CHAPTER IV

RESEARCH METHODS

4.1 Framework of the Study

The procedure used for land suitability assessment in this study is presented in Figure 4.1. The model consists of two sub-models: the first model is crop suitability index model; and the second model is soil loss index. Both were modeled based on fuzzy set methodology in a GIS, and incorporated farmers' perceptions as well as their preferences into the decision-making process by using Analytic Hierarchy Process (AHP).

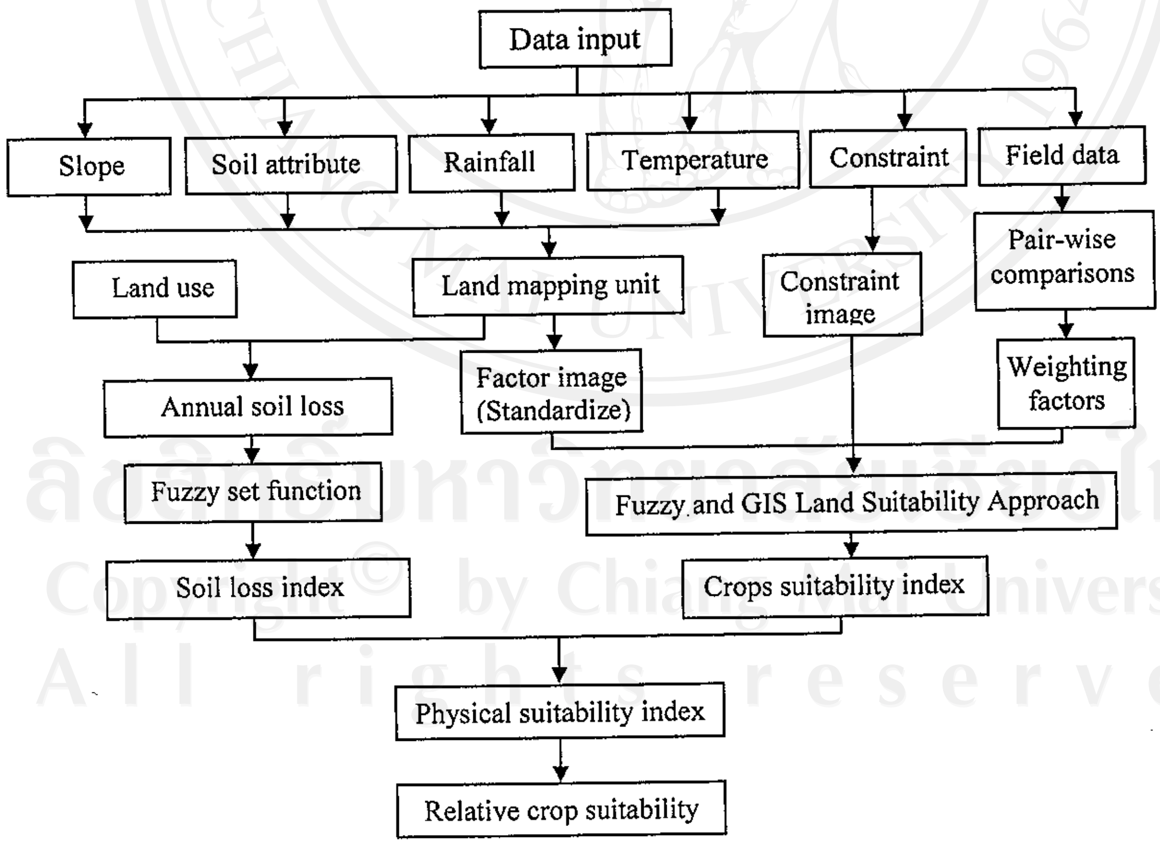

Figure 4.1 The study framework for land suitability assessment implemented in GIS.

4.2 Data Collection

Data set required includes maps of land use, soil types, digital elevation model (DEM) scale 1: 25,000 were collected from Nam Dong cadastral department, with the soil map was classified by the method of FAO/UNESCO in 2005. Monthly precipitation, temperature and sunshine were obtained from Nam Dong statistical department as followed the Nam Dong Weather Observation Station for the five years period, 2001-2005. The land use requirement for eleven crops which are rubber, cassava, maize, bean, sweet potato, paddy rice, citrus, banana, pineapple, sugarcane, and upland rice were adopted Sys *et al.* (1991).

Field work was carried out and workshop were organized to define the score weight of each factor according to AHP (Saaty, 1980). Eleven workshops were organized, each workshop concentrated on one of the crop, twelve to fifteen participants participated in each workshop including agricultural extension, experiment farmers, young farmers (include men and women) who have good personal experience in growing particular crop to obtain data for the weighting factors calculation.

4.3 Multicriteria Decision Making

The multicriteria decision analysis involves a set of alternatives that are evaluated on the basis of conflicting and incommensurate criteria. Criterion is considered a generic term that includes both the concepts of attribute and objective. Accordingly, two broad classes of multicriteria decision making (MCDM) can be distinguished: Multiattribute decision making (MADM) and multiobjective decision making (MODM). Both MADM and MODM problems are further categorized into single-decision-maker problems and group decision problems. These two categories are, in turn, subdivided into deterministic, probabilistic, and fuzzy decisions. Deterministic decision problems assume that the required data and information are known with certainty and that there is a known deterministic relationship between every decision and the corresponding decision consequence. Probabilistic analysis deals with a decision situation under uncertainty about the state of problem's environment and about the relationships between the decision and it consequences. Whereas probabilistic analysis treats uncertainty as randomness, it is also appropriate to consider inherent imprecision of information involved in decision making; fuzzy decision analysis deals with this type of uncertainty. Conventional MCDM techniques have largely been a spatial in the sense that they assume a spatial homogeneity within study area. This assumption is unrealistic in many decision situations because the evaluation criteria vary across space. Consequently, there is a need for an explicit representation of the geographical dimension in multicriteria decision making (MCDM) (Malczewski, 1999).

