives. The first was to determine whether or not the land suitability evaluation, based on pod yield, simulated using the MACROS model was adequate under conditions of Northeast Thailand, where rainfall data were limited to a small number of weather stations. If the land suitability class was sensitive to the weather station data, then the land suitability classification evaluated under conditions of limited rainfall data, would be inadequate. On the other hand, if the suitability class was not sensitive, there should not be a problem due to the limited number of weather stations.

For the application of the MACROS model at the regional scale, pod yield data was simulated under different conditions of soils, water table depths, and planting dates, for ten consecutive growing seasons. These pod yield data would, in turn, be used to assess the level of suitability for each soil, under each assumed combination of water table depth by planting date, in the study area. This classification would be based on the level of pod yield, and the number of years in 10 for a given yield level. As described in Chapter 4, the classification criterion related to the level of yield was defined according to the results of a previous study conducted at the study area. Hence this criterion was considered well defined. The criterion of number of years in 10 was questionable because it must be arbitrarily defined. This could lead to significant differences in the suitability classes assigned for each soil, if the suitability class was sensitive to changes in this criterion. Therefore, the second objective of the study, as reported in Chapter 4, was to investigate the sensitivity of the suitability classification to changes in the criterion of number of years in 10 for a given yield level. Generally, the suitability class of major soils in the study area was not sensitive to either the weather station used to supply the rainfall data or to changes in the classification criterion.

Chapter 5 involves the MACROS application at the regional scale, in which the model was used to generate information on land suitability for non-irrigated, dry season peanut cropping, under a realistic range of assumed planting dates and water table depths. Important assumptions for the effective use of this information are also discussed.

According to the results shown in Chapter 5, yield of peanut crops planted on a later date was significantly less than that of the peanut crops planted on an earlier date, even under conditions where dynamics of soil moisture content during the growth period of peanut crops planted on these 2 dates were similar. It was hypothesized that yield reduction of later planted peanut crops was likely due to a higher air temperature regime during the growing period as compared to that of the earlier planted crops. The study reported in Chapter 6 was carried out to investigate whether or not the pattern of air temperature was related to the reduction of growth and yield of later planted peanut crops in the study area, using the MACROS crop model. Yield reduction simulated in later planted peanut crops was caused by the high temperature regime during the growing period. Therefore, implementation of late dry season peanut cropping may not be worthwhile, even with irrigation.

Adequacy of the land evaluation results could be considerably improved if the information on land suitability generated from pod yield simulated for several seasons in the past, was used in combination with the information on the extent of green crops before the dry season. Hence, a remote sensing study, as presented in Chapter 7, was initiated to determine the most appropriate technique, with respect to the minimum number of image band(s) and the least complex classification method, that would be required to generate reliable information on the extent of green crop areas in the dry season.

Chapter 8 consists of an overall summary, conclusions, and suggestions for future research. Also, a procedure for land evaluation for non-irrigated, dry season cropping in Northeast Thailand using crop modeling, remote sensing, and geographic information system technologies, is proposed. The reader should note that, to maintain consistency for the paper format, general information such as that on the crop model and crop model input parameters, soils, and land use is repeated in several chapters, where appropriate.

## REFERENCES


Bouma, J., R. J. Wagenet, M.R. Hoosbeek, and J.L. Hutson. 1993. Using expert systems and simulation modelling for land evaluation at farm level: a case study from New York State. Soil Use and Management 9(4): 131-139.

Chantorn, P. 1983. Rainfed Peanut After Rice Cropping. M.Sc. Thesis. Khon Kaen University, Khon Kaen, Thailand. (in Thai with English abstract).

Dumanski, J. and C. Onofrei. 1989. Techniques of crop yield assessment for agricultural land evaluation. Soil Use and Management 5: 9-16.

FAO. 1976. A Framework for Land Evaluation. Soils Bull. 29. FAO. Rome.

FAO. 1983. Guidelines: Land Evaluation for Rainfed Agriculture. Soils Bull. 52. FAO. Rome.

Jintrawet, A., S. Smutkupt, C. Wongsamun, R. Katawatin, and V. Kerdsuk. 1985. Extension Activities for Peanuts After Rice in Ban Samjan, Northeast Thailand: A Case Study in Farmer-to-Farmer Extension Methodology. Farming Systems Research Project, Khon Kaen University, Khon Kaen, Thailand.

Jintrawet, A., R. Katawatin, and W. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Khon Kaen University: Cropping Systems Research Project. (in Thai with English abstract).

Jintrawet, A., S. Smutkupt, S. Rattanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya, 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University. (in Thai with English summary).

Kerdsuk, V., and A. Patanothai, 1990. Testing and Implementation for Rainfed Dry Season Peanut: Khon Kaen University Experience. Farm News. Farming System Research Project, Khon Kaen University. 63: 24-35. (in Thai).

Kerdsuk, V. 1986. Effects of Planting Dates and Toposequence on Growth and Yield of Peanut After Rice. M.Sc. Thesis. Faculty of Graduate Studies, Khon Kaen University, Khon Kaen, Thailand.

Klingebiel, A.A., and P.H. Montgomery. 1961. Land Capability Classification. Agricultural Handbook No 210. USDA Soil Conserv. Serv., Washington DC.

Landon, J.R. (Ed). 1991. Booker Tropical Soil Manual: A Handbook for Soil Survey and Agricultural Land Evaluation in the Tropics and Subtropics. Essex: Longman Scientific and Technical.

Limpinuntana, V. 1985. Soil water and crop management practices for rainfed agricultural systems in Northeast Thailand. *In.* Proceedings of the Workshop on Soil, Water, and Crop Management Systems for Rainfed Agriculture in Northeast Thailand. Khon Kaen University. Khon Kaen, Thailand. pp 92-105.

McRae, R.G., and C.P. Burnham. 1981. Land Evaluation. Oxford: Clarendon Press.

Polthanee, A. 1983. Rainfed cropping systems in Northeast Thailand. Working Paper. EAPI, East-West Center, Honolulu, Hawaii.

Soil Survey Division. 1975. Land Capability Classification for Field Crop: Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

Viratphong, S. 1994. Thailand. *In.* Sustainable Agriculture Development in Asia. Report of the APO Study Meeting on Sustainable Agriculture held in Tokyo on 23rd February to 5th March, 1993. Asian Productivity Organization, Tokyo. pp 455-481.

Vorasoot, N. 1985. Agroclimatology in Northeast Thailand. *In.* Proceedings of the Workshop on Soil, Water, and Crop Management Systems for Rainfed Agriculture in Northeast Thailand. Khon Kaen University. Khon Kaen, Thailand. pp 48-60.

# CHAPTER 2

# NORTHEAST THAILAND AND THE STUDY AREA

Northeast Thailand, having an area of approximately 170,000 km$^2$, lies between latitudes 14° and 19° N, and longitudes 101° and 106° E. The study area, Khon Kaen Province, covers approximately 10,600 km$^2$ at the center of this region, between latitudes 16° and 17° N, and longitudes 102° and 103° E. In 1993, the population in the northeast was approximately 20 million, with about 1.6 million living in Khon Kaen (National Statistic Office, 1994). Figure 2.1 shows the location of the northeast region, including the study area. Khon Kaen was selected as the study area because it has typical climatic conditions, and all major landscapes, soils, and agricultural land uses for the region. Also, field data required in the process of land evaluation were available for this province.

The purpose of this chapter is to provide general information that is relevant to all the individual studies which comprise this dissertation. This includes climate, physiography, soil, and agricultural land use. Since the results of this dissertation are intended to be applicable for the entire region, the information presented here is not only for the study area, but also for Northeast Thailand as a whole. In addition to this chapter, the information specific for each study is reported in the corresponding chapter.

## 2.1 CLIMATE

The climate in Northeast Thailand is classified according to Koppen's Climatic Classification as Tropical Savanna (Eelaart, 1972; Vorasoot et al., 1985; Euroconsult, 1989). This includes 3 recognizable seasons namely, rainy season (mid-May to October), winter (cool) season (November to February), and summer season (March to mid-May). These seasons are influenced by the southwest and the northeast monsoon. The former brings air of high humidity from the Indian Ocean, while the latter conveys dry air from the Siberia. In addition, typhoon exerts a pronounced effect locally (Meteorology Department, 1977; Kaida and Surarerks, 1984).

In the study area, the average annual rainfall ranges from 1,100 to 1,500 mm (Vorasoot et al., 1985), which is not significantly different from the mean value for the entire region (approximately 1,200 mm). Approximately 80% of this amount occurs in the rainy season (KKU-FORD Cropping Systems Project, 1982). The average monthly rainfall recorded in Khon Kaen Province is shown in Figure 2.2

In the winter and the summer seasons, the weather is generally dry. Excessive evaporation and drying of the surface soil is normal. The average temperatures are 24° C for the winter, and 30° C for the summer (Keerati-Kasikorn, 1984). Figure 2.3 illustrates the monthly temperature recorded in the study area. In some periods of the summer, the air temperature could be higher than 40° C (FAO, 1971).

## 2.2 PHYSIOGRAPHY

The northeast region is a saucer-shaped plateau with a prominent raised margin of hills and mountain ranges in the south, southeast, and west. In the north, and east, the region is delimited by the "Maekong" international river (FAO, 1971). Hence, this region can easily be delineated from the rest of the country and the neighboring political units. The northeast region can be broadly divided into three main physiographic groups, i.e., hilly terrain, undulating-rolling terrain, and alluvial plain (Hokjaroen and Supajanya, 1982; Hokjaroen, 1986). The predominant group is the undulating-rolling terrain which can be subdivided into high, middle, and low terraces (Eiumnoh and Khewreunrom, 1981). In Khon Kaen, the hilly terrain, undulating-rolling terrain, and alluvial plain occupy approximately 10, 83, and 7 % of the total area, respectively (Soil Survey Division, 1973).

## 2.3 SOILS

The majority of soils in Northeast Thailand are sandy in texture with low water holding capacity, reflecting the bedrock from which they were derived, i.e., primarily sandstone (Kaida and Surarerks, 1984; Panichpong, 1985). Some increase in clay content with depth from the surface is common. Lateritic nodules and layers of compact but not indurated laterite can be found in some soils (FAO, 1971). According to the USDA-Soil Taxonomy of Soil Survey Staff (1975), the soils in this region can be classified into 7 soil orders of which 21 great groups are included. Panichpong (1985) provides the descriptions of these great groups. At the lower categories of the soil classification, Keerati-Kasikorn (1984) demonstrates that soils in the northeast meet the criteria of 72 series, 25 variants of soil series, and 8 phases of soil series. The predominant soils are members of the Korat series (Paleustults), Roi Et series (Paleaquults), Phon Phisai series (Plinthustults), and Nam Phong series (Quartzipsamments), covering 21, 16, 9, and 3 % of the total area of the region, respectively. Korat and Roi Et soils are similar in that they are deep soils which have sandy loam texture at the upper part of the profile, and with depth, the texture becomes finer to sandy clay loam, or sandy clay. The only major difference is that the Korat soils occupy upland areas, whereas the Roi Et soils occupy lowland areas. Phon Phisai and Nam Phong series are upland soils. Phon Phisai includes shallow soils which have laterite gravel within 50 cm of the surface. Members of Nam Phong series are sandy soils, having sandy texture throughout the deep profile.

In Khon Kaen Province, the soils belong to 28 series, 13 variants of soil series, and 2 phases of soil series. Roi Et, Korat, Nam Phong, and Phon Phisai are also dominant, occupying 25, 20, 8, and 5 % of the total area of the province, respectively. More details about each soil series, variant, or phase in the study area are included in Chapter 4, Soil Survey Division (1973), and Keerati-Kasikorn (1984).

## 2.4 AGRICULTURAL LAND USES

Farming in the northeast consists of traditionally small-scale, crop-based systems with limited resources and unreliable environments. The most critical constraint in crop production is water deficiency (KKU-FORD Cropping Systems Project, 1982). Although, the average annual rainfall of 1,200 mm in this region is not less than the rest of Thailand, its distribution is erratic. The erratic rainfall coupled with a low water holding capacity of soils results in a drought condition, which causes a reduction of crop yield, or even a total crop failure (KKU-FORD Cropping Systems Project, 1982; Limpinuntana, 1985). Irrigation is very limited due to the inappropriate topography which is mainly undulating-rolling. It is estimated that the suitable areas for irrigation comprise only 11.5 % of the total agricultural land in the region (KKU-FORD Cropping Systems Project, 1982; Rigg, 1985). In 1991, it was reported that only 7.8 % of the total area was under irrigation (Ammaritsut et al., 1991). Hence, the majority of farming is practiced under rainfed conditions.

With the limitation in water availability, fewer crops can be grown successfully compared to the rest of the country, and the total production for every crop is generally low (Limpinuntana, 1985; Prapertchob, 1987; Viratphong, 1994). The cropping systems under rainfed conditions can be described as monocropping of paddy rice, kenaf, cassava, and sugar cane (Limpinuntana, 1985; Saenjan et al., 1990). Paddy rice, a primary subsistence crop, is grown on an estimated 68 % of the total agricultural land, not only in the lowland areas (i.e., lower paddy fields), but also extends up to the upland areas (i.e., upper paddy fields) (Kerdsuk and Limpinuntana, 1989). Cassava and kenaf, the most important cash crops, are predominant in upland areas because they are drought tolerant. Sugar cane can also be found, but to a lesser extent because of the high investment costs and limitations in acquiring a processing plant quota (Jintrawet et al., 1985; Saenjan, 1990). Small acreages of peanut, cotton, castor bean, sesame, soybean, and mungbean tend to be localized. Fruit trees and vegetables occupy only a small portion of agricultural land (Vorasoot et al., 1985).

Crop calendars for each part of the region are slightly different from one to another mainly due to the variations in rainfall pattern. The calendars for Khon Kaen Province are shown in Figure 2.4. The early varieties of paddy rice (*Oryza sativa*) crops are usually grown in the upper paddy fields from early August to the end of November, while the late varieties are grown in the lower paddy fields from early-July to mid-December. Cassava (*Manihot esculenta*), a year-round crop, can be planted in either mid to late-March, or late November to mid-December. Kenaf (*Hibiscus cannabinus*), a photoperiod-sensitive crop, is planted around mid to late-March and harvested in late-September to mid-October. Sugar cane (*Saccharum officinarum*) is usually planted around mid-March to early-April, and harvested in early to mid-March. To a limited extent, vegetable crops are grown in some areas from mid-December to mid-March.

Low agricultural productivity is the major cause for the poor living conditions of farmers in Northeast Thailand (KKU-FORD Cropping Systems Project, 1976; Viratphong, 1994). At present, expansion of agricultural land is almost impossible because land is very limited. Hence, to develop the potential of this region and its people, many attempts have focused on the augmentation of agricultural land use efficiency. Increasing crop yield is difficult because most farmers are reluctant to use their capital for additional inputs such as pesticides. This is due to the risks involved, especially those related to the erratic rainfall, and fluctuating prices (Viratphong, 1994). The most promising alternative for increasing agricultural efficiency, therefore, to introduce multiple cropping systems, so that farmers can benefit from more than one crop per year from the same piece of land (Kerdsuk and Limpinuntana, 1989).

Despite the problems associated with water availability, previous research conducted in some experimental stations or selected farmers' fields, has revealed the potential of some field crops to be grown successfully in the dry season, in addition to the rainy season crops. This is possible, given sufficient amounts of ground water and/or dry season rainfall are available and carefully utilized (Chantorn, 1983; Jintrawet et al., 1983; Jintrawet et al., 1985; Limpinuntana, 1985; Jintrawet et al., 1986; Kerdsuk, 1986; Kerdsuk and Limpinuntana, 1989; Kerdsuk and Patanothai, 1990). Limpinuntana (1985) listed several potential multiple cropping systems with both rainy season and dry season crops, including kenaf-peanut and kenaf-water melon in the upland fields, as well as sesame-rice, kenaf-rice, rice-water melon, and rice-peanut in the paddy fields. Of all the promising dry season crops, peanut appeared to be most favorable because of its higher tolerance to drought conditions and fewer problems in marketing (Charoenwatana et al., 1975; Charoenwatana et al., 1976; Wongsamun et al., 1988; Kerdsuk and Limpinuntana, 1989). In spite of some success, when practiced in some specific areas, implementation of dry season cropping has not been entirely accomplished. This is mainly due to the lack of information on land suitability for specific crops at the planning stage, especially the suitability in relation to the water availability.

## 2.5 SUMMARY

Khon Kaen, the study area, is a typical northeastern province in terms of climate, landscape, soil, and agricultural land use. Most of the population in this province is engaged in agriculture, and farming is practiced on a small-scale basis. Agricultural land uses are primarily monocropping of paddy rice, cassava, kenaf, and sugar cane, with very low production compared to the other regions of Thailand. The low agricultural productivity is mainly due to water deficiency caused by erratic rainfall coupled with low water holding capacity of soils. Feasibility for irrigation is limited because of inappropriate topography, which is mainly undulating to rolling.

One of the most promising alternatives to improve land use efficiency in Khon Kaen, as well as in the whole northeast region, is the introduction of multiple cropping systems. Research conducted in some specific areas has demonstrated that, if sufficient ground water and/or dry season rainfall are available and utilized efficiently, several field crops such as sesame and peanut have high potential to be grown in the dry season, in addition to the rainy season crops. However, implementation of dry season crops in the farmers' fields is, so far, not entirely successful, mainly due to the lack of information on land suitability for specific crops at the planning stage.

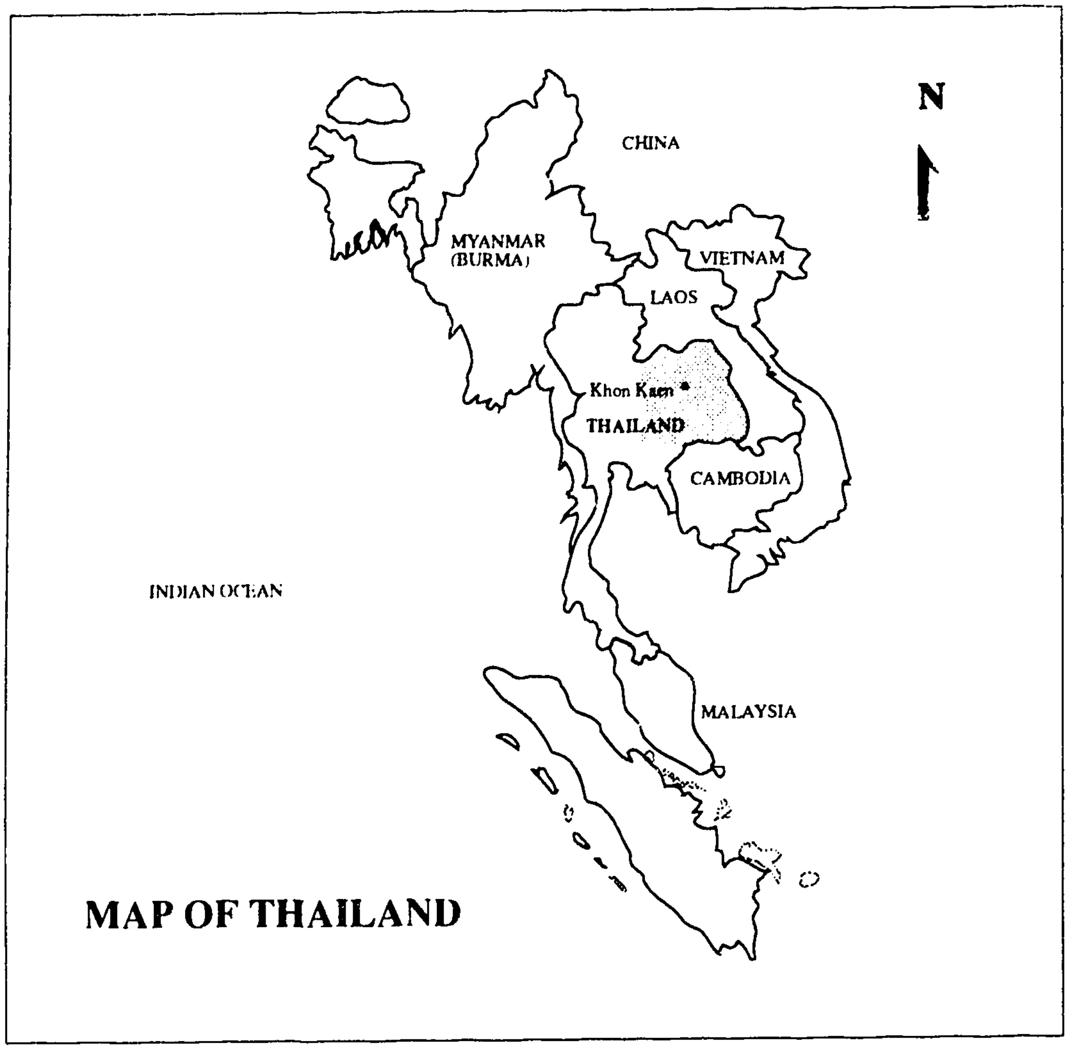


**Figure 2.1** Schematic map of Thailand showing the northeast region (shaded area) with the location of Khon Kaen Province.

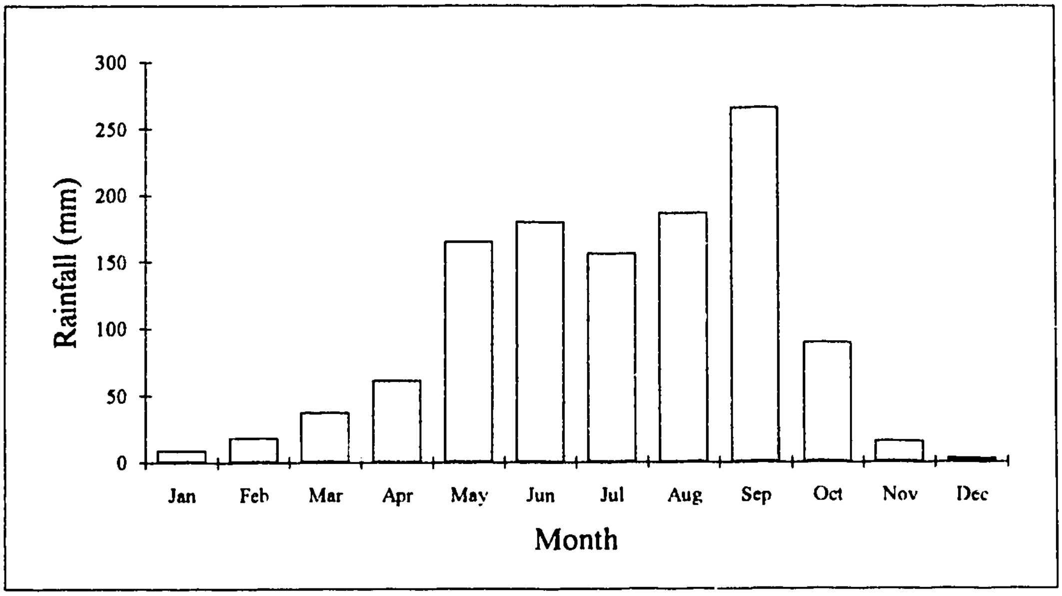


**Figure 2.2** Monthly rainfall recorded in Khon Kaen Province (average of 25 years during 1951-1975; adapted from Keerati-Kasikorn, 1984).

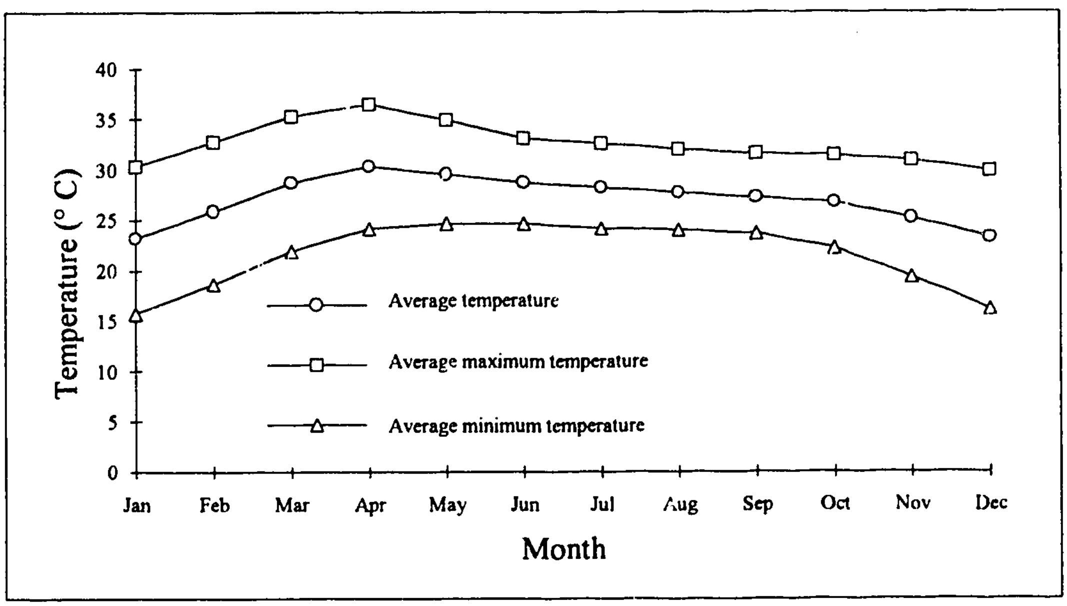


**Figure 2.3** Monthly temperature recorded in Khon Kaen Province (average of 25 years during 1951-1975; adapted from Keerati-Kasikorn, 1984).

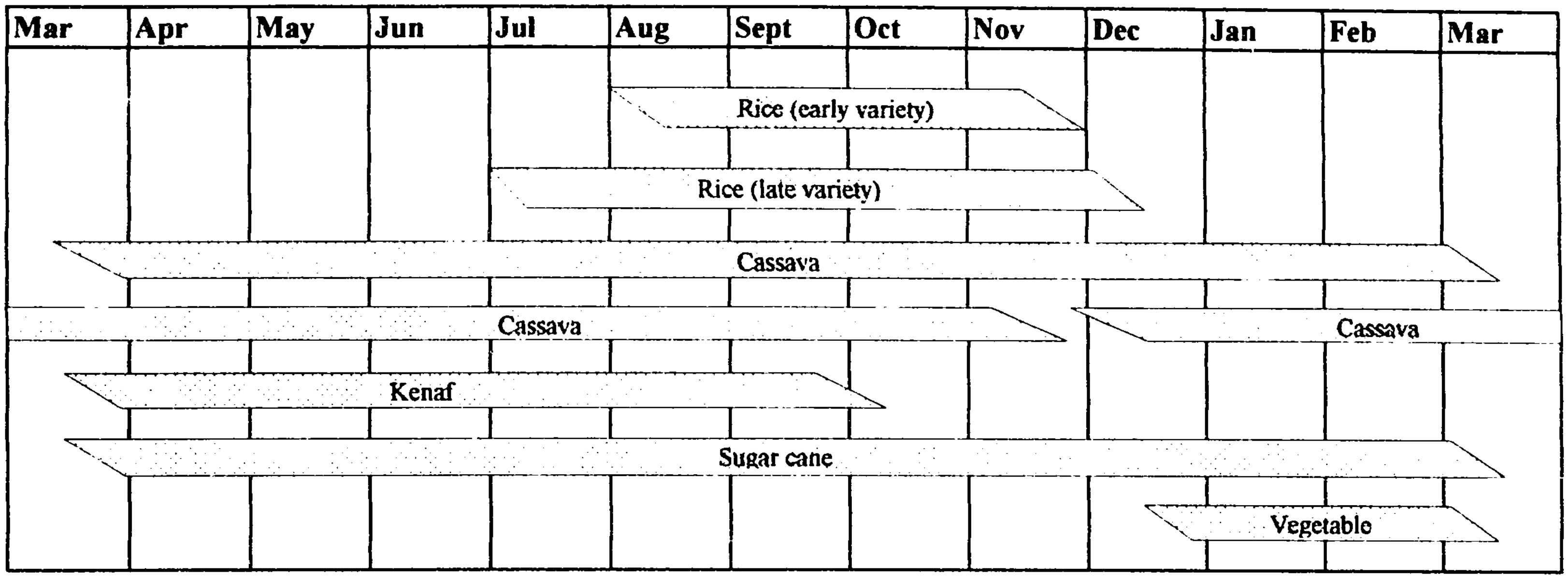


**Figure 2.4** Typical cropping patterns in Khon Kaen Province (modified after Jintrawet et al., 1985).

## 2.6 REFERENCES


Ammaritsut, W., S. Suppamethee, W. Saenjan, and P. Prapertchop. 1991. Agriculture in NE Thailand in the Next Decade. Research and Development Institute, Khon Kaen University, Khon Kaen, Thailand. (in Thai).

Chantorn, P. 1983. Rainfed Peanut After Rice Cropping. M.Sc. Thesis. Khon Kaen University, Khon Kaen, Thailand. (in Thai with English abstract).

Charoenwatana, T., A. Patanothai, and A. Polthanee. 1975. Growing field crops after rice in paddy field. KKU-FORD Cropping System Project, 1975 Annual Report. Khon Kaen University, Khon Kaen, Thailand.

Charoenwatana, T., A. Patanothai, and A. Polthanee. 1976. Growing field crops after rice in upper and lower paddy fields. KKU-FORD Cropping System Project, 1976 Annual Report. Khon Kaen University, Khon Kaen, Thailand.

Eelaart, A.L.J. 1973. Climate and Crops in Thailand. Report SSQ-96. Soil Survey Division, Department of Land Development, Bangkok, Thailand.

Eiumnoh, A., and E. Kheowruenrom. 1981. Evaluation of the Application of Remote Sensing Imagery for Geomorphological Mapping in the Northeast of Thailand. Research Report. Kasetsart University. Bangkok, Thailand.

Euroconsult. 1989. Agricultural Compendium for Rural Development in the Tropics and Subtropics. Elsevier, Amsterdam.

FAO. 1971. Northeast Thailand: An Economic-Geographical Account. UNDP/SF Soil Fertility Research Project in Thailand. Project Working Paper No. 7. Bangkok, Thailand.

Hokjaroen, S. 1986.Photo-interpretation for Geological Mapping of Changwat Khon Kaen and Adjacent Areas. M.Sc. Thesis. Chulalongkorn University, Bangkok, Thailand.

Hokjaroen, S., and T. Supajanya. 1982. Physiographic Features of the lower Northeast region. *In.* Proceedings of the Seminar on History and Culture of the Lower Northeast.. Burirum Teacher College. Burirum, Thailand. pp 1-13.

Jintrawet, A., S. Smutkupt, C. Wongsamun, R. Katawatin, and V. Kerdsuk. 1985. Extension Activities for Peanuts After Rice in Ban Samjan, Northeast Thailand: A Case Study in Farmer-to-Farmer Extension Methodology. Farming Systems Research Project, Khon Kaen University, Khon Kaen, Thailand.

Jintrawet, A., R. Katawatin, and W. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Khon Kaen University: Cropping Systems Research Project. (in Thai with English abstract).

Jintrawet, A., S. Smutkupt, S. Rattanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya, 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University (in Thai with English summary).

Kaida, Y., and V. Surarerks. 1984. Climate and Agricultural Land Use in Thailand. *In.* M.M. Yoshino (Ed.). Climate and Agricultural Land Use in Monsoon Asia. University of Tokyo Press, Tokyo. pp 231-254.

Keerati-Kasikorn, P. 1984. Soils of Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Thailand. (in Thai).

Kerdsuk, V. 1986. Effects of Planting Dates and Toposequence on Growth and Yield of Peanut After Rice. M.Sc. Thesis. Faculty of Graduate Studies, Khon Kaen University, Khon Kaen, Thailand.

Kerdsuk, V., and A. Patanothai, 1990. Testing and Implementation for Rainfed Dry Season Peanut: Khon Kaen University Experience. Farm News. Farming System Research Project, Khon Kaen University. 63: 24-35. (in Thai).

Kerdsuk, V., and V. Limpinuntana. 1989. Growing Peanut After Paddy Rice Without Irrigation. Khon Kaen University, Khon Kaen, Thailand.

Meteorology Department. 1977. Climate of Thailand. Ministry of Communications, Bangkok, Thailand.

National Statistic Office. 1994. Statistical Reports of Changwat Khon Kaen. Office of the Prime Minister, Thailand.

Panichpong, S. 1988. Soil and water resources in Northeast Thailand. *In.* C. Pairintra, K. Wallapapan, J.F. Parr, and C.E. Whitman (Eds.) Soil, Water, and Crop Management Systems for Rainfed Agriculture in Northeast Thailand. USDA/USAID Dry land Agricultural Project.

Prapertchop, P. 1987. Socio-economic condition of the farmers in NE Thailand. Paper presented at the DLD-ADAB-ACIAR Seminar on Salinity in NE Thailand, September 21-23, 1987. Department of Land Development, Bangkok, Thailand.

Rigg, D.J., 1985. The role of the environment in limiting the adoption of new rice technology in Northeast Thailand. Transs. Inst, Br, Geog, N.S. 10. pp 481-494.

Sanjan, P., B.J. Garnier, and P.A. MacClean. 1990. Patterns of wet season rainfall in Northeast Thailand. Proceeding of the Seminar on Remote Sensing and GIS for Soil and Water Management. Khon Kaen University, Khon Kaen, Thailand.

Soil Survey Division. 1973. Detailed-Reconnaissance Soil Map of Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

Soil Survey Staff. 1975. Soil Taxonomy: A Basic System of Soil Classification for Making and Interpreting Soil Surveys. Soil Conservation Service, USDA.

Viratphong, S. 1994. Thailand. *In.* Sustainable Agriculture Development in Asia. Report of the APO Study Meeting on Sustainable Agriculture held in Tokyo on 23rd February to 5th March, 1993. Asian Productivity Organization, Tokyo. pp 455-481.

Vorasoot, N. 1985. Agroclimatology in Northeast Thailand. *In.* Proceedings of the Workshop on Soil, Water, and Crop Management Systems for Rainfed Agriculture in Northeast Thailand. Khon Kaen University. Khon Kaen, Thailand. pp 48-60.

Vorasoot, N., A. Jintrawet, V. Limpinuntana, T. Charoenwatana, and S.M. Virmani. 1985. Rainfall Analysis for the Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Khon Kaen, Thailand.

Wongsamun, C., N. Supanchaimart, W. Park-Uthai., V. Kerdsuk, S. Chaiyasaj, S. Pongsung. 1988. Factors Affecting Farmers' Decision Making in Growing Peanuts After Rice. Farming Systems Research Project, Khon Kaen University, Khon Kaen, Thailand.

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# CHAPTER 3

# SIMULATION MODELING OF LAND SUITABILITY EVALUATION (I): EVALUATION OF THE MACROS CROP MODEL

## 3.1 INTRODUCTION

Water availability is a major land quality that determines the potential of land areas in Northeast Thailand for intensive cropping systems under rainfed conditions. Of special interest are those systems with dry season crop(s) including non-irrigated, dry season peanut cropping, the land use type that is the focus of this study. In the northeast region, the implementation of dry season cropping systems is frequently unsuccessful due to the lack of information on water availability and/or its derivatives, at the planning stage. As such, to improve the efficiency of agricultural extension, information on the suitability of land units for dry season cropping, based on the water availability, is of importance. According to the FAO Framework for Land Evaluation (FAO, 1976), land evaluation involves the definition of land use requirements to be matched with the corresponding qualities of the land units being considered. In this study, the requirements of non-irrigated, dry season peanut cropping, in terms of water availability, would be compared to the corresponding land qualities to generate the required information.

The assessment of water availability as a land quality using computer simulation models is preferred because of the large volume of data involved in the process of calculation. Water availability for crop growth is influenced not only by inherent soil properties, but also by many external factors such as climate, plant type, hydrology, and management. All of these factors can be considered simultaneously using water balance models and high speed computer systems. Water balance models have been successfully used to simulate data on the dynamics of soil moisture content over a period of time. A number of research papers, such as Hanks (1985) and Rao (1987) have reported reasonable agreement between measured and simulated values. According to Bouma et al. (1993) well-tested models of this type are widely available. However, the use of simulated data generated from these models for the evaluation of land suitability based on water availability is limited. The major problem is to determine how to classify the output data for the dynamics of soil moisture content over a period of time into different land suitability classes for a specified cropping system.

Instead of using water balance models and operational procedures for land evaluation as defined by FAO (1976), the use of crop models for simulating crop growth based on water availability may be more appropriate in this case. Crop models simulate growth and yield in relation to water availability, as reflected by many environmental factors such as rainfall, solar radiation, evaporative demand, and available water capacity of the soil. Data on crop yield can be used directly to effectively classify the suitability of land units for that particular cropping system based on water availability. According to Dumanski and Onofrei (1989) crop yield is one of the most reliable estimates of comparative value for land evaluation.

The crop model MACROS (Penning de Vries et al., 1989) was selected for this study because it has been: (*i*) developed with the consideration for circumstances in countries in South-East Asia, including Thailand, especially in terms of data type and availability; (*ii*) well documented, its accompanying monograph (Penning de Vries et al., 1989) contains most of the general information and data required to run the model; and (*iii*) tested and used by researchers in Northeast Thailand for years (Penning de Vries et al., 1989; Pannangpetch, 1994). In this study, the model was specific for crop growth simulation under water stress conditions assuming that other growth factors are not limiting. As mentioned earlier, water availability is the primary limiting factor for dry season cropping in the northeast of Thailand, superseding effects of nutrient deficiencies and other limiting factors.

Prior to the application of a crop model to generate information on land suitability, the performance of the model must be judged. The objective of this study was to evaluate the capability of the MACROS model to adequately estimate growth and yield of dry season peanut crops grown without irrigation in Northeast Thailand. The study focused on Khon Kaen Province (Figure 3.1) because this province has all major landscapes and soils of the northeast region. Also the field experiments with the most complete and frequent observation of parameter inputs needed to evaluate the model, are available for this province.

## 3.2 DESCRIPTION OF THE MACROS CROP MODEL

MACROS (Modules of an Annual **CRO**p Simulator) is a model developed as a set of modules for crop simulation (Penning de Vries et al., 1989). The model, specific for crop growth simulation under water-limited conditions, includes a basic module for crop growth simulation (L1D), a module for simulating the effect of water stress (L2C), a water balance module for soil under the influence of ground water (L2SS), and a terminal section with necessary functions and subroutines (module T12). Detailed descriptions of these modules and their scientific background are given in Penning de Vries et al. (1989). Here only a brief description is presented with an emphasis on important processes responsible for growth and yield of dry season peanut crops grown without irrigation, based on water availability in Northeast Thailand. Inputs required by the model are summarized.

### 3.2.1 Soil water balance

For the simulation of water balance in soil in which the influence of ground water is considered, the soil profile is divided into horizontal compartments or layers. Thickness and physical characteristics of every layer are specified. The simulation output is specific to each of these layers. Since the process of water redistribution within the profile occurs relatively quickly, the time period for the simulation of soil water balance is much less than 24 hrs, while the crop simulation time period is one day. For MACROS, the time periods within the range of 0.001-0.1 day are established by the model, based on thickness and hydraulic properties of the soil layers. The important components for the soil water balance under the dry season conditions in Northeast Thailand including soil water movement, evaporation, and water uptake and transpiration, are described below.

#### 3.2.1.1 Soil water movement

Darcy's law is applied in the simulation of soil water movement. For the movement under unsaturated conditions, the flux density equation used is:

$$q = \left(\frac{1}{\Delta h} - \frac{1}{\Delta z}\right)\left[\int_{h_{i-1}}^{h_i} k_1(h)dh \times \int_{h_{i-1}}^{h_i} k_2(h)dh\right]^{\frac{1}{2}} \text{------} (1)$$

where;

$q$ = flux, cm $d^{-1}$

$h$ = soil moisture suction, cm

$\Delta h$ = difference in soil moisture suction at layer $i$ ($h_i$) and that at layer $i-1$ ($h_{i-1}$)

$\Delta z$ = distance between the centers of 2 adjacent compartments, cm

$k_1$ and $k_2$ = hydraulic conductivity functions of 2 adjacent layers, cm $d^{-1}$

Soil moisture suction relates to soil moisture content and hydraulic conductivity. The empirical equation provided by Driesses (19ₒᵤ) is used to describe the relationship between soil moisture suction and soil moisture content. For the description of the relationship between hydraulic conductivity and soil moisture suction, empirical equations given by Rijtema (1969) and Wösten et al. (1986) are used. To calculate the values of soil moisture suction and hydraulic conductivity in relation to the soil moisture content of each soil layer using these equations, a number of soil texture specific empirical constants are required.

Movement of soil water under saturated conditions is less complex, because the dependence of the transport coefficient on soil moisture has disappeared. Under this condition, the product of pressure gradient and conductivity is equal at every point in the saturated section, as no changes in soil moisture occur. Only at the edges of the saturation section may soil moisture change, related to expansion or contraction of the particular saturated section of the soil profile, occur.

#### 3.2.1.2 Evaporation

To calculate water loss by evaporation, MACROS assumes that an "evaporation front" exists at the surface or at some depth ($z_E$) in the soil. The evaporation front is a sharp transition where liquid water is transformed into a vapor. All liquid transport is below this front, while only vapor transport occurs above the front. The evaporation rate at any moment is a function of the depth of the evaporation front and the rate of vapor diffusion through the dry layer. The balance of liquid supply to the front and the vapor diffusion away from it, determines the movement of the front itself. The rate of water vapor loss from the soil at a front depth is described as:

$$e = \frac{c_2}{z_E} \text{-----------} (2)$$

where;

$e$ = rate of vapor loss from the soil, cm $d^{-1}$

$z_E$ = depth of evaporation front

$c_2$ = constant = 0.1 $cm^2$ $d^{-1}$

The depth of an evaporation front is calculated using a set of equations provided by Penning de Vries et al. (1989). This calculation requires a number of soil characteristics such as air dry soil moisture content, initial soil moisture content, and soil texture specific empirical constants.

Rates of transpiration and water uptake are affected by water stress. Therefore, they are discussed in the next section.

### 3.2.2 Effect of water stress

#### 3.2.2.1 Transpiration

When there is sufficient water the transpiration rate is equal to the potential rate. In MACROS, the potential transpiration rate is calculated per day, based on Penman' s approach (Penman, 1948). For conditions of either insufficient water or flooding, the crop lowers its water uptake, and the actual transpiration becomes lower than the potential rate. The transpiration in each of these cases follows the rate of water uptake.

#### 3.2.2.2 Water uptake

Water uptake is simulated only where there are roots. The weight and density of roots at certain depths are assumed not to play an important role in the water extraction pattern. Thus for this model, it is assumed that the roots in each centimeter of rooting depth absorb the same amount of water, provided that all layers are equally moist.

The potential rate of water uptake per centimeter of rooting depth is calculated by dividing the potential transpiration rate of the canopy by the total rooting depth. For the water stress conditions, the actual rate of water uptake per layer is equal to the potential uptake rate per centimeter of rooting depth multiplied by a "stress multiplication factor" and by the thickness of the layer. To determine the value of the stress multiplication factor, the "water stress sensitivity coefficient" specific for the crop species, the potential transpiration, and the leaf area, are used to calculate the threshold value of soil moisture content above which water uptake is not restrained. The more resistant a species, the higher the sensitivity coefficient, and the lower the threshold value. When soil moisture content is less than the threshold value, the water uptake, as reflected by the value of the stress multiplication factor, is reduced proportionally from 1.0 to 0.0 of its potential value, at water contents equal to the threshold value and equal to the permanent wilting point, respectively. Figure 3.2 (left hand part of the graph) schematically shows the relationship between the stress multiplication factor and the soil moisture content. This method of calculation is described in Doorenbos and Kassam (1979), and Van Keulen and Wolf (1986).

The effect of flooding on water uptake is approximated in a similar manner to the effect of water shortage (Figure 3.2, right part of the graph). This effect is assumed to be proportional to the soil moisture content between field capacity and saturation, and independent of the transpiration rate.

The total rooting depth is calculated from the growth rate of rooting depth. The maximum growth rate of rooting depth for a particular crop species occurs under optimum conditions. For water stress conditions, this rate is decreased. The actual growth rate of rooting depth is computed from the maximum rate and the stress factor. In this model, the stress factor for growth rate of rooting depth is equal to the water uptake in the layer where the root tips are found.

### 3.2.3 Photosynthesis

For the MACROS model, the Rate of Gross Photosynthesis (PL) is calculated as a function of the Maximum Rate of Photosynthesis at Actual Temperature (PLMX) , the Initial Efficiency of the Use of Absorbed Light at Actual Temperature (PLEA), and the Intensity of Absorbed Radiation (PAR). The relationship is expressed as:

$$PL = PLMX \times [1\text{-}EXP(-PLEA \times PAR/PLMX)] \text{ ------------ } (3)$$

PLMX and PLEA are strongly related to the average day temperature. To calculate these values for each specific temperature, the Maximum Rate of Photosynthesis at Reference Temperature (PLMXP), the Initial Efficiency of the Use of Absorbed Light at Reference Temperature (PLEI), the empirical relationship between temperature and the PLMX, and the empirical relationship between temperature and the PLEA, are specified. Then the PLMX and PLEA values in relation to each specific day temperature are calculated.

Photosynthesis is closely related to transpiration. For a particular crop, amounts of water transpired per amount of gross photosynthesis vary little. Thus the constant ratio of transpiration to gross photosynthesis is adopted by MACROS, where amounts of gross photosynthesis vary proportionally with the amount of transpiration.

### 3.2.4 Model inputs

Input data required by the MACROS model can be summarized into those related to crop, soil, weather, and management (Table 3.1).

