Modern Applied Science; Vol. 7, No. 7; 2013
ISSN 1913-1844 E-ISSN 1913-1852
Published by Canadian Center of Science and Education

Reevaluating FMOLP Decision Variable Coefficients Using the SWAT Results for the Optimization of Sustainable Agricultural Land Use in Small Watershed

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Received: May 22, 2013 Accepted: June 15, 2013 Online Published: June 22, 2013

doi:10.5539/mas.v7n7p59 URL: http://dx.doi.org/10.5539/mas.v7n7p59

Abstract

The inappropriate use of agricultural land has caused several environmental and socio-economic problems. Fuzzy multiple objectives linear programming (FMOLP) is a mathematical technique that can be effective in land use planning. It requires decision variable coefficients (DVCs) to formulate the problem model covering all environmental and socio-economic aspects. The solution from a formulated FMOLP model provides optimal land use proportion and then the proportion is relocated t o produce the land use planning map. The map is then transferred to the soil and water assessment tools (SWAT) for assessing the impacts. The SWAT results give out a value which differs from the initial DVCs in the comparable aspects. This difference indicates that the initial DVCs were not realistic for the selected watershed and the land use planning map were not optimal.

This study attempts to reevaluate DVCs in the FMOLP model by designing a method of sustainable agricultural land-use planning which makes use of the outputted results from the SWAT model. The results in terms of soil loss, crop water consumption, crop yields and net profit are simulated by SWAT and then replace to the DVC's value. This procedure will be repeated until a small difference between SWAT results and DVC's values are obtained. The findings of this study show that the final land use map achieves a higher target value than the map that was constructed after the initial phase of testing in all of objective. It is hoped the outcomes of this loop back process can be linked to the optimizing technique, so that environmental models can be utilized in the model output to improve optimum proportional solutions in any decision support system (DSS) for future sustainable agricultural land use planning.

Keywords: linear programming, swat model, optimization, land use planning, decision support system, coefficient estimation

1. Introduction

Inappropriate agricultural land use causes many serious environmental and socio-economic problems such as soil erosion, land degradation, drought, as well as a decrease in crop's yield and a farmer's income. The conflicts between economic demands and environmental protections are challenging for land use planners. The agricultural land use planning becomes a critical task to maintain food productivity, environment protections and the economy of the local community which are limited by the land resources. The land use optimization technique has been widely developed for supporting planners to allocate proper patterns of sustainable watershed resources.

Agricultural land use allocation determines the area of each crop type as a decision variable (DV). To sustain the watershed, the DV allocation requires the integration of both environmental and socio-economic aspects under the condition and limitations of land resources. Multiple objectives decision-making (MODM) has been introduced as an approach which can handle multiple criteria problems. Fuzzy Multi Objective Linear Programming (FMOLP) is one of the most popular MODM techniques used to deal with land use planning problems (Mohaddes et al., 2008; Salski & Noell, 2001).

The FMOLP model consists of multiple decision making equations which are concerned with all of environmental and socio-economic objective functions and constraint functions. Each function consists of the summation of DVs multiplied by its coefficient, which is called the decision variable coefficient (DVC). DVCs represent the magnitude of usage, impact, yield or production per unit of the DV. DVCs as measured in land use optimization techniques typically are concerned with the crop yield, income, soil erosion rate and crop water consumption. Generally, the evaluation of DVCs are derived from databases, statistical data, literature or as a result of related equations, e.g. the agricultural statistics determine the DVCs on crop yield, the universal soil loss equation (USLE) usage which estimates the DVCs for the rate of soil erosion (Makowski, 2003; Sadeghi et al., 2009). However, some coefficients cannot be defined precisely due to variation of information and uncertainty (Zeng et al., 2010).

After the problem model in FMOLP form is solved, the optimal land use solution can be mapped onto a land use planning map. The relocated land use map is expected to be consistent with environmental and socio-economic objectives. Finally, the soil and water assessment tools (SWAT), an environmental model, is used for assessing the impact of the planned land use on soil erosion, water usage, and crop production. Additionally, further calculations are made to extract an estimate of the net profit.

The SWAT model is a physically based model that relies on topographic soil, the characteristics of the climate, as well as any natural phenomena which may affect the process of land management. Consequently, the simulation of this model will produce more realistic results for the watershed than any quantitative statistical data analysis.

Considering the sustainable land use allocation procedures as mention above, it has the ability to show a compatible value on the resamble aspects among DVCs in FMOLP model and SWAT outputs. Comparing two sources of values item by item, the DVCs were derived from references while the SWAT outputs were produced from simulation. The difference in sources may cause the differences in value. If DVCs are less reasonably valued than a simulated value, then, the FMOLP solution might not be the optimal land use solution for the selected watershed. Thus, DVCs should be reevaluated by updating with the realistic value. SWAT outputs are used for adjusting DVCs, repeating process is required because the change in DVCs of objective function may affect the optimal land use solution (Anderson et al., 2007).

This study attempts to reevaluate DVCs in FMOLP models to create a sustainable agricultural land usage by factoring SWAT results, and then repeating the allocation procedure until the adjusted DVCs are able to yield target values that are close to the SWAT results. This loop back process is expected to link the optimizing technique and environmental model to create a model output which will improve the optimum proportional solution for the decision support system (DSS) and ultimately create a model of sustainable agricultural land use planning.

2. FMOLP and SWAT Models

2.1 An Overview of FMOLP

Linear programming (LP) is a mathematical method which determines the optimal solution for a linear objective problem. Patterson (1972) applied LP to the problem of land use allocation. The application of land use planning, decides how to use a proportional area of land use optimally based on the patterns of usage. It creates a set of alternatives from a number of possibilities. The criteria for the optimalization of land use are measured through the objective factors of crop yields, farmer income, soil loss and crop water consumption. The constraints of this optimimalization problem are the boundaries which limit the availability of resources or determine the minimum requirements to dictate the feasibility of applying the technique (Mohaddes et al., 2008). Additionally, the classical LP is unable to handle the problems of having multiple criteria. The FMOLP technique, introduced by Zimmermann (1978), is a quantitative, multi-objective management model in LP form which its objective functions are converted into fuzzy constraints.

In the FMOLP model, DVs are a unit of key items that could have an impact on the solution of the problem. Each DV has coefficients which determine the effectiveness per unit of a DV. An equation in the FMOLP model consists of a summation of DVs multiplied by their coefficients. The constraint equations have a constant value on the right hand side (RHS) which represent the number of available resources required. Another equation, called objective function, describes issues that the decision maker has to make while managing the target. Because the optimal solution to the FMOLP model is influenced by the value of DVC, DVCs thus play an important role in organization of the FMOLP model.

The FMOLP model can be expressed as:

$$Max \;\; \alpha \tag{1}$$

Subject to

$$c_{i1}X_1 + c_{i2}X_2 + \ldots + c_{ij}X_j + u_i\alpha = z_i$$

$$a_{i1}X_1 + a_{i2}X_2 + \ldots + a_{ij}X_j = b_i$$

Where α is the common fulfillment degree for all fuzzy constraints of the model and its value ranges from 0-1, z_i is the target value for an objective function i, u_i is the satisfaction level, X_j is the DVs, c_{ij} and a_{ij} are known DVCs, and b_i is the exact number of the right hand side (RHS) value. The optimal decision X_i by the solution of the problem model can be solved by standard method for the LP or simplex method.

