LAND USE AND LAND COVER SCENARIOS OF ECOSYSTEM SERVICES FOR OPTIMUM WATER YIELD AND SEDIMENT RETENTION IN KLONG U-TAPAO WATERSHED, SONGKHLA, THAILAND

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Geoinformatics

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ภาพเหตุการณ์ของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินต่อการให้บริการระบบนิเวศสำหรับปริมาณน้ำท่าและการดูดยึดตะกอนดินที่เหมาะสมในพื้นที่ลุ่มน้ำคลองอู่ตะเภา สงขลา ประเทศไทย

นายจำรูญ ศรีชัยชนะ

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต

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ปีการศึกษา 2561

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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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จำรูญ ศรีชัยชนะ : ภาพเหตุการณ์ของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินต่อการให้บริการระบบนิเวศสำหรับปริมาณน้ำท่าและการดูดยึดตะกอนดินที่เหมาะสมในพื้นที่ลุ่มน้ำคลองอู่ตะเภา สงขลา ประเทศไทย (LAND USE AND LAND COVER SCENARIOS OF ECOSYSTEM SERVICES FOR OPTIMUM WATER YIELD AND SEDIMENT RETENTION IN KLONG U-TAPAO WATERSHED, SONGKHLA, THAILAND) อาจารย์ที่ปรึกษา : รองศาสตราจารย์ ดร.สุวิทย์ อ๋องสมหวัง, 398 หน้า.

พื้นที่ลุ่มน้ำคลองอู่ตะเภาเป็นแหล่งต้นน้ำสำคัญของน้ำต้นทุนสำหรับเกษตรกรรม อุตสาหกรรม และการบริโภคของครัวเรือนของจังหวัดสงขลา ในปัจจุบันพื้นที่ลุ่มน้ำคลองอู่ตะเภากำลังเผชิญปัญหาสำคัญหลายประการ โดยเฉพาะอย่างยิ่ง ปัญหาน้ำท่วมและการสูญเสียดิน ดังนั้นการระบุภาพเหตุการณ์ของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินที่เหมาะสมต่อการให้บริการของระบบนิเวศด้านปริมาณน้ำท่าและการดูดยึดตะกอนดินนับว่าเป็นสิ่งจำเป็นและมีความสำคัญยิ่ง วัตถุประสงค์ของการศึกษาคือ (1) เพื่อจำแนกสถานภาพการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินและการเปลี่ยนแปลงของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินในระหว่างปี พ.ศ. 2553 และ พ.ศ. 2560 (2) เพื่อคาดการณ์การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินของ 3 ภาพเหตุการณ์ที่แตกต่างกันในระหว่างปี พ.ศ. 2561 ถึง พ.ศ. 2567 (3) เพื่อประเมินปริมาณน้ำท่าและการดูดยึดตะกอนดินในระหว่างปี พ.ศ. 2560 ถึง พ.ศ. 2567 (4) เพื่อระบุภาพเหตุการณ์ของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินสำหรับการให้บริการทางระบบนิเวศของปริมาณน้ำท่าและการดูดยึดตะกอนดินที่เหมาะสม ในการศึกษาครั้งนี้ เริ่มต้นจากการจำแนกข้อมูลการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินในปี พ.ศ. 2553 และ พ.ศ. 2560 จากข้อมูลการรับรู้จากระยะไกลด้วยตัวจำแนก Random Forests และนำผลลัพธ์ที่ได้รับไปใช้ประเมินสภาพภาพและการเปลี่ยนแปลงของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดิน คาดการณ์การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินของ 3 ภาพเหตุการณ์ที่แตกต่างกันในระหว่างปี พ.ศ. 2561 ถึง พ.ศ. 2567 ด้วยแบบจำลอง CLUE-S หลังจากนั้น นำข้อมูลการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินจริงในปี พ.ศ. 2560 และข้อมูลการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินที่ได้จากคาดการณ์ของ 3 ภาพเหตุการณ์ไปใช้ประมาณการให้บริการปริมาณน้ำท่าและการดูดยึดตะกอนดินภายใต้ชุดโปรแกรม InVEST สำหรับใช้ระบุภาพเหตุการณ์การใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินที่เหมาะสมสำหรับการให้บริการปริมาณน้ำท่าและการดูดยึดตะกอนดินด้วยดัชนีการเปลี่ยนแปลงการให้บริการของระบบนิเวศ (Ecosystems Services Change Index)

จากผลการศึกษาที่ได้รับ พบว่า ในการประเมินการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินระหว่างปี พ.ศ. 2553 ถึง พ.ศ. 2560 สวนยางพาราและพื้นที่ชุมชนและสิ่งปลูกสร้างมีพื้นที่เพิ่มขึ้น แต่ป่าดิบชื้นและพื้นที่เบ็ดเตล็ดมีพื้นที่ลดลง ทั้งนี้ ค่าความถูกต้องโดยรวมและค่าสัมประสิทธิ์แคปปาแฮททีได้จากการประเมินความถูกต้องของแผนที่การใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินในปี พ.ศ. 2543 และ พ.ศ. 2560 มีค่าเท่ากับร้อยละ 91.36 84.00 94.32 และ 87.00 ตามลำดับ ในขณะเดียวกัน ผลลัพธ์ที่ได้รับจากการคาดการณ์การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินของ 3 ภาพเหตุการณ์ที่แตกต่างกันคือ ภาพเหตุการณ์แบบที่ 1 วิวัฒนาการการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินในอดีต ภาพเหตุการณ์แบบที่ 2 การอนุรักษ์และการป้องกันป่าไม้และภาพเหตุการณ์แบบที่ 3 การส่งเสริมผลผลิตทางการเกษตร ให้ผลลัพธ์ที่สมเหตุสมผลตามที่คาดหวัง ปัจจัยขับเคลื่อนที่มีนัยสำคัญสูงสุดสำหรับการจัดสรรประเภทการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินได้แก่ ระยะห่างจากชุมชน และผลลัพธ์ของสมการเชิงเส้นตรงแบบหลายตัวแปรจากการวิเคราะห์สมการถดถอยโลจิสติกแบบทวินามให้ค่าพื้นที่ใต้เส้นโค้งอยู่ระหว่าง 0.7239-0.9957 ในทำนองเดียวกัน การประเมินค่าปริมาณน้ำท่าและการดูดยึดตะกอนดินของ 3 ภาพเหตุการณ์ที่แตกต่างกันในระหว่างปี พ.ศ. 2560 ถึง พ.ศ. 2567 ให้ผลการศึกษาสอดคล้องกับคุณลักษณะของคำนิยามของภาพเหตุการณ์และปัจจัยภูมิอากาศ สภาพดิน ภูมิประเทศ และการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินซึ่งนำมาใช้ในแบบจำลอง Water yield และ Sediment delivery ratio ผลลัพธ์สุดท้ายที่ได้รับ พบว่า การใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินของภาพเหตุการณ์แบบที่ 2 สามารถให้บริการทางระบบนิเวศของปริมาณน้ำท่าและการดูดยึดตะกอนดินอย่างเหมาะสม

จากผลการศึกษาสามารถสรุปได้ว่า การบูรณาการเทคโนโลยีการรับรู้จากระยะไกลร่วมกับวิธีการจำแนกขั้นสูงและแบบจำลองเชิงพื้นที่ สามารถนำมาใช้เป็นเครื่องมือสำหรับการระบุภาพเหตุการณ์ของการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินต่อการให้บริการระบบนิเวศสำหรับปริมาณน้ำท่าและการดูดยึดตะกอนดินที่เหมาะสมได้อย่างมีประสิทธิภาพ

สาขาวิชาภูมิสารสนเทศ ลายมือชื่อนักศึกษา__________

ปีการศึกษา 2561 ลายมือชื่ออาจารย์ที่ปรึกษา__________

JAMROON SRICHAICHANA : LAND USE AND LAND COVER SCENARIOS OF ECOSYSTEM SERVICES FOR OPTIMUM WATER YIELD AND SEDIMENT RETENTION IN KLONG U-TAPAO WATERSHED, SONGKHLA, THAILAND. THESIS ADVISOR : ASSOC. PROF. SUWIT ONGSOMWANG, Dr. rer. Nat. 398 PP.

ECOSYSTEM SERVICES EVALUATION/ WATER YIELD AND SEDIMENT RETENTION ESTIMATION/ CLUE-S MODEL/ INVEST MODEL/ KLONG U-TAPAO WATERSHED

The Khlong U-Tapao watershed, is the main source of water supply for agriculture, industry and household consumption of Songkhla province but it is facing with serious problems, particularly flood and soil erosion. So, to identify land use and land cover (LULC) scenario for water yield and sediment retention ecosystem services is necessary and very important. Main objectives of the study were (1) to classify LULC status and its change during 2010 to 2017, (2) to predict LULC change of three different scenarios between 2018 and 2024, (3) to assess water yield and sediment retention during 2017 to 2024, and (4) to identify LULC scenario for optimum water yield and sediment retention ecosystem services. In this study, LULC data in 2010 and 2017 were firstly classified from remotely sensed data using random forests classifier and the derived results were used to assess its status and change, to predict LULC change of three different scenarios during 2018 to 2024 by CLUE-S model. Then, actual LULC data in 2017 and predictive LULC data of three scenarios were used to estimate water yield and sediment retention services under the InVEST software suite for identifying

LULC scenario for optimum water yield and sediment retention ecosystem services using Ecosystems Services Change Index.

As results, LULC change assessment during 2010 to 2017 showed that the major increasing areas of LULC types were rubber plantation and urban and built-up area while the major decreasing areas of LULC classes were evergreen forest and miscellaneous land. Herewith, the derived overall accuracy and Kappa hat coefficient of LULC map in 2010 and 2017 were 91.36% and 84.00% and 94.32% and 87.00%, respectively. Meanwhile, the derived LULC prediction of three different scenarios: Scenario I: Historical LULC evolution; Scenario II: Forest conservation and prevention; and Scenario III: Agriculture production could provide realistic results as expectation. The most significant driving factor for a specific LULC type allocation was a distance to the settlement and the derived multiple linear equations from binomial logistic regression analysis provided area under curve values from 0.7239 to 0.9957. Likewise, water yield and sediment retention estimation of three different scenarios during 2017 and 2024 could provide an expected results according to characteristics of scenarios definition and climate, soil and terrain and LULC factors required by water yield and sediment delivery ratio models. Lastly, LULC of Scenario II was chosen for optimum water yield and sediment retention ecosystem services.

In conclusion, it can be here concluded that integration of remote sensing technology with advanced classification method and geospatial models can be used as proficient tools to identify LULC scenario for optimum ecosystem services on water yield or sediment retention.

School of Geoinformatics Student's Signature______________

Academic Year 2018 Advisor's Signature______________

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Jamroon Srichaichana

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LIST OF ABBREVIATIONS

C	=	Cover factor
CART	=	Classification and Regression Trees
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
EnMAP	=	Environmental Mapping and Analysis Program
ESs	=	Ecosystem Services
GISTDA	=	Geo-Informatics and Space Technology Development Agency
GLCI	=	Gains and Loss Change Index
InVEST	=	Integrated Valuation of Ecosystem Services and Tradeoffs
K	=	Soil erodibility
LDD	=	Land Development Department
LULC	=	Land use and Land Cover
NatCap	=	The Natural Capital Project
NSO	=	National Statistical Office
OAE	=	Office of Agricultural Economics
oob	=	out of bag

LIST OF ABBREVIATIONS (Continued)

ONREPP	=	Office of Natural Resources and Environmental Policy and Planning
P	=	Practice factor (erosion control practice)
R	=	Rainfall erosivity
r^2	=	Coefficient of determination
RF	=	Random Forest
RID	=	Royal Irrigation Department
RTSD	=	Royal Thai Survey Department
RUSLE	=	Revised Universal Soil Loss Equation
SC	=	Scenario
SDR	=	Sediment Delivery Ratio model
SE	=	Soil Erosion
SLB	=	Songkhla Lake Basin
SWIR	=	Shortwave Infrared
TIR	=	Thermal Infrared
TMD	=	Thai Meteorological Department
TPROP	=	Total Probability
RUSLE	=	Revise Universal Soil Loss Equation
VNIR	=	Visible Near Infrared
WSC	=	Watershed Class

CHAPTER I

INTRODUCTION

1.1 Background problem and significance of the study

Ecosystem services are nature's benefits to humans from the natural environment and form appropriately function ecosystems 4 components. The provision of fresh water is the ecosystem service (ES) that offers for the profit of humans in many ways, such as water yield and water supply. Land use and land cover (LULC) is able to variation hydrologic cycles, affecting patterns of evapotranspiration, infiltration and water retention, and changing the timing and volume of water that is available for water supply (World Commission on Dams, 2000; Ennaanay 2006). Water yield is the sum of runoff from the landscape (Tallis et al., 2011). The relative water volume in a given landscape affects the quality of ecology in the area (Shoyama and Yamagata, 2014). Therefore, changes in the landscape that affect the annual average water yield be able to increase or decrease land productivity. For example, replacing forests on slope land or mountainous areas with rubber plantations results in water retention in the subsoil layer and decreases water discharge in the dry season and increases evapotranspiration (Guardiola-Claramonte et al., 2010). In contrast, cultivated area leads to larger average amounts of surface runoff and higher amounts of water losses from the reduced evapotranspiration in the wet season. Consequently, an increase in water yield is disposed to cause floods and landslides. The water yield is reflected as cumulative surface runoff measured at a specific location; therefore, it is not the desired type of regulation of water flow with yield and quality. However, high water yield is an ecosystem service as surface runoff, that is dependent on the vegetation cover under a given land use; thus, over surface runoff is not an appropriate situation as an ecosystem service (Hamilton, 2008; Suryatmojo, Fujimoto, Yamakawa, Kosugi, and Mizuyama, 2013).

Merritt, Letcher, and Jakeman (2003) stated that erosion and overland sediment retention are natural processes that govern the sediment concentration in streams. Sediment dynamics at the watershed scale are mainly control by climate in particular the rain intensity, soil properties, topography, and vegetation and conservation practice. Sedimentation is a natural process that contributes to the health of natural habitats, but in excess, it is lead to harmful outcomes (Sharp et al., 2015). It is the cause by soil erosion resulting from the degeneration of a watershed, showed as greater sediment deposits (Lane, Nichols, Levick, and Kidwell, 2001). Principal sediment source in Thailand is overland erosion (soil particles detached and transported by rain and overland flow (Tangtham, 2002). Vegetation provides a regulating service by preventing soil erosion, however, LULC change usually causes loss of vegetation cover. The prevention of soil erosion or increased sediment retention is regarded as an ecosystem service. Sediment retention not only preserves soil fertility but also maintains water quality. For the land use manager, it is essential to understanding the ways in which sediment retention preserves certain services in a natural landscape (Perrine, Rebecca, Sarah, and Carina, 2015).

The problems relate to Khlong U-Tapao watershed in the Songkhla Lake Basin (SLB) is a broad range of water resources development and management, particularly flood and soil erosion. Water shortage is a problem in the entire area during dry season, mainly affecting water supply, industrial sector and the agricultural sector. Population growth also effectuates LULC change and agricultural land expansion, as an implication of meeting people need's for economic, which might potentially produce water yield and erosion increase (Sunandar, Suhendang, Suhendang, and Marimin, 2014).

Flooding in low land areas of the Klong U-Tapao watershed at Hat Yai city also poses regular problems and heavy rain storms occur every 2 or 3 years causing inundation of the area. In addition, the high water level in the Gulf of Thailand usually mains to drainage problems in the rainy season. In the meantime, soil erosion is another principal issue associated with unsuitable soil management. The cultivation of rubber and other crops on steep hills causes erosion. Deforestation generally results in land being abandoned, and the cleared land rapidly erodes. Rubber plantations have encroached into many areas of the Songkhla Lake Basin, including Kao Pu-Kao Ya National Park. Currently, 30 percent (144 km^2) of Watershed Class I of U-Tapao watershed has been converted to rubber plantations (Doungsuwan, Ratanachai, Sompongchaiyakul, and Sangganjanavanich, 2013). These activities have increased soil erosion and sedimentation in Songkhla Lake (Department of Mineral Resources, 2008). Many factors drive on soil erosion in Khlong U-Tapao watershed include unsuitable practice for rubber plantation and palm oil and deforestation (Gyawali, Techato, Yuangyai, and Musikavong, 2013).

Evaluation of watersheds and development of a management strategy requires accurate measurement of the past and present LULC since LULC changes affect to hydrological, sediment retention and ecological processes taking place in a watershed.

Satellite remote sensing techniques have been widely used in detecting and monitoring LULC change at various scales with useful results (Santillan, Makinano, and Paringit, 2011; Walsh, Crawford, Welsh, and Crews-Meyer, 2001).

Therefore, land use and land cover scenario of ecosystem services for optimum water yield (runoff) and sediment retention in Klong U-Tapao watershed, Songkhla, Thailand is here conducted. The derived results will be useful for planning and management ecosystem services with optimum water yield (runoff) and sediment retention in Klong U-Tapao watershed in the future.

In this study, LULC status and its changes in Klong U-tapao watershed is assessed based on classified multispectral data obtained from Landsat 5 and Landsat 8 in year 2010 and 2017, respectively using Random Forests (RF) classifier. Then, three different LULC scenarios (Historical LULC evolution, Forest conservation and prevention, and Agriculture production extension) in 2024 are simulated under the Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model. After that, water yield and sediment retention services from LULC in 2017 and 2024 of three different scenarios are assessed from related toolset of InVEST software suite. Finally, the LULC scenario for optimum water yield and sediment retention ecosystem services is identified using Ecosystems Services Change Index (ESCI).

1.2 Research objectives

The aim of the research is to identify scenario of LULC for optimum water yield and sediment retention ecosystem services in Klong U-Tapao watershed, Songkhla, Thailand. The specific objectives of the study are as follows:

1. To classify LULC status and its change during 2010 to 2017 from remotely sensed data using Random Forests classifier with post-classification comparison change detection algorithm;

2. To predict LULC change from three different scenarios (Historical LULC evolution, Forest conservation and prevention, and Agriculture production extension) during 2018 to 2024 using CLUE-S model;

3. To assess ecosystem services in terms of water yield and sediment retention based on LULC data in 2017 (baseline data) and three predicted LULC scenarios between 2018 and 2024;

4. To identify LULC scenario for optimum water yield and sediment retention ecosystem services using Ecosystems Services Change Index.

1.3 Scope and limitations of the study

1.3.1 Scope of the study

Scope of the study can be summarized as follows:

(1) LULC data in 2010 and 2017 were classified from Landsat 5 and 8 data using the RF classifier that is performed using machine learning techniques. Herein, LULC classification system consists of (1) urban and built-up area, (2) paddy field, (3) rubber plantation, (4) oil palm plantation, (5) perennial tree and orchard (6) aqua cultural area, (7) evergreen forest, (8) mangrove forest, (9) marsh and swamp, (10) water body, and (11) miscellaneous land (bare land and abandoned mine).

(2) LULC change of three scenarios during 2018 to 2024 were predicted using CLUE-S model. They are Scenario I (Historical LULC evolution), Scenario II

(Forest conservation and prevention), and Scenario III (Agriculture production extension).

(3) Ecosystem service on water yield and sediment retention from present LULC in 2017 and three different LULC scenarios during 2018 to 2024 were assessed using Water Yield and Sediment Delivery Ratio Models of InVEST software suite.

(4) Ecosystem service change on water yield and sediment retention were applied to identify the optimum scenario for water yield and sediment retention service using ESCI in term of gain and loss.

1.3.2 Limitation of the study

Limitation of the study can be summarized as follows:

(1) Due to the limitation of ground reference points on LULC types in 2010, Google Imageries acquired in 2010 were applied as reference ground information for accuracy assessment of LULC classification in 2010.

(2) Monthly rainfall data between 2018 and 2024 for water yield and sediment retention estimation were used from monthly average rainfall of the Global Products and Data Services of National Center for Atmospheric Research (NCAR), USA via website: www.gisclimatechange.org. In this study, average monthly rainfall from 9 locations over the study area were interpolated to generate monthly rainfall data between 2018 and 2024 using Simple Co-Kriging technique.

1.4 Study area

1.4.1 Location

The study area is Khlong U-Tapao watershed of Songkhla Lake basin which consists of 10 sub-watersheds: Khlong Bang Klam, Khong Wa, Khong

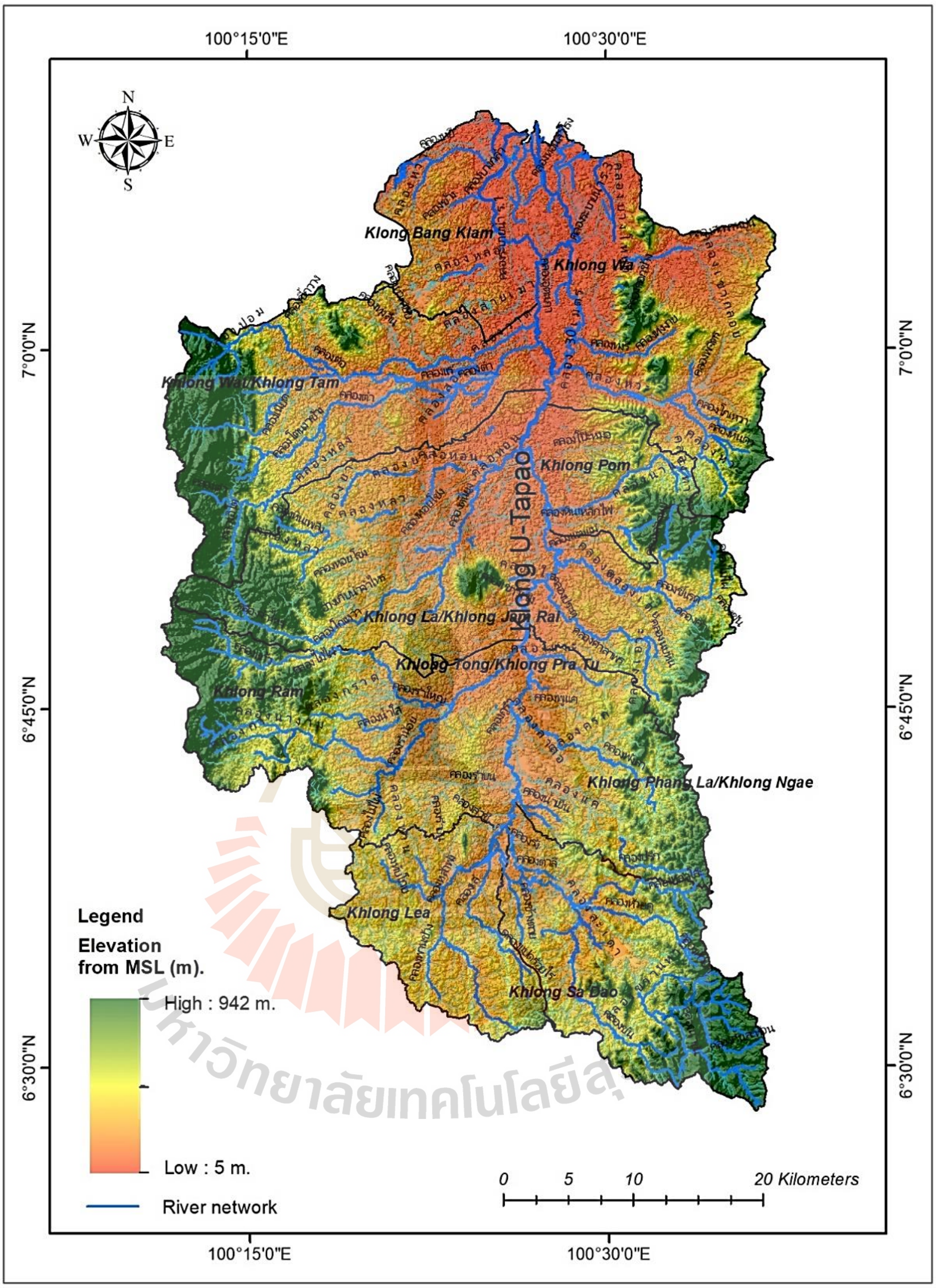
Wat/Khong Tam, Khong Pom, Khong La/Khong Jam Rai, Khong Tong/Khong Pra Tu, Khong Ram, Khong Phang La/Khong Ngae, Khong Lea and Khong Sa Dao. It covers area of 2,406.04 km^2 with 60 km length (north to south) and 40 km width (west to east) (Figure 1.1).

The Khlong U-Tapao watershed was here selected as the study area because it was previously intact forest ecosystems and are being degraded and transformed to be agricultural areas such as rubber plantations, palm trees and fruit orchards (Atienza, 2013). In addition, in these recent decades, the Office of the Rubber Replanting Aid Fund under the Ministry of Agriculture and Cooperatives sets up the Rubber Replanting Aid Fund to encourage farmers to plant rubber trees for export of latex by providing relief funds to farmers. Because large areas of tropical forest in southern of Thailand were changed to be rubber plantations and fruit orchards, especially in the head watershed area (Wiroonratch, 2013). Hereafter, large-scale of the degraded natural forests and occurrence of extreme rainfall events had induced frequency of floods and soil erosion.

According to flood report of GISTDA in 2017, the cumulative of flood in the study area was about 129.31 km^2 during 2005 to 2016 (GISTDA, 2017). It was found that flooded area was mostly found in the lower area up to middle part of the watershed (Figure 1.2). Meanwhile, soil erosion assessment had also conducted in the study area by SOUTHGIST in 2010. According to the report, top three dominant soil loss severity classes are moderate, low and high with the cover area of 984.95 km^2 or 40.94%, 487.61 km^2 or 20.27% and 460.49 km^2 or 19.14%, respectively (Table 1.1 and Figure 1.3).

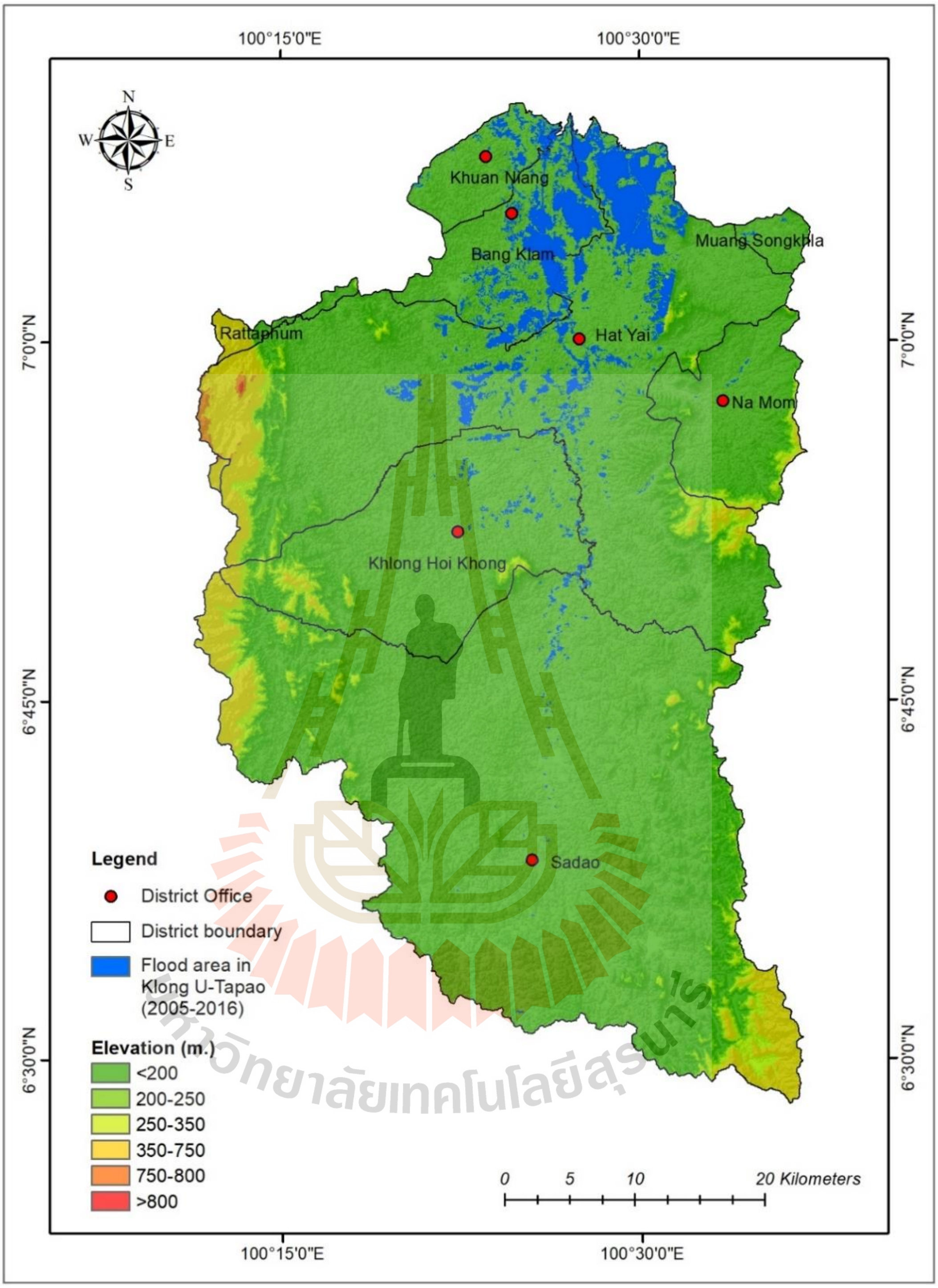
Table 1.1 Area and percentage of erosion classification in the study area.

Erosion rate (ton/ha/y)	Severity class	Area in km^2	Percentage
0-6.25	Very low	167.63	6.97
6.26-31.25	Low	487.61	20.27
31.26-125.00	Moderate	984.95	40.94
125.01-625	High	460.49	19.14
>625	Very high	305.36	12.69
	Total	**2,406.04**	**100.00**



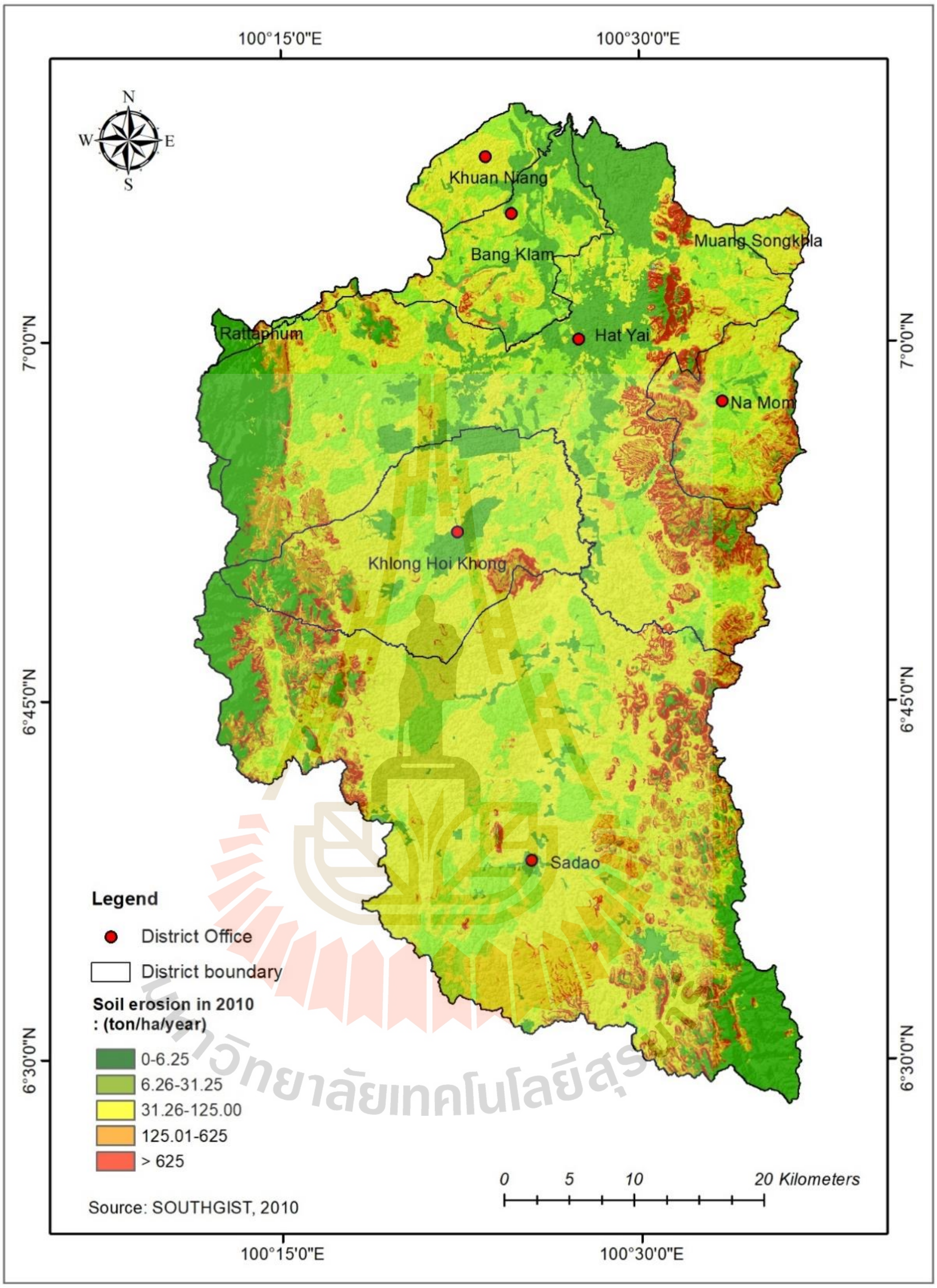
Source: USGS (2015) and RID (2017).

Figure 1.1 Khlong U-Tapao watershed and its sub-watersheds.



Source: GISTDA (2017).

Figure 1.2 Cumulative flooded area during 2005 to 2016 of the Khlong U-Tapao watershed.



Source: SOUTHGIST (2010).

Figure 1.3 Spatial distribution of soil loss severity classification in 2010 of the Khlong U-Tapao watershed.

Furthermore, Nuanmano, Roongtawanreongsri, and Tanavud (2012) had studied soil erosion in rubber plantations at Kho Hong Hill by comparison with bare land and secondary forest. They found that the most severe rate of soil loss occurred on bare land about 126.38 ton/ha, followed with rubber plantation about 97.5 ton/ha and secondary forest about 28.01 ton/ha. The result of soil erosion in rubber plantation was 100.1 t/ha/year, and it is considered very high erosion.

1.4.2 Topography and climate

The elevation of the study area ranges approximately from 5 m to 942 m above mean sea level (see Figure 1.1). The main river in the study area is Khlong U-Tapao river with 68 km length and approximately 3-8 m depth. The headwater of the river starts from Bantad Mountain and flows through Hat Yai City and drains to the south of the SLB. The discharge ranges from less than 6 m^3/s in the dry season to more than 90 m^3/s in the rainy season. The climatic weather is influenced by seasonal monsoons and tropical depressions as Southwest monsoon (May to October) and Northeast monsoon (November to January). The annual mean surface runoff at Hat Yai City where locates in the lower part of the study area is 385 mm (25 m^3/s). It varies from minimum flow in April to May in dry season and maximum flow in November to December in rainy season (Wiwat and Chartchai, 2005).

According to standard elevation classification of LDD (2000), the most dominant elevation class in the study area is less than 200 meters and cover area of 2,146.45 km^2 or 89.21% (Table 1.2 and Figure 1.4). In the meantime, according to standard slope classification of LDD (2000), the most dominant landform in study area is undulating and covers area of 933.09 km^2 or 38.78% (Table 1.3 and Figure 1.5).

Table 1.2 Area and percentage of elevation classification in the study area.

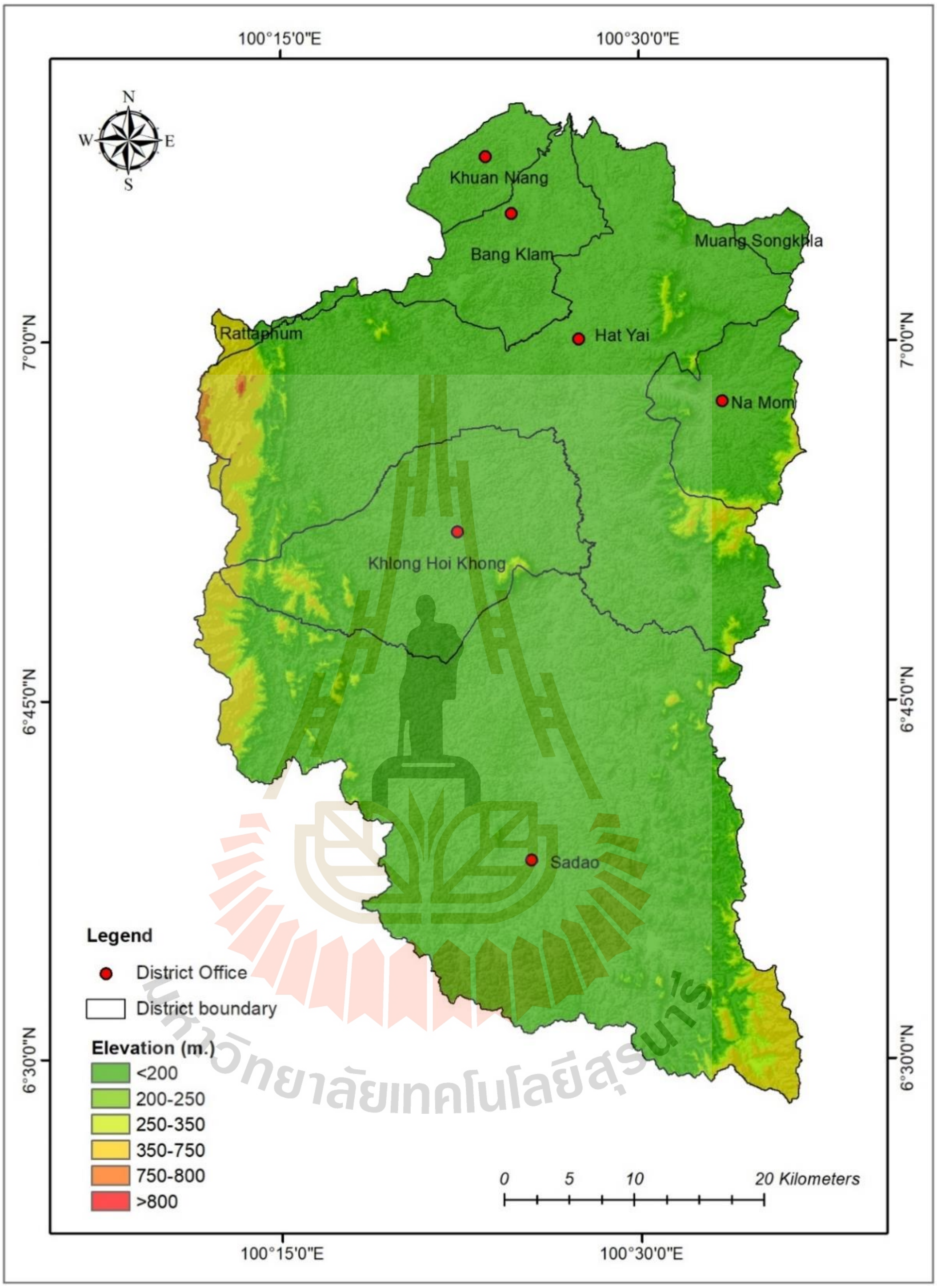
No	Elevation (m)	Area (km^2)	Percent
1	< 200	2,146.45	89.21
2	200-250	67.39	2.80
3	250-350	71.70	2.98
4	350-750	115.45	4.80
5	750-800	4.75	0.20
6	> 800	0.31	0.01
Total		**2,406.04**	**100.00**

Table 1.3 Area and percentage of slope classification in the study area.

No	Slope (%)	Landform	Area (km^2)	Percent
1	0-2	Flat or almost flat	113.63	4.72
2	2-5	Slightly undulating	415.81	17.28
3	5-12	Undulating	933.09	38.78
4	12-20	Rolling	482.22	20.04
5	20-35	Hilly	302.81	12.59
6	>35	Steep	158.49	6.59
Total			**2,406.04**	**100.00**

1.4.3 Land use

According to land use data of LDD in 2009, 2012 and 2016, area and percentage of an aggregate LULC types in the study area is summarized in Table 1.4 and distribution of LULC is displayed in Figures 1.6 to 1.8. It revealed that urban and built up area and perennial tree and orchard have been continuously increased while evergreen forest and paddy field will decrease in the future. Meanwhile, area of rubber and oil palm plantation are unlikely unpredictable. However, area of rubber plantation tends to decrease and oil palm plantation tends to increase due to Government's policy and price crisis.



Source: USGS (2015).

Figure 1.4 Spatial distribution of elevation classification of the Khlong U-Tapao watershed.

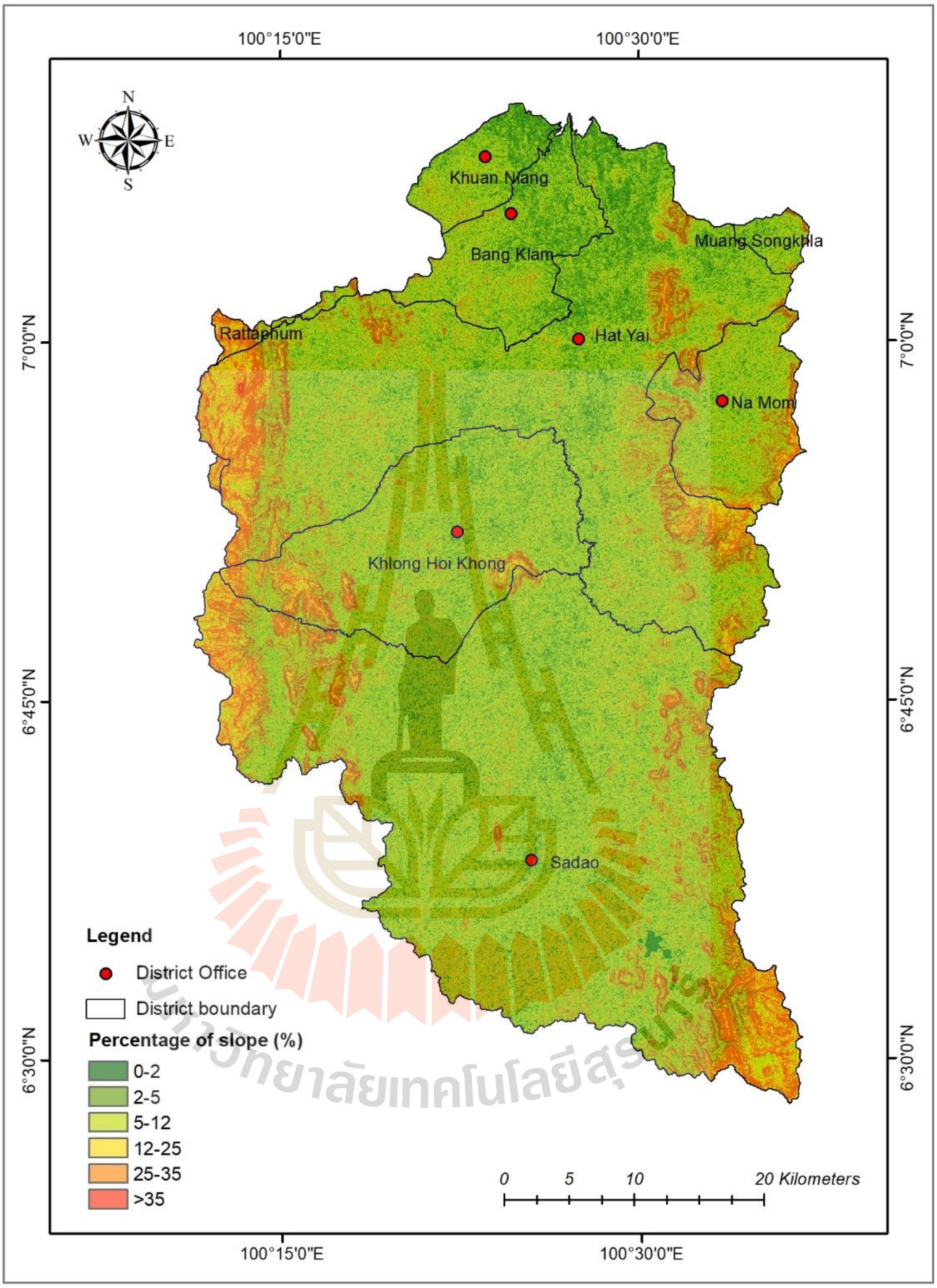
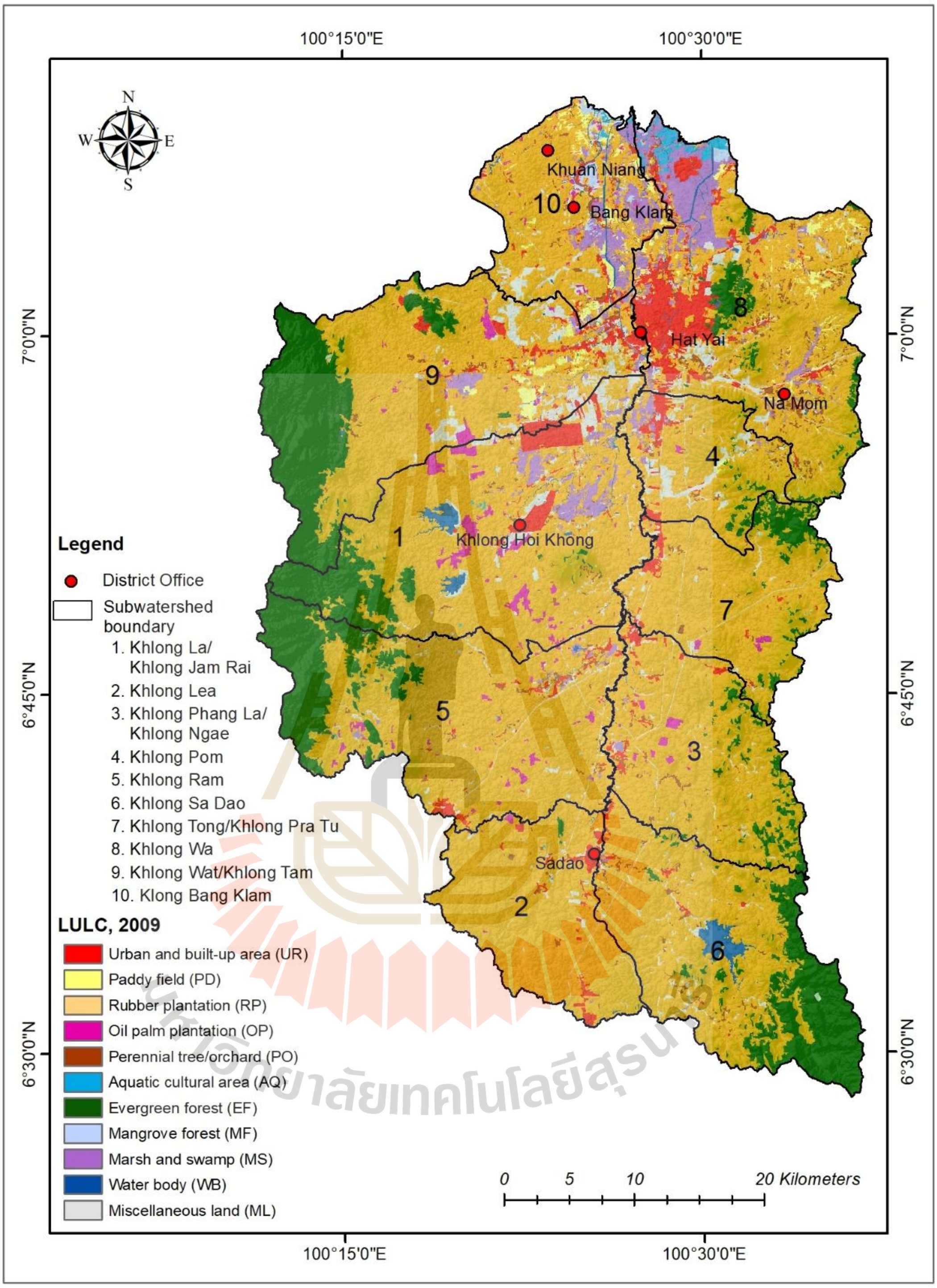


Figure 1.5 Spatial distribution of slope classification of the Khlong U-Tapao watershed.

Table 1.4 Areas and percentage of land use types between 2009 and 2016.

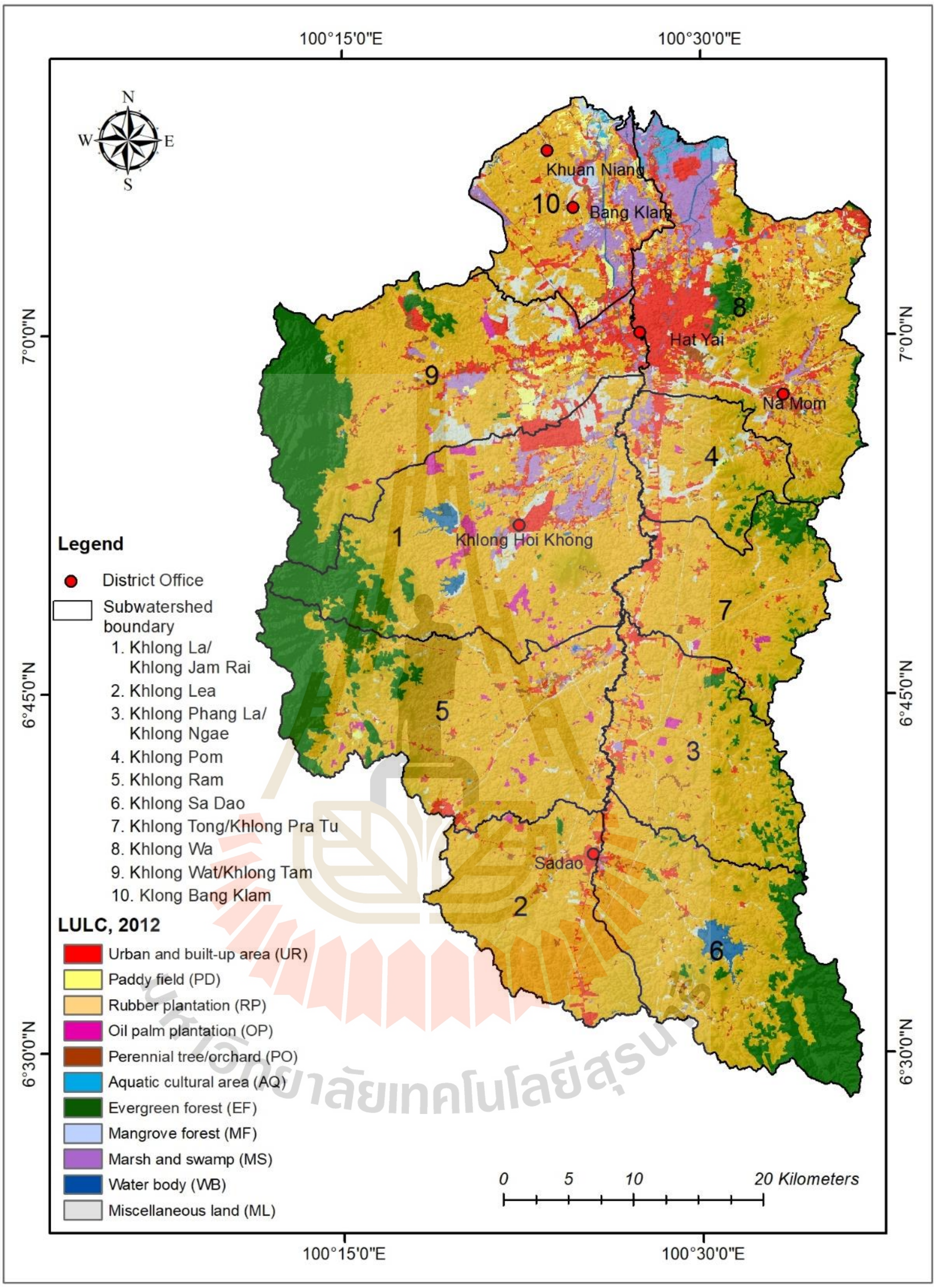
LULC type	**2009**		**2012**		**2016**	
	Km^2	**%**	**Km^2**	**%**	**Km^2**	**%**
Urban and built-up area	101.68	4.23	103.88	4.32	104.13	4.33
Paddy field	24.04	1.00	23.05	0.96	22.09	0.92
Rubber plantation	1,687.95	70.15	1,692.88	70.36	1,680.41	69.84
Oil palm plantation	28.95	1.20	27.95	1.16	28.35	1.18
Perennial tree and orchard	35.46	1.47	36.46	1.52	37.56	1.56
Aquatic cultural area	8.42	0.35	8.41	0.35	8.41	0.35
Evergreen forest	305.00	12.68	300.00	12.47	287.41	11.95
Mangrove forest	5.50	0.23	4.50	0.19	5.50	0.23
Marsh and swamp	79.88	3.32	79.87	3.32	77.85	3.24
Water body	26.70	1.11	26.70	1.11	28.70	1.19
Miscellaneous land	102.46	4.26	102.35	4.25	125.64	5.22
Total	**2,406.04**	**100.00**	**2,406.04**	**100.00**	**2,406.04**	**100.00**

Source: LDD (2009, 2012 and 2016).



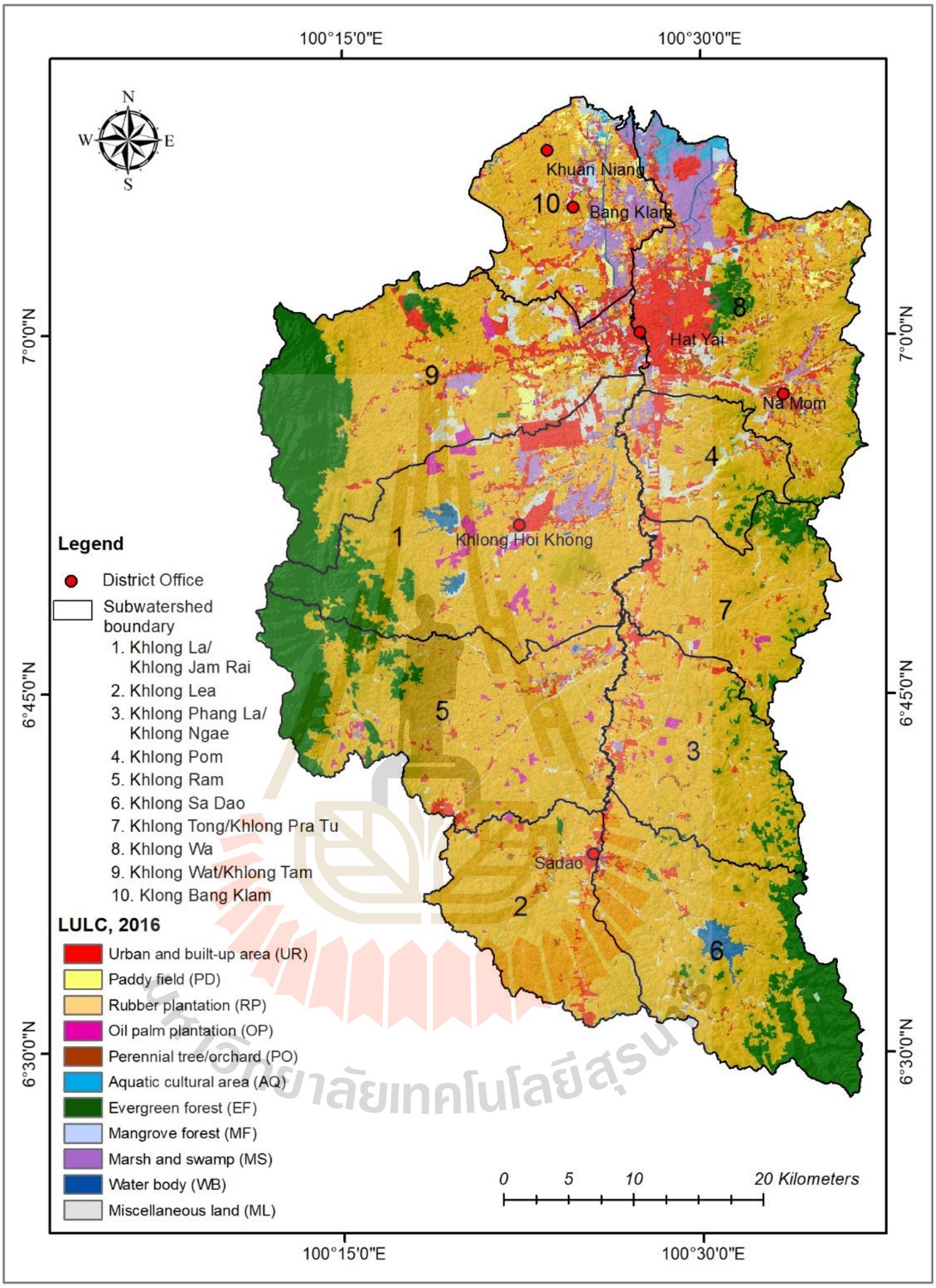
Source: LDD (2017).

Figure 1.6 Spatial distribution of LULC by LDD in 2009.



Source: LDD (2017).

Figure 1.7 Spatial distribution of LULC by LDD in 2012.



Source: LDD (2017).

Figure 1.8 Spatial distribution of LULC by LDD in 2016.

1.5 Benefits of the study

The benefits of the study are as follows:

(1) The Random Forests classifier were here applied to classify LULC data from Landsat imageries and it can provide high accuracy baseline information for LULC assessment and prediction from three different scenarios (Historical LULC evolution, Forest conservation and prevention and Agriculture production extension).

(2) The predictive LULC of three different scenarios with their ecosystem services on water yield and sediment retention can be applied for land use planning and support decision maker.

(3) Details of ecosystem services on water yield and sediment retention can applied to identify critical sub-watershed for mitigation surface runoff over Khlong U-Tapao watershed and reduction sediment export into Songkhla Lake.

CHAPTER II

BASIC CONCEPTS AND LITERATURE REVIEWS

Basic concepts include (1) LULC classification with Random Forests, (2) CLUE-S model, (3) Ecosystem Services, (4) InVEST software suite, (5) Water yield model of InVEST software suite, (6) Sediment Delivery Ratio model of InVEST software suite and literature reviews are summarized in this chapter.

2.1 LULC classification with Random Forests and its application

A relatively new algorithm that uses a binary decision tree classification is called Random Forests (RF). The RF algorithm firstly creates several decision trees and the collection of trees container is then used to classify an image. Classification accuracy using RF is higher than using a single tree approach such as classification and regression trees (CART) (Gislason, Benediktsson, and Sveinsson, 2006) and there is no need to edit the trees, so it is much easier to use when compared to other binary decision tree approaches.

The RF which was firstly developed by Breiman in 2001 is an ensemble and multiple decision-tree classifier for supervised classification. It confides on the assumption that different independent predictors predict incorrectly in changed areas. By combining the prediction results, it is possible to improve the overall prediction accuracy (Polikar, 2006). The RF offers a number of advantages for classification include:

1) Data can be binary, categorical or continuous;

2) The classifier performs internal cross-validation through "boot strapping", which provides a robust estimate of classification accuracy using out of bag estimates;

3) It is a non-parametric classifier and is relatively insensitive to outliers in the training data;

4) It requires little user input (the number of decision trees, and the number of variables for each decision tree);

5) It produces a classification map, but more importantly, probability maps (strength of membership in each lithological class); and

6) It ranks the input variables with respect for their importance in the predictions (Breiman, Friedman, Olshen, and Stone, 1984; Brieman, 2001).

Brieman (2001) stated that training data is required for the RF approach similar to other supervised classifiers. In each tree, the number of decision trees (m) is determined by the operator, a random selection of the input variables (i.e. remotely sensed image bands, n) is then made. The number of variables selected for each tree is a fraction of the total number of variables; the square root of the number of variables is often used. Each tree employs a "bagging" process (i.e. "bootstrap" sample) whereby approximately two-thirds of the training areas (pixels) are used to create a prediction (referred to as in-bag) and one-third to validate the accuracy of the prediction (referred to as out of bag, or oob). This random sampling with replacement of the training dataset is undertaken for every tree. In-bag data are used to create multiple decision trees that are applied to produce independent classifications. At each node of the individual decision tree, the best split is chosen from a random sample of variables. Each tree is grown to the maximum extent with no pruning. In practice, the Gini index is applied to determine the impurity at each node (Harris and Grunsky, 2015) as:

$$Gini\ Index = \sum_{c=1}^{K} g_c(1 - g_c) \tag{2.1}$$

Where K is the number of classes and g_c is the probability or the relative frequency of class c at the considered node and is given by

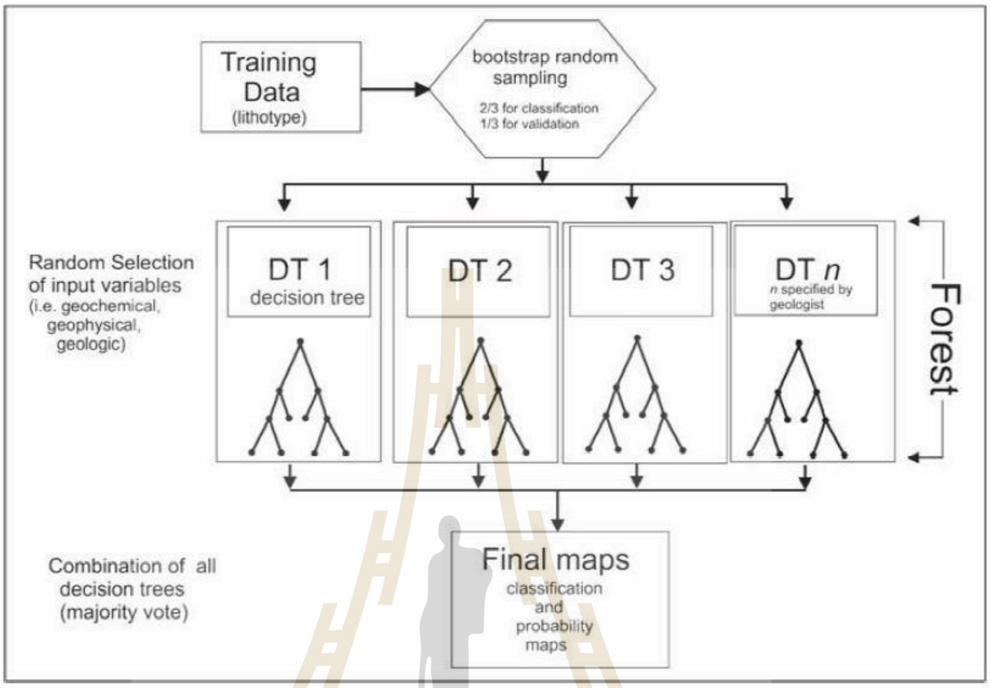
$$g_c = \frac{n_c}{n} \tag{2.2}$$

Where, n_c is the number of samples belonging to class c, and n is the total number of samples within a particular node.

The stop criterion for splitting each node is based on the minimum of samples in a node (used 1) and the minimum impurity in a node (used 0) allowing full growth of the decision tress (no pruning). Thus, an ensemble of trees (predictions) is created, and a voting procedure is employed to assign the majority class to each pixel in the final prediction map (Brieman, 2001).

According to Brieman (2001) and Gislason et al. (2006), the RF is not sensitive to noise or over-fitting and there is no need for cross-validation as it is estimated internally. However, as with any supervised classification method, an independent check of the training dataset of each litho-type is still required to calculate an unbiased and more robust estimate of classification accuracy. Additionally, the probability of membership in each class is also generated, which can be used to assess the uncertainty of the RF classification.

Harris and Grunsky (2015) summarized RF classification process as shown in Figure 2.1.



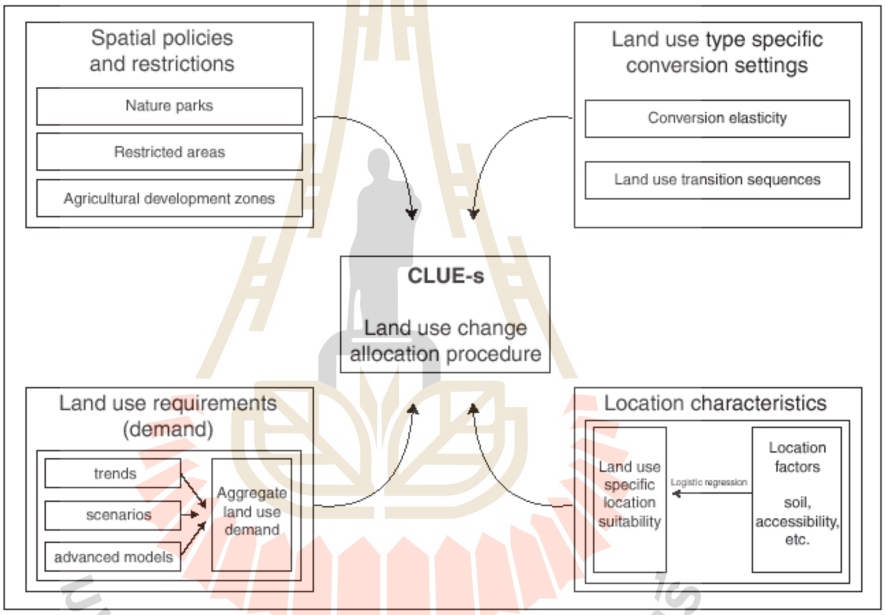
Source: Harris and Grunsky (2015).

Figure 2.1 Summary of the RF classification process.

2.2 CLUE-S model

The CLUE-S model was developed by Verburg, Koning, Kok, Veldkamp and Bouma in 1999 to dynamically allocate land-use changes based upon a combination of empirical, spatial analysis and dynamic modelling. CLUE-S model is a hybrid model using the parameters from the estimation models (scenarios) to simulate simultaneously the changes in spatial term of multiple LULC types. It also uses empirically quantified relation between driving factors of LULC change and statistical methods. Additionally, it can be used at local scales to define the change of LULC based on biophysical and socio-economic factors. CLUE-S can simulate cartographically the future LULC map as the continuation of the former CLUE model (Verburg and Overmars, 2007).

Figure 2.2 shows an overview of the information needed to run the CLUE-S model. The required information of CLUE-S can categorized into four groups: (1) spatial policies and restrictions; (2) land use types specific conversion settings; (3) land requirements and (4) location characteristics.



Source: Verburg et al. (1999).

Figure 2.2 Overview of the information flow in the CLUE-S model.

(1) Spatial policies and restrictions

Spatial policies and restrictions mainly indicate areas where land use changes are restricted through policies or tenure status. Some spatial policies restrict a set of specific land use conversions, e.g. residential construction in designated agricultural areas or permanent agriculture in the buffer zone of a nature reserve. 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 (Verburg et al., 1999).

(2) Land use type specific conversion settings

Land use type specific conversion settings determine the temporal dynamics of the simulations. Two sets of parameters are needed to characterize the individual land use types: conversion elasticities and land use transition sequences. The conversion elasticity is related to the reversibility of land-use change. Examples are residential locations but also plantations with permanent crops (fruit trees). Meanwhile, land use type characteristics that needed to be specified are the land use type, specific conversion settings and their temporal characteristics. The simulation of these interactions combined within the constraints set in the conversion matrix will determine the length of the period before a conversion occurs (Verburg et al., 1999).

(3) Land use requirements (demand)

Land use requirements (demand) are calculated at the aggregate level (the level of the case study as a whole) as part of a specific scenario. The land use requirements constraint the simulation by defining the totally required change in land use (Verburg et al., 1999).

(4) Location characteristics

Land use conversions are expected to take place at locations with the highest preference for the specific type of land use at that moment in time. The preference of a location is empirically estimated from a set of factors that are based on the different, disciplinary, understandings of the determinants of land-use change. The preference is calculated using following equation:

$$R_{ki} = a_k X_{1i} + b_k X_{2i} + \ldots \quad (2.3)$$

Where, *R* is the preference to devote location *i* to land use type *k*, $X_{1,2,..}$ are biophysical or socio-economical characteristics of location *i* and a_k and b_k the relative impact of these characteristics on the preference for land use type *k*.

A statistical model can be developed as a binomial logit model. The function that relates these probabilities with the biophysical and socio-economic location characteristics is defined as a logit model using following equation:

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \ldots.. + \beta_n X_{n,i} \quad (2.4)$$

Where, P_i is the probability of a grid cell for the occurrence of the considered land use type on location *i* and the *X*'s are the location factors. The coefficients (*β*) are estimated through logistic regression using the actual land use pattern as the dependent variable (Verburg et al., 1999).

In summary, the allocation procedure is displayed in Figure 2.3. The following steps are taken to allocate the changes in land use:

1. The first step includes the determination of all grid cells that are allowed to change. Grid cells that are either part of a protected area or presently under a land use type that is not allowed to change are excluded from further calculation.

2. For each grid cell i the total probability ($TPROP_{i,u}$) is calculated for each of the land use types u according to:

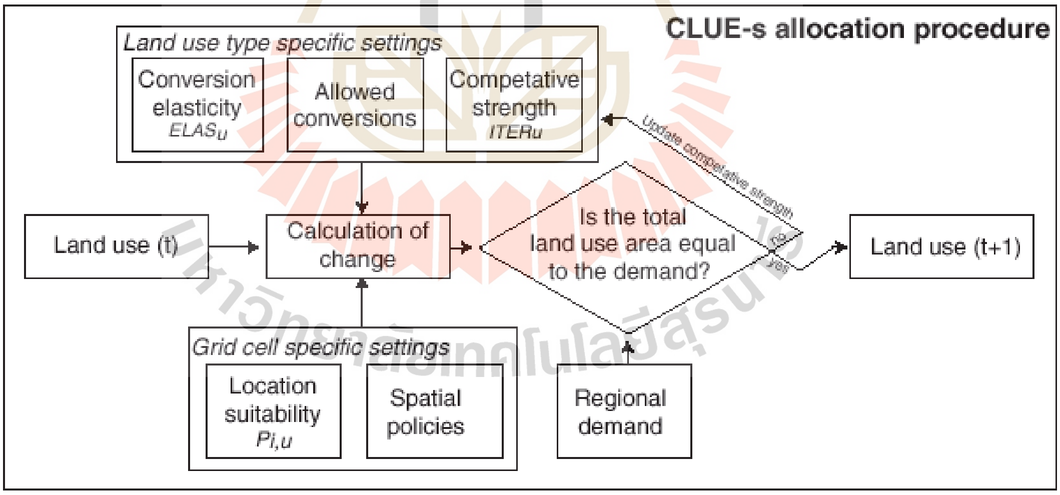
$$TPROP_{i,u} = P_{i,u} + ELAS_u + ITER_u \quad (2.5)$$

Where, $P_{i,u}$ are the suitability of location i for land use type u (based upon the logit model), $ELAS_u$ is the conversion elasticity for land use u and $ITER_u$ is an iteration variable that is specific for the land use type and indicative for the relative competitive strength of the land use type. $ELAS_u$, the land use type specific elasticity to change the value, is only added if grid-cell i is already under land use type u in the year considered. $P_{i,u}$ consists of a part based on the biophysical and socio-economic factors, and a neighborhood interaction part.

3. A preliminary allocation is made with an equal value of the iteration variable ($ITER_u$) for all land use types by allocating the land use type with the highest total probability for the considered grid cell.

4. The total allocated area of each land use is now compared with the land use requirements (demand).

5. Steps 2 to 4 are repeated as long as the demands are not correctly allocated. When allocation equals demand, the final map is saved and the calculations can continue for the next time step.



Source: Verburg et al. (1999).

Figure 2.3 Flow chart of the allocation module of the CLUE-S model.

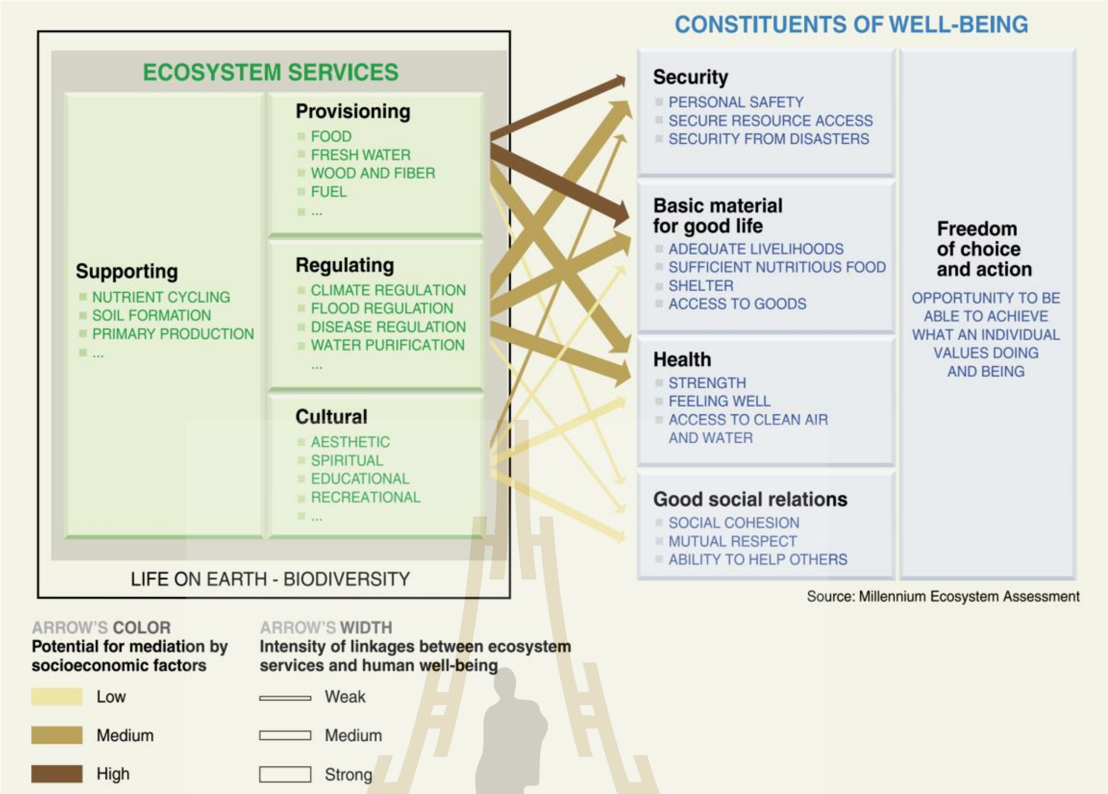
2.3 Ecosystem services

2.3.1 Definition

Daily, Kareiva, Polasky, Ricketts, and Tallis in 2011 defined ecosystem services as "conditions and processes through natural ecosystems and species sustain and fulfill human life". Ecosystems services are of fundamental importance to human well-being, health, livelihoods, and survival (Costanza et al., 1997; Millennium Ecosystem Assessment, 2005; TEEB Foundations, 2010).

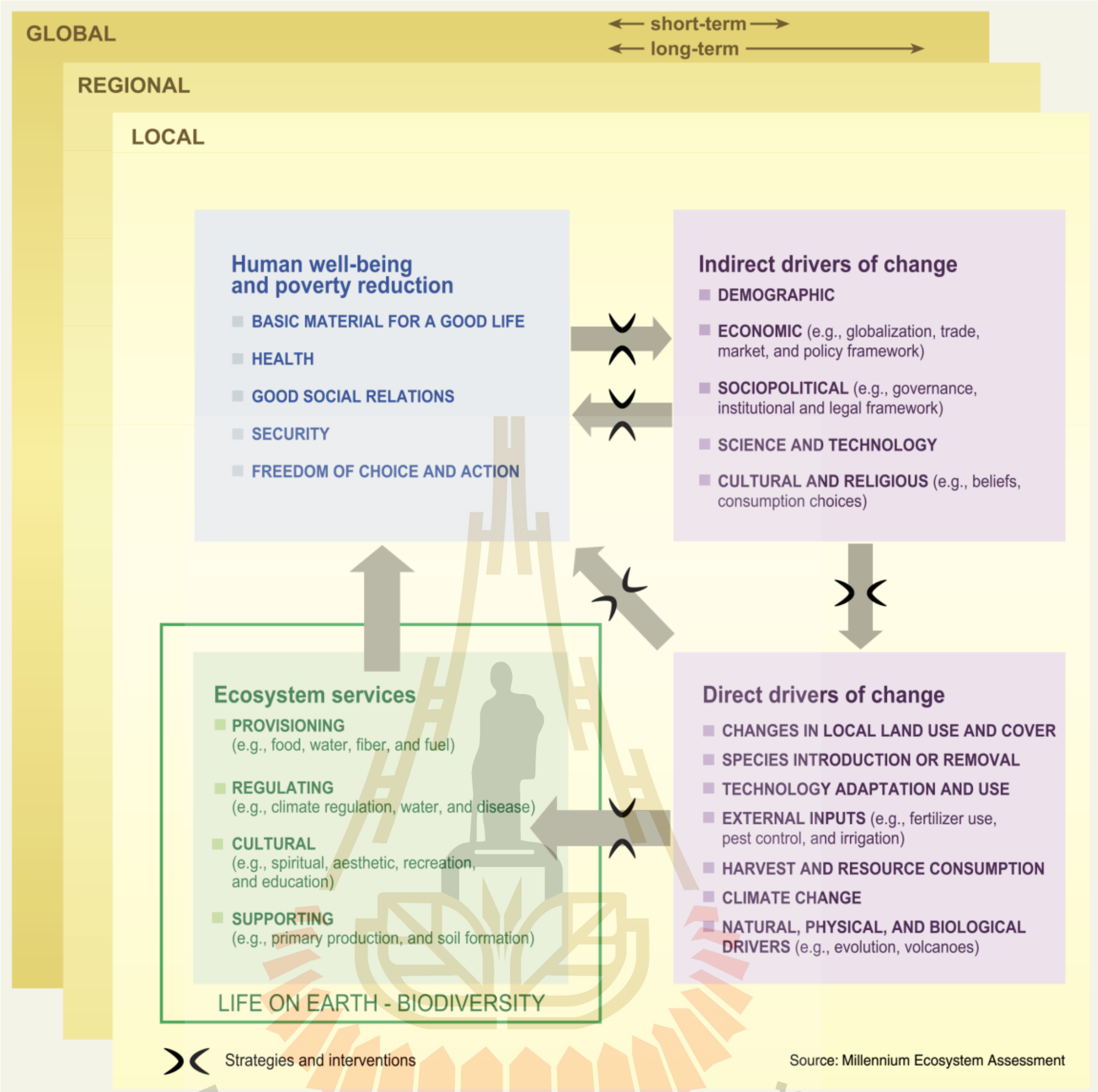
2.3.2 Ecosystem services concept

Ecosystem services connect natural systems and human society (Costanza et al., 1997). People obtain hope to maximize one or several ecosystem service by land use change (Karp et al., 2013). Every ecosystem has a different capacity to provide ecosystem services, depending on its structure and condition (Nelson et al., 2009), the complex interactions between physical (e.g. topography, geology) and biological (vegetation and microorganism) factors, as well as land use and management (Guswa et al., 2014). In order to clarify their assessment, the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) has established a conceptual framework to strengthen the implementation of the Millennium Ecosystem Assessment (Dias, Demissew, Joly, Lonsdale, and Larigauderie, 2015). Figure 2.4 depicts the strength of linkages between categories of ecosystem services and components of human well-being that are commonly encountered, and includes indications of the extent to which it is possible for socioeconomic factors to mediate the linkage. For example, if it is possible to purchase a substitute for a degraded ecosystem service, then there is a high potential for mediation. The strength of the linkages and the potential for mediation differ in different ecosystems and regions. In addition to the influence of ecosystem services on human well-being as shown in the figure, other factors include environmental factors as well as economic, social, technological, and cultural factors influence human well-being, and ecosystems are in turn affected by changes in human well-being (Millennium Ecosystem Assessment, 2005). Millennium ecosystem assessment conceptual framework of interactions between biodiversity, ecosystem services, human well-being, and drivers of change is displayed in Figure 2.5. Changes in drivers that indirectly affect biodiversity, such as population, technology, and lifestyle can lead to changes in drivers directly affecting biodiversity, such as the catch of fish or the application of fertilizers. These result in changes to ecosystems and the services they provide, thereby affecting human well-being. These interactions can take place at more than one scale and can cross scales. For example, an international demand for timber may lead to a regional loss of forest cover, which increases flood magnitude along a local stretch of a river. Similarly, the interactions can take place across different time scales. Different strategies and interventions can be applied at many points in this framework to enhance human well-being and conserve ecosystems (Millennium Ecosystem Assessment, 2005).



Source: Millennium Ecosystem Assessment (2005).

Figure 2.4 Linkages between categories of ecosystem services and components of human well-being.



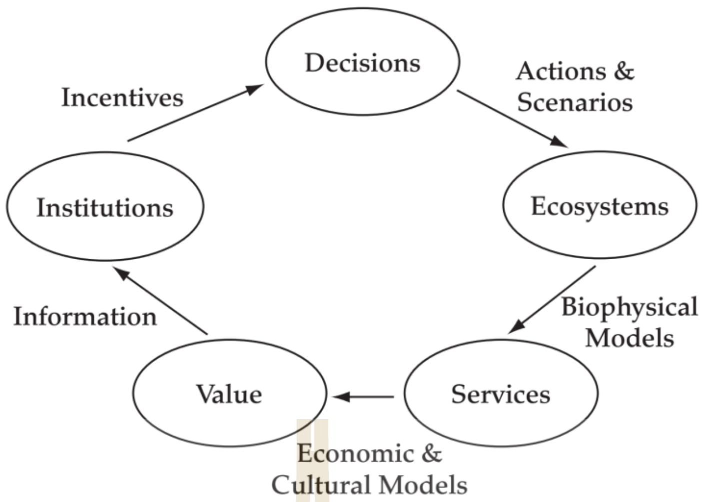
Source: Millennium Ecosystem Assessment (2005).

Figure 2.5 Millennium ecosystem assessment conceptual framework of interactions between biodiversity, ecosystem services, human well-being, and drivers of change.

Fu, Li, Hou, Bi, and Zhang (2017) mentioned that ecosystem services should be considered simultaneously to improve land use planning and decision making. Recently, ecosystem service has become main in environmental planning and management (Hu, Fu, Lu, and Zheng, 2014). Ecosystem service can be an effective link between science and policy by making the trade-offs more transparent (Costanza et al., 1997). General spatially explicit ecosystem assessment tools have built the relationship between landscape structure and ecosystem services (Hu et al., 2014) and they can be used in studying the land use impacts on a range of ecosystem services and analysis of trade-offs (Zheng et al., 2016). Fu et al. (2017) stated that land use change can alter the types, patterns and processes of ecosystem, causing change of ecosystem services.

The ecosystem services had been carried out focusing on policy relevant questions, addressing a multiscale analysis from watershed to global scale and linking between humans and nature. The economical valuations at global scale have been addressed in 2010 under The Economics of Ecosystems and Biodiversity (TEEB) meeting which aimed to highlight the growing cost of biodiversity loss and ecosystem degradation (TEEB, 2010).

Ecosystem services can play important role in decision making. The framework of ecosystem services connects the science of quantifying services with valuation and policy to devise payment schemes and management actions that take account of ecosystem services. Though the framework is a continuous loop, it starts with the decisions oval to emphasize the focus. So it starts and ends there (Figure 2.6). These decisions encourage and constraint actions relating to the use of land, water, and other elements of natural capital (Daily et al., 2011).



Source: Daily, Kareiva, Polasky, Ricketts, and Tallis (2011).

Figure 2.6 A framework showing how ecosystem services can be integrated into decision-making. One could link any two ovals, in any direction.

Continuing clockwise around Figure 2.6, "biophysical sciences" are central to understanding the link between decisions and ecosystems, and along with economics and social science, the links between ecosystems and services. Meanwhile, social sciences are also central to understanding the value of services to people ("economic and cultural models"). Economic valuation techniques are commonly used for this link, to place monetary value on natural capital. Value is often not fully captured in monetary terms, though, so it is important to characterize value in multiple dimensions, including, for example, health, livelihood support, and cultural significance. This will help ensure that valuation and broader decision making approaches are inclusive of the range of benefits and people concerned. Finally, valuing ecosystem services provides useful information that can help shape institutions (e.g. agricultural markets, subsidies, land use policies, conservation NGOs) to guide resource management and policy. Having the right institutions can create incentives so that the decisions of individuals, communities, corporations, and governments promote widely shared values. The links between the value, institutions, and decisions ovals are much more the art and politics of social change than science, though scientists can inform these debates if they target specific decisions and are attuned to the social and political contexts (Daily et al., 2011).

Basically, ecosystem services can be categorized into provisioning, regulating, cultural, and supporting types (Millennium Ecosystem Assessment, 2005) as summary in Table 2.1.

Table 2.1 Classification of ecosystem services.

Ecosystem services	
Supporting services • Nutrient cycling • Soil formation • Primary production	**Provisioning services** • Food (crops, livestock, wild foods, etc...) • Fiber (timber, cotton, wood fuel) • Genetic resources • Biochemical, natural medicines, pharmaceutical • Fresh water **Regulating services** • Air quality regulation • Climate regulation • Water regulation • Erosion regulation • Natural hazard regulation • Pollination • Disease regulation • Pest regulation **Cultural services** • Aesthetic values • Spiritual and religious values • Recreation and ecotourism

Source: Millennium Ecosystem Assessment (2005).

In summary, ecosystem services have represented a dynamic field in current scientific research, linking ecological, economic and social aspects, demanding practical applications and methodologies at different spatial scale, in order to maintain environmental management and decision making process (Costanza et al., 1997; Millennium Ecosystem Assessment, 2005; TEEB, 2010; Fu et al., 2017; Nelson et al., 2009).

2.4 InVEST software suite

The Natural Capital Project (NatCap) that is a partnership of two institutions (Stanford University and University of Minnesota) and two NGOs (The Nature Conservancy and World Wildlife Fund) have developed the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) software tool for integrating the value of ecosystem services and biodiversity in different decision contexts. The InVEST is a component of models and maps the delivery, distribution, and economic value of ecosystem services and biodiversity. It helps decision makers imagine the impacts of decisions and tradeoffs and compatibilities between environmental, economic, and social benefits. The InVEST purpose is to incorporate biophysical factors and economic information about ecosystem services into conservation and natural resource decisions (Kareiva, Tallis, Ricketts, Daily, and Polasky, 2011).

Based on InVEST User Guide, the InVEST software suite consists of various toolsets include models for quantifying, mapping, and valuing the benefits provided by terrestrial, freshwater, and marine systems. Under the InVEST software suite, three primary service categories include (1) supporting services, (2) final services, and (3) tools to facilitate ecosystem service analyses. Herein, supporting services underpin other ecosystem services, but do not directly provide benefits to people. In contrast, final services provide direct benefits to people and it splits the services into biophysical supply and the service to people wherever possible (Sharp et al., 2015).

The characteristics of the supporting and final ecosystem service models under the InVEST software suite includes model type (biophysical and supply), service model, spatial extent, method of valuation, and forms of output is summarized in Table 2.2.

Table 2.2 The supporting and final ecosystem service models currently included in the InVEST software suite (x: available).

Ecosystem services	Biophysical/ supply model	Service model	Spatial extent (given assumed input data resolution*)	Methods of valuation available			Forms of output possible		
				Biophysical amount	S**	Number of people affected	Maps	Relative estimates	Quantitative estimates
Supporting ecosystem services	Habitat quality		Any (with resolution finer than distance over which threats operate)				X	X	
	Habitat risk assessment		Any				X	X	
	Marine water quality		Any				X		X
Final ecosystem services	Carbon storage and sequestration	Climate regulation	Any	X	X		X		X
	Blue carbon (marine carbon storage and sequestration)	Climate regulation	Any	X	X		X		X
	Water yield	Reservoir hydropower production	Watersheds ranging from 1 sq.km.(if least 10 m resolution) – global (for up to 1 km resolution)	X	X	X (with proper delineation of watersheds)	X	X (without calibration)	X (with calibration)
	Nutrient retention	Water purification	Watersheds ranging from 1 sq.km.(if least 10 m resolution) – global (for up to 1 km resolution)	X	X	X (with proper delineation of watersheds)	X	X (without calibration)	X (with calibration)
	Sediment retention	Avoided dredging	Watersheds ranging from 1 sq.km.(if least 10 m resolution) – global (for up to 1 km resolution)	X	X	X (with proper delineation of watersheds)	X	X (without calibration)	X (with calibration)
	Sediment retention	Water purification	Watersheds ranging from 1 sq.km.(if least 10 m resolution) – global (for up to 1 km resolution)	X	X	X (with proper delineation of watersheds)	X	X (without calibration)	X (with calibration)
	Pollinator abundance	Crop pollination	Any (resolution must be less than pollinator foraging distance)				X	X	
	Potential protection form erosion and inundation (Coastal exposure)	Coastal protection screening tool (coastal vulnerability)	Any			X (with detailed population maps)	X	X	
	Wave alternation & erosion reduction	Coastal protection	Local (most feasible over <50 mile extent)	X	X		X		X
	Unobstructed views	Scenic quality provision	Any			X (with detailed population maps)	X	X	X
		Nature-based recreation & tourism	Any	X			X	X	X (with calibration
		Managed timber production	Any	X	X		X		X
		Wave energy production	Any, within global Exclusive Economic Zone	X	X		X	X	X
		Offshore wind energy production	Any, within global Exclusive Economic Zone	X	X		X	X	X
		Marin finfish aquaculture production	Any	X	X		X	X	X

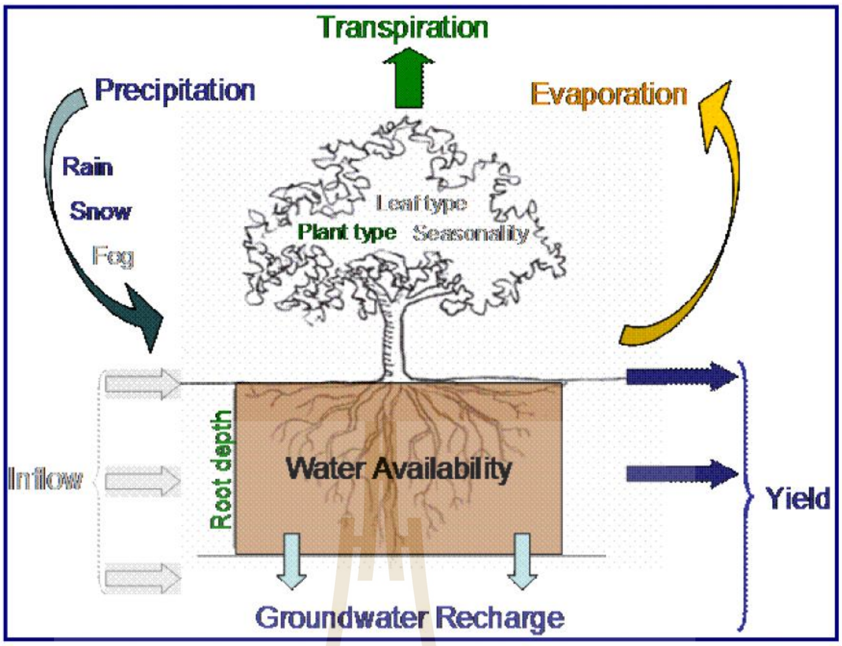
Source: Sharp et al. (2015).

In summary, the InVEST software suite represents a new breed of ecosystem services specific tools, focusing mainly on end services and visualization of these services across a landscape (Tallis and Polasky, 2009; Vigerstol and Aukema, 2011; Redhead et al., 2016; Sharps et al., 2017).

2.5 Water yield model of the InVEST software suite

The water yield model is designed to evaluate how land use and land cover affects annual surface water yield across a landscape. The model runs on a gridded map. It estimates the quantity and value of water used for hydropower production from each sub-watershed in the area of interest. It has three components, which run sequentially. First, it determines the amount of water running off each pixel as the precipitation less the fraction of the water that undergoes evapotranspiration. The model does not differentiate between surface, subsurface and base flow, but assumes that all water yield from a pixel reaches the point of interest via one of these pathways. This model then sums and averages water yield to the sub-watershed level. The pixel-scale calculations allow users to represent the heterogeneity of key driving factors in water yield such as soil type, precipitation, vegetation type (Sharp et al., 2015).

In developing the model, it was designed to accommodate areas with minimal access to data and utilized a water balance model that is drawn from globally available data on annual precipitation and dryness indices that partition the water balance for any place in the world (Budyko and Zubenok 1961; Zhang, Dawes, and Walker, 2001). The relationship between potential and actual evapotranspiration is here described using the Budyko curve, which is based on over 2,000 water balance observations representing catchments of different climates and ecoregions worldwide. The conceptual diagram of the water balance model used in water yield model which based on Budyko curve and annual average precipitation is presented in Figure 2.7.



Source: Sharp et al. (2015).

Figure 2.7 Conceptual diagram of the water balance model used in the water yield model.

The water cycle is simplified, including only the parameters shown in color, and ignoring the parameters shown in gray

To estimate water yield by the model, water yield (Y(x)) for each pixel on the landscape (x) is firstly calculated as:

$$Y(x) = \left(1 - \frac{AET\ (x)}{P(x)}\right) \cdot P(x) \tag{2.6}$$

Where, AET $_{(x)}$ is the annual actual evapotranspiration on pixel x and P$_{(x)}$ is the annual precipitation on pixel x

For vegetated land use, the evapotranspiration partition of the water balance, $\frac{AET\ (x)}{P(x)}$ is based on an expression of the Budyko curve proposed by Fu (1981) and Zhang et al. (2004) as:

$$\frac{AET\ (x)}{P(x)} = 1 + \frac{PET\ (x)}{P(x)} - \left[1 + \left(\frac{PET\ (x)}{P(x)}\right)^{\omega}\right]^{1/\omega} \quad (2.7)$$

Where, $PET_{(x)}$ is the potential evapotranspiration and ω is non-physical parameter that characterizes the natural climatic soil properties, both detailed below.

Potential evapotranspiration $PET_{(x)}$ is defined as:

$$\mathrm{PET\ (x) = K_c(l_x) \cdot ET_0(x)} \quad (2.8)$$

Where is ET_0 (x) the reference evapotranspiration from pixel x and K_c (l_x) is the plant (vegetation) evapotranspiration coefficient associated with the LULC l_x on pixel x.

Meanwhile, the ω (x) is an empirical parameter expressed as a linear function of $\frac{c \times N}{P}$, where N is the number of annual events, and AWC is the measure of water available to plant cover. The InVEST model adopts the equation given by as follows:

$$\omega\ (x) = Z\frac{AWC(x)}{P(x)} + 1.25 \quad (2.9)$$

Where, Z is the Zhang coefficient, defined as a parameter for the characterization of natural climate-soil properties. In this study, the Zhang coefficient was assigned as 4, as recommended by (Tallis et al., 2011) for a tropical watershed. The 1.25 term is the minimum value of ω (x), which can be seen as the value when the root depth is 0, as explained by (Donohue, Roderick, and McVicar, 2012) and the value of ω (x) is capped to a value of 5 (Yang, Yang, Lei, and Sun, 2008).

2.6 Sediment Delivery Ratio model of InVEST software suite

Erosion and overland sediment retention are natural processes that govern the sediment concentration in streams. Sediment dynamics at the catchment scale are mainly determined by climate, soil properties, topography, and vegetation, and anthropogenic factors such as agricultural activities or dam construction and operation. Main sediment sources include overland erosion (soil particles detached and transported by rain and overland flow), gullies (channels that concentrate flow), bank erosion, and mass erosion. Sinks include on slope, floodplain or instream deposition, and reservoir retention (Sharp et al., 2015).

The amount of annual soil loss on pixel i, A_i is given by the Revised Universal Soil Loss Equation (RUSLE) by Renard and Freimund (1994) as:

$$A_i = R_i \cdot K_i \cdot LS_i\ C_i \cdot P_i, \tag{2.10}$$

Where A_i is annual soil erosion (ton. ha^{-1} yr^{-1}),

R_i is rainfall erosivity (MJ mm ha^{-1} h^{-1} y^{-1}),

K_i is soil erodibility (ton·ha·hr $(MJ \cdot ha \cdot mm)^{-1}$),

LS_i is slope length-gradient factor,

C_i is crop-management factor, and

P_i is support practice factor for erosion control.

The LS_i factor is given from the method developed by Desmet and Govers (1996) for two-dimension surface as:

$$LS_i = S_i \frac{(A_{i-in}+D^2)^{m+1} - A_{i-in}^{m+1}}{D^{m+2} \cdot x_i^m (22.13)^m} \tag{2.11}$$

Where

S_i the slope factor for grid cell calculated as function of slope radians (θ), S = 10.8 • sin (θ) + 0.03, where θ < 9%,

S = 16.8 • sin (θ) - 0.50, where θ ≥ 9%.

Where, $A_{i\text{-}in}$ is the contributing area (m^2) at the inlet of a grid cell which is computed from the d-infinity flow direction method, D is the grid cell linear dimension (mm), $x_i = | \sin \alpha_i | + | \cos \alpha_i |$ |where α_i is the aspect direction for grid $cell_i$, m is the RUSLE length exponent factor.