## 3.3 GENERAL INFORMATION ABOUT THE PEANUT CROP

The peanut (*Arachis hypogaea*) is an annual legume, drought tolerant crop. This crop includes a wide variation in the types and strains cultivated in particular localities (Weiss, 1983), but in general the two main types grown commercially are (i) the erect, bunch type, and (ii) the spreading running type (EUROCONSULT, 1989). The former is predominant in Thailand (Kerdsuk, 1986).

The total growing period of peanut ranges from 90 to 150 days, depending on the variety (EUROCONSULT, 1989; Landon, 1991). According to Doorenbos and Kassam (1979) the growing periods include:

| | |
|---|---|
| Establishment | 10-20 days |
| Vegetative | 25-35 days |
| Flowering | 30-40 days |
| Yield formation | 30-35 days |
| Ripening | 10-20 days |

Under favorable conditions, the maximum rooting depth (for main nutrient/water uptake roots) is approximately 100 cm (Boonyatharokul, 1983). The crop is best adapted to well-drained, loose, friable medium textured soils. However, for fine textured soils, if well drained, may also produce high yields, but harvesting is difficult. Nevertheless, in all cases, the top soil should be loose to allow the pegs (on which the fruits are formed) to enter the soil easily (Doorenbos and Kassam, 1979; EUROCONSULT, 1989).

The water requirement for the peanut crop ranges from 500 to 700 mm per season, depending upon climate. The mean daily temperature for optimum growth is 22 to 28° C, and a reduction in yield occurs above 33° C and below 18° C (Doorenbos and Kassam, 1979; Landon, 1991).

Doorenbos and Kassam (1979) reported that, Nitrogen fertilizer at the rate of 10 to 20 kg N $ha^{-1}$should be applied to assure good crop establishment, even though this crop can fix nitrogen from the air. The recommended rates for Phosphorus and Potassium are 15 to 40 kg P $ha^{-1}$, and 25 to 40 kg K $ha^{-1}$, respectively.

In developed countries, the potential farmers' yields ranges from 2,500 to 3,000 kg $ha^{-1}$ under irrigation, and from 1,500 to 2,000 kg $ha^{-1}$ without irrigation

(EUROCONSULT, 1989). For developing countries, the typical yield of peanut grown under rainfed conditions is approximately 800 kg $ha^{-1}$ (Landon, 1991).

## 3.4 MATERIALS AND METHODS

This study of the MACROS model was conducted to judge model performance based on the comparison of simulated data to field data. It consists of two phases: calibration and validation (Makking and Heemst, 1975). The validation was subdivided into validation A: with emphasis on the accuracy of the model results, and validation B: with emphasis on the usefulness and relevance of the model. Materials (the kinds of data available for Northeast Thailand) and methods for each of these phases are described in the following.

### 3.4.1 Field data

#### 3.4.1.1 Research plot data

For the calibration and validation, with emphasis on accuracy (validation A), the data used were from four peanut field experiments conducted at two sites (i.e., Samjan and Muong) in Khon Kaen Province, Northeast Thailand, on two different soils during the 1981-82 and 1982-83 dry seasons (Table 3.2).

The soil at the Samjan site has a loamy fine sand texture throughout the profile, and is classified as a member of the Nam Phong series. At the Muong site, soils are sandy loam in texture at 0-40 cm depth, and become finer to sandy clay loam at depths of 40 to more than 100 cm. The soil is a member of the Korat series. Data sets obtained from the two seasons represent crop performance under different weather conditions , i.e., relatively moist and relatively dry. In the 1981-82 dry season, the amount of rainfall was rather high (140 mm), whereas in 1982-83 it was very low (<30 mm). Data on crop yield, shoot dry weight, and soil moisture content (at 0-10, and 10-20 cm) taken from the experiment conducted during a relatively moist (1981-82) season (experiment #1), were used for model calibration. It has been reported (Davidoff et al., 1992) that model calibration under relatively stressful soil moisture conditions may not be extrapolated accurately. Validation of the model with emphasis on the accuracy was done using data acquired under different (drier) weather conditions but the same soil (experiment #2), and under different soils and weather conditions (experiment #3 and 4). Data on crop yield, shoot dry weight, and soil moisture content (at 0-10, 10-20, and 20-30 cm) were used for this purpose.

These four experiments were initially conducted to investigate the effects of different levels of tillage operations on growth and yield of dry season peanut variety Tainan #9, the recommended variety, grown under rainfed conditions in the northeast region. Fertilizer and pesticides were applied to all experimental fields. Only the data obtained from the experimental plots using maximum tillage, as recommended for dry season peanut cropping by Jintrawet et al. (1983), were used, since this study focused on the use of the MACROS crop model to simulate crop growth under water stress conditions and other growth factors were assumed to be optimum. All of the data values used represent the mean of three replications.

For each replication of every experiment, crop yield was harvested from a $7 \times 7\ m^2$ area, and was air dried to a constant weight. Kilograms of dry pod yield per hectare was then calculated. Shoot dry weight was determined by randomly harvesting above ground plant parts from 15 plants at selected times during crop development. Harvested samples were oven-dried at 85° C to a constant weight. Kilograms of shoot dry weight per hectare was calculated, accordingly. Data on gravimetric soil moisture content were originally measured biweekly. These data were converted to a unit of moisture content by volume (e.g., $m^3\ m^{-3}$ water × dry soil) to be comparable to the corresponding data simulated by the MACROS model.

#### 3.4.1.2 On-farm trial data.

Data acquired from on-farm trials (Jintrawet et al., 1986) conducted in Khon Kaen Province during the dry season of 1984-85 were used for validation with emphasis on the usefulness of the model (validation B). These trials were carried out under a co-operative project between Khon Kaen University and the Department of Agricultural Extension, with the major objective being to investigate the potential of dry season peanut cropping in the region. In that research project, three criteria were used for the selection of test sites (villages), as well as the participating farmers' fields for each site: (*i*) water table depth during January-February was, in general, not deeper than 2 meters, (*ii*) the soil was a deep, sandy to sandy loam in texture, and (*iii*) farmers were interested in growing dry season peanut crop.

Ten test sites (villages), each of which covered sizable land areas and met the above criteria were selected for the above study. The sites were located in various parts of the province. Within each selected test site, a number of participating farmers' fields were chosen for on-farm trials based on the above criteria. For every on-farm trial, approximate water table depth (i.e., 1, 2, or 3 m) within the dry season was noted. Peanut variety Tainan #9 was seeded no later than December 15, 1984, and different rates of fertilizer application were tested. Pod yield was harvested and weighed. Data on dry pod yield obtained using the maximum rate of fertilizer application of the on-farm trials, which had no problems due to weeds, diseases, and other limiting factors, were used for model validation B.

Of all the on-farm trials at these 10 test sites, data from only 36 trials at 5 test sites (Figure 3.1) could be used for model validation B. These 36 on-farm trials were conducted on 3 major soil series of the northeast: Korat (Oxic Paleustults), Roi Et (Aeric Paleaquults), and Nam Phong (Ustoxic Quartzipsamments). These soils cover approximately 43 % of the total area of Khon Kaen Province (Soil Survey Division, 1973), and approximately 40 % of the total area of Northeast Thailand (Keerati-Kasikorn, 1984). Roi Et is a deep soil situated on low terraces. It has a sandy loam to fine sandy loam texture on the surface. The texture becomes finer to a sandy clay loam, with depth. Korat is a deep soil found on middle terraces. This soil has a loamy sand to sandy loam texture at the surface, and a sandy clay loam at the sub-surface. Nam Phong is a middle terrace soil with deep sandy texture throughout the profile.

### 3.4.2 Simulation experiments

#### 3.4.2.1 Crop parameters

Crop parameters for peanut, suggested by Penning de Vries et al. (1989), were used in this study (Table 3.1).

#### 3.4.2.2 Soil parameters

In model calibration and validation A using data from the field experiments, soil parameters for each site including texture, initial moisture content, and water table depth were obtained from Chantorn (1983). Model inputs required to calculate evaporation rate, i.e., texture specific empirical constants, were interpreted based on their relationship with soil texture as provided in Penning de Vries et al. (1989). Other empirical constants and parameters required for calculating relationships between soil moisture content, soil moisture suction, and hydraulic conductivity, were provided by the original values of the model based on the relationship between soil texture and these parameters, as shown in Table 26 , page 152 in Penning de Vries et al. (1989).

For model validation B, existing data were not adequate. Data on approximated water table depth were those estimated by local extension specialists (Jintrawet et al., 1986), but there were no data on soil texture and initial water content available in the literature. To obtain the soil texture data, the geographic position of each on-farm trial field was located on the 1:100,000 Detailed-Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973) based on the site description provided in Jintrawet et al. (1986). The soil series represented at each site was identified and data on soil texture by layer throughout the profile were acquired from the descriptions of typical profiles for each soil series, as presented in Keerati-Kasikorn (1984). Note that, the Detailed-Reconnaissance Soil Map of Khon Kaen Province was originally developed at a scale 1:50,000. However, to lessen the number of map sheets, the map was published at a scale 1:100,000. Initial moisture content data were not measured directly in the field, and MACROS was used to generate these from the water table depth and soil texture data. Other parameters and constants required by the model were obtained by the same manner as those used for model calibration described above.

#### 3.4.2.3 Weather data

Daily weather data including rainfall, maximum temperature, minimum temperature, wind speed, relative humidity, and solar radiation were used for model evaluation. The data recorded in 1981-82 and 1982-83, corresponding to the two years of research plot data, and in 1984-85, corresponding to the year of the on-farm trials, were used for model calibration, validation A, and validation B, respectively.

Rainfall data, in digital format, from three weather stations (stations # 003, 006, and 201; Hydrometeorology Division, 1988) were used for model evaluation. To select the station from which the data were used for each particular test site, the province was divided into Thiessen polygons (Aronoff, 1989) based on five stations (Figure 3.1). The data used for model calibration and validation A were those recorded at station # 201 which is located 15 km Southeast of the site where experiments #1 and 2 (Table 3.2) were conducted, and 10 km East of the site for experiments #3 and 4. The data sets used for simulating crop growth at various test sites in the model validation B were taken from the nearest station to each site (Figure 3.1)

Digital data of maximum and minimum temperature, wind speed, and relative humidity from only one station (station # 201) were used in every step of model evaluation. There were no solar radiation data available in digital format. These data were obtained in hard copy form from Khon Kaen University weather station, located a few kilometers away from station #201, and input manually to MACROS.

#### 3.4.2.4 Management practices

Planting dates used for the model calibration and validation A were those reported in Chantorn (1983). In model validation B, the latest planting date from the on-farm trials (December 15, 1984; Jintrawet et al., 1986) was used. The beginning date for the simulation was assumed to be 1 week after the planting date. The planting depth used in the simulation was 15 cm, corresponding to that recommended by Jintrawet et al. (1983).

#### 3.4.2.5 Model calibration and sensitivity analysis

MACROS was calibrated to the site conditions using existing data obtained from a peanut field experiment conducted in Khon Kaen during the dry season of 1981-82 (experiment #1, Chantorn, 1983) as shown in Table 3.2. Three parameters including Maximum Rate of Photosynthesis at Reference Temperature (PLMXP), Maximum Growth Rate of Rooting Depth (GZRTC), and Water Stress Sensitivity Coefficients (WSSC) were separately and systematically changed within realistic ranges. PLMXP is defined as the rate of photosynthesis at saturated light intensity and optimum (reference) temperature. GZRTC is the rate of increase in rooting depth under optimum conditions. And WSSC is the coefficient used to determine the lowest soil moisture content at which water uptake is unrestrained. This lowest soil moisture content is the threshold value that lies between field capacity and permanent wilting point. The algorithms in which the values of these three parameters are used in MACROS were described previously in the model description. The simulated data sets of pod yield, shoot dry weight, and soil moisture content, generated as a result of each change in these three parameters, were compared with the corresponding observed values to assess the agreement between the model outputs and the experimental data.

Values for each of these three parameters considered in this study, were based on literature. Pallas and Samish (1974) investigated the photosynthetic response of several peanut varieties grown on peat-vermiculite medium in growth chambers. The conditions were controlled at 25° C, 60 % relative humidity, and 350 vppm $CO_2$. The result indicated the maximum rate of photosynthesis ranging from 39 to 51 kg $CO_2$ $ha^{-1}$ $h^{-1}$. Furthermore, Penning de Vries et al. (1989) reviewed a number of research papers (i.e., Pallas and

Samish, 1974; Bhagsari et al., 1976; Bhagsari and Brown, 1976), and suggested the value of 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$ for the PLMXP of peanut crop. Hence, in this model calibration, the values of PLMXP were changed in the order of 40, 50, and 60 kg $CO_2$ $ha^{-1}$ $h^{-1}$.

Data on the growth rate of rooting depth, specific for peanut crop, were not available. However, the GZRTC values of 0.025, 0.030, 0.035, and 0.040 m $d^{-1}$ were used for the following reasons. First, experiments conducted for other legume crops indicated the values of approximately 0.030 m $d^{-1}$. Stone et al. (1976) conducted a soybean experiment on a deep, barrier-free, silt loam soil (fine-silty, mixed, mesic, Pachic Haplustoll), under irrigated conditions, and reported the GZRTC value of 0.035 m $d^{-1}$. In cowpea, an experiment undertaken in semi-arid conditions (Haverman, 1986) indicated the GZRTC of 0.028 m $d^{-1}$. Second, based on experiments carried out for a number of crops, under different climatic conditions, Penning de Vries et al. (1989) states that, generally, the rooting depth can increase at the rate of 0.03 to 0.05 m $d^{-1}$ unless there is limitation due to inappropriate environments.

Penning de Vries et al. (1989) also suggest the use of WSSC = 0.65 in the simulation of peanut crop growth. The value was derived from a study in which Doorenbos and Kassam (1979) have established, for a number of crops, which fraction of water availability can be freely taken up by a specific crop at a given maximum transpiration rate. This fraction is calculated from the WSSC value and the daily maximum transpiration rate. These were based on results of crop water stress related experiments conducted in various parts of the world. Thus, the WSSC values of 0.50, 0.65, and 0.80 were used in this model calibration.

The PLMXP, GZRTC, and WSSC values which resulted in the best overall agreement between observed and simulated values were assumed to be properly adjusted, and were selected to be used as model inputs for further steps of the study. The selected PLMXP, GZRTC, and WSSC values were then used with other relevant crop, soil, weather, and management parameters, to run the model. The outputs generated from this run in terms of pod yield, shoot dry weight, and soil moisture content were compared with the corresponding experimental data sets acquired from Chantorn (1983). Agreement in pod yields was measured by calculating the deviation value (e.g., Davidoff et al., 1992) using the equation:

$$\text{Deviation} = [(\text{simulated} - \text{observed}) / \text{observed}] \times 100 \quad \text{-------------------(4)}$$

Goodness of fit with respect to the shoot dry weight and soil moisture content was evaluated by visually comparing graphs showing dynamics of these values as a function of time. Agreement between observed and simulated shoot dry weight data was also evaluated quantitatively using standardized bias (R) and standardized mean square error (V) (Graf et al., 1991). The equations used to calculate these values are below:

$$R = \frac{\sum_{i=1}^{n}(y_i - x_i)}{\sum_{i=1}^{n} x_i} \quad \text{------------ (5)}$$

$$V = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n} x_i^2} \quad \text{------------ (6)}$$

where;

$n$ = number of field observations,

$x_i$ = observed values at $i^{th}$ observation, and

$y_i$ = simulated values at $i^{th}$ observation.

Note that, the standardized bias (R) can lead to different results than the standardized mean square error (V). In the calculation of R, negative deviations ($y_i$-$x_i$ <0) compensate the positive ones ($y_i$-$x_i$ >0) and vice versa (Equation 5). On the other hand, for the calculation of V, positive deviations do not compensate for negative deviations (Equation 6). A simulation with large but balanced deviations in both the positive and the negative directions would bear small R but very large V values.

Sensitivities of the model in terms of pod yield and shoot dry weight, to changes in PLMXP, GZRTC, and WSSC were analyzed in conjunction with the calibration. Ranges of change in these three parameters were the same as those used for the model calibration.

#### 3.4.2.6 Model validation A

The validation with emphasis on the accuracy of the model was conducted to test whether or not the model yielded correct results under different conditions than those of the calibration. Observed data taken from peanut field experiments conducted in Khon Kaen during the 1982-83 season (Chantorn, 1983) as shown in Table 3.2, were used for this purpose. Each of the shoot dry weight and soil moisture content data sets obtained from three experiments (experiment #2, 3, and 4) were compared with the corresponding simulated data set generated using MACROS. Agreements between observed and simulated data were evaluated by visually comparing graphs showing changes in these values as a function of time. In addition, dynamics of shoot dry weight were also evaluated quantitatively using standardized bias (R in Equation 5) and standardized mean square error (V in Equation 6). To quantify the agreement in terms of pod yield, calculation of the deviation values (Equation 4) was applied.

#### 3.4.2.7 Model validation B

In the validation with emphasis on the model's usefulness and relevance, pod yield data obtained from the on-farm trials conducted during 1984-85 season (Jintrawet et al., 1986) were used. These observed data were compared with the output from the simulation. The simple linear correlation analysis was applied to quantify agreement between observed and simulated data. This validation was conducted to test whether or not the model could be applied under different conditions and "real world" situations in Northeast Thailand, where available values for some important input parameters were obtained by estimation. In the on-farm trials from which data were used, soil texture and water table depth were not measured directly at the sites. In this case, the soil texture parameter was interpreted from the soil map and the qualitative site descriptions provided by local extension specialists. These were presented in the report of Jintrawet et al. (1986). The data on water table depth were also estimated by this same group of people. This situation is common in the agricultural extension activities in the region. Therefore, application of the model at a regional scale would be limited, if the model proved be invalid under the conditions for validation B, even though it was valid under the conditions for validation A.

## 3.5 RESULTS AND DISCUSSION

### 3.5.1 Model calibration and sensitivity analysis

By separately and systematically adjusting the three crop parameters including Maximum Rate of Photosynthesis at Reference Temperature (PLMXP), Maximum Growth Rate of Rooting Depth (GZRTC), and Water Stress Sensitivity Coefficients (WSSC), the values which gave the best agreement between observed and simulated outputs were 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$, 0.035 m $d^{-1}$, and 0.65, respectively. These values were assumed to be properly adjusted, and were used as the model inputs. The model was then considered calibrated. In general, after adjusting these three parameters, the simulated data from the MACROS model agreed well with the field data used for this calibration (data from experiment #1) in every aspect including pod yield, shoot dry weight, and soil moisture content.

For pod yield, the observed (experiment #1) and simulated values were 1735.0 and 1777.7 kg $ha^{-1}$, respectively. The deviation value was 2%.

In terms of shoot dry weight, observed and simulated values were in general agreement throughout the season. The model slightly over-estimated shoot dry weight at week 7 and week 10 after planting (Figure 3.3). However, at harvest time, the simulated shoot dry weight was slightly under-estimated (approximately 7%). Goodness of fit between the dynamic values of observed and simulated shoot dry weight as quantified by the standardized bias (R) and the standardized mean square error (V) were 0.06 and 0.01, respectively.

Dynamics of observed and simulated soil moisture contents at 0-10, and 10-20 cm, are shown in Figures 3.4a, and b, respectively. The model slightly under-estimated the soil moisture content of the surface 0-10 cm soil. However at depth 10-20 cm, the simulated soil moisture content data agree with the field observations from experiment #1.

Simulated pod yield was sensitive to changes in Maximum Rate of Photosynthesis at Reference Temperature (PLMXP), but was not sensitive to changes in Maximum Growth Rate of Rooting Depth (GZRTC), and Water Stress Sensitivity Coefficient (WSSC). Changing PLMXP by $\pm$ 20 % from the calibrated value (while the other 2 parameters were held at the calibrated values) caused more than a $\pm$ 28 % change in simulated pod yield. A $\pm$ 14 % change in GZRTC from the calibrated value resulted in less than $\pm$ 1% change in pod yield, whereas a $\pm$ 23 % change in WSSC from the calibrated value resulted in less than $\pm$ 3 % change in pod yield. Insensitivity of pod yield to changes in GZRTC and WSSC is probably because this sensitivity analysis was conducted under the conditions of experiment #1, which were relatively moist soil due to a shallow water table (2 m) and relatively high amounts of rainfall (140 mm). There is a possibility that, under drier conditions the sensitivity of the model outputs would be different. To investigate the sensitivity of the model to changes in these three parameters, under dry conditions, an additional sensitivity analysis was conducted. The analysis included the conditions of experiment #3 which was dry because of a relatively deep water table (3 m) and little rainfall (< 30 mm), using the same procedure previously described. Under the relatively dry conditions of experiment #3, the sensitivity of the model to changes in the PLMXP values was reduced. The model was not sensitive to increases in PLMXP higher than 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$, because the photosynthesis rate was limited by water stress conditions. Decreasing the PLMXP values by 20 % resulted in an 18 % decrease in simulated pod yield. On the other hand, the model became more sensitive to changes in the GZRTC and WSSC values. Altering the GZRTC values by $\pm$ 14 % resulted in more than $\pm$ 4 % change in pod yield, meanwhile a $\pm$ 23 % change in the WSSC values caused more than $\pm$ 9 % change in pod yield. Therefore, the accuracy and the precision of PLMXP values are more important under moist conditions, whereas under drier conditions, more accurate and more precise GZRTC and WSSC values are necessary.

### 3.5.2 Model validation A

The simulation results for pod yield fit the field data. Comparisons between observed and simulated pod yield data for the three experiments used in model validation A are shown in Table 3.3 and Figure 3.5. From Table 3.3, the deviation values calculated for experiment #2, 3, and 4 were 16.2, -18.2, -50.1 %, respectively. These values, however, reveal that the model tended to over-estimate the field observations for experiment #2, and had the opposite tendency for experiments #3 and 4. Figure 3.5 supports this statement.

For shoot dry weight, Figures 3.6a, b, and c show comparisons over time of observed and simulated data for experiment #2, 3, and 4, respectively. Judging by visual comparison, there is general agreement between the simulated shoot dry weight data and the field data for every experiment. In the quantitative evaluation of these agreements, the R values were 0.22, 0.10, and -0.10; and the V values were 0.05, 0.03, and 0.02 for each of these experiments, respectively (Table 3.4). Based on the R value, among the three experiments used for validation A, the best goodness of fit was found under conditions of experiments #3 and 4. The V values reveal the same trend. The model over-estimated shoot dry weight for experiments #2 and 3 as indicated by the plus (+) R values. However, for experiment #4, the model under-estimated the values as indicated by the minus (-) sign.

The validation results show that the model which was calibrated under moist conditions, can predict pod yield of peanut grown under drier conditions in a satisfactory manner (Table 3.3 and Figure 3.5). In terms of shoot dry weight, good agreement was found between the dynamics of observed and corresponding simulated values throughout the season in every comparison either visually (Figures 3.6a, b, and c) or statistically , i.e., standardized bias (R) and standardized mean square error (V) (Table 3.4).

Shoot dry weight and pod yield obtained under the conditions of experiment #1 were higher than those obtained under the conditions for experiments #2, 3, and 4. The major factor responsible for this was the water availability. For experiment #1, because of shallow water table (2 m) and higher rainfall (140 mm), water availability was more suitable than for other experiments considered in this study (Figure 3.4, 3.7, 3.8, and 3.9). In experiments #2, 3, and 4, there was little rainfall (< 30 mm) during the peanut growing period. Soil moisture content for experiment #2 was more suitable for peanut growth than for experiments #3 and 4, because of the shallower water table. Water table depth in the field for experiment #2 was 2 m, while it was 3 m for experiments #3 and 4. The differences between the corresponding results for experiments #3 and 4 were not significant because the patterns of soil moisture content distributions for these two experiments, were similar. In the MACROS model, it is assumed that the ratio of transpiration to gross photosynthesis is constant. Therefore, the rate of gross photosynthesis varies proportionally with the transpiration rate which is, in this case, controlled by the rate of water uptake. Under the drier conditions, the rate of water uptake, and in turn, the transpiration rate is less than that found under the conditions in which soil moisture content is closer to the optimum level. As a consequence, rates of photosynthesis, crop growth and yield simulated for areas of lower soil moisture content are less than those simulated for areas of more suitable soil moisture content.

In terms of soil moisture content, for the 0-10 cm soil depth, the model under-estimated the field data for experiments #2, 3, and 4 as shown in Figures 3.7a, 3.8a, and 3.9a, respectively. For experiment #2, which was conducted on the same soil (Nam Phong series) as that of the experiment used for model calibration (experiment #1), there is satisfactory agreement between simulated and observed soil moisture content at 10-20, and 20-30 cm over a period of time (Figures 3.7b, and c). For experiments #3 and 4, which were conducted on a different soil (Korat series) from that of experiment used for the model calibration, at depth 10-20 and 20-30 cm from the surface, the agreement between observed and simulated values was not good (Figures 3.8b, c and 3.9b, c).

Generally, changes in soil moisture content within the soil layers, are caused by evaporation of water from the soil surface (Equation 2), water movement between layers (Equation 1), and water uptake by roots. In this study, for the 0-10 cm soil layer, only evaporation and water movement were responsible for the changes. As the planting depth was 15 cm, there was no effect of water uptake by peanut roots within the 0-10 cm layer. Therefore, under-estimation of the simulated soil moisture content at 0-10 cm was mainly due to the inaccurate calculation of water movement and evaporation. As described earlier, MACROS calculates water movement and evaporation using empirical equations which require a number of texture specific empirical constants. These constants were generalized values obtained from Penning de Vries et al. (1989). They were not the specific values for the study area. Nevertheless, relatively poor agreement between observed and simulated soil moisture content at 0-10 cm should not have a significant effect on the differences in crop growth and yield, because for the MACROS model, the simulated water uptake is limited to layers where there are roots. In this study, the planting depth was 15 cm, and it was assumed that there were no peanut roots in the 0-10 cm increment.

For the 10-20 and 20-30 cm soil layers, changes in soil moisture content were mainly caused by water movement and root uptake. Based on equation 2, water lost by evaporation from these soil layers, as calculated by the model, was very little. The rates of water uptake by root are calculated from weather and crop parameters. The weather parameters used for experiments #2, 3, and 4 were almost the same because peanut crops were grown in each experimental field at about the same time. The crop parameters used in each of these experiments were the same. In experiment #2, the results showed good agreement between observed and simulated soil moisture content at both 10-20 and 20-30 cm layers. Thus, crop parameters used for the simulations should be appropriate. Root uptake, therefore, was not the cause of the inaccurate simulated soil moisture content data under conditions of experiments #3 and 4. The relatively poor agreement in experiments #3 and 4 was likely caused by the inaccurate calculation of water movement between the soil layers. The texture specific empirical constants used in the empirical equations to calculate water movement between the soil layers were the generalized values obtained from Penning de Vries et al. (1989). They were not specific values for the study area.

There is another reason to explain the relatively poor agreements between observed and simulated soil moisture content found in this study. The data on soil moisture content collected from the experimental fields were initially expressed as moisture content by weight (Chantorn, 1983). Before comparing the observed data with the simulated data, each value of the original field data was converted to moisture content by volume by multiplication with the value of bulk density for the corresponding soil layer. Determination of the bulk density values, in this case, was difficult because the values could vary rapidly over space and time.

### 3.5.3 Model validation B

Correlation analysis of the simulated and the observed data from 36 on-farm trials at 5 test sites resulted in a simple linear correlation coefficient of 0.91. This value is significantly different from 0 at the 0.01 level of probability (Figure 3.10). Thus, there was strong evidence that the observed and the simulated pod yields have a high degree of linear association. As high as 82 % of variability in the observed pod yield could be accounted for by a linear function of the simulated pod yield and vice versa. This indicates that the model is useful and relevant, when applied under "real world" situations in the northeast region of Thailand, where some important model inputs such as water table depth and soil texture are not measured directly in the field, but qualitatively described or estimated by local extension specialists.

As shown in Figure 3.10, however, the model could either under- or over-estimate the field data depending on situations at the sites. Over-estimation occurred because MACROS was specific for the simulation under water-limited conditions. The model did not consider any other detrimental effects on crop growth. Under field conditions, effects of limiting factors other than water can not be entirely eliminated, even when maximum rate of fertilizer and cultural practices are applied. Hence, over-estimations of the simulation result could be expected.

Under-estimation in the simulation result was, at least partly, because the planting date used for the simulation was December 15, which was the latest date allowed for that research (Jintrawet et al., 1986). For each of the on-farm trials, the planting date was possibly earlier than this. According to Kerdsuk and Patanothai (1990), planting dates for dry season peanut cropping in Khon Kaen Province could be as early as late November. Under weather conditions of the 1984-85 season, changing planting dates from December 15 to November 30, could increase the yield of dry season peanut by 13-27 % depending upon soil types.

## 3.6 CONCLUSION

In general terms, crop growth and yield simulated by MACROS agree well with the field data. The model, which was calibrated under moist conditions, could predict reasonably accurate pod yields (Figure 3.5 and Table 3.3) and shoot dry weight (Figure 3.6 and Table 3.4) of peanut grown under dry conditions. Also, when used in conditions where some important input parameters, such as soil texture and water table depth, were not precise but obtained by estimations, the model was still able to simulate pod yield data which were highly correlated actual field data.

However, in terms of soil moisture content, accuracy of the simulation results depends upon the appropriateness of the empirical constants used in the calculation of soil water movement and evaporation. As previously described, these constants are related to soil texture. In this study they were generalized values obtained from the literature (Penning de Vries et al., 1989). In cases where the appropriate values for these constants are used, the simulation results may be reasonably accurate. Good agreement between observed and simulated soil moisture content at 10-20 and 20-30 cm depth, under the conditions of experiment #2 (Figure 3.7) is an example. In other cases, if inappropriate values of the empirical constants are used, accuracy of the simulation results may be reduced. Relatively poor agreements between observed and simulated soil moisture content at 0-10, 10-20, and 20-30 cm depth, under conditions of experiments #3 and 4 (Figures 3.8 and 3.9) are examples. Therefore, the accuracy of the model could be enhanced through the determination of these texture specific empirical constants which are particular for the soils in Northeast Thailand.

Weather parameters could also have limited model performance. Penning de Vries et al. (1989) suggest that air humidity expressed as water vapor pressure in kPa is preferred. Data expressed as relative humidity should be avoided because it might change drastically during the day. However, relative humidity was used in this study, because this were the only air humidity data available.

Despite some limitations in model performance, MACROS appears to be a model of choice to adequately estimate growth and yield for dry season peanut cropping. Therefore, it is concluded that the model is valid and can be applied to generate information on land suitability based on water availability for non-irrigated, dry season peanut cropping at a regional scale in Khon Kaen Province, Northeast Thailand.

**Table 3.1** Summary of MACROS input data (adapted from Penning de Vries et al., 1989).

| Type of data | Data |
|---|---|
| Crop parameters | Parameters related to:<br>- photosynthesis and respiration,<br>- biomass partitioning,<br>- phenological development, and<br>- crop growth in relation to soil water |
| Soil parameters | Soil characteristics (by layer) including depth, texture, and initial soil moisture content; Parameters and constants related to the storage capacity of soil surface and soil evaporation; Water table depth |
| Weather data (daily) | Rainfall, Maximum and minimum temperature, Air humidity, Wind speed, Solar radiation |
| Management practices | Planting date, Planting depth |

**Table 3.2** Field experiments used for the calibration and validation A of the MACROS crop model (adapted from Chantorn, 1983).

| Experiment no. | Year | Site | Soil series / subgroup (USDA-Soil Taxonomy) |
|---|---|---|---|
| 1[1/] | 1981-82 | Samjan village | Nam Phong / Ustoxic Quartzipsamment |
| 2 | 1982-83 | Samjan village | Nam Phong / Ustoxic Quartzipsamment |
| 3 | 1982-83 | Muong village | Korat / Oxic Paleustult |
| 4 | 1982-83 | Muong village | Korat / Oxic Paleustult |

[1/] Used for model calibration

**Table 3.3** Observed and simulated pod yields for model validation A.

| Experiment no.[1/] | Pod yield (kg ha$^{-1}$) | | Deviation (%) |
|---|---|---|---|
| | Observed [2/] | Simulated | |
| 2 | 913.3 $\pm$ 59.43 | 1061.3 | 16.2 |
| 3 | 328.0 $\pm$ 14.07 | 268.3 | -18.2 |
| 4 | 365.6 $\pm$ 19.44 | 182.6 | -50.1 |

1/ The numbers assigned for each of these experiments are the same as those used in Table 3.2

2/ Mean $\pm$ standard error

**Table 3.4** Standardized Bias (R) and Standardized Mean Square Error (V) for the comparison of observed and simulated shoot dry weight values for 3 field experiments in model validation A.

| Experiment no.[1/] | R | V |
|---|---|---|
| 2 | 0.22 | 0.05 |
| 3 | 0.10 | 0.03 |
| 4 | -0.10 | 0.02 |

1/ The numbers assigned for each of these experiments are the same as those used in Table 3.2

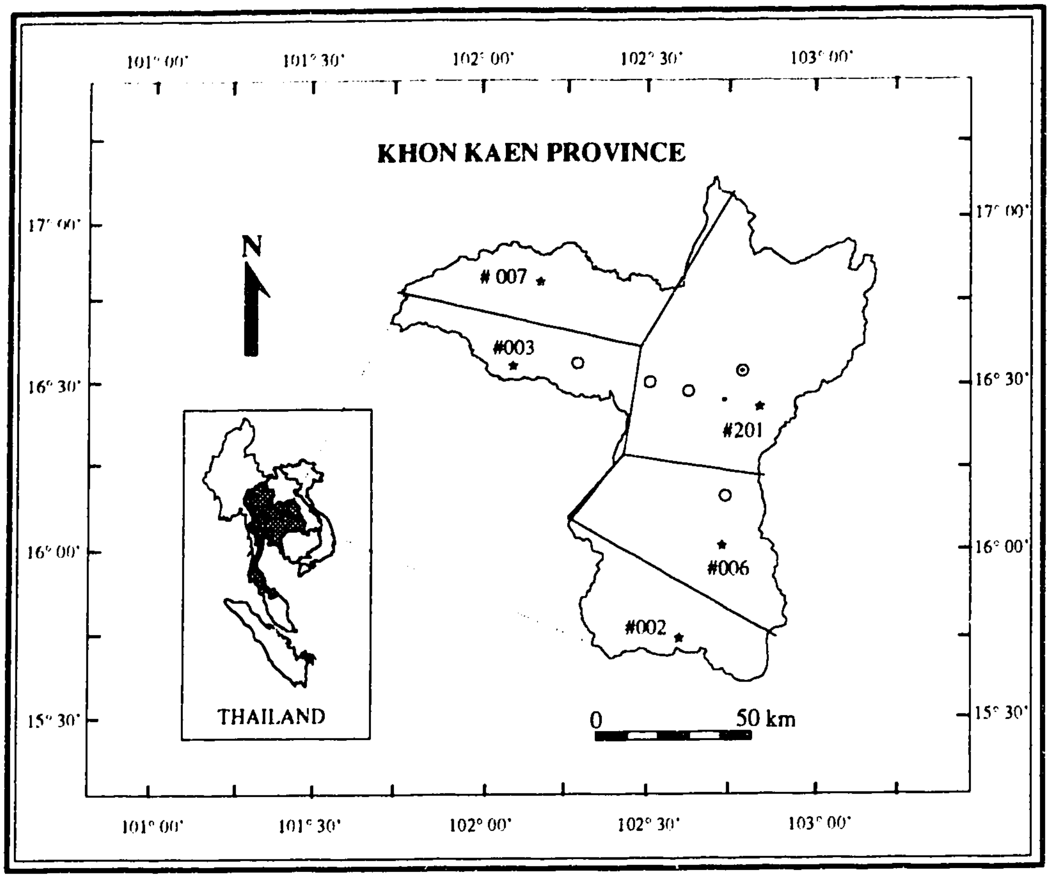


**Figure 3.1** Location of Khon Kaen Province in Thailand with:

( • ) locations of sites for field experiments (adapted from Chantorn, 1983),
( ○ ) locations of sites (villages) for on-farm trials (adapted from Jintrawet et al., 1986)
( ★ ) locations of weather stations with the corresponding station numbers (adapted from Hydrometeorology Division, 1988), and
( ⊤ ) Thiessen polygon boundaries delineated based on 5 weather stations.

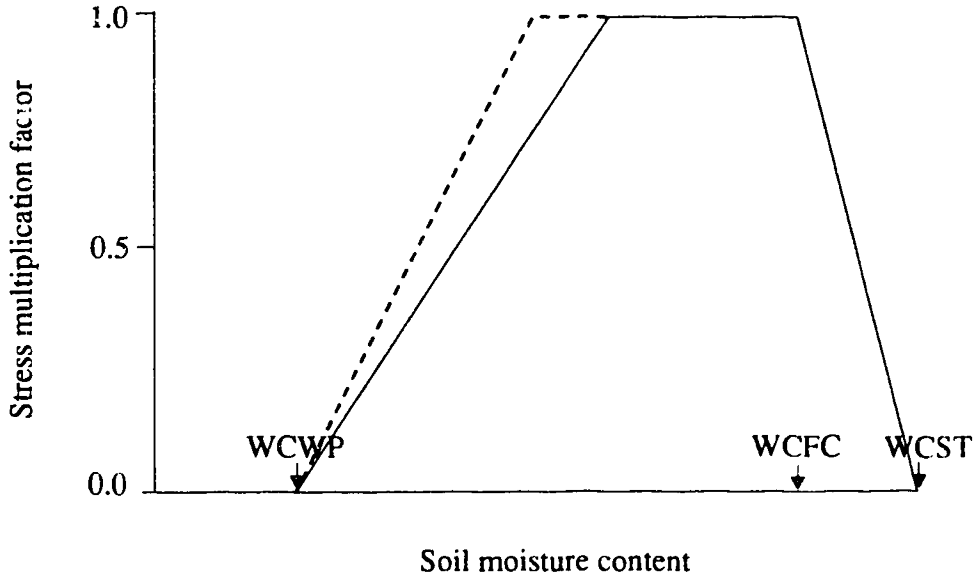


**Figure 3.2** Relationship between soil moisture content and stress multiplication factor. WCWP, WCFC, and WCST represent soil moisture content at wilting point, field capacity, and saturation, respectively. Dashed line represents either a more drought resistant species under the same field conditions, or the same species under a lower evaporative demand (adapted from Penning de Vries et al. 1989).

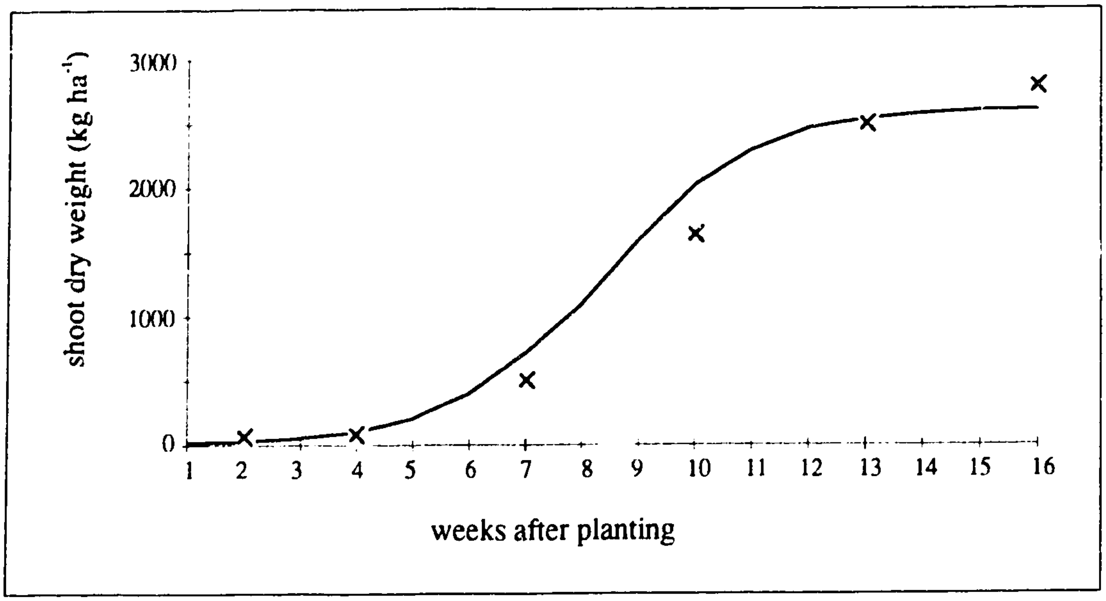


**Figure 3.3** Comparison between observed (X) and simulated (——) shoot dry weights for model calibration.

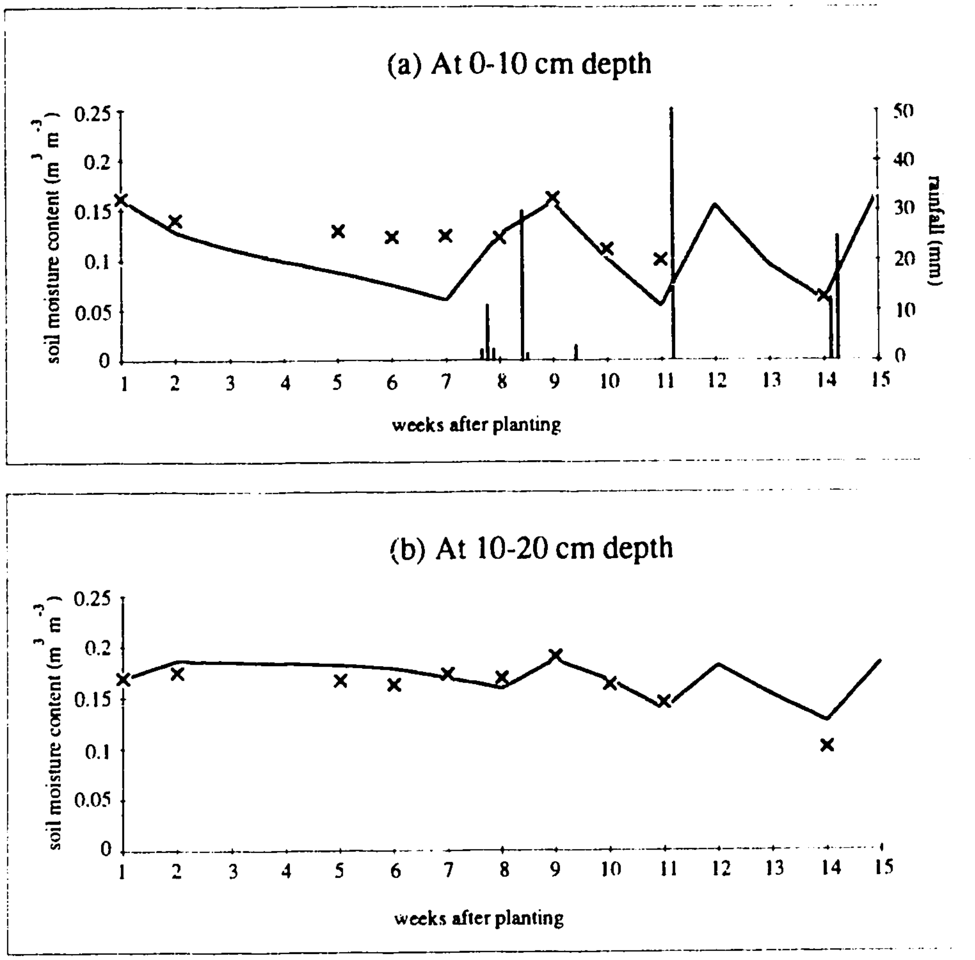


**Figure 3.4** Comparisons between observed (X) and simulated (——) soil moisture contents under conditions of experiment #1 for model calibration. Bar chart represents rainfall amounts.

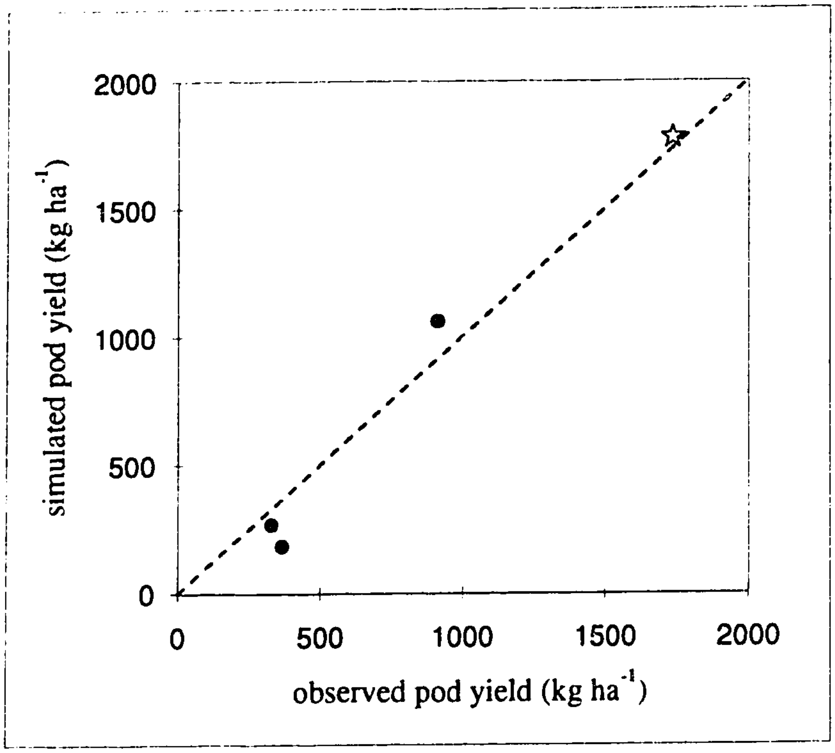


**Figure 3.5** Relationship between observed and simulated pod yields in model calibration (☆) and model validation A ( ● ). Dashed line (-------) represents 1:1 line if simulated yield equalled observed yield.

