INTEGRATION OF GEOSPATIAL MODELS FOR AN OPTIMAL LAND USE ALLOCATION USING LAND USE AND LAND COVER CHANGES AND THEIR IMPACTS IN UPPER LAM PHRA PHLOENG WATERSHED, NAKHON RATCHASIMA PROVINCE, THAILAND

Niti Iamchuen

A Thesis Submitted in Partial Fulfillment of the Requirements for the

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การบูรณาการแบบจำลองเชิงพื้นที่เพื่อการจัดสรรการใช้ประโยชน์ที่ดิน อย่างเหมาะสมจากข้อมูลการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดิน และผลกระทบที่เกิดขึ้นในลุ่มน้ำลำพระเพลิงตอนบน จังหวัดนครราชสีมา ประเทศไทย

นายนิติ เอี่ยมชื่น

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

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นิติ เอี่ยมชื่น : การบูรณาการแบบจำลองเชิงพื้นที่เพื่อการจัดสรรการใช้ที่ดินอย่างเหมาะสมจากข้อมูลการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินและผลกระทบที่เกิดขึ้นในลุ่มน้ำลำพระเพลิงตอนบน จังหวัดนครราชสีมา ประเทศไทย (INTEGRATION OF GEOSPATIAL MODELS FOR AN OPTIMAL LAND USE ALLOCATION USING LAND USE AND LAND COVER CHANGES AND THEIR IMPACTS IN UPPER LAM PHRA PHLOENG WATERSHED, NAKHON RATCHASIMA PROVINCE, THAILAND) อาจารย์ที่ปรึกษา : รองศาสตราจารย์ ดร.สุวิทย์ อ๋องสมหวัง, 240 หน้า.

วัตถุประสงค์หลักของการศึกษาคือ (1) เพื่อประเมินการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินและผลกระทบที่เกิดขึ้นในระหว่างปี พ.ศ. 2546 และ 2556 (2) เพื่อระบุปัจจัยขับเคลื่อนการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดิน (3) เพื่อหาชุดพารามิเตอร์ที่เหมาะสมสำหรับแบบจำลอง CLUE-S และจำลองภาพเหตุการณ์การใช้ที่ดินและสิ่งปกคลุมดินทั้ง 3 รูปแบบในปี พ.ศ. 2566 (4) เพื่อประเมินผลกระทบที่เกิดขึ้นจากการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินในด้านการกร่อนของดิน น้ำท่า และมูลค่าทางเศรษฐกิจ และ (5) เพื่อจัดสรรการใช้ที่ดินและสิ่งปกคลุมดินอย่างเหมาะสมในแต่ละภาพเหตุการณ์ที่แตกต่างกันในปี พ.ศ. 2566 ในการศึกษา นำข้อมูลภาพถ่ายออร์โธสีปี พ.ศ. 2546 และข้อมูลดาวเทียมไทยโชตปี พ.ศ. 2556 มาแปลตีความการใช้ที่ดินและสิ่งปกคลุมดินด้วยสายตาเพื่อประเมินการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินและปัจจัยขับเคลื่อน ถัดมาแบบจำลอง CLUE-S จะถูกใช้ในการจำลองภาพเหตุการณ์ทั้ง 3 แบบ จากนั้นนำข้อมูลการใช้ที่ดินและสิ่งปกคลุมดินจริงในปี พ.ศ. 2556 และข้อมูลการใช้ที่ดินและสิ่งปกคลุมดินจำลองในปี พ.ศ. 2566 ไปใช้ในการประเมินการกร่อนของดินโดยแบบจำลองการสูญเสียดินสากล (USLE model) การประเมินน้ำท่าโดยแบบจำลองพลวัตรของดินและน้ำ (SWAT model) กับวิธี SCS-CN และมูลค่าทางเศรษฐกิจโดยแบบจำลองมูลค่าปัจจุบัน (PV model) และผลกระทบจากการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินที่เกิดขึ้น ในขั้นตอนสุดท้ายจะทำการจัดสรรการใช้ที่ดินตามระดับความเหมาะสมให้กับภาพเหตุการณ์ทั้ง 3 รูปแบบโดยวิธีการถ่วงน้ำหนักอย่างง่าย (SAW) ของการวิเคราะห์การตัดสินใจแบบหลายหลักเกณฑ์ (MCDA)

การประเมินการใช้ที่ดินและสิ่งปกคลุมดินระหว่างปี พ.ศ. 2546 ถึงปี พ.ศ. 2556 พบว่า พื้นที่เมืองและสิ่งปลูกสร้าง มันสำปะหลัง อ้อย แหล่งน้ำและพื้นที่อื่นๆ เพิ่มขึ้น ในขณะที่ ข้าวโพด ไม้ยืนต้นและไม้ผล และพื้นที่ป่าไม้ มีพื้นที่ลดลง และปัจจัยขับเคลื่อนหลักที่ส่งผลต่อการเปลี่ยนแปลงการใช้ที่ดินและสิ่งปกคลุมดินทุกประเภทได้แก่ ความหนาแน่นของประชากร

สำหรับการจำลองการใช้ที่ดินและสิ่งปกคลุมดิน มีการเพิ่มขึ้นของพื้นที่เมืองและสิ่งปลูกสร้าง มันสำปะหลัง อ้อย แหล่งน้ำ และพื้นที่อื่นๆ อยู่ภายใต้ภาพเหตุการณ์แบบที่ 1 ในขณะที่การเพิ่มขึ้นของพื้นที่มันสำปะหลังและอ้อย มาจากพื้นที่ของข้าวโพด ป่าไม้และพื้นที่อื่นๆอยู่ภายใต้ภาพเหตุการณ์แบบที่ 2 ในทางตรงกันข้าม การเพิ่มขึ้นของพื้นที่ป่าไม้มาจากพื้นที่ของข้าวโพด อ้อย และพื้นที่อื่นๆ อยู่ภายใต้ภาพเหตุการณ์แบบที่ 3 ในการประเมินการกร่อนของดิน ปริมาณน้ำท่าและมูลค่าทางเศรษฐกิจ และการเปลี่ยนแปลงที่เกิดขึ้นจริงและภาพเหตุการณ์จำลอง พบว่า ปริมาณการสูญเสียดินจริงโดยรวมมีเท่ากับ 40.21 40.86 87.96 และ 28.78 ล้านตัน/เฮกตาร์/ปี ปริมาณน้ำท่า มีปริมาณเท่ากับ 37.79 38.04 46.13 และ 36.22 ล้านลูกบาศก์เมตร และมูลค่าทางเศรษฐกิจของพื้นที่เกษตรกรรมและพื้นที่ป่าไม้มีค่าเท่ากับ 16,987.05 16,677.33 12,923.64 และ 19,660.13 ล้านบาท

สำหรับการจัดสรรการใช้ที่ดินที่มีความเหมาะสมตามการสูญเสียดิน ปริมาณน้ำท่าและมูลค่าทางเศรษฐกิจของแต่ละภาพเหตุการณ์ในปี พ.ศ. 2566 ภายใต้ภาพเหตุการณ์แบบที่ 1 ถูกจัดสรรในระดับความเหมาะสมปานกลาง ขณะที่พื้นที่ป่าไม้ถูกจัดสรรในระดับความเหมาะสมสูง ภายใต้ภาพเหตุการณ์แบบที่ 2 พื้นที่มันสำปะหลังส่วนใหญ่ถูกจัดสรรในระดับความเหมาะสมต่ำ ขณะที่พื้นที่อ้อยส่วนใหญ่ถูกจัดสรรในระดับความเหมาะสมปานกลางและสูง ภายใต้ภาพเหตุการณ์แบบที่ 3 พื้นที่ป่าไม้ถูกจัดสรรในระดับความเหมาะสมปานกลางและสูง

สาขาวิชาการรับรู้จากระยะไกล	ลายมือชื่อนักศึกษา________________
ปีการศึกษา 2557	ลายมือชื่ออาจารย์ที่ปรึกษา________________

NITI IAMCHUEN : INTEGRATION OF GEOSPATIAL MODELS FOR AN OPTIMAL LAND USE ALLOCATION USING LAND USE AND LAND COVER CHANGES AND THEIR IMPACTS IN UPPER LAM PHRA PHLOENG WATERSHED, NAKHON RATCHASIMA PROVINCE, THAILAND. THESIS ADVISOR : ASSOC. PROF. SUWIT ONGSOMWANG, Dr. rer. Nat. 240 PP.

GEOSPATIAL MODEL / OPTIMUM LAND USE ALLOCATION / LAND USE AND LAND COVER CHANGE / UPPER LAM PRA PHUENG WATERSHED

The main objectives of this study are (1) to assess LULC and its change between 2003 and 2013, (2) to identify driving forces for LULC change, (3) to optimize local parameter of CLUE-S model and simulate three LULC scenarios for year 2023, (4) to assess and evaluate impact of LULC change on soil erosion, water yield and economic value; and (5) to allocate an optimal LULC in different scenarios for year 2023. Herein, color orthoimages in 2003 and Thaichote data in 2013 were visually interpreted LULC data for extracting LULC change and its driving force. Then, CLUE-S model was used to simulate three different scenarios of LULC change. After that actual LULC data in 2013 and three simulated LULC data in 2023 were used to assess soil erosion by USLE model, water yield by SWAT model and SCS-CN method and economic value by PV model with their impact due to LULC change. Finally, an optimum land allocation with suitable class for three scenarios was established by simple additive weighting method.

LULC assessment during 2003 to 2013 showed that urban and built-up land, cassava, sugarcane, water body, and miscellaneous land were increased while maize, perennial trees/orchard and forest land were decreased. The most common driving factor for LULC types change was population density. For LULC simulation, the increased LULC types were urban and built-up land, cassava, sugarcane, water body and miscellaneous land while the decreased LULC types were maize, perennial trees/orchards and forest land under Scenario I. Meanwhile, most of the increasing areas of cassava and sugarcane under Scenario II came from maize, forest land and miscellaneous land. In contrast, most of increased forest land under Scenario III were converted from maize, sugarcane, and miscellaneous land. For assessment of soil loss, water yield, and economic values from actual and three simulated LULC, total soil loss were 40.21, 40.86, 87.96 and 28.78 million ton/ha/year; total water yield were 37.79, 38.04, 46.13, and 36.22 million cu. m, and economic values of agriculture and forest land were 16,987.05, 16,677.33, 12,923.64, and 19,660.13 million Baht.

For optimum land use allocation according to soil loss, water yield and economic values, most of agricultural land in 2023 under Scenario I was allocated in moderate suitability class while all of forest land was located in high suitability class. Under Scenario II, most of cassava was located in low and moderate suitability classes while most of sugarcane was allocated in moderate and high suitability classes. Under Scenario III, forest land was allocated in moderate and high suitability class.

School of Remote Sensing Student's Signature _______________________

Academic Year 2014 Advisor's Signature_______________________

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Niti Iamchuen

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LIST OF ABBREVIATIONS

AHP	=	Analytical Hierarchy Process
CBA	=	Cost Benefit Analysis
CLUE	=	Conversion of Land Use and Its Effects
CLUE-S	=	Conversion of Land Use and Its Effects at Small regional extent
DEM	=	Digital Elevation Model
GDP	=	Gross Domestic Product
GISTDA	=	Geo-Informatics and Space Technology Development Agency
HRU	=	Hydrologic Response Units
LDD	=	Land Development Department
LULC	=	Land use and Land Cover
LUT	=	Land utilization type
MCDA	=	Multi Criteria Decision Analysis
NRPAO	=	Nakhon Ratchasima Provincial Administration Organization
NSE	=	Nash-Sutcliffe efficiency
NSO	=	National Statistical Office
OAE	=	Office of Agricultural Economics
ONREPP	=	Office of Natural Resources and Environmental Policy and Planning

LIST OF ABBREVIATIONS (Continued)

PV	=	Present Value
R^2	=	Coefficient of determination
RID	=	Royal Irrigation Department
ROC	=	Receiver Operating Characteristic
RTSD	=	Royal Thai Survey Department
SAW	=	Simple Additive Weighting
SCS-CN	=	Soil Conservation Service Curve Number
SWAT	=	Soil and Water Assessment Tool
TMD	=	Thai Meteorological Department
USLE	=	Universal Soil Loss Equation
WLC	=	Weighted Linear Combination

CHAPTER I

INTRODUCTION

1.1 Background problem and significance of the study

The study on land use and land cover change is specifically important with respect to a number of aspects including their roles on biodiversity and climate change (Trisurat, Shrestha and Alkemade, 2011). Helming, Pérez-Soba and Tabbush (2008) stated that the term land use implies human activities that exhibit a spatial dimension and change the biogeophysical conditions of land and the environment. From the spatial viewpoint, land use is among those human activities have strongest impacts on the environment worldwide. Concerns about environmental impacts of land use changes are not new. Extensive literature exists on the relations between land use patterns and intensities and environmental impacts, e.g. soil degradation (Zapata, Garcia-Agudo, Ritchie and Appleby, 2003; Boardman and Poesen, 2006), desertification (Geist, 2005; Ci and Yang, 2010), water quality and biotic diversity (Poschlod, Bakker and Kahmen, 2005). Interrelations between land use changes and ecosystem robustness and resilience have also intensively been studied (e.g. Metzger, Rounsevell, Acosta-Michlik, Leemans and Schroter, 2006). In recent years, the role of land use in accelerating/mitigating climate change processes has gained focus [Intergovernmental Panel on Climate Change (IPCC), 2001; Graveland, Bouwman, de Vries, Eickhout and Strengers, 2002]. Increasing understanding of the relations between land use changes and environmental impacts have been triggered by a series of studies related to the land use and cover change project (LUCC) of the International Geosphere-Biosphere Programme (IGBP) and International Human Dimension Programme on Global Environmental Change (IHDP) (Steffen et al., 2005; Lambin and Geist, 2006). When compared to environmental impacts, social and economic aspects of land use changes are less well understood. They are mostly analyzed in the context of driving forces for land use changes.

Thailand has become a newly industrial country (NIC) grown rapidly over the past several decades (Rowntree, Lewis, Price and Wyckoff, 2008). Large parts of the country were active agricultural land (approximately 44 million acres) with rice as the major crop. In fact, Thailand is the world's leader of rice exporter. Agriculture product contributed to around 11% of the GDP. World Bank (2011) stated the Thailand's economic growth from 2002-2006 has averaged 5.6% and has upgraded Thailand's income categorization from a lower-middle income economy to an upper-middle income economy. In addition World Bank claimed that in recognition of Thailand's economic achievements in the past decade in which gross national income (GNI) per capita has almost doubled, while poverty has been significantly reduced. In the meantime, various land use and land cover types were changed due to multi-sectors development in Thailand, especially, an increasing of agricultural products.

Cause and effect relationships between interacting components of social, economic, and environmental systems which included **D**riving forces of land use/land cover change, **P**ressures on the land use/land cover, **S**tate of the land due to the changing situations, **I**mpacts on population, economy, ecosystems, and/or environment and **R**esponse of the society or DPSIR play an important role for land use and land cover change (European Environment Agency, 1999). The most important of DPSIR is driving forces of land use/land cove change. Driving force was used to beginning of changes by human driving force such as population income, technology, political-economic and culture (Meyer and Turner, 1994).

Particularly during 1961-2013, land use and land cover (LULC) change of the forest areas had decreased in the areas of forests from 53.3 to 31.57 percent respectively, (Royal Forest Department, 2014). In addition, loss of agricultural capacity was due to the impact of urban development. For these reasons, it is crucial to have an effective plan to conservation forest, agricultural areas and water body from the urban sprawl phenomenon. Thus, a long-term and integrated approach in land use planning and plans with implementation in mind to optimize the use of land for current and future need is very important, especially to protect conservation areas and agricultural protected areas, water supply and irrigation systems.

Furthermore, immigrants are a major cause of an increasing number of population in many cities. In the case study of Nakhon Ratchasima province, the largest city and the center of the northeast region, the growth of tourism in some specific areas such as Pak Chong and Wang Nam Khiao districts has impacted agricultural and conservation areas. For this reason, it is found that the misuse of suitable lands, deforestation, land degradation, and flood, cause several problems to the cities. Proper plan gives a direction to protect and reduce those problems. Furthermore, alternative goals and plans will also be useful for limited soil and land resources management. However, the potential of the soil and land resources should be considerably used to provide maximize benefits to the public. Consequently, multiple scenarios establishment using prediction and simulation models will provide a good framework for an optimized land use allocation in the future. In these recent years, prediction and simulation studies of land use and land cover change have emerged by combining land use and land cover change into the logical chain of driving forces and impacts such as the studies of Verburg, Van Eck, De Nijs, Dijst and Schot (2004c); Overmars, Verburg and Veldkamp (2007). Also and Lui (2009) stated that it is complicated to understand the complex system so that models are an appropriate ways to generate from reality representing the fundamental features of reality.

Integration of LULC change model (Conversion of Land Use and Its Effects: CLUE), hydrology model (Soil and Water Assessment Tool: SWAT) soil erosion model (Universal Soil Loss Equation: USLE) and economic model (Present Value: PV) are therefore applied for LULC change and its impact simulation for an optimized land use allocation. The expected results would be useful to many stakeholders, such as governors, planners, developers and decision makers for considering the land use allocation in the future.

1.2 Research objectives

In this study, the integration of LULC change model, hydrologic model, soil erosion model and economic value measures were applied for LULC change and its impact assessment for an optimal land use allocation. In order to achieve the aim of this research, the specific objectives of this study are as follows:

(1) To assess LULC and its change between 2003 and 2013;

(2) To identify driving forces for LULC change;

(3) To optimize local parameter of CLUE-S model and simulate triple LULC scenarios for the year 2023;

(4) To assess and evaluate impact of LULC change on soil erosion, water yield and economic value; and

(5) To allocate an optimal LULC in different scenarios for year 2023.

1.3 Scope and limitations of the study

Scope of this study can be summarized as follows.

(1) LULC data in 2003 and 2013 were extracted by means of visual interpretation of color orthoimage and Thaichote data on the screen at the scale of 1: 10,000. Herein land use classification system of Land Development Department (LDD) and Office of Agricultural Economics (OAE) are modified for LULC type extraction. The extracted land use and land cover type include:

(a) Urban and built-up land;

(b) Agricultural land (paddy field, cassava, maize, sugarcane, perennial trees/orchard);

(c) Forest land;

(d) Water body; and

(e) Miscellaneous land (abandoned land).

(2) Physical and socio-economic driving forces for LULC change were identified by stepwise binary logistic regression. The goodness of fit for logistic regression is validated by the receiver operating characteristic (ROC).

(3) An optimized local parameter of CLUE-S model is calibrated based on the comparison of the simulated LULC by the CLUE-S model and the interpreted LULC in 2013. Herewith the acceptance of the overall accuracy and Kappa hat coefficient of agreement should be more than 80 percent.

(4) Three scenarios for year 2023 are simulated under CLUE-S model with an optimum local parameters regarding historical land use evolution, agriculture production extension and forest conservation and prevention.

(5) Impact assessment from LULC change between 2013 and 2023 was evaluated in three aspects: soil loss and its severity using USLE model, water yield using SWAT model and SCS-CN method and economic value with the Present Value (PV).

(6) An optimum LULC allocation within different three scenarios in 2023 was evaluated by simple additive weighting (SAW) method of multi-criteria decision analysis (MCDA) regarding soil loss severity, water yield and economic value from each scenario.

1.4 Study area

1.4.1 Location and topography

Upper Lam Phra Phloeng watershed, which is a sub-watershed Lam Phra Phloeng watershed of Mun basin, situates in upper part of the basin. The main river of the watershed is Lam Phra Phloeng River which downstream flows to Lam Phra Phloeng Dam. Area of the upper Lam Phra Phloeng watershed area is about 77,165 hectares (Figure 1.1). Topography of the area is generally characterized by hilly-rolling terrain, with less undulating and flat areas. Elevation varies from 260 m in the northeastern parts to 1,307 m above mean sea level in the southwestern part of the watershed. The study area covers two main districts (Pak Chong and Wang Nam Khieo).

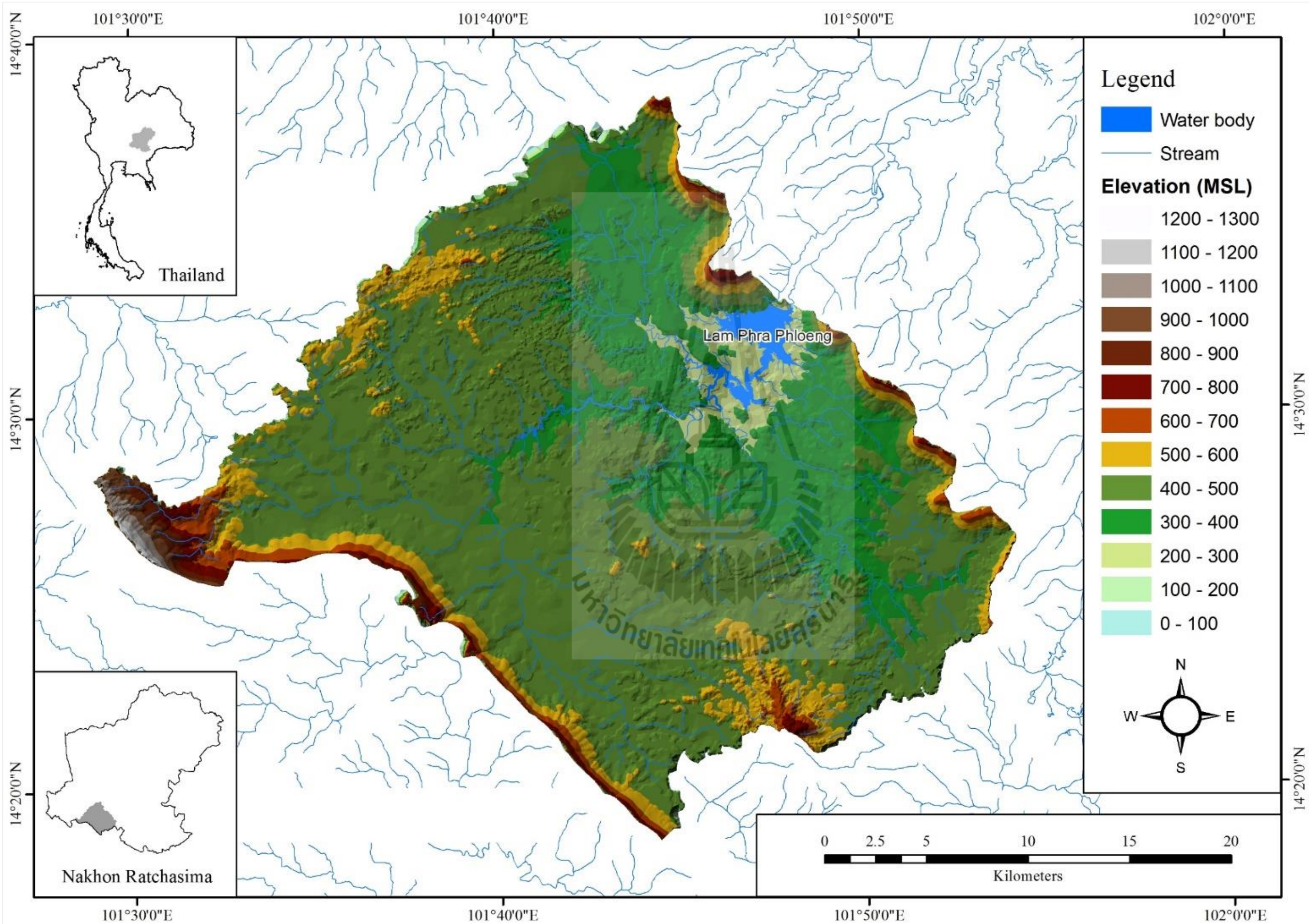


Figure 1.1 Location and topography.

1.4.2 Land use

Based on land use data of LDD from 1980 to 2011, there were two main land use types in 1980, i.e., agricultural land (58%) and forest land (41%), while the rests were urban and built-up land and water body. The characteristic of land use type proportion in this year was similar to other years (2000, 2003, 2007 and 2011) (Table 1.1). As these statistics data, urban and built-up land will be increased in the future while agricultural land will be decreased. Meanwhile forest land, water body and miscellaneous land are quite stable (Figure 1.2).

Furthermore, areas of major field crops in agricultural land between 2000 and 2011 were cassava, maize, and sugarcane and areas of maize and sugarcane were fluctuated in this period while area of cassava was stable (Figure 1.3).

Table 1.1 Areas of major land use types between 1980 and 2011.

Major land use types	**Area in hectare**				
	1980	**2000**	**2003**	**2007**	**2011**
Urban and built-up land	80	843	1,812	2,576	3,835
Agricultural land	44,478	50,976	46,228	41,413	40,710
Forest land	31,998	24,336	26,564	26,386	26,239
Water body	616	261	1,102	1,198	1,264
Miscellaneous land	-	756	1,466	5,600	5,125
Total	**77,172**	**77,172**	**77,172**	**77,172**	**77,172**

Source: LDD (1980, 2000a, 2003, 2007, and 2011)

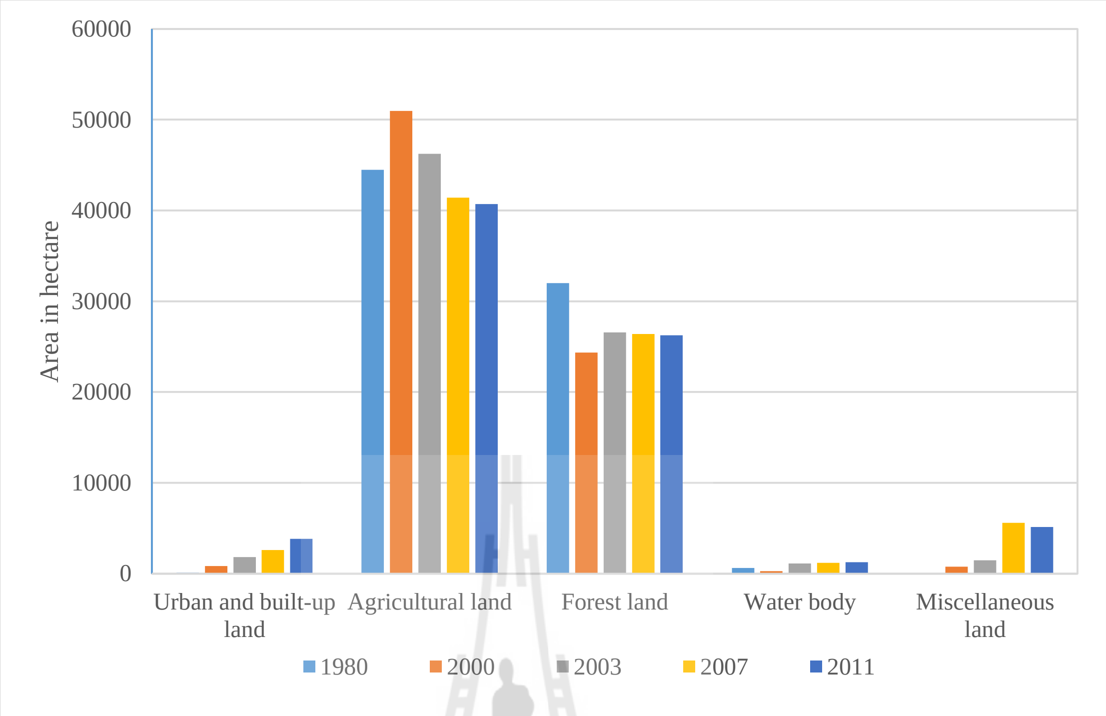


Figure 1.2 Comparison of major land use type areas between 1980 and 2011.

Source: LDD (1980, 2000a, 2003, 2007, and 2011)

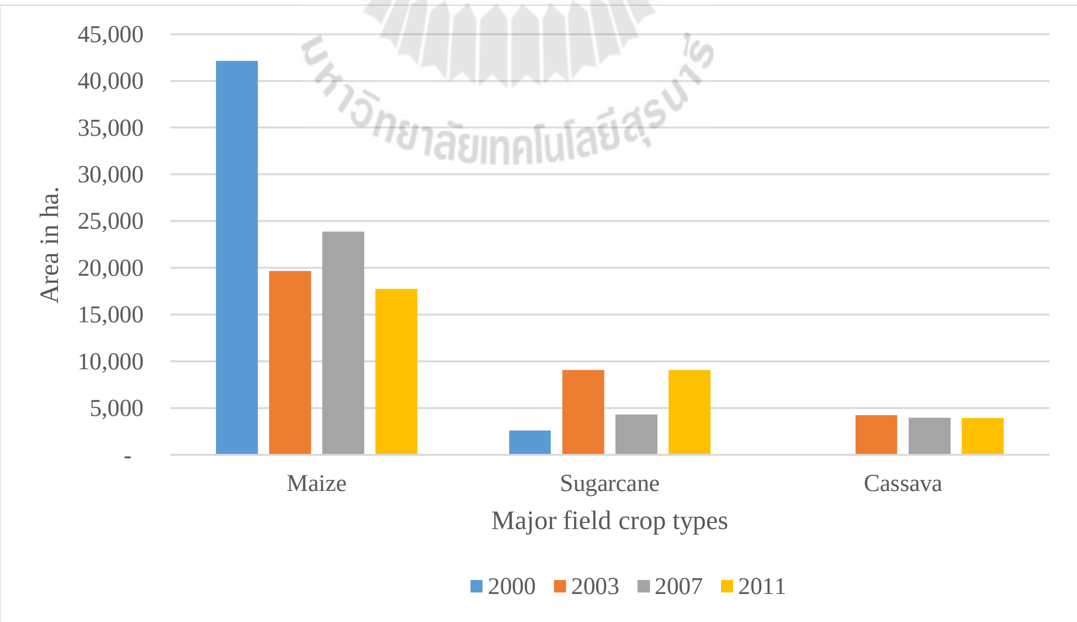


Figure 1.3 Variation of major field crop areas between 2000 and 2011.

Source: LDD (1980, 2000a, 2003, 2007, and 2011)

1.5 Benefits of the study

(1) Understand the situations and changes of LULC development in the study areas in 2003, 2013 and 2023.

(2) Understand the influence of local driving factors (e.g. biophysical and socio-economic) for LULC allocation based on binary logistic regression analysis.

(3) Gain understanding of how to apply CLUE-S model with an optimized local parameters for LULC simulation regarding historical land use evolution, agriculture production extension and forest conservation and prevention scenarios. This finding can be applied to other areas.

(4) Understand the impact of LULC change on soil erosion, water yield and economic value.

(5) Allocate an optimized LULC in different scenarios for year 2023.The tentative outputs are useful for land use planning, forest conservation and protection, environment management and etc.

1.6 Outline of the thesis

The thesis is structured in two parts and follows a hierarchical organization (Figure 1.4) and each part is summarized in the following section.

The first part includes Chapters I “Introduction”, Chapter II “Basic Concepts and Literature Reviews” and Chapter III “Data and Methodology”. Chapter I contains background problem and significance of the study, research objectives, scope and limitations of the study, study area, benefit of the study and outline of the thesis. Chapter II consists of basic concepts including (1) driving force for LULC change, (2) land use change modeling, (3) CLUE-S Model, (4) soil erosion model, (5) hydrological model, (6) economic land evaluation and (7) multi-criteria spatial allocation model and relevant literatures. While, Chapter III presents data and explains details of methodology including Component 1: Historical and recent LULC extraction and driving force identification, Component 2: Local parameter of CLUE-S optimization and validation, Component 3: LULC simulation with three scenarios, Component 4: impact assessment and evaluation: soil erosion, water yield, and economic value and Component 5: an optimized land use allocation.

The second part consists of four chapters of the results with discussion, which separately describes according to objectives and one chapter presents conclusion and recommendation. Chapter IV "LULC Assessment and Its Change and Driving Forces for LULC Change" contains historical and recent LULC extraction and driving force identification for LULC change. Chapter V "Simulation of LULC Scenarios by CLUE-S Model" contains optimum local parameter of CLUE-S model, LULC simulation of three scenarios and comparison of simulated LULC 2023 with LULC 2013. While Chapter VI "Evaluation of LULC Change on Soil Erosion, Water Yield and Economic Values" consists of soil erosion assessment and its impact due to LULC change, water yield estimation and its impact due to LULC change and economic value estimation and its impact due to LULC change. Chapter VII "An Optimal Land Use Allocation" contains an optimal land use allocation of three scenarios based on the integration of soil erosion, water yield and economic value by SAW method. Chapter VIII "Conclusion and Recommendation" comprises conclusion of the study and recommendation.

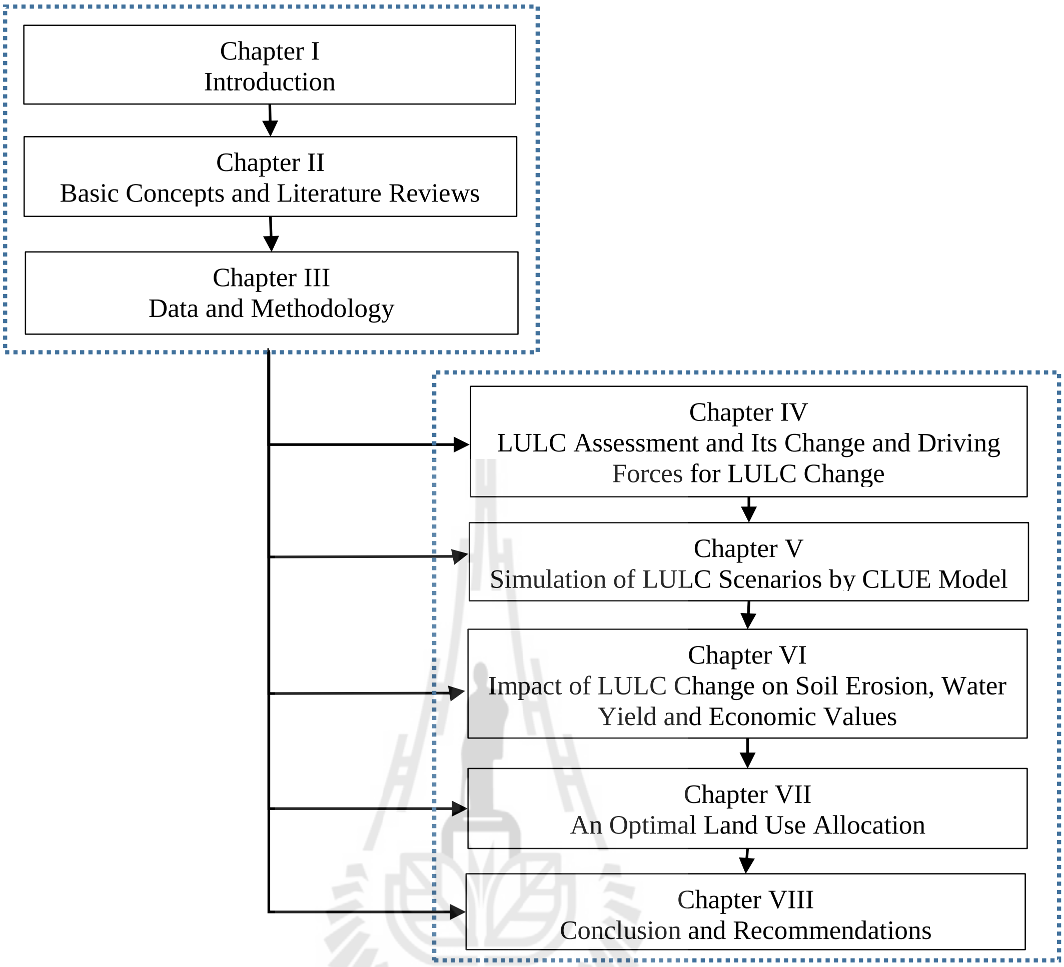


Figure 1.4 Structure of the thesis.

CHAPTER II

BASIC CONCEPTS AND LITERATURE REVIEWS

Basic concepts including (1) driving force for LULC change, (2) land use change modeling, (3) CLUE-S Model, (4) soil erosion model, (5) hydrological model, (6) economic land evaluation, and (7) multi-criteria spatial allocation model and (8) relevant literatures are here reviewed in this chapter.

2.1 Driving force for LULC change

Several studies have been conducted to assess the drivers of land use change (Veldkamp and Fresco, 1996a; Verburg and Veldkamp, 2004a; Verburg et al., 2004c; Luo, Yin, Chen, Xu and Lu, 2010 and Orekan, 2007). Meyer and Turner (1994) stated that changing in LULC are three broad land types: forest/woodland (tree cover), grassland, and settlement and theirs changes take effect to environmental consequences on atmospheric chemistry and air quality, soils and hydrology and water quality by human driving forces such as population income, technology, political-economic and culture and cultural change.

In general, driving force can be classified into two main groups consist of biophysical and human driving forces. Herewith, biophysical driving forces that are abiotic and biotic factors included climate, soils, lithology, topography, relief, hydrology, and vegetation. Stern, Young and Druckman (1992) suggested that the possible human forces driving land-use change can be grouped into five categories:

population, level of affluence, technology, political and economic institutions, and cultural attitudes and values. This classification is similar to Meyer and Turner (1994), Geist et al. (2006), Hersperger and Burgi (2007) and Weng (2010).

In the meantime, human driving forces should be covered population or demographic data (population density and immigration), economic data (income, level of affluence and GDP), policy (national policy, local policy, world trade policy institutional and regime), technology (technological change, internet and network of communication), and culture (change in attitudes, beliefs and values).

(1) Population. On October 31, 2011 the United Nations officially announced that the total population of the World had reached 7 billion people (United Nations, 2011). Lambin et al. (2006) who described the Malthusian model shows between man or demand and food supply and Boserup model shows highly technologies bring up to urban growth. And pressure of population on resources affects to carrying capacity. Population is independent variable about environmental four general ways: (a) population growth can result in expansion area under cultivation and lead to resource depletion and technology, (b) population growth increases investments of human, nature and financial, capital and innovation, (c) population growth to local resource based import food from elsewhere excess population to lead of pressure for agricultural change, and (d) population growth reverse effects on population on feedback loops when change in productive potential of local environment influence the determined of population mortality, fertility and migration.

Each person in a population makes some demands on the environment and the social system for the essentials of life, including food, clean water, clothing, shelter, and so on (Simmons, 1997). On a global scale, population growth has been positively associated with the expansion of agricultural and urban land, land intensification, and deforestation.

(2) Level of affluence. Economic activities have long been major sources of land-use change. Today, economic factors seem to play a strong role. This should not come as a surprise since global economic activity increased nearly sevenfold between 1950 and 2000 (Geist et al., 2006). Economic activity is so extensive that it produces environmental change on a global level (Stern et al., 1992) by arising level of per capita income, as part of the process of economic development through changes in land use and land cover. High levels of affluence and economic development are often associated with higher resource demands, although they could be reduced by advanced technologies (Turner, Ross and Skole, 1993). On the other hand, poverty usually has an affinity with environmental degradation as it has been observed widely in developing countries. The amount of land and resources needed for a given amount of economic growth depends on the patterns of goods and services produced the population and resources base for agricultural development, the forms of national political organization, and development policies.

(3) Technology. Economics as knowledge based includes information, skills and procedures (organization) that related to input and output prices, taxes, subsidies, production and transportation costs, capital flows and investments, credit access, and trade (Barbier, 1997). At the same time technology could be developed for value added (Rubenstein, 1992) and changed the usefulness and societal demand for various natural resources (Turner, Meyer and Skole, 1996), as well as the manner, scope, and intensity of resource use. Different kinds of technology produce different environmental impacts from the same process (e.g., fossil fuel and nuclear energy production have different

influences). Two particular examples are transportation infrastructures such as railways network and energy, which have important implications for an underdeveloped society and inevitably alter its land uses. Technological change has led to far-reaching transformations in agricultural thought increases in land productivity and labor productivity. Transport revolution increased the spatial division of labor large scale export and trade. New transport technologies increased access to land reduce functional distance and connected world system and newly way, internet such as e-commerce like a Amazon.com and knowledge from portal websites www.google.com etc. to lead for everything everywhere and every times when you want to know and bring to change rapidly of LULC (Weng, 2010).

(4) Political-economic Institutions. It is reasonable that the political and economic institutions that control the exchange of goods and services, as well as structure the decisions, of large human groups or by government have a strong influence on land uses and their changes (Geist et al., 2006). These institutions include economic and governmental institutions at all levels of aggregation to which land uses must respond (Stern et al., 1992). Political and economic institutions can affect land use along many causal pathways: markets, governments, and the international political economy. Markets are always imperfect, and the impact of economic activity on the environment depends on which imperfect-market method of environment management is being used such as tariffs and taxes (Summer, 2004). In this case, the international political economy or international organization likes a WTO, APEC, AEC, and EU play important role to governmental policies, agenda, strategies, and price making and subsidies in short term or long term policy, such as natural disaster, sustainable development, global warming, resource management which can have significant

impacts on land use and land cover change. Meyer and Turner (1994) suggested that what is to be done: (a) finding global indicators of LULC change that correspond to high levels of institutional intervention at the international level, (b) creating a metric of country or regional cases sensitive to the range of values possible within a given institution set, (c) determining of sensitive or permeability at various scales to macro scale driving and (d) selecting out indicative cases to explore significance of local institutional variation in the face of external mandate for change.

(5) Cultural attitudes and values. Cultural attitudes and values are related to material possessions, and the relationship between humanity and nature is often seen as a way of adaption to environment limitations (Simmons, 1997). Stern et al. (1992) described this relationship (humanity and nature) is clearly reflected in land-use activities. The effects of cultural attitudes and values on land use and the environment are of long term and should be observed from a historical perspective and using a comparative method. However, within single lifetimes, attitudes and values also may have significant influence on resource-using behavior, even when social and economic variables are held constant. Additional to social organization, humankind, property right, norm, ideologies are representation religious beliefs, literature, art, folk, myths, perception and population belief also exist in pre-legal societies. Information in this factor come from depth interviews of small group of respondent or opinion of group‘s leadership, but biases may be carefully about gender and classes of the poor or the middle, and the rich classes.

2.2 Land use change modeling

As explanation in the previous section about driving force for LULC change, many scientists and researchers have tried to derive the driving forces as causing of LULC change and to integrate them into land use change modeling. The driving forces form a complex system of dependencies and interactions land use change modeling. Furthermore land use change modeling affects a whole range of temporal and spatial levels. In this section land use change modeling are reviewed and briefly summarized based on relevant literatures, especially a review and assessment of land use change models (Agarwal, Green, Grove, Evans and Sheik, 2001).

The Von Thünen Model or "The Isolated State" theory is the classical land use model which was developed by Johann Heinrich von Thünen in 1826 (Lambin, Geist and Rindfuss, 2006). This model showed how market processes could determine and how land in different locations would be used. The use of a piece of land is put to a model is a function of the cost of transport to market and the land rent a farmer can afford to pay. The model generated four concentric rings of agricultural activity around the city: (1) dairy and market gardening, (2) forest for fuel, (3) grains and field crops, and (4) ranching; the outer is wilderness where agriculture is not profitable.

In general, type of model at top-level can be classified into two categories including physical (or hardware) and mathematical models (Mulligan and Wainwright, 2004). Physical models are scaled-down versions of real-world situations and used when mathematical models would be too complex, too uncertain or not possible because of lack of knowledge. Mathematical models are more common and represent states and rates of change according to formally expressed mathematical rules. In addition, they further classified type of environmental model into five major types: conceptual, integration, mathematical, spatial, and temporal models (Table 2.1).

Table 2.1 Type of environmental model.

Types	**Models**
Conceptual	Empirical, conceptual, physically based or mixed
Integration	Analytical, numerical or mixed
Mathematical	Deterministic or stochastic or mixed
Spatial	Lumped, semi-distributed, distributed, GIS, 2D, 3D or mixed
Temporal	Static, dynamic or mixed.

Source: Mulligan and Wainwright (2004)

However, modern land use change modeling is more complicated. Lambin, Rounsevell and Geist (2000) mentioned that modeling of land cover change processes should aim to address at least one of the following questions:

(1) Which environmental and cultural variables contribute most to an explanation of land-cover changes -why? ;

(2) Which locations are affected by land-cover changes -where? , and

(3) At what rate do land cover changes progress -when?

Furthermore, Agarwal et al. (2001) applied three dimensional frameworks consisting of space, time, and human decision-making (Figure 2.1) to review and assess 19 land use change models including (1) General ecosystem model (GEM) by Fitz, De Bellevue, Costanza, Boumans, Maxwell, Wainger and Sklar (1996); (2) Patuxent landscape model (PLM) by Voinov, Costanza, Wainger, Boumans, Villa, Maxwell and

Voinov (1999); (3) CLUE model (conversion of land use and its effects) by Veldkamp and Fresco 1996a); (4) CLUE-CR (conversion of land use and its effects – Costa Rica) by Veldkamp and Fresco (1996b); (5) Area based model by Hardie and Parks (1997); (6) Univariate spatial models by Mertens and Lambin (1997); (7) Econometric (multinomial logit) model by Chomitz and Gray (1996); (8) Spatial dynamic model by Gilruth, Marsh and Itami (1995); (9) Spatial Markov model by Wood, Lewis, Tappan and Lietzow (1997); (10) CUF (California urban futures) by Landis (1995) and Landis, Monzon, Reilly and Cogan (1998); (11) LUCAS (land use change analysis system) by Berry, Hazen, MacIntyre and Flamm (1996); (12) Simple log weights by Wear and Mangold (1998); (13) Logit model by Wear, Liu, Foreman and Sheffield (1999); (14) Dynamic model by Swallow, Talukdar and Wear (1997); (15) NELUP (natural environment research council [NERC]–Economic and Social Research Council [ESRC]: NERC/ESRC land use programme [NELUP]) by O'Callaghan (1995); (16) NELUP – Extension by Oglethorpe and O'Callaghan (1995); (17) FASOM (forest and agriculture sector optimization model) by Adams, Alig, Callaway, McCarl and Winnett (1996); (18) CURBA (California urban and biodiversity analysis model) by Landis, Monzon, Reilly and Cogan (1998); and (19) Cellular automata model by Clarke, Hoppen and Gaydos (1998) and Kirtland, Gaydos, Clarke, DeCola, Acevedo and Bell (2000). Summary of basic information includes type, modules, what the model explains (dependent variables), independent variables and the strengths and weaknesses of each model are summarized as shown in Appendix A.

According to summary of 19 land use change models, the CLUE model can be used for simulating LULC change study since CLUE model is dynamic systems model covers a wide range of biophysical and human drivers at different temporal and spatial scales. CLUE model is consequently selected for land use and land cover change study in this research.

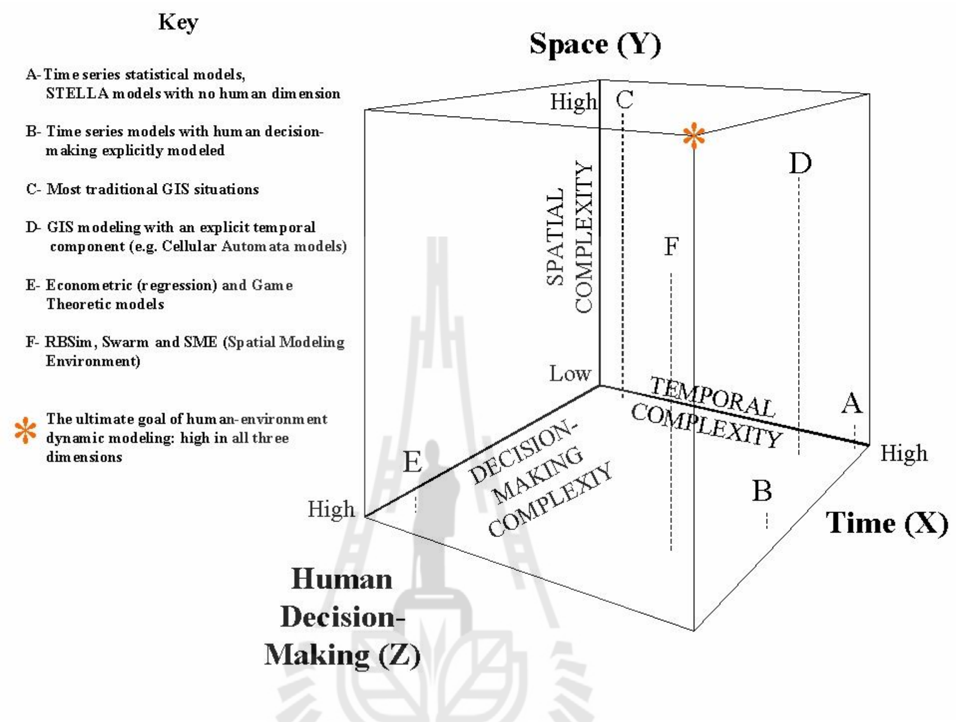


Figure 2.1 A Three-Dimensional Framework for Reviewing and Assessing Land-use Change Models.

Source: Agarwal et al. (2001)

2.3 CLUE-S Model

CLUE model or the **C**onversion of **L**and **U**se and its **E**ffects modeling framework (Veldkamp and Fresco, 1996a; Verburg, De Koning, Kok, Veldkamp and Bouma., 1999) was developed to simulate land use change using empirically quantified relations between land use and its driving factors in combination with dynamic modeling of competition between land use types. The model was developed for the national and continental level. Verburg et al. (2002) stated that the study areas with such a large extent the spatial resolution for analysis was coarse or pixel size varying between 7 X 7 and 32 X 32 sq. km such as Central America (Farrow and Winograd, 2001), Costa Rica (Veldkamp and Fresco, 1996b), China (Verburg and Veldkamp, 2001) and Indonesia (Verburg et al., 1999) are available. Each land use is represented by assigning the relative cover of each land use type to the pixels. The CLUE model cannot directly be applied at the regional scale. Therefore the modeling approach has been modified and is now called **CLUE-S (C**onversion of **L**and **U**se and its **E**ffects at **S**mall regional extent***)***. Verburg (2010) stated that CLUE-S is specifically developed for the spatially explicit simulation of land use change based on an empirical analysis of location suitability combined with the dynamic simulation of competition and interactions between the spatial and temporal dynamics of land use systems. Major characteristics of CLUE-S including (1) CLUE-S module structure, (2) Spatial policies and restrictive, (3) Land use type specific conversion setting, (4) Land use requirement and (5) Location characteristics and allocation procedure are here summarized based on handbook of CLUE model by Verburg (2010).

2.3.1 CULE-S module structure

The model is made up into two distinct modules, a non-spatial module and a spatially module. The non-spatial module calculates the aggregate area, by simple trend extrapolations, the change annual area (demand) for all land use types. In the second part of the model, demands of part one are translated into land use changes at various locations within the study region using a raster-based system. The allocation is based upon a combination of empirical, spatial analysis and dynamic modeling (Verburg et al., 2002). Empirical analysis is applied to determine the relationships between spatial distribution of land use and a number of proximate factors that are driving or constraining land-use change. Based on the competitive advantage of each land use at a location, the competition among land uses for a particular location is simulated.

2.3.2 Spatial policies and restrictions

Spatial policies and restrictions can pressure areas where land use changes are restricted through policies or tenure status (Verburg, Steeg, Van de and Schulp, 2005). The implement of policy to land use types must be supplied such as a forest reserve policy from a logging ban, species-specific habitat of wildlife sanctuary, residential construction in designated agricultural areas or permanent agriculture in the buffer zone of a nature reserve and so on. These policies and restrictions are specific land use conversions condition. It should be mentioned that, the conversions that are restricted by a certain spatial policy can be indicated in a land use conversion matrix: for all possible land use conversions it is indicated if the spatial policy applies.

2.3.3 Land use type specific conversion settings

The temporal dynamics of the simulations upon the setting of land use type specific conversion determines. Two sets of parameters setting are therefore needed to characterize the individual land use types: conversion elasticities and land use transition sequences.

The first parameter set, the conversion elasticities, is related to land use change between types. Because a high cost to change will not easily be converted in other uses as long as there is sufficient demand. Examples are residential locations but also plantations with permanent crops (e.g., fruit trees). Land use type must be specific the relative elasticity to change from ranging between 0 (easy conversion) to 1 (not allow). The user should decide on this factor based on expert knowledge or observed behavior from history. The second set of land use transition sequences likewise the first parameter that needs to be specified are the land use type specific conversion settings and their annual temporal characteristics. These settings are specified in a conversion matrix. Verburg (2010) suggested that the conversion matrix (Figure 2.2) definition should be answered the following questions.

(1) Can be convert other land use types (present)?

(2) The area or region is allowed or not (spatial policy or restriction)?

(3) How many years (or time steps) the land use type at a location should remain the same before it can change into another land use type can be possible?

For example, in case of cropland, it cannot change directly into forest. Nevertheless, after a number of years it is achievable that a cropland will change into forest because of regrowth by natural or man-made.

In addition, Verburg (2010) emphasize the range of conversion or the minimum and maximum number of years before a conversion can or should be happen is indicated in the conversion table. It depends on the land use pressure and location specific conditions (Figure 2.3).

2.3.4 Land use requirements (demand)

The main part of non-spatial are calculated at sum of total area from land use types as part of a specific scenarios. Land use requirements or demand side was determined for CLUE-S model by each area of land use types in processing. The extrapolation of trends in land use change in recent part into the near future is a common technique to calculate land use requirements (Verburg and Overmars 2009; Verburg, 2010). The demand depends on perspective of policy and/or population change or advance model to communicate with CLUE-S model such as SD model (Zheng et al., 2012), SAMBA (Castella, Kamb, Quangc, Verburg and Hoanh, 2007) and LEITAP (Perez-Soba et al., 2010).

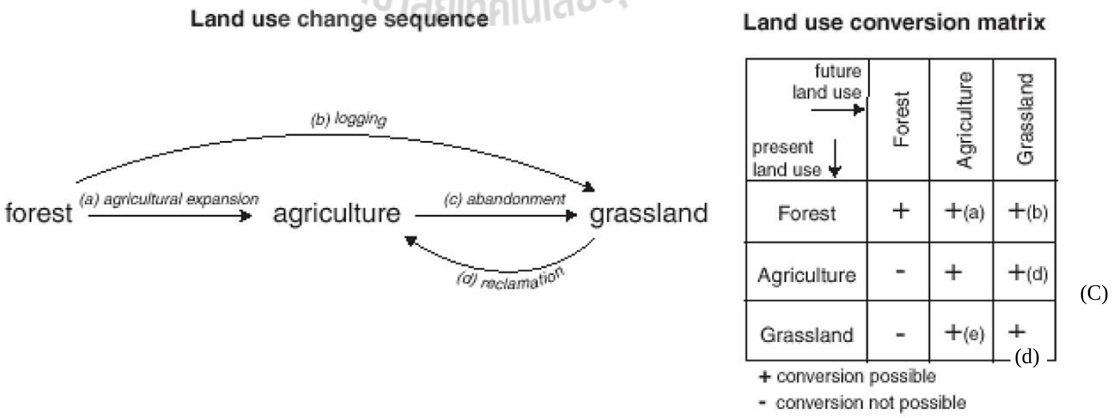


Figure 2.2 Illustration of the translation of a hypothetical land use change sequence into a land use conversion matrix (Verburg, 2010).

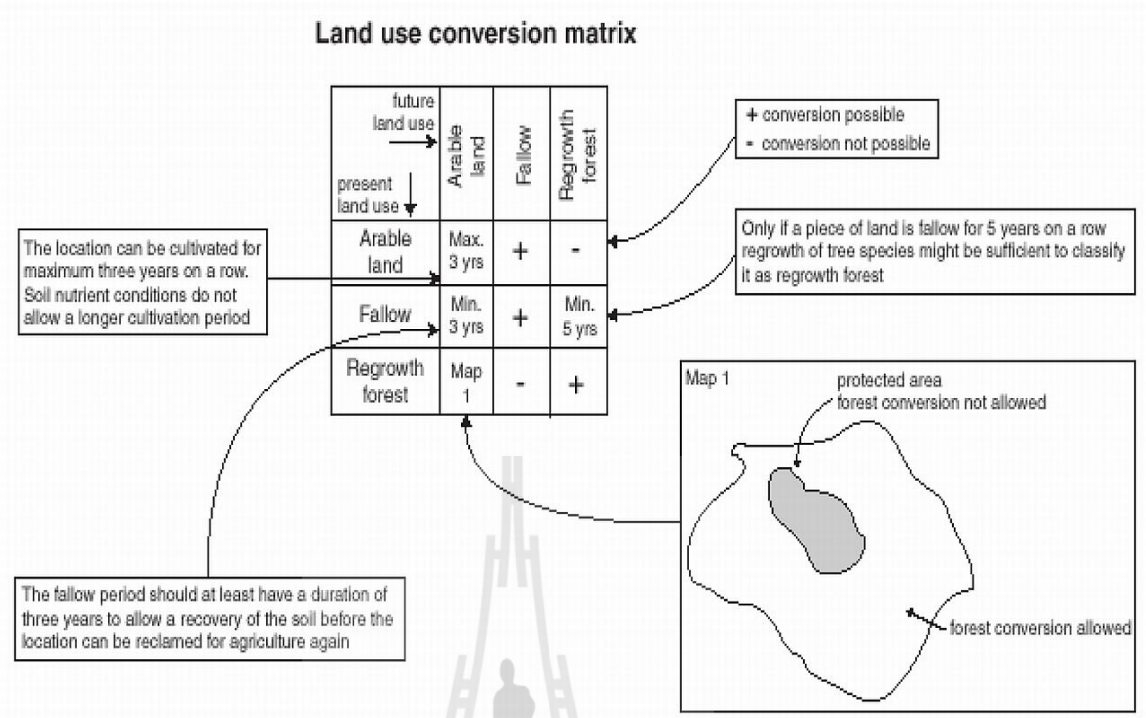


Figure 2.3 Example of a land use conversion matrix with the different options implemented in the model (Verburg, 2010).

2.3.5 Location characteristics

Location of land use conversions are expected to take place at the highest 'preference' for the specific type of land use (Verburg, 2010) based on the relation between the occurrence of a land-use type and the physical and socioeconomic conditions of a specific location factors (Trisurat, Alkemade and Verburg, 2010). Those are based on the different, disciplinary, understandings of the determinants of land use change. The preference is calculated following:

$$R_{ki}= a_kX_{1i} + b_kX_{2i} + ...+n_kX_{ni}\,, \qquad (2.1)$$

where R_{ki} is the preference to devote location i to land use type k, $X_{1,i},...X_{ni}$ are biophysical or socio-economical characteristics of location i, and $a_{k,}$ $b_k…n_k$ are the relative impact of these characteristics on the preference for land use type k.