To avoid overestimation of the LS factor in heterogeneous landscapes, long slope lengths are capped to a value of 333 m. The value of m, the length exponent of LS factor, is based on the classical USLE, as discussed in (Oliveira, Silva, Silva, Curi, Neto, and Freitas, 2013) as:

m = 0.2 m = 0.2 for slope <= 1 %:

m = 0.3 m = 0.3 for l % < slope <= 3.5 %,

m = 0.4 m = 0.4 for 3.5 % < slope <= 5 %,

m = 0.5 m = 0.5 for 5 % < slope <= 9%.

m = β/(1+β) where β = sin θ/0.0986/(3 sin θ0.8+0.56) for slope >= 9 %

Meanwhile, sediment delivery ratio (SDR) is estimated using connectivity index (IC) that reflecting the attributes of each LULC based on the work by Borselli, Cassi, and Torri (2008) as

$$\mathrm{IC} = \log_{10}\left(\frac{D_{up}}{D_{dn}}\right) \tag{2.12}$$

The sediment delivery ratio (SDR) for each pixel is a function of the upslope area (D_{up}) and downslope flow path (Figure 2.8). D_{up} is the upslope component defined as:

$$D_{up} = \overline{CS}\sqrt{A} \tag{2.13}$$

Where, $\overline{CS}$ is the average C factor of the upslope contributing area, S is the average slope gradient of the upslope contributing area and $\sqrt{A}$ is the upslope contributing area, (m^2). Meanwhile, the downslope contributing area (D_{dn}) is delineated from the Type equation here D-infinity flow algorithm (Tarboton, 1997). The D_{dn} is given by:

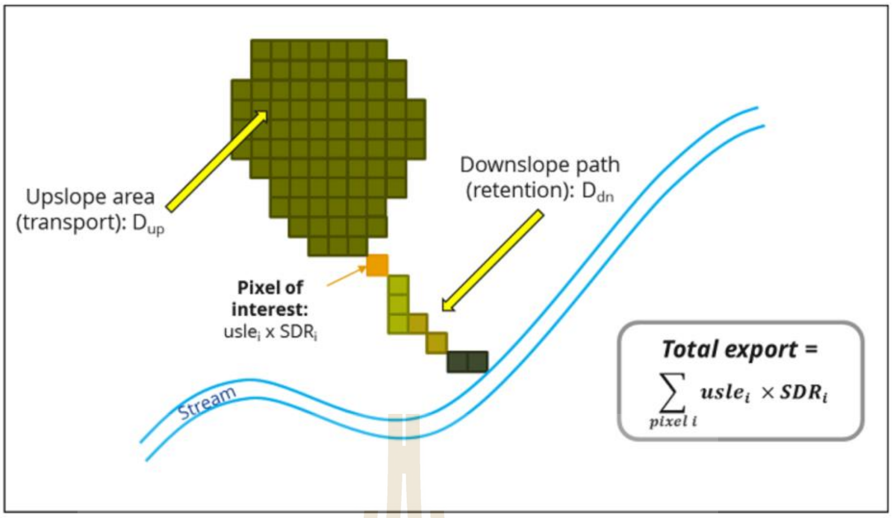
$$D_{dn} = \sum_i \frac{d_i}{C_i S_i} \tag{2.14}$$

Where, d_i is the length of the flow path along the *i* cell according to the steepest downslope direction (m), C_i and S_i are the C factor and the slope gradient of the i^{th} cell, respectively. Again, the downslope flow path is determined from the D-infinity flow algorithm (Cavalli, Trevisani, Comiti, and Marchi, 2013).

The SDR ratio for a pixel i is then derived from the connectivity index IC (Vigiak, Borselli, Newham, Mcinne, and Roberts, 2012) as:

$$SDR_i = \frac{SDR_{max}}{1 + exp\left(\frac{IC_0 - IC_i}{k}\right)} \tag{2.15}$$

Where, SDR_{max} is the maximum theoretical SDR, set to an average value of 0.8 and IC_0 and k are calibration parameters that define the shape of the SDR_{IC} relationship increasing function.



Source: Sharp et al., 2015.

Figure 2.8 Conceptual approach applied in sediment delivery ratio model.

2.7 Literature reviews

The literature reviews relate to this study are here summarized including the application of Random Forests, the CLUE-S model, Water Yield and Sediment Delivery Ratio models of InVEST suite.

2.7.1 Random forests application

Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, and Rigol-Sanchez, (2012) used the RF classifier for land cover classification and evaluated the results based on several criteria: mapping accuracy, sensitivity to data set size and noise. In the study, Landsat-5 TM data in spring and summer times with auxiliary variables derived from a digital terrain model were used to classify 14 land use categories in the South of Spain. They concluded that RF algorithm provided overall accuracy of 92% and Kappa hat coefficient of 0.92. The RF is robust to training data reduction and noise because significant differences in kappa values were only observed for data reduction and noise addition values greater than 50 and 20%, respectively. Additionally, variables that RF identified as most important for classifying land cover coincided with expectations.

Sun and Schulz (2015) applied Landsat 4/5 and Landsat 8 images with multispectral bands and thermal bands for extracting land cover patterns. In the study, the land cover types of Level 1 and Level 2 were assumed to be constant during the periods from 1984 to 1990 and 2006 to 2011. The k-NN and the RF methods were applied to classify LULC and assess accuracy. The accuracy assessment of both methods were the best overall accuracy of 98.7% to 99.1% for Level 1 classification and 93.9% to 96.3% for the Level 2 classification, respectively.

Tatsumi, Yamashiki, Torres, and Taipe (2015) used the RF classifier for eighth crop classification. A time series of medium spatial resolution (Landsat 7 ETM^+) and enhanced vegetation index was used to develop for crop type classification. Evaluation result covered training dataset size, the number of variables, and mapping accuracy. They found that the training dataset size strongly affects the classification accuracy. The RF classifier processed overall accuracy of 81% and a Kappa statistic of 0.70, indicating high model performance.

Midekisa et al. (2017) applied the RF classifier to present LULC classification over a long period of time (15 years) using Landsat data and Google Earth Engine cloud computing platform. In their study, they used Landsat spectral bands, NDVI, NDWI and nighttime light from the 2015 to classify 7 LULC classes. The total train points of 5,664 points were captured across the 7 LULC classes and 1,420 points for validation data. The derived overall accuracy was 88% whereas producer’s and user’s accuracies ranged from 84%–94% and 79%–96%, respectively.

In summary, it can be observed that the RF classified have been applied to classify LULC from moderate spatial resolution image by many researchers. The RF classifier can provide an overall accuracy varies between 81% and 99% and Kappa hat coefficient ranges from 0.70-0.92.

2.7.2 CLUE-S application

Verburg et al. (2002) stated that land use change models are important tools for integrated environmental management. The scenario analysis can help to identify the near future critical locations in the environmental change. The dynamic, spatially explicit and land use change model is presented for the local scale: CLUE-S. The model is developed for the analysis of land use in a watershed or province area at a fine spatial resolution. The model structure is integrated analysis of land use change in relation to socioeconomic and biophysical driving factors. They provided an application of CLUE-S model in the Philippines (Sibuyan Island) and Malaysia (Klang-Langat watershed).

Braimoh and Onishi (2007) applied CLUE-S model to predict land use change. In their study, LULC change was mapped using Landsat TM images and binary logistic regression were used to model the probability of observing the land development as a function of spatially explicit independent variables. They found that the spatial interaction effects and policy variables were the major determinants of land use change in Lagos, Nigeria.

Hu, Zheng, and Zheng (2013) applied CLUE-S model to simulate land use patterns in Beijing in the year 2015. In the study, they quantified number of land demand prediction using the Markov model. The validation of simulations for 2000 and 2005 were confirmed using Kappa analysis. The land use for Beijing in 2015 was simulated assuming two scenarios (1) urban development following existing trends and (2) under a strict farmland control. The simulations suggested that urbanized areas would be expanded form other uses, particularly the extensive loss of farmland between 2005 and 2015.

Trisurat et al. (2014) studied on predicting land use and land cover patterns driven by different scenarios in the emerald triangle protected forests complex. The current land use map was visually interpreted from satellite. The future land use patterns were predicted using the CLUE model based on different land use scenarios in 2030 defined by multi stakeholders from the three countries. The results indicated that dry dipterocarp forest in the north of Dong Khanthung proposed National Biodiversity Conservation Area in Lao PDR and to the west of Pha Taem National Park in Thailand would be threatened by encroachment for agriculture and rubber plantation. If no restriction policy, parts of the Preah Vihear protected forest in Cambodia and Phou Xiang Thong National Biodiversity Conservation Area in Lao PDR would be converted to arable land in 2030. Evergreen forests were predicted to be relatively intact, as at the current stage, because they are found either inside protected areas or in steep terrains, thus become natural barriers for human-intervention.

Han, Yang, and Song (2015) simulated future land use demand by combining a CLUE-S model with a Markov model in Beijing. In the study, the related driving factors from land adaptive variables, socioeconomic variables and regional spatial variables were applied to describe land use change. The simulated future land use scenarios from 2010 to 2020 were a development scenario (natural development and rapid development) and protection scenarios (ecological and cultivated land protection). The result of prediction for land use demand showed the higher elevations and the geographical environment limits the expansion of urban built-up land. However, the conversion of agriculture land to built-up land in mountainous areas were more in 2020 and more pressure in terms of ecological and cultivated land protection.

Ongsomwang and Iamchuen (2015) studied on the integration of geospatial models for optimum land use allocation in three different scenarios in Upper Lam Phra Phloeng Watershed, Nakhon Ratchasima Province, Thailand. The main objectives of the study were (1) to assess historical and recent LULC and its change, (2) to simulate three different LULC scenarios using CLUE-S model, (3) to assess soil erosion, water yield and economic value and its change and (4) to allocate an optimum land use for three different scenarios. In the study, CLUE-S model was firstly used to predict LULC of three different scenarios: Scenario I Historical land use evolution, Scenario II Energy crop extension and Scenario III Forest conservation and prevention. Then the derived results of soil loss using USLE model, water yield using SWAT model with SCS-CN method and economic values using PV model from LULC of each scenario in 2023 were integrated using simple additive weighting (SAW) method to classify suitability classes (low, moderate, and high) for optimum land use allocation. As results, they found that most of agricultural land and forest land of Scenario I was allocated in moderate and high suitability class, respectively. In the meantime, most of cassava and sugarcane as energy crops of Scenario II were located in low and moderate suitability classes and moderate and high suitability classes, respectively while forest land with restriction rules was located in high suitability class. Under Scenario III, forest land was allocated in moderate and high suitability classes and the agricultural land was distributed in all suitability classes.

Jiang, Deng, Tang, Lei, and Chen (2017) used CLUE-S model to analyze the potential impacts of urban expansion on carbon storage in Changsha-Zhuzhou-Xiangtan urban agglomeration from 2014 to 2023 under three urban expansion scenarios, namely Natural Increase Scenario (NIS), Cultivated Protection Scenario (CPS), and Ecological Protection Scenario (EPS). The results indicated carbon storage of Changsha-Zhuzhou-Xiangtan urban agglomeration experienced loss of 8.64 Tg from 1995 to 2009. From 2014 to 2023; the carbon storage will experience the most loss of 8.54 Tg under the NIS, will experience the least loss of 7.12 Tg under the EPS, and will experience moderate loss of 7.92 Tg under the CPS. The conversions of green land ecosystem and cultivated ecosystem to built-up ecosystem are the main cause of regional carbon storage loss in Changsha-Zhuzhou-Xiangtan urban agglomeration.

In summary, the CLUE-S model has been used to simulate the spatial dynamics and spatial allocation of land-use type in the future. The CLUE-S model treats the competition between different types of land uses for land allocation based on logistic model analysis.

2.7.3 Water yield application

Redhead et al. (2016) applied water yield model in 22 UK catchments with widely varying land cover and compared outputs with river flow data from the UK National River Flow Archive. The study tested the transferability of the results within the UK by additional validation in a further 20 catchments. They found that the model performed moderately with linear regression of modeled total water yield empirical data and with widely variation in performance between catchments.

Gao, Li, Gao, Zhou, and Zhang (2017) analyzed land use change and corresponding variations in water-related ecosystem services in the basin from 1980 to

2011. The analysis showed that the increasing of woodland and construction land enhanced water yield. Ecosystem services in the basin were altered by the land use changes. Specifically, water yield decreased (-6.65%) from 1980 to 1995 as a result of woodland expansion and cropland shrinkage. Between 1995 and 2011, the basin experienced accelerated urbanization. Hence, water yield in this period experienced a moderate increase (+8%) resulting from reduced infiltration and faster runoff, since urban growth leads to an increase in impervious surface.

Lang, Song, and Zhang (2017) analyzed the effect of land use and climate change on water yield between 1990 and 2010 in the Sancha River Basin. The variations in water yield in the basin were simulated for different three scenarios using water yield model of the InVEST software suite. The first scenario combined land use and climate change into the model in accordance with actual conditions. The second scenario was simulated without climate change whereas the third scenario was simulated without land use and climate changes. Water yield in basin increased by 17% between the two time periods in the actual scenario. The scenario without climate change reduced water yield about 0.46%. The last scenario increased regional water yield about 17.50% due to precipitation. The impact of rainfall change in the basin provided high water yield 97.44% while land use change contributed only 2.56%.

Lang, Song, and Deng (2018) assessed the water yields in the karst mountain area of China during the periods of 1990–2010 and 2010–2030 by coupling an InVEST software and a CLUE model. Three different land use scenarios included natural growth, economic development, and ecological protection were here developed in 2030. They found that a given land use changes between 1990 and 2010, total water yields in the karst mountain area are characterized by a trend towards fluctuating reduction. However, total water yields of 2030 in the economic development scenario revealed an increase of 1.25% compared to the actual water yields in 2010.

Lüke and Hack (2018) studied on hydrological ecosystem services models in Chiquito watershed where is situated in the Northwest of Nicaragua. In the study, water yield was calculated from the three different land use scenarios. The result of water yield from InVEST model provided water yield per sub watershed varying from 445,497 to 12,000,000 m^3, the water consumption per sub watershed ranked from 9,120 to 1,851,418 m^3, and the water supply per sub watershed varied from 433,737 to 12,000,000 m^3. By comparison water yield among scenarios, the transition scenario had a greater water yield than baseline scenario. The unprotected scenario increased water yield while reduced water retention capacity.

In summary, water yield model of InVEST software suite has been applied to simulate the annual biophysical contribution of LULC to water yield. The water yield model is flexible for use with local or regional scale and the results about water yield, water consumption and water supply mapping can be applied for decision making support.

2.7.4 Sediment Delivery Ratio model application

Zhou, Yu, Chen, Zhang, and Lue (2010) evaluated the effect of different types of forest ecosystem on soil conservation in mountain areas of Beijing. The soil erosion was simulated using the Sediment Delivery Ratio model under the InVEST software suite based on data from forest resources inventory data of Beijing. The results showed that the model was applicable to soil erosion simulation in mountain areas of Beijing, and the total of soil erosion was 1.76 million tons, the average soil conservation capacity was 220 tons/ha/y. All forest types of sediment retention capacity were high in mountain areas of Beijing, and the highest sediment retention capacity was 335 tons/ha/y in natural mixed coniferous forest. The second one was 297 tons/ha/y in nature arborvitae, while the smallest one is 148 tons/ha/y in the artificial larch.

Hamel, Chaplin-Kramer, Sim, and Mueller (2015) applied the Sediment Delivery Ratio model in the North Carolina. The sediment retention service for eight sub-watershed were performing sensitivity analyses and assessing its ability to detect the spatial variation in the different basin area. The sensitivity analyses revealed that rainfall erosivity and soil erodibility factors in agricultural land played important role on sediment export. The sediment exports from SDR model in eight sub-basin were highly correlated with observations.

Trisurat, Eawpanich, and Kalliola (2016) applied integrating land use and climate change scenarios and models to assess forested watershed services in Southern Thailand. As the natural forests, upstream have been largely degraded and transformed to fruit tree and rubber plantations, problems with landslides and flooding have resulted. This research attempted to predict how further land use and land cover changes during 2009-2020 and conceivable changes in rainfall may influence the future sediment load in the Thadee River. Three different land use scenarios (trend, development and conservation) were defined in collaboration with the local stakeholders, and three different rainfall. Spatially explicit empirical modelling, CLUE-S model and Sediment Delivery Ratio model were employed to allocate future land demands and to assess the contributions of land use and rainfall changes, considering both their separate and combined effects. The results suggested that substantial land-use changes may occur from a large expansion of rubber plantations in the upper sub-watersheds, especially under the development land use scenario. However, very high sediment load were predicted on the basis of combined intensified land use and extreme rainfall scenarios. Three conservation activities protection, reforestation and a mixed cropping system were proposed to maintain the functional watershed services of the Thadee watershed region scenarios (average rainfall, climate change and extreme wet).

Saad, Mota, Silva, and Rocha (2016) studied impact of roads and sediment on the simulated river discharge and sediment flux in an experimental catchment for improving ecosystem services. This work showed the impact of roads and barraging has (small sediment retention basins nearby the roads) on the sediment fluxes in a 12 km^2 catchment area in Extrema city, Brazil. Sediment concentration was estimated both with the observation and simulations, and annual comparisons seemed reasonable for mean annual estimates. Unpaved roads produced sediment export 5 times higher compared to a scenario with no roads, and potentiated the effect of barraging has on sediment reduction. This study showed the benefit from understanding effects of representation of the landscape particularities in modelling such as the roads, which apart from affecting calibration, are important issue for providing efficient modelling of the effect of the Best Management Practices in the landscape scale

Bogdan, Pătru-Stupariu, and Zaharia (2016) applied the Sediment Delivery Ratio model for sediment retention service in the Southern Romanian Carpathians. They developed land cover in three different scenarios (Business-as-Usual, Conservation and Development). The results provided sediment retention, sediment export and an amount of potential soil loss. They found that sediment retention service were increased under the Conservation scenario and decreased under the Development scenario. The overall results could be used for local landscape planning.

In summary, the SDR model has been applied by many researchers to assess soil erosion, sediment retention and sediment export. The soil loss is here considered as dependent variable and the rainfall erosion factors, soil erodibility, topography, vegetation cover management, and protective factors were considered as independent variables. High soil erosion potential can be expected in landscapes with high rainfall erosivity, high soil erodibility (e.g. silty soils), and high slopes.

2.7.5 Ecosystem service evaluation

Leh, Matlock, Cummings, Thoma, and Cothren (2013) studied the impact of land use change on ecosystem services in a typical agricultural in the Northwest Arkansas watershed. Ecosystem services on carbon storage, water yield, nutrient cycling were mapped and quantified for three different scenarios (historic, current, potential). The methodology evaluated the impact of land management scenarios on ecosystem services at watershed. Comparison between states of ecosystem service was performed by calculating the change (loss or gain) of each ecosystem service, the number of services represents the Ecosystem Service Status Index (ESSI). The results indicated a substantial change in carbon storage, water yield, and biodiversity; while nutrient cycling showed a low net change.

Leh, Matlock, Cummings, and Nalley (2013) quantified and assessed changes in multiple ecosystem services as a result of land use change in Ghana and Cote D'Ivoire for year 2000, 2005 and 2009 using InVEST software suite. They applied various toolsets to estimate water yield, carbon storage, nutrient retention, and sediment retention and developed a suite of indices (Ecosystems Services Change Index: ESCI, Ecosystems Services Status Index: ESI) to analyze land use change impacts on the status, change and spatial patterns of multiple ecosystem services. The results show a mix of increases in water yield service, little change in sediment retention services, and decreases in biodiversity and carbon storage services from 2000 to 2009. They concluded that the assessment methodology can be used by land managers in multiple scenarios and their implications for multiple ecosystem services change.

Arunyawat and Shrestha (2016) studied the impact of change in land use on ecosystem services using the InVEST model to quantify a set of ecosystem services (sediment retention, water yield, carbon stock, and habitat quality) in northern Thailand. The study also assessed the changes in land use from 1989 to 2013 and their impact on overall ecosystem services using GIS. As results, the LULC major changes were found increased rubber plantation cultivation and built-up areas and reduced forest cover. In addition, a negative impact in ecosystem services was observed in agricultural areas for the study period in the watershed. They concluded that the study results on spatial and temporal distribution of ecosystem services could help guide the development of appropriate land use options to improve ecosystem services.

Niquisse, Cabral, Rodrigues, and Augusto (2017) estimated past and future changes in multiple ecosystem services and biodiversity, as an effect of land cover change in Mozambique. Herein, set of ecosystem services included water yield, water quality, erosion regulation, climate regulation, and biodiversity were estimated using toolsets of the InVEST software suit. Changes in five ecosystem services were mapped between 2005 and 2009. LULC prediction was projected for year 2025 using the Land Change Modeler available in IDRISI. The results revealed that a moderate increase in climate regulating service between 2005 and 2009. The water quality (nutrient retention) and biodiversity decreased. Land cover change for 2025 was expected to have a similar impact on these ecosystem services. They concluded that the research methodology can be useful for monitoring ecosystem services and assist decision policies affecting the ecosystem service provision and trade-offs.

Xie, Gao, Li, Zhou, and Zhang (2018) quantified ecosystem services including water yield, sediment retention in 2000, 2005, 2010 and 2015 using InVEST software suite and explored the relationships of spatial correlation. As results, annual average water yield had increased from 193.41 mm/km^2 in 2000 to 240.35 mm/km^2 in 2015. The sediment retention had high spatial distribution patterns, where the topography was mainly mountain and land coverage was mainly forest and grass. According to Spearman correlation analysis, a positive correlation was found between water yield and sediment retention in each year and the consistent correlation for point in times separated by five years can a stable relationship between each two ecosystem services; changes in water yield and sediment retention in 2000–2015 were positively correlated as well.

In summary, multiple ecosystem service evaluation are here estimated using variety toolsets of InVEST software suite for assessing the impact of land use land scenarios at watershed. The correlation analysis indicates the spatial relationship between the status of land use and its ecosystem service and it can be used to describe its effect to ecosystem service such as water yield and sediment retention. In addition, ecosystem service change index (ESCI) is used to calculate the change (gain and loss) of each ecosystem service and then are integrated each of these changes to provide an overall assessment of ecosystem services status for a location. This provides the critical information needed in the design of management strategies for the ecosystem services.

CHAPTER III

EQUIPMENT DATA AND METHODOLOGY

Equipment, data and methodology including (1) data collection and preparation; (2) LULC assessment and its change; (3) LULC prediction of three different scenarios; (4) ecosystem service assessment: water yield and sediment retention service; and (5) LULC scenario identification for optimum water yield and sediment retention ecosystem services are described in this chapter.

3.1 Equipment

Equipment include hardware and software are summarized below:

- GPS Handheld; Garmin Oregon 450 with digital camera,
- Desktop Computer, Notebook,
- EnMap-Box (LULC classification with RF),
- ERDAS Imagine (change detection analysis),
- ESRI ArcMap (spatial analysis, geoprocessing),
- IDRISI (CA-Markov model),
- CLUE-S (LULC prediction), and
- InVEST software suite (water yield and sediment retention assessment)

3.2 Data collection and preparation

Collection and preparation data that include remotely sensed data, GIS data and primary and secondary data is summarized in Table 3.1.

Table 3.1 List of data collection and preparation for analysis and modeling in the study.

Data	Data collection	Data Preparation	Source	Component
Remote Sensing	Landsat 5 TM 2010	1. Radiometric correction	USGS (2010 and 2017)	1
	Landsat 8 OLI 2017	2. Geometric correction		1
	Google Image 2010		Google (2010)	1
GIS Data	Administrative boundary	-	DEQP (2017)	2
	National parks	-	DNP (1991)	2
	Wildlife sanctuary	-	DNP (1978)	2
	Watershed classification	-	MNRE	2
	SRTM V.3.0	-	USGS (2017)	2 and 3
	Elevation (m)	Create from SRTDEM	-	2
	Slope (%)	Create from SRTDEM	-	2
	Distance from road (m)	Buffering	PSO/MOT (2016)	2
	Distance from settlement (m)	Buffering	LULC data	2
	Distance from water body (m)	Buffering	LULC data	2
	Soil (soil fertility)	Recode	LDD (1971)	2
	Population density	Calculation from population	DOPA (2017)	2
	The average income of the population	Calculation from personal income by sub-district area	CDD (2016)	2
	Root restricting layer depth	Soil map	LDD (1971)	3
	Rainfall erosivity	Calculation from personal	Arnoldus (1980)	4
	Annual rainfall	Co-Kriging interpolation	TMD(2018)	3
	Soil erodibility	Vector to Raster	LDD (197)	4
	LULC in 2010 and 2017	Raster	-	2, 3
	Watershed boundary	-	RID (2018)	1, 2, 3 and 4
	Potential evapotranspiration (PET)	-	FAO (2017)	3
	LULC type	Vector	Field survey	-
Primary data	C-factor and P-factor	-	LDD (2005)	3
Secondary data	Plant available water content	Calculation from personal	Saxton and Rawls (2006)	3
	Predictive rainfall	Simple Co-Kriging interpolation	NCAR (2012)	3

Note: MNRE: Ministry of Natural Resources and Environment; LDD: Land Development Department; RID: Royal Irrigation Department; DEQP: Department of Environmental Quality Promotion; DNP: Department of National Parks, Wildlife and Plant Conservation; RFD: Royal Forest Department; PSO/MOT: Permanent Secretary Office, Ministry of Transport; DOPA: Department of Province Administration; CDD: Community Development Department, FAO: Food and Agriculture Organization.

3.3 Methodology

The overview framework of research methodology which includes (1) LULC assessment and its change; (2) LULC prediction of three different scenarios; (3) ecosystem service assessment: Water yield and sediment retention; and (4) LULC scenario identification for optimum water yield and sediment retention ecosystem services is presented in Figure 3.1. Details of each component excluding data collection and preparation were described in the following sections.

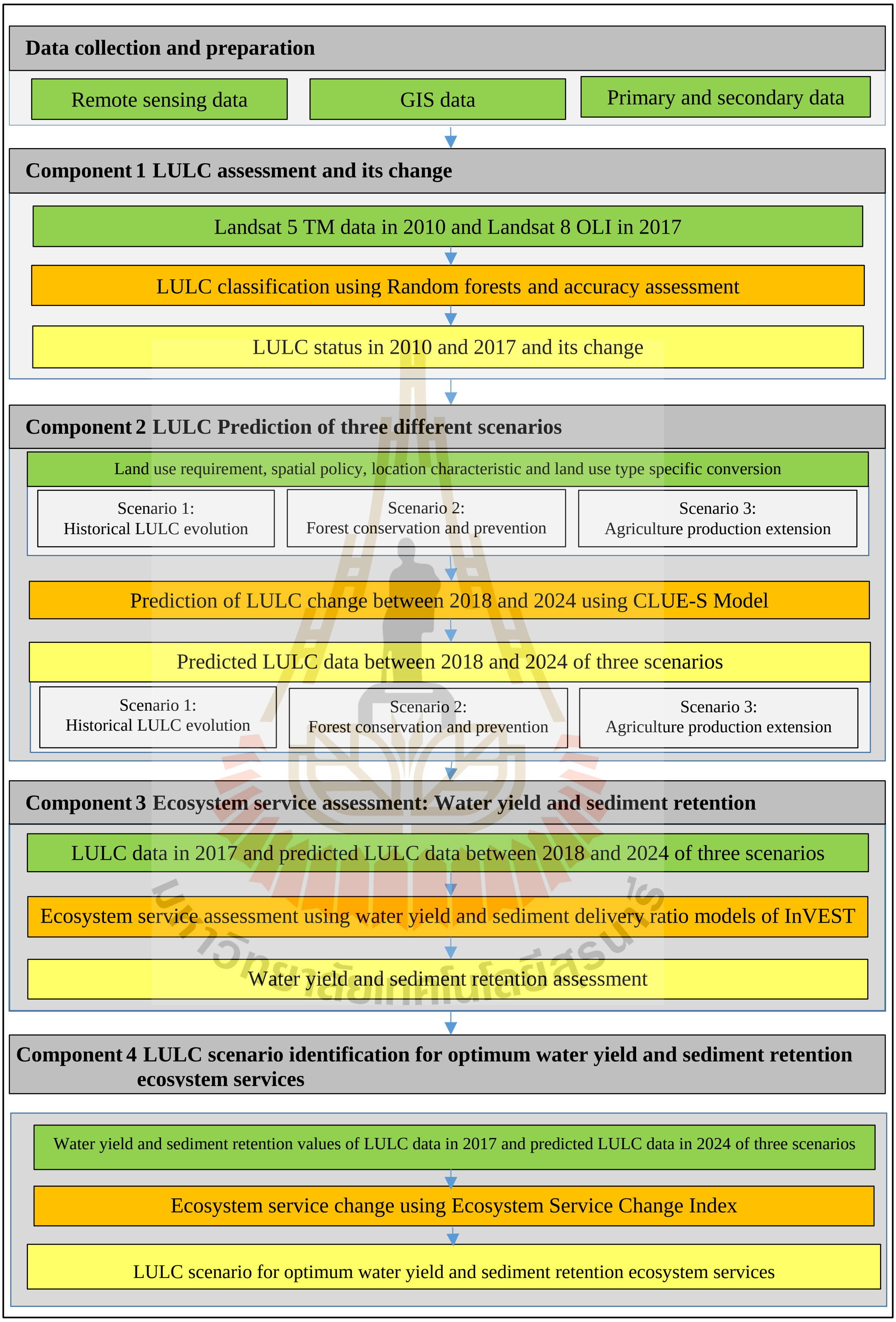


Figure 3.1 Overview research framework.

3.3.1 LULC assessment and its change

Under this component, two Landsat imageries in 2010 and 2017 were firstly downloaded from USGS website (www.earthexplore.usgs.gov) for LULC classification using the RF classifier. Then, the preliminary LULC maps in 2010 and 2017 were assessed accuracy based on the reference data from Google Image in 2010 and field survey in 2017, respectively. Finally, final LULC map in 2010 and 2017 were further used to detect LULC change using post classification comparison algorithm (Figure 3.2). The derived results of this component (LULC in 2010 and 2017) are further applied for LULC change prediction between 2018 and 2024 in three different scenarios using CLUE-S model in the next component.

Brief information of major tasks under this component includes (a) LULC classification using the RF classifier, (b) accuracy assessment, and (c) LULC change detection are summarized in the following sections.

(1) LULC classification using RF classifier.

Training areas of LULC type from two Landsat images were separately prepared to extract multiple decision trees for LULC classification using RF classifier of EnMap-Box software. The EnMAP-Box is a toolbox software that is developed to process and analyze spaceborne hyperspectral imaging spectrometer data acquired by the Germany satellite under Environmental Mapping and Analysis Program (EnMAP). The EnMAP-Box is mainly developed using Interactive Data Language (IDL) for Windows, Mac, and Linux operating systems and distributes with an open source license via website (www.enmap.org). It requires the free-of-charge IDL virtual machine or an IDL/ENVI license (Linden et al., 2015). In this study, standard product of scaled reflectance of Landsat 5-TM at Level 2: band 1, 2, 3, 4, 5, and 7 were applied to classify LULC in 2010 while standard product scaled reflectance of Landsat 8-OLI at Level 2: band 2, 3, 4, 5, 6, and 7 were used to classify LULC in 2017.

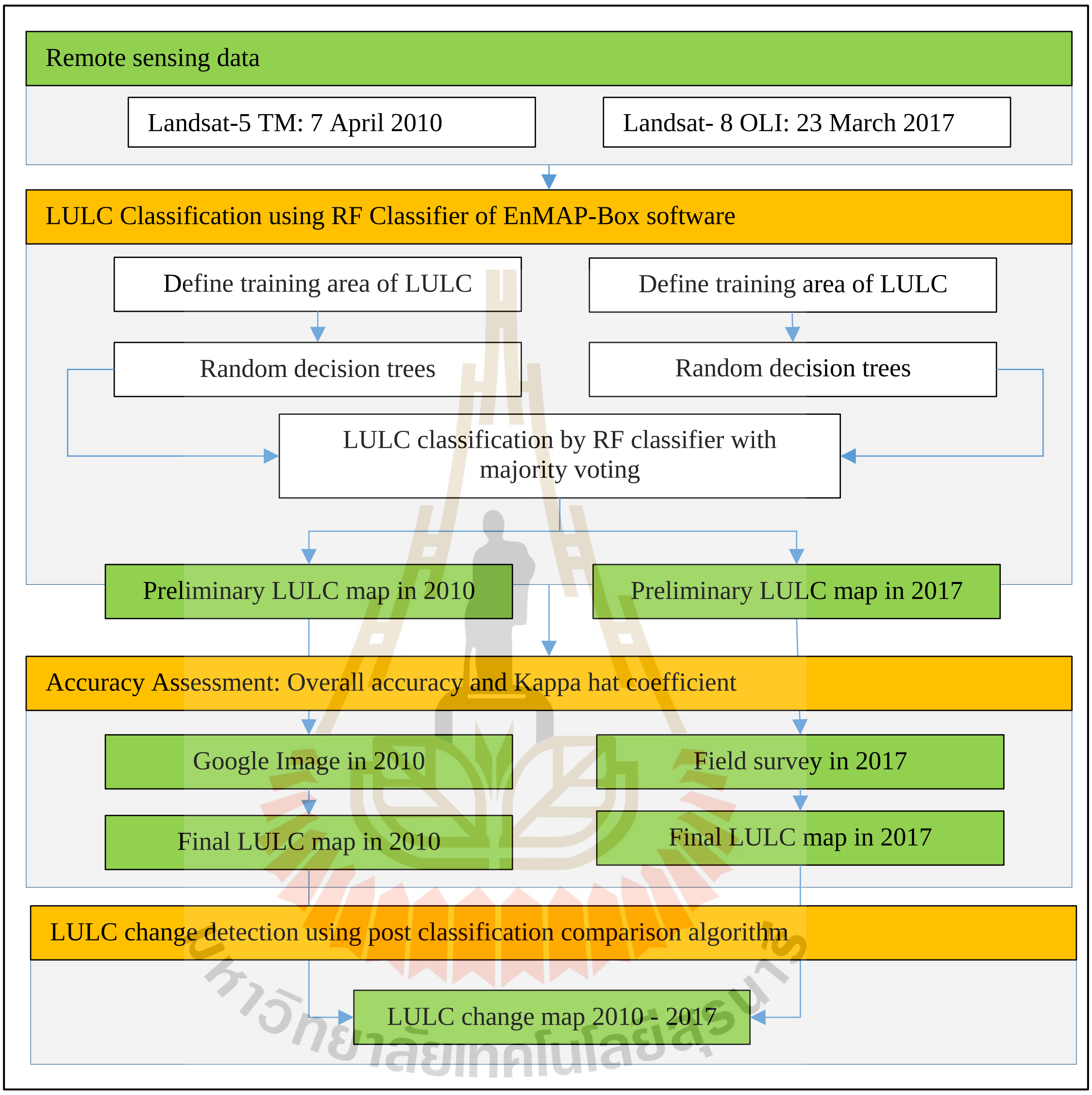


Figure 3.2 Schematic workflow of Component 1: LULC assessment and its change.

In this study, the LULC classification system, which was modified from standard land use classification system of Land Development Department, included (1) urban and built-up area (UR), (2) paddy field (PD), (3) rubber plantation (RP), (4) oil palm plantation (OP), (5) perennial tree and orchard (PO), (6) aquatic culture area (AQ), (7) evergreen forest (EF), (8) mangrove forest (MF), (9) marsh and swamp (MS), (10) water body (WA), and (11) miscellaneous land (bare land and abandoned mine) (ML). Description of LULC type is summarized in Table 3.2.

Table 3.2 Description of LULC classification system.

No.	LULC classes	Description
1	Urban and built-up area	It consists of villages, urban areas, harbors, airports, industrial areas and road network.
2	Paddy field	It is active paddy filed.
3	Rubber plantation	It consists of multi-growth stage of rubber plantation.
4	Oil palm plantation	It consists of multi-growth stage of oil palm plantation.
5	Perennial tree and orchard	It is composed of perennial tree and orchard (e.g. durian, mangosteens, rambutan, and longan).
6	Aquatic cultural area	Aquatic culture area includes shrimp farm and fish pond.
7	Evergreen forest	It is natural forest and mostly situates at hilly and mountainous areas.
8	Mangrove forest	It is natural forest and mostly situates along coastal zone.
9	Marsh and swamp	It is wetland which includes mash and swamp.
10	Water body	It includes rivers and streams, pond and reservoirs.
11	Miscellaneous land	It consists of bare land and abandoned mine.

(2) Accuracy assessment

The preliminary LULC map in 2010 and 2017 were assessed overall accuracy and Kapa hat coefficient based on reference LULC data from Google Image in 2010 and field survey in 2017, respectively. In this study, number of sample sizes for thematic accuracy assessment are estimated based on multivariate statistics with stratified random sampling scheme as suggested by Congalton and Green (2009). Herein, number of sample points for accuracy assessment was 880 points with the desired precision of 95 percent.

(3) LULC change detection

Final LULC maps in 2010 and 2017 were applied to detect LULC change using post classification comparison algorithm to describe from-to change among LULC classes between 2010 and 2017.

3.3.2 LULC prediction of three different scenarios

This study used CLUE-S model to predict LULC between 2018 and 2024 in three different scenarios which consists of (a) Scenario I: Historical LULC evolution, Scenario II: Forest conservation and prevention, and Scenario III: Agriculture production extension. The descriptions of each scenario are defined as following.

Scenario I: Historical LULC evolution. The prediction of LULC in 2024 relies on the historical trend of LULC change between 2010 and 2017. Herein, land requirement (demand) for LULC prediction in 2024 by CLUE-S model is based on annual change rate of LULC between 2010 and 2017 from transition area matrix using Markov Chain model. The Markov Chain is a stochastic process model that describes the probability of change from one state to another, i.e., from one land use type to another, using a transition probability matrix. The transition probability is the probability that a land cover type (pixels) at the time t_0 changes to another land cover type in the time t_1. Therefore, changes in land use between the dates are used to develop a probability transition matrix and then predict land uses for a future time (Cabral and Zamyatin, 2009). The mathematical expression of the transition probability is:

$$\sum_{I=1}^{m} P_{ij} = 1, i = 1,2, \dots m \quad (3.1)$$

$$P = (P_{ij}) = \begin{Bmatrix} P_{11} & P_{12} \dots P_{1m} \\ P_{21} & P_{22} \dots P_{2m} \\ P_{31} & P_{32} \dots P_{3m} \end{Bmatrix}$$

Where, P_{ij} is the probability of transition from one land use to another, m is the type within land use of the area studied, P_{ij} values are within the range 0–1.

Scenario II Forest conservation and prevention. Under this scenario, the existing government policy on forest conservation and prevention is integrated and transformed into forest land demand. Herein, legal boundary of national park, wildlife sanctuary, watershed class IA and an existing forest area in 2017 is used as forest land demand for LULC simulation under CLUE-S model.

Scenario III Agriculture production extension. Under this scenario, government policy on agricultural production extension by zonation in the future is firstly reviewed and transformed into land demand for optimum land utilization for oil palm plantation based on suitability map of Department of Agriculture in 2015. Meanwhile, the existing forest area (evergreen and mangrove forests) in 2017 is preserved for LULC prediction in 2024 under CLUE-S model. The quantitative information of land requirement in 2024 of three different scenarios based on their definitions is summarized in Table 3.3.

Table 3.3 Land requirement of three different scenarios in 2024.

LULC type	**Base line data in 2017 (Km^2)**	**Land requirement in 2024 (Km^2)**		
		Scenario I	**Scenario II**	**Scenario III**
Urban and built-up area	113.21	145.4 [1]	145.41 [1]	145.41 [1]
Paddy field	20.41	14.59 [1]	20.41 [2]	20.41 [2]
Rubber plantation	1,727.46	1,736.85 [1]	1,568.17 [3]	1,524.88 [4]
Oil palm plantation	18.85	32.35 [1]	32.35 [1]	259.51 [5]
Perennial tree/orchard	34.20	37.05 [1]	34.20 [2]	34.20 [2]
Aquatic cultural area	9.38	10.18 [1]	9.38 [2]	9.38 [2]
Evergreen forest	254.01	202.57 [1]	377.47 [6]	254.01 [2]
Mangrove forest	0.85	0.93 [1]	0.85 [2]	0.85 [2]
Marsh and swamp	42.70	37.50 [1]	42.70 [2]	37.50 [1]
Water body	42.43	50.93 [1]	42.43 [2]	42.43 [2]
Miscellaneous land	142.57	137.72 [1]	132.69 [7]	77.49 [8]

Note:

1. Land requirement of each LULC type is based on annual change rate of each LULC between 2010 and 2017 from transition area matrix by Markov Chain model.

2. Land requirement of each LULC type is fixed based on its area in 2017.

3. Land requirement of rubber plantation is decreased since illegal rubber plantation in the protected area (national park, wildlife sanctuary, watershed class IA) will be revoked and replaced by forest plantation.

4. Land requirement of rubber plantation is decreased since rubber plantation that situates in oil palm suitability zones will be replaced by new oil palm plantation.

5. Land requirement of oil palm plantation is increased according to the strategic plan to expand oil palm plantation by replacement rubber plantation and miscellaneous land that situate in suitable zones for oil palm plantation.

6. Land requirement of evergreen forest is increased according to reclamation forest areas back from intruders under reforestation program in illegal rubber plantation and miscellaneous land that situate in the protected forest area (national park, wildlife sanctuary, watershed class IA).

7. Land requirement of miscellaneous land is decreased since it will be replaced by forest plantation.

8. Land requirement of miscellaneous land in 2024 is decreased since it will be replaced by oil palm plantation.

In practice, parameters for LULC prediction include (1) spatial policies and restrictions, (2) land use type specific conversion setting (conversion matrix and elasticity of LULC change), (3) land requirement (demand), and (4) local characteristics were required under CLUE-S model.

LULC change driving factors which are used to identify LULC type location preference by binomial logistic regression analysis for allocating LULC type between 2018 and 2024 include elevation, slope, distance to water bodies, distance to road, distance to settlement, soil fertility, population density at sub-district level and average household income at sub-district level as application by Ongsomwang and Boonchoo (2016).

In practice, multicollinearity test was firstly examined to prevent the correlation of independent variables (driving factors) using variance inflation factor (VIF) value. In this study, if one independent variable has VIF > 10, it will removed from the analysis since it indicates that the variable has a highly correlated with other variables (Hair, Anderson, Tatham, and Black, 1995; Rogerson, 2010). After that, binary logistic regression analysis was conducted to identify significant driving force for specific LULC type allocation.

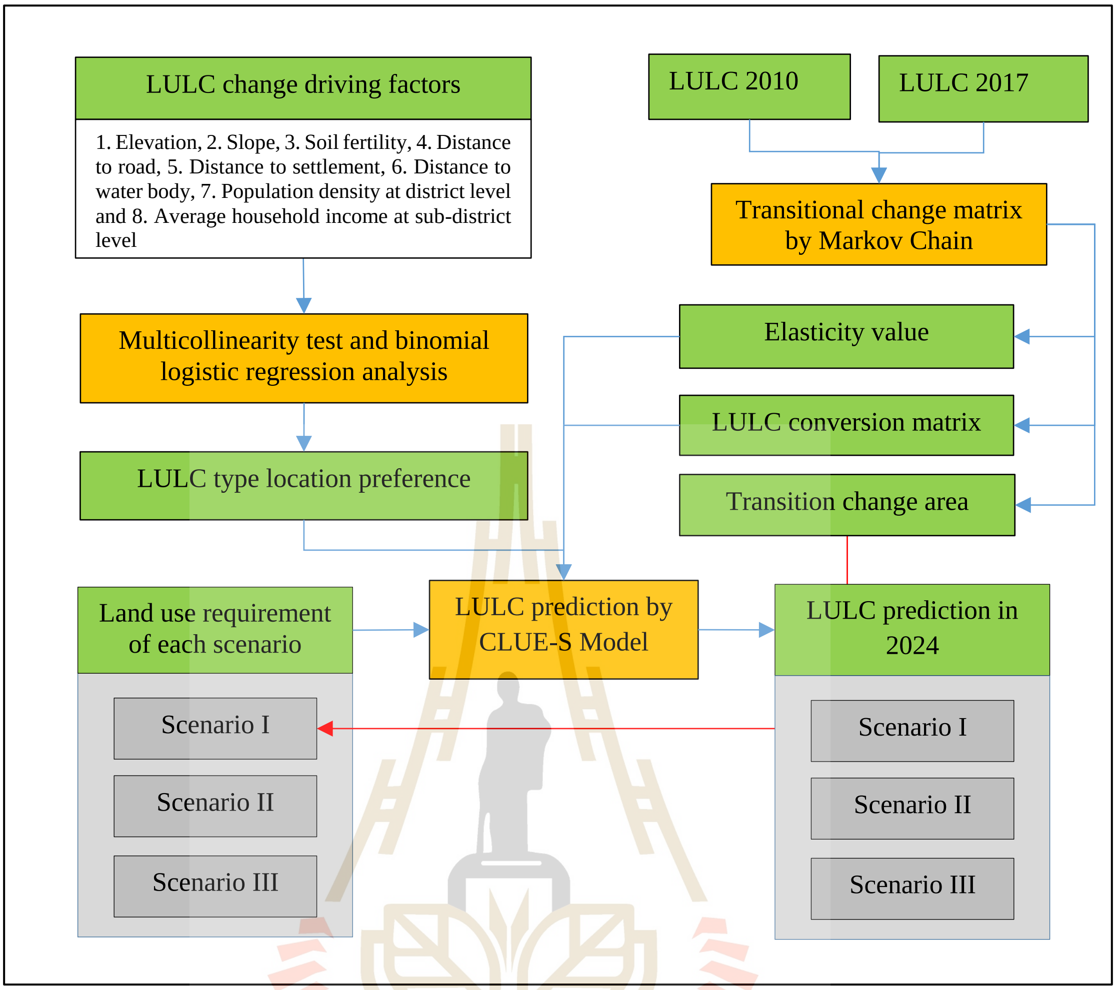


Figure 3.3 Schematic workflow of Component 2: LULC Prediction of three different scenarios.

3.3.3 Ecosystem service assessment: Water yield and sediment retention

This study applied toolset of InVEST software suite, namely water yield model and sediment delivery ratio model, to estimate water yield and sediment retention based on the base year LULC in 2017 and the predicted LULC of each year between 2018 and 2024 of three different scenarios. The description of water yield and sediment retention estimation are separately summarized as following.

3.3.3.1 Water yield estimation

Water yield of LULC in 2017 and the predicted LULC between 2018 and 2024 of three different scenarios were estimated using water yield model (Figure 3.4). The model required five factors (variables) included annual rainfall, root restricting layer depth, plant available water content (PAWC), annual potential evapotranspiration (PET) and biophysical factors of LULC type for water yield estimation (Table 3.3).

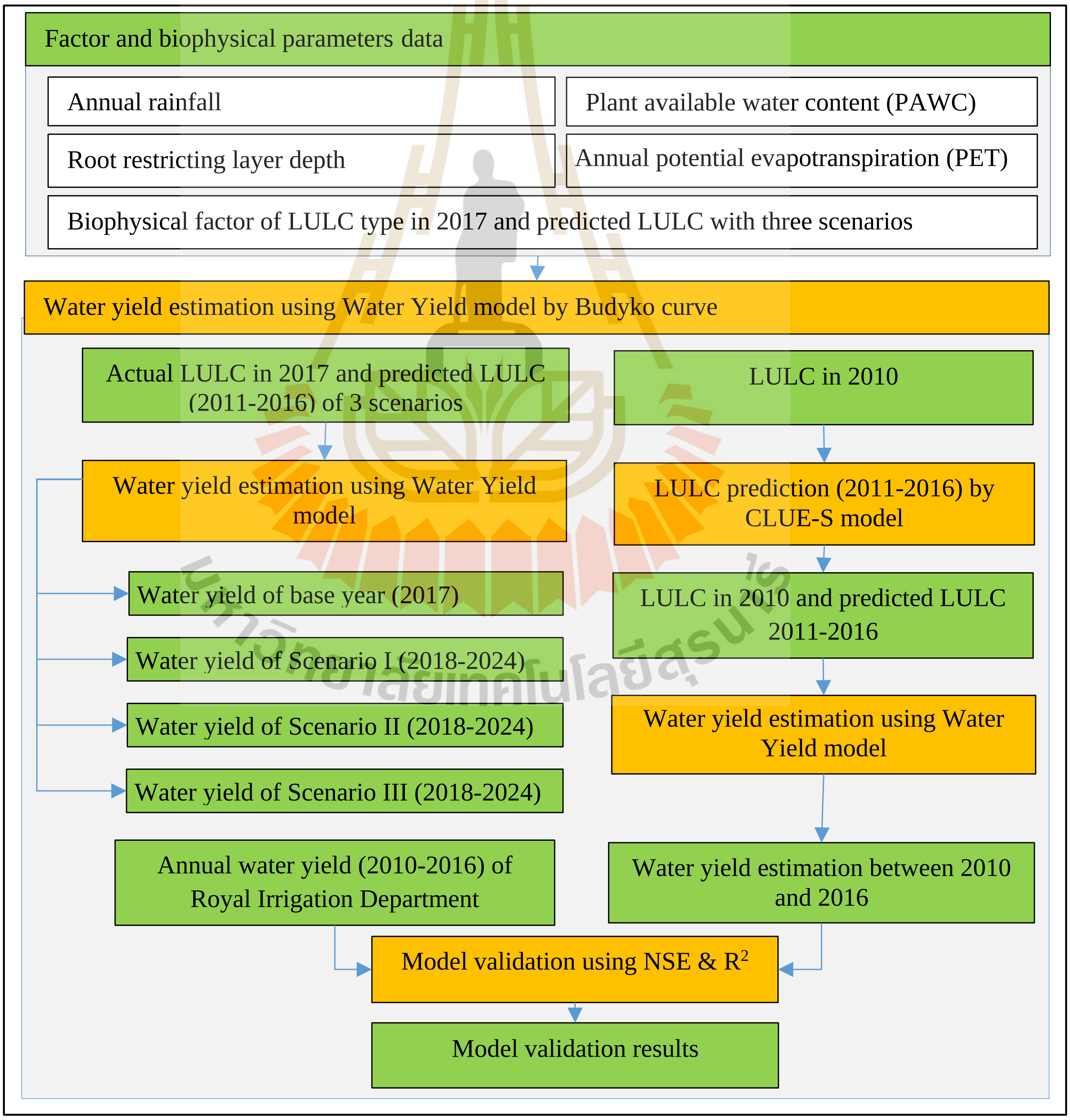


Figure 3.4 Schematic workflow of water yield estimation.

In practice, relevant factors of Water Yield model were firstly prepared in advance as followings.

(1) Annual rainfall. Available annual rainfall record of TMD between 2010 and 2017 was here collected from TMD to calculate water yield for validation (2010-2016) and estimation (2017). Meanwhile future meteorological data between 2018 and 2024 was downloaded from monthly average rainfall of the Global Products and Data Services of the NCAR (www.gisclimatechange.org) to interpolate annual rainfall during 2018 to 2024 by using Simple Co-Kriging technique.

(2) Root restricting layer depth. Soil depth under soil series data of LDD (2001) were here applied to generate root restrict depth layer for water yield estimation.

(3) Plant available water content. The PAWC is defined as the difference between the fraction of volumetric field capacity and permanent wilting point, which is an important influencing factor of crop production, agro-ecological zoning, irrigation planning, and land cover changes. The PAWC was estimated based on the relationship between PAWC and the physical and chemical properties of soil (sand, silt, clay and organic matter) (Zhou, Liu, Pan, and Feng, 2005) as:

$$\begin{aligned} PAWC = {} & 54.509 - 0.132 \times sand\% - 0.003 \times (sand\%)^2 - 0.055 \times silt\% - 0.006 \times (silt\%)^2 \\ & - 0.738 \times clay\% + 0.007 \times (clay\%)^2 - 2.688 \times OM\% + 0.501 \times (OM\%)^2 \end{aligned} \quad (3.2)$$

Where, PAWC is the plant available water fraction (%) represent the measured contents of sand (%), clay (%), silt (%) and organic matter (%).

(4) Annual potential evapotranspiration (PET). Annual PET is here estimate using the modified Hargreaves' equation as suggested by Droogers and Allen (2002) as:

$$PET_0 = 0.0013 \times 0.408 \times RA \times (T_{avg} + 17) \times (TD - 0.0123P)^{0.76} \qquad (3.3)$$

The modified Hargreaves uses the average of the mean daily maximum and mean daily minimum temperatures (T_{avg} in °C), the difference between mean daily maximum and mean daily minimums (TD), extraterrestrial radiation (RA) in $MJm^{-2}d^{-1}$and precipitation (P) in mm per month. Herein, temperature and precipitation data in 2017 and 2024 were extracted and predicted from meteorological stations of TMD while radiation data is generated by solar radiation tool in ESRI ArcGIS software. Then, the PET_0 equation was calculated by Model Builder under ESRI ArcGIS software again.

(5) Biophysical factor. A biophysical factor is required for reflecting the attributes of each LULC type on water yield. It contains LULC code, descriptive name of LULC, the maximum root depth for vegetated land use classes in millimeters and the plant evapotranspiration coefficient for each LULC type. Herein, the evapotranspiration coefficient (Kc) of each land use type was gathered from the previous studies in Thailand included Canadell et al. (1996), Allen, Pereira, Raes, and Smith (1998), Tanaka et al. (2008), Chalermwong (2015), Sharp et al. (2015) and Kramer et al. (2016) as summary in Table 3.3.

After that, all input data were converted from shape file to raster format at size cell of 50 m and applied to estimate water yield based on the Budyko curve developed by Zhang, Dawes, and Walker (2001).

Table 3.3 Minimal root depth and plant evapotranspiration coefficient for each LULC type.

LULC type	Root depth (mm)	Kc	References
Urban and built-up area	0	0.3	Canadell et al. (1996) and Sharp et al. (2015)
Paddy field	400	0.6	Kramer et al. (2016)
Rubber plantation	2500	0.9	Chalermwong (2015) and Sharp et al. (2015)
Oil palm plantation	2000	0.9	Chalermwong (2015) and Sharp et al. (2015)
Perennial tree and orchard	3000	0.95	Canadell et al. (1996) and Sharp et al. (2015)
Aquatic cultural area	0	0	Canadell et al. (1996) and Sharp et al. (2015)
Evergreen forest	7300	1	Canadell et al. (1996) and Sharp et al. (2015)
Mangrove forest	500	1	Tanaka et al. (2008)
Marsh and swamp	200	0.7	Allen, Pereira, Raes, and Smith (1998)
Water body	0	0	Canadell et al. (1996) and Sharp et al. (2015)
Miscellaneous land	0	0	Canadell et al. (1996) and Sharp et al. (2015)

Furthermore, the Nash–Sutcliffe efficiency (NSE) which defined by Nash and Sutcliffe (1970) and coefficient of determination (R^2) were here applied for validation water yield model with observed data between 2010 and 2016 from hydrological station of Royal Irrigation Department (RID) at X90 (Khlong U-Tapao). In this study, LULC data in 2010 and predicted LULC between 2011 and 2016 by CLUE-S model were here applied as data input to estimate water yield for model validation using NSE and R^2.

The value of NSE is dimensionless, being scaled onto the interval [-∞ to 1.0]. As a consequence, the NSE value obtained by the variance of the observations and subtracting that ratio from 1.0 is commonly the measure of choice for reporting (and comparing) model performance. Furthermore, NSE can be interpreted as a classic skill score (Nash and Sutcliffe, 1970; Murphy, 1988), where skill is interpreted as the comparative ability of a model with regards to a baseline model, which in the case of NSE is taken to be the 'mean of the observations' (i.e., if NSE $\leq$ 0, the model is no better than using the observed mean as a predictor). The NSE equation is calculate using Eq. 3.4.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(X_{s,t} - X_{o,t})^2}{\sum_{i=1}^{n}(X_{o,t} - \mu_o)^2} \quad (3.4)$$

Where, n is the total number of time-steps, $X_{s,t}$ is the simulated value at time-step t, $X_{o,t}$ is the observed value at time-step t, and μ_o is the mean and standard deviation of the observed values.

In principle, NSE is independent of flow magnitude which ranges from minus infinity (poor model) to 1.0 (perfect model) (Motovilov, Gottschalk, Engeland, and Rodhe (1999) They suggested that the model's performance is defined as satisfactory for NSE above 0.36 and as good for NSE above 0.75.

In addition, coefficient of determination (R^2) were chosen as index to evaluate the performance of various rainfall data for driving the model as:

$$R^2 = \frac{\sum_{i=1}^{n}(X_{s,t} - \overline{X}_{s,t}) \times (X_{o,t} - \overline{X}_{o,t})}{\sum_{i=1}^{n}(X_{s,t} - \overline{X}_{s,t})^2 \sum_{i=1}^{n}(X_{o,t} - \overline{X}_{o,t})^2} \quad (3.5)$$

Where $\overline{X}_{o,t}$ is observed runoff on time-steps, $\overline{X}_{o,t}$ is average observed runoff, $X_{s,t}$ is the simulated value on time-steps, and $\overline{X}_{s,t}$ is average simulated runoff.

Santhi et al. (2001) suggested that the R^2 ranges from 0.0 (poor model) to 1.0 (perfect model) with typical values greater than 0.5 considered as acceptable.

Under this component, the main output of water yield estimation for LULC in 2017 and LULC between 2018 and 2024 of three different scenarios includes (a) water yield depth in mm and (b) water yield volume in cu. m.

3.3.3.2 Sediment retention estimation

Sediment retention is estimated using multiplication between soil erosion and sediment delivery ratio under Sediment Delivery Ratio model (Figure 3.5). Basically, soil erosion is firstly estimated using RUSLE which requires five factors: rainfall erosivity (R), slope length gradient (LS), soil erodibility (K), cover factor (C) and practice factor for erosion control (P). Brief information of relevant factors for soil erosion estimation are summarized below.

(1) Rainfall erosivity (R). The rainfall erosivity factor was calculated as suggested by Wischmeier and Smith (1978) and modified by Arnoldus (1980). Rainfall data in 2017 collected from the Thailand Meteorological Department (TMD, 2018) and Royal Irrigation Department (RID) were used for calculating R-factor in RUSLE using the following as:

$$R = \sum_{i=1}^{12} 1.735 \times 10^{\left(1.5\, log_{10}\left(\frac{P_i^2}{P}\right) - 0.08188\right)} \tag{3.6}$$

Where R is the rainfall erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1}), P_i is the monthly rainfall (mm), and P is the annual rainfall (mm).

(2) Slope length gradient factor (LS). The LS factor was calculated from the Digital Elevation Model (DEM) with method developed by Desmet and Govers (1996) as mentioned in Section 2.6.

(3) Soil erodibility (K). The K-factor was adopted from standard values of LDD (2001) which are extracted from soil series data (Table 3.4).

(4) Cover factor (C). LULC data in 2010 and 2024 from three scenarios were used as input data to extract C factor value based on the standard assignment of LDD in 2000 (Table 3.5).

(5) Practice factor (P). P factor values were extracted from LULC data based on the standard assignment of LDD in 2000 (Table 3.5).

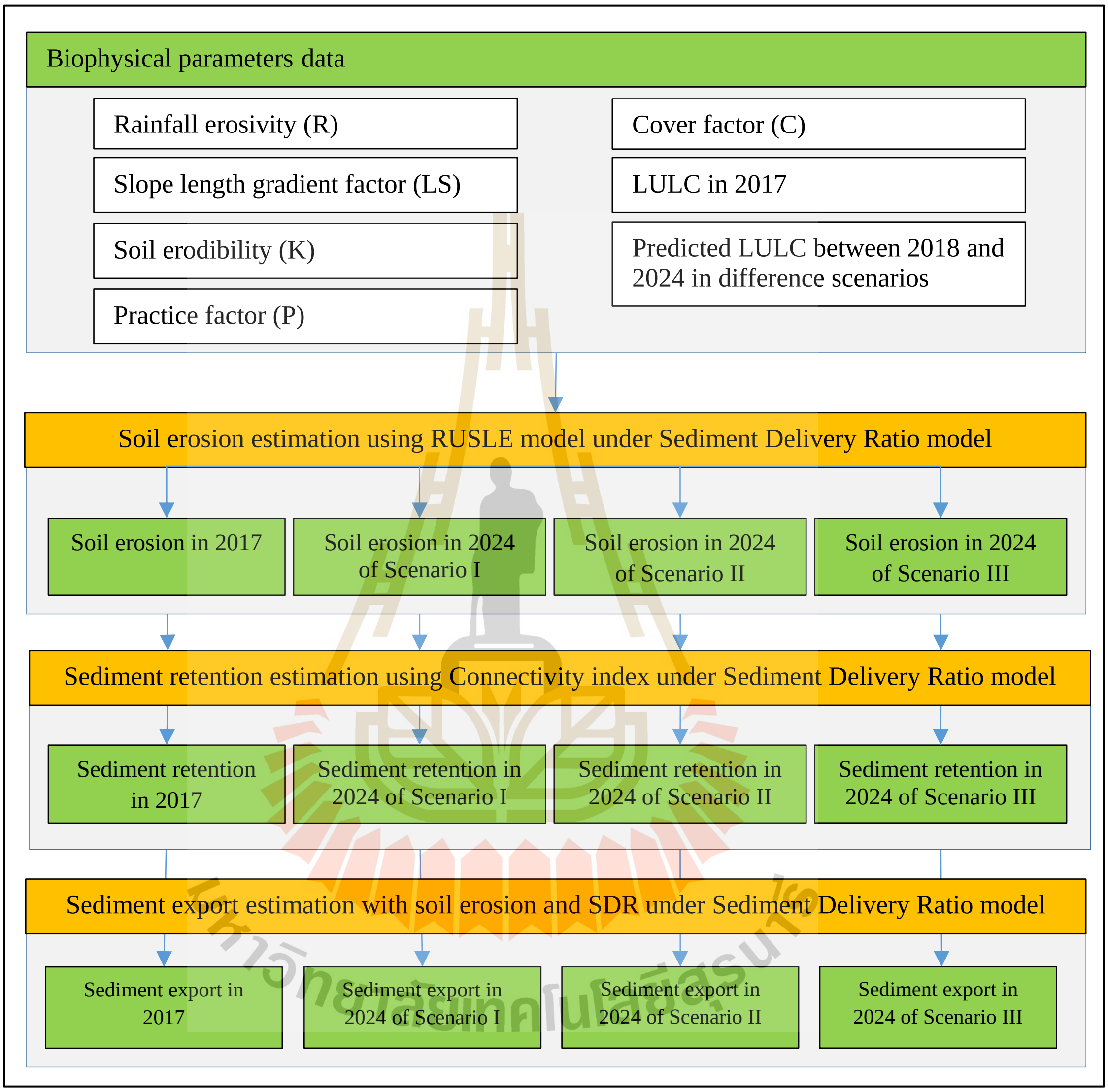


Figure 3.5 Schematic workflow of sediment retention estimation.

Table 3.4 Soil series and soil erodibility factor values.

Soil series	Erodibility factor value	Soil series	Erodibility factor value
Ban Thon series	0.20	Rangae / Tha Chin association	0.14
Bang Klam series	0.12	Rangae series	0.20
Bang Nara / Kokiean association	0.30	Ranong / Hat Yai association	0.32
Bang Nara series	0.26	Ranong / Phato association	0.25
Chumphon / Sawi association	0.28	Ranong series	0.23
Chumphon series	0.28	Ranote series	0.14
Complex of well drained, levee soil	0.22	Rayong series	0.23
Hat Yai / Padang Baser association	0.27	Residential	0.11
Hat Yai series	0.27	Ruso series	0.22
Khlong Nok Kra Thung series	0.20	Sai Buri fine clayey variant	0.26
Khlong Thom series	0.25	Sai Buri, fine clayey variant / Ruso association	0.28
Kho Hong / Tha Sae, mottled variant association	0.27	Sai Kao, somewhat excessively drianed variant	0.25
Kho Hong series	0.24	Samut Prakan series	0.17
Khok Khian fine sand fraction variant	0.17	Sathon series	0.28
Khok Khian series	0.24	Sawi series	0.20
Klaeng series	0.27	Slope Complex	0.21
La Harn series	0.22	Songkla Lake	0.07
Lang Suan series	0.13	Swamp	0.24
Nam Krachai / Kho Hong association	0.23	Tha Sae, mottled variant	0.25
Nam Krachai series	0.23	Tha Sae, mottled variant / Klaeng association	0.27
Padang Besar series	0.28	Thung Wa series	0.21
Pawong / Rangae association	0.23	Tin mine land	0.20
Pawong series	0.14	Visai complex	0.29
Phato series	0.22	Visai series	0.24
Puket series	0.20	Yala series	0.27

Source: LDD, 2000.

Table 3.5 C and P factor corresponding to each LULC class.

LULC type	C factor	P factor
Urban and built-up area	0	0
Paddy field	0.4	1
Rubber plantation	0.22	1
Oil palm plantation	0.3	1
Perennial tree and orchard	0.3	1
Aquatic culture area	0	0
Evergreen forest	0.001	1
Mangrove forest	0	0
Marsh and swamp	0.40	1
Water body	0	0
Miscellaneous land	0.6	1

Source: LDD, 2000.

Then, SDR was estimated using connectivity index (CI) that reflecting the attributes of each LULC type, threshold flow accumulation and maximum SDR. The SDR value was here calculated as suggested by Borselli et al. (2008) as:

$$SDR_i = \frac{SDR_{max}}{1+exp\left(\frac{IC_0-IC_i}{k}\right)} \qquad (3.7)$$

Where, SDR_{max} is the maximum theoretical SDR, set to an average value of 0.8 (Vigiak et al., 2012), and IC_0 and k are calibration parameters that define the shape of the $SDR-IC$ relationship (increasing function).

Finally sediment retention was estimated as suggested by Sharp et al. (2015) as.

$$Sediment\ retention = R \times K \times LS(1-CP) \times SDR \qquad (3.8)$$

Moreover, the existing sediment export data between 2010 and 2017 at X90 station of RID (2018) were used to validate sediment delivery ratio model under the InVEST software suite using NSE and R^2.

3.3.4 LULC scenario identification for optimum water yield and sediment retention ecosystem services

The analyzed ecosystem services change state of water yield and sediment retention due to LULC change was here assessed using ecosystem services change index (ESCI) as suggested by Mansoor, Marty, Eric, and Lanier (2013) as:

$$\mathrm{ESCI}_{\,x} = \left[\frac{ES_{CURx_j}-ES_{HISx_i}}{ES_{HISx_i}}\right] \qquad (3.9)$$

Where, ESCI $_x$ is the Ecosystems Services Change Index of service X, ES_{CURx_j} and ES_{HISx_i} are the current and historic ecosystem service state values of service X at times j and i, respectively.

In this study, historical ecosystem service values (water yield and sediment retention) was based on LULC in 2017 while the current ecosystem service, which varies between 2018 and 2024, was based on the predicted LULC between 2018 and 2024. To extract gain and loss of ecosystem services (water yield and sediment retention), historical ecosystem service values in 2017 and annual ecosystem services values between 2018 and 2024 were separately calculated pair by pair using Eq. 3.9. The derived results were then averaged to identify LULC scenario for optimum ecosystem services on water yield and sediment retention (Figure 3.6).

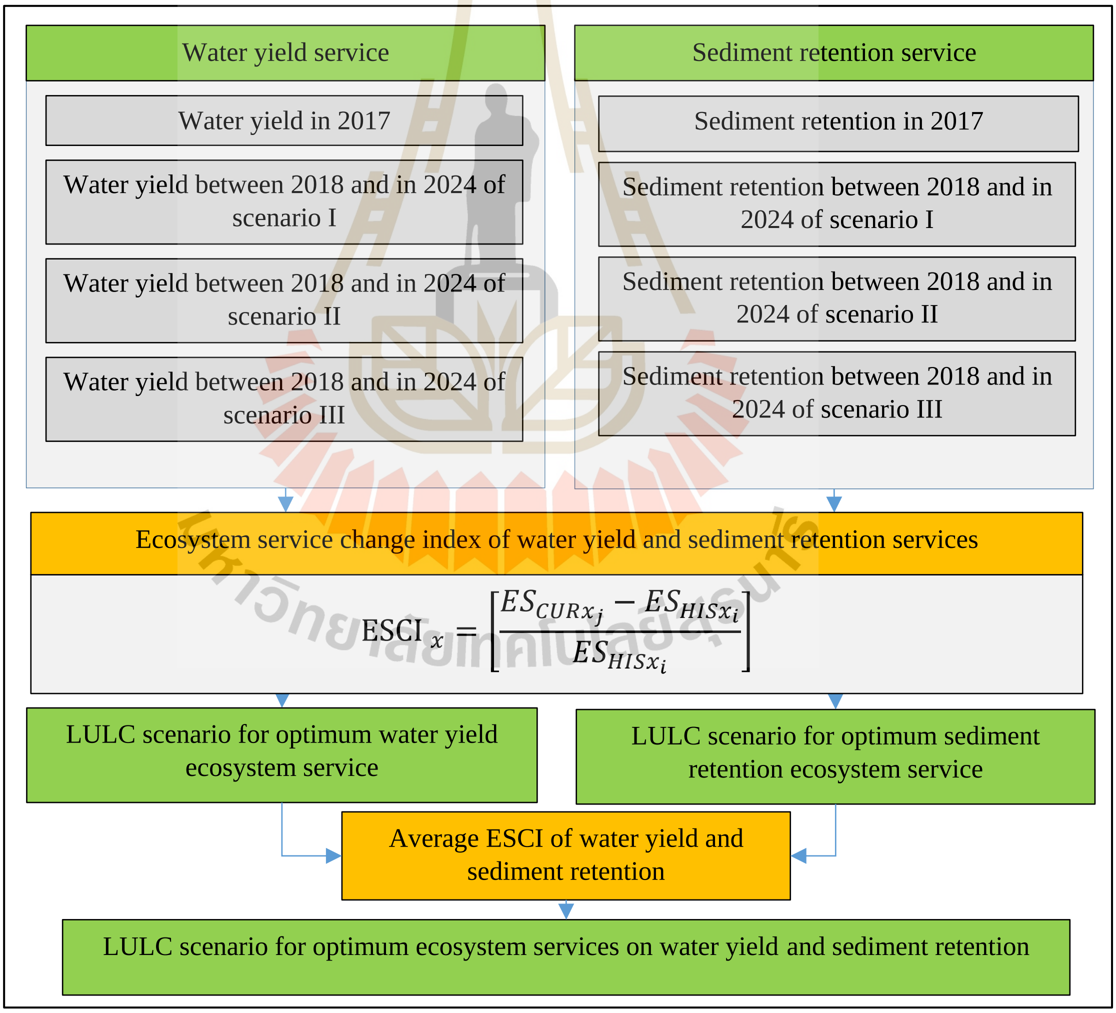


Figure 3.6 Schematic workflow of Component 4: LULC scenario identification for optimum water yield and sediment retention ecosystem services.

CHAPTER IV

LULC ASSESSMENT AND ITS CHANGE

This chapter presents results of the first objective focusing on classification of LULC in 2010 and 2017 using RF classifier and change detection between 2010 and 2017 using post classification comparison algorithm. The main results consist of (1) LULC data in 2010 assessment, (2) LULC data in 2017 assessment, and (3) LULC change between 2010 and 2017 are here described and discussed in details.

4.1 LULC data in 2010 assessment

LULC data in 2010 as historical record, which was classified from Landsat 5 TM imagery (7 May 2010) based on selected homogeneous training sample points using RF classifier. Number of training sample points for LULC classification according to proportional of LULC coverage of LDD in 2009 as summary in Table 4.1 and distribution of training sample points is presented in Figure 4.1. Meanwhile, distribution of LULC classification in 2010 is displayed in Figure 4.2 and area and percentage of LULC data is summarized in Table 4.2.

As results, it was found that top three most dominant LULC types in 2010 are rubber plantation, evergreen forest and miscellaneous land (bare land and abandoned mine) which cover area of 1,672.66 km^2 or 69.52%, 318.52 km^2 or 13.24% and 177.75 km^2 or 7.39%, respectively. In opposite, top three least dominant LULC types in 2010 are mangrove forest, oil palm plantation and aquatic cultural area which cover area of 0.74 km^2 or 0.03%, 5.50 km^2 or 0.23% and 8.42 km^2 or 0.35%, respectively.

Table 4.1 Number of training sample points for LULC classification in 2010 using RF classifier.

No	LULC type	Number of training point
1	Urban and built-up area	11
2	Paddy field	4
3	Rubber plantation	180
4	Oil palm plantation	5
5	Perennial tree and orchard	8
6	Aquatic cultural area	6
7	Evergreen forest	40
8	Mangrove forest	5
9	Marsh and swamp	14
10	Water body	15
11	Miscellaneous land	25
	Total	**313**

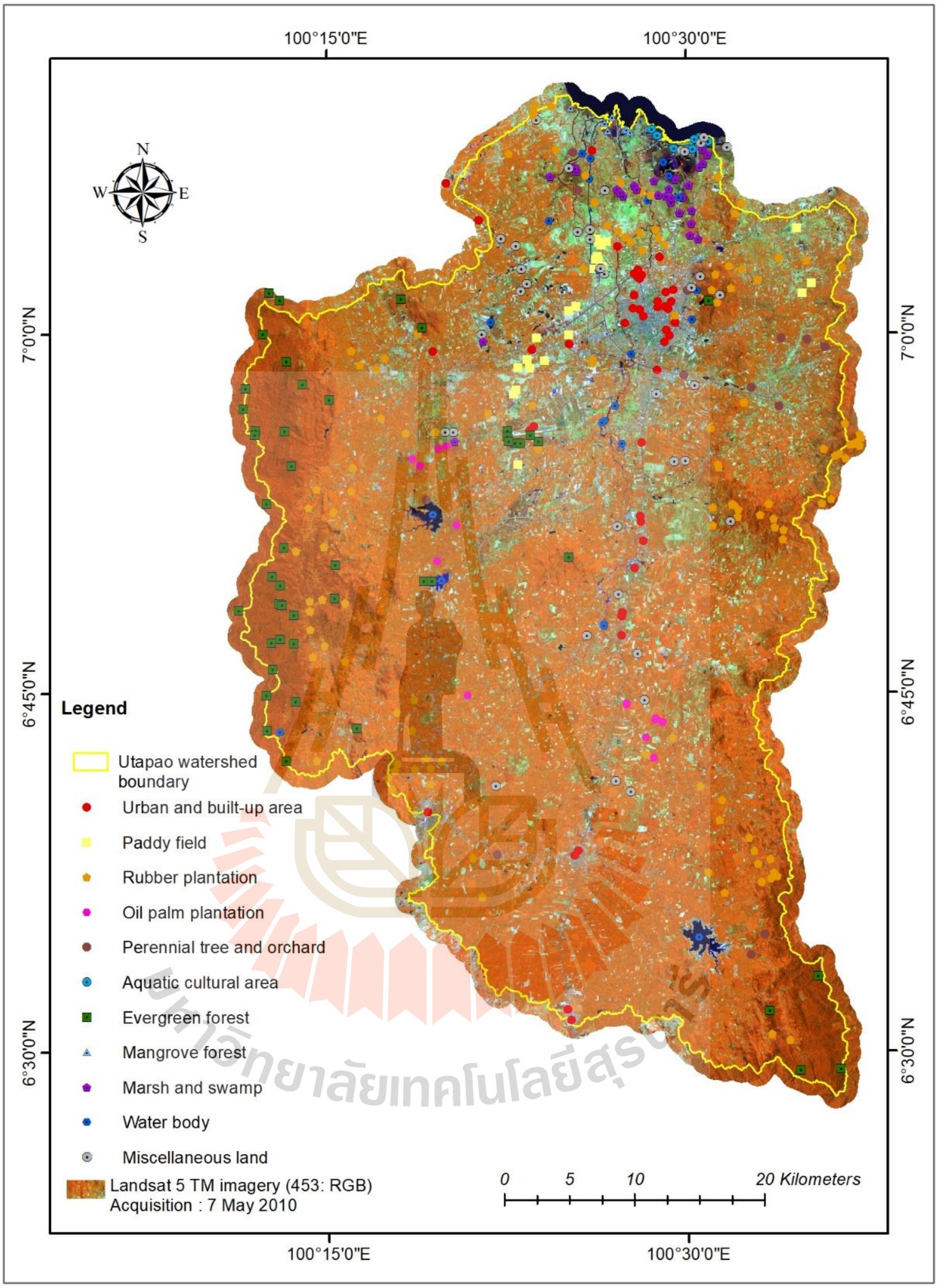


Figure 4.1 Distribution of training sample points for LULC classification in 2010.

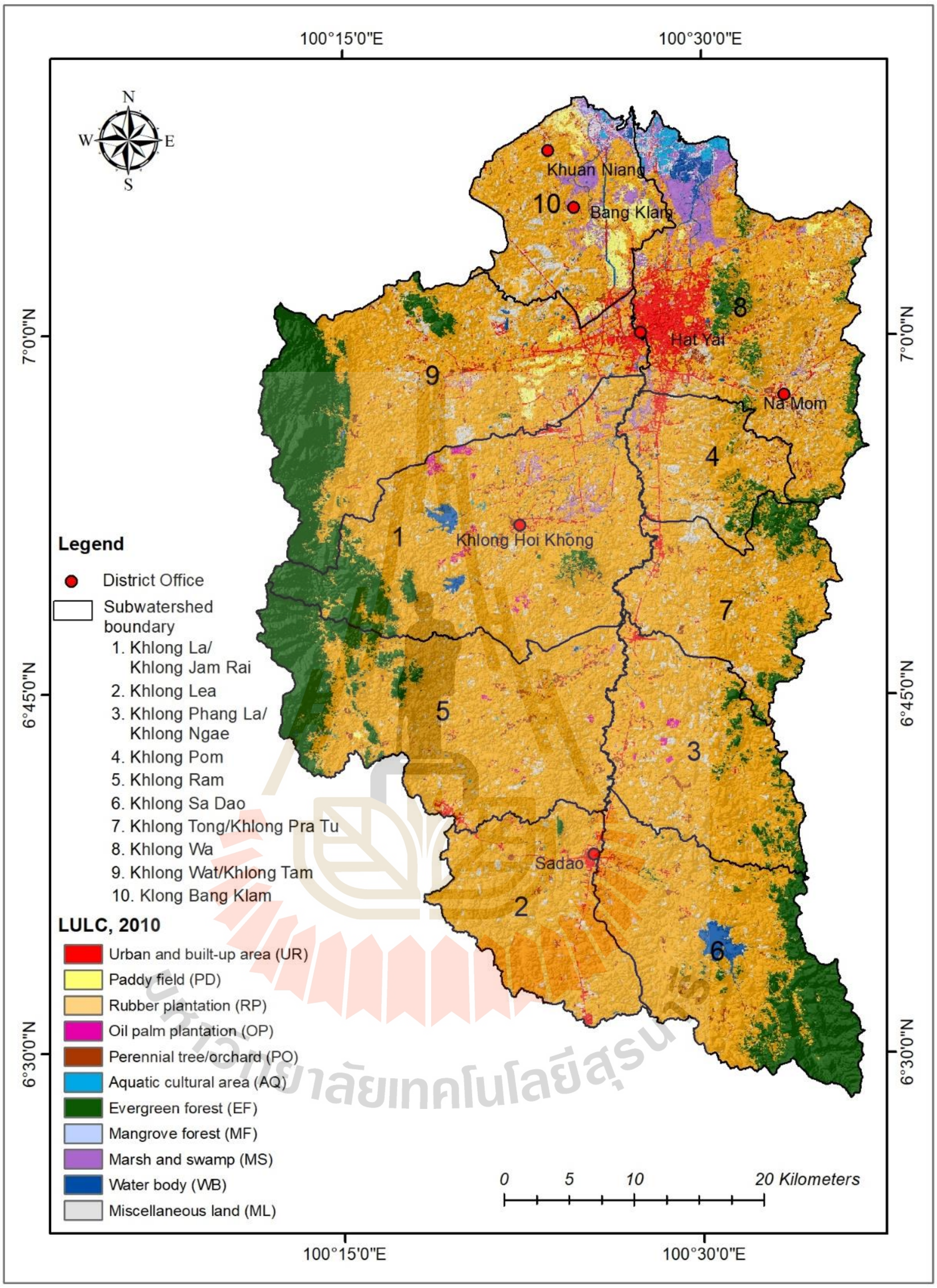


Figure 4.2 Spatial distribution of LULC classification in 2010.

Table 4.2 Area and percentage of LULC data in 2010.

No	LULC type	Area in km^2	Percent
1	Urban and built-up area	80.37	3.34
2	Paddy field	28.56	1.19
3	Rubber plantation	1,672.66	69.52
4	Oil palm plantation	5.50	0.23
5	Perennial tree and orchard	31.66	1.32
6	Aquatic cultural area	8.42	0.35
7	Evergreen forest	318.52	13.24
8	Mangrove forest	0.74	0.03
9	Marsh and swamp	48.61	2.02
10	Water body	33.27	1.38
11	Miscellaneous land	177.75	7.39
	Total	**2,406.04**	**100.00**

In addition, the classified LULC map in 2010 was further assessed its accuracy using 880 stratified random sample points with Google Earth image (Figure 4.3) and error matrix form of thematic LULC accuracy assessment is displayed in Table 4.3.

As results, it reveals that overall accuracy is 91.36% and Kappa hat coefficient is 84.00%. Meanwhile producer's accuracy (PA), which represents omission error, varies between 57.58% for miscellaneous land and 100% for urban and built-up area, paddy field, aquatic cultural area, and mangrove forest whereas user's accuracy (UA), which represents commission error, varies between 66.67% for oil palm plantation and 100% for aquatic cultural area and mangrove forest and water body.

Based on Fitzpatrick-Lins (1981), Kappa hat coefficient more than 80 percent represents strong agreement or accuracy between the classified map and the reference map. In addition, the derived overall accuracy and Kappa hat coefficient in the current study is similar with the previous study of Li, Im, and Beier (2013), who applied RF classifier to land cover from Landsat-TM data at Adirondack Mountains of New York

State, their study provides an overall accuracy at 87.3% and Kappa hat coefficient at 77.3%. Likewise, Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, and Rigol-Sanchez, (2012) applied RF classifier to classify land cover from Landsat-TM at Granada province, South of Spain and their study delivers overall accuracy at 92% and a Kappa index at 92%.

Therefore, the classified LULC in 2010 in this current study can be accepted and can be further applied for LULC change detection between 2010 and 2017.

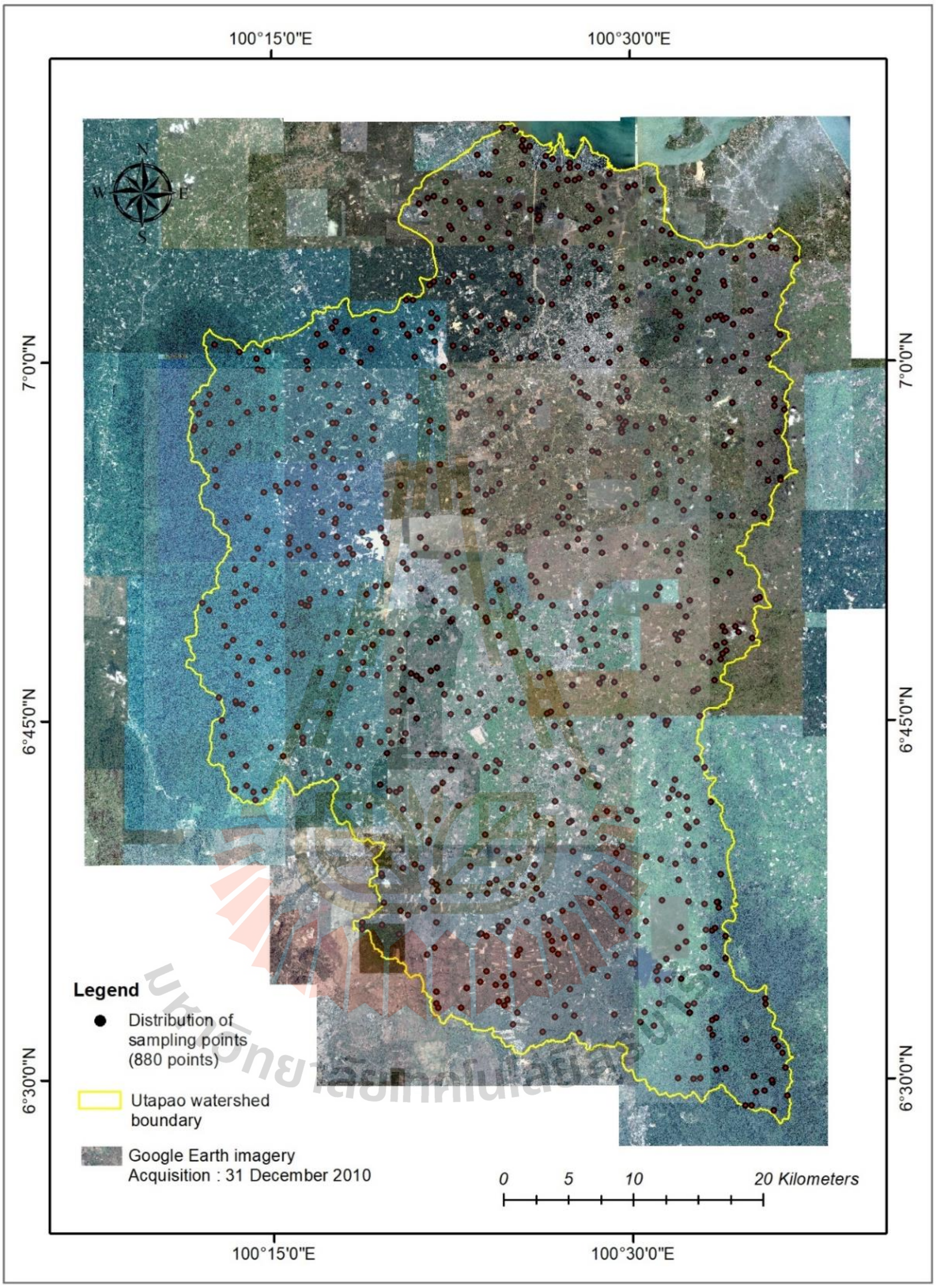


Figure 4.3 Spatial distribution of sampling points superimposed on Google Earth image (31 December 2010) for accuracy assessment of thematic LULC map in 2010.

Table 4.3 Error matrixes and accuracy assessment of LULC in 2010.

	LULC types	Ground reference data from Google Earth in 2010											
		UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WB**	**ML**	**Total**
Classified LULC data in 2010	Urban and built-up area (UR)	**23**		2								1	**26**
	Paddy field (PD)		**8**	2									**10**
	Rubber plantation (RP)			**553**	1	2		5		4		41	**606**
	Oil palm plantation (OP)			1	**2**								**3**
	Perennial tree/orchard (PO)			1		**12**							**13**
	Aquatic cultural area (AQ)						**3**						**3**
	Evergreen forest (EF)			4				**114**					**118**
	Mangrove forest (MF)								**1**				**1**
	Marsh and swamp (MS)			1						**18**			**19**
	Water body (WB)										**13**		**13**
	Miscellaneous land (ML)			6		1				3	1	**57**	**68**
	Total	23	**8**	570	3	15	3	119	1	25	14	99	**880**
	Producer's accuracy	**100.00**	**100.00**	**97.02**	**66.67**	**80.00**	**100.00**	**95.80**	**100.00**	**72.00**	**92.86**	**57.58**	
	User's accuracy	**88.46**	**80.00**	**91.25**	**66.67**	**92.31**	**100.00**	**96.61**	**100.00**	**94.74**	**100.00**	**83.82**	
	Overall accuracy	**91.36**											
	Kappa hat coefficient	**84.00**											

Furthermore, it can be observed that the significant commission error of rubber plantation comes from miscellaneous land because the appearance of clear-cut rubber plantation for new rubber plantation is similar with bare land of miscellaneous land (Figure 4.4). Meanwhile, the significant omission error of rubber plantation mostly comes from evergreen forest and miscellaneous land because the brightness value of old rubber plantation is similar with evergreen forest and very young rubber plantation is similar with bare land of miscellaneous land (Figure 4.5).

Figure 4.4 Ground photograph of clear-cut rubber plantation.

Figure 4.5 Ground photograph of old rubber plantation.

4.2 LULC data in 2017 assessment

LULC data in 2017 as present record which was also classified from Landsat 8 OLI imagery (23 March 2017) based on selected homogeneous training sample points using RF classifier. Number of training sample points for LULC classification according to proportional of LULC coverage of LDD in 2016 as summary in Table 4.4 and distribution of training sample points is presented in Figure 4.6. Characteristic of training sample points (composite image: band 453 (RGB), spectral plot, and ground photograph) for LULC classification with RF is presented in Table 4.5. Meanwhile, distribution of LULC classification in 2017 in Khlong U-Tapao watershed and its sub-watershed is displayed in Figure 4.7. Details of area and percentage of LULC data of Khlong U-Tapao watershed in 2017 is summarized in Table 4.6 while details of area and percentage of LULC data of each sub-watershed of Khlong U-Tapao watershed in 2017 is summarized in Tables 4.7 to 4.8.

As results, it was found that top three most dominant LULC types in 2017 are rubber plantation, evergreen forest and miscellaneous land which cover area of 1,727.46 km^2 or 71.80%, 254.01 km^2 or 10.56% and 142.57 km^2 or 5.93%, respectively. In opposite, top three least dominant LULC types in 2017 are mangrove forest, aquatic cultural area and oil palm plantation which cover area of 0.85 km^2 or 0.04%, 9.38 km^2 or 0.39% and 18.85 km^2 or 0.78%, respectively.

Table 4.4 Number training sample points using random forests classifier of each LULC type in 2017.

No	LULC type	Number of training point
1	Urban and built-up area	11
2	Paddy field	4
3	Rubber plantation	180
4	Oil palm plantation	5
5	Perennial tree and orchard	8
6	Aquatic cultural area	6
7	Evergreen forest	40
8	Mangrove forest	5
9	Marsh and swamp	14
10	Water body	15
11	Miscellaneous land	25
	Total	**313**

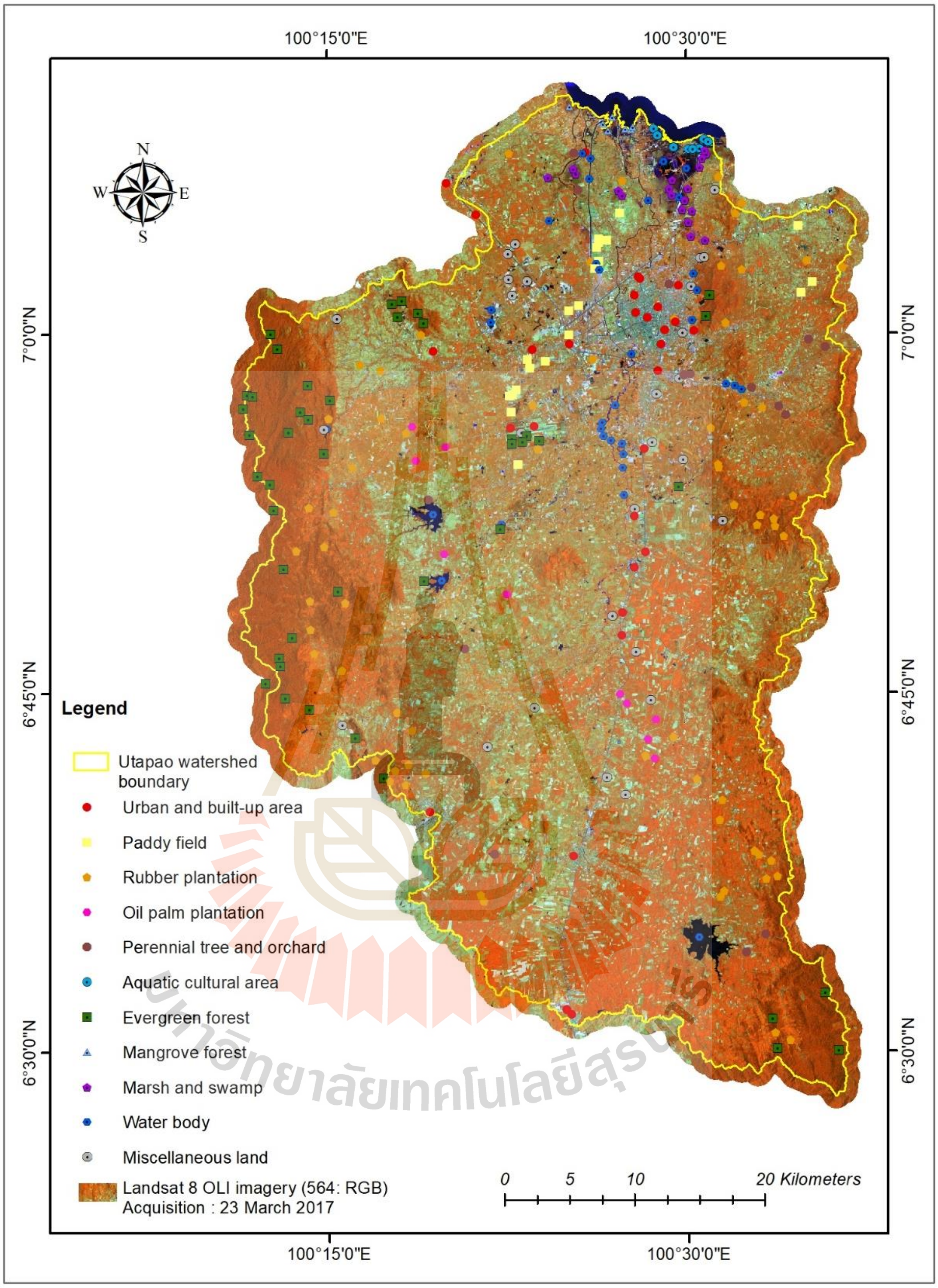


Figure 4.6 Distribution of training sample points in 2017.

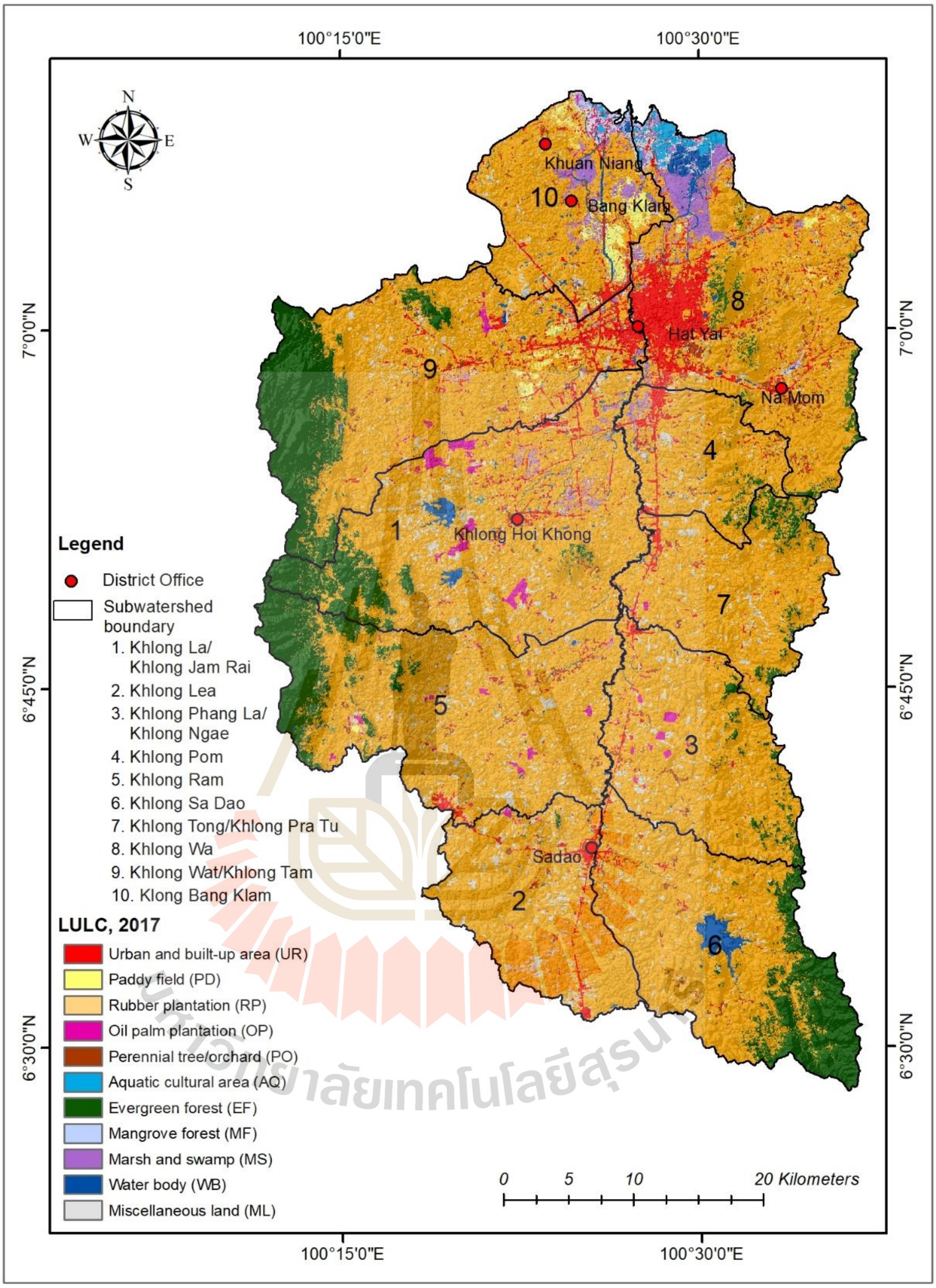


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Figure 4.7 Spatial distribution of LULC classification in 2017.

Table 4.5 Characteristic of training sample points for LULC classification with RF classifier.