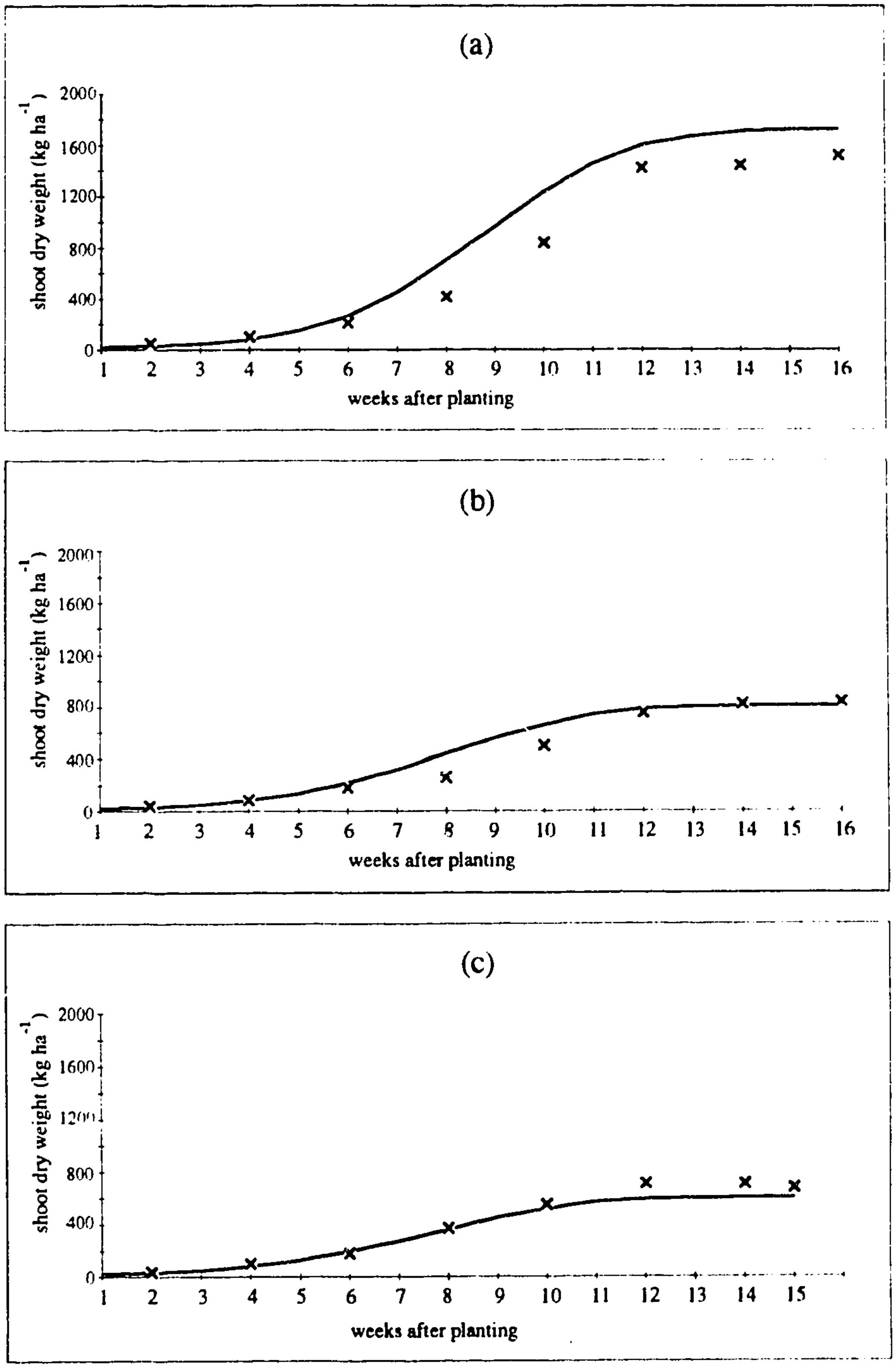


**Figure 3.6** Comparisons between observed (X) and simulated (——) shoot dry weights for model validation A under: (a) conditions of experiment #2, (b) conditions of experiment #3, and (c) conditions of experiment #4.

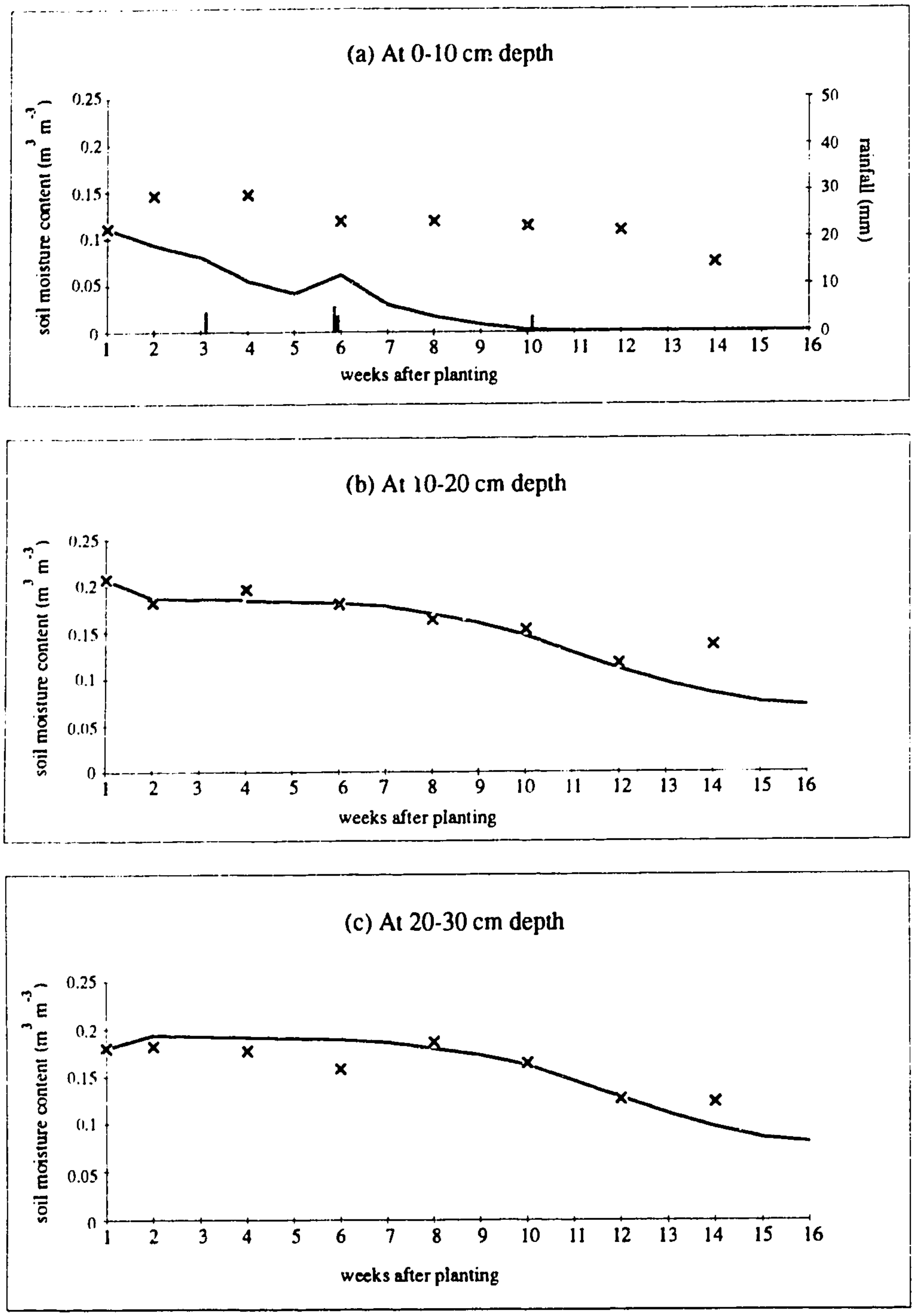


**Figure 3.7** Comparison between observed (X) and simulated ( —— ) soil moisture contents under conditions of experiment #2 for model validation A. Bar chart represents rainfall amounts.

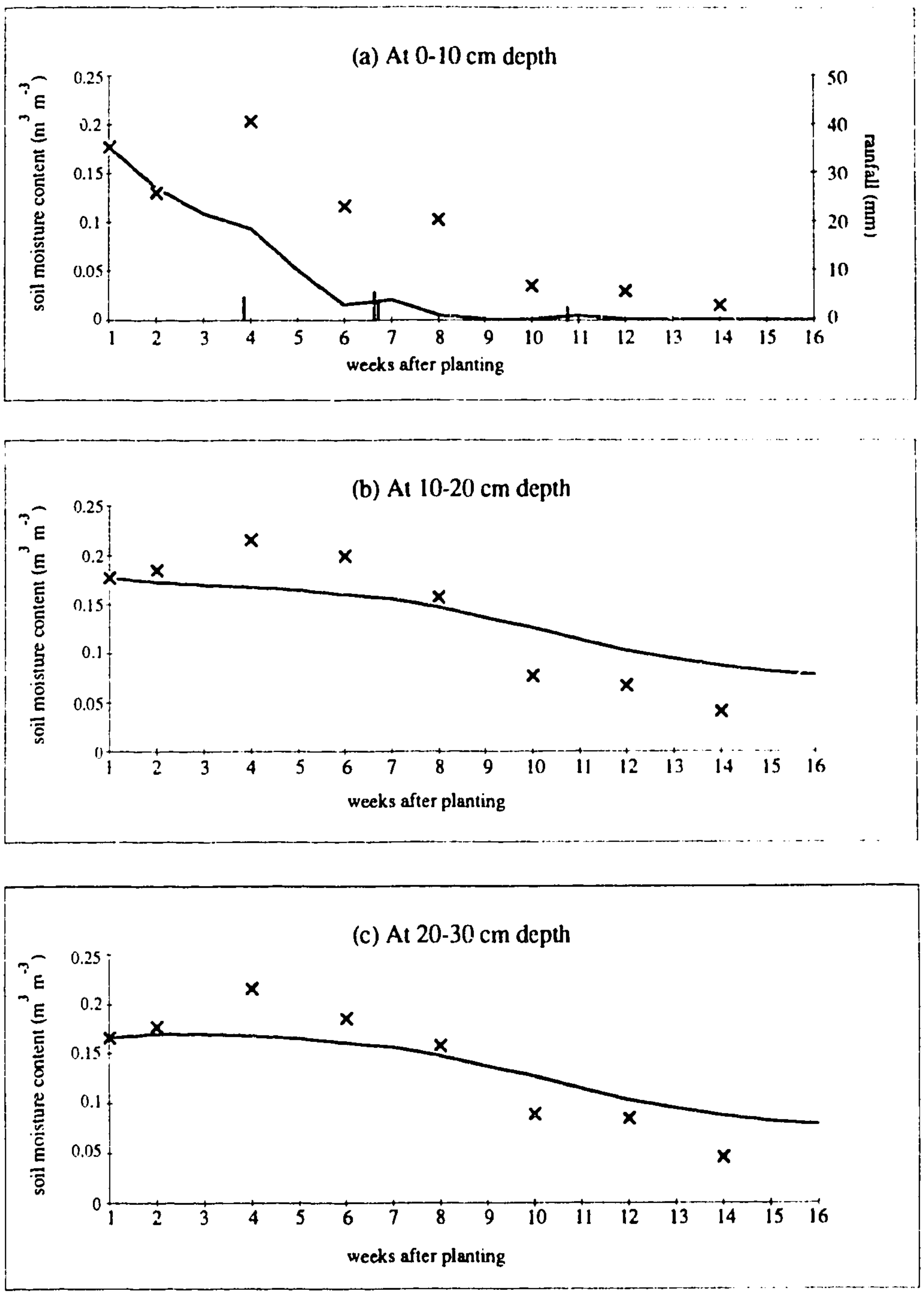


**Figure 3.8** Comparison between observed (X) and simulated (——) soil moisture contents under conditions of experiment #3 for model validation A. Bar chart represents rainfall amounts.

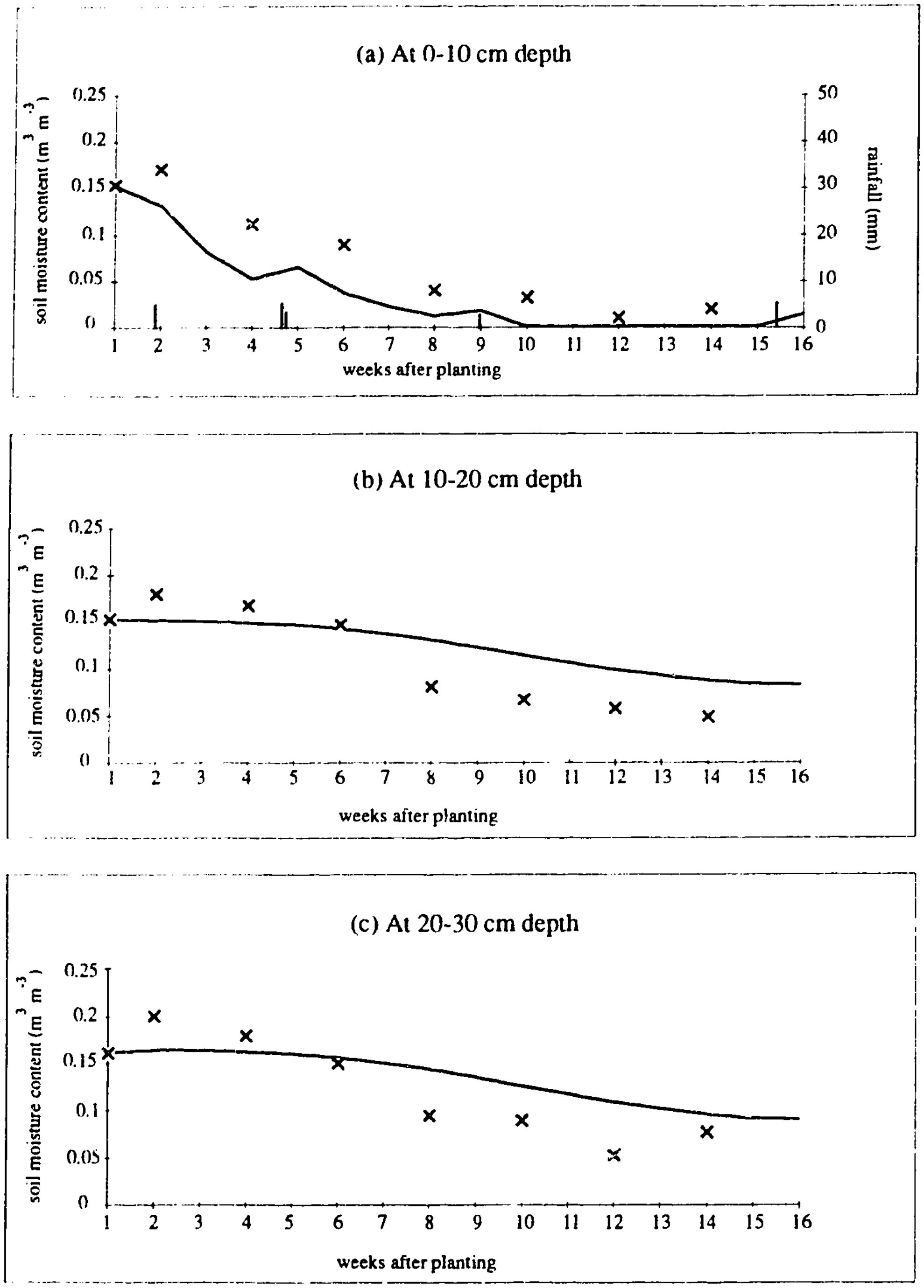


**Figure 3.9** Comparison between observed (X) and simulated ( —— ) soil moisture contents under conditions of experiment #4 for model validation A. Bar chart represents rainfall amounts.

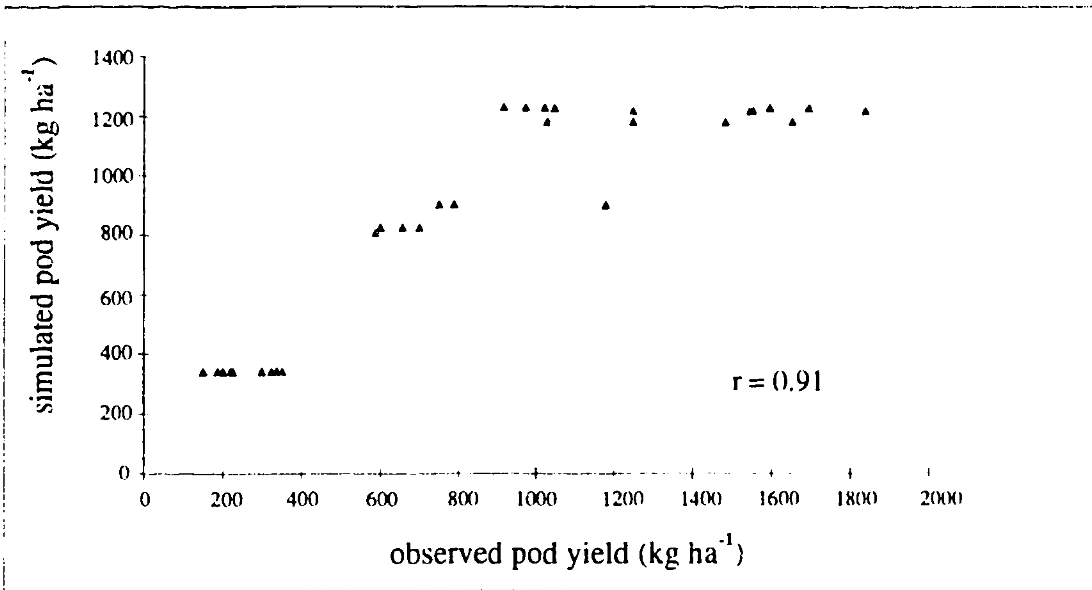


**Figure 3.10** Correlation between observed and simulated pod yields in model validation B.

## 3.7 REFERENCES


Aronoff, S. 1989. Geographic Information Systems: A Management Perspective. WDL Publications, Ottawa, Canada.

Bhagsari, A.S., R.H. Brown, and J.S. Schepers. 1976. Effect of moisture stress on photosynthesis and some related physiological characteristics in peanut. Crop Science. 16: 712-715.

Bhagsari, A.S., and R.H. Brown. 1976. Photosynthesis in peanut (*Arachis*) genotypes. Journal of Peanut Science. 3: 1-5.

Boonyatharokul, W. 1983. Principle of Irrigation. Department of Irrigation Engineering, Kasetsart University. Bangkok, Thailand. (in Thai).

Bouma, J., R.J. Wagenet, M.R. Hoosbeek, and J.L. Hutson. 1993. Using expert systems and simulation modelling for land evaluation at farm level: a case study from New York State. Soil Use and Management 9: 131-139.

Chantorn, P. 1983. Rainfed Dry Season Peanut Cropping Without Irrigation. M.Sc. Thesis. Khon Kaen University, Khon Kaen, Thailand. (in Thai with English abstract).

Davidoff, B., W.W. Wilhelm, and J. Skopp. 1992. Simulating winter wheat production in three tillage systems using the nitrogen tillage residue management model. Agron. J. [illegible] 516-523.

Doorenbos, J., and A.H. Kassam. 1979. Yield Respond to Water. FAO Irrigation and Drainage Paper No. 33. FAO, Rome.

Driessen, P.M., 1986. The water balance of soil. *In*. H. Van Keulen and J. Wolf (Eds.). Modelling of Agricultural Production. Weather, Soils, and Crops , Simulation Monographs. PUDOC, Wageningen. pp 76-116.

Dumanski, J., and C. Onofrei. 1989. Techniques of crop yield assessment for agricultural land evaluation. Soil Use and Management 5: 9-16.

EUROCONSULT. 1989. Agricultural Compendium for Rural Development in the Tropics and Subtropics. Elsevier, Amsterdam.

FAO. 1976. A Framework for Land Evaluation. Soils Bull. 29. FAO. Rome.

Graf, B., M. Dingkuhn, F. Schnier, V. Coronel, and S. Akita. 1991. A simulation model for the dynamics of rice growth and development: III. Validation of the model with high-yielding varieties. Agricultural Systems 36: 329-349.

Hanks, R.J. 1985. Soil water modelling. *In*. M.G. Anderson, and T.P. Burt (Eds.). Hydrological Forecasting. Jonh Wiley and Sons, New York. pp 15-36.

Haverman, P.P. 1986. A characterization of the growth of the cowpea crop in a Sahelian zone. MSc thesis. Department of Theoretical Production Ecology, Agricultural University of Wageningen.

Hydrometeorology Division. 1988. Location of Rainfall Stations of Thailand. Meteorological Department, Bangkok, Thailand.

Jintrawet, A., R. Katawatin, and V. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Cropping Systems Research Project, Khon Kaen University, Thailand. (in Thai with English abstract)

Jintrawet, A., S. Smutkupt, S. Ratanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya. 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University, Thailand. (in Thai with English abstract).

Keerati-Kasikorn, P. 1984. Soils of Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Thailand. (in Thai with English abstract).

Kerdsuk, V., and A. Patanothai. 1990. Testing and Implementation of Rainfed Dry Season Peanut: Khon Kaen University Experience. Farming System Research Project, Khon Kaen University, Thailand. Farm News 6, 24-35. (in Thai).

Kerdsuk, V. 1986. Effects of Planting Dates and Toposequence on Growth and Yield of Peanut After Rice. M.Sc. Thesis. Faculty of Graduate Studies, Khon Kaen University, Khon Kaen, Thailand.

Landon, J.R. (Ed). 1991. Booker Tropical Soil Manual: A Handbook for Soil Survey and Agricultural Land Evaluation in the Tropics and Subtropics. Essex: Longman Scientific and Technical.

Makking, G.F., and H.D.J. Van Heemst. 1975. Simulation of the Water Balance of Arable Land and Pasture. PUDOC, Wageningen.

Pallas, J.E., and Y.B. Samish. 1974. Photosynthetic response of peanut. Crop Science. 14: 478-482.

Pannangpetch, K. 1994. The uptake and distribution of nitrogen in the rice plant, and its effect on growth and yield. *In.* R.B. Matthews, M.J. Kropff, T.M. Thiyagarajan, and A.A. Kareem (Eds.). The Development, Testing and Application of Crop Models for Simulating the Production of Rice. SARP Research Proceeedings. pp 18-32.

Penman, H.L. 1948. Natural evaporation from open water, bare soil and grass. Proceed. Royal Soc., A193, 120-146.

Penning de Vries, F.W.T., D.M. Jansen, H.F.M. Ten Berg, and A. Bakema. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Simulation Monographs. PUDOC, Wageningen, and IRRI, Los Baños.

Rao, N.H. 1987. Field test of a simple soil water balance model for irrigated areas. J. of Hydrology. 91: 179-186.

Rijtema, 1969. Soil Moisture Forecasting. Bulletin 513. Institute of Land and Water Management Research (ICW), Wageningen.

Soil Survey Division. 1973. Detailed-Reconnaissance Soil Map of Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

Stone, L.R., I.D. Teare, C.D. Nickell, and W.C. Mayaki. 1976. Soybean root development and soil water depletion. Agronomy Journal. 68: 677-680.

Van Keulen, H., and J. Wolf. 1986. (Eds.). Modelling of Agricultural Production: Weather, Soils, and Crops. Simulation Monographs. PUDOC, Wageningen.

Weiss, E.A. 1983. Oilseed Crops. Longman, London.

Wösten, J.H.M., M.H. Bannink, and J. Beuving. 1986. Waterretentie-en doorlatendheidskarakteristieken van boven-en ondergronden in Nederland: de Staringreeks. Institute for Land and Water Management, rapport 18. Wageningen.

# CHAPTER 4

# SIMULATION MODELING OF LAND SUITABILITY EVALUATION (II): INVESTIGATION ON THE SENSITIVITY OF THE SUITABILITY CLASS

## 4.1 INTRODUCTION

One of the most promising alternatives for increasing the land use efficiency and the per capita income of farmers in Northeast Thailand is non-irrigated, dry season peanut cropping. To successfully implement this cropping system in the farmers' fields, the suitability of land areas for this specific purpose must be known. Crop growth simulation models are useful tools to generate this kind of information. Prior to the application of a crop model, the model must be evaluated for its practical utility when applied in a particular region. In Chapter 3, the evaluation of the MACROS model revealed its validity in generating information on land suitability for non-irrigated, dry season peanut cropping under conditions of Khon Kaen Province, Northeast Thailand. However, to effectively apply the model at the regional scale, there are several points that must be investigated before beginning the application. This chapter is devoted to these investigations.

For the whole area of Khon Kaen Province (10,628 $km^2$), amount of rainfall can vary considerably from locale to locale. Theoretically, in this case, rainfall data should be obtained from as many weather stations as possible distributed across the province. However, in Khon Kaen, rainfall data from only five stations were available in digital form, for a sufficient number of years of recording. The first objective of this study was to investigate whether or not the rainfall data obtained from these five stations were adequate to generate information on land suitability for non-irrigated, dry season peanut cropping in the province. In other words, whether or not land suitability based on pod yield is sensitive to the weather station used to supply the rainfall data. Note that variations of other weather components, i.e., maximum and minimum temperature, relative humidity, wind speed, and solar radiation could also have effects on the suitability of land areas for this specified land use. However, these variations were not considered in this study, as they are usually less than that of the rainfall (Penning de Vries et al., 1989). Also, the availability of weather data other than rainfall was limited to only 1 station in the province.

For the application of MACROS at the regional scale, it was planned to simulate pod yield data under different conditions of soil, water table depths, and planting dates, for ten consecutive growing seasons. These pod yield data would be used, in turn, to assess the level of suitability for each soil, under each assumed combination of water table depth by planting date, in the study area. This classification would be based on the level of pod yield and the number of years in 10 for a given yield level. As will be described later in this chapter, a criterion related to the level of yield was defined according to the results of a relevant study conducted in the study area. Hence this criterion was considered well defined. The criterion of number of years in 10 was questionable because it must be arbitrarily defined. This could lead to significant differences in the suitability classes assigned to each soil, if the suitability class is sensitive to changes in this criterion. Therefore, the second objective of the study was to investigate the sensitivity of the suitability class to changes in the classification criterion of number of years in 10 for a given yield level, from 7 to 8 years.

### 4.1.1 Study area

The study area is Khon Kaen Province, Northeast Thailand (Figure 4.1). The province lies between latitude 15° 35' to 17° 10' North, and longitude 101° 45' to 103° 15' East. The total area is approximately 10,628 $km^2$. The Khon Kaen Province was selected as the study area for two reasons. First, this province includes all of the major soils and landscape features found in Northeast Thailand. Second, data inputs required by the MACROS model were available for the province. Details on the study area are described in Chapter 2.

### 4.1.2 Soils of the study area

Information on the spatial distribution of soils in the study area was obtained from a 1:100,000 Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973). This map was originally generated at scale 1:50,000, but to reduce the number of map sheets, the map was published at the smaller scale. According to this map, the Khon Kaen area comprises 56 map units named after 28 soil series, 13 variants of soil series, 2 phases of soil series, 6 associations of soil series, 2 complex units, and 5 units of miscellaneous land types (Table 4.1).

From Table 4.1, the Khon Kaen Province includes areas of 4 major types of physiography namely (*i*) Flood plain, (*ii*) Low terrace, (*iii*) Middle and high terraces, and (*iv*) Hill and mountain slopes. In addition, the Miscellaneous land types, i.e., Slope complex, Gravelly land, Rock out crop, Pond and swamp, and Urban areas also occupy parts of this province. Predominant soils are members of Roi Et and Khorat series which together cover approximately 44 % of the total area. Roi Et soils occur on low terrace while Khorat soils are on the middle terrace positions.

Soils on the flood plain include natural levee soils, and river basin soils. The natural levee soils are members of Chiang Mai, Tha Muong, and Sanphaya series that have loamy texture at the surface, and loamy to clayey texture at the sub-surface. Chai Nat, Phimai, Ratchaburi, Si Songkhram, and Si Thon series, as well as Phimai-loamy variant, and Ratchaburi-loamy variant, include river basin soils that have clayey texture throughout the profile. The major soils on the flood plain are members of Ratchaburi and Phimai series covering 1.819 and 0.749 % of the total area of Khon Kaen Province, respectively.

The low terrace soils can be divided into 4 groups, i.e., deep soils, shallow soils, sandy soils, and saline soils. The deep soils are members of Nakhon Phanom, Renu, and Roi Et series as well as variants and phases of the Roi Et series. The texture of these soils is sandy loam to fine sandy loam at the upper part of the profile, becoming finer to sandy clay loam, sandy clay, or clay with depth. The shallow soils are members of Phen series that have laterite gravel within 50 cm of the surface. Ubon series include the sandy soils that have loamy sand to sandy texture from the surface to a depth of more than 80 cm. The saline soils are members of the Udon series, Roi Et-saline variant, and Roi Et-clayey variant, . Soils on the low terrace positions are dominated by members of Roi Et series (24.745 % of the total area of Khon Kaen).

On the middle and high terraces, 3 groups of soils can be distinguished: deep soils, sandy soils, and shallow and gravelly soils. The deep soils are members of Korat, Satuk, Warin, and Yasothon series, as well as Korat-sandy variant, and Warin-high phase. These soils have sandy loam texture at the upper part, and sandy clay loam at the lower part of the profile. Members of Nam Phong series, and Nam Phong-red color variant are the sandy soils having sandy texture throughout the deep profile The shallow and gravelly soils are members of various soil series, and variants of soils series. Phon Phisai includes shallow soils which have laterite gravel within 50 cm of the surface. Khorat-gravelly variant, and Yasothon gravelly variant include gravelly soils whose texture is loamy sand to sandy loam over gravelly sandy clay loam. The Nam Phong-gravelly variant has the texture of loamy sand or sand over gravelly sand or gravelly sandy loam. These middle and high terrace soils are dominated by members of Khorat, Nam Phong, Satuk and Yasothon series which cover 19.691, 8.501, 4.697, and 3.289 % of the total area of Khon Kaen, respectively.

Soils on the hills and mountain slopes can be divided into 2 groups, i.e., deep soils, and shallow soils. The deep soils are members of Pak Chong, Thap Kwang, Lop Buri, Ban Chong and Chatturat series, as well as Chatturat-mottle variant. These soils have loam, silty clay loam, clay loam or clay texture at the surface, and clay loam or clay texture at the sub-surface. Tha Yang, Borabu, and Tha Khli series, and Tha Khli-concretional variant are shallow soils. Tha Yang and Borabu have loamy sand to sandy clay loam texture at the surface, and gravelly sandy clay loam to gravelly sandy clay at the sub-surface. Tha Khli series and Tha Khli-concretional variant include soils that have clay texture over secondary lime concretion or gravelly clay. Dominant soils on the hills and mountain slopes are members of the Pak Chong series (1.582 % of the total area of Khon Kaen). Detailed descriptions of these soils are in the Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973), and Keerati-Kasikorn (1984).

## 4.2 MATERIALS AND METHODS

### 4.2.1 The MACROS crop model

The MACROS crop model was used to simulate data on pod yield for non-irrigated, dry season peanut cropping, with the assumption that only water is the limiting factor for plant growth (Production Level 2, Penning de Vries et al., 1989). These simulated yield data were, in turn, used to express the level of land suitability for this cropping system in Khon Kaen Province. Prior to application, the model was evaluated using both calibration and validation phases (Chapter 3). The results of this evaluation revealed the usefulness of the model to adequately estimate yield of dry season peanut cropping under rainfed conditions. Penning de Vries et al. (1989) provide a detailed description of MACROS and its scientific background. A brief description of the model is in Chapter 3.

### 4.2.2 Crop model inputs

Input parameters required by MACROS include those related to crop, soil, weather, and management (Penning de Vries et al., 1989).

*1) Crop parameters*

Crop parameters are those related to photosynthesis and respiration, biomass partitioning, phenological development, soil water relations and root growth. Some of these parameters including Maximum Rate of Photosynthesis for Reference Temperature (PLMXP), Maximum Growth Rate of Rooting Depth (GZRTC), and Water Stress

Sensitivity Coefficients (WSSC), were adjusted to calibrate the model to the conditions in Khon Kaen Province (Chapter 3). After adjustment, the values of GZRTC, PLMXP, and WSSC were 0.035 m $d^{-1}$, 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$, and 0.65, respectively. These values were used in conjunction with other crop input parameters, suggested by Penning de Vries et al. (1989) to run the model.

*2) Soil parameters*

In this study, the MACROS model was used to simulate growth and yield of dry season peanut crop, for each soil series, variant, or phase of soil series. Note that, all of the problem soils including shallow, gravelly and saline soils as indicated in Table 4.1, were not considered in this study. These soils were assumed unsuitable for non-irrigated, dry season peanut cropping. Therefore, a total of thirty two soils (Table 4.1) were taken into account. The MACROS model requires a number of soil parameters including depth; texture; soil physical characteristics and constants related to the water storage capacity of soil surface, soil water movement, and soil water evaporation; initial soil moisture content; and water table depth (Penning de Vries et al., 1989). The input parameter of soil texture was derived from the description of typical soil profiles for each soil series, variant, or phase as provided by Keerati-Kasikorn (1984). Model inputs required to calculate evaporation rate, i.e., texture specific empirical constants, were interpreted based on their relationship with soil texture as provided in Penning de Vries et al. (1989). Other empirical constants and parameters required for calculating relationships between soil moisture content, soil moisture suction, and hydraulic conductivity, were provided by the original values of the model based on the relationship between soil texture and these parameters as shown in Table 26 , page 152 in Penning de Vries et al. (1989). The parameter of initial moisture content was not measured directly in the field, but was calculated from data on water table depth and soil texture, using MACROS. Precise data of water table depth were not available for the entire study area. Values of this input parameter must be assumed. Previous studies (Jintrawet et al., 1986; Kerdsuk and Patanothai, 1990) have revealed that potential areas for dry season peanut cropping usually have water table ranges from 1 to 4 m depth. Water tables shallower than 1 m may cause unacceptable reduced yield due to wetness. On the other hand, under conditions in which the water table is deeper than 4 m, drought could become a serious problem for crop production. In this study, only median values of this range of water table depths, 2 and 3 m were used.

*3) Weather data*

Daily weather data used as model inputs for MACROS included rainfall, maximum temperature, minimum temperature, wind speed, relative humidity, and solar radiation. These weather data, in digital form, recorded for eleven years from 1978 through 1988, were used to simulate crop yields for ten growing seasons (i.e., dry seasons 1978-79 to 1987-88). Rainfall data were obtained from five weather stations, i.e., stations #002, 003, 006, 007, and 201 (Figure 4.1). Data on maximum and minimum temperature, wind speed, and relative humidity, were taken from only one station (station #201), as this was the only data set available for the study area. There were no solar radiation data available in digital form. Solar radiation data were obtained, in hard copy form, from the Khon Kaen University weather station located a few kilometers away from station #201 and were then input manually into MACROS.

*4) Management practices*

Planting dates vary between farmers and seasons. Based on Kerdsuk and Patanothai (1990), planting dates for dry season peanut cropping in this region are between late November and late December. In this study, simulation of crop growth could not be done for every planting date during this period. Therefore, only two planting dates, which, according to the literature, are most appropriate for the region, were modeled, i.e., December 1, and December 15. Note that, as the simulation of crop growth during the seed germination stage is difficult (Penning de Vries et al., 1989), the simulations were begun after this stage (assuming one week after planting). The planting depth used for model simulation was 15 cm, corresponding to the recommended planting technique (Jintrawet et al., 1983).

### 4.2.3 Simulation of peanut pod yield using MACROS

With the use of the MACROS crop model, pod yield data of non-irrigated, dry season peanut crops were simulated for each soil series, phase, or variant, for:

i) recorded weather data for each of 10 growing seasons from dry seasons of 1978-79 through to 1987-88;

ii) 4 combinations of 2 planting dates (December 1, and December 15) by 2 water table depths (2, and 3 m); and

iii) 5 weather stations.

Table 4.2 illustrates the conditions under which peanut pod yield were simulated. The model was run on a PC 486 DX computer.

### 4.2.4 Land suitability classification criteria

Although the classification was based on crop yield data simulated for each map unit named after soil series, phase, variant, or association, the term "land suitability class" was used to represent the level of suitability for each of these map units. This is because, in addition to soils, other land attributes (i.e., weather conditions) were taken into account.

This land suitability classification is considered "provisional" (FAO, 1983), because it is based on the values of pod yield simulated by MACROS at production level 2 (Penning de Vries et al., 1989). At this production level, it is assumed that, water is the only factor limiting crop growth. The model does not consider any other detrimental factors (e.g., low inherent soil fertility) that can occur in field conditions.

The definitions of suitability classes were, in part, based on the results of a study under the Farming System Research Project, carried out at Khon Kaen University (Kerdsuk and Patanothai, 1990). This study indicated that peanut pod yields greater than 1200 kg $ha^{-1}$ was "satisfactory" for most farmers in Khon Kaen Province, as well as those in other study areas in Northeast Thailand. Pod yields of 900-1200 kg $ha^{-1}$ are still "acceptable" for most farmers. Pod yields of 600-900 kg $ha^{-1}$ are acceptable only in some areas where farmers do not have other alternatives for the dry season. However, in other areas where farmers have other options this level of yield is not acceptable. Yields of less than 600 kg $ha^{-1}$ are unacceptable to most, if not all, of the farmers. In this study, two sets of classification criteria, namely *Classification A* and *Classification B* (Table 4.3), were investigated. These two sets differ only in number of years in ten with a given yield. Each set resulted in four suitability classes, i.e., Highly suitable (s1), Moderately suitable (s2), Marginally suitable (s3), and Not suitable (n).

### 4.2.5 Sensitivity of the suitability class to changes in the rainfall data set

For the rainfall data set from each of the five weather stations, data of ten-season pod yield, simulated for each soil under each of the 4 combinations of 2 planting dates and 2 water table depths, were used to classify the land suitability for the corresponding soils and combinations, based on *classification A*. The suitability classes evaluated for each rainfall data set were then compared among the corresponding soils and combinations

(Table 4.4). The sensitivity of the land suitability class to changes in the rainfall data set was then assessed qualitatively.

### 4.2.6 Sensitivity of the suitability class to changes in the classification criterion of number of years in 10 for a given yield level

Data for 10-season pod yield simulated for each soil, under each of the 4 combinations of 2 planting dates and 2 water table depths, were used to classify the land suitability based on *classification A* and *classification B*. The suitability classes evaluated using the different classification criteria were compared among the corresponding soils, and combinations. The sensitivity of the land suitability class to change in the classification criteria was then assessed qualitatively. Note that weather data inputs used for this purpose, except those of the solar radiation, were obtained from weather station #201. Solar radiation data were obtained from the Khon Kaen University station, located a few kilometers away from the station #201.

## 4.3 RESULTS

### 4.3.1 Sensitivity of the suitability class to changes in the rainfall data set

#### 4.3.1.1 Under condition of 2 m water table depth (Table 4.4a)

For a planting date of December 1, variations in the suitability classes evaluated using different sets of rainfall data were found within Phimai-loamy variant, Nakhon Phanom, and Ubon soils. Combined, these soils cover only 0.983 % of the total area of Khon Kaen. For a planting date of December 15, variations occurred within more soils, i.e., Chai Nat, Ratchaburi-loamy variant, Renu, Roi Et-loamy variant, Korat-sandy variant, Yasothon, and Ban Chong. These soils occupy 6.562 % of the whole province.

#### 4.3.1.2 Under condition of 3 m water table depth (Table 4.4b)

For a planting date of December 1, variations in the suitability classes evaluated using different sets of rainfall data, were found within Renu, Roi Et-loamy variant, Roi Et-high phase, and Khorat-sandy variant soils. These soils cover 5.033 % of the total area. For a planting date of December 15, variations occurred within fewer soils i.e., Si

Songkhram, Phimai-loamy variant, and Ban Chong, which together occupy only 0.554 % of the total area.

### 4.3.2 Sensitivity of the suitability class to changes in the classification criterion of number of years in 10 for a given yield level (Table 4.5)

#### 4.3.2.1 Under condition of 2 m water table depth

For a planting date of December 1, differences in the suitability classes evaluated based on the criteria defined in *classification A* and *classification B*, were found only within Nakhon Phanom soils which occupy 0.021 % of the total area of Khon Kaen. For a planting date of December 15, differences were found in Si Thon, and Roi Et-sandy variant soils, which cover only 0.512 % of the total area.

#### 4.3.2.2 Under condition of 3 m water table depth

For a planting date of December 1, differences in the suitability classes evaluated based on the criteria defined in *classification A* and *classification B*, were found within Renu, Roi Et-loamy variant, Roi Et-high phase, Roi Et-sandy variant, and Yasothon soils. These soils cover 7.910 % of the total area. For a planting date of December 15, the only difference occurred within Phimai-loamy variant soils which occupy only 0.279 % of the total area.

## 4.4 DISCUSSION AND CONCLUSION

On the basis of the raw data for 10-season pod yields, simulated for each soil, under each combination of water table depth and planting date (example in Table 4.6), and the data for corresponding land suitability classes (Tables 4.4a and b), the combination of a water table depth of 2 m for a planting date of December 1 was considered as the "good" condition for non-irrigated, dry season peanut cropping. Meanwhile, a water table of 3 m for a planting date of December 15, was considered as the "poor" condition. The other 2 combinations (i.e., the water table depth of 2 m by planting date of December 15, and the water table depth of 3 m by planting date of December 1) were considered as "intermediate" conditions.

For the "good" and the "poor" combinations, the suitability classes of only a few soils were found sensitive to the changes in either the rainfall data sets or the classification criteria. For the "intermediate" combinations, the suitability class of more soils was found to be sensitive to these changes. Therefore, in comparison to the classifications under conditions similar to those of the "good" and "poor" combinations, the land suitability classification under conditions similar to those of the "intermediate" combinations should be conducted more carefully. This is because the suitability class of significantly higher number of soils would be changed as either the rainfall data sets or the classification criteria were changed. As a result, land evaluators working in areas that have conditions similar to those of the "intermediate" combinations must pay more attention to the selection of the appropriate rainfall data set as well as the classification criteria. In terms of soil characteristics, no common characteristic was found among soils that showed sensitivity in their suitability classes.

As shown in Tables 4.1, 4.4 and 4.5, however, the soils found to have sensitive suitability classes in this study were those occupying only small portions of the province. Furthermore, for each of these soils, changes in the suitability class due to changes in either the rainfall data or the classification criteria were never beyond the adjacent classes. Thus, in general terms, the suitability class of soils in Khon Kaen is not sensitive to these changes. As a consequence, it is concluded that, (*i*) the available rainfall data from the five weather stations, which were considered in this study, are sufficient to generate information on land suitability for non-irrigated. dry season peanut cropping in the Khon Kaen province; and (*ii*) for the majority of soils in the Province, the suitability class is not sensitive to changes in the classification criteria investigated in this study.

**Table 4.1** Soils in Khon Kaen Province, Northeast Thailand (adapted from Soil Survey Division, 1973; Changprai, 1976; Keerati-Kasikorn, 1984).

| Physiography | Soil series, variant, phase, complex, association, or miscellaneous unit [1] | Area [1] (%) |
|---|---|---|
| Flood plain | Chiang Mai (Cm, Typic Ustifluvents) | 0.308 |
| | Tha Muong (Tm, Typic Ustifluvents) | 0.083 |
| | Sanphaya (Sa, Typic Ustifluvents) | 0.067 |
| | Chai Nat (Cn, Aeric Tropaquepts) | 0.002 |
| | Phimai (Pm, Vertic Tropaquepts) | 0.749 |
| | Ratchaburi (Rb, Aeric Tropaquepts) | 1.819 |
| | Si Songkhram (Ss, Vertic Tropaquepts) | 0.146 |
| | Si Thon (St, Aeric Tropaquepts) | 0.216 |
| | Phimai-loamy variant (Pm-l, Vertic Tropaquepts) | 0.279 |
| | Ratchaburi-loamy variant (Rb-l, Aeric Tropaquepts) | 0.003 |
| | Ratchaburi / Phimai association (Rb / Pm, Aeric Tropaquepts / Vertic Tropaquepts | 0.037 |
| | Alluvial complex | 3.097 |
| Low terrace | Nakhon Phanom (Nn, Aeric Paleaquults) | 0.021 |
| | Renu (Rn, Plinthic Paleaquults) | 0.479 |
| | Roi Et (Re, Aeric Paleaquults) | 24.745 |
| | Roi Et-loamy variant (Re-l, Aeric Paleaquults) | 1.882 |
| | Roi Et-dark surface variant (Re-d, Umbric Paleaquults) | 0.058 |
| | Roi Et-high phase (Re-h, Aeric Paleaquults) | 1.894 |
| | Roi Et-sandy variant (Re-s, Arenic Paleaquults) | 0.366 |
| | Phen (Pn, Typic Plinthaquults)[2] | 0.350 |
| | Ubon (Ub, Aquic Dystropepts) | 0.683 |
| | Udon (Ud, Aeric Halaquepts)[3] | 0.683 |
| | Roi Et-saline variant (Re-sa, Typic Natraqualfs)[3] | 0.708 |
| | Roi Et-clayey variant (Re-c, Typic Natraqualfs)[3] | 0.999 |

(cont.)