Although, the preference R_{ki} cannot be observed or measured directly and has therefore to be calculated has a probability (Verburg, 2010). The function, that relates these probabilities with the biophysical and socio-economic location characteristics, is defined in a statistical model can be developed as a binomial logit model of two choices: convert location i into land use type k or not. The preference R_{ki} is assumed to be the underlying response of this choice following:

$$Log\ (\frac{P_i}{1-P_i}) = \beta_0 + \beta_0 X_{1,i} + \beta_2 X_{2,i} \dots\dots + \beta_n X_{n,i}\ , \qquad (2.2)$$

where P_i is the probability of a grid cell for the occurrence of the considered land use type on location I, $X_{n,i}$ are the location factors, and the coefficients β_0 (are estimated through logistic regression using the actual land use pattern as dependent variable.

2.3.6 Allocation procedure

The spatial allocation module allocates the regional level demands to individual grid cells until the demand has been satisfied by iteratively comparing the allocated area of the individual land use types with the area demanded. Figure 2.4 provides a flowchart of the allocation procedure used. The allocation procedure of the Dyna-CLUE (latest version in 2006) at time (t) for each location (i) the land use/cover type (lu) with the highest total probability ($Ptot_{i,t,lu}$). The total probability is defined as the sum of the location suitability ($Ploc_{i,t,lu}$), neighborhood suitability ($Pnbh_{i,t,lu}$), conversion elasticity ($elas_{lu}$) and competitive advantage ($comp_{t,lu}$) (Verburg et al., 2002) as following:

$$Ptot_{i,t,lu} = Ploc_{i,t,lu} + Pnbh_{i,t,lu} + elas_{lu} + comp_{t,lu}\ , \qquad (2.3)$$

Location suitability and neighborhood suitability can be determined by either empirical methods (Verburg et al., 2004c), process and expert knowledge and the (dynamic) analysis of neighborhood interactions similar to constrained cellular automata models (Verburg, De Nijs, Van Eck, Visser and de Jong, 2004b).

The conversion elasticity is a measure of the cost of conversion of one land use type to another land use type and applied only to those locations where the land use type is found at time t. High values indicate high conversion cost (either monetary or institutional) and thus a higher total probability for the location to remain under the current land use type. Low values for elasticity may apply to annual crops, grassland and similar land use types while high values apply to forest, urban areas and permanent crops for which high costs of establishment have been made.

The competitive advantage is iteratively determined for all land use types during an iterative procedure. Values are increased during the iteration when allocated area is smaller than area demanded while values are decreased when allocated area exceeds the demand. In the case of increasing demand, the value of the competitive advantage is likely to increase while lower values are obtained when the demand for a certain land use type decreases. Finally, the maximization of the total probability at each individual location is checked against a set of conversion rules as specified in a conversion matrix

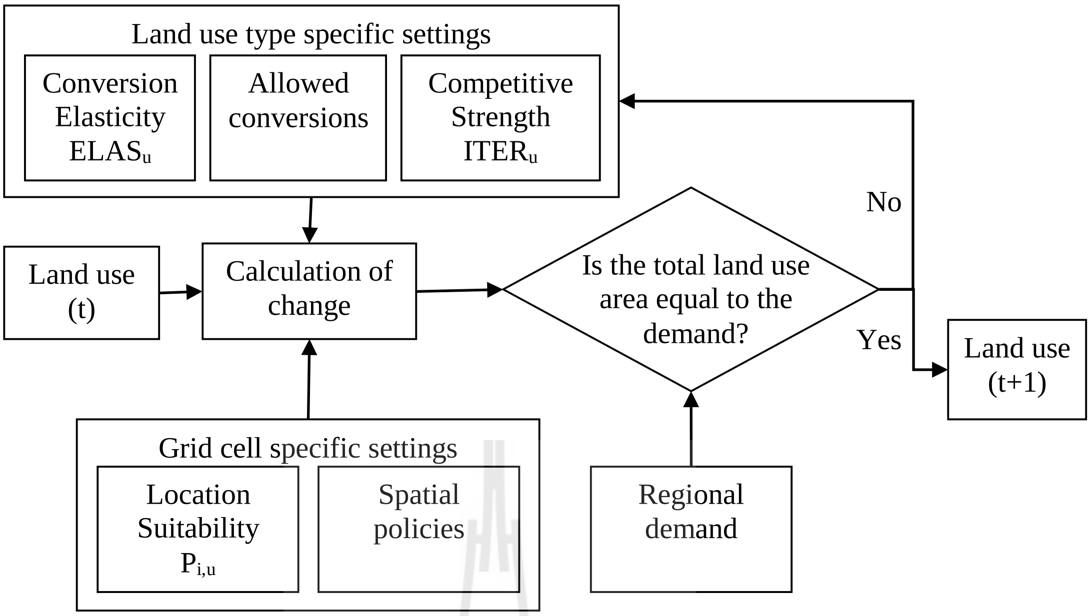


Figure 2.4 Flowchart of the allocation module of the CLUE-S model (Verburg, 2010).

For CLUE-S operation, schematic workflow and requirement parameter with file extension for LULC simulation is displayed in Figure 2.5. The technical limitation of CLUE-S is summarized as shown in Table 2.2.

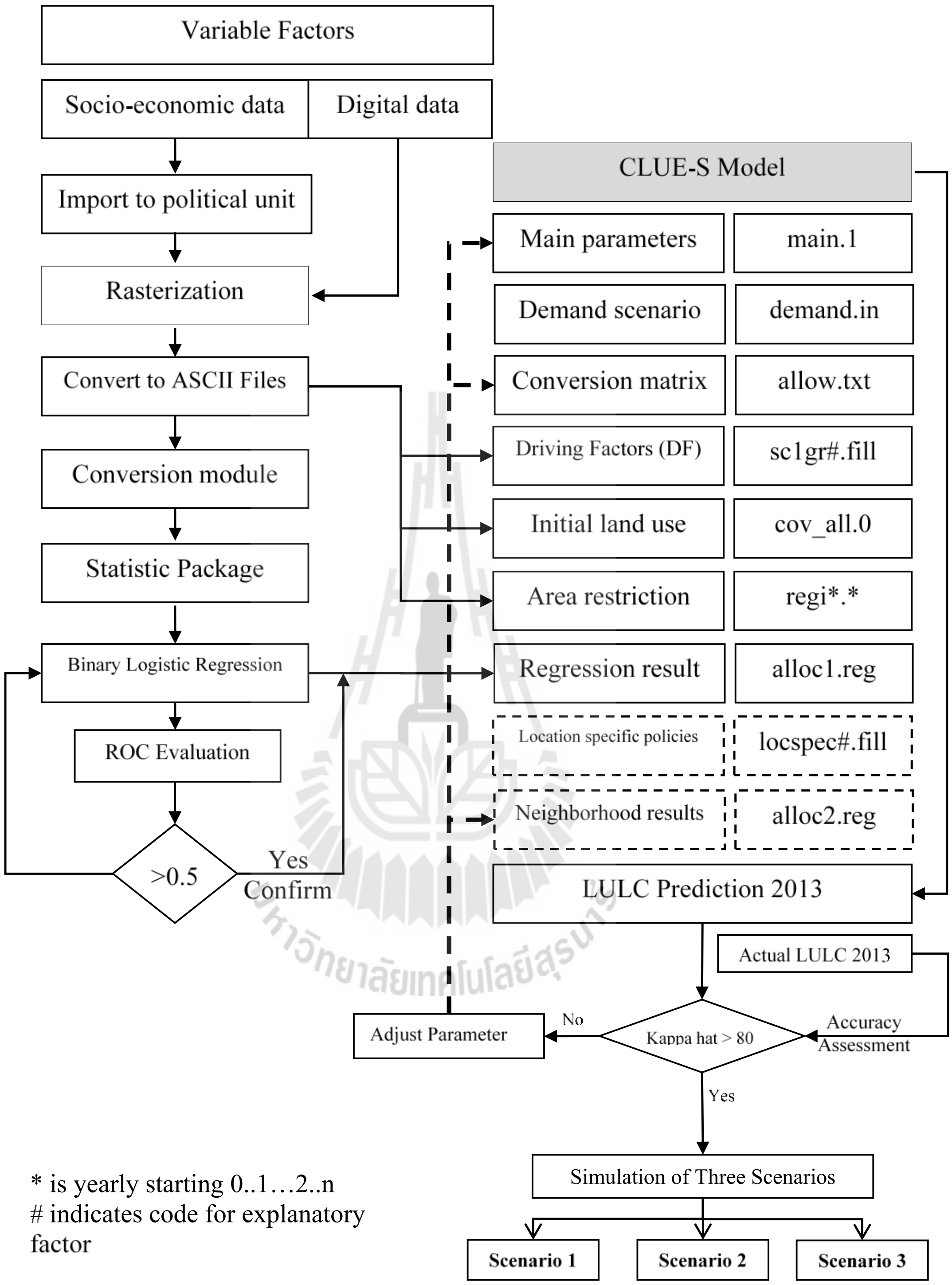


Figure 2.5 Schematic flowchart of CLUE-S for LULC simulation.

Table 2.2 Limitation of CLUE-S model.

Technical limitation of CLUE-S model
1. The maximum number of land use types for land use change simulation is 12 classes.
2. The total number of test sites as splitting areas is not more than 3 areas.
3. The total number of independent variables in a regression equation using in CLUE-S model is not more than 20 variables.
4. The total number of driving factors under stepwise multiple linear regression using in CLUE-S model is not more than 30 variables.
5. Maximum extent of rows (X) and columns (Y) in grid format was 1,000 x 1,000 grid
6. The maximum number of restrictions region is 98 regions.

Source: Verburg et al. (2005) and Verburg (2006)

2.4 Soil erosion model

One of the most significant developments in soil and water conservation in the 20th century is the universal soil loss equation (USLE). Because of long times tested of erosion trials on plots over 10,000 annual records of erosion on plots and small catchments at 46 stations on the Great Plains (Wischmeier and Smith, 1978). The aim of Wischmeier and Smith was to establish an empirical model for predicting erosion on a cultivated field so that erosion control specialists could choose the kind of measures needed in order to keep erosion within acceptable limits given the climate, slope and production factors. The major development of an empirical technology the USLE was the culmination of decades of soil erosion experimentation conducted by university faculties and federal scientists across the United States. A complete technology was first published in 1965 by USDA Agriculture Handbook 282 and 537 (updated version) (Wischmeier and Smith, 1978). Nowadays application of USLE is used in around the world. The erosion prediction equation is composed of five factors for long-term average annual soil loss (A):

$$A = R \times K \times LS \times C \times P, \quad (2.4)$$

where A is annual soil loss (t/ha/yr), R is rainfall–runoff erosivity factor (MJ mm/ha/h per year). This is the kinetic energy of rainfall, multiplied by I30 (maximum intensity of rain in 30 minutes expressed in cm per hour). This index corresponds to the potential erosion risk in a given region where sheet erosion appears on a bare plot with a 9% slope, K is soil erodibility factor (t h/MJ mm). It depends on the organic matter and texture of the soil, its permeability and profile structure. It varies from 70/100 for the most fragile soil to 1/100 for the most stable soil. It is measured on bare reference plots 22.2 m long on 9% slopes, tilted in the direction of the slope and having received no organic matter for three years, LS is slope length and steepness factor. It depends on both the length and gradient of the slope. C is vegetation cover factor. It is a simple relation between erosion on bare soil and erosion observed under a cropping system. The C factor combines plant cover, its production level and the associated cropping techniques. It varies from 1 on bare soil to 1/1000 under forest, 1/100 under grasslands and cover plants, and 1 to 9/10 under root and tuber crops, and P is the conservation support-practice. This factor takes account of specific erosion control practices such as contour tilling or mounding, or contour ridging. It varies from 1 on bare soil with no erosion control to about 1/10 with tied ridging on a gentle slope.

2.5 Hydrologic model

Soil and water assessment tool (SWAT) is a non-point source modeling, physically based, spatially distributed, continuous time hydrological model, and public domain model developed by the United States Department of Agriculture–Agricultural Research Service (USDA-ARS) (Neitsch, Arnold and Williams, 2011). The model operates on a daily time step and allows a basin to be subdivided into grid cells or natural sub basins. There are two main components: (1) routing phase of the hydrologic cycle, and (2) land phase of the hydrologic cycle. Major modules in the model include hydrology, erosion/sedimentation, plant growth, nutrients, pesticides, land management, stream routing, and pond/reservoir routing (Van Griensven, Ndomba, Yalew and Kilonzo, 2012). An attempt is made to simulate the major hydrologic components and their interactions as simply and yet as realistically as possible. An attempt is also made to use inputs that are readily available over large areas so the model can be used routinely in planning and decision making (Arnold et al., 1998).

The hydrology model is based on the water balance equation:

$$SW_t = SW_o + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{deep} - Q_{gw}), \quad (2.5)$$

where SW_t is the final soil water content (mm), SW_o is the initial soil water content on day *i*(mm), *t* is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), W_{deep} is the amount of water percolation into the deep aquifer on day i (mm), and Q_{gw} is the amount of return flow on day i (mm).

The basic SWAT model inputs are rainfall, maximum and minimum temperature, radiation, wind speed, relative humidity, land cover, soil and elevation. The watershed is subdivided into sub-basins that are spatially related to one another, and, further, into hydrological response units (HRUs), which are homogenous units that possess unique land-use/land-cover and soil attributes and account for the complexity of the landscape within the sub-basins. The sub basin watershed components can be categorized as follows: hydrology, weather, erosion and sedimentation, soil temperature, plant growth, nutrients, pesticides and land management. In the land phase of the hydrological cycle, runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. Once the loadings (water, sediment, nutrients and pesticides) to the main channel are determined, they are routed through the stream network of the watershed (Githu, Mutua and Bauwens, 2009).

The US Soil Conservation Service (SCS) curve number method was used to determine surface runoff. This is an empirical model that estimates the amounts of runoff under varying land use and soil types. The ranges of SCS curve number (CN) values originally derived by the SCS Engineering Division are obtained from the SWAT user’s manual. There is a function relate with hydrologic soil group, cover, hydrologic condition, land use classification, and antecedent moisture content (AMC).

Since a significant amount of SWAT's input data are of a spatial character for example those derived from stream network, drainage divide, land use, and soil type maps and GIS tools for extracting information for SWAT from readily available digital spatial data have been developed. Olivera et al. (2006) claimed that many studies used SWAT with spatial for example, developed an interface in many platforms such as GRASS, ARC/INFO, ArcView 3.x, and newly ARCSWAT. The ArcGIS-SWAT data model stores SWAT geographic, numeric, and characteristic input data and results. The geodatabase data structure, considered as a relational database with the capability of storing geographic information in addition to numbers and text, was used for the data model.

Under this research, SWAT model are used to estimating surface runoff based on Soil Conservation Service Curve Number (SCS-CN) method that was developed by the U.S. Soil Conservation Service (SCS). This method has been widely applied to estimate storm-runoff depth for every patch within a watershed based on runoff curve numbers (*CN*) (Soil Conservation Service, 1972). The SCS equation for storm-runoff depth is mathematically shown as follow:

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S}, \tag{2.6}$$

where Q is storm runoff, P is rainfall (mm), and S is potential maximum storage

[S = (1000/CN) – 10] (mm).

CN is the runoff curve number of the hydrologic soil group-land cover complex. To solve this equation, two input values are needed: P and CN. Precipitation data are available from meteorological observations. A runoff curve number is a quantitative description of land-cover and soil conditions that affect the runoff process.

2.6 Economic land evaluation

Economic land evaluation is a method for predicting the micro-economic value of implementing a given land-use system on a given land area. This is a more useful prediction of land performance than a purely physical evaluation, since many land-use decisions are made on the basis of economic value. Measures of economic suitability include the gross margin, net present value, internal rate of return, benefit/cost ratio, and utility functions based on these (Rossiter, 1995). Economic suitability depends on three types of factors: (1) the in-situ resource quality, i.e. the response of the land to the use without regard to its location (Ricardo Theory) for example: predicted crop yield; (2) the accessibility, and by extension, all costs and benefits associated with the specific location as opposed to the resource quality (Von Thünen Theory), for example transportation costs for inputs and products; and (3) other spatial attributes of the site, not including accessibility (e.g. size, shape, adjacency, and contiguity). For example more efficient field work if the parcel is the correct shape and size (Rossiter, 1994).

The land use capacity of a land area for a land use, may be defined as the value of some economic measure, should the land area be dedicated to the use. This definition begs two others: the type of land area to be evaluated, and the economic measure to be used in the evaluation. It also leaves unspecified the key question: how should the physical land characteristics be costed? So, the economic land evaluation has five steps (Rossiter, 1995):

(1) decide on the land units to be analyzed;

(2) decide on the appropriate economic measure;

(3) decide what economic factors to include in the evaluation, and the type of price to use in the analysis;

(4) specify how physical land characteristics affects economic values, perhaps using in situ and geographical Land Qualities;

(5) compute the economic land suitability; and

(6) perform a sensitivity analysis to determine the effect of errors in physical factors and model assumptions on land suitability.

2.6.1 Evaluation units

Land evaluation attempts to determine the relative fitness of different land areas for different uses. Rossiter (1995) classified evaluation units as followings.

(1) Map units of natural resource inventories. When the evaluation starts with data from a natural resources data base (e.g. a soil survey or climate map), the map unit as shown on the resource map as a single legend class, or as derived from an intersection of several maps (e.g., soil type overlaid with climate type), may be

considered sufficiently homogeneous with respect to the land characteristics implied by the legend, and forms the unit of analysis. This has been the usual approach for physical land evaluations based on soil survey interpretations or agro-ecological zones. All delineations of the map unit are considered to be the same, no matter where located, so that only the in-situ characteristics of the map unit, such as natural soil fertility, can be used to determine economic value. Economic results are normalized to a per-unit land area basis.

(2) Map delineations of natural resource inventories. If economic suitability depends on geographical land characteristics, the legend category of a natural resource inventory must be divided into its separate delineations for analysis. Map delineations are individual connected areas of the map unit. The evaluation can consider the location of the delineation (either its centroid or nearest point) in relation to cultural features such as roads and markets; this is especially important for transport costs. The size and shape of the delineation, as well as topological relations such as adjacency and containment, can also be a land characteristic of economic importance. Economic results are usually normalized to a per unit land area basis.

(3) Management units. A management unit is an area of land that the land manager intends to treat or allocate as a unit. Since each management unit has a unique location, the analysis can include geographic considerations. Management units based on the current land-use pattern, such as fields, are usually less homogeneous with respect to natural resources than map delineations of a natural resource inventory, because the boundaries of natural resources rarely correspond to the boundaries of management units. One way to deal with this heterogeneity within the evaluation unit is to ignore it, and simply use the dominant or most prevalent value of each land

characteristic, with a loss of precision in the analysis. Another approach is to define the evaluation unit as a compound unit consisting of several homogeneous constituents in a defined proportion. Each constituent is evaluated separately, and these results are combined in weighted linear proportion to arrive at a result for the management unit as a whole.

(4) Production units. Some economic decisions are taken on a whole-farm (or other production unit) basis. Production units have global objectives (for example, profit maximization and risk minimization) and constraints (for example, labor and capital supply) that apply to a production unit considered as a whole, not to the individual management units of which it is made up. In some land use systems, a production unit must contain a defined mixture of several land uses. The usual way to evaluate a production unit is to evaluate each of its management units separately, and then combine these into an aggregate farm plan, considering whole-farm objectives and constraints.

(5) Planning units. In regional or catchment planning, decisions are taken on the whole area, subject to objectives and constraints that are expressed over the entire region. For example, there may be a limited amount of irrigation water available for an entire irrigation district, or a catchment plan may be required to include a set of land uses. Planning units are evaluated like production units.

2.6.2 Measures of economic suitability

There are various "yardsticks" which may be used for economic land suitability evaluation. The chosen measure should correspond to the economic reality faced by decision makers, as well as their values and attitudes towards money and risk

Rossiter (1995). The EUROCONSULT agricultural compendium (1989) had compared economic measures as following:

(1) Gross margin. This is the cash flow in to the land utilization type (LUT), less the cash flow out of the LUT, on a per unit area (normalized) or aggregate (per-field or per-farm) basis, in one accounting period (usually a year). If the gross margin calculation includes the fixed costs of production, it is called the "net return"; otherwise the "gross return." This measure does not take into account the time value of money. Capital costs can be ignored altogether by using rental prices. Thus, the gross margin is not sensitive to interest rates. It is an appropriate measure of economic suitability for annual or short-term rotational LUTs with few or no capital costs.

(2) Capitalized value. This variant of the gross margin accounts for the time value of money. The annual return from a steady-state investment is a percentage of the total value of the investment determined by the interest rate. So, the total value can be calculated as: EV = GM / IR, where EV is the estate value, GM is the annual gross margin, and IR the interest rate in percent. It is an appropriate measure of economic suitability in the same situations as the gross margin. The capitalized value is an approximation to the portion of the land's value that can be attributed to its productive capacity.

(3) Discounted cash flow analysis. Money received in the future is less valuable than money in hand. To take into account this "time value of money," amounts received or spent in the future are discounted to their present value according to the formula:

$$PV = FV \cdot \left[\frac{100}{100+IR}\right]^{Y}, \tag{2.7}$$

In this formula, PV is the present value, FV is the future value, IR is the interest rate in percent, and Y is the number of years from present, counting from zero. The present value of an annual cash flow becomes insignificant at some point in the future that depends on the interest rate. A typical use of discounted cash flow analysis is to evaluate the economic feasibility of agricultural projects such as land reclamation, where an initial investment is expected to yield benefits in the future. There are three measures derived from the discounted cash flow with which to evaluated land suitability, as follows:

(a) Net present value (NPV). This is the total value of the cash flows to be generated by the LUT, summed over its planning horizon, discounted to the present. The NPV may be normalized if investments are expressed on a per unit area basis, otherwise it must be aggregated over the production unit. The NPV cannot be annualized, since each year is discounted differently.

(b) Internal rate of return (IRR). This is the interest rate below which the "project" (land use option) becomes financially attractive. At higher prevailing interest rates than the IRR, an investor would be better off investing the required capital at the offered rate rather than investing in the project. Mathematically, it is the discount rate below which the NPV becomes positive. The IRR is dimensionless, with no spatial or temporal component, and so can be used to compare land uses with different planning horizons. The IRR is a rough measure of the financial risk of a project that is due to rising interest rates, and is often used to compare investment options.

(c) Benefit-to-cost ratio (BCR). This is the present value of the cash-in divided by the present value of the cash out. A project is evidently, feasible if and only if the BCR>1. The BCR is a measure of the return to investment; thus the BCR is an appropriate measure for the land user who wants to maximize the leverage of a limited investment.

(4) Utility. The economic measures presented to this point are all expected values. Because of uncertainty in the production system, mainly due to uncertain weather and prices, the expected value will not be attained every year; the time series of net returns will rather have some variance. If land users had unlimited reserves to get through low-income years, they would rationally choose the land use with the greatest expected value. In practice, they are willing to trade some total income over the long term for smoother and more certain incomes in the short and medium terms. A measure of risk aversion is the degree to which land users are willing to forego overall benefit (high expected value) for more certainty (low variance).

(5) Non-cash measures. Other measures of value than cash may be appropriate in certain socio-economic settings. Examples are calories or a nutritional index as “income” to be maximized and amount of an input (e.g., labor) to be minimized. The net cash flow must still be favorable.

(6) Economic suitability classes. Once each land use-land area combination has been assigned an economic value by the land evaluation, the question arises as to its “suitability,” that is, the degree to which it satisfies the land user. The land use must be financially feasible (for example, it must result in a positive gross margin), but beyond this minimum standard, the concept of “suitability” depends on the financial expectations of the land users who will implement the LUT. The evaluator assigns dividing points between suitability classes, in the same units of measure as the economic analysis.

2.7 Multi-criteria spatial allocation model

The multiple-criteria decision analysis (MCDA) can be solving the problem involves a set of alternative allocation plans evaluated on the basis of multiple, convicting and non-commensurate criteria by several interest groups Malczewski (2006). MCDA should be provided a rich collection of techniques and procedures for structuring decision problems, and designing, evaluating and prioritizing alternative decisions. Including GIS-MCDA is able to process that transforms and combines geographical data and value judgments to obtain information for decision making

Malczewski (1999) stated that a number of multi-criteria decision rules have been implemented in the GIS environment for tackling land-use suitability problems. The decision rules can be classified into multi-objective and multi-attribute decision making methods. The multi-objective approaches are mathematical programming model oriented methods, while multi-attribute decision making methods are data oriented. Multi-attribute decision analysis (MADA) are also referred to as the discrete methods because they assume that the number of alternatives (plans) is given explicitly, while in the multi-objective decision analysis (MODA) the alternatives must be generated (they are identified by solving a multi-objective mathematical programming problem). Basically, the decision rules in GIS are the most often used both of WLC (weighted linear combination) and Boolean operators (Malczewski, 2004).

This research emphasize on MADA in a part of WLC. The WLC is a decision rules that the most popular method for spatial MADA, sometime referred to as simple additive weighting (SAW) or scoring methods (Malczewski, 1999). SAW applies a concept of a weighted average based on the decision maker and assigned directly weights into each attribute of “relative importance” (Malczewski, 2000). A total score is then obtained for each alternative by multiplying the importance weight assigned for each attribute by scaled value given to the alternative on that attribute, and aggregate the products overall attributes suitability score. Given the input data, the decision rule evaluates each alternative, A_i by the following value function:

$$A_i = \sum_j W_j X_{ij}, \tag{2.8}$$

where

A_i = total score which obtained by multiplying the score and weight,

W_j = The normalized weight,

X_{ij} = The score of the i^{th} alternative with respect to the j^{th} attribute, and

$\sum W_j = 1$.

In SAW procedure involves the following 6 steps:

(1) define the set of evaluation criteria (map layers) and the set of feasible alternatives,

(2) standardize each criterion map layer,

(3) define the weight (of relative importance) to each criterion map layer,

(4) create the weighted standardized map layers,

(5) generate the overall score for each alternative using add overlay operation, and

(6) rank the alternatives according to the overall performance score that the cell with the highest score is the best cell (Malczewski, 2000).

2.8 Literature reviews

2.8.1 CLUE-S model

Verburg and Veldkamp (2001) demonstrated the role of spatially explicit models in land-use change research, a case study for cropping patterns in China. In this research, a modeling methodology was presented aiming at the analysis of the spatial and temporal dynamics of land use at the regional level. The methodology explored the dynamic functioning of land-use systems, which was essential to bridge the gap between studies identifying problems associated with land-use change. In addition the methodology included the nested simulation of different crop types to simulate a scenario of near-future (1991–2010) changes in land-use patterns. Results were presented for changes in the spatial distribution of cultivated land and special emphasis is given to shifts in the distribution of different crops. They found that in the northern part of the country a decrease in the proportion wheat within the cropping system is expected whereas in the southern part the proportion of rice is decreasing. Corn and vegetable crops are expected to become more important within the cropping system in these parts of the country.

Verburg et al. (2002) applied CLUE-S model on land use change in Philippines and Malaysia to illustrate the functioning of the model and its validation. They claimed that the model can help to identify near-future critical locations in the face of environmental change through scenario analysis.

Castella et al. (2007) developed the combining top-down and bottom-up modeling of land use/cover change to support public policies on natural resources management. Bac Kan province in northern Vietnam was selected as study area. Three models included SAMBA, LUPAS, and CLUE belonging to two land use and land cover change approaches, were used in the study. The multi-agent model SAMBA was developed through an adaptive, bottom-up process while LUPAS and CLUE contributed to a top-down process. Applying these three methodologies at the same research site allowed a critical evaluation of their respective utility for land use analysis and planning. As results, they concluded that combined use of these modeling methodologies should be promoted when complex natural resource management issues at multiple scales need to be tackled. Three combined models played complementary roles in bridging knowledge gaps and increasing interactions between stakeholders along the continuum from research to development and policy formulation.

Luo et al. (2010) combined System Dynamic model (SD) and CLUE-S model to improve land use scenario analyses at regional scale as a case study of Sangong watershed in Xinjiang, China. A SD model is used to calculate area changes in demand for land types as a whole while a CLUE model is used to transfer these demands to land use patterns. Without the spatial consideration, the SD model ensures an appropriate treatment of macro-economic, demographic and technology developments, and changes in economic policies influencing the demand and supply for land use in a specific region. With CLUE model the land use change has been simulated at a high spatial resolution with the spatial consideration of land use suitability, spatial policies and restrictions to satisfy the balance between land use demand and supply. The established SD model was fitted or calibrated with the 1987–1998 data and validated with the 1998–2004 data; combining SD model with CLUE-S model, future land use scenarios were analyzed during 2004–2030. As results, they concluded that this methodology have the ability to reflect the complex behaviors of land use system at different scales to some extents and be a useful tool for analysis of complex land use driving factors such as land use policies and assessment of its impacts on land use change. This work could be used for better understanding of the possible impacts of land use change on terrestrial ecosystem and provide scientific support for land use planning and managements of the watershed.

2.8.2 Soil erosion model

Kitahara, Okura, Sammori and Kawanami (2000) showed how to use the USLE in order to roughly estimate erosion yields from limited data of forest terrains in Japan. Herewith C and P factors in the USLE equation were improved and generalized by using erosion experiments and other data which were obtained and derived from previous Japanese studies. As results, they concluded that it is possible applications of the USLE to predictions of the soil losses from large basins or from districts in which both agricultural land and forest land with limited data were included.

Fistikoglu and Harmancioglu (2002) studied environmental impact in the Gediz River, which discharges into the Aegean Sea along the western coast of Turkey. In this study USLE model was combined with GIS to identify soil erosion and examine mean sediment and organic N transport of non-point source (NPS) pollution loading by sediment.

Shinde, Sharma, Tiwari and Singh (2011) studied soil erosion in Upper Damodar Valley catchment of India by using remote sensing and GIS data for predict soil erosion from USLE. In practice, slope steepness and length factor or topographic Factor (LS) which is an integral part of most soil erosion prediction models was extracted from SRTM DEM. While cover factor (C) operated by the supervised classification of LANDSAT ETM images. The soil erodibility factor (K) was computed using field and laboratory estimated physical-chemical properties of the surface soils.

Meanwhile rainfall factor (R) from average annual daily rainfall of six stations was created by Nearest Point method from Thiessen Polygon pattern. Output from ULSE was compared with India Soil and Land Use Survey (AISLUS) priority map.

Song, Du, Kou and Ma (2011) applied USLE and GIS for evaluation of soil erosion and soil nutrients loss (total nitrogen and total phosphorus) in watershed area of the Danjiangkou Reservoir in Henan province, China. The R-factor (rainfall erosivity) was determined by interpolation using meteorological data from five stations. The K value was calculated by using EPIC (Erosion-productivity impact calculator) formula was obtained by using soil survey data. The LS-factors (slope length and steepness) were determined from the digital elevation model (DEM), while the C-factor (crop and management) was determined from remote sensing imageries by NDVI maps in three periods from Landsat 5 TM, ETM+ in 1991, 2000, and 2007. Together with the conservation practice factor (P) is respected by field experiments. Results presented about spatial distribution map of the soil erosion were estimated in study area from 1991 to 2007.

2.8.3 Hydrologic model

Xue-Song, Fang-Hua, Hong-Guang and Dao-Feng (2003) studied the application of SWAT model in the upstream watershed of the Luome River. Integration GRASS-GIS with SWAT was used to examine sediment and runoff in large river basin. Monthly simulated flow and sediment loadings were compared with observed values for calibration and validation period. Coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NSE) were used to evaluate model prediction. It was found that both coefficients are above 0.7 which shows that SWAT model could be a useful tool for water resources and soil conservation planning.

Ndomba, Mtalo and Killingtveit (2008) studied SWAT model application in a data scarce tropical complex catchment in Tanzania. This study showed that the technique in process of SWAT had data scare by the validation process involved the model initialization, calibration, verification and sensitivity analysis. Both manual and auto-calibration procedures were used to facilitate the comparison of the results with past studies in the same catchment. They conclude that a set of important parameters can be identified either by using observed or without observed flow data based on sensitivity analysis from six years simulations. This result suggested that SWAT model can be used in ungauged catchments for identifying hydrological controlling factors/ parameters.

Lam, Schmalz and Fohrer (2011) using the eco-hydrological model soil and water assessment tool (SWAT) to evaluate the cost and effectiveness of best management practices (BMPs) for water quality improvement in the Kielstau catchment, Northern Germany. Herein, SWAT was applied to simulate flow, sediment, and nutrient load (Phosphorus and Nitrogen) from different point and diffuse sources in catchment. The basic input data included climate, topography, soil, land use, and agricultural data. In a part of simulate surface runoff volumes and peak runoff rate for each HRU used daily rainfall or sub-daily rainfall amounts. Surface runoff was calculated using a modification of the Soil Conservation Service curve number (SCS-CN) method, which was a function of the soil's permeability, land use and antecedent soil water conditions. The results of this study showed that good agreement between simulated and measured daily discharges with the Nash–Sutcliffe efficiency (NSE) and R^2. Overall, the SWAT performed satisfactorily in simulating daily flow, sediment, and nutrient load at the Kielstau lowland catchment.

Rathjens and Oppelt (2012) presented a grid-based approach of model interface that enabled the user to incorporate spatial detail such as remote sensing data into a SWAT model run. The application of this concept resulted support in a loss of spatial information in the input data such as land-use or soil type for improving model results. In this study SWATgrid was developed to fill the gap for an interface that incorporates grid-based cell data into SWAT, a model input interface for setting up SWAT based on grid cells. In addition, digital landscape analysis tool TOPAZ (TOpographic PArametriZation) was used to create input file of SWAT model. The functionality of SWATgrid was demonstrated by comparing conventional SWAT model resulted derived by ArcSWAT, which corresponded well.

Chen and Wu (2012) presented the alternative and integrate model by using the TOPographic MODEL (TOPMODEL) features for enhancing the physical representation of hydrologic processes with integration of the SWAT model. The new simulation method of base flow can also reflect the influence of the dynamics of that water table, which contains temporal and spatial information. In practice, a group of empirical equations of SWAT was modified included four hydrologic processes: surface runoff (remodeled), base flow (remodeled), groundwater re-evaporation (refined) and deep aquifer percolation (remove) by using the influences of topography and water table variation on stream flow generation of the TOPMODEL. So TOPMODEL features was integrated into SWAT as a new model called that SWAT-TOP. Comparison of observed and simulated from two models: SWAT-TOP and SWAT was here investigated. It was found that output from both model are similar results. But base flow by SWAT-TOP can indicate the dry and wet seasons distinctly and related soil water availability. While the SWAT simulation does not. SWAT-TOP can model those processes reasonably. Therefore, it is possible to enhance the representations of the terrestrial hydrologic processes in an established model.

2.8.4 Economic land evaluation

In the agricultural sector Hawkins (2009) described CBA was used for agricultural projects or large estates, examples being irrigation projects and estates with perennial crops and corresponding processing facilities, e.g. palm oil. The basic idea here was to find out if the investment in construction and yearly maintenance and operational costs of the irrigation scheme is justified in terms of a higher agricultural production and agricultural incomes (benefits).

Bateman, Lovett and Brainard (2003) studied environmental economic approach by using CBA integrate with GIS in case study of England and Wales. His work showed how farm incomes would change if only the non-market value of land was 'monetized' and added to some of the market values from changed land use (e.g. timber) and adapt transferred values to account for different site characteristics. Currently non-market land services and changed market values are integrated into farm incomes. The external benefit of forest comes from: recreation/education, amenity, wildlife habitat, ecology value, biodiversity, soil stability, hydrological (regulation, storage), carbon sinks (microclimate, regulation), berries/game, fuel, shelter, etc. This aggregate recreation values from forest area of valuation methods, predicting values and predicting visits and results conform well to prior expectations showing predicted demand to be linked to population distribution and site accessibility. In additional to timber valuation using GIS techniques was used to bring together a host of diverse datasets to permit modeling of timber yield and its net value. Moreover carbon sequence was considerate from three sources: the growth of live wood, changes in the carbon content of woodland soils; and carbon liberation from felling waste and timber products. In assessment all the preceding analyses were synthesized provided the net benefit of converting land out of agriculture and into woodland. This appraisal was made from a number of standpoints. For example, two types of agricultural production (sheep and milk) can be assessed in two ways (farm-gate and social values). Similarly, a variety of woodland benefits can be used to assess in many forms (recreation, timber and carbon sequestration) in economic terms.

Samranpong, Ekasingh and Ekasingh (2009) described economic land evaluation for major crops management in the Northern of Thailand. The aim of the study was to assess the economic land use planning dynamic system by using GIS-based system and EconSuit, in a part of physical land evaluation and economic land evaluation. For physical land evaluation, a physical land suitability index was created using the FAO framework and the Project fuzzy land evaluation program. This program was implemented with fuzzy membership function determined using S-membership. The users can enable and assign factors and weights for physical land evaluation by use dynamic graphic interface. Besides economic land evaluation was assigned by field study data to homogeneous land area which was combined between land unit and land use as land mapping units using spatial interpolation. In addition, unit cost of input and outputs can be entered via the graphic user interface, interface, allowing constant updates of economic values in the system. Scenarios of agricultural land use planning may be formulated by users depending on policy or economic circumstances.

2.8.5 Multi-criteria spatial allocation model

Van den Bergh et al. (2001) presented the spatial evaluation from multi-criteria decision analysis (MCDA) for spatial; economic-hydroecological modeling and land use impact evaluation in the Vecht wetlands area, the Netherlands. The study had developed a triple layer models that integrate information and concepts from social and natural sciences to address the analysis and evaluation of land-use scenarios for a wetlands area. The study had resulted in a set of linked spatial hydrological, ecological and economic models, formulated at the level of grids and polders. The main activities incorporated in the system of models were housing, infrastructure, agriculture, recreation, and nature conservation. The formulation of alternative development scenarios was dominated by land use and land cover options that were consistent with the stimulation of agriculture, nature or recreation. Two aggregate performance indicators had been constructed from model output, namely net present value of changes and environmental quality. It was found that the spatial characteristics of these indicators are retained in a spatial evaluation that ranks scenarios.

Nelson et al. (2009) presented Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) as a spatial explicit modeling tool to predict changes in ecosystem services, biodiversity conservation and commodity production levels. They simulated LULC from 1990 to three scenarios in 2050: plan trend, development, and conservation. Invest was used herewith to analyze water quality, soil conservation, storm peak management, carbon sequestration, biodiversity conservation, and market value of commodity production. Besides output from InVEST model were normalized all scores by their LULC. It was evident that scenarios that received high scores for a variety of ecosystem services also had high scores for biodiversity. Quantifying ecosystem services in a spatially explicit manner, and analyzing tradeoffs between them could help to make natural resource decisions more effective, efficient, and defensible.

Jeong, García-Moruno and Hernández-Blanco (2012) presented a spatial assessment for re-mixing buildings on the rural fringe of Spain. They were applied multi criteria decision analysis for rural building suitability. The parameters were categorized into five criterion groups: physical, comprises visual, economical situations, and environmental. These factors were transformed to commensurate unit by standardize from fuzzy set membership functions and assigning weights to factors through the Analytical Hierarchy Process (AHP). After that SAW method was applied for calculation of final grading values. So that the final was created a suitability re-mixing index map for rural building integration with landscape.

Rahman, Shim and Chongfa (2009) developed soil erosion hazard assessment by an integrated use of remote sensing, GIS and statistical approaches. For soil erosion hazard assessment, revised universal soil loss equation (RUSLE) was implemented in the study. Herewith nine factors for soil erosion by water included soil erodibility, slope, soil depth, rainfall, elevation, vegetation, fallow land, population density and presence of existing soil erosion. These factors were transformed to quantitative factor maps for rating score and standardization using the AHP. In addition, a *Z*-score analysis was applied to standardized factor maps for decrease the bias of any factor in the final evaluation. After that pair wise comparison matrix by the AHP was reapplied for factors weight assignment and WLC was then used to calculate soil erosion hazard index (SEHI). Final output of the study was presented in term of four levels of soil erosion hazard: very high, high, moderate, and low. Based on this study, comprehensive erosion hazard management strategies were anticipated for efficient management of present and future erosion disaster in the area.

Bunruamkaew and Murayama (2011) applied GIS with the AHP for ecotourism site suitability evaluation in Surat Thani Province, Thailand. In this study, related five factors (landscape/naturalness, wildlife, topography, accessibility, and community characteristics) were applied for potential ecotourism site assessment. Major criteria were also assigned to those factors included visibility, land use/cover, reservation/protection, species diversity, elevation, slope, proximity to cultural sites, distance from roads, and settlement size. In practice, four main steps of the methodology include: (1) finding suitable factors, (2) assigning factor priority, weight and rating using AHP, (3) generating ecotourism suitability map using WLC, and (4) classifying ecotourism potential sites. As results, it was found that the methodology proposed was useful to identify ecotourism sites by linking the criteria deemed important with the actual resources in the province.

CHAPTER III

DATA AND METHODOLOGY

Summary of collected and prepared data and details of methodology including Component 1: Historical and recent LULC extraction and driving force identification, Component 2: Local parameter of CLUE-S optimization and validation, Component 3: LULC simulation with three scenarios, Component 4: impact assessment and evaluation, soil erosion, water yield, and economic value, and Component 5: an optimal land use allocation are here explained in this chapter.

3.1 Data

The main input data for historical and recent LULC extraction and driving force identification and local parameter of CLUE-S model optimization for LULC scenario simulation include both primary and secondary data. At the same time the major data for impact assessment due to LULC change on soil erosion, water yield, and economic value and an optimal land use allocation in different scenarios for year 2023 are mostly secondary data. The list of data collection and preparation are summarized as shown in Table 3.1.

Table 3.1 List of collection and preparation data.

Component	Collection	Preparation	Scale	Source
Component 1:				
Historical and recent	Color orthoimage data in 2003	LULC 2003 by visual interpretation	1: 4,000	LDD
LULC extraction	Thaichote 2013	LULC 2013 by visual interpretation	1: 10,000	GISTDA
Component 1:				
Driving force	DEM	Elevation extraction	1: 50,000	RTSD
identification	DEM	Slope extraction	1: 50,000	RTSD
	DEM	Aspect extraction	1: 50,000	RTSD
	Rainfall data	Rainfall interpolation	No scale	TMD
	Road network	Buffering by distance	1: 50,000	RTSD
	Stream network	Buffering by distance	1: 50,000	RTSD
	Soil data	Drainage capacity	1: 50,000	LDD
	Demography data	Population density	No scale	NSO
	Demography data	Income	No scale	NSO
	Administrative boundary	Data extraction (Sub district)	1: 50,000	RTSD
	Watershed classification	Data extraction	1: 50,000	ONREPP
Component 2:				
Local parameter of	Main parameters file	Main parameters text file	No scale	CLUE-S
CLUE-S	Regression parameters	Regression parameters file	No scale	CLUE-S
optimization	Change matrix	Change matrix file	No scale	CLUE-S
	Land use requirements	Land use requirements	No scale	CLUE-S
	Static location factor	Static location factor	No scale	CLUE-S

Table 3.1 (Continued).

Component	Collection	Preparation	Scale	Source
	LULC 2003	LULC 2003	1: 10,000	Visual interpretation
	Area restriction file	Area restriction file	No scale	CLUE-S
Component 2:				
CLUE-S	CLUE-S model parameters	Validation	No scale	CLUE-S
optimization and validation	LULC 2013 by simulation	Validation	1: 10,000	CLUE-S
	LULC 2013 by visual interpretation	Validation	1: 10,000	Visual interpretation
Component 3:				
LULC simulation	LULC 2013	LULC 2013 visual interpretation	1: 10,000	Visual interpretation
with three scenarios	Land use requirements in 2023 by Scenario I	Definition of Scenario I	No scale	Rate of LULC change between 2003-2013
	Land use requirements in 2023 by Scenario II	Scenario of Scenario II	No scale	Agriculture production extension policy
	Land use requirements in 2023 by Scenario III	Scenario of Scenario III	No scale	Forest conservation and protection policy
Component 4:				
Impact assessment:	Rainfall data	Rainfall interpolation (R-factor)	No scale	TMD
soil erosion	Soil data	Soil type (K-factor)	1: 50,000	LDD
	DEM	Slope (LS-factor)	1: 50,000	RTSD

Table 3.1 (Continued).

Component	Collection	Preparation	Scale	Source
	LULC 2013 data	LULC 2013 Visual interpretation (C-factor) and (P-factor) comparison	1: 10,000	CLUE-S
	LULC 2023 simulation of Scenario I	LULC 2023 simulation's Scenario I (C-factor) and (P-factor)	1: 10,000	CLUE-S
	LULC 2023 simulation of Scenario II	LULC 2023 simulation's Scenario II (C-factor) and (P-factor)	1: 10,000	CLUE-S
	LULC 2023 simulation of Scenario III	LULC 2023 simulation's Scenario III (C-factor) and (P-factor)	1: 10,000	CLUE-S
Component 4:				
Impact assessment:	DEM	Elevation	1: 50,000	RTSD
water yield	Rainfall data	Rainfall interpolation	No scale	TMD
	Soil data	Soil type	1: 50,000	LDD
	Runoff data (2000-2011), Gage height (2001-2011), climatology data (2002-2013)	Calibration	No scale	RID, TMD
	LULC 2003 by visual interpretation	Calibration	1: 10,000	Visual interpretation
	LULC 2013 by visual interpretation	Comparison	1: 10,000	Visual interpretation
	LULC 2023 simulation of Scenario I	LULC 2023 simulation's Scenario I	1: 10,000	CLUE-S
	LULC 2023 simulation of Scenario II	LULC 2023 simulation's Scenario II	1: 10,000	CLUE-S
	LULC 2023 simulation of Scenario III	LULC 2023 simulation's Scenario III	1: 10,000	CLUE-S

Table 3.1 (Continued).

Component	Collection	Preparation	Scale	Source
Component 4:				
Impact assessment:	LULC 2013	Present value each a LULC types	1: 10,000	Visual interpretation
economic value	LULC 2023 simulation's Scenario I	Present value each a LULC types	1: 10,000	CLUE-S
	LULC 2023 simulation's Scenario II	Present value each a LULC types	1: 10,000	CLUE-S
	LULC 2023 simulation's Scenario III	Present value each a LULC types	1: 10,000	CLUE-S
Component 5:				
An optimal land	Soil erosion 2023 's Scenario I	Reclassification	1: 10,000	USLE
use allocation	Soil erosion 2023 's Scenario II	Reclassification	1: 10,000	USLE
	Soil erosion 2023 's Scenario III	Reclassification	1: 10,000	USLE
	Water yield 's Scenario I	Reclassification	1: 10,000	SWAT
	Water yield 's Scenario II	Reclassification	1: 10,000	SWAT
	Water yield 's Scenario III	Reclassification	1: 10,000	SWAT
	Economic value 's Scenario I	Reclassification	1: 10,000	PV
	Economic value 's Scenario II	Reclassification	1: 10,000	PV
	Economic value 's Scenario III	Reclassification	1: 10,000	PV

3.2 Methodology

Research methodologies are designed to serve the main objectives of the research which are concerned to assess LULC and its change, to identify driving force for LULC change, to optimize local parameter of CLUE-S model for LULC scenario simulation, to assess and evaluate impact of LULC change on soil erosion, water yield and economic value for an optimal LULC in different scenarios allocation. Schematic diagram of research methodology of the study is displayed in Figure 3.1. It consists of one common activity and 5 research components.

(1) Component 1. Historical and recent LULC extraction and driving force identification,

(2) Component 2. Local parameter of CLUE-S optimization and validation,

(3) Component 3. LULC simulation with three scenarios,

(4) Component 4. Impact assessment and evaluation: soil erosion, water yield, and economic value.

(5) Component 5. An optimal land use allocation.

3.2.1 Component 1. Historical and recent LULC extraction and driving force identification

Component 1 consists of two sub-components: historical and recent LULC extraction and driving force identification. For historical and recent LULC extraction, LULC in 2003 and LULC 2013 are visually interpreted from color orthoimage and Thaichote data, respectively by digitized via the screen at the scale of 1:10,000. The interpreted LULC in 2003 are used as baseline for LULC in 2013 simulation by

CLUE-S model while the interpreted LULC in 2013 is used to identify an optimum local parameter of CLUE-S model.

In addition, accuracy assessment is performed for LULC in 2013 based on referenced LULC data from field survey by overall accuracy and Kappa hat coefficient of agreement. Number of samples and sampling method scheme is firstly decided and error matrix is then constructed for accuracy assessment. Sample sizes herein are based on the binomial probability theory by Fitzpatrick-Lins (1981) and stratified random sampling scheme is applied in the study. Schematic diagram for input, process and output of sub-component 1 displayed in Figure 3.2.

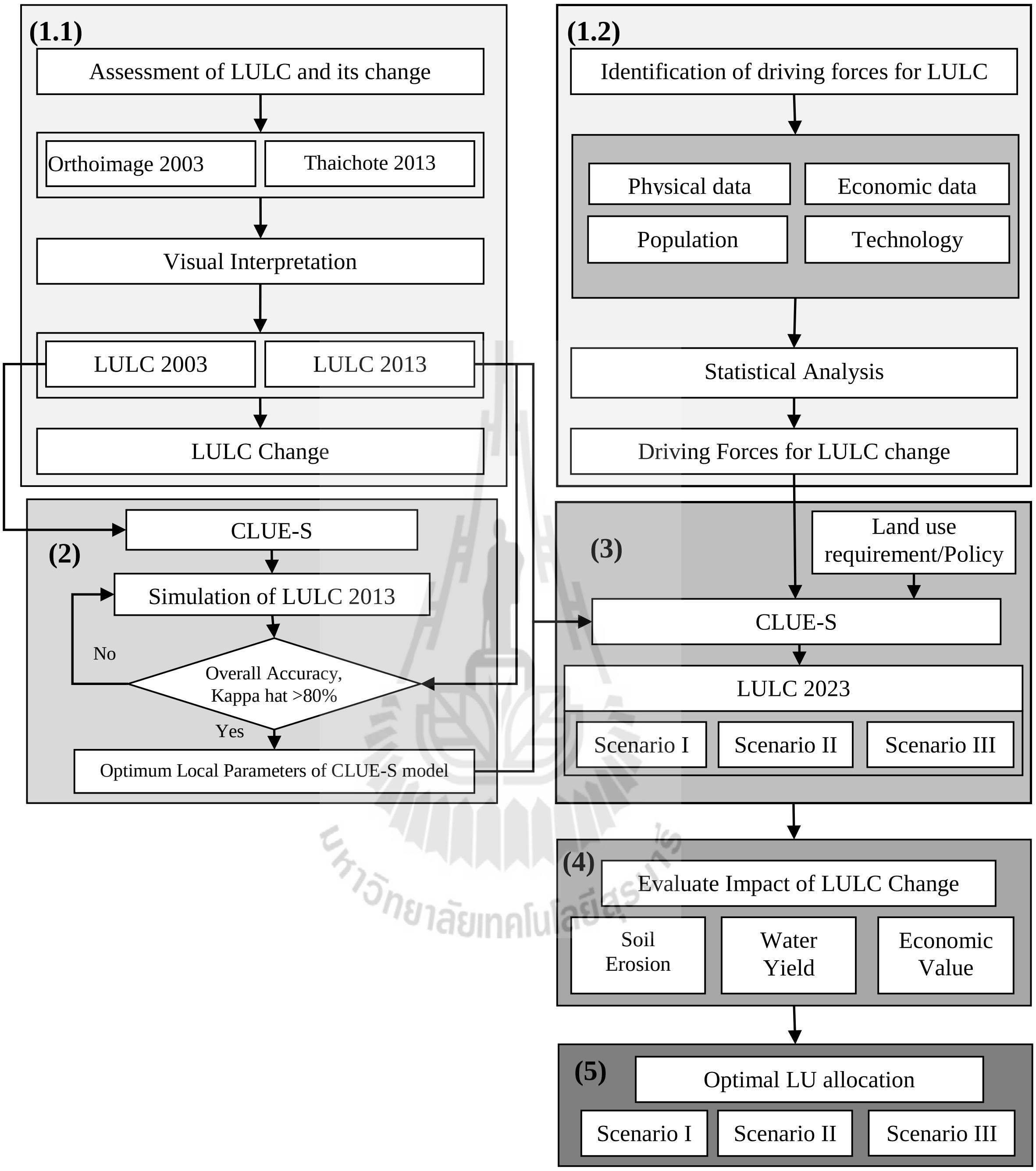


Figure 3.1 Overview of research methodology.

At the same time, driving force for LULC change is reviewed from previous studies (Table 3.2) and identify for stepwise regression analysis. The selected driving force (bio-physical, demographic, economic data and technology) include elevation, slope, aspect, distance from road, distance from stream, income, population density, annual rainfall, soil drainage, and watershed class. Herewith, stepwise binary logistic regression model is applied to predict driving force for LULC change. Verburg et al. (2005) stated that analysis of driving factors on statistical method is used to reveal and quantify the relations between the locations of land use and a set of explanatory factors. The set of explanatory factors is based upon the user's knowledge of the dominant factors causing land use change in the study area.

Table 3.2 Driving force for LULC change from preliminary study.

Study site	No. of driving force	Detail	Researcher (year)
Brazilian Amazon	10	Slope, geomorphology, lithology, soils, land suite, precipitation, cost distance to (main urban areas, mining areas and sawmills), population density and income	De Souza Soler, Verburg and Veldkamp (2007)
Central America	10	Land use index, land use change, distribution of crop, areas affected by erosion compaction and Stalinization, land use projections, deforestation, forest surface, forest fragmentation and reforestation	Farrow, and Winograd (2001)
China	6	Urbanization rate, distance to town, slope, elevation, distance to road, and population density	Zheng et al. (2012)
Kenya	6	Elevation, slope, distances to rivers and towns, and lithology (igneous, metamorphic and sedimentary rocks) Population,	Githui, Mutua and Bauwens(2009)
Philippines and Malaysia	11	Geology, Erosion vulnerability, distance to (stream ,to road ,to coast and to port), and Population density	Verburg et al. (2002)
South Korea	14	Dem, aspect, slope, soil depth, soil drain, soil type, environmental conservation value of national land, distance to (city, highway, national park and local road); Restrict condition to (agricultural promotion zone, ecological zone and preservation zone)	Oh, Yoo, Lee and Choi (2011)
Taiwan		Altitude, slope, distance to (major roads, river, built-up land and urban planning areas), soil drainage, soil erosion coefficient, and population density.	Lin,Lin, Wang, and Hong (2008)
Thailand	8	Altitude, slope, distance to (main roads, streams, village, city), Soil types and population density.	Trisurat, Alkemade and Verburg (2010)
West of Africa	11	Distances from (road, stream and forest), finally distance from settlement and population density (fertile soil, fuel wood collection, grazing in forests (settlements), subsistence agriculture, logging, population growth, and migration)	Orekan (2007)

Therefore these are the explanatory factors in the statistical analysis based on the biophysical and socio-economic conditions of a location the relative probability of finding the different land use types at that location is defined. In this study, this operation is processed using SPSS software. Driving forces that have no significant contribution to the explanation of the LULC change is excluded from the final regression equation.

Besides the test of driving forces with LULC types for probabilities, the goodness of fit for logistic regression is evaluated by receiver operating characteristic (ROC). The ROC characteristic is a measure for the goodness of fit of a logistic regression model similar to the R^2 statistic in ordinary least square regression (Pontius and Schneider, 2001 and Swets, 1986). The ROC is based on a curve relating the true-positive proportion and the false-positive proportion for the complete range of cut-off values in classifying the probability. A completely random model gives a ROC value of 0.5, while a perfect fit results in a ROC value of 1.0. The ROC curve can be defined under "Graphs -ROC curve" (Verburg et al., 2005). Schematic diagram for input, process and output of sub-component 1 is displayed in Figure 3.3.

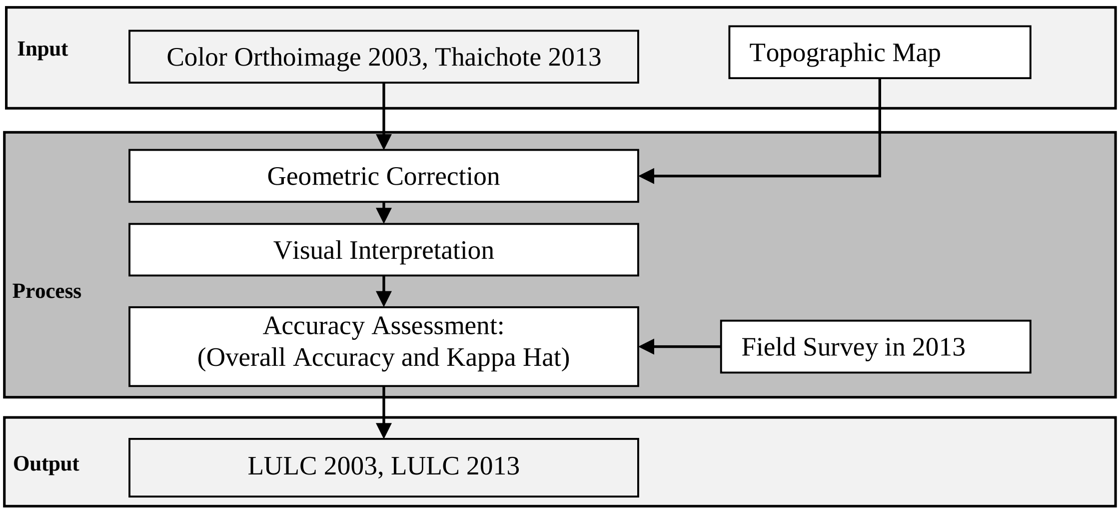


Figure 3.2 Methodology for historical and recent LULC extraction.