2.2 Application of SWAT Model

The SWAT model, developed by Arnold et al. (1990), is a physically based model used for assessing the long-term impact of sediment and water on land management practice in determining a watershed scale. The model simulates the processes of hydrologics, erosion, sediment transport, crop growth and nutrient cycling. The concept of spatial manipulation of the SWAT model has been divided into two parts: (1) subbasin: the watershed has been partitioned by the delineation of topography. And (2) hydrological response unit (HRU): a lumped amount of land within a subbasin that consists of unique land cover, soil and slope gradients (Neitsch et al., 2005). The SWAT model requires the complete input of (1) spatial data: land use, soil, and a digital elevation model (DEM) map, (2) attributive data: consisting of soil and crop properties, and (3) hydro-meterology recorded data. A watershed simulation can configure the crop schedule, management practice and water management system. The model outputs consists of hydrological results, sediment yields and crop yields which are available in daily, monthly, and annual summaries. SWAT is widely used from small watershed sites to large river basins in order to assess land use impacts on stream flow, sediment, non-point source pollutants, and crop yield estimations (Parajuli et al., 2013; Reungsang et al., 2010; Oeurng et al., 2011).

3. Study Site

The current study used the Lam Sonthi watershed as its research site. Lam Somthi is a branch of the Pasak watershed which is situated in central region of Thailand (Figure 1). It covers an area of 1,313.4 km^2 with an elevation range of between 6.7 to 800 meters above mean sea level. Its topography is mostly undulating and plain. The average annual rainfall is 1,198.4 mm. with rainy season starting in April and lasting until November. The maximum monthly rainfall occurs between July and September. The average temperature is 28.1 °C with the highest temperature in April and the lowest in December. The average relative humidity is 71%. Seventy three percent of the watershed area is agricultural land which grows economic crops (such as corn, sugarcane, cassava and rice). There are weir and irrigation systems downstream near the outlet.

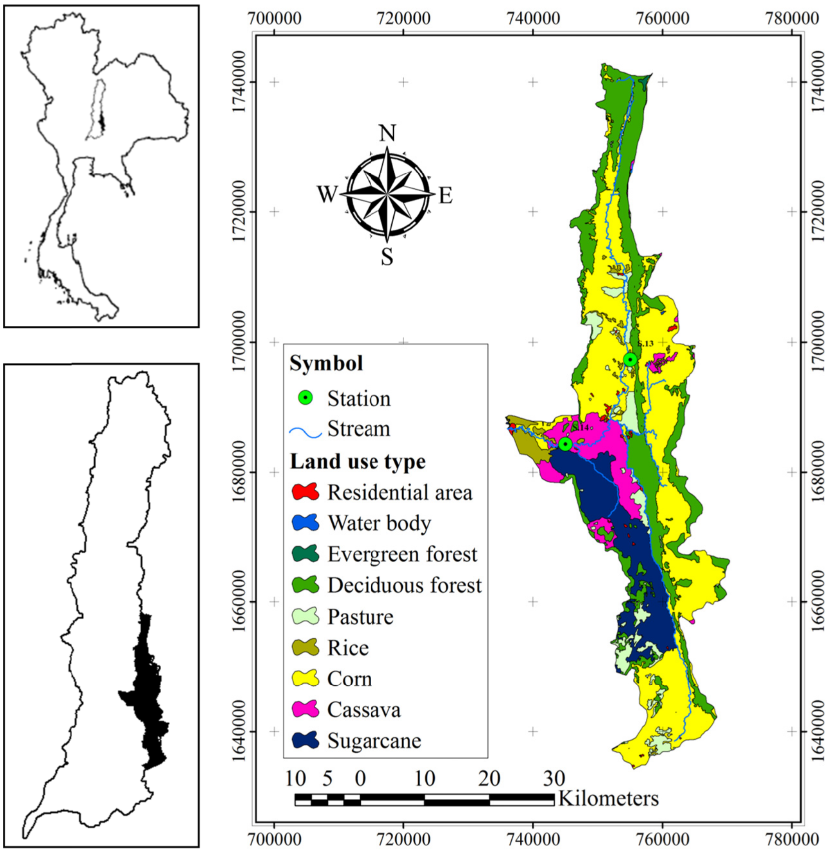


Figure 1. Land use, stream network and station location of Lam Sonthi watershed

4. Materials and Method

4.1 Materials

4.1.1 Map Data Layers

A geographic database with topography, land use, soil, stream line and watershed boundary, provided by Office of Agricultural Economics (Office of Agricultural Economics [OAE], 2007) and Land Development Department (Land Development Department [LDD], 2006), were used for producing the input map in the SWAT model. Shape files were converted into 100-m resolution raster format with a grid cell representing one hectare in area. A Digital Elevation Model (DEM) was generated from the topographic map. Both the stream line and the watershed boundary, in shape file format, were directly used for dividing the subbasin. In this study, the land-use codes for rice, corn, sugarcane, cassava and pasture and are assigned as RICE, CORN, SUGC, CASV and HAY respectively.

4.1.2 Temporal and Attributive Datasets

Historical weather patterns and hydrographical data were collected from two stations located in the Lam Sonthi watershed, obtained from Royal Irrigation Department (Royal Irrigation Department [RID], 2007). The complete daily dataset is available only in the years from 1982 to 1987. To complete the watershed climate database, all parameters were calculated from the recorded data. The maximum 30-minute rainfall (RAINHHMAX as SWAT parameter) was estimated by extracting the information from a rainfall graph, which had been collected during the years 1981-1986. Information regarding crop production, management practices, schedule and economic values were also collected from the literature and in the process of reviewing relevant statistical data. The original soil database was able to provide only the soil texture and some other crucial properties. The available soil database was then employed for an estimate of the missing properties by using a soil characteristic calculator which was developed by Saxton and Rawls (2006). Soil-crop and slope-crop suitability classification data are required to produce crop suitability map.

4.1.3 Applications

The tools used for this study include: (1) the SWAT model (version 2005) with a MapWindow SWAT plugin

(MWSWAT), (2) GIS software - MapWindowGIS and PCRaster, (3) Microsoft Access and Microsoft Excel for manipulating data, and (4) the optimizer, LINDO, as a mathematical optimization model for solving both LP and FMOLP models.

4.2 Method

4.2.1 Formulate FMOLP Model of the Problem

To set up the FMOLP model, DV is defined as the size of the area of each crop type (unit: hectare); X_1 = rice, X_2 = corn, X_3 = cassava, X_4 = sugarcane and X_5 = hay (pasture).

A sustainable land use allocation model was formulated to cover environmental and socio-economic functions, consisting of soil loss, crop water consumption, net profit, minimum crop production requirements, reserved for protection areas and non-suitable area.

4.2.2 Initiate DVC's Value

At first, the initial coefficient values were derived based on the available literature, statistical data or a specific method which could determine the annual effected area per unit of DV in each hectare. The process of determining the DVCs value in each function can be described as follows:

-DVCs for Soil Loss Estimation

DVC for each cropping area represent the loss of soil ($ton \cdot ha^{-1}$) as estimated by USLE (Wischmeier & Smith, 1978). Both rainfall and runoff erosivity (R-factor) were calculated by an equation which measures these factors in the central region of Thailand (as suggested by Srikajon et al., 1981). The annual required rainfall data is shown in Equation 2.

$$R\text{-}factor = (0.866 \times annual\ rainfall) - 323.009 \quad (2)$$

The recorded annual rainfall of the research site is 1,198 mm. the R-factor for this site is thus estimated at 714.81 $ton \cdot ha^{-1} \cdot year^{-1}$. Due to the different types of suitable soil series and slope range for each crop type, the values used in the USLE equation were specifically set for each crop. To ensure an accurate measure of its potential value, the highest amount of soil erodibility (K-factor) as well as the most extreme topographical factors (L- and S-factors, based on 100 m length) were set to indicate the highest possible impact of each crop type. Referenced CP-factor values were drawn from LDD (2000). All USLE factors and the annual loss of soil are described in Table 1.