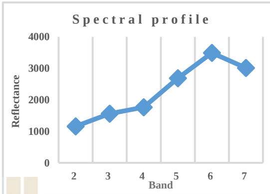
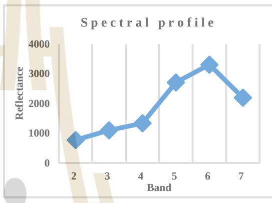
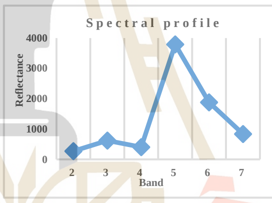
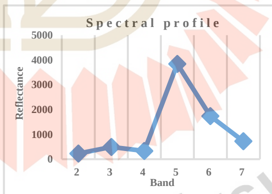
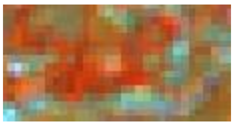
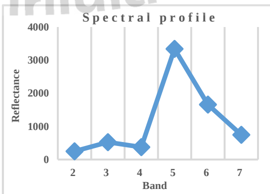
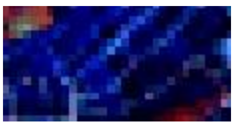
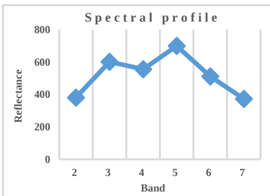
LULC type	Combination image	Spectral plot	Ground photographs
1. Urban and built-up area			
2. Paddy field			
3. Rubber plantation			
4. Oil palm plantation			
5. Perennial tree and Orchard			
6. Aquatic culture area			

Table 4.5 (Continued).

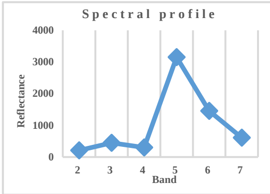
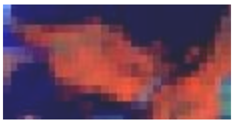
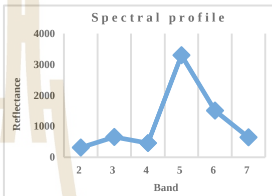
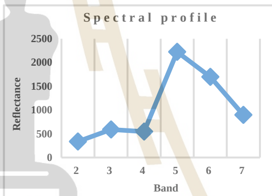
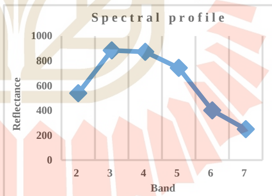
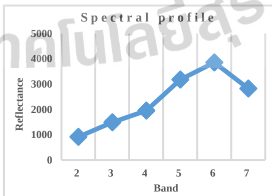
LULC type	Combination image	Spectral plot	Ground photographs
7. Evergreen forest			
8. Mangrove forest			
9. Marsh and swamp			
10. Water body			
11. Miscellaneous land			

Table 4.6 Area and percentage of LULC data of Khlong U-Tapao watershed in 2017.

No	LULC type	Area in km^2	Percent
1	Urban and built-up area	113.21	4.71
2	Paddy field	20.41	0.85
3	Rubber plantation	1,727.46	71.80
4	Oil palm plantation	18.85	0.78
5	Perennial tree and orchard	34.20	1.42
6	Aquatic cultural area	9.38	0.39
7	Evergreen forest	254.01	10.56
8	Mangrove forest	0.85	0.04
9	Marsh and swamp	42.70	1.77
10	Water body	42.43	1.76
11	Miscellaneous land	142.57	5.93
	Total	**2,406.04**	**100.00**

Table 4.7 Area of LULC data in each sub-watershed of Khlong U-Tapao watershed in 2017.

No.	NAME	UR	PD	RP	OP	PO	AQ	EF	MF	MS	WB	ML
1	Khlong La / Khlong Jam Rai	10.23	-	259.24	9.16	2.67	0.38	32.82	-	5.64	8.90	29.04
2	Khlong Lea	6.43	-	142.70	0.60	0.97	0.05	0.37	-	-	0.64	14.75
3	Khlong Phang La/Khlong Ngae	3.05	-	160.33	2.42	2.43	0.04	7.33	-	0.05	0.84	12.41
4	Khlong Pom	6.37	-	83.40	0.28	2.02	0.07	3.11	-	1.84	1.62	4.43
5	Khlong Ram	3.91	0.23	243.40	3.07	4.06	0.19	49.22	-	0.44	1.40	19.02
6	Khlong Sa Dao	2.23	-	179.33	0.08	2.89	0.01	56.06	-	0.01	7.56	11.01
7	Khlong Tong / Khlong Pra Tu	3.68	-	134.94	0.36	1.41	-	11.07	-	-	1.05	9.06
8	Khlong Wa	46.67	2.44	198.18	-	11.71	7.61	10.04	0.21	20.53	11.17	17.29
9	Khlong Wat / Khlong Tam	22.67	4.26	215.81	1.94	3.11	0.06	84.00	-	1.88	3.24	15.18
10	Klong Bang Klam	7.96	13.48	110.15	0.95	2.95	0.98	-	0.65	12.32	6.00	10.38
	Total	**113.21**	**20.41**	**1,727.46**	**18.85**	**34.20**	**9.38**	**254.01**	**0.85**	**42.70**	**42.43**	**142.57**

Table 4.8 Percentage of LULC data in each sub-watershed of Khlong U-Tapao watershed in 2017.

No.	NAME	UR	PD	RP	OP	PO	AQ	EF	MF	MS	WB	ML
1	Khlong La / Khlong Jam Rai	9.04	-	15.01	48.60	7.80	4.00	12.92	-	13.21	20.98	20.37
2	Khlong Lea	5.68	-	8.26	3.16	2.84	0.53	0.15	-	-	1.51	10.35
3	Khlong Phang La/Khlong Ngae	2.69	-	9.28	12.84	7.10	0.45	2.89	-	0.11	1.97	8.70
4	Khlong Pom	5.63	-	4.83	1.46	5.90	0.72	1.22	-	4.31	3.81	3.11
5	Khlong Ram	3.45	1.11	14.09	16.29	11.87	2.03	19.38	-	1.03	3.31	13.34
6	Khlong Sa Dao	1.97	-	10.38	0.40	8.46	0.08	22.07	-	0.01	17.83	7.72
7	Khlong Tong / Khlong Pra Tu	3.25	-	7.81	1.92	4.11	-	4.36	-	-	2.48	6.35
8	Khlong Wa	41.23	11.95	11.47	-	34.23	81.20	3.95	24.05	48.08	26.33	12.13
9	Khlong Wat / Khlong Tam	20.03	20.86	12.49	10.27	9.09	0.59	33.07	-	4.41	7.64	10.65
10	Klong Bang Klam	7.03	66.07	6.38	5.06	8.61	10.40	-	75.95	28.85	14.13	7.28
	Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

In addition, the classified LULC map in 2017 was further assessed its accuracy using 880 stratified random sample points with ground information by field survey in 2018 (Figure 4.8) and error matrix form for thematic LULC accuracy assessment is displayed in Table 4.9.

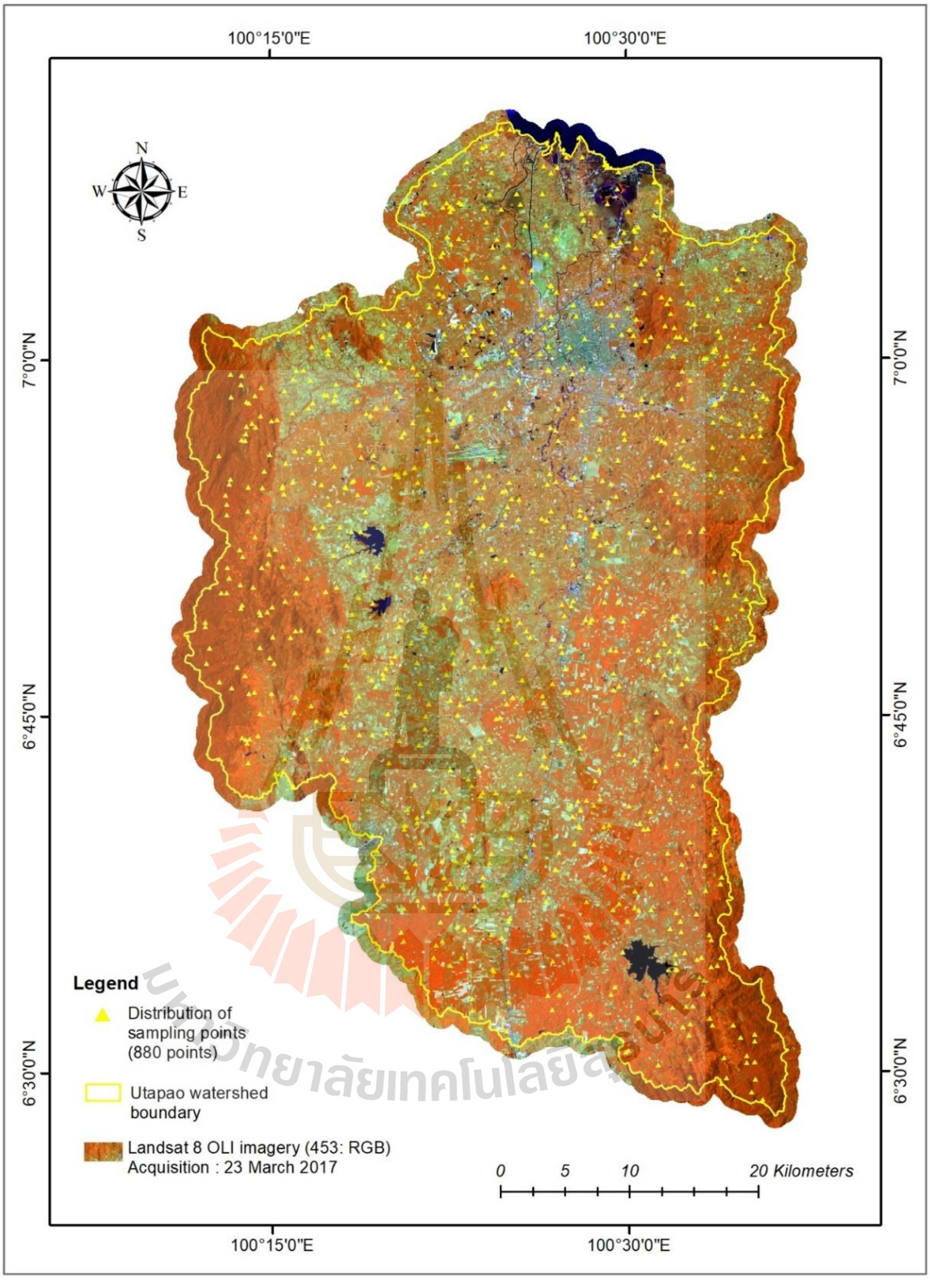


Figure 4.8 Spatial distribution of sampling points superimposed on Landsat-OLI image (23 March 2017) for accuracy assessment of thematic LULC map in 2017.

Table 4.9 Accuracy assessment between reference data and LULC 2017.

	LULC types	Ground reference data from field survey in 2017											
		UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WB**	**ML**	**Total**
Classified LULC data in 2010	Urban and built-up area (UR)	34										7	**41**
	Paddy field (PD)		6									1	**7**
	Rubber plantation (RP)			625				1				6	**632**
	Oil palm plantation (OP)				7								**7**
	Perennial tree/orchard (PO)			1		12							**13**
	Aquatic cultural area (AQ)						3						**3**
	Evergreen forest (EF)			9				84					**93**
	Mangrove forest (MF)								1				**1**
	Marsh and swamp (MS)			4						11			**15**
	Water body (WB)										13	3	**16**
	Miscellaneous land (ML)			17						1		34	**52**
	Total	**34**	**6**	**656**	**7**	**12**	**3**	**85**	**1**	**12**	**13**	**51**	**880**
	Producer's accuracy	**100.00**	**100.00**	**95.27**	**100.00**	**100.00**	**100.00**	**98.82**	**100.00**	**91.67**	**100.00**	**66.67**	
	User's accuracy	**82.93**	**85.71**	**98.89**	**100.00**	**92.31**	**100.00**	**90.32**	**100.00**	**73.33**	**81.25**	**65.38**	
	Overall accuracy	**94.32**											
	Kappa hat coefficient	**87.00**											

As results, it reveals that an overall accuracy is 94.32% and Kappa hat coefficient is 87.00%. Meanwhile PA, which represents omission error, varies between 66.67% for miscellaneous land and 100% for urban and built-up area, paddy field, oil palm plantation, perennial tree/orchard, aquatic cultural area, mangrove forest and water body and UA, which represents commission error, varies between 65.38% for miscellaneous land and 100% for oil palm plantation, aquatic cultural area, and mangrove forest.

Based on Fitzpatrick-Lins (1981), Kappa hat coefficient more than 80 percent represents strong agreement or accuracy between the classified map and the reference map. Additionally, the derived overall accuracy and Kappa hat coefficient in the current study is similar with the previous study of Nguyen, Doan, and Radeloff (2018), who used the RF classifies to classify land cover from Landsat8 OLI data in Dak Lak province of Vietnam and their study provides overall accuracy at 90.32% and Kappa hat coefficient at 0.8434. Likewise, Sakuma, Kameyama, Ono, Kizuka, and Mikami (2017) used the RF classifier to classify land cover from Landsat8 OLI data at Kushiro river watershed in eastern Hokkaido of Japan and their study deliveries overall accuracy at 92% and Kappa hat coefficient at 79%. Thus, the classified LULC in 2017 in this current study can be accepted and can be further applied for LULC change detection between 2010 and 2017.

Similar to LULC 2010 assessment, it can be observed that the significant commission error of rubber plantation comes from miscellaneous land because the appearance of new replanted rubber tree looks like miscellaneous land. Meanwhile, the significant omission error of rubber plantation mostly comes from miscellaneous land and evergreen forest because very young rubber plantation is similar with bare land of miscellaneous land and the brightness value of old rubber plantation is similar with evergreen forest. The phrenological cycle of rubber plantation in each stage which affects brightness value of remotely sensed data is displayed in Figure 4.9.

Clearance stage of rubber plantation | First year of rubber plantation | 3 year of rubber plantation

4-6 years old of rubber plantation | Tapping phase of rubber plantation during 7 to 25 years | The last stage of tapping phase of rubber plantation

Figure 4.9 Field photograph of phenological cycle of rubber plantation.

Furthermore, according to overlay analysis between LULC data in 2017 and standard elevation classification (see Figure 1.3 and Table 1.1), it reveals that most of rubber plantations situate between 0 and 200 m above mean sea level and cover area of 1,668.68 km^2 or 69.34% of its total area. Likewise, most of oil palm plantations locate between 0 and 200 m above mean sea level and cover area of 18.85 km^2 or 0.78% of its total area. On contrary, most of evergreen forests situate between 350 and 750 m above mean sea level and cover area of 111.75 km^2 or 4.64% of its total area (Table 4.10). In the meantime, according to overlay analysis between LULC data in 2017 and slope classification (see Figure 1.4 and Table 1.2), it reveals that most of rubber and oil palm plantations locate at undulating (5-12%) landforms and cover area of 725.94 km^2 or 30.17% and 9.27 km^2 or 0.39% of its total area. In contrast, most of evergreen forests are found at hilly (20-35) and steep (>35%) and cover area of 91.97 km^2 or 3.82% and 89.28 km^2 or 3.71% of its total area, respectively (Table 4.11). These findings reflect an expected distribution of these LULC types accordance with elevation and slope in the study area.

Table 4.10 Area and percentage of LULC type according elevation classification.

Land use and land cover classes	Elevation classification (m)											
	0-200		200-250		250-350		350-750		750-800		> 800	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2.	%
Urban and built-up area	113.21	4.70	-	-	-	-	-	-	-	-	-	-
Paddy field	20.41	0.85	-	-	-	-	-	-	-	-	-	-
Rubber plantation	1,668.68	69.34	31.82	1.32	23.57	0.98	3.39	0.14	-	-	-	-
Oil palm plantation	18.85	0.78	-	-	-	-	-	-	-	-	-	-
Perennial tree and orchard	34.20	1.42	-	-	-	-	-	-	-	-	-	-
Aquatic cultural area	9.38	0.39	-	-	-	-	-	-	-	-	-	-
Evergreen forest	54.82	2.28	34.98	1.45	47.42	1.97	111.75	4.64	3.44	0.14	1.61	0.07
Mangrove forest	0.85	0.04	-	-	-	-	-	-	-	-	-	-
Marsh and swamp	42.70	1.77	-	-	-	-	-	-	-	-	-	-
Water body	42.21	1.75	-	-	0.22	0.01	-	-	-	-	-	-
Miscellaneous land	141.54	5.88	0.54	0.02	0.49	0.02	-	-	-	-	-	-
Total	**2,146.83**	**89.21**	**67.33**	**2.80**	**71.70**	**2.98**	**115.13**	**4.78**	**3.44**	**0.14**	**1.61**	**0.07**

Table 4.11 Area and percentage of LULC type according slope (landform) classification.

Land use and land cover classes	Slope classification (%)											
	0-2		2-5		5-12		12-20		20-35		> 35	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
Urban and built-up area	11.52	0.48	38.11	1.58	50.62	2.10	10.97	0.46	1.80	0.07	0.19	0.01
Paddy field	3.61	0.15	8.84	0.37	7.27	0.30	0.67	0.03	-	-	-	-
Rubber plantation	68.58	2.85	287.06	11.93	725.94	30.17	382.48	15.90	196.29	8.16	67.10	2.79
Oil palm plantation	1.19	0.05	4.64	0.19	9.27	0.39	2.98	0.12	0.72	0.03	0.06	0.00
Perennial tree and orchard	2.02	0.08	8.07	0.34	16.91	0.70	5.90	0.25	1.18	0.05	0.13	0.01
Aquatic cultural area	2.50	0.10	4.03	0.17	2.39	0.10	0.38	0.02	-	-	-	-
Evergreen forest	0.90	0.04	4.51	0.19	23.93	0.99	43.43	1.81	91.97	3.82	89.28	3.71
Mangrove forest	0.33	0.01	0.42	0.02	0.11	0.00	-	-	-	-	-	-
Marsh and swamp	8.57	0.36	19.00	0.79	13.78	0.57	1.26	0.05	-	-	-	-
Water body	6.21	0.26	12.18	0.51	17.01	0.71	5.02	0.21	1.66	0.07	0.47	0.02
Miscellaneous land	8.21	0.34	29.08	1.21	65.88	2.74	29.15	1.21	9.00	0.37	1.26	0.05
Total	**113.64**	**4.72**	**415.94**	**17.29**	**933.11**	**38.78**	**482.24**	**20.04**	**302.62**	**12.58**	**158.49**	**6.59**

In summary, it can be here concluded that the RF classifier under the EnMap BOX software can be used as efficient tool to classify LULC from remotely sensed data since it can provide high classification accuracy. In the current study, overall accuracy varies from 91.36% to 94.32% and Kappa hat coefficient ranges from 84.00% to 87.00%. Additionally, key advantages of RF classifier include their non-parametric nature and capability to determine variable importance. In practice, the random forests classifier calculates a response variable (band variable) by creating many (usually several hundred) different decision trees (the forest of trees) and all trees are compared to classify LULC types using majority voting. However, the split rules for classification are unknown, therefore the RF can be considered to be black box type classifier. The application of the RF classifier under the EnMap BOX software, user requires to observe the preliminary LULC result and add more training sample points to increase accuracy of classification as mentioned by Tatsumi, Yamashiki, Torres, and Taipe (2015).

4.3 LULC change between 2010 and 2017

Simple comparison of LULC change area with its change rate between 2010 and 2017 is presented in Table 4.12 and Figure 4.10.

Table 4.12 Comparison of LULC change between 2010 and 2017.

LULC	LULC type (Area in km^2)										
	UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
In 2010	80.37	28.56	1,672.66	5.50	31.66	8.42	318.52	0.74	48.61	33.27	177.75
In 2017	113.21	20.41	1,727.46	18.85	34.20	9.38	254.01	0.85	42.70	42.43	142.57
Change area	**32.84**	**-8.16**	**54.80**	**13.35**	**2.54**	**0.96**	**-64.51**	**0.12**	**-5.91**	**9.16**	**-35.18**
Annual change rate	**4.69**	**-1.17**	**7.83**	**1.91**	**0.36**	**0.14**	**-9.22**	**0.02**	**-0.84**	**1.31**	**-5.03**
Percentage of change	**1.36**	**-0.34**	**2.28**	**0.55**	**0.11**	**0.04**	**-2.68**	**0.00**	**-0.25**	**0.38**	**-1.46**

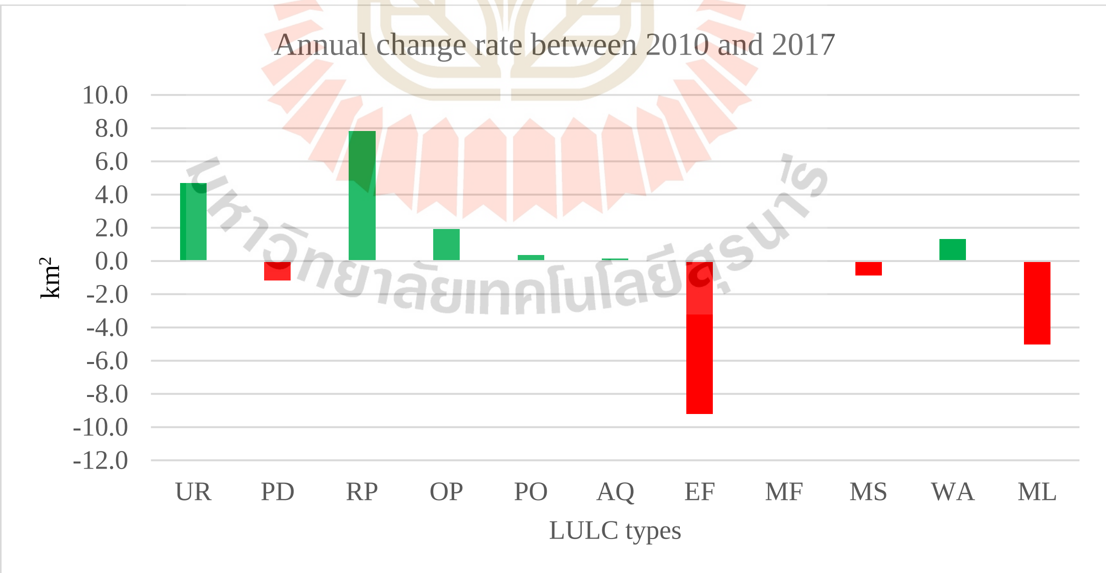


Figure 4.10 Comparison of annual change rate of LULC type between 2010 and 2017.

As results, major increasing LULC types between 2010 and 2017 are rubber plantation and urban and built-up area with annual change rate of 7.83 and 4.69 km^2/year, respectively, and minor increasing LULC types in this period are palm plantation, water body, perennial tree and orchard, aquatic cultural area, and mangrove forest with annual change rate of 1.91, 1.31, 0.36, 0.14 and 0.02 km^2/year, respectively. In opposite, the major decreasing LULC types between 2010 and 2017 are evergreen forest and miscellaneous land with annual change rate of 9.22 and 5.03 km^2/year, respectively, and minor decreasing LULC types in this period are paddy field and marsh and swamp with annual change rate of 1.17 and 0.84 km^2/year, respectively. The change pattern of LULC types between 2010 and 2017 of this study is similar to land use change pattern of land use classes of LDD between 2010 and 2016. (see Table 1.3 and Figures 1.5 to 1.7 in Chapter I).

Meanwhile, a transitional change matrix of LULC between 2010 and 2017 which provides from-to change class information is summarized in Table 4.13 and LULC change map is displayed in Figure 4.11.

Table 4.13 LULC change between 2010 and 2017 as transitional matrix.

	LULC types	LULC 2017 (km^2)											
		UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**	**Total**
LULC2 010 (km^2)	Urban and built-up area (UR)	80.37	-	-	-	-	-	-	-	-	-	-	**80.37**
	Paddy field (PD)	0.61	20.41	6.55	0.02	0.08	-	-	-	-	0.20	0.70	**28.56**
	Rubber plantation (RP)	24.52	-	1,528.37	12.06	-	-	-	-	-	6.78	100.93	**1,672.66**
	Oil palm plantation (OP)	-	-	-	5.50	-	-	-	-	-	-	-	**5.50**
	Perennial tree/orchard (PO)	0.67	-	-	-	30.43	-	-	-	-	-	0.57	**31.66**
	Aquatic cultural area (AQ)	-	-	-	-	-	8.42	-	-	-	-	-	**8.42**
	Evergreen forest (EF)	0.05	-	63.33	0.14	0.30	-	254.01	-	-	0.20	0.49	**318.52**
	Mangrove forest (MF)	-	-	-	0.01	-	0.02	-	0.64	-	0.02	0.06	**0.74**
	Marsh and swamp (MS)	0.93	-	-	0.28	0.16	0.40	-	0.22	42.70	1.37	2.56	**48.61**
	Water body (WA)	-	-	-	-	-	-	-	-	-	32.21	1.06	**33.27**
	Miscellaneous land (ML)	6.07	-	129.21	0.85	3.24	0.54	-	-	-	1.64	36.22	**177.75**
	Total	**113.21**	**20.41**	**1,727.46**	**18.85**	**34.20**	**9.38**	**254.01**	**0.85**	**42.70**	**42.43**	**142.57**	**2,406.04**

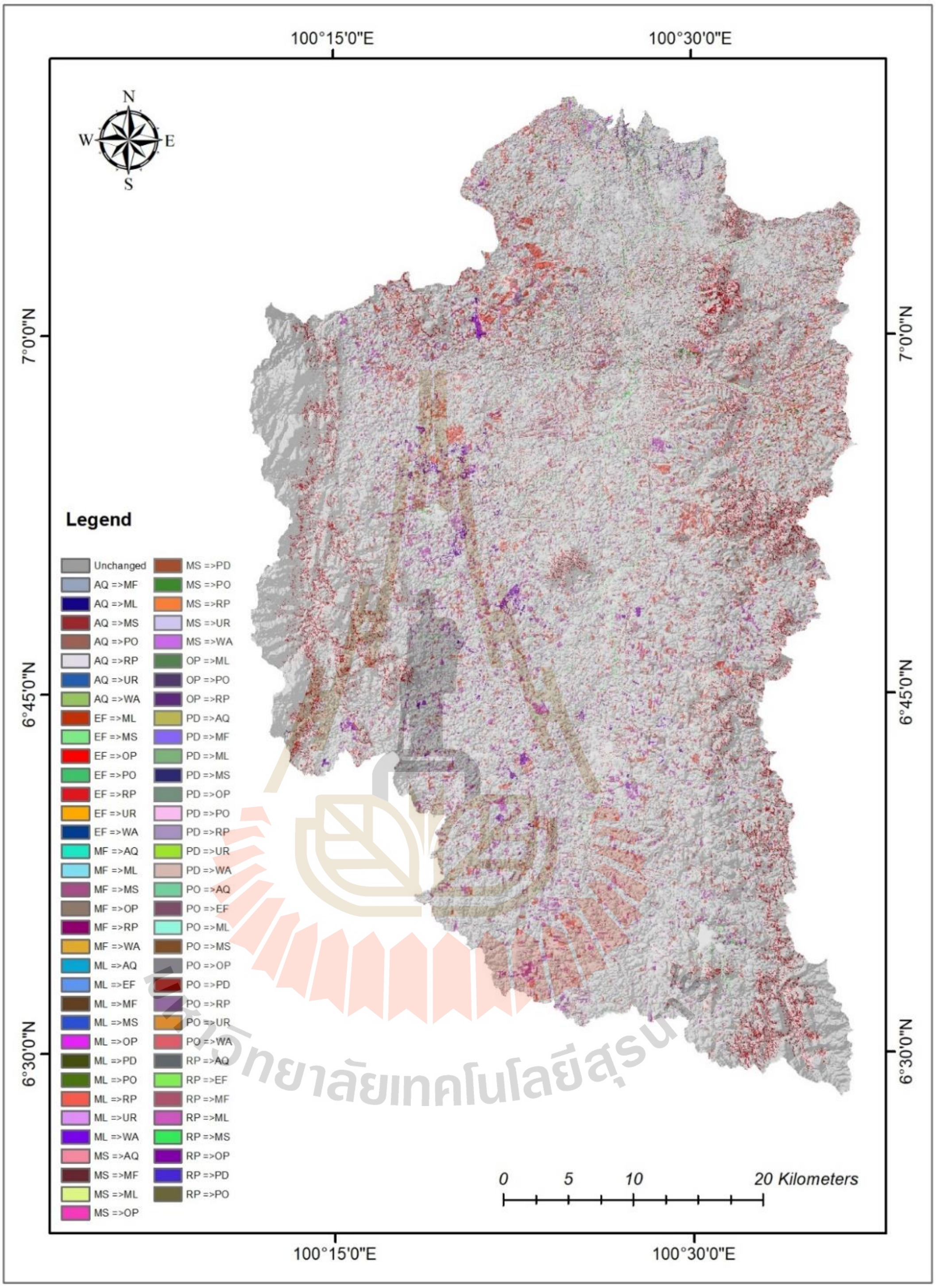


Figure 4.11 Distribution of LULC change between 2010 and 2017.

As results, urban and built-up areas in 2010 are not converted into other LULC classes in 2017 and the increasing area of urban and built area in 2017 mainly comes from rubber plantation (24.52 km^2) and miscellaneous land (6.07 km^2) in 2010. Similarly, oil palm plantation in 2010 are not converted into other LULC classes in 2017 and the increasing areas of oil palm plantation in 2017 mostly come from rubber plantation (12.06 km^2) in 2010. This finding indicates influence of government policy on para-rubber to oil palm conversion (Ministry of Agriculture and Cooperatives, 2014). Likewise, aquatic cultural area in 2010 are not converted into other LULC classes in 2017 and the increasing areas of this type in 2017 mainly come from miscellaneous land (0.54 km^2) and marsh and swamp (0.40 km^2) in 2010.

In contrast, areas of paddy field in 2010 are converted into urban and built-up area (0.61 km^2), rubber plantation (6.55 km^2), oil palm plantation (0.02 km^2), perennial trees and orchard (0.08 km^2), water body (0.20 km^2) and miscellaneous land (0.70 km^2) in 2017. Likewise, rubber plantation in 2010 are converted into urban and built-up area (24.52 km^2), oil palm plantation (12.06 km^2), water body (6.78 km^2) and miscellaneous land (100.93 km^2) in 2017. This finding indicates some old rubber plantations are clear cut after 2010 and their areas appear as bare land in 2017.

Similarly, areas of perennial tree and orchard in 2010 are converted into urban and built-up area (0.67 km^2), and miscellaneous land (0.57 km^2) in 2017. Meanwhile, evergreen forests in 2010 are converted into urban and built-up area (0.05 km^2), rubber plantation (63.33 km^2), oil palm plantation (0.14 km^2), perennial tree and orchard (0.30 km^2), water body (0.20 km^2) and miscellaneous land (0.49 km^2) in 2017. This finding indicates forest encroachment in the study area for rubber plantation. The observation is consistent with the previous study of Doungsuwan et al. (2013) who are found forest land at Watershed Class I of U-Tapao watershed has been converted to rubber plantations. Likewise, Gyawali et al. (2013) mentioned that deforestation that taken place in SLB is converted into rubber plantation.

Likewise, mangrove forests in 2010 are marginally converted into oil palm plantation (0.01 km^2), aquatic cultural area (0.02 km^2), water body (0.02 km^2) and miscellaneous land (0.06 km^2) in 2017. Similarly, marsh and swamp in 2010 are converted into urban and built-up area (0.93 km^2), oil palm plantation (0.28 km^2), perennial tree and orchard (0.16 km^2), aquatic cultural area (0.40 km^2), mangrove forest (0.22 km^2), water body (1.37 km^2) and miscellaneous land (2.56 km^2) in 2017. In the meantime, areas of water body in 2010 are converted in miscellaneous land (1.06 km^2) in 2017. Whilst, miscellaneous land in 2010 are converted into urban and built-up area (6.07 km^2), rubber plantation (129.21 km^2), oil palm plantation (0.85 km^2), perennial tree and orchard (3.24 km^2), aquatic cultural area (0.54 km^2), and water body (1.64 km^2).

The increasing of rubber and oil palm plantations during 2010 and 2017 because of prices of rubber and palm oil. The prices of para-rubber (unsmoked rubber sheets grade III) reached 132.43 Baht/kg in 2011 and oil palm reached 6.02 Baht/kg in 2011 (Bank of Thailand, 2018) as shown in Figure 4.12. However, price of para-rubber tends to decrease in the future but price of oil palm is rather stable in the future.

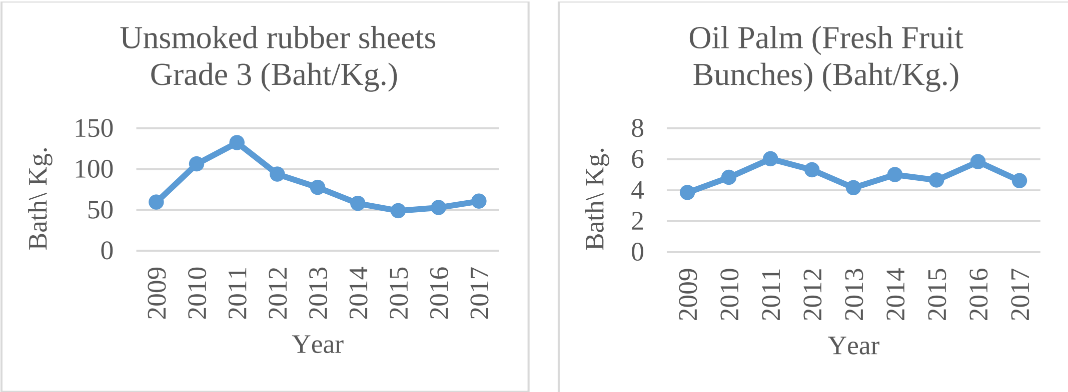


Figure 4.12 Dynamic prices of rubber and palm oil during 2009 to 2017.

According to LULC change between 2010 and 2017 matrix, highlight decreased, increased and unchanged areas of rubber and oil palm plantation during 2010 and 2017 are displayed in Figures 4.13 and 4.14, respectively.

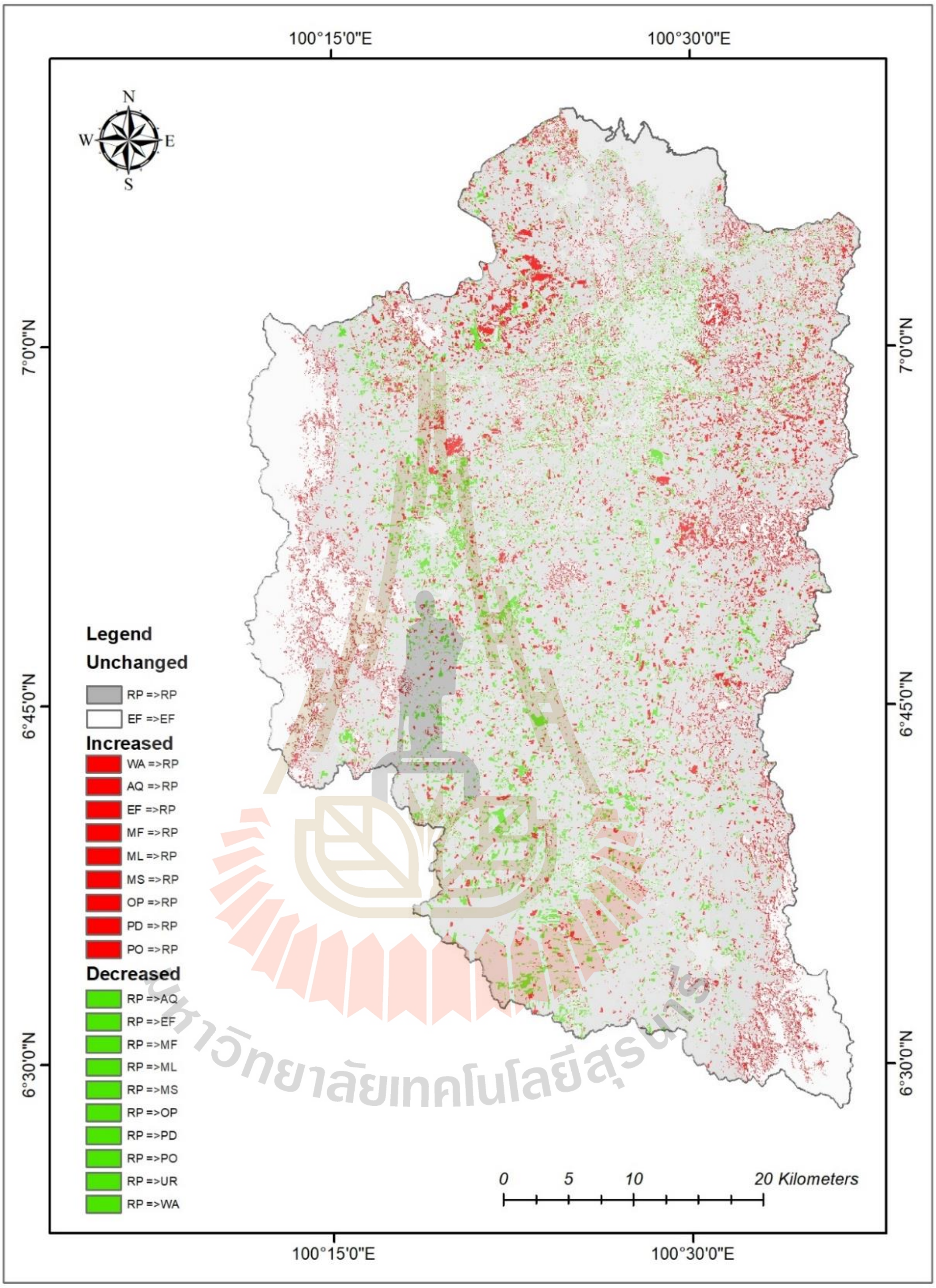


Figure 4.13 Distribution of decreased, increased and unchanged areas of rubber plantation between 2010 and 2017.

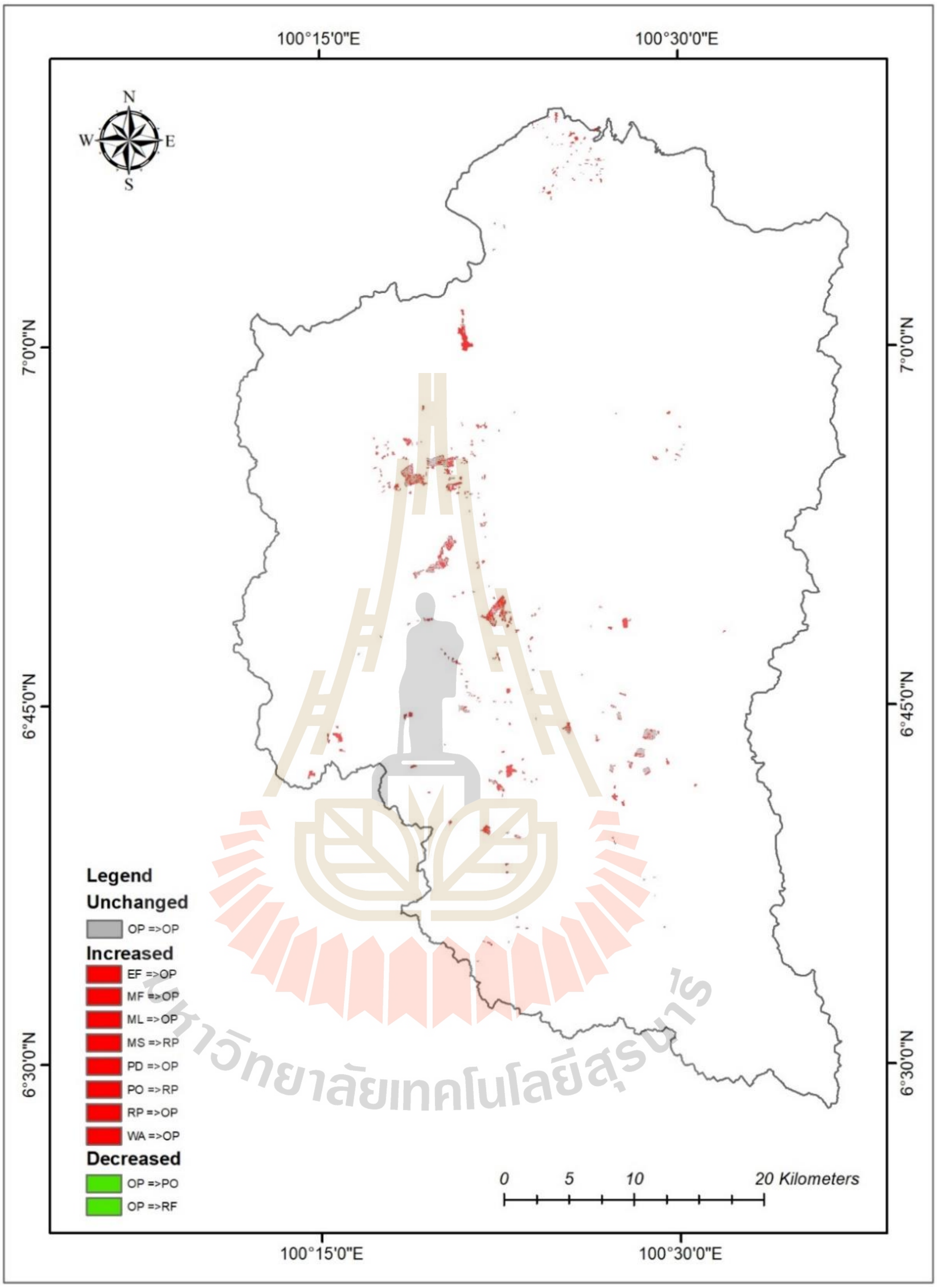


Figure 4.14 Distribution of decreased, increased and unchanged areas of oil palm plantation between 2010 and 2017.

In addition, based on the historical record data of LDD (2009, 2012, and 2016) and the current study data (2010 and 2017), urban and built-up area, rubber plantation, oil palm plantation and evergreen forest can be explored and compared during 2009 to 2017 as display in Figures 4.15 to 4.18, respectively.

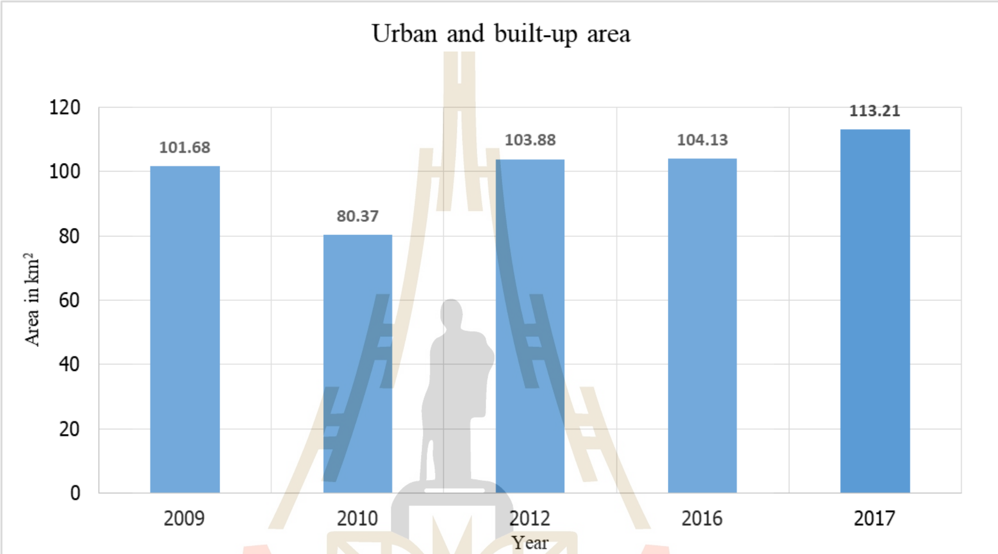


Figure 4.15 Area of urban and built-up area during 2009 to 2017.

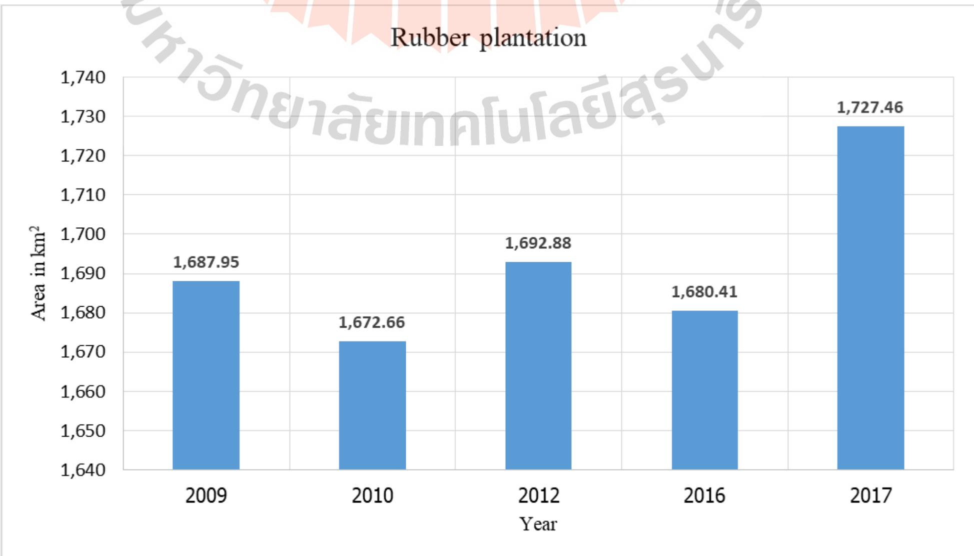


Figure 4.16 Area of rubber plantation during 2009 to 2017.

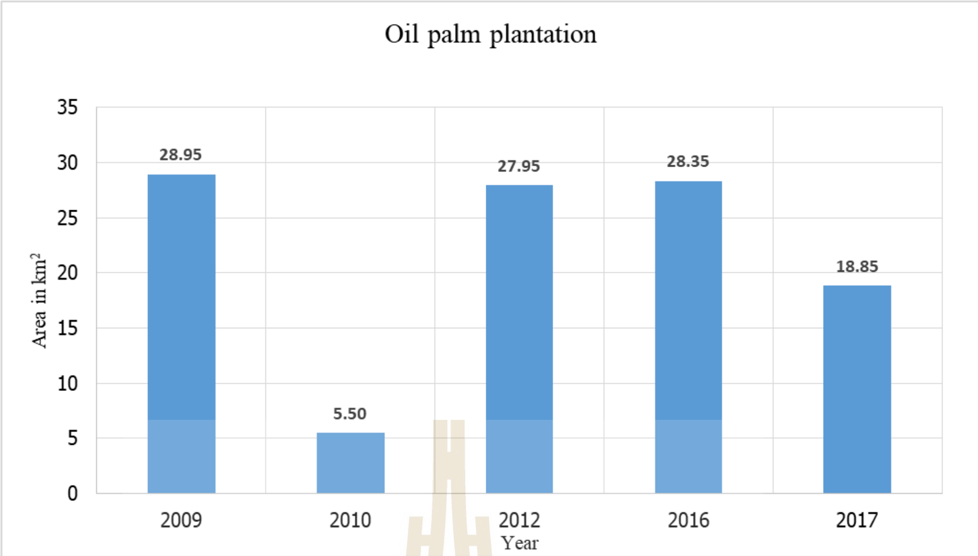


Figure 4.17 Area of oil palm plantation during 2009 to 2017.

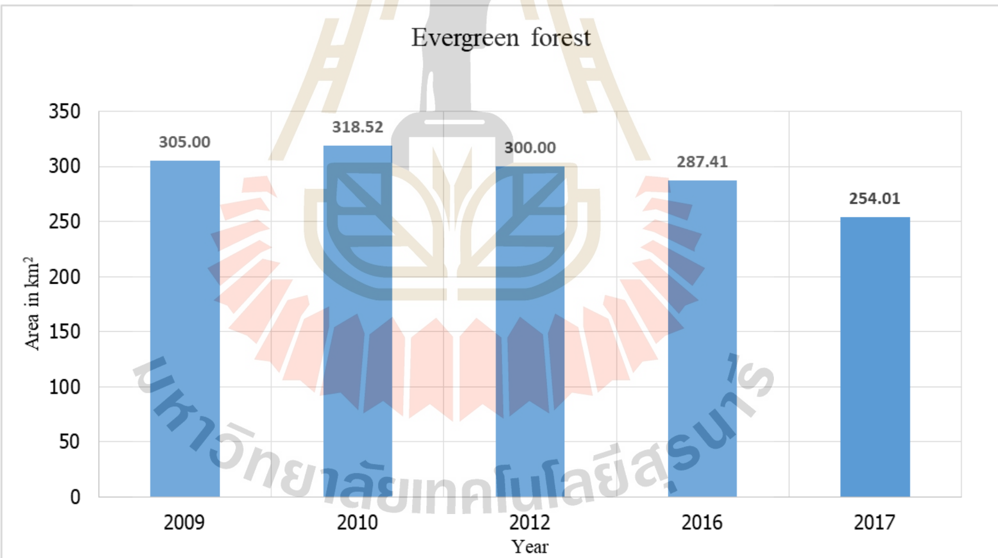


Figure 4.18 Area of evergreen forest area during 2009 to 2017.

As results, it can be here concluded that area of rubber plantation and oil palm plantation in the study area are fluctuate during 2009 to 2017, this finding suggests that the fluctuated areas of rubber and oil palm plantations may be dictated by labor, price, and market. Meanwhile, in this period area of urban and built-up area continuously increase whereas as area of evergreen forest continuously decreases due to socio-economic development and pressure on natural resources. Therefore, government policy on forest conservation and prevention and agriculture production extension should be carefully implemented and people awareness on natural resources and environments should be intensively campaigned.

CHAPTER V

LAND USE AND LAND COVER PREDICTION OF THREE DIFFERENT SCENARIOS

This chapter presents results of the second objective focusing on prediction of LULC in three different LUC scenarios using CLUE-S model. The main results which consist of (1) driving force on LULC change, (2) local parameter of CLUE-S model for LULC prediction, (3) LULC prediction of Scenario I: Historical LULC evolution, (4) LULC prediction of Scenario II: Forest conservation and prevention, (5) LULC prediction of Scenario III: Agriculture production extension and (6) comparison of LULC prediction among three different scenarios are here described and discussed in details.

5.1 Driving force on LULC change

Under CLUE-S model, logistic regression analysis was firstly performed to identify LULC type location preference according to driving force on LULC change. In this study, 8 driving factors on LULC change include elevation, slope, soil fertility, distance to road, distance to settlement, distance to water bodies, population density at sub-district level and average household income at sub-district level (Figure 5.1) were examined as same as Ongsomwang and Boonchoo (2016). The result of multicollinearity test among independent variable with VIF values is summarized in

Table 5.1 while multiple linear regression equation of each LULC type location preference with AUC value by logistic regression analysis is summarized in Table 5.2.

Table 5.1 Multicollinearity statistics test of driving factors effect to LULC type.

Driving factor	Unstandardized Coefficients		Standardized Coefficient	t-test	Sig.	VIF
	Beta	Std. error				
Elevation (X_1)	0.0054	0.0001	0.2743	76.4738	0.0000	3.6138
Slope (X_2)	0.0017	0.0004	0.0094	4.2833	0.0000	1.3602
Distance to water bodies (X_3)	-0.0001	0.0000	-0.0681	-30.1425	0.0000	1.4320
Distance to road (X_4)	0.0000	0.0000	0.0129	3.3755	0.0007	4.1062
Distance to settlement (X_5)	0.0001	0.0000	0.0904	21.1399	0.0000	5.1322
Soil fertility (X_6)	0.1152	0.0065	0.0358	17.7084	0.0000	1.1509
Population density at sub-district level (X_7)	-0.0003	0.0000	-0.0768	-39.4597	0.0000	1.0649
Average household income at sub-district level (X_8)	0.0000	0.0000	0.0077	3.8363	0.0001	1.1218

The details of driving force on each LULC type allocation with its equation are separately explained and discussed in the following section.

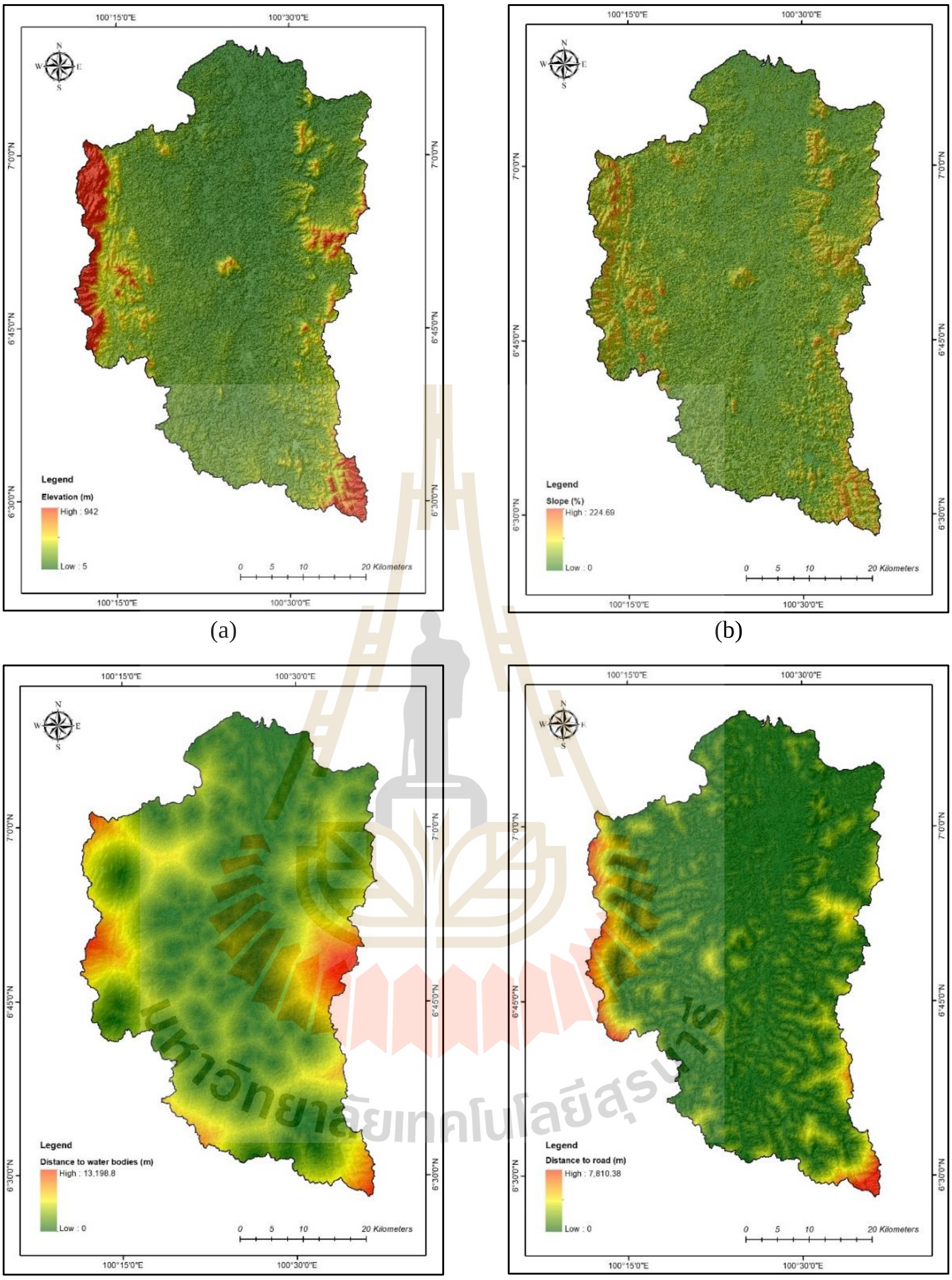
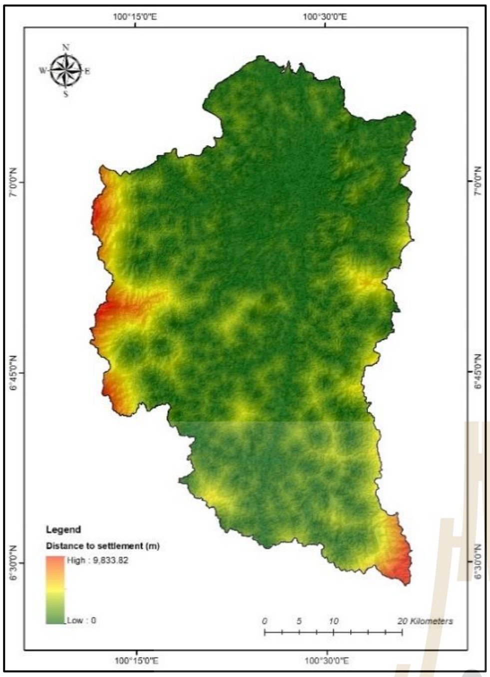
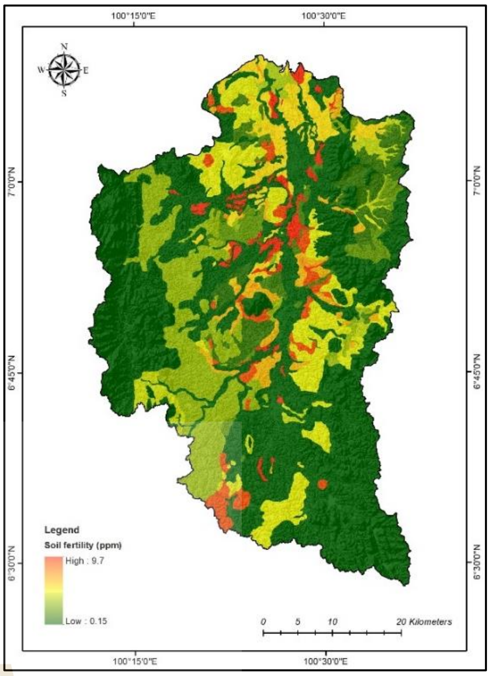


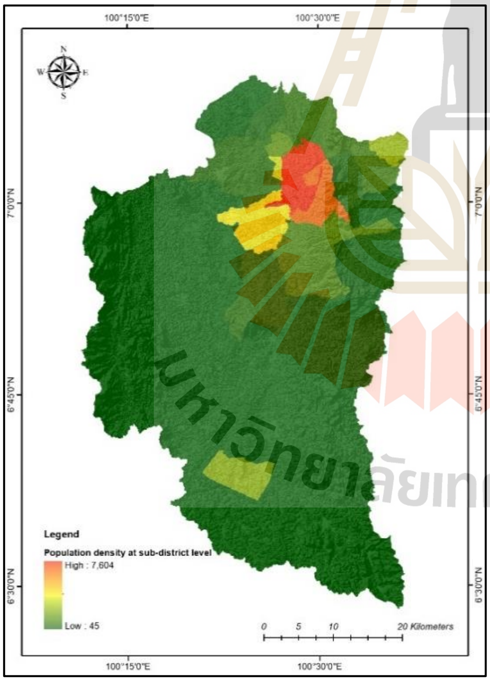
Figure 5.1 Driving factors on LULC change: (a) Elevation (m), (b) Slope (%), (c) Distance to water bodies (m), (d) Distance to road (m), (e) Distance to settlement (m), (f) Soil fertility (ppm), (g) Population density at sub-district level, and (h) Average household income at sub-district level.



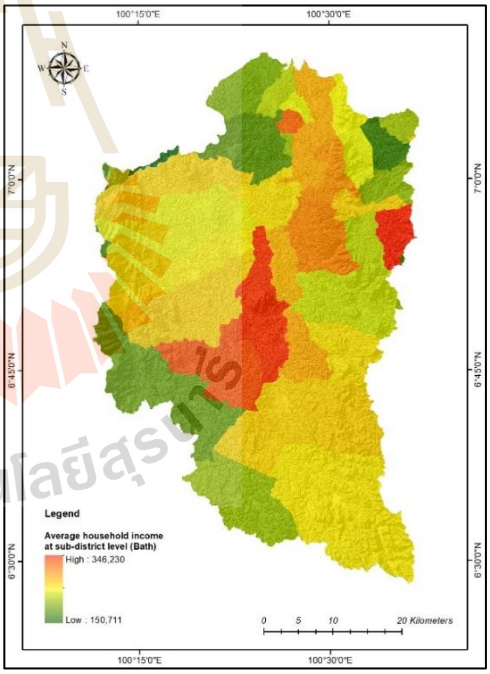
(e)



(f)



(g)



(h)

Figure 5.1 (Continued).

Table 5.2 Multiple linear regression equation of each LULC type location preference and AUC value by logistic regression analysis.

Driving forces	UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
Constance	**1.38385**	**-1.14434**	**1.88992**	**-1.97944**	**-2.24908**	**4.61902**	**-5.86713**	**-5.23663**	**-0.13432**	**-1.72500**	**-2.02410**
Elevation (X_1)	n. s.	-0.14309	-0.00886	-0.04468	n. s.	n. s.	0.01739	-0.16692	-0.18036	-0.01918	-0.00575
Slope (X_2)	n. s.	-0.01492	0.00783	n. s.	-0.01822	-0.02990	0.02535	-0.12290	-0.01977	n. s.	-0.00881
Distance to water bodies (X_3)	n. s.	-0.00007	0.00017	-0.00014	-0.00004	-0.05055	-0.00002	-0.00138	-0.00007	-0.00195	n. s.
Distance to road (X_4)	-0.00525	n. s.	-0.00010	0.00083	-0.00171	0.00349	-0.00018	0.01290	n. s.	0.00225	-0.00013
Distance to settlement (X_5)	-0.08573	0.00060	-0.00010	0.00065	-0.00068	-0.00437	0.00056	-0.00793	0.00146	-0.00062	-0.00009
Soil fertility (X_6)	n. s.	0.13810	0.27457	0.13375	0.32979	n. s.	0.00012	n. s.	n. s.	n. s.	n. s.
Population density at sub-district level (X_7)	0.00014	-0.00030	-0.00113	-0.01051	-0.00034	n. s.	n. s.	n. s.	-0.00035	-0.00012	-0.00037
Average household income at sub-district level (X_8)	0.00005	n. s.	n. s.	n. s.	-0.00004	-0.00056	n. s.	n. s.	n. s.	n. s.	n. s.
AUC	**0.99570**	**0.94190**	**0.91400**	**0.83900**	**0.85610**	**0.99320**	**0.98330**	**0.97100**	**0.96030**	**0.90690**	**0.72390**

Remark: All explanatory variables are significant at $p < 0.05$ error level; n. s. is not significant at 0.05 level; AUC, area under the curve.

5.1.1 Driving force for urban and built-up area allocation

The multiple linear equation of the binomial logit regression model for urban and built-up area allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 1.38385 - 0.00525X_4 - 0.08573X_5 + 0.00014X_7 + 0.00005X_8 \quad (5.1)$$

Where

X_4 is Distance to road (m);

X_5 is Distance to settlement (m);

X_7 is Population density at sub-district level (persons per km^2); and

X_8 is Average household income at sub-district level (baht per household).

According to Eq. 5.1, two driving factors include distance to road and settlement have negative relationship with the probability of urban and built-up area allocation, but two driving factors include population density and average household income at sub-district levels have positive relationship with the probability of urban and built-up area allocation. All significant driving factors truly play an important role for urban and built-up area allocation. These results imply that when the distance to road and settlement decreases, the probability of urban and built-up area's occurrence increases. Meanwhile, when the population density and average household income at sub-district level increase, the probability of urban and built-up area's occurrence increases.

In addition, the AUC value for urban and built-up area allocation with value of 0.99 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.2 Driving force for paddy field allocation

The multiple linear equation of the binomial logit regression model for paddy field allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -1.14434 - 0.14309X_1 - 0.01492X_2 - 0.00007X_3 + 0.0006X_5 + 0.13810X_6 - 0.0003X_7 \quad (5.2)$$

Where

X_1 is Elevation (m);

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_5 is Distance to settlement (m);

X_6 is Soil fertility (N, P, K); and

X_7 is Population density at sub-district level (persons per km^2).

According to Eq. 5.2, four driving factors include elevation, slope, distance to water bodies and population density at sub-district level have negative relationship with the probability of paddy field allocation, but two driving factors include distance to settlement and soil fertility have positive relationship with the probability of paddy field allocation. All significant driving factors play an important role for paddy filed allocation. These results indicate that paddy filed prefers to situate at low elevation and flat area, close to water bodies, far from settlement, area with low population density and high soil fertility.

In addition, the AUC value for paddy field allocation with value of 0.94 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.3 Driving force for rubber plantation allocation

The equation of the binomial logit regression model for rubber plantation allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 1.88992 - 0.00886X_1 + 0.00783X_2 + 0.00017X_3 - 0.0001X_4 - 0.0001X_5 + 0.27457X_6 - 0.00113X_7 \quad (5.3)$$

Where

X_1 is Elevation (m);

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m);

X_6 is Soil fertility (N, P, K); and

X_7 is Population density at sub-district level (person per km^2)

Refer to Eq. 5.3, four driving factors include elevation, distance to road and settlement and population density at sub-district level have negative relationship with the probability of rubber plantation allocation, but three driving factors include slope, distance to water bodies and soil fertility have positive relationship with the probability of rubber plantation allocation. All significant driving factors play an important role for rubber plantation allocation. These results show that rubber plantation prefers to situate at low elevation and steep slope, close to road network and settlement, far from water bodies, area with low population density and high soil fertility.

In addition, the AUC value for rubber plantation allocation with value of 0.91 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.4 Driving force for oil palm plantation allocation

The equation of the binomial logit regression model for oil palm plantation allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -1.97944 - 0.04468X_1 - 0.00014X_3 + 0.00083X_4 + 0.00065X_5 + 0.13375X_6 - 0.01051X_7 \quad (5.4)$$

Where

X_1 is Elevation (m);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m);

X_6 is Soil fertility (N, P, K); and

X_7 is Population density at sub-district level (person per km^2)

According to Eq. 5.4, three driving factors include elevation, distance to water bodies and population density at sub-district level have negative relationship with the probability of oil palm plantation allocation, but three driving factors include distance to road and settlement, and soil fertility have positive relationship with the probability of oil palm plantation allocation. All significant driving factors play an important role for oil palm plantation allocation. These results demonstrate that oil palm plantation prefers to situate at low elevation, close to water bodies, far from road network and settlement, area with low population density at sub-district level and high soil fertility.

In addition, the AUC value for oil palm plantation allocation is 0.84, it suggests good fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.5 Driving force for perennial tree/orchard allocation

The equation of the binomial logit regression model for perennial tree / orchard allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -2.24908 - 0.01822X_2 - 0.00004X_3 - 0.00171X_4 - 0.00068X_5 + 0.32979X_6 - 0.00034X_7 - 0.00004X_8 \quad (5.5)$$

Where

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m);

X_6 is Soil fertility (N, P, K);

X_7 is Population density at sub-district level (person per km^2); and

X_8 is Average household income at sub-district level (baht per household)

According to Eq. 5.5, six driving factors include slope, distance to water bodies, distance to road and settlement, population density and average household income at sub-district level have negative relationship with the probability of perennial tree/orchard allocation, but only one driving factor, namely soil fertility, has positive relationship with the probability of perennial tree/orchard allocation. All significant driving factors play an important role for perennial tree/orchard allocation. These results reveal that perennial tree/orchard prefers to situate at flat area, close to road network, settlement and water bodies, area with low population density and average household income at sub-district levels and high soil fertility.

In addition, the AUC value for perennial tree/orchard allocation is 0.86, it suggests good fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.6 Driving force for aquatic cultural area allocation

The equation of the binomial logit regression model for aquatic cultural area allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = 4.61902 - 0.02990X_2 - 0.05055X_3 + 0.00349X_4 - 0.00437X_5 + 0.00056X_8 \quad (5.6)$$

Where

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m); and

X_8 is Average household income at sub-district level (baht per household)

According to Eq. 5.6, three driving factors include slope, distance to water bodies and settlement have negative relationship with the probability of aquatic cultural area allocation, but two driving factors include distance to road and average household income at sub-district level have positive relationship with the probability of aquatic cultural area allocation. All significant driving factors play an important role for aquatic cultural area allocation. These results disclose that aquatic cultural area prefers to locate at flat area, close to settlement and water bodies, far from road network and area with high average household income at district level.

In addition, the AUC value for aquatic cultural area allocation with value of 0.99 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.7 Driving force for evergreen forest allocation

The equation of the binomial logit regression model for evergreen forest allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -5.86713 + 0.01739X_1 + 0.002535X_2 - 0.00002X_3 - 0.00018X_4 + 0.00056X_5 + 0.00012X_6 \quad (5.7)$$

Where

X_1 is Elevation (m);

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m); and

X_6 is Soil fertility (N, P, K)

According to Eq. 5.7, two driving factors include distance to water bodies and road have negative relationship with the probability of evergreen forest allocation, but four driving factors include elevation, slope, distance to settlement and soil fertility have positive relationship with the probability of evergreen forest allocation. All significant driving factors play an important role for evergreen forest allocation. These results reveal that evergreen forest mostly situate at high elevation, steep slope, close to road network and water bodies, far from settlement and high soil fertility.

In addition, the AUC value for evergreen forest allocation with value of 0.98 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.8 Driving force for mangrove forest allocation

The equation of the binomial logit regression model for mangrove forest allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -5.23663 - 0.16692X_1 - 0.12290X_2 - 0.00138X_3 + 0.0129X_4 - 0.00793X_5 \quad (5.8)$$

Where

X_1	is	Elevation (m);
X_2	is	Slope (%);
X_3	is	Distance to water bodies (m);
X_4	is	Distance to road (m); and
X_5	is	Distance to settlement (m)

According to Eq. 5.8, four driving factors include elevation, slope, distance to water bodies and settlement have negative relationship with the probability of mangrove forest allocation, but only one driving factor, distance to road, has positive relationship with the probability of mangrove forest allocation. All significant driving factors play an important role for mangrove forest allocation. These results disclose that mangrove forest mostly situate at low elevation, flat area, close to water bodies and settlement and far from road network.

In addition, the AUC value for mangrove forest allocation with value of 0.97 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.9 Driving force for marsh and swamp allocation

The equation of the binomial logit regression model for marsh and swamp allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -0.13432 - 0.18036X_1 - 0.01977X_2 - 0.00007X_3 + 0.00146X_5 - 0.00035X_7 \quad (5.9)$$

Where

X_1 is Elevation (m);

X_2 is Slope (%);

X_3 is Distance to water bodies (m);

X_5 is Distance to settlement (m); and

X_7 is Population density at sub-district level (person per km^2)

According to Eq. 5.9, four driving factors include elevation, slope, distance to water bodies and population density at sub-district level have negative relationship with the probability of marsh and swamp allocation, but only one driving factor, distance to settlement, has positive relationship with the probability of marsh and swamp area allocation. All significant driving factors play an important role for marsh and swamp allocation. These results reveal that marsh and swamp mostly situate at low elevation, flat area, close to water bodies, low population density area at district level and far from settlement.

In addition, the AUC value for mangrove forest allocation with value of 0.96 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.10 Driving force for water body allocation

The equation of the binomial logit regression model for water body allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -1.7250 - 0.01918X_1 + 0.00195X_3 + 0.00225X_4 - 0.00062X_5 - 0.00012X_7 \quad (5.10)$$

Where

X_1 is Elevation (m);

X_3 is Distance to water bodies (m);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m); and

X_7 is Population density at sub-district level (person per km^2)

According to Eq. 5.10, three driving factors include elevation, distance to settlement and population density at sub-district level have negative relationship with the probability of water body allocation, but two driving factors include distance to water bodies and road have positive relationship with the probability of water body allocation. All significant driving factors play an important role for water body allocation. These results reveal that water body mostly situate at flat area, close to settlement, far from water bodies and road network and area with low population density area at district level.

In addition, the AUC value for water body allocation with value of 0.91 is more than 0.9, it suggests an excellent fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

5.1.11 Driving force for miscellaneous land allocation

The equation of the binomial logit regression model for miscellaneous land allocation after multicollinearity test is as follows:

$$Log\left(\frac{P_i}{1-P_i}\right) = -2.0241 - 0.00575X_1 - 0.00881X_2 - 0.00013X_4 - 0.00009X_5 - 0.00037X_7 \quad (5.11)$$

Where

X_1 is Elevation (m);

X_2 is Slope (%);

X_4 is Distance to road (m);

X_5 is Distance to settlement (m); and

X_7 is Population density at sub-district level (person per km^2)

According to Eq. 5.11, all five significant driving factors include elevation, slope, distance to road and settlement and population density at sub-district level have negative relationship with the probability of miscellaneous land allocation. All significant driving factors play an important role for miscellaneous land allocation. These results reveal that miscellaneous land mostly situate at low elevation, flat area, close to road network and settlement and area with low population density at sub-district level.

In addition, the AUC value for miscellaneous land allocation is 0.72, it suggests fair fit between the predicted and real LULC transition (Pontius and Schneider, 2001).

In summary, it can be here concluded that the most significant driving factor for all LULC type allocation in the study area is distance to settlement. Meanwhile the second important driving factors for LULC type allocation are distance to water bodies and road network. In the meantime, the third important driving factors for LULC type allocation area are elevation, slope, and population density at sub-district level. In the meantime, soil fertility (N, P, and K) plays important role for land allocation of paddy field, rubber plantation, oil palm plantation, perennial trees/orchard, and evergreen forest. Likewise, an average household income at sub-district level plays important role for land allocation of urban and built-up area, perennial trees/orchard, and aquatic cultural area. The derived driving factors of each LULC type are further used by CLUE-S model for LULC allocation during simulation process.

These findings are similar with the previous works of Boonchoo (2016) who found the most common driving factor for all LULC types (except paddy field) in 9 protected forest areas in Phuket Island is distance to settlement.

Furthermore, the derived AUC values for each LULC type allocation using binomial logit regression analysis exhibit excellent and good fit between the predicted and real LULC transition as mentioned by Pontius and Schneider (2001).

5.2 Local parameter of CLUE-S model for LULC prediction

Two common local parameters of CLUE-S model for LULC prediction of three different scenarios consist of conversion matrix and elasticity of LULC change are here considered and assigned based on transitional change matrix between LULC data in 2017 and 2024. In principle, conversion matrix, which shows the possibility for LULC change among LULC types, are assigned as 1 when it is allowed or as 0 when it is not allowed. In the meantime, elasticity, which represents cost for change among LULC types, is set up according to the transitional probability change matrix in the past period.

According transitional change matrix between LULC data in 2017 and 2024 (Table 4.11), urban and built-up areas, aqua cultural area and oil palm plantation in 2017 are not converted into other LULC classes in 2018 while others LULC classes in 2017 include paddy field, rubber plantation, perennial tree/orchard, evergreen forest, mangrove forest, marsh and swamp, water body and miscellaneous are converted into other various LULC classes in 2024. Therefore, conversion matrix of LULC change between 2017 and 2024 for LULC prediction in 2024 can be assigned as summary in Table 5.3.

Meanwhile, elasticity that is assigned according to the transition probability matrix of LULC change between 2010 and 2024 by Markov chain model is presented in Table 5.4. Herewith elasticity values as probability value for urban and built-up area, paddy field, rubber plantation, oil palm plantation, perennial tree / orchard, aquatic cultural area, evergreen forest, mangrove forest, marsh and swamp, water body and miscellaneous land are 1, 0.72, 0.91, 1, 0.98, 1, 0.80, 0.86, 0.88, 0.97, and 0.20 respectively. This assignment agrees with suggestion of Iamchuen (2014) who found that an optimum local parameter for LULC prediction under CLUE-S model should be probability values of transition probability matrix of LULC change between two periods. (See Table 5.4).

Table 5.3 Conversion matrix of possible LULC change between 2017 and 2024.

	LULC Types	Possible change in 2024										
		UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
LULC in 2017	Urban and built-up area (UR)	1	0	0	0	0	0	0	0	0	0	0
	Paddy field (PD)	1	1	1	1	1	0	0	0	0	1	1
	Rubber plantation (RP)	1	0	1	1	0	0	0	0	0	1	1
	Oil palm plantation (OP)	0	0	0	1	0	0	0	0	0	0	0
	Perennial tree / orchard (PO)	1	0	0	0	1	0	0	0	0	0	1
	Aquatic cultural area (AQ)	0	0	0	0	0	1	0	0	0	0	0
	Evergreen forest (EF)	1	0	1	1	1	0	1	0	0	1	1
	Mangrove forest (MF)	0	0	0	1	0	1	0	1	0	1	1
	Marsh and swamp (MS)	1	0	0	1	1	1	0	1	1	1	1
	Water body (WA)	0	0	0	0	0	0	0	0	0	1	1
	Miscellaneous land (ML)	1	0	1	1	1	1	0	0	0	1	1

Note 0 is not allowed and 1 is allowed

Table 5.4 Elasticity of LULC change for LULC prediction between 2017 and 2024.

	LULC Types	LULC in 2024										
		UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
LULC in 2017	Urban and built-up area (UR)	1.000	-	-	-	-	-	-	-	-	-	-
	Paddy field (PD)	0.021	0.715	0.229	0.001	0.003	-	-	-	-	0.007	0.024
	Rubber plantation (RP)	0.015	-	0.914	0.007	-	-	-	-	-	0.004	0.060
	Oil palm plantation (OP)	-	-	-	1.000	-	-	-	-	-	-	-
	Perennial tree / orchard (PO)	0.021	-	-	-	0.979	-	-	-	-	-	-
	Aquatic cultural area (AQ)	-	-	-	-	-	1.000	-	-	-	-	-
	Evergreen forest (EF)	-	-	0.199	-	0.001	-	0.798	-	-	0.001	0.002
	Mangrove forest (MF)	-	-	-	0.007	-	0.024	-	0.864	-	0.031	0.075
	Marsh and swamp (MS)	0.019	-	-	0.006	0.003	0.008	-	0.004	0.878	0.028	0.053
	Water body (WA)	-	-	-	-	-	-	-	-	-	0.968	0.032
	Miscellaneous land (ML)	0.034	-	0.727	0.005	0.018	0.003	-	-	-	0.009	0.204

After that, the local parameters of CLUE-S model for LULC prediction were further applied to predict LULC change between 2017 and 2024 of three different Scenario I: Historical LULC evolution, Scenario II: Forest conservation and prevention, and Scenario III: Agriculture production extension with a specific land requirement of each scenario under CLUE-S model.

5.3 LULC prediction of Scenario I: Historical LULC evolution

Refer to definition of Scenario I (Historical LULC evolution) as mentioned in Chapter 3, land requirement is calculated based on the rate of LULC change from transition area matrix between LULC in 2010 and 2017 using Markov Chain model as result shown in Table 5.5. The result of annual land demand of Scenario I between 2017 and 2024 is presented in Table 5.6.

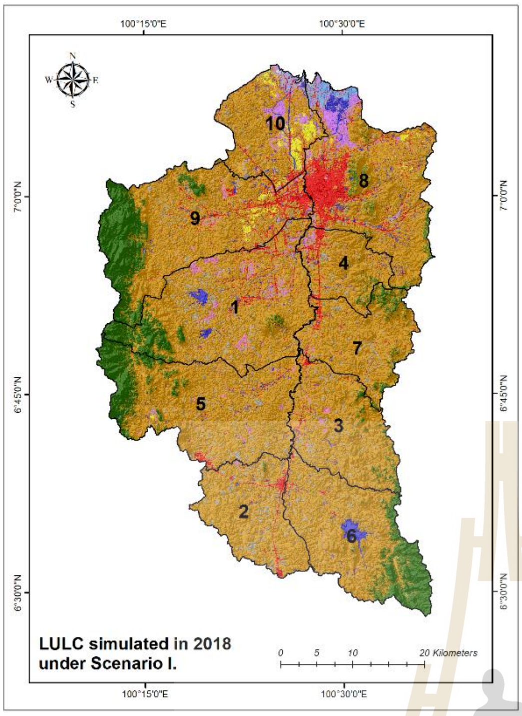
Table 5.5 Transition area matrix of LULC change between 2017 and 2024 from Markov Chain model.

LULC Change	**LULC in 2024**										
LULC in 2017	**UR**	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**
Urban and built-up area (UR)	113.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Paddy field (PD)	0.44	14.59	4.68	0.02	0.06	0.00	0.00	0.00	0.00	0.14	0.50
Rubber plantation (RP)	25.32	0.00	1578.44	12.45	0.00	0.00	0.00	0.00	0.00	7.01	104.24
Oil palm plantation (OP)	0.00	0.00	0.00	18.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Perennial tree/orchard (PO)	0.73	0.00	0.00	0.00	33.47	0.00	0.00	0.00	0.00	0.00	0.00
Aquatic cultural area (AQ)	0.00	0.00	0.00	0.00	0.00	9.38	0.00	0.00	0.00	0.00	0.00
Evergreen forest (EF)	0.04	0.00	50.51	0.11	0.24	0.00	202.57	0.00	0.00	0.16	0.39
Mangrove forest (MF)	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.74	0.00	0.03	0.06
Marsh and swamp (MS)	0.82	0.00	0.00	0.25	0.14	0.35	0.00	0.19	37.50	1.20	2.25
Water body (WA)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	41.08	1.35
Miscellaneous land (ML)	4.85	0.00	103.22	0.68	3.15	0.43	0.00	0.00	0.00	1.31	28.93

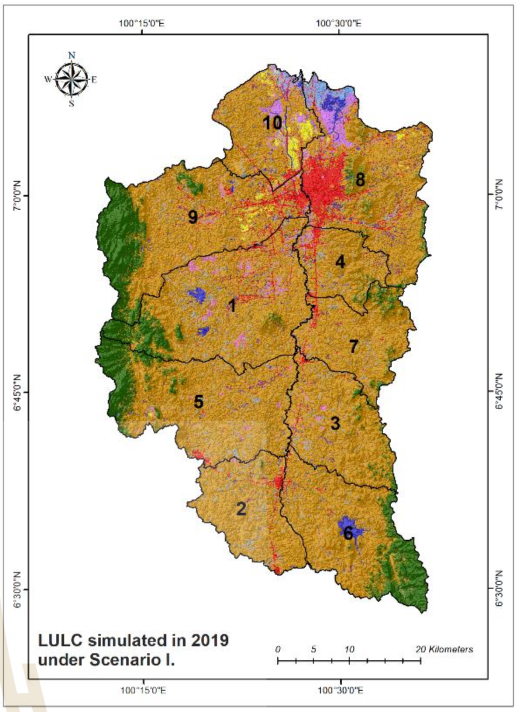
Table 5.6 Annual land requirement of Scenario I (Historical LULC evolution) by each LULC type.

Year	Area in km^2										
	UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**
2017	113.21	20.41	1,727.46	18.85	34.20	9.38	254.01	0.85	42.70	42.43	142.57
2018	117.81	19.57	1,728.98	20.78	34.44	9.49	246.66	0.87	41.95	43.65	141.87
2019	122.41	18.73	1,730.50	22.71	34.68	9.60	239.31	0.89	41.20	44.87	141.17
2020	127.01	17.89	1,732.02	24.64	34.92	9.71	231.96	0.91	40.45	46.09	140.47
2021	131.61	17.05	1,733.54	26.57	35.16	9.82	224.61	0.93	39.70	47.31	139.77
2022	136.21	16.21	1,735.06	28.50	35.40	9.93	217.26	0.95	38.95	48.53	139.07
2023	140.81	15.37	1,736.58	30.43	35.64	10.04	209.91	0.97	38.20	49.75	138.37
2024	145.40	14.59	1,736.85	32.35	37.05	10.18	202.57	0.93	37.50	50.93	137.72
Annual rate	**4.60**	**-0.83**	**1.34**	**1.93**	**0.41**	**0.11**	**-7.35**	**0.01**	**-0.74**	**1.21**	**-0.69**

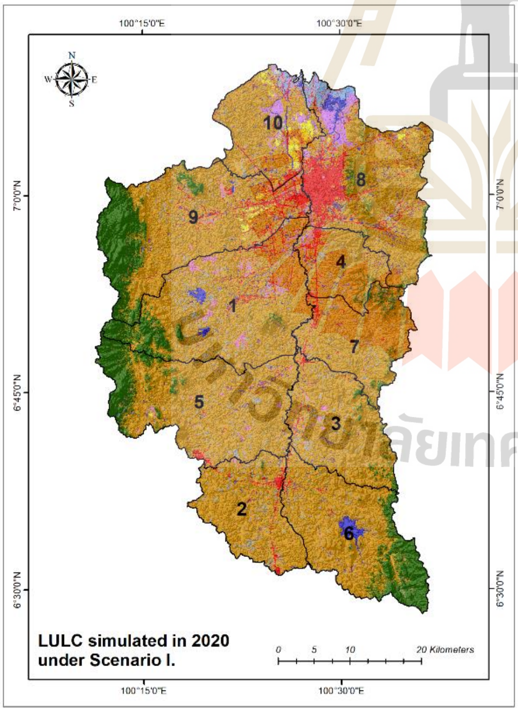
Herein, the increasing LULC classes are urban and built-up area, rubber plantation, oil palm plantation, perennial tree/orchard, aquatic cultural area, mangrove forest, and water body with annual increasing rate of 4.60, 1.34, 1.93, 0.41, 0.11, 0.01, and 1.21 km^2, respectively. In contrast, the decreasing LULC classes are paddy field, evergreen forest, marsh and swamp and miscellaneous land with annual decreasing rate of 0.83, 7.35, 0.74, and 0.69 km^2, respectively. In principle, land requirement dictates the final area of each LULC type in 2024 under of CLUE-S model. The distribution of the predicted LULC of Scenario I at watershed and sub-watershed levels between 2018 and 2024 is presented in Figure 5.2 and area and percentage of LULC classes of Scenario I at watershed level between 2018 and 2024 is summarized in Tables 5.7 and 5.8, respectively.



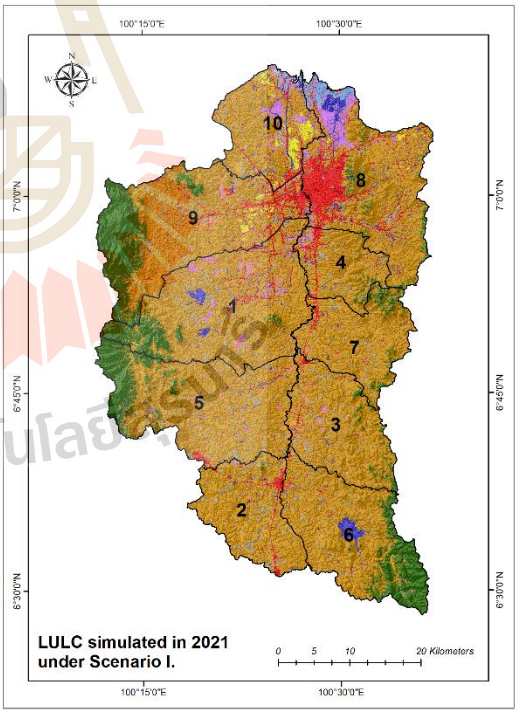
2018



2019

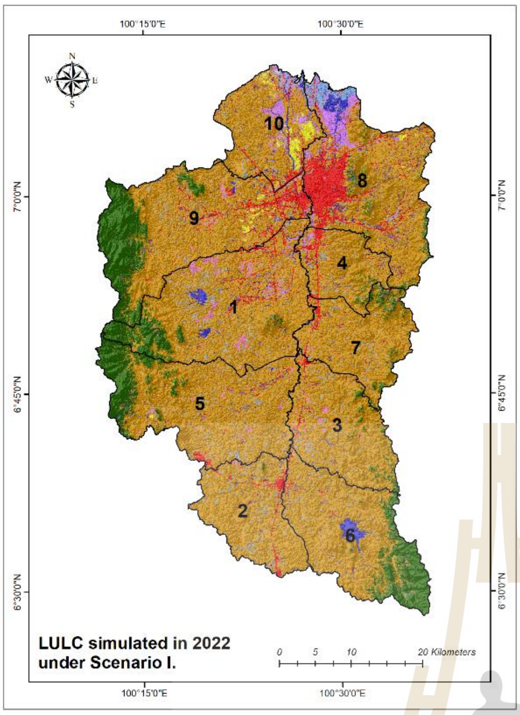


2020

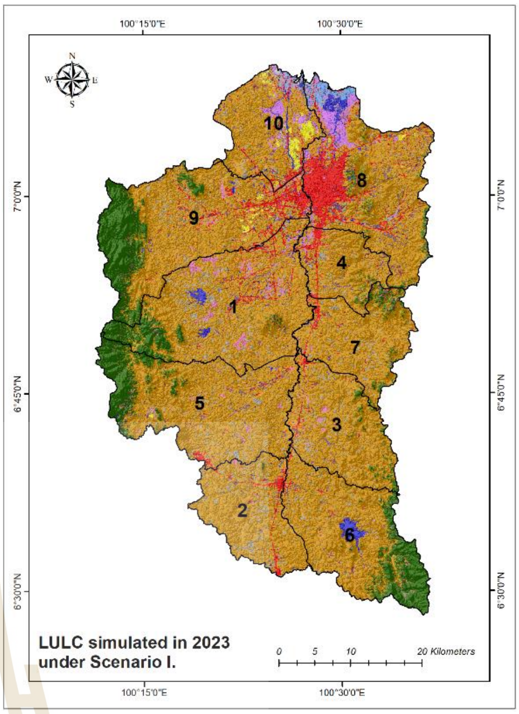


2021

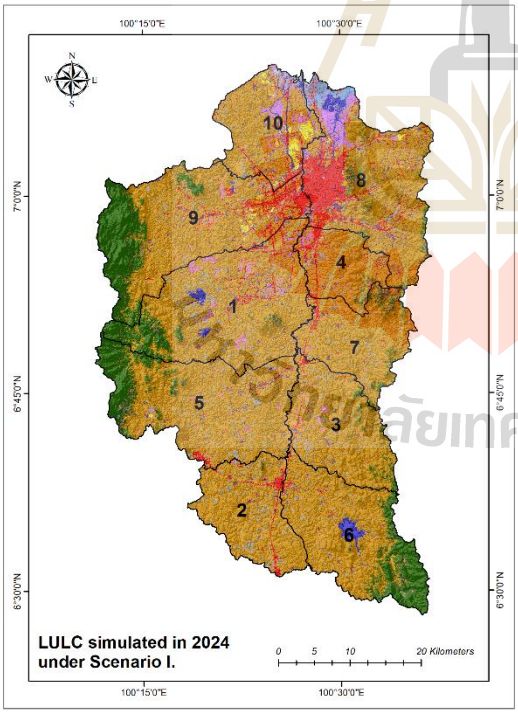
Figure 5.2 Spatial distribution of LULC prediction of Scenario I during 2018 to 2024.



2022



2023



2024

1. Khlong La/Khlong Jam Rai
2. Khlong Lea
3. Khlong Phang La/Khlong Ngae
4. Khlong Pom
5. Khlong Ram
6. Khlong Sa Dao
7. Khlong Tong/Khlong Pra Tu
8. Khlong Wa
9. Khlong Wat/Khlong Tam
10. Klong Bang Klam

Map legend

Figure 5.2 (Continued).

Table 5.7 Area of predicted LULC of Scenario I: Historical LULC evolution between 2018 and 2024.

LULC types	Area in km^2 in						
	2018	2019	2020	2021	2022	2023	2024
Urban and built-up area (UR)	117.18	121.68	125.76	130.90	135.41	139.87	144.17
Paddy field (PD)	19.50	18.70	17.88	16.91	16.11	15.33	14.48
Rubber plantation (RP)	1,728.39	1,727.84	1,727.62	1,727.39	1,727.17	1,726.99	1,726.77
Oil palm plantation (OP)	20.68	22.92	24.56	26.44	28.36	30.06	32.35
Perennial tree/orchard (PO)	34.10	34.36	34.56	34.73	35.23	35.35	37.19
Aquatic cultural area (AQ)	9.41	9.55	9.61	9.70	9.81	9.96	10.09
Evergreen forest (EF)	249.50	243.05	238.32	233.22	227.79	222.57	215.46
Mangrove forest (MF)	0.87	0.89	0.90	0.93	0.95	0.97	0.93
Marsh and swamp (MS)	41.69	41.16	40.75	39.72	38.65	37.95	37.26
Water body (WA)	43.52	44.86	45.73	46.77	48.18	49.48	50.44
Miscellaneous land (ML)	141.21	141.05	140.36	139.33	138.40	137.51	136.91
Total	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**

Table 5.8 Percentage of predicted LULC of Scenario I: Historical LULC evolution between 2018 and 2024.

LULC types	Percent in						
	2018	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Urban and built-up area (UR)	4.87	5.06	5.23	5.44	5.63	5.81	5.99
Paddy field (PD)	0.81	0.78	0.74	0.70	0.67	0.64	0.60
Rubber plantation (RP)	71.84	71.81	71.80	71.79	71.78	71.78	71.77
Oil palm plantation (OP)	0.86	0.95	1.02	1.10	1.18	1.25	1.34
Perennial tree/orchard (PO)	1.42	1.43	1.44	1.44	1.46	1.47	1.55
Aquatic cultural area (AQ)	0.39	0.40	0.40	0.40	0.41	0.41	0.42
Evergreen forest (EF)	10.37	10.10	9.91	9.69	9.47	9.25	8.96
Mangrove forest (MF)	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Marsh and swamp (MS)	1.73	1.71	1.69	1.65	1.61	1.58	1.55
Water body (WA)	1.81	1.86	1.90	1.94	2.00	2.06	2.10
Miscellaneous land (ML)	5.87	5.86	5.83	5.79	5.75	5.72	5.69
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

As results, LULC types which area will increase in 2024 according to rate of LULC change from transition area matrix between LULC in 2017 and 2024 consist of urban and built-up area, oil palm plantation, perennial tree and orchard, aquatic cultural area, mangrove forest, and water body. They cover area of 144.17 km^2 or 5.99%, 32.35 km^2 or 1.34%, 37.19 km^2 or 1.55%, 10.09 km^2 or 0.42%, 0.93 km^2 or 0.04% and 50.44 km^2 or 2.10%, respectively. On contrary, LULC types which area will decrease in 2024 are paddy field, rubber plantation, evergreen forest, marsh and swamp and miscellaneous land and cover area in 2024 of 14.48 km^2 or 0.60%, 1,726.77 km^2 or 71.77%, 215.46 km^2 or 8.96%, 37.26 km^2 or 1.55%, and 136.91 km^2 or 5.69%, respectively.

In addition, area and percentage of predictive LULC at sub-watershed level of Scenario I between 2018 and 2024 is summarized in Table 5.9.

Table 5.9 Predictive LULC types at sub-watershed level of Scenario I between 2018 and 2024.