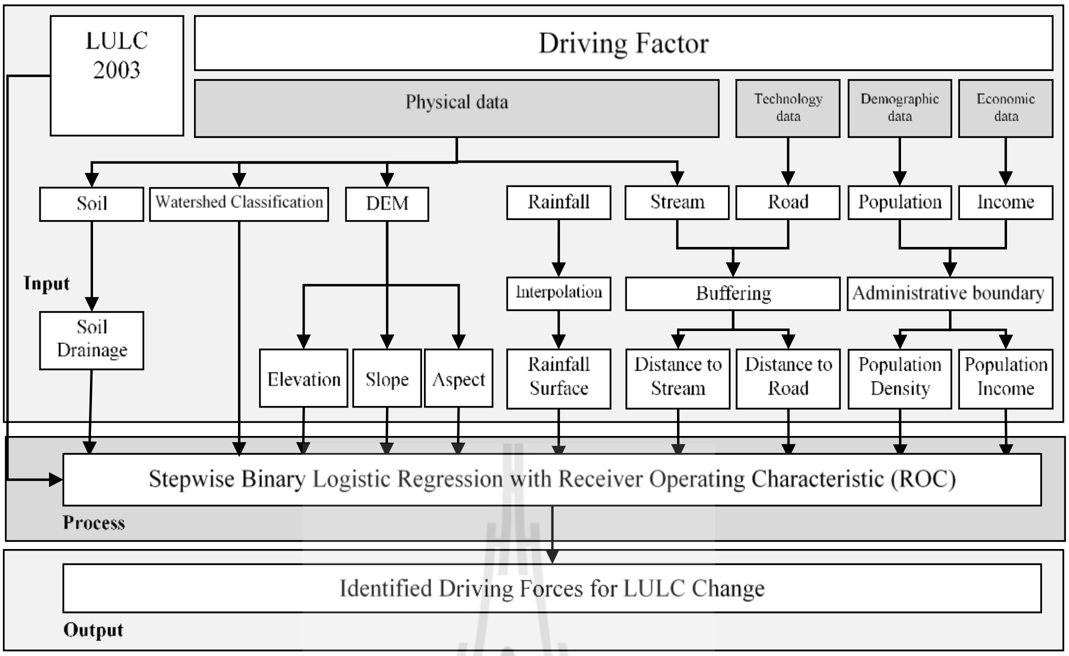


Figure 3.3 Methodology for driving force identification.

3.2.2 Component 2. Local parameter of CLUE-S optimization and validation

Under the component 2, the extracted significant driving factors for LULC change from the previous component is applied as initial land use allocation in 2013 under CLUE-S model. Description of parameter file of CLUE-S model is summarized as shown in Table 3.3.

In this study, an optimum local parameter of CLUE-S model is identified by comparison between the simulated LULC in 2013 from CLUE-S model and the interpreted LULC in 2013 from Thaichote data using Kappa analysis. If the overall accuracy and Kappa hat coefficient of agreement between the simulated LULC in 2013 and actual LULC in 2013 is equal or more than 80 percent, the assigned parameter values of elasticity and conversion matrix are acceptance as optimum local parameters of CLUE-S model. This CLUE-S configuration then applies for LULC in 2023 simulation with triple scenarios based on historical land use evolution, agriculture production extension and forest conservation and prevention in the next component. Schematic diagram for input, processing, and output of component 2 is illustrated in Figure 3.4.

Table 3.3 Description of local parameters optimization of CLUE-S model.

Filename	Description
MAIN.1	**Main parameters file**. Listed on exactly 19 lines. Some parameters settings will dictate whether the optional files must be specified or not.
ALLOC1.REG	**Regression parameters**. Length of file depends on number of land use types and location factors.
ALLOC2.REG	**Neighbourhood results**. These are additional regression parameters based on the enrichment factor equation. (It will be used if it requires)
ALLOW.TXT	**Change matrix**. The number of rows and columns equal the land cover types, here 5 X 5
NEIGHMAT.TXT	**Neighbourhood settings**. Defines the shape and size (in the form of a small weight matrix) of the analysis neighbourhood for every land use type. (It will be used if it requires)
REGI*.*	**Area restriction file**. A grid that defines where land use changes can and cannot occur. The * is a wildcard here; it does not indicate the simulate year. All active cells must have the value 0, restricted cells a value of –9998, and all others cells –9999 (No data).
DEMAND.IN*	**Land use requirements**. Calculated at the aggregate level and organized by rows (simulated years starting at 0) and columns (for every land use types). The * denotes a unique number, not simulated year.
COV_ALL.0	**Initial land use**. A grid of all land use types at the start (year 0). Grid values must match the land use codes listed in the main parameters file.
SC1GR#.FIL	**Static location factor grid**, where # is the number of the location factor
SC1GR#.*	**Dynamic location factor grid**, where # is the number of a location factor. The * is the simulated year starting at 0, not a wildcard. (It will be used if it requires)

Source: Adapted from Luijten, Miles and Cherrington (2006)

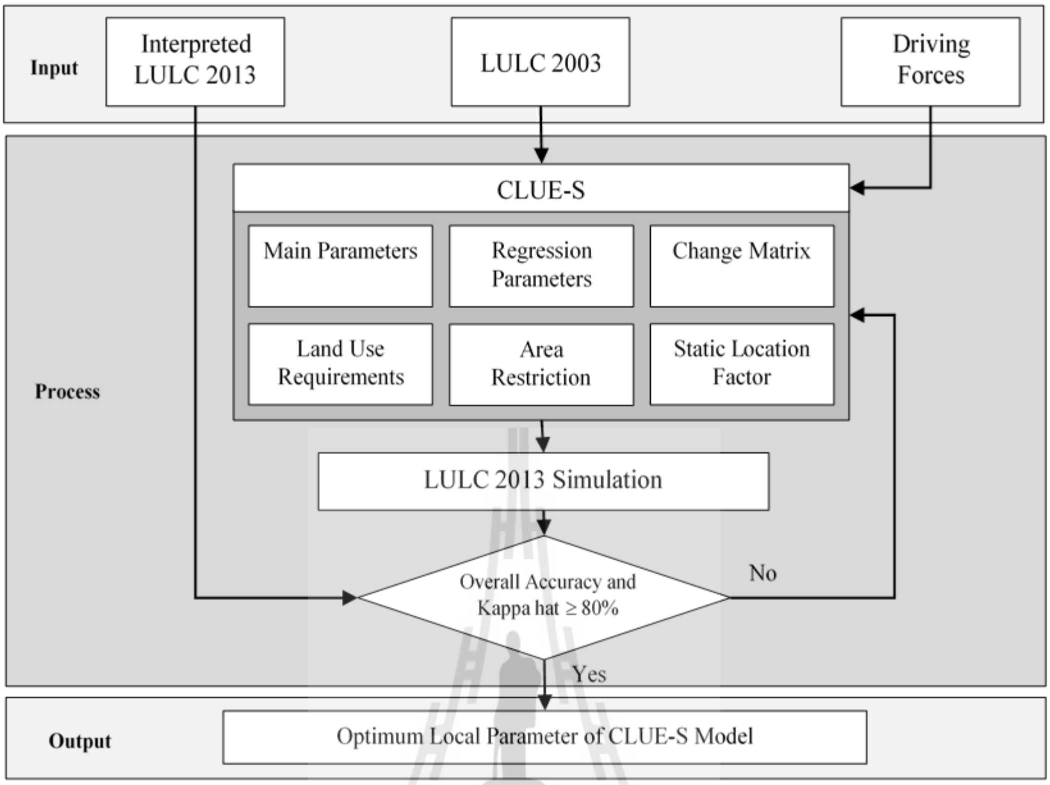


Figure 3.4 Local parameter of CLUE-S optimization and validation.

3.2.3 Component 3 LULC simulation with three scenarios

Basically, scenario definition describes about story line of the study area for the conversion of land use. It can define by historical record or condition of economic and conversation aspects as land use requirement (land demand). In this study, three scenarios are defined for LULC change simulation in 2023 including (1) historical land use evolution, (2) agriculture production extension, and (3) forest conservation and prevention.

Scenario I: Historical land use evolution. The land use requirement (land demand) for LULC in 2023 simulation is based on annual change rate of each LULC class between 2003 and 2013.

Scenario II: Agriculture production extension. Under this scenario, government policy for alternative energy in the future is firstly reviewed and transformed into land demand for energy crops: cassava and sugarcane. Meanwhile, national park and watershed class I is preserved as a restriction areas for LULC in 2023 simulation under CLUE-S model.

Scenario III: Forest conservation and prevention. In contrast to the Scenario II, the existing government policy on forest conservation and prevention is investigated and transformed into forest land demand. Herewith boundary of national park, watershed class I and II and an existing forest area in 2013 is used as forest land demand for LULC simulation under CLUE-S model.

In practice, parameters for land allocation include (1) spatial policies and restrictions, (2) land use type specific conversion setting with conversion elasticity and land use transition sequences, and (3) land use requirement are required under CLUE-S model. Schematic diagram for input, processing, and output of component 3 is depicted in Figure 3.5.

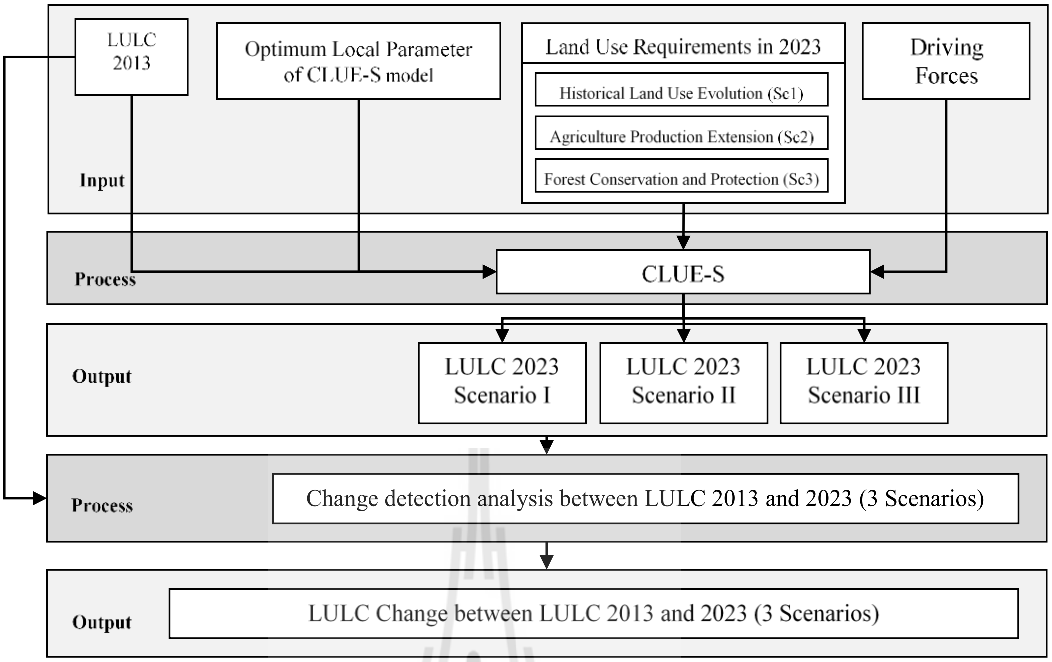


Figure 3.5 Methodology for LULC simulation with three scenarios.

3.2.4 Component 4. Impact assessment: Soil erosion, water yield, and economic value

This component is the one of major component for the research methodology which are composed of three models: USLE, SWAT and PV models for impact assessment due to LULC change. Under this component LULC in 2013 by visual interpretation is firstly used to estimate soil loss using USLE model, water yield using SWAT model with SCS-CN method and economic value with present value (PV). Similarly, the triple derived simulated LULC scenario in 2023 by CLUE-S model are also used to estimate soil loss, water yield and economic value with corresponding models. After that the results about soil loss, water yield and economic value from year 2013 are compared with the results from triple LULC scenarios from year 2023 for impact assessment. Schematic diagram for input, processing, and output of component 4 is illustrated in Figure 3.6.

In practice, additional required data for estimation of soil loss by USLE model, water yield by SWAT model with SCS-CN method and economic value with PV from the interpreted LULC in 2013 and simulated LULC in 2023 of three scenarios are compiled from the concerned government agencies.

For USLE model, rainfall-runoff erosivity (R), soil erodibility (K) and slope length (L) and steepness (S) factors are assumed as static for two periods while vegetation cover (C) and conservation support-practice (P) factors are dynamic as LULC change. Herein, average annual rainfall between 2003 and 2013 is applied for soil loss estimation in 2013 and 2023. The summary procedure for generating USLE factors are as follows:

For R-factor, equation defined by LDD (2000b) for Northeastern Region of Thailand has been adopted in this study as:

$$R = 0.4669\ X - 12.1415. \qquad (3.1)$$

Where, R is rainfall-runoff erosivity factor in MJ mm/ha/h per year and X is average annual rainfall (mm). In this study, Inverse Weighted Distance (IDW) has been used to interpolate the derived R value at four meteorological stations to be continuous data with grid cell of 25 m.

For K factor, soil erodibility which is related to soil texture of soil group data was adopted from standard value of LDD (2000b) as summary in Table 3.4.

Table 3.4 Soil erodibility (K) value based on soil texture using in USLE.

Soil Group	Soil Texture	Soil erodibility (K) value
17	sandy clay loam	0.20
25	loam	0.35
29	silty clay	0.23
31	silt loam	0.37
35	sandy loam	0.29
40	loamy sand	0.04
46	clay loam	0.25
47	clay	0.13
48	loam	0.35
52	silty clay loam	0.46
55	silt loam	0.37
56	loam	0.35
62	loam	0.35

Source: LDD (2000b)

For Slope length and steepness factor (LS), the reviewed equations is used to prepare LS factor from DEM as follows:

(a) Slope Length,

$$L = (\lambda/22.13)^m, \quad (3.2)$$

Where, m is a variable slope-length exponent related to the ratio β of rill erosion (caused by flow) to interrill erosion (principally caused by raindrop impact) by the following equation (Foster *et al*., 1977):

$$m = \beta / (1 + \beta) \quad \text{and} \quad (3.3)$$

β can be computed from (McCool *et. al*., 1989) as:

$$\beta = (\sin\theta / 0.0896) / (3.0 (\sin\theta)^{0.8} + 0.56) \quad (3.4)$$

(b) Steepness factor, S is computed from (McCool et al., 1987) as:

$$S = (10.8 \sin\theta + 0.03) \text{ for slope} < 9\% \quad (3.5)$$

$$S = (16.8\sin\theta - 0.5) \text{ for slope} \geq 9\% \quad (3.6)$$

Where, λ = Slope Length (cell size in meters) and θ = slope gradient map (degree)

For vegetation cover (C) and conservation support-practice (P) factors, these factors which are related to LULC data were adopted from standard value of LDD (2000b) as summary in Table 3.5.

Table 3.5 Value of C and P factors for LULC type using in USLE.

LULC Type	Vegetation cover (C)	Conservation support practice (P)
Urban and built up land	0.000	0.0
Paddy field	0.280	0.1
Cassava	0.525	1.0
Maize	0.525	1.0
Sugarcane	0.525	1.0
Perennial tree/ orchard	0.150	1.0
Forest land	0.003	0.1
Water body	0.000	0.0
Miscellaneous land	0.015	1.0

Source: LDD (2000b)

Similarly, for SWAT model with SCS-CN method, DEM and soil are assumed as static data for two periods while rainfall is dynamic as LULC change. In the study, actual daily rainfall in 2013 is applied for local optimum parameter of SWAT model to generate CN value and average annual rainfall between 2003 and 2013 is applied for water yield estimation in 2013 and 2023 by SCS-CN method. In this sub-component, SWAT model is used to generate CN value for each hydrologic response unit (HRU) while SCS-CN method is used to estimate water yield.

For economic value using PV, present value of price and yield of agricultural land use types (paddy field, sugarcane, cassava, maize) are compiled from Agricultural Situation between 2006 and 2013 of OAE and perennial trees from Market

Organization for Farmers. Meanwhile, price and yield value of forest is compiled from the Technical report of Royal Forest Department by Wittawatchutikul and Jirasuktaveekul (2005). All of complied prices and yields are here used to predict economic value of LULC in 2023 for actual LULC in 2013 and three LULC scenarios.

Finally, impact assessment of triple LULC change scenarios on soil erosion, water yield and economic values changes are subsequently analyzed in term of gain as positive impact and loss as negative impact between 2013 and 2023. Details of workflow for impact assessment based on soil loss using USLE model, water yield using SWAT model with SCS-CN method and economic value using PV are presented in Figures 3.7 - 3.9, respectively.

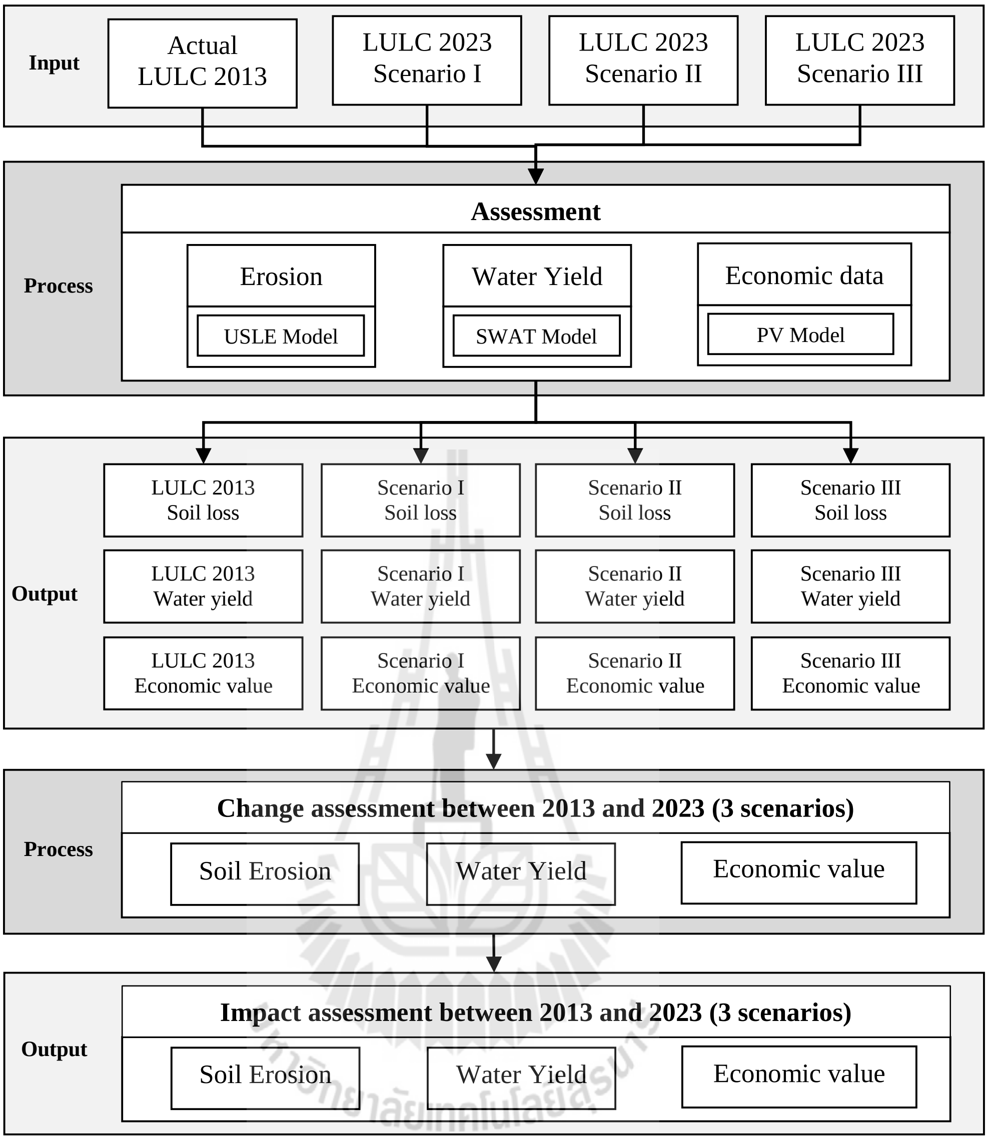


Figure 3.6 Overview of impact assessment and evaluation component.

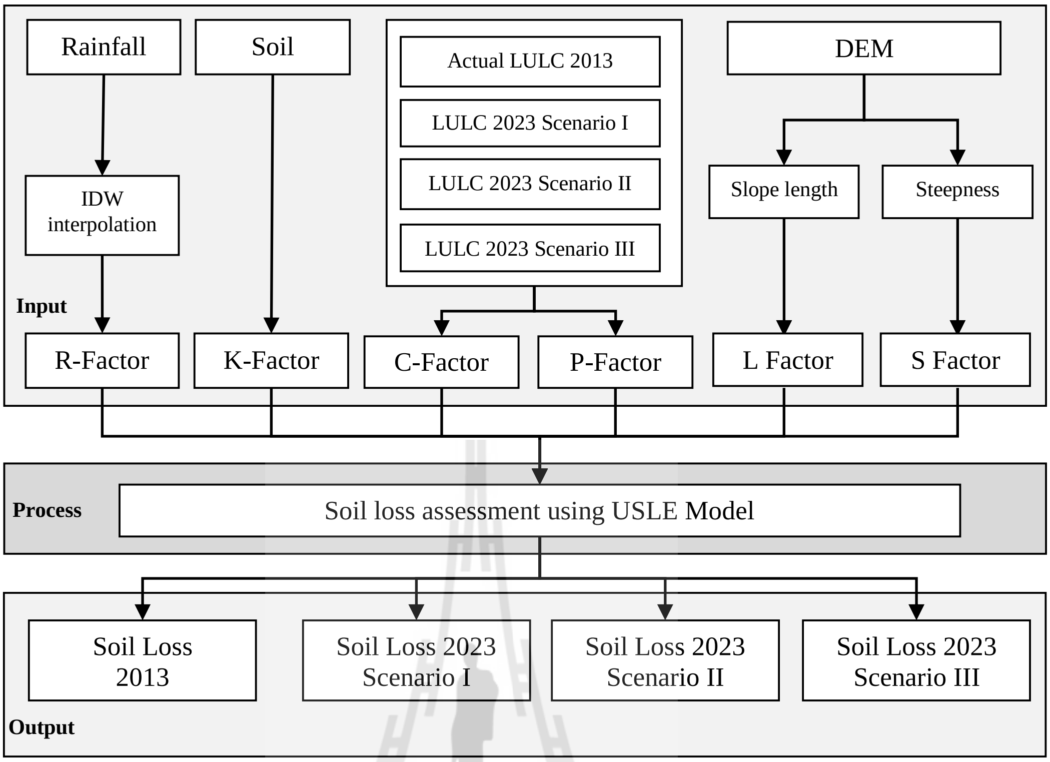


Figure 3.7 Methodology for soil erosion assessment and its impact by USLE model.

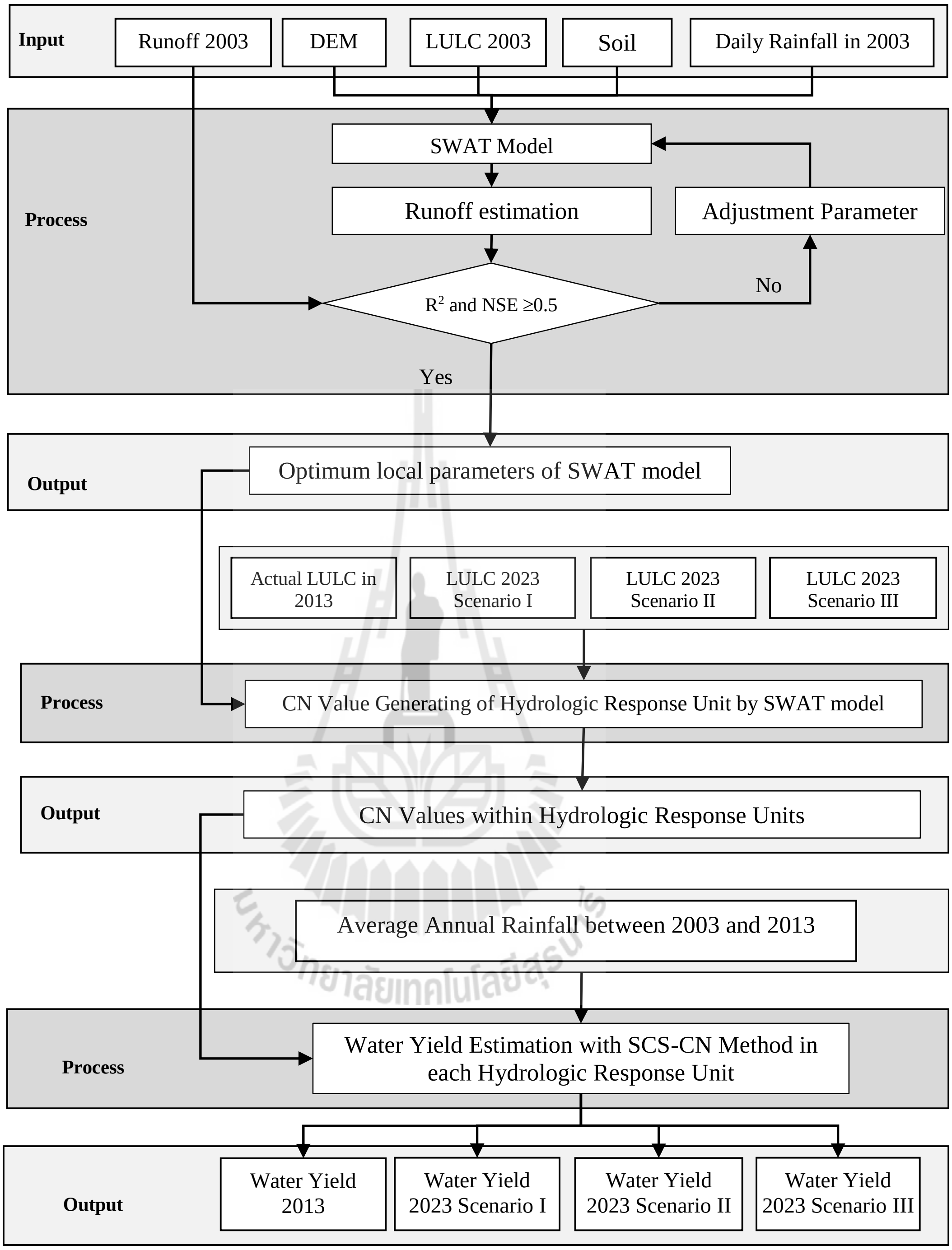


Figure 3.8 Methodology for water yield assessment and its impact by SWAT model and SCS-CN method.

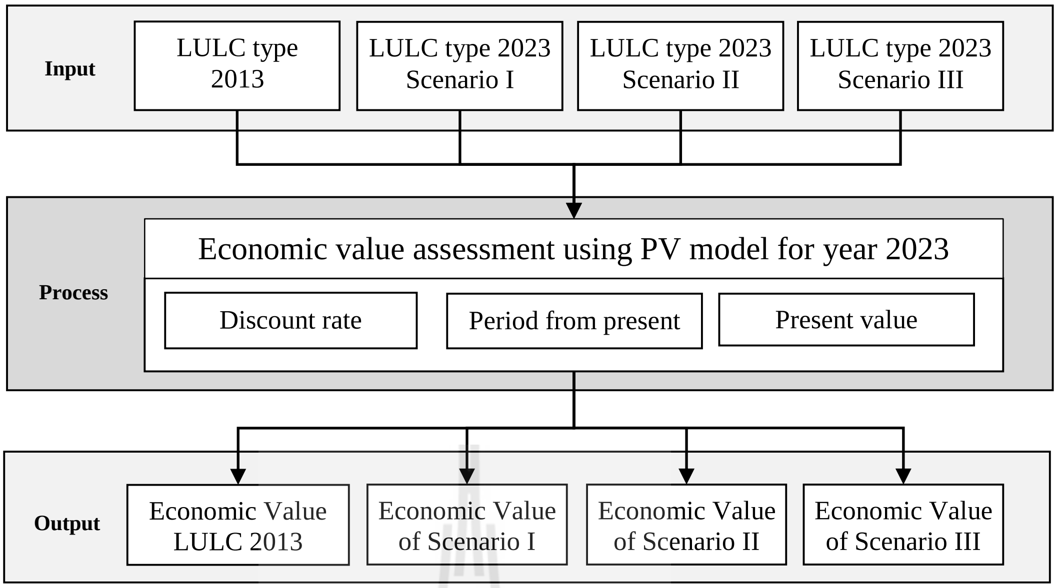


Figure 3.9 Methodology for economic assessment and its impact by PV model

3.2.5 Component 5. An optimal land use allocation

Under this component, extracted soil loss, water yield and economic values in triple scenarios in 2023 are combined based on MCDA basis to generate overall indices with SAW method. That the derived results are later classified as suitability classes (low, moderate, and high) for an optimal land use allocation according historical land use evolution, agriculture production extension and forest conservation and prevention scenarios.

In the study, areas of urban and built-up land, water body and miscellaneous in 2023 of each scenarios are excluded for optimal land use allocation under SAW operation because these areas are not used to estimate economic values. The normalization process for each criteria (soil loss, water yield, and economic data) are prepared according to its characteristics as following.

For soil loss data, which represents effect of LULC change on the land, is normalized based on score range procedure for cost criteria (Young, Rinner and Patychuk, 2010) as:

$$\acute{x}_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \tag{3.7}$$

Meanwhile, water yield which is here assigned for availability of water for certain area (pixel) indicates positive effect on the land. The water yield is normalized based on score range procedure for benefit criteria ((Young et al., 2010) as:

$$\acute{x}_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{3.8}$$

At the same time, economic value is normalized based on maximum score procedure for benefit criteria as:

$$x'_{ij} = x_{ij}/x_j^{max} \tag{3.9}$$

where

x'_{ij} is the standardized score for the i^{th} object and the j^{th} attribute;

x_{ij} is the raw score, $x_j^{\max}$ is the maximum score for the j^{th} attribute;

$x_j^{\min}$ is minimum score for the j^{th} attribute; and

$x_j^{\max} - x_j^{\min}$ is the range of a given criterion.

Then the standardized score for each criterion are combined using SAW method with the specific weight according scenario characteristics as follows:

For Scenario I: Historical land use evolution. The land use requirement (land demand) for LULC in 2023 simulation is based on annual change rate of each LULC class between 2003 and 2013. Weighting for soil loss, water yield and economic values based on relative importance are 1, 1, and 1, respectively.

For Scenario II: Agriculture production extension. Under this scenario, government policy for alternative energy in the future is transformed into land demand for energy crops: cassava and sugarcane. Weighting for soil loss, water yield and economic values based on relative importance are 1, 2, and 3, respectively.

For Scenario III: Forest conservation and prevention. The existing government policy on forest conservation and prevention is transformed into forest land demand. Weighting for soil loss, water yield and economic values based on relative importance are 3, 2, and 1, respectively.

Detail workflow for an optimized land allocation using MCDA basis and SAW method for triple scenarios are presented in Figure 3.10.

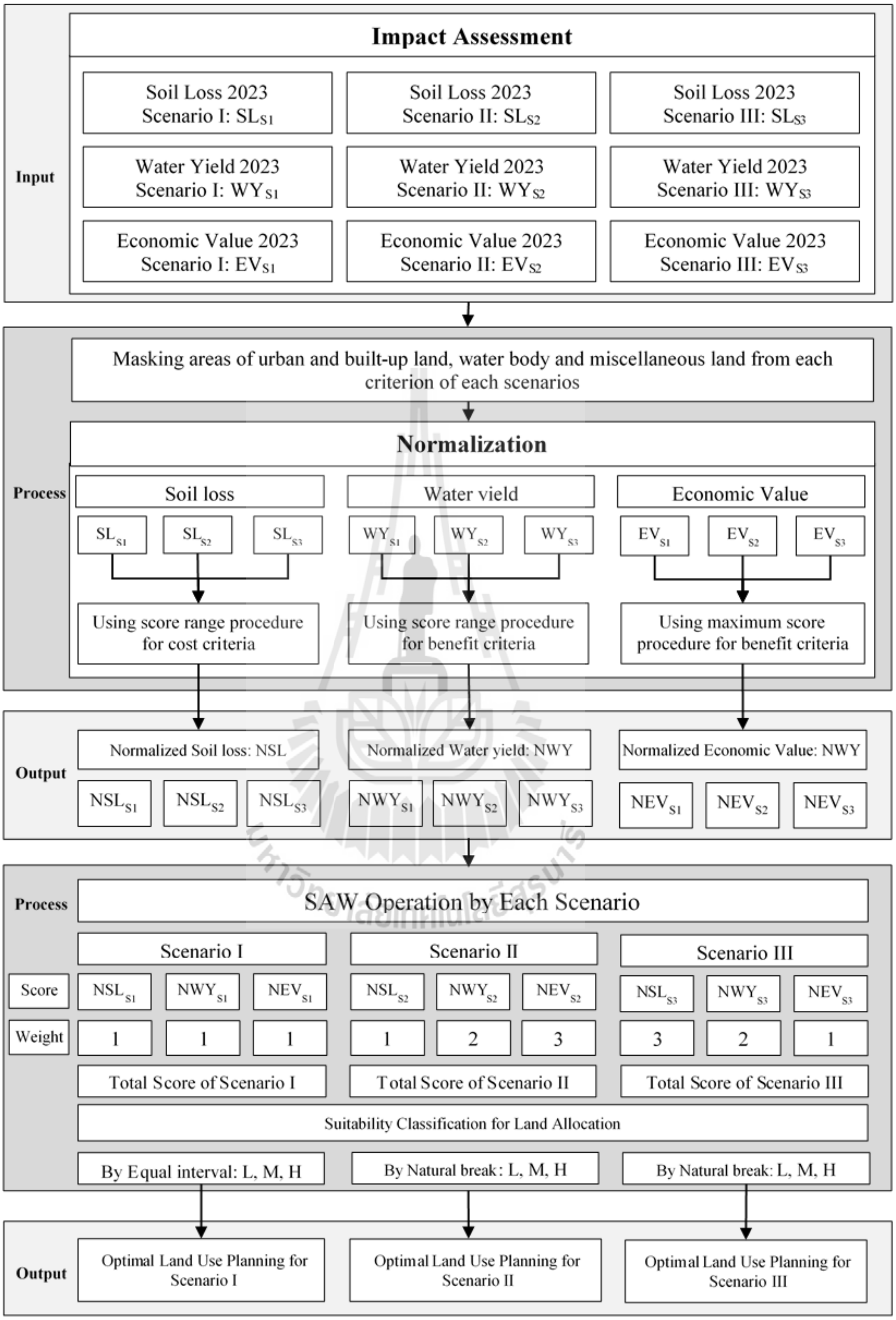


Figure 3.10 Methodology for an optimal land use allocation.

CHAPTER IV

LULC ASSESSMENT AND ITS CHANGE AND DRIVING FORCES FOR LULC CHANGE

All recent experiment results related to historical and LULC extraction with accuracy assessment of LULC in 2013 and driving force identification of LULC change for each LULC type were presented with discussions in this chapter.

4.1 Historical and recent LULC extraction

LULC data in 2003 as historical record and recent LULC data in 2013 which were visually interpreted from color orthoimage and THAICHOTE data, respectively were displayed in Figures 4.1 and 4.2, respectively. Meanwhile, area of each LULC type was compared as shown in Table 4.1 and Figure 4.3.

As results, it was found that major increasing LULC types were sugarcane and urban and built-up land with annual change rate of 171 and 66.5 ha per year, respectively and minor increasing LULC types were miscellaneous land, cassava, and water body with annual change rate of 28, 21.5 and 5.15 ha per year, respectively. In contrary major decreasing LULC types were perennial trees/orchard and maize with annual change rate of 128.5 and 108.9 ha per year, respectively and minor decreasing LULC type was forest land with annual change rate of 55.3 ha per year. Meanwhile, paddy field in this period was stable. The derived LULC change pattern of major LULC classes (urban and built-up land, agricultural land, forest land, water body and miscellaneous land) between 2003 and 2013 from the study was similar to land use change pattern of land use classes of LDD between 2008 and 2011 (see Figure 1.2).

In addition a transitional change matrix of LULC between 2003 and 2013 which provides from-to change class information was summarized as shown in Table 4.2 and displayed as LULC change map in Figure 4.4. Highlight from-to change class of energy crops (cassava and sugarcane) was also presented in Figure 4.5. As results, it was found that the exchangeable areas among field crops was existence. For example, areas of cassava in 2003 was changed to be maize and sugarcane in 2013 about 454 and 168 ha, respectively. Similarly, maize in 2003 was converted to be cassava and sugarcane in 2013 about 661 and 1,383 ha, respectively. However, sugarcane in 2003 was only changed to be maize in 2013 about 287 ha. These exchangeable areas might be relate to price, landform, labors, and available of water. According to report of LDD on economic crop zonation in 2009, sugarcane provide higher return than cassava and maize.

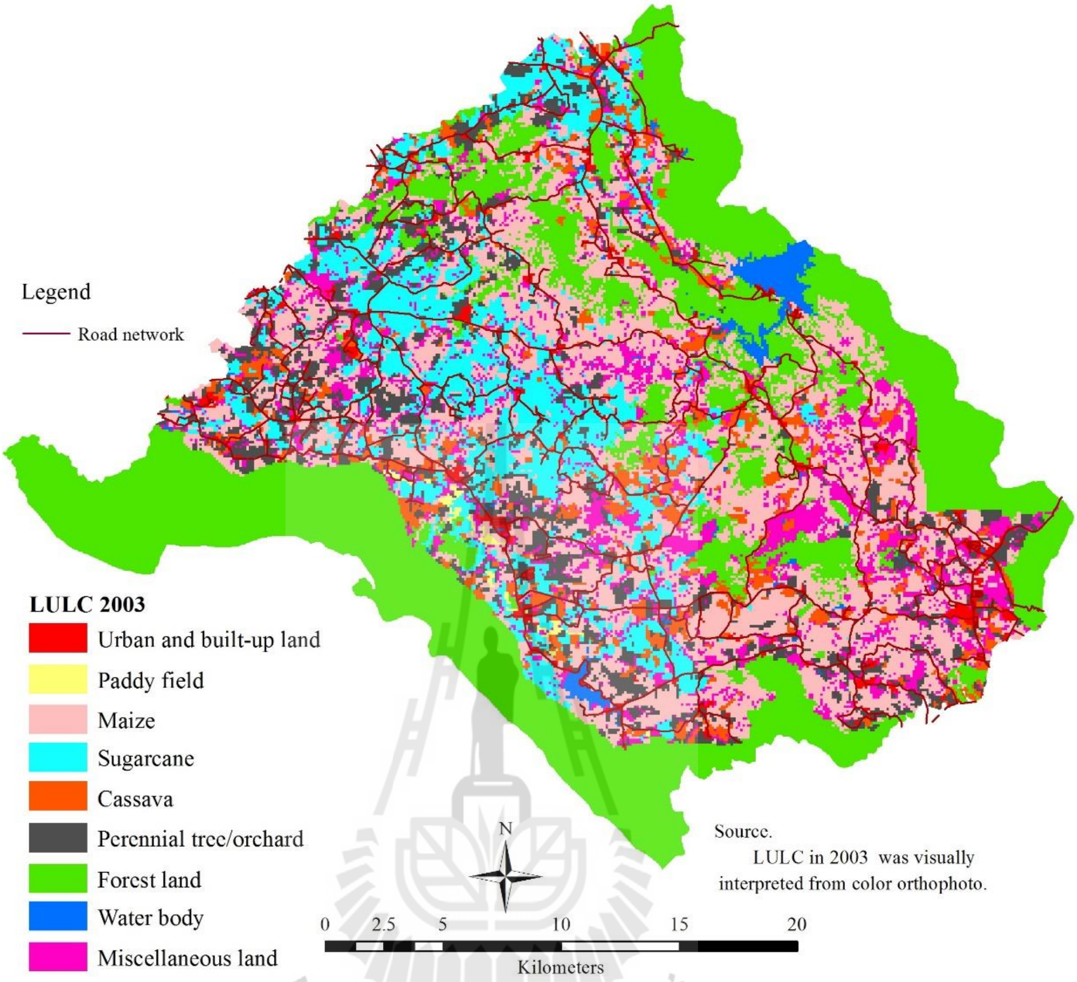


Figure 4.1 Distribution of LULC in 2003.

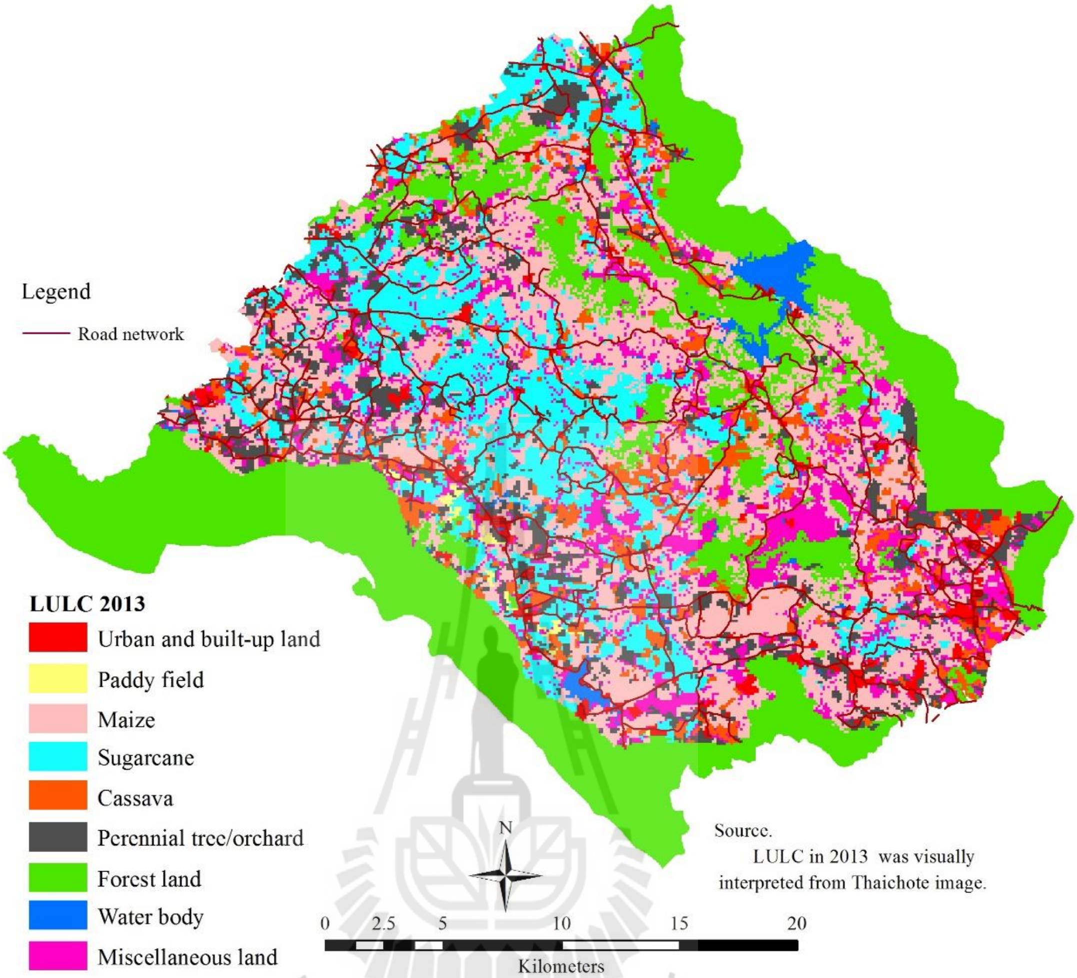


Figure 4.2 Distribution of LULC in 2013.

Table 4.1 Comparison of LULC change between 2003 and 2013.

LULC	Area in ha								
	UR	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**
In 2003	1,800	237	4,232	19,694	9,074	7,452	26,522	1,108	7,046
In 2013	2,465	237	4,446	18,603	10,786	6,167	25,970	1,165	7,326
Change area	665	0	214	-1,091	1,712	-1,285	-552	57	280
Annual change rate	66.5	0	21.4	-109.1	171.2	-128.5	-55.2	5.7	28
Percentage of change	36.92	0	5.08	-5.53	18.85	-17.25	-2.08	5.15	3.98

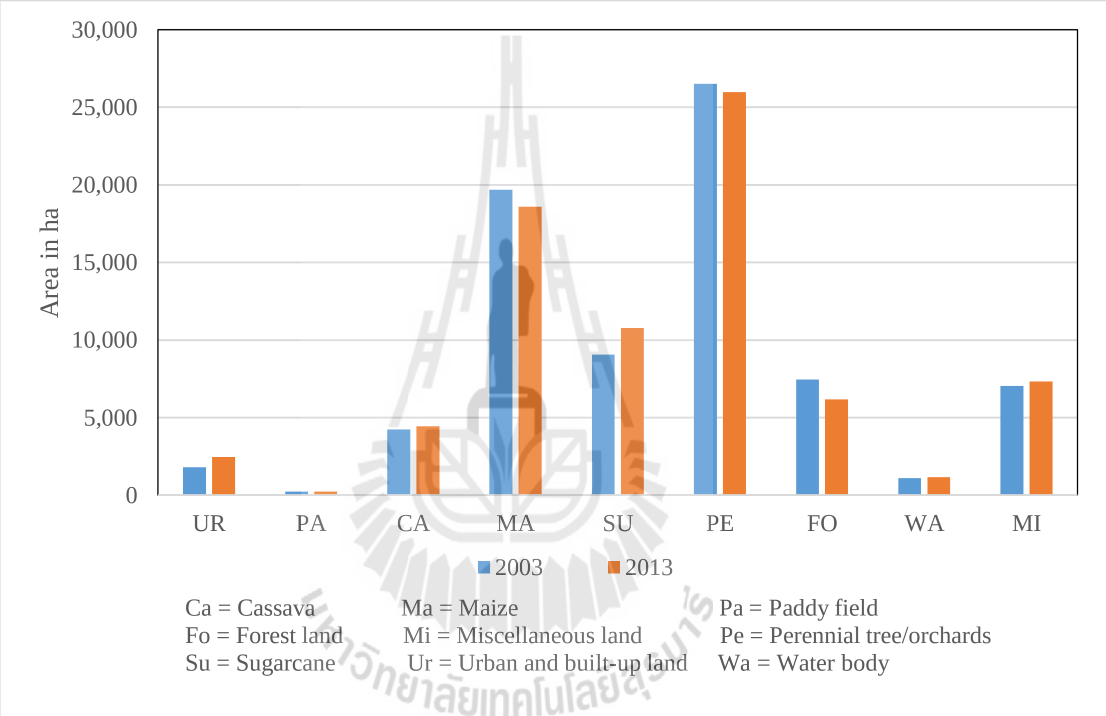


Figure 4.3 Area comparison of LULC types between 2003 and 2013.

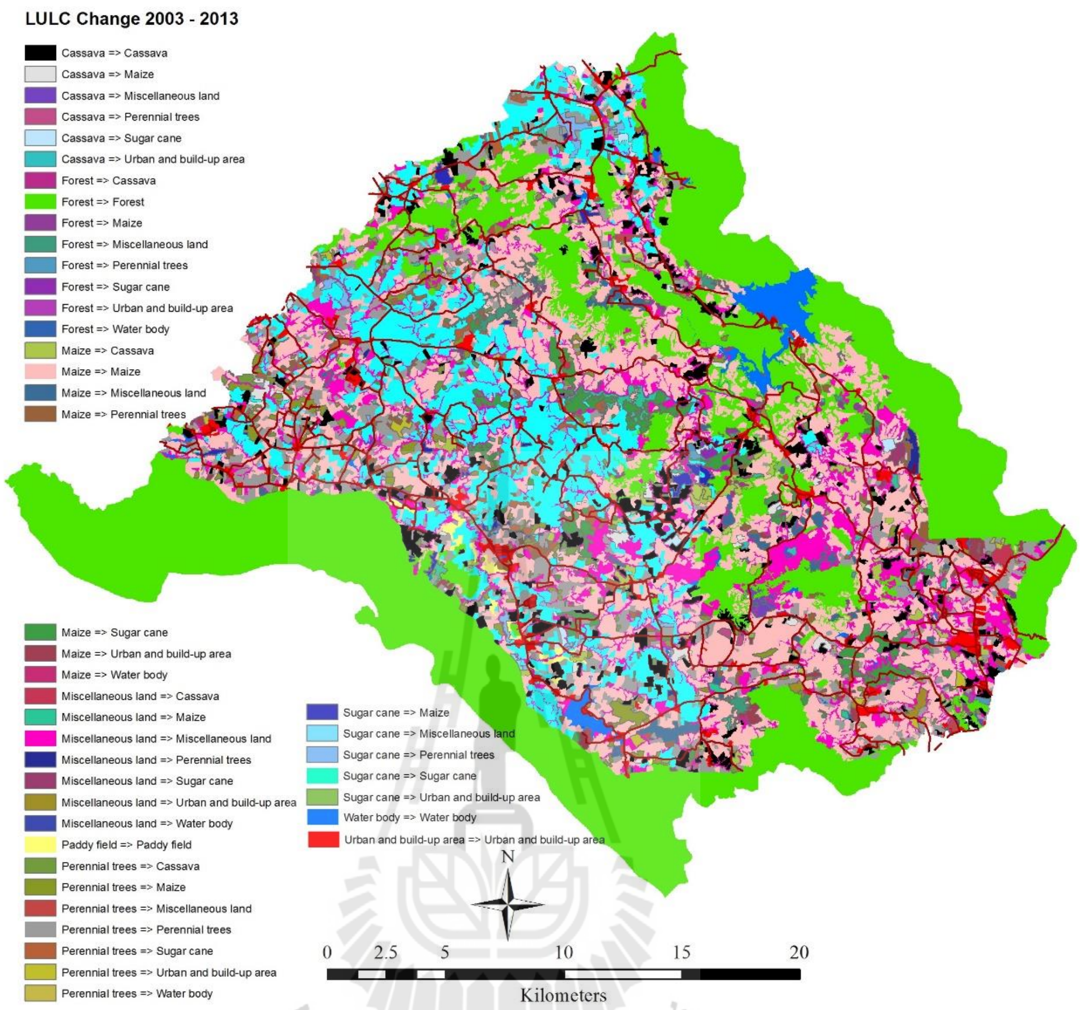


Figure 4. 4 Distribution of LULC change between 2003 and 2013.

Table 4.2 LULC change between 2003 and 2013 as transitional matrix.

		LULC 2013 (ha)									
	LULC types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
	Urban and built-up land (UR)	**1,800**	-	-	-	-	-	-	-	-	1,800
	Paddy field (PA)	-	**237**	-	-	-	-	-	-	-	237
LULC 2003 (ha)	Cassava (CA)	18	-	**3,316**	454	168	133	-	-	143	4,231
	Maize (MA)	313	-	661	**16,141**	1,383	551	-	8	637	19,693
	Sugarcane (SU)	21	-	-	287	**8,448**	293	-	-	25	9,074
	Perennial tree/orchard (PE)	163	-	340	1,165	659	**5,014**	-	2	109	7,452
	Forestland (FO)	17	-	28	174	34	42	**25,970**	10	247	26,523
	Water body (WA)	-	-	-	-	-	-	-	**1,108**	-	1,108
	Miscellaneous land (MI)	133	-	101	382	94	134	-	37	**6,165**	7,046
	Total	**2,465**	**237**	**4,446**	**18,603**	**10,786**	**6,167**	**25,970**	**1,165**	**7,326**	**77,165**

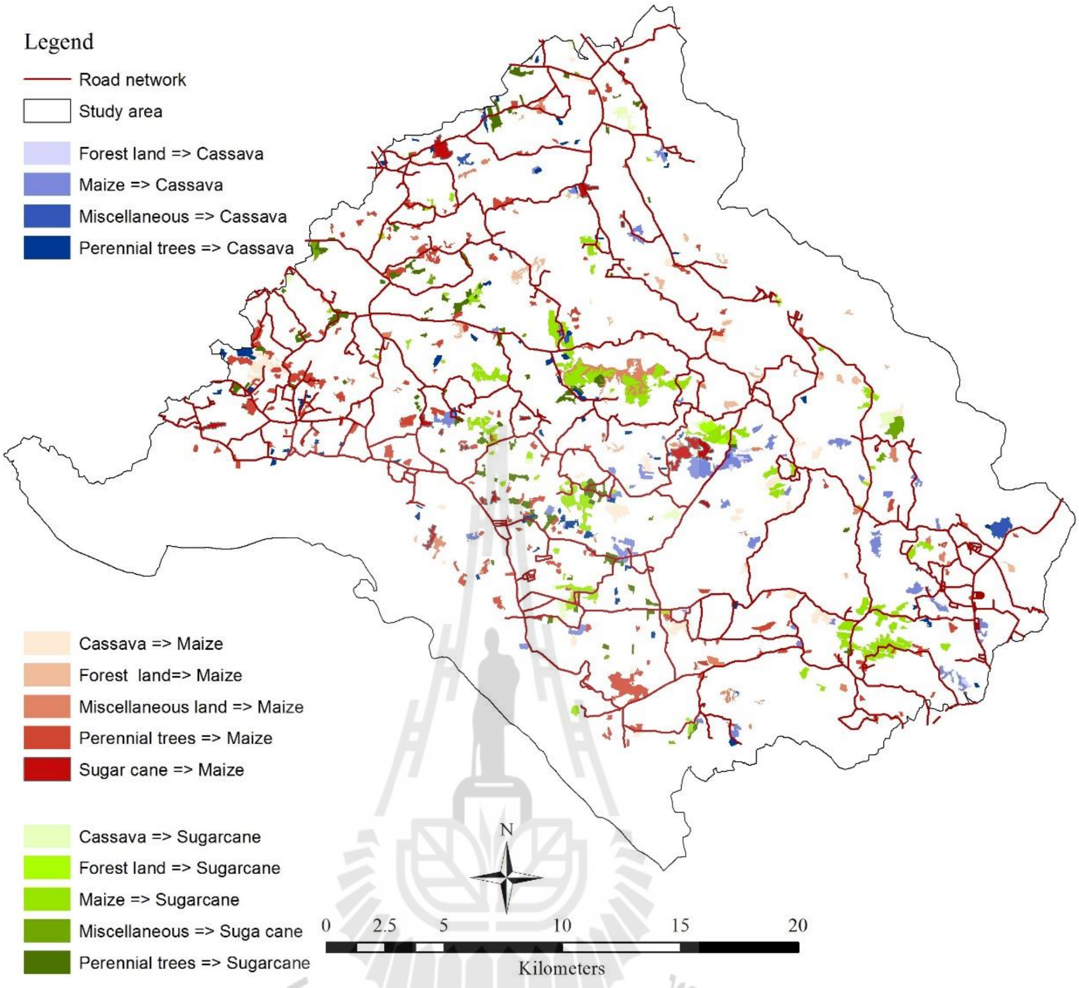


Figure 4.5 Highlight of from-to change information from various classes to cassava and sugarcane between 2003 and 2013.

4.1.1 Accuracy assessment of LULC in 2013

LULC data in 2013 which was visually interpreted from THAICHOTE data was assessed accuracy based on the stratified random sampling scheme with sample points of 203 points (Figure 4.6). Detail of sample point for accuracy assessment was represented in Table 1 of Appendix B. It was found that overall accuracy and Kappa hat coefficient were 90.15 and 87.21 percent, respectively (Table 4.3). Based on

Fitzpatrick-Lins (1981), Kappa hat coefficient more than 80 percent represents strong agreement or accuracy between the interpretation map and the ground reference information. In addition, producer's accuracy of most LULC types, which directly relates to omission error, provided accuracy more than 80 percent except cassava and miscellaneous land while user's accuracy of most LULC types, which directly relates to commission error, provided accuracy more than 80 percent except cassava. Because many areas of cassava grew more than one year and its appearance was similar a bush or scrub in miscellaneous land.

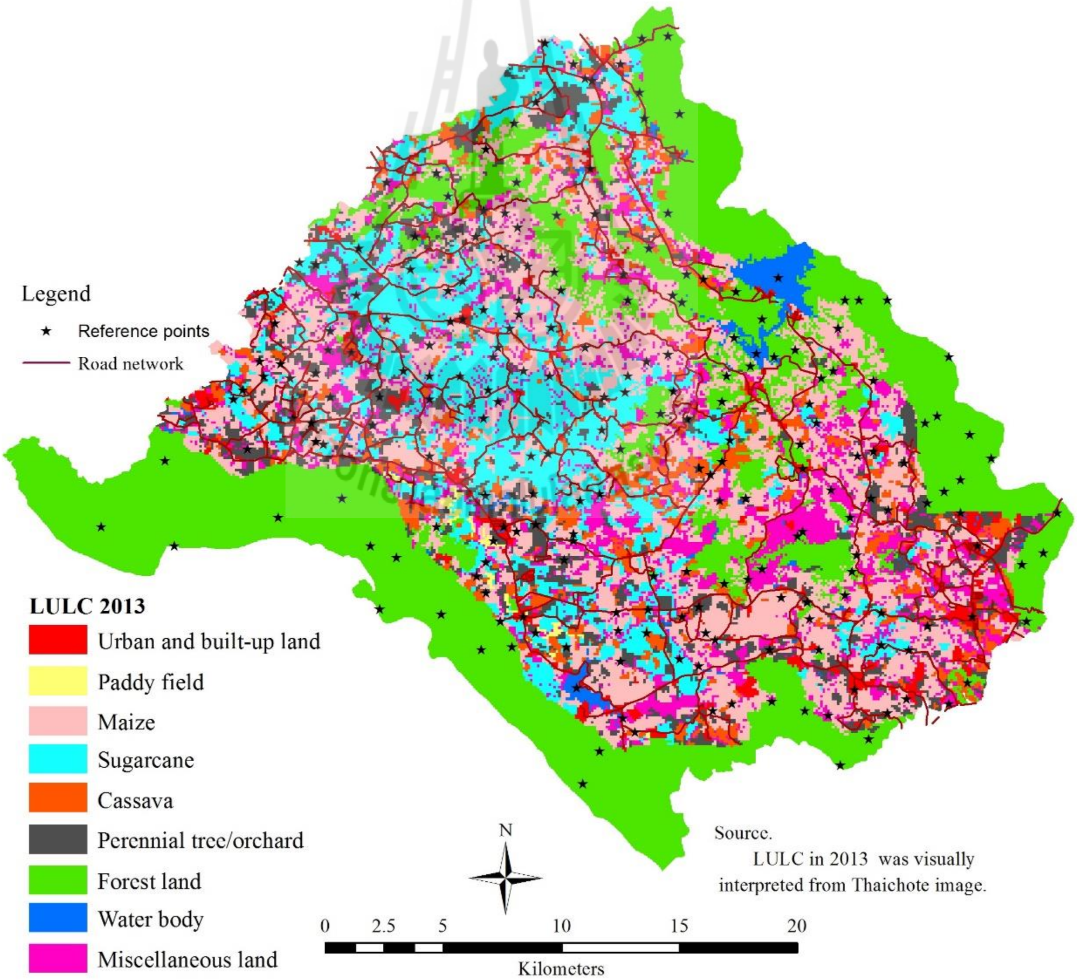


Figure 4.6 Distribution of sampling points for accuracy assessment.