**Table 4.1** (cont.) Soils in Khon Kaen Province, Northeast Thailand (adapted from Soil Survey Division, 1973; Changprai, 1976; Keerati-Kasikorn, 1984).

| Physiography | Soil series, variant, phase, complex, association, or miscellaneous unit [1/] | Area[4/] (%) |
|---|---|---|
| Middle and high terraces | Korat / Roi Et association (Kt / Re, Oxic Paleustults / Aeric Paleaquults) | 0.050 |
| | Korat (Kt, Oxic Paleustults) | 19.691 |
| | Satuk (Suk, Oxic Paleustults) | 4.697 |
| | Warin (Wn, Oxic Paleustults) | 0.516 |
| | Yasothon (Yt, Typic Haplustults) | 3.289 |
| | Korat-sandy variant (Kt-s, Ustoxic Dystropepts) | 0.778 |
| | Warin-high phase (Wn-h, Oxic Paleustults) | 0.025 |
| | Nam Phong (Ng, Ustoxic Quartzipsamments) | 8.501 |
| | Nam Phong-red color variant (Ng-r, Ustoxic Quartzipsamments) | 0.341 |
| | Phon Phisai (Pp, Typic Plinthustults)[2/] | 5.27 |
| | Korat-gravelly variant (Kt-g, Oxic Paleustults)[2/] | 0.895 |
| | Yasothon-gravelly variant (Yt-g, Typic Haplustults) [2/] | 0.096 |
| | Nam Phong-gravelly variant (Ng-g, Ustoxic Quartzipsamments)[2/] | 0.092 |
| | Korat / Phon Phisai (Kt / Pp, Oxic Paleustults / Typic Plinthustults) | 1.282 |
| | Satuk / Phon Phisai (Suk / Pp, Oxic Paleustults / Typic Plinthustults) | 0.087 |
| | Nam Phong / Phon Phisai (Ng / Pp, Ustoxic Quartzipsamments / Typic Plinthustults) | 0.025 |
| | Korat / Tha Yang association (Kt / Ty, Oxic Paleustults / Vertic Haplustalfs) | 0.042 |

(cont.)

Table 4.1 (cont.) Soils in Khon Kaen Province, Northeast Thailand (adapted from Soil Survey Division, 1973; Changprai, 1976; Keerati-Kasikorn, 1984).

| Physiography | Soil series, variant, phase, complex, association, or miscellaneous unit [1] | Area [4] (%) |
|---|---|---|
| Hill and mountain slopes | Pak Chong (Pc, Oxic Paleustults) | 1.582 |
| | Thap Kwang (Tw, Vertic Haplustalfs) | 0.129 |
| | Lop Buri (Lb, Typic Paleusterts) | 0.05 |
| | Ban Chong (Bg, Typic Paleustults) | 0.129 |
| | Chatturat (Ct, Typic Haplustalfs) | 0.008 |
| | Chatturat-mottle variant (Ct-m, Aquic Haplustalfs) | 0.042 |
| | Tha Yang (Ty, Typic Paleustults)[2] | 0.375 |
| | Borabu (Bb, Aquic Plinthustults)[2] | 0.092 |
| | Tha Khli (Tk, Typic Calciustolls)[2] | 0.683 |
| | Tha Khli-concretionary variant (Tk-cn, Typic Calciustolls)[2] | 0.087 |
| Miscellaneous land type | Gravelly land | 0.191 |
| | Slope complex | 5.744 |
| | Rock out crop | 1.215 |
| | Pond and swamp | 3.814 |
| | Urban area | 0.108 |

[1] Corresponding abbreviations and US-Soil Taxonomy sub-groups' names are in parentheses.
[2] Shallow or gravelly soils
[3] Saline soils
[4] Total area of the province = 10.628 $km^2$

**Table 4.2** Conditions under which the peanut pod yields were simulated.

| Weather station | Water table | Planting date | Season | Soil |
|---|---|---|---|---|
| #002 | 2 m | 1-Dec | 1978-79 | Chiang Mai |
| | | | | Tha Moung |
| | | | | ↓ |
| | | | | Tha Khli |
| | | | ↓ | |
| | | | 1987-88 | Chiang Mai |
| | | | | Tha Moung |
| | | | | ↓ |
| | | | | Tha Khli |
| | | 15-Dec | 1978-79 | Chiang Mai |
| | | | | Tha Moung |
| | | | | ↓ |
| | | | | Tha Khli |
| | | | ↓ | |
| | | | 1987-88 | Chiang Mai |
| | | | | Tha Moung |
| | | | | ↓ |
| | | | | Tha Khli |
| | 3 m | Repeat for the same sets of planting date, season, and soil | | |
| #003 | Repeat for the same sets of water table depth, planting date, season, and soil | | | |
| #006 | Repeat for the same sets of water table depth, planting date, season, and soil | | | |
| #007 | Repeat for the same sets of water table depth, planting date, season, and soil | | | |
| #201 | Repeat for the same sets of water table depth, planting date, season, and soil | | | |

**Table 4.3** Classification criteria used in the study.

| Set of criteria | Level of suitability | Definition |
|---|---|---|
| Classification A | Highly suitable, s1 | Pod yields of more than 1200 kg $ha^{-1}$ were obtained at least 8 years in 10 |
| | Moderately suitable, s2 | Pod yields of more than 900 kg $ha^{-1}$ were obtained at least 8 years in 10, but did not meet requirement of s1 |
| | Marginally suitable, s3 | Pod yields of more than 600 kg $ha^{-1}$ were obtained at least 8 years in 10, but did not meet requirements of s2 |
| | Not suitable, n | Pod yields did not meet requirements of s1, s2, or s3 |
| Classification B | Highly suitable, s1 | Pod yields of more than 1200 kg $ha^{-1}$ were obtained at least 7 years in 10 |
| | Moderately suitable, s2 | Pod yields of more than 900 kg $ha^{-1}$ were obtained at least 7 years in 10, but did not meet requirement of s1 |
| | Marginally suitable, s3 | Pod yields of more than 600 kg $ha^{-1}$ were obtained at least 7 years in 10, but did not meet requirements of s2 |
| | Not suitable, n | Pod yields did not meet requirements of s1, s2, or s3. |

**Table 4.4a** Comparisons of land suitability classes evaluated for different conditions of soils, planting dates, and weather stations (when water table depth = 2 m).

| Soil[1] | Planting date: 1-Dec | | | | | Planting date: 15-Dec | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | #002[2] | #003 | #006 | #007 | #201 | #002[2] | #003 | #006 | #007 | #201 |
| Cm | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 |
| Tm | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 |
| Sa | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Cn | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s2 | s3 | s3 |
| Pm | s3 | s3 | s2 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Rb | [illegible] | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Ss | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| St | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Pm-l | s3 | s3 | s3 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Rb-l | s3 | s3 | s3 | s3 | s3 | [illegible] | s3 | s3 | s3 | n |
| Nn | s2 | s3 | s3 | s2 | s3 | [illegible] | s3 | s3 | s3 | s3 |
| Rn | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s2 | s3 | s2 |
| Re | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Re-l | s1 | s1 | s1 | s1 | s1 | s1 | s1 | s1 | s2 | s1 |
| Re-d | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Re-h | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Re-s | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Ub | s1 | s2 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Kt | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 |
| Suk | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Wn | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Yt | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s2 | s2 | s2 |
| Kt-s | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s2 | s2 | s2 |
| Wn-h | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Ng | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Ng-r | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Pc | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 |
| Tw | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 | s2 |
| Lb | s3 | s3 | s3 | s3 | s3 | s3 | s3 | [illegible] | s3 | s3 |
| Bg | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s2 | s3 | s3 |
| Ct | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |
| Ct-m | s1 | s1 | s1 | s1 | s1 | s2 | s2 | s2 | s2 | s2 |

1/ Soil names corresponding to each abbreviation are in Table 4.1
2/ Weather station number

**Table 4.4b** Comparisons of land suitability classes evaluated for different conditions of soils, planting dates, and weather stations (when water table depth = 3 m).

| Soil[1] | Planting date: 1-Dec | | | | | Planting date: 15-Dec | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | #002[2] | #003 | #006 | #007 | #201 | #002[2] | #003 | #006 | #007 | #201 |
| Cm | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Tm | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Sa | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Cn | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Pm | s3 | s3 | s3 | s3 | s3 | n | n | n | n | n |
| Rb | s3 | s3 | s3 | s3 | s3 | n | n | n | n | n |
| Ss | s3 | s3 | s3 | s3 | s3 | s3 | n | s3 | n | n |
| St | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Pm-l | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | n |
| Rb-l | s3 | s3 | s3 | s3 | s3 | n | n | n | n | n |
| Nn | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Rn | s3 | s3 | s3 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Re | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Re-l | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Re-d | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Re-h | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Re-s | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Ub | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Kt | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Suk | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Wn | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Yt | s3 | s2 | s3 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Kt-s | s3 | s2 | s3 | s2 | s3 | s3 | s3 | s3 | s3 | s3 |
| Wn-h | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Ng | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Ng-r | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Pc | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Tw | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 |
| Lb | s3 | s3 | s3 | s3 | s3 | n | n | n | n | n |
| Bg | s3 | s3 | s3 | s3 | s3 | s3 | n | s3 | n | n |
| Ct | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |
| Ct-m | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 | s3 |

[1] Soil names corresponding to each abbreviation are in Table 4.1
[2] Weather station number

**Table 4.5** Comparisons of the land suitability classes evaluated based on *classification A*, and *classification B*.

| Soil | Water table: 2 m | | | | Water table: 3m | | | |
|---|---|---|---|---|---|---|---|---|
| | Planting date 1 | | Planting date 2 | | Planting date 1 | | Planting date 2 | |
| | A[1/] | B[1/] | A | B | A | B | A | B |
| Cm | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s3 |
| Tm | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s3 |
| Sa | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Cn | s2 | s2 | s3 | s3 | s2 | s2 | s3 | s3 |
| Pm | s3 | s3 | s3 | s3 | s3 | s3 | n | n |
| Rb | s3 | s3 | s3 | s3 | s3 | s3 | n | n |
| Ss | s3 | s3 | s3 | s3 | s3 | s3 | n | n |
| St | s1 | s1 | **s2** | **s1** | s2 | s2 | s3 | s3 |
| Pm-l | n3 | s3 | s3 | s3 | s3 | s3 | **n** | **s3** |
| Rb-l | s3 | s3 | n | s3 | s3 | s3 | n | n |
| Nn | **s3** | **s2** | s3 | s3 | s3 | s3 | s3 | s3 |
| Rn | s2 | s2 | s2 | s2 | **s3** | **s2** | s3 | s3 |
| Re | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Re-l | s1 | s1 | s1 | s1 | **s3** | **s2** | s3 | s3 |
| Re-d | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Re-h | s1 | s1 | s2 | s2 | **s3** | **s2** | s3 | s3 |
| Re-s | s1 | s1 | **s2** | **s1** | **s3** | **s2** | s3 | s3 |
| Ub | s1 | s1 | s2 | s2 | s3 | s3 | s3 | s3 |
| Kt | s2 | s2 | s2 | s2 | s2 | s2 | s3 | s3 |
| Suk | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Wn | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Yt | s2 | s2 | s2 | s2 | **s3** | **s2** | s3 | s3 |
| Kt-s | s2 | s2 | s2 | s2 | s3 | s2 | s3 | s3 |
| Wn-h | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Ng | s1 | s1 | s2 | s2 | s3 | s3 | s3 | s3 |
| Ng-r | s1 | s1 | s2 | s2 | s3 | s3 | s3 | s3 |
| Fc | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 |
| Tw | s2 | s2 | s2 | s2 | s3 | s3 | s3 | s3 |
| Lb | s3 | s3 | s3 | s3 | s3 | s3 | n | n |
| Bg | s2 | s2 | s3 | s3 | s3 | s3 | n | n |
| Ct | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |
| Ct-m | s1 | s1 | s2 | s2 | s2 | s2 | s3 | s3 |

[1/] "*Classification A*", and "*Classification B*"

**Table 4.6** An example of pod yield (kg ha$^{-1}$) data by soils and seasons, and the corresponding land suitability classes. The data were simulated for conditions where water table depth was 2 m, and planting date was December 1. Weather data were from station # 201.

| Soil [1] | Pod yield (kg ha$^{-1}$) | | | | | | | | | | | | | Suitability class [2] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 78-79 [3] | 79-80 | 80-81 | [illegible] | 82-83 | 83-84 | 84-85 | 85-86 | 86-87 | 87-88 | 88-89 | 89-90 | 90-91 | |
| Cm | 1048.6 | 1108.7 | [illegible] | [illegible] | 1256.0 | 1191.3 | 1234.5 | 1370.9 | 1222.7 | 1126.5 | 956.5 | 865.9 | 534.4 | s2 |
| Tm | 1063.0 | 1134.0 | [illegible] | [illegible] | 1286.8 | 1212.6 | 1260.4 | 1381.6 | 1231.4 | 1134.4 | 956.5 | 870.5 | 534.4 | s2 |
| Sa | 1151.3 | 1298.3 | [illegible] | [illegible] | 1448.0 | 1306.0 | 1413.4 | 1456.9 | 1272.5 | 1162.0 | 971.7 | 890.4 | 559.3 | s1 |
| Cn | 1000.8 | 1024.6 | 1061.0 | [illegible] | 1151.6 | 1094.3 | 1158.7 | 1342.6 | 1205.2 | 1122.0 | 993.7 | 917.8 | 568.4 | s2 |
| Pm | 729.7 | [illegible] | [illegible] | [illegible] | 833.1 | 804.9 | 841.9 | 956.2 | 832.8 | 731.6 | 698.1 | 607.1 | 375.5 | s3 |
| Rb | [illegible] | [illegible] | [illegible] | [illegible] | 833.1 | 804.9 | 841.9 | 956.2 | 832.8 | 731.6 | 698.1 | 607.1 | 375.5 | s3 |
| Ss | 764.5 | 807.1 | [illegible] | [illegible] | 913.9 | 870.0 | 915.6 | 1027.0 | 903.9 | 786.8 | 733.3 | 615.1 | 389.4 | s3 |
| St | 1278.8 | 1412.3 | [illegible] | 2162.1 | 1553.8 | 1402.4 | 1489.1 | 1594.6 | 1417.7 | 1309.1 | 1091.2 | 1014.7 | 644.3 | s1 |
| Pa-l | 832.2 | 808.0 | 828.7 | 1330.4 | 897.6 | 907.9 | 932.7 | 1122.2 | 1037.4 | 968.5 | 898.3 | 839.8 | 516.6 | s3 |
| Rb-l | 726.8 | 672.8 | 683.9 | 1209.8 | 724.7 | 771.0 | 781.5 | 942.9 | 910.4 | 872.8 | 841.3 | 869.8 | 538.7 | s3 |
| Na | 855.5 | 853.8 | 890.2 | [illegible] | 962.4 | 948.5 | 978.3 | 1143.1 | 1023.6 | 928.4 | 855.4 | 744.7 | 469.9 | s3 |
| Rn | 1014.1 | 1016.5 | 1053.9 | [illegible] | 1139.4 | 1113.7 | 1141.3 | 1360.4 | 1268.5 | 1146.1 | 1011.5 | 956.1 | 598.0 | s2 |
| Re | 1150.1 | 1308.7 | 1320.0 | 2016.4 | 1445.3 | 1333.5 | 1406.1 | 1442.7 | 1276.3 | 1167.0 | 956.5 | 883.4 | 534.4 | s1 |
| Re-l | 1354.2 | 1484.3 | [illegible] | 2202.7 | 1623.9 | 1414.6 | 1524.8 | 1635.7 | 1479.8 | 1357.9 | 1193.3 | 1069.2 | 697.5 | s1 |
| Re-d | 1150.1 | 1308.7 | [illegible] | 2016.4 | 1446.3 | 1333.5 | 1406.1 | 1442.7 | 1276.3 | 1167.0 | 956.5 | 883.4 | 534.4 | s1 |
| Re-h | 1150.1 | 1308.7 | 1320.0 | 2016.4 | 1446.3 | 1333.5 | 1406.1 | 1442.7 | 1276.3 | 1167.0 | 956.5 | 883.4 | 534.4 | s1 |
| Re-s | 1292.3 | 1413.9 | [illegible] | 2172.7 | 1550.4 | 1403.6 | 1485.8 | 1613.2 | 1436.0 | 1325.7 | 1113.5 | 1030.9 | 660.5 | s1 |
| Ub | 1207.4 | 1298.5 | [illegible] | 2137.3 | 1434.1 | 1325.2 | 1393.8 | 1535.9 | 1394.0 | 1268.8 | 1066.4 | 998.2 | 627.8 | s1 |
| Kt | 1047.9 | 1108.4 | [illegible] | 1742.8 | 1255.9 | 1190.7 | 1234.5 | 1370.9 | 1222.7 | 1126.5 | 956.5 | 865.9 | 534.4 | s2 |
| Suk | 1134.8 | 1290.8 | 1302.7 | 1996.4 | 1429.2 | 1325.4 | 1386.2 | 1430.0 | 1261.0 | 1148.3 | 937.6 | 864.8 | 524.2 | s1 |
| Wn | 1150.1 | 1308.7 | 1320.0 | 2016.4 | 1446.3 | 1333.5 | 1406.1 | 1442.7 | 1276.3 | 1167.0 | 956.5 | 883.4 | 534.4 | s1 |
| Yt | 1023.2 | 1033.5 | 1072.9 | [illegible] | 1161.4 | 1128.7 | 1159.6 | 1364.6 | 1269.9 | 1145.3 | 1001.3 | 941.3 | 589.3 | s2 |
| Kt-s | 1023.2 | 1033.5 | 1072.9 | 1844.2 | 1161.4 | 1128.7 | 1159.6 | 1364.6 | 1269.9 | 1145.3 | 1001.3 | 941.3 | 589.3 | s2 |
| Wn-h | 1150.1 | 1308.7 | 1320.0 | 2016.4 | 1446.3 | 1333.5 | 1406.1 | 1442.7 | 1276.3 | 1167.0 | 956.5 | 883.4 | 534.4 | s1 |
| Ng | 1207.4 | 1298.5 | 1320.3 | 2137.3 | 1434.1 | 1325.2 | 1393.8 | 1535.9 | 1394.0 | 1268.8 | 1066.4 | 998.2 | 627.8 | s1 |
| Ng-r | 1207.4 | 1298.5 | 1320.3 | 2137.3 | 1434.1 | 1325.2 | 1393.8 | 1535.9 | 1394.0 | 1268.8 | 1066.4 | 998.2 | 627.8 | s1 |
| Pc | 1010.5 | 1124.4 | 1150.7 | 1759.2 | 1261.9 | 1164.3 | 1226.1 | 1279.4 | 1109.1 | 985.0 | 847.8 | 759.5 | 467.8 | s2 |
| Tw | 1010.5 | 1124.4 | 1150.7 | 1759.2 | 1261.9 | 1164.3 | 1226.1 | 1279.4 | 1109.1 | 985.0 | 847.8 | 759.5 | 467.8 | s2 |
| Lb | 780.9 | 837.1 | 859.8 | 1267.7 | 937.0 | 862.4 | 929.6 | 997.4 | 880.6 | 738.3 | 682.3 | 550.8 | 362.2 | s3 |
| Bg | 949.9 | 950.5 | 976.7 | 1624.2 | 1054.1 | 1025.8 | 1086.4 | 1207.7 | 1116.0 | 1052.7 | 948.8 | 892.4 | 562.5 | s2 |
| Ct | 1143.9 | 1226.9 | 1254.7 | 2004.2 | 1365.4 | 1240.2 | 1342.8 | 1456.1 | 1309.7 | 1213.4 | 1037.4 | 956.8 | 605.7 | s1 |
| Ct-m | 1143.9 | 1226.9 | 1254.7 | 2004.2 | 1365.4 | 1240.2 | 1342.8 | 1456.1 | 1309.7 | 1213.4 | 1037.4 | 956.8 | 605.7 | s1 |

1/ Soil name corresponding to each abbreviation is in Table 4.1

2/ s1 = highly suitable s2 = moderately suitable s3 = marginally suitable n = not suitable

3/ Dry season year

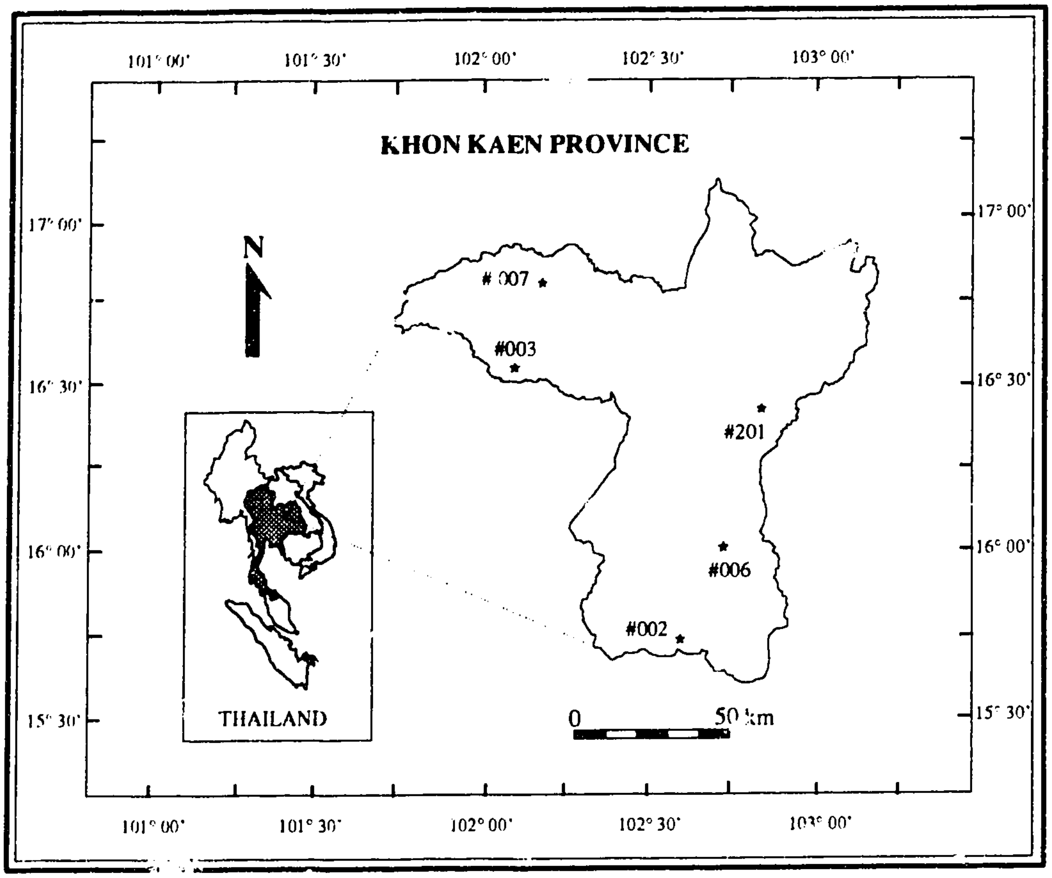


**Figure 4.1** Location of Khon Kaen Province in Thailand with locations of weather stations ( * ) and the corresponding station numbers (adapted from Hydrometeorology Division, 1988).

## 4.5 REFERENCES


Changprai, C. 1976. Classification and Uses of Soils in Northeast Thailand. Soil Survey Division, Department of Land Development, Bangkok, Thailand. (in Thai).

FAO. 1983. Guidelines: Land Evaluation for Rainfed Agriculture. Soils Bull. 52. FAO. Rome.

Jintrawet, A., R. Katawatin, and W. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Khon Kaen University: Cropping Systems Research Project. (in Thai with English abstract).

Jintrawet, A., S. Smutkupt, S. Rattanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya, 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University (in Thai with English summary).

Keerati-Kasikorn, P. 1984. Soils of Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Thailand. (in Thai).

Kerdsuk, V., and A. Patanothai, 1990. Testing and Implementation for Rainfed Dry Season Peanut: Khon Kaen University Experience. Farm News. Farming System Research Project, Khon Kaen University. 63: 24-35. (in Thai).

Penning De Vries F.W.T., D.M. Jansen, H.F.M. ten Berg, and A. Bakema. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Simulation Monograph 29. Pudoc, Wageningen, and IRRI, Los Baños.

Soil Survey Division. 1973. Detailed-Reconnaissance Soil Map of Khon Kaen Province. Department of Land Development, Bangkok, Thailand.


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# CHAPTER 5

# SIMULATION MODELING OF LAND SUITABILITY EVALUATION (III): A CASE STUDY OF THE MACROS CROP MODEL APPLICATION AT THE DISTRICT LEVEL

## 5.1 INTRODUCTION

The northeast third of Thailand is the poorest region of the country in terms of per capita income and living conditions of people. Most of the population are small scale farmers. Various attempts have been made to improve economic conditions in this region by increasing agricultural land use efficiency and per capita income. One promising alternative is to introduce dry season cropping, so that farmers can gain benefit from more than one crop per year from the same piece of land. Research at experimental stations and selected farmers' fields has shown that peanut has high potential as a crop to grow in the dry season after main crops under rainfed conditions. However, implementation of the non-irrigated, dry season peanut cropping in the farmers' fields frequently failed due to lack of appropriate information on the performance of land areas when used for this purpose. Existing information is the Land Capability Classification published in the form of 1:100,000 maps and accompanying reports (Soil Survey Division, 1975). This kind of information was generated based on the USDA system of Klingebiel and Montgomery (1961) which is primarily designed for soil conservation and sustainable agricultural production. The land capability classification system was criticized for being unquantified and too generalized (La[illegible], 1991). McRae and Burnham (1981) stated that the system was subjective and depends largely on the opinion of the evaluator who may or may not be sufficiently experienced to make the correct value judgments. Furthermore, there is no indication of the suitability of a land area for a specific crop. Different crops are very diverse in their requirements, and limitations which are critical for some may not be significant for others. Therefore, this system is not considered to be sufficiently detailed to assess land suitability for non-irrigated, dry season peanut cropping in Northeast Thailand. As a result, there is a need to generate information specific for the desired purpose.

The land evaluation procedure suggested in the FAO Framework for Land Evaluation (FAO, 1976) has been widely used to assess land potential for specified agricultural uses. This procedure involves the definition of a number of requirements for each type of use. These requirements are then compared with the corresponding land qualities (FAO, 1983) associated with the land unit being considered. These land qualities are usually expressed in terms of a number of land characteristics which can be acquired either in the field or from the soil survey publications (Bouma et al., 1993). Since this present study was conducted in Northeast Thailand where the most critical limiting factor for crop production is water, problems could occur if the FAO land evaluation procedure was applied. The "water availability" land quality (FAO, 1983) is difficult to express in terms of available land characteristics. This is because it is a complex function of various factors related to soil and its environment such as rainfall, evaporative demand, and physical properties of soil as expressed by soil water retention and hydraulic conductivity. The commonly used expressions for water availability, as a land quality, in terms of soil texture, available water capacity, and rooting depth provide only very generalized characterization, mainly useful in studies comparing different land units in a large area but not in the assessment of land potential for a specific use (Bouma et al., 1993).

The use of crop modeling techniques for simulating crop growth based on water availability is a promising alternative, to assess land potential for specified uses. Because of its capacity to handle large volumes of data simultaneously, computerized crop models can simulate crop growth and yield for each land unit in relation to water availability, as reflected by various environmental factors mentioned earlier. Data on crop yield can be used directly in land evaluation to express the potential of land for that particular crop (Dumanski and Onofrei, 1989). For this study, the MACROS model for crop growth simulation under conditions in which only water is limiting (production level 2, Penning de Vries et al., 1989), was applied. This model has already been calibrated and validated for non-irrigated, dry season peanut cropping in Khon Kaen Province, Northeast Thailand (Chapter 3). Application of simulation models for land evaluation purposes can be effectively facilitated through the use of geographic information systems (GIS) (McBride and Bober, 1993; Magnusson and Söderström, 1994). The objective of this study was, therefore, to investigate the use of the MACROS crop model, assisted by a geographic information system, to generate information on land suitability for non-irrigated, dry season peanut cropping at the District level, in Khon Kaen Province, Northeast Thailand.

### 5.1.1 Study Area

The study area is Kranuan District, Khon Kaen Province, Northeast Thailand. The district lies between latitude 16° 28′ and 16° 55′ north, and longitude 102° 55′ and 103° 13′ east. The total area is approximately 685 km$^2$ (Figure 5.1).

The Kranuan District was selected as the study area for two reasons. First, the district includes all of the major soils and landscape features found in Northeast Thailand. Second, field surveys, local researchers, and related research papers (Jintrawet et al., 1986; Kerdsuk and Patanothai, 1990) suggested that many farmers in this district are interested in growing peanut in the dry season. In some parts of the district, farmers have grown dry season peanut crops without irrigation successfully for some years. Thus there is a pressing need for information on the suitability of land areas for this type of land use.

## 5.2 MATERIALS AND METHODS

### 5.2.1 The MACROS crop model

The MACROS crop model was used to simulate data on pod yield of dry season peanut crop grown without irrigation, with the assumption that water is the only limiting factor for plant growth (Production Level 2, Penning de Vries et al., 1989). The simulated yield data were, in turn, used to express the degree of land suitability for this cropping system in Kranuan District. Prior to the application, the model was evaluated using both calibration and validation phases (Chapter 3). The results of this evaluation have revealed the usefulness of the model to adequately estimate yield of non-irrigated, dry season peanut cropping. Penning de Vries et al. (1989) provide detailed descriptions of MACROS and its scientific background. A brief description of the model is in Chapter 3.

### 5.2.2 Crop model inputs

Input data required by MACROS consists of those related to crop, soil, weather, and management parameters.

*1) Crop parameters*

Crop parameters are those related to photosynthesis and respiration, biomass partitioning, phenological development, soil water relations and root growth. Some of these parameters, including Maximum Rate of Photosynthesis for Reference Temperature (PLMXP), Maximum Growth Rate of Rooting Depth (GZRTC), and Water Stress Sensitivity Coefficients (WSSC), were adjusted to calibrate the model to the conditions in Khon Kaen Province (Chapter 3). After adjustment, the values of GZRTC, PLMXP, and WSSC were 0.035 m $d^{-1}$, 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$, and 0.65, respectively. These values were used in conjunction with other crop input parameters, suggested by Penning de Vries et al. (1989) to run the model.

*2) Soil paramet*

The study area comprises 17 map units named after 11 soil series, 2 variants of soil series, 2 phases of soil series, 1 soil association, and 1 slope complex unit (Table 5.1) Predominant soils are members of the Roi Et and Korat series which, all together, cover 62.5 % of the whole area of the Kranuan District. This soil information was derived from the 1:100,000 Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973). The map was originally made at scale 1:50,000 , but to decrease the number of map sheets, the scale was reduced to 1:100,000.

From Table 5.1, Phimai and Sithon series include poorly drained, clayey textured soils, found in river basins. Roi Et, Phen, and Renu series are located on low terrace position. Roi Et and Renu have sandy loam to fine sandy loam texture in the upper part of the profiles. The texture becomes finer, to sandy clay loam, with depth. Phen has laterite gravel in the subsoil within 50 cm of the surface. Korat, Satuk, Yasothon, Nam Phong, and Phon Phisai series include soils on middle to high terrace positions. Korat, Satuk, and Yasothon are deep soils of similar characteristics. These soils have loamy sand to sandy loam texture at the surface, and sa y clay loam in the sub-soil. Nam Phong has sandy texture throughout the profile. Phon Phisai is a shallow soil which has laterite gravel within 50 cm of the surface. Tha Yang is a shallow soil found on hill slopes. Its texture is sandy loam to sandy clay loam over gravelly sandy clay loam to gravelly sandy clay. The majority of soils in the study area, like most soils in Northeast Thailand, have low inherent fertility. Detailed descriptions for each of these soils can be found in the Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973), and Keerati-Kasikorn (1984).

In this study, the MACROS model was used to simulate crop growth on soil series, phase, or variant basis. Note that five map units were not considered in the simulation, viz. Phen, Phon Phisai, Tha Yang, Slope Complex, and Korat / Phon Phisai association. These units were assumed unsuitable for the non-irrigated, dry season peanut cropping. Phen, Phon Phisai and Tha Yang are the map units of shallow soils while Slope Complex is the map unit of steep sloped areas. The map unit of Korat / Phon Phisai association has shallow soils of the Phon Phisai series, and this unit occupies only 19 ha (0.03 % of the total study area).

The MACROS model requires a number of soil parameters including depth, texture, soil physical characteristics and constants related to the water storage capacity of soil surface and soil evaporation, initial soil moisture content, and water table depth (Penning de Vries et al., 1989). The input parameter of soil texture was derived from the description of typical soil profiles for each soil series, variant, or phase as provided by Keerati-Kasikorn (1984). Model inputs required to calculate evaporation rate, i.e., texture specific empirical constants, were interpreted based on their relationship with soil texture as provided in Penning de Vries et al. (1989). Other empirical constants and parameters required for calculating relationships between soil moisture content, soil moisture suction, and hydraulic conductivity, were provided by the original values of the model based on the relationship between soil texture and these parameters as shown in Table 26 , page 152 in Penning de Vries et al. (1989). The parameter of initial moisture content was not measured directly in the field, but was calculated from data on water table depth and soil texture, using MACROS.

It must be noted that, in Northeast Thailand, water table depth is one of the most important factors that determines the success of dry season cropping (Chantorn, 1983; Jintrawet et al., 1986; Penning de Vries et al., 1989; Kerdsuk and Patanothai, 1990). The most important source of water for dry season cropping is ground water. Unfortunately, data on water table depth, precise enough for crop simulation, were not available for the entire study area or elsewhere in the region (except for a few small areas where specific research projects were conducted). Values of this input parameter must be assumed and in this study, 4 water table depths were used, viz. 1, 2, 3, and 4 m. In this region, a water table shallower than 1 m may cause reduced yield due to wetness (Jintrawet, et al., 1986). On the other hand, a water table deeper than 4 m generally does not have a significant effect on crop production (Penning de Vries et al., 1989).

*3) Weather data*

Weather data used as model inputs for MACROS included rainfall, maximum temperature, minimum temperature, wind speed, relative humidity, and solar radiation. In Khon Kaen Province, five weather stations were found to have adequate sets of the required data in digital form. To select the station from which the data were used to represent weather conditions of Kranuan District, the province was divided into Thiessen polygons (Aronoff, 1989) based on these five weather stations (Figure 5.1). The station within the polygon that covers Kranuan District (station #201) was selected. This station is approximately 40 km away from the center of the study area. Weather data recorded at this station for eleven years (i.e., 1978 through 1988) were used to simulate crop yield data for ten seasons (i.e., dry season 1978-79 through 1987-88). Note that data on solar radiation were not available at station #201. This type of data was obtained, in hard copy form, from the Khon Kaen University weather station, located a few kilometers away from station #201, and was input manually to MACROS.

*4) Management practices*

Planting dates for cropping vary between farmers and seasons. According to Kerdsuk and Patanothai (1990), the planting date for non-irrigated, dry season peanut cropping in this region is between late-November and late-December. Hence four planting dates were modeled: November 15, December 1, December 15, and January 1. Note that the beginning date for the simulation was assumed to be 1 week after the planting date because the simulation of crop growth during the seed germination stage is difficult (Penning de Vries et al., 1989). The planting depth used in the sim[illegible]n was 15 cm, corresponding to that recommended by Jintrawet et al. (1983).

### 5.2.3 Geographic Information System (GIS)

A geographic information system is a computer system for collecting, storing, retrieving at will, transforming, and displaying spatial data from the real world for a particular set of purposes (Burrough, 1986). In this study, GRASS 4.1 (Shapiro et al., 1993), a publicly available geographic information system, was used to facilitate the process of land suitability evaluation.

In Northeast Thailand, at present, the availability of historic weather data in digital form, is limited to a small number of meteorological stations, and a few years of recording. Moreover, some soil parameters needed to run the model are not specific for the conditions in the northeast (Chapter 3). This might affect accuracy of the simulation results. In such a case, the geographic information system (GIS) can help maintain flexibility to revise the results as larger amounts and / or more precise data become available.

### 5.2.4 Definition of Land Suitability Classes

Although the classification was based on crop yield data simulated for each map unit named after soil series, phase, variant, or association, the term "land suitability class" was used to represent the level of suitability for each of these map units. This is because, not only the soils, but also other land attributes (i.e., weather conditions) were taken into account.

This land suitability classification is considered "provisional" (FAO, 1983), because it is based on the values of pod yield simulated by MACROS at production level 2 (Penning de Vries et al., 1989). At this production level, it is assumed that only water is limiting crop growth. The model does not consider any other detrimental effects (e.g., low inherent soil fertility) that could occur in field conditions.

The definition of suitability classes was based on results of the Farming System Research Project, carried out at Khon Kaen University (Kerdsuk and Patanothai, 1990) which indicated that peanut pod yield greater than 1200 kg $ha^{-1}$ was "satisfactory" to most farmers in Khon Kaen Province, as well as those in other study areas in Northeast Thailand. Pod yield of 900-1200 kg $ha^{-1}$ is still "acceptable" for most farmers. Pod yield of 600-900 kg $ha^{-1}$ is acceptable only in some areas where farmers do not have other alternatives for the dry season. However, in other areas where farmers have alternative options this amount of yield is not acceptable. Yield of less than 600 kg $ha^{-1}$ is unacceptable to most, if not all, of the farmers. Accordingly, four suitability classes were defined:

Highly suitable, s1: pod yields of more than 1200 kg $ha^{-1}$ were obtained at least 8 years in 10,

Moderately suitable, s2: pod yields of more than 900 kg $ha^{-1}$ were obtained at least 8 years in 10, but did not meet requirements of s1,

Marginally suitable, s3: pod yields of more than 600 kg $ha^{-1}$ were obtained at least 8 years in 10, but did not meet requirements of s2, and

Not suitable, n: pod yields did not meet requirements of s1, s2, or s3.

### 5.2.5 Study methods

The study proceeded through three phases to generate information on land suitability for non-irrigated, dry season peanut cropping.

*1) Digitizing and storing soil data*

Soil map polygons named after soil series, covering the whole area of Kranuan District, were digitized from the 1:100,000 Detailed Reconnaissance Soil Map of Khon

Kaen Province (Soil Survey Division, 1973), and stored in the GRASS geographic information system for further use.

*2) Simulating peanut yield data*

The MACROS crop model was used to simulate pod yield data of dry season peanut crop grown without irrigation. Peanut yield data were simulated for each soil series, phase, or variant for:

*i*) 16 combinations of 4 planting dates (November 15, December 1, December 15, and January 1) by 4 water table depths (1, 2, 3, and 4 m); and

*ii*) recorded weather data for each of 10 growing seasons from the dry seasons of 1978-79 to 1987-88.

The model was run on a PC 486 DX computer.

*3) Suitability classification*

For each soil, data of 10-season simulated pod yield under each of the 16 combinations (of 4 planting dates by 4 water table depths), were used to classify the "provisional" land suitability based on the definition of land suitability classes described above as s1, s2, s3 and n. Once information on the suitability class for each soil map polygon under each condition was obtained, a land suitability map for each condition was generated. Therefore, a total of 16 maps representing the above combinations were generated using the GRASS geographic information system.

**5.2.6 Assumptions concerning management conditions**

As mentioned earlier, the outputs of this land suitability classification were derived from pod yield data generated using MACROS at production level 2, which assumes that only water is limiting for plant growth. Therefore, ideally, all other growth factors must be controlled to optimum conditions. This includes maximum rate of fertilizer and pesticide applications, and regular weed control. However, in Northeast Thailand, dry season cropping with high management inputs is, generally, not practical because of being considered too risky due to inherent low productivity of the land and the poverty of farmers. Thus the following management conditions were assumed to reach a compromise between theory and practice.

*1) Land preparation*

Maximum level of land preparation should be applied to obtain a good seed bed, and to control weeds. Many related research papers (e.g., Jintrawet et al., 1983; Kerdsuk and Patanothai, 1990) report that good land preparation is a key for the success of non-irrigated, dry season peanut cropping in this region. Also, most farmers in the northeast can afford the maximum land preparation because they have enough labor. As the simulation of crop growth during the seed germination stage is difficult (Penning de Vries et al., 1989), in this study, the simulations were begun after this stage (1 week after planting). Therefore, the importance of a good seed bed, existing in field conditions, was not taken into account by the model.

*2) Fertilizer application*

The recommended rate of fertilizer for a specific area would be applied.

*3) Pest control*

Problems of pests for dry season cropping, either from weeds, diseases, or insects are, usually, not severe because of relatively dry conditions. However, if the problems occur, counter measures would be applied only when there would be an expectation of significant yield increase.

## 5.3 RESULTS AND DISCUSSION

### 5.3.1 Outputs of the Land Suitability Classification

Outputs of the land suitability classification for non-irrigated, dry season peanut cropping, under 16 combinations of 4 planting dates by 4 water table depths were generated in 2 forms: *(i)* table (Table 5.2), and *(ii)* 16 digital maps in the GRASS geographic information system. In addition, hard copies of these maps (e.g., Figure 5.2) can be generated, if required. Based on data presented in Table 5.2, effects of soil, water table depth, and planting date on the suitability of land for non-irrigated, dry season peanut cropping are discussed in the following paragraphs.

### 5.3.2 Effects of soil

Each soil series, phase or variant has its own characteristics. Therefore, results of the classification showed that even under the same condition of planting date by water table depth, many of these soils have been assigned to different land suitability classes. In addition to the shallow soils and the soils in slope complex areas which were assumed to be not suitable, fine textured soils of the Phimai, and Sithon series were assigned to the lowest suitability class for dry season peanut cropping without irrigation. They were classified as marginally suitable or not suitable for almost every condition of planting date and water table depth considered in this study. This is because, these heavily clayey textured soils have a relatively low available water capacity, and relatively narrow range of water content between field capacity and saturation (Keerati-Kasikorn, 1984; Penning de Vries et al., 1989). As described in Chapter 3, section 3.2.2.2, the actual rate of water uptake and, in turn, the crop growth, is reduced under either water stress or flooding conditions. In MACROS, for the water stress conditions (e.g., water table depths ≥ 3 m), the actual rate of water uptake is calculated from the potential uptake rate and the stress multiplication factor ranging from 1.0 to 0.0. In comparison to those from the soils with higher available water capacity, the stress multiplication factors for the soils with lower available water capacity decrease more rapidly as the soil moisture decreases from field capacity. This results in the greater reduction of water uptake rate. The effect of flooding on water uptake is approximated in a similar manner to the effect of water shortage. This effect is assumed to be proportional to the soil moisture content between field capacity and saturation. In the soils with a narrower range of water content between field capacity and saturation, the reduction of water uptake as soil water content increases from field capacity (e.g., under conditions where water table depth = 1 m) is more rapid than that of the soils with the wider range.

For the other soils that have coarser texture, ranging from fine sandy to sandy clay, the suitability classes may vary from highly suitable to not suitable, depending upon planting date and water table depth.

### 5.3.3 Effects of water table depth

A shallow water table (i.e., 1 m) has a strong adverse effect, due to wet conditions, on the suitability levels of fine and relatively fine textured soils including Phimai, Sithon, and Renu series, as well as Roi Et series, variants and phase. Figure 5.3 shows an example of dynamics of soil moisture content in a fine textured Pimai soil, which was considerably higher than field capacity throughout the season. However, for coarser textured soils such as Korat, Yasothon, and Nam Phong, this adverse effect was not significant because of better soil moisture conditions (Figure 5.4). This is true for every planting date, and every season considered in this study Due to the relatively low amount of rainfall, soil moisture content during the dry season heavily depends on ground water. A water table at 2 m from the surface was the depth at which all soils are at their highest suitability class (Table 5.2). This is also true for every planting date. This might be because, for any particular soil, a water table at 2 m depth results in more suitable soil moisture content throughout the season, as compared to those resulting from higher or lower water table depths (Figure 5.5).

For every soil and every planting date, water table depths of 3 m or deeper result in a lower suitability class (Table 5.2). This might be because the effect of dryness becomes stronger with depth of water table. At a water table depth 4 m, the majority of soils were classified as marginally suitable or not suitable.

### 5.3.4 Effects of planting date

In general, under every condition of soil and water table depth, the later the planting date the lower the pod yield and thus the suitability class. The reductions in suitability class, in this case, are not necessarily due to the stronger drought effect for crops under conditions of a later planting date. Under the same water table depth, either 1, 2, 3, or 4 m, the dynamic of water content for an early planting date was not significantly different from that for later dates. In Figure 5.6, the dynamics of soil moisture content for planting date 1 (November 15) is compared with that for planting date 4 (January 1), under the same conditions of Korat soil and a water table of 2 m depth in 1978-79 season. The dynamics of soil moisture for these two planting dates are similar. Although this kind of similarity was found for every soil, every water table depth, and every season considered in this study (season 1978-79 through 1987-88), the suitability class for a particular soil seeded on planting date 1 is different from that seeded on planting date 4. In the case of Korat soil with water table of 2 m depth, the suitability classes are s1 and s3 for planting date 1 and 4, respectively. This reveals that, for a particular soil, the difference in simulated pod yield obtained and, in turn, the land suitability classes found as a result of different dates of planting, was most likely due to differences in weather conditions under which the crop developed beginning with these two planting dates.