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%	(km^2)	%
2018	1	10.87	3.04	-	-	261.03	72.90	9.32	2.60	2.68	0.75	0.38	0.11	32.91	9.19	-	-	5.43	1.52	9.76	2.73	25.69	7.17
	2	6.46	3.88	-	-	141.72	85.12	0.61	0.37	0.95	0.57	0.05	0.03	0.34	0.20	-	-	-	-	0.64	0.38	15.74	9.45
	3	3.20	1.69	-	-	159.97	84.69	2.65	1.40	2.43	1.29	0.05	0.03	6.83	3.62	-	-	0.04	0.02	0.59	0.31	13.14	6.96
	4	6.45	6.25	-	-	82.31	79.81	0.41	0.40	1.97	1.91	0.07	0.07	2.74	2.66	-	-	1.78	1.73	1.29	1.25	6.12	5.93
	5	3.99	1.23	0.23	0.07	244.05	75.11	3.38	1.04	4.05	1.25	0.19	0.06	48.24	14.85	-	-	0.40	0.12	1.74	0.54	18.66	5.74
	6	2.38	0.92	-	-	180.65	69.70	0.41	0.16	2.91	1.12	0.01	0.00	55.38	21.37	-	-	-	-	7.62	2.94	9.81	3.79
	7	3.74	2.31	-	-	135.00	83.56	0.40	0.25	1.38	0.85	-	-	10.73	6.64	-	-	-	-	0.69	0.43	9.65	5.97
	8	48.34	14.84	2.17	0.67	198.37	60.88	0.46	0.14	11.69	3.59	7.66	2.35	9.08	2.79	0.21	0.06	20.15	6.18	11.84	3.63	15.86	4.87
	9	23.64	6.71	3.99	1.13	215.46	61.19	2.09	0.59	3.10	0.88	0.06	0.02	83.25	23.64	0.01	0.00	1.72	0.49	3.65	1.04	15.19	4.31
	10	8.12	4.90	13.11	7.91	109.84	66.25	0.96	0.58	2.94	1.77	0.96	0.58	-	-	0.65	0.39	12.18	7.35	5.71	3.44	11.36	6.85
2019	1	11.24	3.14	-	-	261.02	72.89	9.56	2.67	2.69	0.75	0.38	0.10	32.41	9.05	0.00	0.00	5.30	1.48	9.79	2.73	25.69	7.18
	2	6.55	3.94	-	-	141.71	85.11	0.61	0.37	0.95	0.57	0.05	0.03	0.29	0.17	-	-	-	-	0.64	0.39	15.72	9.44
	3	3.50	1.85	-	-	159.97	84.69	2.97	1.57	2.44	1.29	0.05	0.02	6.18	3.27	-	-	0.03	0.02	0.63	0.33	13.14	6.95
	4	6.74	6.54	-	-	82.29	79.80	0.50	0.48	2.00	1.94	0.07	0.07	2.38	2.30	-	-	1.76	1.70	1.30	1.26	6.11	5.92
	5	4.52	1.39	0.23	0.07	244.05	75.11	3.85	1.18	4.07	1.25	0.20	0.06	47.17	14.52	-	-	0.37	0.11	1.84	0.57	18.64	5.74
	6	2.71	1.04	-	-	180.64	69.70	1.04	0.40	2.95	1.14	0.01	0.00	54.38	20.98	-	-	-	-	7.66	2.96	9.80	3.78
	7	3.98	2.46	-	-	135.04	83.58	0.51	0.31	1.38	0.85	-	-	10.36	6.41	-	-	-	-	0.69	0.43	9.64	5.96
	8	49.99	15.34	1.92	0.59	197.96	60.76	0.59	0.18	11.75	3.61	7.76	2.38	7.71	2.37	0.22	0.07	19.95	6.12	12.15	3.73	15.83	4.86
	9	24.16	6.86	3.81	1.08	215.34	61.15	2.36	0.67	3.20	0.91	0.06	0.02	82.19	23.34	0.02	0.01	1.64	0.46	4.18	1.19	15.19	4.31
	10	8.30	5.00	12.75	7.69	109.83	66.24	0.96	0.58	2.94	1.77	0.99	0.60	-	-	0.65	0.39	12.12	7.31	5.99	3.61	11.31	6.82
2020	1	11.59	3.24	-	-	261.01	72.89	9.74	2.72	2.69	0.75	0.38	0.11	32.01	8.94	0.00	0.00	5.23	1.46	9.82	2.74	25.62	7.15
	2	6.65	3.99	-	-	141.70	85.11	0.61	0.37	0.95	0.57	0.05	0.03	0.25	0.15	-	-	-	-	0.65	0.39	15.67	9.41
	3	3.76	1.99	-	-	159.97	84.69	3.18	1.68	2.44	1.29	0.05	0.02	5.72	3.03	-	-	0.03	0.02	0.63	0.33	13.12	6.95
	4	7.01	6.79	-	-	82.28	79.79	0.55	0.54	2.00	1.94	0.07	0.07	2.14	2.07	-	-	1.71	1.66	1.31	1.27	6.07	5.89
	5	5.04	1.55	0.23	0.07	244.05	75.11	4.11	1.27	4.07	1.25	0.20	0.06	46.40	14.28	-	-	0.37	0.11	1.87	0.57	18.62	5.73
	6	3.04	1.17	-	-	180.64	69.70	1.44	0.56	2.95	1.14	0.01	0.00	53.65	20.70	-	-	-	-	7.68	2.96	9.77	3.77
	7	4.19	2.59	-	-	135.04	83.58	0.56	0.34	1.38	0.85	-	-	10.11	6.26	-	-	-	-	0.69	0.43	9.62	5.95
	8	51.21	15.72	1.80	0.55	197.83	60.72	0.72	0.22	11.80	3.62	7.80	2.39	6.74	2.07	0.23	0.07	19.82	6.08	12.29	3.77	15.60	4.79
	9	24.84	7.05	3.62	1.03	215.29	61.14	2.59	0.73	3.33	0.95	0.06	0.02	81.32	23.09	0.03	0.01	1.56	0.44	4.45	1.26	15.06	4.28
	10	8.46	5.10	12.25	7.39	109.81	66.23	1.06	0.64	2.95	1.78	1.01	0.61	-	-	0.65	0.39	12.03	7.26	6.37	3.84	11.22	6.77

Table 5.9 (Continued).

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%	(km²)	%
2021	1	12.00	3.35	-	-	260.99	72.89	9.97	2.79	2.70	0.75	0.38	0.11	31.61	8.83	0.00	0.00	5.01	1.40	9.92	2.77	25.48	7.12
	2	6.78	4.07	-	-	141.70	85.11	0.61	0.37	0.95	0.57	0.05	0.03	0.18	0.11	-	-	-	-	0.65	0.39	15.59	9.36
	3	4.16	2.20	-	-	159.97	84.69	3.37	1.78	2.44	1.29	0.05	0.02	5.20	2.75	-	-	0.02	0.01	0.63	0.33	13.06	6.91
	4	7.24	7.02	-	-	82.27	79.78	0.63	0.61	2.00	1.94	0.07	0.07	1.93	1.87	-	-	1.67	1.62	1.32	1.28	6.02	5.84
	5	5.74	1.77	0.22	0.07	244.05	75.11	4.40	1.35	4.08	1.25	0.20	0.06	45.48	14.00	-	-	0.33	0.10	1.90	0.59	18.55	5.71
	6	3.48	1.34	-	-	180.64	69.70	1.84	0.71	2.95	1.14	0.01	0.00	52.82	20.38	-	-	-	-	7.69	2.97	9.75	3.76
	7	4.49	2.78	-	-	135.04	83.58	0.59	0.36	1.38	0.85	-	-	9.81	6.07	-	-	-	-	0.69	0.43	9.59	5.93
	8	52.49	16.11	1.56	0.48	197.71	60.68	0.91	0.28	11.86	3.64	7.85	2.41	5.95	1.82	0.25	0.08	19.48	5.98	12.48	3.83	15.30	4.70
	9	25.90	7.36	3.37	0.96	215.22	61.12	2.97	0.84	3.40	0.97	0.06	0.02	80.25	22.79	0.03	0.01	1.41	0.40	4.67	1.33	14.87	4.22
	10	8.64	5.21	11.77	7.10	109.81	66.23	1.16	0.70	2.97	1.79	1.04	0.62	-	-	0.65	0.39	11.81	7.12	6.84	4.12	11.13	6.71
2022	1	12.44	3.47	-	-	260.98	72.89	10.26	2.86	2.76	0.77	0.39	0.11	31.10	8.69	0.00	0.00	4.75	1.33	10.07	2.81	25.33	7.07
	2	6.88	4.13	-	-	141.69	85.10	0.61	0.37	0.96	0.58	0.05	0.03	0.13	0.08	-	-	-	-	0.65	0.39	15.55	9.34
	3	4.57	2.42	-	-	159.97	84.69	3.59	1.90	2.44	1.29	0.05	0.02	4.62	2.44	-	-	0.02	0.01	0.64	0.34	13.01	6.89
	4	7.44	7.21	-	-	82.27	79.78	0.68	0.66	2.00	1.94	0.07	0.07	1.71	1.66	0.01	0.01	1.64	1.59	1.33	1.29	5.99	5.81
	5	6.47	1.99	0.22	0.07	244.03	75.10	4.74	1.46	4.09	1.26	0.21	0.06	44.42	13.67	-	-	0.31	0.09	1.96	0.60	18.49	5.69
	6	3.97	1.53	-	-	180.64	69.70	2.22	0.86	2.96	1.14	0.02	0.01	51.95	20.05	-	-	-	-	7.70	2.97	9.71	3.75
	7	4.79	2.96	-	-	135.04	83.58	0.63	0.39	1.38	0.85	-	-	9.51	5.88	-	-	-	-	0.70	0.43	9.54	5.91
	8	53.35	16.37	1.39	0.43	197.58	60.64	1.02	0.31	12.04	3.69	7.92	2.43	5.28	1.62	0.26	0.08	19.13	5.87	12.82	3.94	15.06	4.62
	9	26.72	7.59	3.18	0.90	215.17	61.10	3.37	0.96	3.58	1.02	0.06	0.02	79.07	22.45	0.03	0.01	1.26	0.36	4.98	1.41	14.73	4.18
	10	8.80	5.31	11.33	6.83	109.81	66.23	1.25	0.75	3.03	1.83	1.06	0.64	-	-	0.65	0.39	11.55	6.96	7.35	4.43	10.99	6.63
2023	1	12.79	3.57	-	-	260.98	72.88	10.52	2.94	2.77	0.77	0.39	0.11	30.63	8.55	0.00	0.00	4.60	1.28	10.21	2.85	25.18	7.03
	2	6.96	4.18	-	-	141.68	85.09	0.61	0.37	0.96	0.58	0.05	0.03	0.09	0.05	-	-	-	-	0.65	0.39	15.53	9.33
	3	4.95	2.62	-	-	159.97	84.69	3.77	1.99	2.44	1.29	0.05	0.02	4.07	2.15	-	-	0.02	0.01	0.65	0.34	12.99	6.87
	4	7.63	7.39	-	-	82.26	79.77	0.72	0.69	2.00	1.94	0.07	0.07	1.55	1.50	0.03	0.02	1.58	1.53	1.36	1.31	5.96	5.78
	5	7.23	2.23	0.20	0.06	244.03	75.10	5.06	1.56	4.09	1.26	0.21	0.06	43.37	13.35	-	-	0.29	0.09	2.02	0.62	18.44	5.68
	6	4.49	1.73	-	-	180.64	69.70	2.55	0.98	2.96	1.14	0.02	0.01	51.12	19.72	-	-	-	-	7.72	2.98	9.68	3.73
	7	5.06	3.13	-	-	135.04	83.58	0.68	0.42	1.38	0.85	-	-	9.22	5.71	-	-	-	-	0.71	0.44	9.50	5.88
	8	54.13	16.61	1.32	0.40	197.47	60.61	1.08	0.33	12.08	3.71	8.01	2.46	4.76	1.46	0.26	0.08	18.89	5.80	13.06	4.01	14.78	4.54
	9	27.75	7.88	3.00	0.85	215.13	61.09	3.69	1.05	3.62	1.03	0.07	0.02	77.78	22.09	0.03	0.01	1.19	0.34	5.29	1.50	14.59	4.14
	10	8.90	5.37	10.82	6.53	109.80	66.22	1.38	0.83	3.06	1.84	1.10	0.66	-	-	0.66	0.40	11.39	6.87	7.84	4.73	10.87	6.56

Table 5.9 (Continued).

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km²)	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**	**(km²)**	**%**
2024	1	13.21	3.69	-	-	260.96	72.88	10.99	3.07	2.90	0.81	0.40	0.11	29.77	8.31	0.00	0.00	4.48	1.25	10.28	2.87	25.09	7.01
	2	6.98	4.19	-	-	141.67	85.09	0.61	0.37	1.01	0.60	0.05	0.03	0.04	0.02	-	-	-	-	0.65	0.39	15.52	9.32
	3	5.30	2.80	-	-	159.97	84.69	4.05	2.14	2.49	1.32	0.05	0.02	3.42	1.81	-	-	0.02	0.01	0.65	0.34	12.95	6.86
	4	7.85	7.61	-	-	82.25	79.76	0.72	0.70	2.01	1.94	0.07	0.07	1.34	1.30	0.03	0.02	1.56	1.51	1.36	1.32	5.95	5.77
	5	8.01	2.46	0.19	0.06	244.01	75.10	5.59	1.72	4.36	1.34	0.22	0.07	41.83	12.87	-	-	0.28	0.08	2.05	0.63	18.41	5.66
	6	5.04	1.95	-	-	180.64	69.70	3.03	1.17	3.08	1.19	0.03	0.01	49.98	19.29	-	-	-	-	7.72	2.98	9.65	3.72
	7	5.55	3.44	-	-	135.03	83.58	0.74	0.46	1.38	0.86	-	-	8.71	5.39	-	-	-	-	0.71	0.44	9.45	5.85
	8	54.65	16.77	1.10	0.34	197.37	60.57	1.12	0.34	12.58	3.86	8.09	2.48	4.22	1.29	0.26	0.08	18.61	5.71	13.25	4.07	14.59	4.48
	9	28.63	8.13	2.75	0.78	215.08	61.08	4.09	1.16	4.19	1.19	0.07	0.02	76.16	21.63	0.03	0.01	1.12	0.32	5.52	1.57	14.50	4.12
	10	8.95	5.40	10.44	6.30	109.79	66.21	1.42	0.86	3.21	1.93	1.12	0.68	-	-	0.62	0.37	11.20	6.75	8.25	4.98	10.81	6.52

Note: 1. Khlong La/Khlong Jam Rai, 2. Khlong Lea, 3. Khlong Phang La/Khlong Ngae, 4. Khlong Pom, 5. Khlong Ram, 6. Khlong Sa Dao, 7. Khlong Tong/Khlong Pra Tu, 8. Khlong Wa, 9. Khlong Wat/Khlong Tam, and 10. Klong Bang Klam.

As result, it reveals that at sub-watershed level, percentage of evergreen forest in each sub-watershed between 2018 and 2024 are rather low that varies from 0% to 23.64% (See detail in Table 5.9), when they are compared with target area of forest cover at 40% of total country area under Thailand National Forest Policy (Royal Forest Department, 1986). In fact, forest cover under the policy is divided into two categories: (1) protective forest, accounting for 15% of total country area and (2) productive forest, accounting for 25% of total country area.

According to Thailand National Forest Policy, it can observed that most of 10 sub-watersheds in Khlong U-Tapoa watershed are critical except Khlong Sa Dao and Khlong Wat/Khlong Tam sub-watersheds wherein evergreen forest as protective forest are greater than 15%.

Furthermore, transition LULC change matrix between 2017 and 2024 of Scenario I is displayed in Table 5.10. As results, urban and built-up area in 2017 is not converted in other LULC types in 2024 and its area will increase from 113.21 km^2 in 2017 to 144.17 km^2 in 2024. The increasing areas of urban and built area in 2024 come from paddy field (1.42 km^2), rubber plantation (2.37 km^2), perennial tree and orchard (0.10 km^2), evergreen forest (19.99 km^2), marsh and swamp (1.99 km^2) and miscellaneous land (5.11 km^2) in 2017. Likewise, oil palm plantation in 2017 is not converted into other LULC classes in 2024 and its area will increase from 18.85 km^2 in 2017 to 32.35 km^2 in 2024, the increasing areas of oil palm plantation in 2024 come from paddy field (0.71 km^2), evergreen forest (12.17 km^2), marsh and swamp (0.48 km^2) and miscellaneous land (0.15 km^2) in 2017. Similarly, aquatic cultural area in 2017 is not converted into other LULC classes in 2024 and its area will increase from

9.38 km^2 in 2017 to 10.09 km^2 in 2024, the increasing areas of this type in 2024 come from marsh and swamp (0.25 km^2) and miscellaneous land (0.46 km^2) in 2017. Also, water body in 2017 is not converted into other LULC classes in 2024 and its area will increase from 42.43 km^2 in 2017 to 50.44 km^2 in 2024, the increasing areas of water body in 2024 come from paddy field (2.63 km^2), evergreen forest (2.52 km^2), mangrove forest (0.04 km^2), marsh and swamp (1.86 km^2) and miscellaneous land (0.96 km^2) in 2017.

On contrary, paddy field in 2017 is converted into urban and built-up area (1.42 km^2), rubber plantation (0.04 km^2), oil palm plantation (0.71 km^2), perennial tree and orchard (0.78 km^2), water body (2.63 km^2) and miscellaneous land (0.36 km^2) in 2024 and its area will decrease from 20.40 km^2 in 2017 to 14.48 km^2 in 2024. Likewise, rubber plantation in 2017 is converted into urban and built-up area (2.37 km^2) in 2024 and its area will decrease from 1,727.45 km^2 in 2017 to 1,726.77 km^2 in 2024. Similarly, perennial tree and orchard in 2017 is converted into urban and built-up area (0.10 km^2) in 2024, but its area will increase from 34.20 km^2 in 2017 to 37.19 km^2, the increasing areas of perennial tree and orchard come from paddy field (0.78 km^2), evergreen forest (1.78 km^2), marsh and swamp (0.50 km^2) and miscellaneous land (0.04 km^2) in 2017. Likewise, evergreen forest in 2017 is converted into urban and built-up area (19.99 km^2), rubber plantation (1.65 km^2), oil palm plantation (12.17 km^2), perennial tree and orchard (1.78 km^2), water body (2.52 km^2) and miscellaneous land (0.45 km^2) in 2024 and areas of evergreen forest will decrease from 254.01 km^2 in 2017 to 215.46 km^2 in 2024. Similarly, mangrove forest in 2017 is converted into water body (0.04 km^2) in 2024 but its area will increase from 0.85 km^2 in 2017 to 0.93 km^2 in 2024, the increasing areas of mangrove forests come from marsh and swamp (0.12 km^2). Meanwhile, marsh and swamp in 2017 is converted into urban and built-up area (1.99 km^2), oil palm plantation (0.48 km^2), perennial tree and orchard (0.50 km^2), aquatic cultural area (0.25 km^2), mangrove forest (0.12 km^2), water body (1.86 km^2) and miscellaneous land (0.24 km^2) in 2024, and its area will decrease from 42.70 km^2 in 2017 to 37.26 km^2 in 2024. In the meantime, miscellaneous land in 2017 is converted into urban and built-up area (5.11 km^2), oil palm plantation (0.15 km^2), perennial tree and orchard (0.04 km^2), aquatic cultural area (0.46 km^2), and water body (0.96 km^2) in 2024, and its area will decrease from 142.58 km^2 in 2017 to 136.91 km^2 in 2024. The characteristics of from to change among LULC types between 2017 and 2024 are regulated by driving factors on LULC change, conversion matrix and elasticity of LULC change and their land requirements which are applied for LULC prediction of Scenario I under CLUE-S model. The derived predictive LULC data between 2018 and 2024 is consistent with definition of Scenario I which allows LULC change (decreased or increased area) according to historical LULC development during 2010 and 2017.

Furthermore, it was found that there is slightly difference between the required land area and the predicted area of each LULC type in 2024 under Scenario I. For example, the required area of rubber plantation in 2024 is 1,736.85 km^2 but it is allocated only 1,726.77 km^2 whereas the required area of evergreen forest in 2024 is 202.57 km^2 but it is allocated 215.46 km^2. In this study, the deviation values between the required land area and the predicted area of each LULC type under Scenario I vary from -0.1008% to 0.1290% or from -10.08 km^2 (under estimation) to 12.89 km^2 (over estimation). The summation of deviation values, which are trade-off between over and under estimation among LULC types is 0.0% and -0.02 km^2 (see Table 5.10). Since the deviation value depends on iteration driving factors of each LULC type which indicates the maximum different allowance between the required and allocated area of LULC type under CLUE-S model (van Asselen and Verburg, 2013; Liu, Wang, Li, and Xia (2013); and Xu, Li, Song, and Yin, (2013). Therefore, the LULC prediction under Scenario I using CLUE-S model can be validated and accepted for ecosystem service assessment in terms of water yield and sediment retention.

Table 5.10 Transition LULC change matrix between 2017 (Base year) and 2024 of Scenario I: Historical LULC evolution.

LULC2 017 (km^2)

	LULC 2024 (km^2)											
LULC types	**UR**	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**	**Total**
Urban and built-up area (UR)	113.21	-	-	-	-	-	-	-	-	-	-	**113.21**
Paddy field (PD)	1.42	14.48	0.04	0.71	0.78	-	-	-	-	2.63	0.36	**20.40**
Rubber plantation (RP)	2.37	-	1,725.08	-	-	-	-	-	-		-	**1,727.45**
Oil palm plantation (OP)	-	-	-	18.85	-	-	-	-	-	-	-	**18.85**
Perennial tree/orchard (PO)	0.10	-	-	-	34.10	-	-	-	-	-	-	**34.20**
Aquatic cultural area (AQ)	-	-	-	-	-	9.38	-	-	-	-	-	**9.38**
Evergreen forest (EF)	19.99	-	1.65	12.17	1.78	-	215.46	-	-	2.52	0.45	**254.01**
Mangrove forest (MF)	-	-	-	-	-	-	-	0.81	-	0.04	-	**0.85**
Marsh and swamp (MS)	1.99	-	-	0.48	0.50	0.25	-	0.12	37.26	1.86	0.24	**42.70**
Water body (WA)	-	-	-	-	-	-	-	-	-	42.43	-	**42.43**
Miscellaneous land (ML)	5.11	-	-	0.15	0.04	0.46	-	-	-	0.96	135.87	**142.58**
Total	**144.17**	**14.48**	**1,726.77**	**32.35**	**37.19**	**10.09**	**215.46**	**0.93**	**37.26**	**50.44**	**136.91**	**2,406.04**
Land use requirement	**145.40**	**14.59**	**1,736.85**	**32.35**	**37.05**	**10.18**	**202.57**	**0.93**	**37.50**	**50.93**	**137.72**	
Deviation value (%)	**-0.0123**	**-0.0011**	**-0.1008**	**-**	**0.0014**	**-0.0009**	**0.1290**	**-**	**-0.0024**	**-0.0048**	**-0.0081**	
Deviation value (km^2)	**-1.23**	**-0.11**	**-10.08**	**0.00**	**0.14**	**-0.09**	**12.89**	**0.00**	**-0.24**	**-0.49**	**-0.81**	**-0.02**

5.4 LULC prediction of Scenario II: Forest conservation and prevention

Refer to definition of Scenario II (Forest conservation and prevention) as mentioned in Chapter 3, land requirement is calculated based on the rate of LULC change developing between 2010 and 2017 using Markov Chain model and forest conservation prevention policy. The result of annual land demand of Scenario II between 2018 and 2024 is presented in Table 5.11. The characteristics of land demand of each LULC type under this scenario can be grouped and described below.

(1) Historical rate of LULC change. Land requirement of urban and built-up area and oil palm plantation was calculated based on historical rate of LULC change between 2010 and 2017 by using Markov Chain model.

(2) Unchanged area. Land requirement of paddy field, perennial tree/orchard, aquatic cultural area, mangrove forest, mash and swamp, and water bodies were fixed based their areas in 2017.

(3) Decreased area. Land requirement of rubber plantation and miscellaneous land were calculate based on the excluded existing area of rubber plantation and miscellaneous land in 2017 over forest legal boundaries (national park and wildlife sanctuary, Watershed Class I and conservation zone of National Reserved Forest).

(4) Increased area. Land requirement of evergreen forest is based on declared protected forest area (Khao Nam Khang National Park and Ton Nga Chang Wildlife Sanctuary) and Watershed class 1A, and Conservation zone of National Reserved Forest (see Figure 5.3 and Table 5.12).

Table 5.11 Annual land requirement for Scenario II by each LULC type.

Year	Area in km^2										
	UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**
2017	113.21	20.41	1,727.46	18.85	34.20	9.38	254.01	0.85	42.70	42.43	142.57
2018	117.81	20.41	1,704.70	20.78	34.20	9.38	271.65	0.85	42.70	42.43	141.16
2019	122.41	20.41	1,681.94	22.71	34.20	9.38	289.29	0.85	42.70	42.43	139.75
2020	127.01	20.41	1,659.18	24.64	34.20	9.38	306.93	0.85	42.70	42.43	138.34
2021	131.61	20.41	1,636.42	26.57	34.20	9.38	324.57	0.85	42.70	42.43	136.93
2022	136.21	20.41	1,613.66	28.50	34.20	9.38	342.21	0.85	42.70	42.43	135.52
2023	140.81	20.41	1,590.90	30.43	34.20	9.38	359.85	0.85	42.70	42.43	134.11
2024	145.41	20.41	1,568.17	32.35	34.20	9.38	377.47	0.85	42.70	42.43	132.69
Annual Change	**4.60**	**-**	**-22.76**	**1.93**	**-**	**-**	**17.64**	**-**	**-**	**-**	**-1.41**

Table 5.12 Details of land requirement of evergreen forest.

Forest conservation and protection by laws	**Area (km^2)**
1.Khao Nam Khang national park [1]	56.59
2.Ton Nga Chang wildlife sanctuary [2]	16.97
3.Watershed class 1A[3]	108.00
4.Conservation zone of National Reserved Fores[4]	195.91
Land requirement of evergreen forest in 2024	**377.47**

[1]DNP: Department of National Parks, Wildlife and Plant Conservation (Published in Royal Gazette Vol. 108, No. 127, dated July 22, 1991, is the 65th National Park of Thailand)

[2]DNP: Department of National Parks, Wildlife and Plant Conservation (The Royal Decree declared a Wildlife Sanctuary, July 2, 1978)

[3]MNRE: Ministry of Natural Resources and Environment (Cabinet Resolutions on watershed classification and suggestions for land use measures in the watershed area in the South, November 7, 1989)

[4]RFD: Royal Forest Department (Notification of Ministry of Natural Resources and Environment, Zone C (Conservation Forest Zone), March 10, 1992)

The distribution of the predicted LULC of Scenario II between 2018 and 2024 is presented in Figures 5.4 and area and percentage of LULC classes of Scenario II between 2018 and 2024 is displayed in Tables 5.13 and 5.14, respectively.

Herein, increasing LULC classes are urban and built-up area, oil palm plantation, and evergreen forest with annual increasing rate of 4.60, 1.93, and 17.64 km^2, respectively. In contrast, decreasing LULC classes are rubber plantation, and miscellaneous land with annual decreasing rate of 22.76 and 1.41 km^2, respectively. Meanwhile area of LULC types include paddy field, perennial tree and orchard, aquatic cultural area, mangrove forest, marsh and swamp, and water body are fixed during 2018 to 2024. In principle, land requirement dictates the final area of each LULC type in 2024 under of CLUE-S model.

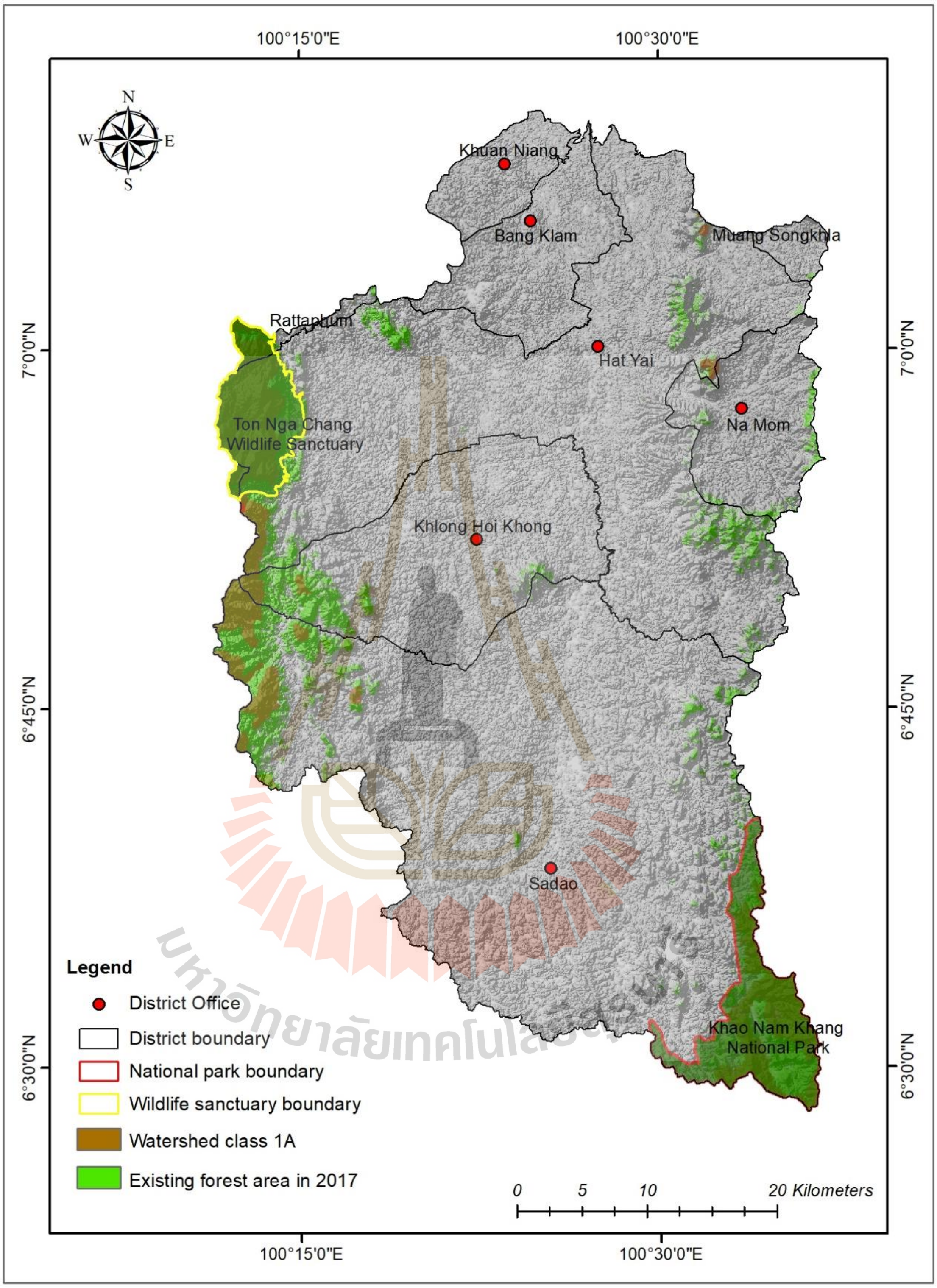
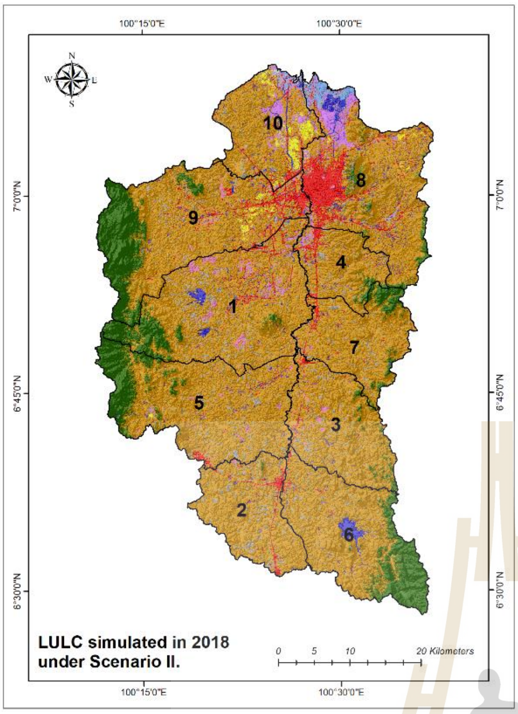
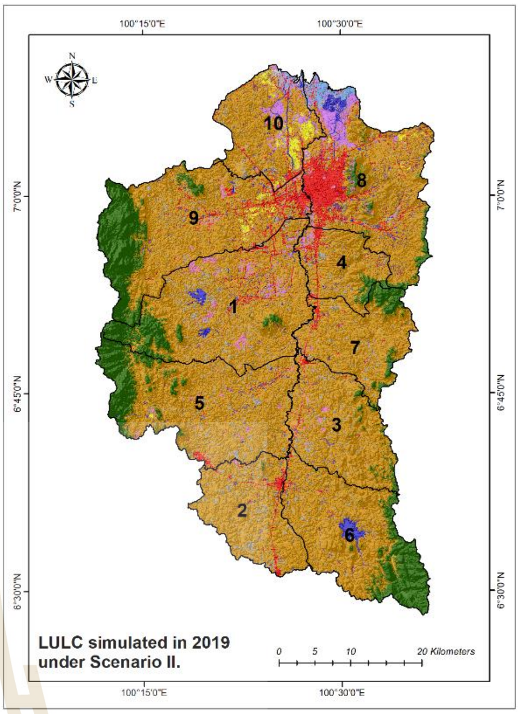


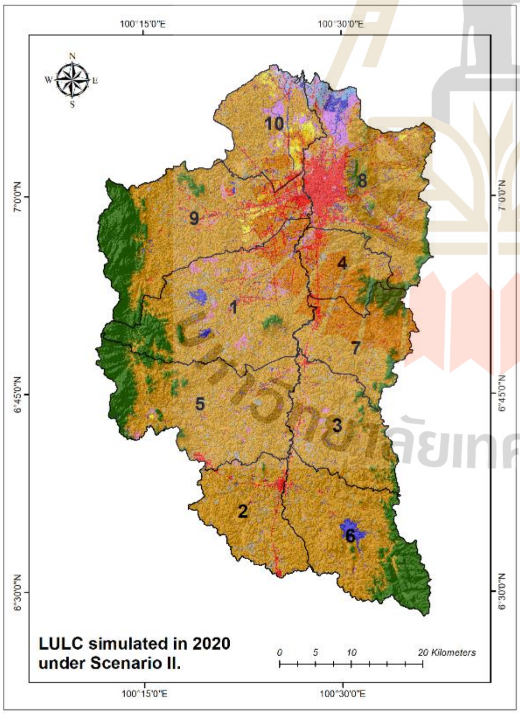
Figure 5.3 Spatial distribution of land requirement of evergreen forest based on conservation and prevention policy.



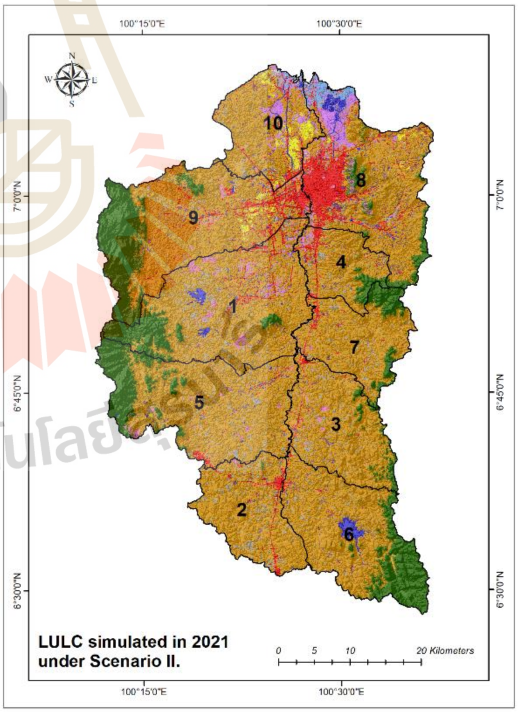
2018



2019

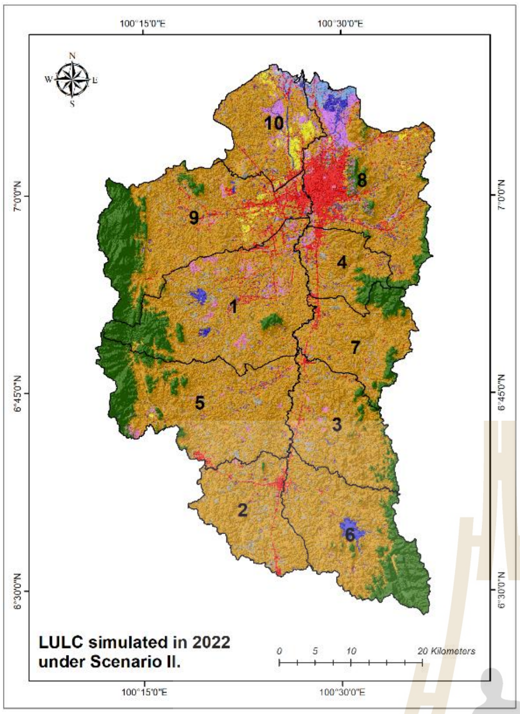


2020

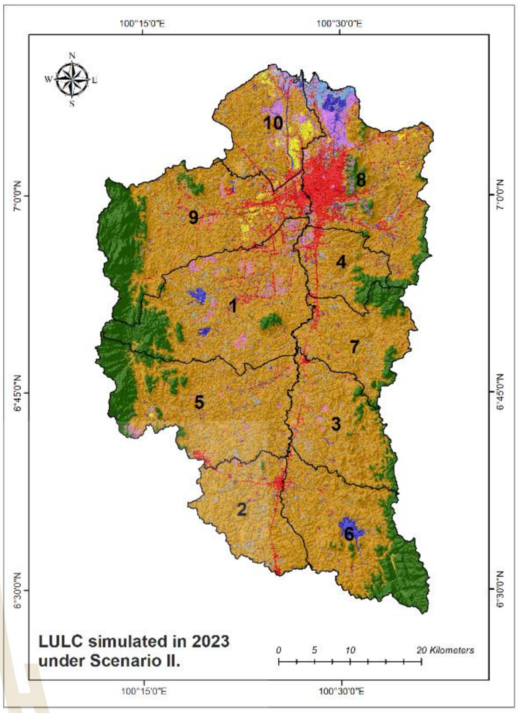


2021

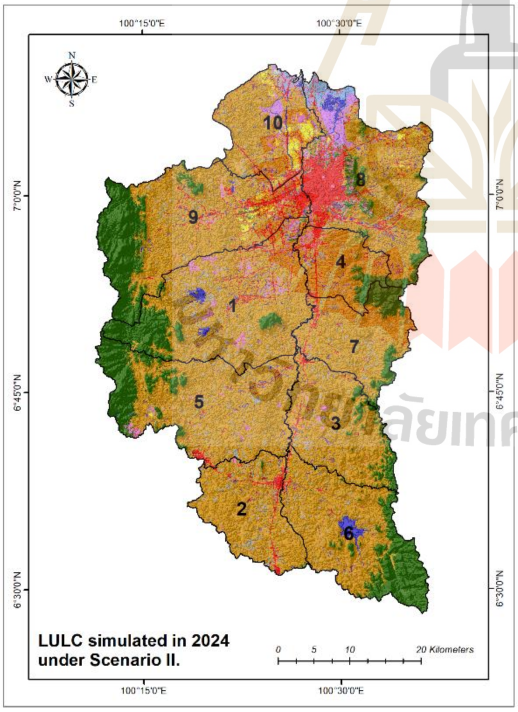
Figure 5.4 Spatial distribution of LULC prediction of Scenario II during 2018 to 2024.



2022



2023



2024

1. Khlong La/Khlong Jam Rai
2. Khlong Lea
3. Khlong Phang La/Khlong Ngae
4. Khlong Pom
5. Khlong Ram
6. Khlong Sa Dao
7. Khlong Tong/Khlong Pra Tu
8. Khlong Wa
9. Khlong Wat/Khlong Tam
10. Klong Bang Klam

Map legend

Figure 5.4 (Continued).

Table 5.13 Area of predicted LULC of Scenario II: Forest conservation and prevention.

LULC types	Area in km^2 in						
	2018	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Urban and built-up area (UR)	116.63	122.00	126.31	130.89	136.16	140.46	145.10
Paddy field (PD)	20.36	20.34	20.30	20.26	20.26	20.25	20.25
Rubber plantation (RP)	1,707.79	1,686.08	1,664.43	1,640.07	1,614.61	1,592.74	1,569.66
Oil palm plantation (OP)	20.72	22.72	24.63	26.47	28.50	30.40	32.34
Perennial tree/orchard (PO)	34.10	34.03	33.98	33.91	33.91	33.91	33.90
Aquatic cultural area (AQ)	9.38	9.38	9.38	9.38	9.38	9.38	9.38
Evergreen forest (EF)	270.03	286.41	304.29	323.36	342.22	359.49	377.33
Mangrove forest (MF)	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Marsh and swamp (MS)	42.53	42.42	42.35	42.28	42.27	42.27	42.27
Water body (WA)	42.43	42.43	42.43	42.43	42.43	42.43	42.43
Miscellaneous land (ML)	141.22	139.41	137.10	136.16	135.49	133.88	132.56
Total	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**

Table 5.14 Percentage of predicted LULC of Scenario II: Forest conservation and prevention.

LULC types	Percent in						
	2018	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Urban and built-up area (UR)	4.85	5.07	5.25	5.44	5.66	5.84	6.03
Paddy field (PD)	0.85	0.85	0.84	0.84	0.84	0.84	0.84
Rubber plantation (RP)	70.98	70.08	69.18	68.16	67.11	66.20	65.24
Oil palm plantation (OP)	0.86	0.94	1.02	1.10	1.18	1.26	1.34
Perennial tree/orchard (PO)	1.42	1.41	1.41	1.41	1.41	1.41	1.41
Aquatic cultural area (AQ)	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Evergreen forest (EF)	11.22	11.90	12.65	13.44	14.22	14.94	15.68
Mangrove forest (MF)	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Marsh and swamp (MS)	1.77	1.76	1.76	1.76	1.76	1.76	1.76
Water body (WA)	1.76	1.76	1.76	1.76	1.76	1.76	1.76
Miscellaneous land (ML)	5.87	5.79	5.70	5.66	5.63	5.56	5.51
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

As results, LULC types which area will increase in 2024 are urban and built-up area, oil palm plantation, and evergreen forest and cover area of 145.10 km^2 or 6.03%, 32.34 km^2 or 1.34% and 377.33 km^2 or 15.68%, respectively. On contrary, LULC types which area will decrease in 2024 are rubber plantation and miscellaneous land and cover area of 1,569.66 km^2 or 65.24% and 132.56 km^2 or 5.51%, respectively. Meanwhile LULC types with the fixed area during 2018 to 2024 consist of paddy field, perennial tree and orchard, aquatic cultural area, mangrove forest, marsh and swamp, and water body and cover area of 20.25 km^{2}or 0.84%, 33.90 km^2 or 1.41%, 9.38 km^2 or 0.39%, 0.85 km^2 or 0.04%, 42.27 km^2 or 1.76%, and 42.43 km^2 or 1.76%, respectively.

In addition, area and percentage of predictive LULC at sub-watershed level of Scenario II between 2018 and 2024 is summarized in Table 5.15.

Table 5.15 Predictive LULC types at sub-watershed level of Scenario II between 2018 and 2024.

Year	Sub-watershed	UR (km²)	UR %	PD (km²)	PD %	RP (km²)	RP %	OP (km²)	OP %	PO (km²)	PO %	AQ (km²)	AQ %	EF (km²)	EF %	MF (km²)	MF %	MS (km²)	MS %	WA (km²)	WA %	ML (km²)	ML %
2018	1	10.73	3.00	-	-	259.09	72.36	9.25	2.58	2.68	0.75	0.38	0.10	34.86	9.73	-	-	5.59	1.56	9.72	2.72	25.78	7.20
	2	6.48	3.89	-	-	141.61	85.05	0.62	0.37	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	15.81	9.49
	3	3.14	1.66	-	-	159.56	84.47	2.44	1.29	2.43	1.29	0.04	0.02	7.48	3.96	-	-	0.05	0.02	0.56	0.30	13.18	6.98
	4	6.41	6.21	-	-	81.23	78.77	0.30	0.29	1.97	1.91	0.07	0.07	4.00	3.88	-	-	1.83	1.77	1.22	1.18	6.12	5.93
	5	3.97	1.22	0.23	0.07	241.15	74.21	3.17	0.97	4.05	1.25	0.19	0.06	51.47	15.84	-	-	0.43	0.13	1.70	0.52	18.58	5.72
	6	2.36	0.91	-	-	177.27	68.40	0.17	0.06	2.91	1.12	0.01	0.00	59.20	22.84	-	-	0.01	0.00	7.53	2.91	9.72	3.75
	7	3.71	2.29	-	-	130.92	81.03	0.37	0.23	1.38	0.85	-	-	15.09	9.34	-	-	-	-	0.69	0.43	9.43	5.83
	8	48.47	14.88	2.43	0.74	194.69	59.75	1.04	0.32	11.69	3.59	7.63	2.34	11.66	3.58	0.21	0.06	20.48	6.29	11.44	3.51	16.08	4.94
	9	23.47	6.67	4.24	1.20	212.58	60.37	2.37	0.67	3.10	0.88	0.06	0.02	85.91	24.40	-	-	1.86	0.53	3.43	0.97	15.13	4.30
	10	7.89	4.76	13.47	8.12	109.69	66.15	1.02	0.61	2.94	1.77	0.96	0.58	-	-	0.65	0.39	12.29	7.41	5.51	3.32	11.41	6.88
2019	1	11.33	3.16	-	-	256.20	71.55	9.46	2.64	2.68	0.75	0.38	0.10	37.19	10.39	-	-	5.57	1.55	9.72	2.72	25.56	7.14
	2	6.78	4.07	-	-	141.35	84.89	0.64	0.38	0.95	0.57	0.05	0.03	0.38	0.23	-	-	-	-	0.63	0.38	15.74	9.45
	3	3.34	1.77	-	-	158.85	84.10	2.44	1.29	2.43	1.29	0.04	0.02	8.14	4.31	-	-	0.04	0.02	0.56	0.30	13.04	6.90
	4	6.69	6.48	-	-	79.38	76.97	0.36	0.35	1.97	1.91	0.07	0.07	5.67	5.49	-	-	1.83	1.77	1.22	1.18	5.97	5.78
	5	4.14	1.27	0.23	0.07	238.74	73.47	3.25	1.00	4.05	1.24	0.19	0.06	53.75	16.54	-	-	0.43	0.13	1.70	0.52	18.47	5.68
	6	2.49	0.96	-	-	175.06	67.55	0.19	0.07	2.91	1.12	0.01	0.00	61.42	23.70	-	-	0.01	0.00	7.53	2.91	9.56	3.69
	7	3.83	2.37	-	-	127.75	79.07	0.38	0.23	1.38	0.85	-	-	18.28	11.31	-	-	-	-	0.69	0.43	9.28	5.75
	8	50.62	15.53	2.43	0.74	189.35	58.11	2.06	0.63	11.65	3.57	7.63	2.34	14.42	4.42	0.21	0.06	20.43	6.27	11.44	3.51	15.61	4.79
	9	24.59	6.98	4.23	1.20	210.23	59.70	2.66	0.76	3.08	0.88	0.06	0.02	87.17	24.76	-	-	1.85	0.52	3.43	0.97	14.85	4.22
	10	8.20	4.95	13.46	8.12	109.19	65.85	1.29	0.78	2.94	1.77	0.96	0.58	-	-	0.65	0.39	12.28	7.41	5.51	3.32	11.34	6.84
2020	1	11.75	3.28	-	-	253.25	70.72	9.87	2.76	2.68	0.75	0.38	0.10	39.64	11.07	-	-	5.55	1.55	9.72	2.72	25.23	7.05
	2	6.96	4.18	-	-	141.13	84.76	0.70	0.42	0.95	0.57	0.05	0.03	0.49	0.30	-	-	-	-	0.63	0.38	15.62	9.38
	3	3.46	1.83	-	-	157.70	83.49	2.54	1.34	2.43	1.29	0.04	0.02	9.37	4.96	-	-	0.04	0.02	0.56	0.30	12.74	6.74
	4	6.94	6.73	-	-	77.74	75.38	0.43	0.41	1.97	1.91	0.07	0.07	7.19	6.97	-	-	1.82	1.77	1.22	1.18	5.77	5.60
	5	4.25	1.31	0.23	0.07	236.12	72.67	3.43	1.06	4.05	1.24	0.19	0.06	56.32	17.33	-	-	0.43	0.13	1.70	0.52	18.23	5.61
	6	2.58	1.00	-	-	172.97	66.74	0.23	0.09	2.90	1.12	0.01	0.00	63.62	24.55	-	-	0.00	0.00	7.53	2.91	9.34	3.60
	7	3.92	2.43	-	-	125.68	77.78	0.42	0.26	1.38	0.85	-	-	20.30	12.56	-	-	-	-	0.69	0.43	9.20	5.69
	8	52.31	16.05	2.42	0.74	183.71	56.38	2.51	0.77	11.62	3.56	7.63	2.34	18.40	5.65	0.21	0.06	20.40	6.26	11.44	3.51	15.19	4.66
	9	25.59	7.27	4.21	1.19	207.50	58.93	2.92	0.83	3.08	0.87	0.06	0.02	88.94	25.26	-	-	1.83	0.52	3.43	0.97	14.59	4.14
	10	8.55	5.16	13.46	8.11	108.66	65.53	1.61	0.97	2.94	1.77	0.96	0.58	0.03	0.02	0.64	0.39	12.27	7.40	5.51	3.32	11.20	6.75

Table 5.15 (Continued).

Year	Sub-watershed	UR (km^2)	UR %	PD (km^2)	PD %	RP (km^2)	RP %	OP (km^2)	OP %	PO (km^2)	PO %	AQ (km^2)	AQ %	EF (km^2)	EF %	MF (km^2)	MF %	MS (km^2)	MS %	WA (km^2)	WA %	ML (km^2)	ML %
2021	1	12.27	3.43	-	-	249.96	69.81	10.40	2.90	2.68	0.75	0.38	0.10	41.99	11.73	-	-	5.54	1.55	9.72	2.72	25.14	7.02
	2	7.23	4.34	-	-	140.65	84.47	0.70	0.42	0.95	0.57	0.05	0.03	0.78	0.47	-	-	-	-	0.63	0.38	15.53	9.33
	3	3.55	1.88	-	-	156.26	82.73	2.65	1.40	2.43	1.29	0.04	0.02	10.67	5.65	-	-	0.04	0.02	0.56	0.30	12.69	6.72
	4	7.29	7.06	-	-	76.00	73.70	0.44	0.42	1.96	1.90	0.07	0.07	8.66	8.39	-	-	1.82	1.77	1.22	1.18	5.69	5.52
	5	4.37	1.35	0.23	0.07	233.42	71.83	3.63	1.12	4.05	1.24	0.19	0.06	58.79	18.09	-	-	0.43	0.13	1.70	0.52	18.15	5.58
	6	2.67	1.03	-	-	170.81	65.91	0.26	0.10	2.90	1.12	0.01	0.00	65.74	25.37	-	-	0.00	0.00	7.53	2.91	9.25	3.57
	7	4.01	2.48	-	-	123.97	76.73	0.45	0.28	1.38	0.85	-	-	21.92	13.57	-	-	-	-	0.69	0.43	9.17	5.68
	8	53.77	16.50	2.41	0.74	177.29	54.41	2.69	0.83	11.58	3.55	7.63	2.34	23.50	7.21	0.21	0.06	20.36	6.25	11.44	3.51	14.95	4.59
	9	26.84	7.62	4.19	1.19	204.08	57.95	3.13	0.89	3.06	0.87	0.06	0.02	91.09	25.87	-	-	1.82	0.52	3.43	0.97	14.45	4.10
	10	8.90	5.37	13.44	8.11	107.65	64.92	2.13	1.29	2.93	1.77	0.96	0.58	0.23	0.14	0.64	0.39	12.27	7.40	5.51	3.32	11.15	6.73
2022	1	13.01	3.63	-	-	246.29	68.78	10.98	3.07	2.68	0.75	0.38	0.10	44.43	12.41	-	-	5.54	1.55	9.72	2.72	25.05	7.00
	2	7.66	4.60	-	-	139.93	84.04	0.70	0.42	0.95	0.57	0.05	0.03	1.13	0.68	-	-	-	-	0.63	0.38	15.47	9.29
	3	3.75	1.98	-	-	154.74	81.92	2.74	1.45	2.43	1.29	0.04	0.02	11.95	6.33	-	-	0.04	0.02	0.56	0.30	12.63	6.69
	4	7.63	7.40	-	-	74.46	72.20	0.44	0.43	1.96	1.90	0.07	0.07	9.89	9.59	-	-	1.82	1.77	1.22	1.18	5.65	5.48
	5	4.58	1.41	0.23	0.07	230.84	71.04	3.86	1.19	4.05	1.24	0.19	0.06	60.94	18.76	-	-	0.43	0.13	1.70	0.52	18.12	5.58
	6	2.79	1.07	-	-	168.80	65.13	0.30	0.12	2.90	1.12	0.01	0.00	67.62	26.09	-	-	0.00	0.00	7.53	2.91	9.23	3.56
	7	4.14	2.56	-	-	122.44	75.78	0.48	0.30	1.38	0.85	-	-	23.29	14.41	-	-	-	-	0.69	0.43	9.16	5.67
	8	55.03	16.89	2.41	0.74	170.42	52.30	2.79	0.86	11.58	3.55	7.63	2.34	29.19	8.96	0.21	0.06	20.36	6.25	11.44	3.51	14.77	4.53
	9	28.14	7.99	4.19	1.19	200.55	56.95	3.33	0.94	3.06	0.87	0.06	0.02	93.25	26.48	-	-	1.82	0.52	3.43	0.97	14.33	4.07
	10	9.43	5.69	13.44	8.10	106.14	64.02	2.87	1.73	2.93	1.77	0.96	0.58	0.53	0.32	0.64	0.39	12.27	7.40	5.51	3.32	11.09	6.69
2023	1	13.72	3.83	-	-	243.04	67.87	11.55	3.23	2.68	0.75	0.38	0.10	46.61	13.02	-	-	5.54	1.55	9.72	2.72	24.83	6.93
	2	8.03	4.82	-	-	139.22	83.61	0.72	0.43	0.95	0.57	0.05	0.03	1.63	0.98	-	-	-	-	0.63	0.38	15.30	9.19
	3	3.88	2.05	-	-	153.37	81.20	2.85	1.51	2.43	1.29	0.04	0.02	13.15	6.96	-	-	0.04	0.02	0.56	0.30	12.56	6.65
	4	7.94	7.70	-	-	73.10	70.88	0.45	0.44	1.96	1.90	0.07	0.07	11.02	10.68	-	-	1.82	1.77	1.22	1.18	5.57	5.40
	5	4.78	1.47	0.23	0.07	228.41	70.29	4.27	1.31	4.05	1.24	0.19	0.06	62.92	19.36	-	-	0.43	0.13	1.70	0.52	17.96	5.53
	6	2.91	1.12	-	-	167.03	64.45	0.35	0.13	2.90	1.12	0.01	0.00	69.30	26.74	-	-	0.00	0.00	7.53	2.91	9.14	3.53
	7	4.26	2.64	-	-	121.28	75.06	0.53	0.33	1.38	0.85	-	-	24.33	15.06	-	-	-	-	0.69	0.43	9.11	5.64
	8	55.91	17.16	2.41	0.74	164.64	50.53	2.85	0.88	11.58	3.55	7.63	2.34	34.41	10.56	0.21	0.06	20.36	6.25	11.44	3.51	14.40	4.42
	9	29.18	8.29	4.18	1.19	197.47	56.08	3.51	1.00	3.06	0.87	0.06	0.02	95.41	27.09	-	-	1.82	0.52	3.43	0.97	14.04	3.99
	10	9.84	5.94	13.44	8.10	105.19	63.44	3.33	2.01	2.93	1.77	0.96	0.58	0.73	0.44	0.64	0.39	12.27	7.40	5.51	3.32	10.98	6.62

Table 5.15 (Continued).

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km^2)	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**
2024	1	14.57	4.07	-	-	239.46	66.87	12.15	3.39	2.68	0.75	0.38	0.10	48.95	13.67	-	-	5.54	1.55	9.72	2.72	24.63	6.88
	2	8.37	5.02	-	-	138.39	83.12	0.73	0.44	0.95	0.57	0.05	0.03	2.21	1.33	-	-	-	-	0.63	0.38	15.20	9.13
	3	4.10	2.17	-	-	151.83	80.38	3.01	1.59	2.43	1.29	0.04	0.02	14.40	7.62	-	-	0.04	0.02	0.56	0.30	12.47	6.60
	4	8.25	7.99	-	-	71.72	69.54	0.47	0.45	1.96	1.90	0.07	0.07	12.14	11.77	-	-	1.82	1.77	1.22	1.18	5.51	5.34
	5	5.05	1.55	0.23	0.07	225.78	69.48	4.71	1.45	4.05	1.24	0.19	0.06	64.96	19.99	-	-	0.43	0.13	1.70	0.52	17.85	5.49
	6	3.02	1.16	-	-	165.14	63.72	0.40	0.16	2.90	1.12	0.01	0.00	71.09	27.43	-	-	0.00	0.00	7.53	2.91	9.09	3.51
	7	4.42	2.74	-	-	120.17	74.38	0.62	0.38	1.38	0.85	-	-	25.25	15.63	-	-	-	-	0.69	0.43	9.05	5.60
	8	56.86	17.45	2.40	0.74	159.04	48.81	2.94	0.90	11.58	3.55	7.63	2.34	39.26	12.05	0.21	0.06	20.36	6.25	11.44	3.51	14.11	4.33
	9	30.10	8.55	4.18	1.19	194.02	55.10	3.70	1.05	3.06	0.87	0.06	0.02	97.98	27.83	-	-	1.82	0.52	3.43	0.97	13.80	3.92
	10	10.37	6.26	13.44	8.10	104.12	62.80	3.62	2.18	2.93	1.77	0.96	0.58	1.10	0.66	0.64	0.39	12.27	7.40	5.51	3.32	10.86	6.55

Note: 1. Khlong La/Khlong Jam Rai, 2. Khlong Lea, 3. Khlong Phang La/Khlong Ngae, 4. Khlong Pom, 5. Khlong Ram, 6. Khlong Sa Dao, 7. Khlong Tong/Khlong Pra Tu, 8. Khlong Wa, 9. Khlong Wat/Khlong Tam, and 10. Klong Bang Klam.

As result, it reveals that at sub-watershed level, percentage of evergreen forest in each sub-watershed between 2018 and 2024 are low that varies from 0% to 27.83% (See detail in Table 5.15), when they are compared with target area of forest cover at 40% of total country area under Thailand National Forest Policy (Royal Forest Department, 1986). Like Scenario I, according to Thailand National Forest Policy, it can observed that sub-watersheds under Khlong U-Tapoa watershed which are critical include (1) Khlong La/Khlong Jam Rai, (2) Khlong Lea, (3) Khlong Phang La/Khlong Ngae, (4) Khlong Pom, (5) Khlong Wa, and (6). Klong Bang Klam sub-watersheds wherein evergreen forest as protective forest are less than 15%.

Furthermore, transition LULC change matrix between 2017 and 2024 of Scenario II is displayed in Table 5.16. As results, urban and built-up in 2017 as expected increasing area under Scenario II is not converted in other LULC types in 2024 and its area will increase from 113.21 km^2 in 2017 to 145.10 km^2 in 2024. The increasing areas of urban and built area in 2024 mainly come from rubber plantation (26.57 km^2) and miscellaneous land (4.47 km^2) in 2017. Likewise, oil palm plantation in 2017 as expected increasing area under Scenario II is not converted into other LULC classes in 2024 and its area will increase from 18.85 km^2 in 2017 to 32.34 km^2 in 2024, the increasing areas of oil palm plantation in 2024 mostly come from rubber plantation (12.36 km^2) and miscellaneous land (1.10 km^2) in 2017. Likewise, evergreen forest in 2017 as expected increasing area under Scenario II is not converted into other LULC types in 2024 and its area will increase from 254.01 km^2 in 2017 to 377.33 km^2 in 2024, this indicates influence of transformation of forest conservation and prevention policy of Scenario-II.

On contrary, rubber plantation in 2017 as expected decreasing area under Scenario II is converted into urban and built-up area (26.57 km^2), oil palm plantation (12.36 km^2), and evergreen forest (119.23 km^2) in 2024 and its area will decrease from 1,727.46 km^2 in 2017 to 1,569.66 km^2 in 2024. Herein, the illegal rubber plantation in protected areas will be replaced by reforestation program for evergreen forest according to forest conservation and prevention policy. Likewise, miscellaneous land in 2017 as expected decreasing area under Scenario II is converted into urban and built-up area (4.47 km^2), rubber plantation (0.36 km^2), oil palm plantation (1.10 km^2), and evergreen forest (4.09 km^2) and its area will decrease from 142.57 km^2 in 2017 to 132.56 km^2 in 2024. This also reflects the effect of forest conservation and prevention policy.

Meanwhile, other LULC types with fixed land requirement area during 2017 and 2024 under Scenario II include paddy field, perennial tree and orchard, aquatic cultural area, mangrove forest, marsh and swamp and water body show variety of from-to change pattern during 2017 to 2024. Herein, paddy field in 2017 is converted into urban and built-up area (0.16 km^2) and its area will decrease from 20.41 km^2 in 2017 to 20.25 km^2 in 2024. Likewise, perennial tree and orchard in 2017 is converted into urban and built-up area (0.30 km^2), and its area will decrease from 34.20 km^2 in 2017 to 33.90 km^2 in 2024. In the meantime, mangrove forest in 2017 is converted into oil palm plantation (0.01 km^2) in 2024 but its area is stable during 2017 to 2024 as defining under Scenario II. Similarly, marsh and swamp in 2017 is converted into urban and built-up area (0.40 km^2) and oil palm plantation (0.03 km^2) but its area is stable during 2017 to 2024 as defining under Scenario II. In contrast, aquatic cultural area and water body in 2017 are not converted into other LULC classes in 2024 and areas of both LULC types are stable during 2017 to 2024 as defining under Scenario II.

Like Scenario I, it was found that there is slightly difference between the required land area and the predicted area of each LULC type in 2024 under Scenario II. For example, the required area of rubber plantation in 2024 is 1,568.17 km^2 but it is allocated 1,569.66 km^2 whereas the required area of marsh and swamp in 2024 is 42.70 km^2 but it is allocated only 42.27 km^2. In this study, the deviation values between the required land area and the predicted area of each LULC type under Scenario II vary from -0.0042% to 0.0149% or from -0.43 km^2 (under estimation) to 1.49 km^2 (over estimation). The summation of deviation values, which are trade-off between over and under estimation among LULC types is 0.0000% and -0.01 km^2 (see Table 5.16). Since the deviation value depends on iteration driving factors of each LULC type which indicates the maximum different allowance between the required and allocated area of LULC type under CLUE-S model (van Asselen and Verburg, 2013; Liu, Wang, Li, and Xia (2013); and Xu, Li, Song, and Yin, (2013). Therefore, the LULC prediction under Scenario II using CLUE-S model can be validated and accepted for ecosystem service assessment in terms of water yield and sediment retention.

Table 5.16 Transition matrix of LULC change between 2017 and 2024 of Scenario II: Forest conservation and prevention.

LULC2 017 (km^2)	LULC 2024 (km^2)											
LULC types	**UR**	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**	**Total**
Urban and built-up area (UR)	113.21	-	-	-	-	-	-	-	-	-	-	113.21
Paddy field (PD)	0.16	20.25	-	-	-	-	-	-	-	-	-	20.41
Rubber plantation (RP)	26.57	-	1,569.30	12.36	-	-	119.23	-	-	-	-	1,727.46
Oil palm plantation (OP)	-	-	-	18.85	-	-	-	-	-	-	-	18.85
Perennial tree/orchard (PO)	0.30	-	-	-	33.90	-	-	-	-	-	-	34.20
Aquatic cultural area (AQ)	-	-	-	-	-	9.38	-	-	-	-	-	9.38
Evergreen forest (EF)	-	-	-	-	-	-	254.01	-	-	-	-	254.01
Mangrove forest (MF)	-	-	-	0.01	-	-	-	0.85	-	-	-	0.85
Marsh and swamp (MS)	0.40	-	-	0.03	-	-	-	-	42.27	-	-	42.70
Water body (WA)	-	-	-	-	-	-	-	-	-	42.43	-	42.43
Miscellaneous land (ML)	4.47	-	0.36	1.10	-	-	4.09	-	-	-	132.56	142.57
Total	**145.10**	**20.25**	**1,569.66**	**32.34**	**33.90**	**9.38**	**377.33**	**0.85**	**42.27**	**42.43**	**132.56**	**2,406.04**
Land use requirement	**145.41**	**20.41**	**1,568.17**	**32.35**	**34.20**	**9.38**	**377.47**	**0.85**	**42.70**	**42.43**	**132.69**	
Deviation value (%)	**-0.0031**	**-0.0016**	**0.0149**	**-0.0002**	**-0.0030**	**-**	**-0.0015**	**-**	**-0.0042**	**-**	**-0.0013**	**0.0000**
Deviation value (km^2)	**-0.31**	**-0.16**	**1.49**	**-0.01**	**-0.30**	**-**	**-0.14**	**-**	**-0.43**	**-**	**-0.13**	**0.01**

5.5 LULC prediction of Scenario III: Agriculture production extension

Refer to definition of Scenario III (Agriculture production extension) as mentioned in Chapter III, land requirement is calculated based on the rate of LULC change developing between 2010 and 2017 using Markov Chain model and policy on agriculture production extension.

The result of annual land demand of Scenario III between 2010 and 2024 is presented in Table 5.17. The characteristics of land demand of each LULC type under this scenario can be grouped and described below.

(1) Historical rate of LULC change. Land requirement of urban and built-up area and marsh and swamp was calculated based on historical rate of LULC change between 2010 and 2017 by using Markov Chain model.

(2) Unchanged area. Land requirement of paddy field, perennial tree/orchard, aquatic cultural area, evergreen forest, mangrove forest, and water bodies were fixed based their areas in 2017.

(3) Decreased area. Land requirement of rubber plantation and miscellaneous land were calculate based on the excluded existing area of rubber plantation and miscellaneous land in 2017 over suitability classes (highly, moderate, and marginally suitability) of oil palm plantation by Department of Agriculture in 2015 (See Figure 5.5). The total excluded area of rubber plantation and miscellaneous land oil palm suitability zonation for oil palm plantation in 2024 is about 240.66 km^2.

(4) Increased area. Land requirement of oil palm plantation is assigned based on driving policy of Government to reduce rubber plantation area with miscellaneous land

over oil palm suitability zonation by Department of Agriculture in 2015. Herewith the total land requirement of oil palm plantation in 2024 is 259.51 km^2.

Table 5.17 Annual land requirement for Scenario III by each LULC type.

Year	Area in km^2										
	UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**
2017	113.21	20.41	1,727.46	18.85	34.20	9.38	254.01	0.85	42.70	42.43	142.57
2018	117.81	20.41	1,698.52	53.23	34.20	9.38	254.01	0.85	41.95	42.43	133.28
2019	122.41	20.41	1,669.59	87.61	34.20	9.38	254.01	0.85	41.20	42.43	123.98
2020	127.01	20.41	1,640.65	121.99	34.20	9.38	254.01	0.85	40.45	42.43	114.69
2021	131.61	20.41	1,611.72	156.37	34.20	9.38	254.01	0.85	39.70	42.43	105.39
2022	136.21	20.41	1,582.78	190.75	34.20	9.38	254.01	0.85	38.95	42.43	96.10
2023	140.81	20.41	1,553.85	225.13	34.20	9.38	254.01	0.85	38.20	42.43	86.80
2024	145.41	20.41	1,524.88	259.51	34.20	9.38	254.01	0.85	37.50	42.43	77.49
Annual rate	**4.60**	-	**-28.94**	**34.38**	-	-	-	-	**-0.74**	-	**-9.30**

The distribution of the predicted LULC of Scenario III between 2018 and 2024 is presented in Figures 5.6 and area and percentage of LULC classes of Scenario III between 2018 and 2024 is displayed in Tables 5.18 and 5.19, respectively. Herein, increasing LULC classes are urban and built-up area, and oil palm plantation with annual increasing rate of about 4.60 and 34.38 km^2 per year, respectively. In contrast, decreasing LULC classes are rubber plantation, marsh and swamp and miscellaneous land with annual decreasing rate of about 28.94, 0.74 and 9.30 km^2 per year, respectively. In general, land requirement dictates the final area of each LULC type in 2024 under of CLUE-S model.

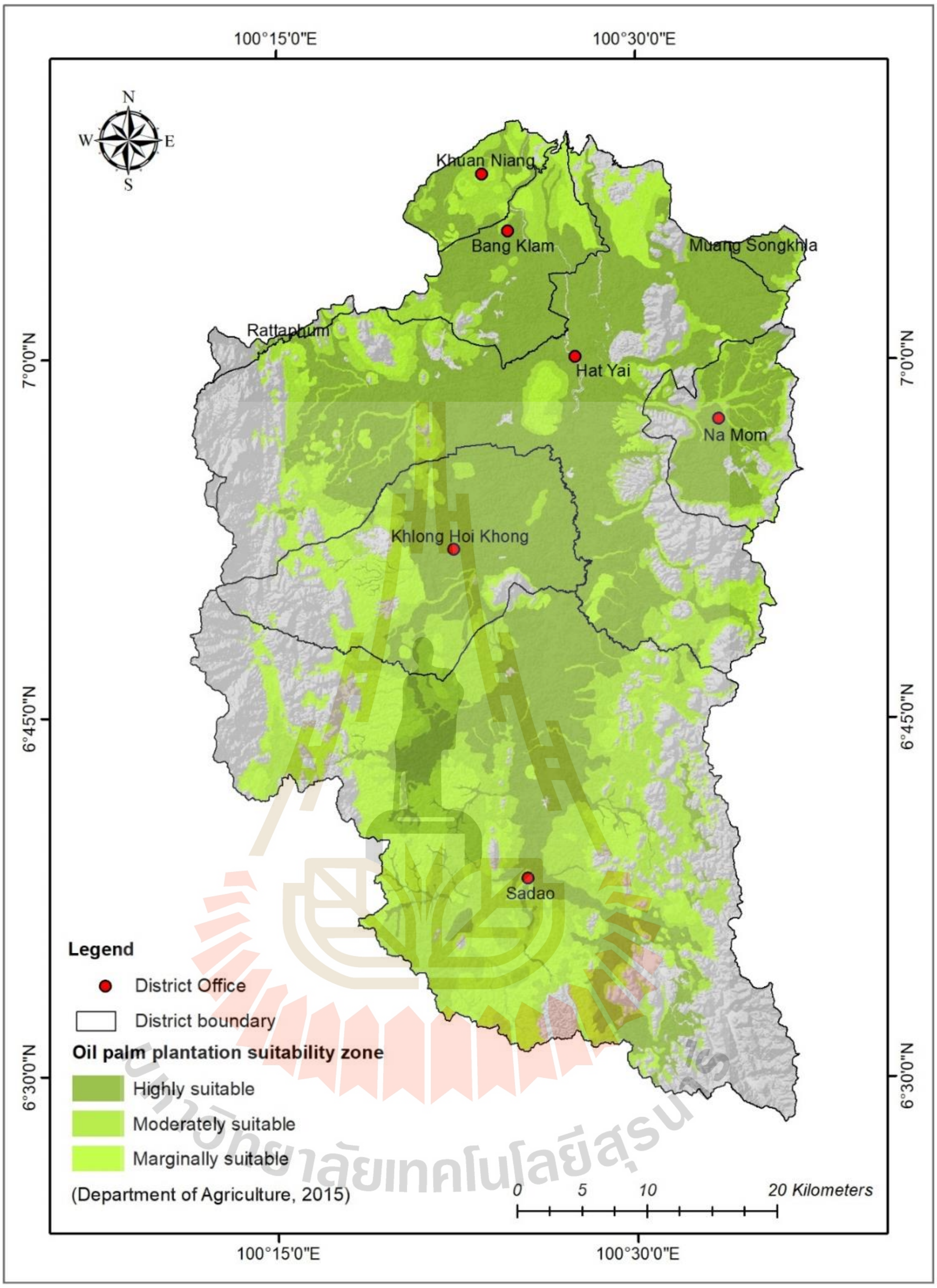
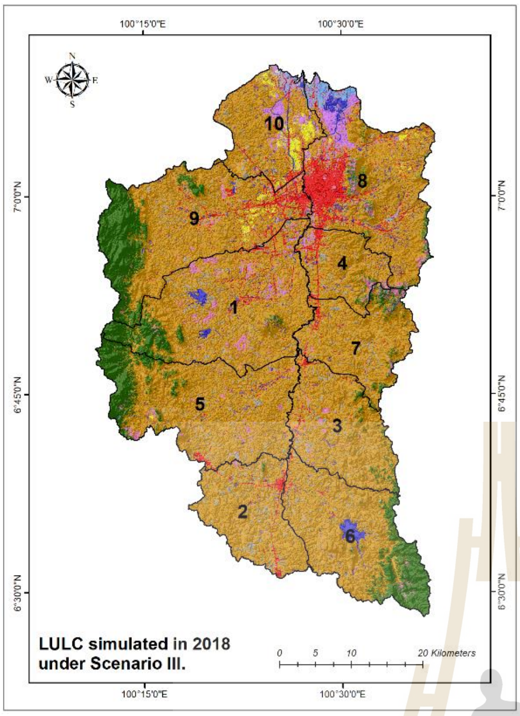
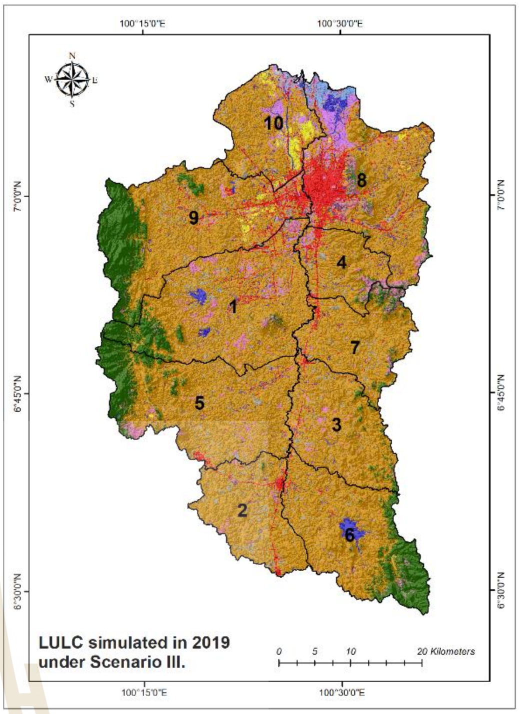


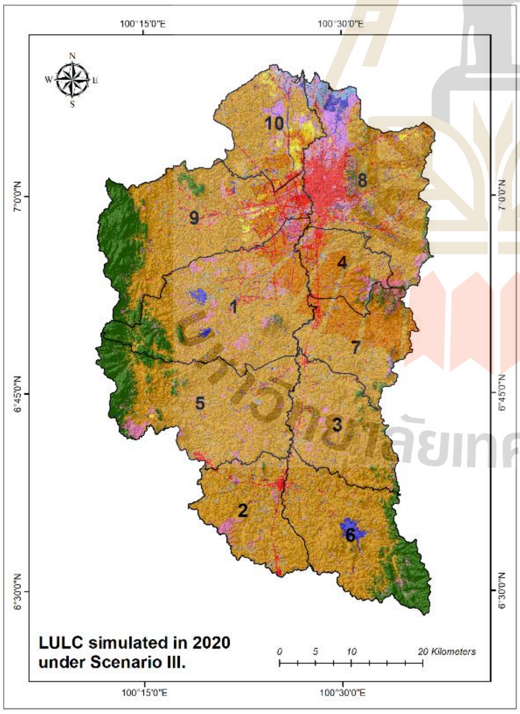
Figure 5.5 Spatial distribution of land suitability classification for oil palm plantation.



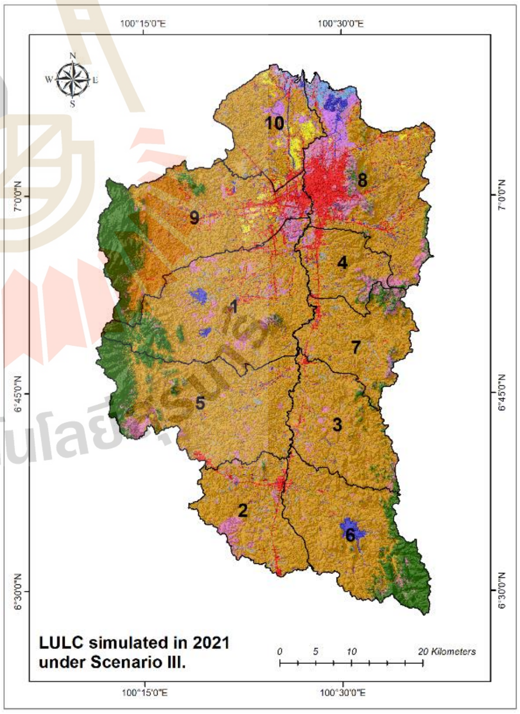
2018



2019

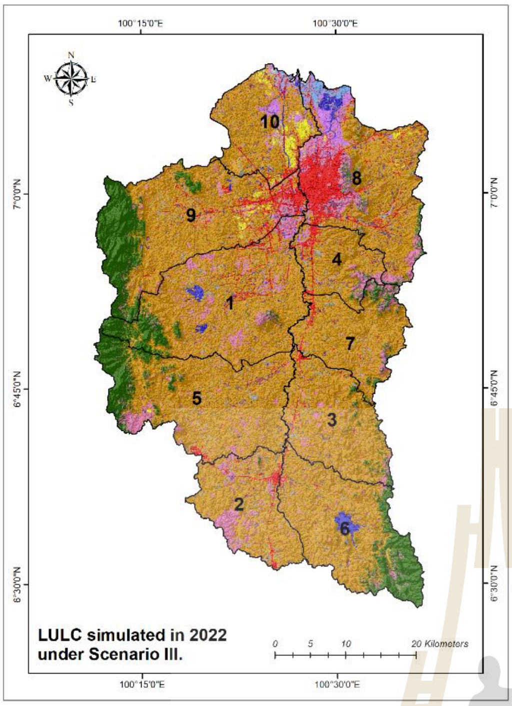


2020

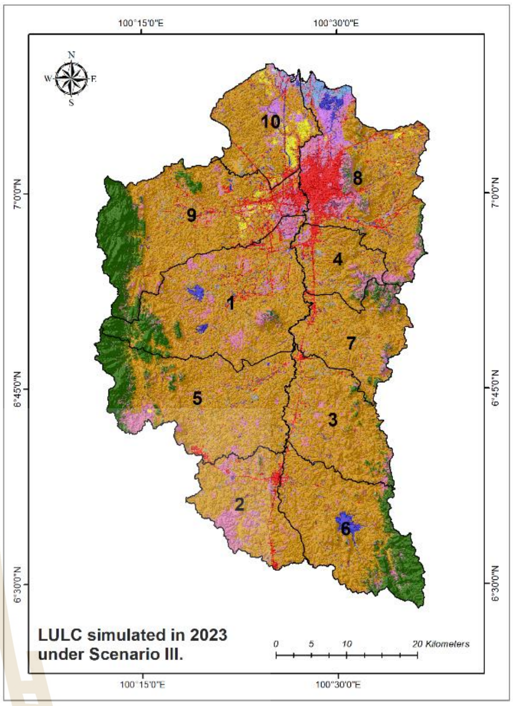


2021

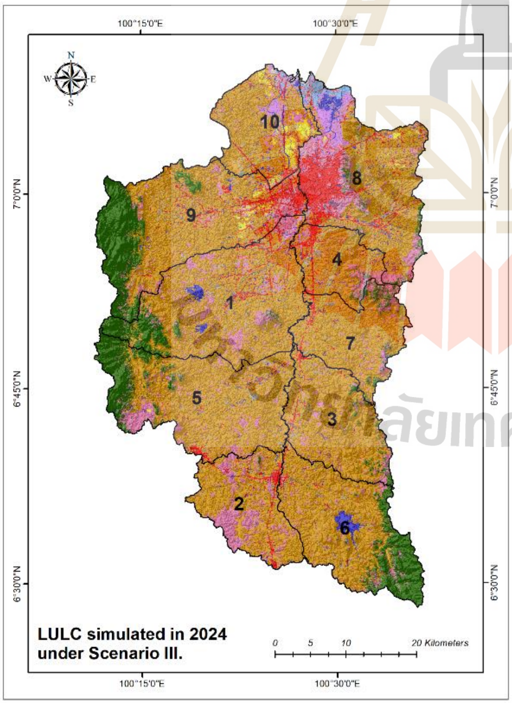
Figure 5.6 Spatial distribution of LULC prediction of Scenario III during 2018 to 2024.



2022



2023



2024

1. Khlong La/Khlong Jam Rai
2. Khlong Lea
3. Khlong Phang La/Khlong Ngae
4. Khlong Pom
5. Khlong Ram
6. Khlong Sa Dao
7. Khlong Tong/Khlong Pra Tu
8. Khlong Wa
9. Khlong Wat/Khlong Tam
10. Klong Bang Klam

Map legend

Figure 5.6 (Continued).

Table 5.18 Area of predicted LULC of Scenario III: Agriculture production extension between 2018 and 2024.

LULC types	Area in km^2 in						
	2018	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Urban and built-up area (UR)	117.37	122.22	122.55	129.55	136.15	136.15	140.16
Paddy field (PD)	20.41	20.41	20.41	20.41	20.41	20.41	20.41
Rubber plantation (RP)	1,697.51	1,669.07	1,641.78	1,608.26	1,582.08	1,548.65	1,528.48
Oil palm plantation (OP)	52.64	86.92	121.79	156.50	188.15	227.99	257.44
Perennial tree/orchard (PO)	34.20	34.20	34.20	34.20	34.20	34.20	34.20
Aquatic cultural area (AQ)	9.38	9.38	9.38	9.38	9.38	9.38	9.38
Evergreen forest (EF)	257.55	257.55	257.55	257.55	257.93	257.93	257.93
Mangrove forest (MF)	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Marsh and swamp (MS)	40.28	39.56	38.84	38.66	38.47	38.47	36.89
Water body (WA)	42.43	42.44	42.44	42.44	42.44	42.44	42.44
Miscellaneous land (ML)	133.43	123.46	116.26	108.26	95.99	89.58	77.87
Total	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**	**2,406.04**

Table 5.19 Percentage of predicted LULC of Scenario III: Agriculture production extension between 2018 and 2024.

LULC types	Percent in						
	2018	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Urban and built-up area (UR)	4.88	5.08	5.09	5.38	5.66	5.66	5.83
Paddy field (PD)	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Rubber plantation (RP)	70.55	69.37	68.24	66.84	65.75	64.36	63.53
Oil palm plantation (OP)	2.19	3.61	5.06	6.50	7.82	9.48	10.70
Perennial tree/orchard (PO)	1.42	1.42	1.42	1.42	1.42	1.42	1.42
Aquatic cultural area (AQ)	0.39	0.39	0.39	0.39	0.39	0.39	0.39
Evergreen forest (EF)	10.70	10.70	10.70	10.70	10.72	10.72	10.72
Mangrove forest (MF)	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Marsh and swamp (MS)	1.67	1.64	1.61	1.61	1.60	1.60	1.53
Water body (WA)	1.76	1.76	1.76	1.76	1.76	1.76	1.76
Miscellaneous land (ML)	5.55	5.13	4.83	4.50	3.99	3.72	3.24
Total	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**

As results, LULC types which will increase in 2024 are urban and built-up area and oil palm plantation and cover area of 140.16 km^2 or 5.83% and 257.44 km^2 or 10.70%, respectively. On contrary, LULC types which will decrease in 2024 are rubber plantation, marsh and swamp and miscellaneous land and cover area of 1,528.48 km^2 or 63.53%, 36.89 km^2 or 1.53%, and 77.87 km^2 or 3.24%, respectively. Meanwhile LULC types with the fixed area during 2018 to 2024 consist of paddy field, perennial tree and orchard, aquatic cultural area, evergreen forest, mangrove forest, and water body and cover area of 20.41 km^2or 0.85%, 34.20 km^2 or 1.42%, 9.38 km^2 or 0.39%, 257.93 km^2 or 10.72%, 0.85 km^2 or 0.04% and 42.44 km^2 or 1.76%, respectively.

In addition, area and percentage of predictive LULC at sub-watershed level of Scenario III between 2018 and 2024 is summarized in Table 5.20.

Table 5.20 Predictive LULC types at sub-watershed level of Scenario III between 2018 and 2024.

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km^2)	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**
2018	1	10.80	3.02	-	-	257.49	71.91	14.63	4.09	2.69	0.75	0.38	0.10	33.40	9.33	-	-	5.49	1.53	9.72	2.72	23.47	6.55
	2	6.58	3.95	-	-	131.34	78.88	10.95	6.58	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	15.65	9.40
	3	3.19	1.69	-	-	160.54	84.99	2.91	1.54	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.05	0.02	0.56	0.30	11.85	6.27
	4	6.47	6.27	-	-	81.86	79.37	0.50	0.49	1.98	1.92	0.07	0.07	3.16	3.06	-	-	1.83	1.78	1.22	1.18	6.06	5.87
	5	4.00	1.23	0.23	0.07	242.39	74.60	5.23	1.61	4.07	1.25	0.19	0.06	49.21	15.15	-	-	0.44	0.13	1.70	0.52	17.49	5.38
	6	2.37	0.91	-	-	180.05	69.47	0.56	0.22	2.92	1.12	0.01	0.00	56.69	21.87	-	-	0.01	0.00	7.53	2.91	9.05	3.49
	7	3.70	2.29	-	-	133.59	82.68	0.81	0.50	1.39	0.86	-	-	12.50	7.74	-	-	-	-	0.69	0.43	8.90	5.51
	8	48.73	14.96	2.44	0.75	189.22	58.07	8.76	2.69	11.74	3.60	7.63	2.34	10.51	3.23	0.21	0.06	19.11	5.87	11.44	3.51	16.04	4.92
	9	23.61	6.71	4.26	1.21	210.81	59.87	6.58	1.87	3.11	0.88	0.06	0.02	84.38	23.96	-	-	1.83	0.52	3.43	0.97	14.08	4.00
	10	7.93	4.78	13.48	8.13	110.24	66.49	1.71	1.03	2.94	1.77	0.96	0.58	-	-	0.65	0.39	11.54	6.96	5.51	3.32	10.87	6.55
2019	1	11.30	3.16	-	-	256.90	71.75	16.84	4.70	2.69	0.75	0.38	0.10	33.40	9.33	-	-	5.47	1.53	9.72	2.72	21.37	5.97
	2	6.65	3.99	-	-	118.08	70.92	24.47	14.70	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	15.32	9.20
	3	3.35	1.77	-	-	161.28	85.39	3.94	2.09	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.05	0.02	0.56	0.30	9.91	5.25
	4	6.57	6.37	-	-	80.77	78.32	1.57	1.52	1.98	1.92	0.07	0.07	3.16	3.06	-	-	1.83	1.77	1.22	1.18	5.98	5.80
	5	4.17	1.28	0.23	0.07	236.57	72.81	12.05	3.71	4.07	1.25	0.19	0.06	49.21	15.15	-	-	0.44	0.13	1.70	0.52	16.32	5.02
	6	2.45	0.94	-	-	179.59	69.29	2.11	0.81	2.92	1.12	0.01	0.00	56.69	21.87	-	-	0.01	0.00	7.53	2.91	7.89	3.04
	7	3.85	2.38	-	-	133.15	82.41	1.71	1.06	1.39	0.86	-	-	12.50	7.74	-	-	-	-	0.69	0.43	8.29	5.13
	8	51.46	15.79	2.44	0.75	183.12	56.20	12.89	3.96	11.74	3.60	7.63	2.34	10.51	3.23	0.21	0.06	18.68	5.73	11.45	3.51	15.70	4.82
	9	24.22	6.88	4.26	1.21	209.24	59.42	8.69	2.47	3.11	0.88	0.06	0.02	84.38	23.96	-	-	1.83	0.52	3.44	0.98	12.92	3.67
	10	8.21	4.95	13.48	8.13	110.38	66.57	2.66	1.61	2.94	1.77	0.96	0.58	-	-	0.65	0.39	11.27	6.79	5.51	3.32	9.77	5.89
2020	1	11.30	3.16	-	-	254.76	71.15	20.60	5.75	2.69	0.75	0.38	0.10	33.40	9.33	-	-	5.46	1.52	9.72	2.72	19.76	5.52
	2	6.65	3.99	-	-	110.19	66.18	33.45	20.09	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	14.22	8.54
	3	3.35	1.77	-	-	159.54	84.47	6.70	3.55	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.05	0.02	0.56	0.30	8.89	4.71
	4	6.57	6.37	-	-	80.12	77.69	2.28	2.21	1.98	1.92	0.07	0.07	3.16	3.06	-	-	1.83	1.77	1.22	1.18	5.92	5.74
	5	4.17	1.28	0.23	0.07	231.24	71.16	18.52	5.70	4.07	1.25	0.19	0.06	49.21	15.15	-	-	0.44	0.13	1.70	0.52	15.18	4.67
	6	2.45	0.94	-	-	177.88	68.63	4.69	1.81	2.92	1.12	0.01	0.00	56.69	21.87	-	-	0.01	0.00	7.53	2.91	7.01	2.70
	7	3.85	2.38	-	-	131.66	81.49	3.72	2.30	1.39	0.86	-	-	12.50	7.74	-	-	-	-	0.69	0.43	7.76	4.80
	8	51.75	15.88	2.44	0.75	180.50	55.40	16.02	4.92	11.74	3.60	7.63	2.34	10.51	3.23	0.21	0.06	18.24	5.60	11.45	3.51	15.33	4.71
	9	24.26	6.89	4.26	1.21	206.85	58.74	11.51	3.27	3.11	0.88	0.06	0.02	84.38	23.96	-	-	1.83	0.52	3.44	0.98	12.45	3.53
	10	8.21	4.95	13.48	8.13	109.03	65.76	4.29	2.58	2.94	1.77	0.96	0.58	-	-	0.65	0.39	11.01	6.64	5.51	3.32	9.75	5.88

Table 5.20 (Continued).

Year	Sub-watershed	UR (km²)	UR %	PD (km²)	PD %	RP (km²)	RP %	OP (km²)	OP %	PO (km²)	PO %	AQ (km²)	AQ %	EF (km²)	EF %	MF (km²)	MF %	MS (km²)	MS %	WA (km²)	WA %	ML (km²)	ML %
2021	1	11.65	3.25	-	-	252.08	70.40	24.62	6.88	2.69	0.75	0.38	0.10	33.40	9.33	-	-	5.41	1.51	9.72	2.72	18.12	5.06
	2	6.70	4.02	-	-	103.40	62.10	41.92	25.18	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	12.50	7.51
	3	3.35	1.77	-	-	157.03	83.13	10.22	5.41	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.04	0.02	0.56	0.30	7.89	4.17
	4	7.31	7.09	-	-	78.51	76.12	3.23	3.13	1.98	1.92	0.07	0.07	3.16	3.06	-	-	1.83	1.77	1.22	1.18	5.84	5.66
	5	4.22	1.30	0.23	0.07	226.12	69.59	24.98	7.69	4.07	1.25	0.19	0.06	49.21	15.15	-	-	0.43	0.13	1.70	0.52	13.80	4.25
	6	2.61	1.01	-	-	175.31	67.64	7.95	3.07	2.92	1.12	0.01	0.00	56.69	21.87	-	-	0.01	0.00	7.53	2.91	6.17	2.38
	7	4.80	2.97	-	-	128.55	79.56	6.22	3.85	1.39	0.86	-	-	12.50	7.74	-	-	-	-	0.69	0.43	7.44	4.60
	8	55.27	16.96	2.44	0.75	175.50	53.86	18.09	5.55	11.74	3.60	7.63	2.34	10.51	3.23	0.21	0.06	18.15	5.57	11.45	3.51	14.84	4.55
	9	25.39	7.21	4.26	1.21	203.55	57.80	14.15	4.02	3.11	0.88	0.06	0.02	84.38	23.96	-	-	1.80	0.51	3.44	0.98	12.01	3.41
	10	8.26	4.98	13.48	8.13	108.23	65.27	5.13	3.09	2.94	1.77	0.96	0.58	-	-	0.65	0.39	11.00	6.63	5.51	3.32	9.68	5.84
2022	1	12.18	3.40	-	-	249.77	69.75	28.88	8.06	2.69	0.75	0.38	0.10	33.46	9.35	-	-	5.36	1.50	10.07	2.81	25.33	7.07
	2	6.89	4.14	-	-	98.73	59.30	49.79	29.91	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.65	0.39	15.55	9.34
	3	3.37	1.78	-	-	154.72	81.91	13.79	7.30	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.04	0.02	0.64	0.34	13.01	6.89
	4	8.08	7.83	-	-	77.06	74.73	4.07	3.94	1.98	1.92	0.07	0.07	3.17	3.07	-	-	1.83	1.77	1.33	1.29	5.99	5.81
	5	4.58	1.41	0.23	0.07	222.29	68.41	30.31	9.33	4.07	1.25	0.19	0.06	49.29	15.17	-	-	0.43	0.13	1.96	0.60	18.49	5.69
	6	3.09	1.19	-	-	172.79	66.67	10.88	4.20	2.92	1.12	0.01	0.00	56.74	21.89	-	-	0.01	0.00	7.70	2.97	9.71	3.75
	7	5.59	3.46	-	-	125.79	77.85	8.69	5.38	1.39	0.86	-	-	12.60	7.80	-	-	-	-	0.70	0.43	9.54	5.91
	8	57.62	17.68	2.44	0.75	172.40	52.91	19.42	5.96	11.74	3.60	7.63	2.34	10.52	3.23	0.21	0.06	18.09	5.55	12.82	3.94	15.06	4.62
	9	26.44	7.51	4.26	1.21	200.81	57.03	16.67	4.73	3.11	0.88	0.06	0.02	84.47	23.99	-	-	1.75	0.50	4.98	1.41	14.73	4.18
	10	8.35	5.03	13.48	8.13	107.74	64.98	5.66	3.42	2.94	1.77	0.96	0.58	-	-	0.65	0.39	10.97	6.62	7.35	4.43	10.99	6.63
2023	1	12.18	3.40	-	-	246.51	68.84	33.37	9.32	2.69	0.75	0.38	0.10	33.46	9.35	-	-	5.36	1.50	9.72	2.72	14.41	4.02
	2	6.89	4.14	-	-	91.73	55.09	58.85	35.34	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	7.06	4.24
	3	3.37	1.78	-	-	150.56	79.71	18.48	9.78	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.04	0.02	0.56	0.30	6.08	3.22
	4	8.08	7.83	-	-	75.85	73.55	5.33	5.17	1.98	1.92	0.07	0.07	3.17	3.07	-	-	1.83	1.77	1.22	1.18	5.63	5.46
	5	4.58	1.41	0.23	0.07	216.73	66.70	36.94	11.37	4.07	1.25	0.19	0.06	49.29	15.17	-	-	0.43	0.13	1.70	0.52	10.80	3.32
	6	3.09	1.19	-	-	169.31	65.33	14.72	5.68	2.92	1.12	0.01	0.00	56.74	21.89	-	-	0.01	0.00	7.53	2.91	4.86	1.88
	7	5.59	3.46	-	-	122.46	75.79	12.50	7.74	1.39	0.86	-	-	12.60	7.80	-	-	-	-	0.69	0.43	6.36	3.94
	8	57.62	17.68	2.44	0.75	170.83	52.43	21.08	6.47	11.74	3.60	7.63	2.34	10.52	3.23	0.21	0.06	18.09	5.55	11.45	3.51	14.22	4.37
	9	26.44	7.51	4.26	1.21	197.70	56.14	20.25	5.75	3.11	0.88	0.06	0.02	84.47	23.99	-	-	1.75	0.50	3.44	0.98	10.67	3.03
	10	8.35	5.03	13.48	8.13	106.97	64.52	6.49	3.92	2.94	1.77	0.96	0.58	-	-	0.65	0.39	10.97	6.62	5.51	3.32	9.50	5.73

Table 5.20 (Continued).

Year	Sub-watershed	UR		PD		RP		OP		PO		AQ		EF		MF		MS		WA		ML	
		(km^2)	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**	**(km^2)**	**%**
2024	1	12.50	3.49	-	-	244.53	68.29	37.30	10.42	2.69	0.75	0.38	0.10	33.46	9.35	-	-	5.29	1.48	9.72	2.72	12.21	3.41
	2	6.98	4.19	-	-	88.50	53.15	65.15	39.13	0.95	0.57	0.05	0.03	0.37	0.22	-	-	-	-	0.63	0.38	3.89	2.34
	3	3.40	1.80	-	-	148.38	78.56	21.58	11.43	2.43	1.29	0.04	0.02	7.32	3.88	-	-	0.04	0.02	0.56	0.30	5.12	2.71
	4	8.62	8.36	-	-	74.87	72.60	5.85	5.67	1.98	1.92	0.07	0.07	3.17	3.07	-	-	1.81	1.76	1.22	1.18	5.57	5.40
	5	4.80	1.48	0.23	0.07	213.70	65.76	42.11	12.96	4.07	1.25	0.19	0.06	49.29	15.17	-	-	0.42	0.13	1.70	0.52	8.45	2.60
	6	3.35	1.29	-	-	167.34	64.57	17.02	6.57	2.92	1.12	0.01	0.00	56.74	21.89	-	-	0.00	0.00	7.53	2.91	4.26	1.64
	7	6.08	3.76	-	-	120.33	74.47	15.18	9.40	1.39	0.86	-	-	12.60	7.80	-	-	-	-	0.69	0.43	5.32	3.29
	8	59.13	18.15	2.44	0.75	168.68	51.77	22.77	6.99	11.74	3.60	7.63	2.34	10.52	3.23	0.21	0.06	17.21	5.28	11.45	3.51	14.05	4.31
	9	26.90	7.64	4.26	1.21	195.64	55.56	22.97	6.52	3.11	0.88	0.06	0.02	84.47	23.99	-	-	1.71	0.48	3.44	0.98	9.59	2.72
	10	8.42	5.08	13.48	8.13	106.52	64.24	7.52	4.54	2.94	1.77	0.96	0.58	-	-	0.65	0.39	10.41	6.28	5.51	3.32	9.41	5.68

Note: 1. Khlong La/Khlong Jam Rai, 2. Khlong Lea, 3. Khlong Phang La/Khlong Ngae, 4. Khlong Pom, 5. Khlong Ram, 6. Khlong Sa Dao,

7. Khlong Tong/Khlong Pra Tu, 8. Khlong Wa, 9. Khlong Wat/Khlong Tam, and 10. Klong Bang Klam.

As result, it reveals that at sub-watershed level, percentage of evergreen forest in each sub-watershed between 2018 and 2024 are also rather low that varies from 0% to 23.99% (See detail in Table 5.20), when they are compared with target area of forest cover at 40% of total country area under Thailand National Forest Policy (Royal Forest Department, 1986). According to Thailand National Forest Policy, it can observed that most of sub-watershed under Khlong U-Tapoa watershed are critical except Khlong Sa Dao, Khlong Wat/Khlong Tam and Khlong Ram sub-watersheds wherein evergreen forest as protective forest are greater than 15%.

Furthermore, transition LULC change matrix between 2017 and 2024 of Scenario III is displayed in Table 5.21. As results, urban and built-up area in 2017 as expected increasing area under Scenario III is not converted in other LULC types in 2024 and its area will increase from 113.21 km^2 in 2017 to 140.16 km^2 in 2024. The increasing areas of urban and built area in 2024 mainly come from rubber plantation (24.51 km^2) and miscellaneous land (1.68 km^2) in 2017. Likewise, oil palm plantation in 2017 as expected increasing area under Scenario III is not converted into other LULC classes in 2024 and its area will increase from 18.85 km^2 in 2017 to 257.44 km^2 in 2024, the increasing areas of oil palm plantation in 2024 mostly come from rubber plantation (188.47 km^2) and miscellaneous land (45.09 km^2) in 2017.