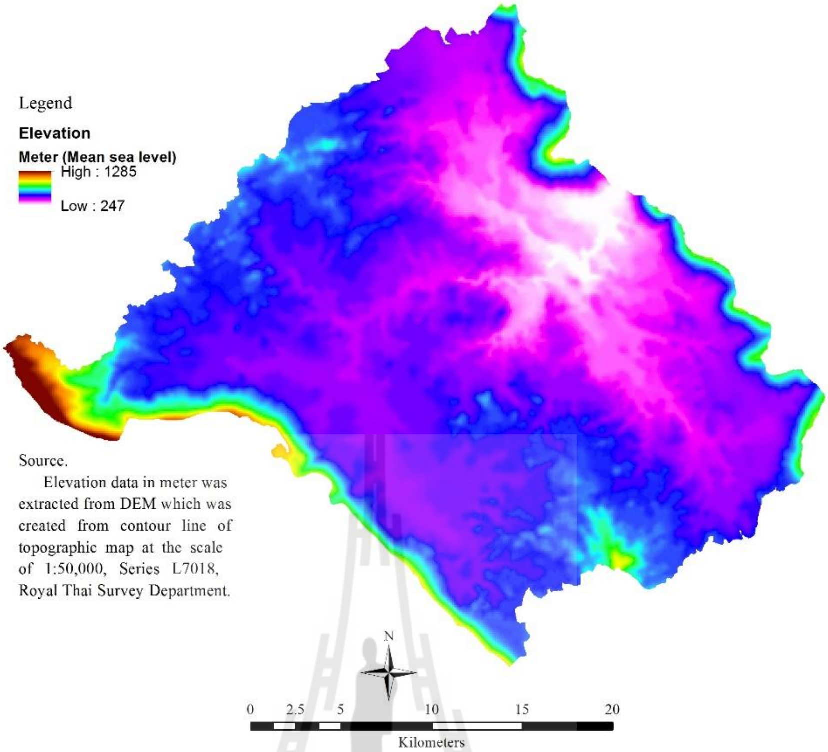
Table 4.3 Accuracy assessment between reference data and LULC 2013.

		Ground reference data in 2014									
	LULC types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**total**
Interpreted LULC data in 2013	Urban and built-up land (UR)	**7**	-	-	-	-	-	-	-	-	7
	Paddy field (PA)	-	**1**	-	-	-	-	-	-	-	1
	Cassava (CA)	-	-	**6**	2	-	-	-	-	-	8
	Maize (MA)	-	-	1	**47**	2	-	1	-	4	55
	Sugarcane (SU)	-	-	-	-	**24**	-	-	-	2	26
	Perennial tree/orchard (PE)	-	-	-	3	-	**17**	-	-	-	20
	Forest land (FO)	-	-	-	2	2	-	**69**	-	-	73
	Water body (WA)	-	-	-	-	-	-	-	**1**	-	1
	Miscellaneous land (MI)	-	-	1	-	-	-	-	-	**11**	12
	Total	**7**	**1**	**8**	**54**	**28**	**17**	**70**	**1**	**17**	**203**
	Producer's accuracy	100.00	100.00	75.00	87.04	85.71	100.00	98.57	100.00	64.71	
	User's accuracy	100.00	100.00	75.00	85.45	92.31	85.00	94.52	100.00	91.67	
	Overall accuracy	90.15									
	Kappa hat coefficient	87.21									

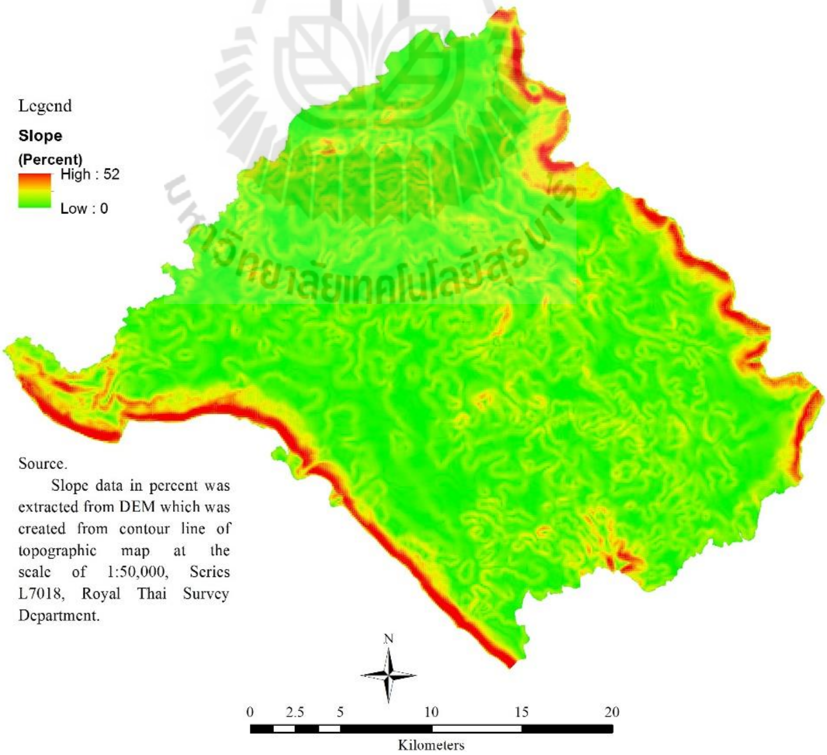
4.2 Driving force identification for LULC change

With reference to Section 3.2, selected driving factor for LULC change included elevation, slope, aspect, distance from road, distance from stream, income, population density, annual rainfall, soil drainage, watershed classes (Figure 4.7) were firstly prepared in raster format with cell size of 100 m. Then they used to identify driving force for each LULC type by stepwise binary logistic regression. The output of the identified driving force for each LULC type with Receiver Operating Characteristic (ROC) was summarized in Table 4.4. It was found that ROC which represents the goodness of fit for logistic regression analysis varied between 0.651 and 0.929 for miscellaneous land and paddy field, respectively. These values can be acceptable when they vary between 0.5 (completely random) and 1.0 (perfect discrimination) as suggestion by Pontius and Schneider (2001) and Swets (1986).

Details of driving force for each LULC and multiple linear regression equation from binary logistic regression analysis were separately explained in the following section.

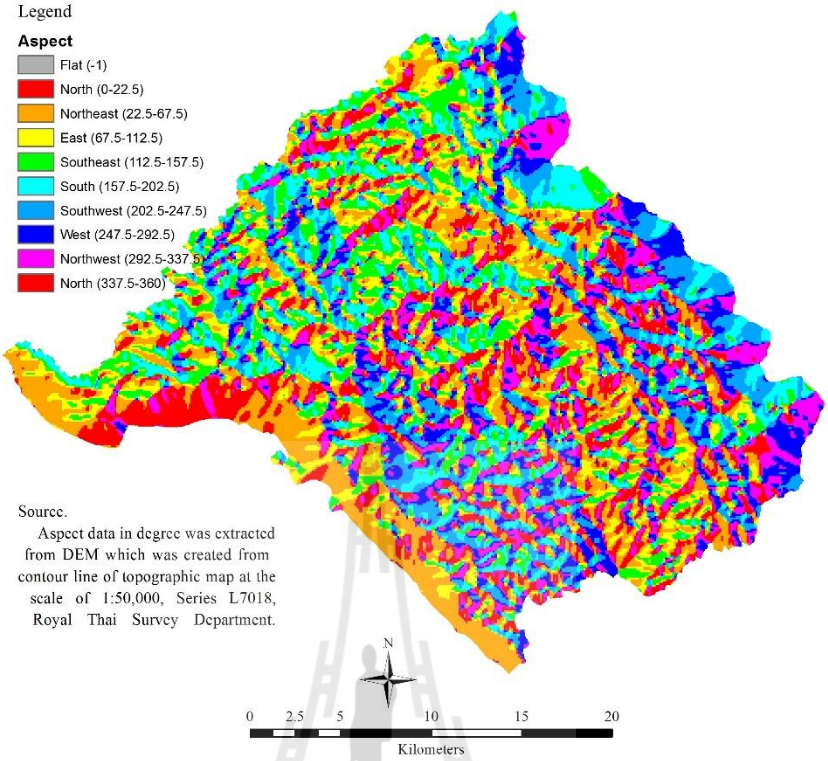


(a) Elevation (m)

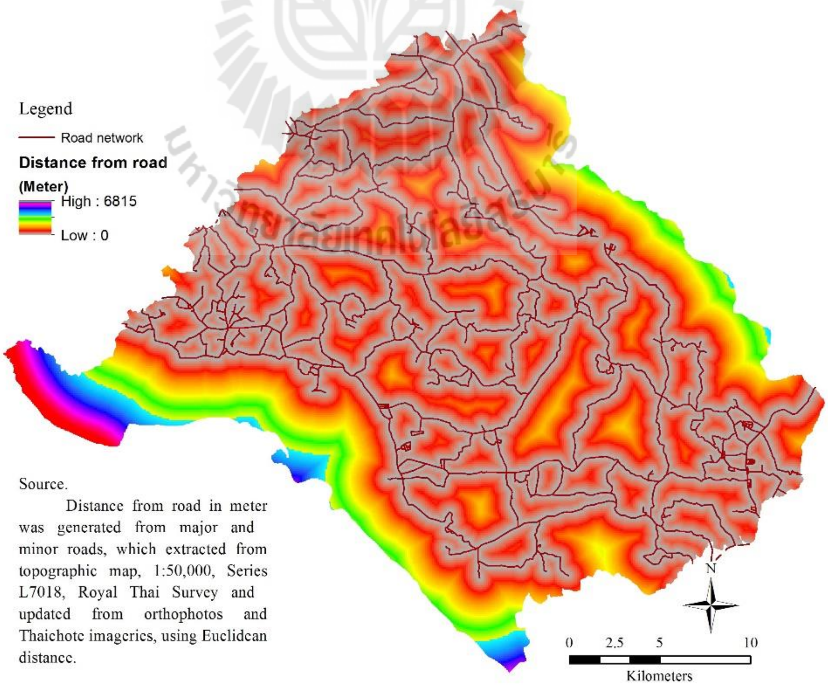


(b) Slope (%)

Figure 4.7 Driving factors for LULC change.

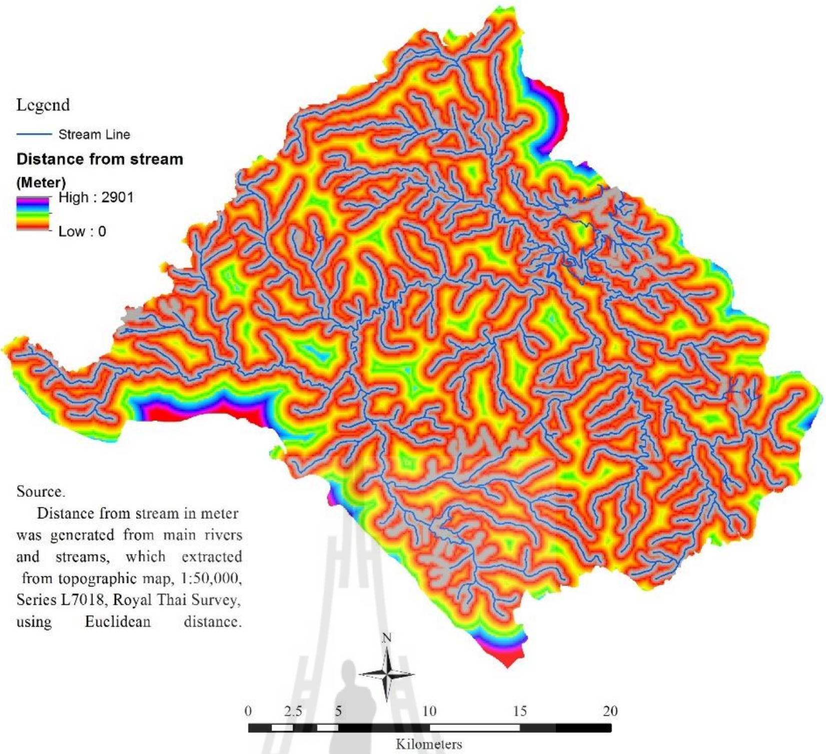


(c) Aspect (directions)

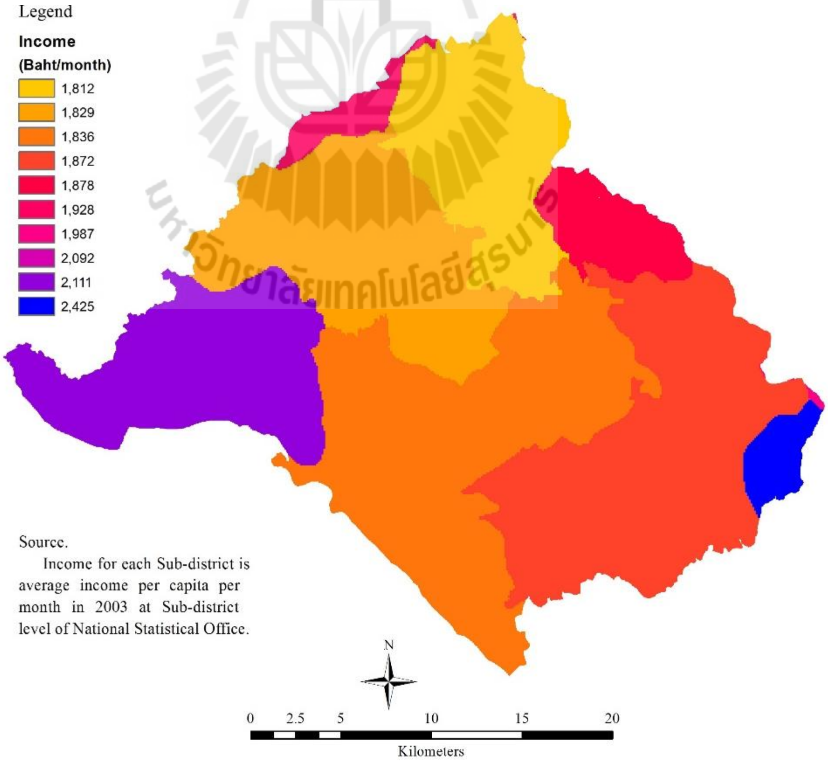


(d) Distance from road (m)

Figure 4.7 Driving factors for LULC change (Continued).

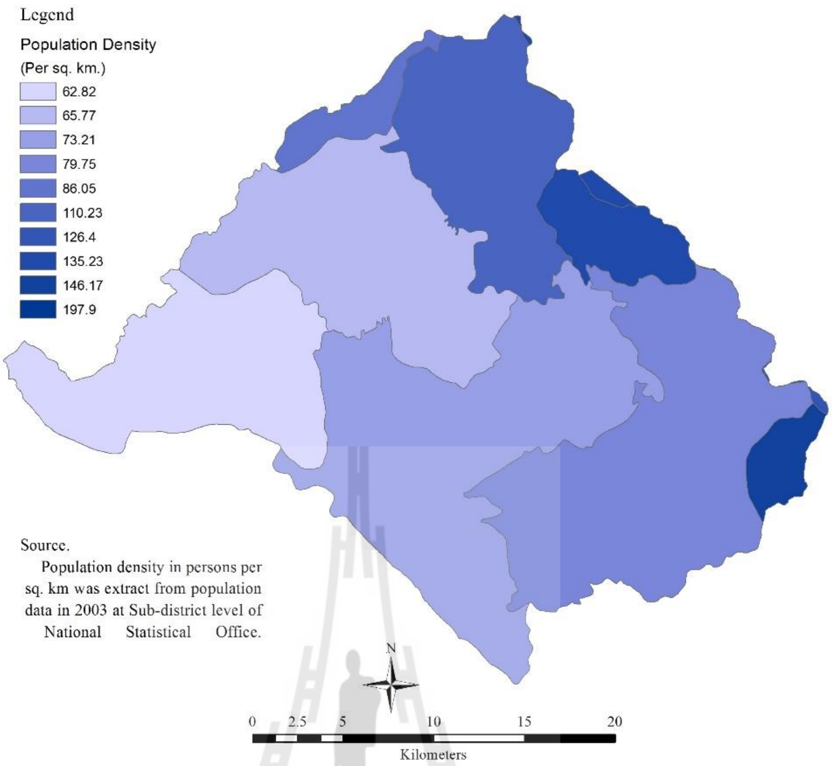


(e) Distance from stream (m)

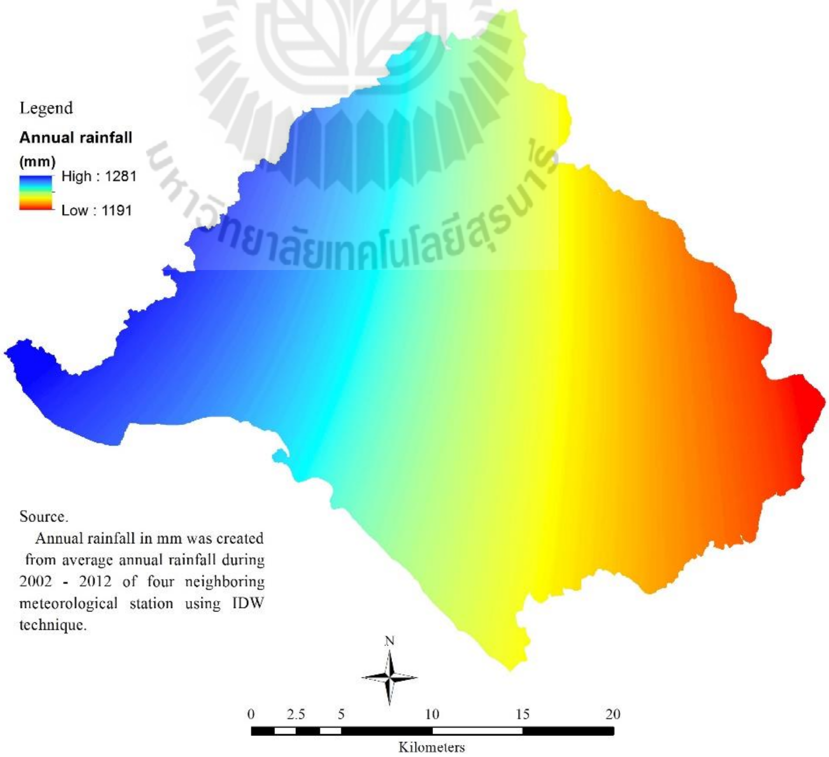


(f) Income (Average monthly income per capita in baht)

Figure 4.7 Driving factors for LULC change (Continued).

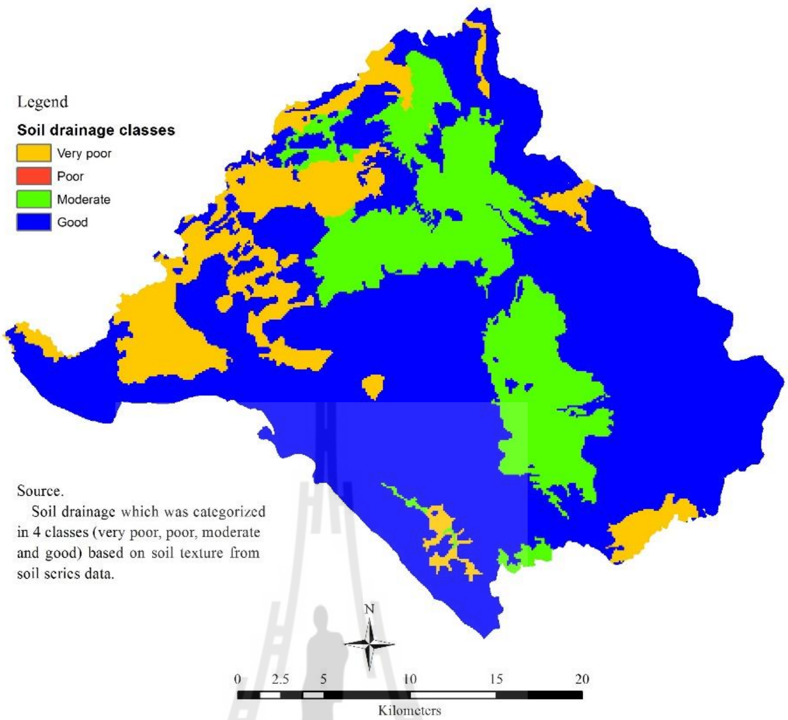


(g) Population density (persons per sq. km)

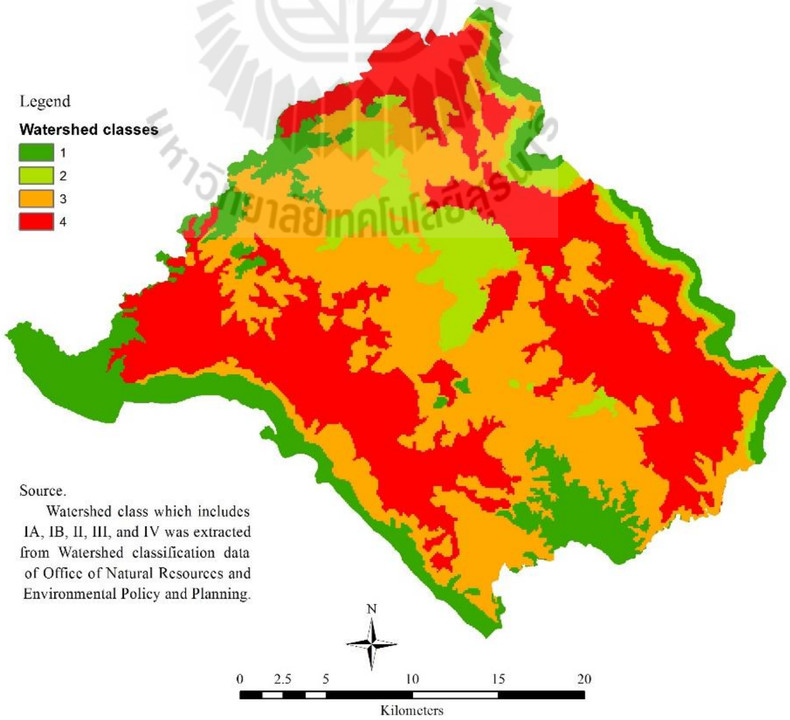


(h) Annual rainfall (mm)

Figure 4.7 Driving factors for LULC change (Continued).



(i) Soil drainage classes



(j) Watershed classes

Figure 4.7 Driving factors for LULC change (Continued).

Table 4.4 Identified driving force for each LULC type as equation form with ROC.

Driving forces	UR	PA	CA	MA	SU	PE	FO	WA	MI
Constant	-8.329	-60.9	2.225	15.047	-52.655	-16.829	5.456	-0.949	10.338
Elevation (X_1)	-	-	0.001	-0.003	-	0.008	-0.005	-0.031	-
Slope (X_2)	0.023	-0.48	-0.029	-0.01	-0.04	-0.018	0.049	-0.033	0.004
Aspect (X_3)	-0.001	0.007	-	-	0.001	-	0.001	-	-0.001
Distance from road (X_4)	-0.005	-	-0.001	-0.0004	-0.001	-0.001	0.002	0.001	-0.0004
Distance from stream (X_5)	-	-	0.001	-0.001	-	-0.0002	-0.001	-0.004	-0.001
Income (X_6)	0.002	-0.01	-0.001	-	-0.008	-	0.002	0.005	0.001
Population density (X_7)	0.813	-4.88	0.297	-1.393	-2.178	-0.56	1.211	-2.31	-1.593
Annual rainfall (X_8)	-	0.049	-0.002	-0.01	0.054	0.009	-0.007	-	0.001
Soil drainage (X_9)	0.195	0.956	0.036	-0.108	0.14	-	-0.085	-0.933	-
Watershed classes (X_{10})	-	2.864	0.337	-0.304	0.253	0.113	-0.575	0.94	-
ROC	**0.82**	**0.929**	**0.681**	**0.627**	**0.808**	**0.703**	**0.894**	**0.893**	**0.651**
Numbers of DF	**6**	**7**	**9**	**8**	**8**	**7**	**10**	**8**	**7**

4.2.1 Driving force for urban and built-up land

Multivariate linear regression equation as a binomial logit model for urban and built-up land was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -8.329 + 0.023X_2 - 0.001X_3 - 0.005X_4 + 0.002X_6 + 0.813X_7 + 0.195X_9\,, \qquad (4.1)$$

where

X_2 is Slope (%);

X_3 is Aspect (degree);

X_4 is Distance from road (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km); and

X_9 is Soil drainage (very poor, poor, moderate, and good).

According to Equation 4.1, four factors including slope, income, population density, and soil drainage had positive relationship to a probability for urban and built-up land occurrence while two factors including aspect, and distance from road had negative relationship to its probability. The most important factor for urban and built-up land occurrence was population density. This implies that when population densities increases, the probability for urban and built-up land occurrence increases.

4.2.2 Driving force for paddy field

Multivariate linear regression equation as a binomial logit model for paddy field are as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -60.9 - 0.48X_2 + 0.0007X_3 - 0.01X_6 - 4.88X_7 + 0.049X_8 + 0.956X_9 + 2.864X_{10}\,, \qquad (4.2)$$

where

X_2 is Slope (%);

X_3 is Aspect (degree);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.2, four factors including aspect, annual rainfall, soil drainage and watershed class had positive relationship to a probability for paddy field occurrence while three factors including slope, income and population density had negative relationship to its probability. The most important factors for paddy field occurrence were population density and watershed class. This implies that when population densities decreases and watershed class increases (i.e. undulating or flood plain), the probability for paddy field occurrence increases. In study site most of paddy field situates in flood plain along the main rivers within watershed class IV.

4.2.3 Driving force for cassava

Multivariate linear regression equation as a binomial logit model for cassava was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 2.225 + 0.001X_1 - 0.029X_2 - 0.001X_4 + 0.001X_5 - 0.002X_6 + 0.297X_7 - 0.002X_8 + 0.036X_9 + 0.337X_{10}, \quad (4.3)$$

where

X_1 is Elevation (m);

X_2 is Slope (%);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.3, five factors including elevation, distance from stream, population density, soil drainage and watershed class had positive relationship to a probability for cassava occurrence while four factors including slope, distance from road, income and annual rainfall had negative relationship to its probability. The most important factors for cassava occurrence were watershed class and population density. This implies that when watershed class (i.e. watershed class 3 or 4) and population densities increases, the probability for cassava occurrence increases. In the study area cassava was frequently found in undulating terrain.

4.2.4 Driving force for maize

Multivariate linear regression equation as a binomial logit model for cassava was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 15.047 - 0.003X_1 - 0.01X_2 - 0.0004X_4 - 0.001X_5 - 1.393X_7 - 0.01X_8 - 0.108X_9 - 0.304X_{10}, \quad (4.4)$$

where

X_1 is Elevation (m);

X_2 is Slope (%);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.4, all eight factors including elevation, slope, distance from road, distance from stream, population density, annual rainfall, soil drainage and watershed class had negative relationship to a probability for maize occurrence. The most important factors for maize occurrence were population density, watershed class and soil drainage. This implies that when these factors decreases, the probability for maize occurrence increases. Maize is frequently occurred in hilly areas with poor soil drainage in remote area far from settlement in the study area.

4.2.5 Driving force for sugarcane

Multivariate linear regression equation as a binomial logit model for sugarcane was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -52.655 - 0.04X_2 + 0.001X_3 - 0.001X_4 - 0.008X_6 - 2.178X_7 + 0.054X_8 + 0.14X_9 + 0.253X_{10}, \quad (4.5)$$

where

X_2 is Slope (%);

X_3 is Aspect (degree);

X_4 is Distance from road (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.5, four factors including aspect, annual rainfall, soil drainage and watershed class had positive relationship to a probability for sugarcane occurrence while four factors including slope, distance from road, elevation, distance from stream, income, and population density had negative relationship to its probability. The most important factor for sugarcane occurrence was population density. This implies that when population densities decreases, the probability for sugarcane occurrence increases. Most of sugarcane plantations in the study area situates in lowland up to undulating areas with large patches and far from settlement areas.

4.2.6 Driving force for perennial tree/orchard

Multivariate linear regression equation as a binomial logit model for perennial tree/orchard was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -16.829 + 0.008X_1 - 0.018X_2 - 0.001X_4 - 0.0002X_5 - 0.56X_7 + 0.009X_8 + 0.113X_{10}, \quad (4.6)$$

where

X_1 is Elevation (m);

X_2 is Slope (%);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.6, three factors including elevation, annual rainfall, and watershed class had positive relationship to a probability for perennial tree/orchard occurrence while four factors including slope, distance from road, distance from stream and population density had negative relationship to its probability. The most important factor for perennial tree/orchard occurrence was population density. This implies that when population densities increases, the probability for perennial tree/orchard occurrence decreases. In fact, perennial tree/orchard might be more utilized as number of population increase.

4.2.7 Driving force for forest land

Multivariate linear regression equation as a binomial logit model for cassava was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 5.456 - 0.005X_1 + 0.049X_2 + 0.001X_3 + 0.002X_4 - 0.001X_5 + 0.002X_6 - 1.211X_7 - 0.007X_8 - 0.085X_9 - 0.894X_{10}, \quad (4.7)$$

where

X_1 is Elevation (m);

X_2 is Slope (%);

X_3 is Aspect (degree);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km);

X_8 is Annual rainfall (mm);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.7, five factors including slope, aspect, distance from road, income and population density had positive relationship to a probability for forest land occurrence while five factors including elevation, distance from stream, annual rainfall, soil drainage and watershed class had negative relationship to its probability. The most important factors for forest land occurrence were population density and watershed class. This implies that when watershed class (i.e. watershed class I or II) and population densities decreases, the probability for forest land occurrence increases. Most of forest land in the study area situates in the mountainous areas and far from settlement areas.

4.2.8 Driving force for water body

Multivariate linear regression equation as a binomial logit model for water body was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -0.949 - 0.031X_1 - 0.033X_2 + 0.001X_4 - 0.004X_5 + 0.005X_6 - 2.31X_7 - 0.933X_9 + 0.94X_{10}, \quad (4.8)$$

where

X_1 is Elevation (m);

X_2 is Slope (%);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km);

X_9 is Soil drainage (very poor, poor, moderate, and good); and

X_{10} is Watershed class (I, II, III, and IV).

According to Equation 4.8, three factors including distance from road, income, and watershed class had positive relationship to a probability for water body occurrence while five factors including elevation, slope, distance from stream, population density, and soil drainage had negative relationship to its probability. The most important factor for water body occurrence was population density. This implies that when population densities decreases, the probability for water body occurrence increases. Major source for water use in the study area is Lam Phra Phloeng Dam.

4.2.9 Driving force for miscellaneous land

Multivariate linear regression equation as a binomial logit model for miscellaneous land was as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 10.338 + 0.004X_2 - 0.001X_3 - 0.0004X_4 - 0.001X_5 + 0.001X_6 - 1.593X_7 + 0.001X_8, \quad (4.9)$$

where

X_2 is Slope (%);

X_3 is Aspect (degree);

X_4 is Distance from road (m);

X_5 is Distance from stream (m);

X_6 is Income (baht per capita);

X_7 is Population density (person per sq. km); and

X_8 is Annual rainfall (mm),

According to Equation 4.9, three factors including slope, income, and annual rainfall had positive relationship to a probability for miscellaneous land occurrence while four factors including aspect, distance from road, distance from stream, and population density had negative relationship to its probability. The most important factor for miscellaneous land occurrence was population density. This implies that when population densities increases, the probability for miscellaneous land decreases. In turn miscellaneous land which includes abandoned cultivated areas might be more utilized as number of population increase.

As results mentioned in Sections 4.2.1 - 4.2.9, it was found that the most common important driving force for all LULC types change was population density while the most important driving force for field crops (cassava, maize, and sugarcane) included slope, distance from road, population density, annual rainfall, soil drainage, and watershed classes. Specific driving force factors for LULC type change were used by CLUE-S model for LULC simulation in each scenario.

CHAPTER V

SIMULATION OF LULC SCENARIOS BY CLUE-S MODEL

An optimum parameters for LULC change simulated by CLUE-S model and LULC simulation of three scenarios including (1) historical land use evolution, (2) agriculture production extension, and (3) forest conservation and prevention were here explained and discussed.

5.1 Optimum local parameter of CLUE-S model

For local parameter of CLUE-S model optimization, conversion matrix which shows the possibility for LULC change among LULC types was firstly considered and set up. Elasticity which represents cost for change among LULC types was then set up according to the transitional LULC change matrix between 2003 and 2013 and run the CLUE-S model for LULC simulation in 2013. After that the simulated LULC in 2013 was compared with the interpreted LULC in 2013 for accuracy assessment (overall accuracy and Kappa hat coefficient of agreement). If the overall accuracy and kappa hat coefficient equal or more than 80 percent, the assigned parameter values of elasticity and conversion matrix are acceptance as optimum local parameter of CLUE-S model.

Under CLUE-S model, change of LULC in conversion matrix can be assigned as 1 when it was allowed or as 0 when it not allowed. In this study any LULC classes in

2003 do not allow to change to be paddy field because area of paddy field between 2003 and 2013 do not change. At the same time paddy field in 2003 allows to change to be any classes of LULC in 2013. In contrast, urban and built-up land in 2003 do not allow to change to be any classes of LULC in 2013. Similarly, water body in 2003 do not allow to change to be any classes of LULC in 2013 except urban and built-up land. Conversion matrix for LULC change between 2003 and 2013, which applied under CLUE-S model in this study, displayed in Table 5.1.

Meanwhile the default value of elasticity for each LULC type change was set up according to the transition probability matrix for LULC change between 2003 and 2013 as shown in Table 5.2. Herewith elasticity values for urban and built-up land, paddy field, cassava, maize, sugarcane, perennial tree/orchard, forest land, water body, and miscellaneous land were 1.0, 1.0, 0.8, 0.8, 0.9, 0.7, 1.0, 1.0, and 0.9, respectively.

Both conversion matrix and elasticity values were then used to simulate LULC in 2013 under CLUE-S model. Later on the simulated LULC in 2013 was compared with the interpreted LULC in 2013 for accuracy assessment (overall accuracy and Kappa hat coefficient).

Table 5.1 Conversion matrix of possible change between 2003 and 2013.

		Possible change in 2013								
	LULC Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**
LULC in 2003	Urban and built-up land (UR)	1	0	0	0	0	0	0	0	0
	Paddy field (PA)	1	1	1	1	1	1	1	1	1
	Cassava (CA)	1	0	1	1	1	1	1	1	1
	Maize (MA)	1	0	1	1	1	1	1	1	1
	Sugarcane (SU)	1	0	1	1	1	1	1	1	1
	Perennial tree/orchard (PE)	1	0	1	1	1	1	1	1	1
	Forest land (FO)	1	0	1	1	1	1	1	1	1
	Water body (WA)	1	0	0	0	0	0	0	1	0
	Miscellaneous land (MI)	1	0	1	1	1	1	1	1	1

Note 0 is not allowed and 1 is allowed

Table 5.2 Transition probability matrix for LULC change between 2003 and 2013.

		LULC in 2013									
	LULC Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
LULC in 2003	Urban and built-up land (UR)	**1**	0	0	0	0	0	0	0	0	1
	Paddy field (PA)	0	**1**	0	0	0	0	0	0	0	1
	Cassava (CA)	0	0	**0.78**	0.11	0.04	0.03	0	0	0.03	1
	Maize (MA)	0.02	0	0.03	**0.82**	0.07	0.03	0	0	0.03	1
	Sugarcane (SU)	0	0	-	0.03	**0.93**	0.03	0	0	0	1
	Perennial tree/orchard (PE)	0.02	0	0.05	0.15	0.09	**0.68**	0	0	0.01	1
	Forestland (FO)	0	0	0	0.01	0	0	**0.98**	0	0.01	1
	Water body (WA)	0	0	0	0	0	0	0	**1**	0	1
	Miscellaneous land (MI)	0.02	0	0.01	0.05	0.01	0.02	0	0.01	**0.87**	1

As results, it was found that overall accuracy and Kappa hat coefficient was 84.194 and 80.004 percent, respectively (Table 5.3). Both accuracy values were more than 80 percent as requirement. However, in the study systematic trials by varying elasticity values was also conducted to examine the change of accuracy as a result shown in Table 5.4 and Figure 5.1. It was found that overall accuracy and Kappa hat coefficient by varying elasticity values do not have a significant change. Therefore, an optimum local parameter for LULC simulation in 2013 under CLUE-S model was default values according to the transition probability matrix of LULC change between 2003 and 2013. This findings can be used as guideline for set up elasticity value when CLUE-S model was applied for LULC prediction.

Table 5.3 Accuracy assessment by comparison of interpreted LULC in 2013 (column) and simulated LULC in 2013 (row).

		Interpreted LULC in 2013 (ha)									
	Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
Simulated LULC in 2013 (ha)	Urban and built-up land (UR)	1,800	-	23	99	4	248	275	-	21	2,470
	Paddy field (PA)	-	237	-	-	-	-	-	-	-	237
	Cassava (CA)	18	-	3,317	525	170	197	44	-	143	4,414
	Maize (MA)	313	-	637	15,253	1,363	472	-	8	632	18,678
	Sugarcane (SU)	25	-	14	1,173	8,578	817	116	-	37	10,760
	Perennial tree/orchard (PE)	144	-	319	968	529	4,095	-	-	87	6,142
	Forestland (FO)	17	-	28	165	30	39	25,462	10	229	25,980
	Water body (WA)	10	-	-	3	1	30	11	1,108	-	1,163
	Miscellaneous land (MI)	138	-	108	417	111	269	62	39	6,177	7,321
	Total	**2,465**	**237**	**4,446**	**18,603**	**10,786**	**6,167**	**25,970**	**1,165**	**7,326**	**77,165**
	Overall accuracy	84.194									
	Kappa hat coefficient	80.004									
	Producer's accuracy	73.03	100	74.6	81.99	79.53	66.4	98.04	95.11	84.31	
	User's accuracy	72.87	100	75.14	81.67	79.72	66.67	98.01	95.31	84.37	

Table 5.4 Systematic adjustment for elasticity value and accuracy assessment.

No.	UR	PA	CA	MA	SU	PE	FO	WA	MI	Overall Accuracy	Kappa hat
sim01	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.9	84.194	80.004
sim02	1.0	1.0	0.9	0.9	1.0	0.8	1.0	1.0	1.0	85.461	81.542
sim03	1.0	0.9	0.7	0.7	0.8	0.6	0.9	1.0	0.8	85.442	81.517
sim04	1.0	0.8	0.6	0.6	0.7	0.5	0.8	1.0	0.7	85.366	81.420
sim05	1.0	0.7	0.5	0.5	0.6	0.4	0.7	1.0	0.6	85.061	81.033
sim06	1.0	1.0	1.0	0.8	0.9	0.7	1.0	1.0	0.9	85.460	81.540
sim07	1.0	1.0	0.9	0.8	0.9	0.7	1.0	1.0	0.9	85.461	81.541
sim08	1.0	1.0	0.7	0.8	0.9	0.7	1.0	1.0	0.9	85.463	81.543
sim09	1.0	1.0	0.6	0.8	0.9	0.7	1.0	1.0	0.9	85.424	81.495
sim10	1.0	1.0	0.5	0.8	0.9	0.7	1.0	1.0	0.9	85.385	81.445
sim11	1.0	1.0	0.4	0.8	0.9	0.7	1.0	1.0	0.9	85.215	81.228
sim12	1.0	1.0	0.3	0.8	0.9	0.7	1.0	1.0	0.9	84.811	80.717
sim13	1.0	1.0	1.0	1.0	0.9	0.7	1.0	1.0	0.9	85.465	81.546
sim14	1.0	1.0	0.8	0.9	0.9	0.7	1.0	1.0	0.9	85.458	81.537
sim15	1.0	1.0	0.8	0.7	0.9	0.7	1.0	1.0	0.9	85.458	81.537
sim16	1.0	1.0	0.8	0.6	0.9	0.7	1.0	1.0	0.9	85.459	81.539
sim17	1.0	1.0	0.8	0.5	0.9	0.7	1.0	1.0	0.9	85.451	81.529
sim18	1.0	1.0	0.8	0.4	0.9	0.7	1.0	1.0	0.9	85.466	81.548
sim19	1.0	1.0	0.8	0.3	0.9	0.7	1.0	1.0	0.9	85.474	81.557
sim20	1.0	1.0	0.8	0.8	0.9	0.7	0.9	1.0	0.9	85.452	81.530
sim21	1.0	1.0	0.8	0.8	0.9	0.7	0.8	1.0	0.9	85.402	81.465
sim22	1.0	1.0	0.8	0.8	0.9	0.7	0.7	1.0	0.9	85.140	81.133
sim23	1.0	1.0	0.8	0.8	0.9	0.7	0.6	1.0	0.9	84.762	80.653
sim24	1.0	1.0	0.8	0.8	0.9	0.7	0.5	1.0	0.9	84.273	80.033
sim25	1.0	1.0	0.8	0.8	0.9	0.7	0.4	1.0	0.9	83.782	79.410
sim26	1.0	1.0	0.8	0.8	0.9	0.7	0.3	1.0	0.9	83.407	78.934
sim27	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	1.0	85.458	81.537
sim28	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.8	85.460	81.540
sim29	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.7	85.463	81.543
sim30	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.6	85.466	81.548
sim31	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.5	85.455	81.534
sim32	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.4	85.459	81.538
sim33	1.0	1.0	0.8	0.8	0.9	0.7	1.0	1.0	0.3	85.455	81.534
sim34	1.0	1.0	0.8	0.8	0.9	1.0	1.0	1.0	0.9	85.461	81.541
sim35	1.0	1.0	0.8	0.8	0.9	0.9	1.0	1.0	0.9	85.461	81.541
sim36	1.0	1.0	0.8	0.8	0.9	0.8	1.0	1.0	0.9	85.464	81.544
sim37	1.0	1.0	0.8	0.8	0.9	0.6	1.0	1.0	0.9	85.468	81.549
sim38	1.0	1.0	0.8	0.8	0.9	0.5	1.0	1.0	0.9	85.456	81.535
sim39	1.0	1.0	0.8	0.8	0.9	0.4	1.0	1.0	0.9	85.458	81.537
sim40	1.0	1.0	0.8	0.8	0.9	0.3	1.0	1.0	0.9	85.459	81.539
sim41	1.0	1.0	0.8	0.8	1.0	0.7	1.0	1.0	0.9	85.459	81.538
sim42	1.0	1.0	0.8	0.8	0.8	0.7	1.0	1.0	0.9	85.454	81.532
sim43	1.0	1.0	0.8	0.8	0.7	0.7	1.0	1.0	0.9	85.463	81.543
sim44	1.0	1.0	0.8	0.8	0.6	0.7	1.0	1.0	0.9	85.465	81.546
sim45	1.0	1.0	0.8	0.8	0.5	0.7	1.0	1.0	0.9	85.459	81.538
sim46	1.0	1.0	0.8	0.8	0.4	0.7	1.0	1.0	0.9	85.459	81.538
sim47	1.0	1.0	0.8	0.8	0.3	0.7	1.0	1.0	0.9	85.464	81.544

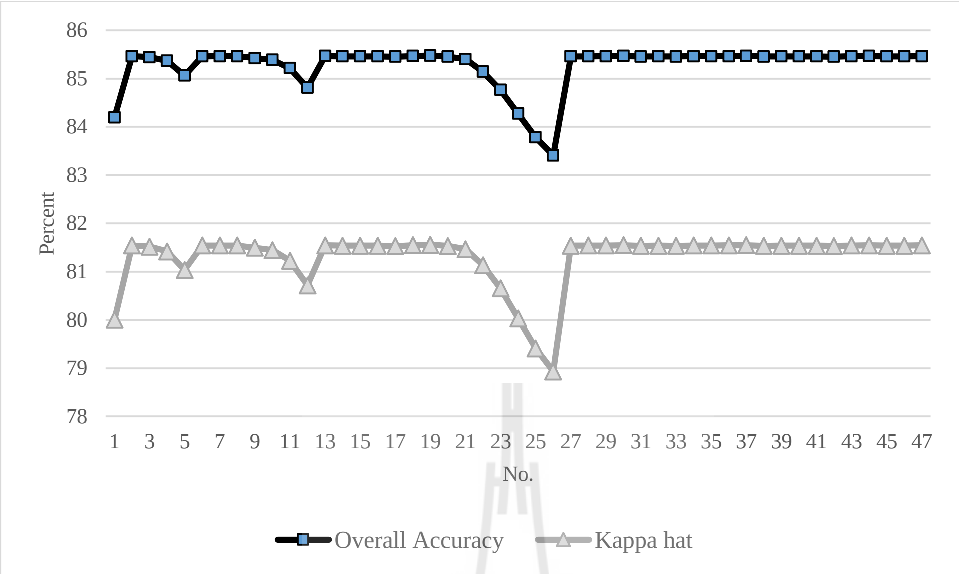


Figure 5.1 Variation of overall accuracy and kappa hat coefficient during adjustment of elasticity value.

With reference to Table 5.3, it was found that the highest producer's accuracy for each LULC type simulation in 2013 was paddy field with value of 100 percent while the lowest producer's accuracy was perennial trees/orchards with value of 66.40 percent. This result implied that the best output for LULC simulation by CLUE-S model was paddy field while the worst was perennial trees/orchards. At the same time, the highest user's accuracy for each LULC type simulation in 2013 was also paddy field with value of 100 percent while the lowest producer's accuracy was also perennial trees/orchards with value of 66.67 percent. This result inferred that the best preference simulated LULC from the users should be paddy field while the worst preference from the users should be perennial trees/orchards.

5.2 LULC simulation of three scenarios

Three scenarios of LULC in 2023 included Scenario I: Historical land use evolution, Scenario II: Agriculture production extension, and Scenario III: Forest conservation and prevention were simulated based on an optimum local parameters of CLUE-S model with a specific land use requirement for each scenario which was derived in the previous section. In addition, land use requirement for each scenario had to be prepared in advance according the characteristics of each scenario and then used to simulate LULC in 2023under CLUE-S model.

5.2.1 LULC in 2023 simulation of Scenario I (Historical land use evolution)

Land use requirement for Scenario I (Historical land use evolution) was based on the rate of LULC change occurring between 2003 and 2013 (see Table 4.1). Herewith, annual land use demand for Scenario I between 2013 and 2023 was calculated and presented in Table 5.5. Herein, increasing LULC classes were urban and built-up land, cassava, sugarcane, water body and miscellaneous land with annual increasing rate about 66.5, 21.4, 171.2, 5.7, and 28 ha per year, respectively. On the contrary decreasing LULC classes were maize, perennial trees/orchards and forest land with annual decreasing rate about 109.1, 128.5 and 55.2 ha per year, respectively. In principle, the land use requirement dictates the final area of each LULC type in 2023 by using simulation of CLUE-S model. The distribution of the simulated LULC in 2023 for Scenario I was presented in Figure 5.2 while Table 5.6 represented the transition matrix of LULC change between the existing LULC in 2013 by visual interpretation and the simulated LULC in 2023 under Scenario I and Figure 5.3 displayed LULC change between actual LULC in 2013 and the simulated LULC in 2023 of Scenario I.

Table 5.5 Annual land use requirement for Scenario I by each LULC type.

Year	Area in ha								
	UR	PA	CA	MA	SU	PE	FO	WA	MI
2013	2,465	237	4,446	18,603	10,786	6,167	25,970	1,165	7,326
2014	2,532	237	4,468	18,494	10,955	6,039	25,915	1,171	7,354
2015	2,598	237	4,489	18,385	11,129	5,910	25,859	1,176	7,382
2016	2,665	237	4,511	18,276	11,298	5,782	25,804	1,182	7,410
2017	2,731	237	4,532	18,167	11,470	5,653	25,749	1,188	7,438
2018	2,798	237	4,554	18,059	11,638	5,525	25,694	1,194	7,466
2019	2,864	237	4,575	17,950	11,812	5,396	25,638	1,199	7,494
2020	2,931	237	4,597	17,841	11,981	5,268	25,583	1,205	7,522
2021	2,997	237	4,618	17,732	12,153	5,139	25,528	1,211	7,550
2022	3,064	237	4,640	17,623	12,324	5,011	25,472	1,216	7,578
2023	3,130	237	4,661	17,514	12,496	4,882	25,417	1,222	7,606

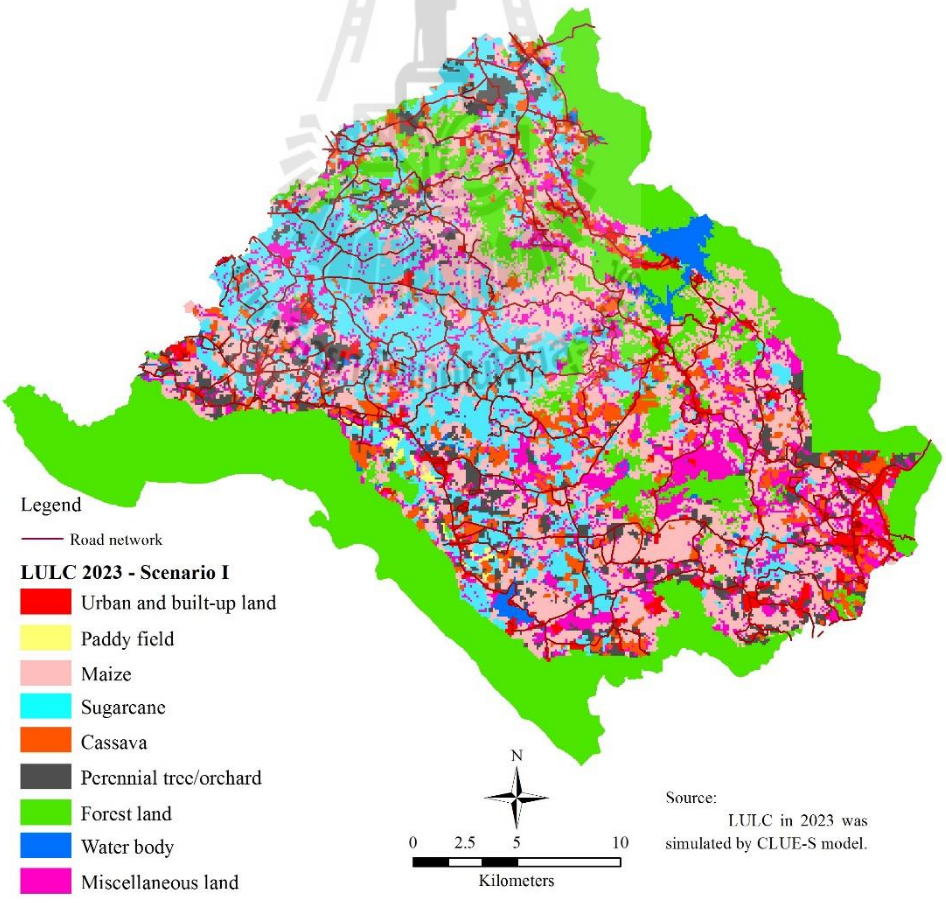


Figure 5.2 Distribution of simulated LULC in 2023 for Scenario I.

Table 5.6 Transition matrix of LULC change between 2013 and 2023 of Scenario I.

		LULC 2023 of Scenario I (ha)									
	Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
LULC 2013 (ha)	Urban and built-up land (UR)	**2,465**	-	-	-	-	-	-	-	-	2,465
	Paddy field (PA)	-	**237**	-	-	-	-	-	-	-	237
	Cassava (CA)	-	-	**4,446**	-	-	-	-	-	-	4,446
	Maize (MA)	28	-	58	**17,593**	924	-	-	-	-	18,603
	Sugarcane (SU)	-	-	-	-	**10,786**	-	-	-	-	10,786
	Perennial tree/orchard (PE)	358	-	89	-	623	**4,843**	-	41	213	6,167
	Forestland (FO)	285	-	40	-	145	-	**25,428**	7	65	25,970
	Water body (WA)	-	-	-	-	-	-	-	**1,165**	-	1,165
	Miscellaneous land (MI)	-	-	-	-	-	-	-	-	**7,326**	7,326
	Total	**3,136**	**237**	**4,633**	**17,593**	**12,478**	**4,843**	**25,428**	**1,213**	**7,604**	**77,165**
	Land use requirement	3,130	237	4,661	17,514	12,496	4,882	25,417	1,222	7,606	
	Deviation value (%)	-0.19	0	0.6	-0.45	0.14	0.8	-0.04	0.74	0.03	

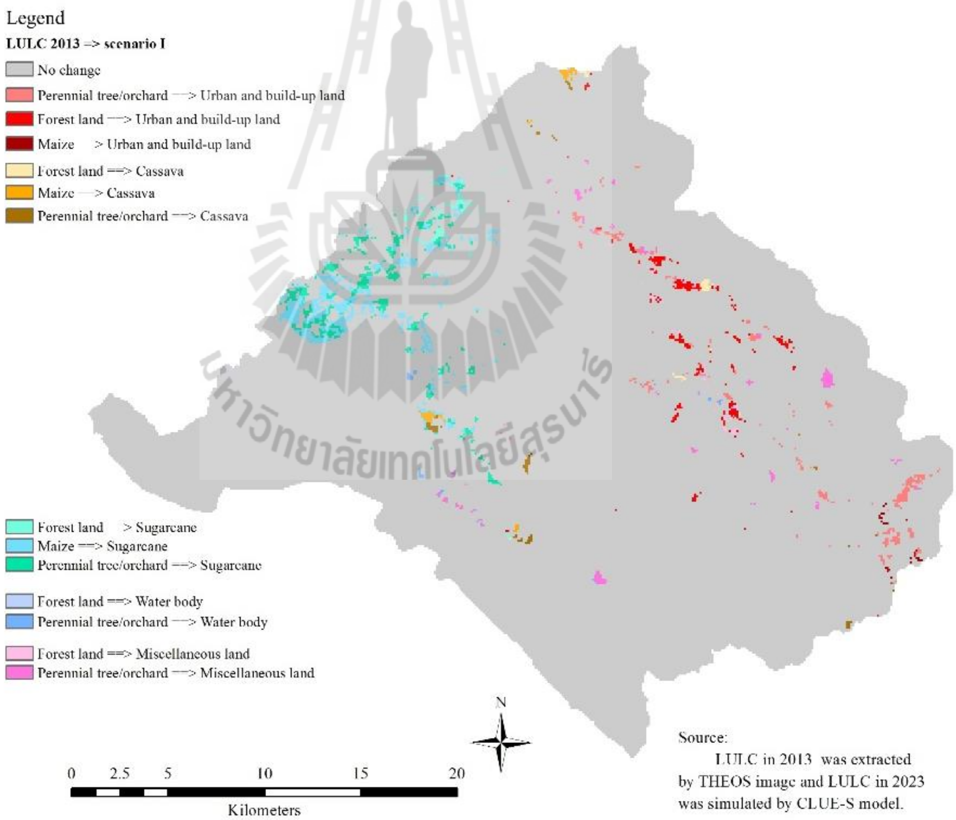


Figure 5.3 Distribution of LULC change between actual LULC in 2013 and the simulated LULC in 2023 of Scenario I.

As results, it was found that areas of LULC type which had been increased were urban and built-up land, cassava, sugarcane, water body and miscellaneous land while area of maize, perennial tree/orchard, and forest land had been decreased, and paddy field. Herein, the increased area of urban and built-up land, cassava, and sugarcane came from maize, perennial tree/orchard and forest land and the increased area of water body and miscellaneous land came from perennial tree/orchard and forest land. In contrary, some areas of perennial tree/orchard and forest land was converted to urban and built-up land, cassava, sugarcane, water body and miscellaneous land and some areas of maize was changed to urban and built-up land, cassava, and sugarcane. The pattern of LULC change between 2013 and 2023 as simulated LULC of Scenario I was identical to LULC change pattern between 2003 and 2013. This finding implies the CLUE-S model can provides the good result for LULC prediction according the historical land use evolution in the past.

However, it was found that there were some difference between the area of each LULC types which was specified in land use requirement for CLUE-S model and the actual allocated areas. The deviation value varied between -0.45 to 0.80 percent. In principle, the deviation value depends on iteration variables which indicates the maximum different allowance between the required and allocated area of CLUE-S model.

5.2.2 LULC in 2023 simulation of Scenario II (Agriculture production extension)

Under this scenario, areas of cassava and sugarcane are intensively extension due to government policy on energy crop for LULC simulation in 2023. At the same time forest land need to conserve and preserve and area of urban and built-up, paddy field and water body is fixed.

For land use requirement of Scenario II, areas of urban and built-up land, paddy field and water body were fixed for every year. Meanwhile area of the simulated forest land in 2023 was modified by considering the existing forest land in 2013 and boundary of watershed class I and national park. At the same time, the rest areas from others LULC types in 2013 (maize, perennial tree/orchards and miscellaneous land) were devoted for cassava and sugarcane expansion in 2023 at the ratio of 50 and 50 (Bank of Thailand, 2012). The annual land use requirement for Scenario II between 2013 and 2023 was presented in Table 5.7. Whilst the distribution of the simulated LULC in 2023 for Scenario II was presented in Figure 5.4 and the transition matrix of LULC change between the existing LULC in 2013 by visual interpretation and the simulated LULC in 2023 under Scenario II was presented in Table 5.8 and Figure 5.5 presented LULC change between actual LULC in 2013 and the simulated LULC in 2023 for cassava and sugarcane of Scenario II.

As results obtaining from this scenario, most of the increasing area of cassava and sugarcane came from maize, forest land and miscellaneous land. Herein, areas of maize, perennial tree/orchard, forest land, and miscellaneous land in 2013 were converted to be cassava and sugarcane about 18,603, 6,167, 13,769, and 7,326 ha, respectively. This result was dictated by the specified land use requirement accordance with the government policy on energy crop.

Table 5.7 Annual land use requirement of Scenario II by each LULC type.