Further explanation lies in a consideration of the scientific background used for the development of the MACROS model, and the dynamics of weather components (i.e., rainfall, minimum temperature, maximum temperature, relative humidity, wind speed, and solar radiation) during the growing period of peanut crop planted on different dates. It is probable that the yield reduction of late planted peanut was due to a higher temperature regime during its growing period compared to that of the early planted peanut. The temperature, in this case, is referred to as the "effective temperature for photosynthesis" (Penning de Vries et al., 1989) which is assumed to be the average day temperature, calculated as the mean of the 24 hour average and the maximum temperature. Figure 5.7 illustrates a comparison of the dynamics of "effective temperature for photosynthesis" during the growing period of early and late planted peanut cropping in the 1978-79 season in which the temperature regime for the late planted peanut cropping was, in general, considerably higher than that of the early planted one. The effective temperature for photosynthesis from the 30 th day to the 90 th day range from approximately 28-38° C and 22-32° C for peanut planted on the late date and the early date, respectively. Similar phenomenon was found in every season considered in this study.

The MACROS model simulates the photosynthesis rate using the fact that temperature has an effect on Maximum Rate of Photosynthesis (PLMX) and Initial Efficiency of the Use of Absorbed Light at Actual Temperature (PLEA). For a C3 plant such as peanut, the highest value of PLMX is found between 20-30° C (Pannangpetch, 1992). Also the PLEA value is reduced considerably at temperatures of 30° C or higher (Penning de Vries et al., 1989). Further investigation on the temperature effects on yield reduction of late planted peanut is warranted. For example, if the research result shows that pod yield of peanut grown in late dry season is limited by high temperature, then it may not be worthwhile to implement peanut cropping in late dry season even with irrigation.

### 5.3.5 On the use of the Suitability Classification outputs

To properly use the outputs of this suitability classification, the following should be taken into account.

1) This suitability classification is only for "Non-Irrigated, Dry Season Peanut Cropping" under the assumed management conditions described earlier. It may not be appropriate for other types of land use.

2) As previously mentioned, the information on precise water table depth was not available for the study area, and planting date varied between farmers and seasons. In order to generate information on the suitability of land areas which cover all important conditions, the suitability classification was done for 16 scenarios of 4 planting dates by 4

water table depths. Users must decide which scenario(s) of planting date and water table depth to use for a specific area and farmer. Reliable estimations of water table depth and planting date can usually be obtained from farmers or local extension specialists familiar with a specific location.

3) In cases where the land suitability maps are not available, results of the suitability classification shown on Table 5.2 can be used in conjunction with the Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973) to assess the suitability class of each map unit in the study area, under each condition of planting date and water table depth.

4) For areas classified as marginally suitable (s3), application of fertilizer should be made only when an economic benefit might be expected. These areas have inherent higher risk of failure due to either drought or wetness.

### 5.3.6 Factors affecting the adequacy of the classification outputs

*1) Limitations inherent in the crop model*

The MACROS model, in this study, was used under the assumption that water is the only limiting factor for plant growth. This condition rarely happens in the region. even when the maximum rate of fertilizer and cultural practices are applied. There are, however, other detrimental effects on crop growth.

*2) The use of constant water table depth as a model input parameter*

Due to lack of data, the input parameter of water table depth was assumed to be constant throughout the season. This assumption might cause error in simulated pod yields and , in turn, suitability classes for each map unit. In field situations, water table depth increases with time following the end of rainy season. However, under the conditions of this study area, error caused by using a constant water table depth is probably not severe. In Chapter 3, a study was conducted to validate the MACROS model using pod yield data from 36 on-farm trials, carried out in various parts of Khon Kaen Province. In that study, the input parameter of water table depth was assumed to be constant throughout the season. Results showed a high degree of correlation between simulated and observed values (r=0.91).

*3) Limitations of some other parameter inputs*

Some crop and soil parameter inputs, including those related to phenological development of crop and soil texture specific constants, were not specific for the peanut variety used (Tainan #9) and the conditions in the study area (Chapter 3; Penning de Vries et al., 1989).

*4) Soil spatial variability*

The map units included in a soil map are usually not homogeneous for agricultural applications. They are generally delineated based only on the physical geography of the region and the relevant soil forming processes (De Wit and Van Keulen, 1987). Soil spatial variability within a map unit may cause considerable error in the results of simulation and, in turn, the classification outputs. A study on detailed modeling of spring wheat production (Van Keulen and Siligman, 1987) showed a significant effect of soil spatial variability on simulated crop yields.

*5) Limitation of weather data*

In this study, weather data used to run the crop simulation model were limited to those obtained from only one station located approximately 40 km away from the center of the study area, and eleven years of recording. Because of this limited amount of data, variability in weather conditions, both spatially and temporally (seasonal conditions), could have effects on limiting the adequacy and accuracy of the classification outputs.

## 5.4 CONCLUSION

The computerized crop simulation model and the geographic information system are appropriate tools to generate information on land suitability for non-irrigated, dry season peanut cropping, based on water availability, in Northeast Thailand, because of the large volume of data involved and the requirement for timely updates. Without these tools, the generation of 16 land suitability maps representing the suitability of land areas for non-irrigated, dry season peanut cropping under 16 combinations of 4 planting dates by 4 water table depths, would be impossible.

According to the results of this land suitability classification, the kind of soil, especially texture, water table depth, and planting date, had effects on the suitability class.

Fine textured soils, viz. Phimai and Sithon series, were less suitable as compared to other soils under the same conditions of water table depth and planting date. For coarser textured soils, the suitability class varied depending upon water table depth and planting date. Water table depth had a strong effect on suitability class. A shallow water table (1 m depth) suppressed the suitability level because of wetness. Water tables at 3 m or greater depth reduced the suitability level because of drought. A water table at 2 m was found to be the most appropriate depth. Effects of planting date on the suitability class indicated that the later the planting date, the lower the suitability level. As described in section 5.3.4, this is probably not because of the stronger adverse effects of drought conditions during the growing period of later seeded crop. It could, however, be due to the fact that the effective temperature for photosynthesis during the growing period of later seeded peanut was so high that it had a significant adverse effect on yield.

**Table 5.1** Soils of the study area (adapted from Soil Survey Division, 1973; Keerati-Kasikorn, 1984).

| Physiographic position | Soil series, variant, phase, association, and complex | Subgroup (US Soil Taxonomy) | Area (ha) |
|---|---|---|---|
| Alluvial plain | Phimai | Vertic Tropaquepts | 183 |
| | Sithon | Aeric Tropaquepts | 286 |
| Low terrace | Roi Et | Aeric Paleaquults | 18322 |
| | Roi Et-loamy variant | Aeric Paleaquults | 536 |
| | Roi Et-high phase | Aeric Paleaquults | 113 |
| | Roi Et-sandy variant | Aeric Paleaquults | 113 |
| | Renu | Plinthic Paleaquults | 2280 |
| | Phen | Typic Plinthaquults | 18 |
| Middle and high terraces | Korat | Oxic Paleustults | 24479 |
| | Korat-sandy variant | Ustoxic Dystropepts | 2841 |
| | Satuk | Oxic Paleustults | 5438 |
| | Yasothon | Oxic Paleustults | 6994 |
| | Nam Phong | Ustoxic Quartzipsamments | 3078 |
| | Phon phisai | Typic Plinthustults | 716 |
| | Korat / Phon phisai association | Oxic Paleustults / Typic Plinthustults | 19 |
| Hill and mountain slope | Tha Yang | Typic Paleustults | 2310 |
| | Slope complex | - | 729 |

**Table 5.2** Land suitability classification for non-irrigated, dry season peanut cropping, under 16 combinations of 4 planting dates by 4 water table depths.

| Map unit | Water table 1 m | | | | Water table 2 m | | | | Water table 3 m | | | | Water table 4 m | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | D1[1] | D2 | D3 | D4 | D1 | D2 | D3 | D4 | D1 | D2 | D3 | D4 | D1 | D2 | D3 | D4 |
| Phimai | n[2] | n | n | n | s2 | s3 | s3 | n | s3 | s3 | n | n | s3 | n | n | n |
| Sithon | n | n | n | n | s2 | s3 | s3 | n | s3 | s3 | n | n | s3 | n | n | n |
| Roi Et | n | n | n | n | s1 | s1 | s2 | s3 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n |
| Roi Et-loamy variant | n | n | n | n | s1 | s1 | s1 | s2 | s2 | s3 | s3 | s3 | s2 | s3 | s3 | n |
| Roi Et-high phase | n | n | n | n | s1 | s1 | s2 | s3 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n |
| Roi Et-sandy variant | n | n | n | n | s1 | s1 | s2 | s3 | s2 | s3 | s3 | n | s2 | s3 | s3 | n |
| Renu | n | n | n | n | s1 | s1 | s2 | s3 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n |
| Phen | nc[3] | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc |
| Korat | s2 | s2 | s3 | n | s1 | s2 | s2 | s3 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n |
| Korat-sandy variant | s1 | s2 | s3 | s3 | s1 | s2 | s3 | s3 | s2 | s3 | s3 | n | s3 | s3 | s3 | n |
| Satuk | s2 | s2 | s3 | n | s1 | s2 | s2 | s3 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n |
| Yasothon | s1 | s2 | s3 | s3 | s1 | s2 | s3 | s3 | s2 | s3 | s3 | n | s3 | s3 | s3 | n |
| Nam Phong | s2 | s2 | s3 | s3 | s1 | s1 | s2 | s3 | s2 | s3 | s3 | n | s3 | s3 | n | n |
| Phon Phisai | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc |
| Korat/Phon Phisai association | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc |
| Tha Yang | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc |
| Slope Complex | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc | nc |

1/ Planting date: D1 = November 15 D2 = December 1 D3 = December 15 D4 = January 1

2/ Suitability classes: s1 = Highly suitable s2 = Moderately suitable s3 = Marginally suitable n = Not suitable

3/ nc = Not considered and assumed to be "not suitable"

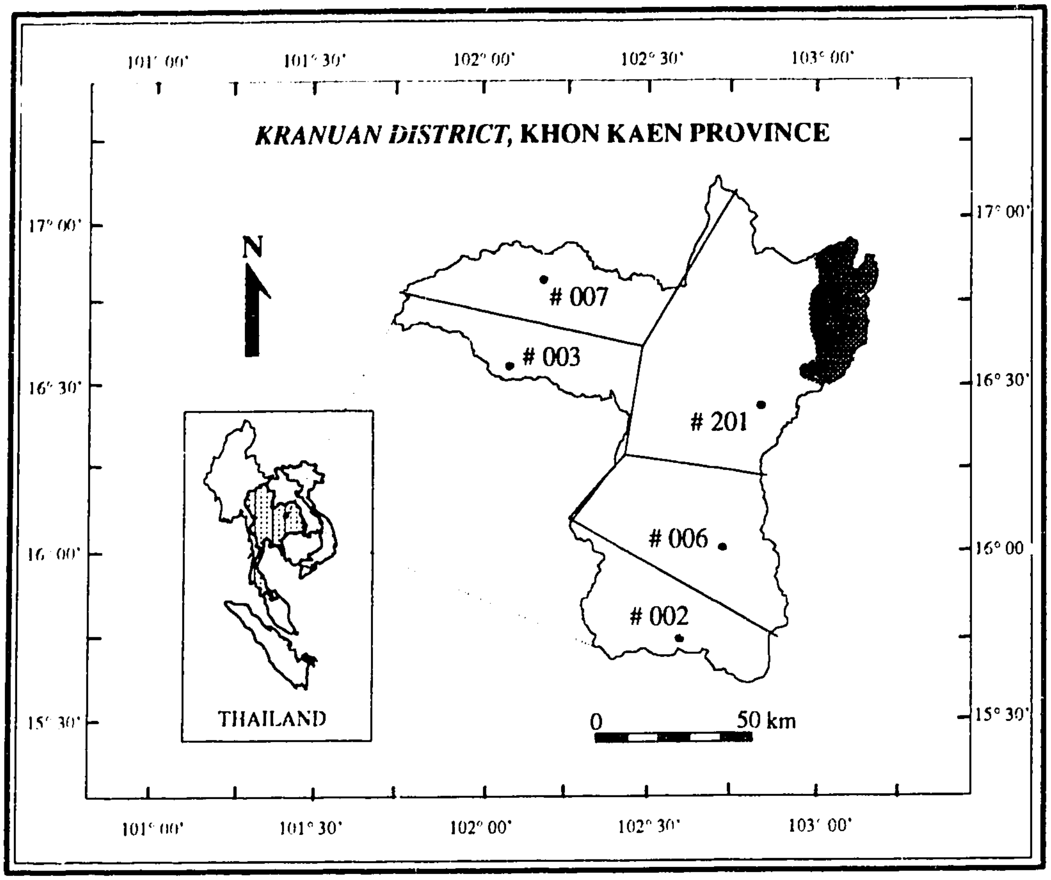


**Figure 5.1** Location of Kranuan District (shaded area) in Khon Kaen Province with:

( • ) locations of weather stations and the corresponding station numbers (adapted from Hydrometeorology Division, 1988), and
(-7--) Thiessen polygon boundaries delineated based on 5 weather stations.

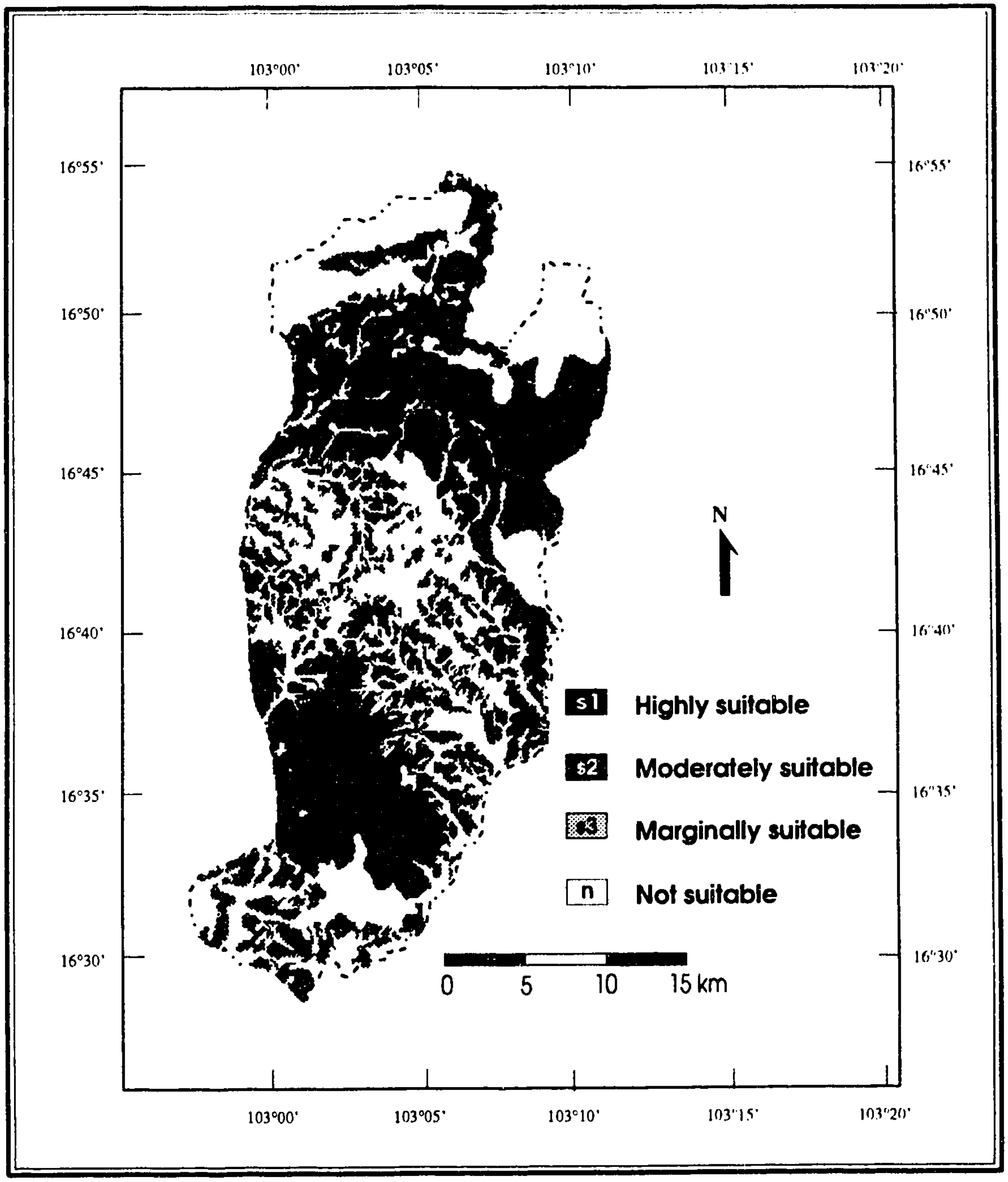


**Figure 5.2** An example of a Land Suitability Map for Non-Irrigated, Dry Season Peanut Cropping under conditions where assumed planting date is November 15, and water table depth is 1 m.

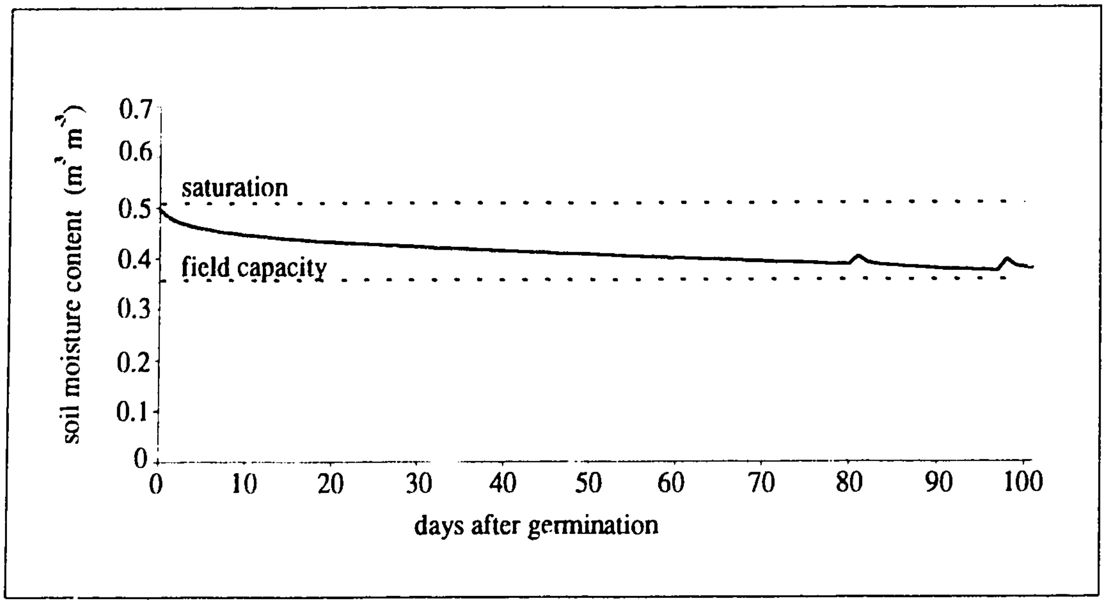


**Figure 5.3** Simulated soil moisture contents in Phimai (fine textured) soil at 0-30 cm, throughout the 1978-79 season. Data for planting date 1 (November 15) and water table depth 1 (1 m).

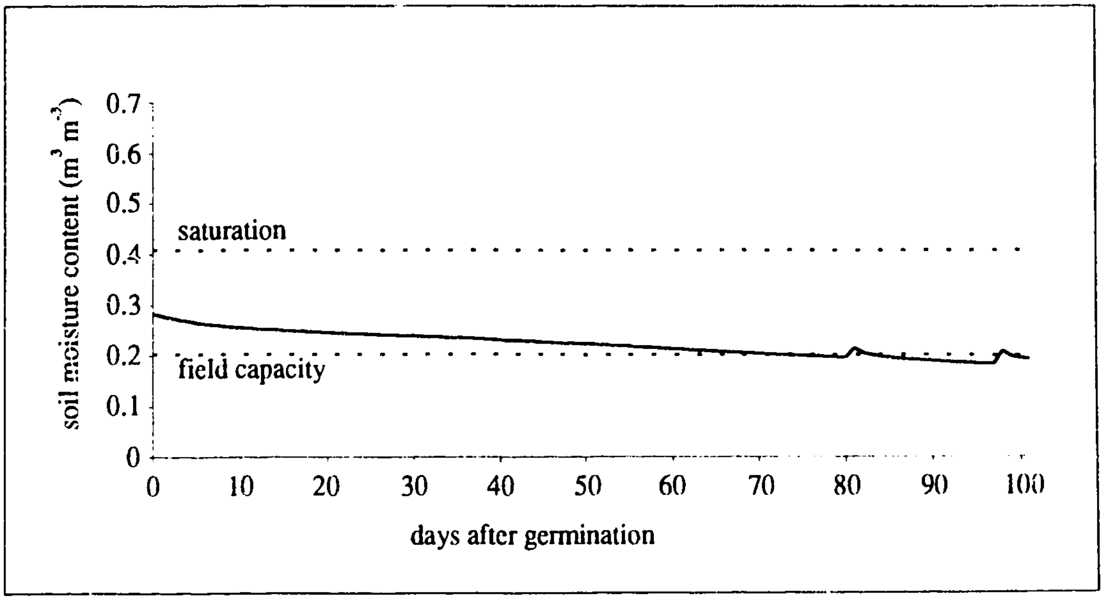


**Figure 5.4** Simulated soil moisture contents in Korat (medium textured) soil at 0-30 cm, throughout the 1978-79 season. Data for planting date 1 (November 15) and water table depth 1 (1 m).

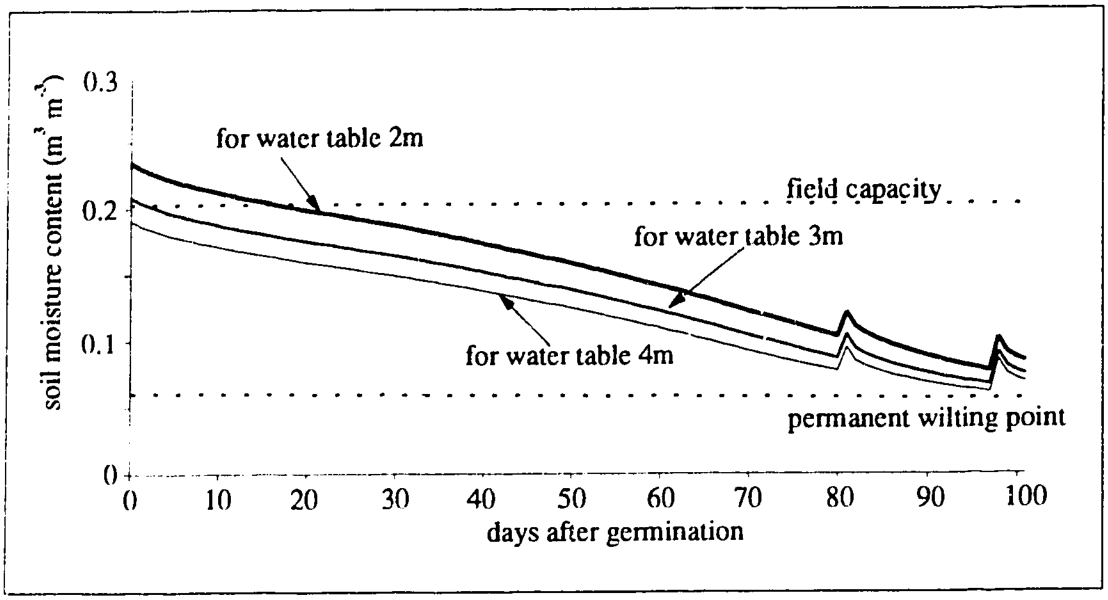


**Figure 5.5** Comparison between dynamics of simulated soil moisture contents under conditions of water table 2, 3, and 4 m throughout the 1978-79 season. Data for Korat (medium textured) soil at 0-30 cm, planting date 1 (November 15).

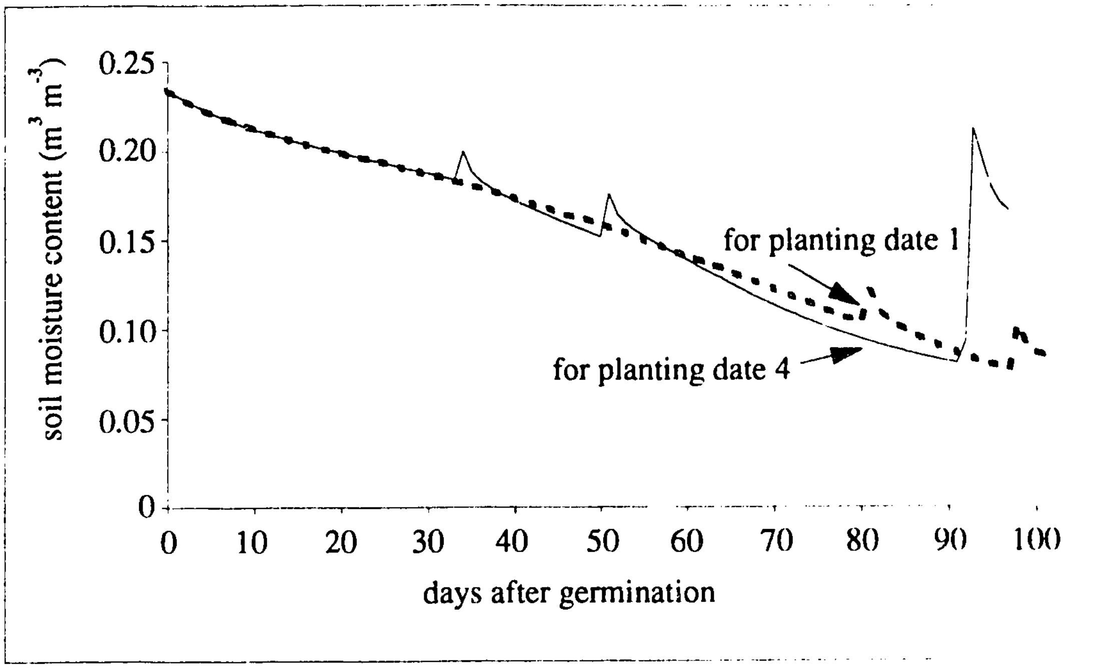


**Figure 5.6** Comparison between dynamics of simulated soil moisture contents for planting date 1 (November 15) and planting date 4 (January 1). Data for Korat soil at 0-30 cm and water table 2 m depth.

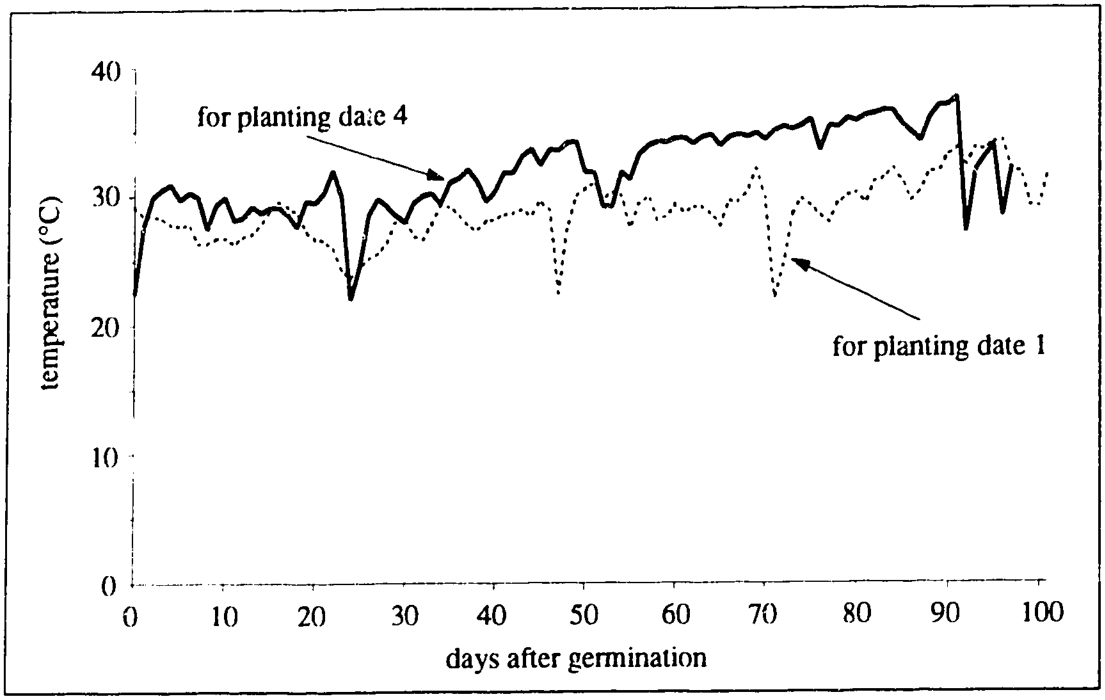


**Figure 5.7** Comparison of the effective temperature for photosynthesis during the growing periods between planting date 1 (November 15) and planting date 4 (January 1). Data for 1978-79 season.

## 5.5 REFERENCES


Aronoff, S. 1989. Geographic Information Systems: A Management Perspective. Ottawa, Canada: WDL Publications.

Bouma, J., R.J. Wagenet, M.R. Hoosbeek, and J.L. Hutson. 1993. Using expert systems and simulation modelling for land evaluation at farm level: a case study from New York State. Soil Use and Management 9: 131-139.

Burrough, P.A. 1986. Principles of Geographical Information Systems for Land Resources Assessment. Clarendon Press, Oxford.

Chantorn, P. 1983. Rainfed Peanut After Rice Cropping. M.Sc. Thesis. Khon Kaen University, Khon Kaen, Thailand. (in Thai with English abstract).

De Wit, C.T., and H. Van Keulen. 1987. Modeling production of field crops and its requirements. Geoderma. 40:253-265.

Dumanski, J., and C. Onofrei. 1989. Techniques of crop yield assessment for agricultural land evaluation. Soil Use and Management 5: 9-16.

FAO. 1976. A Framework for Land Evaluation. Soils Bull. 29. FAO. Rome.

FAO. 1983. Guidelines: Land Evaluation for Rainfed Agriculture. Soils Bull. 52. FAO. Rome.

Jintrawet, A., R. Katawatin, and V. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Cropping Systems Research Project, Khon Kaen University, Thailand. (in Thai with English abstract).

Jintrawet, A., S. Smutkupt, S. Ratanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya. 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University, Thailand. (in Thai with English abstract).

Keerati-Kasikorn, P. 1984. Soils of Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Thailand. (in Thai with English abstract).

Kerdsuk, V., and A. Patanothai. 1990. Testing and Implementation for Rainfed Dry Season Peanut: Khon Kaen University Experience. Farming System Research Project, Khon Kaen University, Thailand. Farm News 6, 24-35. (in Thai).

Klingebiel, A.A., and P.H. Montgomery. 1961. Land Capability Classification. Agricultural Handbook No 210. USDA Soil Conservation Service, Washington DC.

Landon, J.R. (Ed). 1991. Booker Tropical Soil Manual: A Handbook for Soil Survey and Agricultural Land Evaluation in the Tropics and Subtropics. Longman Scientific and Technical, Essex.

Magnusson, B., and M. Söderström. 1994. Combined crop growth models and geographical information systems for agricultural management: A case study of lay production potential as affected by local temperature variation and soil water capacity. Acta Agric. Scan., Sect. B, Soil and Plant Sci. 44: 65-74.

McBride, R.A., and M.L. Bober. 1993. Quantified evaluation of agricultural soil capability at the local scale: a GIS-assisted case study from Ontario, Canada. Soil Use and Management 9: 58-66.

McRae, R.G., and C.P. Burnham. 1981. Land Evaluation. Clarendon Press, Oxford.

Panangpetch, K. 1992. Introduction to Simulation of Crop Growth on Microcomputer. Department of Agronomy, Khon Kaen University, Khon Kaen, Thailand.

Penning de Vries, F.W.T., D.M. Jansen, H.F.M. Ten Berg, and A. Bakema. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Simulation Monographs, PUDOC, Wageningen, and IRRI, Los Banõs.

Shapiro, M., J. Westervelt, D. Gerdes, M. Larson., and K.R. Brownfield.1993. GRASS 4.1 Users Manual. US Army Construction Engineering Research Laboratory, Champaign, Illinois.

Soil Survey Division. 1973. Detailed-Reconnaissance Soil Map of Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

Soil Survey Division. 1975. Land Capability Classification for Field Crop: Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

Van Keulen, H., and N.G. Seligman. 1987. Simulation of Water Use, Nitrogen Nutrition, and Growth of Spring Wheat Crop. Simulation Monographs, PUDOC, Wageningen.

# CHAPTER 6

# EFFECTS OF AIR TEMPERATURE ON GROWTH AND YIELD OF DRY SEASON PEANUT PLANTED ON DIFFERENT DATES: AN INVESTIGATION USING CROP SIMULATION MODELING

## 6.1 INTRODUCTION

Non-irrigated, dry season peanut cropping is one of the most promising alternatives to increase the land use efficiency and the per capita income of farmers in Northeast Thailand. According to Kerdsuk and Patanothai (1990) possible planting dates for this crop in the region is during late November to late December. However, to ensure a higher yield and a lower risk of failure, it has been recommended that the crop should be planted as early as possible. Some relevant research papers (e.g., Jintrawet et al., 1983; Jintrawet et al., 1986; Kerdsuk and Patanothai, 1990) suggested that, for late planted peanut crop, reduction of crop growth and yield may be due to dryer soil moisture conditions. However, other growth factors might also be responsible for the reported yield reduction. In the previous chapter (Chapter 5), the MACROS (Penning de Vries et al., 1989) crop model was used to simulate growth and yield for dry season peanut crop grown without irrigation, under different conditions of soil, water table depth, and planting date in Kranuan District, Khon Kaen Province, Northeast Thailand. On the basis of that study, yield of peanut planted on a later date (e.g., January 1) was significantly less than that of peanut planted on an earlier date (e.g., November 15), even under conditions where dynamics of soil moisture content during the growth periods of peanut planted on these two dates did not considerably differ. It was suggested that, yield reduction of later planted peanut crop was likely due to higher temperature regimes during its growing period as compared to that of the early planted crop. The temperature regime, in this case, is referred to as the "effective temperature for photosynthesis" (Penning de Vries et al., 1989) which is assumed to be the average day temperature, calculated as the mean of the 24 hour average and the maximum temperature.

In planning for the implementation of non-irrigated, dry season peanut cropping, information related to whether or not the air temperature regime (or other weather components , i.e., rainfall, relative humidity, wind speed, and solar radiation) is involved in the yield reduction of later planted peanut, is of importance. For example, if higher air temperature conditions strongly limit yield of this crop, then it may not be worthwhile to implement late planted, dry season peanut cropping even with irrigation. Moreover, this knowledge should be useful for the improvement of more suitable peanut varieties to grow in the dry season in Northeast Thailand.

This study was initiated as a consequence of Chapter 5. Its hypothesis was that, temperature is responsible for yield reduction in the late planted, non-irrigated, dry season peanut cropping. Since crop simulation modeling can be applied to study the behavior of a crop under a wide range of environmental conditions, this technique may be employed to investigate the effects of temperature on growth and yield of the peanut crop planted on different dates. The objective of this study was, therefore, to determine whether or not the pattern of air temperature was related to the reduction of growth and yield of late planted peanut crops in Kranuan District, Northeast Thailand, using the MACROS crop model.

### 6.1.1 Study area

The study area is Kranuan District, Khon Kaen Province, Northeast Thailand. The district lies between latitude $16^{O}$ 28′ and $16^{O}$ 55′ north, and longitude $102^{O}$ 55′ and $103^{O}$ 13′ east. The total area is approximately 685 $km^2$. This area was used for the study on using a crop model for land suitability evaluation that was reported in Chapter 5. More details about the area are in that chapter.

## 6.2 MATERIALS AND METHODS

### 6.2.1 The MACROS crop model

The MACROS crop model was used to simulate data on growth and yield of peanut, with the assumption that only water is limiting for plant growth. Prior to its application, the model was calibrated and validated as described in Chapter 3. The results of this evaluation revealed the capability of the model to adequately estimate growth and yield of the dry season peanut cropping under non-irrigated conditions. Penning de Vries et al. (1989) provide a detailed description of MACROS and its scientific background. A brief description of the model is in Chapter 3.

Regarding the effects of temperature on crop growth, Penning de Vries et al. (1989) indicate that two parameters characterizing the rate of photosynthesis, i.e., Maximum Rate of Photosynthesis, and Initial Efficiency of the Use of Absorbed Light, are related to the temperature. Based on the MACROS model, gross photosynthesis of leaf is calculated by the equation:

$$PL = PLMX * [1-EXP(-PLEA*PAR/PLMX)] \text{ ----------------(1)}$$

where,

PL = Rate of Gross Photosynthesis, kg $CO_2$ $ha^{-1}$ $h^{-1}$

PLMX = Maximum Rate of Photosynthesis at Actual Temperature, kg $CO_2$ $ha^{-1}$ $h^{-1}$

EXP = Exponential

PLEA = Initial Efficiency of the Use of Absorbed Light at Actual Temperature, (kg $CO_2$ $ha^{-1}$ $h^{-1}$) / (J $m^{-2}$ $s^{-1}$)

PAR = Intensity of Absorbed Radiation, J $m^{-2}$ $s^{-1}$

To calculate PLMX and PLEA values for each specific temperature, first, the relationship between temperature and the PLMX, and the relationship between temperature and the PLEA, are specified. Then the PLMX and PLEA values in relation to each specific day temperature are calculated.

For C3 plant, such as peanut, the highest value of PLMX is found between 20-30° C (Pannangpetch, 1992). Also the PLEA is reduced considerably at temperature around 30° C or higher (Pallas et al., 1974; Penning de Vries et al., 1989). For this study, the value of PLMX used to calculate PL was 50 kg $CO_2$ $ha^{-1}$ $h^{-1}$ at temperatures of 25-30° C. The PLMX values were decreased proportionally to 40, and 25 kg $CO_2$ $ha^{-1}$ $h^{-1}$ at a temperature of 35° C, and 40° C, respectively. This relationship was compiled by Penning de Vries et al. (1989), from experiments in which the effects of temperature on irradiance response of photosynthesis were studied under controlled environments in growth chambers (Pallas and Samish, 1974; Pallas et al., 1974; Bhagsari and Brown, 1976).

With respect to the relationship between temperature and PLEA. the value of PLEA was 0.5 (kg $CO_2$ $ha^{-1}$ $h^{-1}$) / (J $m^{-2}$ $s^{-1}$) at temperatures of 0-10° C, and decreased proportionally to 0.45, 0.3, and 0.1 (kg $ha^{-1}$ $h^{-1}$) / (J $m^{-2}$ $s^{-1}$) at 20°, 30°, and 40° C, respectively. This relationship was also compiled by Penning de Vries et al. (1989) from a number of well documented experiments which were conducted under different climatic conditions, i.e., temperate, sub-humid, and semi-arid. Summation of the rates of photosynthesis of all leaves is the canopy photosynthesis, which is expressed in kg $ha^{-1}d^{-1}$. Daily photosynthesis is related directly to carbohydrates available for the crop growth process.

### 6.2.2 Crop model inputs

Input parameters required by MACROS include those related to crop, soil, weather, and management (Penning de Vries et al., 1989). Details about using these parameters to run the model were described in Chapter 3 , and Penning de Vries et al. (1989). Here reference is made only to input data which are specific for this study.

*1) Soil parameters*

The MACROS model requires a number of soil parameters, including depth, texture, constants related to soil surface storage capacity and evaporation, initial soil moisture content, and water table depth. In this study, water table depth was assumed to be 2 m. This depth was found (in Chapter 5) as the most suitable depth for providing satisfactory soil moisture content distribution throughout the season for peanut. Other soil data inputs used in this study were the same as those described in Chapter 3 and Penning de Vries et al. (1989).

All of these soil input parameters used in this study are characteristic of Korat (Oxic Paleustults), a major soil series of the study area (and Northeast Thailand). Korat is a deep soil with loamy sand to sandy loam texture at the surface, and sandy clay loam at the sub-surface. A detailed description of this soil series can be found in the Detailed Reconnaissance Soil Map of Khon Kaen Province (Soil Survey Division, 1973), and Keerati-Kasikorn (1984).

*2) Weather data*

Daily weather data used as model inputs for MACROS, include rainfall, maximum temperature, minimum temperature, wind speed, relative humidity, and solar radiation. These data, recorded in 1978-79 (>30 mm of rainfall during the growing period of dry season peanut crops), were used in this study. All of the weather data except those for solar radiation were recorded at station #201 (Hydrometeorology Division, 1988) located approximately 40 km away from the center of the study area. The solar radiation data was obtained from Khon Kaen University weather station located a few kilometers away from station #201.

*3) Management practices*

To assess the effect of planting date on growth and yield of peanut, 2 planting dates were modeled , i.e., "early" (November 15), and "late" (January 1). The beginning date for the actual simulation was assumed to be 1 week after the planting date, since the simulation of crop growth during the seed germination stage is difficult (Penning de Vries et al., 1989). The planting depth used in the simulation was 15 cm, corresponding to the recommended planting technique (Jintrawet et al., 1983).

### 6.2.3 Study methods

To test the hypothesis that temperature is responsible for yield reduction in the late planted dry season peanut crop grown without irrigation, the MACROS crop model was used to simulate growth and yield for this crop under three following conditions.

Condition #1: Peanut was planted on the early date (November 15). The simulation was done using weather data recorded since seed germination (1 week after the planting date) to crop maturation (101 days of recording).

Condition #2. Peanut was planted on the late date (January 1). The simulation was done using weather data recorded since seed germination (1 week after the planting date) to crop maturation (97 days of recording).

Condition #3: Peanut was planted on late date (January 1). The simulation was done using weather data recorded since seed germination (1 week after the planting date) to crop maturation (101 days of recording) except for the temperature data (minimum and maximum values). The temperature data used, in this case, were those used for condition #1.

Condition #3 was also used as a cross test to investigate if some other weather parameter played a role. The model was run using weather data recorded during the 1978-79 season and soil data of Korat series. Comparisons of simulated output data were made in terms of:

*(i)* dynamics of soil moisture content at 0-30 cm depth during the growing periods of peanut planted on the early and the late planting dates,

(ii) dynamics of the effective temperature for photosynthesis during the growing periods of peanut planted on the early and the late planting dates, and

(iii) crop growth and yield simulated for all three "conditions" described above.

## 6.3 RESULTS

### 6.3.1 Soil moisture content

Dynamics of soil moisture content at 0-30 cm depth from the soil surface during the growing periods of peanut planted on the early and the late planting dates were very similar in both amount and distribution, except for the 93rd to 97th day after germination of the late planted peanut. The amount of soil moisture content during this period was increased to approximately 0.22 to 0.17 $m^3$ $m^{-3}$, due to rainfall. Similarity in soil moisture was controlled mainly by ground water. In this study, a constant water table depth of 2 m was used in the simulation of every condition (Figure 6.1).

### 6.3.2 Effective temperature for photosynthesis

In the 1978-79 dry season, the effective temperature for photosynthesis during the growing period of late planted peanut was, in general, considerably higher than that of the early planted one. The effective temperatures during the 30th day to the 90th day after germination were approximately 22-32° C and 28-38° C for peanut planted on the early date and the late date, respectively (Figure 6.2).

### 6.3.3 Pod yield

Pod yields simulated under the three conditions previously described , i.e., early planting, late planting, and late planting but using temperature data of early planting; were 1226, 743, and 1242 kg $ha^{-1}$, respectively. Pod yield simulated for condition #3 was higher than those simulated for the other conditions.

### 6.3.4 Crop growth rate

In general, the crop growth rate, simulated for late planted peanut using temperature data of early planted peanut (condition #3) was higher than that of early planted peanut (condition #1) and late planted peanut (condition #2), respectively. Figure

6.3 shows that, during the 30th to the 90th day after germination, crop growth rates simulated for conditions #3 were considerably higher than those simulated for condition #1 and #2, respectively.

### 6.3.5 Shoot dry weight

Accumulations of shoot dry weights over the growing period of peanut simulated for the three conditions (Figure 6.4) corresponded to the crop growth rate described earlier. For condition #3, increases in simulated shoot dry weight was higher than that simulated for conditions #1 and #2, respectively. After the 30th day since seed germination, shoot dry weight simulated for condition #3 and #1 were considerably higher than that simulated for condition #2. Also, from the 42nd day after germination, shoot dry weight simulated for condition #3 were considerably higher than that simulated for condition #1.

## 6.4 DISCUSSION AND CONCLUSION

According to the results of the MACROS model simulation, distribution of soil moisture content, under conditions where the water table is constant throughout the season, is not the cause for the difference in growth and yield of peanut planted on early and late dates. As shown in Figure 6.1, dynamics of soil moisture content during the growing period of peanut planted on these two different dates were very similar. The difference in the amount of soil moisture content due to rainfall at the end of the growing period of the late planted peanut crop should not have had a significant effect on the difference in growth and yield of the crop planted on these two dates, as the crop had almost reached the maturation stage.