Table 1. USLE parameters and estimated soil loss coefficients for FMOLP expressions

Crop type (DV)	USLE parameters					Estimated soil loss
	R-factor	K-factor	L-factor	S-factor	CP-factor	($ton \cdot ha^{-1} year^{-1}$)
Rice (X_1)	714.8054	0.47	2.13	0.841	0.028	16.85
Corn (X_2)	714.8054	0.34	2.87	2.406	0.502	842.46
Cassava (X_3)	714.8054	0.34	2.87	2.406	0.600	1,006.92
Sugarcane (X_4)	714.8054	0.34	2.13	1.584	0.400	327.99
Hay (X_5)	714.8054	0.34	2.87	2.992	0.100	208.69

-DVCs for the Estimate of Crop Water Consumption

The DVC for each crop type is represented by its annual crop water consumption ($m^2 \cdot ha^{-1}$), as estimated by LDD (2002) and the CROPWAT model (Food and Agriculture Organization [FAO], 1998).

-DVCs for Crop Yield Derivation

The statistical data from LDD (2000) and OAE (2011) has provided an annual crop yield for the researched area.

-DVCs for Net Profit Calculation

Net profit is calculated as a farmer's income, consisting of the items that are sold as raw, fresh crop production at farms, subtracted by the cost of farming for the period of one year. The coefficients (DVCs) for each cropping area (DVs) are represented by the annual net profit ($baht \cdot ha^{-1} \cdot year^{-1}$) which can be calculated by using Equation 3. The referenced data has been provided by OAE (2010).

$$net\ profit = (y \cdot p) - c \tag{3}$$

Where net profit = annual net profit (baht·ha^{-1}·year^{-1}), y is the average annual crop production (ton·ha^{-1}), p represents the crop yield price per weight (baht·ton^{-1}) and c is the production cost (baht·ha^{-1}·year^{-1}).

Initial DVC's value which were used in the first step of the FMOLP model for soil loss, crop water consumption, crop production and net profit are shown in Table 2.

Table 2. Initial DVC values of LP/FMOLP models for different DVs

Aspects of functions in FMOLP model	Initial DVC's value for crop land use type (orDV)				
	Rice (X_1)	Corn (X_2)	Cassava (X_3)	Sugarcane (X_4)	Hay (X_5)
Soil loss (ton·ha^{-1}·year^{-1})	16.9	842.5	1,006.9	328.0	208.7
Crop water consumption (m^3·ha^{-1}·year^{-1})	9,207.0	7,291.0	9,545.0	12,713.0	10,671.0
Crop production (ton·ha^{-1}·year^{-1})	2.900	8.788	20.340	68.773	39.462
Net profit (baht·ha^{-1}·year^{-1})	9,617	14,459	10,618	2,622	24,433

4.2.3 Designing the FMOLP Model

The formulated FMOLP Model was solved to optimize the objectives of the DV's value which had already met the requirements. Each DV value result represents the optimal number for each crop type area.

4.2.4 Spatial Crop Land Use Allocation

The optimal crop type proportion from the FMOLP solution was then relocated onto a map. The rating score considered both soil- and slope-crop suitability classes, as provided by LDD (2002) and FAO (1993). The rating score had 4 classes, ranging from: most suitable (S1), moderately suitable (S2), less suitable (S3) and non-suitable (N). The weighted rating score for the mentioned suitability class was determined (based on S1 = 7, S2 = 5, S3 = 3, N = 1) as 0.44, 0.31, 0.19 and 0.06, respectively. Reclassification technique in GIS used to produce soil- and slope-crop suitability map.

A summation of the rating score defined the selected crop types as a benefit, while those non-selected crop types were defined as an opportunity cost. The Benefit/Opportunity Cost ratio (BOC) can be calculated as shown in Equation 4.

$$BOC_i = L_i \Big/ \left(\sum_{c=1}^{n} L_c - L_i \right) \tag{4}$$

Where BOC_i is BOC for the grid i, L_i is a summation of the rating score of selected crop types on the grid i, L_c is a summation of the rating score of non-selected crop types con grid i. The crop relocation process begins with the sorting of descended grid cells by the BOC. Grid cells which have the highest BOC are designated for the selected crop types in as much as is proportionally required. Non-assigned grid cells are then available for other crop types to be produced. This procedure was continuously operated until all crop types were completely allocated as shown in Figure 2. The output of this procedure created a land use planning map which represents the optimal amount of land use patterns.