Year	Area in ha								
	UR	PA	CA	MA	SU	PE	FO	WA	MI
2013	2,465	237	4,446	18,603	10,786	6,167	25,970	1,165	7,326
2014	2,465	237	7,037	16,743	12,743	5,550	24,632	1,165	6,593
2015	2,465	237	9,628	14,882	14,699	4,934	23,294	1,165	5,861
2016	2,465	237	12,218	13,022	16,657	4,317	21,956	1,165	5,128
2017	2,465	237	14,809	11,162	18,613	3,700	20,618	1,165	4,396
2018	2,465	237	17,400	9,302	20,569	3,084	19,280	1,165	3,663
2019	2,465	237	19,991	7,441	22,527	2,467	17,942	1,165	2,930
2020	2,465	237	22,582	5,581	24,483	1,850	16,604	1,165	2,198
2021	2,465	237	25,173	3,721	26,440	1,233	15,266	1,165	1,465
2022	2,465	237	27,763	1,860	28,397	617	13,928	1,165	733
2023	2,465	237	30,354	-	30,354	-	12,590	1,165	-

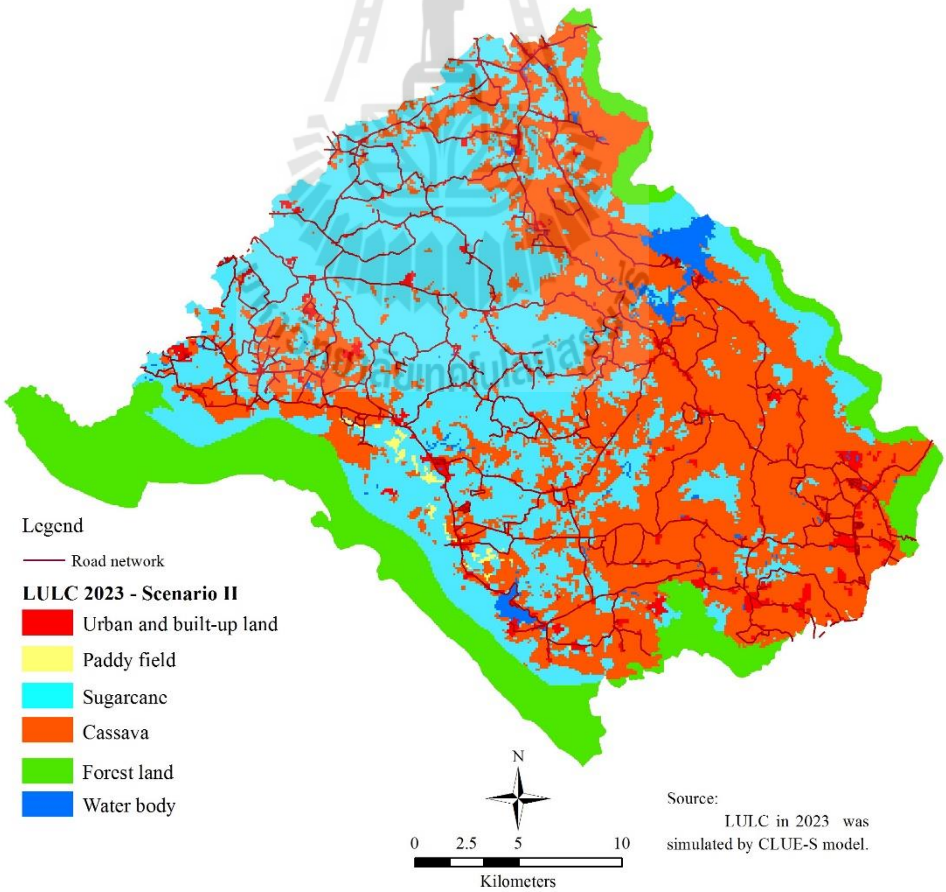


Figure 5.4 Distribution of the simulated LULC in 2023 for Scenario II.

Table 5.8 Transition matrix of LULC change between 2013 and 2023of Scenario II.

		LULC 2023 of Scenario II (ha)									
	Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
LULC 2013 (ha)	Urban and built-up land (UR)	**2,465**	-	-	-	-	-	-	-	-	2,465
	Paddy field (PA)	-	**237**	-	-	-	-	-	-	-	237
	Cassava (CA)	-	-	**4,446**	-	-	-	-	-	-	4,446
	Maize (MA)	-	-	11,517	-	7,086	-	-	-	-	18,603
	Sugarcane (SU)	-	-	-	-	**10,786**	-	-	-	-	10,786
	Perennial tree/orchard (PE)	-	-	3,813	-	2,354	-	-	-	-	6,167
	Forestland (FO)	-	-	6,375	-	7,394	-	**12,199**	2	-	25,970
	Water body (WA)	-	-	-	-	-	-	-	**1,165**	-	1,165
	Miscellaneous land (MI)	-	-	4,547	-	2,779	-	-	-	-	7,326
	Total	**2,465**	**237**	**30,698**	-	**30,399**	-	**12,199**	**1,167**	-	**77,165**
	Land use requirement	2,465	237	30,354	-	30,354	-	12,590	1,165	-	
	Deviation value (%)	0	0	-1.13	-	-0.15	-	3.11	-0.17	-	

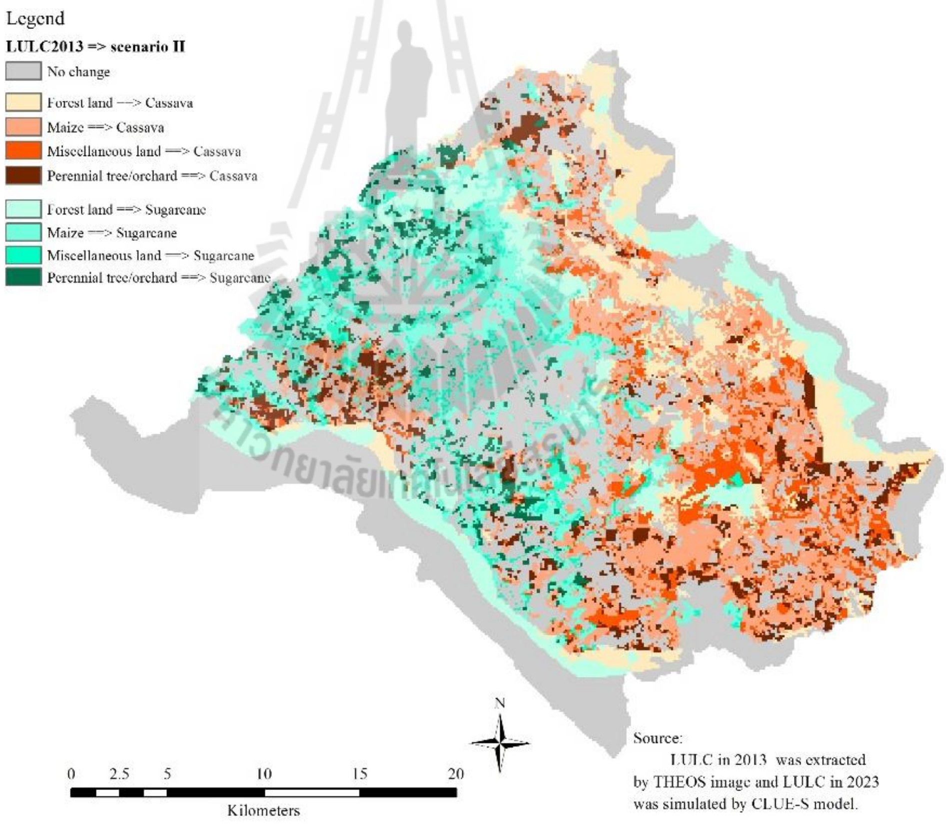


Figure 5.5 Distribution of LULC change between actual LULC in 2013 and the simulated LULC in 2023 for cassava and sugarcane of Scenario II.

In addition, there were some difference between the area of each LULC types specified in the land use requirement of CLUE-S model and the actual allocated areas. It was found that the deviation value ranked between -1.13 to 3.11 percent. Herein, area of water body which was fixed for land use requirement under CLUE-S model increased 2 ha.

5.2.3 LULC in 2023 simulation of Scenario III (Forest conservation and prevention)

Under this scenario, land use requirement for each LULC was based on the national conservation and preservation program on forest (National Economic and Social Development Board, 2011). Herein a simulated forest land in 2023 was calculated according to areas of watershed class I and II, national park's boundary and existing forest in 2013. Similarly to Scenario II areas of urban and built-up, paddy field and water body were fixed for every year. The other LULC types (cassava, maize, perennial tree/orchards, and miscellaneous land) were modified according LULC change rate between 2003 and 2013. Annual land use demand for Scenario III between 2013 and 2023 was presented in Table 5.9 while the distribution of simulated LULC in 2023 for scenario III was presented in Figure 5.6. At the same time, the transition matrix of LULC change between the existing LULC in 2013 by visual interpretation and the simulated LULC in 2023 under Scenario III was presented in Table 5.10 and Figure 5.7 presented LULC change between actual LULC in 2013 and the simulated LULC in 2023 for forest land of Scenario III.

Table 5.9 Land use requirement of Scenario III by each LULC type.

Year	Area in ha								
	UR	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**
2013	2465	237	4,446	18603	10,786	6167	25970	1165	7326
2014	2,465	237	4,370	18,286	10,602	6,062	26,777	1,165	7,201
2015	2,465	237	4,294	17,969	10,419	5,957	27,583	1,165	7,076
2016	2,465	237	4,219	17,652	10,234	5,852	28,390	1,165	6,951
2017	2,465	237	4,143	17,335	10,050	5,747	29,196	1,165	6,827
2018	2,465	237	4,067	17,018	9,866	5,642	30,003	1,165	6,702
2019	2,465	237	3,991	16,701	9,684	5,536	30,809	1,165	6,577
2020	2,465	237	3,916	16,384	9,499	5,431	31,616	1,165	6,452
2021	2,465	237	3,840	16,067	9,316	5,326	32,422	1,165	6,327
2022	2,465	237	3,764	15,750	9,132	5,221	33,229	1,165	6,202
2023	2,465	237	3,688	15,433	8,948	5,116	34,035	1,165	6,078

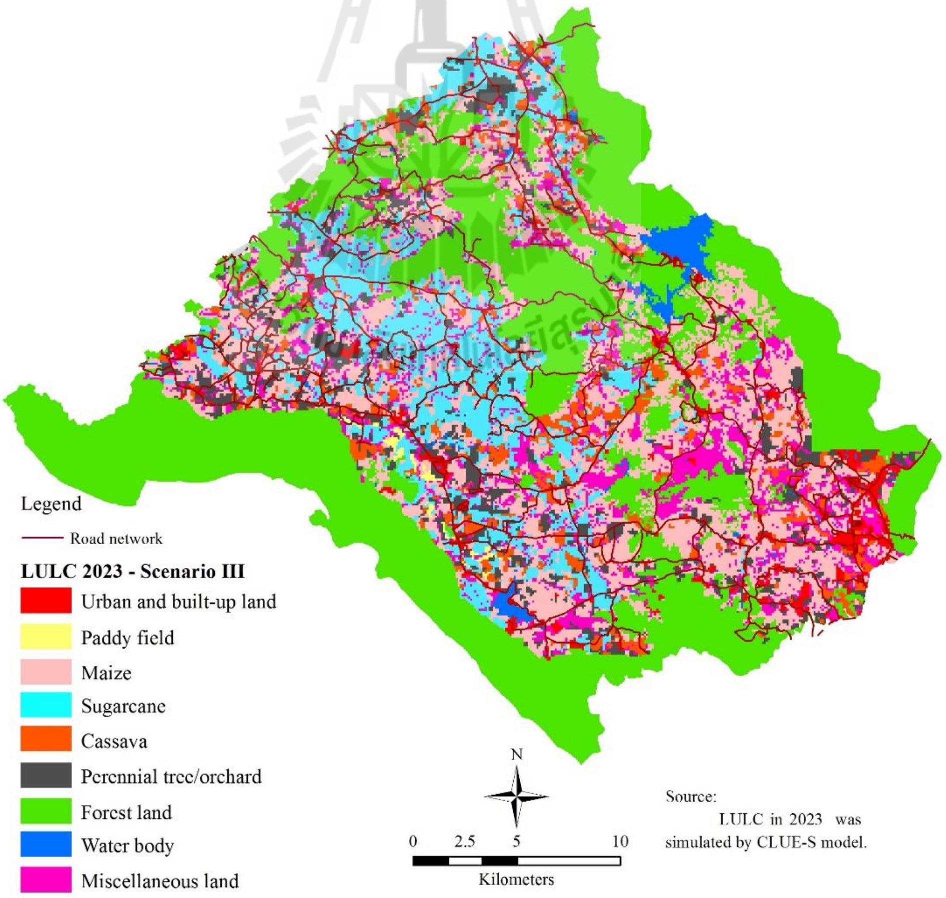


Figure 5.6 Distribution of the simulated LULC in 2023 for Scenario III.

Table 5.10 Transition matrix of LULC change between 2013 and 2023of Scenario III.

		LULC 2023 of Scenario III (ha)									
	Types	**UR**	**PA**	**CA**	**MA**	**SU**	**PE**	**FO**	**WA**	**MI**	**Total**
LULC 2013 (ha)	Urban and built-up land (UR)	**2,149**	-	-	-	-	-	316	-	-	2,465
	Paddy field (PA)	-	**237**	-	-	-	-	-	-	-	237
	Cassava (CA)	10	-	**3,815**	357	-	-	264	-	-	4,446
	Maize (MA)	-	-	-	**15,143**	-	-	3,460	-	-	18,603
	Sugarcane (SU)	122	-	-	407	**9,225**	-	1,032	-	-	10,786
	Perennial tree/orchard (PE)	157	-	-	84	-	**5,347**	579	-	-	6,167
	Forestland (FO)	-	-	-	-	-	-	**25,970**	-	-	25,970
	Water body (WA)	-	-	-	-	-	-	10	**1,155**	-	1,165
	Miscellaneous land (MI)	77	-	-	-	-	-	970	-	**6,279**	7,326
	Total	**2,515**	**237**	**3,815**	**15,991**	**9,225**	**5,347**	**32,601**	**1,155**	**6,279**	**77,165**
	Land use requirement	2,465	237	3,688	15,433	8,948	5,116	34,035	1,165	6,078	
	Deviation value (%)	-2.03	0	-3.43	-3.62	-3.1	-4.51	4.21	0.86	-3.31	

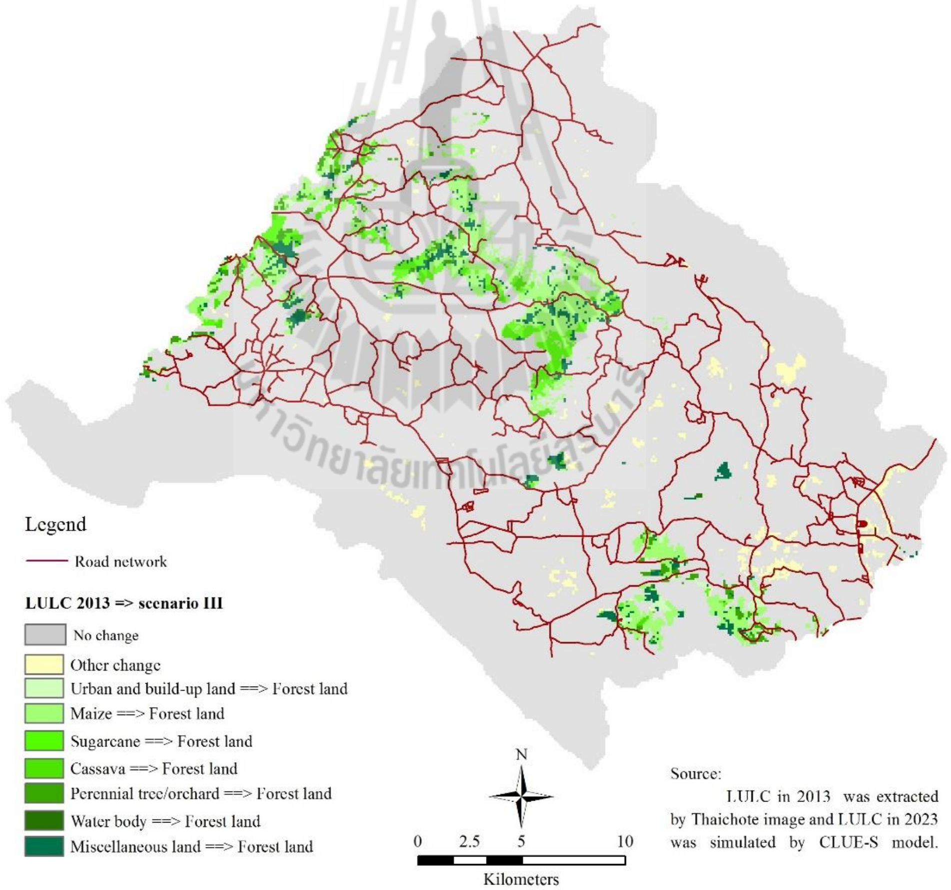


Figure 5.7 Distribution of LULC change between actual LULC in 2013 and the simulated LULC in 2023 for forest land of Scenario III.

As results, most of increasing area of forest land came from maize, sugarcane, and miscellaneous land. Herein areas of maize, sugarcane, and miscellaneous land were converted to be forest land about 3,460, 1,032 and 970 ha, respectively. Meanwhile forest land between 2013 and 2023 had increased about 6,631 ha. Similar to Scenario II, this result was dictated by the specified land use requirement according to the national conservation and preservation program of the Government.

Furthermore, there were some difference between the area of each LULC types specified in the land use requirement and the actual allocated areas. It was found that the deviation value ranked between -4.51 to 4.21 percent. The deviation values depend on iteration variables which determine a criteria for model convergence. Herein, urban and built-up land increased about 366 ha and water body decreased about 10 ha even though they were fixed for land use requirement under CLUE-S model.

5.3 Comparison of simulated LULC 2023 with LULC 2013

According to the summary table of the simulated data in three scenarios (Table 5.11 and Figure 5.8), the areas of each simulated LULC type in 2023 reflect the characteristics of each scenario as defined in Section 3.2.3 of Chapter III.

For Scenario I: Historical land use evolution, increasing LULC types were urban and built-up land, cassava, sugarcane, water body and miscellaneous land while decreasing LULC types were maize, perennial trees/orchards and forest land. In fact, change of LULC between the baseline data (LULC in 2013) and simulated LULC of Scenario I (LULC in 2023) were increased and decreased according to the transition probability matrix for LULC change between 2003 and 2013. In another word, LULC change for Scenario I was based on the evolution of LULC change during 2003-2013 without any policy. The characteristic of this scenario are frequently applied in LULC change simulation under CLUE-S model for baseline data generation and its result is then used to compare with other scenarios with policy such as the previous works of Verburg et al. (2002), Verburg and Veldkamp (2004a), Orekan (2007), Verburg et al. (2008), Warlina (2009), Luo et al. (2010), Soba et al. (2010), Zhang, Liu, Pan and Yu (2011), Sun et al. (2012), Zhou et al. (2013), El-Khoury et al. (2014) and Zheng et al. (2015).

In contrast, Scenario II: Agriculture production extension and Scenario III: Forest conservation and prevention, areas of both the simulated LULC types in 2023 had increased and decreased according to policies setting for each scenario. In case of Scenario II, areas of cassava and sugarcane had increased about 26,252 and 19,613 ha, respectively between 2013 and 2023 meanwhile forest land had decreased about 13,771 ha. Likewise, in case of Scenario III, area of forest land had increased from 25,970 ha in 2013 to 32,601 ha in 2023 while areas of major agricultural type including cassava, maize, sugarcane, and perennial trees/orchards had decreased about 631, 2,612, 1,561, and 820 ha, respectively in this period. The characteristic of these scenarios (II and III) had been applied in LULC change simulation under CLUE-S model such as the previous works of Verburg and Veldkamp (2004) about impact of land use change on forest fragmentation, Castella et.al (2007) and Orekan (2007) on sustainable management of natural, Githui et al. (2009) for estimating the impacts of land-cover change on runoff, Trisurat et al. (2010) about effects of development on the forest biodiversity, Zhang et al. (2011) on effects of the non-point source pollution control and El-Khoury et al. (2014) for monitoring environmental degradation in basin.

Table 5.11 Area and change of LULC type between 2013 (by visual interpretation) and 2023 (by simulation of 3 scenarios).

Item	Year	LULC Types (ha)								
		UR	PA	CA	MA	SU	PE	FO	WA	MI
Baseline data	2013	2,465	237	4,446	18,603	10,786	6,167	25,970	1,165	7,326
Simulated data	Scenario I	3,136	237	4,633	17,593	12,478	4,843	25,428	1,213	7,604
	Scenario II	2,465	237	30,698	-	30,399	-	12,199	1,167	-
	Scenario III	2,515	237	3,815	15,991	9,225	5,347	32,601	1,155	6,279
Change	Scenario I	671	-	187	-1,010	1,692	-1,324	-542	48	278
	Scenario II	-	-	26,252	-18,603	19,613	-6,167	-13,771	2	-7,326
	Scenario III	50	-	-631	-2,612	-1,561	-820	6,631	-10	-1,047

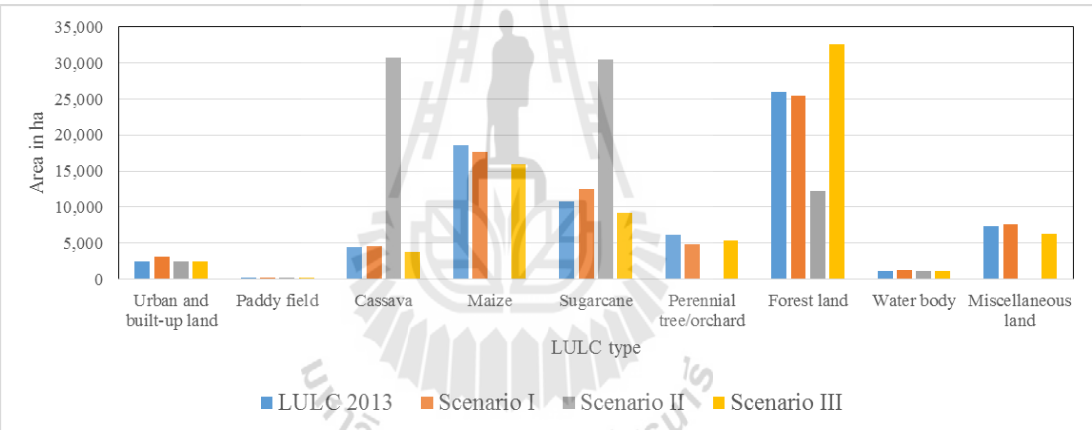


Figure 5.8 Comparison of LULC type area between LULC in 2013 and the simulated LULC in 2023 of three scenarios.

CHAPTER VI

IMPACT OF LULC CHANGE ON SOIL EROSION, WATER YIELD AND ECONOMIC VALUES

Under this chapter, three models included USLE model, SWAT model with SCS-CN method, and PV were used to assess and evaluate impact (positive, negative and neural) due to LULC change in 2023. In this study, impact of LULC change on soil loss, water yield, and economic values between actual LULC in 2013 and simulated LULC in 2023 of three scenarios and among three scenarios were separately described and discussed.

6.1 Soil erosion assessment and its impact due to LULC change

The USLE model (Equation 2.4) was here used to assess soil loss of actual LULC in 2013 and the simulated LULC in 2023 for each scenario. Herewith common static factors of soil erosion included rainfall-runoff erosivity (R), soil erodibility (K), slope length (L), and steepness (S) were firstly generated as shown in Figures 6.1 - 6.4. At the same time dynamic factors according to actual LULC in 2013 and the simulated LULC in 2023 for each scenario included vegetation cover (C) and conservation support practice (P) which vary with LULC types were also separately generated as shown in Figures 6.5 - 6.12.

After that soil loss assessment for each relevant LULC was calculated using Model Builder under ArcGIS environment (Figure 6.13). Distribution of soil loss and its severity for actual LULC in 2013 and the simulated LULC in 2023 for each scenario according LDD standard was separately displayed in Figures 6.14 - 6.17.

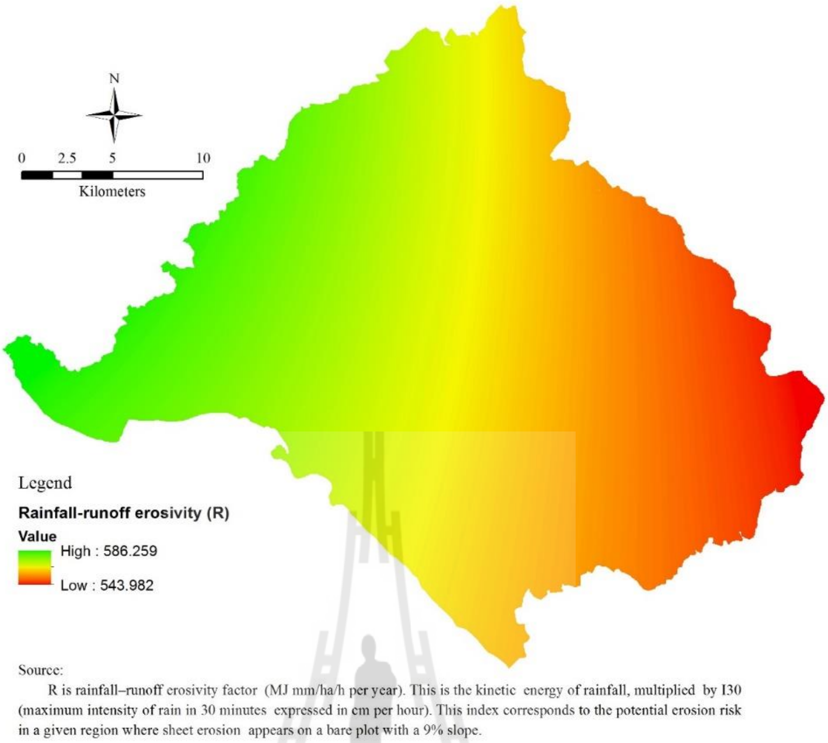


Figure 6.1 Rainfall-runoff erosivity (R) factor map.

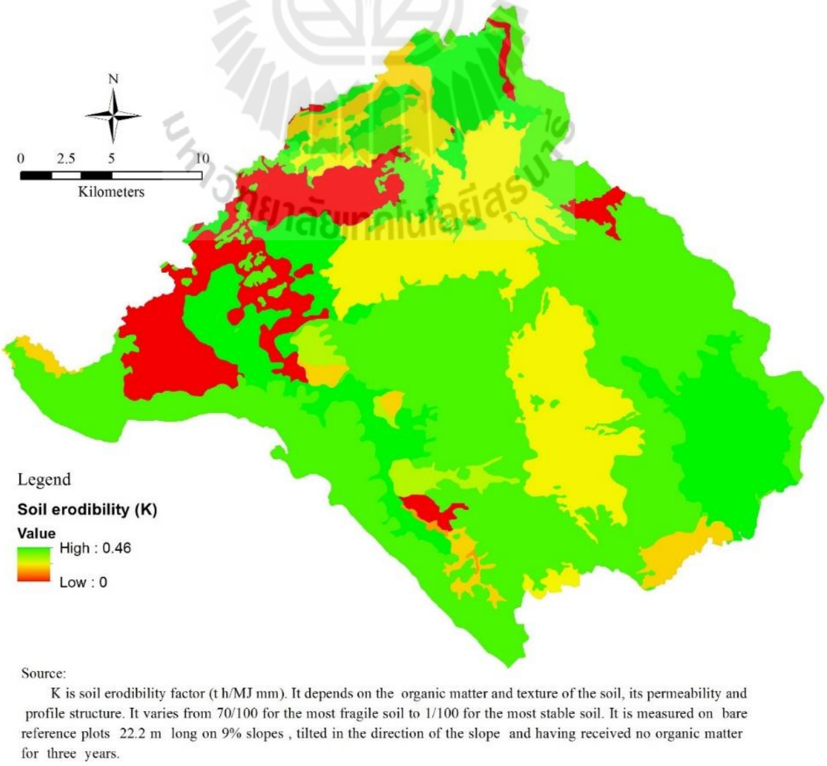


Figure 6.2 Soil erodibility (K) factor map.

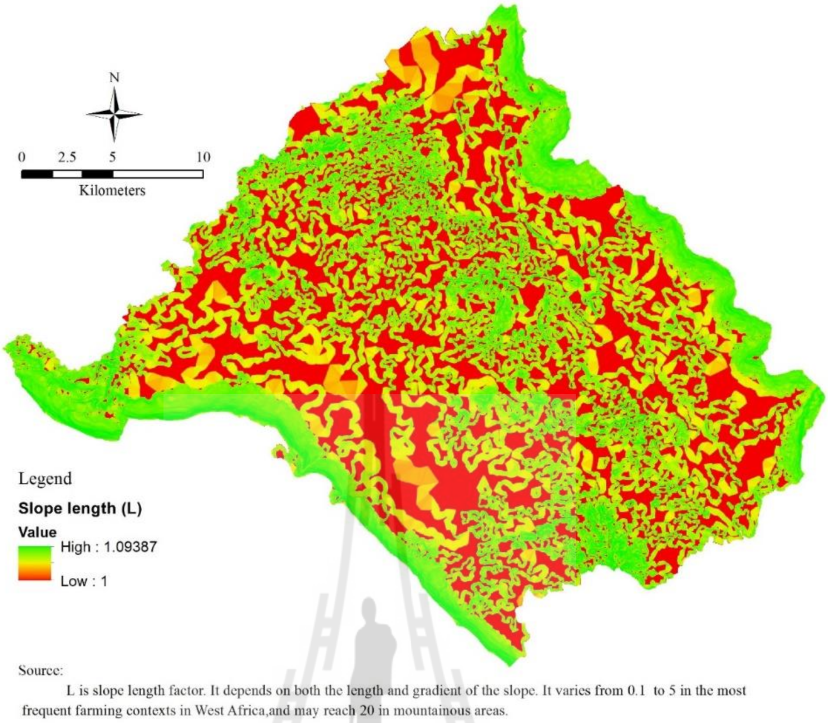


Figure 6.3 Slope length (L) factor map.

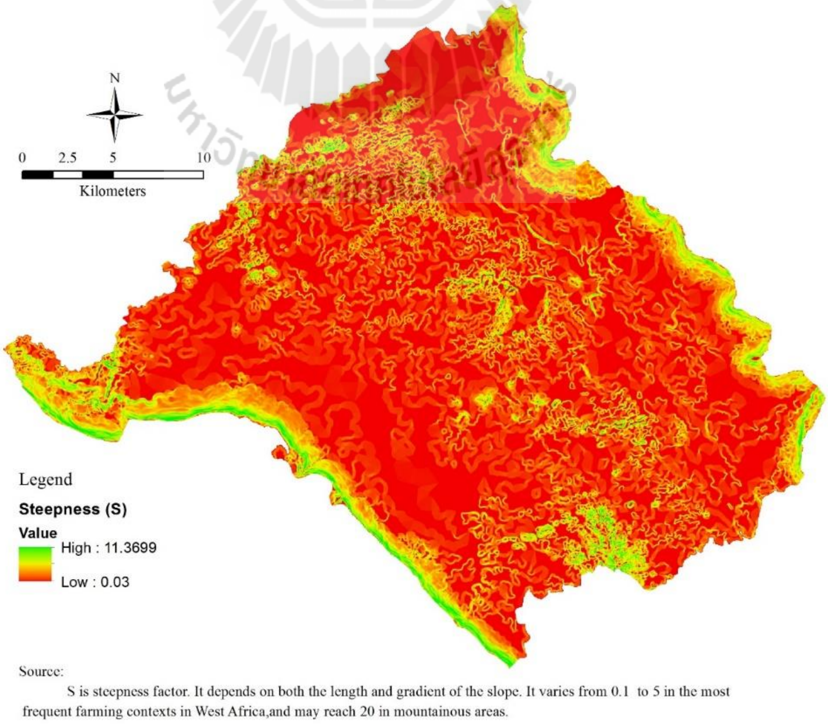


Figure 6.4 Steepness (S) factor map.

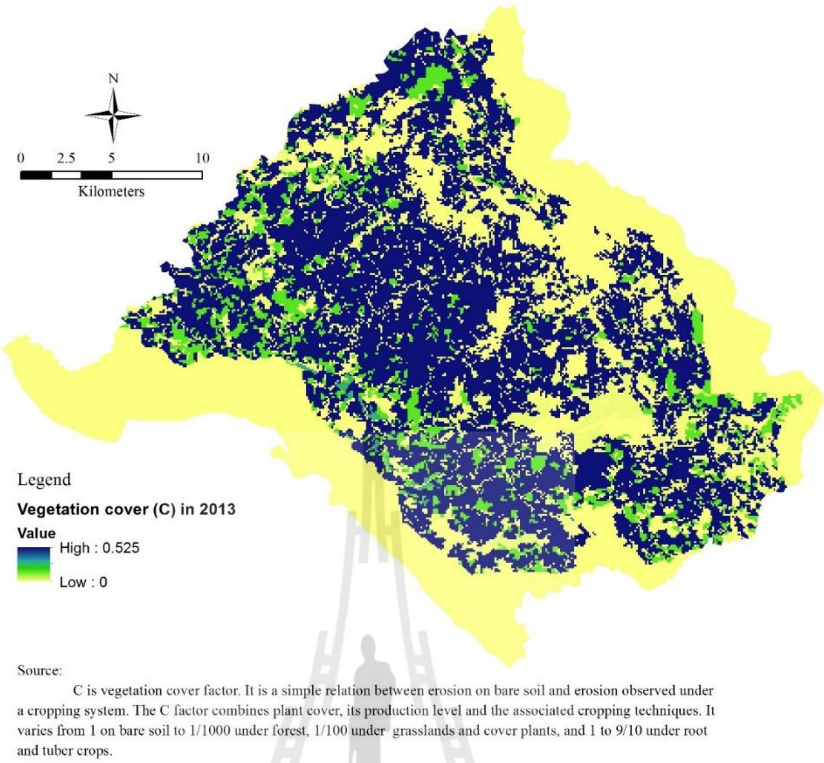


Figure 6.5 Vegetation cover (C) factor map for actual LULC in 2013.

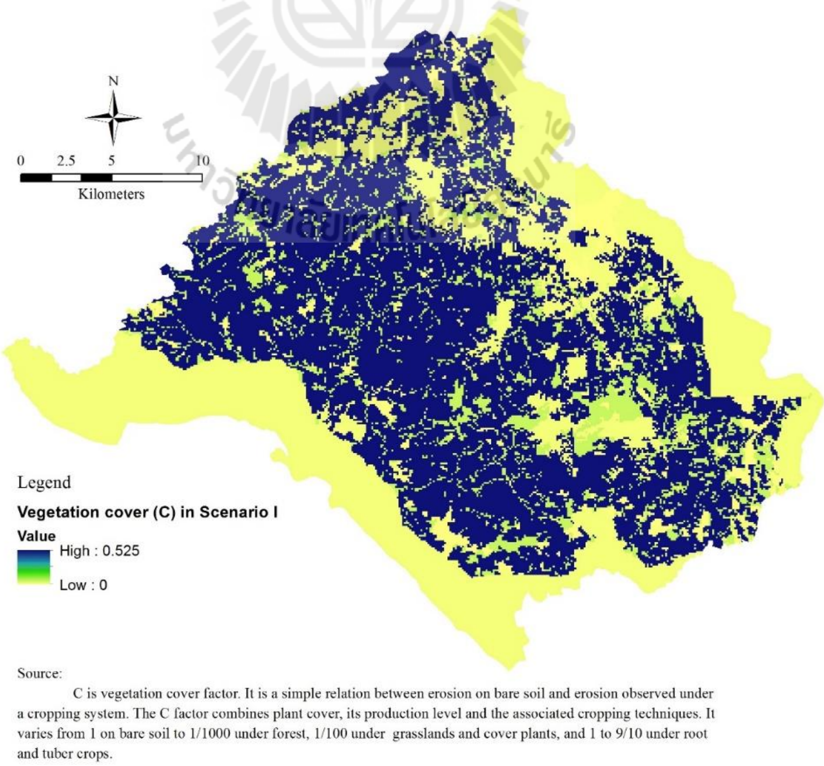


Figure 6.6 Vegetation cover (C) factor map for LULC in 2023 of Scenario I.

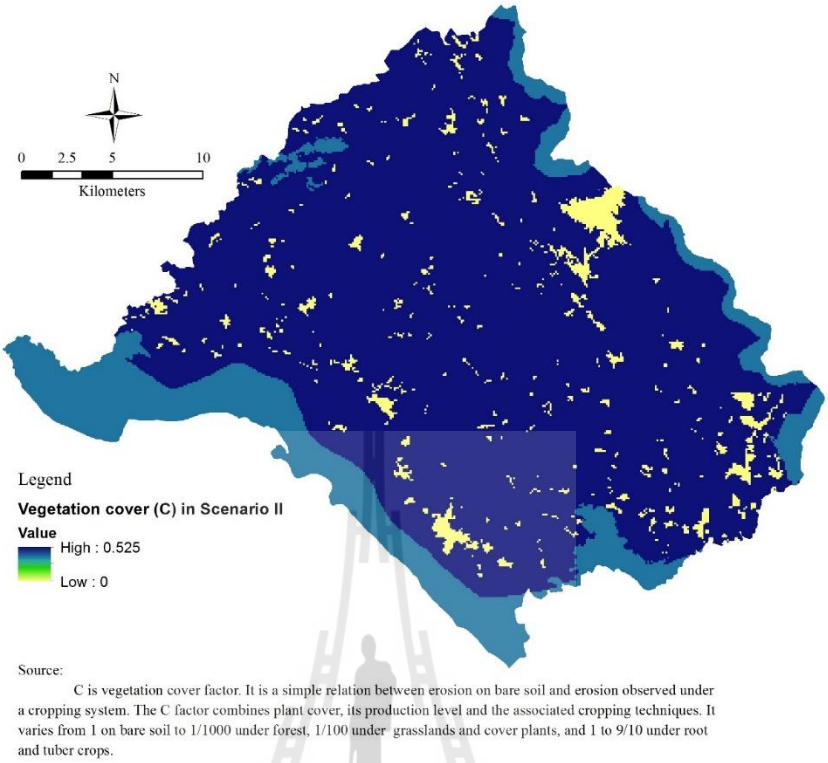


Figure 6.7 Vegetation cover (C) factor map for LULC in 2023 of Scenario II.

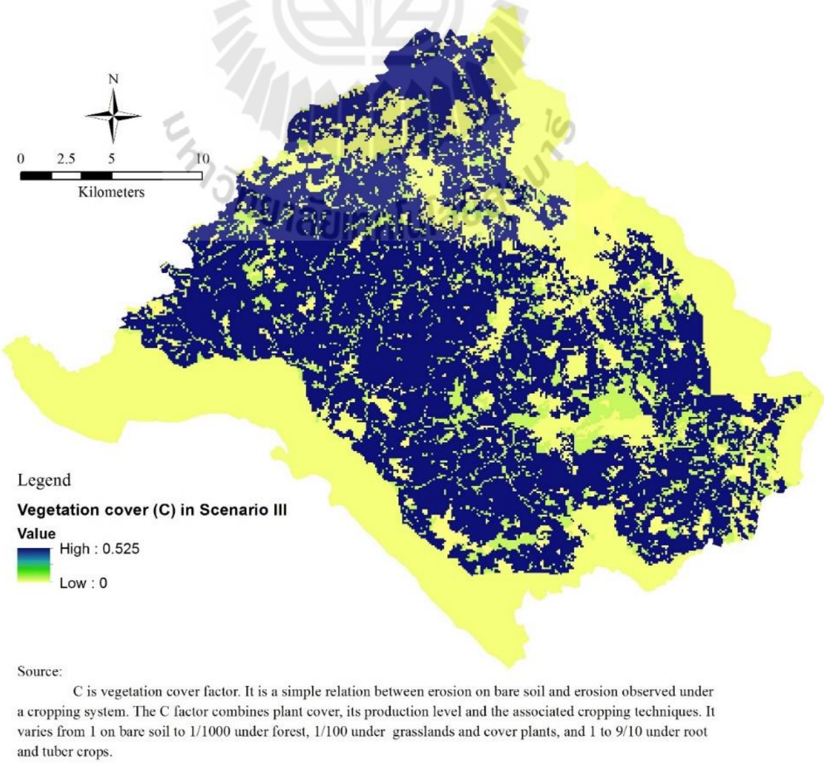


Figure 6.8 Vegetation cover (C) factor map for LULC in 2023 of Scenario III.

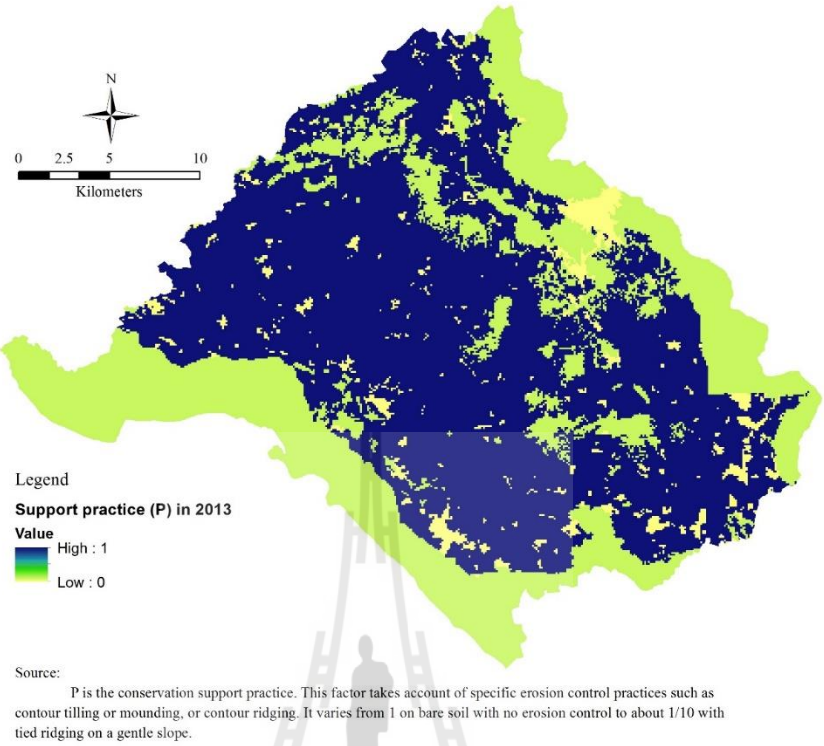


Figure 6.9 Conservation support practice (P) factor map for actual LULC in 2013.

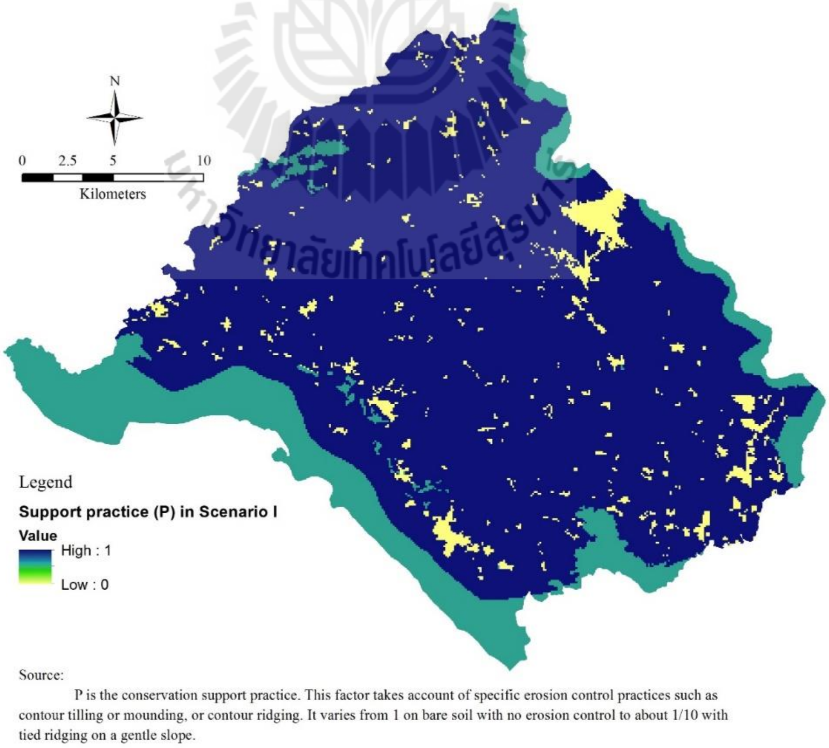


Figure 6.10 Conservation support practice (P) factor map for LULC in 2023 of Scenario I.

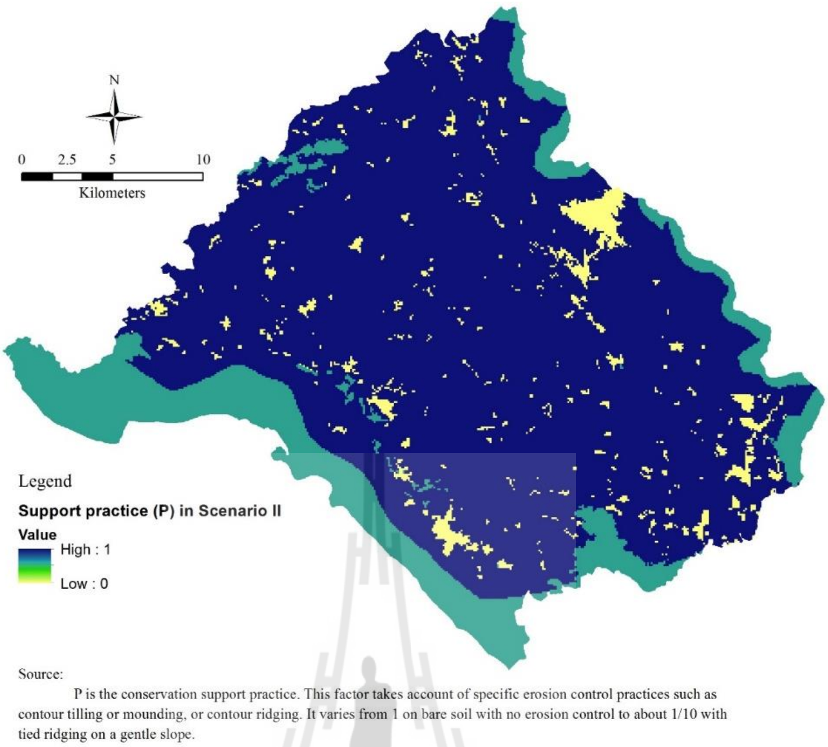


Figure 6.11 Conservation support practice (P) factor map for LULC in 2023 of Scenario II.

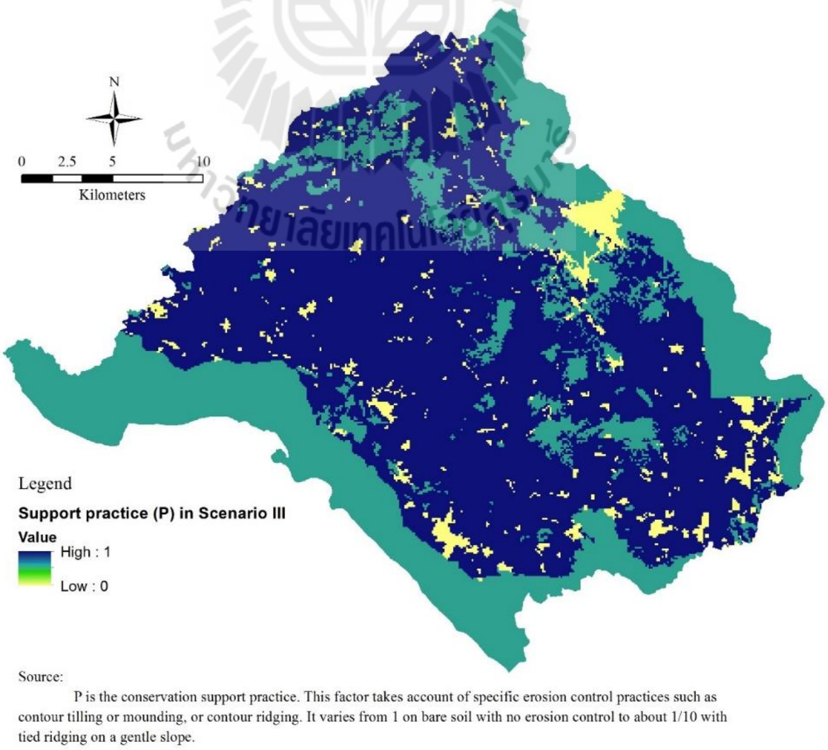


Figure 6.12 Conservation support practice (P) factor map for LULC in 2023 of Scenario III.

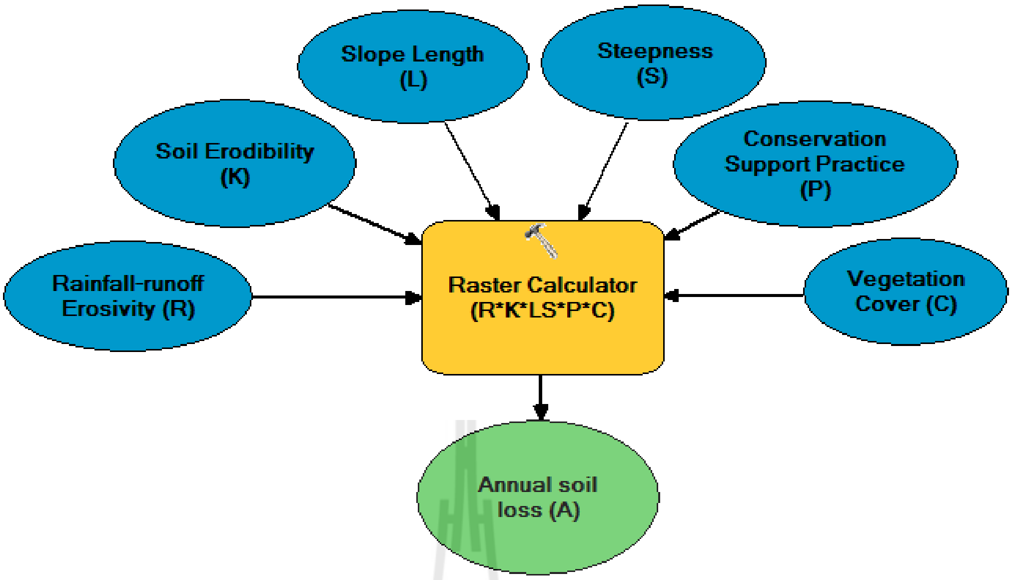


Figure 6.13 Schematic diagram of Model Builder for soil loss assessment.

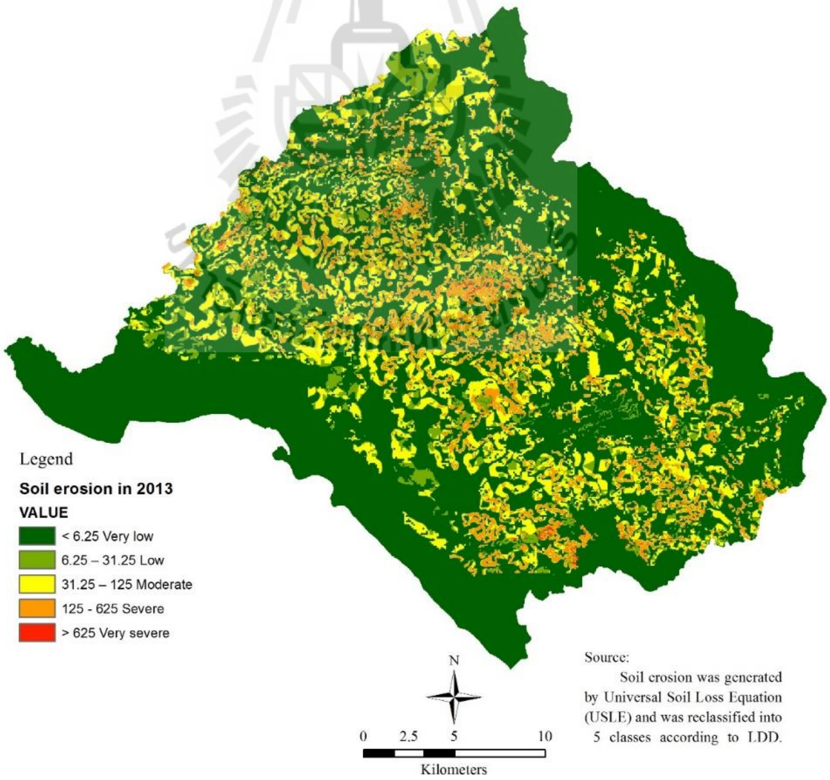


Figure 6.14 Distribution of soil loss and its severity for actual LULC in 2013.

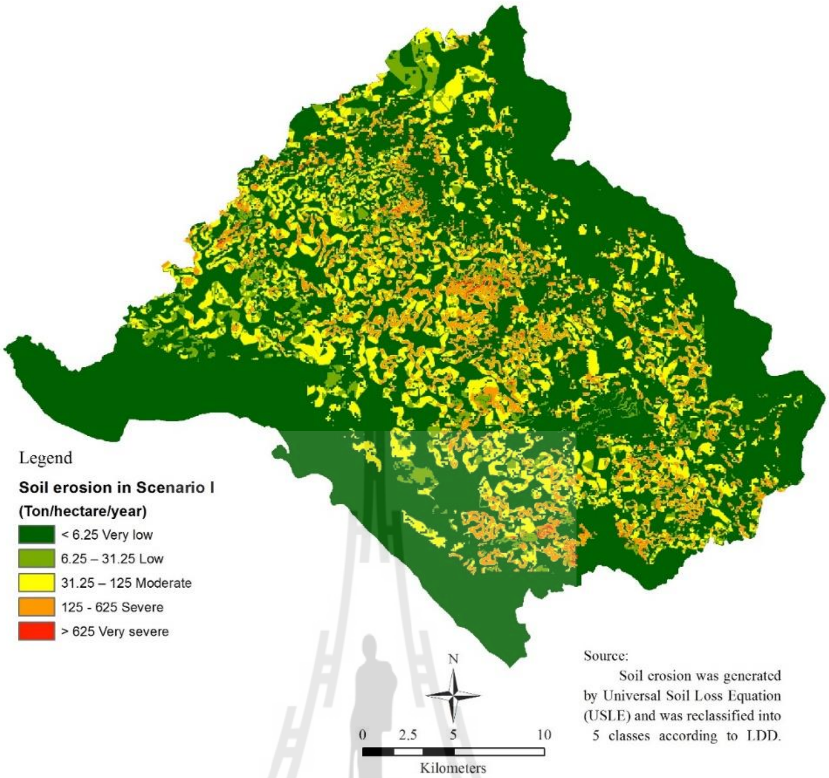


Figure 6.15 Distribution of soil loss and its severity for LULC in 2023 of Scenario I.

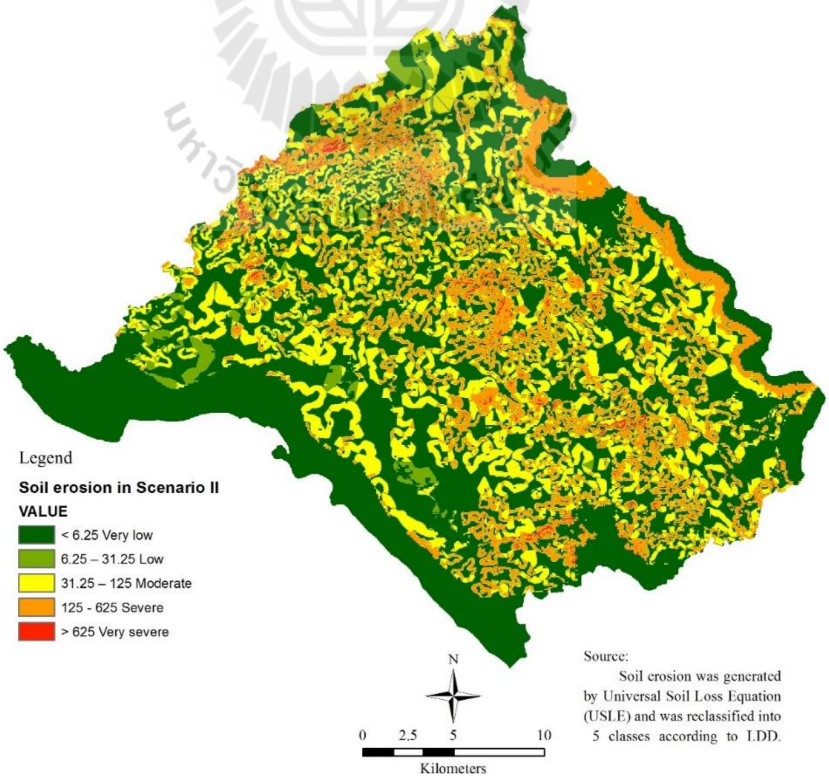


Figure 6.16 Distribution of soil loss and its severity for LULC in 2023 of Scenario II.

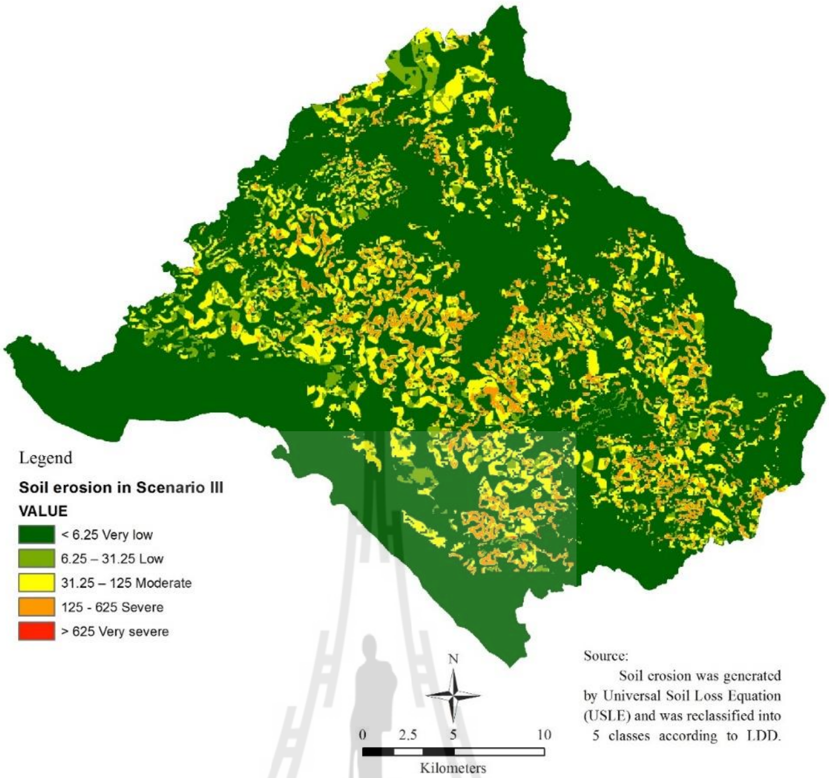


Figure 6.17 Distribution of soil loss and its severity for LULC in 2023 of Scenario III.