In general, MCDM problems involve six components (1) a goal or a set of goals the decision maker (interest group) attempts to achieve; (2) the decision maker or group of decision makers involved in decision making process along with their preferences with respect to evaluation criteria; (3) a set of evaluation criteria (objectives and or attributes) on the basis of which the decision makers evaluate alternatives courses of action; (4) the set of decision alternatives, that is, the decision or action variables; (5) the set of uncontrollable variables or states of nature (decision environment); and (6) the set of out comes or consequences associated with each alternative-attribute pair (Keeney and Raiffa, 1976; Pitz and McKillip, 1984).

4.4 Decision Rule

A decision rule is procedure that allows for ordering alternatives (Malczewski, 1999). It is the decision rule that dictates how best to order alternatives or to decide which alternative is preferred to another. It integrates the data and information on alternative and decision maker's preferences into an overall assessment of the alternatives. Specifically, the decision rule orders the decision space by means of one-to-one or one-to-many relationship outcomes to decision alternatives. This means that a given course of action (alternative) has a corresponding certain consequence (one-to-one relationship) or uncertain (one-to-many relationship). Thus, at the most general level, multicriteria decision problem involves ordering the set of outcomes and identifying the decision alternatives yielding there outcomes.

Fuzzy set theory was introduced by Zadeh (1965) and the definitions of fuzzy set and fuzzy membership (Kauffman and Gupta, 1985; Zimmermann, 1955) are as follows: Let U be a universe of a collection of distinct objects. In the present context, the universe is a map, the sets are land use classes and elements are the pixels. A crisp set A consists of members {x} if the characteristic function $\mu_A(x) = 1$ (i.e. $x \in A$) and members {x} do not belong to crisp set A if $\mu_A(x) = 0$. Thus the boundary of set A is rigid and sharp. Fuzzy set eliminates the sharp boundary that divides members from non-members in the group by providing a transition (partial membership) between the full membership and non-membership (Wang, 1990).

A fuzzy set (A) in a space of points, x = {x}; is a class of events with a continuum of grades of membership. The fuzzy set is characterized by a membership function, $\mu_A(x)$, which associates a real number in the interval (0,1) representing the grade of membership of x in A with each point in x. This characteristic function, in fact, can be viewed as a weighting coefficient which reflects the ambiguity in a set and as it approaches unity; the grade of membership of an event A becomes higher. For example, $\mu_A(x) = 1$; indicates that it is strictly a member of that class and $\mu_A(x) = 0$ indicates that it is not a member of that class (Nisar Ahamed *et al.*, 2000).

With this approach, the attribute values will be converted to common membership grades (from 0.0 to 1.0), according to the class limits specified by crop requirements (Sys *et al.*, 1991).

According to Baja *et al.* (2002), if $MF(x_i)$ represents individual membership value for *i*th land property *x*, then, the basic model function take the following form in the computation process:

$$MF(x_i) = [1/(1 + \{(x_i - b)/d\}^2)] \quad (4.1)$$

where: d = width of transition zone (x at MF = 0.5 or at crossover point)

x_i = value of i^{th} land property x

b = value of land attribute x at the ideal point or standard index.

Model functions used for fuzzy membership classification of land attributes are based on the Semantic Import model approach, which utilizes a bell-shaped curve. This approach consists of two basic functions: symmetric and asymmetric. The first function, also called an 'optimum range', distinguishes two variants: one that uses a single ideal point (Model 1), while the other employs a range of ideal points (Model 2). The second function, an asymmetric model, is used where only the lower and upper boundary of a class has practical importance. This function consists of two variants: asymmetric left (Model 3) and asymmetric right (Model 4).

In this modeling process, computation of criterion membership functions was based on Equation 4.1, which applies to Model 1. In addition to that, the following forms also apply to Models 2, 3, 4, and Figure 4.2

For optimum range (Model 2):

$$MF(x_i) = 1 \text{ if } (b_1 + d_1) < x_i < (b_2 - d_2) \quad (4.2)$$

For asymmetric left (Model 3):

$$MF(x_i) = [1/(1 + \{(x_i - b_1 - d_1)/d_1\}^2)] \text{ if } x_i < (b_1 + d_1) \quad (4.3)$$

For asymmetric right (Model 4):

$$MF(x_i) = [1/(1 + \{(x_i - b_2 + d_2)/d_2\}^2)] \text{ if } x_i > (b_2 - d_2) \quad (4.4)$$

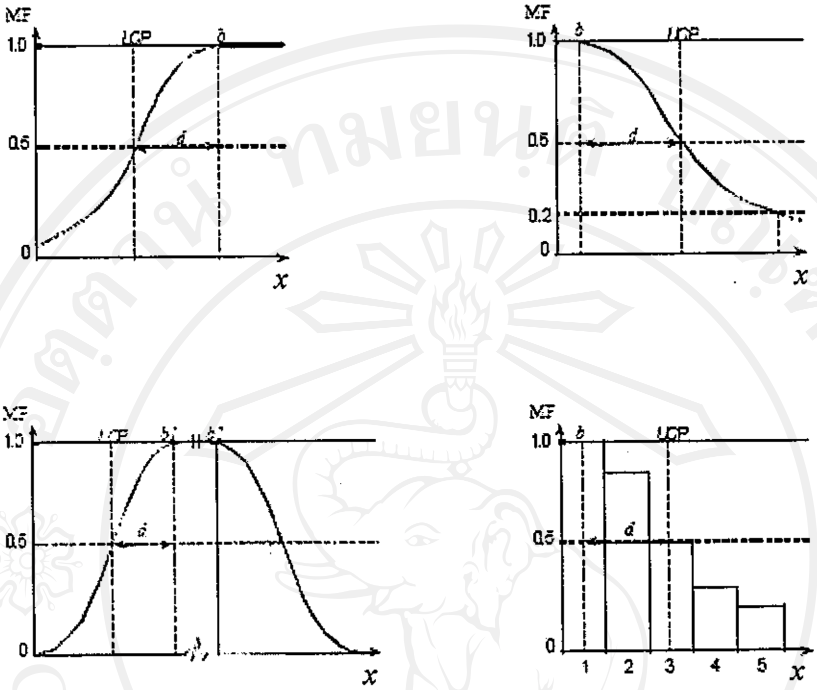

Figure 4.2 Membership functions of selected land properties.
Source: Baja *et al.*, 2002.