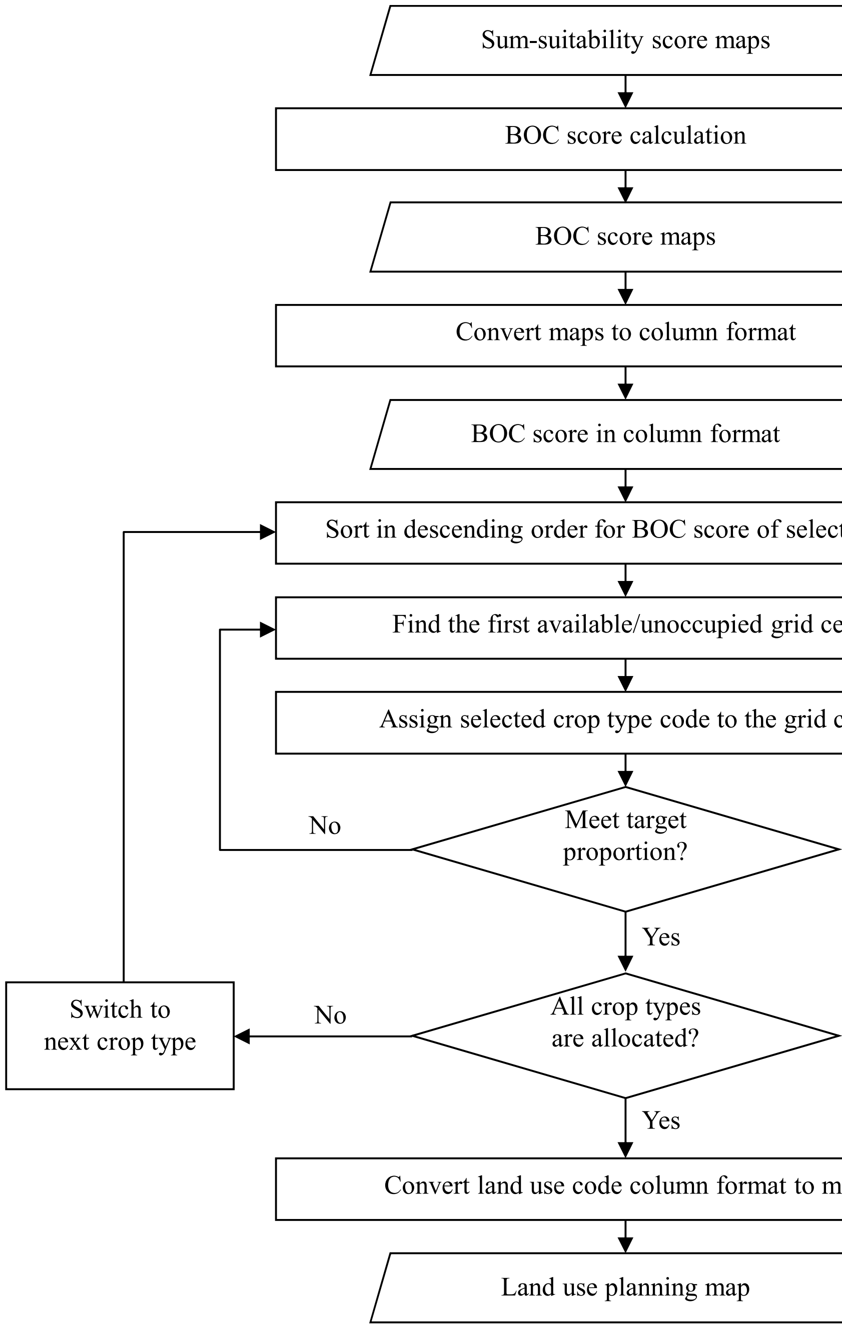


Figure 2. GIS procedure on land use allocation using BOC technique

4.2.5 SWAT Simulation

4.2.5.1 Model Configuration

A Map Window SWAT (MWSWAT) was used for generating the SWAT input data. A DEM map generated the subbasins for the studied watershed area. A weir was located near the outlet of the watershed area. For the creation of a HRU, a soil map and a land use planning map which had already been produced in the previous process was used. Then, the slope band set 0, 2, 5, 8, 16, 30, 45% and above were inputted at discrete slope range intervals. SWAT input parameters were adjusted to the real situation. Both the crop practice schedule and irrigation area were applied into management files (.mgt), while the other SWAT crop parameters were set by default.

4.2.5.2 Calculation Method for the Outputs of SWAT

Each SWAT output has to be calculated by a particular method as shown in the following equation:

-*Crop Water Consumption*

Crop water consumption, which is measured in terms of the total water volume evapotranspiration, was calculated into an annual average volumetrics evapotranspiration per hectare as shown in Equation 5.

$$crop\ \ water\ \ consumption\ =\ \sum_{i=1}^{n}(AREAkm2_i \cdot 1000 \cdot ETmm_i) \Big/ \sum_{i=1}^{n}(AREAkm2_i \cdot 100) \qquad (5)$$

Where crop water consumption is the average annual water loss volume ($m^3 \cdot ha^{-1}$) in the evapotranspiration process, $AREAkm2_i$ represents the area of an HRU i^{th} (km^2), $ETmm_i$ is the annual depth of evapotranspirated water (mm) for an HRU i^{th} as estimated by SWAT.

-*Soil Loss*

Soil loss, in term of sediment was calculated as an annual average weight of sediment per hectare as shown in Equation 6.

$$soil\ \ loss\ =\ \sum_{i=1}^{n}(AREAkm2_i \cdot 100 \cdot SEDth_i) \Big/ \sum_{i=1}^{n}(AREAkm2_i \cdot 100) \qquad (6)$$

Where soil loss is the average annual soil loss ($ton \cdot ha^{-1}$), $SEDth_i$ represents the annual sediment ($ton \cdot ha^{-1}$) for an HRU i^{th} as estimated by SWAT.

-*Crop Production*

Originally, the SWAT output was able to give the dry weight of crop yield per hectare for each crop type or HRU. Crop production, in the form of fresh crop yield, requires additional manual calculations by adding the moisture content into the SWAT crop yield output. Thus, the estimated crop production was calculated by adding moisture into the dry weight of the crop yield as shown in Equation 7.

$$crop\ \ production\ =\ \left(\frac{\sum_{i=1}^{n}(AREAkm2_i \cdot 100 \cdot SEDth_i)}{(100-m)/100} \right) \Bigg/ \sum_{i=1}^{n}(AREAkm2_i \cdot 100) \qquad (7)$$

Where Crop production is the average annual crop production in wet weight ($ton \cdot ha^{-1}$), $YLDth_i$ is the annual crop yield in terms of dry weight ($ton \cdot ha^{-1}$) for an HRU i^{th} as estimated by SWAT, and m represents the percentage of moisture content in the yield. The crop yield moisture content of rice, corn, cassava, sugarcane and hay are 14, 15, 65, 70 and 75% of the total amount of fresh weight respectively (OAE, 2011).

4.2.5.3 Verification and Calibration Process

There were three SWAT outputs considered in the verification and calibration process for this study:

(a) Hydrological process—a monthly measured stream flow rate data was compared with simulated runoff in order to verify the model. The criterion used for calibrating the model was to minimize the difference of stream flow rates and to match them at their peak flow. This calibration was done by adjusting the runoff curve numbers for condition II (CN2), the soil available water capacity (SOL_AWC) and the depth of soil profile (SOL_Z).

(b) The erosion process—an available monthly measurement of sediment data was used to verify predictable sediment output rates. The calibration of the erosion process must consider two parts which are (1) the on-site erosion process: a cropping management factor (C-factor or USLE_C) is adjusted by comparing the reference C-factor in Thailand with the LDD (2000) and Sudjarit and Pukngam (2008). This is due to the fact that the default USLE_C value gives an underestimated sediment output rate (Maski et al., 2006). The other part to consider for the calibration for the erosion process is (2) sediment transportation: the calibration process covers the adjustable linear parameters (SPCON) and exponent parameters (SPEXP) in order to calculate the channel sediment routing, which includes the peak rate adjustment factor for sediment routing (PRF) (Oeurng et al., 2011).

(c) Crop yield—recorded data of crop yield per hectare was compared with the SWAT simulated yield. The SWAT model used a heat unit to regulate the crop growth. Cumulative heat units which reach the potential heat unit (PHU or Heat Units to Maturity) indicates a plant's maturity. In this approach, however, the heat unit is believed to directly affect the rate of growth without harming the plant at a high temperature, especially in tropical zones (Neitsch et al., 2005). The calibration of this process was adjusted by using the PHU and the Harvest index (HVSTI) in order to make a better weight which meets the amount of fresh crop yield for the existing land use (year 2000).

4.2.6 Comparing and Adjusting DVCs

The DVC values were then compared to the SWAT results in their respective compatible outputs. If the difference between the SWAT output and DVC value is greater than 5%, a repetition of land use allocation is required. In the next loop of the FMOLP model, DVC values were replaced with SWAT outputs. This procedure was repeated until the difference in value between the two is less than 5%.

The design of the method procedure is showed in Figure 3.