During the 1978-79 season, the effective temperature for photosynthesis during the growing period of late planted peanut was considerably higher than that of the early planted one. The high temperature regime, in this case, caused the reduction of growth and yield of the late planted peanut crop. The significant increase in pod yield, growth rate (Figure 6.3), and shoot dry weight (Figure 6.4) of the late planted peanut crop when simulated, using the more benign temperature data recorded during the growing period of early planted peanut (condition #3), support this conclusion. As previously described, leaf photosynthesis is characterized by two parameters which are related to air temperature, i.e., PLMX and PLEA (Equation 1). When the temperature is above 30° C, these parameters decrease considerably (Pallas and Samish, 1974; Bhagsari and Brown, 1976;

Penning de Vries et al., 1989). Therefore, based on Equation 1, the simulated leaf photosynthesis was reduced. In addition, higher growth rates of peanut were simulated using temperature data for the early planted peanut crop (condition #1 and #3) than for late planted peanut (condition #2) during the $30^{th}$ to $90^{th}$ day after germination (Figure 6.3). These correspond with the patterns of temperature change during growing periods of peanut planted on these two dates (Figure 6.2).

The higher crop growth rate and shoot dry weight of condition #3 over condition #1 is probably due to the fact that, during the growing period of late planted peanut, some of the other weather components, such as solar radiation were more suitable for crop growth, as compared to the conditions during the growing period of the early planted crop. However, according to the results of this study, temperature is the major factor causing the difference in growth and yield of peanut planted on these 2 dates.

It must be noted that this study is based only on the simulation values using the MACROS crop model. Its result should be verified by field experiments. Also, the results may be used as a guide for field research in the future. For example, in the field of plant breeding, where appropriate, studies may be conducted to modify the PLMX - Temperature relationship in such a way that the adverse effect of high temperature during the growing period of late planted peanut is alleviated.

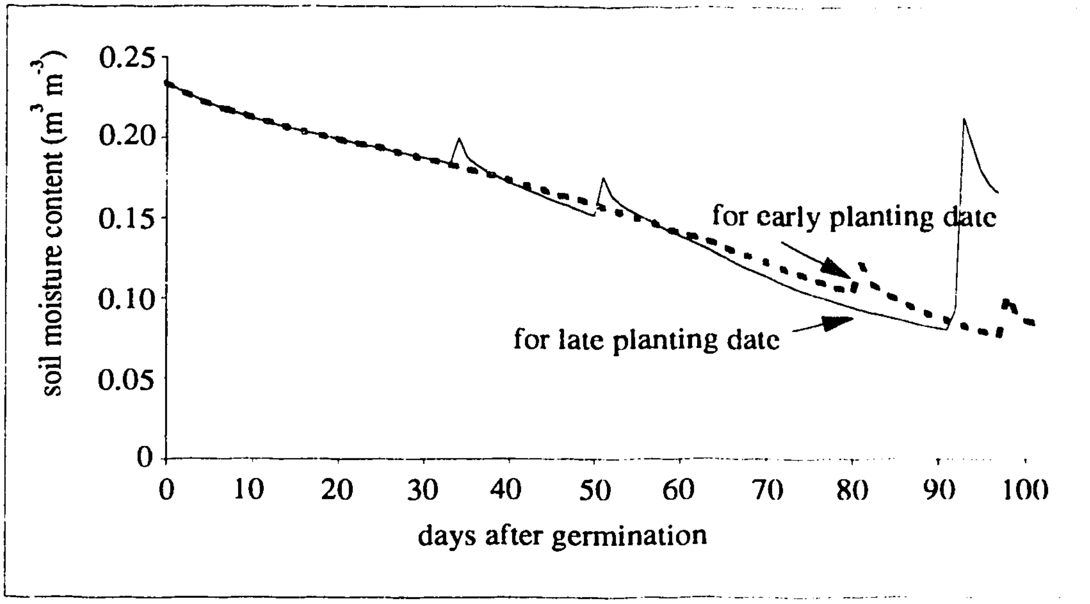


**Figure 6.1** Comparison between dynamics of simulated soil moisture contents during growing periods of the early (November 15) and the late (January 1) planted peanut crops. Data for Korat soil at 0-30 cm, where water was 2 m depth, in 1978-79 season.

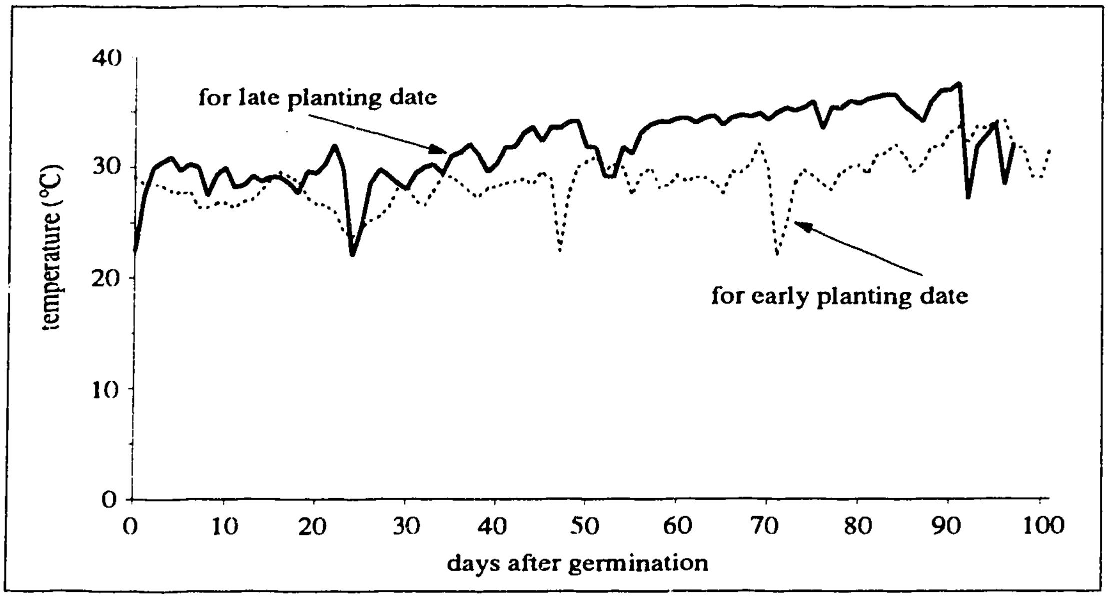


**Figure 6.2** Comparison of the effective temperatures for photosynthesis during the growing periods of the early (November 15) and the late (January 1) planted peanut crops. Data for 1978-79 season.

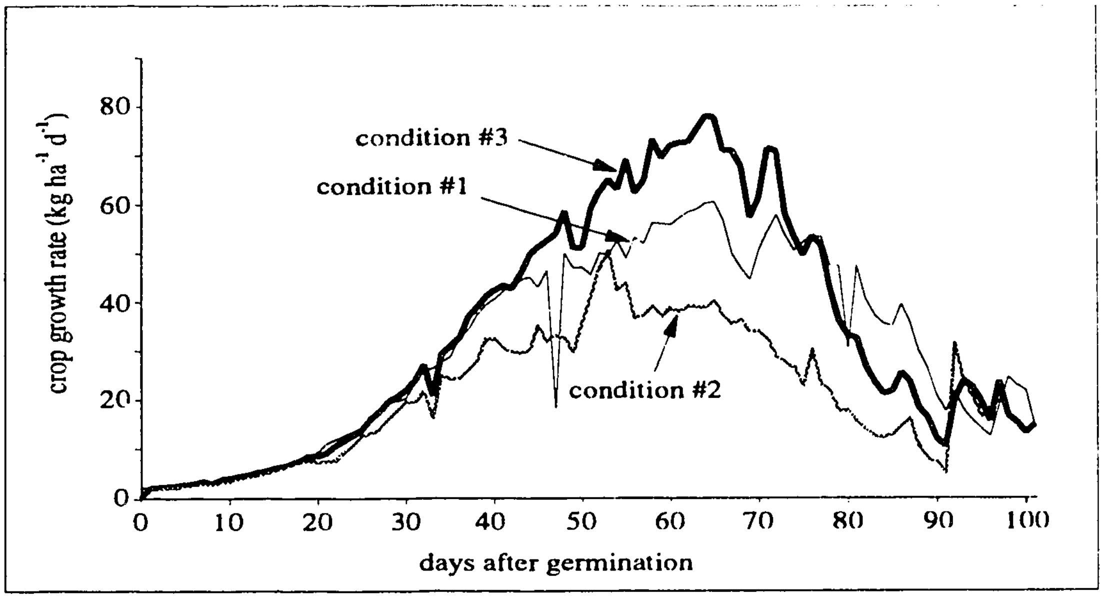


**Figure 6.3** Comparison of simulated crop growth rates during growing periods of the early planted peanut crop (condition #1), the late planted peanut crop (condition #2), and the late planted peanut crop using temperature data of the early planted peanut crop (condition #3). Data for peanut grown on Korat soil in 1978-79 season.

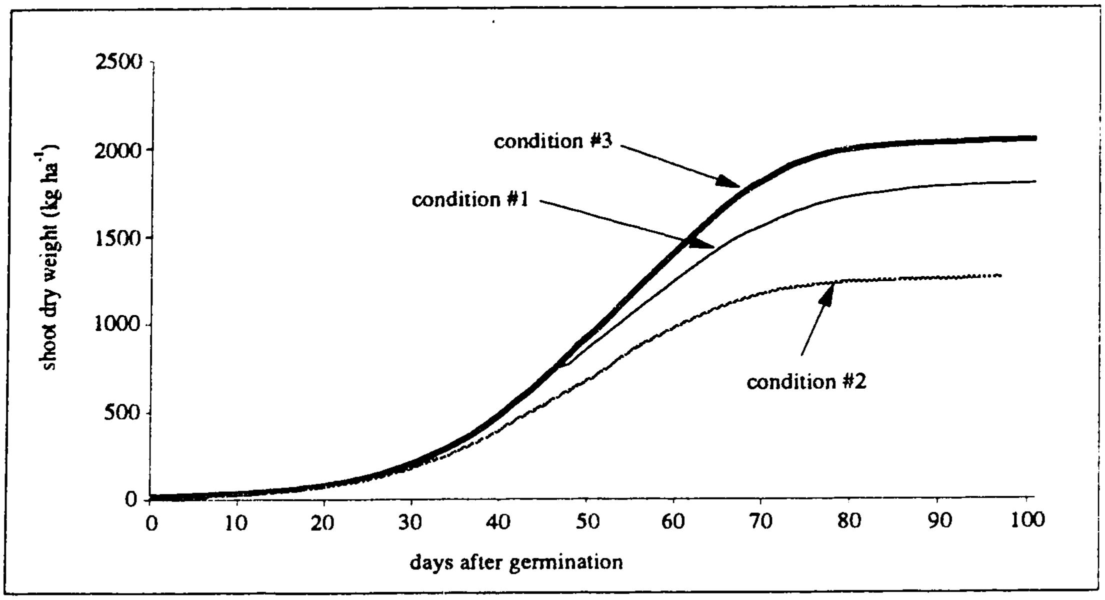


**Figure 6.4** Comparison of simulated shoot dry weights during growing periods of the early planted peanut crop (condition #1), the late planted peanut crop (condition #2), and the late planted peanut crop using temperature data of the early planted peanut crop (condition #3). Data for peanut grown on Korat soil in 1978-79 season.

## 6.5 REFERENCES


Bhagsari, A.S., and R.H. Brown. 1976. Photosynthesis in peanut (*Arachis*) genotypes. Journal of Peanut Science. 3: 1-5.

Hydrometeorology Division. 1988. Location of Rainfall Station of Thailand. Meteorology Department, Bangkok.

Jintrawet, A., S. Smutkupt, S. Rattanasophon, C. Wongsamun, A. Lila, M. Danthanin, and S. Lojaya, 1986. Farmer - Extension - Research: A Case Study. Farming System Research Project, Khon Kaen University. (in Thai with English summary).

Jintrawet, A., R. Katawatin, and W. Kerdsuk. 1983. Study on Dry Season Peanut Cropping at Amphoe Prasart, Changwat Surin. Khon Kaen University: Cropping Systems Research Project. (in Thai with English abstract).

Keerati-Kasikorn, P. 1984. Soils of Northeast Thailand. Faculty of Agriculture, Khon Kaen University, Thailand. (in Thai).

Kerdsuk, V., and A. Patanothai, 1990. Testing and Implementation for Rainfed Dry Season Peanut: Khon Kaen University Experience. Farm News. Farming System Research Project, Khon Kaen University. 63: 24-35. (in Thai).

Pallas, J.E., Y.B. Samish, and C.M. Willmer. 1974. Endogenous rhyt'imic activity of photosynthesis, transpiration, dark respiration, and carbon dioxide compensation point of peanut leaves. Plant Physiol. 53: 907-911.

Pallas, J.E., and Y.B. Samish. 1974. Photosynthetic response of peanut. Crop Science. 14: 478-482.

Pannangpetch, K. 1992. Introduction to Simulation of Crop Growth on Microcomputer. Department of Agronomy, Khon Kaen University, Thailand.

Penning De Vries F.W.T., D.M. Jansen, H.F.M. ten Berg, and A. Bakema. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Simulation Monograph 29. Pudoc, Wageningen, and IRRI, Los Banos.

Soil Survey Division. 1973. Detailed-Reconnaissance Soil Map of Khon Kaen Province. Department of Land Development, Bangkok, Thailand.

# CHAPTER 7

# MAPPING GREEN CROPS IN THE DRY SEASON USING LANDSAT-5 TM DATA

## 7.1 INTRODUCTION

Non-irrigated, dry season cropping is a highly promising alternative to improve land use efficiency in Northeast Thailand (Kerdsuk and Patanothai, 1990). Successful implementation of this activity in the farmers' fields requires precise agricultural land evaluation, taking into account physical, biological and socio-economic conditions of the specific sites of interest. The extent to which agricultural areas are covered by arable crops just before the dry season is one of the important conditions that should be considered. It is usually not necessary, or even possible, to introduce dry season cropping to fields in which other crops already exist.

Satellite remote sensing is an effective means for generating information on the area covered by green crops at a particular time of the year. This is a relatively simple land cover class to identify and is comparable to Level 2 of the USGS - Land Use / Land Cover Classification System (Anderson et al., 1976), which is the classification scheme developed for use with high altitude or orbital remote sensing data. However, this information must be produced quickly, within a limited time at the very beginning of the dry season. Note that the terms "land cover" and "land use" are not the same. While "land cover" relates to the type of feature present on the earth's surface, "land use" relates to the human activity associated with a specific piece of land (Lillesand and Kiefer, 1994). Hence, land cover information can be directly interpreted from appropriate remote sensing imagery, but information on land use must be inferred from land cover and other related information which is not always possible. In this study, the term "land cover" was used because the information required would be directly interpreted from satellite data.

Analysis of satellite data to generate information on land cover can be done using a *manual approach* and/or *quantitative* (*computer-aided*) *approach*. For the former, variation in image characteristics such as tone (color), texture, pattern, size, and shape are used as clues for visual identification of different land cover classes (Bowden and Pruitt, 1975). In the latter approach, a data analysis technique called *pattern recognition* is most widely adopted. Lillesand and Kiefer (1994) explained that pattern recognition involves analysis of multispectral image data and the application of statistically based decision rules for determining the land cover identity of each pixel in an image. When the decision rules are based on the spectral radiance observed in the data, the classification process is referred to as *spectral pattern recognition*. On the other hand, if these decision rules are based on the geometrical shapes, sizes, and patterns represented in the image data, this classification process will be referred to as *spatial pattern recognition*. In either case, the classification process is intended to categorize all pixels in a digital image into one of several land cover classes, or *themes*.

The spectral recognition technique includes two different methods, i.e., *supervised classification* and *unsupervised classification*, each of which has its own advantages and disadvantages as described elsewhere (e.g., Swain and Davis, 1978; Jensen, 1986; Lillesand and Kiefer, 1994). This study focuses only on the supervised classification as it is, in general, considered more effective in characterizing informational classes such as those related to different land cover types (Swain and Davis, 1978). Within this method of classification, there is a diversity of possible analysis methods such as *Maximum Likelihood, Parallelepiped,* and *Minimum-Distance-to-Mean* (Lillesand and Kiefer, 1994). These methods are different in terms of algorithms, speed of computation, and accuracy of outputs (Swain and Davis, 1978; Lillesand and Kiefer, 1994; PCI, 1994). With respect to the selection of the optimum subset of image band(s) to be used in the classification, the *feature selection* is a promising algorithm (Swain and Davis, 1978; Jensen, 1986) that has been widely employed in remote sensing. Application of this algorithm can minimize the cost of the classification while maintaining acceptable accuracy for the results.

Under conditions of Northeast Thailand, to generate information on the coverage of green crops from satellite data, a number of requirements must be considered including time for data analysis, computer storage space for imagery data, and reliability of the classification results. As a consequence, a suitable method of image classification, and the optimum subset of image band(s) to be used in the classification have to be determined.

The first objective of this study was to determine the most appropriate procedure for use in Northeast Thailand to generate information about the extent of green crops in non-irrigated agricultural areas in the dry season. The term "appropriate procedure", in this case, includes the least complex method of classification, the minimum subset of image band(s) required, and the accurate results.

In addition to the original image bands acquired from satellite, various mathematical combinations of radiance recorded at the visible red spectral bands and at the infrared bands (usually referred to as the *vegetation indices*) have been reported to be sensitive indicators of the presence and conditions of green vegetation (Lillesand and Kiefer, 1994). Thus the use of these indices for classification of agriculturally related land cover types is considered promising. The second objective was, therefore, to investigate the use of vegetation indices to generate information on the coverage of green crops in agricultural areas in the dry season.

### 7.1.1 Study area

The study area was Kranuan District, Khon Kaen Province, Northeast Thailand (Figure 7.1). The district lies between latitude $16^{O}$ 28′ and $16^{O}$ 55′ north, and longitude $102^{O}$ 55′ and $103^{O}$ 13′ east. The total area is approximately 685 $km^2$. Kranuan is a good representation of Northeast Thailand in terms of topography, soils, land cover, and land use. More details about topography and soils of this district are in Chapter 5. Major types of land cover in this district include forest, water reservoir, built-up area, and agricultural land. Agricultural land includes both irrigated and non-irrigated areas. This study focuses on the non-irrigated agricultural areas in the dry season. Like most parts of the northeast region at the beginning of the dry season (mid November to early December), only a few crops occupy non-irrigated agricultural land, or otherwise the land is left idle (Jintrawet et al., 1985; Kerdsuk, 1986). Except for the senescent paddy rice crop that is being harvested, cassava is the only dominant crop in the vicinity Sugarcane cropping is also practiced, but to a limited extent. Other crops such as vegetables exist only on a very small percentage of agricultural land.

### 7.1.2 Supervised classification

Supervised classification includes two basic steps, definition of spectral classes based on known or assumed ground conditions and the application of these classes to the image data for classification. Among the most widely used methods for classification are Maximum Likelihood, Parallelepiped, Ties, and Minimum-Distance-to-Means (Lillesand and Kiefer, 1994; PCI, 1994). Under the assumption of multivariate normal distribution of classes examined, Maximum Likelihood is generally a very accurate method especially when used with normally distributed remotely sensed data (Maselli et al., 1993; PCI, 1994). Parallelepiped is of importance when a quick classification result is required, because this method involves less computation than Maximum Likelihood. However the drawback is, in many cases, poorer accuracy and a large number of pixels classified as "ties" (or overlap). Ties method, a cross between Maximum Likelihood and Parallelepiped, has been developed to solve the problem of too many tied pixels. The basic concept of this method is to use Parallelepiped classifier unless a tie is obtained. In such cases the tie is resolved using Maximum Likelihood classifier (PCI, 1994). Minimum Distance is mathematically simple and computationally efficient, but it inherits certain limitations. Most importantly, as stated in Lillesand and Kiefer (1994), this method is insensitive to different degrees of variance in the spectral response data. Therefore, the use of the Minimum Distance is restricted to applications in which (i) simple classification is sufficient, (ii) a quick examination of the classification results is required, and/or (iii) spectral response patterns of land cover classes of interest are not normally distributed (PCI, 1994).

### 7.1.3 Signature separability

Prior to the supervised classification of land cover for the area of interest, the qualities of training sites and class signatures should be examined. This examination can be done using a *signature separability* algorithm (Swain and Davis, 1978). One statistical parameter commonly used in this algorithm is called the *divergence*, which is basically a covariance-weighted distance between category means (Lillesand and Kiefer, 1994). In general terms, the higher the value of divergence, the better between-class separation and the higher probability of correct classification of classes. Low values of divergence on the other hand, reveal that the quality of the training sites and, in turn, the quality of class signatures are so poor that improvement measures have to be made. A divergence value is computed from the mean and covariance matrices of the class statistics acquired in the training phase of the supervised classification. Jensen (1986) explained that the degree of divergence or separability between two classes is calculated using the formula:

$$\mathrm{Diverg}_{cd} = 0.5\,\mathrm{Tr}\,[(V_c - V_d)(V_d^{-1} - V_c^{-1})] \\ +0.5\,\mathrm{Tr}\,[(V_c^{-1}+V_d^{-1})(M_c-M_d)(M_c-M_d)^T] \text{ ----- (1)}$$

where;

$\mathrm{Diverg}_{cd}$ = divergence between 2 different classes, *c* and *d*;

Tr [·] = trace of a matrix (the sum of the diagonal elements of the covariance matrix);

$V_c$ and $V_d$ = covariance matrices of the 2 classes, c and d, under investigation;

$M_c$ and $M_d$ = mean vectors for classes *c* and *d*; and

*T* = Transpose of matrix.

For PCI EASI/PACE image processing system (PCI, 1994), the transformed divergence, expressed as the equation below, is used instead of the divergence:

$$\text{Diverg}^{T}_{cd} = 2\,[1\text{-exp}\,(-\text{Diverg}_{cd} / 8)] \text{ --------- (2)}$$

where;

$\text{Diverg}^{T}_{cd}$ = transformed divergence between 2 different classes, $c$ and $d$ ; and
$\text{Diverg}_{cd}$ = divergence between 2 different classes, $c$ and $d$.

This transformed divergence is more appropriate to use as a parameter indicating class separability than divergence, as it gives an exponential decreasing weight to increasing distance between the classes (Kumar and Silva, 1977). PCI (1994) recommended that transformed divergence values of above 1.9 to 2.0 indicate good between-class separability, above 1.0 to 1.9 indicate poor separation, and 1.0 or below are very poor. Other statistical methods that can be used to assess signature separability are described elsewhere such as Swain and Davis (1978), Kalayeh et al. (1983), and Jensen (1986).

### 7.1.4 Feature selection

In the supervised classification approach, the use of all available multispectral image channels (such as all 7 channels of LANDSAT-5 TM) in a given remote sensing classification is generally not practical, because too much computation and hardware may be required. Moreover, in a situation involving limited availability of training data, better classifier performance is not always obtained by having more image channels. This can occur where all selected training areas do not cover all the possible spectral patterns of classes, and the classifier performance could even be degraded (Swain and Davis, 1978).

In the land cover classification, the *feature selection* algorithm (some times referred to as *channel selection* or *band selection*) has been developed to use for selection of the best image channel combination from a set of channels (PCI, 1994). Jensen (1986) explained that in this algorithm, the degree of between-class separability in the remote sensing training data set is determined by using the divergence or transformed divergence values. Combinations of bands are normally ranked according to their potential ability to discriminate each class from all others using "n" bands at a time.

### 7.1.5 Vegetation indices

In agricultural crop inventory, remotely sensed data acquired from many spectral bands have been found useful. However, the bands covering ranges of visible red, and near infrared provide most of the information necessary for this purpose (Szekielda, 1988). Various mathematical combinations of data from these two bands, usually referred to as *Vegetation Indices*, have been used successfully in a variety of different vegetation situations including tropical forests, grasslands, and agricultural crops (Tucker, 1979; 1980). One of the most commonly used vegetation indices is the *Normalized Difference Vegetation Index* (NDVI) which can be expressed (Jackson et al., 1983) as:

$$NDVI = \frac{NIR - R}{NIR + R} \text{ --------------- } (3)$$

where;

NIR = radiance recorded at the near infrared bands; and

R = radiance recorded at the visible red bands.

The NDVI values range from -1 to +1.

To avoid working with negative values and values less than 1, which is less convenient in the quantitative approach of remote sensing, the *Transformed Vegetation Index* (TVI) was introduced. The TVI is computed (Lillesand and Kiefer, 1994) as:

$$TVI = \left[\frac{NIR - R}{NIR + R} + 0.5\right]^{\frac{1}{2}} * 100 \text{ ------- } (4)$$

where;

NIR = radiance recorded at the near infrared bands; and

R = radiance recorded at the visible red bands.

Application of the band ratioed vegetation indices can reduce adverse effects of topography, and temporal / spectral differences in sun elevation or atmospheric conditions on quality of the remotely sensed data (Holben and Justices, 1981; Mather, 1987; Shoshany et al., 1994). However, like other kinds of band ratioing, these indices must be used with caution. Most importantly, the band ratioed vegetation indices result in "intensity blind" image data (Lillesand and Kiefer, 1994). That is dissimilar materials with different absolute radiance, but having similar slopes on the spectral curves, could be incorrectly identified as the same material.

### 7.1.6 Accuracy assessments

The most common and effective way to represent classification accuracy is the use of an *error matrix*. The error matrix is a square array of numbers set out in rows and columns which express the number of sample units (i.e., pixels, cluster of pixels, or polygons) assigned to a particular class relative to actual land cover class (Congalton, 1991). A series of statistical analyses including *overall accuracy*, *producer's accuracy*, *user's accuracy*, and *KAPPA analysis* can be performed on the basis of the error matrix.

Congalton (1991) states that the overall accuracy is the simplest statistic. It is computed by dividing the total number of correctly identified sample units by the total number of sample units in the error matrix. The producer's accuracy is calculated by dividing the total number of correctly identified sample units in a class by the total number of sample units in that class. This accuracy measure indicates the probability of a reference sample unit being correctly classified. The user's accuracy is the result of dividing the total number of correctly identified sample units in a class by the total number of sample units assigned to that class. This measure is indicative of the probability that a pixel classified on the map or on the image actually represents that class on the ground (Story and Congalton, 1986).

For the KAPPA analysis, Congalton (1991) noted that the result of performing this analysis is a KHAT ($\hat{K}$) coefficient (an estimate of KAPPA). $\hat{K}$ is a measure of agreement between the classified data (e.g., classified image) and the reference data obtained from field survey or reference images / maps. This coefficient tests the overall agreement for each error matrix based on the difference between the actual agreement of the classification with respect to reference data and the chance agreement which is indicated by the row and column marginal of the error matrix (Dutta et al., 1994). The $\hat{K}$ coefficient can be expressed (Bishop et al., 1975) as:

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} x_{i+}x_{+i}}{N^2 - \sum_{i=1}^{r} x_{i+}x_{+i}} \quad \text{---------} \ (5)$$

where;

$r$ = number of rows in the matrix;

$x_{ii}$ = number of observations in row i and column i;

$x_{i+}$ and $x_{+i}$ = marginal totals of row i and column i, respectively; and

$N$ = total number of observations.

In addition to being a measure of accuracy, KAPPA is also a powerful analytical technique in its ability to provide information about statistical significance of a single error matrix as well as that of the compared matrices (Congalton, 1991). A test of significance of $\hat{K}$ coefficients can be done using the Z-Statistic which is expressed as (Congalton and Mead, 1983):

$$Z \sim \frac{\hat{K}_1 - \hat{K}_2}{\sqrt{\hat{\sigma}_1^{\,2} + \hat{\sigma}_2^{\,2}}} \text{ -------------(6)}$$

where;

$\hat{K}_1 = \hat{K}$ of the error matrix $1^{st}$;

$\hat{K}_2 = \hat{K}$ of the error matrix $2^{nd}$;

$\hat{\sigma}_1^2$ = variance of $\hat{K}$ of the error matrix 1; and

$\hat{\sigma}_2^2$ = variance of $\hat{K}$ of the error matrix 2.

The estimate of large sample variance of $\hat{K}$ is calculated by:

$$\hat{\sigma}^2[\hat{K}] = \frac{1}{N}\left[\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4}\right] \text{ ------------------(7)}$$

where;

$\theta_1 = \sum_{i=1}^{r} x_{ii}/N$;

$\theta_2 = \sum_{i=1}^{r} x_{i+}\, x_{+i}/N^2$;

$\theta_3 = \sum_{i=1}^{r} x_{ii}(x_{i+} + x_{+i})/N^2$;

$\theta_4 = \sum_{\substack{i=1 \\ j=1}}^{r} x_{ij}(x_{j+} + x_{+i})^2/N^3$;

$x_{ij}$ = number of observation in row $i$ and column $j$;

$x_{j+}$ = marginal total of row $j$; and

$x_{+i}$ = marginal total of column $i$.

The test of significance of $\hat{K}$ for each individual matrix is performed to determine whether or not the agreement between the classification and the reference data is significantly greater than zero. In other words, this test is performed to see if the classification is significantly better than a random assignment of land cover classes to pixels. The pairwise test of significance of $\hat{K}$ is conducted between two independent values of this coefficient to determine if the two error matrices are significantly different (Congalton and Mead, 1983). Review of the KAPPA analysis including the $\hat{K}$ coefficient, its variance, its use for testing of significant difference can be found in literature such as Bishop et al. (1975); Congalton et al. (1983); Congalton and Mead (1983); Rosenfield and Fitzpatrick-Lins (1986); Hudson and Ramm; (1987); and Congalton (1991).

## 7.2 MATERIALS AND METHODS

This study consists of 2 parts:

(1) Generation of a major land cover types map: Manual approach
(2) Mapping areas of green crops on non-irrigated agricultural land in the dry season: Quantitative approach

The study proceeded in a stepwise fashion with the result from one step dictating the method for the next. Because of this, where appropriate, some of the results may be presented in section 7.2 together with the related methods.

### 7.2.1 Generation of major land cover types map: Manual approach

For this first part of the study, visual interpretation of satellite imagery was conducted to map areas of the major land cover types including irrigated agriculture, water reservoir, built-up area, forest, and non-irrigated agriculture. The imagery used for this purpose was a portion of a SPOT-1 HRV scene J266 K317, as a black and white print, scale 1:50,000. It was taken in Band 1, on December 25, 1988. The interpretation was based on image characteristics, i.e., tone, texture, pattern and shape. In addition to the image characteristics, other kinds of important reference data consisting of topographic maps at a scale of 1:50,000, and a schematic map showing boundaries of irrigated areas were also employed. The criteria used for this visual interpretation are summarized in Table 7.1.

The topographic maps used for this purpose were those of sheet 5541 I, 5542 I, 5542 II, 5641 IV, 5642 III, 5642 IV (Royal Survey Department, 1983a to f). The schematic map was the map of Nongwai-Nam Phong Irrigation Project (Royal Irrigation Department Regional Office 4, 1990). By using the schematic map as a guideline, the area of irrigated agriculture was delineated easily on the SPOT imagery, as it was bordered by irrigation channels that were shown distinctly on the imagery. Boundaries of water reservoirs were depicted according to their locations shown on the topographic maps, and the criteria that they appear on the imagery in irregular shape with black or dark gray tones and no (or very smooth) texture. Information presented on these topographic maps was also used to help locate the built-up areas so that these areas were accurately identified. Built-up areas' boundaries were also delineated based on the criteria that they appear on the imagery as objects with alternating gray tones and rectangular pattern due to arrangement of roads and residences. Because of their unique characteristics, these built-up areas were sharply separated from the surrounding areas. Forest areas were delineated based on the image characteristics of dark gray tone and coarse texture. Areas of non-irrigated agriculture were shown in various gray tones ranging from dark to light, depending upon the field conditions. In this study, however, areas that were not assigned to the classes of irrigated agriculture, water reservoir, built-up area, or forest, were assumed to be non-irrigated agriculture.

A field survey was conducted to verify the result of this land cover mapping. All map delineations assigned to the classes of irrigated agriculture, water reservoir, built-up area, and forest were visited. After finishing the image interpretation and the field survey, the resultant map was transferred to the relevant topographic maps at a scale of 1 : 50,000 (Royal Survey Department, 1983a to f) using landmarks, e.g., irrigation channels, roads, and road intersections as the ground control objects. The transference was made by means of a reflecting projector to assure that the final land cover map generated in this part of the study was geometrically correct. This land cover map was employed as a bit map for the *masking* technique (PCI, 1994) that was applied to assist in the mapping process in the second part of the study.

### 7.2.2 Mapping areas of green crops on non-irrigated agricultural land in the dry season: Quantitative approach

#### 7.2.2.1 Satellite image data

LANDSAT-5 TM data, quadrant 4 of path 128, row 48 scene, and quadrant 2 of path 128, row 49 scene, were used as the bases for this mapping. These data were acquired on November 13, 1992. The data set of each quadrant was geometrically corrected using co-ordinate transformation and resampling phases. The co-ordinate transformation was carried out using a first-order polynomial (Lillesand and Kiefer, 1994; PCI, 1994). The number of ground control points used in this process were 27 and 25 for quadrant 4 and quadrant 2 data sets, respectively. The co-ordinates of these points were obtained from the topographic maps, scale 1:50,000 (Royal Survey Department, 1983) corresponding to the imagery data of these quadrants. The root mean square error was kept at less than 0.3 pixels. Image pixels were resampled to a 30 m size during the resampling phase which was performed using the nearest neighbor technique (Lillesand and Kiefer, 1994).

Since Kranuan district covers only a part in each of the two imagery quadrants, segments of the data which belong to this district were cut out of the full quadrants. Then the relevant data segments from each quadrant were mosaicked. The first-order polynomial transformation and the nearest neighbor resampling techniques were applied in the mosaicking process (PCI, 1994).

#### 7.2.2.2 Classification scheme

In the preliminary stage of this study, the classification scheme included four classes, i.e., cassava, sugarcane, senescent and harvested paddy rice, and idle land. The result of this preliminary study showed that if a subset of 4 image bands or less were used in the classification, the signature separability between the classes of cassava and the sugarcane would be very poor. In this study, information on the extent of green crops regardless of their species, was of interest. Therefore, to be able to efficiently utilize a subset of less image bands (≤ 4 bands), while maintaining adequate results, spectral signatures of cassava and sugarcane classes were merged into one. Thus, the finalized classification scheme included three classes:

(1) green crops;

(2) senescent and harvested paddy rice; and

(3) idle land.

#### 7.2.2.3 Field work

The field work was carried out during 7-20 November, 1992 (approximately 1 week before and after the acquisition date of the image data to be analyzed). This work was done to collect the necessary field data for the further image classification and accuracy assessment. Data of actual land cover were obtained from 80 sampling sites and divided into 2 sets. The data from 37 sites would be used as the *training data set* for the classification. The other 43 sampling sites would be used as the *test data set* for the accuracy assessment of the classification.

#### 7.2.2.4 Digital classification procedures

This part of the study focuses on the use of supervised classification for mapping green crop areas in the dry season of Northeast Thailand. This included three aspects (i) performances of various methods of supervised classification including Maximum Likelihood, Ties, and Minimum-Distance-to-Mean (PCI, 1994); (ii) optimum numbers of image bands to be used in the classification; and (iii) performance of Transformed Normalized Vegetation Index (TVI) data when used as a basis for the classification. The PCI EASI/PACE image processing system software package (PCI, 1994) was used for this quantitative classification in which the following six steps were carried out.

*Step 1. Generation of a bit map of major land cover types*

In this step, the final land cover map generated in Part I of the study was digitized and stored in the computer using the GRASS Geographic Information System software, version 4.1 (Shapiro et al., 1993). Then the map (in vector format) was transferred from GRASS 4.1 to the PCI image processing system. In PCI, these vector data were transformed to a bit map that later would be used in the masking technique. The masking technique was applied in every classification algorithm involved in this part of the study. This was done to eliminate areas of irrigated agriculture, water reservoir, built-up area, and forest, in order to limit the classification to non-irrigated agricultural areas, which were the only the areas of interest. Hence, the masking was expected to help reduce the complexity of the areas mapped and the amount of data to be analyzed, and, as a consequence, to improve the classification process in terms of computation time and number of bands required to generate adequate results.

*Step 2. Generation of the Transformed Normalized Vegetation Index (TVI) data*

The Transformed Normalized Vegetation Index data were generated using the Multispectral Modelling program available in PCI (PCI, 1994). The equation used to calculate these TVI values was described previously (Equation 4). The TVI values were then stored in a PCI data base channel (PCI, 1994) for further analysis.

*Step 3. Histogram analyses*

For each particular land cover class considered in this study (i.e., green crops, senescent and harvested paddy rice, and idle land), the histograms were generated from training areas to illustrate the distribution of spectral values recorded in every image channel including bands 1 to 7 and the TVI data (Figures 7.2, 7.3, and 7.4). As shown in Figure 7.2, for the class of green crops, spectral values recorded in bands 5 and 7 were not normally distributed. Moreover, Figure 7.3 shows that, for the class of senescent and harvested paddy rice, spectral values recorded in band 6 were not normally distributed. Data sets of bands 1 to 4 and the TVI were, however, found normally distributed for every land cover class (Figures 7.2, 7.3, and 7.4). In this study only imagery data of bands 1 to 4 and TVI were employed for three reasons. First, the Maximum Likelihood, and the Ties classification methods, both require normally distributed image data and were of interest in this study. Second, results of the signature separability analysis, that is described later in this chapter (section 7.3.2.1), revealed that the three land cover classes considered in this study had very well separated spectral signatures when imagery data from 4 bands (i.e., bands 1 to 4) were used. Third, even though, when the classification was based on TVI data, the classes of green crops, and senescent and harvested paddy rice were not spectrally separated very well (Table 7.3), to fulfill the second objective of this study, the TVI data were also considered.

*Step 4. Feature selections*

Initial feature (band) selection was based on the results of the histogram analyses. Then a feature selection was applied to determine the best subsets of 3, 2, and 1 band(s) from bands 1 to 4, for the classification. For instance, the best subset of 3 bands is the combination of 3 bands which results in the best signature separability among the land cover classes of interest when compared to combinations of any other 3 bands. The transformed divergence values were used as indicative of the signature separability between classes. The results of the selections suggested that, the best subsets of 3, 2, and 1 band(s) were bands 2, 3, and 4; bands 3, and 4; and band 4, respectively.

*Step 5. Digital classifications*

A total of 15 sets of classification methods by band combinations as shown in Table 7.2, were considered. Classification methods consisted of (i) Maximum Likelihood; (ii) Ties; and (iii) Minimum-Distance-to-Mean. Combinations of image bands include (i) bands 1, 2, 3, and 4; (ii) bands 2, 3, and 4; (iii) bands 3, and 4; (iv) band 4; and (v) Transformed Normalized Vegetation Index (TVI). Each of these sets were used to classify land cover types in the study area.

Data from a total of 37 training sites were used to develop training site statistics for the supervised classifications. These data were obtained as a result of the field work described earlier in section 7.2.2.3. Note that, as previously mentioned, to eliminate complexity in the classifications due to other irrelevant land cover types and to limit the classifications to the non-irrigated agricultural areas, the masking technique was applied using the bit map of major land cover types generated in Step 1.

*Step 6. Accuracy assessments*

To evaluate performances of the above 15 sets of classification methods by band combinations as shown in Table 7.2, an error matrix was constructed for the result of each set. In each error matrix, the result of LANDSAT-5 TM data classification was compared to the corresponding cover type data obtained from the field work. The comparison was undertaken on the basis of corresponding pixels in the test sites. Statistics employed in these accuracy assessments consist of overall accuracy, producer's accuracy, user's accuracy, and KAPPA analysis ($\hat{K}$). The Z-Statistic was applied to test the significant difference of the $\hat{K}$ coefficients for each individual matrix as well as for the compared matrices.

## 7.3 RESULTS AND DISCUSSION

### 7.3.1 Generation of a major land cover types map: Manual approach

The field survey conducted to verify the visual interpretation of SPOT imagery for land cover types mapping revealed satisfactory results. All map delineations were found to be identified with the correct classes, i.e., irrigated agriculture, water reservoir, built-up area, or forest. This is because the use of topographic maps to help indicate water reservoirs and built-up areas was a very effective means for interpretation. Also, the classification scheme employed in this task was so simple, comparable to Level 1 of the USGS - Land Use / Land Cover Classification System (Anderson et al., 1976), that it was not difficult to obtain highly accurate results.

### 7.3.2 Mapping areas of green crops on the non-irrigated agricultural land in the dry season: Quantitative approach

#### 7.3.2.1 Signature separability

Values of transformed divergence, the statistical parameter used to represent the signature separability between land cover classes, were considerably changed when the number of image bands used in the classification was changed. Judging from values of the average transformed divergence, the greater the number of bands involved in the band combinations, the better the signature separability(Table 7.3). The use of the band 1, 2, 3, and 4 combination resulted in greater values for the average transformed divergence than those of combination of bands 2, 3, and 4; combination of bands 3, and 4; Transformed Vegetation Indices (TVI); or band 4, respectively.

From Table 7.3, however, most of the band combinations considered in this study yielded good signature separability between land cover classes as indicated by the transformed divergence values of greater than 1.9 (PCI, 1994). Combinations of bands 1,2,3,4; bands 2,3,4; and bands 3,4; resulted in good signature separability for every pair of land cover class comparisons. When only remotely sensed data from band 4 were used, even though the signature separability between class 1 (green crops) and either class 2 (senescent and harvested paddy rice) or class 3 (idle land) was good, the separability between classes 2 and 3 was very poor. With the TVI data, very poor spectral separability between class 1 and class 2 (transformed divergence = 0.84) was found.

#### 7.3.2.2 Accuracy assessment

Results of the accuracy assessment undertaken on the basis of pixels in the test sites were as follows:

*Overall accuracy*

The classification accuracy as represented by the overall accuracy, the percentage of correctly identified pixels, is shown in Table 7.4. According to Anderson et al. (1976), an overall accuracy of at least 85 % is required for satisfactory use of land cover data for resource management. Based on this statement, the use of most sets of classification methods by band combinations provided satisfactory classification results, as the overall accuracy of more than 90 % were achieved when data from two image bands or more were used, regardless the classification methods applied. Nevertheless, if only data from one band (band 4) were used, the overall accuracy was low (60-63 %).

*Producer's and User's accuracy*

Since the producer's and the user's accuracy measures are closely related, these two statistical measures are discussed together. Table 7.5 to 7.9 show both accuracy measures assessed for different classification methods when data of combinations of bands 1, 2, 3, and 4; bands 2, 3, and 4; bands 3, and 4; band 4; and TVI; were used, respectively. For land cover classification using combinations of bands 1, 2, 3, and 4; bands 2, 3, and 4; or bands 3, and 4 (Table 7.5 to 7.7); both producer's and user's accuracy measures calculated for every land cover class were higher than 97 %. This is true for every classification method, except when the set of combination of bands 1,2,3,4 by Maximum Likelihood classification was used (Table 7.5a). In this case, the producer's accuracy was approximately 86 %. When more image bands are used the more specific the signature becomes. As a consequence, more individual training areas were required to obtain an appropriate representative signature that covers the whole range of spectral variation within each land cover class, otherwise the number of unclassified pixels increases. Thus for this study, when the data from a relatively high number of bands (4 bands) were used in the Maximum Likelihood classification, the number of unclassified pixels increased and in turn, the producer's accuracy decreased. Nevertheless, the producer's accuracies of > 86 %, and the user's accuracies of > 97 % are still considered very high, and at least 86 % of the areas of each land cover class has been correctly identified. Also more than 97 % of areas classified as classes 1, 2, or 3 were the same classes on the ground. Interpretation of the producer's and user's accuracy values for the relevant discussions would be in this fashion.

For every classification method, the classification using data from only band 4 (Table 7.8) resulted in high classification accuracy for land cover class 1, i.e., 100 % and 94-97 % for producer's and user's accuracy measures, respectively. However, for land cover classes 2 and 3, the classification accuracies were significantly lower than that of class 1. For class 2, the producer's accuracies were low (approximately 50-57 %), and the user's accuracies were fair (approximately 72 %). In the case of land cover class 3, the classification accuracies were low. The producer's accuracies were 40-45 %, and the user's accuracies were approximately 26 %. The low classification accuracies for land cover classes 2 and 3 can be explained by the poor signature separability between these two classes. As shown earlier, the transformed divergence value between classes 2 and 3 was only 0.04 (Table 7.3).

The use of TVI data together with any of the classification methods (Table 7.9) also provided accurate classification results. The producer's accuracies were approximately 80 %, and the user's accuracies were approximately 85 % for land cover class 1. For classes 2 and 3, values of both accuracy measures were higher than 92 %. The less accurate classification results for class 1 were probably because the TVI, like other band ratioed vegetation indices, inherits limitation in such a way that dissimilar material with different absolute radiance but having similar slope of the spectral curves could be incorrectly identified as the same materials (Lillesand and Keifer, 1994). The senescent and harvested paddy rice, when compared with the green crops, had lower reflectance of radiance in both near infrared (NIR) and red (R) wavelength ranges. This is because the reflectance characteristic of the senescent leaves (land cover class 2) reflect less of NIR radiance, when compared to the reflectance from the mature green leaves of land cover class 1 (Lillesand and Kiefer, 1994). Further, as the areas of the senescent and harvested paddy rice were usually under conditions of higher soil moisture content than those of the green crops, the reflectance in red wavelengths from the areas of the senescent and harvested paddy rice was lower (Mulders, 1987). Since the TVI index is basically the ratio of reflectance in NIR and R wavelength ranges, the TVI for classes 1 and 2 were so close that the separability between these 2 classes was poor as indicated by the transformed divergence of 0.84 (Table 7.3).