At the same time, area of soil loss severity class from LULC in 2013 and LULC in 2023 of each scenario (I to III) were compared and summarized as shown in Table 6.1 and Figure 6.18. It was evident that the most dominate soil loss severity class occurred in 2013 and 2023 in the study area was very low (0-6.25 ton/ha/year). It covered area of 67.70, 67.89, 49.82 and 73.66 percent for LULC 2013 and LULC in 2023 of Scenario I, II and III, respectively. In contrast, the least dominant soil loss class occurring in this period was very severe (more than 625 ton/ha/year) and covered area of 0.16, 0.17, 0.71 and 0.03 percent, respectively. Meanwhile, the moderate severity class from LULC in 2023 of Scenario II was higher than others and covered area of 24.05 percent.

Table 6.1 Area of soil loss and its severity for LULC in 2013 and LULC in 2023 of each scenario.

Severity Class	Loss Rate (t/ha/y)	LULC2013		Scenario I		Scenario II		Scenario III	
		ha	%	ha	%	ha	%	ha	%
Very low	≤ 6.25	52,241	67.70	52,391	67.89	38,452	49.82	56,838	73.66
Low	6.25 – 31.25	6,380	8.27	6,039	7.83	5,364	6.95	5,311	6.88
Moderate	31.25 – 125	12,018	15.57	12,074	15.65	18,556	24.05	10,456	13.55
Severe	125 - 625	6,402	8.30	6,532	8.46	14,248	18.46	4,535	5.88
Very serve	> 625	124	0.16	129	0.17	545	0.71	25	0.03
Minimum value by cell (t/ha/y)			0		0		0		0
Maximum value by cell (t/ha/y)			1,165.9		1,165.9		1,256.3		984.0
Mean value by cell (t/ha/y)			32.6		33.1		71.2		23.3
Actual soil loss (t/ha/y)			40,213,210		40,856,714		87,959,870		28,779,226

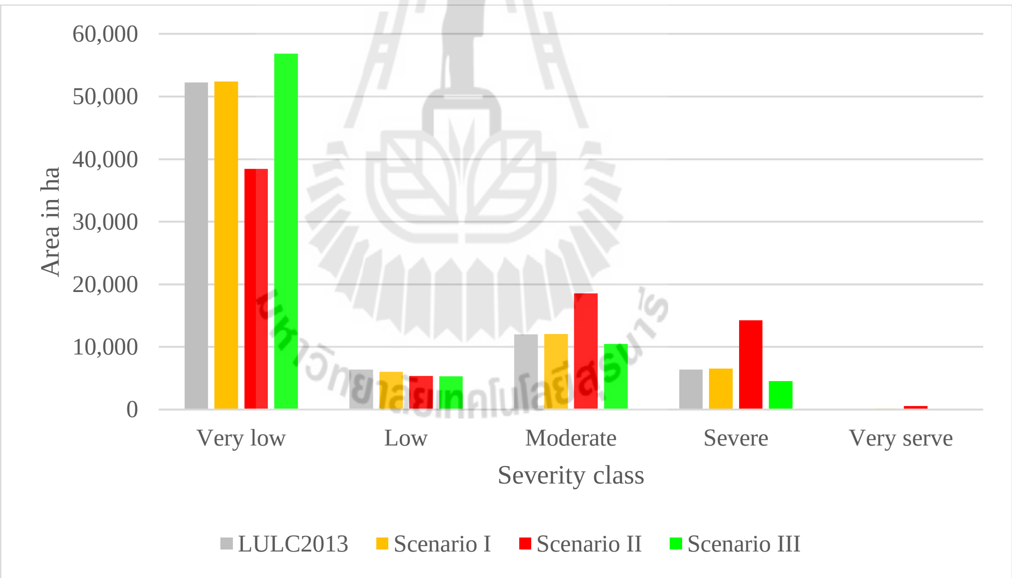


Figure 6.18 Comparison of soil loss severity level for LULC in 2013 and LULC in 2023 of each scenario.

In addition, mean annual soil loss from LULC in 2013 and LULC in 2023 of each scenario by cell were 32.6, 33.1, 71.2 and 23.3 ton/ha/year, respectively. Meanwhile actual total soil loss from LULC in 2013 and LULC in 2023 of each scenario by summation of all cells were 40,213,210, 40,856,714, 87,959,870, and 28,779,226 ton/ha/year respectively.

As results, it was clear that LULC in 2023 of Scenario II, which represents for agriculture production extension for energy crops, comparatively generates actual total soil loss higher than LULC in 2013 and others scenarios. In fact actual total soil loss under Scenario II was higher than LULC in 2013 and LULC in 2023 of Scenario I about twofold and higher than LULC in 2023 of Scenario III about threefold.

For impact of LULC change on soil loss, soil loss severity class which was derived from LULC in 2013 was used as baseline data to compare with soil loss severity class from LULC in 2023 of each scenario as gain and loss using post classification algorithm. The results of soil loss change as gain and loss due to LULC change between actual LULC in 2013 and simulated LULC in 2023 of three scenario were presented in term of gain and loss of severity classes in Table 6.2 to 6.4. At the same time, spatial distribution of gain (positive change) and loss (negative change) of severity classes between LULC in 2013 and LULC in 2023 of each scenario which represented a quantity from-to change information of soil loss severity during two periods were displayed in Figures 6.19 - 6.21.

Table 6.2 Soil loss severity class change between LULC in 2013 and LULC in 2023 of Scenario I.

	Soil loss severity class	LULC in 2023 of Scenario I (ha)					
		Very low	Low	Moderate	Severe	Very severe	Total
LULC in 2013 (ha)	Very low	52,050	72	63	52	4	52,241
	Low	230	5,950	200	0	0	6,380
	Moderate	105	14	11,811	88	0	12,018
	Severe	6	3	0	6,392	1	6,402
	Very severe	0	0	0	0	124	124
	Total	52,391	6,039	12,074	6,532	129	77,165

Table 6.3 Soil loss severity class change between LULC in 2013 and LULC in 2023 of Scenario II.

	Soil loss severity class	LULC in 2023 of Scenario II (ha)					
		Very low	Low	Moderate	Severe	Very severe	Total
LULC in 2013 (ha)	Very low	38,451	1,933	5,437	6,117	303	52,241
	Low	1	3,431	1,894	952	102	6,380
	Moderate	0	0	11,225	792	1	12,018
	Severe	0	0	0	6,387	15	6,402
	Very severe	0	0	0	0	124	124
	Total	38,452	5,364	18,556	14,248	545	77,165

Table 6.4 Soil loss severity class change between LULC in 2013 and LULC in 2023 of Scenario III.

	Soil loss severity class	LULC in 2023 of Scenario III (ha)					
		Very low	Low	Moderate	Severe	Very severe	Total
LULC in 2013 (ha)	Very low	52,238	3	0	0	0	52,241
	Low	1,043	5,308	29	0	0	6,380
	Moderate	1,573	0	10,427	18	0	12,018
	Severe	1,885	0	0	4,517	0	6,402
	Very severe	99	0	0	0	25	124
	Total	56,838	5,311	10,456	4,535	25	77,165

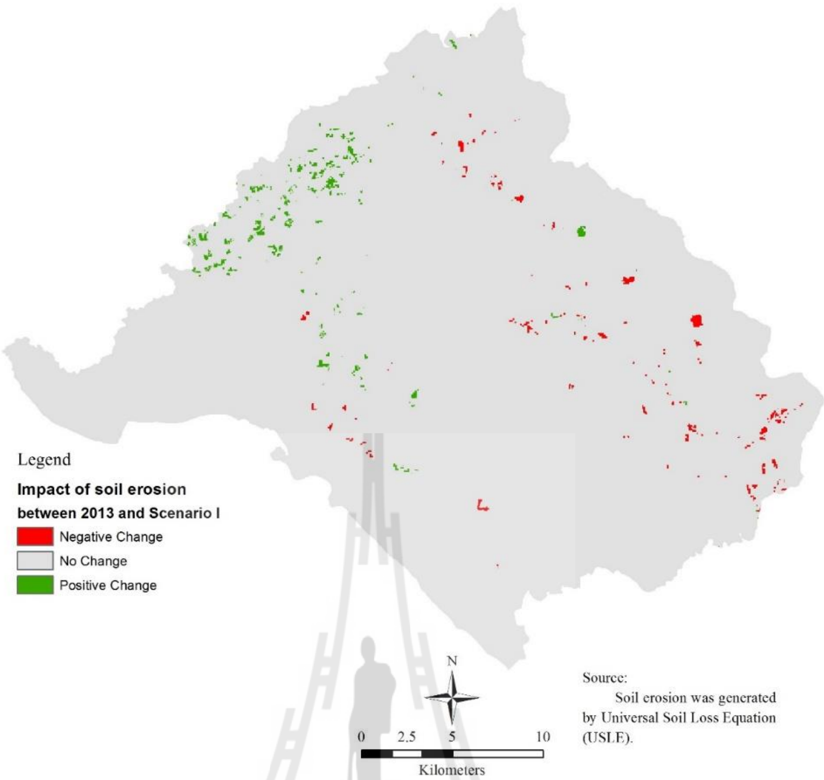


Figure 6.19 Distribution of gain and loss severity class of Scenario I.

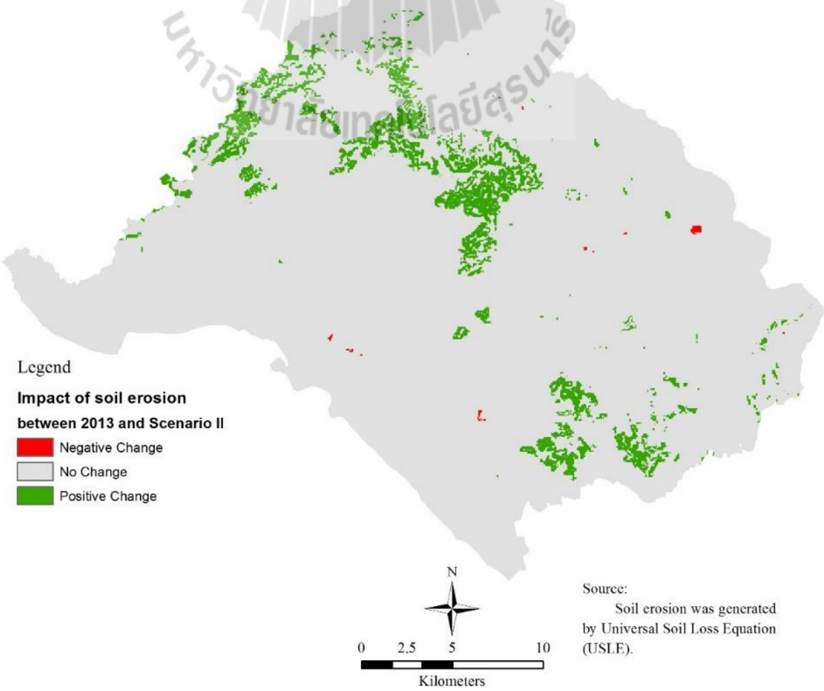


Figure 6.20 Distribution of gain and loss severity class of Scenario II.

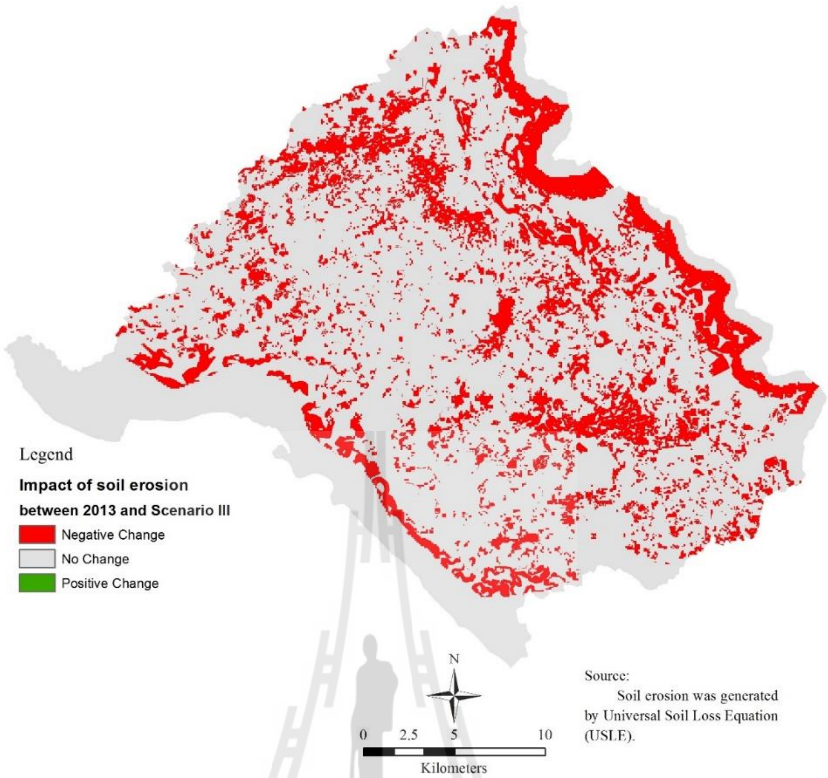


Figure 6.21 Distribution of gain and loss severity class of Scenario III.

As results, it was found that areas of gain and loss severity classes for LULC in 2023 of Scenario I, which represented historical land use evolution, were 358 and 480 ha, respectively with gain and loss ratio about 0.7458. In contrast, areas of gain and loss severity classes for LULC in 2023 of Scenario II, which represented agriculture production extension for energy crops, were 1 and 17,546 ha, respectively with gain and loss ratio about 0.0001. Meanwhile areas of gain and loss severity classes for LULC in 2023 of Scenario III, which represented forest conservation and prevention, were 4,600 and 50 ha, respectively with gain and loss ratio about 92. These results implied that the simulated LULC 2023 for Scenario I creates more soil loss in the future due to LULC change according to historical land use evolution. Herein, areas of cassava and sugarcane in 2023, which create more soil loss according to C and P factors (see Table

3.5), increased while areas of perennial trees/orchards and forest land in 2023, which create less soil loss, decrease.

In contrast, the simulated LULC 2023 for Scenario II, which aims to increase areas of cassava and sugarcane as energy crops, generates more soil loss in the future. Because area of perennial tree/orchard, forest land, and miscellaneous land in 2013 were converted to be cassava and sugarcane in 2023. In the opposite direction, the simulated LULC 2023 for Scenario III, which aims to conserve and preserve forest land, creates less soil loss in the future. Because area of maize, sugarcane and miscellaneous land were converted to be forest land. In fact, forest land increased about 6,631 ha between 2013 and 2023.

In addition, soil loss severity class change between Scenario I and Scenario II and Scenario I and Scenario III as transition matrix were also extracted as presented in Tables 6.5 - 6.6, respectively. Herewith both tables also explain from-to change of severity class between two scenarios in term of gain and loss. It was found that areas of gain and loss severity class of simulated LULC in 2023 between Scenario I (historical land use evolution) and Scenario II (agriculture production extension) were 0 and 17,114 ha, respectively. This result implies that the simulated LULC in 2023 of Scenario II create more soil loss than Scenario I and increases more soil loss severity. For example, very low severity class of Scenario I was changed to be low, moderate, severe and very severe classes in Scenario II about 1,876, 5,612, 6,152 and 300, ha, respectively. On the contrary, it was found that areas of gain and loss severity class of simulated LULC in 2023 between Scenario I (historical land use evolution) and Scenario III (forest conservation and preservation) were 21,265 and 0 ha, respectively. This result implies that the simulated LULC in 2023 of Scenario III create less soil loss than Scenario I and reduce soil loss severity. For example, areas of very severe (492 ha), severe (8,549 ha), moderate (7,019 ha), and low (2,328 ha) classes of Scenario I became very low severity class in Scenario III. These results show severe negative impact of LULC change under Scenario II when it compares to Scenario III as representing forest conservation and prevention or even Scenario I as representing the historical land use evolution.

Table 6.5 Soil loss severity class change between Scenario I and Scenario II.

	Soil loss severity class	**Scenario II (ha)**					
		Very low	**Low**	**Moderate**	**Severe**	**Very severe**	**Total**
Scenario I (ha)	Very low	38,451	**1,876**	**5,612**	**6,152**	**300**	52,391
	Low	0	3,488	**1,479**	**970**	**102**	6,039
	Moderate	0	0	11,465	**608**	**1**	12,074
	Severe	0	0	0	6,518	**14**	6,532
	Very severe	0	0	0	0	129	129
	Total	38,451	5,364	18,556	14,248	546	77,165

Table 6.6 Soil loss severity class between Scenario I and Scenario III.

	Soil loss severity class	**Scenario III (ha)**					
		Very low	**Low**	**Moderate**	**Severe**	**Very severe**	**Total**
Scenario I (ha)	Very low	38,451	0	0	0	0	38,451
	Low	**2,328**	3,036	0	0	0	5,364
	Moderate	**7,019**	**1,678**	9,859	0	0	18,556
	Severe	**8,549**	**572**	**597**	4,530	0	14,248
	Very severe	**492**	**25**	**1**	**4**	24	546
	Total	56,839	5,311	10,457	4,534	24	77,165

In summary, it can be here stated that vegetation cover (C) and conservation support practice (P) factors, which are dynamic and directly relate to LULC type of LULC change play an important role on amount of soil erosion because other factors including rainfall-runoff erosivity (R), soil erodibility (K), slope length (L), and steepness (S) are here assumed as static factors to estimate soil loss for LULC in 2013 and LULC in 2023 of three scenarios. As results, it can be concluded that LULC change creates a positive and negative effect to soil erosion. In this study, increasing of cassava and sugarcane under Scenario II created more actual total soil loss. In contrast, increasing of forest land under Scenario III reduce actual total soil loss. These characteristics was conformed to the previous work of Ongsomwang and Thinley (2009) who assessed soil erosion and its change in Upper Lam Phra Phloeng watershed between 2000 and 2008. They stated that the higher erosion rate can be attributed to increasing usage of land for agricultural purpose. Furthermore, this observation can be confirmed by simple linear regression using Trend Analysis of MS-Excel. Herewith the relationship between the percentage of agricultural land (paddy field, cassava, maize, sugarcane, and perennial tree/orchard) and forest land from actual LULC in 2013 and simulated LULC of three scenario, which represent LULC change, were regressed with actual total soil loss as shown in Figure 6.22. Herein the simple linear equation between percentage of agricultural land and actual total soil loss showed positive relationship with R^2 at 99.93% as:

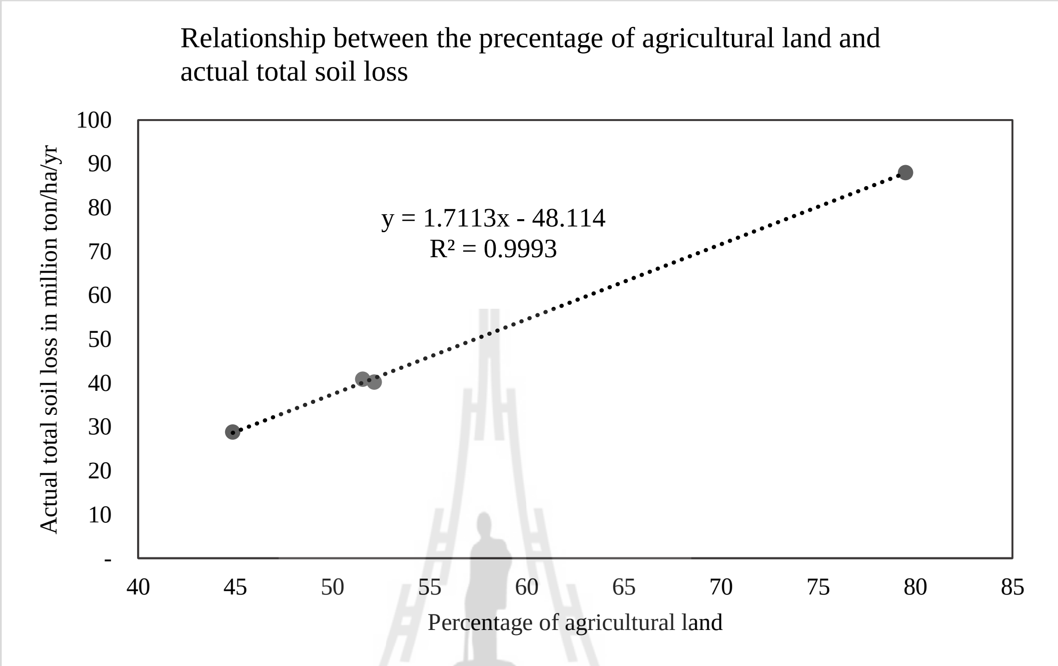
$$y = 1.7113x - 48.114, \tag{6.1}$$

where y is actual total soil loss in million ton/ha/year and x is the percentage of agricultural land of the watershed area.

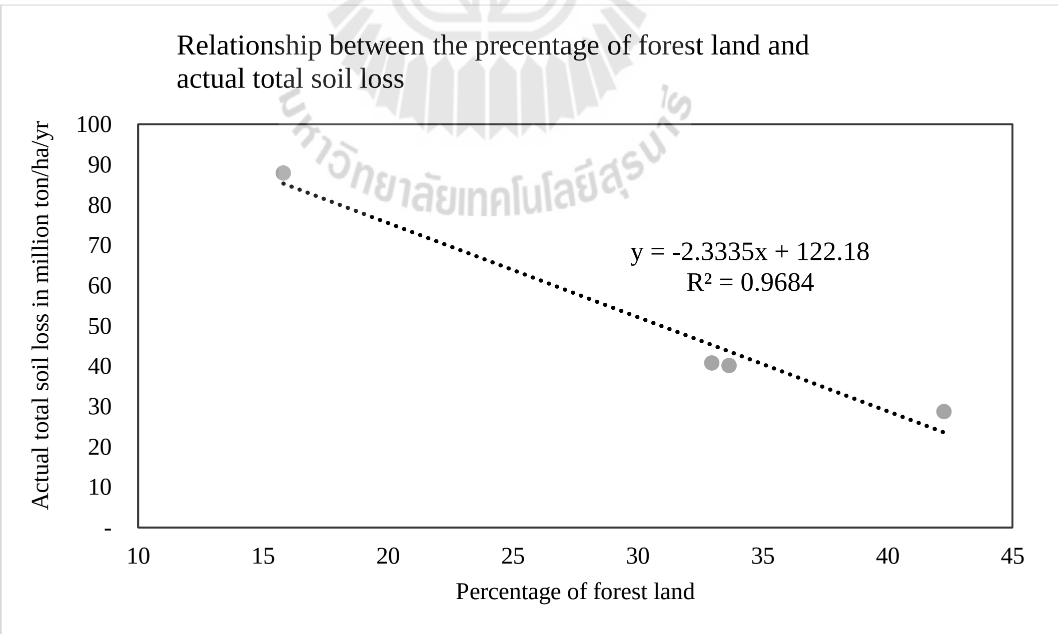
Meanwhile the simple linear equation between percentage of forest land and actual total soil loss showed negative relationship with R^2 at 96.84% as:

$$y = 122.18 - 2.3335x, \tag{6.2}$$

Where y is actual total soil loss in million ton/ha/year and x is percentage of forest land of the watershed area.



(a)



(b)

Figure 6.22 Simple linear regression analysis between percentage of agricultural land (a) and forest land (b) with actual total soil loss**.**

6.2 Water yield estimation and its impact due to LULC change

SWAT model with SCS-CN method was here used to estimate water yield of actual LULC in 2013 and the simulated LULC in 2023 for each scenarios. Herein SWAT model with an optimum local parameters was firstly used to generate CN value in each hydrologic response unit (HRU) for LULC in 2013 and SCS-CN method were then used to estimate theirs water yield (runoff depth).

6.2.1 CN value of hydrologic response unit by SWAT model

In this study the basic biophysical factors included actual LULC in 2003, soil data, and DEM which cover two hydrological station two, namely M145 for model calibration, and M171 for model validation, and daily rainfall and runoff in 2003 were prepared to simulate water yield and to identify an optimum local parameters identification for creating CN value in hydrologic response unit of LULC in 2013 and the simulated LULC in 2023 of three scenario. Figures 6.23 - 6.25 displayed three basic biophysical factors including LULC in 2003, soil data, and DEM, respectively; and Table 6.7 summarized monthly rainfall from Chok Chai meteorological station (431401) and runoff data from M145 and M171 stations, respectively.

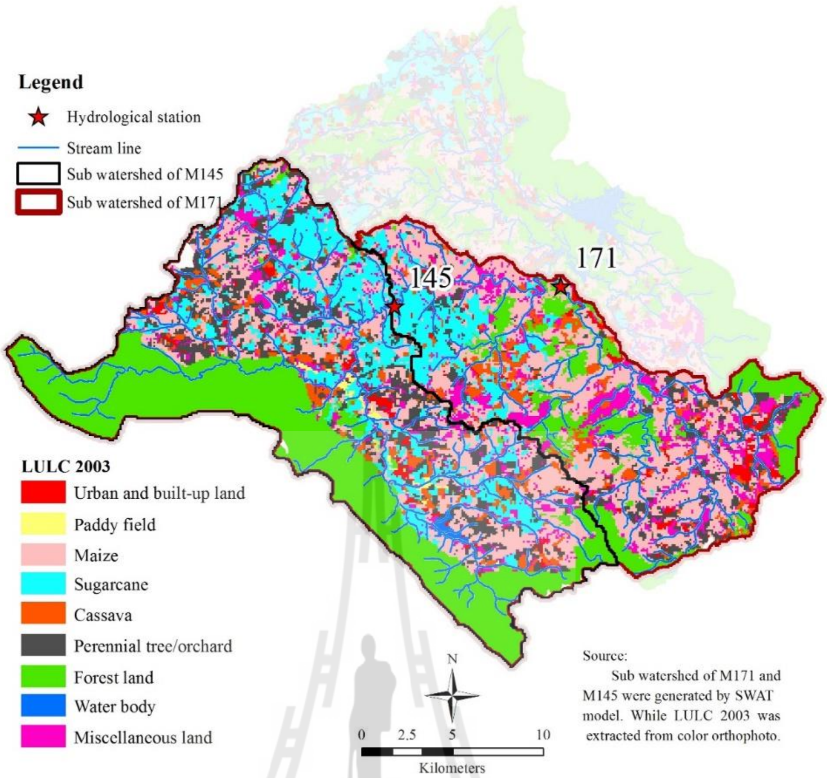


Figure 6.23 LULC in 2003 and sub watershed of hydrological station.

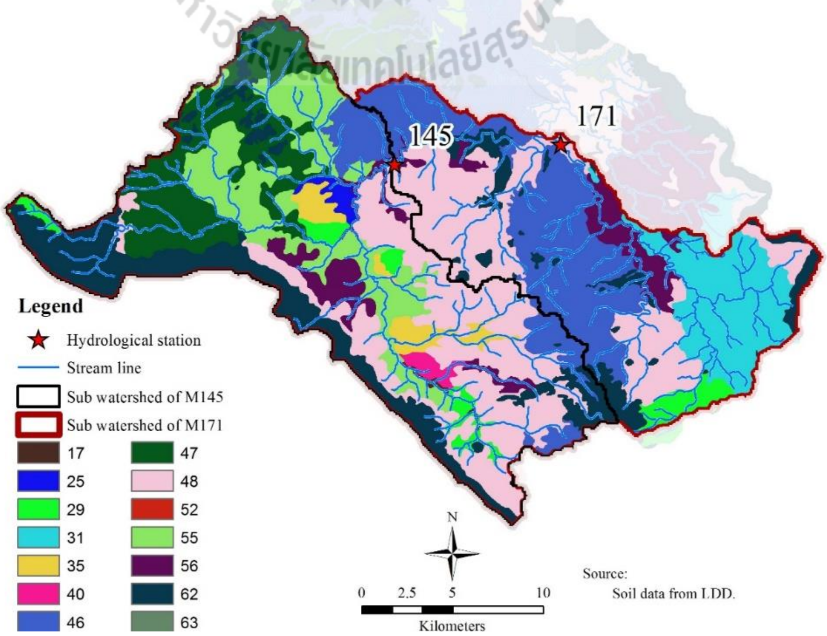


Figure 6.24 Distribution of soil data and sub watershed of hydrological station.

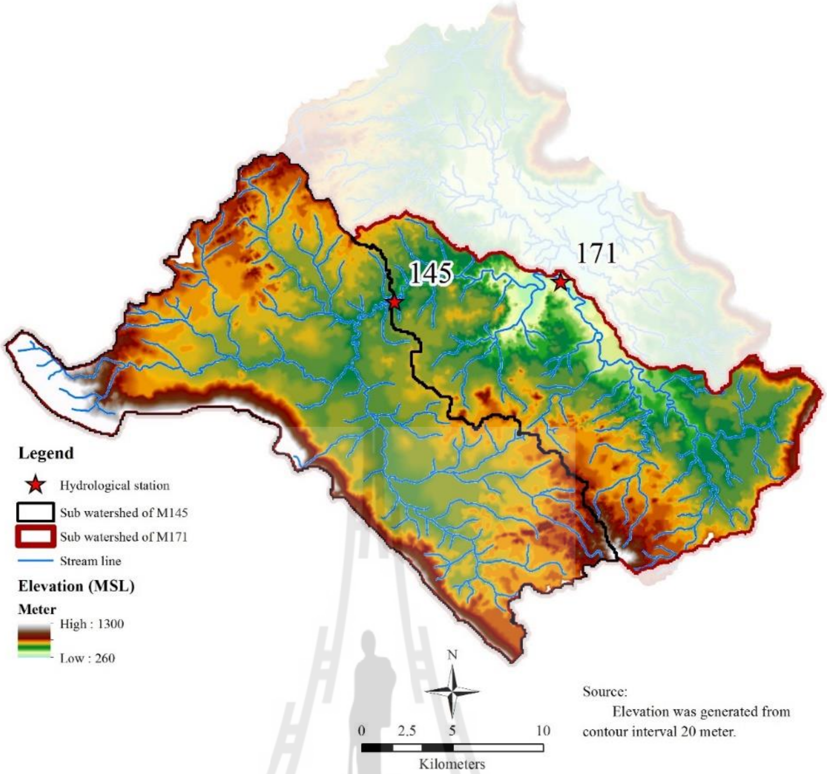


Figure 6.25 Distribution of elevation and sub watershed of hydrological station.

Table 6.7 Monthly rainfall from Chok Chai meteorological station (431401) and runoff data from M145 and M171 stations.

Month	**Monthly rainfall (mm)**		
	Hydrological station		**Rain station**
	M145	**M171**	**431401**
January	4.81	8.63	0.00
February	2.83	6.20	26.70
March	10.34	16.37	48.10
April	15.40	19.15	2.80
May	15.58	23.06	106.70
June	11.85	17.05	185.90
July	21.94	37.16	127.20
August	20.48	23.02	114.90
September	56.45	71.59	164.70
October	88.45	119.08	83.70
November	5.04	12.89	0.40
December	1.25	4.54	0.00
Total	**254.43**	**358.75**	**861.10**

For SWAT model calibration under sub-watershed of M145 station, input variables included land use, soil and slope class which are related to hydrologic response unit were proportional set up as 0, 0, and 0, respectively. Herewith, original size of each land use type which are related to soil and slope was used to generate hydrologic response unit. Meanwhile, selected hydrologic parameters included surface runoff lag times (Surlag), base flow alpha factor (Alpha_BF), and available water capacity of the first layer (SOL_AWC1) were varied to identify the optimum local parameters of SWAT model using Nash-Sutcliffe efficiency (NSE) and R^2. The optimum local parameters of SWAT model which provides the optimized accuracy of NSE and R^2 were as follows.

(1) Surface runoff lag times equals 0.1 day.

(2) Base flow alpha factor equals 0.9 day.

(3) Available water capacity of the first layer equals 0 mm.

Herein, the accuracy of NSE and R^2 were 0.74 and 0.76, respectively. Table 6.8 compared the actual and estimated monthly runoff of M145 station sub-watershed and Figure 6.26 demonstrated the runoff duration curve between the actual and estimated runoff values from station and SWAT model. Meanwhile Figure 6.27 displayed a simple linear regression between the actual runoff values from station M145 and estimated values from SWAT model. Detail of model calibration and accuracy assessment was represented in Table 1 of Appendix C.

Table 6.8 Comparison between actual and estimated monthly runoff of M145 station.

Month	Runoff (mm)	
	Actual	Estimate
January	4.81	0.00
February	2.83	0.28
March	10.34	1.21
April	15.40	0.12
May	15.58	0.99
June	11.85	14.92
July	21.94	29.69
August	20.48	31.74
September	56.45	36.23
October	88.45	86.19
November	5.04	29.31
December	1.25	11.03
Total	**254.43**	**241.71**

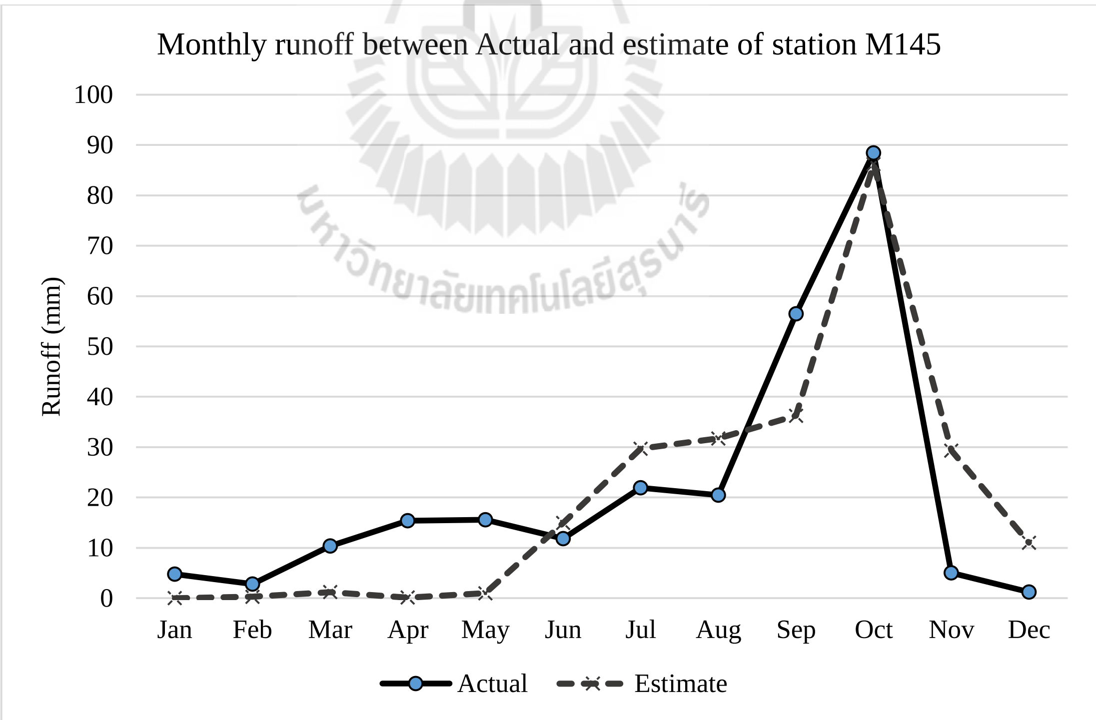


Figure 6.26 Actual and estimated runoff from station and SWAT model of M145.

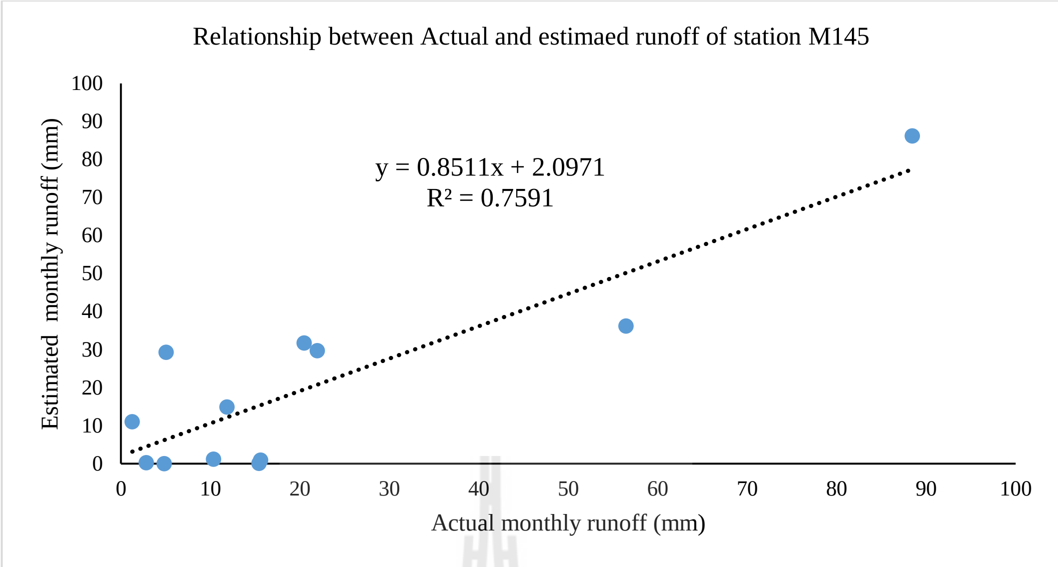


Figure 6.27 Simple linear regression analysis between actual runoff from station M145 and estimated runoff from SWAT model.

For SWAT model validation under Sub-watershed of M171, the derived optimum local parameters of SWAT model from M145 sub-watershed was validated to reconfirm the efficient of the SWAT model. The derived accuracy of NSE and R^2 were 0.75 and 0.79, respectively. This result was similar to calibration process. Therefore, the derived optimum local parameters of SWAT model were further used to generate CN value in each hydrologic response unit of actual LULC in 2013 and the simulated LULC in 2023 of three scenarios as shown in Figures 6.28 - 6.31.

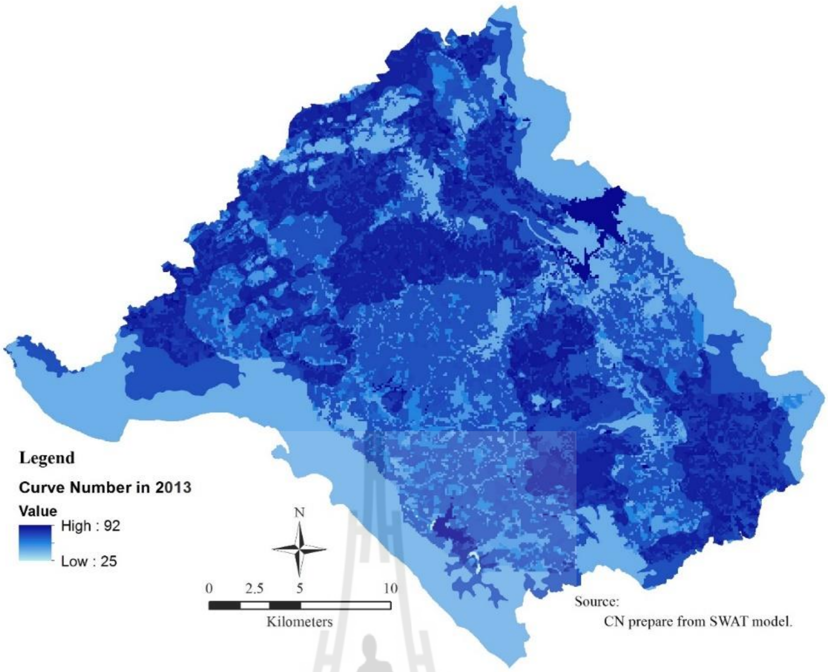


Figure 6.28 Distribution of runoff curve numbers for actual LULC in 2013.

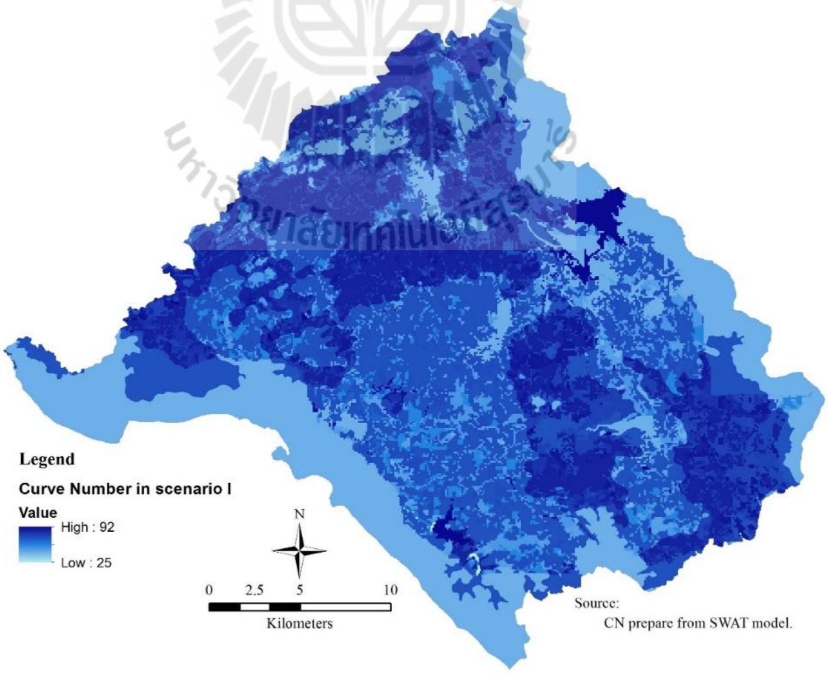


Figure 6.29 Distribution of runoff curve numbers for the simulated LULC in 2023 of Scenario I.

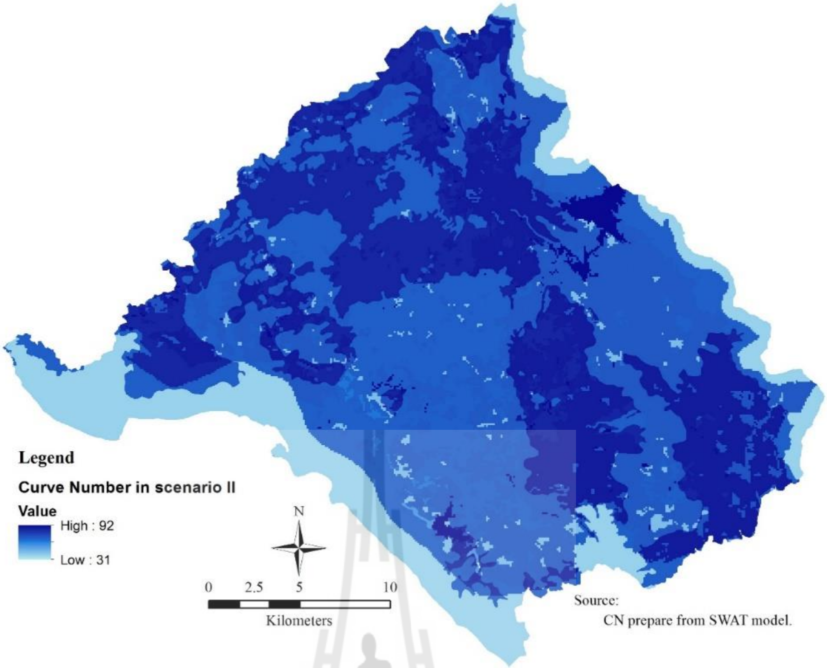


Figure 6.30 Distribution of runoff curve numbers for the simulated LULC in 2023 of Scenario II.

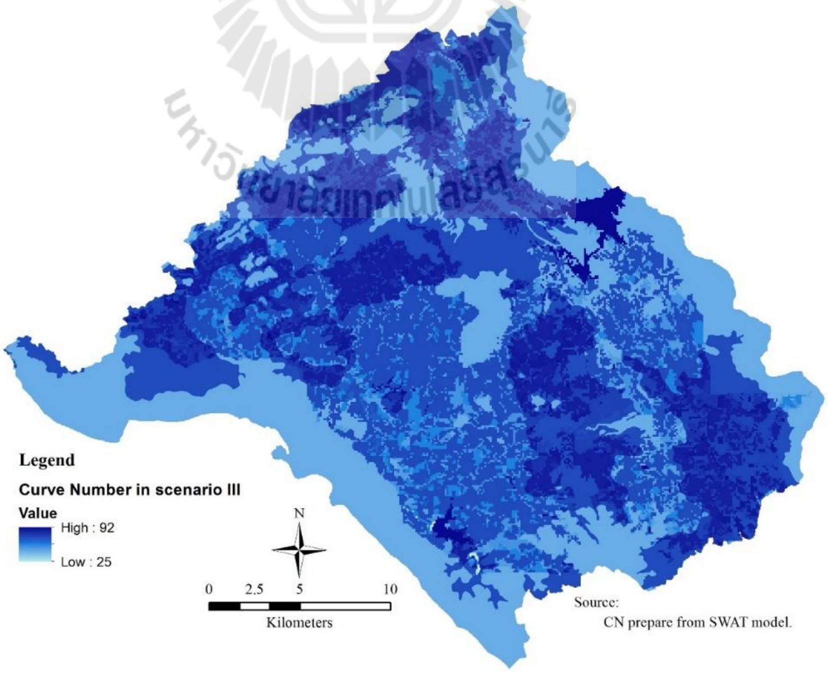


Figure 6.31 Distribution of runoff curve numbers for the simulated LULC in 2023 of Scenario III.

6.2.2 Water yield estimation using SCS-CN method

Based on the derived runoff curve numbers (CN) of hydrologic soil groups (HSG) from each hydrologic response unit from SWAT model, the potential maximum storage (S) of actual LULC in 2013 and the simulated LULC in 2023 of three scenario were calculated as:

$$S = 25.4 \times \frac{1000}{CN} - 10 \; ; \tag{6.3}$$

Where S is potential maximum storage in mm, and CN is runoff curve number of hydrologic soil group–land cover complex. Figures 6.32 - 6.35 displayed potential maximum storage (S) for actual LULC in 2013 and the simulated LULC in 2023 of three scenario.

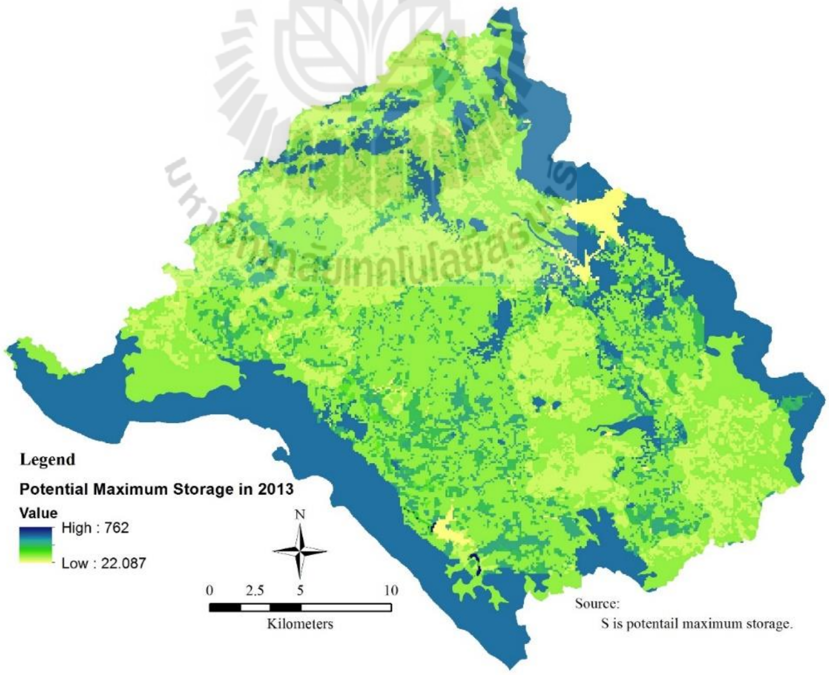


Figure 6.32 Distribution of potential maximum storage (S) for LULC in 2013.

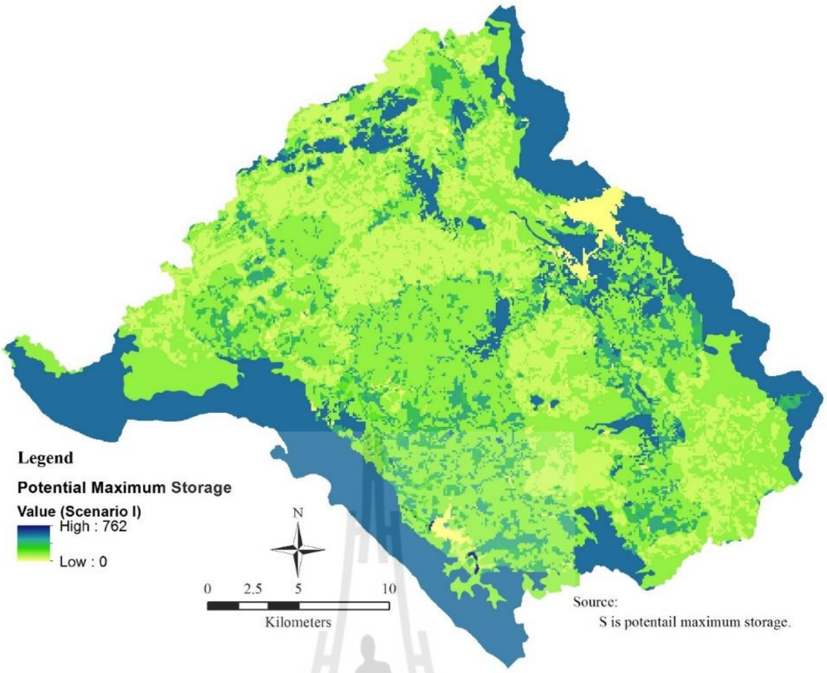


Figure 6.33 Distribution of potential maximum storage (S) for the simulated LULC in 2023 of Scenario I.

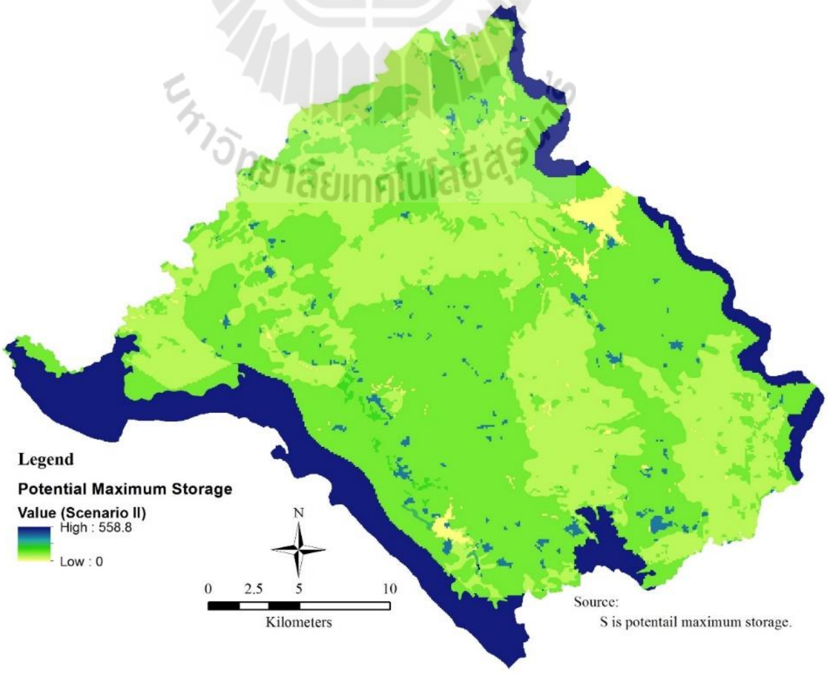


Figure 6.34 Distribution of potential maximum storage (S) for the simulated LULC in 2023 of Scenario II.

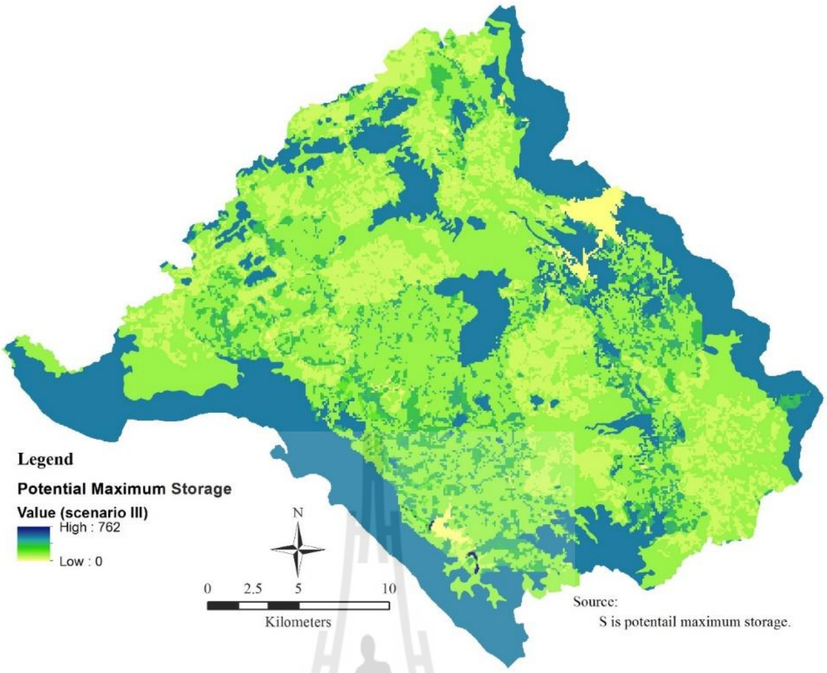


Figure 6.35 Distribution of potential maximum storage (S) for the simulated LULC in 2023 of Scenario III.

After that water yield was estimated based on the average monthly rainfall from 2002-2011 (Figure 6.36) using runoff depth equation (Equation 2.6). In practice, water yield (runoff depth) estimation for actual LULC in 2013 and the simulated LULC in 2023of each scenario was separately implemented using Model Builder under ArcGIS environment (Figure 6.37). Distribution of water yield by pixel for actual LULC in 2013 and the simulated LULC in 2023of each scenario displayed in Figure 6.38 to Figure 6.41 while summary of water yield by pixel for actual LULC in 2013 and the simulated LULC in 2023of each scenario was presented in Table 6.9.

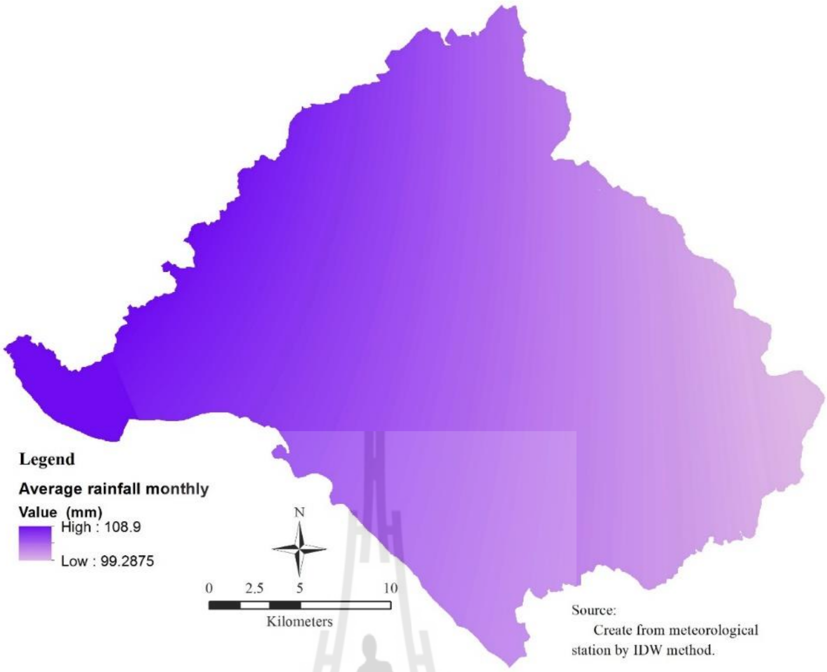


Figure 6.36 Average monthly rainfall from 2002-2011.

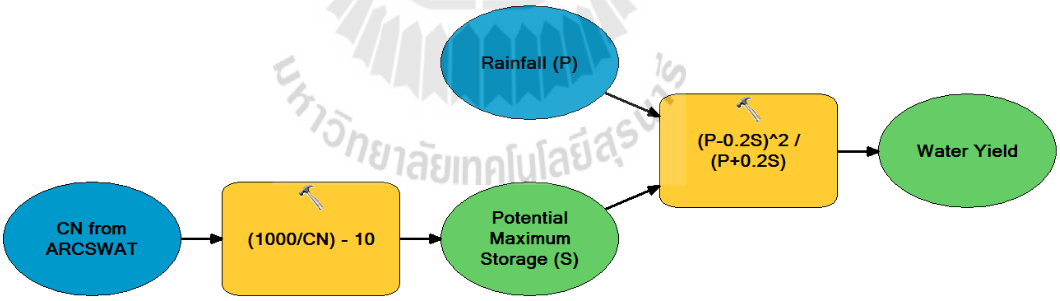


Figure 6.37 Schematic diagram of Model Builder for water yield estimation.