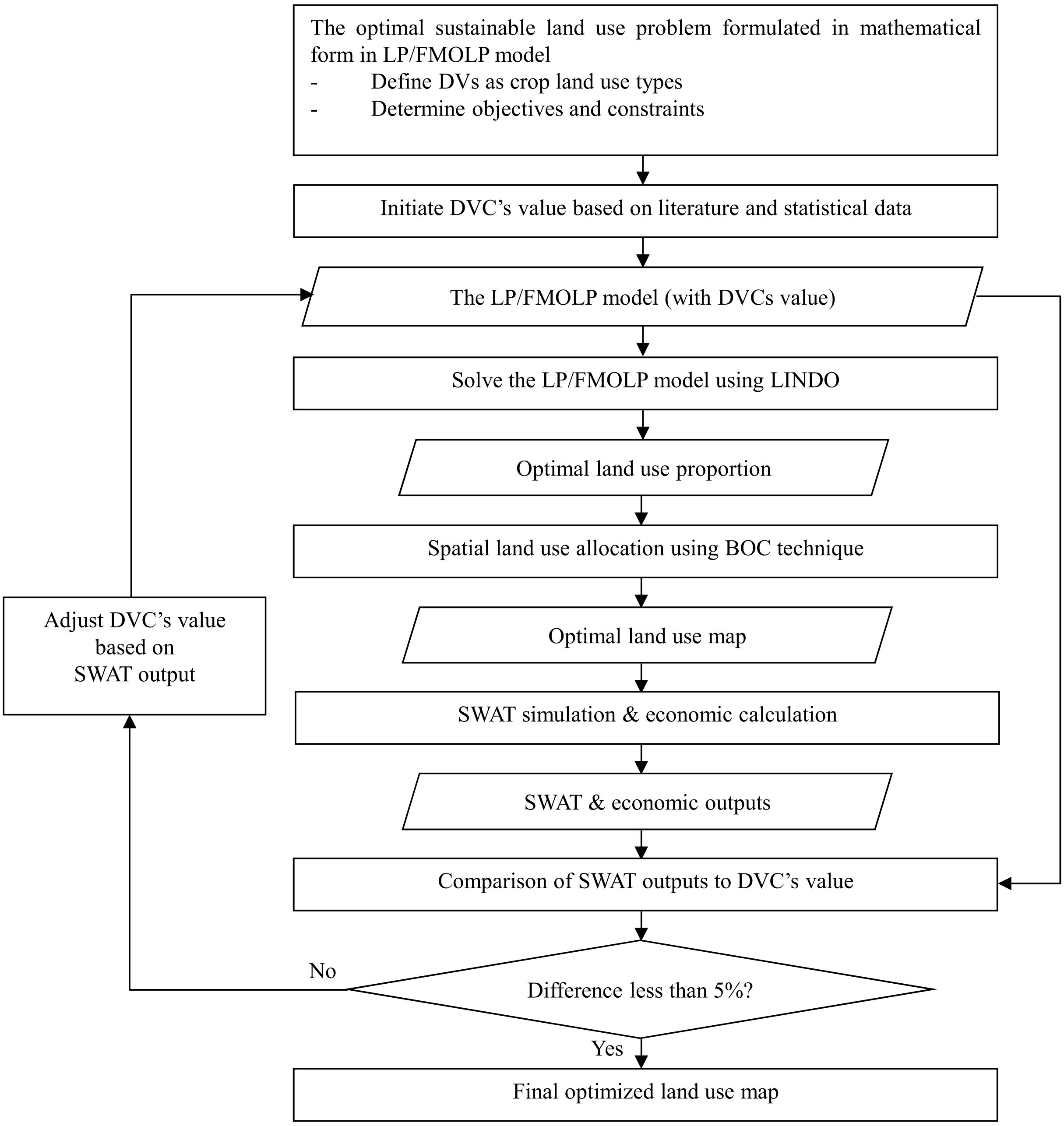
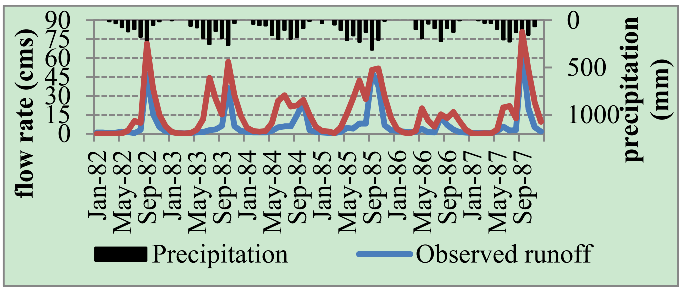


Figure 3. Procedures in reevaluating FMOLP-DVCs for the mapping of land use allocation which meets sustainability criteria

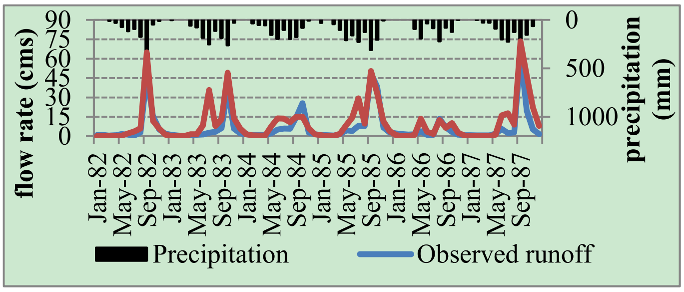
5. Results and Discussion

5.1 SWAT Model Calibration

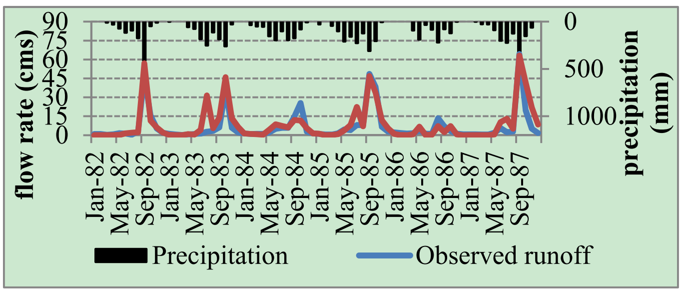
(a) Hydrologic results—Before the model calibration, the simulated monthly runoff was higher than the observed data as shown in Figure 4a. It was noticed that SWAT output produced two peaks of hydrograph for each year, while the observed runoff had only one peak of hydrograph. The intention of the calibration process is to reduce the overestimated runoff by increasing the soil available water content parameter (SOL_AWC) to 25% and reducing the land cover curve number parameter (CN2) to 5%. After the adjustments, the simulated monthly runoff showed a closer approximization of the peak flow in the overall data (as shown in Figure 4b). Especially, the peak which corresponded to the peak of monthly rainfall (on September) was a closer approximation for measuring runoff.



a) before calibration ($r^2 = 0.726$)



b) after 1st calibration (SOIL_AWC,CN2 adjusted) ($r^2 = 0.796$)



c) after 2nd calibration (SOIL_AWC,CN2,SOL_Z adjusted) ($r^2 = 0.811$)

Figure 4. Comparison of simulated and observed runoff

The first peak flow (in July) of the simulated hydrograph was still an overestimation, but the second peak flow (in September) was mostly equal to the measured data. Normally, the soil moisture status would be fully or nearly-saturated in the late rainy season period (between August—October). During the early rainy season period (May-July), soil becomes moist by rainfall, but this soil was still unsaturated, and less surface runoff occurred. The first peak of simulated runoff could have been caused by the soil saturating too early, which consequentially made an overestimation of the surface runoff. It is possible that the storage capacity of all soil profiles (soil porosity and depth) interpreted from the soil texture and other properties provided by the LDD could have been underestimated. Unfortunately, the collected data from the soil pit was not available at the research site. The available LDD database gives the range of soil profile depth between 330-2400 mm. with its average equalling 1,263 mm. Based on an National Research Council of Thailand (National Research Council of Thailand [NRCT], 2007) investigation which studied the northern region of Thailand, the soil depth of clay to sand textural soil, ranging from about 1,800-2,800 mm. had an average of 2,493 mm. Figure 4c shows the results after calibration by adding more 1,000 mm of depth to the lower soil layer. The results after the second adjustment showed a closer approximation with r^2 increasing.

(b) Sediment results—After comparing both the simulated sediment and measured data, it was found that the model results were an underestimation. The USLE_C of each crop type was adjusted by using a C-factor reference for Thailand. The sediment transportation parameters of SPCON, SPEXP and PRF were modified to 0.005, 1.5 and 0.58, respectively. This calibration gave a higher amout of sediment value which was more suitable to the observed data. But there was still a significant difference of sediment from the observed monthly sediment when it was higher than 40,000 tons.

(c) Crop yield—The suitable parameter values which gave a simulated yield which was close to the statistical data as set for rice, corn, cassava, sugarcane and hay in (1) PHU equal to 1,400, 1,020, 3,500, 5,200 and 4,000, respectively, and (2) HVSTI equal to 0.5, 0.5, 0.6, 0.8 and 0.9, respectively. The highest error was 5.48% of the actual crop yield.