After factors standardized with fuzzy method by selecting suitable membership function with MF values of individual land characteristics and then combined using a convex combination function to produce a joint membership function (JMF) of all attributes, Y as follows: (Baja *et al.*, 2002).

$$JMF(Y) = \sum_{i=1}^{n} W_i MF(x_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4.5)$$

where: W_i = weighting factor for the i^{th} land property x
$MF(x_i)$ = membership grade for the i^{th} land property x

4.5 Criteria Weighting

Pairwise comparison method was developed by Saaty (1980) in the context of the analytic hierarchy process (AHP), this is a multicriteria decision making technique which decomposes a complex problem into a hierarchy, in which each level is composed of specific elements. The overall objective of the decision lies at the top of the hierarchy, then the criteria, sub-criteria and decision alternatives are on descending levels of the hierarchy.

Once the hierarchical model has been structured for the problem, the participating decision makers provide pairwise comparison for each level of the hierarchy, in order to obtain in the next higher level. This weighting factor provides a measure of the relative importance of this element for the decision maker.

To compute the weighting factors of n element, the input consists of comparing each pair of the elements using the following the scale set:

$$S=\left\{\frac{1}{9},\ \frac{1}{8},\ \frac{1}{7},\ \frac{1}{6},\ \frac{1}{5},\ \frac{1}{4},\ \frac{1}{3},\ \frac{1}{2},\ 1,\ 2,\ 3,\ 4,\ 5,\ 6,\ 7,\ 8,\ 9\right\} \qquad (4.6)$$

The pairwise comparison of element i with element j is placed in the position of a_{ij} of the pairwise comparion matrix A as bellowing:

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \qquad (4.7)$$

The reciprocal value of this comparison is placed in the position a_{ji} of A in order to preserve consistency of judgement. Given n elements, the participating decision maker thus compares the relative importance of one element with respect to the second element, using the 9-point scale shown in Table 4.1. The pairwise comparison matrix is called a reciprocal matrix for obvious reasons.

After the pairwise comparison matrix is developed, the criterion weighting would be calculated, that step involves the following operations (Malczewski, 1999): (i) sum the value in each column of the pairwise comparison matrix; (ii) divide each element in the matrix by its column total (the resulting matrix is referred to as normalized pairwise comparison matrix), and (iii) compute the average of the elements in each row of the normalized matrix. Their averages provide an estimate of the relative weights of the criteria being compared.

Table 4.1 The 9-point scale for comparisons.

Importance	Definition	Explanation
1	Equal importance	Two elements contribute identically to the objective
3	Weak dominance	Experience or judgement slightly favors one element over another
5	Strong dominance	Experience or judgement strongly favors one element over another
7	Demonstrate dominance	An element's dominance is demonstrated in practice
9	Absolute dominance	The evidence favoring an element over another is affirmed to the highest possible order
2, 4, 6, 8	Intermediate value	Further subdivision or compromise is needed

Source: Saaty, 1980.

Consistency ratio was estimated. In this step involves the following operations (Malczewski, 1999): (i) determine the weighted sum vector by multiplying the weight of the first criterion times the first column of the original pairwise comparison matrix, then multiply the second weight times the second column and so on multiply the n^{th} weight times the n^{th} column, finally sum these values over the rows, and (ii) determine the consistency vector by dividing the weighted sum vector by the criterion weights determined previously.

The consistency vector have been calculated, we need to compute values for two more terms, lambda (λ) and the consistency index (CI).

The value for lambda is simply the average value of the consistency vector.

Calculation of *CI* is based on the observation that λ is always greater than or equal to the number of criteria under consideration (n) for positive, reciprocal matrixes, and $\lambda = n$ if the pairwise comparison matrix is a consistent matrix. Accordingly, $\lambda = n$ can be considered as a measure of the degree of consistency. This measure can be normalized as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \qquad (4.8)$$

The *CI* term, refer to as the consistency index, provide a measure of the departure from consistency. Further we can calculate the consistency ratio (*CR*), which is defined as follows:

$$CR = \frac{CI}{RI} \qquad (4.9)$$

where *RI* is the random index (Table 4.2), the consistency index of a randomly generated pairwise comparison matrix. It can be shown that *RI* depends on number of elements being compared.

The consistency ratio provides the user with a value that can be used to the judge the relative quality of the results. If the consistency ratio of less than 0.10 is obtained, then the results are sufficiently accurate, and further evaluation is not needed. However, if the consistency ratio is greater than 0.10, the results may arbitrary and the preferences should be re-evaluated or discarded.

Table 4.2 Random consistency index (*RI*) for n = 1, 2, ..., 15.

n	*RI*	n	*RI*	n	*RI*
1	0.00	6	1.24	11	1.51
2	0.00	7	1.32	12	1.48
3	0.58	8	1.41	13	1.56
4	0.90	9	1.45	14	1.57
5	1.12	10	1.49	15	1.59

Source: Saaty, 1980.

Narasimhan (1983) identified the three advantages of AHP used as follow:

- It formalizes and renders systematic what is largely a subjective decision process and as a result facilitates 'accurate' judgement;

- As a by-product of the method, decision makers receive information about the implicit weights that are placed on the evaluate criteria, and

- The use of computers makes it possible to conduct sensitive analysis on the results.

Another advantage of using AHP is that it results in better communication, leading to a clearer understanding and consensus among members of decision making groups so that they are likely to become more committed to the alternatives selected (Harker and Vargas, 1987).

AHP also has the ability to identify and take into consideration the decision maker's personal inconsistencies. Decision makers are rarely consistent in their judgements with respect to qualitative aspects. The AHP method incorporates such inconsistencies into the model and provides the decision maker with a measure of there inconsistencies.

The great advantage of the AHP lies in its ability to hand complex real life problems and its ease of use. Compared with five different utility models for determining weights and priorities, AHP was found to produce the most credible results of the models tested (Schoemaker and Waid, 1982).