On contrary, rubber plantation in 2017 as expected decreasing area under Scenario III is converted into urban and built-up area (24.51 km^2), oil palm plantation (188.47 km^2), evergreen forest (3.93 km^2) and water body (0.02 km^2) in 2024 and its area will decrease from 1,727.46 km^2 in 2017 to 1,528.48 km^2 in 2024. Herein, rubber plantation, which locates in highly, moderate and marginally suitable classes for oil palm, will be replaced by oil palm plantation according to reduction policy on rubber plantation area by the Government. Likewise, marsh and swamp in 2017 as expected decreasing area under Scenario III is converted into urban and built-up area (0.77 km^2) and oil palm plantation (5.04 km^2) and its area will decrease from 42.70 km^2 in 2017 to 36.89 km^2 in 2024. Similarly, miscellaneous land in 2017 as expected decreasing area under Scenario II is converted into urban and built-up area (1.68 km^2), rubber plantation (17.94 km^2) and oil palm plantation (45.09 km^2) in 2024 and its area will decrease from 142.57 km^2 in 2017 to 77.87 km^2 in 2024. This reflects the transformation agriculture production extension on oil palm.

Meanwhile, most of LULC types with fixed land requirement area during 2017 and 2024 under Scenario III include paddy field, perennial tree and orchard, aquatic cultural area, evergreen forest, mangrove forest, and water body show stable areas during 2017 to 2024 except evergreen forest and water body. Herein, evergreen forest in 2017 is not converted into other LULC classes in 2024 and its area will increase from 254.01 km^2 in 2017 to 257.92 km^2 in 2024. The increasing areas of evergreen forest in 2024 solely come from rubber plantation (3.93 km^2) in 2017. Likewise, water body in 2017 is not converted into other LULC classes in 2024 and its area will increase from 42.43 km^2 in 2017 to 42.44 km^2 in 2024. The increasing areas of water body in 2024 solely come from rubber plantation (0.01 km^2) in 2017.

Like Scenario II, it was found that there is slightly difference between the required land area and the predicted area of each LULC type in 2024 under Scenario III. For example, the required area of evergreen forest in 2024 is 254.01 km^2 but it is allocated 257.93 km^2 whereas the required area of urban and built-up area in 2024 is 145.41 km^2 but it is allocated only 140.16 km^2. In this study, the deviation values between the required land area and the predicted area of each LULC type under Scenario III vary from -0.0524% to 0.0393% or from -5.25 km^2 (under estimation) to 3.92 km^2 (over estimation).The summation of deviation values, which are trade-off between over and under estimation among LULC types is 0.0001% and -0.02 km^2 (see Table 5.21). Since the deviation value depends on iteration driving factors of each LULC type which indicates the maximum different allowance between the required and allocated area of LULC type under CLUE-S model (van Asselen and Verburg, 2013; Liu, Wang, Li, and Xia (2013); and Xu, Li, Song, and Yin, (2013). Therefore, the LULC prediction under Scenario III using CLUE-S model can be validated and accepted for ecosystem service assessment in terms of water yield and sediment retention.

Table 5.21 Transition matrix of LULC change between 2017 and 2024 of Scenario III: Agriculture production extension.

		LULC 2024 (km^2)											
	LULC types	**UR**	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**	**Total**
LULC2 017 (km^2)	Urban and built-up area (UR)	113.21	-	-	-	-	-	-	-	-	-	-	113.21
	Paddy field (PD)	-	20.41	-	-	-	-	-	-	-	-	-	20.41
	Rubber plantation (RP)	24.51	-	1,510.54	188.47	-	-	3.93	-	-	0.02	-	1,727.46
	Oil palm plantation (OP)	-	-	-	18.85	-	-	-	-	-	-	-	18.85
	Perennial tree/orchard (PO)	-	-	-	-	34.20	-	-	-	-	-	-	34.20
	Aquatic cultural area (AQ)	-	-	-	-	-	9.38	-	-	-	-	-	9.38
	Evergreen forest (EF)	-	-	-	-	-	-	254.01	-	-	-	-	254.01
	Mangrove forest (MF)	-	-	-	-	-	-	-	0.85	-	-	-	0.85
	Marsh and swamp (MS)	0.77	-	-	5.04	-	-	-	-	36.89	-	-	42.70
	Water body (WA)	-	-	-	-	-	-	-	-	-	42.43	-	42.43
	Miscellaneous land (ML)	1.68	-	17.94	45.09	-	-	-	-	-	-	77.87	142.57
	Total	**140.16**	**20.41**	**1,528.48**	**257.44**	**34.20**	**9.38**	**257.93**	**0.85**	**36.89**	**42.44**	**77.87**	**2,406.04**
	Land use requirement	**145.41**	**20.41**	**1,524.88**	**259.51**	**34.20**	**9.38**	**254.01**	**0.85**	**37.50**	**42.43**	**77.49**	
	Deviation value (%)	**-0.0524**	**-**	**0.0360**	**-0.0207**	**-**	**-**	**0.0393**	**-**	**-0.0061**	**0.0002**	**0.0038**	**0.0001**
	Deviation value (km^2)	**-5.25**	**-**	**3.60**	**-2.07**	**-**	**-**	**3.92**	**-**	**-0.61**	**0.01**	**0.38**	**-0.02**

5.6 Comparison of LULC prediction among three different scenarios

The predicted LULC data during 2018 and 2024 of three different scenarios (historical LULC evolution, forest conservation and prevention and agriculture production extension) for estimating water yield and sediment retention are here compared and characterized. Table 5.22 shows area of the predicted LULC types of three different scenarios between 2018 and 2024 and its change accordance with LULC types in 2017 and Figure 5.7 displays comparison of LULC type change between actual LULC in 2017 (base year) and the predicted LULC in 2024 of three different scenarios.

As results, it reveals that the significant LULC types with increasing area between 2017 and 2024 under Scenario I: Historical LULC evolution are urban and built-up area, oil palm plantation, perennial trees/orchards, and water bodies. In contrast the dominant LULC types with decreasing area in the same period are paddy field, evergreen forest, marsh and swamp, and miscellaneous land. The LULC change under this scenario is dictated by historical LULC change between 2010 and 2017 which represents socio-economic development in the study area.

Table 5.22 Comparison area of predicted LULC in three different scenarios and its change.

LULC type and scenario	LULC in 2017 (base year)	Area of predicted LULC in km^2							Change	Land demand
		2018	2019	2020	2021	2022	2023	2024		
UR-Scenario-I	113.21	117.18	121.68	125.76	130.9	135.41	139.87	144.17	30.96	Markov
UR-Scenario-II	113.21	116.63	122	126.31	130.89	136.16	140.46	145.1	31.89	Markov
UR-Scenario-III	113.21	117.37	122.22	122.55	129.55	136.15	136.15	140.16	26.95	Markov
PD-Scenario-I	20.41	19.5	18.7	17.88	16.91	16.11	15.33	14.48	-5.93	Markov
PD-Scenario-II	20.41	20.36	20.34	20.3	20.26	20.26	20.25	20.25	-0.16	Fix
PD-Scenario-III	20.41	20.41	20.41	20.41	20.41	20.41	20.41	20.41	0	Fix
RP-Scenario-I	1727.46	1728.39	1727.84	1727.62	1727.39	1727.17	1726.99	1726.77	-0.69	Markov
RP-Scenario-II	1727.46	1707.79	1686.08	1664.43	1640.07	1614.61	1592.74	1569.66	-157.8	Decrease
RP-Scenario-III	1727.46	1697.51	1669.07	1641.78	1608.26	1582.08	1548.65	1528.48	-198.98	Decrease
OP-Scenario-I	18.85	20.68	22.92	24.56	26.44	28.36	30.06	32.35	13.5	Markov
OP-Scenario-II	18.85	20.72	22.72	24.63	26.47	28.5	30.4	32.34	13.49	Markov
OP-Scenario-III	18.85	52.64	86.92	121.79	156.5	188.15	227.99	257.44	238.59	Increase
PO-Scenario-I	34.2	34.1	34.36	34.56	34.73	35.23	35.35	37.19	2.99	Markov
PO-Scenario-II	34.2	34.1	34.03	33.98	33.91	33.91	33.91	33.9	-0.3	Fix
PO-Scenario-III	34.2	34.2	34.2	34.2	34.2	34.2	34.2	34.2	0	Fix
AQ-Scenario-I	9.38	9.41	9.55	9.61	9.7	9.81	9.96	10.09	0.71	Markov
AQ-Scenario-II	9.38	9.38	9.38	9.38	9.38	9.38	9.38	9.38	0	Fix
AQ-Scenario-III	9.38	9.38	9.38	9.38	9.38	9.38	9.38	9.38	0	Fix
EF-Scenario-I	254.01	249.5	243.05	238.32	233.22	227.79	222.57	215.46	-38.55	Markov
EF-Scenario-II	254.01	270.03	286.41	304.29	323.36	342.22	359.49	377.33	123.32	Increase
EF-Scenario-III	254.01	257.55	257.55	257.55	257.55	257.93	257.93	257.93	3.92	Fix
MF-Scenario-I	0.85	0.87	0.89	0.9	0.93	0.95	0.97	0.93	0.08	Markov
MF-Scenario-II	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0	Fix
MF-Scenario-III	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0	Fix
MS-Scenario-I	42.7	41.69	41.16	40.75	39.72	38.65	37.95	37.26	-5.44	Markov
MS-Scenario-II	42.7	42.53	42.42	42.35	42.28	42.27	42.27	42.27	-0.43	Fix
MS-Scenario-III	42.7	40.28	39.56	38.84	38.66	38.47	38.47	36.89	-5.81	Markov
WA-Scenario-I	42.43	43.52	44.86	45.73	46.77	48.18	49.48	50.44	8.01	Markov
WA-Scenario-II	42.43	42.43	42.43	42.43	42.43	42.43	42.43	42.43	0	Fix
WA-Scenario-III	42.43	42.43	42.44	42.44	42.44	42.44	42.44	42.44	0.01	Fix
ML-Scenario-I	142.57	141.21	141.05	140.36	139.33	138.4	137.51	136.91	-5.66	Markov
ML-Scenario-II	142.57	141.22	139.41	137.1	136.16	135.49	133.88	132.56	-10.01	Decrease
ML-Scenario-III	142.57	133.43	123.46	116.26	108.26	95.99	89.58	77.87	-64.7	Decrease

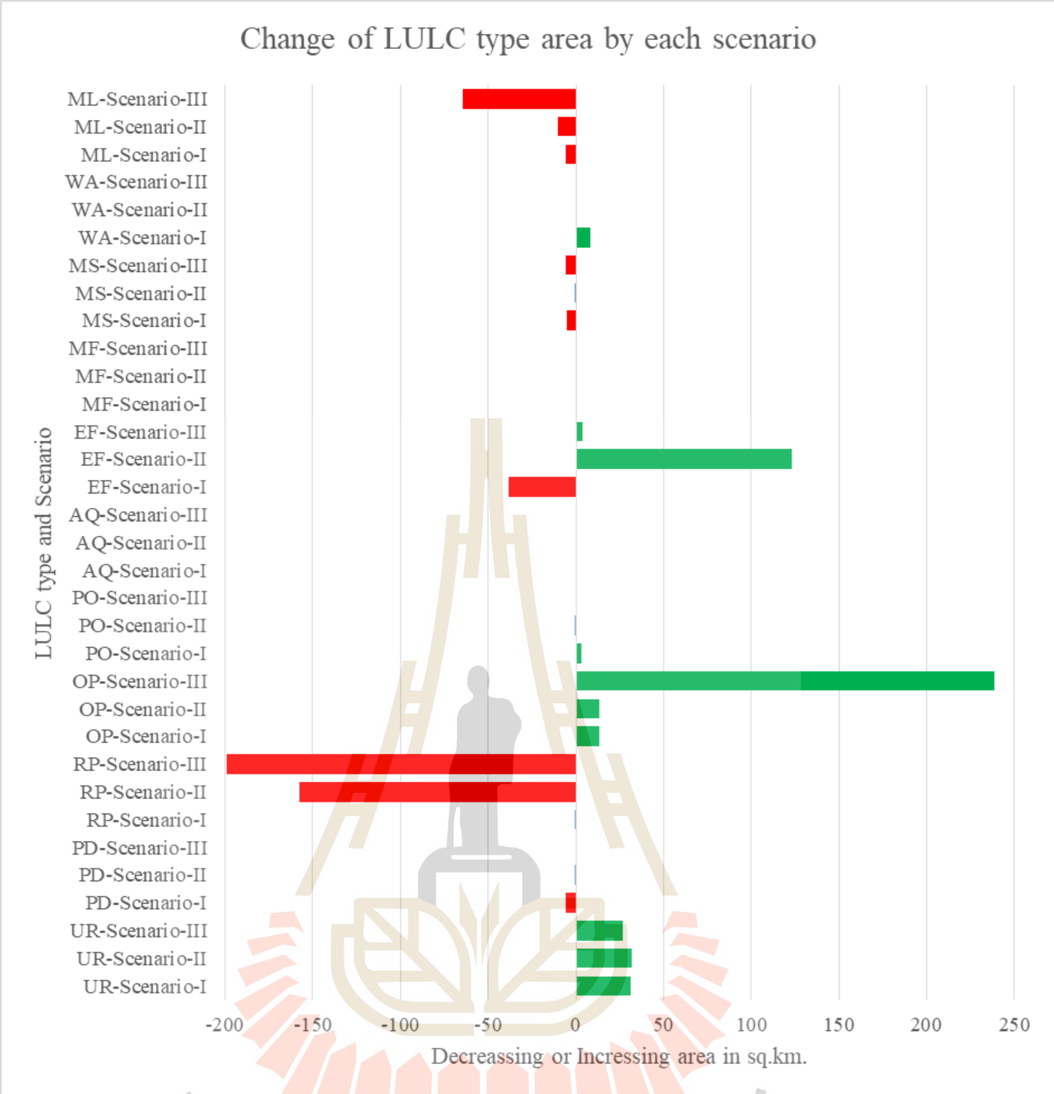


Figure 5.7 Comparison of LULC type change between actual LULC in 2017 (base year) and the predicted LULC in 2024 of three different scenarios.

Meanwhile, the significant LULC types with increasing area between 2017 and 2024 under Scenario II: Forest conservation and prevention are urban and built-up area, perennial trees/orchards, and evergreen forest. In contrast, the dominant LULC types with decreasing area in the same period are rubber plantation, and miscellaneous land.

The LULC change under this scenario is mostly dictated by policy on forest conservation and prevention transformation, particularly the increasing of evergreen forest by reforestation program on illegal rubber plantation in the protected forest area. This scenario fits with the recent policy on forest conservation and prevention of Thai Government who try to reclaim forest areas back from intruders and to enforce strict laws based on jurisprudence and political principles (Chan-o-cha, 2016).

In the meantime, the significant LULC types with increasing area between 2017 and 2024 under Scenario III: Agriculture production extension are urban and built-up area, oil palm plantation, and evergreen forest. On contrary, the dominant LULC types with decreasing area in the same period are rubber plantation, marsh and swamp and miscellaneous land. The LULC change under this scenario is mostly dictated by policy on agriculture production extension, particularly the increasing of oil palm plantation and decreasing of rubber plantation. In fact, the Office of Agricultural Economics has set up strategic plan to expand oil palm plantation area from 7,200 km^2 to 12,000 km^2 during 2015 to 2026 by replacement old rubber plantation (Raksaseri, 2016).

In summary, it can be here concluded that the predicted LULC data in three different scenarios using CLUE-S model can provide realistic results as expectation. The CLUE-S model can be used as an efficiently tool to predict LULC based on specific policies as scenarios. In practice, the optimum derived multiple linear equation from the binomial logit regression analysis for LULC allocation, land requirement of different scenarios which assigned by policy transformation, and model parameters (elasticity and LULC conversion matrix) are very important for predicting LULC of scenario under CLUE-S model.

In this study, the determination of the 8 driving factors on LULC change include elevation, slope, soil fertility, distance to road, distance to settlement, distance to water bodies, population density at sub-district level and average household income at sub-district level. The LULC prediction of three scenarios applies specific multiple linear equations from the binomial logistic regression analysis, which provide AUC values from 0.7239 (fair fit) to 0.9957 (excellent fit) for specific LULC type allocation. The deviation values between the required land area and the predicted area of each LULC type under three different scenarios vary from -0.1008% to 0.1290% or -10.08 km^2 (under estimation) to 12.89 km^2 (over estimation).

CHAPTER VI

WATER YIELD ASSESSMENT

This chapter presents results of the third objective focusing on water yield assessment using water yield model of the InVEST software suite from actual LULC in 2017 and predictive LULC between 2018 and 2024 of three different scenarios. The main results which consist of (1) basic information of water yield estimation (2) water yield estimation of actual LULC in 2017, (3) water yield estimation of predictive LULC of Scenario I, (4) water yield estimation of predictive LULC of Scenario II, (5) water yield estimation of predictive LULC of Scenario III, and (6) comparison of water yield estimation among three different scenarios are here described and discussed in details.

6.1 Basic information of water yield estimation

In this study, water yield is the amount of water running off the landscape and it is important to control water yield in Khlong U-Tapao watershed because this area is a territory prone to floods. Herein, water yield (runoff) of actual LULC in 2017 and predictive LULC between 2018 and 2024 of three different scenarios are separately estimated using water yield model of InVEST software suite. In practice, water yield model, which is based on the Budyko curve requires specific input data and parameters for water yield estimation under watershed including annual rainfall, annual potential evapotranspiration, plant available water content, root restricting layer depth, sub-watershed boundaries and its main rivers and LULC data and its evapotranspiration coefficient (Kc).

Figure 6.1 displays annual rainfall map in 2017 of the TMD and the predictive annual rainfall map between 2018 and 2024 of NCAR which represents as dynamic variable under water yield model. Likewise, annual potential evapotranspiration between 2017 and 2024 as dynamic variable are estimated using the modified Hargreaves 'equation (Eq. 3.3) as shown in Figure 6.2. Additionally, Table 6.1 and Figure 6.3 comparatively displays annual rainfall data of the TMD between 2001 and 2017 and the predictive rainfall data between 2018 and 2024 under scenario RCP 8.5 of NCAR. It shows the existing of the return period of extreme highly rainfall data in every 6 years occurring in the past during 2001 to 2017. Thus, the selection of the predictive rainfall data of NCAR under scenario RCP 8.5 which was estimated from historical record data from 1850 to 2005 as average data for estimating water yield is reasonable.

In addition, actual LULC in 2017 and predictive LULC between 2018 and 2024 of three different scenarios as dynamic variables, which were reported and presented in ChapterIV and V are prepared to extract evapotranspiration coefficient (Kc) as summary in Table 3.3. These dynamic variables play important role for water yield estimation under three different scenarios between 2018 and 2024.

Meanwhile, Figure 6.4 presents static variable for water yield estimation of actual LULC in 2017 and predictive LULC between 2018 and 2024 of three different scenarios include plant available water content, root restricting layer depth based on soil depth, sub-watershed boundaries, main rivers in watershed boundary.

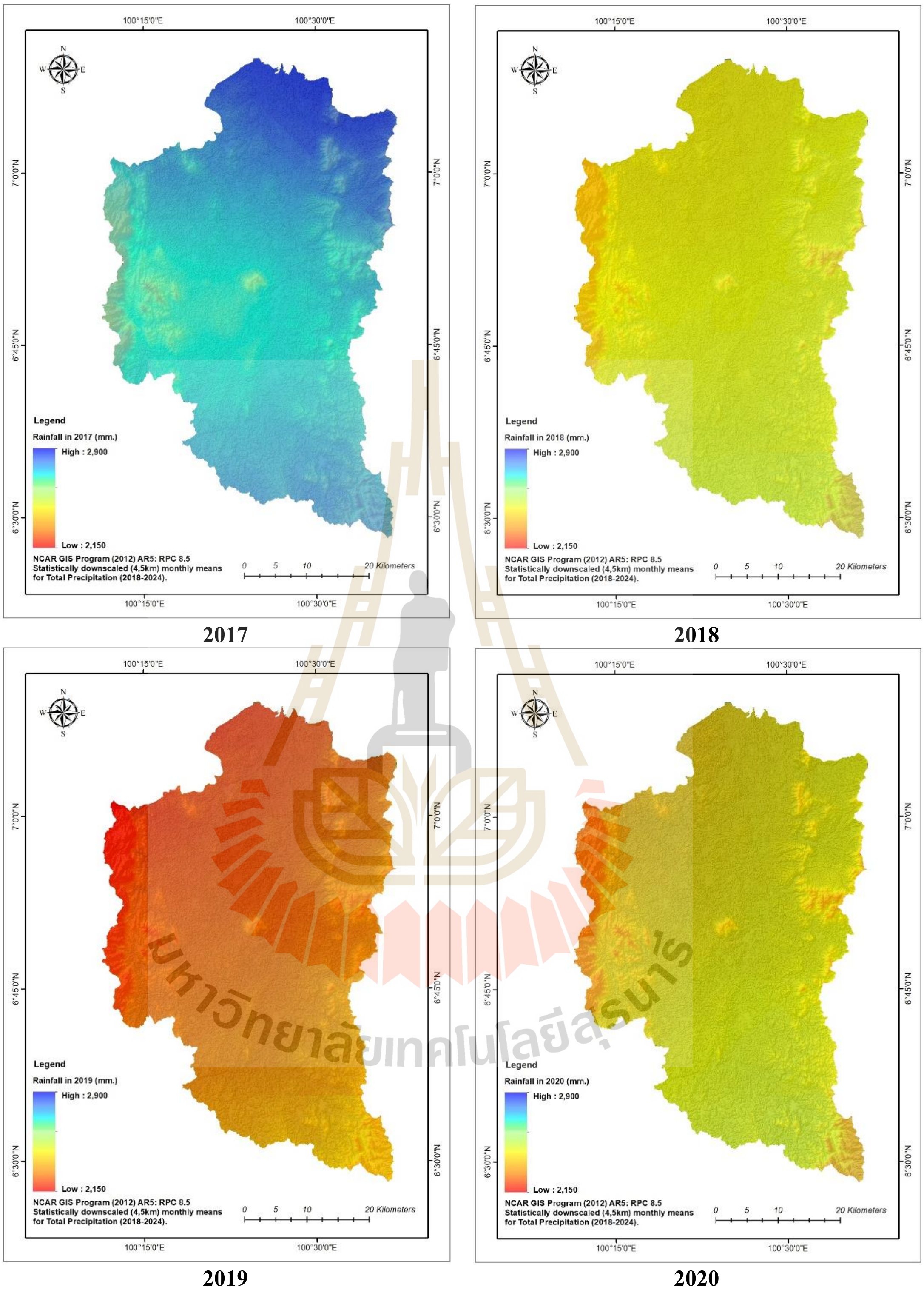


Figure 6.1 Spatial distribution of annual rainfall between 2017 and 2024.

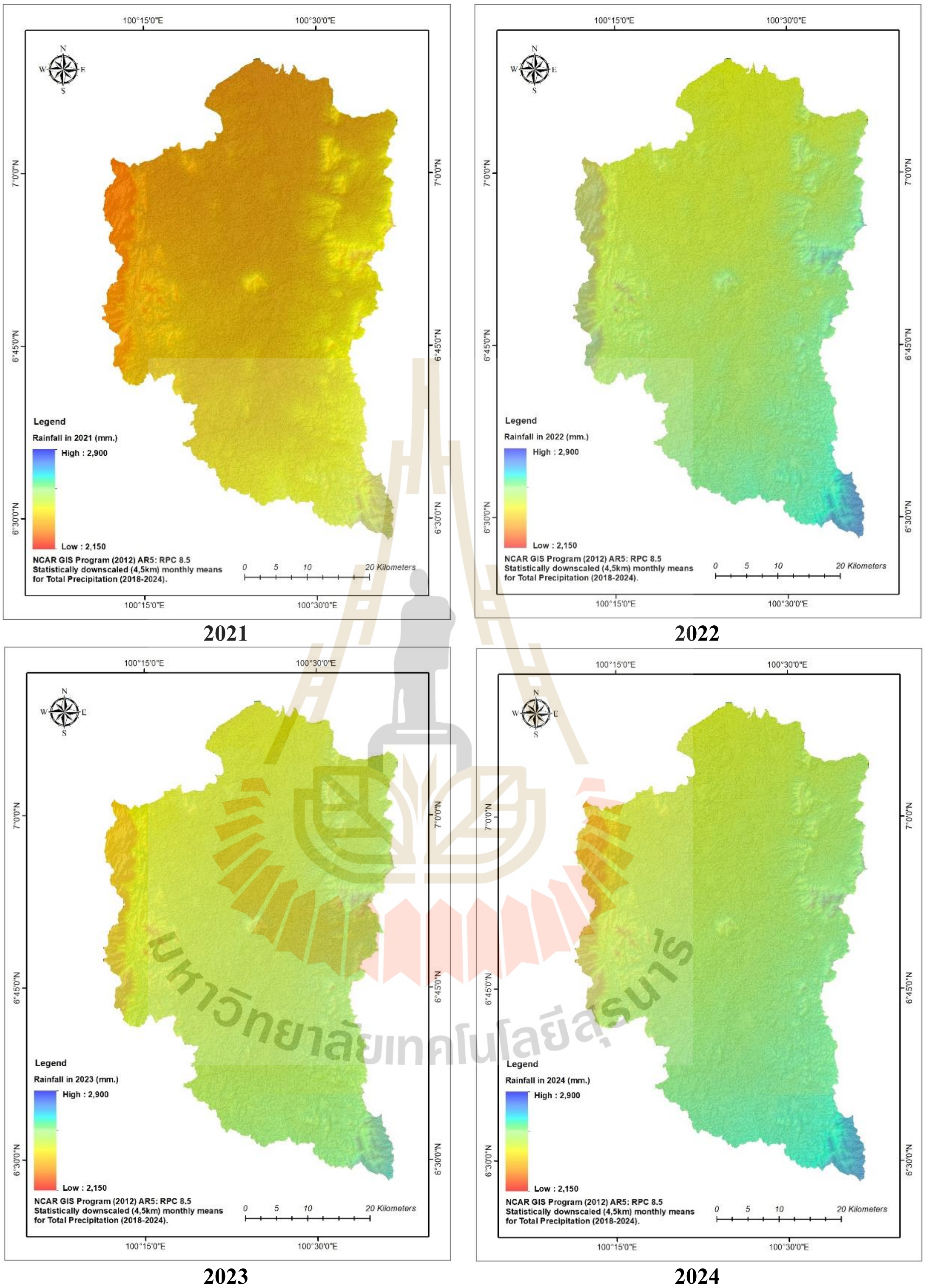


Figure 6.1 (Continued).

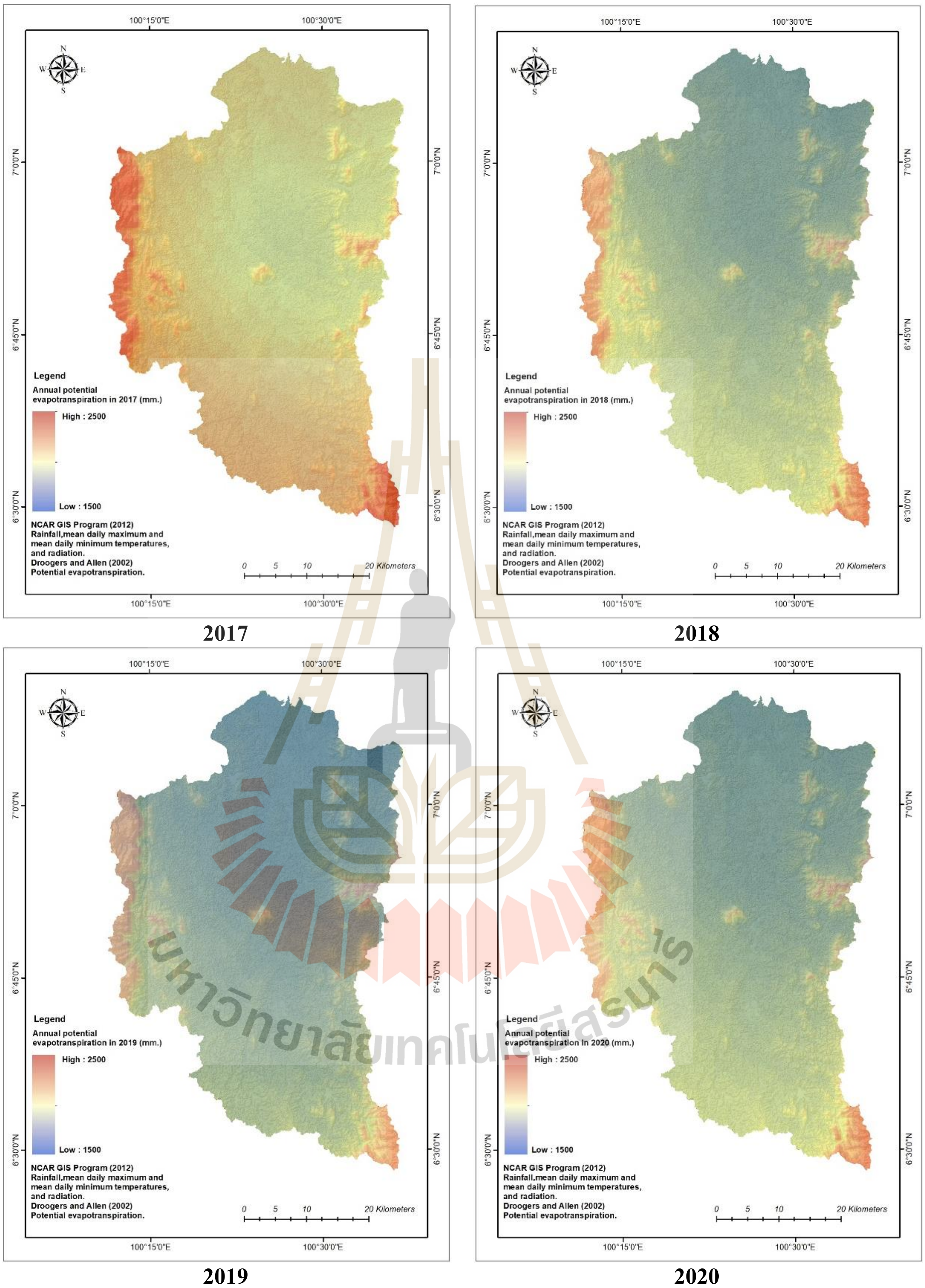


Figure 6.2 Spatial distribution of annual potential evapotranspiration (2017-2024).

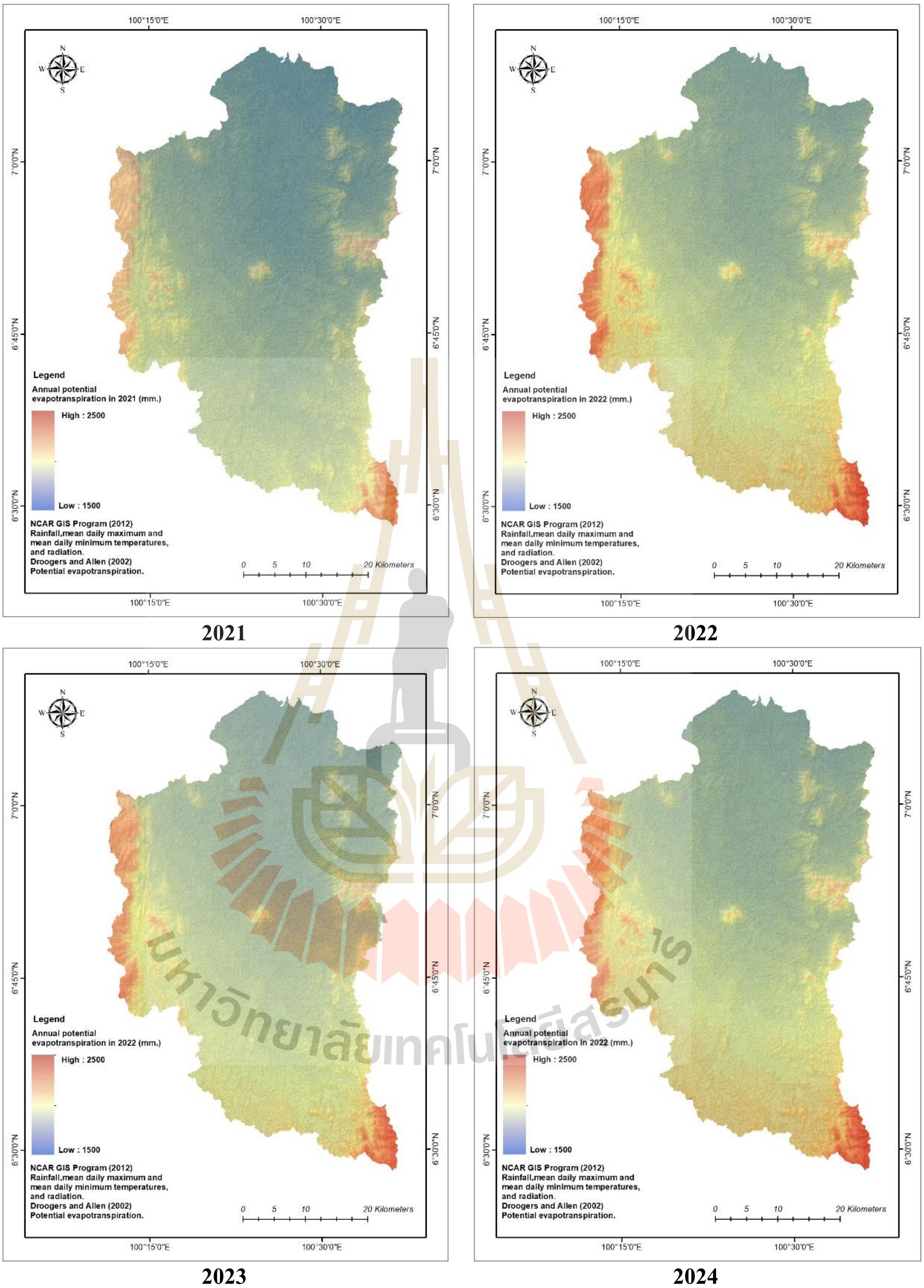


Figure 6.2 (Continued).

Table 6.1 Annual rainfall data of TMD (2001-2017) and the predictive rainfall data of NCAR (2018-2024).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2001	197	3	107	95	51	84	41	92	88	393	118	302	**1,572**
2002	5	0	16	128	88	16	50	112	165	331	328	189	**1,427**
2003	31	2	86	16	96	202	130	95	88	514	237	216	**1,712**
2004	16	74	105	140	222	132	48	65	173	289	167	101	**1,530**
2005	8	0	11	143	61	2	87	119	172	408	456	790	**2,257**
2006	39	92	88	167	148	103	55	55	282	138	47	169	**1,382**
2007	141	0	35	58	142	195	201	18	89	261	171	262	**1,573**
2008	78	82	85	144	47	156	77	101	43	259	618	349	**2,040**
2009	59	0	120	25	118	0	96	48	68	160	1,064	49	**1,805**
2010	77	0	27	57	15	219	126	266	178	397	371	267	**1,998**
2011	190	4	138	115	91	71	138	231	247	181	458	462	**2,323**
2012	382	15	70	182	44	91	40	21	116	129	102	293	**1,485**
2013	46	195	2	98	177	112	44	189	90	315	528	248	**2,043**
2014	8	0	20	72	84	36	73	196	109	278	221	685	**1,782**
2015	4	0	0	60	140	159	103	135	130	57	210	45	**1,042**
2016	133	14	0	0	47	40	104	69	36	125	150	429	**1,146**
2017	440	9	91	214	106	84	20	214	343	81	775	145	**2,519**
2018	93	43	48	97	183	175	208	174	210	367	413	317	**2,328**
2019	93	31	56	65	208	175	223	248	232	304	289	165	**2,090**
2020	62	39	46	89	168	168	201	216	275	270	374	298	**2,205**
2021	89	38	44	91	190	201	220	227	267	233	350	254	**2,205**
2022	105	56	51	94	172	192	218	193	296	280	348	354	**2,359**
2023	128	45	36	72	192	168	182	236	271	285	400	266	**2,282**
2024	97	49	65	90	209	158	200	242	296	257	319	338	**2,320**

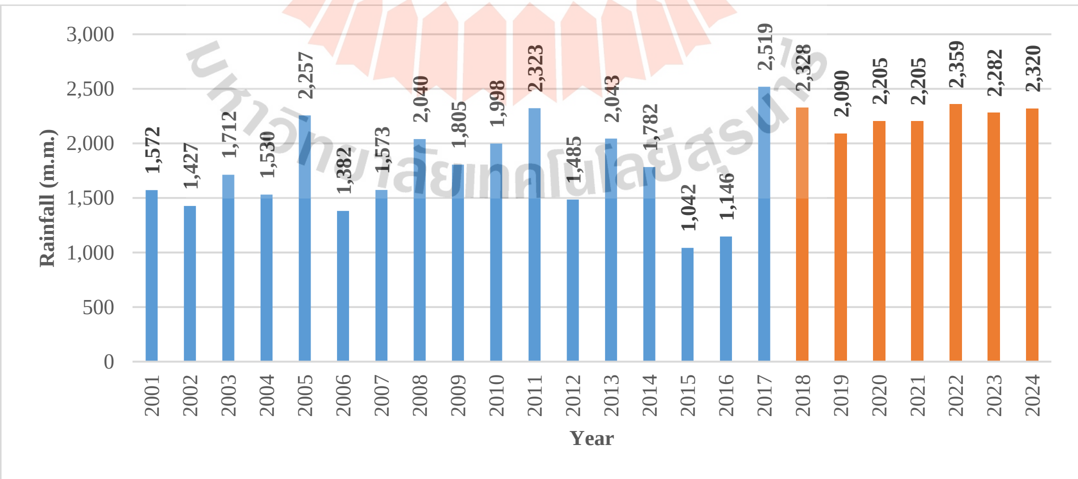


Figure 6.3 Comparison annual rainfall data of TMD between 2001 and 2017 (blue) and the predicted rainfall data under scenario RCP 8.5 of NCAR between 2018 and 2024.

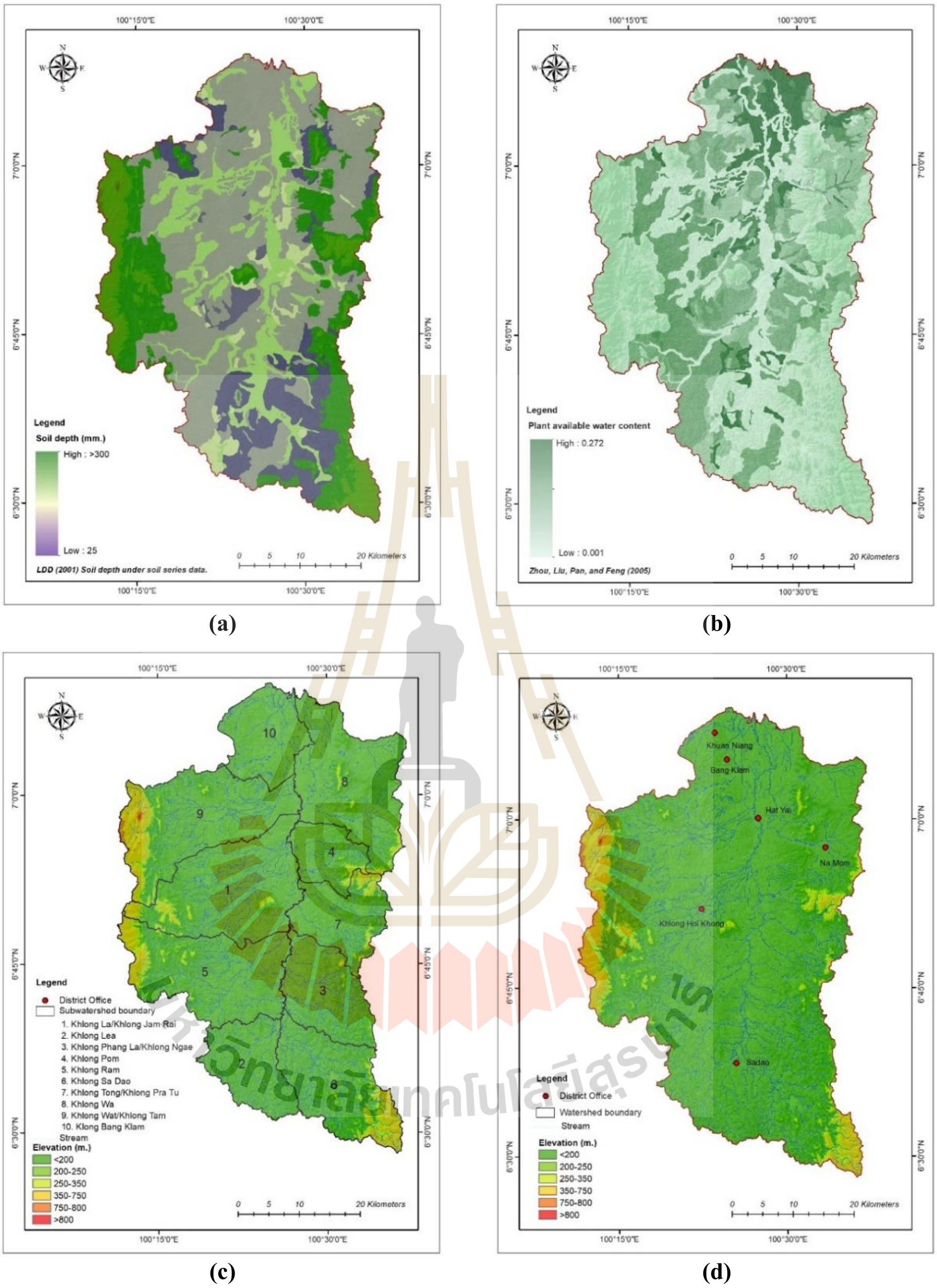


Figure 6.4 Spatial distribution of static variables: (a) root restricting layer depth, (b) plant available water content, (c) sub-watershed boundary, and (d) main rivers in watershed.

6.2 Water yield estimation of actual LULC in 2017

Water yield estimation of actual LULC in 2017 is presented in Table 6.2. It was found that water yield volume in 2017 in Khlong U-Tapao watershed is about 1,863,795,715 m^3. The proportion of water yield estimation in each sub-watershed is summarized in Table 6.3 and the spatial distribution of water yield of actual LULC in 2017 is displayed in Figure 6.5.

As results, top three dominant sub-watersheds in the study area which provide the highest water yield (runoff) are Khlong Wat/Khlong Tam, Khlong La/Khlong Jam Rai, and Khlong Wa with yield of 275,300,558.01 m^3 or 14.77%, 266,805,400.69 m^3 or 14.32% and 250,805,801 m^3 or 13.46% of total yield.

In addition, it can be observed that when area of sub-watershed increases, water yield (runoff) will increase. Thus, the relationship between water yield and its sub-watershed area was analyzed using simple linear regression. It was found that area of sub-watershed has positive high correlation with water yield (runoff) with r of 0.999 and R^2 of 0.997 as shown in Eq. 6.1 and Figure 6.6.

$$y = 5,260,905.561 + 752,757.260x \quad (6.1)$$

Where, y is water yield (runoff) volume in m^3 and x is sub-watershed area in km^2.

Table 6.2 Water yield estimation of actual LULC in 2017.

Year	Annual rainfall (mm)	PET (mm)	AET (mm)	Water yield (mm)	Water yield (m^3)
2017	2,242.25	1,380.86	808.04	1,899.96	1,863,795,714.87

Table 6.3 Water yield estimation in each sub-watershed actual LULC in 2017.

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	266,805,400.69	745,131.19	14.32
2. Khlong Lea	166.52	129,865,712.79	779,903.99	6.97
3. Khlong Phang La/Khlong Ngae	188.88	148,622,570.51	786,851.99	7.97
4. Khlong Pom	103.13	81,240,229.56	787,726.75	4.36
5. Khlong Ram	324.94	249,103,827.52	766,626.64	13.37
6. Khlong Sa Dao	259.17	206,378,689.53	796,306.25	11.07
7. Khlong Tong/Khlong Pra Tu	161.58	127,786,577.27	790,880.87	6.86
8. Khlong Wa	325.83	250,805,800.67	769,756.16	13.46
9. Khlong Wat/Khlong Tam	352.14	275,300,558.01	781,804.02	14.77
10. Klong Bang Klam	165.81	127,886,348.32	771,305.74	6.86
Total	**2,406.04**	**1,863,795,714.87**		**100.00**

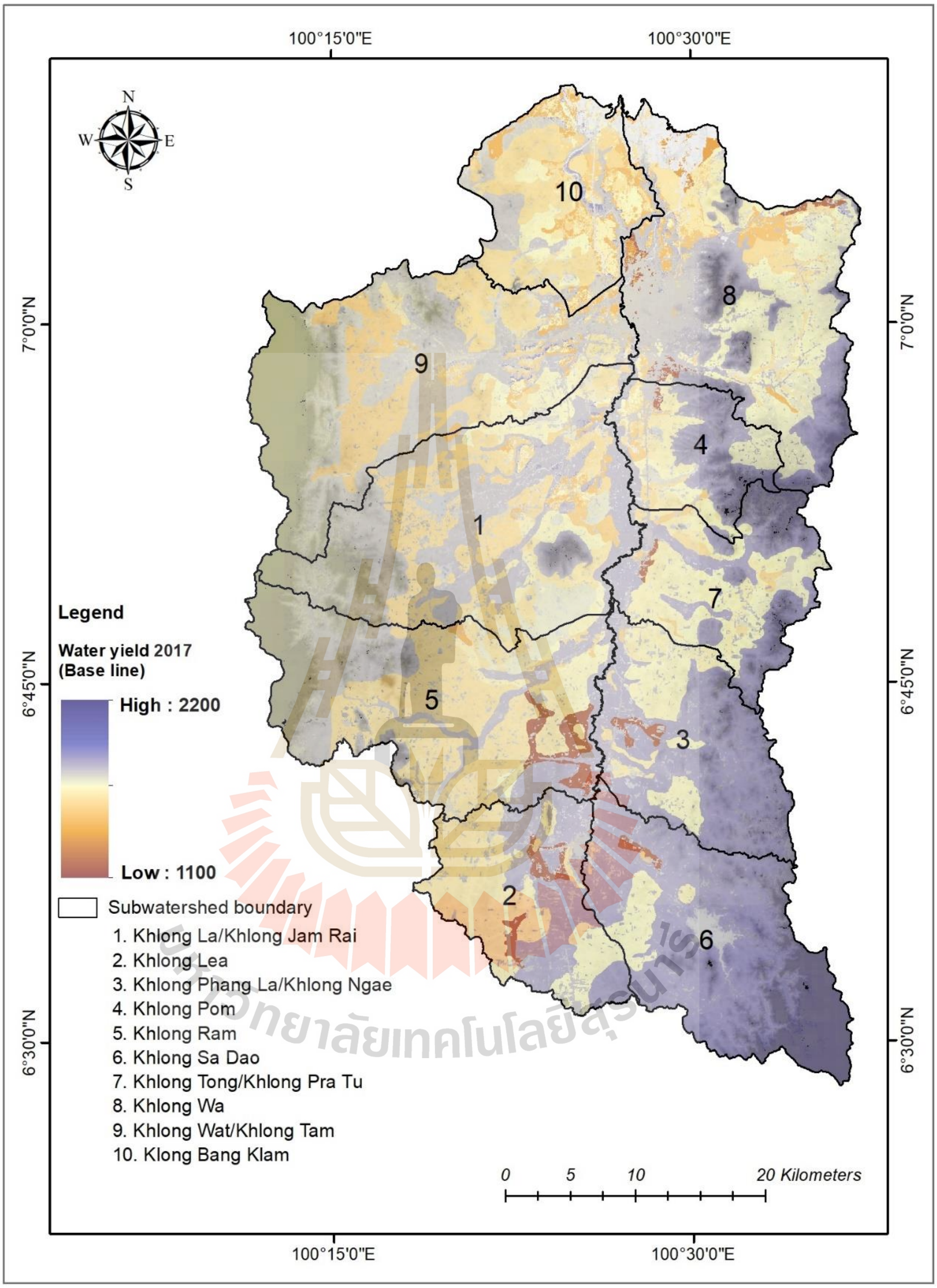


Figure 6.5 Spatial distribution of water yield of each sub-watersheds in 2017 (base year).

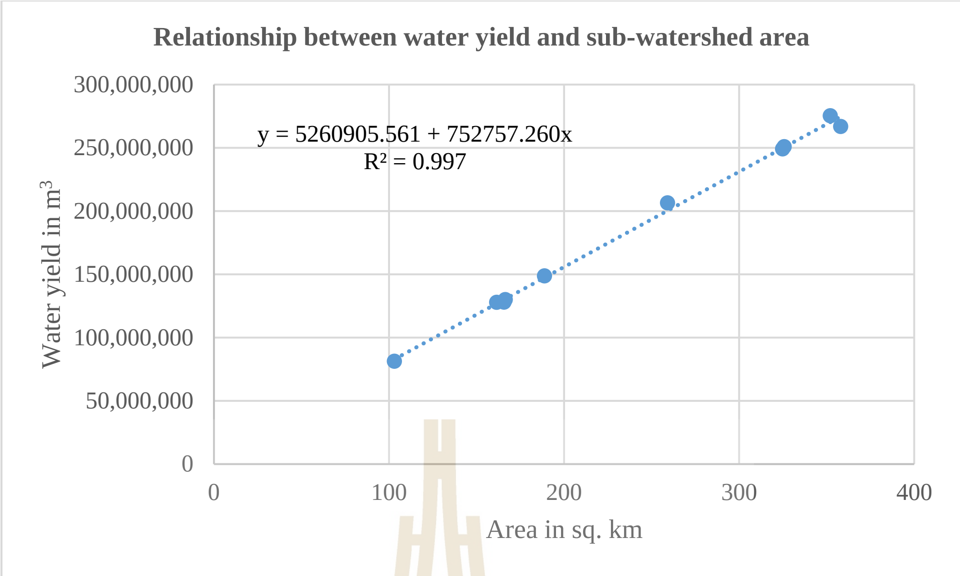


Figure 6.6 Relationship between water yield (runoff) and its sub-watershed area.

Meanwhile, the relationship between water yield (runoff) and the variation of drainage morphometric characteristics of sub-watershed include (1) cumulative length of streams (L), (2) bifurcation ratio (Rb), (3) basin relief (Bh), (4) ruggedness number (Rn), (5) drainage density (Dd), (6) stream frequency (Fu), (7) texture ratio (T), (8) form factor (Rf) and (9) elongation ratio (Re) as summary in Table 6.4 was here examined as suggested by Reddy, Maji, and Gajbhiye (2004) using stepwise regression analysis (Table 6.5). It was found that the two significant geomorphological factors including cumulative length of streams and texture ratio show positive correlation with total water yield (runoff) of each sub-watershed whereas drainage density shows negative correlation with its total water yield. The multiple linear equation with r of 0.998 and R^2 of 0.995 is displayed in Eq. 6.2

$$y = 81.06 + 1.12L - 126.79Dd + 18.95T \quad (6.2)$$

Where, y is total water yield (runoff) in million m^3;

L is cumulative length of streams (km),

Dd is drainage density (number/sq.km),

T is texture ratio (unitless).

These finding reflects that water yield (runoff) of each sub-watershed is directly related with its area size and drainage morphometric characteristics. Pilgrim, Cordery, and Baron (1982) stated that the hydrological relationships between small and large watershed area are including the various processes and mechanisms by which water yield occurs, the watershed characteristics such as land use, soils and geology, the variation of geomorphological characteristics with watershed size, small-scale nonhomogeneity of hydrological characteristics, and data errors

Table 6.4 Morphometric parameters and their mathematical expressions.

No.	Morphometric parameter	Formula	Description
1	Cumulative length of streams (L)	$L = \sum Nu$	L was calculated as the number of streams in each order and total length of each order was computed at sub basin level.
2	Bifurcation ratio (Rb)	$Rb = Nu/(Nu+1)$	Rb was computed as the ratio between the number of streams of any given order to the number of streams in the next higher order.
3	Basin relief (Bh)	$Bh = h_{max} - h_{min}$	Bh was defined as the maximum vertical distance between the lowest and the highest points of a sub basin.
4	Ruggedness number (Rn)	$Rn = Bh \times Dd$	Rn was calculated as the product of the basin relief and its drainage density
5	Drainage density (Dd)	$Dd = L/A$	Dd was measured as the length of stream channel per unit area of drainage basin.
6	Stream frequency (Fu)	$Fu = N/A$	Fu was computed as the ratio between the total number of streams and area of the basin.
7	Texture ratio (T)	$T = N(\frac{1}{P})$	T was estimated as the ratio between the first order streams and perimeter of the basin
8	Form factor (Rf)	$Rf = A/(Lb)^2$	Rf was computed as the ratio between the basin area and square of the basin length..
9	Elongation ratio (Re)	$Re = \left(\frac{2}{Lb}\right) \times A/\sqrt{A/\pi}$	Re was computed as the ratio between the diameter of the circle having the same area (as that of basin) and the maximum length of the basin.

Furthermore, the relationship between actual LULC type in 2017 and estimated water yield (runoff) in sub-watershed using overlay analysis is presented in Table 6.6. As result, the top three dominant LULC types which delivers highest average water yield (runoff) are marsh and swamp, evergreen forest and rubber plantation with value of 916,277, 814,928 and 804,194 m^3 per km^2. In contrast, aquatic cultural area and water bodies do not distribute any water yield (runoff).

These findings indicate the influence of LULC on water yield (runoff). Petchprayoon, Blanken, Ekkawatpanit, and Hussein (2010) mentioned that change in LULC, particularly an increase in urban areas and a decrease in forested areas, slightly increase discharge. Also, Guardiola-Claramonte et al. (2010) mentioned that annual water yield losses through evapotranspiration from rubber dominated landscapes compared to tropical rain forest reduces water yield (runoff) from the watershed.

Table 6.5 Drainage morphometric parameters in of each sub-watershed and its total water yield.

No.	Sub watershed name	Drainage morphometric parameters									Total water yield (m^3)
		L (km)	Rb(unitless)	Bh	Rn	Dd (km/km^2)	Fu	T	Rf	Re	
1	Khlong La/Khlong Jam Rai	227.3814	5.0294	640.0000	0.4150	0.6485	0.2795	0.8130	0.3206	0.6389	266,805,400.69
2	Khlong Lea	102.7630	3.4630	202.0000	0.1260	0.6180	0.2853	0.6205	0.5208	0.8143	129,865,712.79
3	Khlong Phang La/Khlong Ngae	123.5999	3.9242	397.0000	0.2626	0.6614	0.3211	0.7032	0.3932	0.7076	148,622,570.51
4	Khlong Pom	64.4978	4.2500	412.0000	0.2578	0.6257	0.2231	0.3923	0.4804	0.7821	81,240,229.56
5	Khlong Ram	211.5883	4.0417	718.0000	0.4742	0.6461	0.2716	0.6894	0.3832	0.6985	249,103,827.52
6	Khlong Sa Dao	166.3303	3.8611	737.0000	0.4807	0.6329	0.2824	0.7710	0.3460	0.6637	206,378,689.53
7	Khlong Tong/Khlong Pra Tu	98.1401	4.1786	476.0000	0.2928	0.6152	0.2695	0.8493	0.5665	0.8493	127,786,577.27
8	Khlong Wa	208.2791	3.4064	519.0000	0.6369	0.6485	0.3238	0.8858	0.3470	0.6647	250,805,800.67
9	Khlong Wat/Khlong Tam	231.3281	4.4206	932.0000	0.6182	0.6445	0.3068	0.9152	0.3679	0.6844	275,300,558.01
10	Klong Bang Klam	92.3216	3.6667	150.0000	0.0840	0.5562	0.3216	0.7408	0.5136	0.8087	127,886,348.32

Table 6.6 Proportion of water yield in each LULC type in sub-watershed.

Sub-watershed	Area of LULC type in km²											Area in km²
	UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML	
1. Khlong La/Khlong Jam Rai	10.50	0.00	260.96	9.18	2.69	0.38	33.14	0.00	5.62	9.72	25.90	358.07
2. Khlong Lea	6.33	0.00	141.72	0.60	0.95	0.05	0.37	0.00	0.00	0.63	15.86	166.52
3. Khlong Phang La/Khlong Ngae	3.09	0.00	159.75	2.42	2.43	0.04	7.32	0.00	0.05	0.56	13.23	188.88
4. Khlong Pom	6.29	0.00	82.27	0.28	1.98	0.07	3.00	0.00	1.84	1.22	6.20	103.13
5. Khlong Ram	3.89	0.23	243.76	3.07	4.07	0.19	48.96	0.00	0.44	1.70	18.64	324.94
6. Khlong Sa Dao	2.32	0.00	180.34	0.08	2.92	0.01	56.18	0.00	0.01	7.53	9.80	259.17
7. Khlong Tong/Khlong Pra Tu	3.66	0.00	134.66	0.36	1.39	0.00	11.10	0.00	0.00	0.69	9.72	161.58
8. Khlong Wa	46.66	2.44	198.76	0.00	11.74	7.63	10.11	0.21	20.54	11.44	16.30	325.83
9. Khlong Wat/Khlong Tam	22.78	4.26	215.43	1.92	3.11	0.06	83.84	0.00	1.89	3.43	15.44	352.14
10. Klong Bang Klam	7.69	13.48	109.83	0.96	2.94	0.96	0.00	0.65	12.32	5.51	11.49	165.81
Total	**113.21**	**20.41**	**1,727.46**	**18.85**	**34.20**	**9.38**	**254.01**	**0.85**	**42.70**	**42.43**	**142.57**	**2,406.04**
Water yield in m³	**81,712,519.47**	**15,601,462.10**	**1,389,208,689.59**	**14,781,061.55**	**27,427,434.37**	**0.00**	**206,997,893.17**	**645,892.21**	**39,120,452.90**	**0.00**	**88,300,309.52**	**1,863,795,714.87**
Average water yield in cm³	**721,794.22**	**764,590.15**	**804,193.85**	**784,349.25**	**801,971.77**	**0.00**	**814,928.27**	**757,644.82**	**916,277.15**	**0.00**	**619,336.19**	**774,632.06**

6.3 Validation of water yield model

In this study, the classified LULC in 2010 was firstly used to predict LULC between 2011 and 2016 with CLUE-S model. Then, the classified LULC in 2010, the predicted LULC between 2011 and 2016 and classified LULC in 2017 was separately used to estimate water yield between 2010 and 2017 with water yield model of InVEST software suite. The derived water yield during 2010 to 2017 was further applied to validate with observed data from hydrological station of RID at X.90 (Khlong U-Tapao) using NSE and coefficient R^2. Table 6.7 shows the comparison between observed and estimated water yield between 2010 and 2017 and Figure 6.7 displays simple linear relationship between observed and estimated water yield and R^2.

Table 6.7 Comparison of the observed and estimated water yield between 2010 and 2017 in Khlong U-Tapao watershed (X.90).

No	Year	Water yield in million m^3	
		Observed data at X.90	**Estimated data**
1	2010	1,230.44	1,429.44
2	2011	1,297.21	1,395.05
3	2012	1,559.08	1,574.92
4	2013	566.62	696.41
5	2014	683.47	944.58
6	2015	783.86	961.69
7	2016	780.76	524.51
8	2017	1,644.31	1,863.80

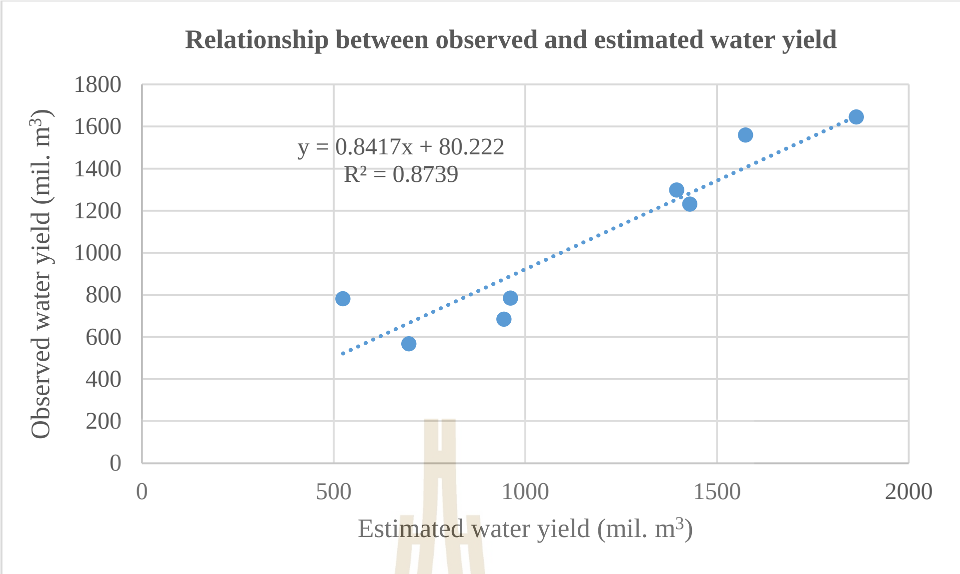


Figure 6.7 Relationship between the estimated and observed water yield.

As results, the NSE value is 0.8132 shows a good fit for water yield estimation (Motovilov et al., 1999) with very high correlation between the observed and estimated water yield with R^2 of 0.8739. Thus, water yield model of InVEST software suite can be accepted and further applied to estimate water yield in the current study.

6.4 Water yield estimation of predictive LULC of Scenario I

Water yield estimation of predictive LULC between 2018 and 2024 of Scenario I (Historical LULC evolution) is presented in Table 6.8. It was found that the highest water yield (runoff) in Khlong U-tapao watershed shall occur in 2024 is about 1,823,490,354 m^3 while the lowest water yield (runoff) volume shall occur in 2019 is about 1,616,257,947 m^3. The proportion of water yield estimation in each sub-watershed of predictive LULC between 2018 and 2024 of Scenario-I is summarized in Tables 6.9 to 6.15 and the spatial distribution of water yield is displayed in Figure 6.8.

Table 6.8 Water yield estimation of predictive LULC between 2018 and 2024 of Scenario I (Historical LULC evolution).

Year	Annual rainfall (mm)	PET (mm)	AET (mm)	Water yield (mm)	Water yield (m^3)
2018	2,406.08	1,486.07	487.06	1,918.68	1,755,154,110.51
2019	2,221.32	1,369.99	450.67	1,770.33	1,616,257,946.91
2020	2,371.75	1,459.44	479.99	1,891.41	1,726,525,208.33
2021	2,330.22	1,433.56	472.20	1,857.69	1,695,370,640.42
2022	2,502.55	1,538.25	506.21	1,995.98	1,820,993,958.11
2023	2,462.50	1,509.36	497.97	1,964.18	1,790,466,081.66
2024	2,509.89	1,536.40	507.29	2,002.23	1,823,490,354.39

Table 6.9 Water yield estimation in each sub-watershed of predictive LULC in 2018 of Scenario I (Historical LULC evolution).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	260,726,133.47	728,153.08	14.85
2. Khlong Lea	166.52	123,094,494.86	739,239.68	7.01
3. Khlong Phang La/Khlong Ngae	188.88	141,588,602.27	749,612.07	8.07
4. Khlong Pom	103.13	77,096,065.73	747,543.85	4.39
5. Khlong Ram	324.94	238,733,501.60	734,711.56	13.60
6. Khlong Sa Dao	259.17	191,730,657.36	739,787.23	10.92
7. Khlong Tong/Khlong Pra Tu	161.58	121,260,821.37	750,492.47	6.91
8. Khlong Wa	325.83	236,444,336.54	725,678.93	13.47
9. Khlong Wat/Khlong Tam	352.14	244,782,969.58	695,139.56	13.95
10. Klong Bang Klam	165.81	119,696,527.73	721,911.45	6.82
Total	**2,406.04**	**1,755,154,110.51**		**100.00**

Table 6.10 Water yield estimation in each sub-watershed of predictive LULC in 2019 of Scenario I (Historical LULC evolution).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	238,642,843.91	666,479.11	14.77
2. Khlong Lea	166.52	114,356,044.00	686,761.22	7.08
3. Khlong Phang La/Khlong Ngae	188.88	131,851,825.56	698,062.69	8.16
4. Khlong Pom	103.13	71,098,512.84	689,389.99	4.40
5. Khlong Ram	324.94	219,130,004.76	674,381.04	13.56
6. Khlong Sa Dao	259.17	180,355,406.56	695,896.16	11.16
7. Khlong Tong/Khlong Pra Tu	161.58	112,486,082.03	696,184.94	6.96
8. Khlong Wa	325.83	217,320,316.95	666,984.78	13.45
9. Khlong Wat/Khlong Tam	352.14	222,096,133.79	630,713.03	13.74
10. Klong Bang Klam	165.81	108,920,776.51	656,920.94	6.74
Total	**2,406.04**	**1,616,257,946.91**		**100.00**

Table 6.11 Water yield estimation in each sub-watershed of predictive LULC in 2020 of Scenario I (Historical LULC evolution).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	255,897,891.07	714,668.82	14.82
2. Khlong Lea	166.52	121,957,467.54	732,411.30	7.06
3. Khlong Phang La/Khlong Ngae	188.88	140,454,092.03	743,605.64	8.14
4. Khlong Pom	103.13	75,968,463.02	736,610.31	4.40
5. Khlong Ram	324.94	234,649,278.56	722,142.21	13.59
6. Khlong Sa Dao	259.17	190,399,072.10	734,649.35	11.03
7. Khlong Tong/Khlong Pra Tu	161.58	119,659,578.79	740,582.26	6.93
8. Khlong Wa	325.83	233,130,817.99	715,509.30	13.50
9. Khlong Wat/Khlong Tam	352.14	237,216,926.20	673,653.36	13.74
10. Klong Bang Klam	165.81	117,191,621.04	706,803.90	6.79
Total	**2,406.04**	**1,726,525,208.33**		**100.00**

Table 6.12 Water yield estimation in each sub-watershed of predictive LULC in 2021 of Scenario I (Historical LULC evolution).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	250,454,026.42	699,465.25	14.77
2. Khlong Lea	166.52	119,595,112.30	718,224.26	7.05
3. Khlong Phang La/Khlong Ngae	188.88	138,163,122.79	731,476.57	8.15
4. Khlong Pom	103.13	74,670,703.89	724,026.90	4.40
5. Khlong Ram	324.94	230,220,253.64	708,511.71	13.58
6. Khlong Sa Dao	259.17	189,101,344.39	729,642.11	11.15
7. Khlong Tong/Khlong Pra Tu	161.58	118,086,826.27	730,848.38	6.97
8. Khlong Wa	325.83	227,952,843.36	699,617.41	13.45
9. Khlong Wat/Khlong Tam	352.14	233,229,518.72	662,329.84	13.76
10. Klong Bang Klam	165.81	113,896,888.62	686,932.77	6.72
Total	**2,406.04**	**1,695,370,640.42**		**100.00**

Table 6.13 Water yield estimation in each sub-watershed of predictive LULC in 2022 of Scenario I (Historical LULC evolution).

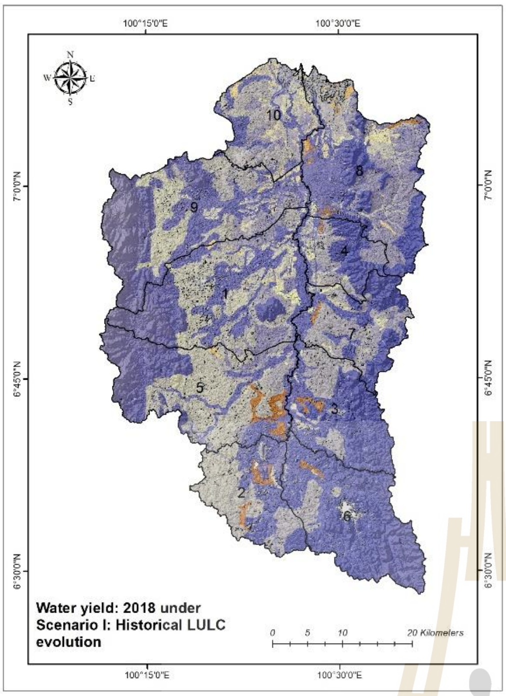
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	268,969,134.99	751,174.05	14.77
2. Khlong Lea	166.52	128,845,135.10	773,774.95	7.08
3. Khlong Phang La/Khlong Ngae	188.88	148,762,421.12	787,592.40	8.17
4. Khlong Pom	103.13	80,220,687.65	777,841.01	4.41
5. Khlong Ram	324.94	248,291,809.53	764,127.62	13.63
6. Khlong Sa Dao	259.17	203,620,085.02	785,662.25	11.18
7. Khlong Tong/Khlong Pra Tu	161.58	127,063,405.34	786,405.11	6.98
8. Khlong Wa	325.83	243,432,526.14	747,126.61	13.37
9. Khlong Wat/Khlong Tam	352.14	250,687,132.63	711,906.32	13.77
10. Klong Bang Klam	165.81	121,101,620.59	730,385.82	6.65
Total	**2,406.04**	**1,820,993,958.11**		**100.00**

Table 6.14 Water yield estimation in each sub-watershed of predictive LULC in 2023 of Scenario I (Historical LULC evolution).

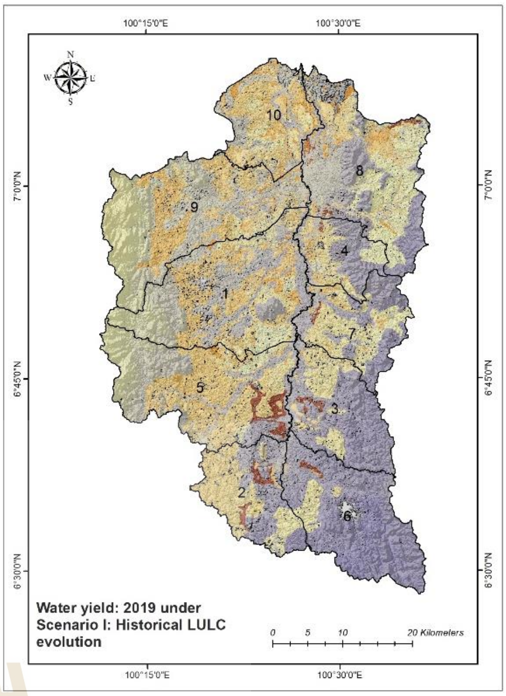
Sub-watershed	Area (km²)	Water yield (m³)	Water yield	
			Average (m³)	%
1. Khlong La/Khlong Jam Rai	358.07	265,513,985.84	741,524.54	14.83
2. Khlong Lea	166.52	126,292,875.27	758,447.44	7.05
3. Khlong Phang La/Khlong Ngae	188.88	145,769,746.97	771,748.29	8.14
4. Khlong Pom	103.13	79,063,943.46	766,624.91	4.42
5. Khlong Ram	324.94	243,584,512.71	749,640.74	13.60
6. Khlong Sa Dao	259.17	198,327,296.45	765,240.18	11.08
7. Khlong Tong/Khlong Pra Tu	161.58	124,837,271.13	772,627.39	6.97
8. Khlong Wa	325.83	240,939,395.40	739,474.86	13.46
9. Khlong Wat/Khlong Tam	352.14	245,989,562.78	698,566.07	13.74
10. Klong Bang Klam	165.81	120,147,491.66	724,631.29	6.71
Total	**2,406.04**	**1,790,466,081.66**		**100.00**

Table 6.15 Water yield estimation in each sub-watershed of predictive LULC in 2024 of Scenario I (Historical LULC evolution).

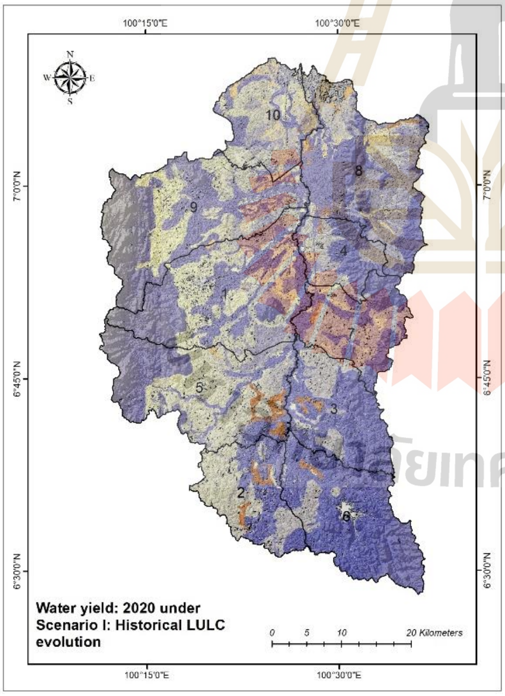
Sub-watershed	Area (km²)	Water yield (m³)	Water yield	
			Average (m³)	%
1. Khlong La/Khlong Jam Rai	358.07	269,631,671.58	753,024.37	14.79
2. Khlong Lea	166.52	129,887,751.81	780,036.34	7.12
3. Khlong Phang La/Khlong Ngae	188.88	149,355,770.48	790,733.77	8.19
4. Khlong Pom	103.13	80,289,517.85	778,508.40	4.40
5. Khlong Ram	324.94	248,573,132.14	764,993.41	13.63
6. Khlong Sa Dao	259.17	204,454,005.72	788,879.91	11.21
7. Khlong Tong/Khlong Pra Tu	161.58	127,280,867.00	787,750.99	6.98
8. Khlong Wa	325.83	244,300,688.60	749,791.11	13.40
9. Khlong Wat/Khlong Tam	352.14	248,407,193.01	705,431.70	13.62
10. Klong Bang Klam	165.81	121,309,756.22	731,641.12	6.65
Total	**2,406.04**	**1,823,490,354.39**		**100.00**



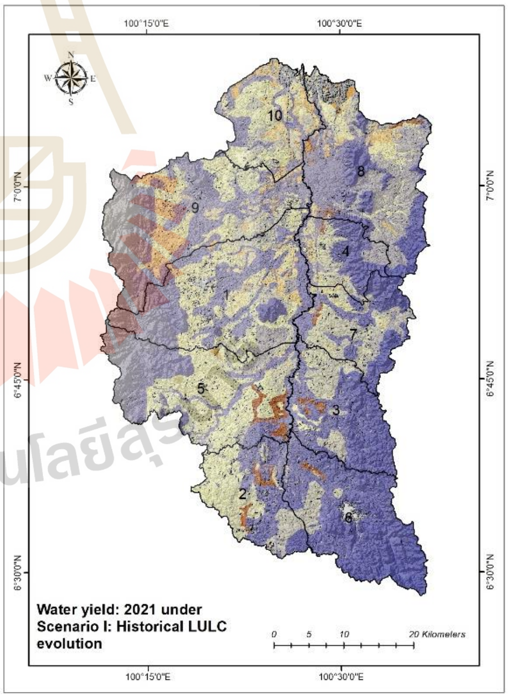
2018



2019

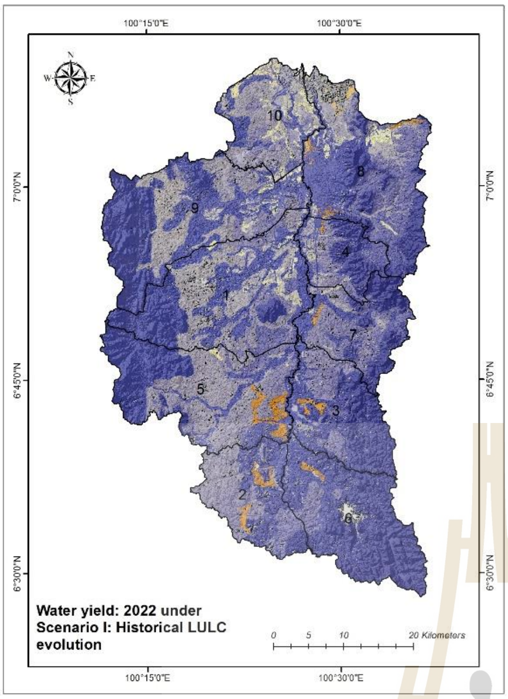


2020

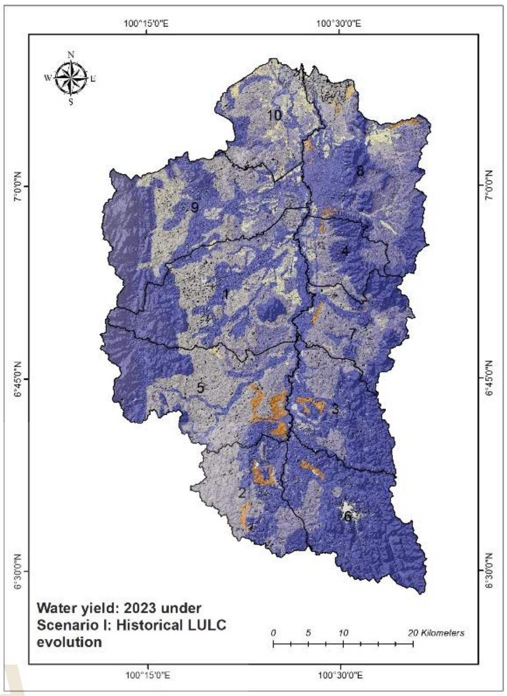


2021

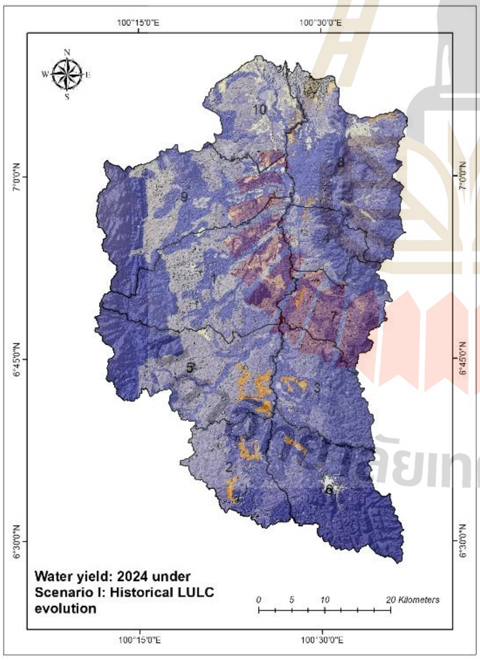
Figure 6.8 Spatial distribution of water yield between 2018 and 2024 of Scenario I.



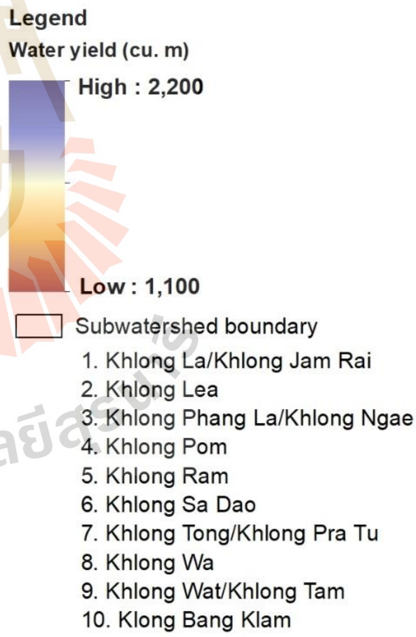
2022



2023



2024



Map legend

Figure 6.8 (Continued).

According to water yield estimation in Khlong U-Tapao watershed during 2018 and 2024 (Table 6.8), it was found that annual water yield (runoff) is diectly related with annual rainfall, PET and AET. In this study, the predictive water yield shows positively high correlation with predictive annual rainfall with R^2 of 0.9900 (Figure 6.9). Likewise, the predictive water yield (runoff) shows positively high correlation with PET with R^2 of 0.9964 (Figure 6.10). Similarly, predictive water yield (runoff) shows positively high correlation with AET with R^2 of 0.9999 (Figure 6.11). These findings is similar with the results of Canqiang, Wenhua, Biao, and Moucheng (2012) who applied linear regression analysis to identify relationship between rainfall and water yield (runoff) in the Xitiaoxi river basin, China.

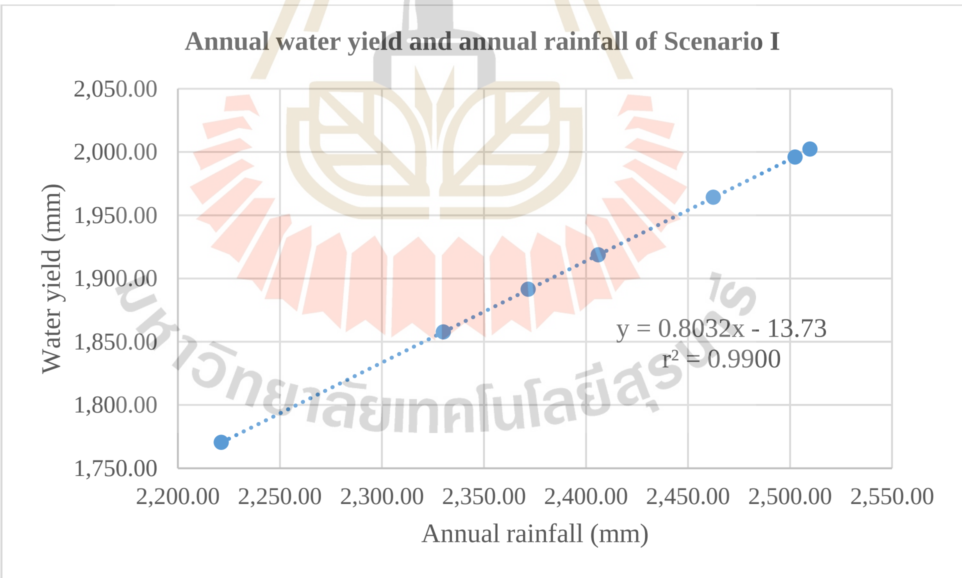


Figure 6.9 Relationship between water yield and annual rainfall under Scenario I.

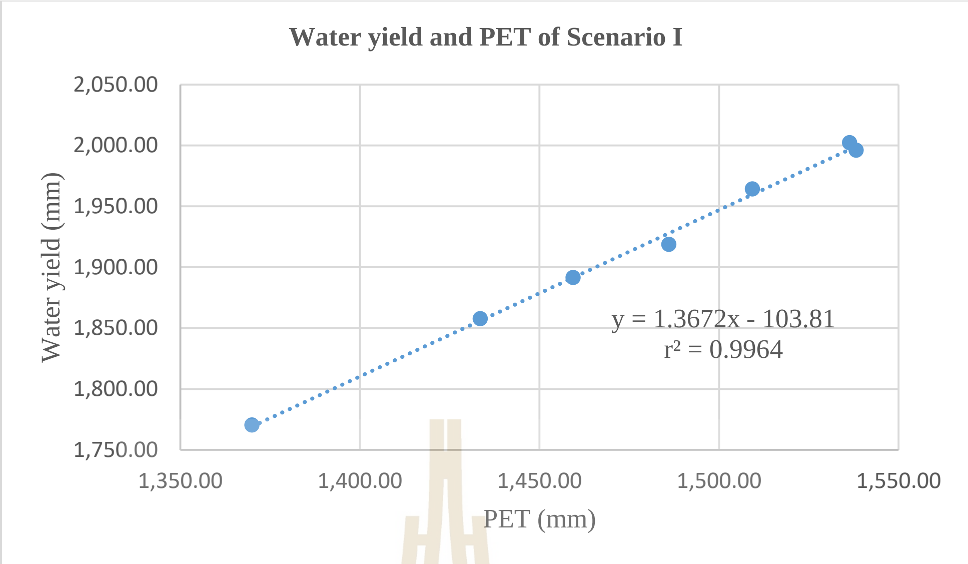


Figure 6.10 Relationship between water yield and PET under Scenario I.

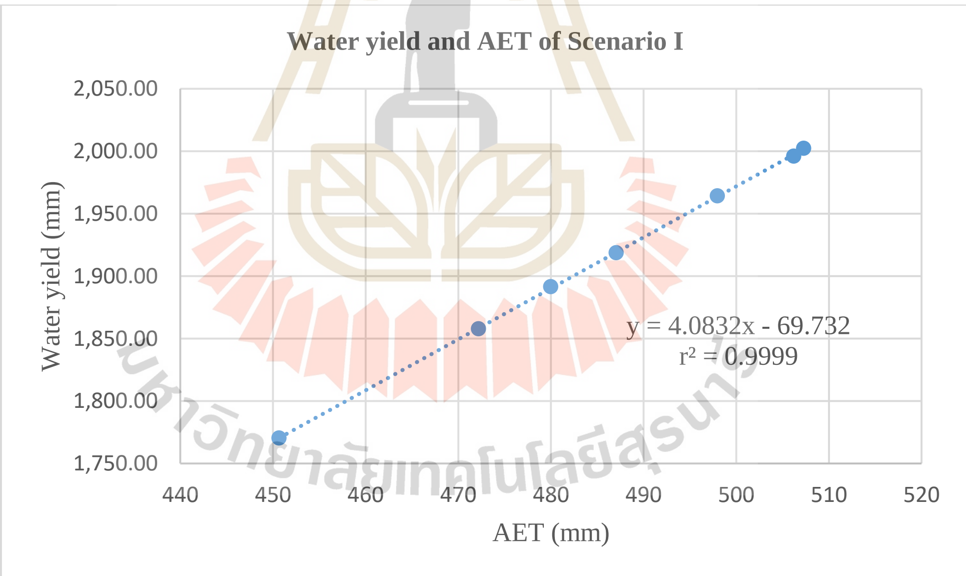


Figure 6.11 Relationship between water yield and AET under Scenario I.

Refer to Tables 6.9 to 6.15, during 2018 to 2024 the highest average water yield occurs in Khlong Tong/Khlong Pra Tu sub-watersheds, while the lowest average water yield always occurs in Khlong Wat/Khlong Tam sub-watershed in these periods.

In addition, characteristics of water yield (runoff) and its average of LULC type of Scenario I is summarized in Table 6.16 and Figure 6.12, which displays average yield volume of LULC types excluding aquatic cultural area and water bodies during 2018 to 2024.

Table 6.16 Characteristics of water yield volume and its average of LULC type under Scenario I during 2018 to 2024.

Item	Year	LULC type										
		UR	**PD**	**RP**	**OP**	**PO**	**AQ**	**EF**	**MF**	**MS**	**WA**	**ML**
Area in km^2	2018	117.18	19.50	1,728.39	20.68	34.10	9.41	249.50	0.87	41.69	43.52	141.21
	2019	121.68	18.70	1,727.84	22.92	34.36	9.55	243.05	0.89	41.16	44.86	141.05
	2020	125.76	17.88	1,727.62	24.56	34.56	9.61	238.32	0.90	40.75	45.73	140.36
	2021	130.90	16.91	1,727.39	26.44	34.73	9.70	233.22	0.93	39.72	46.77	139.33
	2022	135.41	16.11	1,727.17	28.36	35.23	9.81	227.79	0.95	38.65	48.18	138.40
	2023	139.87	15.33	1,726.99	30.06	35.35	9.96	222.57	0.97	37.95	49.48	137.51
	2024	144.17	14.48	1,726.77	32.35	37.19	10.09	215.46	0.93	37.26	50.44	136.91
Water yield in million m^3	2018	87.31	13.86	1,299.32	15.47	25.46	0.00	184.26	0.60	34.35	0.00	94.52
	2019	83.24	12.11	1,197.60	15.77	23.63	0.00	165.37	0.56	30.98	0.00	87.00
	2020	92.46	12.52	1,280.12	18.10	25.47	0.00	171.44	0.62	33.12	0.00	92.66
	2021	93.72	11.48	1,256.40	19.15	25.03	0.00	167.68	0.62	31.27	0.00	90.03
	2022	103.65	11.65	1,349.46	22.08	27.21	0.00	177.98	0.67	32.40	0.00	95.90
	2023	106.17	11.05	1,328.54	23.04	26.97	0.00	168.30	0.68	31.70	0.00	94.01
	2024	111.16	10.57	1,354.19	25.28	28.88	0.00	165.83	0.66	31.54	0.00	95.38
Average water yield in million m^3	2018	0.75	0.71	0.75	0.75	0.75	0.00	0.74	0.69	0.82	0.00	0.67
	2019	0.68	0.65	0.69	0.69	0.69	0.00	0.68	0.63	0.75	0.00	0.62
	2020	0.74	0.70	0.74	0.74	0.74	0.00	0.72	0.68	0.81	0.00	0.66
	2021	0.72	0.68	0.73	0.72	0.72	0.00	0.72	0.66	0.79	0.00	0.65
	2022	0.77	0.72	0.78	0.78	0.77	0.00	0.78	0.70	0.84	0.00	0.69
	2023	0.76	0.72	0.77	0.77	0.76	0.00	0.76	0.70	0.84	0.00	0.68
	2024	0.77	0.73	0.78	0.78	0.78	0.00	0.77	0.71	0.85	0.00	0.70

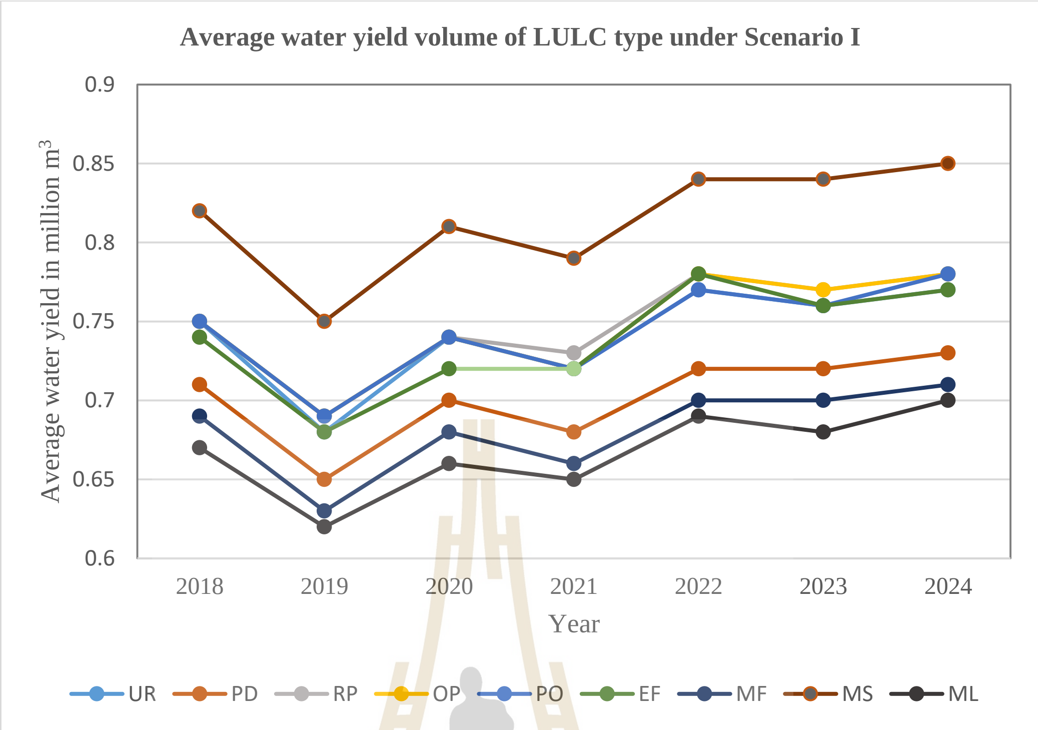


Figure 6.12 Average yield volume of LULC type under Scenario I during 2018 to 2024.

As results, it can be observed that marsh and swamp provides the highest average water yield (runoff) in every year while miscellaneous land provides the lowest water yield (runoff) in every year. Meanwhile average water yield (runoff) of rubber plantation, oil palm plantation and evergreen forest are similar. These findings indicate the influence of coefficient of evapotranspiration (Kc) of each LULC type on water yield (runoff).

6.5 Water yield estimation of predictive LULC of Scenario II

Water yield estimation of predictive LULC between 2018 and 2024 of Scenario II: Forest conservation and prevention is presented in Table 6.17. It was found that the highest water yield (runoff) in Kholng U-Tapao watershed shall occur in 2024 is about 1,829,037,584 m^3 while the lowest water yield (runoff) volume shall occur in 2019 is about 1,617,767,875 m^3. The proportion of water yield estimation in each sub-watershed of predictive LULC between 2018 and 2024 of Scenario-II is summarized in Tables 6.18 to 6.24 and the spatial distribution of water yield is displayed in Figure 6.13.

Table 6.17 Water yield estimation of predictive LULC between 2018 and 2024 of Scenario II (Forest conservation and prevention).

Year	Annual rainfall (mm)	PET (mm)	AET (mm)	Water yield (mm)	Water yield (m^3)
2018	2,406.08	1,487.86	549.16	1,661.83	1,755,799,564.77
2019	2,221.32	1,375.16	512.42	1,530.54	1,617,767,874.74
2020	2,371.75	1,467.64	543.07	1,638.97	1,728,733,356.91
2021	2,330.22	1,444.35	535.32	1,610.73	1,698,139,630.56
2022	2,502.55	1,552.68	570.72	1,735.93	1,824,878,523.67
2023	2,462.50	1,526.27	562.81	1,708.10	1,795,291,837.77
2024	2,509.89	1,556.62	572.95	1,743.51	1,829,037,584.00

Table 6.18 Water yield estimation in each sub-watershed of predictive LULC in 2018 of Scenario II (Forest conservation and prevention).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	260,730,351.67	728,164.86	14.85
2. Khlong Lea	166.52	123,094,606.15	739,240.35	7.01
3. Khlong Phang La/Khlong Ngae	188.88	141,596,473.88	749,653.75	8.06
4. Khlong Pom	103.13	77,121,751.94	747,792.91	4.39
5. Khlong Ram	324.94	238,728,194.38	734,695.23	13.60
6. Khlong Sa Dao	259.17	191,742,010.31	739,831.04	10.92
7. Khlong Tong/Khlong Pra Tu	161.58	121,224,809.79	750,269.59	6.90
8. Khlong Wa	325.83	236,622,266.87	726,225.02	13.48
9. Khlong Wat/Khlong Tam	352.14	245,151,712.05	696,186.72	13.96
10. Klong Bang Klam	165.81	119,787,387.74	722,459.44	6.82
Total	2,406.04	1,755,799,564.77		100.00

Table 6.19 Water yield estimation in each sub-watershed of predictive LULC in 2019 of Scenario II (Forest conservation and prevention).

Sub-watershed	Area (km^2)	Water yield (cm^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	238,654,984.50	666,513.02	14.75
2. Khlong Lea	166.52	114,358,248.96	686,774.46	7.07
3. Khlong Phang La/Khlong Ngae	188.88	131,876,975.90	698,195.84	8.15
4. Khlong Pom	103.13	71,123,649.95	689,633.72	4.40
5. Khlong Ram	324.94	219,158,423.94	674,468.51	13.55
6. Khlong Sa Dao	259.17	180,369,806.07	695,951.72	11.15
7. Khlong Tong/Khlong Pra Tu	161.58	112,424,686.93	695,804.96	6.95
8. Khlong Wa	325.83	217,662,461.64	668,034.87	13.45
9. Khlong Wat/Khlong Tam	352.14	223,006,039.86	633,297.00	13.78
10. Klong Bang Klam	165.81	109,132,596.98	658,198.47	6.75
Total	**2,406.04**	**1,617,767,874.74**		**100.00**

Table 6.20 Water yield estimation in each sub-watershed of predictive LULC in 2020 of Scenario II (Forest conservation and prevention).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	255,918,879.82	714,727.44	14.80
2. Khlong Lea	166.52	121,965,251.51	732,458.05	7.06
3. Khlong Phang La/Khlong Ngae	188.88	140,488,294.45	743,786.72	8.13
4. Khlong Pom	103.13	75,995,340.80	736,870.93	4.40
5. Khlong Ram	324.94	234,683,524.05	722,247.60	13.58
6. Khlong Sa Dao	259.17	190,411,796.19	734,698.45	11.01
7. Khlong Tong/Khlong Pra Tu	161.58	119,575,303.20	740,060.67	6.92
8. Khlong Wa	325.83	233,550,659.23	716,797.85	13.51
9. Khlong Wat/Khlong Tam	352.14	238,538,904.46	677,407.54	13.80
10. Klong Bang Klam	165.81	117,605,403.20	709,299.50	6.80
Total	**2,406.04**	**1,728,733,356.91**		**100.00**

Table 6.21 Water yield estimation in each sub-watershed of predictive LULC in 2021 of Scenario II (Forest conservation and prevention).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	250,507,418.32	699,614.37	14.75
2. Khlong Lea	166.52	119,600,236.78	718,255.03	7.04
3. Khlong Phang La/Khlong Ngae	188.88	138,181,682.63	731,574.83	8.14
4. Khlong Pom	103.13	74,691,011.06	724,223.80	4.40
5. Khlong Ram	324.94	230,253,372.08	708,613.64	13.56
6. Khlong Sa Dao	259.17	189,095,928.88	729,621.21	11.14
7. Khlong Tong/Khlong Pra Tu	161.58	117,982,533.81	730,202.90	6.95
8. Khlong Wa	325.83	228,424,346.53	701,064.52	13.45
9. Khlong Wat/Khlong Tam	352.14	234,881,477.35	667,021.11	13.83
10. Klong Bang Klam	165.81	114,521,623.12	690,700.66	6.74
Total	**2,406.04**	**1,698,139,630.56**		**100.00**

Table 6.22 Water yield estimation in each sub-watershed of predictive LULC in 2022 of Scenario II (Forest conservation and prevention).