5.2 FMOLP Model with Initial DVC's Value

The LP/FMOLP model with initial DVCs for sustainable land use allocation can be formulated as follows:

5.2.1 Environmental Goal Functions

-Minimization of Soil Loss

The minimum soil loss objective function for FMOLP can be expressed as:

$$Min\ \ 16.85X_1+842.46X_2+1,006.92X_3+327.99X_4+208.69X_5 \tag{8}$$

-Minimization of Crop Water Consumption

The minimum crop water consumption objective can be expressed as:

$$Min\ \ 10,404X_1+9,878X_2+9,702.3X_3+12,712.8X_4+10,671.3X_5 \tag{9}$$

5.2.2 Economic Goal Functions

-Maximization of Net Profit

The maximum net profit objective can be expressed as:

$$Max\ \ 9,617.25X_1+14,458.5X_2+10,617.88X_3+2,621.67X_4+24,433.41X_5 \tag{10}$$

5.2.3 Constraint Equations

These equations represent the criteria of limiting factors and/or requirements, which are the hard constraints required for allocating each cropping area. It is assumed the existing forest, residential and water body areas will not change. Both, the non-suitable soil area and high slope gradient area (which represent greater than 35% of the land) were preserved for forested area. A GIS application calculated the size of the suitable agricultural area based on the following constraints.

-Allowable/Suitable Agricultural Area

$$X_1+X_2+X_3+X_4+X_5 = 88,749\ \ ha \tag{11}$$

-Size of Suitable Area for Rice or Paddy Field

$$X_1 \le 4,713\ \ ha \tag{12}$$

-Preserved Irrigation Area for Rice or Paddy Field

$$X_1 \ge 2,086\ \ ha \tag{13}$$

-Size of Suitable Area for Upland Crops and Pasture Area

$$X_2+X_3+X_4+X_5 \le 85,285\ \ ha \tag{14}$$

-Minimum Requirement of Rice Production for Local Consumption

The estimated amount of rice demand for local community consumption is 9,145.01 tons per year. Each hectare of paddy field in the selected watershed area produced an average of 2.9 tons of rice.

$$2.9X_1 \ge\ 9,145.01\ \ tons \tag{15}$$

-Preserved 70% of Existing Crop Production

A new allocated cropping area has to provide economic crop yields not less than 70% of existing crop production.

The total amount of crop production was calculated by the existing cropping area multiplied by its yield per hectare. The average crop yield is referred to in Table 2.

-Minimum Corn Production Requirement

$$8.788X_2 \geq 354{,}625.71 \ tons \quad (16)$$

-Minimum Cassava Production Requirement

$$20.34X_3 \geq 150{,}797.78 \ tons \quad (17)$$

-Minimum Sugarcane Production Requirement

$$68.773X_4 \geq 855{,}904.72 \ tons \quad (18)$$

5.2.4 Optimal Land Use Proportion Solution

To solve this multi-objective model, the first stage is to obtain the pay-of the table as shown in Table 3.

Table 3. Target value and optimal DV solution of each individual objective

	Soil loss (F1)	Crop Water Consumption (F2)	Net profit (F3)	Optimal DV solution of individual objective(unit: ha)				
				Rice (X_1)	Corn (X_2)	Cassava (X_3)	Sugarcane (X4)	Hay (X_5)
Min F1	50,595,680	932,016,447	1,322,189,833	4,713.00	40,355.70	7,413.70	12,445.30	23,821.30
Min F2	70,847,154	908,057,200	994,335,714	3,464.00	40,355.70	32,484.00	12,445.30	0
Max F3	50,835,289	932,350,304	1,340,695,000	3,464.00	40,355.70	7,413.70	12,445.30	25,070.30
μ	20,251,474	24,293,104	346,359,286					

Note: F1 is Equation 8, F2 is Equation 9, F3 is Equation 10.

Each single objective model had been transformed into multiple objective models by using the values as shown in Table 3. The FMOLP model can be formulated as follows:

$$Max \ \alpha \quad (19)$$

Subject to:

$$16.85X_1+842.46X_2+1{,}006.92X_3+327.99X_4+208.69X_5+20{,}251{,}474\alpha = 70{,}847{,}154$$

$$10{,}404X_1+9{,}878X_2+9{,}702.3X_3+12{,}712.8X_4+10{,}671.3X_5+23{,}293{,}104\alpha = 932{,}350{,}304$$

$$9{,}617.25X_1+ 14{,}458.5X_2+ 10{,}617.88 X_3+ 2{,}621.67X_4+ 24{,}433.41X_5- 346{,}359{,}286\alpha = 994{,}335{,}714$$

After resolving the FMOLP model, the optimal sustainable land use solution of X_1 is (rice) = 3,578, X_2 (corn) = 40,356, X_3 (cassava) = 19,872, X_4 (sugarcane) = 12,445 and X_5 (hay) = 12,498.

5.3 Mapping of Land Use

The land suitability map for each crop type was determined as the in-process material for land use allocation. The procedure begins with summing up the soil- and slope-suitability score, as shown in Figure 5. Then, the BOC map is produced by calculating BOC score for a grid cell as shown in Equation 4 (the results are provided in Figure 6). BOC is the proportional value that shows an appropriate comparative score of the selected land use types available among the alternatives. It is consistent with BCR analysis approach in economics. The results of land use allocation are shown in Figure 7b.