The ability of the AHP to analyze different decision factors without the need for a common numerate, other than the decision maker's assessments, makes it one of the favorable multicriteria decision support tools when dealing with complex problems.

4.6 Models Construction

4.6.1 Land Mapping Unit Delineation

Most land evaluation studies require physical resource surveys, although occasionally there may be sufficient information already available. The surveys will frequently include a soil or soil-landform survey, and sometimes such work as pasture resource or other ecological surveys, forest inventory, surveys of surface-water or groundwater resources, or road engineering studies. The objects of such surveys are to define and determine boundaries of the land mapping units and to determine their land qualities.

LMU were defined by FAO (1976) as "an area or parcel, which has a relatively homogenous of natural factors and a differentiation of one or many factors comparing with neighboring area". Each LMU has a quality and suitability with fixed land utilization types. LMU is a premise for calculation of land evaluation and land use planning. Soil mapping unit are commonly selected as LMU. In other word, land includes soil characteristics and other characteristics such as topography, geology, climate, and hydrography, creatures that effect to ability of use a fixed parcel or region.

All agricultural and unused lands in Nam Dong district were evaluated following FAO framework for Land Evaluation. LMUs were determined by a grid cell with grid cell resolution of 30x30 meter form soil map with land characteristics, and topography were obtained from digital elevation model (DEM), which were acquired from Nam Dong cadastral department.

4.6.2 Land Utilization Types (LUTs)

The first step in evaluating land starts with the decision about the alternative LUTs that were separately evaluated. LUTs that is technical term used to present common term 'land use' (Rossiter, 1994). It is a kind of land use described or defined in a degree of detail greater than that a major kind of land use (FAO, 1976). It consists of set of technical specifications within a given time incorporate with environment or some of major land improvements (FAO, 1983 and 1984). This relates to land use requirements and limitations of land for specified use.

The information needed for constructing the model were the factors and their levels that effect or limit crop production. In this study, LUTs were selected based on existing cropping systems in the study area such as rubber, beans, maize, sweet-potato, citrus, pineapple, banana, sugarcane, cassava, irrigated-rice, and upland-rice.

4.6.3 Land Use Requirements (LUR)

Land use requirements are used to describe the requirement for a successful and sustained practice of the given land utilization type that are expressed in term of land quality. They are later matching with soil qualities of soil unit to determine the suitability of each land unit for specific land use type.

In this study the LUR of eleven crops were selected based on LUTs in the study area. The requirements and limitations of the crops in the study area were adopted Sys et al. 1991, with the criteria for LUR are temperature, precipitation, soil depth, soil drainage, cation exchange capacity (CEC), pH, organic matter (OM), and slope. The precipitation criteria in irrigated rice were ignored (water are supplied), and in sugarcane were replaced with sunshine, which summarized in Table 4.3 to 4.13.

Table 4.3 Land use requirements for rubber.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean annual tem.	^{0}C	> 22	22-20	20-18	< 18
	Mean annual pre.	mm	>1700	1700-1450	1450-1250	< 1250
Sufficiency of water	Soil depth	m	>150	150-100	100-50	< 50
	Soil drainage	class	good	moderate	imperf.	Poor, not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/kg clay)	Any	-	-	-
	pH		5.3-5.0 5.3-6.0	5-4.5 6.0-6.5	4.5-4.0 6.5-7.0	< 4.0 > 7.0
	OM	%	>1.2	<1.2	-	-
Topography	Slope	%	0-8	8-16	16-30	> 30

Source: Sys *et al.*, 1991.

Table 4.4 Land use requirements for cassava.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean annual tem.	^0C	23-18 23-30	18-16 >30	16-12 -	< 12 -
Sufficiency of water	Mean annual pre.	mm	1600-1000 1600-2400	1000-600 >2400	600-500 -	< 500 -
	Soil depth	m	>100	100-75	75-50	< 50
	Soil drainage	class	good	moderate	imperf.	Poor, not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	-	-	-
	pH		6.0-5.2 6.0-7.0	5.2-4.8 7.0-7.6	4.8-4.5 7.6-8.2	< 4.5 > 8.2
	OM	%	>1.5	1.5-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.5 Land use requirements for maize.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean tem. of the growing cycle	^0C	24-18 24-32	18-16 32-35	16-14 35-49	< 14 > 40
Sufficiency of water	Mean pre. of the growing cycle	mm	750-500 1200-750	500-400 1200-1600	400-300 > 1600	< 300 -
	Soil depth	m	>75	75-50	50-20	< 20
	Soil drainage	class	good	moderate	poor	not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		6.6-5.8 6.6-7.8	5.5-5.8 7.8-8.2	5.2-5.5 8.2-8.5	< 5.2 > 8.5
	OM	%	>1.2	1.2-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-16	>16

Source: Sys *et al.*, 1991.

Table 4.6 Land use requirements for bean.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean tem. of the growing cycle	^{0}C	18-12 18-24	12-10 24-27	10-8 27-38	<8 > 30
Sufficiency of water	Mean pre. of the growing cycle	mm	450-350 450-600	350-300 600-1000	300-250 > 1000	< 250 -
	Soil depth	m	>75	75-50	50-20	< 20
	Soil drainage	class	good	moderate	poor	Poor,not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		6.5-5.6 6.5-7.6	5.6-5.4 7.6-8	5.4-5.2 8-8.2	< 5.2 > 8.2
	OM	%	>1.2	1.2-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.7 Land use requirements for sweet potato.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean tem. of the growing cycle	^{0}C	25-22 25-32	22-20 32-35	20-16 35-40	<16 >40
Sufficiency of water	Mean annual pre.	mm	950-650 950-1500	650-500 1500-1700	500-400 >1700	< 400 -
	Soil depth	m	>75	75-50	50-20	< 20
	Soil drainage	class	moderate	imperf.	poor	poor, not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		6.6-5.2 6.6-8.2	5.2-4.8 82-8.4	4.8-4.5 8.4-.5	< 4.5 > 8.5
	OM	%	>2	2-1	< 1	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.8 Land use requirements for irrigated rice.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean tem. of the growing cycle	^0C	31-24 31-36	24-18 > 36	18-10 -	< 10 -
Sufficiency of water	Soil depth	m	>75	75-50	50-20	< 20
	Soil drainage	class	moderate	poor good	very poor	-
Sufficiency of nutrients	CEC	(cmol(+)/kg clay)	>16	< 16	-	-
	pH		6.5-5.5 6.5-8.2	5.5-5 8.2-8.5	5.0-4.5 8.5-9	< 4.5 > 9
	OM	%	>1.5	1.5-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-25	> 25

Source: Sys *et al.*, 1991.