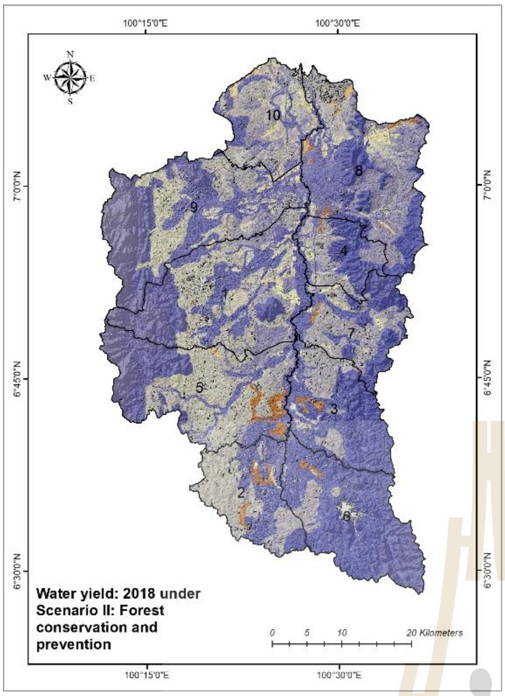
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	269,086,309.47	751,501.29	14.75
2. Khlong Lea	166.52	128,843,912.56	773,767.60	7.06
3. Khlong Phang La/Khlong Ngae	188.88	148,769,213.27	787,628.36	8.15
4. Khlong Pom	103.13	80,235,090.22	777,980.66	4.40
5. Khlong Ram	324.94	248,332,182.76	764,251.87	13.61
6. Khlong Sa Dao	259.17	203,599,555.41	785,583.04	11.16
7. Khlong Tong/Khlong Pra Tu	161.58	126,933,493.02	785,601.07	6.96
8. Khlong Wa	325.83	244,075,711.06	749,100.62	13.37
9. Khlong Wat/Khlong Tam	352.14	252,978,167.57	718,412.45	13.86
10. Klong Bang Klam	165.81	122,024,888.33	735,954.21	6.69
Total	**2,406.04**	**1,824,878,523.67**		**100.00**

Table 6.23 Water yield estimation in each sub-watershed of predictive LULC in 2023 of Scenario II (Forest conservation and prevention).

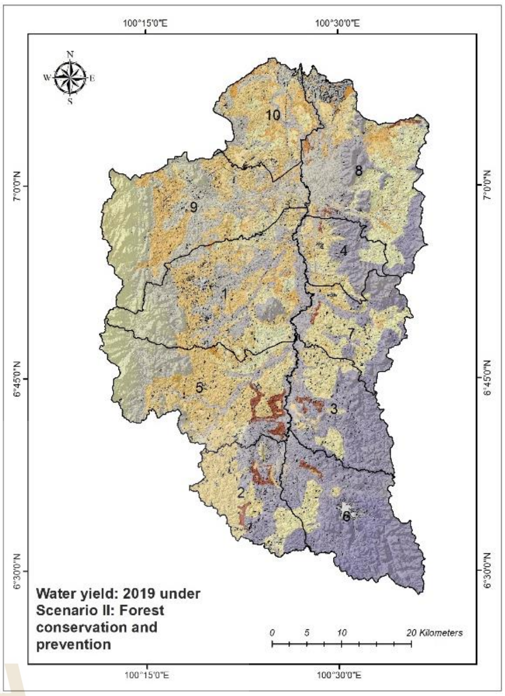
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	265,693,838.97	742,026.84	14.80
2. Khlong Lea	166.52	126,295,540.57	758,463.45	7.03
3. Khlong Phang La/Khlong Ngae	188.88	145,768,801.51	771,743.29	8.12
4. Khlong Pom	103.13	79,089,480.00	766,872.52	4.41
5. Khlong Ram	324.94	243,649,037.15	749,839.31	13.57
6. Khlong Sa Dao	259.17	198,301,990.00	765,142.53	11.05
7. Khlong Tong/Khlong Pra Tu	161.58	124,703,217.20	771,797.72	6.95
8. Khlong Wa	325.83	228,817,034.82	702,269.73	12.75
9. Khlong Wat/Khlong Tam	352.14	261,655,413.32	743,054.26	14.57
10. Klong Bang Klam	165.81	121,317,484.23	731,687.73	6.76
Total	**2,406.04**	**1,795,291,837.77**		**100.00**

Table 6.24 Water yield estimation in each sub-watershed of predictive LULC in 2024 of Scenario II (Forest conservation and prevention).

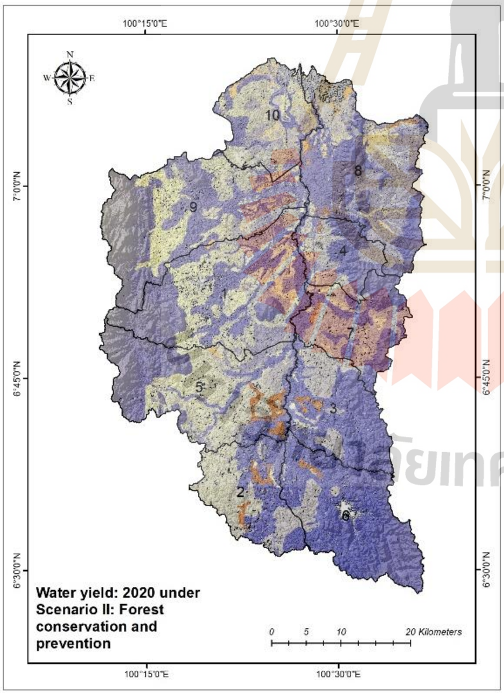
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	269,836,226.06	753,595.65	14.75
2. Khlong Lea	166.52	129,886,887.92	780,031.16	7.10
3. Khlong Phang La/Khlong Ngae	188.88	149,341,385.37	790,657.61	8.17
4. Khlong Pom	103.13	80,310,943.69	778,716.15	4.39
5. Khlong Ram	324.94	248,637,671.04	765,192.03	13.59
6. Khlong Sa Dao	259.17	204,412,052.95	788,718.03	11.18
7. Khlong Tong/Khlong Pra Tu	161.58	127,135,491.41	786,851.25	6.95
8. Khlong Wa	325.83	245,161,308.04	752,432.47	13.40
9. Khlong Wat/Khlong Tam	352.14	251,600,717.93	714,500.74	13.76
10. Klong Bang Klam	165.81	122,714,899.60	740,115.80	6.71
Total	**2,406.04**	**1,829,037,584.00**		**100.00**



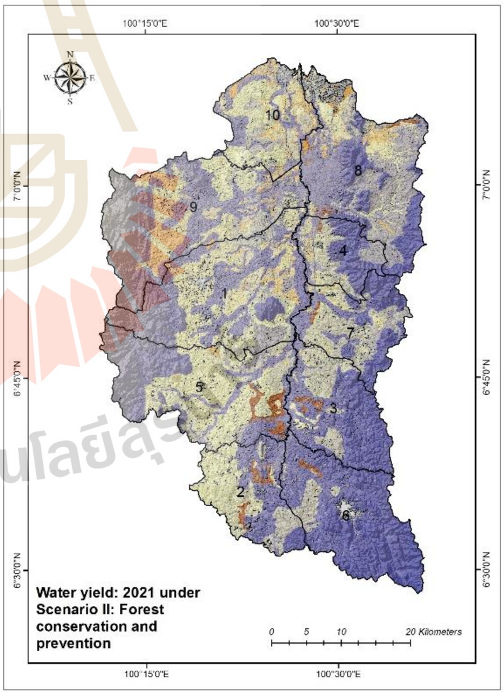
2018



2019

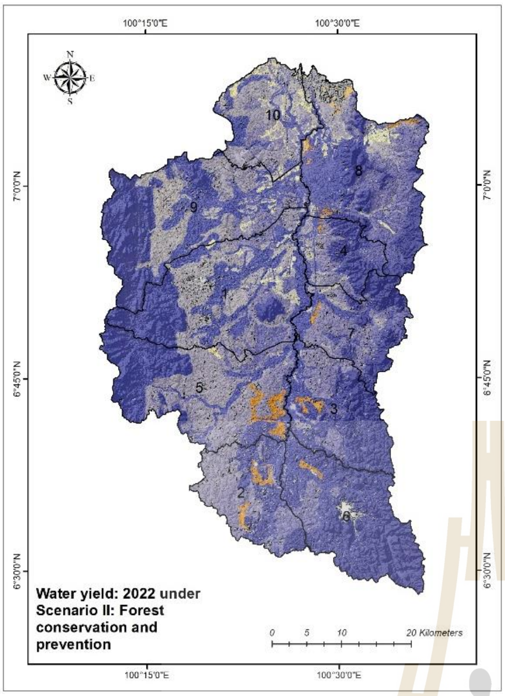


2020

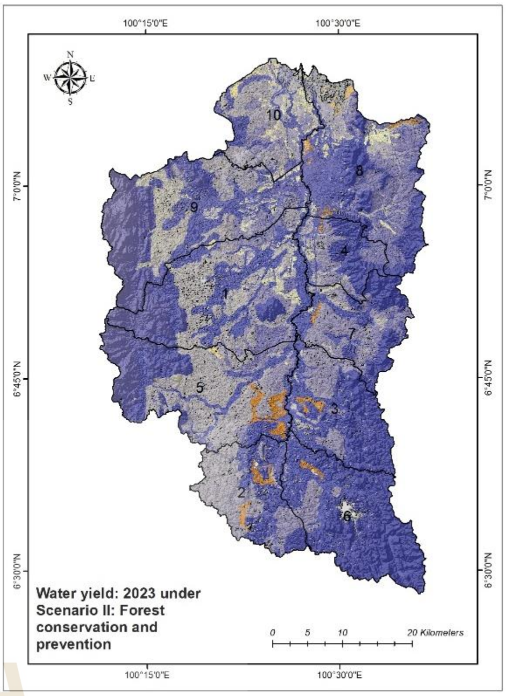


2021

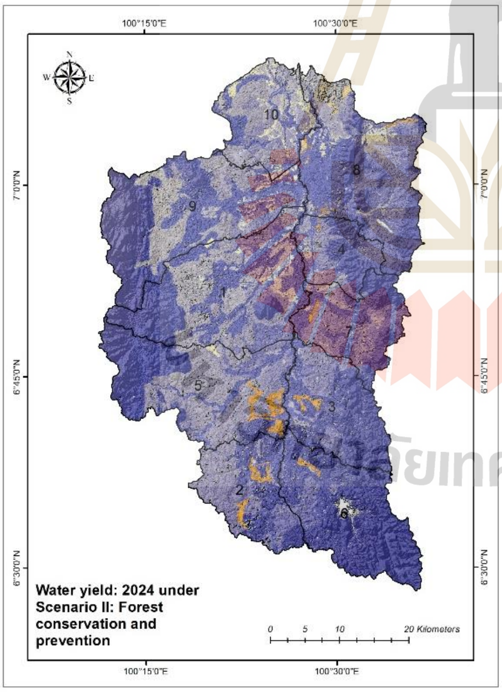
Figure 6.13 Spatial distribution of water yield between 2018 and 2024 of Scenario II.



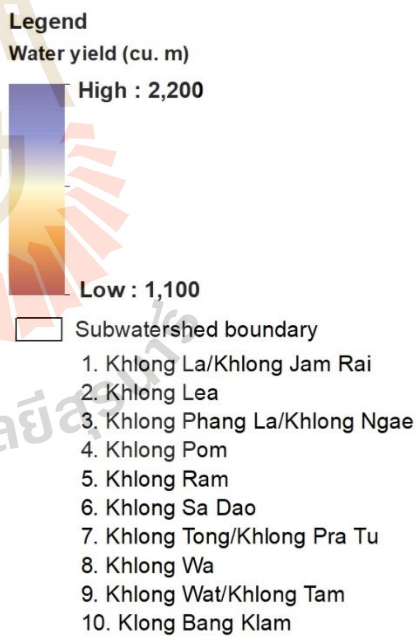
2022



2023



2024



Map legend

Figure 6.13 (Continued).

Similar to Scenario I, according to water yield estimation of Scenario II during 2018 and 2019 (Table 6.17), annual water yield (runoff) is generally related with annual rainfall, PET and AET. It was found that predictive water yield (runoff) shows positively high correlation with predictive annual rainfall with R^2 of 0.9994 (Figure 6.14). Likewise, predictive water yield (runoff) shows positively high correlation with PET with R^2 of 0.9998 (Figure 6.15). Similarly, predictive water yield (runoff) shows positively high correlation with AET with R^2 of 0.9999 (Figure 6.16).

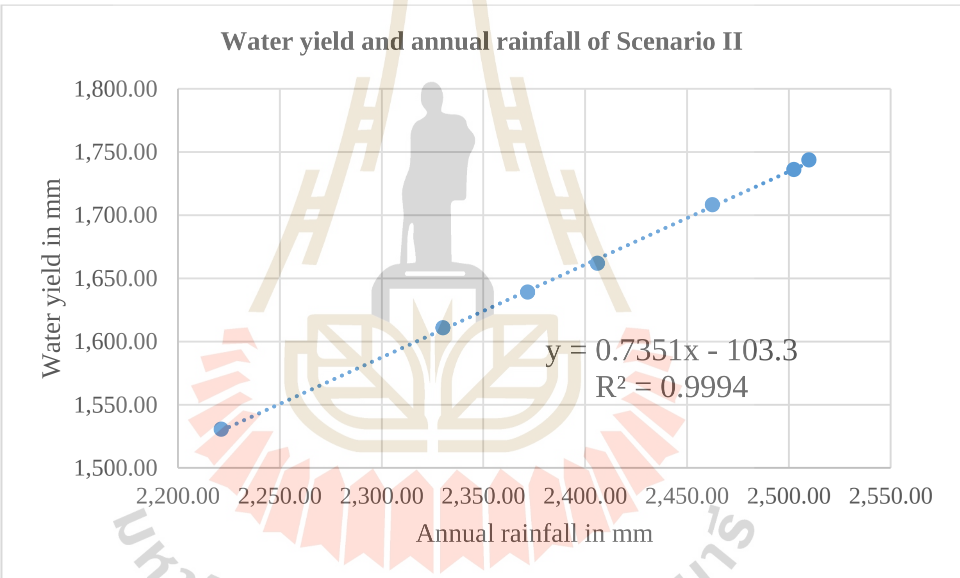


Figure 6.14 Relationship between water yield and annual rainfall under Scenario II.

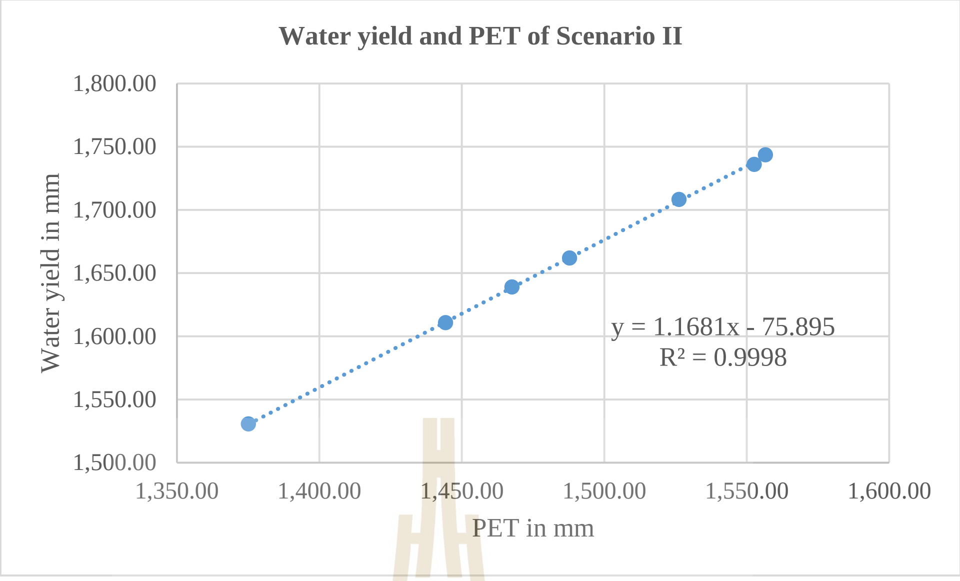


Figure 6.15 Relationship between water yield and PET under Scenario II.

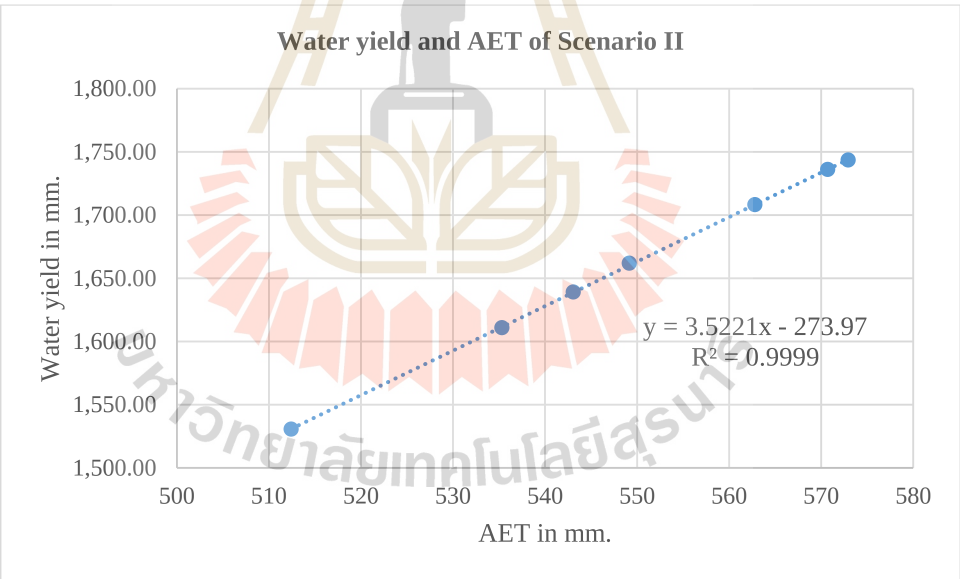


Figure 6.16 Relationship between water yield and AET under Scenario II.

Refer to Tables 6.18 to 6.24, during 2018 to 2024 the highest average water yield (runoff) occurs in sub-watersheds including Khlong Phang La/Khlong Ngae sub-watersheds while the lowest average water yield (runoff) always occurs in Khlong Wat/Khlong Tam sub-watershed.

In addition, characteristics of water yield and its average of LULC type of Scenario II is summarized in Table 6.25 and Figure 6.17 displays average yield volume of LULC type excluding aquatic cultural area and water bodies during 2018 to 2024.

Table 6.25 Characteristics of water yield volume and its average of LULC type under Scenario II during 2018 to 2024.

Item	Year	LULC type										
		UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
	2018	116.63	20.36	1,707.79	20.72	34.10	9.38	270.03	0.85	42.53	42.43	141.22
	2019	122.00	20.34	1,686.08	22.72	34.03	9.38	286.41	0.85	42.42	42.43	139.41
	2020	126.31	20.30	1,664.43	24.63	33.98	9.38	304.29	0.85	42.35	42.43	137.10
Area in km^2	2021	130.89	20.26	1,640.07	26.47	33.91	9.38	323.36	0.85	42.28	42.43	136.16
	2022	136.16	20.26	1,614.61	28.50	33.91	9.38	342.22	0.85	42.27	42.43	135.49
	2023	140.46	20.25	1,592.74	30.40	33.91	9.38	359.49	0.85	42.27	42.43	133.88
	2024	145.10	20.25	1,569.66	32.34	33.90	9.38	377.33	0.85	42.27	42.43	132.56
	2018	86.91	14.47	1,283.72	15.48	25.46	0.00	199.59	0.59	35.04	0.00	94.53
	2019	83.45	13.18	1,168.36	15.56	23.40	0.00	195.37	0.54	31.94	0.00	85.97
Water yield	2020	92.91	14.22	1,233.20	18.10	25.05	0.00	219.74	0.57	34.43	0.00	90.52
in million m^3	2021	93.65	13.76	1,192.11	18.99	24.44	0.00	233.39	0.56	33.29	0.00	87.96
	2022	104.05	14.66	1,260.48	21.89	26.20	0.00	267.71	0.59	35.46	0.00	93.84
	2023	106.59	14.60	1,224.58	23.10	25.88	0.00	273.12	0.59	35.33	0.00	91.51
	2024	111.84	14.79	1,230.48	24.99	26.35	0.00	291.87	0.60	35.81	0.00	92.32
	2018	0.75	0.71	0.75	0.75	0.75	0.00	0.74	0.69	0.82	0.00	0.67
	2019	0.68	0.65	0.69	0.68	0.69	0.00	0.68	0.63	0.75	0.00	0.62
Average	2020	0.74	0.70	0.74	0.73	0.74	0.00	0.72	0.68	0.81	0.00	0.66
water yield	2021	0.72	0.68	0.73	0.72	0.72	0.00	0.72	0.66	0.79	0.00	0.65
in million m^3	2022	0.76	0.72	0.78	0.77	0.77	0.00	0.78	0.70	0.84	0.00	0.69
	2023	0.76	0.72	0.77	0.76	0.76	0.00	0.76	0.70	0.84	0.00	0.68
	2024	0.77	0.73	0.78	0.77	0.78	0.00	0.77	0.71	0.85	0.00	0.70

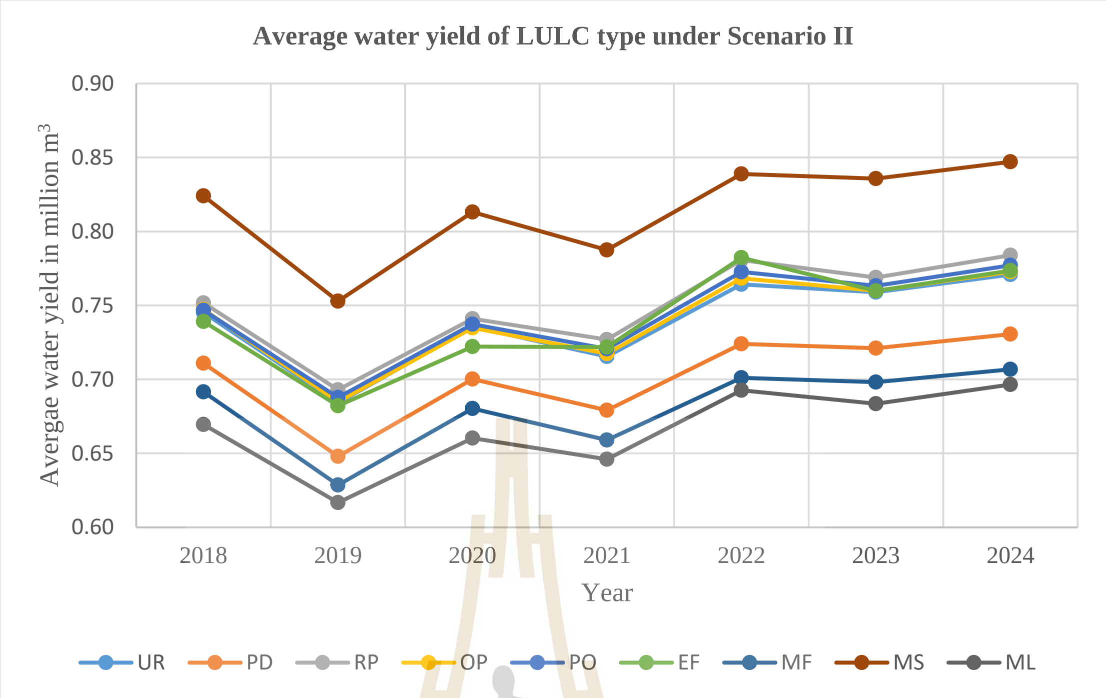


Figure 6.17 Average water yield of LULC type under Scenario II during 2018 to 2024.

As results, it can be observed that marsh and swamp provides the highest average water yield (runoff) in every year while miscellaneous land provides the lowest water yield in every year. Meanwhile average water yield (runoff) of rubber plantation, oil palm plantation and evergreen forest are similar with Scenario I as mentioned earlier in the previous section.

6.6 Water yield estimation of predictive LULC of Scenario III

Water yield estimation of predictive LULC between 2018 and 2024 of Scenario III: Agriculture production extension is presented in Table 6.26. It was found that the highest water yield (runoff) in Khlong U-tapao watershed shall occur in 2024 is about 1,834,815,602 m^3 while the lowest water yield (runoff) volume shall occur in 2019 is about 1,619,029,718 m^3. The proportion of water yield estimation in each sub-watershed of predictive LULC between 2018 and 2024 of Scenario-I is summarized in Tables 6.27 to 6.33 and the spatial distribution of water yield is displayed in Figure 6.18.

Table 6.26 Water yield estimation of predictive LULC between 2018 and 2024 of Scenario III (Agriculture production extension).

Year	Annual rainfall (mm)	PET (mm)	AET (mm)	Water yield (mm)	Water yield (m^3)
2018	2,406.08	1,491.48	550.69	1,666.84	1,756,375,718.37
2019	2,221.32	1,382.56	515.57	1,540.99	1,619,029,718.35
2020	2,371.75	1,479.99	548.27	1,656.60	1,730,702,036.99
2021	2,330.22	1,460.51	542.44	1,634.81	1,700,840,701.27
2022	2,502.55	1,575.22	580.42	1,768.37	1,828,995,825.16
2023	2,462.50	1,552.91	574.49	1,746.19	1,799,989,836.18
2024	2,509.89	1,587.71	586.66	1,787.78	1,834,815,601.78

Table 6.27 Water yield estimation in each sub-watershed of predictive LULC in 2018 of Scenario III (Agriculture production extension).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	260,936,504.78	728,740.61	14.86
2. Khlong Lea	166.52	123,108,698.21	739,324.97	7.01
3. Khlong Phang La/Khlong Ngae	188.88	141,708,191.42	750,245.21	8.07
4. Khlong Pom	103.13	77,137,115.15	747,941.87	4.39
5. Khlong Ram	324.94	238,829,196.94	735,006.07	13.60
6. Khlong Sa Dao	259.17	191,834,068.47	740,186.24	10.92
7. Khlong Tong/Khlong Pra Tu	161.58	121,292,044.94	750,685.72	6.91
8. Khlong Wa	325.83	236,511,047.03	725,883.67	13.47
9. Khlong Wat/Khlong Tam	352.14	245,255,130.18	696,480.41	13.96
10. Klong Bang Klam	165.81	119,763,721.25	722,316.70	6.82
Total	**2,406.04**	**1,756,375,718.37**		**100.00**

Table 6.28 Water yield estimation in each sub-watershed of predictive LULC in 2019 of Scenario III (Agriculture production extension).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	239,016,722.55	667,523.28	14.76
2. Khlong Lea	166.52	114,394,849.05	686,994.26	7.07
3. Khlong Phang La/Khlong Ngae	188.88	132,122,397.27	699,495.17	8.16
4. Khlong Pom	103.13	71,150,859.16	689,897.55	4.39
5. Khlong Ram	324.94	219,348,098.49	675,052.24	13.55
6. Khlong Sa Dao	259.17	180,570,600.98	696,726.48	11.15
7. Khlong Tong/Khlong Pra Tu	161.58	112,552,177.61	696,594.01	6.95
8. Khlong Wa	325.83	217,537,646.25	667,651.80	13.44
9. Khlong Wat/Khlong Tam	352.14	223,175,857.16	633,779.25	13.78
10. Klong Bang Klam	165.81	109,160,509.84	658,366.82	6.74
Total	**2,406.04**	**1,619,029,718.35**		**100.00**

Table 6.29 Water yield estimation in each sub-watershed of predictive LULC in 2020 of Scenario III (Agriculture production extension).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	256,443,507.96	716,192.61	14.82
2. Khlong Lea	166.52	122,099,715.58	733,265.57	7.05
3. Khlong Phang La/Khlong Ngae	188.88	140,835,499.16	745,624.92	8.14
4. Khlong Pom	103.13	76,031,997.95	737,226.36	4.39
5. Khlong Ram	324.94	235,003,429.62	723,232.12	13.58
6. Khlong Sa Dao	259.17	190,718,029.91	735,880.04	11.02
7. Khlong Tong/Khlong Pra Tu	161.58	119,774,238.37	741,291.90	6.92
8. Khlong Wa	325.83	233,424,505.46	716,410.67	13.49
9. Khlong Wat/Khlong Tam	352.14	238,764,527.01	678,048.27	13.80
10. Klong Bang Klam	165.81	117,606,585.97	709,306.63	6.80
Total	**2,406.04**	**1,730,702,036.99**		**100.00**

Table 6.30 Water yield estimation in each sub-watershed of predictive LULC in 2021 of Scenario III (Agriculture production extension).

Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	251,164,271.20	701,448.82	14.77
2. Khlong Lea	166.52	119,886,463.82	719,973.96	7.05
3. Khlong Phang La/Khlong Ngae	188.88	138,618,696.47	733,888.51	8.15
4. Khlong Pom	103.13	74,731,803.22	724,619.33	4.39
5. Khlong Ram	324.94	230,706,020.30	710,006.68	13.56
6. Khlong Sa Dao	259.17	189,493,037.12	731,153.44	11.14
7. Khlong Tong/Khlong Pra Tu	161.58	118,206,255.73	731,587.53	6.95
8. Khlong Wa	325.83	228,352,766.39	700,844.83	13.43
9. Khlong Wat/Khlong Tam	352.14	235,153,505.36	667,793.62	13.83
10. Klong Bang Klam	165.81	114,527,881.66	690,738.41	6.73
Total	**2,406.04**	**1,700,840,701.27**		**100.00**

Table 6.31 Water yield estimation in each sub-watershed of predictive LULC in 2022 of Scenario III (Agriculture production extension).

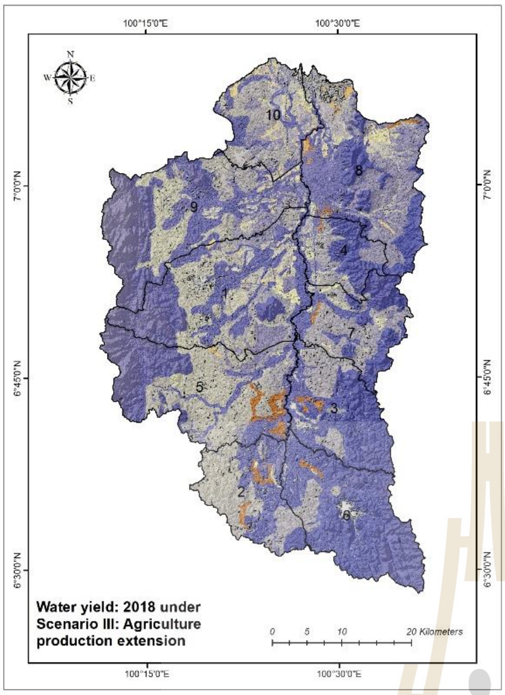
Sub-watershed	Area (km^2)	Water yield (m^3	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	270,016,214.24	754,098.32	14.76
2. Khlong Lea	166.52	129,481,675.29	777,597.67	7.08
3. Khlong Phang La/Khlong Ngae	188.88	149,366,406.69	790,790.08	8.17
4. Khlong Pom	103.13	80,295,522.43	778,566.62	4.39
5. Khlong Ram	324.94	249,010,446.20	766,339.26	13.61
6. Khlong Sa Dao	259.17	204,129,480.90	787,627.74	11.16
7. Khlong Tong/Khlong Pra Tu	161.58	127,222,907.53	787,392.28	6.96
8. Khlong Wa	325.83	244,082,991.44	749,122.97	13.35
9. Khlong Wat/Khlong Tam	352.14	253,349,732.17	719,467.63	13.85
10. Klong Bang Klam	165.81	122,040,448.27	736,048.06	6.67
Total	**2,406.04**	**1,828,995,825.16**		**100.00**

Table 6.32 Water yield estimation in each sub-watershed of predictive LULC in 2023 of Scenario III (Agriculture production extension).

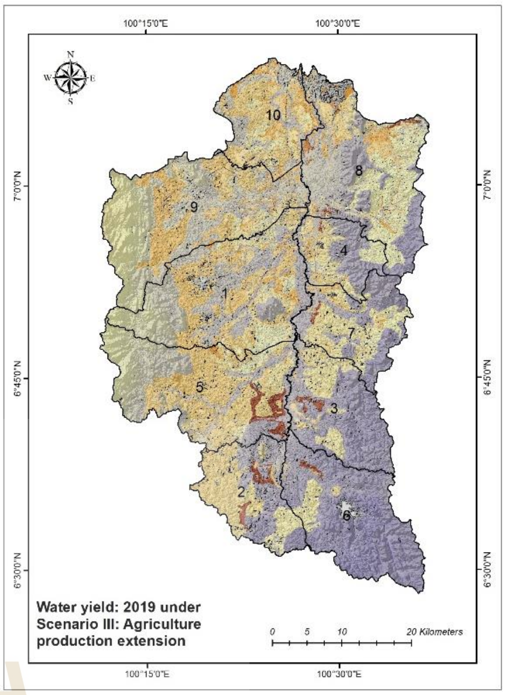
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	266,723,877.06	744,903.51	14.82
2. Khlong Lea	166.52	127,103,669.81	763,316.64	7.06
3. Khlong Phang La/Khlong Ngae	188.88	146,408,925.62	775,132.29	8.13
4. Khlong Pom	103.13	79,159,442.27	767,550.89	4.40
5. Khlong Ram	324.94	244,421,069.37	752,215.27	13.58
6. Khlong Sa Dao	259.17	198,870,096.78	767,334.56	11.05
7. Khlong Tong/Khlong Pra Tu	161.58	125,033,400.83	773,841.26	6.95
8. Khlong Wa	325.83	241,747,238.57	741,954.23	13.43
9. Khlong Wat/Khlong Tam	352.14	249,188,553.97	707,650.63	13.84
10. Klong Bang Klam	165.81	121,333,561.89	731,784.70	6.74
Total	**2,406.04**	**1,799,989,836.18**		**100.00**

Table 6.33 Water yield estimation in each sub-watershed of predictive LULC in 2024 of Scenario III (Agriculture production extension).

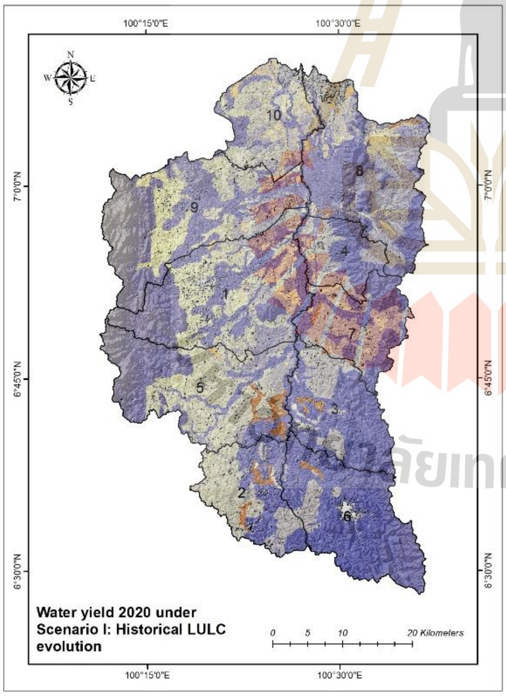
Sub-watershed	Area (km^2)	Water yield (m^3)	Water yield	
			Average (m^3)	%
1. Khlong La/Khlong Jam Rai	358.07	271,072,074.62	757,047.11	14.77
2. Khlong Lea	166.52	131,015,953.94	786,811.72	7.14
3. Khlong Phang La/Khlong Ngae	188.88	150,091,716.30	794,630.08	8.18
4. Khlong Pom	103.13	80,389,629.51	779,479.11	4.38
5. Khlong Ram	324.94	249,648,213.17	768,302.01	13.61
6. Khlong Sa Dao	259.17	205,065,943.64	791,241.05	11.18
7. Khlong Tong/Khlong Pra Tu	161.58	127,550,961.96	789,422.63	6.95
8. Khlong Wa	325.83	245,179,909.25	752,489.55	13.36
9. Khlong Wat/Khlong Tam	352.14	252,115,267.91	715,961.97	13.74
10. Klong Bang Klam	165.81	122,685,931.50	739,941.08	6.69
Total	**2,406.04**	**1,834,815,601.78**		**100.00**



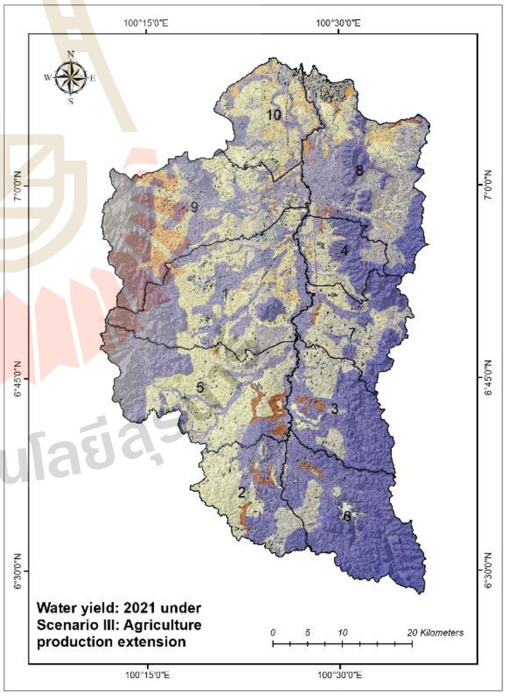
2018



2019

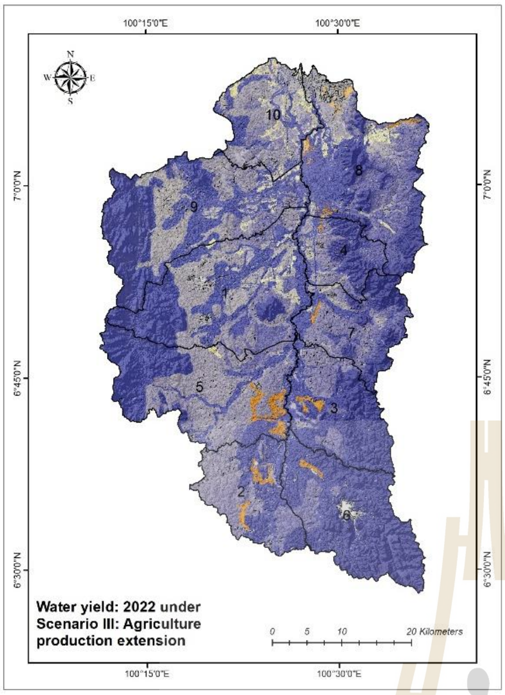


2020

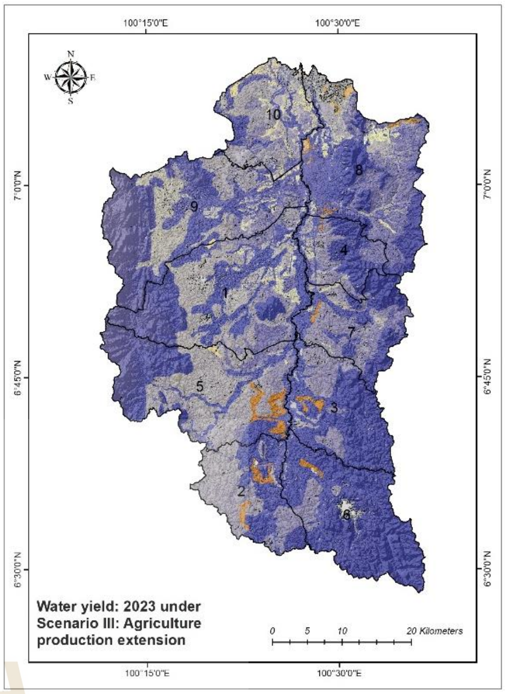


2021

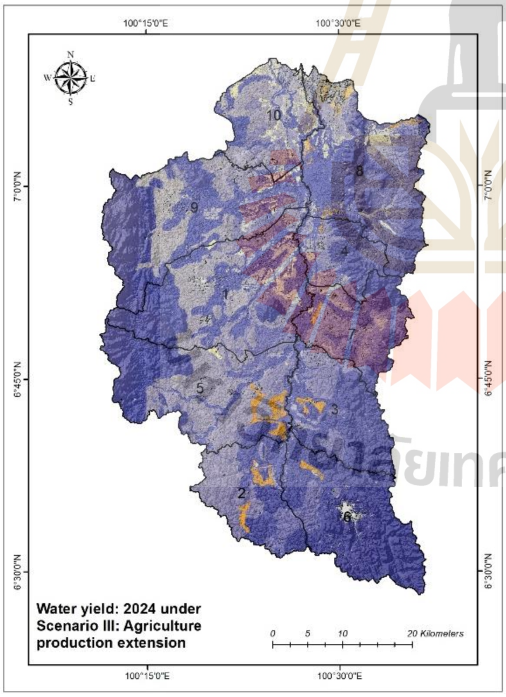
Figure 6.18 Spatial distribution of water yield between 2018 and 2024 of Scenario III.



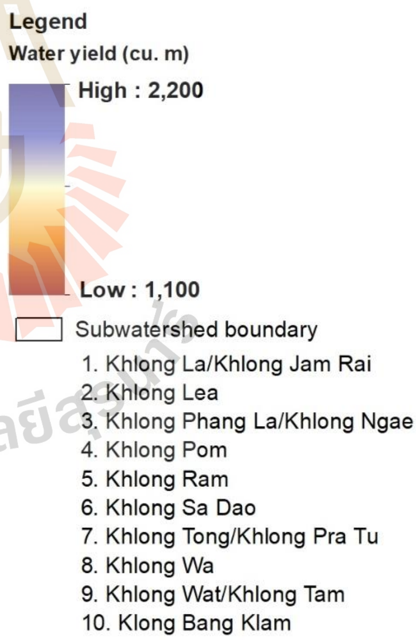
2022



2023



2024



Map legend

Figure 6.18 (Continued).

Similar to Scenario II, according to water yield estimation of Scenario III during 2018 and 2019 (Table 6.26), annual water yield is generally related with annual rainfall, PET and AET (Droogers and Allen, 2002). It was found that predictive water yield (runoff) shows positively high correlation with predictive annual rainfall with R^2 of 0.9811 (Figure 6.19). Likewise, predictive water yield (runoff) shows positively high correlation with PET with R^2 of 0.9993 (Figure 6.20). Similarly, predictive water yield (runoff) shows positively high correlation with PET with R^2 of 0.9997 (Figure 6.21).

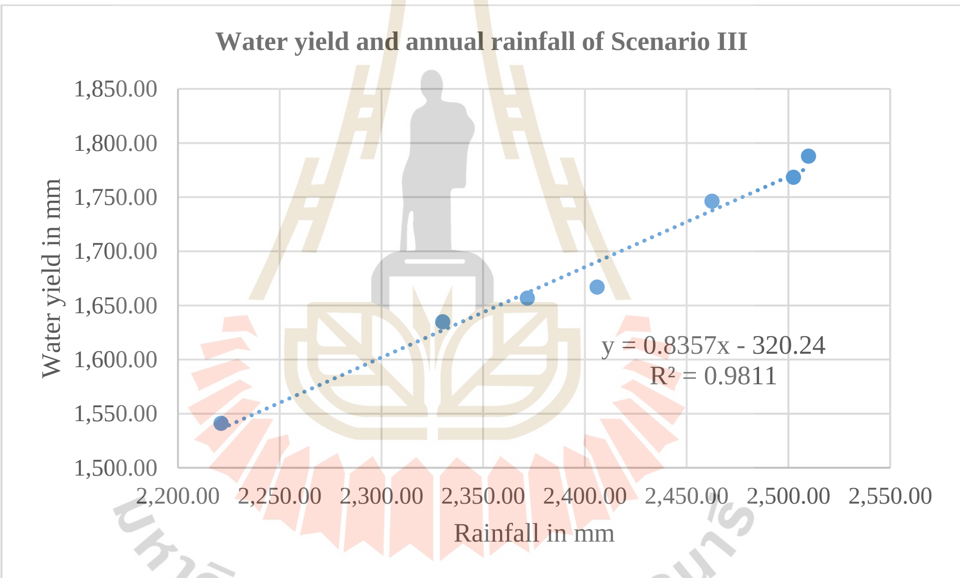


Figure 6.19 Relationship between water yield and annual rainfall under Scenario III.

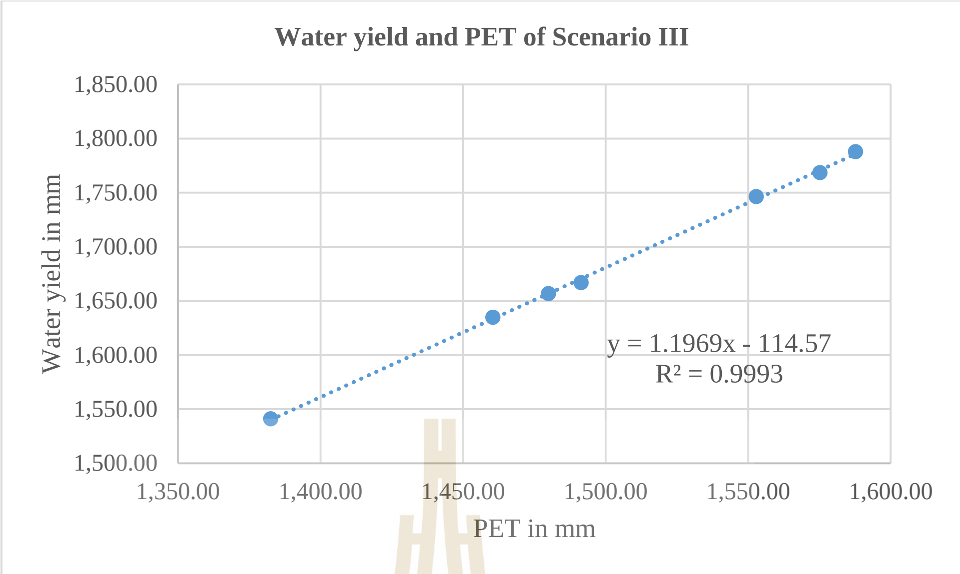


Figure 6.20 Relationship between water yield and PET under Scenario III.

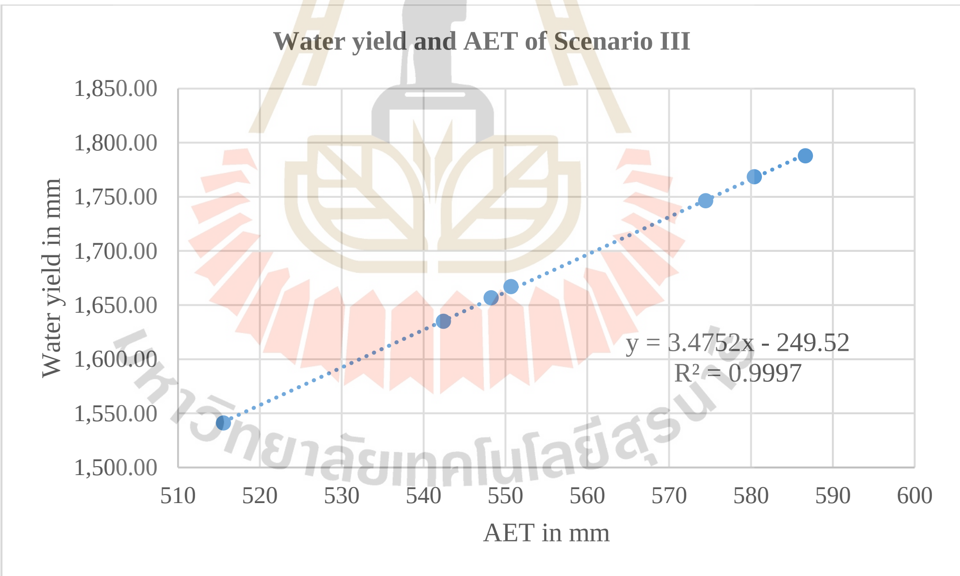


Figure 6.21 Relationship between water yield and AET under Scenario III.

Refer to Tables 6.27 to 6.33, during 2018 to 2024 the highest average water yield (runoff) occurs in two sub-watersheds including Khlong Tong/Khlong Pra Tu and Khlong Phang La/Khlong Ngae sub-watershed while the lowest average water yield (runoff) always occurs in Khlong Wat/Khlong Tam sub-watershed.

In addition, characteristics of water yield and its average of LULC type under Scenario III is summarized in Table 6.34 and Figure 6.22 displays average yield volume of LULC type excluding aquatic cultural area and water bodies during 2018 to 2024.

Table 6.34 Characteristics of water yield volume and its average of LULC type under Scenario III during 2018 to 2024.

Item	Year	LULC type										
		UR	PD	RP	OP	PO	AQ	EF	MF	MS	WA	ML
Area in km^2	2018	117.37	20.41	1,697.51	52.64	34.20	9.38	257.55	0.85	40.28	42.43	133.43
	2019	122.22	20.41	1,669.07	86.92	34.20	9.38	257.55	0.85	39.56	42.44	123.46
	2020	122.55	20.41	1,641.78	121.79	34.20	9.38	257.55	0.85	38.84	42.44	116.26
	2021	129.55	20.41	1,608.26	156.50	34.20	9.38	257.55	0.85	38.66	42.44	108.26
	2022	136.15	20.41	1,582.08	188.15	34.20	9.38	257.93	0.85	38.47	42.44	95.99
	2023	136.15	20.41	1,548.65	227.99	34.20	9.38	257.93	0.85	38.47	42.44	89.58
	2024	140.16	20.41	1,528.48	257.44	34.20	9.38	257.93	0.85	36.89	42.44	77.87
Water yield volume in million m^3	2018	87.46	14.51	1,276.02	39.48	25.53	0.00	190.27	0.59	33.19	0.00	89.32
	2019	83.60	13.22	1,156.72	60.09	23.52	0.00	175.38	0.54	29.78	0.00	76.17
	2020	90.14	14.29	1,216.56	90.01	25.21	0.00	185.52	0.58	31.58	0.00	76.81
	2021	92.78	13.86	1,169.39	113.76	24.65	0.00	185.40	0.56	30.44	0.00	70.01
	2022	104.25	14.77	1,235.37	147.16	26.42	0.00	201.62	0.60	32.27	0.00	66.53
	2023	103.43	14.71	1,191.06	175.19	26.10	0.00	195.38	0.60	32.15	0.00	61.36
	2024	108.15	14.91	1,198.14	201.95	26.58	0.00	198.93	0.60	31.25	0.00	54.31
Water yield in million m^3	2018	0.75	0.71	0.75	0.75	0.75	0.00	0.74	0.69	0.82	0.00	0.67
	2019	0.68	0.65	0.69	0.69	0.69	0.00	0.68	0.63	0.75	0.00	0.62
	2020	0.74	0.70	0.74	0.74	0.74	0.00	0.72	0.68	0.81	0.00	0.66
	2021	0.72	0.68	0.73	0.73	0.72	0.00	0.72	0.66	0.79	0.00	0.65
	2022	0.77	0.72	0.78	0.78	0.77	0.00	0.78	0.70	0.84	0.00	0.69
	2023	0.76	0.72	0.77	0.77	0.76	0.00	0.76	0.70	0.84	0.00	0.69
	2024	0.77	0.73	0.78	0.78	0.78	0.00	0.77	0.71	0.85	0.00	0.70

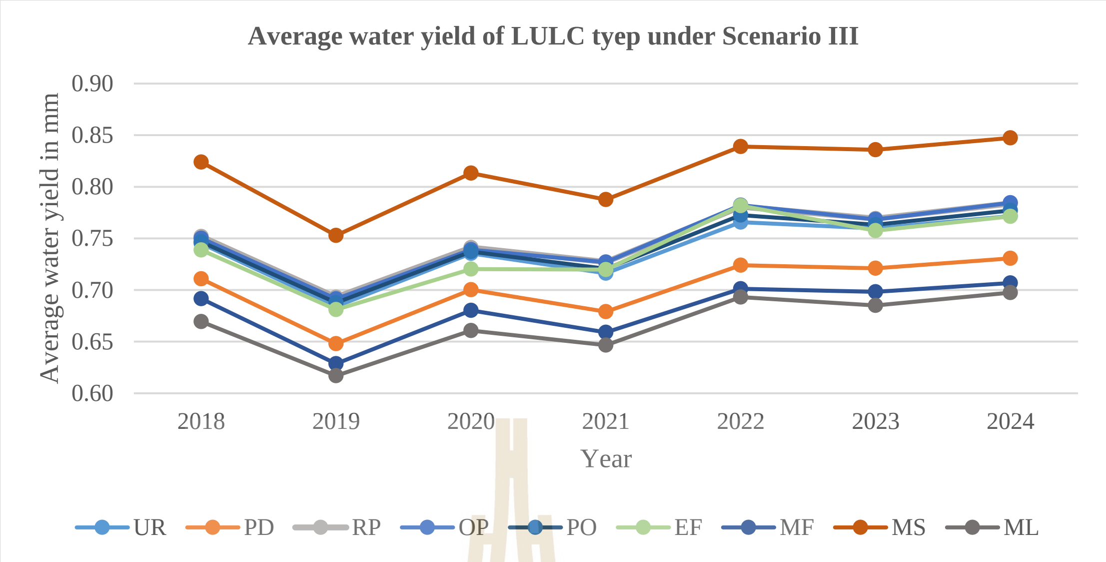


Figure 6.22 Average water yield of LULC type under Scenario III during 2018 to 2024.

As results, it can be observed that marsh and swamp provides the highest average water yield in every year while miscellaneous land provides the lowest water yield in every year. Meanwhile average water yield of rubber plantation, oil palm plantation and evergreen forest are similar with Scenario I and II as mentioned earlier in two previous sections.

6.7 Comparison of water yield estimation among three different scenarios

Under this section, an important information of water yield (runoff) from three different scenarios are here compared and discussed. Table 6.35 and Figure 6.23 displays water yield of three different scenarios and its annual rainfall between 2018 and 2024.

As results, it reveals that dynamic pattern of water yield (runoff) in three different scenarios during 2018 to 2024 dictates by annual rainfall data which are extracted from NCAR GIS Program, USA. In addition, the significant different of annual water yield volume of three different scenarios (Table 6.36) depends on predictive LULC change of three scenarios since annual rainfall data of three different scenarios are similar. It can be observed that Scenario I provides the lowest water yield (runoff) volume in every year during 2018 to 2024 since LULC of Scenario I (Historical LULC evolution) is solely predicted based on annual rate of LULC change from transition area matrix between 2010 and 2017, it does not represent dramatic LULC change under this scenario. The contribution of each LULC type on water yield is insignificant. Herewith, the increasing LULC classes under this scenario are urban and built-up area, rubber plantation, oil palm plantation, perennial tree/orchard, aquatic cultural area, mangrove forest, and water body while the decreasing LULC classes are paddy field, evergreen forest, marsh and swamp and miscellaneous land. In contrast, LULC of Scenario II (Forest conservation and prevention) and Scenario III (Agriculture production extension) are predicted based on transformation of Government policy in forestry and agriculture sectors. Under Scenario II, increasing LULC classes are urban and built-up area, oil palm plantation, and evergreen forest, decreasing LULC classes are rubber plantation, and miscellaneous land, and other LULC types including paddy field, perennial tree and orchard, aquatic cultural area, mangrove forest, marsh and swamp, and water body are fixed during 2018 to 2024. Likewise, under Scenario III, increasing LULC classes are urban and built-up area and oil palm plantation, decreasing LULC classes are rubber plantation, marsh and swamp and miscellaneous land, and other LULC types including paddy field, perennial tree and orchard, aquatic cultural area, evergreen forest, mangrove forest and water body are fixed during 2018 to 2024. The contribution of LULC from Scenario II and III higher reflect on water yield (runoff) than Scenario I.

Tarigan et al. (2016) found that the conversion of evergreen forest into rubber plantation and oil palm plantation affects the local hydrological cycle by decreasing infiltration and increasing the flooding frequency (Comte, Colin, Whalen, Gruenberger, and Caliman, 2012; Tarigan et al., 2016 and Meijide et al., 2017). The evapotranspiration from evergreen forest in general generated lower water yields per unit area compared to the less forested in watersheds area (Trisurat et al., 2016).

Table 6.35 Comparison of water yield among three different scenarios.

Year	Annual rainfall	Water yield					
		Scenario I		Scenario II		Scenario III	
	(mm)	(mm)	(m^3)	(mm)	(m^3)	(mm)	(m^3)
2018	2,406.08	1,918.68	1,755,154,110.51	1,661.83	1,755,799,564.77	1,666.84	1,756,375,718.37
2019	2,221.32	1,770.33	1,616,257,946.91	1,530.54	1,617,767,874.74	1,540.99	1,619,029,718.35
2020	2,371.75	1,891.41	1,726,525,208.33	1,638.97	1,728,733,356.91	1,656.60	1,730,702,036.99
2021	2,330.22	1,857.69	1,695,370,640.42	1,610.73	1,698,139,630.56	1,634.81	1,700,840,701.27
2022	2,502.55	1,995.98	1,820,993,958.11	1,735.93	1,824,878,523.67	1,768.37	1,828,995,825.16
2023	2,462.50	1,964.18	1,790,466,081.66	1,708.10	1,795,291,837.77	1,746.19	1,799,989,836.18
2024	2,509.89	2,002.23	1,823,490,354.39	1,743.51	1,829,037,584.00	1,787.78	1,834,815,601.78

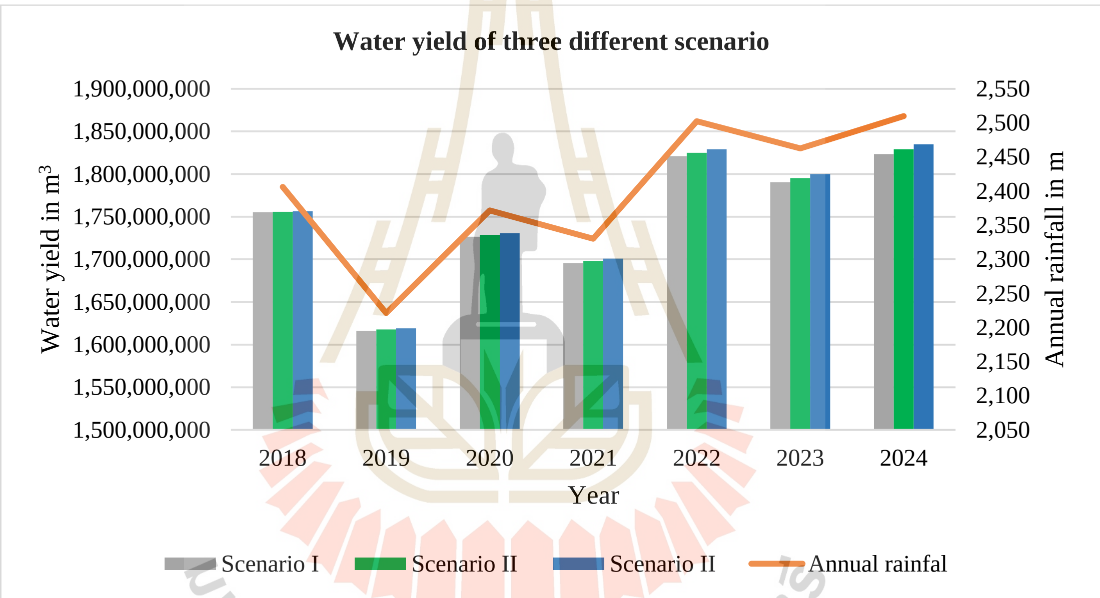


Figure 6.23 Comparison of water yield of three different scenarios and its annual rainfall between 2018 and 2024.

Table 6.36 Details of t-Test for water yield volume estimation in three different scenarios.

Water yield volume Paired Samples t-Test	Mean		Variance		df	t- Stat	t Critical 2-tail	P(T<=t) 2-tail
	Variable 1	Variable 2	Variable 1	Variable 2				
Scenario I - Scenario II (mm)	1.7469E+09	1.7499E+09	5.5766E+15	5.7610E+15	6	-4.5400*	2.4469	0.0039
Scenario I - Scenario III (mm)	1.7469E+09	1.7530E+09	5.5766E+15	5.9757E+15	6	-4.3547*	2.4469	0.0048
Scenario II - Scenario III (mm)	1.7499E+09	1.7530E+09	5.7610E+15	5.9757E+15	6	-4.1749*	2.4469	0.0058

Remark: * Signifcant at 95%.

CHAPTER VII

SEDIMENT RETENTION ASSESSMENT

This chapter presents results of the third objective focusing on sediment retention assessment using sediment delivery ratio model of the InVEST software suite from actual LULC in 2017 and predictive LULC between 2018 and 2024 of three different scenarios. The main results which consist of (1) basic information of sediment retention estimation (2) sediment retention estimation of actual LULC in 2017, (3) sediment retention estimation of predictive LULC of Scenario I, (4) sediment retention estimation of predictive LULC of Scenario II, (5) sediment retention estimation of predictive LULC of Scenario III, and (6) comparison of sediment retention estimation among three different scenarios are here described and discussed in details.

7.1 Basic information of sediment retention estimation

In this study, the ability of each sub-watershed to retain sediment is quantified by evaluating the interaction between the sediment retention capacity of each LULC, rainfall, soil characteristics and topography. In practice, soil erosion is firstly estimated using RUSLE which requires five factors: rainfall erosivity (R), slope length gradient (LS), soil erodibility (K), cover factor (C) and practice factor for erosion control practice (P). Then, sediment delivery ratio (SDR) was applied to estimate sediment retention based on connectivity index (CI) that reflects the attributes of each LULC type, threshold flow accumulation and maximum SDR using Eq. 3.8. Herein, soil loss, sediment retention and sediment export of actual LULC in 2017 and predictive LULC of three different scenarios between 2018 and 2024 are separately estimated using sediment delivery ratio model of the InVEST software suite.

Figure 7.1 displays spatial distribution of annual rainfall erosivity (R) between 2017 and 2024 which was generated using Eq. 3.6. Meanwhile, slope length gradient factor (LS) which was applied to extract DEM and soil erodibility (K) which was quantified from soil series data of LDD (see Table 3.4) as static variables of RUSLE model is presented in Figure 7.2. Additionally, cover factor (C) and practice factor (P) as presented in Table 3.5 were extracted from LULC data using standard assignment of LDD in 2000. In this study, annual rainfall erosivity (R), cover factor (C) and practice factor (P) during 2018 to 2024 as dynamic variables play important role for sediment retention assessment under three different scenarios.

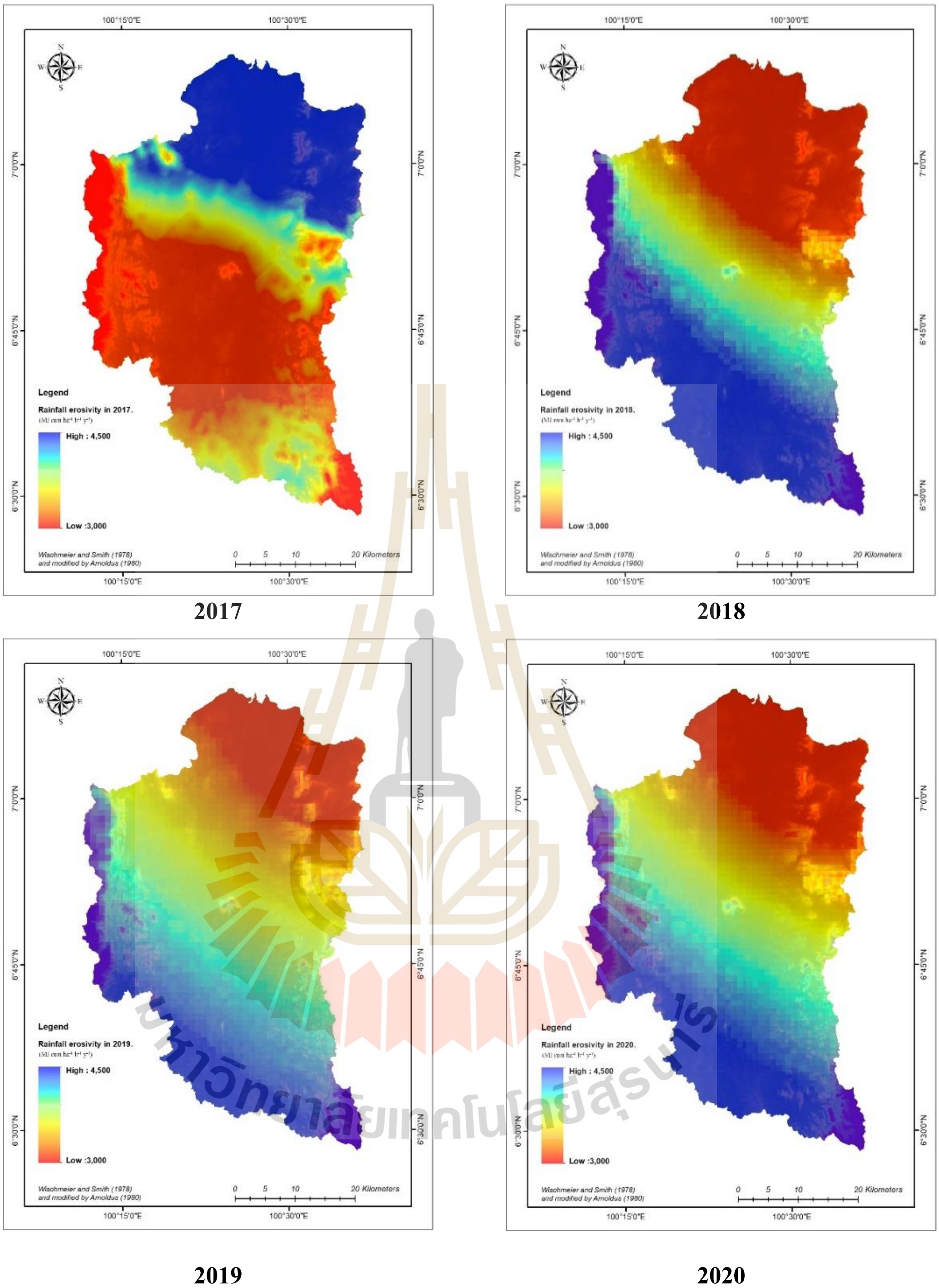
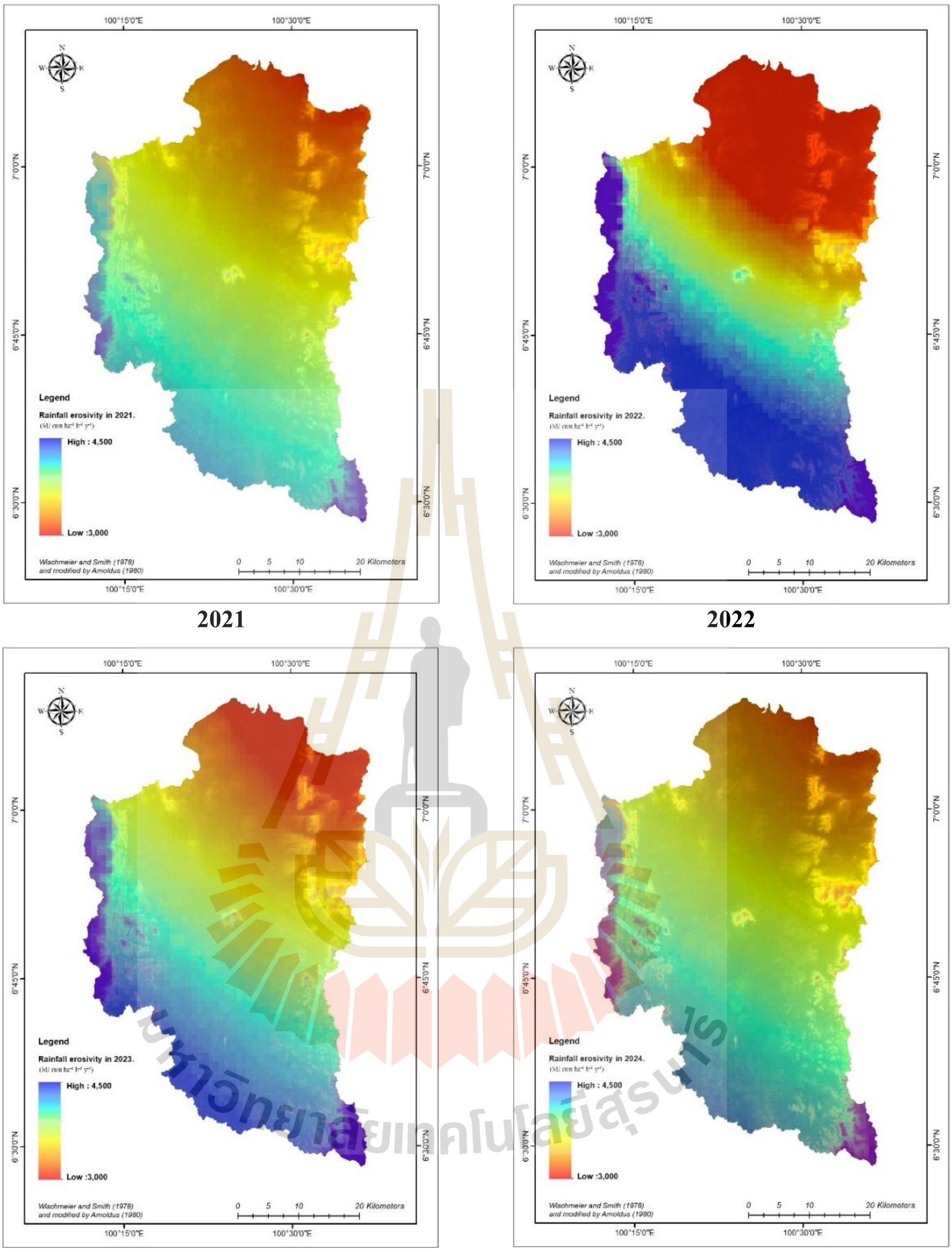


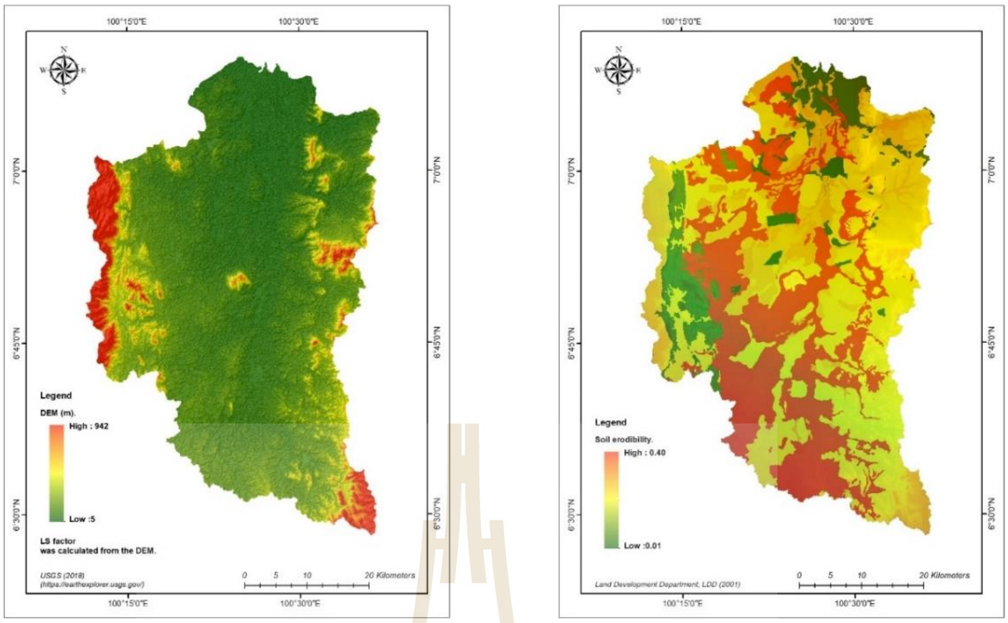
Figure 7.1 Spatial distribution of annual rainfall erosivity between 2017 and 2024.



2021 2022

2023 2024

Figure 7.1 (Continued).



(a) **(b)**

Figure 7.2 Spatial distribution of static variables for soil erosion estimation: (a) DEM and (b) soil erodibility.

7.2 Sediment retention estimation of actual LULC in 2017

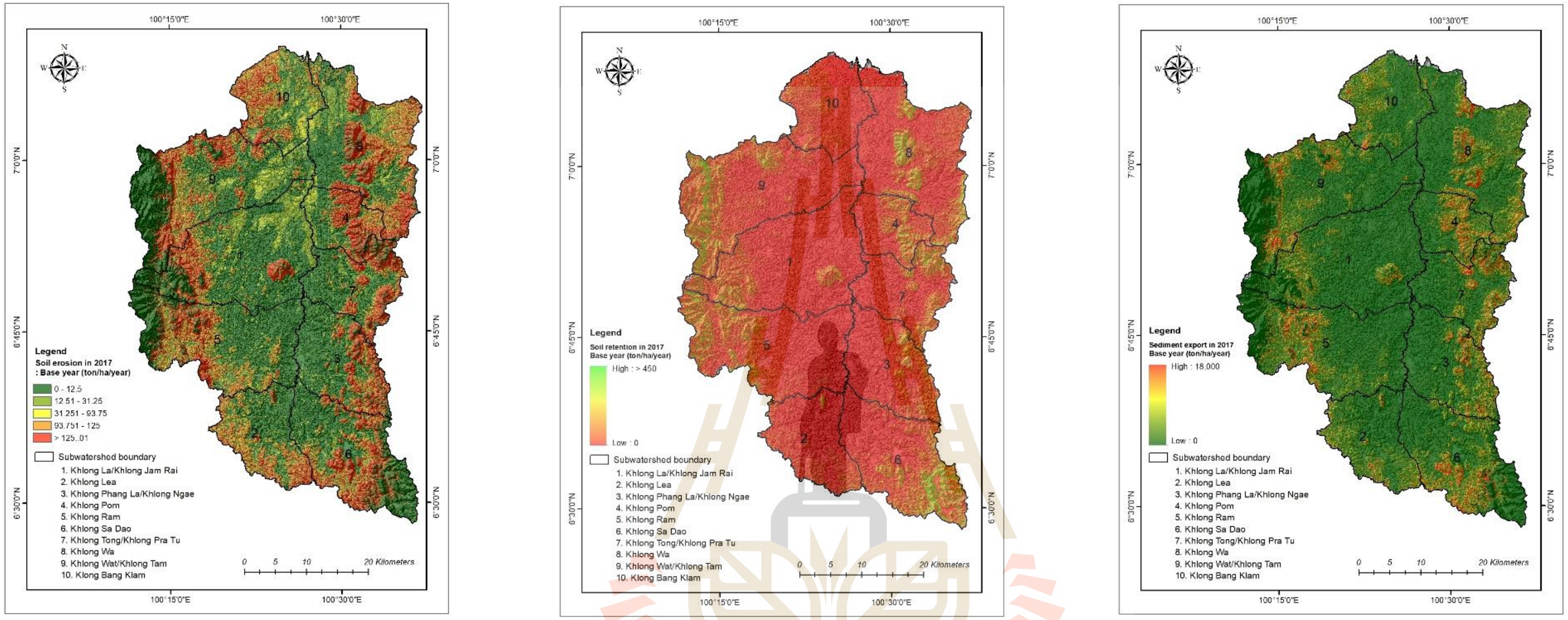
Estimation of total and average soil erosion, sediment retention and sediment export with water yield of actual LULC in 2017 is presented in Table 7.1. It was found that total and average soil erosion, sediment retention and sediment export in 2017 is about 24,765,819.51 tons and 10,293.19 tons/km^2, 6,959,665.61 tons and 2,892.58 tons/km^2, 547,124.97 tons and 227.40 tons/km^2, respectively. The spatial distribution of soil erosion, sediment retention and sediment export of LULC in 2017 is displayed in Figure 7.3. Additional, the derived soil loss in 2017 is further classified its severity according to LDD standard (2000) as shown in Figure 7.4 and area and percentage of its severity classification is presented in Table 7.2.

Table 7.1 Summary data on soil erosion, sediment retention, sediment export and water yield of actual LULC in 2017.

Area (km^2)	**2,406.04**
Total soil loss (tons)	24,765,819.51
Average soil loss (tons/km^2)	**10,293.19**
Total sediment retention (tons)	6,959,665.61
Average sediment retention (tons/km^2)	**2,892.58**
Total sediment export (tons)	547,124.97
Average sediment export (tons/km^2)	**227.40**
Total water yield (mil.m^3)	1,863.80
Average water yield (mil.m^3)	**0.7746**

Table 7.2 Soil loss severity classification according to LDD standard.

No	**Severity class**	**Erosion rate (t/ha/y)**	**Area in km^2**	**Percentage**
1	Very low	0-6.25	475.40	19.76
2	Low	6.25-31.25	355.63	14.78
3	Moderate	31.26-125.00	764.86	31.79
4	High	125.01-625	558.79	23.22
5	Very high	>625	251.36	10.45
		Total	**2,406.04**	**100.00**



Soil erosion **Sediment retention** **Sediment export**

Figure 7.3 Spatial distribution of soil erosion, sediment retention, and sediment export in 2017.

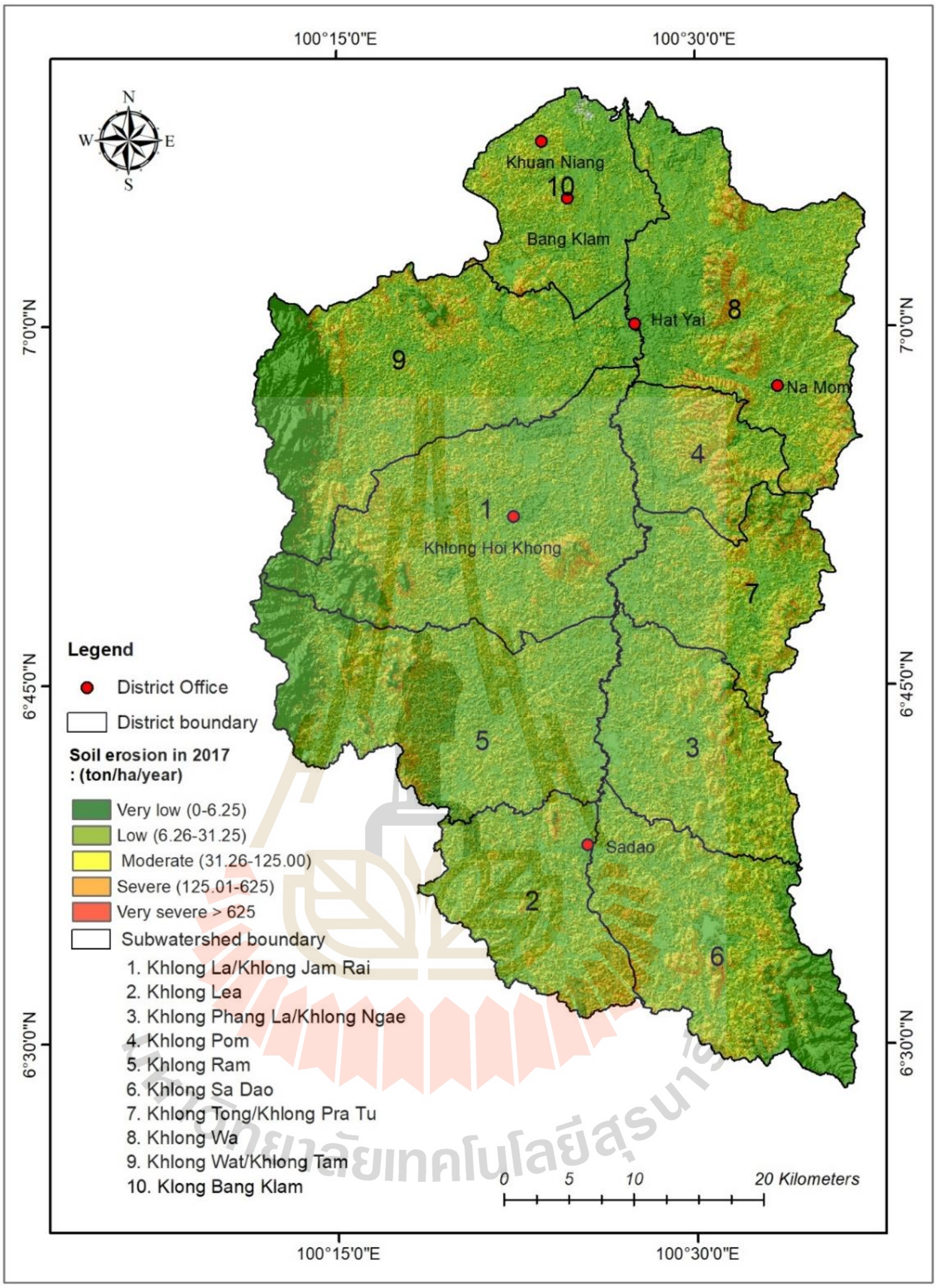


Figure 7.4 Spatial distribution of soil loss severity classification.

As a result it reveals that the most dominant soil loss severity class in the study area is moderate severe (31.26-125.00 ton/ha/year) and it covers area of 764.86 km^2 or about 31.79% of the total study area. Meanwhile, high and very high severity classes cover area of 810.15 km^2 or 33.67% of the total study area, respectively. These results indicate that most area of Khlong U-Tapao watershed is vulnerable on soil erosion with moderate to very high severity.

According to overlay analysis between soil erosion severity classification and LULC data in 2017 (Table 7.3), the most dominant LULC type in very low soil severity class is evergreen forest and covers area of 216.02 km^2 or 8.98% of the study area whereas, the most dominant LULC type in low soil severity class is rubber plantation and covers area of 280.10 km^2 or 11.64% of the study area. Meanwhile, the most dominant LULC type in moderate soil severity class is also rubber plantation and covers area of 688.10 km^2 or 28.60% of the study area. In meantime, the most dominant LULC type in high soil severity class is also rubber plantation and covers area of 478.10 km^2 or 19.87% of the study area whereas the most dominant LULC type in very high soil severity class is also rubber plantation and covers area of 203.72 km^2 or 8.47% of the study area. These results reflect the effect of LULC types on soil erosion process, particular soil severity. In this study, rubber plantation generates the highest soil loss and covers area of 1,727.47 km^2 or 71.80% of the study area since rubber plantation is the most dominant LULC in the area.

Table 7.3 Soil loss severity classification and LULC classes.

LULC types	Soil severity classification									
	Very low		Low		Moderate		High		Very high	
	km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
Urban and built-up area (UR)	113.21	4.71	-	-	-	-	-	-	-	-
Paddy field (PD)	1.57	0.07	7.76	0.32	8.50	0.35	2.34	0.10	0.24	0.01
Rubber plantation (RP)	77.45	3.22	280.10	11.64	688.10	28.60	478.10	19.87	203.72	8.47
Oil palm plantation (OP)	1.24	0.05	4.92	0.20	8.06	0.34	3.84	0.16	0.80	0.03
Perennial tree/orchard (PO)	2.48	0.10	7.71	0.32	14.33	0.60	7.66	0.32	2.03	0.08
Aquatic cultural area (AQ)	9.38	0.39	-	-	-	-	-	-	-	-
Evergreen forest (EF)	216.02	8.98	37.99	1.58	-	-	-	-	-	-
Mangrove forest (MF)	0.85	0.04	-	-	-	-	-	-	-	-
Marsh and swamp (MS)	3.66	0.15	10.49	0.44	17.89	0.74	8.84	0.37	1.83	0.08
Water body (WA)	42.40	1.76	-	-	-	-	-	-	-	-
Miscellaneous land (ML)	7.15	0.30	6.66	0.28	27.99	1.16	58.02	2.41	42.75	1.78
Total	**475.40**	**19.76**	**355.63**	**14.78**	**764.86**	**31.79**	**558.79**	**23.22**	**251.36**	**10.45**

Likewise, according to overlay analysis between soil erosion severity and elevation classifications (Table 7.4), it reveals that most of very low and low severity class situates below 200 m above mean sea level and cover area of 304.54 km^2 or 12.66% and 324.74 km^2 or 13.50% of the total study area, respectively. Meanwhile, most of moderate soil severity class is also found below 200 m above mean sea level and covers area of 754.86 km^2 or 31.37% of the total study area. Similarly, most of high and very high severity class situates below 200 m above mean sea level and cover area of 535.48 km^2 or 22.26% and 226.83 km^2 or 9.43% of the total study area, respectively. These results indicate about human activity on agriculture occurring below 200 m above mean sea level, and it creates soil erosion problem with variety severity classes.

Table 7.4 Soil loss severity classification and elevation classes.

Elevation (m)	Soil severity classification									
	Very low		Low		Moderate		High		Very high	
	km²	%	km²	%	km²	%	km²	%	km²	%
< 200	304.54	12.66	324.74	13.50	754.86	31.37	535.48	22.26	226.83	9.43
200-250	29.59	1.23	6.46	0.27	5.66	0.24	12.68	0.53	12.99	0.54
250-350	39.91	1.66	8.69	0.36	3.72	0.15	9.29	0.39	10.10	0.42
350-750	96.50	4.01	15.55	0.65	0.62	0.03	1.35	0.06	1.43	0.06
750-800	4.62	0.19	0.13	0.01	-	-	-	-	-	-
> 800	0.25	0.01	0.06	0.00		-		-	-	-
Total	**475.41**	**19.76**	**355.63**	**14.78**	**764.86**	**31.79**	**558.79**	**23.22**	**251.36**	**10.45**

In the meantime, according to overlay analysis between soil erosion severity and slope classification (Table 7.5), it reveals that most of very low severity class occurs at undulating landform with slope between 5% and 12% and covers area of 136.93 km^2 or 5.69% of the total study area. Meanwhile, most of low soil severity class is found at slightly undulating landform with slope between 2% and 5% and covers area of 137.66 km^2 or 5.72% of the total study area whereas most of moderate severity class locates at undulating landform and covers area of 437.83 km^2 or 18.20% of the total study area. In the meantime, most of high soil severity class is found at rolling landform with slope between 12% and 20% and covers area of 201.07 km^2 or 8.36% of the total study area whereas most of very high soil severity class is found at hilly landform with slope between 20% and 35% and covers area of 85.45 km^2 or 3.55% of the total study area.

These results indicates the effect of terrain on soil erosion and its severity. Especially, rolling, hilly and steep landform create high and very high soil loss severity.

Table 7.5 Soil loss severity classification and slope classes.

Slope (%)	Landform	Soil severity classification									
		Very low		Low		Moderate		High		Very high	
		km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
0-2	Flat or almost flat	30.08	1.25	50.95	2.12	27.70	1.15	4.312	0.18	0.59	0.02
2-5	Slightly undulating	86.57	3.60	137.66	5.72	154.91	6.44	31.86	1.32	4.815	0.20
5-12	Undulatin g	136.93	5.69	116.13	4.83	437.83	18.20	199.48	8.29	42.725	1.78
12-20	Rolling	68.46	2.85	15.01	0.62	130.73	5.43	201.07	8.36	66.96	2.78
20-35	Hilly	86.62	3.60	12.39	0.51	12.95	0.54	105.41	4.38	85.45	3.55
>35	Steep	66.76	2.77	23.49	0.98	0.74	0.03	16.67	0.69	50.82	2.11
	Total	**475.41**	**19.76**	**355.63**	**14.78**	**764.86**	**31.79**	**558.79**	**23.22**	**251.36**	**10.45**

Details of soil erosion, sediment retention and sediment export in each sub-watershed is summarized in Table 7.6.

Table 7.6 Soil erosion, sediment retention and sediment export in each sub-watershed from actual LULC in 2017.

Sub-watershed	Area (km^2)	Water yield (m^3)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
			Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	266,805,400.69	3,057,735.36	8,539.49	693,671.39	1,937.25	64,203.98	179.31
2. Khlong Lea	166.50	129,865,712.79	1,525,089.80	9,159.70	131,505.88	789.83	28,830.34	173.16
3. Khlong Phang La/Khlong Ngae	188.88	148,622,570.51	2,047,557.11	10,840.52	308,062.78	1,631.00	47,781.02	252.97
4. Khlong Pom	103.13	81,240,229.56	1,827,475.10	17,720.11	403,590.13	3,913.41	54,996.88	533.28
5. Khlong Ram	324.94	249,103,827.52	2,477,582.59	7,624.74	945,152.22	2,908.70	53,442.60	164.47
6. Khlong Sa Dao	259.17	206,378,689.53	2,783,407.12	10,739.70	1,287,667.16	4,968.43	59,085.59	227.98
7. Khlong Tong/Khlong Pra Tu	161.58	127,786,577.27	2,233,720.98	13,824.24	555,665.11	3,438.95	61,554.19	380.95
8. Khlong Wa	325.83	250,805,800.67	4,189,217.36	12,857.06	814,159.82	2,498.73	89,785.49	275.56
9. Khlong Wat/Khlong Tam	352.14	275,300,558.01	3,299,629.90	9,370.22	1,730,916.63	4,915.42	71,276.12	202.41
10. Klong Bang Klam	165.80	127,886,348.32	1,324,404.19	7,987.96	89,274.50	538.45	16,168.75	97.52
Total	**2,406.04**	**1,863,795,714.87**	**24,765,819.51**	**10,293.19**	**6,959,665.61**	**2,892.58**	**547,124.97**	**227.40**

At sub-watershed level, it reveals that Khlong Pom sub-watershed generates the highest average soil erosion with value of 17,720.11 tons/km^2 while Khlong Ram sub-watershed generates the lowest average soil erosion with value of 7,624.74 tons/km^2. Meanwhile, Khlong Sa Dao sub-watershed retains the highest average sediment retention with value of 4,968.43 tons/km^2 while Klong Bang Klam sub-watershed retains the lowest average sediment retention with value of 538.45 tons/km^2. In the meantime, Khlong Pom sub-watershed delivers the highest average sediment export with value of 533.28 tons/km^2 while Klong Bang Klam sub-watershed delivers the lowest average sediment export with value of 97.52 tons/km^2. These finding implies the local influential factors in each sub-watershed which include rain fall, soil and terrain and LULC on soil erosion, sediment retention and sediment export estimation.

As results, it can be observed that total soil loss as a budget of sediment retention and sediment export varies according to water yield of sub-watershed (Figure 7.5). Thus, simple linear and non-linear relationship between total soil erosion and total water yield of sub-watershed using linear, exponential, logarithmic and power models were here examined. It was found that the best fit relationship between total soil erosion and total water yield is exponential model that provides the highest R^2 of 0.676 as shown in Eq. 7.1 and Figure 7.6.

$$y = 1E{+}06e^{4E-09x} \tag{7.1}$$

Where, y is total soil erosion in ton and x is total water yield in m^3.

These results reveal that total of soil erosion is non-linearly related with total water yield in each sub-watershed. This finding is consistent with the previous study of Zhang et al. (2018) who studied effects of topographic factors on runoff and soil loss in Southwest China and they found that soil loss showed significant power function relationship with runoff.

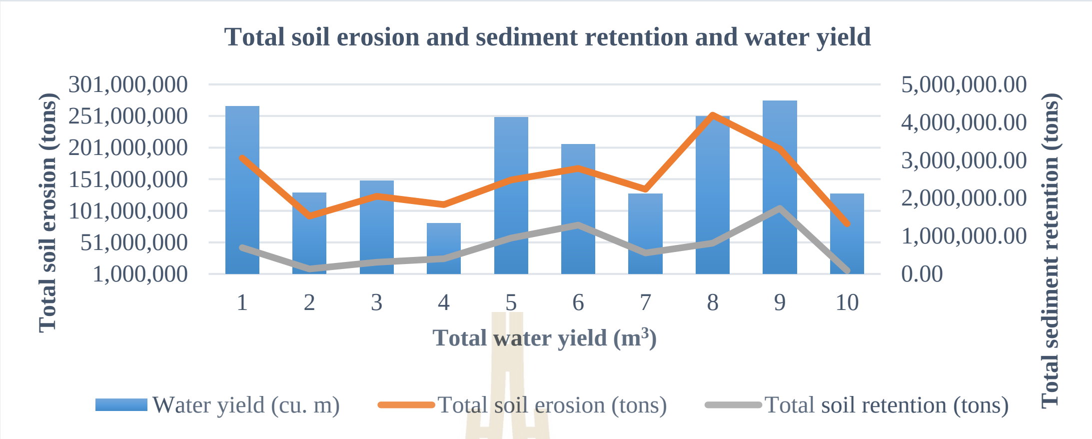


Figure 7.5 Variation of total soil loos and sediment retention and total water yield of 10 sub-watersheds.

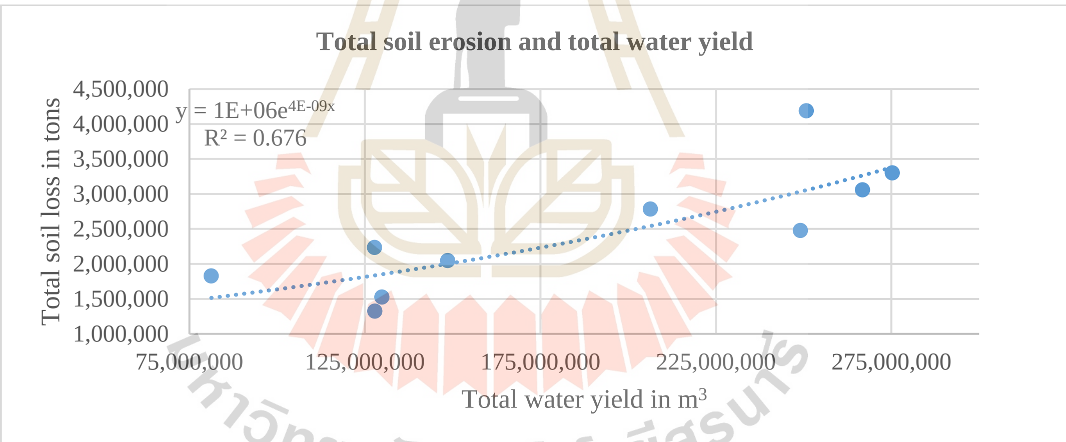


Figure 7.6 Relationship between total soil loss and water yield of 10 sub-watersheds.

Furthermore, the relationship between total soil erosion, sediment retention, sediment export and the variation of drainage morphometric characteristics of sub-watershed including (1) cumulative length of streams (L), (2) bifurcation ratio (Rb), (3) basin relief (Bh), (4) ruggedness number (Rn), (5) drainage density (Dd), (6) stream frequency (Fu), (7) texture ratio (T), (8) form factor (Rf) and (9) elongation ratio (Re) which represents soil and terrain characteristic in each sub-watershed (see detail in Table 6.4) was examined as suggested by Reddy et al. (2004) using stepwise regression analysis (Table 7.7).

As results, it was found that the two significant geomorphological factors: ruggedness number and bifurcation ratio show positive correlation with total soil erosion of each sub-watersheds whereas drainage density shows negative correlation with its total soil erosion. The multiple linear equation with R value of 0.986 and R^2 value of 0.976 is displayed in Eq. 7.2. This results implies that the most significant geomorphological factor on soil loss process in the study area is ruggedness number which is calculated as the product of the basin relief and its drainage density characteristic in each sub-watershed.

$$y = -0.3990 + 7.2588Rn - 0.0028Bh + 0.4253Rb \qquad (7.2)$$

Where, y is total soil erosion in million tons;

Rn is ruggedness number (unit less),

Bh is basin relief (unit less),

Rb is bifurcation ratio (unit less).

Meanwhile, only one significant geomorphological factors, basin relief shows positive correlation with total sediment retention of each sub-watersheds. The simple linear equation with R value of 0.955 and R^2 value of 0.912 is shown in Eq. 7.3. This finding indicates that basin relief as most significant geomorphological factor stimuluses quantity of sediment retention in each sub-watershed.

$$y = -0.3588 + 2{,}035.103Bh \quad (7.3)$$

Where, y is total sediment retention in million tons;

Bh is basin relief (unit less).

Likewise, one significant geomorphological factors, ruggedness number shows positive correlation with total sediment export of each sub-watersheds. The simple linear equation with R value of 0.891 and R^2 value of 0.793 is displayed in Eq. 7.4. This finding indicates that ruggedness number as most significant geomorphological factor dictates sediment export in each sub-watershed.

$$y = 0.0195 + 96{,}542.042Rn \quad (7.4)$$

Where, y is total sediment export in million tons;

Rn is ruggedness number (unit less).

Moreover, relationship between actual LULC type in 2017 excluding urban and built-up area, aquatic cultural area, mangrove forest, and water bodies and estimated soil erosion, sediment retention and sediment export by using overlay analysis is presented in Table 7.8.

Table 7.7 Drainage morphometric parameters and total soil loss, sediment retention, and sediment export in each sub-watershed.

No.	Sub watershed name	Drainage morphometric parameters									Total soil erosion (mil. tons)	Total soil erosion (mil. tons)	Total soil erosion (mil. tons)
		L (km)	Rb (unit less)	Bh	Rn	Dd (km/km^2)	Fu	T	Rf	Re			
1	Khlong La/Khlong Jam Rai	227.3814	5.0294	640	0.4150	0.6485	0.2795	0.8130	0.3206	0.6389	3.0577	0.6937	0.0642
2	Khlong Lea	102.7630	3.4630	202	0.1260	0.6180	0.2853	0.6205	0.5208	0.8143	1.5251	0.1315	0.0288
3	Khlong Phang La/Khlong Ngae	123.5999	3.9242	397	0.2626	0.6614	0.3211	0.7032	0.3932	0.7076	2.0476	0.3081	0.0478
4	Khlong Pom	64.4978	4.2500	412	0.2578	0.6257	0.2231	0.3923	0.4804	0.7821	1.8275	0.4036	0.0550
5	Khlong Ram	211.5883	4.0417	718	0.4742	0.6461	0.2716	0.6894	0.3832	0.6985	2.4776	0.9452	0.0534
6	Khlong Sa Dao	166.3303	3.8611	737	0.4807	0.6329	0.2824	0.7710	0.3460	0.6637	2.7834	1.2877	0.0591
7	Khlong Tong/Khlong Pra Tu	98.1401	4.1786	476	0.2928	0.6152	0.2695	0.8493	0.5665	0.8493	2.2337	0.5557	0.0616
8	Khlong Wa	208.2791	3.4064	519	0.6369	0.6485	0.3238	0.8858	0.3470	0.6647	4.1892	0.8142	0.0898
9	Khlong Wat/Khlong Tam	231.3281	4.4206	932.	0.6182	0.6445	0.3068	0.9152	0.3679	0.6844	3.2996	1.7309	0.0713
10	Klong Bang Klam	92.3216	3.6667	150	0.0840	0.5562	0.3216	0.7408	0.5136	0.8087	1.3244	0.0893	0.0162

Table 7.8 Contribution soil erosion, sediment retention and sediment export by LULC type in 2017.