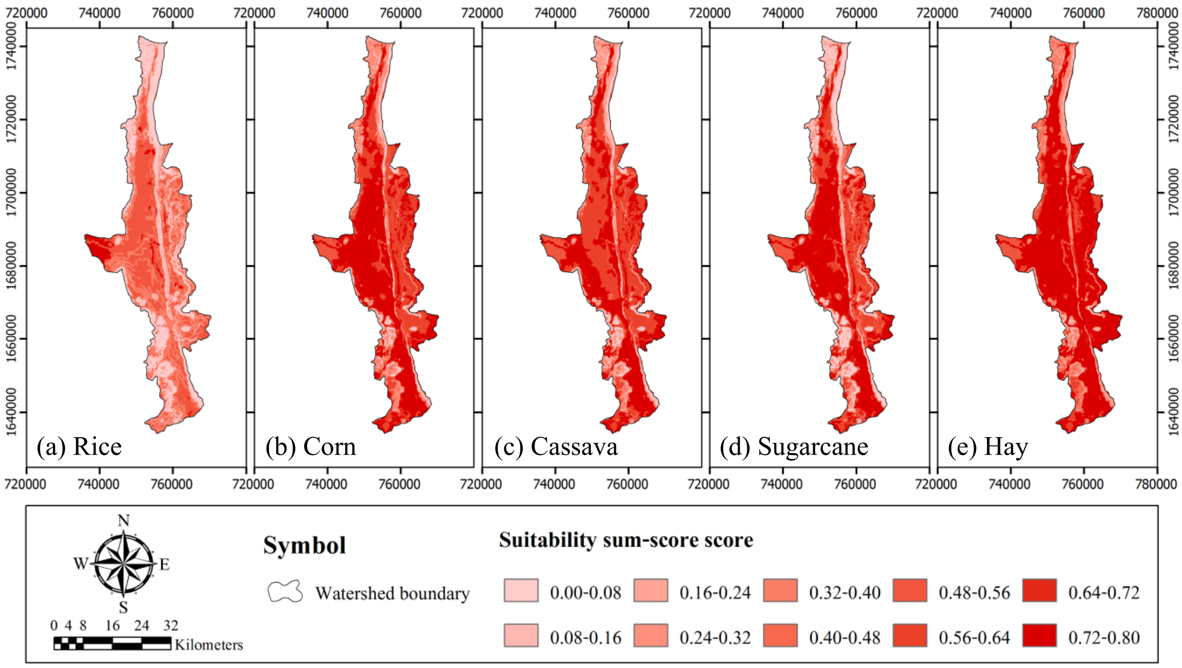


Figure 5. Suitability sum-score map for each crop type

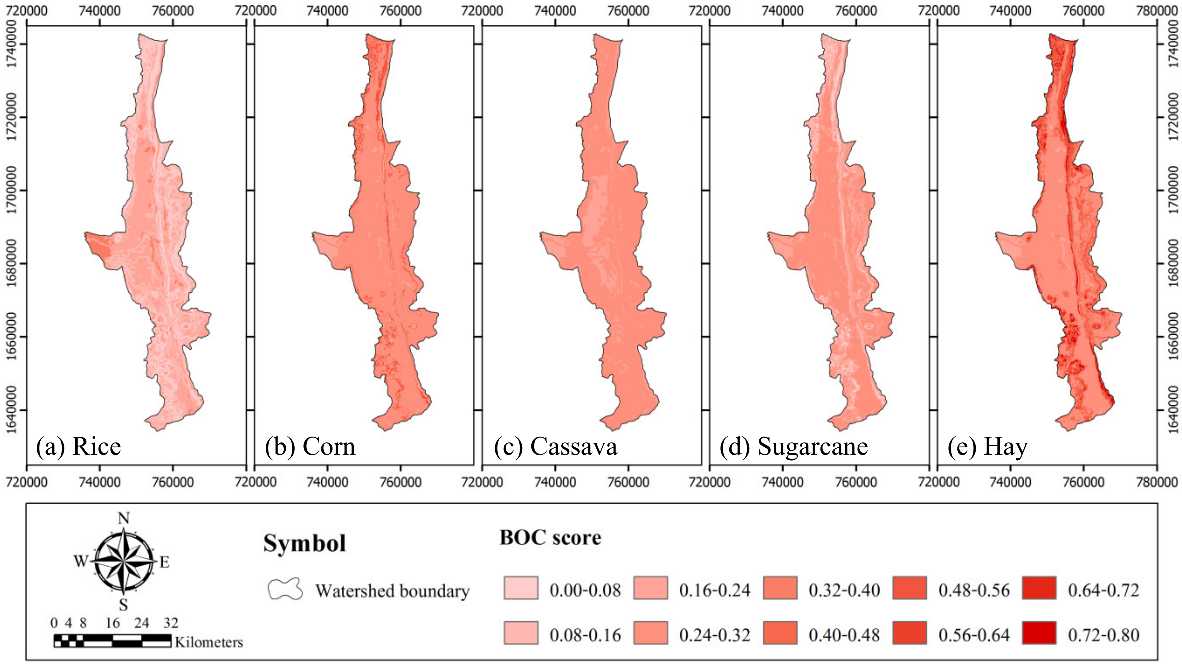


Figure 6. BOC score map of each crop type

BOC technique developed herein is a simple spatial allocation method which considers on comparison the suitability among alternative land use types. However, this technique still not concerns about spatial distribution. Santé et al. (2008a; 2008b) applied land allocation algorithms to produce suitable land use map such as hierarchical optimization, ideal point analysis, simulated annealing and multi-objective land allocation. These allocation algorithms gave the suitability and compactness of the areas for each land use. It is rather complicate and need more time for computer processing.

5.4 Coefficient Reevaluation and the Looping Process

After the optimal land use map was initially simulated by the SWAT model, the SWAT outputs were then used for adjusting the new DVC's value in the FMOLP. These processes were repeated for several loops until a difference of less than 5% of the DVC's value from the previous loop to the next loop was able to be obtained. The results for each looping and its change are shown in Tables 4 to 6. The land use map results from each loop are shown in Figures 7 b-d. There was difference in land use between the existing and the new allocated map. The new allocated agricultural area was reduced in order to preserve non-suitable and high impact protential area. Land use in the new map was much more fragmented than in the existing map. Distribution of each crop type was influenced by land suitability. The spatial difference between both land use maps was more likely occurred within the similar land suitability zone. Although the distribution of relocated corn, sugarcane and cassava area was changed, it was mostly occurred inside upland crop area in the existing map.

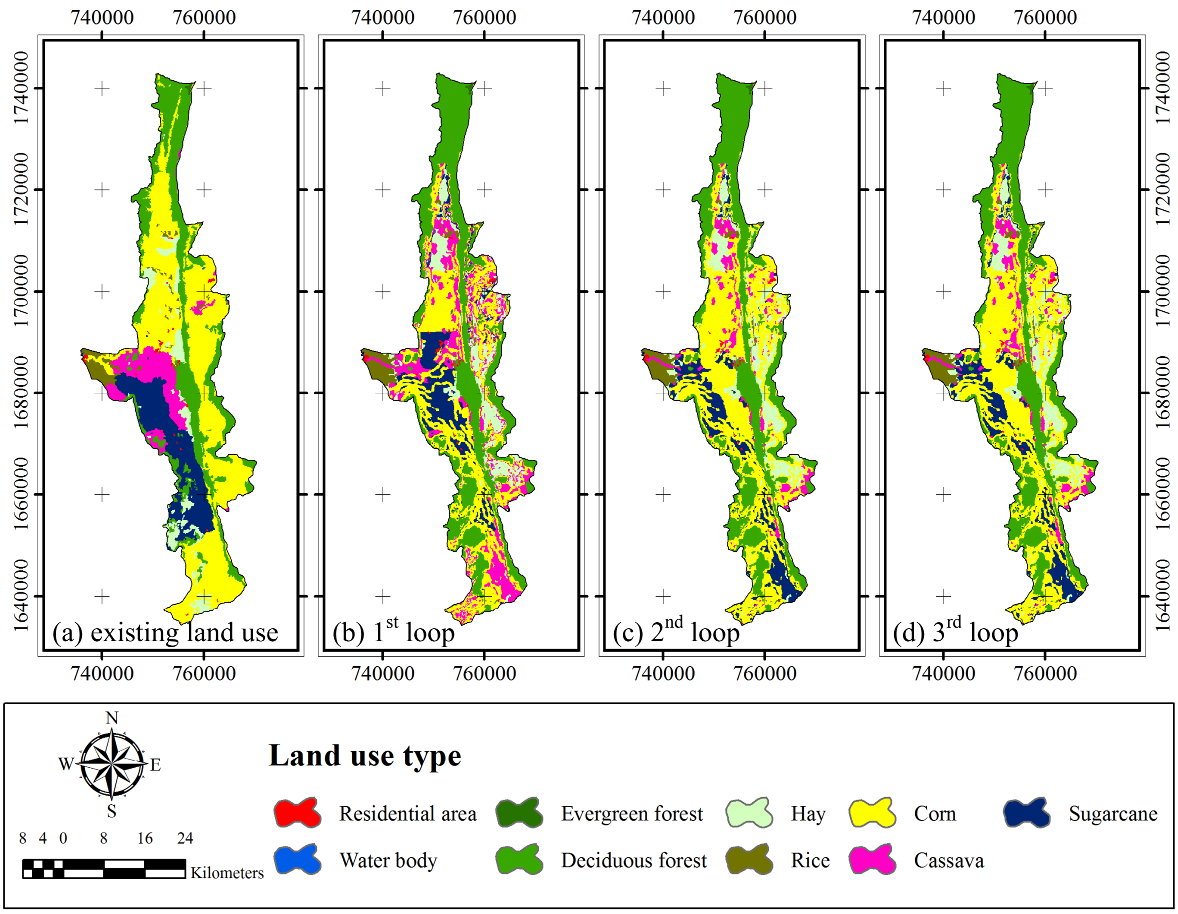


Figure 7. Land use planning map of each loop

In the calibration period, there was a small difference of soil loss, crop water consumption and crop yield value between the literature and SWAT simulated outputs. In the first FMOLP loop, the literature was exclusively used for determining the DVC's value. It can be noticed that soil loss coefficients were extremely different due to the fact that each crop type has its own soil suitability set and the highest potential K-factor of the soil suitability set was used for all soil loss estimates. Furthermore, the highest potential slope that could still be suitable for each crop type was used by calculating the LS-factor.