Table 4.9 Land use requirements for citrus.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean annual tem.	^0C	26-19 26-33	19-16 33-36	16-13 36-39	< 13 >39
Sufficiency of water	Mean annual pre.	mm	2300-1200 2300-3000	1200-1000 >3000	1000-800 -	< 800 -
	Soil depth	m	>150	150-100	100-75	< 75
	Soil drainage	class	good	moderate	imperf.	Poor, not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		6.5 -5.5 6.5-7.6	5.5-5.2 7.6-8.0	5.5-5.0 8.0-8.2	< 5.0 > 8.2
	OM	%	≥ 0.8	-	-	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.10 Land use requirements for banana.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean annual tem.	^{0}C	18	18-16	16-14	< 14
Sufficiency of water	Mean annual pre.	mm	> 1500	1500-1250	1250-1000	< 1000
	Soil depth	m	>75	75-50	50-25	< 25
	Soil drainage	class	moderate	imperf.	poor	not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		6.4-5.6	5.6-5.2	5.2-4.5	< 4.5
			6.4-7.5	7.5-8.0	8.0-8.2	> 8.2
	OM	%	>1.5	1.5-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.11 Land use requirements for pineapple.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean annual tem.	^{0}C	23-20	20-18	18-16	< 16
			23-26	26-30	30-35	> 35
Sufficiency of water	Mean annual pre.	mm	1300-1000	1000-800	800-600	< 600
			1300-1600	1600-2000	> 2000	-
	Soil depth	m	>60	60-40	40-20	< 20
	Soil drainage	class	moderate	imperf.	poor	not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/ kg clay)	>16	< 16	-	-
	pH		5.7-5.0	5.0-4.3	4.3-4.0	< 4.0
			5.7-6.5	6.5-7.0	7.0-7.8	> 7.8
	OM	%	>1.2	1.2-0.8	< 0.8	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.12 Land use requirements for sugarcane.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean day tem. for vegetative stage	^0C	26-22 26-32	22-20 32-35	20-18 >35	< 18 -
Sufficiency of water	Sunshine	mm	>1800	1800-1400	1400-1200	< 1200
	Soil depth	m	>80	80-50	50-25	< 25
	Soil drainage	class	moderate	imperf.	poor	poor, not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/kg clay)	>16	< 16	-	-
	pH		6.5-5.5 6.5-7.5	5.5-5 7.5-8.0	5.0-4.5 8.0-8.5	< 4.5 > 8.5
	OM	%	>1.5	1.5-1.0	< 1.0	-
Topography	Slope	%	0-4	4-8	8-16	> 16

Source: Sys *et al.*, 1991.

Table 4.13 Land use requirements for rainfed upland rice.

Land quality	Diagnostic land characteristic	Unit	S1	S2	S3	N
Temperature	Mean tem. of the growing cycle	^0C	31-24 31-36	24-18 > 36	18-10 -	< 10 -
Sufficiency of water	Mean pre. of the growing cycle	mm	200-50 200-400	- 400-550	- 550-650	< 50 > 650
	Soil depth	m	>90	90-50	50-20	< 20
	Soil drainage	class	moderate	good	poor	not drainab.
Sufficiency of nutrients	CEC	(cmol(+)/kg clay)	>16	< 16	-	-
	pH		6.5-5.5 6.5-7.5	5.5-5 7.5-7.9	5.0-4.5 7.9-8.2	< 4.5 > 8.2
	OM	%	>1.5	1.5-0.8	< 0.8	-
Topography	Slope	%	0-8	8-16	16-30	> 30

Source: Sys *et al.*, 1991.

4.6.4 Crop Suitability Modeling

The crop suitability factors were determined based on the land use requirement. Suitable fuzzy membership function (Equation 4.2, Equation 4.3 and Equation 4.4) were selected to standardize those factors, and then that were combined together by using join membership function (Equation 4.5) as the model in Figure 4.3. The crop suitability index obtained, which are express continuous values, ranging from 0 (very poor or not suitable) to 1.0 (excellent or highly suitable).