*KAPPA analysis*

The classification accuracy, as represented by $\hat{K}$ coefficient, for each set of classification method by band combination is shown in Table 7.10. For every classification method, using combinations of bands 1, 2, 3, and 4; bands 2, 3, and 4; or bands 3, and 4 resulted in the high values of $\hat{K}$ (> 0.93) meaning that the classifications have achieved the accuracy that is at least 93 % better than would be expected from random assignment of classes to pixels. For the classifications in which only band 4 data were used, the $\hat{K}$ coefficients were as low as 0.37. The use of TVI data resulted in $\hat{K}$ coefficients of > 0.84. Interpretation of $\hat{K}$ coefficients for the classifications using band 4 data or TVI data was the same as for the other band combinations described above.

The $\hat{K}$ coefficient was also used as a basis for (1) the test of significance for individual matrices to determine whether or not the result presented in each individual matrix was significantly better than a random result; and (2) the test of significance for the compared matrices to determine whether or not each pair of error matrices were significantly different. In other words, whether or not each pair of classification results, generated using different sets of classification methods by band combinations, were significantly different in terms of accuracy. Results of the analyses are discussed in the following.

(1) Test of significance for individual matrices.

According to the Z-statistics given in Table 7.10, every set of classification method by band combination provided a classification result which was significantly better than a result generated by random assignment of classes to pixels ($\hat{K}$ was significantly different from 0 at the 95 % confidence level).

(2) Test of significance for compared matrices.

Results of the comparisons between error matrices, two at a time, are shown in Table 7.11. To ease the recognition of differences between error matrices, results shown in Table 7.11 were re-tabulated, and presented in Table 7.12. Discussions of these results are separated into three conditions as follows.

i) When data from combinations of bands 1,2,3,4; bands 2,3,4; or bands 3,4 were used.

The classifications using the sets of Minimum-Distance-to-Mean by any of these band combinations provided the most accurate results, which resulted in no significant differences between these sets. The results, however, were significantly different from those generated using other sets of classification methods by band combinations.

The use of the Ties classification method with any of these band combinations gave the second most accurate results. There was no significant difference within the results generated using Ties, but significant differences were found when these results were compared with the results generated from other sets of classification methods by band combinations.

In general terms, application of the Maximum Likelihood method coupled with any of these band combinations also provided highly accurate results. However, the $\hat{K}$ coefficients suggested that these classification results were significantly less accurate than the results obtained when either Ties or Minimum-distance-to-Mean was used. The exception was the set of Maximum Likelihood by combination of bands 3,4; as this set gave a non-significance classification result in terms of accuracy, when compared with those generated using Ties. In addition, there were significant differences within the results generated using the sets of Maximum Likelihood by each of these band combinations.

ii) When data of band 4 were used.

Between the results generated using band 4 data but different classification methods, there was no significant difference in terms of accuracy. These classification results were, however, significantly less accurate ($\hat{K} < 0.41$, Table 7.10) than those generated using data from other band combinations.

iii) When data of TVI were used.

Between the results generated using TVI data but different classification methods, there was no significant difference in terms of accuracy. Even though the results of using TVI data with any of the classification methods were significantly less accurate than those obtained using data from other combinations of two bands or more, the classification using this kind of data still provided adequate results ($\hat{K} > 0.84$, Table 7.10).

## 7.4 GENERAL DISCUSSION AND CONCLUSION

Any of the 15 sets of classification methods by band combinations provided a classification result that was significantly better than a random result. According to the test of significance using the Z-statistic (Table 7.10), the $\hat{K}$ coefficients for all individual matrices were significantly different from 0 at the 95 % confident level.

In general terms, for every classification method applied, results of the classifications using TM data from two bands or more (except the TVI ), i.e., bands 1, 2, 3, and 4; bands 2, 3, and 4; and bands 3, and 4; were highly accurate. The $\hat{K}$ coefficients of these classifications were found to range from approximately 0.93-0.99 (Table 7.10). The producer's, user's, and overall accuracies were about 85-100 % (Table 7.5 to 7.7), 98-100 % (Table 7.5 to 7.7), and 96-99 % (Table 7.4), respectively. Moreover, when data from two bands or more were used, the tests of significance between the error matrices (Table 7.11, 12) showed that there were significant differences between the accuracies of classification results generated using different classification methods. Minimum-Distance-to-Mean yielded the best results and was significantly different from the results generated using Ties and Maximum Likelihood, respectively. The fact that Maximum Likelihood resulted in a considerable amount of unclassified pixels (Table 7.5 to 7.7) was an important factor explaining the significantly less accurate results when this classification method was applied.

For the classifications using data from band 4 together with any of the classification methods, the accuracies were generally very low as indicated by the $\hat{K}$ coefficients of approximately 0.38-0.41 (Table 7.10) and overall accuracies of about 60-63 % (Table 7.4). These poor accuracies were mainly due to the poor signature separability between land cover class 2 (senescent and harvested paddy rice) and class 3 (idle land) as indicated by a transformed divergence of only 0.04 (Table 7.3). The relevant error matrices (Table 7.8a, b, and c) suggested that a high percentage of areas actually belonging to land cover class 2 were incorrectly identified as land cover class 3, and vice versa. The producer's accuracies for land cover classes 2 and 3 were approximately 40-57 %, and the user's accuracies for these two land cover classes were 27-73 %. The classification accuracies for class 1 (green crops), however, were very high as indicated by the producer's accuracies of 100 % and the user's accuracies of 94-97 %. The signature separability analysis has shown that between classes 1 and 2, and classes 1 and 3, the spectral signatures were highly separable as indicated by the transformed divergence values of 1.96 and 1.98, respectively (Table 7.3). The classification methods, in this case, did not make any difference in the accuracy of the results. For this study, in which mapping of land cover class 1 was the major concern, the low accuracies for the classifications of classes 2 and 3 might not be of importance. Hence, the classification using only band 4 data may be adequate. An additional accuracy assessment was undertaken to investigate the classification accuracies obtained when land cover classes 2 and 3 were combined into one class. This assessment showed that the classification results were highly accurate. The $\hat{K}$ coefficients were 0.98, 0.98, and 0.96 for Maximum Likelihood, Ties, and Minimum-Distance-to-Mean, respectively. The overall accuracy was about 99 % for every classification method.

When the TVI data were used with any of the classification methods, the classification results were significantly less accurate than those obtained using data from other combinations of two imagery bands or more (Table 7.9). The less accurate classification results, in this case, were mainly due to poor signature separability between land cover classes 1 and 2 as indicated by the transformed divergence of 0.84 (Table 7.3). This poor separability occurred as a result of ratioing remotely sensed data from band 3 (red) and band 4 (near-infrared) as discussed previously in section 7.3.2.2. Despite the poor separability, the land cover classifications using TVI data still yielded adequate results because the classification scheme applied in this study was very simple comparable to Level 2 of the USGS - Land Use / Land Cover Classification System (Anderson et al., 1976). Various accuracy measures support this statement. The $\hat{K}$ coefficients were about 0.84-0.86 (Table 7.10). The producer's, user's, and overall accuracies were 80-97 % (Table 7.9), 85-99 % (Table 7.9), and 91-92 % (Table 7.4), respectively . The classification methods did not cause the difference in terms of classification accuracies when the TVI data were used.

In conclusion, generally, if only the spatial distribution of areas belonging to class 1 is of interest, the use of Minimum-Distance-to-Mean classification method together with the LANDSAT-5 TM data recorded in band 4 should be sufficient. This set of classification method by band combination provided adequate classification results for land cover class 1 (producer's accuracy = 100%, user's accuracy > 94 %), but required less remotely sensed data and a relatively simple classification method. In a practical sense, this means less money would be required for purchasing satellite data, as well as reduced computing time and computer storage.

However, if a highly accurate result for all three land cover classes were required, the use of Minimum-Distance-to-Mean together with data from the combination of LANDSAT-5 TM bands 3 and 4 would be most appropriate. It yielded the most accurate classification result that, according to this study, was significantly different from the results generated using many of the other sets of classification methods by band combinations (Table 7.10). Even though, in terms of accuracy, there was no significant difference between the results generated using bands 1, 2, 3, and 4; bands 2, 3, and 4; or bands 3, and 4 together with the Minimum-Distance-to-Mean; the use of band 3, 4 combination would be preferable since it requires less satellite data.

Although adequate classification results were obtained with the use of TVI data, this data was not appropriate for this study. It required extra work, computing time, and computer storage space (e.g., for band ratioing), and the results were less accurate than those generated using the band 3, 4 combination.

**Table 7.1** Criteria used in the visual interpretation of SPOT, band 1, black and white print, for major land cover types classification in Kranuan District.

| Class | Image characteristics | | | | Additional reference data |
|---|---|---|---|---|---|
| | Tone | Texture | Pattern | Shape | |
| Irrigated agriculture | - | - | - | - | Schematic map of Nongwai-Nam Phong Irrigation Project |
| Water reservoir | Black to dark gray | No or very smooth | - | Irregular | Topographic maps |
| Built-up area | White to dark gray | - | Rectangular | - | Topographic maps |
| Forest | Dark | Coarse | - | - | - |

**Table 7.2** List of 15 sets of classification methods by band combinations that were considered in this study.

| Set number | Classification method | Bands combination *or* vegetation index [1/] |
|---|---|---|
| 1 | Maximum Likelihood | 1, 2, 3, 4 |
| 2 | | 2, 3, 4 |
| 3 | | 3,4 |
| 4 | | 4 |
| 5 | | TVI |
| 6 | Ties | 1, 2, 3, 4 |
| 7 | | 2, 3, 4 |
| 8 | | 3,4 |
| 9 | | 4 |
| 10 | | TVI |
| 11 | Minimum-Distance-to-Mean | 1, 2, 3, 4 |
| 12 | | 2, 3, 4 |
| 13 | | 3,4 |
| 14 | | 4 |
| 15 | | TVI |

[1/] Band 1 = 0.45-0.52 μm
Band 2 = 0.52-0.60 μm
Band 3 = 0.63-0.69 μm
Band 4 = 0.76-0.90 μm
TVI = Transformed Vegetation Index

**Table 7.3** Signature separability, as represented by the transformed divergence values, for different class comparisons.

| Band combination | Average transformed divergence | Transformed divergence | | |
|---|---|---|---|---|
| | | Class comparison | | |
| | | Class 1 vs Class 2 [1/] | Class 1 vs Class 3 | Class 2 vs Class 3 |
| 1,2,3,4 | 1.99472 | 1.98653 | 2.00000 | 1.99763 |
| 2,3,4 | 1.99414 | 1.98552 | 2.00000 | 1.99690 |
| 3,4 | 1.99057 | 1.97605 | 2.00000 | 1.99565 |
| 4 | 1.32972 | 1.96466 | 1.98281 | 0.04168 |
| TVI | 1.60974 | 0.83666 | 2.00000 | 1.99257 |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.4** Overall accuracy (%) for different classification methods and band combinations.

| Band combination | Classification method | | |
|---|---|---|---|
| | Maximum Likelihood | Ties | Minimum-Distance-to-Mean |
| 1,2,3,4 | 96.38 | 99.36 | 99.74 |
| 2,3,4 | 98.09 | 99.32 | 99.76 |
| 3,4 | 99.06 | 99.36 | 99.76 |
| 4 | 62.96 | 62.96 | 59.82 |
| TVI | 91.02 | 91.02 | 91.83 |

**Table 7.5** Performances of the digital classification using data recorded in *bands 1, 2, 3, and 4*, with different classification techniques. (The performances were assessed on the basis of pixels in the test sites).

(a) Maximum Likelihood

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 852 | 41 | 0 | 98 | 991 | 85.97 |
| Class 2 | 0 | 2574 | 2 | 2 | 2578 | 99.84 |
| Class 3 | 0 | 11 | 963 | 11 | 985 | 97.77 |
| Total | 852 | 2626 | 965 | 111 | 4554 | |
| User's accuracy (%) | 100 | 98.02 | 99.79 | | | |

(b) Ties

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 989 | 1 | 0 | 1 | 991 | 99.80 |
| Class 2 | 1 | 2574 | 2 | 1 | 2578 | 99.84 |
| Class 3 | 13 | 10 | 962 | 0 | 985 | 97.66 |
| Total | 1003 | 2585 | 964 | 2 | 4554 | |
| User's accuracy (%) | 98.60 | 99.57 | 99.79 | | | |

(c) Minimum-Distance-to-Mean

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 986 | 0 | 5 | 0 | 991 | 99.50 |
| Class 2 | 2 | 2571 | 5 | 0 | 2578 | 99.73 |
| Class 3 | 0 | 985 | 0 | 0 | 985 | 100.00 |
| Total | 988 | 3556 | 10 | 0 | 4554 | |
| User's accuracy (%) | 99.80 | 100.00 | 98.99 | | | |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.6** Performances of the digital classification using data recorded in *bands 2, 3, and 4*, with different classification techniques. (The performances were assessed on the basis of pixels in the test sites).

(a) Maximum Likelihood

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 927 | 19 | 0 | 45 | 991 | 93.54 |
| Class 2 | 0 | 2575 | 2 | 1 | 2578 | 99.88 |
| Class 3 | 0 | 11 | 965 | 9 | 985 | 97.97 |
| Total | 927 | 2605 | 967 | 55 | 4554 | |
| User's accuracy (%) | 100.00 | 98.85 | 99.79 | | | |

(b) Ties

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 987 | 3 | 0 | 1 | 991 | 99.60 |
| Class 2 | 1 | 2574 | 2 | 1 | 2578 | 99.84 |
| Class 3 | 13 | 10 | 962 | 0 | 985 | 97.66 |
| Total | 1001 | 2587 | 964 | 2 | 4554 | |
| User's accuracy (%) | 98.60 | 99.50 | 99.79 | | | |

(c) Minimum-Distance-to-Mean

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 986 | 0 | 5 | 0 | 991 | 99.50 |
| Class 2 | 2 | 2572 | 4 | 0 | 2578 | 99.77 |
| Class 3 | 0 | 0 | 985 | 0 | 985 | 100.00 |
| Total | 988 | 2572 | 994 | 0 | 4554 | |
| User's accuracy (%) | 99.80 | 100.00 | 99.09 | | | |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.7** Performances of the digital classification using data recorded in *bands 3, and 4*, with different classification techniques. (The performances were assessed on the basis of pixels in the test sites).

(a) Maximum Likelihood

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 974 | 0 | 0 | 17 | 991 | 98.28 |
| Class 2 | 0 | 2577 | 0 | 1 | 2578 | 99.96 |
| Class 3 | 0 | 16 | 960 | 9 | 985 | 97.46 |
| Total | 974 | 2593 | 960 | 27 | 4554 | |
| User's accuracy (%) | 100.00 | 99.38 | 100.00 | | | |

(b) Ties

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 990 | 0 | 0 | 1 | 991 | 99.90 |
| Class 2 | 1 | 2576 | 0 | 1 | 2578 | 99.92 |
| Class 3 | 11 | 15 | 959 | 0 | 985 | 97.36 |
| Total | 1002 | 2591 | 959 | 2 | 4554 | |
| User's accuracy (%) | 98.80 | 99.42 | 100.00 | | | |

(c) Minimum-Distance-to-Mean

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 987 | 0 | 4 | 0 | 991 | 99.60 |
| Class 2 | 2 | 2572 | 4 | 0 | 2578 | 99.77 |
| Class 3 | 1 | 0 | 984 | 0 | 985 | 99.90 |
| Total | 990 | 2572 | 992 | 0 | 4554 | |
| User's accuracy (%) | 99.70 | 100.00 | 99.19 | | | |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.8** Performances of the digital classification using data recorded in *band 4*, with different classification techniques. (The performances were assessed on the basis of pixels in the test sites).

(a) Maximum Likelihood

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 991 | 0 | 0 | 0 | 991 | 100.00 |
| Class 2 | 0 | 1475 | 1102 | 1 | 2578 | 57.21 |
| Class 3 | 26 | 558 | 401 | 0 | 985 | 40.71 |
| Total | 1017 | 2033 | 1503 | 1 | 4554 | |
| User's accuracy (%) | 97.44 | 72.55 | 26.68 | | | |

(b) Ties

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 991 | 0 | 0 | 0 | 991 | 100.00 |
| Class 2 | 0 | 1475 | 1102 | 1 | 2578 | 57.21 |
| Class 3 | 26 | 558 | 401 | 0 | 985 | 40.70 |
| Total | 1017 | 2033 | 1503 | 1 | 4554 | |
| User's accuracy (%) | 97.44 | 72.55 | 26.68 | | | |

(c) Minimum-Distance-to-Mean

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 991 | 0 | 0 | 0 | 991 | 100.00 |
| Class 2 | 3 | 1281 | 1294 | 0 | 2578 | 49.69 |
| Class 3 | 51 | 482 | 452 | 0 | 985 | 45.89 |
| Total | 1045 | 1763 | 1746 | 0 | 4554 | |
| User's accuracy (%) | 94.83 | 72.66 | 25.89 | | | |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.9** Performances of the digital classification using *Transformed Vegetation Index (TVI)*, with different classification techniques. (The performances were assessed on the basis of pixels in the test sites).

(a) Maximum Likelihood

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 795 | 196 | 0 | 0 | 991 | 80.22 |
| Class 2 | 139 | 2438 | 1 | 0 | 2578 | 94.57 |
| Class 3 | 0 | 73 | 912 | 0 | 985 | 92.59 |
| Total | 934 | 2707 | 913 | 0 | 4554 | |
| User's accuracy (%) | 85.12 | 90.06 | 99.89 | | | |

(b) Ties

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 795 | 196 | 0 | 0 | 991 | 80.22 |
| Class 2 | 139 | 2438 | 1 | 0 | 2578 | 94.57 |
| Class 3 | 0 | 73 | 912 | 0 | 985 | 92.59 |
| Total | 934 | 2707 | 913 | 0 | 4554 | |
| User's accuracy | 85.12 | 90.06 | 99.89 | | | |

(c) Minimum-Distance-to-Mean

| Reference data (field work) | Digital Classification | | | | | Producer's accuracy (%) |
|---|---|---|---|---|---|---|
| | Class 1[1/] | Class 2 | Class 3 | Unclassified | Total | |
| Class 1[1/] | 797 | 194 | 0 | 0 | 991 | 80.42 |
| Class 2 | 139 | 2425 | 14 | 0 | 2578 | 94.07 |
| Class 3 | 0 | 25 | 960 | 0 | 985 | 97.46 |
| Total | 936 | 2644 | 974 | 0 | 4554 | |
| User's accuracy (%) | 85.15 | 91.72 | 98.56 | | | |

[1/] class 1 = Green crops; class 2 = Senescent and harvested paddy rice; class 3 = Idle land

**Table 7.10** Results of the KAPPA Analysis Test of Significance for individual error matrices.

| Matrix number | Classification technique | Band combination | $\hat{K}$ coefficient | Z-Statistic | Result |
|---|---|---|---|---|---|
| 1 | Maximum Likelihood | 1,2,3,4 | 0.9383 | 203.09 | *S* [1] |
| 2 | | 2,3,4 | 0.9674 | 282.04 | *S* |
| 3 | | 3,4 | 0.9839 | 403.23 | *S* |
| 4 | | 4 | 0.4095 | 33.81 | *S* |
| 5 | | TVI | 0.8439 | 113.74 | *S* |
| 6 | Ties | 1,2,3,4 | 0.9891 | 492.09 | *S* |
| 7 | | 2,3,4 | 0.9884 | 475.17 | *S* |
| 8 | | 3,4 | 0.9891 | 492.09 | *S* |
| 9 | | 4 | 0.4095 | 33.81 | *S* |
| 10 | | TVI | 0.8439 | 113.74 | *S* |
| 11 | Minimum Distance | 1,2,3,4 | 0.9955 | 765.77 | *S* |
| 12 | | 2,3,4 | 0.9959 | 803.13 | *S* |
| 13 | | 3,4 | 0.9959 | 803.13 | *S* |
| 14 | | 4 | 0.3799 | 30.96 | *S* |
| 15 | | TVI | 0.8592 | 122.05 | *S* |

[1]/ *S* = Significant at the 95 % confidence level

**Table 7.11** Comparison between error matrices using Z Statistic.

| Matrix no.[1] | Z - Statistic | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| 1 | | | | | | | | | | | | | | | |
| 2 | -3.06 | | | | | | | | | | | | | | |
| 3 | -8.73 | -3.91 | | | | | | | | | | | | | |
| 4 | 40.80 | 44.33 | 46.50 | | | | | | | | | | | | |
| 5 | 10.79 | 15.10 | 17.91 | -30.59 | | | | | | | | | | | |
| 6 | -10.09 | -5.46 | -1.66[2] | -47.22 | -18.88 | | | | | | | | | | |
| 7 | -9.88 | -5.23 | -1.40[2] | -47.11 | -18.74 | 0.26[2] | | | | | | | | | |
| 8 | -10.09 | -5.46 | -1.63[2] | -47.22 | -18.88 | 0.00[2] | -0.26[2] | | | | | | | | |
| 9 | 40.80 | 44.33 | 46.50 | 0.00[2] | 30.59 | 47.22 | 47.11 | 47.22 | | | | | | | |
| 10 | 10.79 | 15.10 | 17.91 | -30.59 | 0.00[2] | 18.88 | 18.74 | 18.88 | -30.59 | | | | | | |
| 11 | -11.92 | -7.66 | -4.21 | -48.12 | -20.12 | -2.67 | -2.91 | -2.67 | -48.12 | -20.12 | | | | | |
| 12 | -12.04 | -7.81 | -4.39 | -48.17 | -20.20 | -2.87 | -3.11 | -2.87 | -48.17 | -20.20 | -0.21[2] | | | | |
| 13 | -12.04 | -7.81 | -4.39 | -48.17 | -20.20 | -2.87 | -3.11 | -2.87 | -48.17 | -20.20 | -0.21[2] | 0.00[2] | | | |
| 14 | 42.59 | 46.12 | 48.28 | 1.72[2] | 32.37 | 49.00 | 48.90 | 49.00 | 1.72[2] | 32.37 | 49.90 | 49.95 | 49.95 | | |
| 15 | 9.39 | 13.81 | 16.73 | -32.11 | -1.50[2] | 17.74 | 17.59 | 17.74 | -32.11 | -1.50[2] | 19.03 | 19.11 | 19.11 | -33.89 | |

[1] Description for each matrix number representing classification technique by band combination is in Table 7.2.

[2] Non - Significant at the 95 % confidence level.

**Table 7.12** Results of the KAPPA Analysis Test of Significance between error matrices.

| Matrix number | Classification technique | Band combination | $\hat{K}$ coefficient | Result 1/ |
|---|---|---|---|---|
| 1 | Maximum Likelihood | 1,2,3,4 | 0.9383 | d |
| 2 | | 2,3,4 | 0.9674 | c |
| 3 | | 3,4 | 0.9839 | b |
| 4 | | 4 | 0.4095 | f |
| 5 | | TVI | 0.8439 | e |
| 6 | Ties | 1,2,3,4 | 0.9891 | b |
| 7 | | 2,3,4 | 0.9884 | b |
| 8 | | 3,4 | 0.9891 | b |
| 9 | | 4 | 0.4095 | f |
| 10 | | TVI | 0.8439 | e |
| 11 | Minimum Distance | 1,2,3,4 | 0.9955 | a |
| 12 | | 2,3,4 | 0.9959 | a |
| 13 | | 3,4 | 0.9959 | a |
| 14 | | 4 | 0.3799 | f |
| 15 | | TVI | 0.8592 | e |

1/ the same letters indicate the $\hat{K}$ coefficients are not different at the 95 % confidence level.

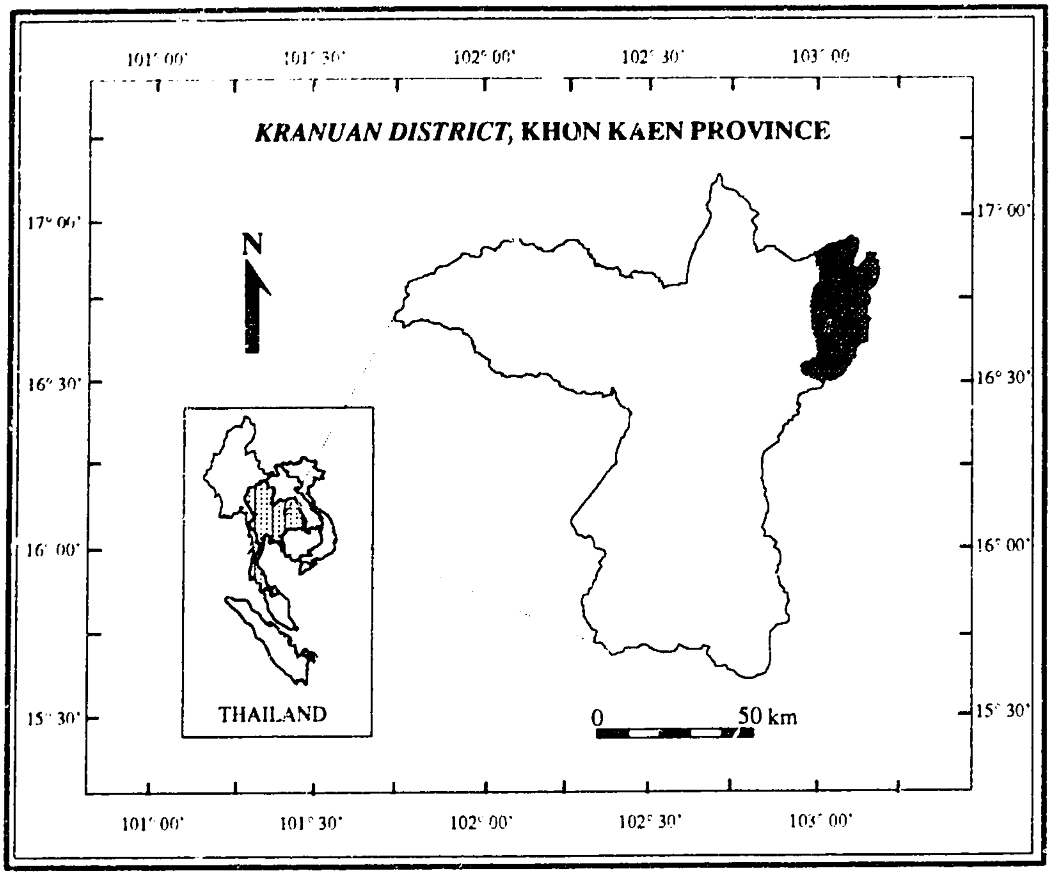


**Figure 7.1** Location of Kranuan District (shaded area) in Khon Kaen Province..

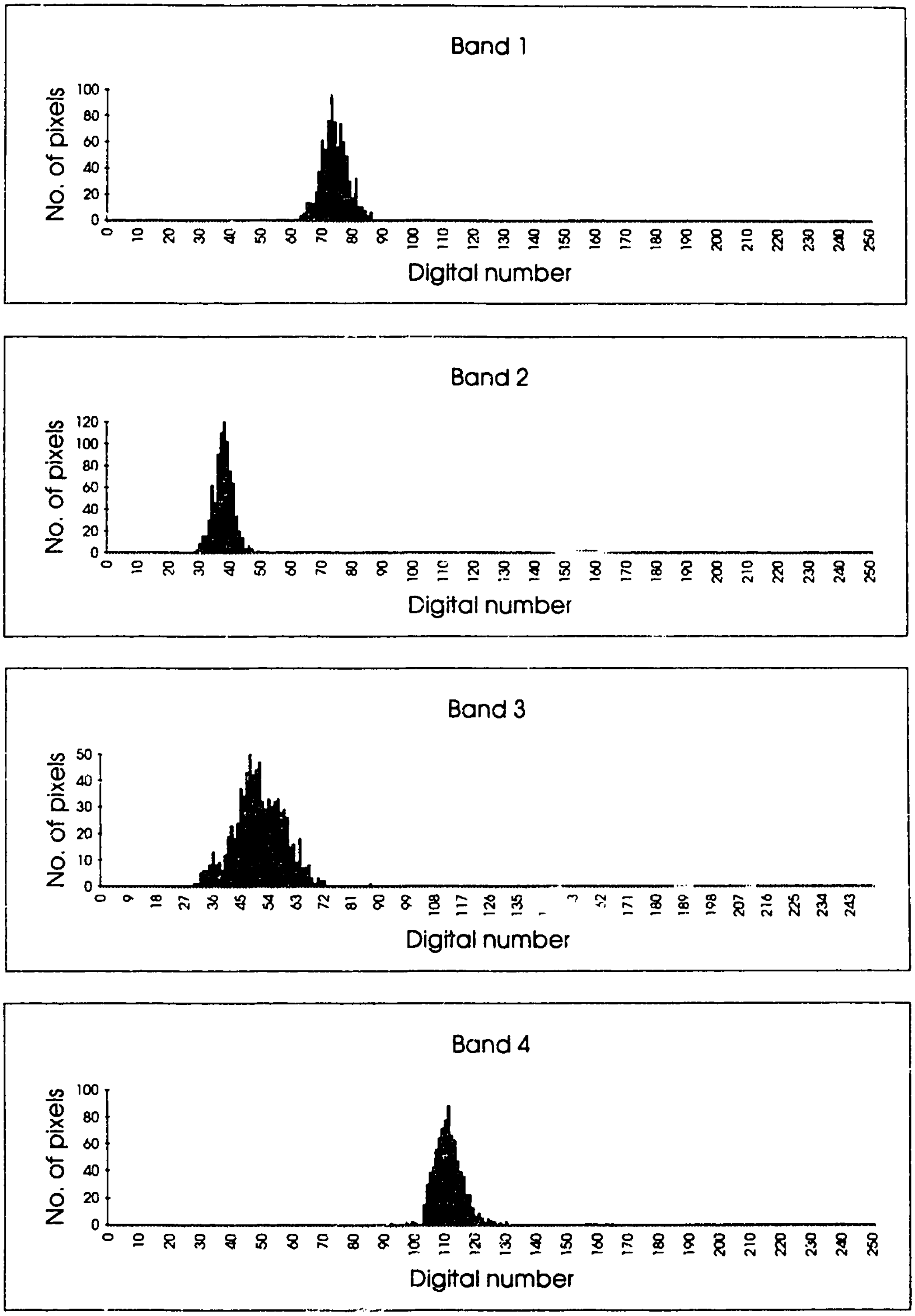


**Figure 7.2** Histogram of land cover class 1 (Green crops) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

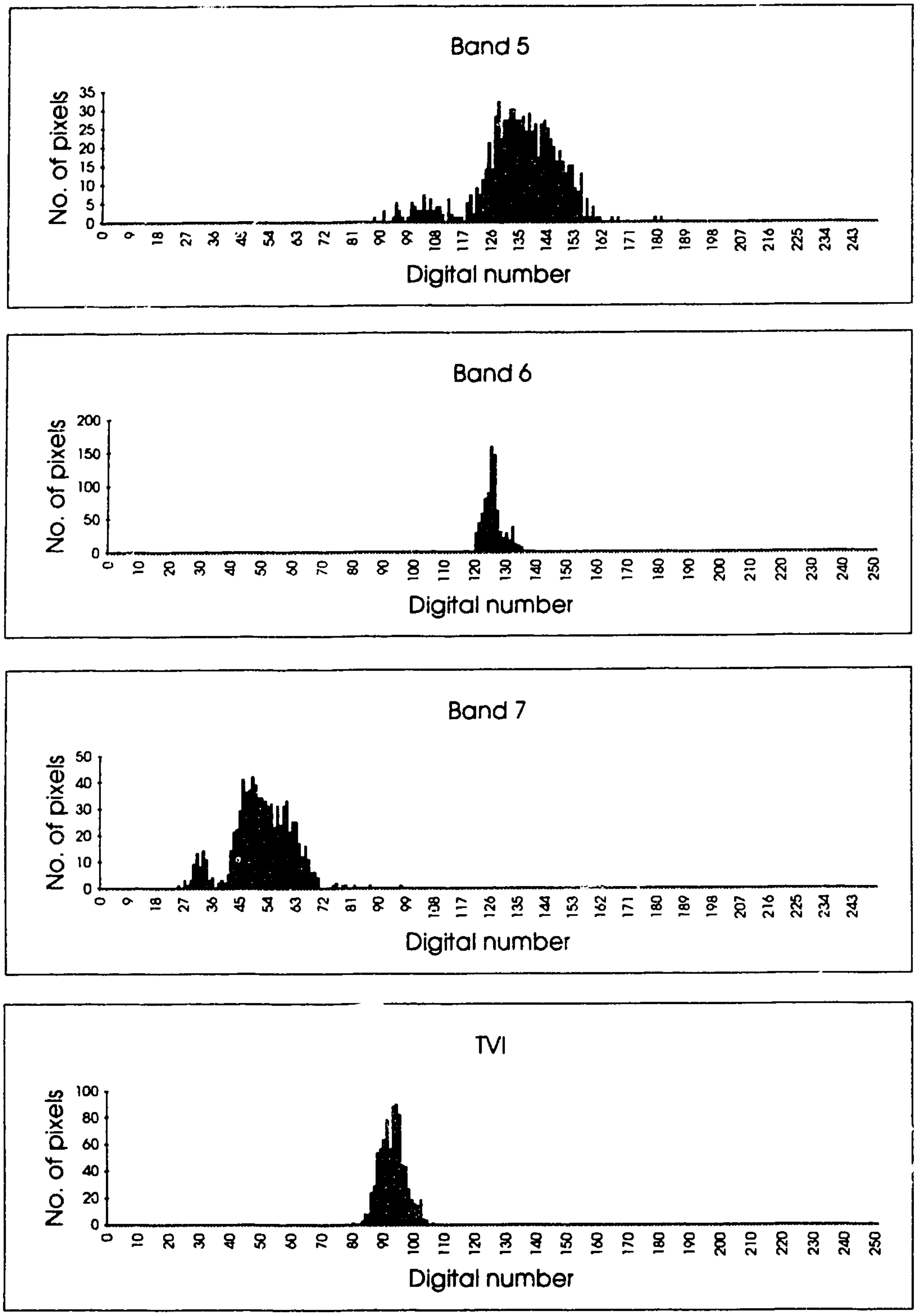


**Figure 7.2** (cont.) Histogram of land cover class 1 (Green crops) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

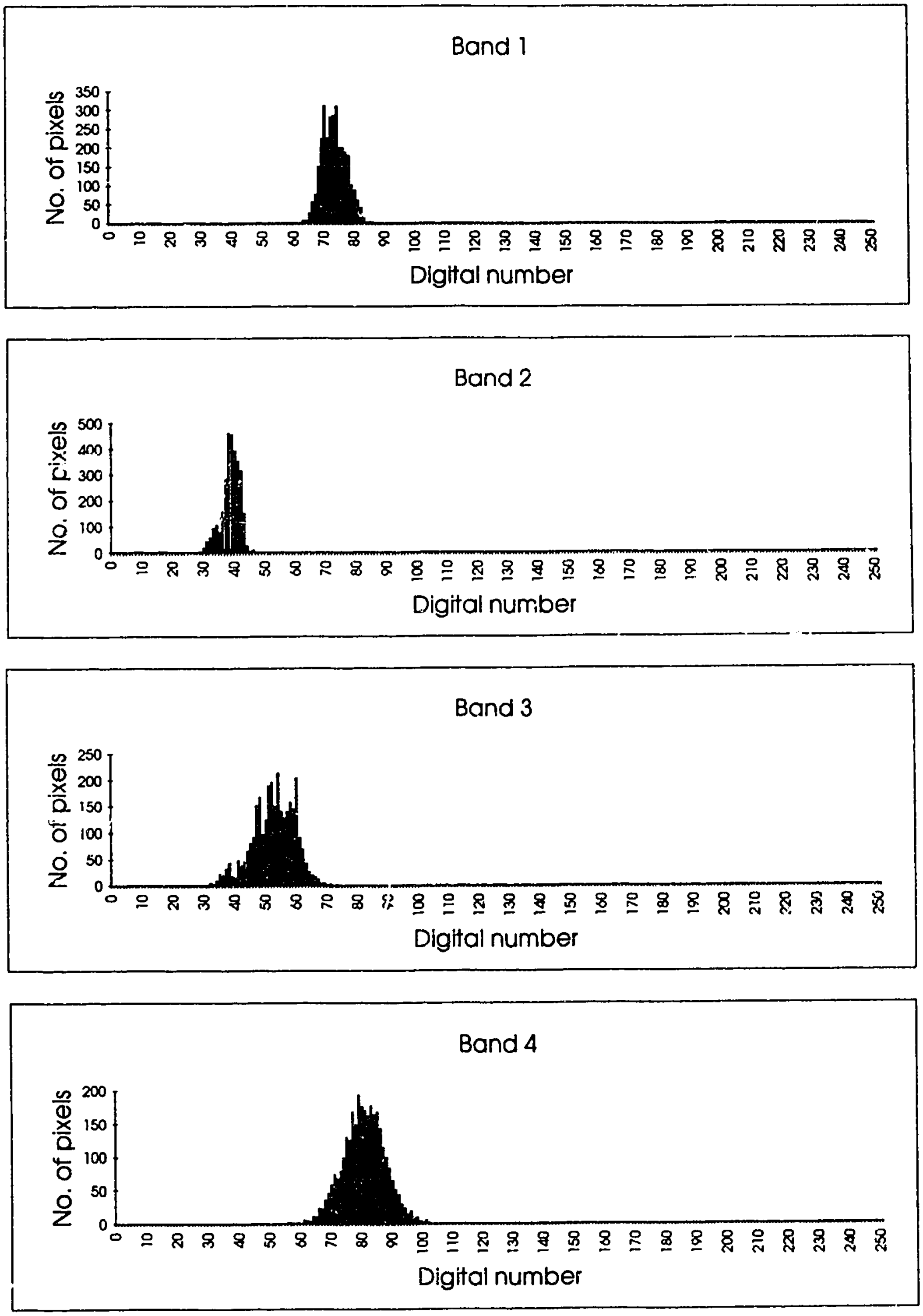


**Figure 7.3** Histogram of land cover class 2 (Senescent and harvested paddy rice) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

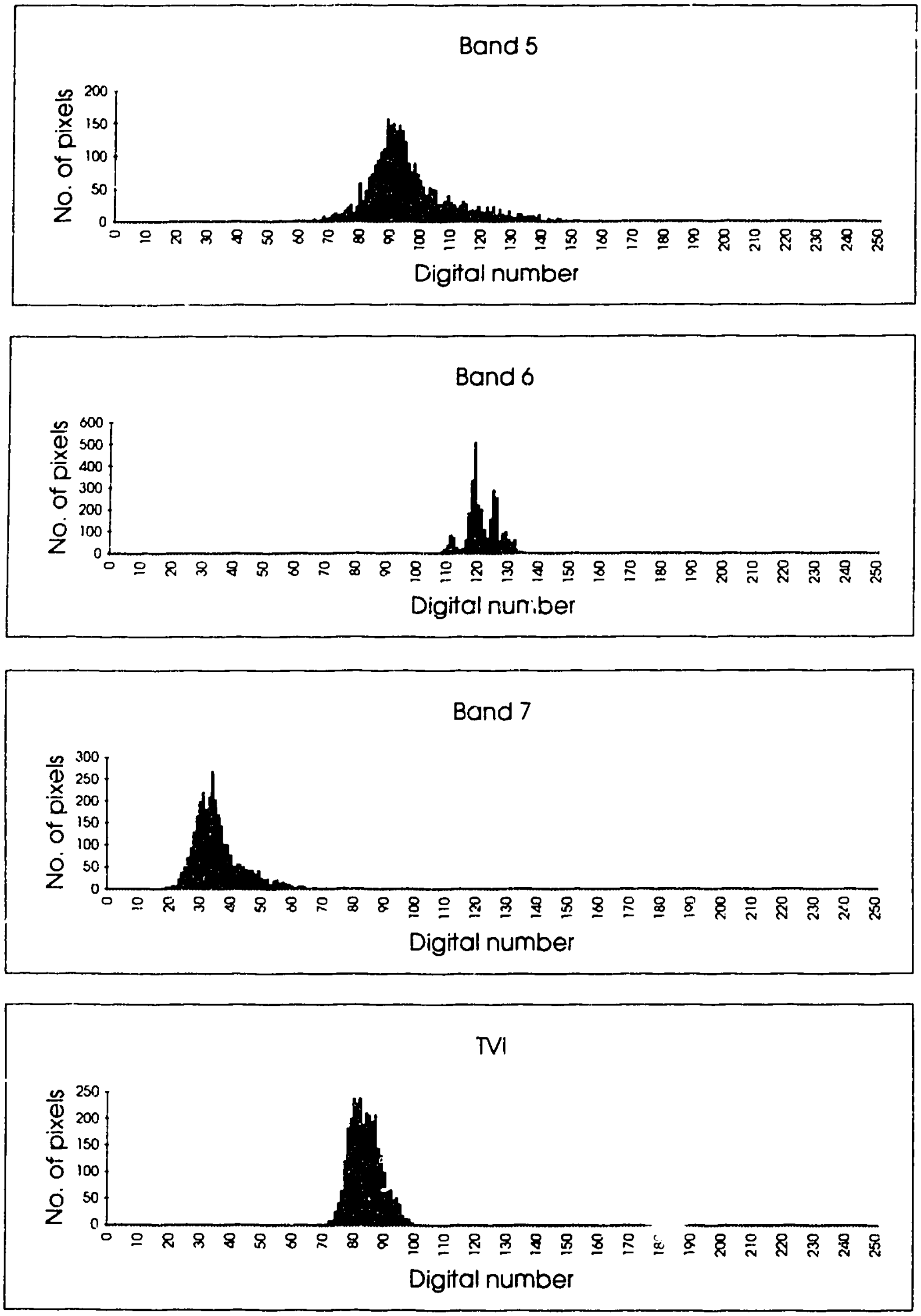


**Figure 7.3** (cont.) Histogram of land cover class 2 (Senescent and harvested paddy rice) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

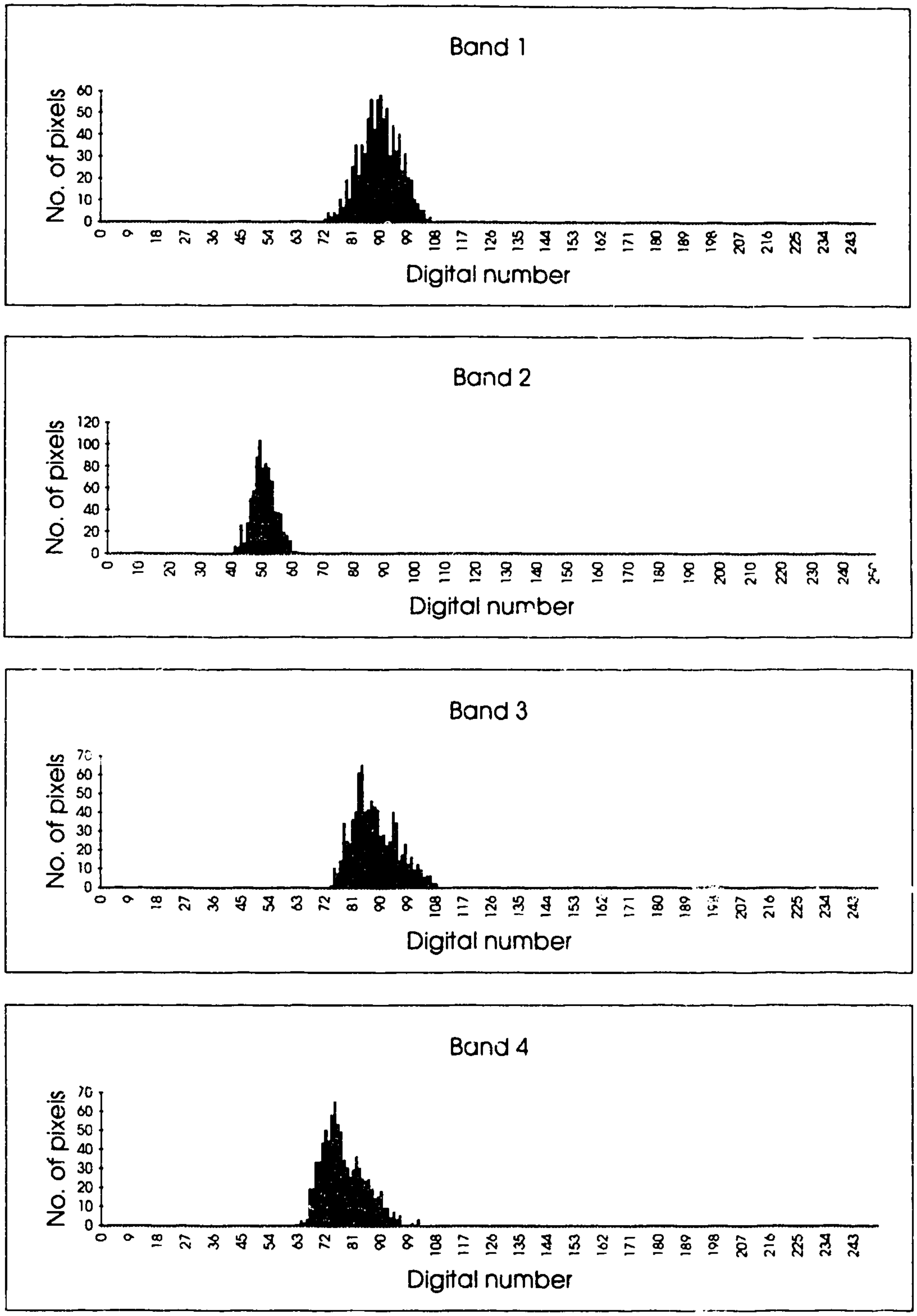


**Figure 7.4** Histogram of land cover class 3 (Idle land) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

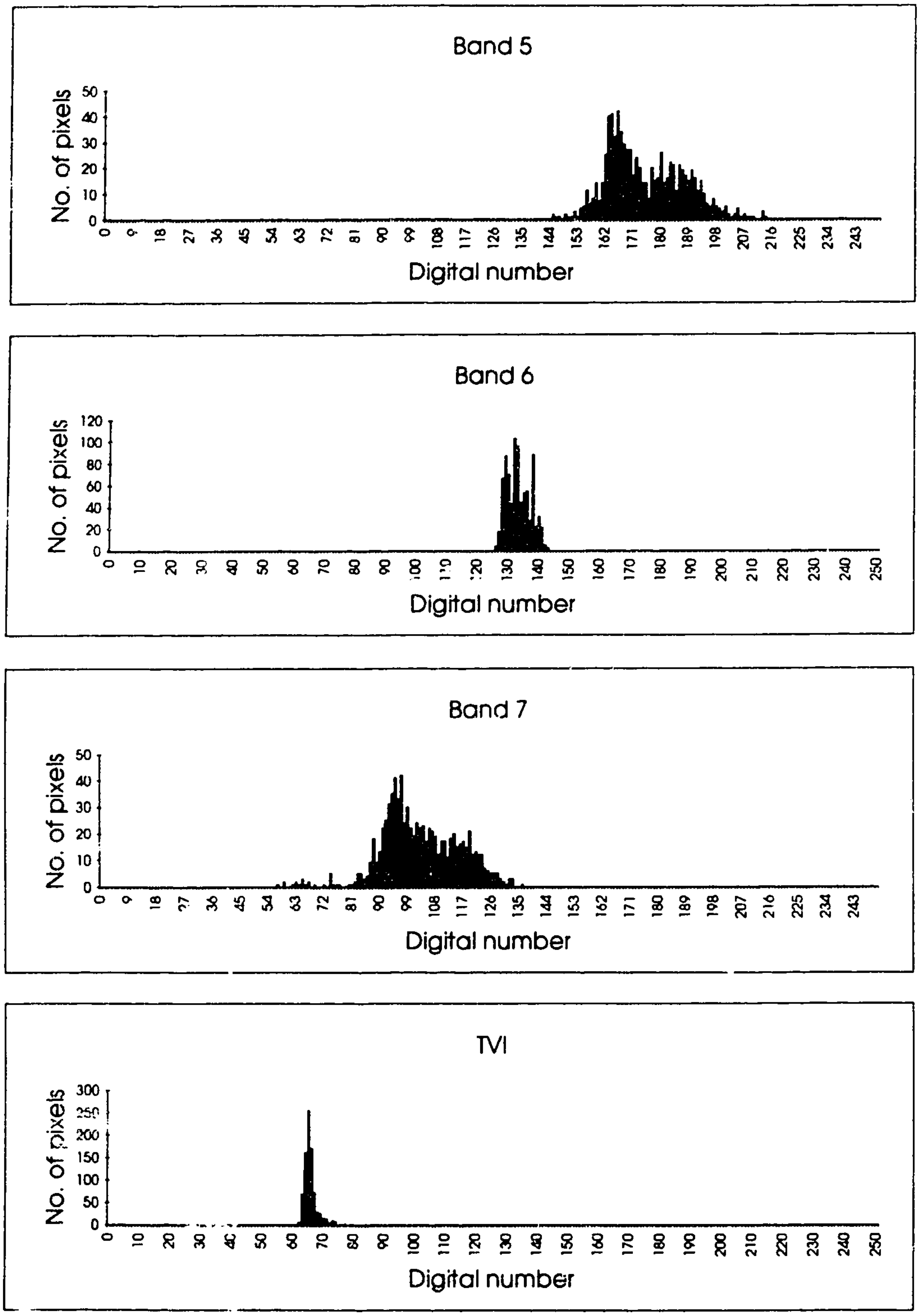


**Figure 7.4** (cont.) Histogram of land cover class 3 (Idle land) for imagery bands 1 to 7, and Transformed Vegetation Indices (TVI).