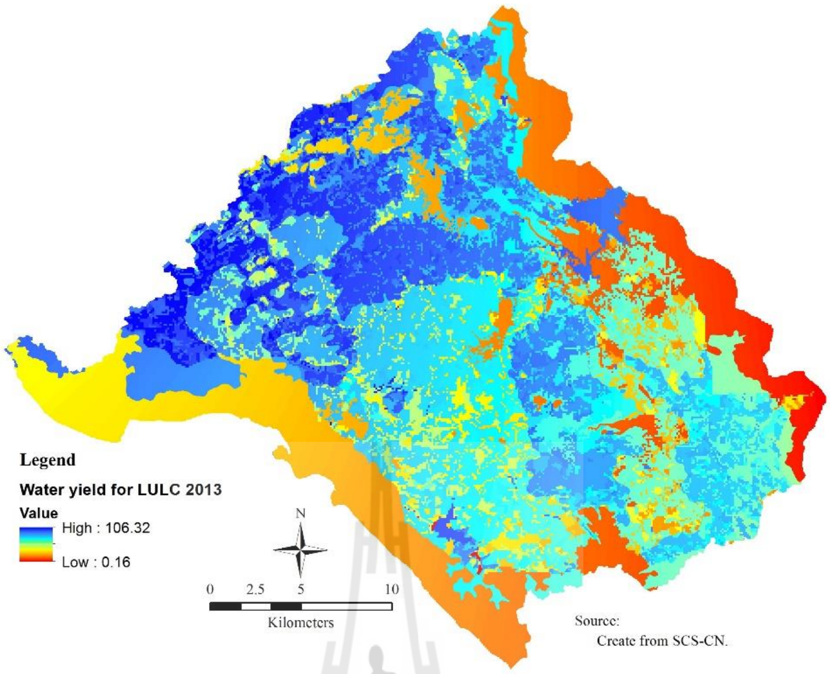


Figure 6.38 Distribution of water yield for LULC in 2013.

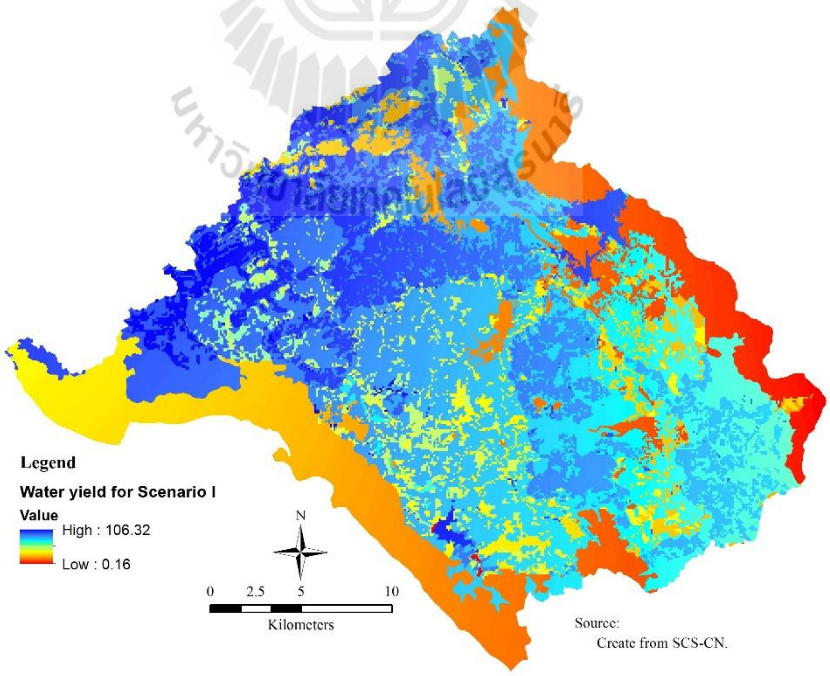


Figure 6.39 Distribution of water yield for the simulated LULC in 2023 of Scenario I.

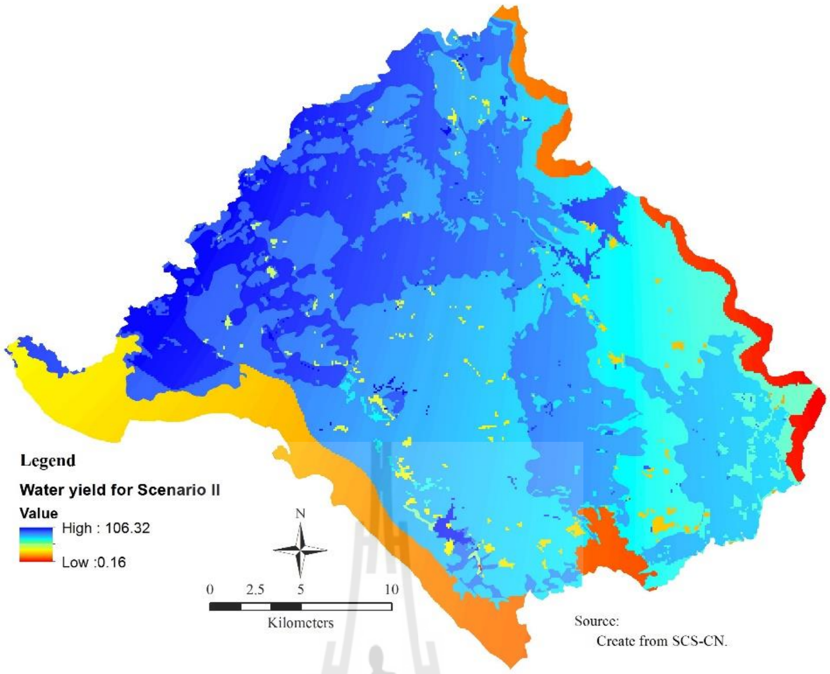


Figure 6.40 Distribution of water yield for the simulated LULC in 2023 of Scenario II.

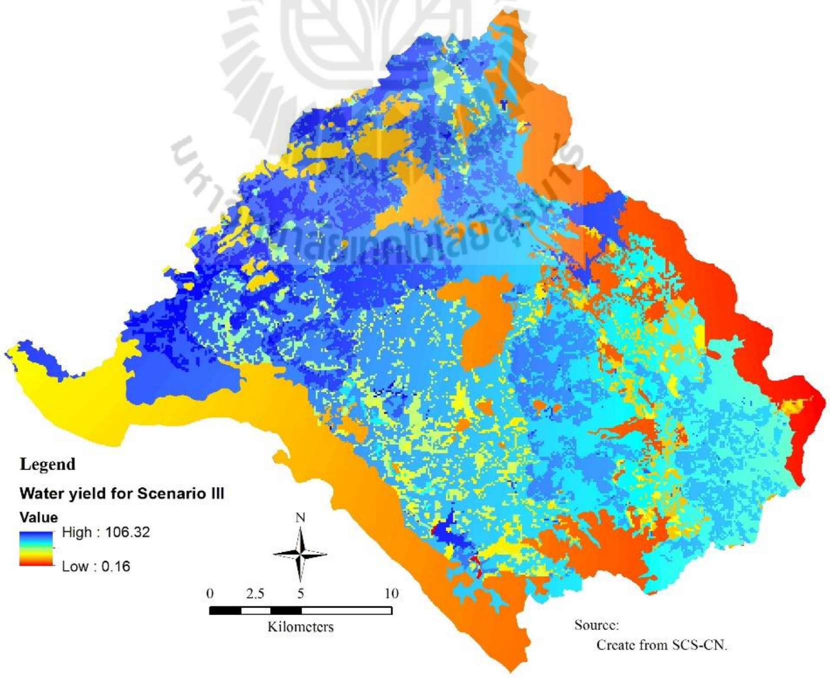


Figure 6.41 Distribution of water yield for the simulated LULC in 2023 of Scenario III.

Table 6.9 Summary of water yield value by pixel for three scenarios.

Water yield data	LULC 2013	Scenario I	Scenario II	Scenario III
Minimum (mm)	0.16	0.16	0.16	0.16
Maximum (mm)	106.32	106.32	106.32	106.32
Mean (mm)	48.97	49.30	59.79	46.93
Total in mm	**60,460,484.79**	**60,856,521.32**	**73,813,681.57**	**57,945,451.26**
Total in million cu. m	**37.79**	**38.04**	**46.13**	**36.22**

As results, it was found that the minimum and maximum values of water yield by pixel for LULC in 2013 and the simulated LULC in 2023 of Scenario I, II, and III were equal with value of 0.16 mm and 106.32 mm, respectively. These results occur because the derived water yield (runoff depth) was directly relate rainfall and CN value, which associated with LULC and soil types data, were stable. Herewith the common minimum and maximum CN value which exist in LULC in 2013 and the simulated LULC in 2023 generate water yield with the same values. However, the value of mean and total water yield from LULC in 2013 and the simulated LULC in 2023 of three scenarios were different from each other. In fact, the highest total water yield (runoff depth) was occurred in Scenario II with amount of 46.13 million cu. m. These results shows influence of LULC changes on water yield because soil types and rainfall values for LULC in 2013 and the simulated LULC in 2023 of three scenarios were stable and identical.

In addition, the total water yield value, which directly relate to surface runoff, reflects the characteristics of LULC. Herewith, the simulated LULC in 2023 of Scenario III, which represents forest conservation and prevention, provides the lowest water yield for surface runoff meanwhile the simulated LULC in 2023 of Scenario II, which represents agriculture production extension for energy crops, provides the highest water yield for surface runoff.

For impact of LULC change on water yield, the relationship between the percentage of agricultural land and forest land from actual LULC in 2013 and simulated LULC in 2023 of three scenarios was separately regressed with total water yield (runoff depth) as results shown in Figure 6.42. Herein the simple linear equation between percentage of agricultural land and total water yield (depth) showed positive relationship with R^2 at 99.72% as:

$$y = 36.748 + 0.4652x, \tag{6.4}$$

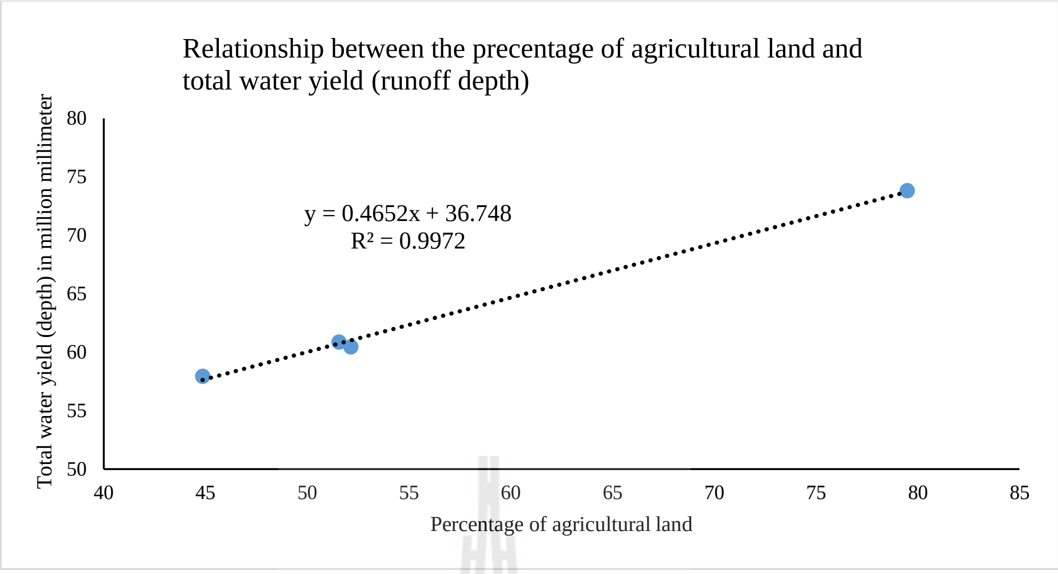
where y is total water yield (runoff depth) in million millimeter and x is percentage of agricultural land of the watershed area.

Meanwhile the simple linear equation between percentage of forest land and total water yield (runoff depth) showed negative relationship with R^2 at 95.63% as:

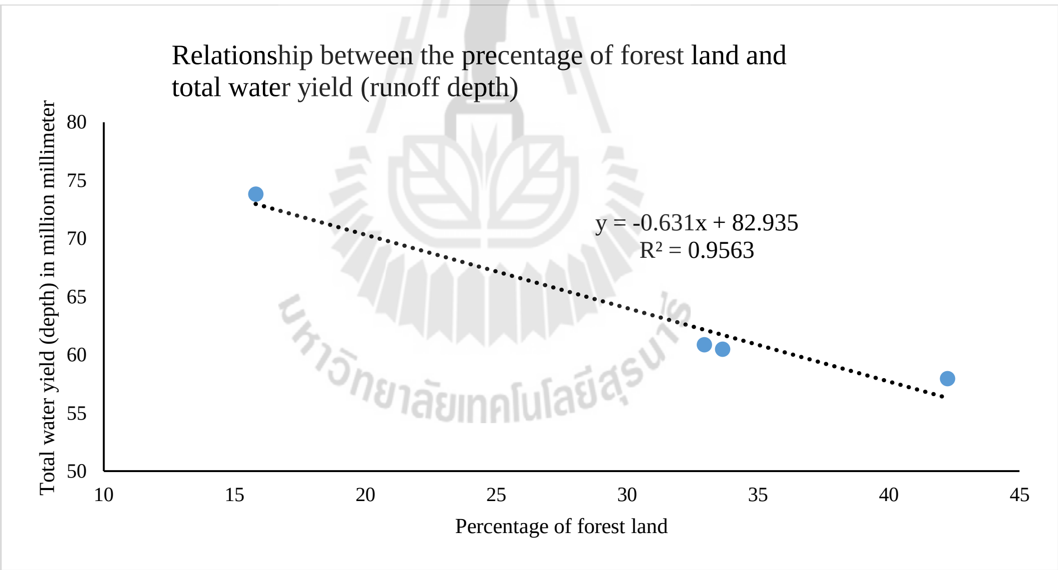
$$y = 82.935 - 0.631x, \tag{6.5}$$

where y is total water yield (runoff depth) in million millimeter and x is the percentage of forest land of the watershed area.

As results, it was found that when percentage of agricultural land increases, water yield (runoff depth) increases. In the opposite direction, when percentage of forest land increases, water yield (runoff depth) decreases. It was implied that LULC change impact on total water yield for surface runoff. This finding agreed with the study of Ongsomwang and Koonto (2013) about the impact of land use change on water runoff using SWAT model. They stated that the most important factors on water runoff quantity were land use types and land use changes.



(a)



(b)

Figure 6.42 Simple linear regression analysis between percentage of agricultural land (a) and forest land (b) with total water yield (runoff depth)

6.3 Economic value estimation and its impact due to LULC change

Future value for LULC in 2013 and the simulated LULC in 2023 of three scenarios was estimated from its present return value using PV equation (Equation 2.7).

Table 6.10 showed present value (income) for agricultural types and forest land which were derived from government agencies' reports meanwhile the future value of LULC types was displayed in Table 6.11. These future value in 2023 of LULC types except urban and built-up land, water body and miscellaneous land were directly applied to generate distribution map of economic value for LULC in 2013 and the simulated LULC in 2023 of three scenarios as shown in Figures 6.43 - 6.46. Basic statistic data of economic value by pixel for LULC in 2013 and the simulated LULC in 2023 of three scenarios was summarized as shown in Table 6.12.

Table 6.10 Present value (price, yield and income) of LULC type in agricultural and forest land.

LULC type	Price (baht/kg.)	Yield (kg/hectare)	Income (baht/hectare)
Paddy field [1]	14.62	2,530	36,996.70
Cassava [1]	2.02	20,835	42,114.48
Maize [1]	7.84	4,093	32,098.16
Sugarcane [1]	1	73,238	72,973.85
Perennial tree [2]	13.33	6,846	91,232.14
Forest land [3]			250,000

Source
1 OAE (2012-2013)
2. Market Organization for Farmers (2014)
3. Wittawatchutikul and Jirasuktaveekul (2005)

Table 6.11 Future value of LULC type in agricultural and forest land by year 2023.

LULC type	Present value (Baht)	Discount Rate* in %	Period from Present (year)	Future value (Baht)
Paddy field	36,996.70	7	10	72,778
Cassava	42,114.48	7	10	82,846
Maize	32,098.16	7	10	63,142
Sugarcane	72,973.85	7	10	143,551
Perennial tree	91,232.14	7	10	179,467
Forest	250,000	7	10	491,788

* Discount rate was based on Bank for Agriculture and Agricultural Cooperatives (2014)

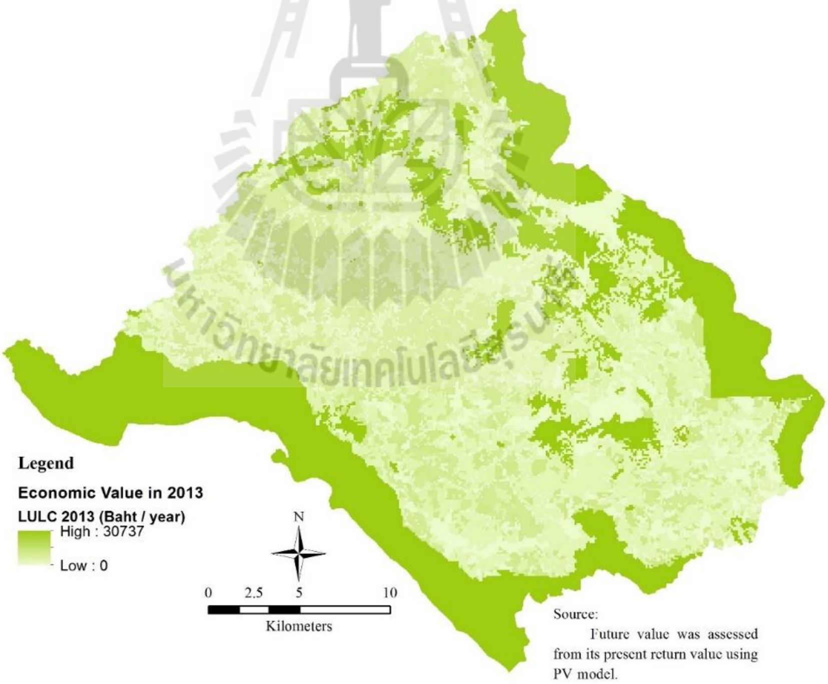


Figure 6.43 Distribution of economic value from agriculture and forest land for LULC in 2013.

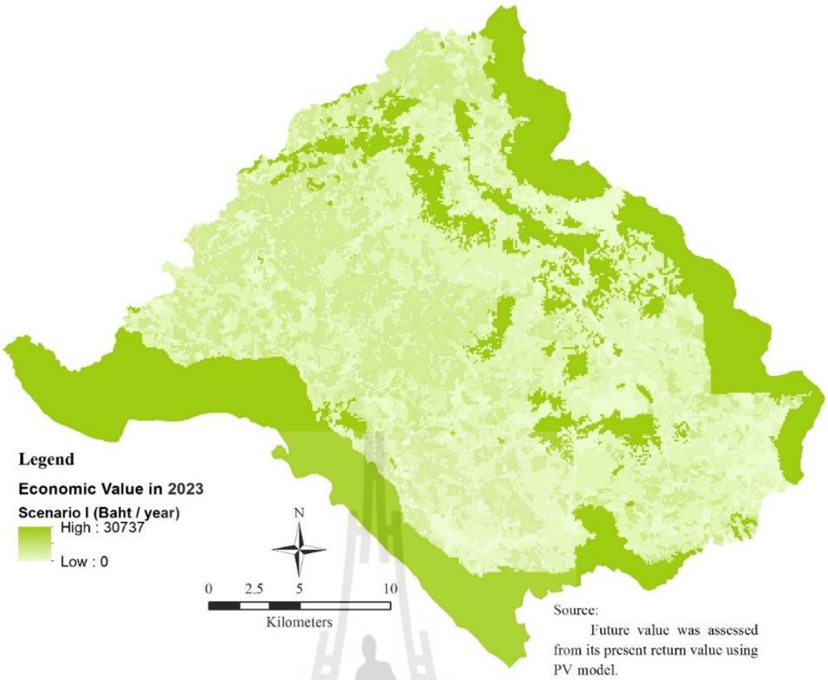


Figure 6.44 Distribution of economic value from agriculture and forest land for the simulated LULC in 2023 of Scenario I.

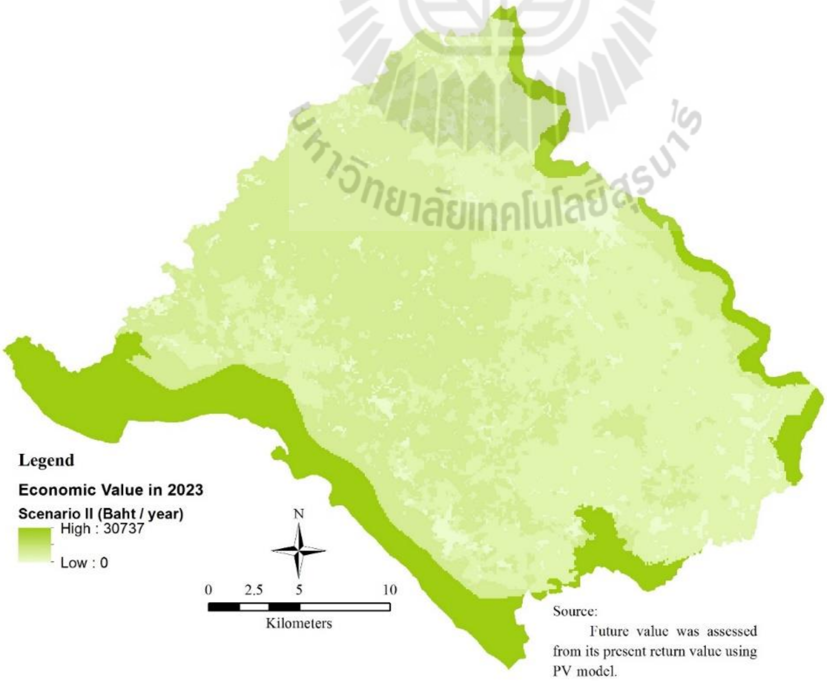


Figure 6.45 Distribution of economic value from agriculture and forest land for the simulated LULC in 2023 of Scenario II.

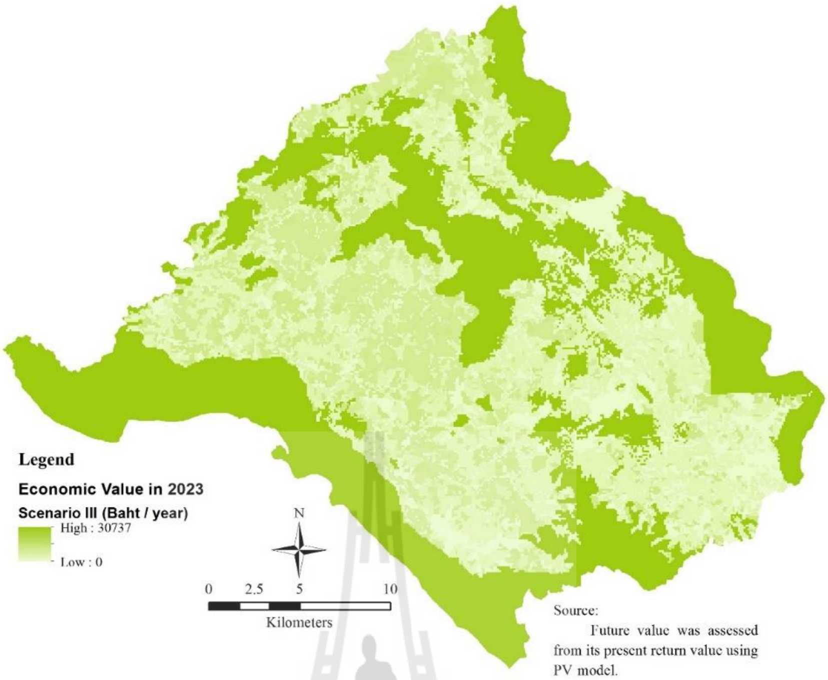


Figure 6.46 Distribution of economic value from agriculture and forest land for the simulated LULC in 2023 of Scenario III.

In summary, economic value of agriculture and forest land for LULC in 2013 and the simulated LULC in 2023 of three scenarios were 16,987.05 million Baht, 16,677.33 million Baht, 12,923.64 million Baht and 19,660.13 million Baht, respectively. Meanwhile basic statistic data of economic value by pixel for LULC in 2013 and the simulated LULC in 2023 was presented in Table 6.12.

Table 6.12 Basic statistic of economic value for LULC in 2013 and the simulated LULC in 2023 of three scenarios.

Economic value	**LULC2013**	**Scenario I**	**Scenario II**	**Scenario III**
Minimum (Baht)	3,946	3,946	4,549	3,946
Maximum (Baht)	30,737	30,737	30,737	30,737
Mean (Baht)	13,759	13,508	10,468	15,924
Total in Baht	**16,987,053,440**	**16,677,332,110**	**12,923,638,890**	**19,660,126,530**
Total in million Baht	**16,987.05**	**16,677.33**	**12,923.64**	**19,660.13**

As results, it was found that the future minimum and maximum economic values by pixel for LULC in 2013 and the simulated LULC in 2023 of Scenario I and III were equal to value of 0 baht and 30,737 baht, respectively. These results occurred because the derived economic values was directly relate income of LULC type. Herein urban and built-up land, water body and miscellaneous land were not estimated future economic value while forest land provided the highest economic value. However, the mean and total economic values from LULC in 2013 and the simulated LULC in 2023 of three scenarios were different from each other. In fact, the future highest economic value was occurred in Scenario III while future lowest economic value was occurred in Scenario II. These results show influence of LULC changes on economic return.

For impact of LULC change on economic value, the relationship between the percentage of agricultural land and forest land from LULC in 2013 and simulated LULC in 2023 was separately regressed with total economic value to demonstrate the impact of LULC change on economic value as shown in Figure 6.47. Herein, the simple linear equation between percentage of agricultural land and total economic value showed negative relationship with R^2 at 91.69% as:

$$y = 26.421 - 0.1729x \quad (6.6)$$

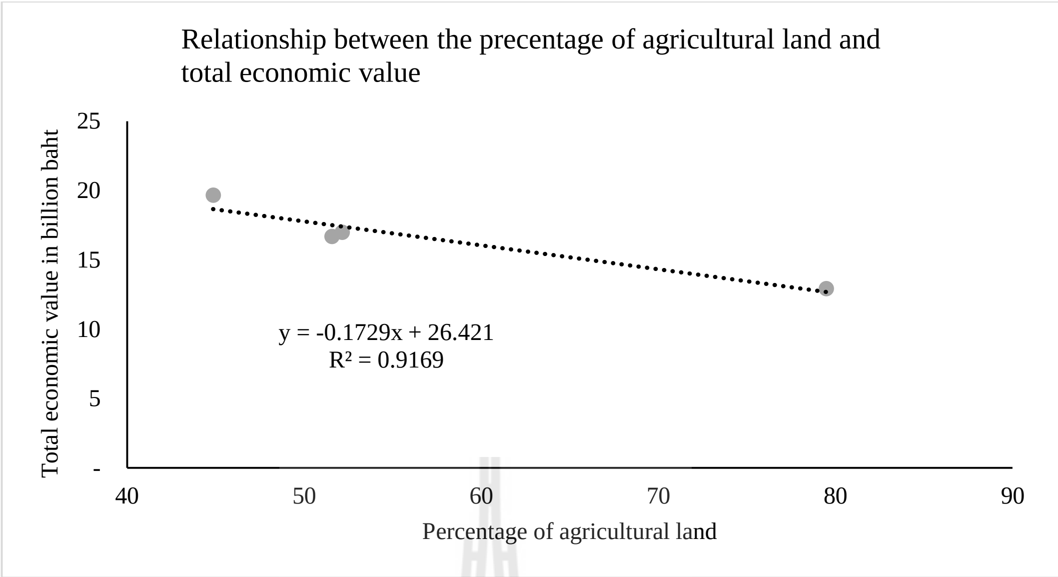
where y is total economic value in billion baht, and x is the percentage of agricultural land of the watershed area.

In the meantime the simple linear equation between percentage of forest land and total economic value in billion baht showed positive relationship with R^2 at 98.72% as:

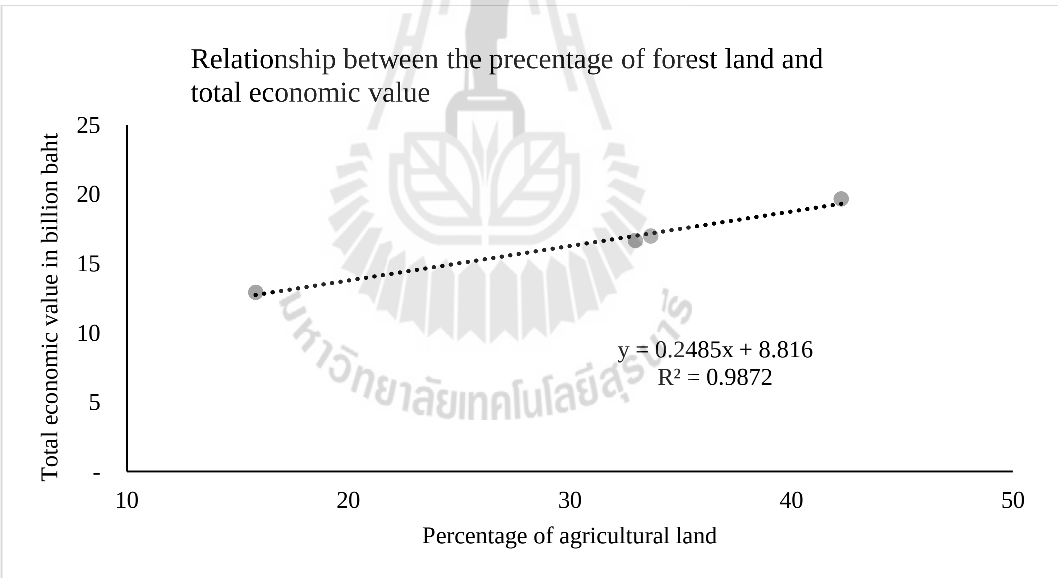
$$y = 8.816 + 0.2485x \quad (6.7)$$

Where y is total future value in billion baht, and x is the percentage of forest land of the watershed area.

As results, it was found that when percentage of agricultural land increases, total future value decrease. In the opposite direction, when percentage of forest land increases, total future value increase. This finding implies that LULC change impact on economic value. However, when economic value of agricultural land and forest land are compared, it is required to consider the return period of the product, i.e. field crops require short term period (1-3) while forestry product need long term period (30 years).



(a)



(b)

Figure 6.47 Simple linear regression analysis between percentage of agricultural land (a) and forest land (b) with total economic value.

CHAPTER VII

AN OPTIMAL LAND USE ALLOCATION

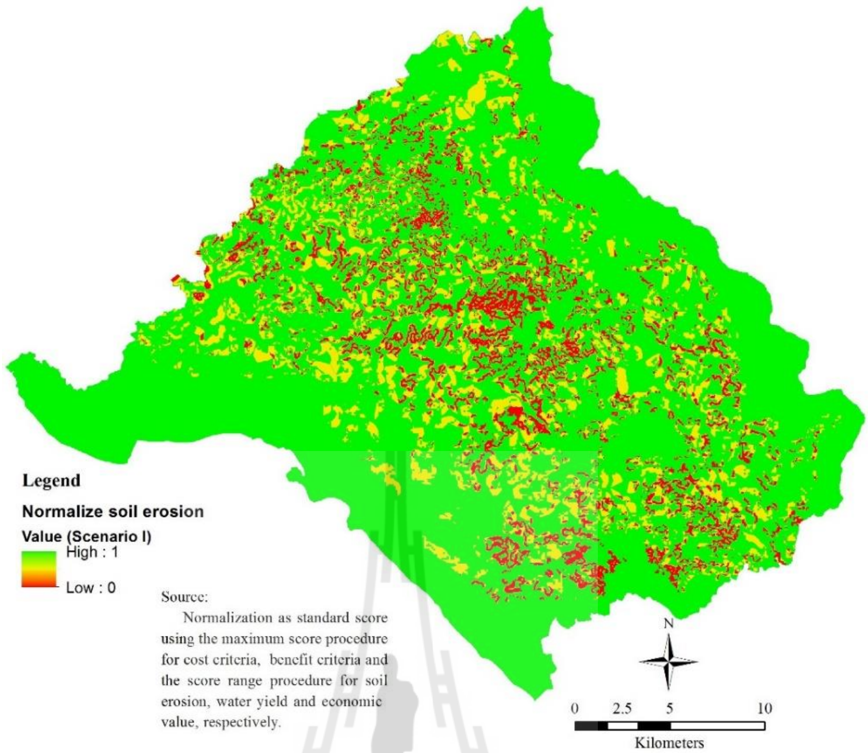
7.1 An optimal land use allocation with three scenarios

Under this component, the derived soil loss, water yield and economic values of each scenario in 2023 were firstly separately normalized and combined using SAW method of MCDA to create total scores with specific weight according scenario characteristics. The total score from each scenario was then classified for suitability classes (low, moderate and high) for land use allocation. After that the result was overlaid with the simulated LULC in 2023 for an optimal land use allocation in 2023. The derived land use allocation with suitability class was further analyzed by overlay analysis with actual LULC in 2013 for land use allocation of each scenario in detail.

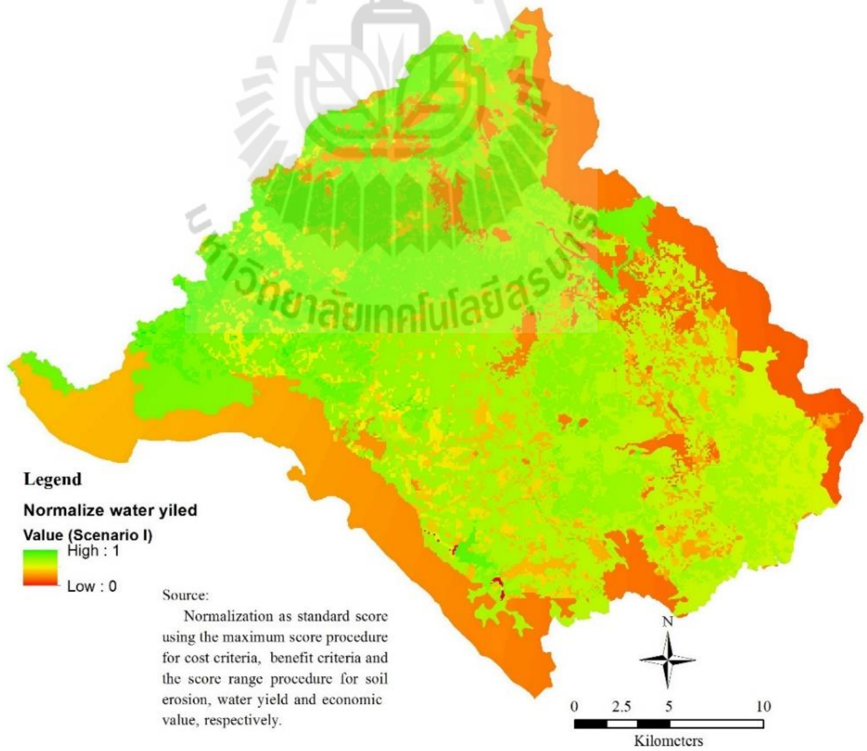
In this study, the derived soil loss, water yield and economic values form each scenario were normalized with a specific procedure to represent negative, positive and neutral factors for SAW operation. Herein, soil loss as negative factor was normalized using score range procedure for cost criteria (Equation 3.1) meanwhile water yield as positive factor was normalized using score range procedure for benefit criteria (Equation 3.2.). At the same time, economic value of LULC as neutral factor was normalized using maximum score procedure for benefit criteria (Equation 3.3). The minimum and maximum value of each factors from three scenarios before and after normalization was summarized in Table 7.1. The normalized data of soil loss, water yield and economic values of Scenario I, II, and III were presented in Figures 7.1, 7.2 and 7.3, respectively.

Table 7.1 Minimum and maximum values for each scenario factor before and after normalization of three scenarios.

Scenario	Factors	Before normalization		After normalization	
		Minimum	**Maximum**	**Minimum**	**Maximum**
I	Soil loss	0.00	1,256.33	0	1
	Water yield/runoff	3.51	80.99	0	1
	Economic value	3,946.00	30,737.00	0.128379	1
II	Soil loss	0.00	1,256.33	0	1
	Water yield/runoff	3.51	80.99	0	1
	Economic value	4,549.00	30,737.00	0.147998	1
III	Soil loss	0.00	1,256.33	0	1
	Water yield/runoff	3.51	80.99	0	1
	Economic value	3,946.00	30,737.00	0.128379	1

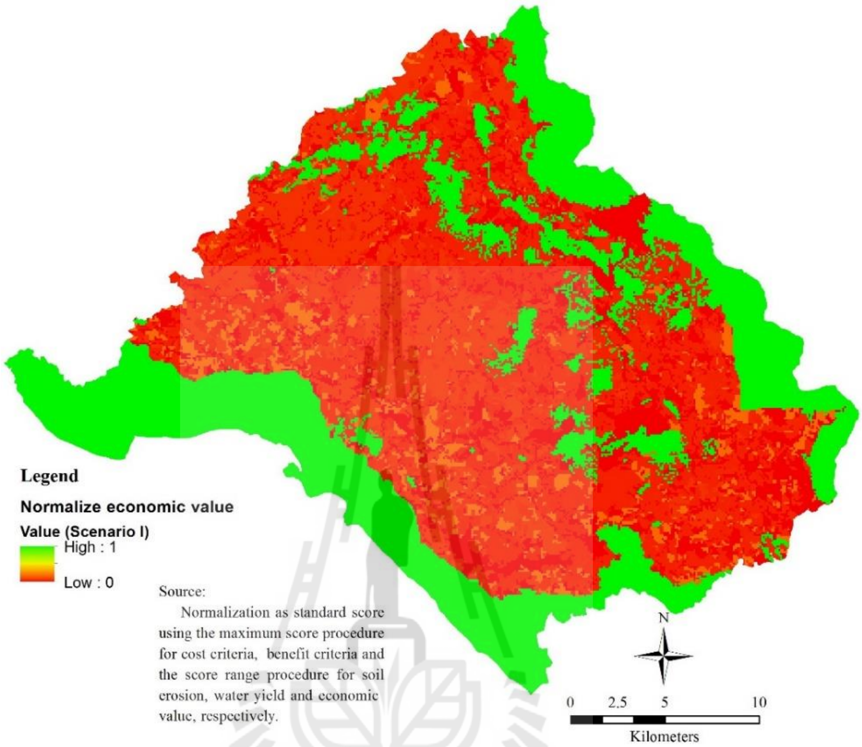


(a)



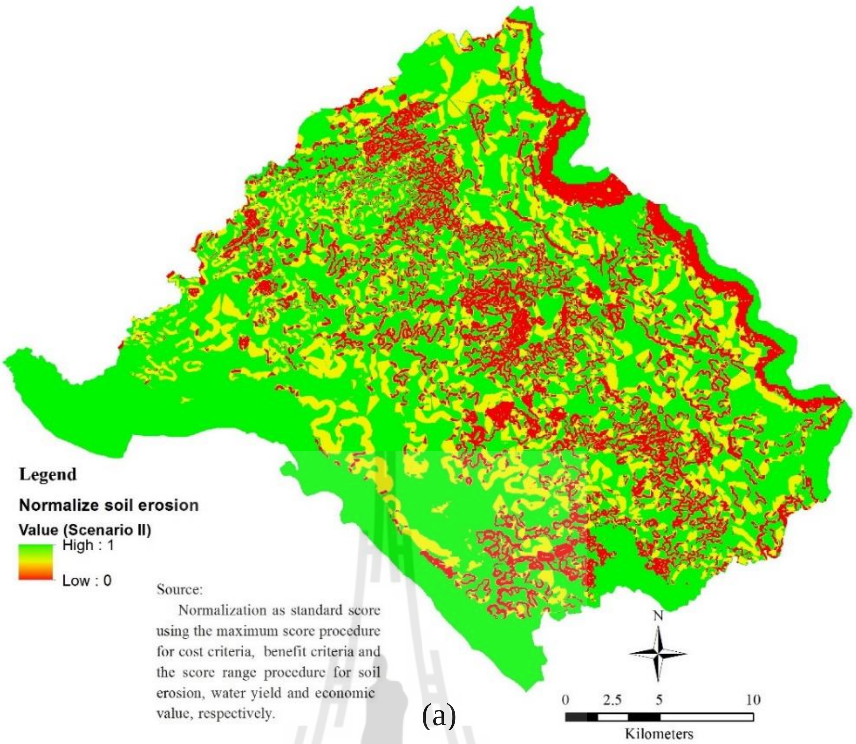
(b)

Figure 7.1 Normalized factors of Scenario I: (a) soil loss, (b) water yield, and (c) economic values.

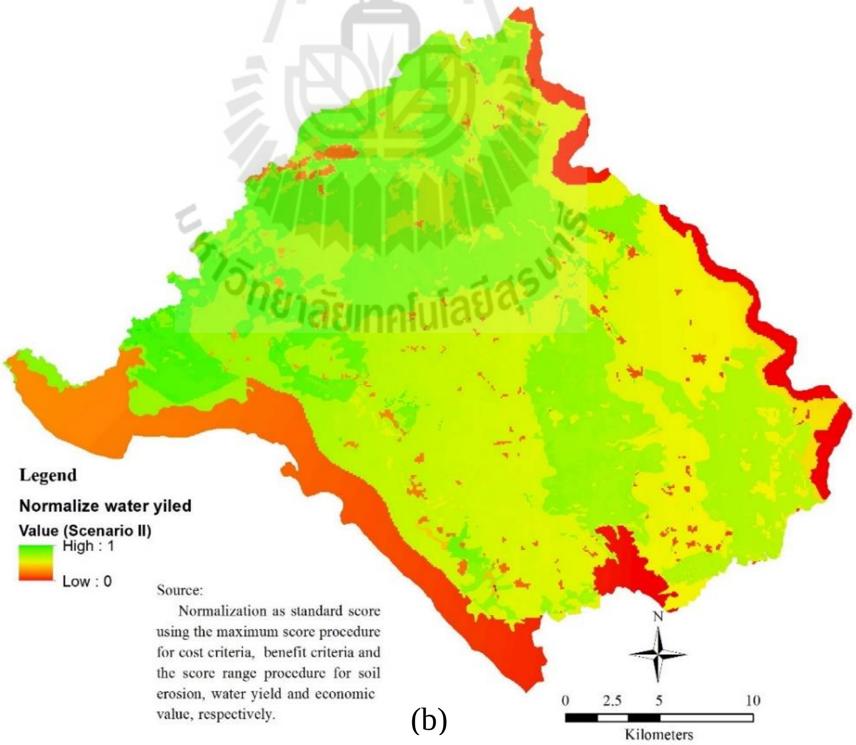


(c)

Figure 7.1 Normalized factors of Scenario I: (a) soil loss, (b) water yield, and (c) economic values (Continued).



(a)



(b)

Figure 7.2 Normalized factors of Scenario II: (a) soil loss, (b) water yield, and (c) economic values.

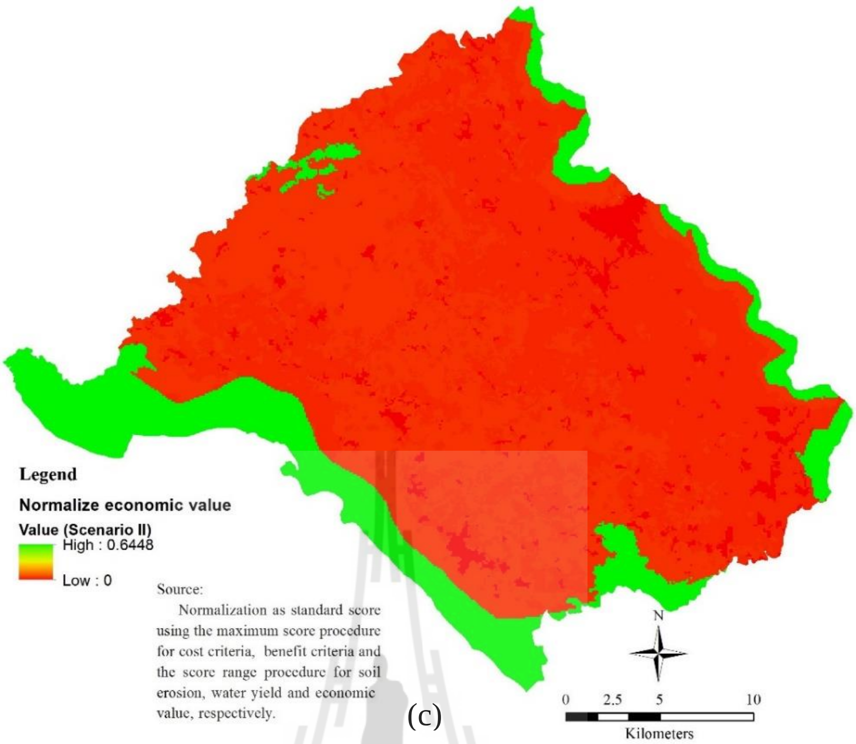


Figure 7.2 Normalized factors of Scenario II: (a) soil loss, (b) water yield, and (c) economic values (Continued).

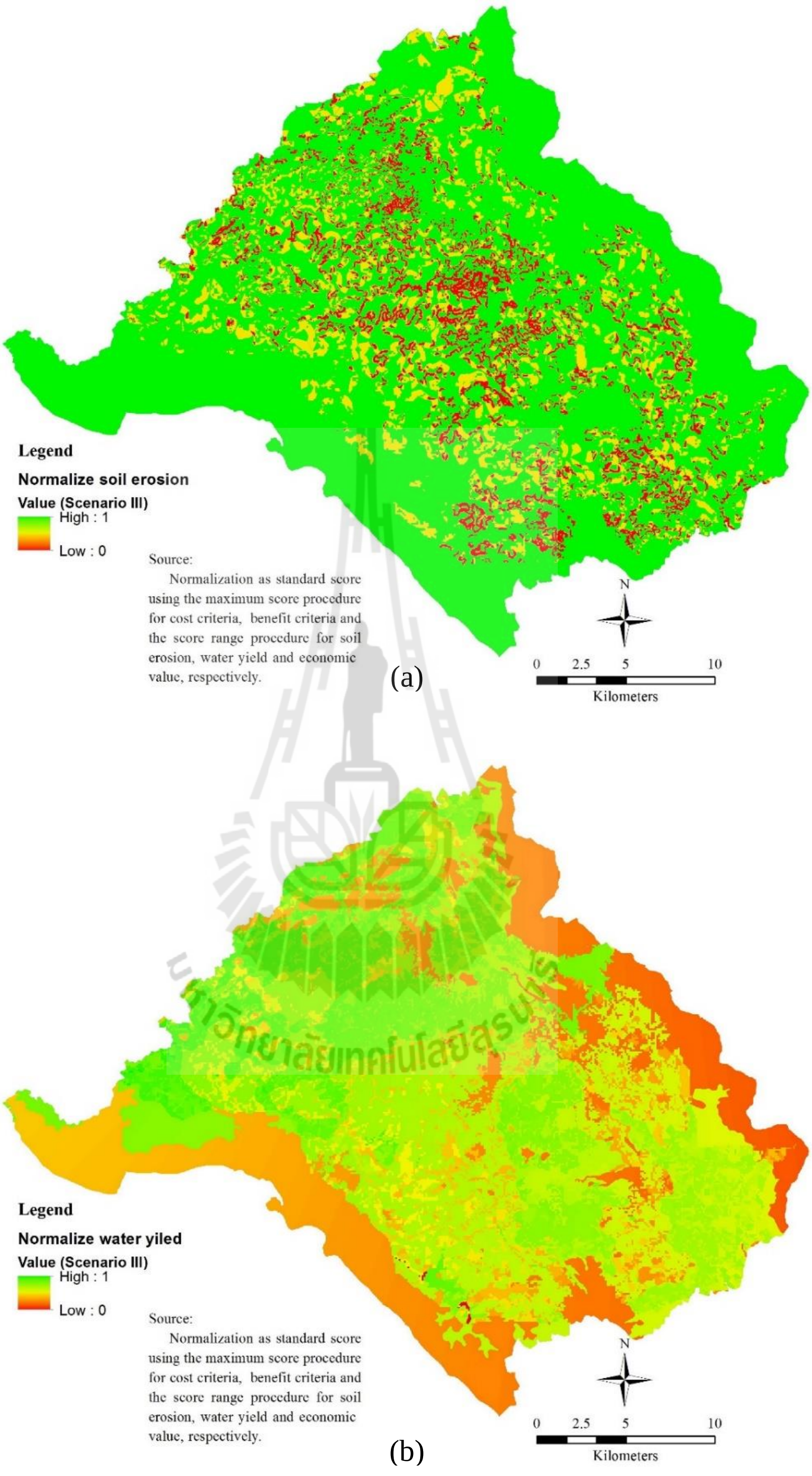
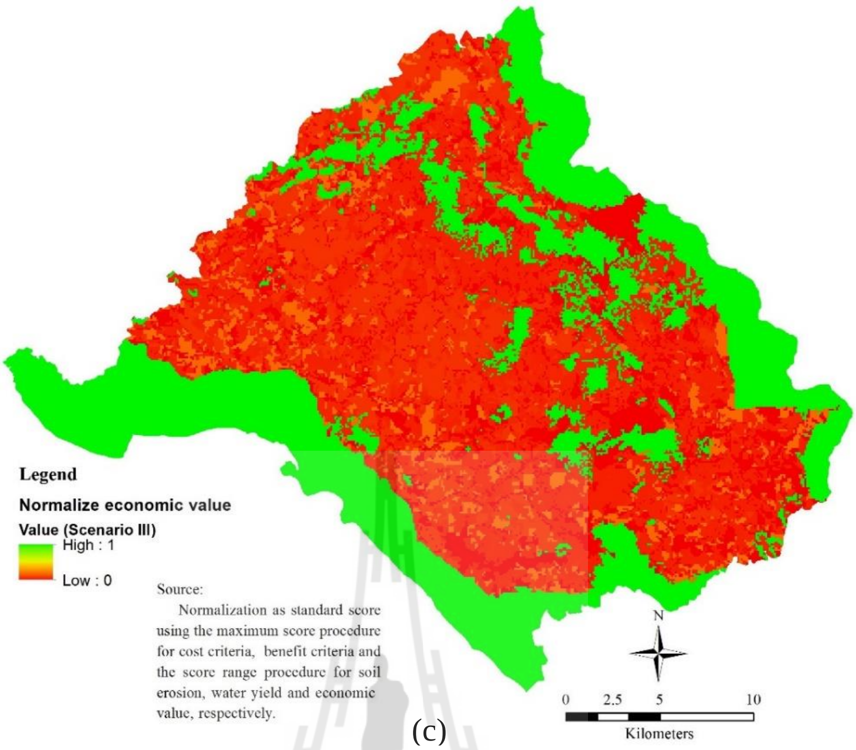


Figure 7.3 Normalized factors of Scenario III: (a) soil loss, (b) water yield, and (c) economic values.



(c)

Figure 7.3 Normalized factors of Scenario III: (a) soil loss, (b) water yield, and (c) economic values (Continued).

In addition, an optimal weight, which was assigned according to characteristics of defined scenario and the relative important of three factors were here summarized as shown in Table 7.2.

Table 7.2 Assigned weight of each factor for three scenarios.

Scenario	Weighting		
	Soil loss	Water yield/runoff	Economic value
I	1	1	1
II	1	2	3
III	3	2	1

Later on, all three factors for each scenario were separately combined with SAW method to calculate total score and then reclassified into three suitability classes (low, moderate, and high) for land use allocation. Herein, equal interval method was applied for Scenario I as same as the assignment of factor weighting which was assigned as equal weight. Because Scenario I, which represents the historical land evolution, has no relative important among three factors. Suitability classes with equal interval method for Scenario I was therefore reasonable. At the same time, natural break method, which appropriates for the skewed distribution data, was applied for Scenario II and III which have relative important among three factors. For Scenario II, economic value which represents positive impact is the most important factor while soil loss which represents negative impact is the most important factor in Scenario III (see Table 7.2). The suitability classes (low, moderate, and high) for land use allocation of Scenario I to III were displayed in Figures 7.4 - 7.6, respectively. Areas of suitability classes (low, moderate, and high) for land allocation of each scenario was summarized in Table 7.3.

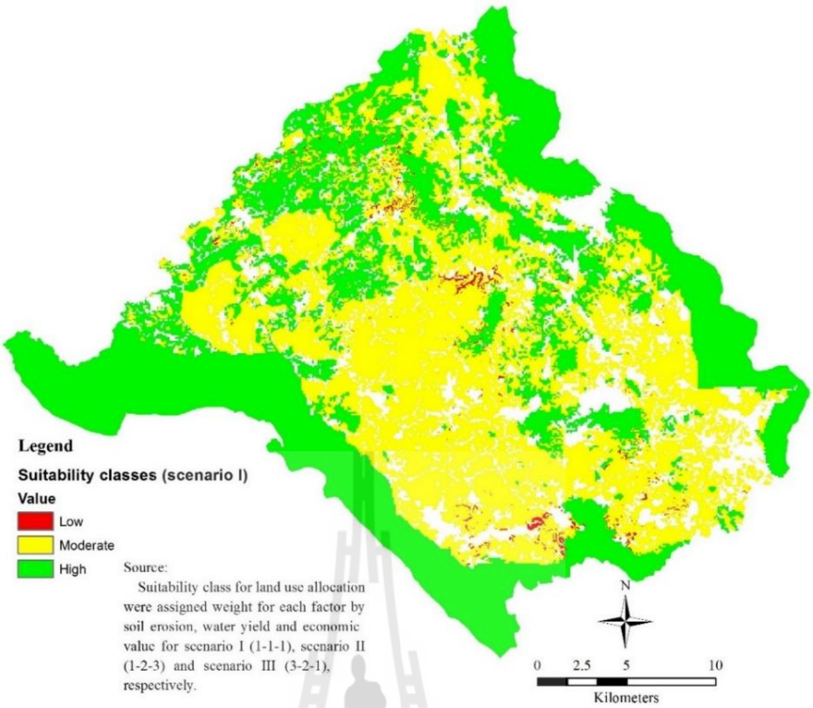


Figure 7.4 Suitability class for land use allocation of Scenario I (Historical land use evolution).

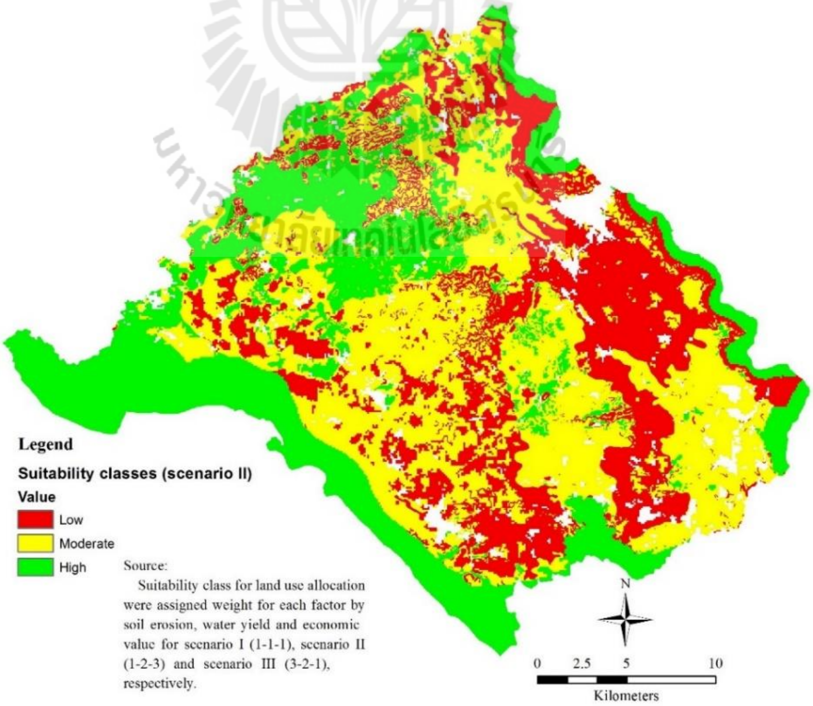


Figure 7.5 Suitability class for land use allocation of Scenario II (Agriculture production extension).

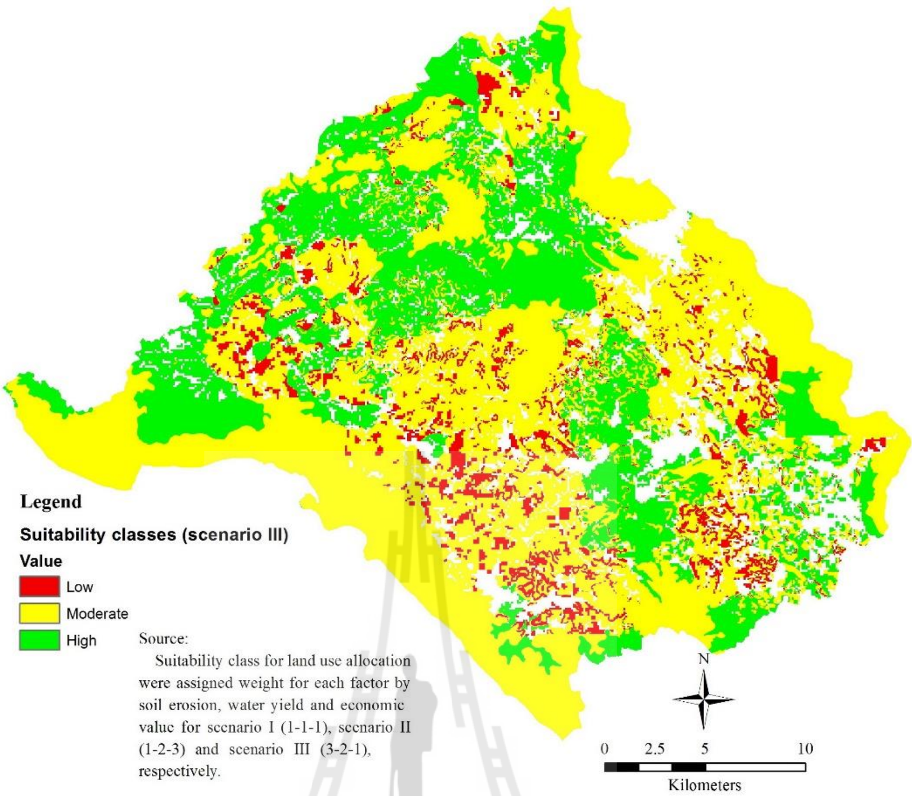


Figure 7.6 Suitability class for land use allocation of Scenario III (Forest conservation and prevention).

Table 7.3 Area and percent of suitability class for land use allocation of Scenario I to III.