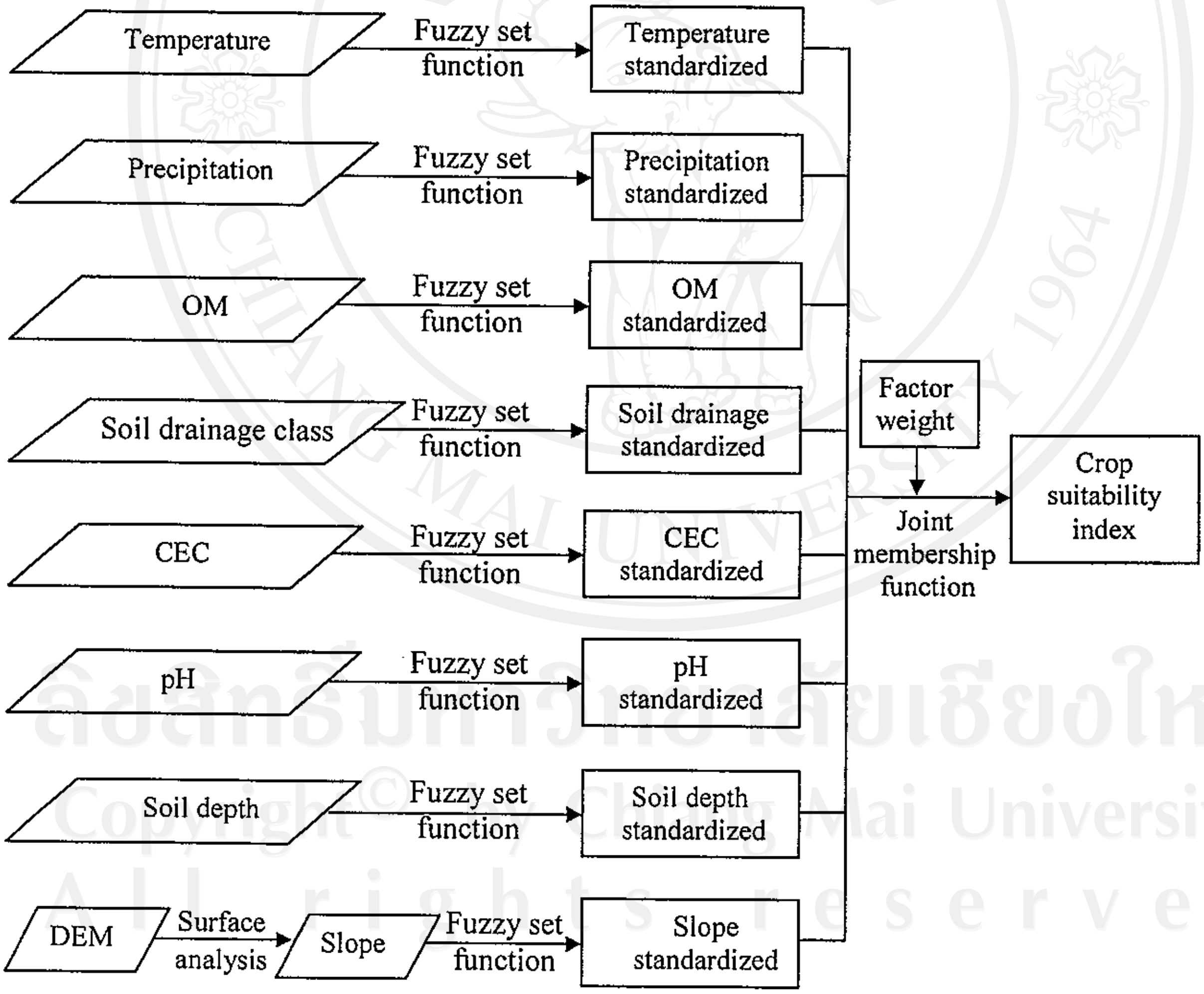

Figure 4.3 The model to determine crop suitability index.

4.6.5 Erosion Modeling

The Revised Universal Soil Loss Equation (RUSLE) is an erosion model designed to predict the longtime average annual soil loss (A) carried by runoff from specific field slopes in specified cropping and management systems as well as from rangeland. Widespread use has substantiated the usefulness and validity of RUSLE for this purpose. It is also applicable to nonagricultural conditions such as construction sites. The RUSLE developed by Renard *et al.* (1997) will be used to estimate the annual soil in the study area. The model to determine annual soil loss was shown in Figure 4.4.

$$A = R \, x \, K \, x \, LS \, x \, C \, x \, P \ldots\ldots\ldots\ldots \quad (4.10)$$

where: A = annual soil loss (t/ha/y)
R = rainfall erosivity factor
K = soil erodibility factor
LS = topographic factor (L = slope length, and S = slope steepness)
C = land cover management factor
P = conservation practice factor.

4.6.5.1 Rainfall Erosivity Factor (R)

Rainfall erosivity factor is the rainfall erosion index plus a factor for any significant runoff from snowmelt. It will be estimated by using equation that was developed by Xiem and Phien (1999) using linear regression between rainfall erosivity index and set of 30 year annual rainfall data in Vietnam

$$R = 0.548527P - 59.9 \ldots\ldots\ldots\ldots \quad (4.11)$$

where: R = rainfall erosivity factor ($MJ.mm.ha^{-1}.h^{-1}.yr^{-1}$)
P = annual precipitation (mm).

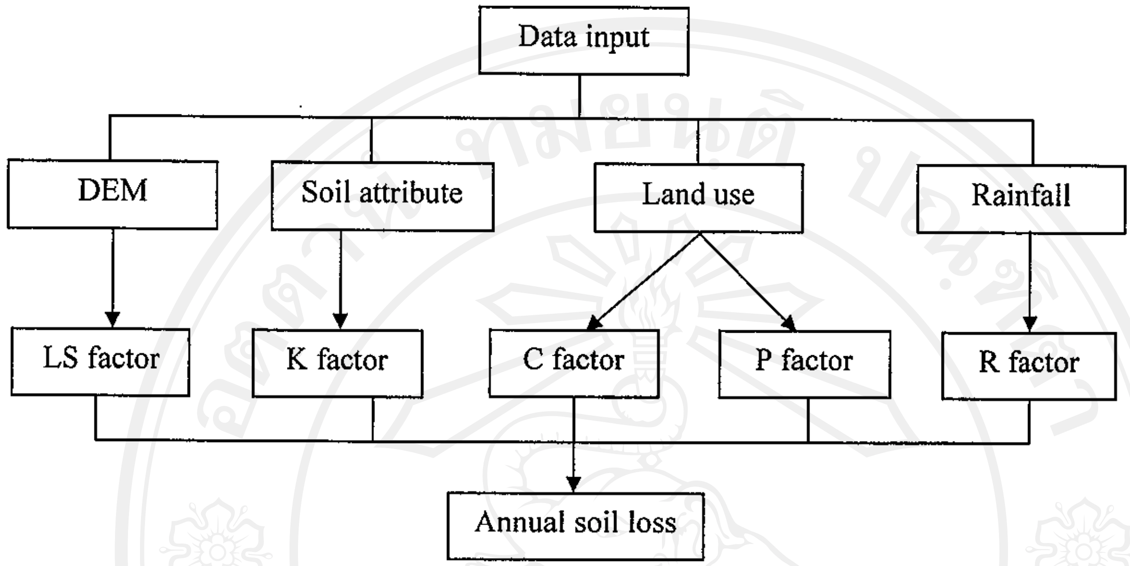

Figure 4.4 The model to determine annual soil loss.