DVC values still vary between the 1st to 2nd and 2nd to 3rd loop as shown in Tables 4, 5 and 6. The adjusted DVCs in the 3rd loop are almost equal with the final value and it remained insignificantly unchanged throughout the testing.

Table 4. Changing of adjusted soil loss coefficients in FMOLP expressions

Looping step	Soil loss (ton·ha^{-1})				
	RICE (X_1)	CORN (X_2)	CASV (X_3)	SUGC (X_4)	HAY (X_5)
SWAT output (calibrated)					
Existing land use	9.5	164.2	67.3	107.8	9.6
Initial DVCs (by USLE)					
1st FMOLP	16.9	842.5	1006.9	328.0	208.7
DVCs adjusted by SWAT output					
2nd FMOLP	12.0	153.3	119.3	67.2	12.5
3rd FMOLP	13.0	137.3	121.1	93.6	13.3
Final value	13.0	138.4	115.8	93.5	12.9

Note: underlined values represent the value of coefficients as determined by the literature and recorded data, otherwise simulated by SWAT

Table 5. Changing of adjusted crop production and net profit coefficients in FMOLP expressions

Looping step	Crop production (ton·ha^{-1})					Net profit (baht·ha^{-1})*				
	X_1	X_2	X_3	X_4	X_5	X_1	X_2	X_3	X_4	X_5
	RICE	CORN	CASV	SUGC	HAY	RICE	CORN	CASV	SUGC	HAY
SWAT output (calibrated)										
Existing LU	2.997	8.850	20.781	72.542	40.283	10,601	14,857	11,252	1,631	25,115
Initial DVCs (by LDD (2000))										
1st FMOLP	2.900	8.788	20.340	68.773	39.462	9,617	14,459	10,618	2,622	24,433
DVCs Adjusted by SWAT output										
2nd FMOLP	3.000	9.117	20.166	73.470	41.271	10,633	16,550	10,372	2,235	25,935
3rd FMOLP	3.003	9.208	19.864	72.069	41.076	10,660	17,129	9,941	1,324	25,774
Final value	3.003	9.206	19.915	72.058	41.138	10,660	17,116	10,013	1,317	25,825

Note: underlined values mean the value of coefficients as determined by the literature and recorded data, otherwise as simulated by SWAT, * the values were manually calculated for crop production.

Table 6. The changing of adjusted crop water consumption coefficients in FMOLP expressions

Looping step	Crop water consumption (m^3·ha^{-1})				
	X_1	X_2	X_3	X_4	X_5
	RICE	CORN	CASV	SUGC	HAY
SWAT output (calibrated)					
Existing land use	8,964.2	8,700.0	10,102.2	9,466.1	9,497.4
Initial DVCs (by LDD (2000) and estimated by CROPWAT 8.0)					
1st FMOLP	9,207.0	7,291.0	9,545.0	12,713.0	10,671.0
DVCsadjusted by SWAT output					
2nd FMOLP	8,988.7	8,820.0	9,678.4	9,693.1	9,914.3
3rd FMOLP	9,007.3	8,886.8	9,700.3	9,369.0	9,882.3
Final value	9,007.3	8,885.4	9,708.5	9,368.5	9,899.6

Note: underlined values mean the value of coefficients as determined by the literature and recorded data, otherwise as simulated by SWAT

5.5 The Changing of FMOLP Target Values

The adjusted DVCs make the changes in the optimal crop land use proportional to the affects of the changes on the FMOLP target value. The difference in land proportion for each cropping area between the 1st and 2nd loop is significantly quite large. Its changing, however, is diminished in the following loops, as shown in Table 7.

Table 7. Changing of optimum proportional crop land use area

Looping Step	Optimum crop land use area (ha)				
	X_1	X_2	X_3	X_4	X_5
	RICE	CORN	CASV	SUGC	HAY
Existing land use	3,306	57,651	10,591	17,779	7,894
1st FMOLP	3,578	40,356	19,872	12,445	12,498
2nd FMOLP	3,464	52,526	7,478	11,651	13,630
3rd FMOLP	3,464	52,164	7,592	11,877	13,653

Table 8 shows the changing of target values in each FMOLP loop. The key of comparison is the value between individual objectives in the 1st and final loop. The results showed a significantly higher level of objective achievement. The total net profit target had increased 11.25%, while the total soil loss and crop water consumption, the minimum target, had decreased to about 19.45% and 11.79% respectively.

Table 8. The changing of goal target values for individual objectives

Looping Step	Goal target value of individual objectives (based-on SWAT outputs)					
	Net profit (baht) (objective-maximize)		Soil loss (tons) (objective-minimize)		Crop water consumption (m^3) (objective-minimize)	
	Total	%	Total	%	Total	%
Existing Land Use	1,237,975,708	92.34	12,202,834	127.21	881,462,013	97.07
1st FMOLP	1,340,695,000	100.00	9,592,769	100.00	908,057,200	100.00
2nd FMOLP	1,491,150,000	111.22	8,019,734	83.60	799,941,000	88.09
3rd FMOLP	1,491,528,000	111.25	7,726,554	80.55	801,014,400	88.21

Zeng et al. (2010) employed FMOLP to optimize crop area with the model coefficients estimated from experiment data. The results showed that yield and net return increased when irrigation area and evapotranspiration increased. Without SWAT simulation and DVC reevalution process, the target values will depend on the amount of resources. Increasing in target value of the present study was not influenced by the changing available resources. It could be indicated that the output from the SWAT model used for adjusting the DVC's value was able to support the land use optimization by the FMOLP technique.

6. Conclusions

A sustainable agricultural land use plan requires multiple processes to deal with the problems in both constraints and objectives. FMOLP is an optimization technique which is designed for multiple objective problems; it was applied to find the optimum land use proportional solution for sustainabilty. A GIS technique combined with a suitability rating score is generally used to relocate new suitable land use on maps. Significantly, the results prove the SWAT model can be applied to predict the impact and yield for a land use map. Although each technique and/or model has been linked, in the passing to the next process, by its results, a lack of harmony occurred and few applications of linkage between SWAT and FMOLP could be used. The results of this study showed the local optimum problem of land use planning methods by using the continuous processes as mentioned. Because of unrealistic initial DVC's value, the FMOLP model gave an unrealistic solution to the optimum land use map. The applied SWAT model was able to adjust the coefficients of the FMOLP as newly reevaluated coefficients to repeat the FMOLP and follow a process of looping, until it showed zero or insignificant amount of changes in the coefficient value. The last SWAT outputs estimate a better land use planning map solution. An overall consideration on changing of the goal target values in manipulating optimal land use in watershed scales could be decided by using repeated loop processes for improving efficiency on sustainable agricultural land use planning. This study is part of an attempt to improve the optimum method for the further development of DSS for sustainable agricultural land use planning using FMOLP in cooperation with the SWAT model.

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