Year 2017	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,727.46	18.85	34.20	254.01	42.70	142.57	2,240.20
Total soil loss (tons)	64,579.52	19,939,464.71	113,609.71	251,329.85	588.88	255,487.98	4,140,758.86	24,765,819.51
Percent	0.26	80.51	0.46	1.01	0.00	1.03	16.72	100.00
Average soil loss (tons/km^2)	3,164.11	11,542.65	6,027.04	7,348.83	2.32	5,983.33	29,043.69	
Total sediment retention (tons)	18,770.72	3,523,871.53	23,404.46	49,427.13	3,203,086.85	19,975.14	121,129.79	6,959,665.61
Percent	0.27	50.63	0.34	0.71	46.02	0.29	1.74	100.00
Average sediment retention (tons/km^2)	919.68	2,039.91	1,241.62	1,445.24	12,610.08	467.80	849.62	
Total sediment export (tons)	1,257.54	439,577.30	2,359.30	6,413.04	1.30	3,460.34	94,056.16	547,124.97
Percent	0.23	80.34	0.43	1.17	0.00	0.63	17.19	100.00
Average sediment export (tons/km^2)	61.61	254.46	125.16	187.52	0.01	81.04	659.72	

As results, it reveals that miscellaneous land (bare land and abandoned mine) generates the highest average soil erosion with value of 29,043.69 tons/km^2 while evergreen forest generates the lowest average soil erosion with value of 2.32 tons/km^2. Meanwhile evergreen forest retains the highest average sediment retention with value of 12,610.08 tons/km^2 while marsh and swamp retains the lowest average sediment retention with value of 467.80 tons/km^2. In the meantime, miscellaneous land (bare land and abandoned mine) generates the highest average sediment export with value of 659.72 tons/km^2 while evergreen forest generates the lowest average sediment export with value of 0.01 tons/km^2. These findings obviously present an expected results about influence of LULC types on soil erosion, sediment retention, and sediment export as mentioned by many researchers. The average actual erosion rate was 2.0 times higher in the rubber plantation than in the rainforest (Liu et al., 2013).

Furthermore, the main LULC type which contributes the highest actual soil erosion, sediment retention, and sediment export is rubber plantation with proportion of 80.51%, 50.63%, and 80.34%, respectively. Since area of rubber plantation is the highest coverage area (1,727.46 km^2) in the study site. Moreover, it can be observed that contribution of evergreen forest on sediment retention is quite high with proportion of 46.02%, even though it covers area of 254.01 km^2.

7.3 Validation of sediment delivery ratio model

In this study, the classified LULC in 2010 was firstly used to predict LULC between 2011 and 2016 with CLUE-S model. Then, the classified LULC in 2010, the predicted LULC between 2011 and 2016 and classified LULC in 2017 was separately used to estimate sediment export between 2010 and 2017 with sediment delivery ratio model of the InVEST software suite. The derived sediment export during 2010 to 2017 was applied to validate with observed data from hydrological station of RID at X90 (Khlong U-Tapao) using NSE and R^2. Table 7.9 shows the comparison between observed and estimated sediment export between 2010 and 2017 and Figure 7.7 displays simple linear relationship between observed and estimated sediment export and R^2.

Table 7.9 Comparison of the observed and estimated sediment export between 2010 and 2017 in Khlong U-Tapao watershed (X90).

No	**Year**	**Sediment export in tons**	
		Observed data at X.90	**Estimated data**
1	2010	158.72	183.62
2	2011	202.86	173.98
3	2012	390.81	330.67
4	2013	80.04	108.82
5	2014	230.74	243.77
6	2015	192.49	131.41
7	2016	105.56	152.22
8	2017	220.75	227.4

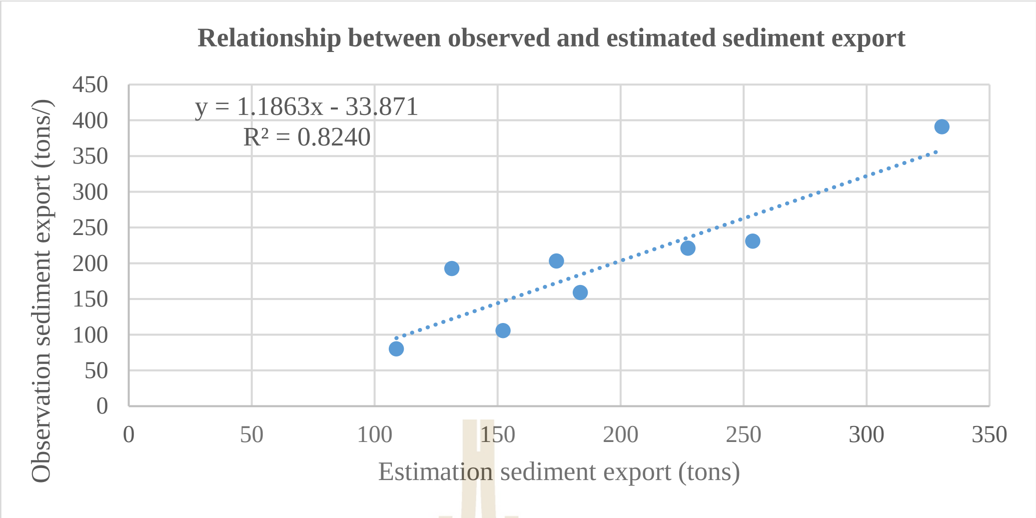


Figure 7.7 Relationship between the estimated and observed sediment export.

As results, the NSE value is 0.6634 provided acceptable for sediment export estimation (Motovilov et al., 1999) with very high correlation between the observed and estimated sediment export with R^2 value of 0.8240. Hence, sediment delivery ratio model of the InVEST software suite can be accepted and further applied to estimate soil loss, sediment retention and sediment export in the current study.

7.4 Sediment retention estimation of predictive LULC of Scenario I

Estimation of total and average soil erosion, sediment retention and sediment export with water yield of predictive LULC between 2018 and 2024 under Scenario I: Historical LULC evolution is presented in Table 7.10.

Table 7.10 Estimation of soil erosion, sediment retention, and sediment export between 2018 and 2024 under Scenario I.

Year	Area	Soil erosion		Sediment retention		Sediment export		Water yield	
	km^2	**Total (mil. tons)**	**Average (tons)**	**Total (mil. tons)**	**Average (tons)**	**Total (mil. tons)**	**Average (tons)**	**Total (mil. m^3)**	**Average (mil.m^3)**
2018	2,406.04	22.96	9,541.79	7.97	3,310.83	0.53	219.60	1,755.15	0.73
2019	2,406.04	21.30	8,850.74	7.35	3,053.91	0.50	206.75	1,616.26	0.67
2020	2,406.04	22.73	9,445.76	7.78	3,235.46	0.53	222.12	1,726.53	0.72
2021	2,406.04	22.46	9,334.90	7.75	3,221.15	0.53	220.84	1,695.37	0.70
2022	2,406.04	24.22	10,066.07	8.39	3,487.20	0.58	240.05	1,820.99	0.76
2023	2,406.04	23.80	9,891.33	8.16	3,391.58	0.57	236.47	1,790.47	0.74
2024	2,406.04	24.39	10,135.12	8.31	3,454.56	0.59	243.75	1,823.49	0.76

As results, it was found that the highest total and average soil erosion under Scenario I are 24.39 million tons and 10,135.12 tons/km^2 occurring in 2024 while the lowest total and average soil erosion are 21.30 million tons and 8,850.74 tons/km^2 occurring in 2019. Likewise, the highest total and average sediment export under Scenario I are 0.59 million tons and 243.75 tons/km^2 occurring in 2024 while the lowest total and average sediment export are 0.50 million tons and 206.75 tons/km^2 occurring in 2019. Meanwhile, the highest total and average sediment retention under Scenario I are 8.39 million tons and 3,487.20 tons/km^2 occurring in 2022 while the lowest total and average sediment retention are 7.35 million tons and 3,053.91 tons/km^2 occurring in 2019. These results indicate the influence of dynamic factor of RUSLE model, which includes annual rainfall erosivity (R) (Table 7.11), soil erodibility (K), slope length - gradient factor (LS) and cover factor (C) and practice factor (P) for erosion control practice from LULC data (see in Table 3.5), on soil erosion, sediment retention, and sediment export.

In addition, simple linear regression between average water yield as independent variable and soil erosion, sediment retention, and sediment export of Scenario I between 2018 and 2024 as dependent variables were here examined. It was found that the relationship between average water yield and average soil erosion shows positively very high correlation with R^2 of 0.9822 (Figure 7.8) as:

$$y = 14{,}556x - 958.57 \qquad (7.5)$$

Where, y is average soil erosion in tons and x is average water yield in mil. m^3.

Likewise, the relationship between average water yield and average sediment retention shows positively very high correlation with R^2 of 0.9817 (Figure 7.9) as:

$$y = 4{,}840.6x - 206.66 \qquad (7.6)$$

Where, y is average sediment retention in tons and x is average water yield in mil. m^3.

Meanwhile, the relationship between average water yield and average sediment export shows positively very high correlation with R^2 of 0.8984 (Figure 7.10) as:

$$y = 407.24x - 68.589 \qquad (7.7)$$

Where, y is average sediment export in tons and x is average water yield in mil. m^3.

These findings infers the influence of rainfall as main factor of water yield on soil erosion, sediment retention and sediment export under this scenario. Herewith, soil erosion, sediment retention and sediment export as dependent variables can be predictable from water yield as independent variable about 98.22%, 98.17%, and 89.84%, respectively.

Table 7.11 Basic statistics of predictive rainfall erosivity factor between 2018 and 2024.

	Rainfall erosivity (MJ mm ha^{-1} h^{-1} y^{-1})				
Year	**MIN**	**MAX**	**RANGE**	**MEAN**	**STD**
2018	2,366.89	2,495.64	128.75	2,408.54	23.65
2019	2,148.52	2,389.05	240.53	2,220.64	45.59
2020	2,275.70	2,460.48	184.79	2,371.95	36.59
2021	2,259.26	2,541.09	281.83	2,330.23	48.32
2022	2,400.79	2,728.90	328.11	2,502.90	59.35
2023	2,386.84	2,628.65	241.81	2,462.98	41.86
2024	2,412.04	2,709.22	297.18	2,509.13	57.26

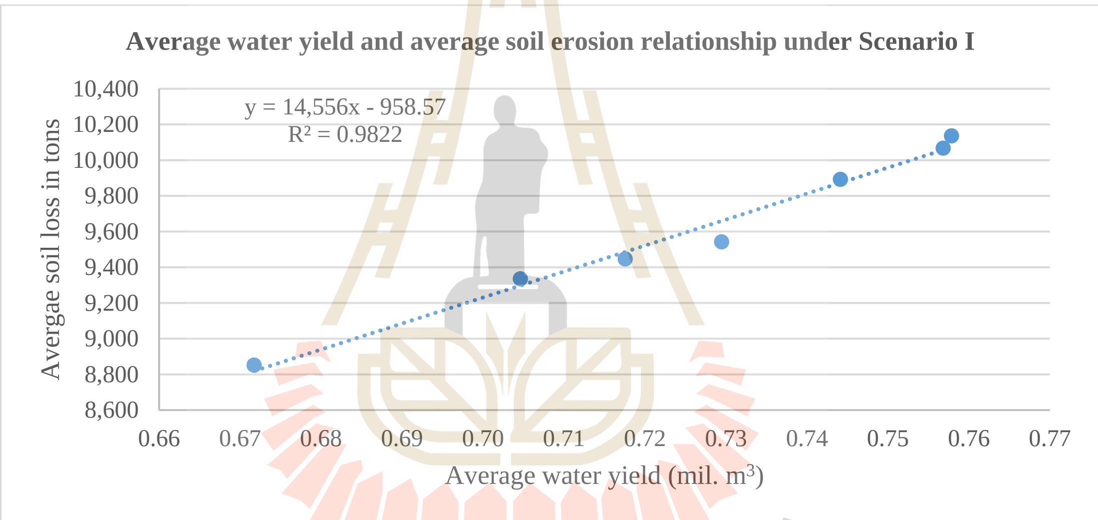


Figure 7.8 Relationship between average water yield and average soil erosion under Scenario I.

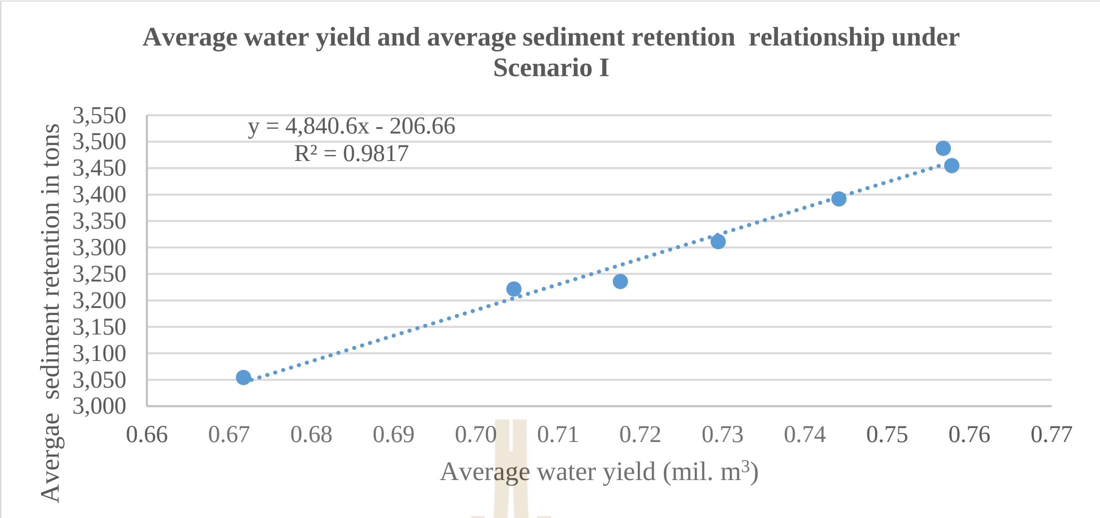


Figure 7.9 Relationship between average water yield and average sediment retention under Scenario I.

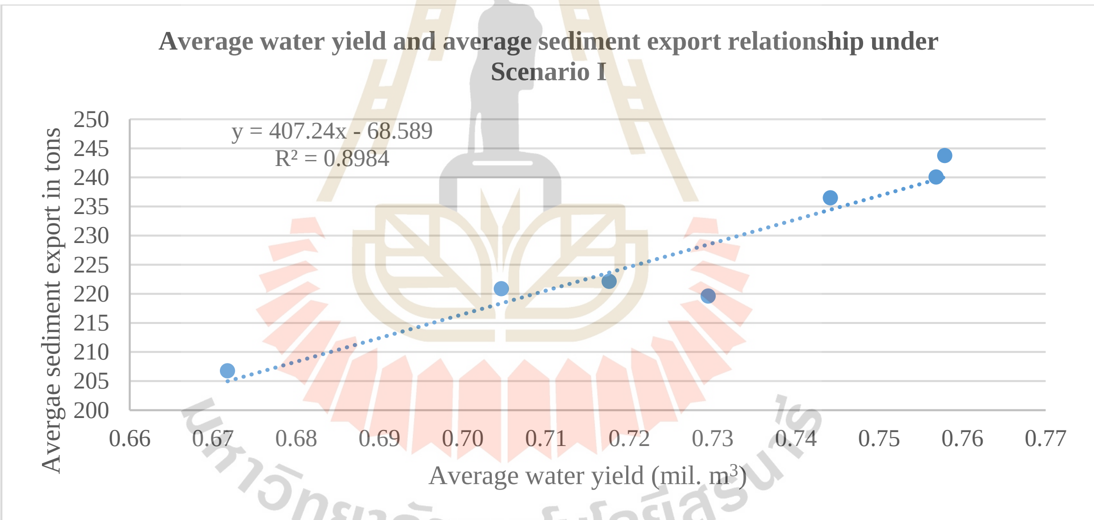


Figure 7.10 Relationship between average water yield and average sediment export under Scenario I.

The contribution of the predictive LULC of Scenario I on soil erosion, sediment retention, sediment export between 2018 and 2024 is summarized in Tables 7.12 to 7.18 and the spatial distribution of soil erosion, sediment retention and sediment export of the predictive LULC between 2018 and 2024 of Scenario I is displayed in Figures 7.11 to 7.17. Detail of soil erosion, sediment retention and sediment export in each sub-watershed from predictive LULC of Scenario I between 2018 and 2024 are presented in Tables 7.19 to 7.25.

Table 7.12 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2018 under Scenario I.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	19.50	1,728.39	20.68	34.10	249.50	41.69	141.21	2,236.76
Total soil loss (tons)	26,790.58	18,663,073.83	169,461.02	176,845.35	781.26	113,747.70	3,807,230.06	22,957,929.79
Average soil loss (tons/km^2)	1,373.88	10,797.95	8,194.44	5,186.08	3.13	2,728.42	26,961.48	10,263.94
Total sediment retention (tons)	12,699.07	3,400,346.71	34,481.28	36,284.12	4,357,058.38	13,616.97	111,491.44	7,965,977.96
Average sediment retention (tons/km^2)	651.23	1,967.35	1,667.37	1,064.05	17,463.16	326.62	789.54	3,561.40
Total sediment export (tons)	478.20	426,300.12	4,611.06	4,686.81	1.44	1,560.41	90,736.90	528,374.94
Average sediment export (tons/km^2)	24.52	246.65	222.97	137.44	0.01	37.43	642.57	236.22

Table 7.13 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2019 under Scenario I.

Year 2019	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	18.70	1,727.84	22.92	34.36	243.05	41.16	141.05	2,229.06
Total soil loss (tons)	23,107.95	17,256,599.16	235,238.28	165,827.92	708.62	101,272.61	3,512,487.22	21,295,241.75
Average soil loss (tons/km^2)	1,235.72	9,987.38	10,263.45	4,826.19	2.92	2,460.46	24,902.43	9,553.45
Total sediment retention (tons)	14,796.87	3,145,885.10	62,013.58	37,135.59	3,966,324.92	15,723.16	105,945.26	7,347,824.49
Average sediment retention (tons/km^2)	791.28	1,820.70	2,705.65	1,080.78	16,318.97	382.00	751.12	3,296.37
Total sediment export (tons)	407.86	399,403.35	8,071.92	4,366.06	1.27	1,387.88	83,815.73	497,454.07
Average sediment export (tons/km^2)	21.81	231.16	352.18	127.07	0.01	33.72	594.23	223.17

Table 7.14 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2020 under Scenario I.

Year 2020	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	17.88	1,727.62	24.56	34.56	238.32	40.75	140.36	2,224.04
Total soil loss (tons)	23,728.64	18,367,308.21	307,004.85	179,862.86	739.46	106,992.66	3,741,236.06	22,726,872.75
Average soil loss (tons/km^2)	1,327.11	10,631.57	12,500.20	5,204.37	3.10	2,625.59	26,654.57	10,218.76
Total sediment retention (tons)	19,133.19	3,345,449.00	86,243.07	43,346.99	4,154,195.45	20,162.57	116,110.56	7,784,640.83
Average sediment retention (tons/km^2)	1,070.09	1,936.45	3,511.53	1,254.25	17,431.17	494.79	827.23	3,500.23
Total sediment export (tons)	421.37	426,948.38	11,574.13	4,682.67	1.29	1,438.69	89,365.16	534,431.68
Average sediment export (tons/km^2)	23.57	247.13	471.26	135.49	0.01	35.31	636.69	240.30

Table 7.15 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2021 under Scenario I.

Year 2021	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	16.91	1,727.39	26.44	34.73	233.22	39.72	139.33	2,217.74
Total soil loss (tons)	21,226.92	18,142,892.25	361,039.75	178,489.33	728.98	97,522.37	3,658,238.65	22,460,138.25
Average soil loss (tons/km^2)	1,255.29	10,503.07	13,655.06	5,139.34	3.13	2,455.25	26,255.93	10,127.50
Total sediment retention (tons)	22,769.20	3,318,792.65	107,449.23	47,187.14	4,112,433.40	23,740.08	117,835.11	7,750,206.81
Average sediment retention (tons/km^2)	1,346.49	1,921.28	4,063.89	1,358.69	17,633.28	597.69	845.73	3,494.65
Total sediment export (tons)	373.16	423,704.91	13,986.80	4,611.52	1.24	1,304.16	87,379.86	531,361.64
Average sediment export (tons/km^2)	22.07	245.29	529.00	132.78	0.01	32.83	627.14	239.60

Table 7.16 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2022 under Scenario I.

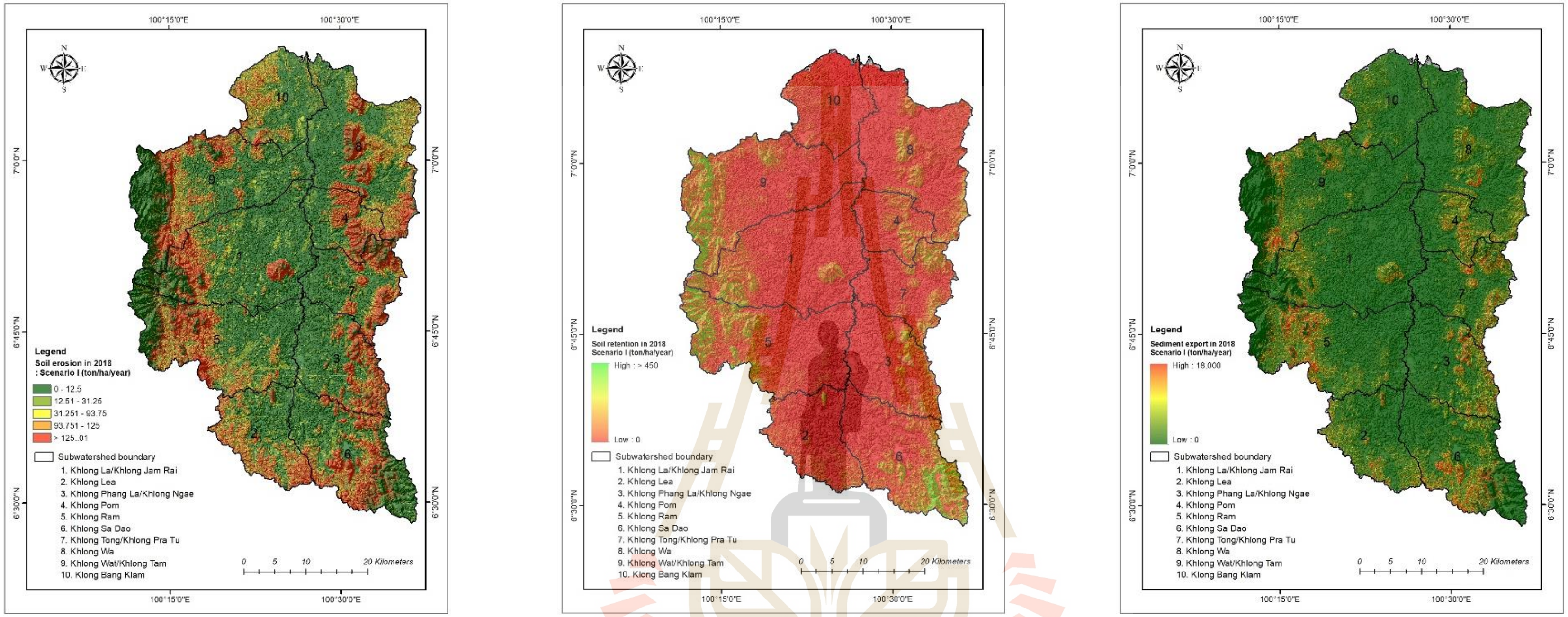
Year 2022	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	16.11	1,727.17	28.36	35.23	227.79	38.65	138.40	2,211.69
Total soil loss (tons)	21,217.52	19,517,537.32	467,010.62	197,577.52	779.16	99,236.96	3,916,019.67	24,219,378.78
Average soil loss (tons/km^2)	1,317.04	11,300.30	16,467.23	5,608.22	3.42	2,567.58	28,294.94	10,950.62
Total sediment retention (tons)	25,164.97	3,583,964.04	147,976.48	56,703.07	4,414,315.10	30,602.27	131,608.64	8,390,334.57
Average sediment retention (tons/km^2)	1,562.07	2,075.05	5,217.79	1,609.51	19,378.88	791.78	950.93	3,793.63
Total sediment export (tons)	376.31	458,309.12	18,890.34	4,965.94	1.28	1,344.13	93,692.22	577,579.35
Average sediment export (tons/km^2)	23.36	265.35	666.09	140.96	0.01	34.78	676.97	261.15

Table 7.17 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2023 under Scenario I.

Year 2023	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	15.33	1,726.99	30.06	35.35	222.57	37.95	137.51	2,205.76
Total soil loss (tons)	19,990.23	19,137,218.20	519,757.86	195,377.71	742.20	95,338.58	3,830,518.33	23,798,943.10
Average soil loss (tons/km^2)	1,303.99	11,081.26	17,290.68	5,526.95	3.33	2,512.22	27,856.29	10,789.48
Total sediment retention (tons)	13,450.62	3,526,444.06	166,250.19	60,317.32	4,226,844.41	34,487.51	132,491.37	8,160,285.49
Average sediment retention (tons/km^2)	877.40	2,041.96	5,530.61	1,706.29	18,991.08	908.76	963.50	3,699.54
Total sediment export (tons)	351.44	449,753.31	20,828.38	4,895.20	1.19	1,292.90	91,826.26	568,948.67
Average sediment export (tons/km^2)	22.92	260.43	692.89	138.48	0.01	34.07	667.78	257.94

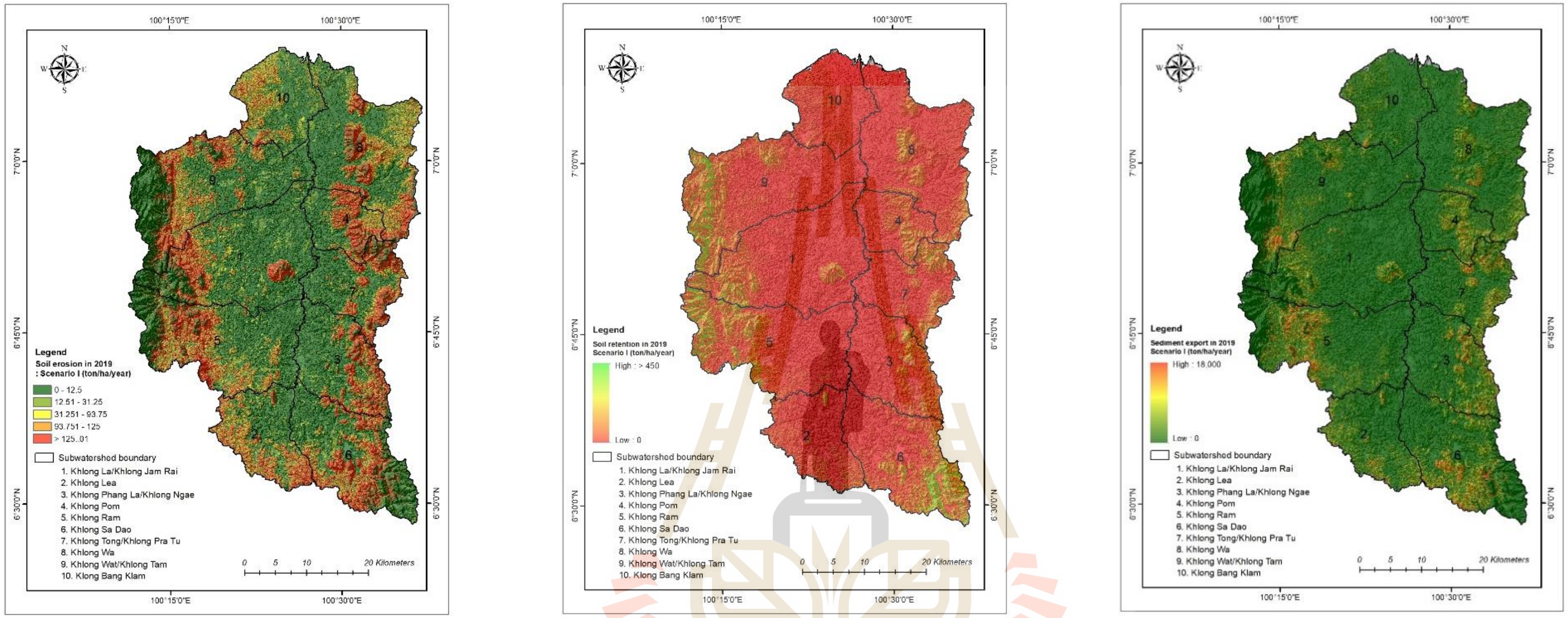
Table 7.18 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2024 under Scenario I.

Year 2024	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	14.48	1,726.77	32.35	37.19	215.46	37.26	136.91	2,200.42
Total soil loss (tons)	18,696.74	19,515,507.90	633,778.86	246,043.46	737.43	94,174.18	3,876,558.92	24,385,497.50
Average soil loss (tons/km^2)	1,291.21	11,301.74	19,591.31	6,615.85	3.42	2,527.49	28,314.65	11,082.21
Total sediment retention (tons)	15,792.04	3,603,946.95	207,834.04	77,347.75	4,225,019.56	41,947.30	139,923.86	8,311,811.49
Average sediment retention (tons/km^2)	1,090.61	2,087.10	6,424.55	2,079.80	19,609.30	1,125.80	1,022.01	3,777.38
Total sediment export (tons)	317.94	460,524.49	25,348.34	5,622.74	1.15	1,279.33	93,378.81	586,472.80
Average sediment export (tons/km^2)	21.96	266.70	783.57	151.19	0.01	34.34	682.05	266.53



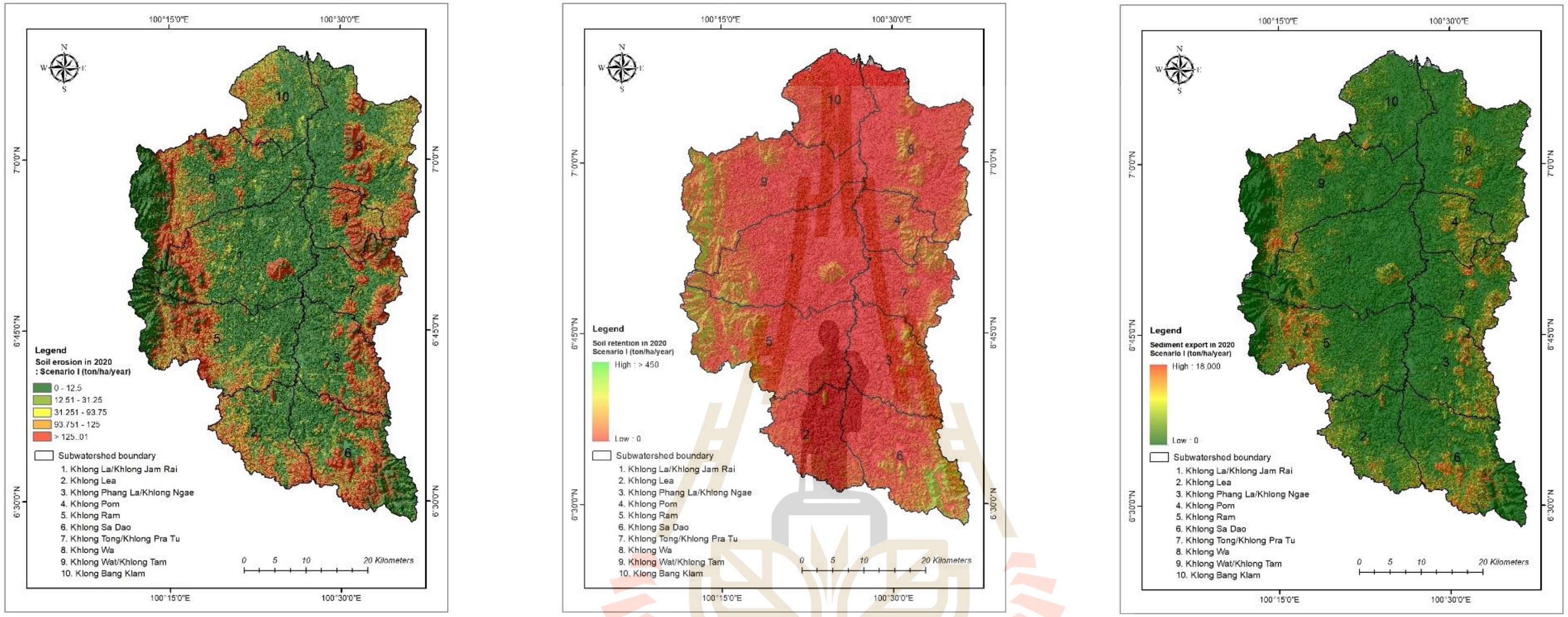
Soil erosion **Sediment retention** **Sediment export**

Figure 7.11 Spatial distribution of soil erosion, sediment retention, and sediment export in 2018 under Scenario I.



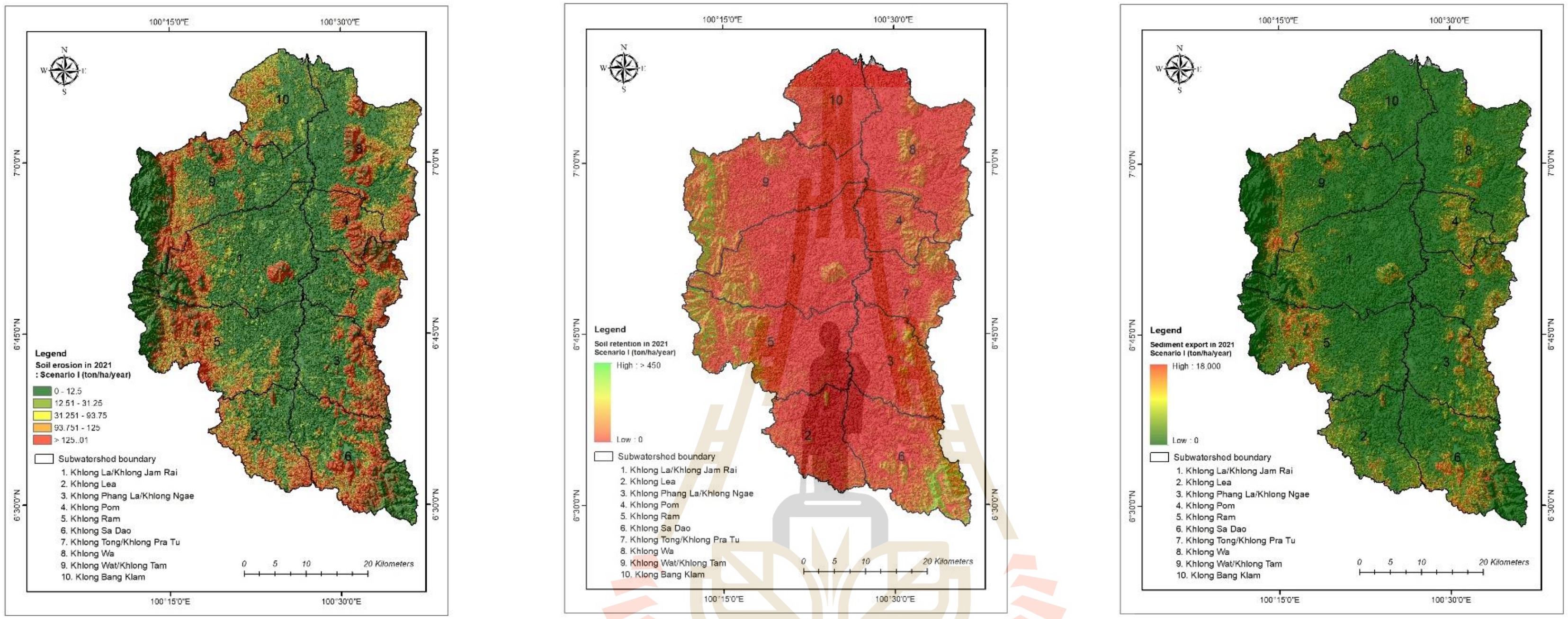
Soil erosion **Sediment retention** **Sediment export**

Figure 7.12 Spatial distribution of soil erosion, sediment retention, and sediment export in 2019 under Scenario I.



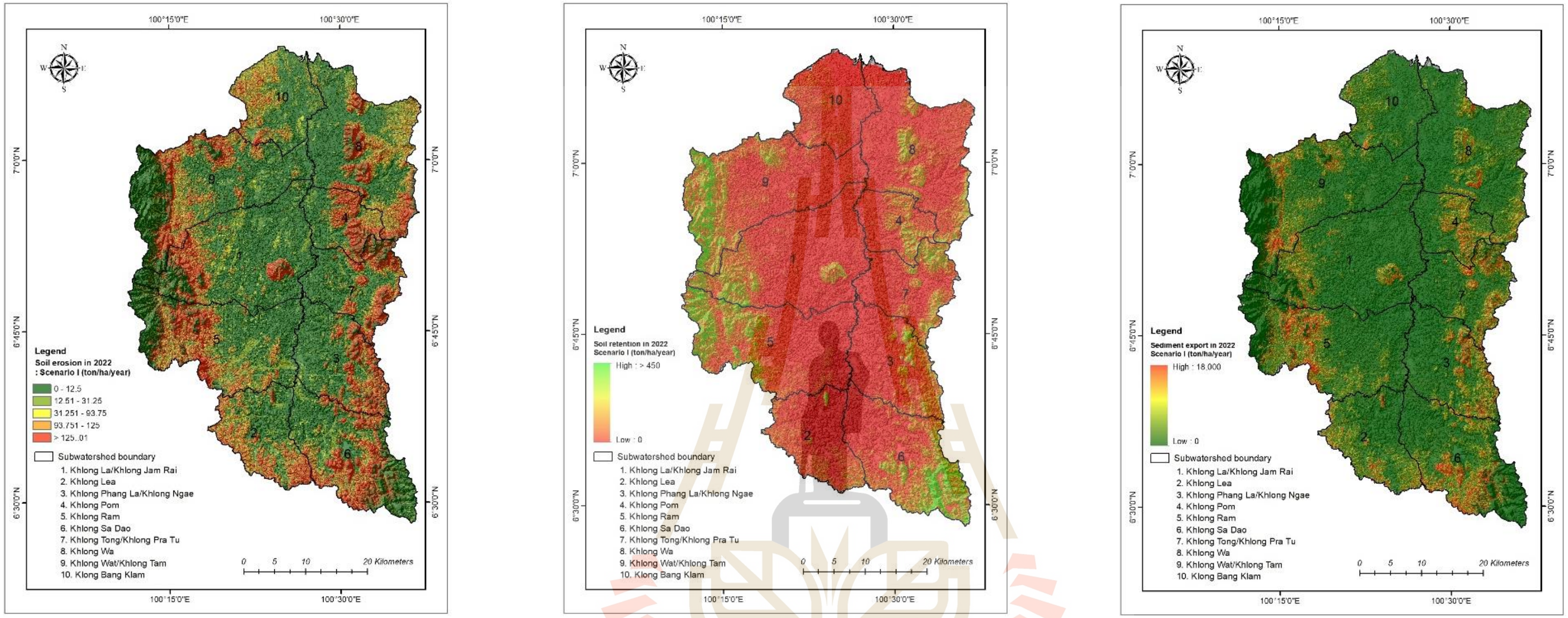
Soil erosion **Sediment retention** **Sediment export**

Figure 7.13 Spatial distribution of soil erosion, sediment retention, and sediment export in 2020 under Scenario I.



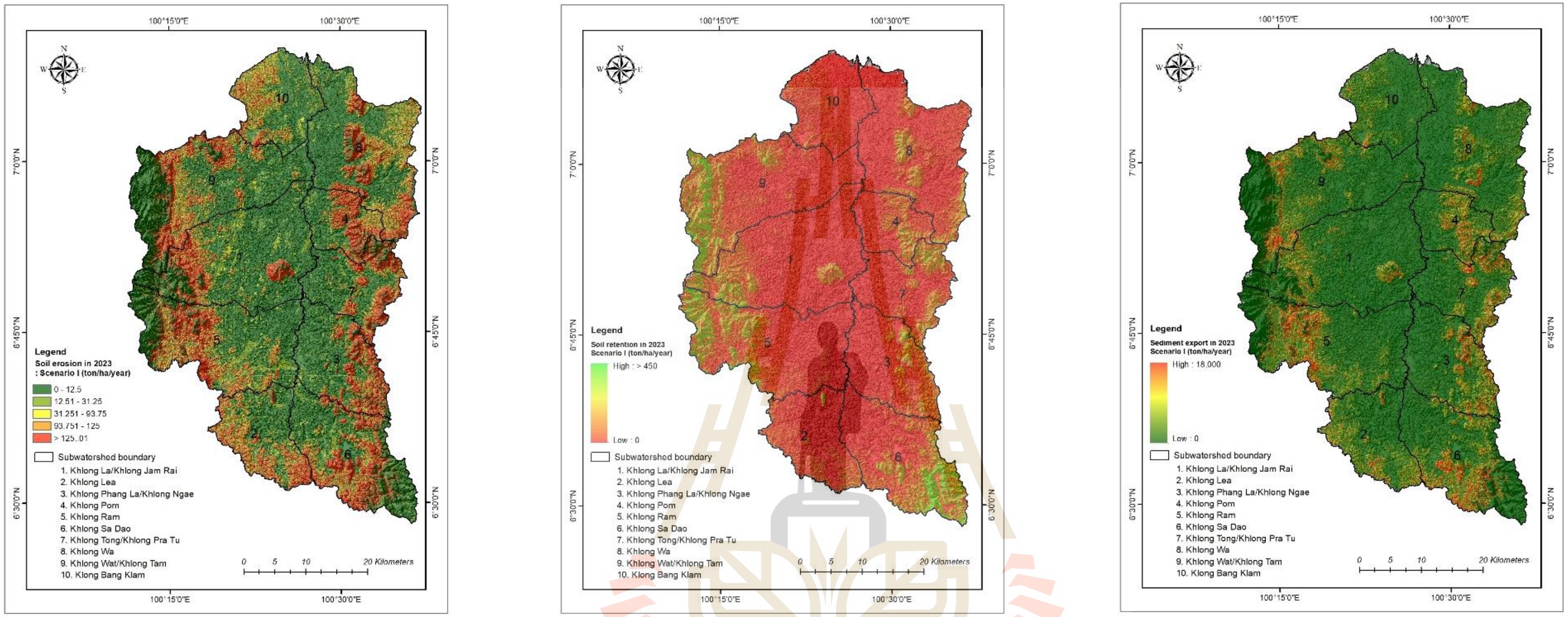
Soil erosion **Sediment retention** **Sediment export**

Figure 7.14 Spatial distribution of soil erosion, sediment retention, and sediment export in 2021 under Scenario I.



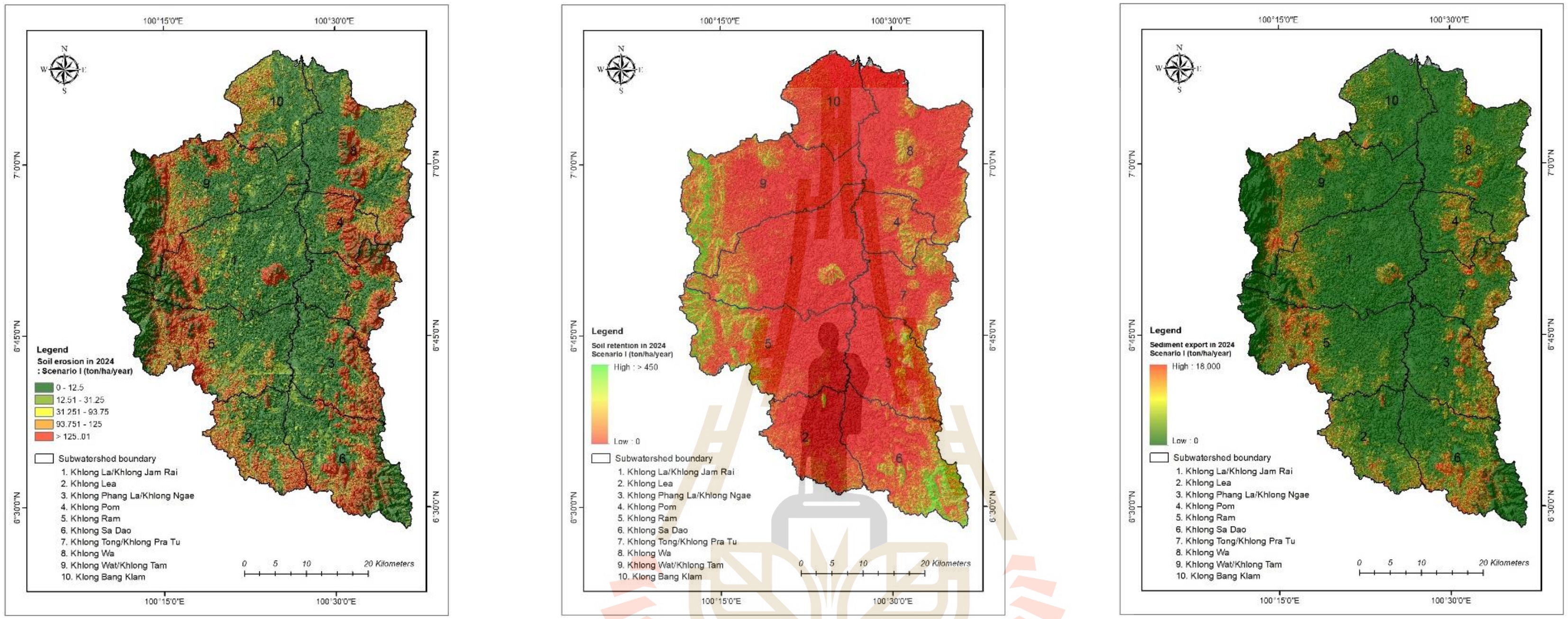
Soil erosion **Sediment retention** **Sediment export**

Figure 7.15 Spatial distribution of soil erosion, sediment retention, and sediment export in 2022 under Scenario I.



Soil erosion **Sediment retention** **Sediment export**

Figure 7.16 Spatial distribution of soil erosion, sediment retention, and sediment export in 2023 under Scenario I.



Soil erosion **Sediment retention** **Sediment export**

Figure 7.17 Spatial distribution of soil erosion, sediment retention, and sediment export in 2024 under Scenario I.

Table 7.19 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2018).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,360,840.80	9,385.99	902,844.84	2,521.42	75,256.63	210.17
2. Khlong Lea	166.50	1,927,137.55	11,574.40	166,147.90	997.89	36,299.78	218.02
3. Khlong Phang La/Khlong Ngae	188.88	2,253,945.30	11,933.21	336,339.11	1,780.70	54,910.86	290.72
4. Khlong Pom	103.13	1,295,068.66	12,557.63	292,586.58	2,837.07	39,878.74	386.68
5. Khlong Ram	324.94	3,393,255.20	10,442.71	1,461,585.17	4,498.02	75,817.90	233.33
6. Khlong Sa Dao	259.17	3,242,601.82	12,511.49	1,677,968.19	6,474.39	71,557.76	276.10
7. Khlong Tong/Khlong Pra Tu	161.58	1,959,593.40	12,127.70	488,345.76	3,022.32	54,198.86	335.43
8. Khlong Wa	325.83	2,068,770.52	6,349.23	425,634.05	1,306.31	48,131.01	147.72
9. Khlong Wat/Khlong Tam	352.14	2,831,988.41	8,042.22	2,172,362.77	6,169.03	64,792.14	184.00
10. Klong Bang Klam	165.80	624,728.15	3,767.96	42,163.59	254.30	7,531.25	45.42
Total	**2,406.04**	**22,957,929.79**	**9,541.79**	**7,965,977.96**	**3,310.83**	**528,374.94**	**219.60**

Table 7.20 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2019).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,085,095.44	8,615.90	824,589.50	2,302.87	69,637.59	194.48
2. Khlong Lea	166.50	1,792,498.80	10,765.76	154,653.82	928.85	33,776.32	202.86
3. Khlong Phang La/Khlong Ngae	188.88	2,112,861.71	11,186.26	314,037.82	1,662.63	52,291.66	276.85
4. Khlong Pom	103.13	1,200,655.36	11,642.15	270,580.85	2,623.69	37,428.57	362.93
5. Khlong Ram	324.94	3,129,454.96	9,630.87	1,334,641.72	4,107.35	70,363.21	216.54
6. Khlong Sa Dao	259.17	3,081,425.61	11,889.59	1,590,430.32	6,136.63	71,169.37	274.60
7. Khlong Tong/Khlong Pra Tu	161.58	1,824,811.26	11,293.55	454,427.95	2,812.40	51,080.14	316.13
8. Khlong Wa	325.83	1,914,381.46	5,875.40	393,454.52	1,207.55	44,755.83	137.36
9. Khlong Wat/Khlong Tam	352.14	2,585,395.81	7,341.95	1,972,556.41	5,601.63	60,104.84	170.68
10. Klong Bang Klam	165.80	568,661.34	3,429.80	38,451.56	231.92	6,846.55	41.29
Total	**2,406.04**	**21,295,241.75**	**8,850.74**	**7,347,824.49**	**3,053.91**	**497,454.07**	**206.75**

Table 7.21 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2020).

Sub-watershed	Area (km²)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,305,976.73	9,232.77	880,469.23	2,458.93	75,034.63	209.55
2. Khlong Lea	166.50	1,908,151.56	11,460.37	164,633.67	988.79	35,956.45	215.95
3. Khlong Phang La/Khlong Ngae	188.88	2,251,358.46	11,919.52	332,732.82	1,761.61	56,265.44	297.89
4. Khlong Pom	103.13	1,282,417.61	12,434.96	287,384.70	2,786.63	40,310.54	390.87
5. Khlong Ram	324.94	3,353,829.84	10,321.38	1,423,325.99	4,380.27	75,891.84	233.56
6. Khlong Sa Dao	259.17	3,271,681.91	12,623.69	1,658,786.21	6,400.38	76,902.54	296.73
7. Khlong Tong/Khlong Pra Tu	161.58	1,934,119.88	11,970.05	479,771.76	2,969.25	54,199.12	335.43
8. Khlong Wa	325.83	2,041,625.88	6,265.92	418,261.42	1,283.68	47,994.90	147.30
9. Khlong Wat/Khlong Tam	352.14	2,768,061.57	7,860.68	2,097,940.70	5,957.69	64,559.82	183.34
10. Klong Bang Klam	165.80	609,649.32	3,677.02	41,334.31	249.30	7,316.40	44.13
Total	**2,406.04**	**22,726,872.75**	**9,445.76**	**7,784,640.83**	**3,235.46**	**534,431.68**	**222.12**

Table 7.22 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2021).

Sub-watershed	Area (km²)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,249,889.33	9,076.13	870,138.64	2,430.08	73,944.22	206.51
2. Khlong Lea	166.50	1,871,851.39	11,242.35	161,730.30	971.35	35,276.58	211.87
3. Khlong Phang La/Khlong Ngae	188.88	2,229,289.52	11,802.68	329,940.11	1,746.82	55,849.37	295.69
4. Khlong Pom	103.13	1,270,232.76	12,316.81	285,188.18	2,765.33	40,094.98	388.78
5. Khlong Ram	324.94	3,305,911.42	10,173.91	1,408,381.06	4,334.28	74,944.77	230.64
6. Khlong Sa Dao	259.17	3,265,660.18	12,600.46	1,674,900.20	6,462.55	78,056.52	301.18
7. Khlong Tong/Khlong Pra Tu	161.58	1,922,721.84	11,899.50	479,685.74	2,968.72	54,300.37	336.06
8. Khlong Wa	325.83	2,015,626.95	6,186.13	415,404.66	1,274.91	47,714.38	146.44
9. Khlong Wat/Khlong Tam	352.14	2,734,555.66	7,765.54	2,084,442.08	5,919.36	64,053.93	181.90
10. Klong Bang Klam	165.80	594,399.19	3,585.04	40,395.84	243.64	7,126.52	42.98
Total	**2,406.04**	**22,460,138.25**	**9,334.90**	**7,750,206.81**	**3,221.15**	**531,361.64**	**220.84**

Table 7.23 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2022).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,497,838.62	9,768.59	940,533.13	2,626.67	80,175.08	223.91
2. Khlong Lea	166.50	2,014,424.20	12,098.64	174,125.97	1,045.80	37,961.78	228.00
3. Khlong Phang La/Khlong Ngae	188.88	2,406,258.14	12,739.61	355,164.41	1,880.37	60,349.78	319.51
4. Khlong Pom	103.13	1,367,318.12	13,258.20	306,795.50	2,974.84	44,124.26	427.85
5. Khlong Ram	324.94	3,568,511.73	10,982.06	1,531,124.85	4,712.02	81,134.73	249.69
6. Khlong Sa Dao	259.17	3,540,969.19	13,662.73	1,803,308.35	6,958.01	85,814.86	331.11
7. Khlong Tong/Khlong Pra Tu	161.58	2,074,719.43	12,840.20	516,587.78	3,197.10	59,196.73	366.36
8. Khlong Wa	325.83	2,160,334.34	6,630.25	445,553.40	1,367.44	51,294.09	157.43
9. Khlong Wat/Khlong Tam	352.14	2,957,759.18	8,399.38	2,274,067.93	6,457.85	69,977.70	198.72
10. Klong Bang Klam	165.80	631,245.85	3,807.27	43,073.26	259.79	7,550.35	45.54
Total	**2,406.04**	**24,219,378.78**	**10,066.07**	**8,390,334.57**	**3,487.20**	**577,579.35**	**240.05**

Table 7.24 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2023).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,448,840.54	9,631.75	919,807.06	2,568.79	79,153.31	221.06
2. Khlong Lea	166.50	1,972,963.79	11,849.63	170,601.94	1,024.64	37,180.17	223.30
3. Khlong Phang La/Khlong Ngae	188.88	2,360,193.49	12,495.73	346,638.58	1,835.23	59,262.76	313.76
4. Khlong Pom	103.13	1,341,429.22	13,007.17	300,753.26	2,916.25	43,350.16	420.34
5. Khlong Ram	324.94	3,506,273.45	10,790.53	1,488,470.26	4,580.75	79,880.75	245.83
6. Khlong Sa Dao	259.17	3,469,647.39	13,387.53	1,745,165.22	6,733.67	84,773.48	327.10
7. Khlong Tong/Khlong Pra Tu	161.58	2,036,362.34	12,602.81	504,245.70	3,120.72	58,416.63	361.53
8. Khlong Wa	325.83	2,123,865.41	6,518.32	437,693.47	1,343.32	50,389.91	154.65
9. Khlong Wat/Khlong Tam	352.14	2,914,363.35	8,276.15	2,204,141.11	6,259.28	69,080.92	196.17
10. Klong Bang Klam	165.80	625,004.13	3,769.63	42,768.88	257.95	7,460.59	45.00
Total	**2,406.04**	**23,798,943.10**	**9,891.33**	**8,160,285.49**	**3,391.58**	**568,948.67**	**236.47**

Table 7.25 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario I, 2024).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,522,014.00	9,836.10	933,027.69	2,605.71	81,596.59	227.88
2. Khlong Lea	166.50	2,031,328.39	12,200.17	175,382.45	1,053.35	38,320.21	230.15
3. Khlong Phang La/Khlong Ngae	188.88	2,424,535.43	12,836.38	355,168.21	1,880.39	61,121.51	323.60
4. Khlong Pom	103.13	1,361,394.70	13,200.76	305,297.93	2,960.32	43,983.73	426.49
5. Khlong Ram	324.94	3,602,394.72	11,086.34	1,514,244.43	4,660.07	82,453.43	253.75
6. Khlong Sa Dao	259.17	3,613,379.38	13,942.12	1,800,688.94	6,947.91	89,578.53	345.64
7. Khlong Tong/Khlong Pra Tu	161.58	2,072,322.51	12,825.37	513,523.19	3,178.14	59,515.93	368.34
8. Khlong Wa	325.83	2,160,492.04	6,630.73	443,887.63	1,362.33	51,219.96	157.20
9. Khlong Wat/Khlong Tam	352.14	2,966,906.48	8,425.36	2,227,345.19	6,325.17	71,189.19	202.16
10. Klong Bang Klam	165.80	630,729.83	3,804.16	43,245.85	260.83	7,493.73	45.20
Total	**2,406.04**	**24,385,497.50**	**10,135.12**	**8,311,811.49**	**3,454.56**	**586,472.80**	**243.75**

As results (Tables 7.12 to 7.18), it reveals that during 2018 to 2024 miscellaneous land (bare land and abandoned mine) generates the highest average soil erosion with values between 24,902.43 tons/km^2 in 2019 and 28,314.65 tons/km^2 in 2024 while evergreen forest generates the lowest average soil erosion with values between 2.92 tons/km^2 in 2019 and 3.42 tons/km^2 in 2024. Meanwhile evergreen forest retains the highest average sediment retention with values between 16,318.97 tons/km^2 in 2019 and 19,609.30 tons/km^2 in 2024 while marsh and swamp retains the lowest average sediment retention with values between 653.25 tons/km^2 in 2018 and 2,251.60 tons/km^2 in 2024. In the meantime, miscellaneous land (bare land and abandoned mine) generates the highest average sediment export with values between 326.62 tons/km^2 in 2018 and of 1,125.80 tons/km^2 in 2024 while evergreen forest generates the lowest average sediment export with values 0.01 tons/km^2 in between 2018 and 2024. This finding suggests the influence of LULC types on soil erosion, sediment retention, and sediment export as mentioned in early section.

In addition, at sub-watershed (Tables 7.19 to 7.25), it reveals that during 2018 to 2024 Khlong Sa Dao sub-watershed generates the highest average soil erosion with minimum and maximum values between 6,136.63 tons/km^2 in 2019 and 6,958.01 tons/km^2 in 2024 while Khlong Bang Klam sub-watershed generates the lowest average soil erosion with minimum and maximum values between 3,429.80 tons/km^2 in 2019 and 3,807.27 tons/km^2 in 2022. Meanwhile, Khlong Sa Dao sub-watershed retains the highest average sediment retention with minimum and maximum values between 6,136.63 tons/km^2 in 2019 and 6,958.01 tons/km^2 in 2022 while Klong Bang Klam sub-watershed retains the lowest average sediment retention with minimum and maximum values between 231.92 tons/km^2 in 2019 and 260.83 tons/km^2 in 2024. In the meantime, Khlong Pom sub-watershed delivers the highest average sediment export with minimum and maximum values between 362.93 tons/km^2 in 2019 and 427.85 tons/km^2 in 2022 while Klong Bang Klam sub-watershed delivers the lowest average sediment export with minimum and maximum values of 41.29 tons/km^2 in 2019 and 45.54 tons/km^2 in 2022.

Furthermore, it can be observed that under Scenario I (Historical LULC evolution) the highest average soil erosion mostly occurs at Khlong Pom sub-watershed, except in 2018 and the lowest average soil erosion always occurs at Khlong Bang Klam sub-watershed. Likewise the highest average sediment retention always occurs at Khlong Sa Dao sub-watershed and the lowest average sediment retention always occurs at Klong Bang Klam sub-watershed. Similarly, the highest average sediment export always occurs at Khlong Pom sub-watershed and the lowest average sediment export always occurs at Klong Bang Klam sub-watershed. This finding suggest that variation of predictive annual rainfall during 2018 to 2024 leads to soil erosion, sediment retention, and sediment export higher than LULC data under this scenario. Since LULC data of Scenario I is simulated based on annual rate of LULC change from transition area matrix between 2010 and 2017, it does not represent dramatic LULC change under this scenario.

7.5 Sediment retention estimation of predictive LULC of Scenario II

Estimation of total and average soil erosion, sediment retention and sediment export with water yield of predictive LULC between 2018 and 2024 of Scenario II: Forest conservation and prediction is presented in Table 7.26.

It was found that the highest total and average soil erosion are 22.05 million tons and 9,166.44 tons/km^2 occurring in 2018 while the lowest total and average soil erosion are 19.56 million tons and 8,127.66 tons/km^2 occurring in occurring in 2021, respectively. Meanwhile, the highest total and average sediment retention are 8.43 million tons and 3,502.96 tons/km^2 occurring in 2022 while the lowest total and average sediment retention are 7.36 million tons and 3,060.66 tons/km^2 occurring in 2019. In the meantime, the highest total and average sediment export are 0.49 million tons and 204.65 tons/km^2 occurring in 2018 while the lowest total and average sediment export are 0.41 million tons and 169.57 tons/km^2 occurring in 2024.

Similar to Scenario I, these results indicate the influence of dynamic factor of RUSLE model on soil erosion, sediment retention, and sediment export.

Table 7.26 Estimation of soil erosion, sediment retention, and sediment export between 2018 and 2024 under Scenario II.

Year	Area	Soil erosion		Sediment retention		Sediment export		Water yield	
	km^2	Total (mil. tons)	Average (tons)	Total (mil. tons)	Average (tons)	Total (mil. tons)	Average (tons)	Total (mill m^3)	Average (mil.m^3)
2018	2,406.04	22.05	9,166.44	7.98	3,314.86	0.49	204.65	1,755.80	0.73
2019	2,406.04	19.77	8,215.66	7.36	3,060.66	0.44	181.75	1,617.77	0.67
2020	2,406.04	20.39	8,472.76	7.81	3,245.68	0.44	184.25	1,728.73	0.72
2021	2,406.04	19.56	8,127.66	7.78	3,233.53	0.42	174.99	1,698.14	0.71
2022	2,406.04	20.50	8,519.22	8.43	3,502.96	0.44	181.68	1,824.88	0.76
2023	2,406.04	19.67	8,174.51	8.20	3,409.01	0.41	171.92	1,795.29	0.75
2024	2,406.04	19.61	8,148.53	8.36	3,474.59	0.41	169.57	1,829.04	0.76

In addition, simple linear regression between average water yield as independent variable and soil erosion, sediment retention, and sediment export of Scenario I between 2018 and 2024 as dependent variables were also examined. It was found that the relationship between average water yield and average soil loss and sediment export are not exist under simple linear regression analysis (Figures 7.18 and 7.19).

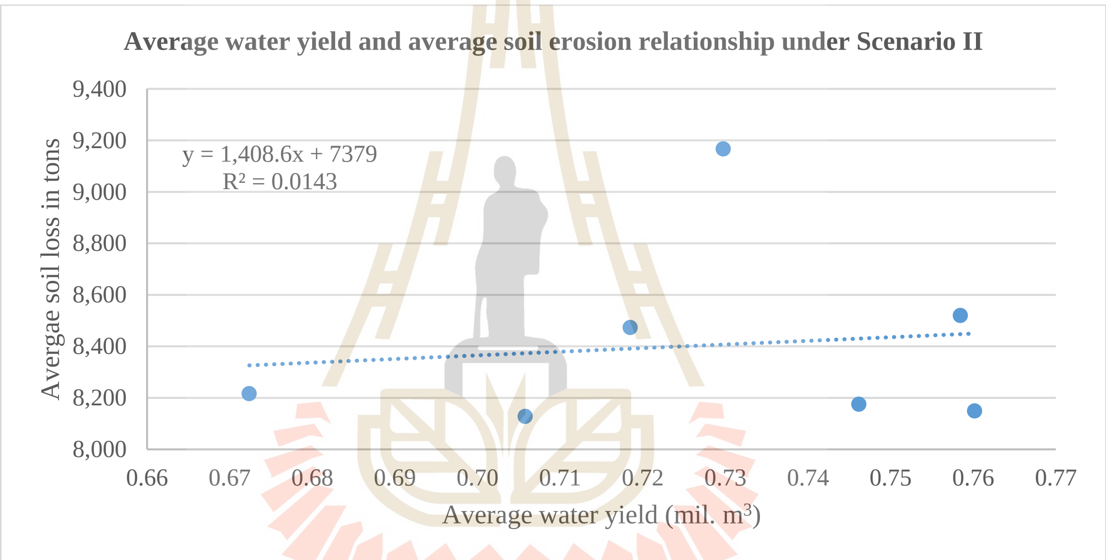


Figure 7.18 Relationship between average water yield and average soil erosion under Scenario II.

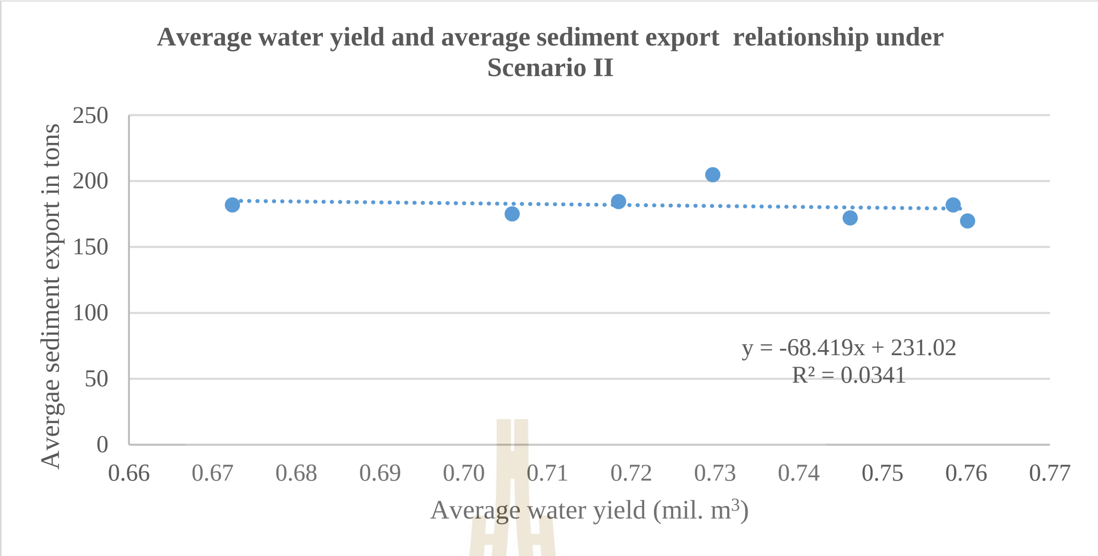


Figure 7.19 Relationship between average water yield and average sediment export under Scenario II.

On contrary, the relationship between average water yield and average sediment retention provides positively very high correlation with R^2 of 0.9815 (Figure 7.20) as:

$$y = 4{,}891.9x - 237.75 \quad (7.8)$$

Where, y is average water yield volume in m^3 and x is average sediment retention in tons.

These finding shows the influence of rainfall as main factor of water yield on sediment retention under this scenario. Herewith, sediment retention as dependent variable can be predictable from water yield as independent variable about 98.15%.

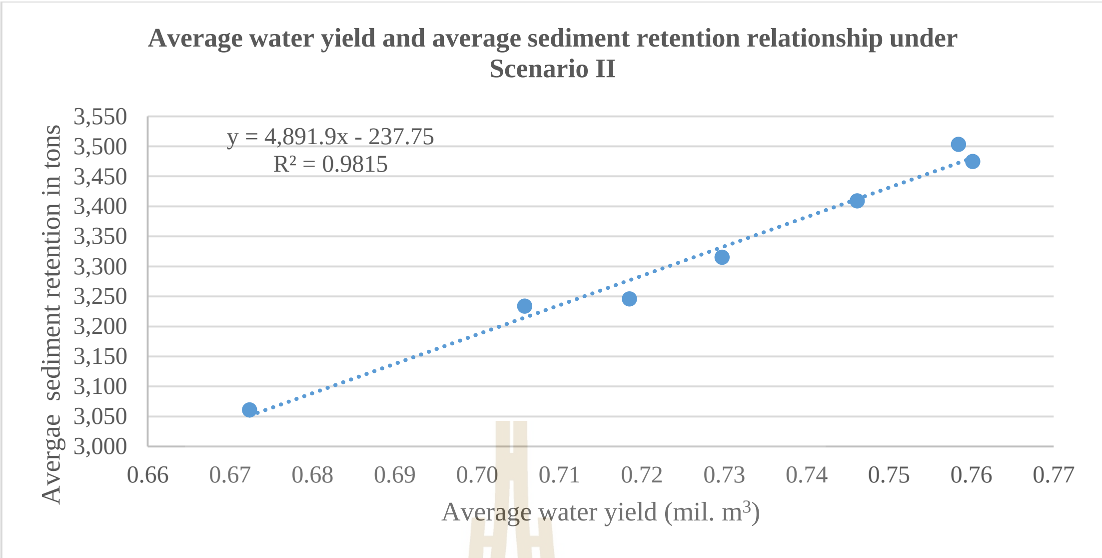


Figure 7.20 Relationship between average water yield and average sediment retention under Scenario II.

The contribution of the predictive LULC of Scenario II on soil erosion, sediment retention, sediment export between 2018 and 2024 is summarized in Tables 7.27 to 7.33 and the spatial distribution of soil erosion, sediment retention and sediment export of the predictive LULC between 2018 and 2024 of Scenario II is displayed in Figures 7.21 to 7.27. Details of soil erosion, sediment retention and sediment export in each sub-watershed from predictive LULC of Scenario II between 2018 and 2024 are presented in Tables 7.34 to 7.40.

Table 7.27 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2018 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.36	1,707.79	20.72	34.10	270.03	42.53	141.22	2,236.76
Total soil loss (tons)	28,933.12	17,864,532.10	135,815.73	176,845.35	837.30	118,692.59	3,729,158.73	22,054,814.91
Average soil loss (tons/km^2)	1,421.08	10,460.61	6,554.81	5,186.08	3.10	2,790.80	26,406.73	9,860.18
Total sediment retention (tons)	12,405.79	3,078,183.24	24,686.19	35,645.37	4,708,806.64	13,177.26	102,784.93	7,975,689.42
Average sediment retention (tons/km^2)	609.32	1,802.44	1,191.42	1,045.32	17,438.09	309.83	727.84	3,565.74
Total sediment export (tons)	545.89	397,173.00	2,494.17	4,660.39	1.10	1,642.39	85,889.73	492,406.68
Average sediment export (tons/km^2)	26.81	232.57	120.38	136.67	0.01	38.62	608.20	220.14

Table 7.28 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2019 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.34	1,686.08	22.72	34.03	286.41	42.42	139.41	2,231.39
Total soil loss (tons)	26,412.45	15,974,046.98	136,388.34	162,868.85	807.07	108,364.18	3,358,327.33	19,767,215.19
Average soil loss (tons/km^2)	1,298.55	9,474.07	6,003.01	4,786.04	2.82	2,554.55	24,089.57	8,858.70
Total sediment retention (tons)	11,662.22	2,699,391.69	24,389.08	33,106.25	4,493,604.30	12,355.61	89,557.07	7,364,066.22
Average sediment retention (tons/km^2)	573.36	1,600.99	1,073.46	972.85	15,689.41	291.27	642.40	3,300.21
Total sediment export (tons)	498.09	351,202.79	2,342.74	4,244.09	0.90	1,486.72	77,524.28	437,299.61
Average sediment export (tons/km^2)	24.49	208.30	103.11	124.72	0.01	35.05	556.09	195.98

Table 7.29 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2020 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.30	1,664.43	24.63	33.98	304.29	42.35	137.10	2,227.09
Total soil loss (tons)	28,422.97	16,435,697.96	153,987.40	174,107.98	891.08	116,364.30	3,476,325.42	20,385,797.11
Average soil loss (tons/km^2)	1,400.15	9,874.67	6,252.03	5,123.84	2.93	2,747.68	25,356.13	9,153.58
Total sediment retention (tons)	12,718.39	2,712,018.56	26,995.08	35,622.51	4,917,228.10	13,457.02	91,204.38	7,809,244.04
Average sediment retention (tons/km^2)	626.52	1,629.40	1,096.02	1,048.34	16,159.68	317.76	665.24	3,506.49
Total sediment export (tons)	526.52	354,693.42	2,604.37	4,473.76	0.90	1,592.21	79,417.64	443,308.82
Average sediment export (tons/km^2)	25.94	213.10	105.74	131.66	0.01	37.60	579.27	199.05

Table 7.30 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2021 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.26	1,640.07	26.47	33.91	323.36	42.28	136.16	2,222.50
Total soil loss (tons)	27,554.86	15,705,679.78	156,465.09	170,571.82	923.16	112,519.19	3,381,763.18	19,555,477.09
Average soil loss (tons/km^2)	1,360.06	9,576.23	5,911.03	5,030.13	2.85	2,661.29	24,836.69	8,798.85
Total sediment retention (tons)	12,764.03	2,560,522.20	27,259.91	35,289.07	5,041,398.03	13,473.42	89,286.17	7,779,992.81
Average sediment retention (tons/km^2)	630.01	1,561.23	1,029.84	1,040.67	15,590.67	318.67	655.74	3,500.56
Total sediment export (tons)	499.90	335,315.03	2,612.98	4,319.05	0.87	1,527.55	76,767.90	421,043.29
Average sediment export (tons/km^2)	24.67	204.45	98.71	127.37	0.01	36.13	563.81	189.45

Table 7.31 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2022 under Scenario II.

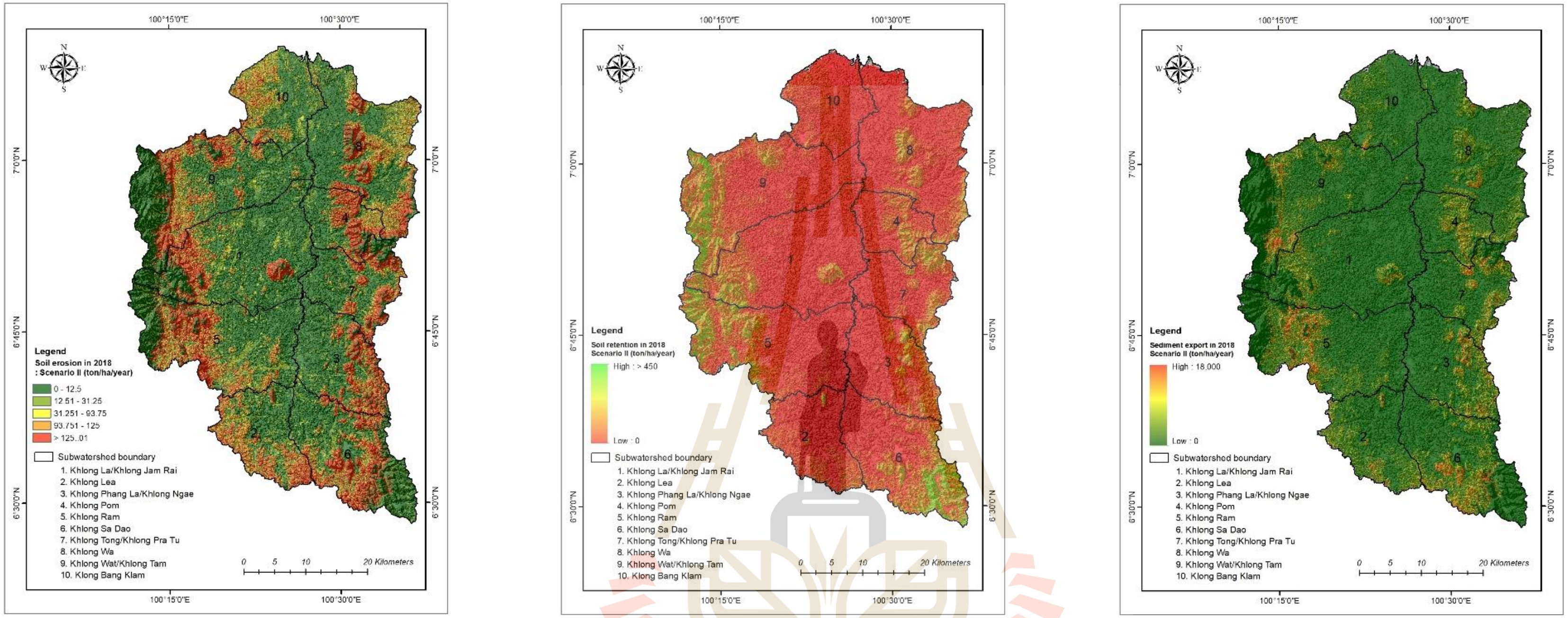
Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.26	1,614.61	28.50	33.91	342.22	42.27	135.49	2,217.24
Total soil loss (tons)	29,332.05	16,372,832.05	175,872.47	182,979.69	1,034.07	119,902.89	3,615,639.29	20,497,592.51
Average soil loss (tons/km^2)	1,447.78	10,140.43	6,170.96	5,396.04	3.02	2,836.60	26,685.65	9,244.64
Total sediment retention (tons)	14,019.46	2,642,890.20	31,130.15	38,239.97	5,591,368.20	14,792.02	95,813.52	8,428,253.52
Average sediment retention (tons/km^2)	691.98	1,636.86	1,092.29	1,127.69	16,338.52	349.94	707.16	3,801.24
Total sediment export (tons)	524.42	345,959.03	3,088.89	4,528.81	0.93	1,572.40	81,464.49	437,138.96
Average sediment export (tons/km^2)	25.88	214.27	108.38	133.55	0.01	37.20	601.26	197.15

Table 7.32 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2023 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.25	1,592.74	30.40	33.91	359.49	42.27	133.88	2,212.94
Total soil loss (tons)	29,210.30	15,635,717.01	182,885.24	180,467.86	1,029.72	119,373.41	3,519,507.90	19,668,191.43
Average soil loss (tons/km^2)	1,442.48	9,816.87	6,015.96	5,321.97	2.86	2,824.07	26,288.53	8,887.81
Total sediment retention (tons)	14,198.38	2,495,140.57	32,254.31	38,063.80	5,514,017.24	14,972.57	93,573.52	8,202,220.40
Average sediment retention (tons/km^2)	701.15	1,566.57	1,061.00	1,122.49	15,338.44	354.21	698.94	3,706.48
Total sediment export (tons)	513.99	326,158.39	3,181.00	4,381.74	0.90	1,534.01	77,864.35	413,634.38
Average sediment export (tons/km^2)	25.38	204.78	104.64	129.22	0.01	36.29	581.60	186.92

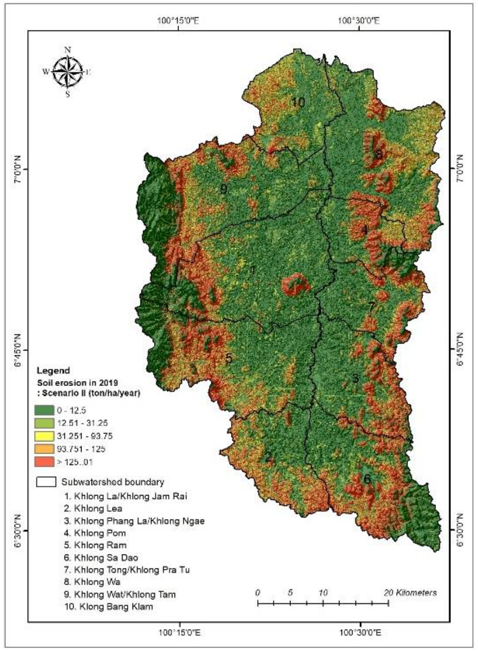
Table 7.33 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2024 under Scenario II.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.25	1,569.66	32.34	33.90	377.33	42.27	132.56	2,208.30
Total soil loss (tons)	29,586.27	15,513,726.66	195,760.72	183,710.66	1,075.85	121,036.72	3,560,793.81	19,605,690.68
Average soil loss (tons/km^2)	1,461.05	9,883.49	6,053.21	5,419.19	2.85	2,863.42	26,861.75	8,878.19
Total sediment retention (tons)	14,746.62	2,453,409.94	34,034.03	39,067.25	5,707,986.89	15,537.49	95,216.22	8,359,998.44
Average sediment retention (tons/km^2)	728.23	1,563.02	1,052.38	1,152.43	15,127.31	367.58	718.29	3,785.72
Total sediment export (tons)	514.46	320,403.08	3,329.10	4,386.22	0.92	1,535.00	77,834.04	408,002.81
Average sediment export (tons/km^2)	25.41	204.12	102.94	129.39	0.01	36.31	587.16	184.76

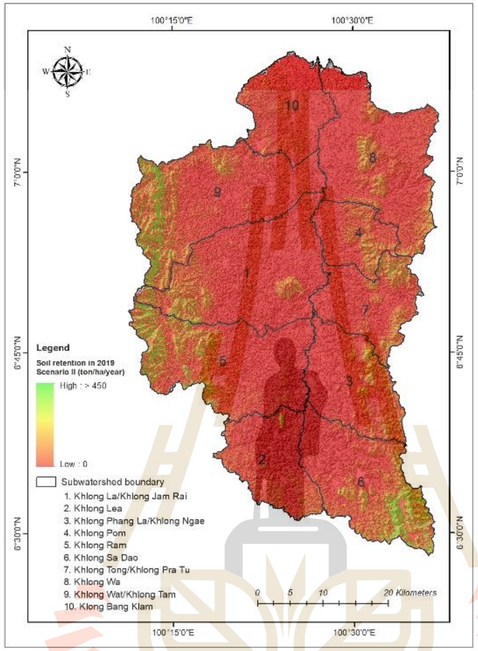


Soil erosion **Sediment retention** **Sediment export**

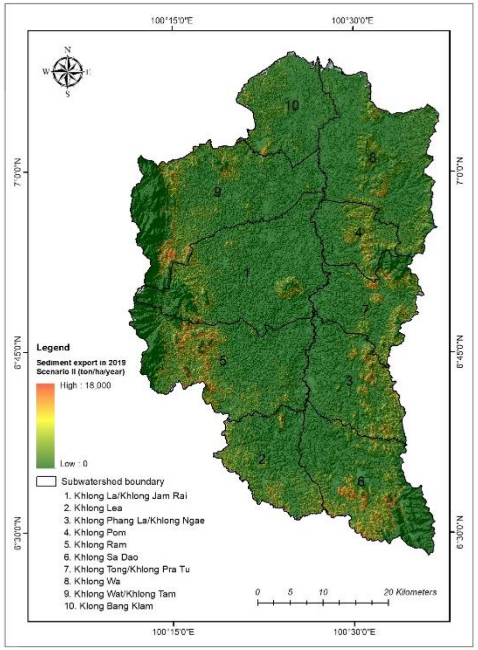
Figure 7.21 Spatial distribution of soil erosion, sediment retention, and sediment export in 2018 under Scenario II.



Soil erosion

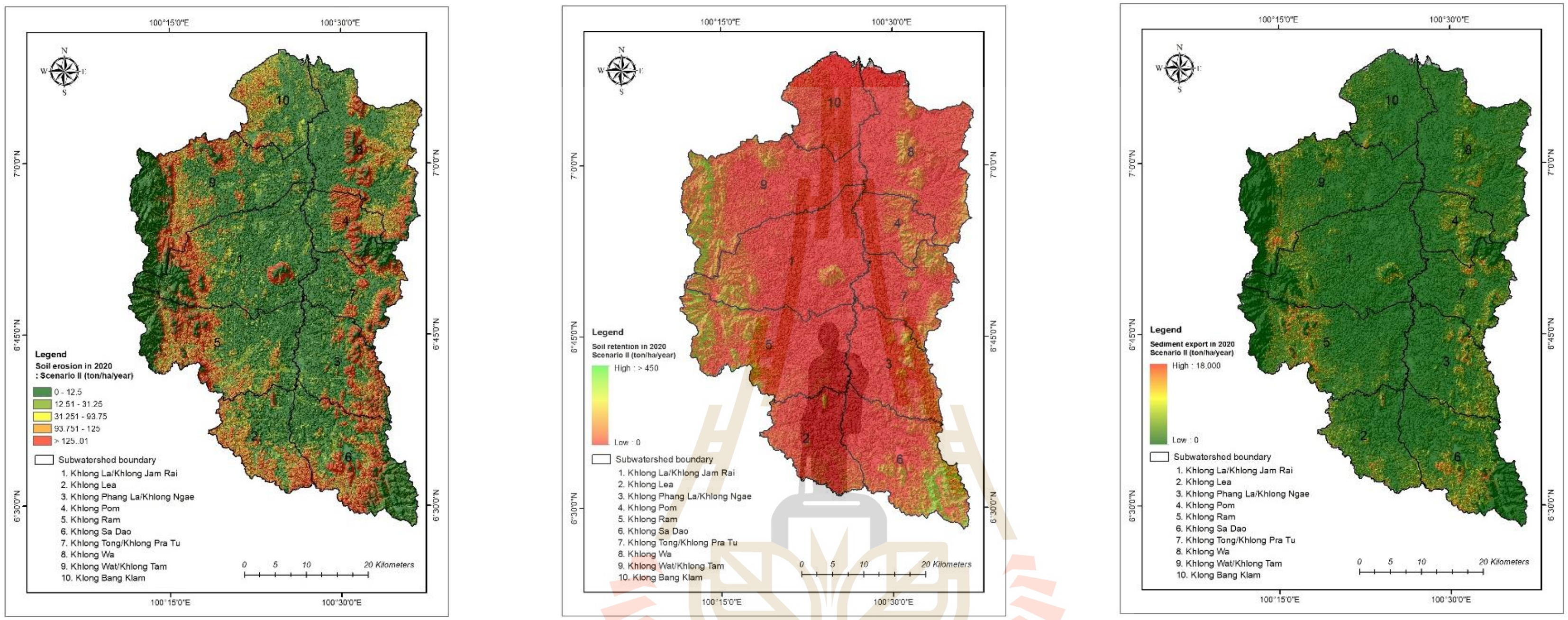


Sediment retention



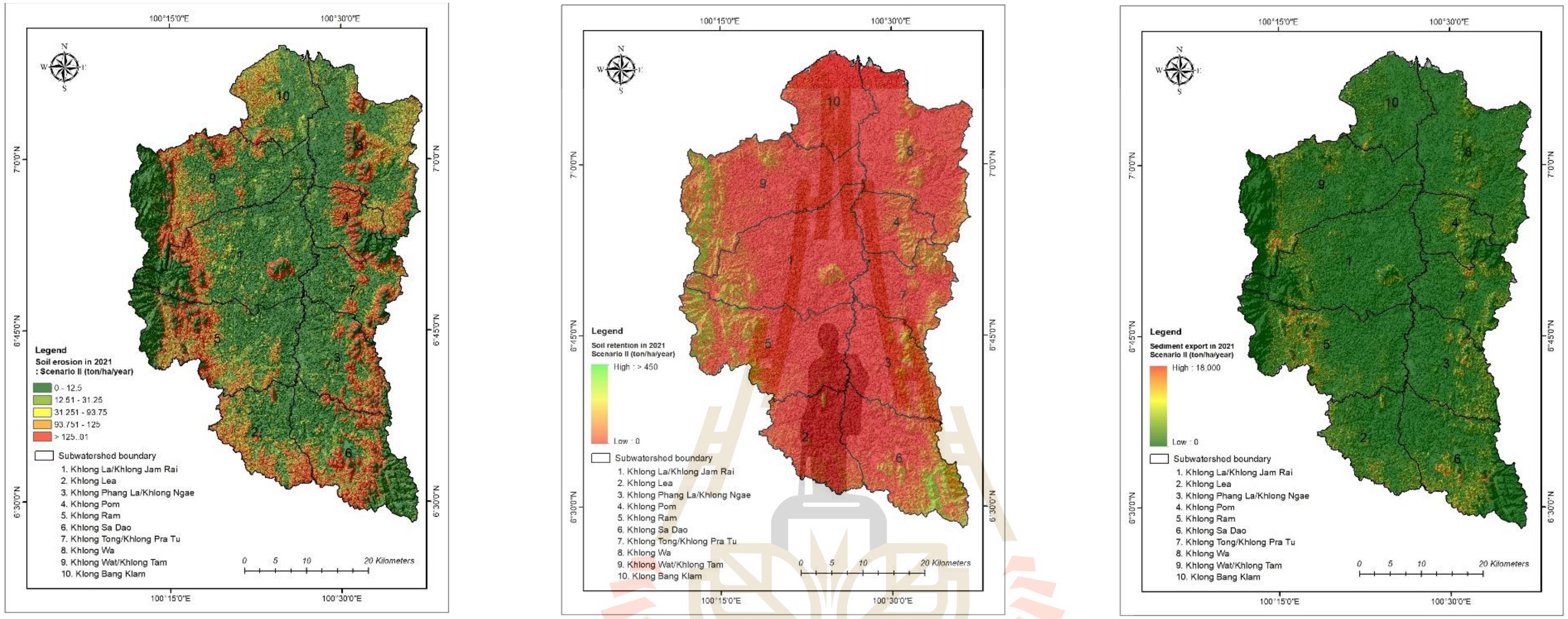
Sediment export

Figure 7.22 Spatial distribution of soil erosion, sediment retention, and sediment export in 2019 under Scenario II.



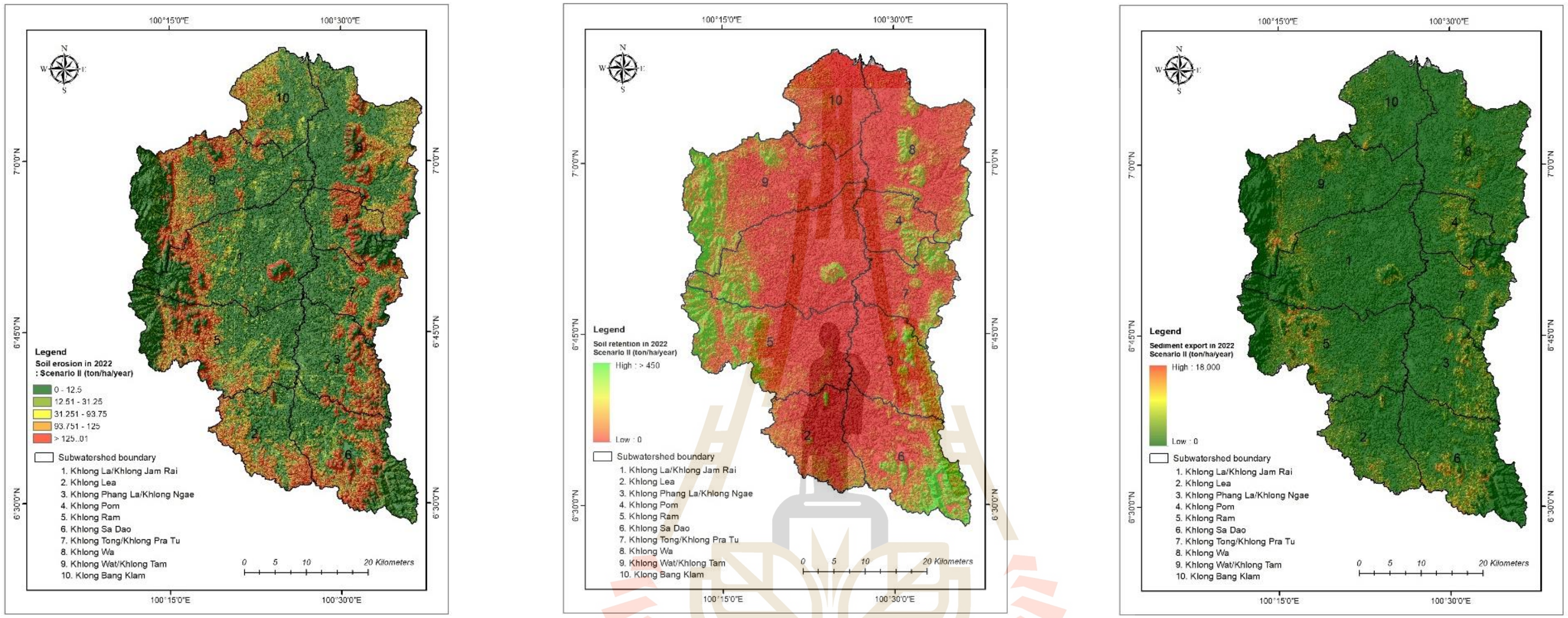
Soil erosion **Sediment retention** **Sediment export**

Figure 7.23 Spatial distribution of soil erosion, sediment retention, and sediment export in 2020 under Scenario II.



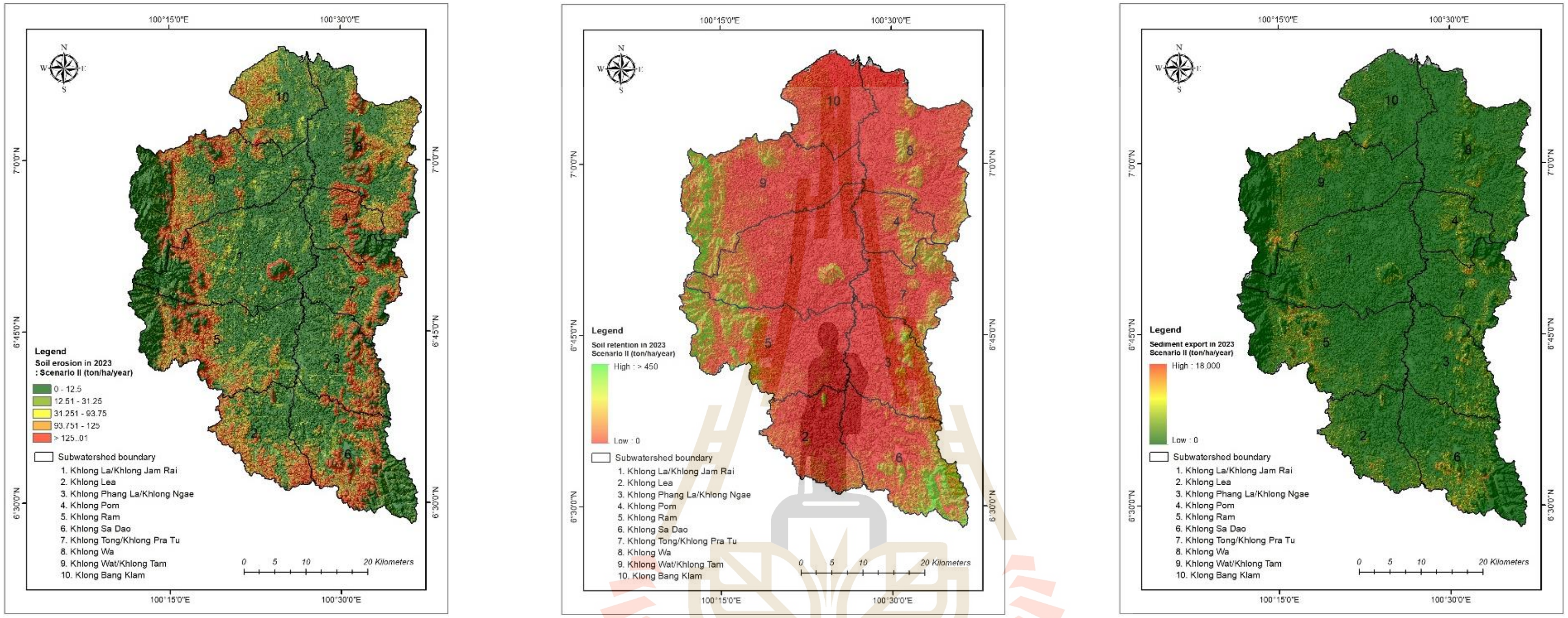
Soil erosion **Sediment retention** **Sediment export**

Figure 7.24 Spatial distribution of soil erosion, sediment retention, and sediment export in 2021 under Scenario II.



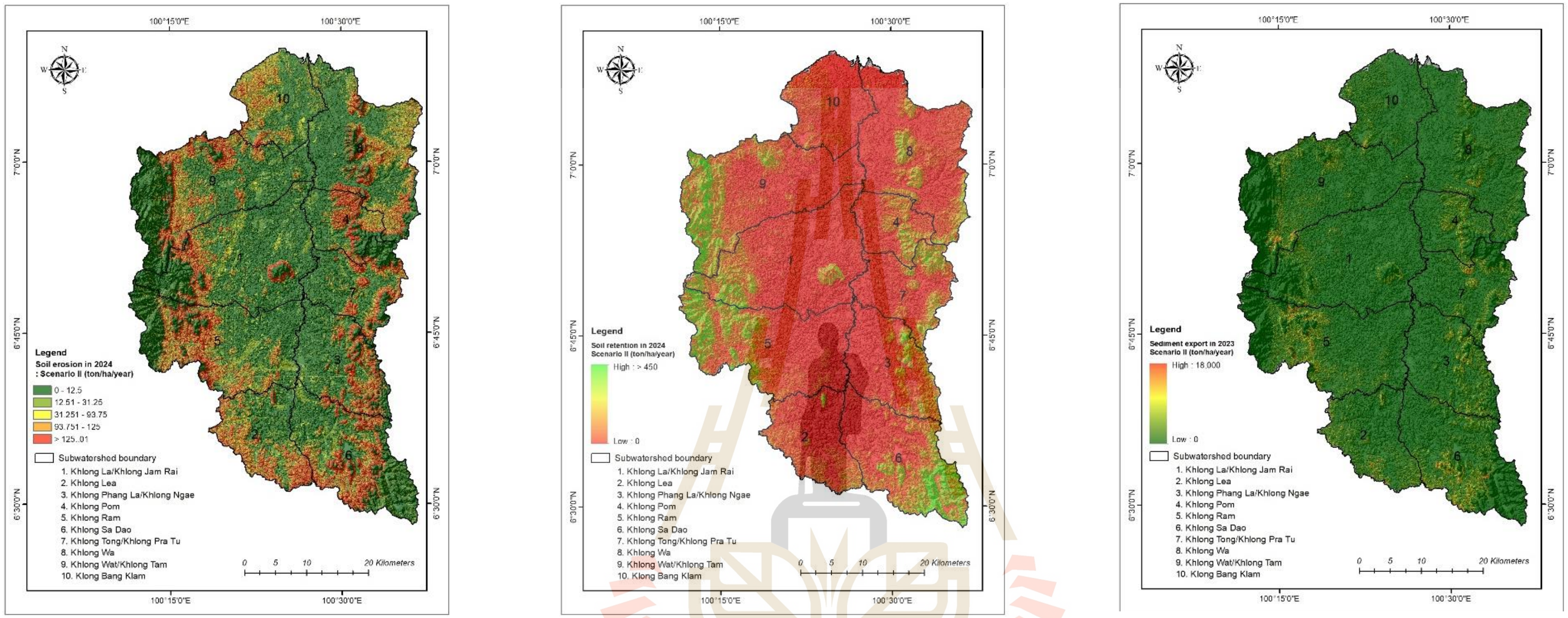
Soil erosion **Sediment retention** **Sediment export**

Figure 7.25 Spatial distribution of soil erosion, sediment retention, and sediment export in 2022 under Scenario II.