4.6.5.2 Soil Erodibility Factor (K)

Soil erodibility factor is soil-loss rate per erosion index unit for a specified soil as measured on a standard plot, which is defined based on regression equation was built by Wischmeier and Smith (1978).

$$K = 2.8*10^{-7}*M^{1.14}(12-a)+4.3*10^{-3}(b+2)+33*10^{-3}(c-3) \quad (4.12)$$

where: K = Soil erodibility factor ($t.ha^{-1}.MJ^{-1}.ha.mm^{-1}.h$)

M = particle size parameter

M = (% silt + % very fine sand)*(100 - % clay)

a = percentage of content organic matter

b = soil structure code

c = permeability class.

4.6.5.3 Topographic Factors (LS)

The topographic factor represents the ratio of soil loss on a given slope length and steepness to soil loss. Topographic factor was calculated by using the equation proposed by Moore and Burch (1986) from unit stream-power theory and a variant used in place of the length-slope factor in RUSLE as follows Equation 4.13.

$$LS = (m+1)\left(\frac{A_s}{22.13}\right)^m \left(\frac{Sin\beta}{0.0896}\right)^n \ldots\ldots\ldots\ldots\ldots \quad (4.13)$$

where: LS = topographic factor

m = 0.4

n = 1.3

β = slope gradient in degrees

A_s = specific catchment area or drainage area per unit width orthogonal to flow line (m^2/m)

4.6.5.4 Land Cover Management Factor (C)

The C-factor is used to reflect the effect of cropping and management practices on erosion rates. It is the factor used most often to compare the relative impacts of management options on conservation plans. The C-factor indicates how the conservation plan will affect the average annual soil loss and how that soil-loss potential will be distributed in time during crop rotations or other management schemes.

C-factor was defined by using the previous works of Wischmeier and Smith (1978) and Mongkolsawat *et al.* (1994) which based on the crops and tree. The land use map provides the information type of crops, tree. The C-factor was defined (Table 4.14).

Table 4.14 The values of land cover management factor (C).

Ordinal	Land use	C-factor	Ordinal	Land use	C-factor
1	Rice	0.280	8	Planted tree	0.010
2	Cassava	0.600	9	Mixed forest, close canopy	0.002
3	Sugarcane	0.450	10	Mixed forest, open canopy	0.001
4	Maize	0.520	11	Bare soil	1.000
5	Potatoes	0.450	12	Construction site	0.000
6	Fruit tree	0.300	13	Water body	0.000
7	Annuals	0.470			

Source: Wischmeier and Smith (1978), Mongkolsawat *et al.* (1994).

4.6.5.5 Conservation Practice Factor (P)

P-factor reflects the impact of support practices an the average annual erosion rate. It is the ratio of soil loss with contouring and/or stripcropping to that with straight row farming up-and-down slope.

As with the other factors, the P-factor differentiates between cropland and rangeland or permanent pasture. Both options allow for terracing or contouring, but the cropland option contains a stripcropping routine whereas the rangeland/permanent-pasture option contains an "other mechanical disturbance" routine. For the purpose of this factor, the rangeland/permanent-pasture option is based on the support operation being performed infrequently, whereas in the cropland option the support operation is part of the annual management practice. P-factor was defined based on the previous works of Wischmeier and Smith (1978) as in Table 4.15.

Table 4.15 The values of Conservation practice factor (P).

Ordinal	Erosion control practices	P-factor value
1	Contouring in the $0\text{-}1^0$ slope lands	0.6
2	Contouring in the $2\text{-}5^0$ slope lands	0.5
3	Contouring in the $6\text{-}7^0$ slope lands	0.6
4	Contouring in the $8\text{-}9^0$ slope lands	0.7
5	Contouring in the $10\text{-}11^0$ slope lands	0.8
6	Contouring in the $12\text{-}14^0$ slope lands	0.9
7	Level bench terrace	0.14
8	Reverse-slope bench terrace	0.05
9	Outward-sloping bench terrace	0.35
10	Level retention bench terrace	0.01
11	Tied-ridging	0.1-0.2

Source: Wischmeier and Smith (1978).

4.6.5.6 Determining Soil Loss Index

Environmental suitability is based on soil erosion index, the soil erosion index was generated by using fuzzy membership of soil loss tolerance (or T-value).

Soil loss tolerance is defined as the maximum rate of soil erosion that permits an optimum level of crop productivity to be sustained economically and indefinitely. It is also sometimes called permissible soil loss which is related to the average annual soil loss a given soil type may experience and still maintain its productivity over an extended period of time (Baja *et al.*, 2002). In many situations, the establishment of a T-value is intended to provide basic information for the maintenance of soil productivity, which becomes one of the foci of sustainability of agricultural land use. Therefore, T-values may be determined based on the factors affecting long-term productivity. For practical purposes, T-values may be estimated based on favorable rooting depth. The generally accepted maximum limit of soil loss (or T-value) is 11.2 t/ha/y (Wischmeier and Smith, 1978). An average soil loss of 5 t/ha/y has been considered as the limit for shallow soils (Hudson, 1986). Lal (1985) observed that for shallow soils with root-restrictive layers at 0.2 to 0.3 m depth, a T-value is set at 1 t/ha/y. A comprehensive guideline for the estimation of T-values based on the favorable rooting depth can be found in USDA-SCS (1973). Furthermore, for general purposes DLWC (1997) outlined a recommended maximum acceptable soil loss for agricultural and forestry areas, with three different ranges of soil depth, as follows:

· For deep soils (>1.5 m), T-value is set to 10 t/ha per year

· For moderately thick soils (1.0 - 1.5 m), T-value is set to 5 t/ha per year

· For shallow soils (< 1.0 m), T-value is 1 t/ha per year.