Scenario	Suitability class for land use allocation	Area in	
		ha	%
I	Low	519	0.80
	Moderate	31,793	48.75
	High	32,900	50.45
	Total	**65,212**	**100.00**
II	Low	19,665	26.74
	Moderate	30,618	41.64
	High	23,250	31.62
	Total	**73,533**	**100.00**
III	Low	5,175	7.70
	Moderate	40,979	60.97
	High	21,062	31.33
	Total	**67,216**	**100.00**

As results it was found that the dominant suitability classes for an optimal land use allocation of Scenario I were moderate and high and covered area of 31,793 and 32,900 ha or 48.75 and 50.45 percent, respectively. At the same time, the suitability classes for an optimal land use allocation of Scenario II were low, moderate and high and covered area of 19,665, 30,618 and 23,250 ha or 26.74, 41.64 and 31.62 percent, respectively. Meanwhile, the dominant suitability classes for an optimal land use allocation of Scenario III were moderate and high covered area of 40,979 and 21,062 ha or 60.97 and 31.33 percent, respectively.

Details of an optimal land use allocation in 2023 for each scenario by overlay analysis between the simulated LULC in 2023 by CLUE-S model and suitability class by SAW method can be separately described in following sections.

7.1.1 An optimal land use allocation for Scenario I

By means of overlay analysis between the simulated LULC type in 2023 of Scenario I and the suitability classes for land use allocation based on its scenario characteristic (Table 7.4), it was found that most of the simulated agricultural land in 2023 (paddy field, cassava, maize, sugarcane and perennial tree/orchard) were allocated in moderate suitability class which covered area of 31,793 ha or 48.75 percent and some areas of agricultural land were located in high suitability class. Meanwhile, all simulated forest land in 2023 were allocated in high suitability class and covered area of 25,427 ha or 38.99 percent. The distribution of an optimal land use allocation of Scenario I by each suitability class was displayed in Figure 7.7.

Table 7.4 Area of suitability class for an optimal land use allocation of Scenario I.

Suitability Class	**Land use type (ha)**							
	Paddy field	**Cassava**	**Maize**	**Sugarcane**	**Perennial tree/orchard**	**Forest land**	**Total**	**Percentage**
Low	0	18	475	24	3	0	520	0.80
Moderate	205	3,678	16,297	7,805	3,808	0	31,793	48.75
High	32	937	821	4,649	1,033	25,428	32,900	50.45
Total	**237**	**4,633**	**17,593**	**12,478**	**4,843**	**25,428**	**65,212**	**100.00**

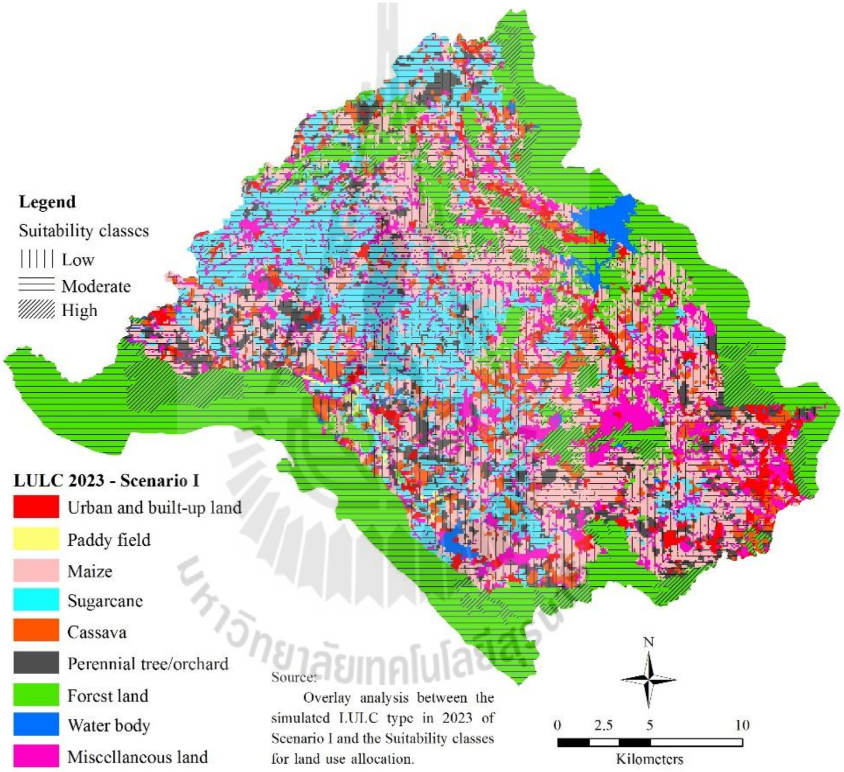


Figure 7.7 Distribution of an optimal land use allocation with suitability class of Scenario I.

Furthermore, the relationship between the simulated LULC in 2023 of Scenario I with suitability class and actual LULC in 2013 can be identified by overlay analysis as summary in Table 7.5. As results, it can be observed that most of allocated agricultural land and forest land in 2023 in moderate and high suitability classes came from actual LULC in 2013 and their areas covered area of 65,213 ha or about 96.34 percent of total areas (62,824 ha). Few changed LULC type between actual LULC in 2013 and the simulated LULC in 2023 located in multiple suitability classes and covered area of 1,880 ha or 2.88 percent of total area. These areas play important role in term of environment impact. Therefore, low or moderate suitability classes of changed LULC type between actual LULC in 2013 and the simulated LULC in 2023, which covered area of 10 and 927 ha, should be carefully implemented in long term (8-10 years) and medium term (4 - 7 years), respectively to minimize environmental impact.

Table 7.5 Relationship between the simulated LULC in 2023 of Scenario I with suitability class and actual LULC in 2013.

Actual LULC in 2013	**Simulated LULC 2023**	**Suitability class (ha)**				**Remark**
		Low	**Moderate**	**High**	**total**	
Paddy field	Paddy field	0	205	32	237	Non-change
Cassava	Cassava	18	3,511	917	4,446	Non-change
Maize	Cassava	0	55	3	58	Change
Forest	Cassava	0	34	7	41	Change
Miscellaneous land	Cassava	0	79	10	89	Change
Maize	Maize	475	16,297	821	17,593	Non-change
Sugarcane	Sugarcane	14	7,046	3,726	10,786	Non-change
Maize	Sugarcane	4	422	498	924	Change
Forest land	Sugarcane	4	46	95	145	Change
Miscellaneous land	Sugarcane	2	291	330	623	Change
Perennial tree/orchard	Perennial tree/orchard	3	3,808	1,033	4,844	Non-change
Forest land	Forest land	0	0	25,428	25,428	Non-change

7.1.2 An optimal land use allocation for Scenario II

According to overlay analysis between the simulated LULC type in 2023 of Scenario II and the suitability classes for land use allocation based on its scenario characteristic (Table 7.6), it was revealed that most of the simulated cassava areas in 2023 which totally required 30,699 ha were allocated in low and moderate suitability classes and covered area of 15,921 and 14,777 ha, respectively. Meanwhile the simulated sugarcane areas in 2023, which also totally required 30,699 ha, were allocated in low, moderate, and high suitability classes and covered area of 3,539, 15,808, and 11,052 ha, respectively. At the same time the simulated forest land in 2023 with some restriction rules were only allocated in high suitability class and covered area of 12,199 ha. The distribution of an optimal land use allocation of Scenario II by each suitability class was displayed in Figure 7.8.

Table 7.6 Area of suitability class for an optimal land use allocation of Scenario II.

	Land use type (ha)					
Suitability Class	**Paddy field**	**Cassava**	**Sugarcane**	**Forest land**	**Total**	**Percent**
Low	205	15,921	3,539	0	19,665	26.74
Moderate	32	14,777	15,808	0	30,618	41.64
High	0	0	11,052	12,199	23,250	31.62
Total	**237**	**30,699**	**30,399**	**12,199**	**73,533**	**100.00**

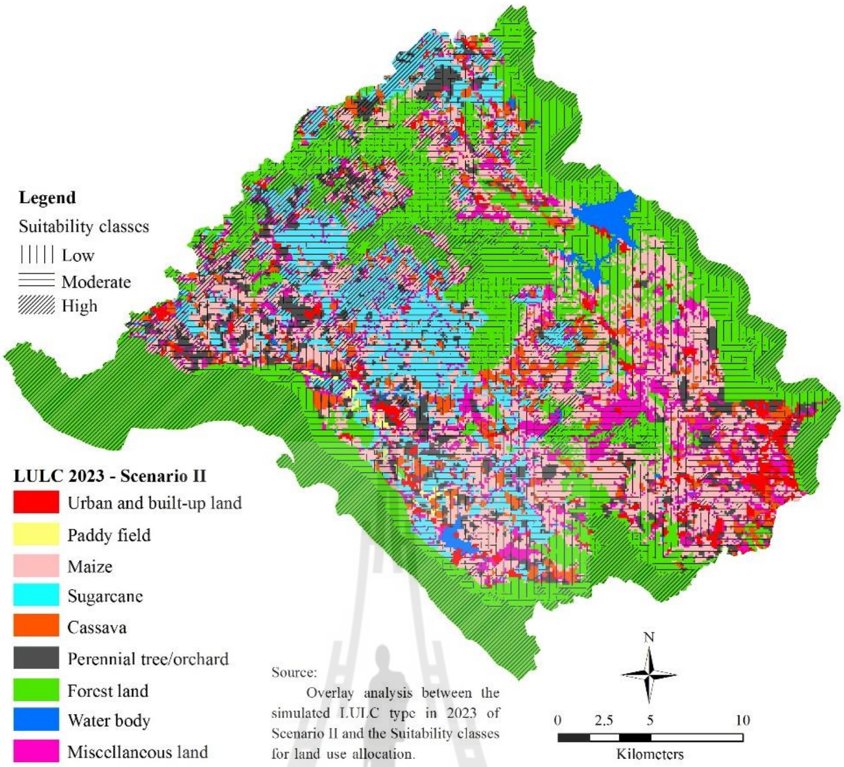


Figure 7.8 Distribution of an optimal land use allocation with suitability class of Scenario II.

In addition, the relationship between the simulated LULC in 2023 of Scenario II with suitability class and actual LULC in 2013 can be identified by overlay analysis as summary in Table 7.7. As results, it was found that changed LULC type between actual LULC in 2013 and the simulated LULC in 2023 which located with multiple suitability classes covered area of 45,865 ha or 62.37 percent of total area (73,533 ha). This phenomena occurred due to policy setting for energy crop. Therefore, these areas should pay more attention during implementation due to environment impact by soil erosion. Herewith, low and moderate suitability classes of cassava and sugarcane in 2023, which covered area of 16,832 and 21,719 ha, respectively, should be carefully implemented in long term (8-10 years) and medium term (4-7 years), respectively. In contrast, high suitability class of cassava and sugarcane which covered area of 7,315 ha in 2023 could be implemented in short term (1-3 years) due to minimal environmental impact by soil erosion.

Table 7.7 Relationship between the simulated LULC in 2023 of Scenario II with suitability class and actual LULC in 2013.

Actual LULC2013	Simulated LULC2023	Suitability class (ha) Low	Moderate	High	total	Remark
Paddy field	Paddy field	205	32	0	237	Non-change
Cassava	Cassava	2,265	2,181	0	4,446	Non-change
Maize	Cassava	5,957	5,561	0	11,517	Change
Perennial tree	Cassava	1,876	1,937	0	3,813	Change
Forest	Cassava	3,782	2,594	0	6,375	Change
Miscellaneous land	Cassava	2,042	2,505	0	4,547	Change
Sugarcane	Sugarcane	363	6,686	3,737	10,786	Non-change
Maize	Sugarcane	610	3,147	3,329	7,086	Change
Perennial tree	Sugarcane	83	1,242	1,029	2,354	Change
Forest land	Sugarcane	2,178	3,402	1,814	7,394	Change
Miscellaneous land	Sugarcane	306	1,331	1,143	2,779	Change
Forest land	Forest land	0	0	12,199	12,199	Non-change

7.1.3 An optimal land use allocation for Scenario III

By means of overlay analysis between the simulated LULC type in 2023 of Scenario III and the suitability classes for land use allocation according its scenario characteristic (Table 7.8), it was found that the simulated forest land in 2023 were allocated in moderate and high suitability classes and covered area of 22,682 and 9,920 ha, respectively. Meanwhile the simulated agricultural land (paddy field, cassava, maize, sugarcane, and perennial tree/orchard) in 2023 were allocated in low, moderate and high suitability classes. The distribution of an optimal land use allocation of Scenario II by each suitability class was displayed in Figure 7.9.

Table 7.8 Area of suitability class for an optimal land use allocation of Scenario III.

Suitability Class	Land use type (ha)							
	Paddy field	**Cassava**	**Maize**	**Sugarcane**	**Perennial tree/orchard**	**Forest land**	**Total**	**Percent**
Low	0	228	1,710	385	2,852	0	5,175	7.70
Moderate	205	2,195	8,971	5785	1,141	22,682	40,979	60.97
High	32	1,392	5,309	3055	1,354	9,920	21,062	31.33
Total	**237**	**3,815**	**15,990**	**9225**	**5,347**	**32,602**	**67,216**	**100.00**

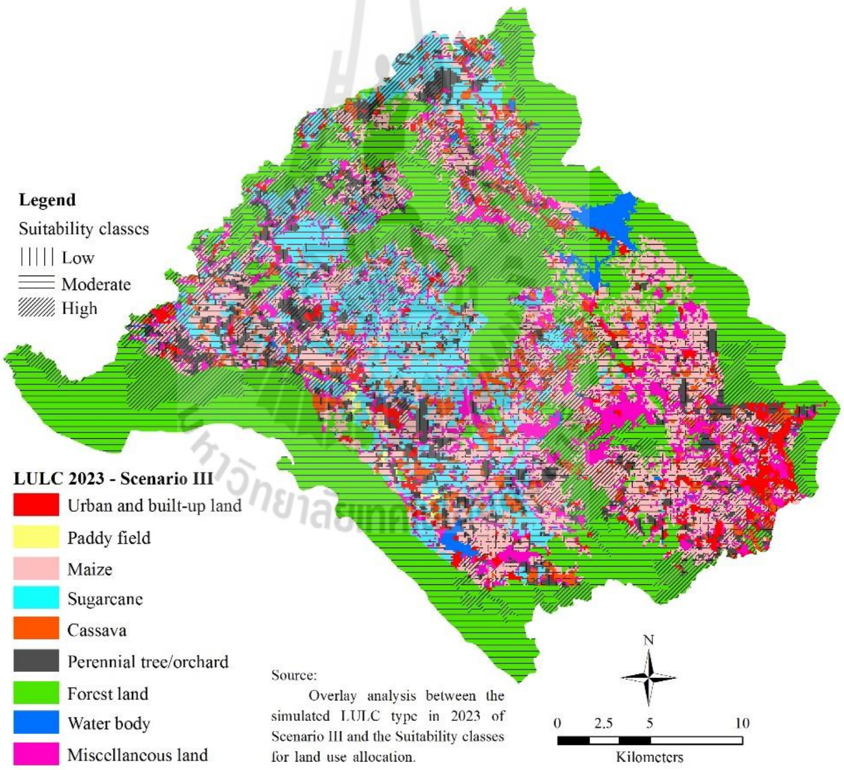


Figure 7. 9 Distribution of an optimal land use allocation with suitability class of Scenario III.

The relationship between the simulated LULC in 2023 of Scenario III with suitability class and actual LULC in 2013 can be further identified by overlay analysis as summary in Table 7.9. As results, it was found that some unusual changed LULC type between actual LULC in 2013 and the simulated LULC in 2023 can be occurred due to policy setting for conservation and prevention forest land. In this study, land requirement of forest land were calculated from areas of watershed class I and II, national park's boundary and existing forest in 2013. In fact, any LULC type in 2013 can be changed to be forest land in 2023. Herein, urban and built-up land (316 ha) and water body (10 ha) in 2013 became forest land in 2023. Consequently, the changed LULC type between actual LULC in 2013 and the simulated LULC in 2023 should carefully considered during implementation due to environment impact by soil erosion. Herewith, low and moderate suitability classes of forest land in 2023 which covered area of 3,142 and 3,490 ha, respectively should be carefully implemented in long term (8-10 years) and medium term (4-7 years), respectively. Conversely, high suitability class of forest land in 2023 which covered area of 6,631 ha can be implemented in short term (1-3 years) due to minimal environmental impact of soil erosion. Meanwhile, non-changed area of forest land between actual LULC in 2013 and the simulated LULC in 2023 covered area of 25,970 ha. In addition, changed areas of maize between actual LULC in 2013 and the simulated LULC in 2023 covered area of 848 ha should be carefully considered according suitability classes. In this case, low and moderate suitability classes of maize in 2023 which covered area of 184 and 514 ha should be implemented in long term (8-10 years) and medium term (4-7 years) while high suitability class which covered area of 150 ha can be implemented in short term (1-3 years).

Table 7.9 Relationship between the simulated LULC in 2023 of Scenario III with suitability class and actual LULC in 2013.

Actual LULC in 2013	**Simulated LULC in 2023**	**Suitability class (ha)**				**Remark**
		Low	**Moderate**	**High**	**total**	
Paddy field	Paddy field	0	205	32	237	Non-change
Cassava	Cassava	228	2,195	1,392	3,815	Non-change
Maize	Maize	1,525	8,457	5,160	15,143	Non-change
Sugarcane	Maize	113	244	50	407	Change
Cassava	Maize	54	209	94	357	Change
Perennial tree/Orchard	Maize	17	61	6	84	Change
Sugarcane	Sugarcane	385	5,785	3,055	9,225	Non-change
Perennial tree/Orchard	Perennial tree/Orchard	2,852	1,141	1,354	5,347	Non-change
Forest land	Forest land	0	19,540	6,429	25,970	Non-change
Urban and built-up land	Forest land	0	179	137	316	Change
Maize	Forest land	0	1,558	1,902	3,460	Change
Sugarcane	Forest land	0	525	507	1,032	Change
Cassava	Forest land	0	82	182	264	Change
Perennial tree/Orchard	Forest land	0	224	356	579	Change
Miscellaneous land	Forest land	0	570	400	970	Change
Water body	Forest land	0	4	6	10	Change

In brief, an optimal land use allocation of each scenario based on suitability class, which was generated by combination of negative, neural and positive factors under MCDA with SAW method can provide easily solution to minimized environmental impact. However, the detail of annual allocated land use type in short, medium and long terms should be prepared in operation plan.

CHAPTER VIII

CONCLUSION AND RECOMMENDATIONS

Under this chapter, four main results which were reported according to objectives in the study including (1) LULC assessment and its change and driving forces for LULC change (Chapter IV), (2) simulation of LULC scenarios by CLUE-S model (Chapter V), (3) impact of LULC change on soil erosion, water yield and economic values (Chapter VI) and (4) an optimal land use allocation (Chapter VII) are here separately concluded and recommended for future research and development.

8.1 Conclusion

8.1.1 LULC assessment and its change and driving forces for LULC change

Major LULC data in 2003 as historical record and recent LULC data in 2013, which were visually interpreted from color orthophoto and Thaichote data, were urban and built-up land and sugarcane with annual change rate of 66.5 and 171 ha per year, respectively. At the same period minor increasing LULC types were cassava, water body, and miscellaneous land with annual change rate of 21.5, 5.15, and 28 ha per year, respectively. On the contrary major decreased LULC types were maize and perennial trees/orchard with annual change rate of 108.9 and 128.5 ha per year, respectively and minor decreased LULC type was forest land with annual change rate of 55.3 ha per year. Meanwhile, paddy field in this period was stable. The derived LULC change pattern of major LULC classes between 2003 and 2013 from the study was similar to land use change pattern of LDD between 2008 and 2011. The major cause of exchangeable areas may related to price, landform, labors, and available of water. In addition, accuracy assessment of the visually interpreted LULC in 2013 by overall accuracy and Kappa hat coefficient were 90.625 and 87.418 percent, respectively.

Furthermore, the most common important driving force for all LULC types change was population density while the most important driving force for field crops (cassava, maize, and sugarcane) included slope, distance from road, population density, annual rainfall, soil drainage, and watershed classes.

8.1.2 Simulation of LULC scenarios by CLUE-S model

Three scenarios of LULC in 2023 included Scenario I: Historical land use evolution, Scenario II: Agriculture production extension, and Scenario III: Forest conservation and prevention were here simulated based on an optimum local parameters of CLUE-S model with a specific land use requirement for each scenario.

For Scenario I (Historical land use evolution) based on annual change rate between 2003 and 2013, it was found that increased LULC types were urban and built-up land, cassava, sugarcane, water body and miscellaneous land while decreased LULC types were maize, perennial trees/orchards and forest land. The pattern of LULC change during 2013 to 2023 was identical to LULC change pattern between 2003 and 2013.

On the contrary, for Scenario II (Agriculture production extension) based on energy crop policy with some limitations of conserved and preserved forest land and fixing of urban and built-up land, paddy field and water body areas, it was found that most of the increased area of cassava and sugarcane came from maize, perennial tree/orchard, forest land and miscellaneous land. Herein, areas of them in 2013 were converted to be cassava and sugarcane about 18,603, 6,167, 13,769, and 7,326 hectares, respectively. Meanwhile, for Scenario III (Forest conservation and prevention) based on the national conservation and preservation program on forests and fixing of urban and built-up land, paddy field and water body areas, it was revealed that most of increased area of forest land came from maize, sugarcane, and miscellaneous land. Herein areas of them were converted to be forest land about 3,460, 1,032 and 970 ha, respectively. Meanwhile forest land between 2013 and 2023 had increased about 6,631 ha.

As a result, it can be concluded that the CLUE-S model can provides the good result for LULC prediction according the historical land use evolution in the past and the derived results from CLUE-S model are controlled by the specified land use requirement in each scenario.

8.1.3 Impacts of LULC change on soil erosion, water yield and economic values

Three models included USLE model, SWAT model with SCS-CN method, and PV model were here used to assess and evaluate impact (positive, negative and neural) due to LULC change in 2023.

(1) Soil erosion assessment and its impact due to LULC change

For soil erosion assessment, the most dominate soil loss severity class from actual LULC in 2013 and simulated LULC in 2023 of three scenarios was very low (0-6.25 ton/ha/year) and covered area of 67.70, 67.89, 49.82 and 73.66 percent, respectively. In contrast, the least dominant soil loss severity class occurring in this period was very severe (more than 625 ton/ha/year) and covered area of 0.16, 0.17, 0.71 and 0.03, respectively. Meanwhile, areas of the moderate soil loss severity class (31.25–125 ton/ha/year) from LULC in 2023 of Scenario II was greater than others and covered area of 18,556 ha or 24.05 percent of the study area. In addition, mean annual soil loss from LULC in 2013 and LULC in 2023 of each scenario by cell were 32.6, 33.1, 71.2 and 23.3 ton/ha/year, respectively and actual total soil loss from them by summation of all cells were 40,213,210, 40,856,714, 87,959,870, and 28,779,226 ton/ha/year respectively. As results, it was found that LULC in 2023 of Scenario II, which represents for agriculture production extension for energy crops, generates actual total soil loss higher than LULC in 2013 and others scenarios. Herein actual total soil loss under Scenario II was higher than LULC in 2013 and LULC in 2023 of Scenario I about twofold and higher than LULC in 2023 of Scenario III about threefold.

For impact of LULC change on soil loss, soil loss severity class which was derived from LULC in 2013 was used as baseline data to compare with soil loss severity class from LULC in 2023 of each scenario as gain and loss using post classification comparison algorithm. It was evident that areas of gain and loss of soil loss severity classes for LULC in 2023 of Scenario I were 358 and 480 ha, respectively with gain and loss ratio about 0.7458. On the contrary, areas of gain and loss severity classes for LULC in 2023 of Scenario II were 1 and 17,546 ha, respectively with gain and loss ratio about 0.0001. Meanwhile areas of gain and loss severity classes for LULC in 2023 of Scenario III were 4,600 and 50 ha, respectively with gain and loss ratio about 92. As results, it can concluded that LULC change creates a positive and negative effect to soil erosion. In this study, increasing of cassava and sugarcane under Scenario II created more actual total soil loss while increasing of forest land under Scenario III reduce actual total soil loss.

(2) Water yield estimation and its impact due to LULC change

SWAT model with SCS-CN method was here used to estimate water yield of actual LULC in 2013 and the simulated LULC in 2023 for each scenarios. Herein SWAT model with an optimum local parameters was firstly used to generate CN value in each hydrologic response unit (HRU) for LULC in 2013 and SCS-CN method were then used to estimate theirs water yield (runoff depth). In this study, an optimum local parameter of SWAT model which provides the optimized accuracy of NSE (0.75) and R^2 (0.76) by calibration process over M145 hydrological station sub-watershed were (1) surface runoff lag times of 0.1 day, (2) base flow alpha factor of 0.9 day, and (3) available water capacity of the first layer of 0 mm.

For water yield estimation by SCS-CN method, the minimum and maximum values of water yield by pixel for LULC in 2013 and the simulated three scenarios LULC in 2023 were equal with value of 0.16 and 106.32 mm, respectively. However, the value of mean and total water yield from LULC in 2013 and the simulated three scenarios LULC in 2023 were different from each other. These results shows influence of LULC changes on water yield because soil types and rainfall values for LULC in 2013 and the simulated LULC in 2023 of three scenarios were stable and identical. In addition, the total water yield value, which directly relate to surface runoff, reflected the characteristics of LULC. Herein, the simulated LULC in 2023 of Scenario III, which represents forest conservation and prevention, provides the lowest water yield for surface runoff meanwhile the simulated LULC in 2023 of Scenario II, which represents agriculture production extension for energy crops, provides the highest water yield for surface runoff. It was clear that total water yield as runoff depth of LULC in 2013 and

LULC in 2023 of Scenario I, II, and III were 37.79, 38.04, 46.13, and 36.22 million cu. m, respectively.

For impact of LULC change on water yield, the relationship between the percentage of agricultural land and forest land from actual LULC in 2013 and simulated LULC in 2023 of three scenarios was separately regressed with total water yield. It was discovered that when the percentage of agricultural land increases, water yield (runoff depth) increases while the percentage of forest land increases, water yield (runoff depth) decreases.

(3) Economic value estimation and its impact due to LULC change

Future values for LULC in 2013 and the simulated LULC in 2023 of three scenarios except urban and built-up land, water body and miscellaneous land were estimated using PV model based on present return value from government agencies' reports and spatially compared for its impact due to LULC change.

It was found that economic value of agriculture and forest land for LULC in 2013 and the simulated LULC in 2023 of three scenarios were 16,987.05, 16,677.33, 12,923.64, and 19,660.13 million Baht, respectively. The future maximum values of economic by pixel for LULC in 2013 and the simulated LULC in 2023 of three scenarios was equal with value of 30,737 Baht, respectively. But the minimum value for LULC 2023 of Scenario II was different from others because maize disappeared in LULC data of Scenario II. These results occurred because the derived economic values directly related to LULC types. At the same time, mean and total economic values from LULC in 2013 and the simulated LULC in 2023 of three scenarios were different from each other. These results showed the influence of LULC changes on economic return.

For impact of LULC change on economic value, the relationship between the percentage of agricultural land and forest land from LULC in 2013 and simulated LULC in 2023 was separately regressed with total economic value to demonstrate the impact of LULC change on economic value. As results, it was clear that when the percentage of agricultural land increases, total future value decreases while when the percentage of forest land increases, total future value increases.

8.1.4 An optimal land use allocation

The derived soil loss, water yield and economic values of each scenario in 2023 were here firstly separately normalized and combined using SAW method of MCDA to create total scores with specific weight according scenario characteristics. Then the total score from each scenario was classified for suitability classes (low, moderate and high) for land use allocation in 2023. The results were further compared with actual LULC in 2013 for an optimal land use allocation in 2023 of each scenario in detail later on.

As a result, it was found that the dominant suitability classes for an optimal land use allocation of Scenario I were moderate and high and covered area of 31,793 and 32,900 ha or 48.75 and 50.45 percent, respectively. The suitability classes for an optimal land use allocation of Scenario II were low, moderate and high and covered area of 19,665, 30,618 and 23,250 ha or 26.74, 41.64 and 31.62 percent, respectively. Meanwhile, the dominant suitability classes for an optimal land use allocation of Scenario III were moderate and high covered area of 40,979 and 21,062 ha or 60.97 and 31.33 percent, respectively.

For an optimal land use allocation of Scenario I in detail, low or moderate suitability classes of changed LULC type between actual LULC in 2013 and the simulated LULC in 2023 covered area of 10 and 927 ha should be carefully implemented in long term (8-10 years) and medium term (4-7 years), respectively to minimize environmental impact.

For an optimal land use allocation of Scenario II in detail, low and moderate suitability classes of cassava and sugarcane in 2023 covered area of 16,832 and 21,719 ha, respectively should be carefully implemented in long term (8-10 years) and medium term (4-7 years), respectively. While high suitability class of cassava and sugarcane covered area of 7,315 ha can be implemented in short term (1-3 years) due to minimal environmental impact by soil erosion.

For an optimal land use allocation of Scenario III in detail, low and moderate suitability classes of forest land in 2023 covered area of 3,142 and 3,490 ha, respectively should be carefully implemented in long term (8-10 years) and medium term (4-7 years), respectively. In contrast, high suitability class of forest land in 2023 covered area of 6,631 ha can be implemented in short term (1-3 years) due to minimal environmental impact of soil erosion. Meanwhile, non-changed area of forest land between actual LULC in 2013 and the simulated LULC in 2023 covered area of 25,970 ha.

In conclusion, it appears that integration of LULC change model (CLUE-S model), hydrologic model (SWAT model and SCS-CN method), soil erosion model (USLE model) and economic value measures (PV model) can be used as an efficiently tools for an optimal land use allocation by considering LULC change and its impact.

8.2 Recommendations

Many objectives were here investigated including LULC assessment and change its driving forces, simulation of LULC scenario, the impact of LULC change on soil erosion, water yield and economic values and an optimal land use allocation in Upper Lam Phra Phloeng Watershed, Nakhon Ratchasima, Thailand. The possibly expected recommendations could be made for further studies as follows.

(1) For study driving force for LULC change, it should be considered more significant factors at local scale (social attitude and culture) as driving factor plays an important role for land allocation under CLUE-S model based on binary logistic regression.

(2) According to LULC change simulation using CLUE-S model, it can provides the optimal information about spatial and non-spatial data for land use planner or managers based on the specified land use requirement in each scenario, especially Scenario II and III. These simulated scenarios were set up based on government policy as top-down approach. Therefore, bottom-up approach for LULC change simulation based the requirement of local people or local government organization should be examined in the future using a participatory approach.

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APPENDICES

APPENDIX A

OVERVIEW OF EXISTING LAND USE CHANGE MODELS

Table A-1 Overview of existing land use change models.

Model Name/ Citation *Name of model, if any, and citation*	**Model Type** *Technical, descriptive terms*	**Components/ Modules** *Different models, or sub models or modules, that work together*	**What It Explains / Dependent Variable**	**Other Variables** *Description of other sets of variables in the model*	**Strengths**	**Weaknesses**
1.General Ecosystem Model (GEM) (Fitz et al., 1996)	Dynamic systems model	14 Sectors (modules), e.g. Hydrology, Macrophytes Algae Nutrients Fire Dead organic matter Separate database for each sector	Captures feedback among abiotic and biotic ecosystem components	103 input parameters, in a set of linked databases, representing the modules, e.g., Hydrology Macrophytes Algae Nutrients Fire Dead organic matter	Spatially dependent model, with feedback between units and across time Includes many sectors Modular, can add or drop sectors Can adapt resolution, extent, and time step to match the process being modeled	Limited human decision making
2.Patuxent Landscape Model (PLM) (Voinov et al., 1999)	Dynamic systems model	Based on the GEM model (#1, above), includes the following modules, with some modification: 1) Hydrology 2) Nutrients 3) Macrophytes 4) Economic model	Predicts fundamental ecological processes and land-use patterns at the watershed level	In addition to the GEM variables, it -adds dynamics in carbon-to-nutrient ratios -introduces differences between evergreen and deciduous plant communities -introduces impact of land management through fertilizing, planting, and harvesting of crops and trees	In addition to the strengths of the GEM, the PLM incorporates several other variables that add to its applicability to assess the impacts of land management and best management practices	Limited consideration of institutional factors
3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkampet and Fresco, 1996a)	Discrete, finite state model	1) Regional biophysical module 2) Regional land-use objectives module 3) Local land-use allocation module	Predicts land cover in the future	*Biophysical drivers*: Land suitability for crops, Temperature/Precipitation, Effects of past land use (may explain both biophysical degradation and improvement of land, mainly for crops) Impact of pests, weeds, diseases *Human Drivers:* Population size and density Technology level, Level of affluence Political Structures (through command and control, or fiscal mechanisms) Economic conditions Attitudes and values	Covers a wide range of biophysical and human drivers at differing temporal and spatial scales	Limited consideration of institutional and economic variables
4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b)	Discrete finite state model	CLUE-CR an application of CLUE (#3, above) Same modules	Simulates top-down and bottom-up effects of land-use change in Costa Rica	Same as CLUE (#3, above)	Multiple scales - local, regional, and national Uses the outcome of a nested analysis, a set of 6x5 scale-dependent land-use linear regressions as model input, which is reproducible, unlike a specific calibration exercise	Authors acknowledge limited consideration of institutional and economic factors

Table A-1 Overview of existing land use change models. (Continued).

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
5. Area base model (Hardieetand Parks,1997)	Area base model, using a modified multinomial logit model	Single module	Predicts land-use proportions at county level	Land base - classified as farmland, forest, and urban/other uses County average farm revenue Crop costs per acre Standing timber prices Timber production costs Land quality (agricultural suitability) Population per acre Average per capita personal income Average age of farm owners Irrigation	Uses publicly available data Incorporates economic (rent), and landowner characteristics (age, income) and population density Incorporates the impact of land heterogeneity Can account for sampling error in the county-level land-use proportions and for measurement error incurred by the use of county averages	An extended dataset over longer time periods would improve the model's predictions Long-term forecasts run the risk of facing an increasing probability of structural change, calling for revised procedures
6. Mertensetand Lambin, 1997	Univariate spatial models	Multiple univariate models, based on deforestation pattern in study area 1) Total study area 2) Corridor pattern 3) Island pattern 4) Diffuse pattern Each model runs with all four independent variables separately	Frequency of deforestation	All four models run with all four independent variables: 1) Road proximity 2) Town proximity 3) Forest-cover fragmentation 4) Proximity to a forest/non-forest edge	Presents a strategy for modeling deforestation by proposing a typology of deforestation patterns In all cases, a single variable model explains most of the variability in deforestation	Does not model interaction between factors
7. Chomitzetand Gray, 1996	Econometric (multinomial logit) model	Single module, with multiple equations	Predicts land use, aggregated in three classes: Natural vegetation Semi-subsistence agriculture Commercial farming	Soil nitrogen Available phosphorus Slope Ph Wetness Flood hazard Rainfall National land Forest reserve Distance to markets, based on impedance levels (relative costs of transport) Soil fertility	Used spatially disaggregated information to calculate an integrated distance measure based on terrain and presence of roads Also, strong theoretical underpinning of Von Thünen's model	Strong assumptions that can be relaxed by alternate specifications Does not explicitly incorporate prices
8. Gilruth et al., 1995	Spatial dynamic model	Several subroutines for different tasks	Predicts sites used for shifting cultivation in terms of topography and proximity to population centers	Site productivity (# of fallow years) Ease of clearing, Erosion hazard, Site proximity and Population, as function of village size	Replicable Tries to mimic expansion of cultivation over time	Long gap between data collection; does not include impact of land-quality and socioeconomic variables

Table A-1 Overview of existing land use change models. (Continued).

Model Name/ Citation	**Model Type**	**Components/ Modules**	**What It Explains / Dependent Variable**	**Other Variables**	**Strengths**	**Weaknesses**
9.Wood et al.,1997	Spatial Markov model	Temporal and spatial land-use change Markov models	Land-use change	Models under development	Investigating Markov variations, which relax strict assumptions associated with the Markov approach Explicitly considers both spatial and temporal change	Not strictly a weakness, this is a work in progress and, hence, has not yet included HDM factors
10. CUF (California Urban Futures) (Landis 1995, Landis et al., 1998)	Spatial simulation	Population growth sub model Spatial database, various layers merged to project Developable Land Units (DLUs) Spatial Allocation sub model Annexation-incorporation sub model	Explains land use in a metropolitan setting, in terms of demand (population growth) and supply of land (underdeveloped land available for redevelopment)	Population growth, DLUs, and intermediate map layers with: Housing prices Zoning Slope Wetlands Distance to city center Distance to freeway or BART station Distance to sphere-of-influence boundaries	Underlying theory of parcel allocation by population growth projections and price, and incorporation of incentives for intermediaries -developers, a great strength Large-scale GIS map layers with detailed information for each individual parcel in 14 counties provide high realism and precision	Compresses long period (20 years) in a single model run Has no feedback of mismatch between demand and supply on price of developable land/housing stock Does not incorporate impact of interest rates, economic growth rates, etc.
11. LUCAS (Land-use Change Analysis System) (Berry et al., 1996)	Spatial stochastic model	1) Socioeconomic module 2) Landscape change module 3) Impacts module	Transition probability matrix (of change in land cover) Module 2 simulates the landscape change Module 3 assesses the impact on species habitat	Module 1 variables: Land cover type (vegetation) Slope Aspect Elevation Land ownership Population Density Distance to nearest road Distance to nearest economic market center Age of trees Module 2: Transition matrix and same as Module 1, to produce land-cover maps Module 3: Utilizes land-cover maps	Model shows process (the TPM), output (new land-use map), and impact (on species habitat), all in one, which is rare and commendable Is modular and uses low-cost open source GIS software (GRASS)	LUCAS tended to fragment the landscape for low-proportion land uses, due to the pixel-based independent-grid method Patch-based simulation would cause less fragmentation, but patch definition requirements often lead to their degeneration into one-cell patches

Table A-1 Overview of existing land use change models. (Continued).

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
12. Wear and Mangold, 1998	Simple log weights	Single module	Predicts area of timberland adjusted for population density	Raw timberland Population density (per county)	Simple and powerful indicator of forest sustainability, of the impact of human settlement decisions on one forest function --its role as timberland	Limited consideration of human decision making and other forest goods and services
13. Wear et al.,1999	Logit model	Single module	Predicts the probability of land being classified as potential timberland	Population per square mile Site index Slope Two dummy variables defining ease of access to a site	Includes several biophysical variables	Includes only basic human choice variables, e.g., population density
14. Swallow et al., 1997	Dynamic model	Three components: 1) Timber model 2) Forage production function 3) Non-timber benefit function	Simulates an optimal harvest sequence	Present values of alternative possible states of the forest, using the three model components	The long time horizon, and the annual checking of present values under alternate possible states of the forest makes it a useful forest management tool for maximizing multiple-use values	Authors note that the optimal management pattern on any individual stand or set of stands requires specific analysis rather than dependence on rules of thumb
15. NELUP (O'Callaghan 1995)	General systems framework Economic component uses a recursive linear planning model	1) Regional agricultural economic model of land use at catchment levels 2) Hydrological model 3) Ecological model	Explains patterns of agricultural and forestry land use under different scenarios	Variable types include: Soil characteristics Meteorological data Parish census data Input/output farm data Species Land cover	Uses land cover to link market forces, hydrology, and ecology in a biophysical model of land use Uses mostly publicly available data, especially in the economic model, which greatly aids transferability	Limited institutional variables

Table A-1 Overview of existing land use change models. (Continued).

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
16. NELUP - Extension (Oglethorpe and O'Callaghan 1995)	Linear planning model at farm level	Four submodels for farm types 1) Lowland and mainly arable 2) Lowland mainly grazing livestock 3) Dairy 4) Hill	Maximizes income Profit is the dependent variable.	Level of farm activity Gross margin per unit of farm activity, Fixed resources, represented as physical constraints	Detailed farm -level model, with extensive calibration, Farmers shown as rational profit-maximizing beings, but also includes the impact of off-farm income	Limited institutional variables
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al.,1996)	Dynamic, non-linear, price endogenous, mathematical programming model	Three submodels : 1) Forest sector transition timber supply model 2) Agricultural sector that is optimized with the forest sector sub model 3) Carbon sector for terrestrial carbon	Allocation of land in the forest and agricultural sectors Objective function maximizes the discounted economic welfare of producers and consumers in the U.S. agriculture and forest sectors over a nine-decade time horizon	*Forest sector variable groups:* Demand functions for forest products Timberland area, age-class dynamics Production technology and costs *Agricultural sector variables:* Water Grazing Labor Agricultural demand Imports/exports *Carbon sector variables:* Tree and ecosystem carbon *Additional variables:* Land transfer variables	Incorporates both agriculture and forest land uses Price of products and land is endogenous The model is dynamic, thus changes in one decade influence land-use change in the next decade Good for long-term policy impacts	Broad scale r land capability variations within regions are not taken into account
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al., 1998)	Overlay of GIS layers with statistical urban growth projections	1) Statistical model of urban growth 2) Policy simulation and evaluation model 3) Map and data layers of habitat types, biodiversity, and other natural factors	The interaction among the probabilities of urbanization, its interaction with habitat type and extent, and, impacts of policy changes on the two	Slope and elevation Location and types of roads Hydrographic features Jurisdictional boundaries Wetlands and flood zones Jurisdictional spheres of influence Various socioeconomic data Local growth policies Job growth Habitat type and extent maps	Increases understanding of factors behind recent urbanization patterns Allows projection of future urban growth patterns, and of the impact of projected urban growth on habitat integrity and quality	Human decision making not explicitly considered Further, errors are likely from misclassification of data at grid level or misalignment of map feature boundaries Errors also possible from limitations in explaining historical urban growth patterns
19. Clarke et al.,1998, Kirtland et al., 2000	Cellular automata model	Simulation module consists of complex rules Digital dataset of biophysical and human factors	Change in urban areas over time	Extent of urban areas Elevation Slope Roads	Allows each cell to act independently according to rules, analogous to city expansion as a result of hundreds of small decisions Fine-scale data, registered to a 30 m UTM grid	Does not unpack human decisions that lead to spread of built areas Does not yet include biological factors

Source: Agarwal et al., 2001

APPENDIX B

LIST OF REFERENCE POINTS

Table B.1 Detail of sample point for accuracy assessment.

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
1	795,125	1,596,236	Forest land	Forest land
2	781,125	1,601,836	Maize	Maize
3	788,525	1,603,636	Miscellaneous land	Miscellaneous land
4	790,925	1,609,136	Forest land	Forest land
5	801,425	1,598,136	Miscellaneous land	Miscellaneous land
6	798,525	1,606,336	Maize	Maize
7	801,725	1,594,436	Maize	Maize
8	801,725	1,603,536	Maize	Maize
9	803,025	1,588,236	Forest land	Forest land
10	789,125	1,593,236	Forest land	Forest land
11	791,225	1,608,836	Forest land	Forest land
12	796,525	1,596,436	Maize	Maize
13	804,225	1,589,336	Forest land	Forest land
14	795,725	1,619,136	Forest land	Forest land
15	794,825	1,605,336	Maize	Maize
16	785,625	1,601,336	Maize	Maize
17	783,125	1,597,536	Forest land	Forest land
18	768,525	1,601,636	Forest land	Forest land
19	796,825	1,608,336	Forest land	Forest land
20	805,725	1,601,036	Maize	Maize
21	786,625	1,608,836	Sugarcane	Sugarcane
22	791,325	1,596,936	Perennial tree/orchard	Perennial tree/orchard
23	789,425	1,607,336	Maize	Maize
24	795,925	1,608,136	Maize	Maize
25	799,225	1,605,136	Forest land	Forest land
26	789,625	1,604,936	Maize	Maize
27	792,225	1,617,336	Maize	Maize
28	789,425	1,607,936	Maize	Maize
29	769,725	1,600,336	Forest land	Forest land
30	788,025	1,595,536	Perennial tree/orchard	Perennial tree/orchard
31	789,325	1,598,136	Maize	Maize
32	787,825	1,593,136	Forest land	Forest land
33	789,925	1,601,336	Sugarcane	Sugarcane
34	783,525	1,594,836	Forest land	Forest land
35	803,625	1,591,436	Urban and built-up land	Urban and built-up land
36	805,025	1,607,936	Forest land	Forest land
37	786,425	1,608,336	Maize	Maize
38	796,325	1,594,536	Cassava	Cassava
39	788,025	1,614,336	Maize	Maize
40	799,725	1,607,136	Forest land	Forest land

Table B.1 Detail of sample point for accuracy assessment. (Continued)

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
41	777,325	1,603,736	Sugarcane	Sugarcane
42	791,725	1,617,936	Maize	Maize
43	790,025	1,599,736	Cassava	Cassava
44	808,425	1,591,736	Forest land	Forest land
45	803,825	1,607,936	Forest land	Forest land
46	788,525	1,605,936	Sugarcane	Sugarcane
47	808,825	1,597,536	Urban and built-up land	Urban and built-up land
48	779,225	1,598,736	Forest land	Forest land
49	789,025	1,606,736	Sugarcane	Sugarcane
50	798,425	1,590,836	Cassava	Cassava
51	794,625	1,619,036	Forest land	Forest land
52	770,625	1,599,336	Forest land	Forest land
53	795,525	1,605,036	Maize	Maize
54	784,525	1,604,936	Sugarcane	Sugarcane
55	774,425	1,601,136	Forest land	Forest land
56	797,925	1,599,436	Miscellaneous land	Miscellaneous land
57	800,125	1,590,936	Miscellaneous land	Miscellaneous land
58	801,625	1,595,136	Maize	Maize
59	794,525	1,587,236	Forest land	Forest land
60	783,225	1,602,636	Perennial tree/orchard	Perennial tree/orchard
61	800,525	1,595,336	Maize	Maize
62	810,725	1,596,736	Forest land	Forest land
63	783,525	1,603,836	Perennial tree/orchard	Perennial tree/orchard
64	792,625	1,587,736	Forest land	Forest land
65	811,425	1,597,136	Forest land	Forest land
66	792,025	1,599,436	Sugarcane	Sugarcane
67	791,425	1,593,236	Perennial tree/orchard	Perennial tree/orchard
68	782,525	1,608,136	Sugarcane	Sugarcane
69	802,125	1,593,136	Maize	Maize
70	794,725	1,615,636	Forest land	Forest land
71	803,525	1,596,436	Forest land	Forest land
72	770,025	1,601,336	Forest land	Forest land
73	785,625	1,603,736	Miscellaneous land	Miscellaneous land
74	806,725	1,594,136	Miscellaneous land	Miscellaneous land
75	785,425	1,604,936	Maize	Maize
76	802,925	1,606,736	Maize	Maize
77	786,525	1,607,036	Maize	Maize
78	794,025	1,604,736	Maize	Maize
79	793,625	1,593,936	Maize	Maize
80	783,825	1,607,136	Sugarcane	Sugarcane

Table B.1 Detail of sample point for accuracy assessment. (Continued)

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
81	793,925	1,604,036	Sugarcane	Sugarcane
82	784,225	1,597,036	Forest land	Forest land
83	792,825	1,588,836	Forest land	Forest land
84	803,425	1,591,736	Urban and built-up land	Urban and built-up land
85	785,925	1,598,336	Maize	Maize
86	783,825	1,612,936	Miscellaneous land	Miscellaneous land
87	803,725	1,597,136	Maize	Maize
88	807,625	1,590,836	Miscellaneous land	Miscellaneous land
89	797,625	1,590,536	Maize	Maize
90	791,725	1,597,736	Sugarcane	Sugarcane
91	769,625	1,598,236	Forest land	Forest land
92	774,825	1,597,536	Forest land	Forest land
93	792,125	1,587,436	Forest land	Forest land
94	792,925	1,602,436	Sugarcane	Sugarcane
95	812,225	1,598,936	Forest land	Forest land
96	799,025	1,599,536	Maize	Maize
97	790,125	1,593,836	Perennial tree/orchard	Perennial tree/orchard
98	796,225	1,615,836	Forest land	Forest land
99	807,125	1,603,036	Forest land	Forest land
100	786,925	1,604,736	Sugarcane	Sugarcane
101	787,025	1,607,136	Urban and built-up land	Urban and built-up land
102	788,025	1,596,836	Maize	Maize
103	791,725	1,598,036	Maize	Maize
104	775,125	1,600,836	Forest land	Forest land
105	794,325	1,589,636	Maize	Maize
106	779,725	1,604,636	Maize	Maize
107	796,325	1,607,836	Forest land	Forest land
108	808,825	1,601,636	Forest land	Forest land
109	779,325	1,605,236	Maize	Maize
110	778,425	1,605,336	Maize	Maize
111	772,325	1,596,636	Forest land	Forest land
112	800,025	1,593,136	Perennial tree/orchard	Perennial tree/orchard
113	788,825	1,611,636	Maize	Maize
114	785,025	1,610,636	Perennial tree/orchard	Perennial tree/orchard
115	780,125	1,609,536	Sugarcane	Sugarcane
116	788,625	1,594,336	Maize	Maize
117	772,025	1,598,536	Forest land	Forest land
118	793,725	1,601,636	Maize	Maize
119	782,625	1,610,136	Sugarcane	Sugarcane
120	772,225	1,598,336	Forest land	Forest land

Table B.1 Detail of sample point for accuracy assessment. (Continued)

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
121	779,825	1,602,936	Urban and built-up land	Urban and built-up land
122	809,425	1,601,236	Forest land	Forest land
123	803,225	1,607,936	Forest land	Forest land
124	797,025	1,592,436	Maize	Maize
125	788,325	1,611,736	Maize	Maize
126	805,025	1,590,436	Maize	Maize
127	811,625	1,597,236	Forest land	Forest land
128	793,725	1,617,936	Maize	Maize
129	798,025	1,603,636	Forest land	Forest land
130	789,125	1,607,936	Maize	Maize
131	805,825	1,591,036	Maize	Maize
132	804,525	1,599,236	Perennial tree/orchard	Perennial tree/orchard
133	787,925	1,607,536	Sugarcane	Sugarcane
134	776,125	1,597,636	Forest land	Forest land
135	785,925	1,613,336	Maize	Maize
136	801,225	1,597,936	Forest land	Forest land
137	787,025	1,608,736	Sugarcane	Sugarcane
138	795,725	1,605,636	Maize	Maize
139	797,225	1,608,836	Cassava	Cassava
140	774,625	1,600,336	Forest land	Forest land
141	774,025	1,598,336	Forest land	Forest land
142	785,625	1,604,736	Sugarcane	Sugarcane
143	792,525	1,617,236	Urban and built-up land	Urban and built-up land
144	800,725	1,591,236	Forest land	Forest land
145	787,925	1,611,736	Perennial tree/orchard	Perennial tree/orchard
146	780,825	1,609,436	Perennial tree/orchard	Perennial tree/orchard
147	781,925	1,598,736	Forest land	Forest land
148	795,725	1,611,636	Forest land	Forest land
149	796,525	1,609,036	Forest land	Forest land
150	803,225	1,595,436	Maize	Maize
151	789,225	1,615,436	Forest land	Forest land
152	800,225	1,605,536	Forest land	Forest land
153	787,525	1,593,536	Forest land	Forest land
154	793,025	1,603,836	Maize	Maize
155	802,525	1,590,336	Miscellaneous land	Miscellaneous land
156	807,625	1,605,536	Forest land	Forest land
157	801,125	1,605,836	Forest land	Forest land
156	807,625	1,605,536	Forest land	Forest land
157	801,125	1,605,836	Forest land	Forest land
158	781,425	1,603,836	Perennial tree/orchard	Perennial tree/orchard

Table B.1 Detail of sample point for accuracy assessment. (Continued)

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
159	790,525	1,618,836	Sugarcane	Sugarcane
160	797,525	1,600,536	Cassava	Cassava
161	801,325	1,601,836	Maize	Maize
162	797,325	1,593,836	Maize	Maize
163	802,725	1,604,936	Forest land	Forest land
164	790,125	1,598,436	Perennial tree/orchard	Perennial tree/orchard
165	788,325	1,597,736	Paddy field	Paddy field
166	794,525	1,616,736	Forest land	Forest land
167	769,625	1,601,736	Forest land	Forest land
168	773,525	1,596,736	Forest land	Forest land
169	794,025	1,607,936	Forest land	Forest land
170	798,225	1,604,736	Forest land	Forest land
171	801,025	1,609,436	Water body	Water body
172	796,225	1,592,736	Sugarcane	Sugarcane
173	810,925	1,594,336	Forest land	Forest land
174	793,725	1,592,636	Perennial tree/orchard	Perennial tree/orchard
175	785,625	1,606,036	Maize	Maize
176	794,925	1,610,136	Forest land	Forest land
177	801,425	1,590,036	Forest land	Forest land
178	787,925	1,602,936	Sugarcane	Sugarcane
179	780,825	1,601,936	Maize	Maize
180	804,425	1,601,536	Maize	Maize
181	802,025	1,602,736	Sugarcane	Sugarcane
182	794,825	1,593,836	Cassava	Cassava
183	771,725	1,598,336	Forest land	Forest land
184	811,725	1,597,936	Forest land	Forest land
185	769,525	1,600,636	Forest land	Forest land
186	808,125	1,600,336	Forest land	Forest land
187	788,325	1,605,536	Miscellaneous land	Miscellaneous land
188	781,425	1,606,636	Sugarcane	Sugarcane
189	781,325	1,605,836	Miscellaneous land	Miscellaneous land
190	806,625	1,602,736	Forest land	Forest land
191	780,825	1,604,836	Perennial tree/orchard	Perennial tree/orchard
192	792,225	1,605,936	Maize	Maize
193	804,325	1,599,536	Perennial tree/orchard	Perennial tree/orchard
194	787,625	1,596,236	Cassava	Cassava
195	788,125	1,604,136	Sugarcane	Sugarcane
196	777,725	1,604,136	Sugarcane	Sugarcane
197	780,625	1,602,736	Perennial tree/orchard	Perennial tree/orchard
198	797,025	1,594,936	Perennial tree/orchard	Perennial tree/orchard

Table B.1 Detail of sample point for accuracy assessment. (Continued)

ID	Easting (X)	Northing (Y)	Visual interpretation	Ground reference
199	804,425	1,604,536	Maize	Maize
200	792,825	1,599,736	Sugarcane	Sugarcane
201	790,125	1,616,336	Sugarcane	Sugarcane
202	797,725	1,593,536	Maize	Maize
203	784,825	1,609,236	Sugarcane	Sugarcane

APPENDIX C

MODEL CALIBRATION AND ACCURACY ASSESSMENT FOR MONTHLY RUNOFF OF M145

Table C1 Calibration and validation parameters of SWAT model in M145 and M171.

No.	Sub watershed	Weather Data					Year		HUR proportion			Parameters			Modified				Accuracy	
		Temp	Rain	R. Hum	Solar R	Wind Sp	LULC	Start	LU	Soil	Slope	Surlag	Alpha	Slope class	CN	SOL_Z	SOL_AWC1	ESCO	Nash	R^2
1	Sta. 145	sim	sim	sim	sim	sim	2003	2003	20	10	20	default	default	1	0	0	0	0	-0.62	0.51
2	Sta. 145	input	sim	sim	sim	sim	2003	2003	20	10	20	default	default	1	0	0	0	0	-0.64	0.51
3	Sta. 145	sim	input	sim	sim	sim	2003	2003	20	10	20	default	default	1	0	0	0	0	0.45	0.56
4	Sta. 145	input	input	sim	sim	sim	2003	2003	20	10	20	default	default	1	0	0	0	0	0.46	0.56
5	Sta. 145	sim	input	sim	sim	sim	2003	2002	20	10	20	default	default	1	0	0	0	0	0.42	0.53
6	Sta. 145	sim	sim	sim	sim	sim	2003	2000	20	10	20	default	default	1	0	0	0	0	0.16	0.19
7	Sta. 145	sim	input	sim	sim	sim	2003	2003	10	10	10	default	default	1	0	0	0	0	0.45	0.57
8	Sta. 145	sim	input	sim	sim	sim	2003	2003	20	20	20	default	default	1	0	0	0	0	0.46	0.56
9	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	default	default	3	0	0	0	0	0.50	0.60
10	Sta. 145	sim	input	sim	sim	sim	2003	2003	20	10	20	default	default	3	0	0	0	0	0.45	0.56
11	Sta. 145	sim	input	sim	sim	sim	2003	2003	20	10	20	default	default	3	5	0	0	0	0.48	0.57
12	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	default	default	3	5	0	0	0	0.52	0.59
13	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	20	default	3	5	0	0	0	0.51	0.58
14	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.5	default	3	5	0	0	0	0.602	0.680
15	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0	default	3	5	0	0	0	0.517	0.586
16	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	default	3	5	0	0	0	0.610	0.673
17	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	default	3	0	0	0	0	0.55	0.63
18	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.01	3	5	0	0	0	0.55	0.68
19	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.1	3	5	0	0	0	0.64	0.70
20	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.5	3	5	0	0	0	0.68	0.73

Table C1 Calibration and validation parameters of SWAT model in M145 and M171. (Continued)

No.	Sub watershed	Weather Data					Year		HUR proportion			Parameters			Modified				Accuracy	
		Temp	Rain	R. Hum	Solar R	Wind Sp	LULC	Start	LU	Soil	Slope	Surlag	Alpha	Slope class	CN	SOL_Z	SOL_AWC1	ESCO	Nash	R^2
21	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	1	3	5	0	0	0	0.68	0.73
22	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	5	0	0	0	0.68	0.73
23	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0	0.66	0.73
24	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0	0.736	0.748
25	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0	0.740	0.756
26	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0.5	0.740	0.756
27	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0.1	0.740	0.756
28	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	-z1	0	0	0.741	0.757
29	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	-30_z1	0	0	0.746	0.759
30	Sta. 145	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	-30_z1, -100_z2	0	0	0.744	0.758
31	Sta. 145	input	input	input	input	input	2003	2003	0	0	0	0.1	0.9	3	0	-30_z1, -100_z2	0	0	-0.477	0.502
32	Sta. 171	sim	input	sim	sim	sim	2003	2003	0	0	0	D	D	3	0	0	0	0	0.354	0.601
33	Sta. 171	sim	input	sim	sim	sim	2003	2003	0	0	0	0.1	0.9	3	0	0	0	0	0.745	0.792

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