## 7.5 REFERENCES


Anderson, J.R., E.E. Hardy, J.T. Roach, and R.E. Witmer.1976. A land use and land cover classification system for use with remote sensor data U.S. Geol. Survey Prof. Paper 964.

Bishop, Y., S. Fienberg, and P. Holland. 1975. Discrete Multivariate Analysis - Theory and Practice. Cambridge, MA: MIT Press.

Bowden, L.W., and E.L. Pruitt. 1975. Manual of Remote Sensing Volume II: Interpretation and Applications. American Society of Photogrammetry, Falls Church, Virginia.

Congalton, R., and R.A. Mead. 1983. A Quantitative method to test for consistency and correctness in photo interpretation. Photogramm. Eng. Remote Sensing. 49 (1): 69-74.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Environ. 37(1): 35-46.

Congalton., R.G., R.G. Oderwald, and R.A. Mead. 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques.Photogramm. Eng. Remote Sensing. 49 (12): 1671-1678.

Dutta, S., S A. Sharma, A.P. Khera, A.M. Yadev, R.S. Hooda, K.E. Mothikumar, and M.L. Manchanda. 1994. Accuracy assessment in cotton coverage estimation using Indian remote sensing satellite data. ISPRS Journal of Photogrammetry and Remote Sensing. 49 (6): 21-26.

Holben, B.N., and C.O. Justice. 1981. An examination of spectral band ratioing to reduce the topographic effect on remotely-sensed data. Int. J. Remote Sensing. 2: 115-133.

Hudson, W.D.,and C.W. Ramm.1987. Correct formulation of kappa coefficient of agreement. Photogramm. Eng. Remote Sensing. 53: 421-422.

Jackson, R.D., P.N. Slater, and P.J. Pinter. 1983. Discrimination of growth and water stress in wheat by various vegetation indices through clear and turbid atmospheres. Remote Sensing Environ. 15: 187-195.

Jensen, J.R., 1986. Introductory Digital Image Processing: A Remote Sensing Perspective. Prentice-Hall, New Jersey.

Jintrawet, A., S. Smutkupt, C. Wongsamun, R. Katawatin, and V. Kerdsuk. 1985. Extension Activities for Peanuts After Rice in Ban Samjan, Northeast Thailand: A Case Study in Farmer-to-Farmer Extension Methodology. Farming Systems Research Project, Khon Kaen University, Khon Kaen, Thailand.

Kalayeh, H.M., M.J. Muasher, and D.A. Landgrebe. 1983. Feature selection with limited training samples. IEEE Transaction on Geoscience and Remote Sensing. 21:434-437.

Kerdsuk, V. 1986. Effects of Planting Dates and Toposequence on Growth and Yield of Peanut After Rice. M.Sc. Thesis. Faculty of Graduate Studies, Khon Kaen University, Khon Kaen, Thailand. (in Thai with English abstract).

Kumar, R., and L.F. Silva. 1977. Separability of agricultural cover types by remote sensing in the visible and infrared wavelength regions. IEEE Transaction on Geoscience Electronics. GE-14: 19-26.

Lillesand, T.M., and R.W. Kiefer. 1994. Remote Sensing and Image Interpretation. 4th Edition. John Wiley and Sons, New York.

Maselli, F., C. Conese, L.Petkov, R. Resti. 1992. Inclusion of prior probabilities derived from a nonparametric process into the Maximum Likelihood classifier. Photogramm. Eng. Remote Sensing. 58 (2): 201-207.

Mather, P.M., 1987. Computer Processing of Remotely-Sensed Images: An Introduction. Wiley, New York.

Mulders, M.A. 1987. Remote Sensing in Soil Science. Elsevier Science Publishers, Amsterdam.

PCI. 1994. Manual of PACE Multispectral Analysis Version 5.3. PCI, Ontario, Canada.

Rosenfield, G.H., and K. Fitzpatrick-Lins. 1986. A coefficient of agreement as a measure of thematic classification accuracy. Photogramm. Eng. Remote Sensing. 52: 223-227.

Royal Irrigation Department Regional Office 4. 1990. The Commemorative Issue of the Opening of the New Royal Irrigation Department Regional Office 4 Building. Royal Irrigation Department, Bangkok.

Royal Survey Department. 1983a. Topographic Map, Scale 1:50,000, Map Sheet 5541 I. Ministry of Defence, Bangkok.

Royal Survey Department. 1983b. Topographic Map, Scale 1:50,000, Map Sheet 5542 I. Ministry of Defence, Bangkok.

Royal Survey Department. 1983c. Topographic Map, Scale 1:50,000, Map Sheet 5542 II. Ministry of Defence, Bangkok.

Royal Survey Department. 1983d. Topographic Map, Scale 1:50,000, Map Sheet 5641 IV. Ministry of Defence, Bangkok.

Royal Survey Department. 1983e. Topographic Map, Scale 1:50,000, Map Sheet 5642 III. Ministry of Defence, Bangkok.

Royal Survey Department. 1983f. Topographic Map, Scale 1:50,000, Map Sheet 5642 IV. Ministry of Defence, Bangkok.

Shoshany, M., P. Kutiel, H. Lavee, and M. Eichler. 1994. Remote sensing of vegetation cover along a climatological gradient. ISPRS Journal of Photogrammetry and Remote Sensing. 49 (4): 2-10.

Story, M., and R.G. Congalton. 1986. Accuracy assessment: A user's perspective. Photogramm. Eng. Remote Sensing. 52: 397-399.

Swain, P.H., and S.M. Davis. 1972. Remote Sensing: The Quantitative Approach. McGraw Hill, New York.

Szekielda, K. 1988. Satellite Monitoring of the Earth. John Wiley and Sons, New York.

Tucker, C.J., 1979. Red and photographic infrared linear combination for monitoring vegetation. Remote Sensing Environ. 8: 127-150.

Tucker, C.J., 1980. Nondestructive estimation of green-leaf biomass. Grass Forage Sci. 35: 177-182.

# CHAPTER 8

# SYNTHESIS

## 8.1 SUMMARY OF THE DISSERTATION

This dissertation had two major objectives, firstly to study the feasibility of using crop modeling technique to generate information on land suitability for non-irrigated, dry season peanut cropping. Secondly, to determine the most appropriate remote sensing technique for obtaining information on the extent of green crops just before the dry season of a particular year. In addition, the use of a Geographic Information System (GIS) to store the information generated using the crop modeling and remote sensing techniques and to facilitate the process of land suitability evaluation were also explored. Khon Kaen Province was selected as the study area because it has all of the major landscapes, soils, and land uses of the northeast region of Thailand. Furthermore, the field data required for the process of land evaluation were available for this province.

### 8.1.1 Crop modeling studies

This part of the dissertation focuses on the use of the MACROS crop model (Penning de Vries et al., 1989) to simulate pod yield data for non-irrigated, dry season peanut crops. This model is specific for conditions where crop growth is limited by water stress. These yield data were, in turn, used as basis for the land suitability classification for this cropping system. The crop modeling studies included four phases: (i) model evaluation, (ii) sensitivity analysis of land suitability class to changes in the weather station used to supply rainfall data, and to changes in the classification criterion, (iii) a case study to investigate the application of MACROS to generate information on land suitability at a regional scale, and (iv) an application of MACROS to investigate the effect of air temperature on growth and yield of the peanut crop planted on different dates. Chapter 3 to 6 are devoted to each of these phases, respectively.

In the first phase, MACROS was evaluated for its utility to adequately estimate growth and yield of peanut crops. The evaluation consisted of model calibration and model validation. In the model calibration, some parameter inputs which were site specific and/or not well understood, were adjusted until satisfactory agreement between the simulated and the corresponding experimental plot data was obtained. This was indicated by a deviation value of 2 % for pod yield, as well as the standardized bias (R) of 0.06, and standardized mean square error (V) of 0.01 for the dynamics of shoot dry weights. The adjusted parameters including Maximum Rate of Photosynthesis at Reference Temperature, Maximum Growth Rate of Rooting Depth, and Water Stress Sensitivity Coefficient were 50 kg $ha^{-1}$ $h^{-1}$, 0.035 m $d^{-1}$, and 0.65, respectively. These values were assumed to be properly adjusted and were used as model inputs for all the further crop modeling studies. The model was then considered calibrated.

The model validation was divided into "validation A" which emphasized the accuracy, and "validation B" which emphasized the usefulness of the model. In validation A, MACROS was used to simulate crop growth and yield under different conditions reported for three field experiments. There was acceptable agreement between simulated and observed data from every field experiment. In terms of pod yield, the deviation values were 16.2, -18.2, and -50.2 %. For the goodness of fit between the dynamics of simulated and observed shoot dry weight, the R values were 0.22, 0.10, and -0.10, and the V values were 0.05, 0.03, and 0.02. Based on the results presented in Chapter 3, it was concluded that the model accuracy was acceptable. MACROS, which was calibrated under relatively moist conditions, was able to predict growth and yield of peanut crops grown under both relatively moist and relatively dry conditions in a satisfactory manner.

Nevertheless, it must be noted that, validation A was conducted using data from field experiments in which soil and weather data were carefully and accurately collected. At the regional scale, data available for use as model inputs are usually less accurate. Therefore, the question was: "When the model was applied under regional conditions, what would be its performance ?" To answer this question, the model was further validated (validation B) using data from 36 on-farm trials conducted at 5 different test sites (villages) across the Khon Kaen province. For validation B, the soil input data were obtained from both published soil survey and from local extension specialists. Weather data were obtained from stations located up to 70 km away. MACROS was used to simulate pod yield under conditions for each on-farm trial. Statistical analysis revealed a high positive correlation between observed and simulated pod yield (r=0.91). The result indicated that the model was useful when applied at the regional scale.

In the application of MACROS to generate information on land suitability at the regional scale, simulation of pod yields under different conditions of soils, water table depths, and planting dates, for ten consecutive dry seasons was planned. Two major problems existed as (i) data for water table depth, precise enough to run the model, were not available, and (ii) planting dates varied between farmers and seasons. Therefore, based on the literature, four water table depths and four planting dates were assumed. The water table depths were 1, 2, 3, and 4 m; and the planting dates were Nov 15, Dec 1, Dec 15, and Jan 1. Based on this, MACROS was used to simulate pod yield data for (i) each soil, (ii) recorded weather data for each of ten seasons, and (iii) 16 combinations of 4 water table depths by 4 planting dates. The simulated pod yield data was used to identify the suitability class for each soil under each assumed combination of water table depth and planting date. This classification was based on the adopted definition of the land suitability classes according to level of pod yields and the number of years in 10 for a given yield level. For instance, the definition of highly suitable land (s1) was "pod yield >1200 kg $ha^{-1}$ obtained at least 8 years in 10". Although the criterion of pod yield level was based on the literature, the criterion of number of years in 10 was arbitrarily defined. As a consequence, problems could arise if significant differences in the suitability classes assigned for each soil were sensitive to changes in the criterion of number of years in 10. Also, in the application of MACROS at the regional scale, another potential problem was the limited number of weather stations. It was necessary to investigate whether or not the suitability classes were sensitive to the stations used to supply the rainfall data. If classes were sensitive, then the adequacy of the classification would be low, otherwise, there should not be a problem due to limited number of weather stations.

In the second phase of crop modeling studies, prior to the regional scale application it was important to evaluate the sensitivity of the land suitability classes to changes in the criterion of number of years in 10, and to changes in the weather station used to supply rainfall data. In the study on the sensitivity of the suitability classes to changes in the criterion of number of years in 10, pod yield data were simulated for (i) each soil in the province, (ii) recorded weather data for each of ten growing seasons, (iii) each of the 4 assumed combinations of 2 water table depths, i.e., 2 and 3 m by 2 planting dates, i.e., Dec 1 and Dec 15, and (iv) one weather station. These data were used to classify the suitability level for each soil under different conditions of water table depth, and planting date. This classification was repeated twice, based on two sets of suitability class definitions, i.e., classification A and classification B. These two sets differ in number of years in 10 for a given yield level. The former used "8 years in 10" while the latter used "7 years in 10". The suitability classes evaluated using the two sets of definitions were compared between the same soil evaluated for the same combination of water table depth and planting date. Then the sensitivity of the suitability class to changes in this criterion was assessed qualitatively. The result revealed that, generally, the suitability classes of soils in the province were not sensitive to changes in the classification criterion.

In the study on the sensitivity of the suitability classes to changes in weather stations, MACROS was used to simulated pod yield data for (i) each soil in the province, (ii) recorded weather data for each of ten growing seasons, (iii) each of the 4 assumed combinations of 2 water table depths, i.e., 2 and 3 m by 2 planting dates, i.e., Dec 1 and Dec 15, and (iv) each of the 5 weather stations used to supply rainfall data. The yield data were used to classify the land suitability for each soil under each combination of water table depth and planting date, for conditions of five weather stations. This classification was based on the same definition of land suitability classes that would be used in the application of MACROS at the regional scale in phase three of these crop modeling studies. The suitability classes evaluated using rainfall data sets from each weather station were compared between the same soil evaluated for the same combination of water table depth and planting date. Then the sensitivity of the suitability class to changes in the weather station was assessed qualitatively. In general terms, the suitability classes of soils in Khon Kaen were not sensitive to changes in the weather station used to supply the rainfall data.

After finishing phase two, it was concluded that the MACROS model was sufficiently valid to be used at the regional scale. It should be noted that, in this phase of the crop modeling studies only combinations of 2 water table depths by 2 planting dates were taken into account. This is because the preliminary study indicated that for conditions in which water table depth was 1 or 4 m, and/or planting date was Nov 15 or Jan 1, the suitability classes of soils in the study area were likely not sensitive to either the weather station or the classification criterion.

In the third phase, a case study of model application to generate information on land suitability for the specific cropping system at the district level of the province was undertaken. As previously described, the model was used to generate pod yield data under different circumstances. These data were, in turn, used as the basis for evaluating the suitability levels of each soil for 16 scenarios of 4 planting dates by 4 water table depths. Users would have to decide which scenario(s) to use for a specific area and farm, taking into consideration the information on water table depth and planting date at the particular site. The GRASS 4.1 geographic information system appeared to be an effective tool to help facilitate the generation of this information and maintain flexibility to revise the results.

One result of the study in phase three, was a reduction in pod yield for late planted peanut crops. A possible reason for this could be a higher temperature regime during the growing period. Therefore, the fourth phase of the study was to test whether or not this hypothesis was true. MACROS was used to simulate crop yield data for three conditions: (i) early planting date, i.e., Nov 15, (ii) late planting date, i.e., Jan 1, and (iii) late planting date but using temperature data of the early planting date. The results demonstrated that the dynamic of Effective Temperature for Photosynthesis (Penning de Vries et al., 1989) during the growing period of late planted peanut cropping was considerably higher than that of the early planted one. Pod yields simulated using temperature data recorded during the growing period for early planted peanut (1226 kg $ha^{-1}$ for condition #1, and 1242 kg $ha^{-1}$ for conditions #3) were significantly higher than that simulated using temperature data recorded during the growing period for late planted peanut (743 kg $ha^{-1}$ for condition #2). Simulated crop growth rate and shoot dry weight data were corresponding to the pod yield data. Because of this, it was concluded that the yield reduction in the late planted peanut was caused by the high temperature regime during the later growing period.

### 8.1.2 Remote sensing study

This part of the dissertation was conducted to determine the most appropriate remote sensing technique in terms of number of image band(s) required, complexity of the classification method, and reliability of the result, to generate information about the extent of green crops on non-irrigated agricultural land in the dry season. It included two phases: (i) generation of a major land cover types map using a manual approach, and (ii) mapping areas of green crops on non-irrigated agricultural land in the dry season using a quantitative approach.

In the first phase, major land cover types, including irrigated agriculture, water reservoir, built-up area, forest, and non-irrigated agriculture were visually interpreted from 1: 50,000 hard copy of black and white SPOT imagery of band 1. The field survey conducted to verify the result of this interpretation revealed that all map delineations were identified with the correct land cover class. This very satisfactory result was due to the fact that topographic maps were effectively used as additional reference data to help indicate water reservoirs and built-up areas for the interpretation. Also, the classification scheme employed in this task was relatively simple, comparable to Level 1 of the USGS - Land Use / Land Cover Classification System (Anderson et al., 1976), making it relatively easy to obtain highly accurate results.

In the second phase, LANDSAT-5 TM digital data were used as the bases for mapping areas of green crops. The major land cover map generated in phase 1 was used as a bit map for the "masking" technique (PCI, 1994) applied to limit the classification to non-irrigated agricultural land. A supervised classification approach was employed. The classification scheme for land cover on non-irrigated agricultural land included three classes: (i) green crops, (ii) senescent and harvested paddy rice, and (iii) idle land. A total of 15 sets of 3 classification methods, i.e., Maximum Likelihood, Ties, and Minimum

Distance by 5 combinations of image bands, i.e., bands 1,2,3,4; bands 2,3,4; bands 3,4; band 4; and Transformed Vegetation Indices (TVI) were investigated for their performance when applied to this mapping task. Accuracy assessments were undertaken to determine the most appropriate set. An error matrix was constructed for the results of each set. In each error matrix, the results of LANDSAT-5 TM data classification were compared to the corresponding cover type data obtained from the field work. The comparison was undertaken on the basis of corresponding pixels in the test sites. Statistics employed in these accuracy assessments consisted of overall accuracy, producer's accuracy, user's accuracy, and KAPPA analysis ($\hat{K}$) (Congalton, 1991). The Z-Statistic (Congalton and Mead, 1983) was applied to test for significant differences in the $\hat{K}$ coefficients for each individual matrix, as well as for the compared matrices. The test for each matrix was undertaken to determine whether or not the result was significantly better than a random result. The test for the compared matrices was conducted to determine whether or not significant differences existed between each pair of error matrices, in other words, whether or not each pair of classification results, generated using different sets of classification methods by band combinations, were significantly different in terms of accuracy.

If only the spatial distribution of areas belonging to class 1 (green crops) was of interest, the use of the Minimum Distance classification method, together with the LANDSAT-5 TM data recorded in band 4, would be sufficient. This set of classification method by band combination provided adequate classification results for land cover class 1 (producer's accuracy = 100%, user's accuracy > 94 %). It also required less remotely sensed data and followed a relatively simple classification method. In a practical sense, this would mean a lower amount of money would be needed for purchasing satellite data, as well as requiring less computing time and storage space.

However, if highly accurate results for all three land cover classes were required, the use of Minimum Distance, together with data from the combination of LANDSAT-5 TM bands 3 and 4 would be most appropriate. This combination yielded the most accurate classification result and, according to this study, was significantly different from the results generated using many of the other sets of classification methods by band combinations. Even though, in terms of accuracy, there was no significant difference between the results generated using bands 3,4; bands 2,3,4; or bands 1,2,3,4 together with the Minimum Distance classifier, the use of the band 3,4 combination would be preferable as it would require less satellite data.

Although adequate classification results were obtained with the use of TVI data, this type of data was not appropriate for this study. It required an extra computational step and thus increased computing time and storage space (i.e., for band ratioing), and the result was less accurate than those generated using bands 3,4.

## 8.2 THE PROPOSED LAND EVALUATION PROCEDURE

In Northeast Thailand, the appropriate land evaluation procedure is an important factor in the successful generation of adequate information for implementation of dry season cropping. As described in Chapter 5, the traditional and widely used procedures, such as those outlined in the USDA-Land Capability Classification System (Klingebiel and Montgomery, 1961), and FAO Framework for Land Evaluation (FAO, 1976), are not pertinent because their results are too generalized for the desired purpose (Landon, 1991; Bouma, 1993). The use of crop modeling is a promising alternative. A computerized crop model, because of its capacity to handle large volumes of data simultaneously, can simulate crop growth and yield for each land unit as reflected by various environmental factors. At present, the model used for this purpose should be specific for the conditions where crop growth is limited only by water stress (production level 2, Penning de Vries et al., 1989). This is because water availability is the most important land quality for dry season cropping. Also there are no precise data or information to run the model for conditions where other growth factors are also limiting (production level 3 and 4, Penning de Vries et al., 1989). Data on crop yield can be used directly to effectively classify the suitability of land for a particular cropping system based on water availability.

The adequacy of land evaluation results could be considerably improved if the information on land suitability, generated based on crop yields simulated from crop, soil, and historical weather data, was used in combination with the information on the extent of green crops just before the dry season. This is because it is usually not necessary, or even possible, to introduce dry season cropping to fields in which other crops already exist.

Based on the results of this dissertation, the following procedure is proposed as an alternative to evaluate land suitability for non-irrigated, dry season peanut cropping in Northeast Thailand. This procedure may also be applicable for other kinds of cropping, provided that modifications will be made where necessary.

The proposed procedure includes four parts:

1) Crop model evaluation
2) Application of crop model to generate information on land suitability for the specified crop
3) Mapping the extent of green crops using LANDSAT-5 TM data
4) Combining information on land suitability generated using the crop model with information on the extent of green crops

1) Crop model evaluation

Prior to the application of a crop model in a specific locale, the model must be evaluated. The evaluation includes calibration, and validation for accuracy and usefulness of the model. Chapter 3 demonstrates this kind of study in detail. In the case of the MACROS model, although it has been evaluated under conditions of Khon Kaen Province, the model should be evaluated again for conditions of the specific area before applying this model in another province of the northeast. This is because the results of the model evaluation under conditions of only one province may not be sufficient to apply to the whole region, even though Khon Kaen is a typical province in Northeast Thailand in terms of landscapes, soils, and agricultural land uses. Additional field experiments and on-farm trials might be necessary if existing data for the evaluation a not sufficient. Once a satisfactory evaluation result is obtained, the model can be used in the next part.

2) Appl ation of the crop model to generate information on land suitability for the specified crop

In this part, a satisfactory crop model is used to simulate crop yield data under different conditions of soil, weather, and management practice, for at least 10 seasons. The yield data will be used as a basis for land suitability classification. Chapter 3 and 5 provide details about the methods of selecting and collecting the model input parameters, including those related to crop, soil, weather, and management practice. Methods of evaluating land suitability based on the simulated yields are desc ibed in Chapter 5.

At present, data on two critical parameter inputs for th simulation of crop yield, namely water table depths and planting dates, cannot be ob ed. Water table de h data, precise enough to run the model, are not available. Plant ng ates vary by farms and seasons. This problem occurs in every province of the re n. Therefore, realistic values of the two parameters must be assumed, based on relevant research reports conducted at a specific locale (e.g., province). According to Chapter 5, for conditions of Khon Kaen which is typical for Northeast Thailand, the assumed water table depths of 1, 2, 3, and 4 m; and planting dates of Nov 15, Dec 1, Dec 15, and Jan 1 appeared to be realistic.

The model will then be used to simulate crop yield data for (i) each soil, (ii) recorded weather data for each of at least 10 seasons, and (iii) each combination of water table depth by planting date. The classification will be based on the adopted definition of land suitability classes defined according to the level of pod yields and the criterion of number of years in 10 for a given yield level as described in Chapter 5. The definition can be modified or changed according to the situation at the particular locale. As a result of the classification, information on land suitability is generated for several scenarios of water table depth and planting date. It is important to explicitly stated in the accompanying report of this land evaluation, that data on water table depths and planting dates must be known before making decision about which scenario(s) to be used in a specific area. Reliable estimation of these parameters can usually be obtained from local extension specialists or farmers familiar with a specific location.

For the proposed procedure, GIS is needed for the generation of information on land suitability based on simulated crop yield data. The system can be effectively used to collect, store, retrieve, transform, and display the relevant data. It also helps maintain flexibility for correcting or revising the results. Experience from this dissertation has shown that without the computerized crop model and GIS, the proposed procedure would not be possible.

3) Mapping the extent of green crops using LANDSAT-5 TM data

The mapping of the extent of green crops on non-irrigated agricultural land before the dry season, must be finished in time for use in that particular season. According to the results of the remote sensing study in Chapter 7, the use of the Minimum Distance method and LANDSAT-5 TM band 4 data for this mapping is promising in terms of accuracy of the results, computing time, computer storage requirement, and the cost of purchasing the satellite data. This assumes that areas of other major land covers except non-irrigated agriculture, would be eliminated using a "masking" technique (PCI, 1994) prior to the classification.

4) Combining information on land suitability generated using the crop model with information on the extent of green crops

A geographic information system (GIS) can be effectively applied to store all the necessary information and to facilitate combining information. In the case of this dissertation, for example, the information on land suitability in the forms of sixteen raster maps, representing different scenarios of planting date and water table depth, and the accompanying attribute data, was already stored in the GRASS 4.1 GIS (Shapiro et al., 1993). The information on the extent of green crops in the form of digital maps was originally generated and stored in the PCI image processing system (PCI, 1994). The map was transferred to GRASS using the FEXPORT program in the "image analysis kernel" (PCI, 1994). Once these two kinds of information were stored in the same map set in GRASS, information from many of these maps could be considered simultaneously as desired, using various GRASS commands (e.g., "d.what.rast" and "r.what"). Similarly, other GIS software packages, such as SPANS (INTRA TYDAC Technology Inc., 1993) could be used for the same purpose. However, this kind of GIS utility may have limitations, as some GIS software including GRASS 4.1, may not be able to display information from all of the desired maps at the same time. For GRASS 4.1, the "d.what.rast", and "r.what" are not capable of displaying information from more than fifteen, and fourteen maps, respectively (Shapiro et al., 1993). To effectively use this information in the implementation of non-irrigated, dry season peanut cropping, the number of the maps (and accompanying attribute data) to be considered simultaneously, could be up to seventeen including the sixteen land suitability maps, and a map showing the spatial distribution of green crops. This problem is, however, not difficult to solve. In GRASS 4.1, for example, a shell script program may be written to enhance the capability of displaying information from a greater number of maps, as shown in Appendix 1.

## 8.3 OVERALL CONCLUSIONS

This dissertation demonstrated the usefulness of crop modeling, remote sensing, and geographic information system technologies to generate the information necessary to evaluate land suitability for non-irrigated, dry season peanut cropping in a particular year under conditions of Northeast Thailand. The MACROS crop model, which was specific for the conditions where water is the only limiting factor for crop production, appeared to be the model of choice to simulate pod yields from crop, soil, and historical weather data at the regional scale. The yield data simulated for 10 seasons were, in turn, effectively used to evaluate the suitability of land areas under different combinations of water table depths and planting dates. The model was also applied to demonstrate the effects of high temperature regimes on yield reduction in late planted dry season peanut crops. This result could be important for further research, such as in the area of plant breeding, i.e., breeding for new peanut variety tolerant to higher temperature regimes.

For a particular dry season, to improve the adequacy of the evaluation result, information on the extent of green crops on the agricultural land just before the dry season should also be considered. This information was effectively acquired using remote sensing techniques. According to the study in Kranuan, a typical northeast district in terms of landscapes, soils, and agricultural land uses, the use of the Minimum Distance method and LANDSAT-5 TM, band 4 data appeared to be the most appropriate remote sensing technique, because it not only provided accurate results, but also required minimal computing time, computer storage space, and cost for satellite data.

A geographic information system (GIS) was an effective tool for the type of land evaluation procedure proposed as a result of this dissertation. The system was used to stored the information generated using crop modeling and remote sensing in the forms of maps and associated attribute data which could be easily displayed or retrieved. It also provided flexibility for correcting and updating the results, as well as the capability for displaying information from many maps simultaneously.

To this end, this dissertation has contributed to the knowledge of agricultural land evaluation under conditions of Northeast Thailand as follows:

1. The MACROS crop model was calibrated and validated. It is ready for application in Khon Kaen Province.

2. The information on land suitability is available for non-irrigated, dry season peanut cropping in Kranuan District, Khon Kaen Province in the form of maps and relevant attribute data. The classification of land suitability based on pod yields simulated from crop, soil, and historical weather data using the MACROS model is reasonable. The generated information can be used for implementation of this cropping system in the district.

3. The effects of high temperature regimes on yield reduction in late planted dry season peanut was demonstrated using crop simulation modeling technique.

4. An appropriate remote sensing technique was determined to generate information on the extent of green crops before the dry season. The technique included the use of Minimum Distance method and LANDSAT-5 TM, band 4 data.

5. A land evaluation procedure for non-irrigated, dry season peanut cropping in Northeast Thailand is proposed. This procedure includes the appropriate use of crop modeling, remote sensing, in a geographic information system.

## 8.4 SUGGESTION FOR FUTURE RESEARCH

As a result of this dissertation several suggestions are presented for future research. These involve further studies in areas of crop modeling and remote sensing.

### 8.4.1 Crop modeling studies

Despite the fact that the MACROS crop model appeared to be capable of adequately estimating crop growth and yield for peanut cropping, there are several studies which may lead to improvement in model accuracy. First, according to Penning de Vries et al. (1989), MACROS employs a series of empirical equations which require several soil texture related coefficients to calculate soil water movement and evaporation. Based on the model evaluation in Chapter 3, if the coefficients are based on generalized values obtained from literature, then less accurate results will be obtained. A study to determine specific values for each of these coefficients under conditions of soils in Northeast Thailand would be significant.

Second, the model sensitivity should be tested for weather components, i.e., air humidity, air temperature, solar radiation, and wind speed. Note that the sensitivity test for rainfall has already been undertaken (Chapter 4). Ideally, Penning de Vries et al. (1989) suggest that the air humidity as a model input should be expressed as the water vapor pressure in kPa. Data in the form of relative humidity should be avoided because it might change drastically during the day. However, in the northeast region, relative humidity is the only air humidity data available in digital form at a regional scale. This could cause significant reduction in model accuracy, if the model is sensitive to air humidity. As a consequence, sensitivity of the model to changes in the type of air humidity data, relative humidity and vapor pressure, should be conducted.

The impact of weather stations used to supply data of the weather components is also important and should be tested. In Northeast Thailand, the number of weather stations that have sufficient data of all the weather components for the simulation at the regional scale is very limited, even a large province such as Khon Kaen has only one station. If the model is sensitive to other weather components, the reliability of the simulation results could be improved by increasing number of weather stations that record data for a particular component.

Third, studies on the utilization of MACROS should be conducted for conditions in which (i) nitrogen and water availability are limited (production level 3, Penning de Vries et al., 1989), and (ii) nitrogen, water availability, and other nutrients and growth factors such as disease and insect are limited (production level 4, Penning de Vries et al., 1989). These may include experiments related to the theoretical background of the model, model evaluation, and model application. At production levels 3 and 4, the simulation could be undertaken for conditions closer to those of the region. Therefore, the pod yields simulated at either production level 3 or 4 should be more accurate as compared to those simulated for conditions in which water availability is the only limiting factor (production level 2, Penning de Vries et al., 1989).

Fourth, the feasibility of using the MACROS model to assess land suitability for other promising dry season crops may be investigated.

### 8.4.2 Remote sensing studies

For land evaluation in a particular dry season, information on the spatial distribution of green crops and soil moisture content before the season begins, is an important consideration, in addition to the information on land suitability generated based on pod yields simulated for a number of years in the past. The appropriate remote sensing techniques to map green crop areas has already been determined (Chapter 7). Future research, therefore, may relate to investigation of appropriate techniques for mapping areas of different soil moisture contents, e.g., wet, moist, and dry etc. This information is of importance because it is related to soil workability (i.e., ease of tillage), and seed germination. A variety of remote sensing techniques, such as those related to the use of gamma, visible / infrared, thermal infrared, and microwave data are theoretically possible and have already been investigated to a certain level (Reginato et al., 1977; Jackson et al., 1978; Wetzel and Atlas, 1981; Schmugge, 1983; Wetzel and Atlas, 1983; Musick and Pelletier, 1986; Carlson et al., 1984; Engman, 1991). At present, however, these techniques do not appear to be uniformly useful because there are limitations regarding the instrument configuration, and the target and target-sensor characteristics, such as atmospheric conditions, surface roughness, and vegetation (Engman, 1991; Lillesand and Kiefer, 1994). The microwave techniques seem to be the most promising as they have a strong theoretical basis. They are also, not limited to cloud-free and bare-soil conditions (Owe et al., 1988; Schultz, 1988; Brown et al., 1991; Engman, 1991; Lillesand and Kiefer, 1994). Therefore, future research may focus on applications of these techniques. such as those related to the use of ERS-1 data, in mapping areas of different soil moisture conditions.

## 8.5 REFERENCES


Bouma, J., R. J. Wagenet, M.R. Hoosbeek, and J.L. Hutson. 1993. Using expert syste and simulation modelling for land evaluation at farm level: a case study from New York State. Soil Use and Management 9(4): 131-139.

Brown, R. J., R. Leconte, B.G. Brisco, C.A. Hutton, D. Mullins, G.J. Gairns, Q.H.J. Gwyn, R. Protz, J. Fischer, P.J. Howarth, P.M. Treitz, J.B. Boisvert, K.P.B. Thomson. 1991. Oxford County soil moisture experiment (OXSOME) overview. *In* S.E. Franklin, M.D. Thomson, and F.J. Ahern (Eds.) Proceeding of the 14th Canadian Symposium on Remote Sensing. 6-10 May, 1991. Calgary, AB, Canada

Carlson, T.N., F.G. Rose, and P.M. Perry. 1984. Regional-scaleestimates of surface moisture availability from GOES infrared satellite measurements. Agron. J. 76: 972-978.

Congalton, R., and R.A. Mead. 1983. A Quantitative method to test for consistency and correctness in photo interpretation. Photogramm. Eng. Remote Sensing. 49 (1): 69-74.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Environ. 37(1): 35-46.

Engman, E.T. 1991. Application of microwave remote sensing of soil moisture for water resources and agriculture. Remote Sens. Environ. 35: 213-226.

FAO. 1976. A Framework for Land Evaluation. Soils Bull. 29. FAO. Rome.

INTERA TYDAC Technologies Inc. 1993. SPANS GIS: Learning System. INTERA TYDAC Technologies Inc., Ontorio.

Klingebiel, A.A., and P.H. Montgomery. 1961. Land Capability Classification. Agricultural Handbook No 210. USDA Soil Conserv. Serv., Washington DC

Landon, J.R. (Ed). 1991. Booker Tropical Soil Manual: A Handbook for Soil Survey and Agricultural Land Evaluation in the Tropics and Subtropics. Longman Scientific and Technical, Essex.

Lillesand, T.M., and R.W. Kiefer. 1994. Remote Sensing and Image Interpretation. 4th Edition John Wiley and Sons, New York.

Musick, [illegible] and R.E. Pelletier. 1986. Response of some thematic mapper band ratios to va[illegible] soil water content. Photogramm. Eng. Rem. Sens. 52 (10): 1661-1668.

Owe. M., A.Chang, and Golus, R.E. 1988. Estimating surface soil moisture from satellite microwave measurements and a satellite derived vegetation index. Remote Sens. Environ. 24: 331-345.

PCI. 1994. Manual of PACE Multispectral Analysis Version 5.3. PCI Inc., Ontario, Canada.

Penning De Vries F.W.T., D.M. Jansen, H.F.M. ten Berg, and A. Bakema. 1989. Simulation of Ecophysiological Processes of Growth in Several Annual Crops. Simulation Monograph 29. Pudoc, Wageningen, and IRRI, Los Baños.

Reginato, R.J., J.F. Vedder, S.B. Idso, R.D. Jackson, M.B. Blanchard, and R.Goettelman. 1977. An evaluation of solar reflectance and spectral band rationing techniques for estimating soil water content. J. of Geophysical Research. 82: 2101-2104.

Schmugge, T.J. 1983. Remote sensing of soil moisture: Recent advances. IEEE Trans. Geosci. Remote Sens. GE-21 (3): 336-344.

Schultz, G.A.1988. Remote sensing in hydrology. J. of Hydrology 100: 239-265.

Shapiro, M., J. Westervelt, D. Gerdes, M. Larson, and K.R. Brownfield. 1993. GRASS 4.1 Users Manual. US Army Construction Engineering Research Laboratory, Champaign, Illinois

Wetzel, P.J., and D. Atlas.1983. Inference of soil moisture from geosynchronous satellite infrared observations. *In.* Proceeding of the 16th AMS Conference on Agriculture and Forest Meteorology. Ft. Collins. CO.

Wetzel, P.J., and D. Atlas. 1981. Inference of precipitation through thermal infrared measurements of soil moisture. *In.* D. Atlas and O.W. Thiele (Eds.) Precipitation Measurements from Space Workshop Report No. 23. Goddard Laboratory for Atmospheric Sciences, Goddard Space Flight Center, Greenbelt, MD. pp D-170 to D-172.

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## APPENDIX 1

## AN EXAMPLE OF THE USE OF A SIMPLE SHELL SCRIPT PROGRAM TO ENHANCE THE REPORTING CAPABILITIES OF A GEOGRAPHIC INFORMATION SYSTEM

This appendix presents an example of the use of a simple shell script program to enhance the reporting capabilities of the GRASS 4.1 Geographic Information System. The standard commands available in GRASS such as *d.what.rast* and *r.what* cannot be used to extract information from more than fifteen maps, simultaneously. However, shell scripts can be written to execute two or more sequential extractions and combine the results, as if a single extraction had been performed.

The program shown in Listing A1 below, was written in PERL, by Tim Martin of the Spatial Information Systems Laboratory, University of Alberta. In the listing, line numbers are used only for identification, and are not part of the PERL program. Lines starting with a pound (#) sign contain comments. The *d.where* (line 15), and *r.what* (lines 20 and 22) are GRASS commands, used for extracting information. The maps containing information to be shown, are listed by the corresponding file names on lines 20 and 22, i.e., soils.bound.water.kra, current.landuse, ..., land-suit.W4D4. This program is to be used in combination with GRASS and it is assumed that a GRASS window is open. The user will be asked to identify locations of interest by using the mouse arrow and mouse buttons. The information from all the maps listed above is extracted and displayed in tabular form. Table A1 demonstrates an example of the result, where information on soil series, current land use, and land suitability under different combinations of 4 planting dates (Date 1, Date 2, Date 3, and Date 4) by 4 water table depths (W1, W2, W3, and W4) is displayed. Note that, s1, s2, s3, and n represent the land suitability level of highly suitable, moderately suitable, marginally suitable, and not suitable, respectively.

**Listing A1** An example of the simple shell script program that can be used with the GRASS 4.1 GIS, to display information from several related maps.

```
#!/usr/bin/perl
#
# A simple PERL script to demonstrate how to get information from several
# related maps.
#
# By Tim Martin
# Spatial Information Systems
# University of Alberta
# April 26, 1995

print "\n   KhonKaen Peanut Suitability Displayer";
print "\n   ----------------------------";
print "\n\nPoint the mouse arrow at the map location of interest, and press";
print "\nthe left mouse button.  Press the right button to quit.\n";
`d.where >tmpfile 2> /dev/null`;

print "\n              Current       Date 1            Date 2            Date 3            Date 4";
print "\n Soil           Use   W1 W2 W3 W4   W1 W2 W3 W4   W1 W2 W3 W4   W1 W2 W3 W4";
print "\n-----------------------------------------------------------------------\n";
`r.what -f input=soils.bound.water.kra,current.landuse,land-suit.W1D1,land-suit.W2D1,land-suit.W3D1,land-suit.W4D1,land-suit.W1D2,land-suit.W2D2,land-suit.W3D2, <tmpfile
>tmpfile1`;
`r.what -f input=land-suit.W4D2,land-suit.W1D3,land-suit.W2D3,land-suit.W3D3,land-suit.W4D3,land-suit.W1D4,land-suit.W2D4,land-suit.W3D4,land-suit.W4D4 <tmpfile >tmpfile2`;
open(TMPFILE1, "tmpfile1");
open(TMPFILE2, "tmpfile2");
while(<TMPFILE1>) {
@Fi = split(/\|/,$_);
@Se = split(/\|/,<TMPFILE2>);
chop @Fi[20]; chop @Se[20];
printf"%-15.15s %-7.7s %3.3s%3.3s%3.3s%3.3s %3.3s%3.3s%3.3s%3.3s %3.3s%3.3s%3.3s%3.3s %3.3s%3.3s%3.3s%3.3s\n",
    @Fi[4],@Fi[6],@Fi[8],@Fi[10],@Fi[12],@Fi[14],@Fi[16],@Fi[18],@Fi[20],
    @Se[4],@Se[6],@Se[8],@Se[10],@Se[12],@Se[14],@Se[16],@Se[18],@Se[20]
}
print "-----------------------------------------------------------------------\n";
close TMPFILE1; close TMPFILE2;
`rm tmpfile tmpfile1 tmpfile2`;
```

**Table A1** An example of the result generated using a simple shell script program in addition to the GRASS 4.1 GIS, to display information from several maps. In this table, the information at 5 specific sites from 18 related maps is shown.

KhonKaen Peanut Suitability Displayer

| Soil | Current Use | Date 1 W1 | Date 1 W2 | Date 1 W3 | Date 1 W4 | Date 2 | Date 2 W2 | Date 2 W3 | Date 2 W4 | Date 3 W1 | Date 3 W2 | Date 3 W3 | Date 3 W4 | Date 4 W1 | Date 4 W2 | Date 4 W3 | Date 4 W4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nam Phong | DryRice | s2 | s1 | s2 | s3 | s2 | s1 | s3 | s3 | s3 | s2 | s3 | n | s3 | s3 | n | n |
| Yasothon | Crops | s1 | s1 | s2 | s3 | s2 | s2 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | s3 | n | n |
| Korat | Idle | s2 | s1 | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n | s3 | s3 | n |
| Korat | DryRice | s2 | s1 | s2 | s2 | s2 | s2 | s2 | s3 | s3 | s2 | s3 | s3 | n | s3 | s3 | n |
| Roi Et | DryRice | n | s1 | s2 | s2 | n | s1 | s2 | s3 | n | s2 | s3 | s3 | n | s3 | s3 | n |