The T-values will be estimate from soil depth in meters (D): if soil with depth is more than 1.5m, T-value is 10t/ha/year, while those are less than 0.5m, T-value is 1t/ha/year. Between 0.5 - 1.5), T-value will be calculated from the following equation (Baja *et al.*, 2002).

$$T\text{-}value = 9D - 3.5 \quad (4.14)$$

In this study the ideal value *b* and marginal (or cross point) for membership function of soil erosion was adopted Baja *et al.*, (2002), which was set to 5 t/ha/y for ideal value and 20 t/h/y for crossover point. This means that the membership grade of soil loss will be dramatically decreased at the points where erosion rate exceeds 20 t/ha/y.

When annual soil loss is defined that would be standardized by using suitable fuzzy member function. The result, soil loss index would be expressed in continuous values from 0 (high vulnerability) to 1.0 (almost no risk).

4.7 Determination of Physical Suitability Class

The process of matching land use requirements with land qualities and environmental suitability (soil loss index) for physical land suitability has been done. The physical suitability of eleven crops in Nam Dong district were classified based on guideline for definitions of classes for factors rating followed Dent and Young (1981) and FAO (1983) as in Table 4.16.

Table 4.16 Guideline for definitions of classes for factors rating

Class	Definition in term of yields [1]
S1	> 80 %
S2	40 - 80 %
S3	20 - 40 %
N	< 20 %

Source: Dent and Young (1981) and FAO (1983).
Note: [1] expected crop yields, as a percentage of yield under optimum condition

4.8 Relative Crop Suitability

Relative crop suitability assessment helps in production of a potential land use map based on land suitability for different crops. The physical suitability index grids of eleven crops were overlaid on each other by using maximum command in ArcGIS. Eleven crops namely bean, banana, cassava, citrus, irrigated-rice, maize, pineapple, sugarcane, rubber, sweet-potato and upland-rice were symbolized by grids C1 to C11 in Figure 4.5. The highest value in each pixel (S_m) of the physical suitability maps could be identified.

The name of the crop in each pixel that has highest value was defined by using the Con command in ArcGIS such that Con ([S_m] - [$\mathbf{C_i}$]) = = 0, **i**, 0) (**i** = 1, 2 ….11). The Con command was used eleven times with eleven crops. Each crop was encoded by unique value (**i** = 1, 2 ….11). After that the Plus command was used to obtain the relative crop suitability from the resulting encoded value associated with the corresponding crop.

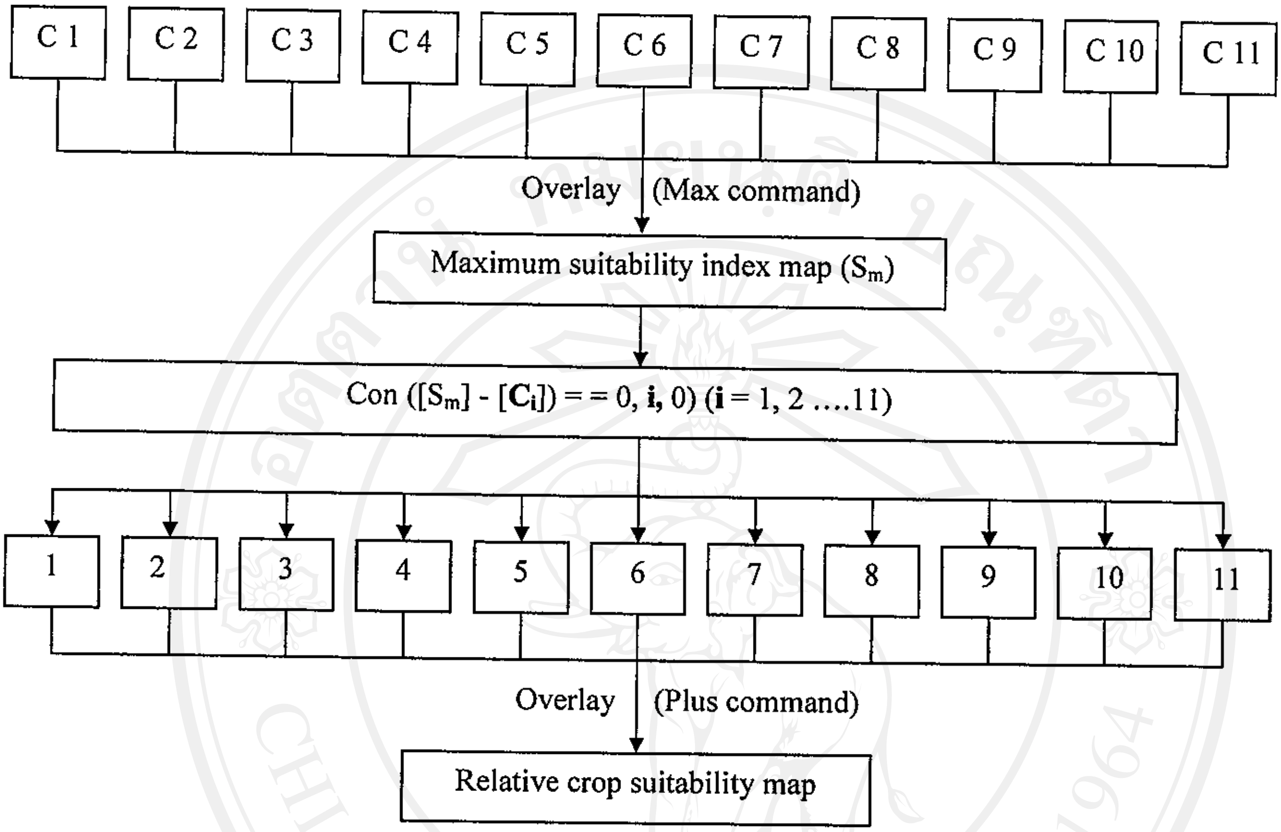

Figure 4.5 The procedures for relative crop suitability assessment.

4.9 Geoprocessing Models Construction

Geoprocessing models were built by using Model Builder extension in ArcGIS. Once the models have been built, long and complex steps of spatial analysis could be processed, easy to update any map parameters or functions in the model diagram with short time consuming, and without human errors. Models were developed in a raster environment with grid format map layers. The raster system has used because it can store, manage, and analyze the data needed in a suitability analysis, as well as display the results effectively.