Soil erosion **Sediment retention** **Sediment export**

Figure 7.26 Spatial distribution of soil erosion, sediment retention, and sediment export in 2023 under Scenario II.



Soil erosion **Sediment retention** **Sediment export**

Figure 7.27 Spatial distribution of soil erosion, sediment retention, and sediment export in 2024 under Scenario II.

Table 7.34 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2018).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,284,665.94	9,173.25	903,798.94	2,524.08	71,722.95	200.30
2. Khlong Lea	166.50	1,926,816.31	11,572.47	166,150.12	997.90	36,291.56	217.97
3. Khlong Phang La/Khlong Ngae	188.88	2,236,698.09	11,841.90	337,138.21	1,784.93	51,951.24	275.05
4. Khlong Pom	103.13	1,259,031.93	12,208.20	293,096.67	2,842.01	37,989.53	368.37
5. Khlong Ram	324.94	3,238,700.79	9,967.07	1,463,105.06	4,502.69	70,188.69	216.01
6. Khlong Sa Dao	259.17	3,067,709.18	11,836.67	1,679,673.85	6,480.97	65,240.52	251.73
7. Khlong Tong/Khlong Pra Tu	161.58	1,826,097.85	11,301.51	489,629.37	3,030.26	49,444.75	306.01
8. Khlong Wa	325.83	2,005,833.72	6,156.07	426,703.18	1,309.59	44,171.28	135.57
9. Khlong Wat/Khlong Tam	352.14	2,583,862.89	7,337.60	2,174,234.47	6,174.35	57,859.97	164.31
10. Klong Bang Klam	165.80	625,398.20	3,772.00	42,159.56	254.28	7,546.18	45.51
Total	**2,406.04**	**22,054,814.91**	**9,166.44**	**7,975,689.42**	**3,314.86**	**492,406.68**	**204.65**

Table 7.35 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2019).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	2,930,684.05	8,184.67	826,273.94	2,307.58	63,398.94	177.06
2. Khlong Lea	166.50	1,789,253.20	10,746.27	154,674.00	928.97	33,701.60	202.41
3. Khlong Phang La/Khlong Ngae	188.88	2,060,693.40	10,910.07	315,236.32	1,668.98	47,852.79	253.35
4. Khlong Pom	103.13	1,123,937.86	10,898.26	271,496.36	2,632.56	34,037.80	330.05
5. Khlong Ram	324.94	2,895,578.69	8,911.12	1,336,954.54	4,114.47	61,797.25	190.18
6. Khlong Sa Dao	259.17	2,774,378.03	10,704.86	1,593,656.44	6,149.08	59,220.83	228.50
7. Khlong Tong/Khlong Pra Tu	161.58	1,579,548.17	9,775.64	456,943.23	2,827.97	41,764.31	258.47
8. Khlong Wa	325.83	1,762,748.89	5,410.03	395,397.42	1,213.51	37,559.90	115.27
9. Khlong Wat/Khlong Tam	352.14	2,280,597.02	6,476.39	1,974,989.74	5,608.54	51,092.51	145.09
10. Klong Bang Klam	165.80	569,795.90	3,436.65	38,444.24	231.87	6,873.68	41.46
Total	**2,406.04**	**19,767,215.19**	**8,215.66**	**7,364,066.22**	**3,060.66**	**437,299.60**	**181.75**

Table 7.36 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2020).

Sub-watershed	Area (km²)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,039,947.13	8,489.81	883,280.33	2,466.78	64,623.17	180.48
2. Khlong Lea	166.50	1,898,773.25	11,404.04	164,730.63	989.37	35,597.34	213.80
3. Khlong Phang La/Khlong Ngae	188.88	2,141,218.96	11,336.40	334,631.59	1,771.66	49,232.97	260.66
4. Khlong Pom	103.13	1,143,378.94	11,086.77	288,966.54	2,801.96	34,451.89	334.06
5. Khlong Ram	324.94	2,991,815.27	9,207.29	1,426,911.90	4,391.31	62,610.76	192.68
6. Khlong Sa Dao	259.17	2,822,203.43	10,889.39	1,663,582.32	6,418.88	59,139.19	228.19
7. Khlong Tong/Khlong Pra Tu	161.58	1,596,977.59	9,883.51	483,213.77	2,990.55	41,450.97	256.54
8. Khlong Wa	325.83	1,782,477.59	5,470.58	421,183.95	1,292.65	37,170.73	114.08
9. Khlong Wat/Khlong Tam	352.14	2,358,317.75	6,697.10	2,101,416.46	5,967.56	51,686.70	146.78
10. Klong Bang Klam	165.80	610,687.21	3,683.28	41,326.56	249.26	7,345.11	44.30
Total	**2,406.04**	**20,385,797.11**	**8,472.76**	**7,809,244.04**	**3,245.68**	**443,308.82**	**184.25**

Table 7.37 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2021).

Sub-watershed	Area (km²)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	2,910,074.53	8,127.11	873,654.27	2,439.90	60,923.38	170.14
2. Khlong Lea	166.50	1,854,624.97	11,138.89	161,916.32	972.47	34,587.64	207.73
3. Khlong Phang La/Khlong Ngae	188.88	2,073,650.96	10,978.67	332,178.30	1,758.67	47,559.78	251.80
4. Khlong Pom	103.13	1,094,218.52	10,610.09	287,187.30	2,784.71	32,690.83	316.99
5. Khlong Ram	324.94	2,858,409.02	8,796.73	1,412,586.46	4,347.22	59,369.28	182.71
6. Khlong Sa Dao	259.17	2,704,799.26	10,436.39	1,680,811.09	6,485.36	56,164.39	216.71
7. Khlong Tong/Khlong Pra Tu	161.58	1,522,177.55	9,420.58	483,819.43	2,994.30	38,990.39	241.31
8. Khlong Wa	325.83	1,673,612.39	5,136.46	418,977.58	1,285.88	34,481.38	105.83
9. Khlong Wat/Khlong Tam	352.14	2,269,015.17	6,443.50	2,088,466.89	5,930.79	49,147.28	139.57
10. Klong Bang Klam	165.80	594,894.70	3,588.03	40,395.18	243.64	7,128.95	43.00
Total	**2,406.04**	**19,555,477.09**	**8,127.66**	**7,779,992.81**	**3,233.53**	**421,043.29**	**174.99**

Table 7.38 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2022).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,050,696.62	8,519.83	945,227.46	2,639.78	62,788.71	175.35
2. Khlong Lea	166.50	1,988,319.62	11,941.86	174,385.90	1,047.36	36,999.07	222.22
3. Khlong Phang La/Khlong Ngae	188.88	2,191,083.27	11,600.40	357,913.84	1,894.93	50,166.70	265.60
4. Khlong Pom	103.13	1,141,357.90	11,067.18	309,522.16	3,001.28	34,025.51	329.93
5. Khlong Ram	324.94	2,996,218.15	9,220.84	1,536,299.85	4,727.95	61,968.11	190.71
6. Khlong Sa Dao	259.17	2,828,632.63	10,914.20	1,810,794.50	6,986.90	58,088.40	224.13
7. Khlong Tong/Khlong Pra Tu	161.58	1,587,689.87	9,826.03	521,767.06	3,229.16	40,014.21	247.64
8. Khlong Wa	325.83	1,702,955.32	5,226.51	450,095.22	1,381.38	34,472.55	105.80
9. Khlong Wat/Khlong Tam	352.14	2,378,748.45	6,755.12	2,279,175.67	6,472.36	51,060.20	145.00
10. Klong Bang Klam	165.80	631,890.66	3,811.16	43,071.87	259.78	7,555.50	45.57
Total	**2,406.04**	**20,497,592.51**	**8,519.22**	**8,428,253.52**	**3,502.96**	**437,138.96**	**181.68**

Table 7.39 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2023).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	2,938,967.28	8,207.80	925,103.89	2,583.58	59,535.46	166.27
2. Khlong Lea	166.50	1,937,836.02	11,638.65	171,066.87	1,027.43	35,458.21	212.96
3. Khlong Phang La/Khlong Ngae	188.88	2,104,343.67	11,141.17	349,751.55	1,851.71	47,733.25	252.72
4. Khlong Pom	103.13	1,093,036.89	10,598.63	303,666.28	2,944.50	32,561.22	315.73
5. Khlong Ram	324.94	2,869,700.18	8,831.48	1,494,270.23	4,598.60	58,399.44	179.72
6. Khlong Sa Dao	259.17	2,690,347.68	10,380.63	1,753,331.92	6,765.18	54,526.46	210.39
7. Khlong Tong/Khlong Pra Tu	161.58	1,518,749.28	9,399.36	509,856.08	3,155.44	37,637.47	232.93
8. Khlong Wa	325.83	1,598,900.42	4,907.16	442,739.39	1,358.80	31,701.35	97.29
9. Khlong Wat/Khlong Tam	352.14	2,291,644.65	6,507.77	2,209,660.39	6,274.95	48,639.21	138.12
10. Klong Bang Klam	165.80	624,665.34	3,767.58	42,773.82	257.98	7,442.31	44.89
Total	**2,406.04**	**19,668,191.43**	**8,174.51**	**8,202,220.40**	**3,409.01**	**413,634.38**	**171.92**

Table 7.40 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario II, 2024).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	2,919,818.53	8,154.32	939,291.27	2,623.21	58,398.18	163.09
2. Khlong Lea	166.50	1,979,826.25	11,890.85	176,052.34	1,057.37	35,839.11	215.25
3. Khlong Phang La/Khlong Ngae	188.88	2,113,272.42	11,188.44	358,771.11	1,899.47	47,777.43	252.95
4. Khlong Pom	103.13	1,083,620.02	10,507.32	308,554.04	2,991.89	31,924.03	309.55
5. Khlong Ram	324.94	2,857,813.09	8,794.89	1,520,876.95	4,680.49	57,888.58	178.15
6. Khlong Sa Dao	259.17	2,704,693.90	10,435.98	1,810,193.79	6,984.58	54,375.39	209.81
7. Khlong Tong/Khlong Pra Tu	161.58	1,513,956.85	9,369.70	519,732.71	3,216.57	36,517.73	226.00
8. Khlong Wa	325.83	1,547,550.23	4,749.56	449,534.64	1,379.66	30,305.10	93.01
9. Khlong Wat/Khlong Tam	352.14	2,257,310.37	6,410.26	2,233,736.49	6,343.32	47,517.74	134.94
10. Klong Bang Klam	165.80	627,829.02	3,786.66	43,255.09	260.89	7,459.53	44.99
Total	**2,406.04**	**19,605,690.68**	**8,148.53**	**8,359,998.44**	**3,474.59**	**408,002.81**	**169.57**

As results (Tables 7.27 to 7.33), it also reveals that during 2018 to 2024 miscellaneous land (bare land and abandoned mine) generates the highest average soil erosion with values between 24,089.57 tons/km^2 in 2019 and 26,861.75 tons/km^2 in 2024 while evergreen forest generates the lowest average soil erosion with values between 2.82 tons/km^2 in 2019 and 3.10 tons/km^2 in 2018. Meanwhile evergreen forest retains the highest average sediment retention with values between 15,127.31 tons/km^2 in 2024 and 17,438.09 tons/km^2 in 2018 while marsh and swamp retains the lowest average sediment retention with values between 291.27 tons/km^2 in 2019 and 367.58 tons/km^2 in 2024. In the meantime, miscellaneous land (bare land and abandoned mine) generates the highest average sediment export with values between 556.09 tons/km^2 in 2019 and of 608.20 tons/km^2 in 2018 while evergreen forest generates the lowest average sediment export with value of 0.01 tons/km^2 between 2018 and 2024. This finding also suggests the influence of LULC types on soil erosion, sediment retention, and sediment export as mentioned in early section.

In addition, at sub-watershed (Tables 7.34 to 7.40), it reveals that during 2018 to 2024 Khlong Pom sub-watershed generates the highest average soil erosion with minimum value of 10,507.32 tons/km^2 in 2024 and the highest average soil erosion with maximum value of 12,208.20 tons/km^2 in 2018 while Khlong Bang Klam sub-watershed generates the lowest average soil erosion with minimum and maximum values between 3,436.65 tons/km^2 in 2019 and 3,811.16 tons/km^2 in 2022. Meanwhile, Khlong Sa Dao sub-watershed retains the highest average sediment retention with minimum and maximum values between 6,149.08 tons/km^2 in 2019 and 6,986.90

tons/km^2 in 2022 while Klong Bang Klam sub-watershed retains the lowest average sediment retention with minimum and maximum values between 231.87 tons/km^2 in 2019 and 260.89 tons/km^2 in 2024. In the meantime, Khlong Pom sub-watershed delivers the highest average sediment export with minimum and maximum values between 309.55 tons/km^2 in 2024 and 368.37 tons/km^2 in 2018 while Klong Bang Klam sub-watershed delivers the lowest average sediment export with minimum and maximum values between 41.46 tons/km^2 in 2019 and 45.57 tons/km^2 in 2022.

Furthermore, it can be observed that under Scenario II (Forest conservation and prevention) the highest average soil erosion frequently occurs at Khlong La/Khlong Jam Rai sub-watershed, except in 2018 and 2019 while the lowest average soil erosion always occurs at Khlong Bang Klam sub-watershed. Likewise the highest average sediment retention always occurs at Khlong Sa Dao sub-watershed and the lowest average sediment retention always occurs at Klong Bang Klam sub-watershed. Similarly, the highest average sediment export always occurs at Khlong Pom sub-watershed and the lowest average sediment export always occurs at Klong Bang Klam sub-watershed. This finding suggest that variation of predictive annual rainfall during 2018 to 2024 still leads to soil erosion, sediment retention, and sediment export under this scenario. However, since LULC data of Scenario II is simulated based on annual rate of LULC change from transition area matrix between 2010 and 2017 for some LULC types and transformation of forest conservation and prevention policy, particular conversion of rubber plantation and miscellaneous land into evergreen forest in the future, it exhibits dramatic LULC change under this scenario.

7.6 Sediment retention estimation of predictive LULC of Scenario III

Estimation of total and average soil erosion, sediment retention and sediment export with water yield of predictive LULC between 2018 and 2024 of Scenario III: Agriculture production extension is presented in Table 7.41.

It was found that the highest total and average soil erosion are 22.57 million tons and 9,380.56 tons/km^2 occurring in 2022 while the lowest total and average soil erosion are 20.64 million tons and 8,578.79 tons/km^2 occurring in 2019, respectively. Likewise, the highest total and average sediment export are 0.50 million tons and 209.58 tons/km^2 occurring in 2022 while the lowest total and average sediment export occurring in 2019 is about 0.46 million tons and 191.32 tons/km^2. Meanwhile, the highest total and average sediment retention are 8.41 million tons and 3,495.42 tons/km^2 occurring in 2022 while the lowest total and average sediment retention are 7.36 million tons and 3,058.07 tons/km^2 occurring in 2019, respectively. These results indicate the influence of dynamic factor of RUSLE model, which includes rainfall erosivity (R), soil erodibility (K), slope length-gradient factor (LS) and cover factor (C) and practice factor (P) for erosion control practice from LULC data on soil erosion as a budget of sediment retention and sediment export like Scenario I and II.

In addition, simple linear regression between average water yield and soil erosion, sediment retention, sediment export between 2018 and 2024 of Scenario III were examined. It was found that the relationship between average water yield and average soil erosion shows positively high correlation with R^2 of 0.7967 (Figure 7.28). The simple linear equation is as follows:

$$y = 7,937.7x + 3309.8 \quad (7.9)$$

Where, x is average water yield in m^3 and y is average soil erosion in tons.

Table 7.41 Estimation of soil erosion, sediment retention, and sediment export with water yield (2018-2024) under Scenario III.

Year	Area	Soil erosion		Sediment retention		Sediment export		Water yield	
	km^2	Total (mil. tons)	Average (tons)	Total (mil. tons)	Average (tons)	Total (mil. tons)	Average (tons)	Total (mill m^3)	Average (mil.m^3)
2018	2,406.04	22.50	9,352.96	7.97	3,313.82	0.50	208.52	1,756.38	0.73
2019	2,406.04	20.64	8,578.79	7.36	3,058.07	0.46	191.32	1,619.03	0.67
2020	2,406.04	21.84	9,076.33	7.80	3,240.85	0.49	202.15	1,730.70	0.72
2021	2,406.04	21.33	8,866.48	7.77	3,227.32	0.48	197.99	1,700.84	0.71
2022	2,406.04	22.57	9,380.56	8.41	3,495.42	0.50	209.58	1,829.00	0.76
2023	2,406.04	22.06	9,169.52	8.18	3,400.00	0.49	205.31	1,799.99	0.75
2024	2,406.04	22.20	9,226.04	8.34	3,464.58	0.50	206.65	1,834.82	0.76

Likewise, the relationship between average water yield and average sediment retention shows positively very high correlation with R^2 of 0.9831 (Figure 7.29). The simple linear equation is as follows:

$$y = 4{,}736.8x - 136.76 \quad (7.10)$$

Where, x is average water yield in m^3 and y is average sediment retention in tons.

Meanwhile, the relationship between average water yield and average sediment export shows positively very high correlation with R^2 of 0.8410 (Figure 7.30). The simple linear equation is as follows:

$$y = 185.89x + 67.637 \quad (7.11)$$

Where, x is average water yield in m^3 and y is average sediment export in tons.

These findings infers the influence of rainfall as main factor of water yield on soil erosion, sediment retention and sediment export under this scenario. Herewith, soil erosion, sediment retention and sediment export as dependent variables can be predictable from water yield as independent variable about 79.67%, 98.31 %, and 84.10%, respectively.

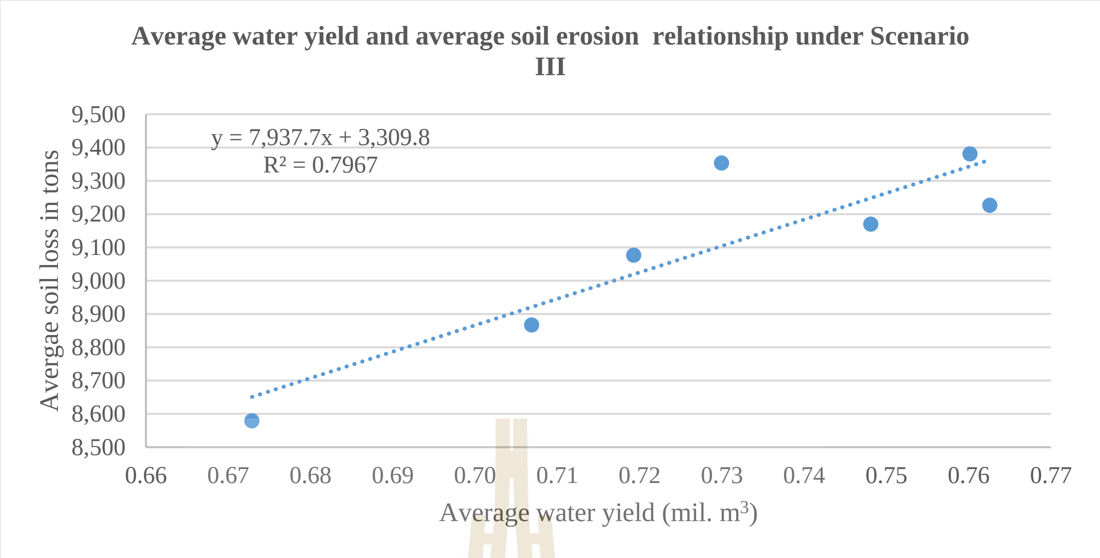


Figure 7.28 Relationship between average water yield and average soil loss under scenario III.

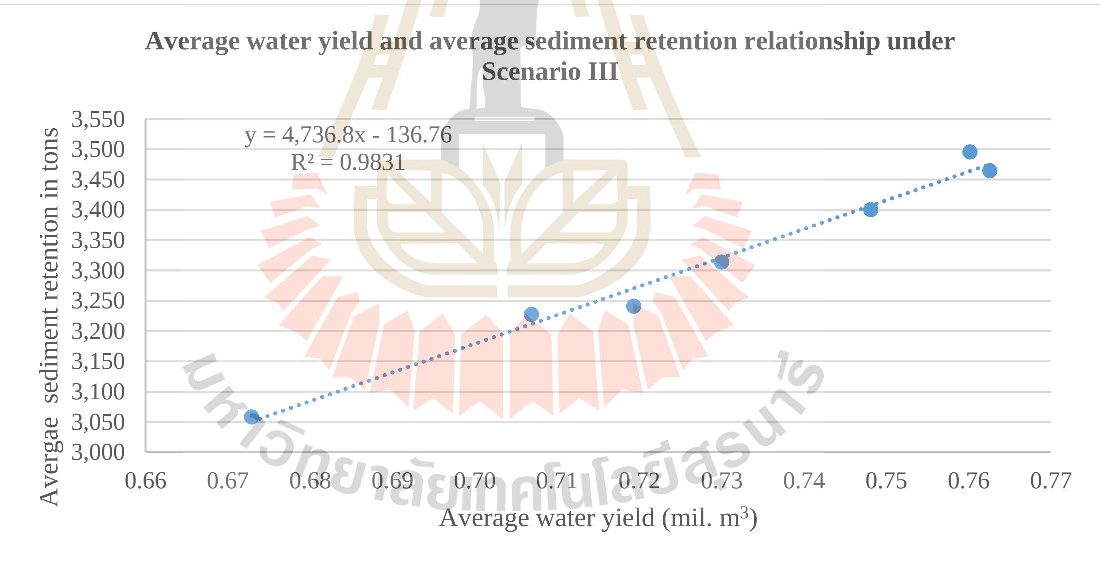


Figure 7.29 Relationship between average water yield and average sediment retention under scenario III.

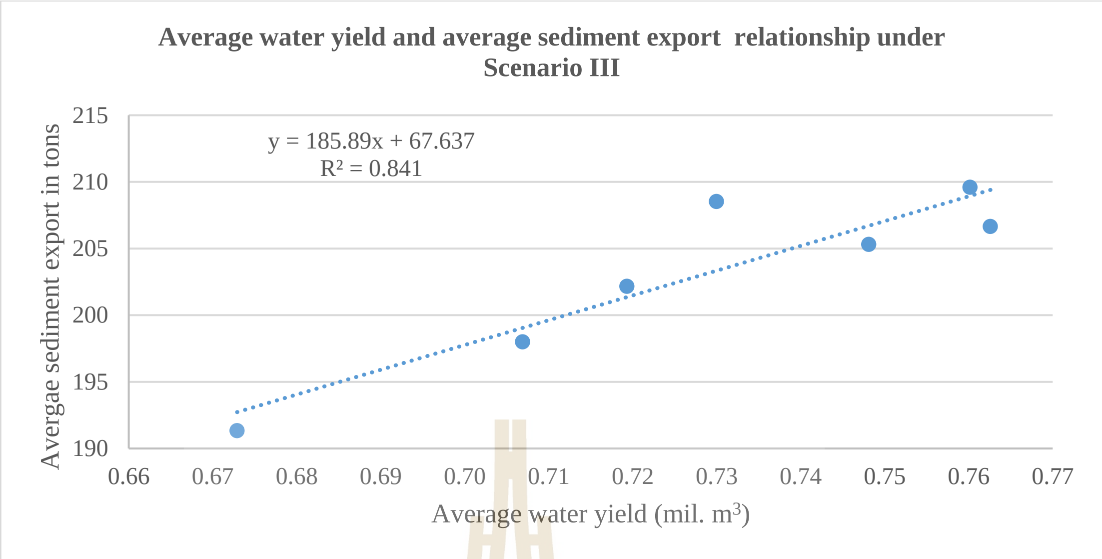


Figure 7.30 Relationship between average water yield and average sediment export under scenario III.

The contribution of the predictive LULC of Scenario III on soil erosion, sediment retention, sediment export between 2018 and 2024 is summarized in Tables 7.42 to 7.48 and the spatial distribution of soil erosion, sediment retention and sediment export of the predictive LULC between 2018 and 2024 of Scenario III is displayed in Figures 7.31 to 7.37. Detail of soil erosion, sediment retention and sediment export in each sub-watershed from predictive LULC of Scenario III between 2018 and 2024 are presented in Tables 7.49 to 7.55.

Table 7.42 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2018 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,697.51	52.64	34.20	257.55	40.28	133.43	2,236.02
Total soil loss (tons)	28,981.71	18,215,607.35	502,711.50	177,100.82	798.50	110,426.97	3,467,966.70	22,503,593.56
Average soil loss (tons/km^2)	1,420.32	10,730.76	9,549.99	5,178.39	3.10	2,741.65	25,990.42	10,064.13
Total sediment retention (tons)	12,455.62	3,278,131.12	79,663.97	35,722.42	4,454,494.49	12,920.54	99,792.26	7,973,180.41
Average sediment retention (tons/km^2)	610.42	1,931.14	1,513.37	1,044.52	17,295.82	320.79	747.89	3,565.79
Total sediment export (tons)	554.95	405,322.43	11,606.77	4,663.98	1.39	1,484.95	78,064.74	501,699.21
Average sediment export (tons/km^2)	27.20	238.77	220.49	136.37	0.01	36.87	585.05	224.37

Table 7.43 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2019 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,669.07	86.92	34.20	257.55	39.56	123.46	2,231.16
Total soil loss (tons)	26,501.15	16,589,071.70	822,813.62	163,301.67	736.01	99,777.97	2,938,718.43	20,640,920.55
Average soil loss (tons/km^2)	1,298.76	9,939.13	9,466.60	4,774.90	2.86	2,522.19	23,803.48	9,251.21
Total sediment retention (tons)	11,688.16	2,993,562.91	118,192.59	33,162.35	4,103,912.41	12,090.31	85,239.66	7,357,848.38
Average sediment retention (tons/km^2)	572.81	1,793.55	1,359.82	969.66	15,934.58	305.62	690.44	3,297.77
Total sediment export (tons)	500.43	370,096.08	18,933.14	4,297.17	1.28	1,343.52	65,156.94	460,328.57
Average sediment export (tons/km^2)	24.52	221.74	217.83	125.65	0.01	33.96	527.77	206.32

Table 7.44 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2020 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,641.78	121.79	34.20	257.55	38.84	116.26	2,231.16
Total soil loss (tons)	28,556.72	17,426,588.84	1,224,207.03	174,663.64	778.08	106,139.89	2,877,079.33	21,838,013.54
Average soil loss (tons/km^2)	1,399.50	10,614.45	10,052.20	5,107.12	3.02	2,732.75	24,746.94	9,787.74
Total sediment retention (tons)	12,563.19	3,150,170.14	163,751.77	35,486.09	4,337,876.90	12,974.74	84,791.59	7,797,614.42
Average sediment retention (tons/km^2)	615.69	1,918.75	1,344.60	1,037.60	16,843.02	334.06	729.33	3,494.87
Total sediment export (tons)	539.14	389,259.31	27,730.37	4,623.47	1.36	1,435.87	62,791.85	486,381.36
Average sediment export (tons/km^2)	26.42	237.10	227.70	135.19	0.01	36.97	540.10	217.99

Table 7.45 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2021 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,608.26	156.50	34.20	257.55	38.66	108.26	2,223.83
Total soil loss (tons)	27,737.83	16,891,124.53	1,551,341.39	171,233.22	778.09	101,918.09	2,588,978.97	21,333,112.13
Average soil loss (tons/km^2)	1,359.36	10,502.75	9,912.88	5,006.82	3.02	2,636.61	23,913.90	9,592.98
Total sediment retention (tons)	14,560.97	3,074,979.62	202,526.98	37,088.06	4,340,074.73	14,903.79	80,917.54	7,765,051.69
Average sediment retention (tons/km^2)	713.60	1,911.99	1,294.12	1,084.45	16,851.55	385.56	747.42	3,491.75
Total sediment export (tons)	522.02	378,809.78	34,790.97	4,535.76	1.31	1,381.32	56,339.49	476,380.64
Average sediment export (tons/km^2)	25.58	235.54	222.31	132.62	0.01	35.73	520.40	214.22

Table 7.46 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2022 under Scenario III.

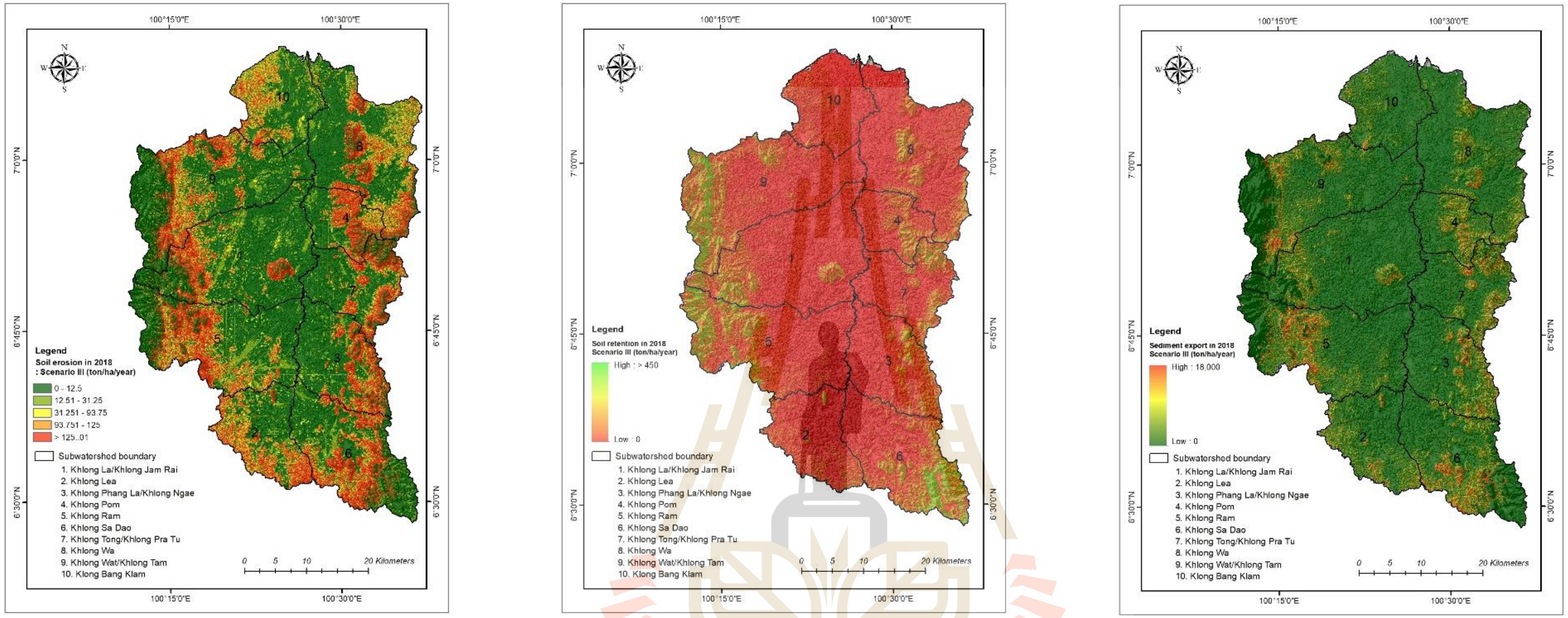
Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,582.08	188.15	34.20	257.93	38.47	95.99	2,217.22
Total soil loss (tons)	29,528.95	17,843,750.00	2,002,938.14	183,687.10	847.09	107,709.68	2,401,536.30	22,569,997.26
Average soil loss (tons/km^2)	1,447.14	11,278.66	10,645.72	5,370.97	3.28	2,799.84	25,019.91	10,179.42
Total sediment retention (tons)	19,712.11	3,253,405.75	257,753.24	43,914.16	4,731,753.36	20,046.90	83,543.82	8,410,129.35
Average sediment retention (tons/km^2)	966.04	2,056.41	1,369.97	1,284.04	18,344.93	521.10	870.38	3,793.10
Total sediment export (tons)	553.70	400,681.21	44,285.21	4,842.79	1.35	1,445.75	52,455.38	504,265.39
Average sediment export (tons/km^2)	27.14	253.26	235.38	141.60	0.01	37.58	546.50	227.43

Table 7.47 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2023 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,548.65	227.99	34.20	257.93	38.47	89.58	2,217.22
Total soil loss (tons)	29,408.67	17,188,285.65	2,390,046.20	181,169.27	820.13	107,255.16	2,165,250.27	22,062,235.35
Average soil loss (tons/km^2)	1,441.25	11,098.92	10,483.35	5,297.35	3.18	2,788.02	24,171.13	9,950.42
Total sediment retention (tons)	19,376.56	3,142,855.87	298,104.80	43,202.24	4,579,094.71	19,710.17	78,184.39	8,180,528.73
Average sediment retention (tons/km^2)	949.60	2,029.42	1,307.56	1,263.22	17,753.07	512.35	872.79	3,689.55
Total sediment export (tons)	551.41	386,989.82	52,552.20	4,780.21	1.31	1,439.32	47,659.47	493,973.74
Average sediment export (tons/km^2)	27.02	249.89	230.51	139.77	0.01	37.41	532.03	222.79

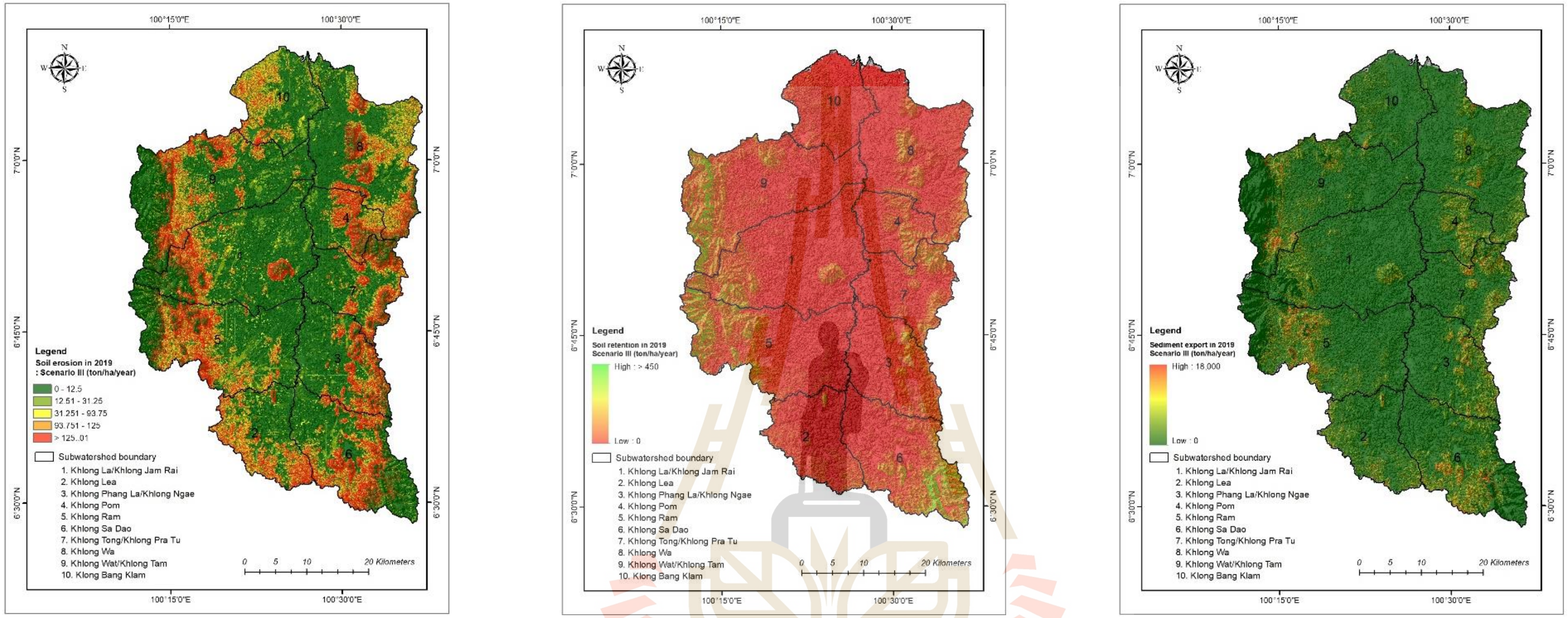
Table 7.48 Contribution of LULC type on soil erosion, sediment retention, sediment export in 2024 under Scenario III.

Year 2018	LULC type							Total
	PD	RP	OP	PO	EF	MS	ML	
Area (km^2)	20.41	1,528.48	257.44	34.20	257.93	36.89	77.87	2,213.21
Total soil loss (tons)	29,792.00	17,303,534.00	2,728,493.86	184,426.15	835.12	104,703.62	1,846,440.37	22,198,225.14
Average soil loss (tons/km^2)	1,460.03	11,320.75	10,598.67	5,392.58	3.24	2,838.46	23,713.35	10,029.88
Total sediment retention (tons)	22,656.43	3,166,279.00	336,336.93	46,921.07	4,665,400.63	22,881.69	75,439.69	8,335,915.43
Average sediment retention (tons/km^2)	1,110.34	2,071.52	1,306.48	1,371.96	18,087.68	620.31	968.85	3,766.44
Total sediment export (tons)	555.59	389,713.74	59,296.28	4,851.86	1.31	1,384.14	41,396.08	497,199.01
Average sediment export (tons/km^2)	27.23	254.97	230.33	141.87	0.01	37.52	531.64	224.65



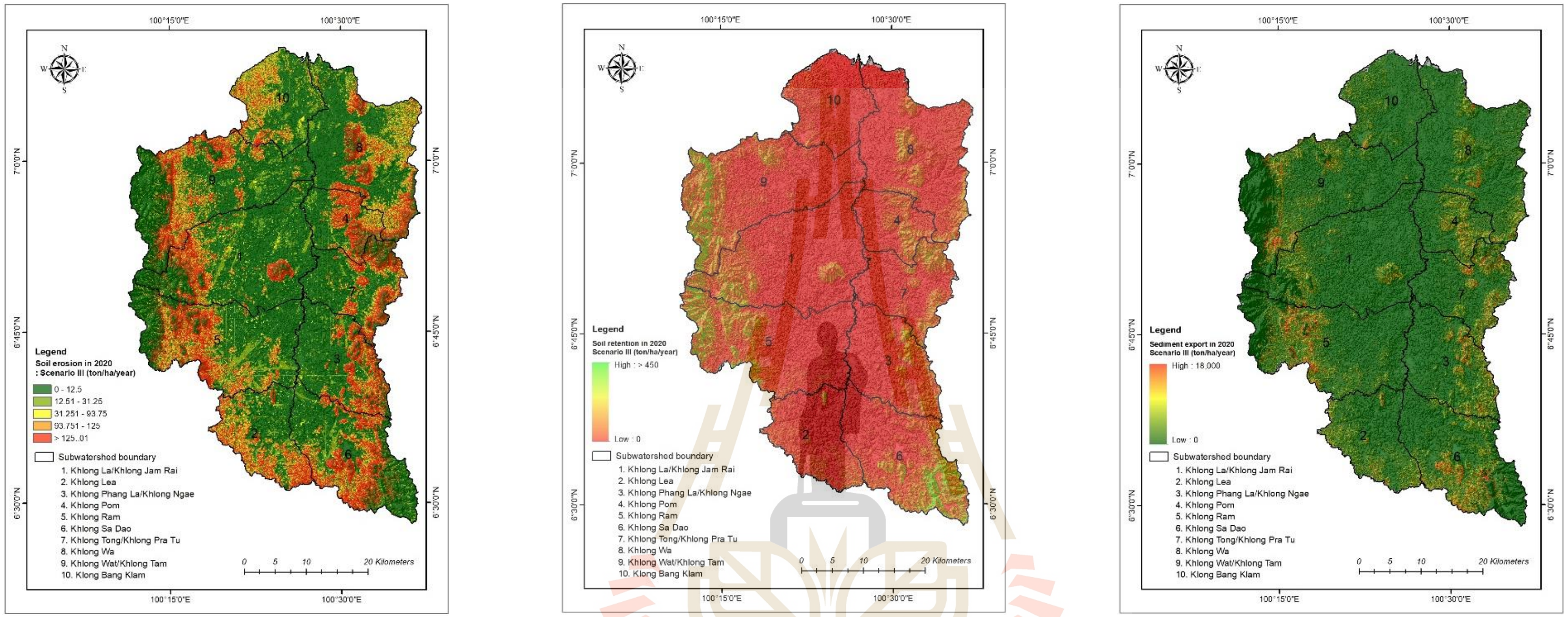
Soil erosion **Sediment retention** **Sediment export**

Figure 7.31 Spatial distribution of soil erosion, sediment retention, and sediment export in 2018 under Scenario III.



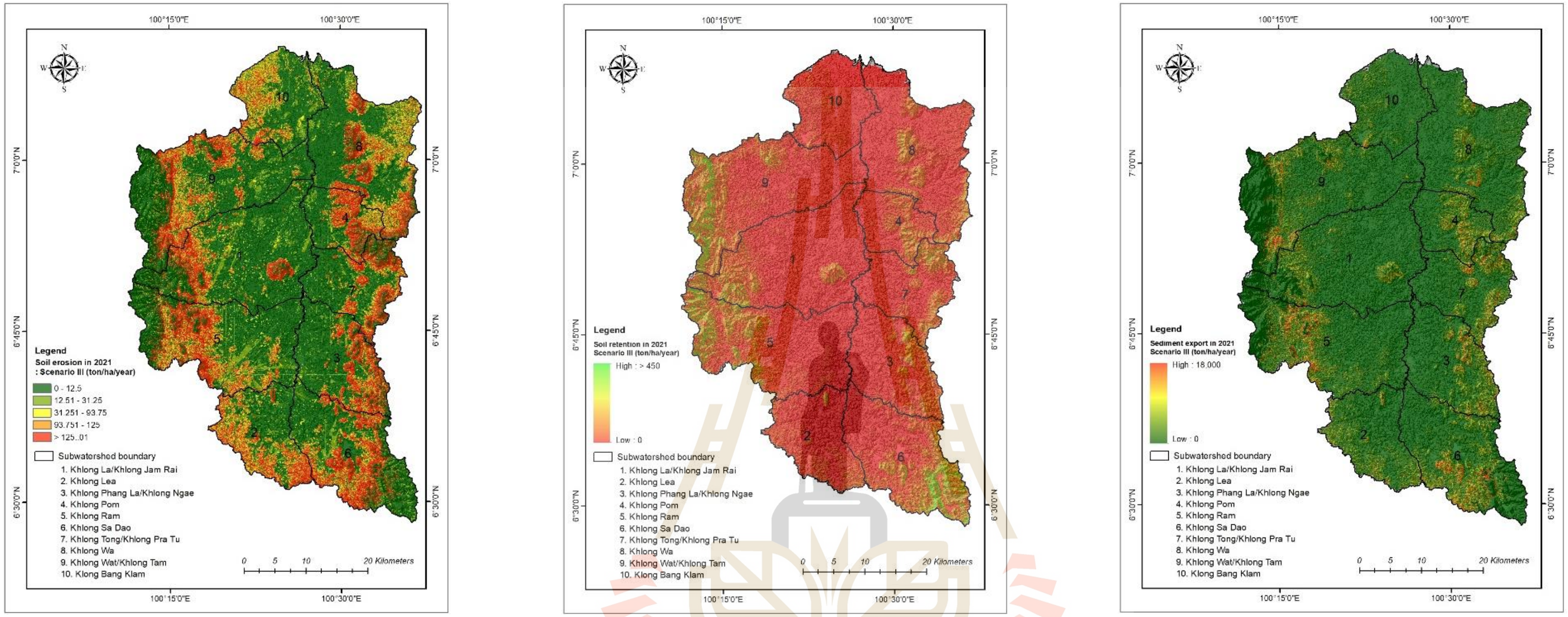
Soil erosion **Sediment retention** **Sediment export**

Figure 7.32 Spatial distribution of soil erosion, sediment retention, and sediment export in 2019 under Scenario III.



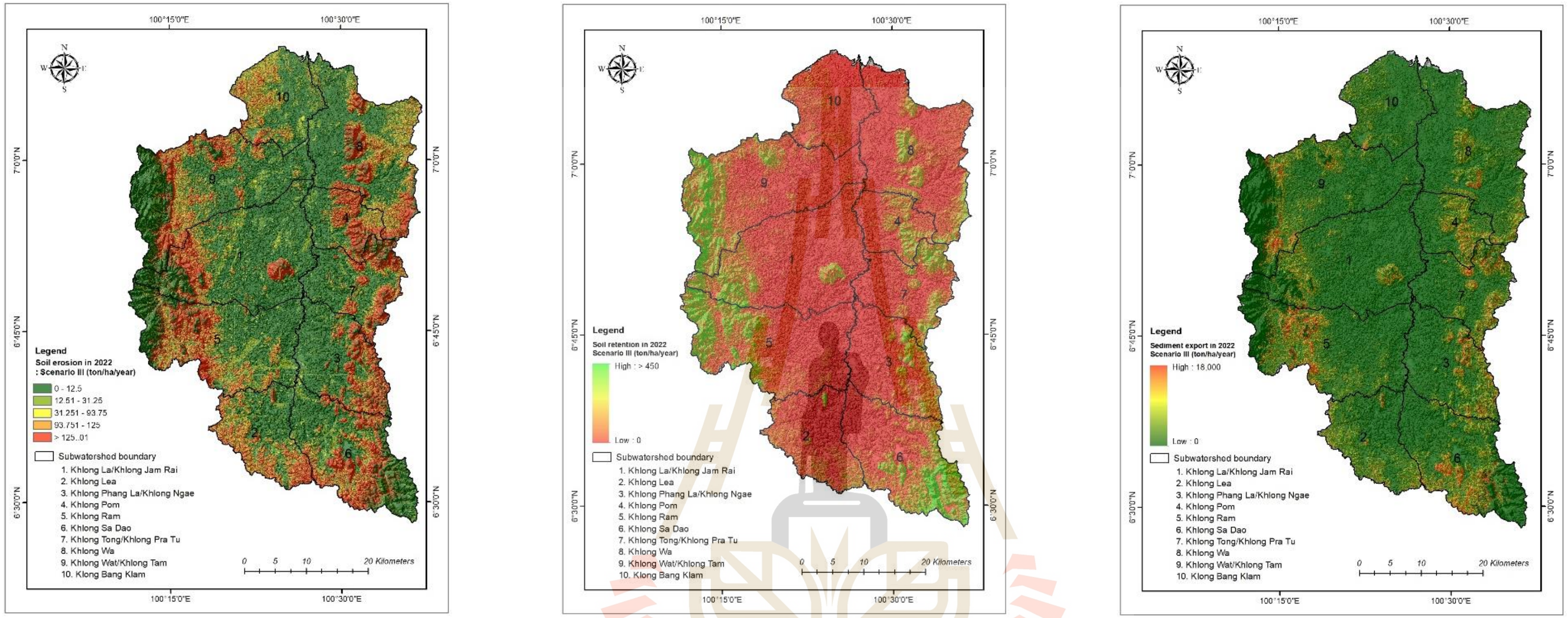
Soil erosion **Sediment retention** **Sediment export**

Figure 7.33 Spatial distribution of soil erosion, sediment retention, and sediment export in 2020 under Scenario III.



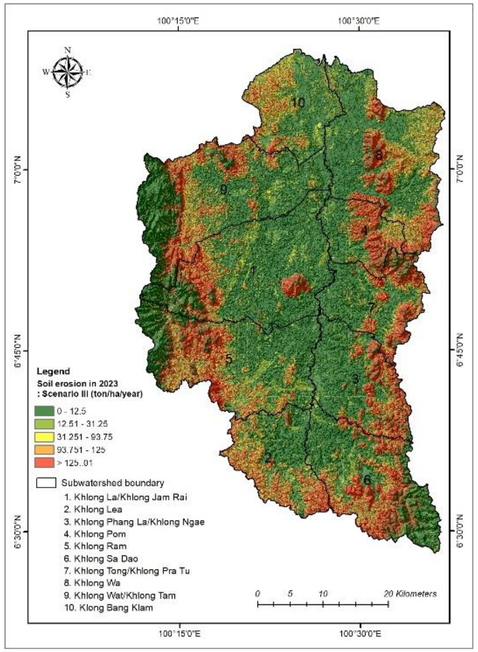
Soil erosion **Sediment retention** **Sediment export**

Figure 7.34 Spatial distribution of soil erosion, sediment retention, and sediment export in 2021 under Scenario III.

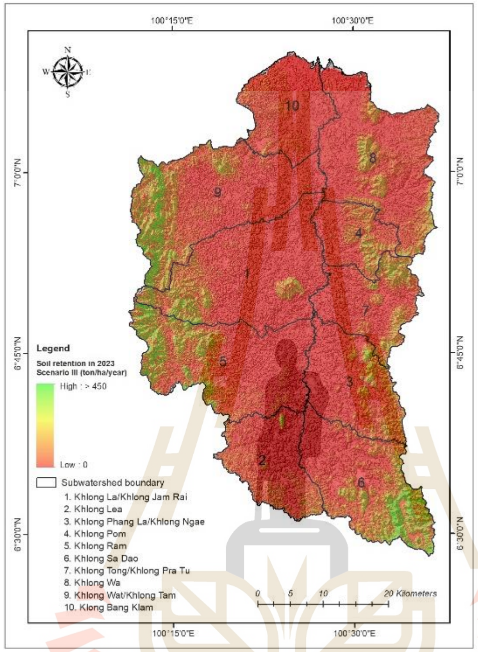


Soil erosion | **Sediment retention** | **Sediment export**

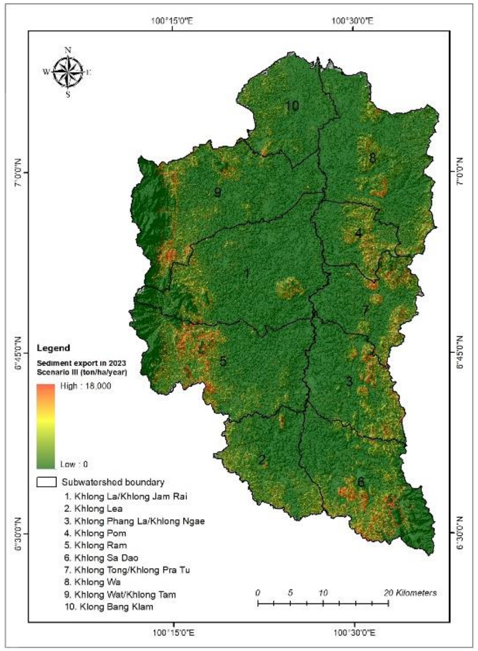
Figure 7.35 Spatial distribution of soil erosion, sediment retention, and sediment export in 2022 under Scenario III.



Soil erosion

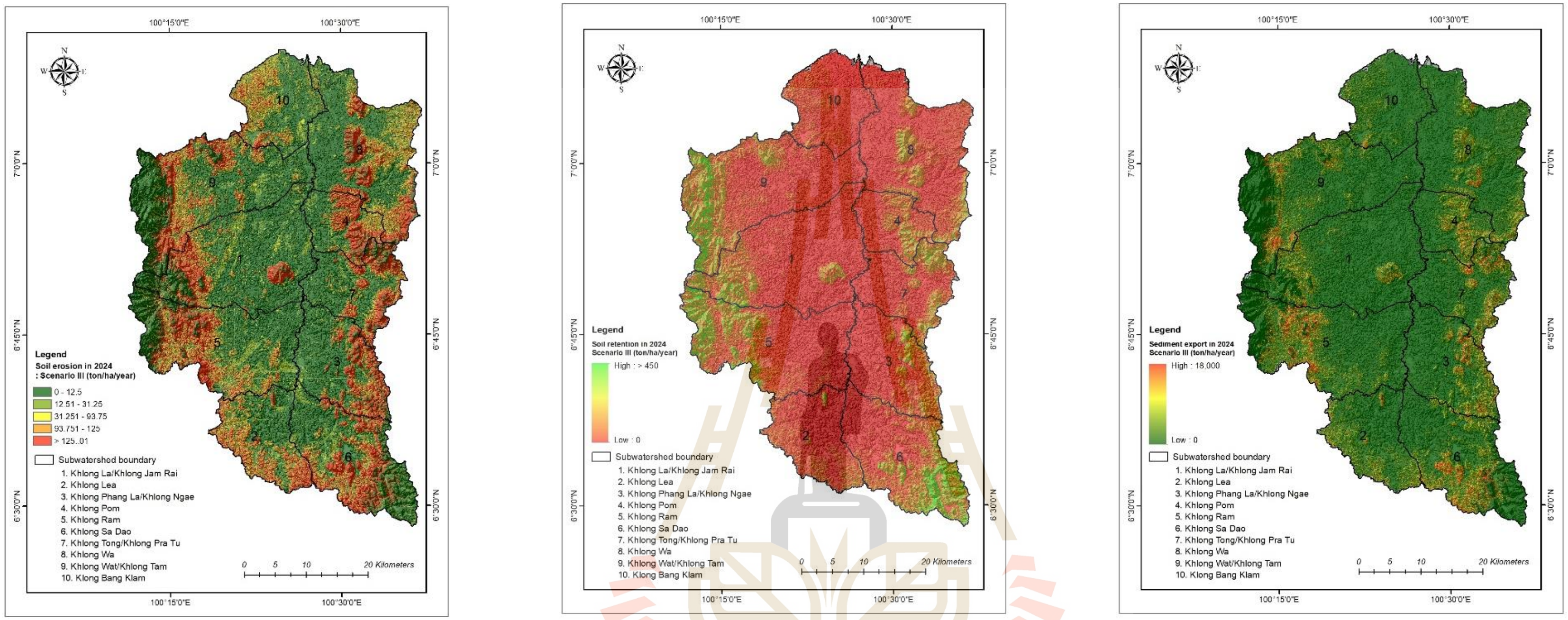


Sediment retention



Sediment export

Figure 7.36 Spatial distribution of soil erosion, sediment retention, and sediment export in 2023 under Scenario III.



Soil erosion **Sediment retention** **Sediment export**

Figure 7.37 Spatial distribution of soil erosion, sediment retention, and sediment export in 2024 under Scenario III.

Table 7.49 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2018).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,297,831.66	9,210.02	903,877.22	2,524.30	71,433.00	199.49
2. Khlong Lea	166.50	1,930,639.60	11,595.43	166,063.12	997.38	36,613.77	219.90
3. Khlong Phang La/Khlong Ngae	188.88	2,203,778.10	11,667.61	337,423.99	1,786.45	50,892.80	269.45
4. Khlong Pom	103.13	1,282,118.50	12,432.06	293,028.20	2,841.35	38,243.11	370.82
5. Khlong Ram	324.94	3,330,888.08	10,250.78	1,462,702.27	4,501.45	71,680.49	220.60
6. Khlong Sa Dao	259.17	3,175,920.46	12,254.20	1,679,251.19	6,479.34	66,805.91	257.77
7. Khlong Tong/Khlong Pra Tu	161.58	1,908,316.95	11,810.35	489,059.40	3,026.73	51,555.75	319.07
8. Khlong Wa	325.83	2,057,852.89	6,315.73	425,916.40	1,307.17	47,085.27	144.51
9. Khlong Wat/Khlong Tam	352.14	2,699,838.06	7,666.95	2,173,650.35	6,172.69	60,023.35	170.45
10. Klong Bang Klam	165.80	616,409.25	3,717.79	42,208.28	254.57	7,365.75	44.43
Total	**2,406.04**	**22,503,593.56**	**9,352.96**	**7,973,180.41**	**3,313.82**	**501,699.21**	**208.52**

Table 7.50 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2019).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	2,982,625.45	8,329.73	826,034.42	2,306.91	64,286.04	179.53
2. Khlong Lea	166.50	1,800,192.43	10,811.97	154,490.05	927.87	34,382.90	206.50
3. Khlong Phang La/Khlong Ngae	188.88	2,025,854.36	10,725.62	315,606.72	1,670.94	46,480.92	246.09
4. Khlong Pom	103.13	1,182,322.41	11,464.39	271,223.14	2,629.92	35,049.73	339.86
5. Khlong Ram	324.94	3,043,116.07	9,365.16	1,335,960.57	4,111.41	65,478.57	201.51
6. Khlong Sa Dao	259.17	2,957,043.56	11,409.67	1,592,857.73	6,146.00	62,178.99	239.92
7. Khlong Tong/Khlong Pra Tu	161.58	1,768,240.01	10,943.43	455,298.82	2,817.79	47,854.71	296.17
8. Khlong Wa	325.83	1,890,260.22	5,801.37	393,679.54	1,208.24	43,922.44	134.80
9. Khlong Wat/Khlong Tam	352.14	2,434,429.07	6,913.24	1,974,183.70	5,606.25	54,077.83	153.57
10. Klong Bang Klam	165.80	556,836.97	3,358.49	38,513.69	232.29	6,616.46	39.91
Total	**2,406.04**	**20,640,920.55**	**8,578.79**	**7,357,848.38**	**3,058.07**	**460,328.57**	**191.32**

Table 7.51 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2020).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,156,067.27	8,814.11	882,479.69	2,464.55	67,588.49	188.76
2. Khlong Lea	166.50	1,897,763.48	11,397.98	164,462.51	987.76	36,590.39	219.76
3. Khlong Phang La/Khlong Ngae	188.88	2,129,755.50	11,275.71	334,751.00	1,772.29	48,790.72	258.32
4. Khlong Pom	103.13	1,257,149.11	12,189.95	288,199.95	2,794.53	37,291.10	361.59
5. Khlong Ram	324.94	3,239,292.21	9,968.89	1,425,047.18	4,385.57	69,517.08	213.94
6. Khlong Sa Dao	259.17	3,100,311.93	11,962.46	1,661,983.13	6,412.71	65,062.12	251.04
7. Khlong Tong/Khlong Pra Tu	161.58	1,860,446.45	11,514.09	480,843.13	2,975.88	50,231.09	310.87
8. Khlong Wa	325.83	2,007,195.35	6,160.25	418,594.43	1,284.70	46,761.51	143.52
9. Khlong Wat/Khlong Tam	352.14	2,591,776.87	7,360.08	2,099,865.13	5,963.15	57,432.31	163.10
10. Klong Bang Klam	165.80	598,255.38	3,608.30	41,388.27	249.63	7,116.57	42.92
Total	**2,406.04**	**21,838,013.54**	**9,076.33**	**7,797,614.42**	**3,240.85**	**486,381.36**	**202.15**

Table 7.52 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2021).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,074,047.73	8,585.05	872,285.83	2,436.08	65,991.66	184.30
2. Khlong Lea	166.50	1,832,538.55	11,006.24	161,655.50	970.90	35,553.63	213.54
3. Khlong Phang La/Khlong Ngae	188.88	2,089,131.27	11,060.63	332,158.09	1,758.57	47,634.64	252.20
4. Khlong Pom	103.13	1,234,700.35	11,972.27	286,131.89	2,774.48	36,599.74	354.89
5. Khlong Ram	324.94	3,164,528.00	9,738.81	1,410,237.37	4,339.99	68,069.58	209.48
6. Khlong Sa Dao	259.17	3,058,921.02	11,802.76	1,678,614.94	6,476.89	64,298.24	248.09
7. Khlong Tong/Khlong Pra Tu	161.58	1,822,927.73	11,281.89	481,035.79	2,977.08	49,300.19	305.11
8. Khlong Wa	325.83	1,933,269.44	5,933.37	415,964.32	1,276.63	45,641.59	140.08
9. Khlong Wat/Khlong Tam	352.14	2,538,901.22	7,209.92	2,086,524.79	5,925.27	56,340.22	159.99
10. Klong Bang Klam	165.80	584,146.81	3,523.20	40,443.19	243.93	6,951.15	41.92
Total	**2,406.04**	**21,333,112.13**	**8,866.48**	**7,765,051.69**	**3,227.32**	**476,380.64**	**197.99**

Table 7.53 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2022).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,249,476.97	9,074.98	943,299.36	2,634.40	69,929.78	195.30
2. Khlong Lea	166.50	1,899,738.31	11,409.84	174,468.96	1,047.86	36,691.44	220.37
3. Khlong Phang La/Khlong Ngae	188.88	2,232,332.57	11,818.79	357,721.87	1,893.91	50,877.71	269.37
4. Khlong Pom	103.13	1,308,413.97	12,687.04	308,262.18	2,989.06	38,692.07	375.18
5. Khlong Ram	324.94	3,356,138.67	10,328.49	1,533,573.22	4,719.56	72,066.68	221.78
6. Khlong Sa Dao	259.17	3,251,046.94	12,544.07	1,807,954.43	6,975.94	68,607.15	264.72
7. Khlong Tong/Khlong Pra Tu	161.58	1,931,719.70	11,955.19	518,497.12	3,208.92	52,125.08	322.60
8. Khlong Wa	325.83	2,030,378.53	6,231.40	446,404.36	1,370.05	48,142.40	147.75
9. Khlong Wat/Khlong Tam	352.14	2,689,748.21	7,638.29	2,276,831.70	6,465.70	59,741.51	169.65
10. Klong Bang Klam	165.80	621,003.39	3,745.50	43,116.13	260.05	7,391.55	44.58
Total	**2,406.04**	**22,569,997.26**	**9,380.56**	**8,410,129.35**	**3,495.42**	**504,265.39**	**209.58**

Table 7.54 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2023).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,184,255.24	8,892.83	922,626.82	2,576.67	68,709.76	191.89
2. Khlong Lea	166.50	1,825,134.20	10,961.77	171,138.14	1,027.86	35,194.25	211.38
3. Khlong Phang La/Khlong Ngae	188.88	2,177,611.33	11,529.07	349,193.39	1,848.76	49,800.48	263.66
4. Khlong Pom	103.13	1,286,319.38	12,472.80	302,163.84	2,929.93	38,125.81	369.69
5. Khlong Ram	324.94	3,273,019.29	10,072.69	1,490,966.75	4,588.44	70,634.50	217.38
6. Khlong Sa Dao	259.17	3,166,268.06	12,216.95	1,749,963.18	6,752.18	67,003.27	258.53
7. Khlong Tong/Khlong Pra Tu	161.58	1,890,415.15	11,699.56	506,235.49	3,133.03	51,047.02	315.92
8. Khlong Wa	325.83	1,999,397.11	6,136.32	438,483.45	1,345.74	47,464.09	145.67
9. Khlong Wat/Khlong Tam	352.14	2,643,833.70	7,507.91	2,206,959.19	6,267.28	58,643.59	166.53
10. Klong Bang Klam	165.80	615,981.89	3,715.21	42,798.48	258.13	7,350.98	44.34
Total	**2,406.04**	**22,062,235.35**	**9,169.52**	**8,180,528.73**	**3,400.00**	**493,973.74**	**205.31**

Table 7.55 Soil erosion, sediment retention and sediment export in each sub-watershed of predictive LULC (Scenario III, 2024).

Sub-watershed	Area (km^2)	Soil erosion (tons)		Sediment retention (tons)		Sediment export (tons)	
		Total	Average	Total	Average	Total	Average
1. Khlong La/Khlong Jam Rai	358.07	3,185,740.60	8,896.98	936,463.84	2,615.31	68,870.09	192.34
2. Khlong Lea	166.50	1,797,215.01	10,794.08	176,508.60	1,060.11	34,149.29	205.10
3. Khlong Phang La/Khlong Ngae	188.88	2,219,229.24	11,749.41	357,968.64	1,895.22	50,749.54	268.69
4. Khlong Pom	103.13	1,296,565.36	12,572.15	306,786.69	2,974.76	38,469.77	373.02
5. Khlong Ram	324.94	3,282,653.51	10,102.34	1,517,366.12	4,669.68	70,891.63	218.17
6. Khlong Sa Dao	259.17	3,247,058.26	12,528.68	1,806,283.93	6,969.49	68,856.32	265.68
7. Khlong Tong/Khlong Pra Tu	161.58	1,898,945.32	11,752.35	515,768.38	3,192.03	51,200.40	316.87
8. Khlong Wa	325.83	2,006,216.34	6,157.25	444,829.92	1,365.22	47,730.00	146.49
9. Khlong Wat/Khlong Tam	352.14	2,644,703.28	7,510.37	2,230,662.51	6,334.59	58,902.84	167.27
10. Klong Bang Klam	165.80	619,898.22	3,738.83	43,276.80	261.02	7,379.12	44.51
Total	**2,406.04**	**22,198,225.14**	**9,226.04**	**8,335,915.43**	**3,464.58**	**497,199.01**	**206.65**

As results (Tables 7.42 to 7.48), it also reveals that during 2018 to 2024 miscellaneous land (bare land and abandoned mine) generates the highest average soil erosion with values between 23,713.35 tons/km^2 in 2019 and 25,990.42 tons/km^2 in 2018 while evergreen forest generates the lowest average soil erosion with values between 2.86 tons/km^2 in 2019 and 3.28 tons/km^2 in 2022. Meanwhile evergreen forest retains the highest average sediment retention with values between 15,934.58 tons/km^2 in 2019 and 18,344.93 tons/km^2 in 2022 while marsh and swamp retains the lowest average sediment retention with values between 305.62 tons/km^2 in 2019 and 620.31 tons/km^2 in 2024. In the meantime, miscellaneous land (bare land and abandoned mine) generates the highest average sediment export with values between 520.40 tons/km^2 in 2019 and 585.05 tons/km^2 in 2018 while evergreen forest generates the lowest average sediment export with value of 0.01 tons/km^2 in this period. This finding suggests the influence of LULC types on soil erosion, sediment retention, and sediment export as mentioned in early section.

In addition, at sub-watershed (Tables 7.49 to 7.55), it reveals that during 2018 to 2024 Khlong Pom sub-watershed generates the highest average soil erosion with minimum and maximum values between 11,464.39 tons/km^2 in 2019 and 12,687.04 tons/km^2 in 2022 while Khlong Bang Klam sub-watershed generates the lowest average soil erosion with minimum and maximum values between 3,358.49 tons/km^2 in 2019 and 3,745.50 tons/km^2 in 2022. Meanwhile, Khlong Sa Dao sub-watershed retains the highest average sediment retention with minimum and maximum values between 6,146.00 tons/km2 in 2019 and 6,975.94 tons/km^2 in 2022 while Klong Bang Klam sub-watershed retains the lowest average sediment retention with minimum and maximum values of 232.29 tons/km^2 in 2019 and 261.02 tons/km^2 in 2024. In the meantime, Khlong Pom sub-watershed delivers the highest average sediment export with minimum and maximum values between 339.86 tons/km^2 in 2019 and 375.18 tons/km^2 in 2022 while Klong Bang Klam sub-watershed delivers the lowest average sediment export with minimum and maximum values of 39.91 tons/km^2 in 2019 and 44.58 tons/km^2 in 2022.

Furthermore, it can be observed that under Scenario III (Agriculture production extension) the highest average soil erosion always occurs at Khlong Pom sub-watershed, while the lowest average soil erosion always occurs at Khlong Bang Klam sub-watershed. Meanwhile, the highest average sediment retention always occurs at Khlong Sa Dao sub-watershed and the lowest average sediment retention always occurs at Klong Bang Klam sub-watershed. Like soil erosion, the highest average sediment export always occurs at Khlong Pom sub-watershed and the lowest average sediment export always occurs at Klong Bang Klam sub-watershed. This finding suggest that variation of predictive annual rainfall during 2018 to 2024 still leads to soil erosion, sediment retention, and sediment export under this scenario. Herein, LULC data of Scenario III is simulated based on annual rate of LULC change from transition area matrix between 2010 and 2017 for some LULC types and transformation of agriculture production extension policy, particular conversion of rubber plantation and miscellaneous land into oil palm plantation in the future. However, it does not exhibit dramatic LULC change under this scenario as Scenario II.

7.7 Comparison of sediment retention estimation among three different scenarios

Under this section, important information of soil erosion, sediment retention, and sediment export between 2018 and 2024 of three different scenarios are here compared and discussed. Table 7.56 summaries average soil erosion, sediment retention, and sediment export between 2018 and 2024 of three different scenarios and they are separately compared and displayed in Figures 7.38 to 7.40, respectively.

Table 7.56 Average soil erosion, sediment retention, and sediment export (tons/km^2) between 2018 and 2024 of three different scenarios.

Year	Soil erosion			Sediment retention			Sediment export		
	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III	Scenario I	Scenario II	Scenario III
2018	9,541.79	9,166.44	9,352.96	3,310.83	3,314.86	3,313.82	219.60	204.65	208.52
2019	8,850.74	8,215.66	8,578.79	3,053.91	3,060.66	3,058.07	206.75	181.75	191.32
2020	9,445.76	8,472.76	9,076.33	3,235.46	3,245.68	3,240.85	222.12	184.25	202.15
2021	9,334.90	8,127.66	8,866.48	3,221.15	3,233.53	3,227.32	220.84	174.99	197.99
2022	10,066.07	8,519.22	9,380.56	3,487.20	3,502.96	3,495.42	240.05	181.68	209.58
2023	9,891.33	8,174.51	9,169.52	3,391.58	3,409.01	3,400.00	236.47	171.92	205.31
2024	10,135.12	8,148.53	9,226.04	3,454.56	3,474.59	3,464.58	243.75	169.57	206.65
Average	9,609.39	8,403.54	9,092.96	3,307.81	3,320.18	3,314.29	227.08	181.26	203.07

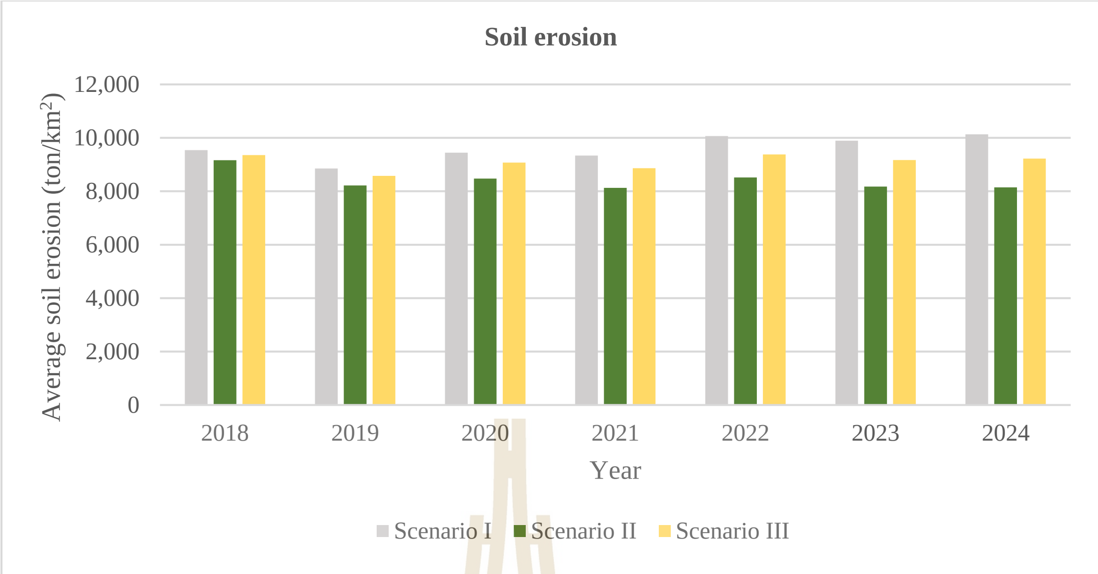


Figure 7.38 Comparison of soil erosion between 2018 and 2024 of three different scenarios.

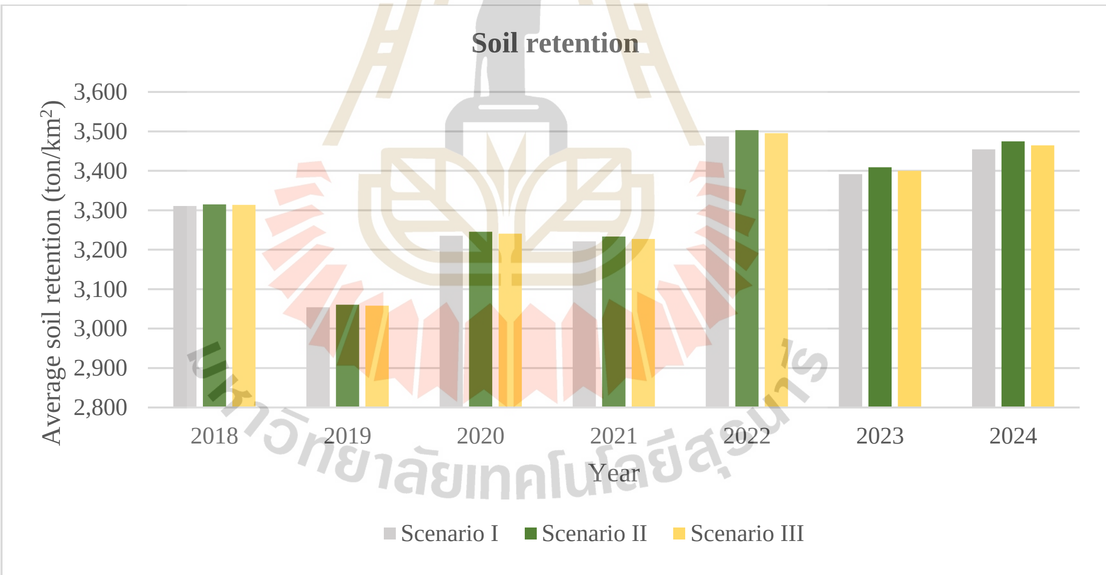


Figure 7.39 Comparison of sediment retention between 2018 and 2024 of three different scenarios.

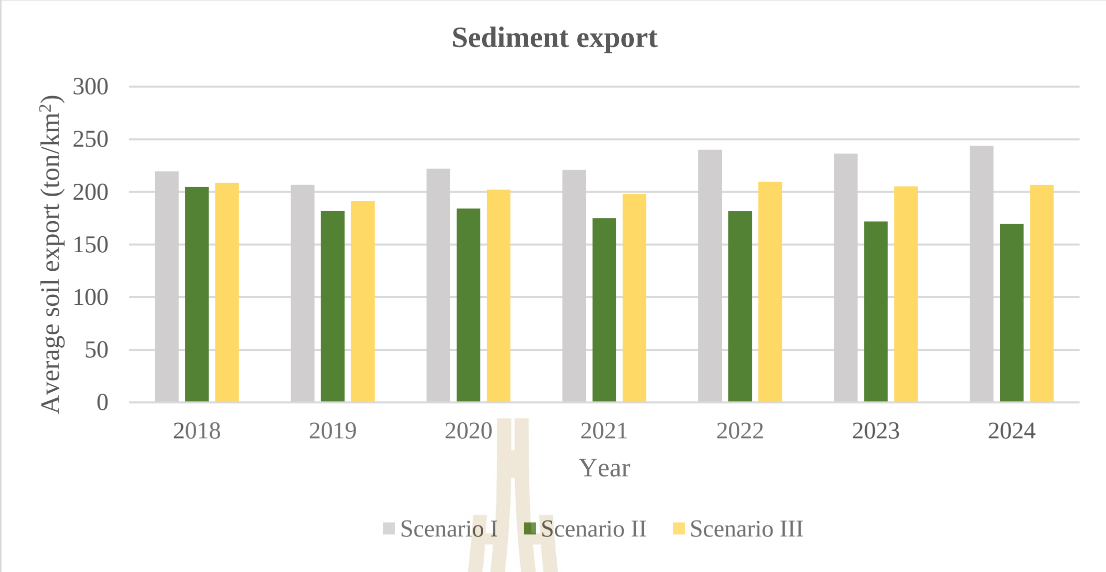


Figure 7.40 Comparison of sediment export between 2018 and 2024 of three different scenarios.

As results, it reveals that the predictive LULC between 2018 and 2024 of Scenario I (Historical LULC evolution) generates the highest annual soil erosion than Scenario II and III with average value of 9,609.39 tons/km^2. In contrast, the predictive LULC between 2018 and 2024 of Scenario II (Forest conservation and prevention) generates the lowest annual soil erosion than Scenario I and Scenario III (Agriculture production extension) with average value of 8,403.54 tons/km^2 since Scenario II increase more evergreen forest than other scenarios. In fact, area of evergreen forest of Scenario II with value of 254.01 km^2 in 2017 increases to 377.33 km^2 in 2024, while area of evergreen forest of Scenario I with value of 254.01 km^2 in 2017 decreases to 215.46 km^2 in 2024.

Likewise, the predictive LULC between 2018 and 2024 of Scenario II retains the highest annual sediment retention than Scenario I and Scenario II with average value of 3,320.18 tons/km^2, since Scenario II generates the lowest soil erosion than other scenarios. In contrast, the predictive LULC between 2018 and 2024 of Scenario I retains the lowest annual sediment retention than Scenario II and III with average value of 3,307.81 tons/km^2.

Similarly, the predictive LULC between 2018 and 2024 of Scenario II delivers the lowest annual sediment export than Scenario I and III with average value of 181.26 tons/km^2, since Scenario II generates the lowest soil erosion than other scenarios. On contrary, the predictive LULC between 2018 and 2024 of Scenario I delivers the highest annual sediment export than Scenario II and III with average value of 227.08 tons/km^2.

Furthermore, the comparison of average sediment export of actual LULC in 2017 and predictive LULC of three different scenarios during 2018 to 2024 and field observation data of sediment export by RID between 2010 and 2017 is displayed again in Figure 7.41. These results clearly show that the predictive LULC Scenarios II can provide minimum soil loss and sediment export and maximum sediment retention in the future.

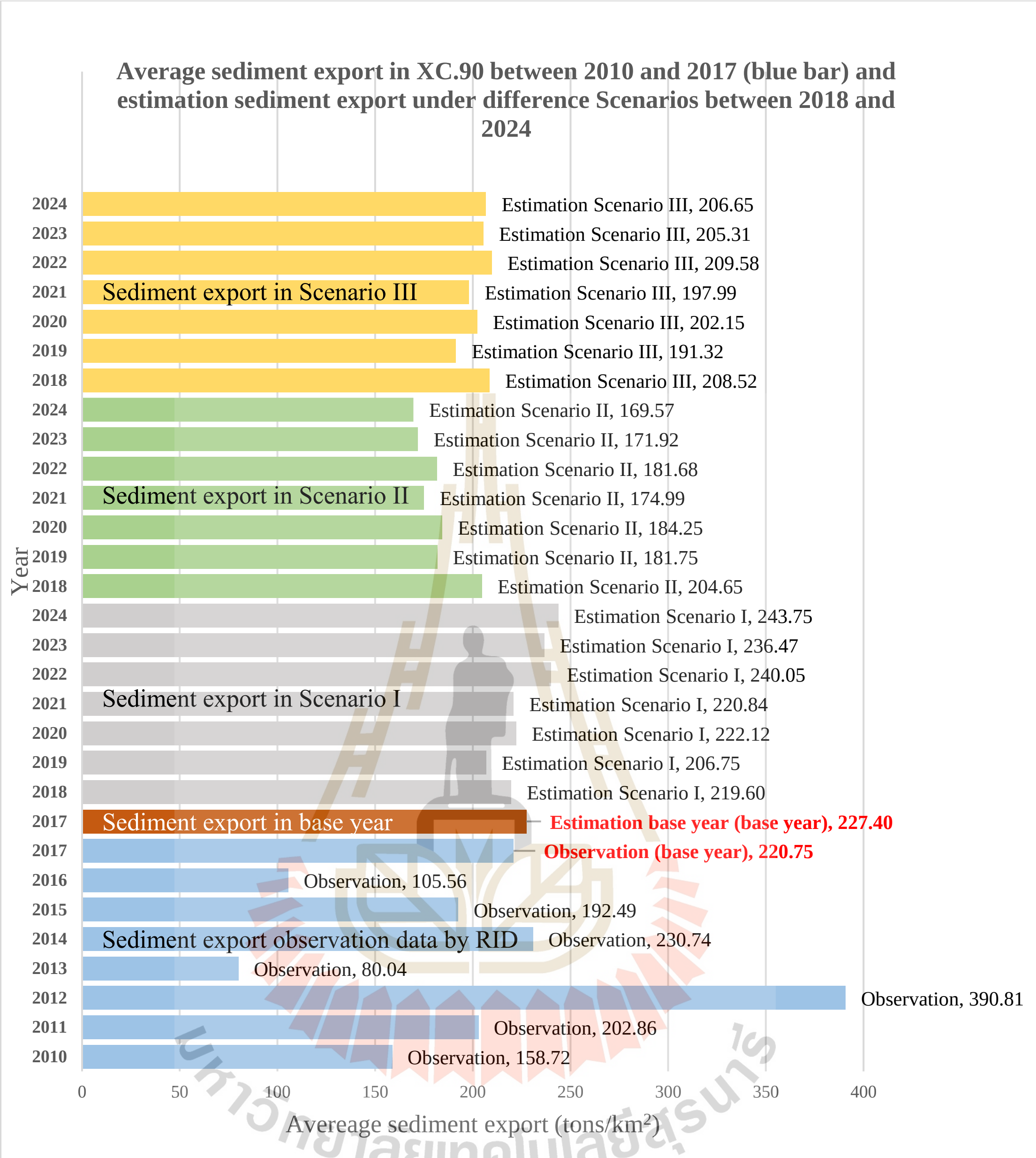


Figure 7.41 Comparison of actual and predictive sediment export of three different scenarios during 2017 to 2024 and observation sediment export data at XC.90 station between 2010 and 2017 (blue bar).

CHAPTER VIII

LAND USE AND LAND COVER SCENARIO FOR OPTIMUM WATER YIELD AND SEDIMENT RETENTION ECOSYSTEM SERVICES

This chapter presents results of the fourth objective focusing on the LULC scenario for optimum water yield and sediment retention ecosystem services using ecosystems services change index (ESCI). The main results that consist of (1) LULC scenario for optimum water yield ecosystem service, (2) LULC scenario for optimum sediment retention ecosystem service and (3) LULC scenario for optimum water yield and sediment retention ecosystem services are here reported and discussed in details.

In principle, the ESCI represents the relative gain or loss of individual ecosystem service in specific period and it is a unit less measure of the cumulative status of all considered ecosystem services for a specific site. The domain value of ESCI ranges between -1 to +1. An ESCI value of 0 indicates no change in ecosystem service, while a negative ESCI value indicates a cumulative loss of ecosystem service relative to baseline and a positive ESCI value indicates a cumulative gain of ecosystem service over the reference period. Each ecosystem service informs management differently, while the ESCI provides insight on the temporal change of a particular service. In this study, the ESCI were evaluated at watershed and sub-watershed levels based on the actual LULC data in 2017 and the predictive LULC between 2018 and 2024 of three different scenarios using Map Algebra module of ArcGIS software. The derived ESCI were further applied to identify LULC scenario for optimum water yield (runoff) and sediment retention ecosystem services to mitigate flood risk in Khlong U-Tapao watershed and to reduce sediment export into Songkhla Lake.

8.1 LULC scenario for optimum water yield ecosystem service

Under this section, characteristics of ESCI of water yield (runoff) from three different scenarios at watershed and sub-watershed levels are firstly reported and then compared to identify LULC scenario for optimum water yield ecosystem service.

8.1.1 Ecosystem service change on water yield of Scenario I

At Khlong U-Tapao watershed, ecosystem service on water yield of Scenario I: Historical LULC evolution and its ESCI is summarized in Table 8.1 and comparatively displayed in Figure 8.1.

As results, it reveals that according to predictive LULC and climate data between 2018 and 2024, the lowest runoff volume of Scenario I will occur in 2019 with value of 1,616,257,946.91 m^3 and the highest runoff volume of Scenario I will occur in 2024 with value of 1,823,490,354.39 m^3. Additionally, it was found that all predictive runoff between 2018 and 2024 of Scenario I is lower than runoff of actual LULC 2017 as base year data. This result indicates the decreasing ecosystem service on water yield (runoff) of Scenario I during 2018 and 2024 when it was compared with water yield (runoff) of base year data in 2017 (see Table 8.1 and Figure 8.1).

In addition, the ecosystem service change index (ESCI) which provides the lowest cumulative ecosystem system loss on runoff under this scenario during 2017 to 2024 will occur in 2019 with value of -0.1328. In contrast, the ecosystem service change index which provides the highest cumulative ecosystem service loss on runoff under this scenario during 2017 to 2024 will occur in year in 2024 with value of -0.0216. These findings show effect of annual predictive rainfall and LULC change on water yield (runoff) prediction under this scenario as mentioned in Section 6.3 of Chapter 6, particularly, influence of temporal change of annual predictive rainfall on predictive water yield (runoff) during 2018 to 2024.

Table 8.1 Ecosystem service on water yield (runoff) and its ESCI value in Klong U-Tapao watershed under Scenario I.

Year	Water yield (runoff) volume (m^3)	ESCI	Period
2017	1,863,795,714.87		
2018	1,755,154,110.51	-0.0583	2017-2018
2019	1,616,257,946.91	-0.1328	2017-2019
2020	1,726,525,208.33	-0.0737	2017-2020
2021	1,695,370,640.42	-0.0904	2017-2021
2022	1,820,993,958.11	-0.0230	2017-2022
2023	1,790,466,081.66	-0.0393	2017-2023
2024	1,823,490,354.39	-0.0216	2017-2024
	Average	**-0.0627**	

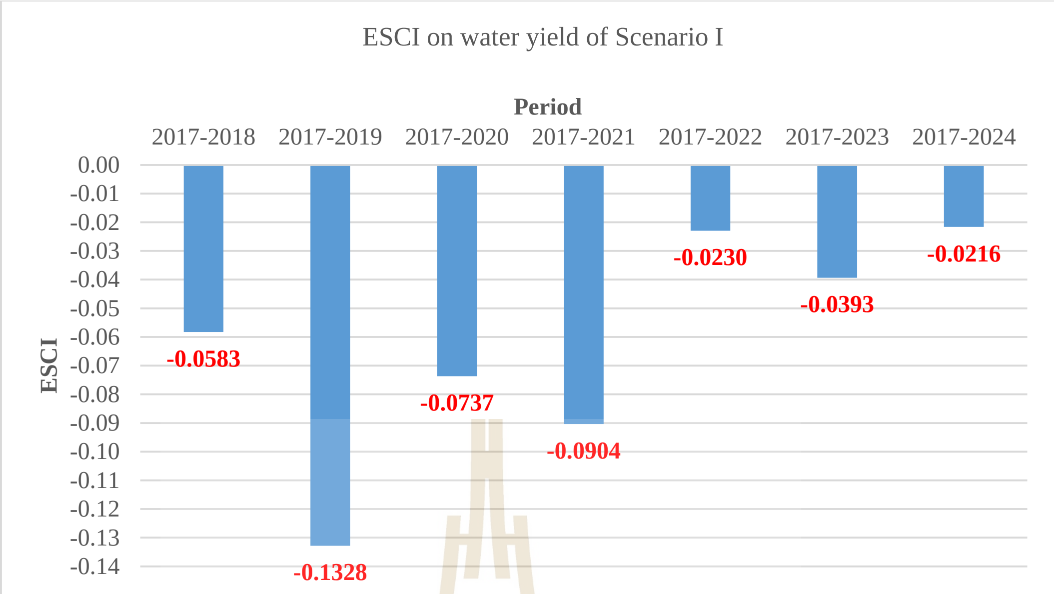


Figure 8.1 ESCI on water yield (runoff) in Klong U-Tapao under Scenario I.

Furthermore, ecosystem service on runoff of Scenario I: Historical LULC evolution and its ESCI at sub-watershed level of Khlong U-Tapao watershed is summarized in Table 8.2 and comparatively displayed in Figure 8.2.

Table 8.2 Ecosystem service on water yield (runoff) and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario I.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	-0.0228	-0.1056	-0.0409	-0.0613	0.0081	-0.0048	0.0106
2. Khlong Lea	-0.0521	-0.1194	-0.0609	-0.0791	-0.0079	-0.0275	0.0002
3. Khlong Phang La/Khlong Ngae	-0.0473	-0.1128	-0.0550	-0.0704	0.0009	-0.0192	0.0049
4. Khlong Pom	-0.0510	-0.1248	-0.0649	-0.0809	-0.0125	-0.0268	-0.0117
5. Khlong Ram	-0.0416	-0.1203	-0.0580	-0.0758	-0.0033	-0.0222	-0.0021
6. Khlong Sa Dao	-0.0710	-0.1261	-0.0774	-0.0837	-0.0134	-0.0390	-0.0093
7. Khlong Tong/Khlong Pra Tu	-0.0511	-0.1197	-0.0636	-0.0759	-0.0057	-0.0231	-0.0040
8. Khlong Wa	-0.0573	-0.1335	-0.0705	-0.0911	-0.0294	-0.0393	-0.0259
9. Khlong Wat/Khlong Tam	-0.1109	-0.1933	-0.1383	-0.1528	-0.0894	-0.1065	-0.0977
10. Klong Bang Klam	-0.0640	-0.1483	-0.0836	-0.1094	-0.0531	-0.0605	-0.0514

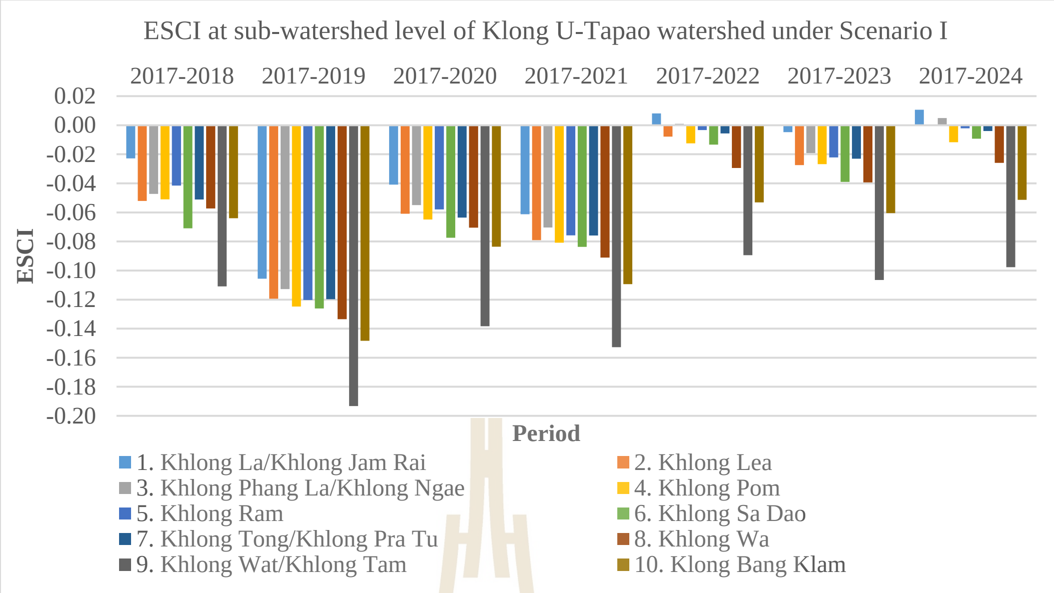


Figure 8.2 ESCI of water yield (runoff) at sub-watershed level of Khlong U-Tapao watershed under Scenario I.

As results, most of ESCI values of all sub-watershed during 2017 to 2024 will provide negative ecosystem service (loss) on runoff, except some period under specific sub-watershed. Herein, Khlong La/Khlong Jam Rai sub-watershed will provide positive ESCI value of 0.0081 and 0.0106 in period of 2017-2022 and 2017-2024, respectively. Likewise, Khlong Lea sub-watershed will provide positive ESCI value of 0.0002 in period of 2017-2024 and Khlong Phang La/Khlong Ngae sub-watershed will provide positive ESCI value of 0.0009 and 0.0049 in period of 2017-2022 and 2017-2024, respectively. These results suggest the effect of the predictive LULC change at sub-watershed level on predictive water yield (runoff).

8.1.2 Ecosystem service change on water yield of Scenario II

At Khlong U-Tapao watershed, ecosystem service on water yield (runoff) of Scenario II: Forest conservation and prevention and its ESCI is summarized in Table 8.3 and comparative displayed in Figure 8.3.

As results, it reveals that according to predictive LULC and climate data between 2018 and 2024, the lowest runoff volume under this scenario will occur in 2019 with value of 1,617,767,874.74 m^3 and the highest runoff volume will occur in 2024 with value of 1,829,037,584.00 m^3. The pattern of runoff change of Scenario II is similar with Scenario I, the results also indicates the decreasing ecosystem service on water yield (runoff) during 2018 to 2024 (see Table 8.3 and Figure 8.3).

In addition, the ESCI which provides the lowest cumulative ecosystem service loss on runoff under this scenario during 2017 to 2024 will occurs in 2019 with value of -0.1320. In contrast, the ESCI which provides the highest cumulative ecosystem service loss on runoff under this scenario will occur in 2024 with value of -0.0186. The dynamic change of annual predictive rainfall also plays important role on predictive water yield (runoff) under Scenario II.

Table 8.3 Ecosystem service on water yield (runoff) and its ESCI value in Klong U-Tapao watershed under Scenario II.

Year	Water yield (runoff) volume (m^3)	ESCI	Period
2017	1,863,795,714.87		
2018	1,755,799,564.77	-0.0579	2017-2018
2019	1,617,767,874.74	-0.1320	2017-2019
2020	1,728,733,356.91	-0.0725	2017-2020
2021	1,698,139,630.56	-0.0889	2017-2021
2022	1,824,878,523.67	-0.0209	2017-2022
2023	1,795,291,837.77	-0.0368	2017-2023
2024	1,829,037,584.00	-0.0186	2017-2024
	Average	**-0.0611**	

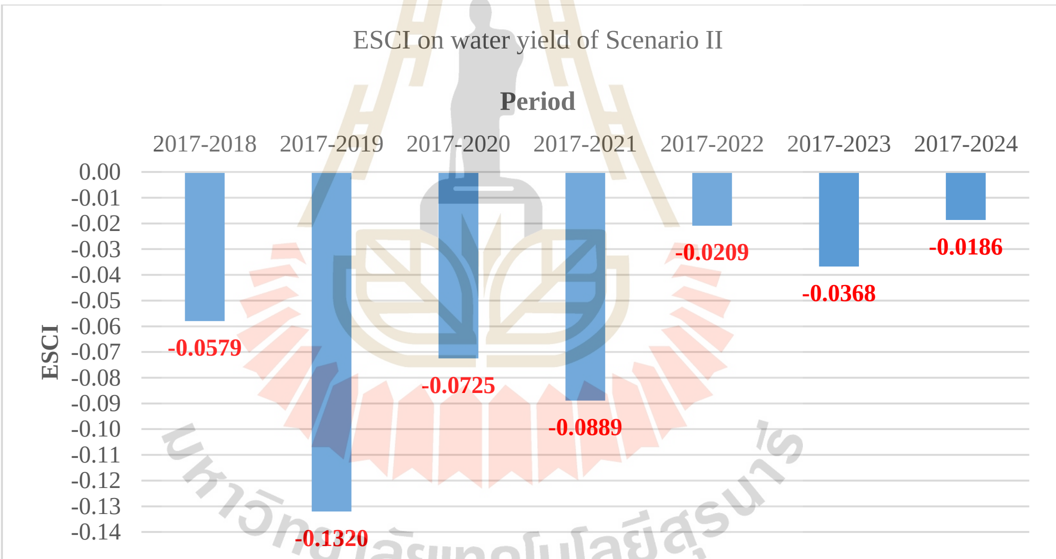


Figure 8.3 ESCI on water yield (runoff) in Klong U-Tapao under Scenario II.

Furthermore, ecosystem service on water yield (runoff) of Scenario II: Forest conservation and prevention and its ESCI at sub-watershed level of Khlong U-Tapao watershed is summarized in Table 8.4 and comparatively displayed in Figure 8.4.

Table 8.4 Ecosystem service on water yield (runoff) and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario II.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	-0.0228	-0.1055	-0.0408	-0.0611	0.0085	-0.0042	0.0114
2. Khlong Lea	-0.0521	-0.1194	-0.0608	-0.0790	-0.0079	-0.0275	0.0002
3. Khlong Phang La/Khlong Ngae	-0.0473	-0.1127	-0.0547	-0.0703	0.0010	-0.0192	0.0048
4. Khlong Pom	-0.0507	-0.1245	-0.0646	-0.0806	-0.0124	-0.0265	-0.0114
5. Khlong Ram	-0.0417	-0.1202	-0.0579	-0.0757	-0.0031	-0.0219	-0.0019
6. Khlong Sa Dao	-0.0709	-0.1260	-0.0774	-0.0837	-0.0135	-0.0391	-0.0095
7. Khlong Tong/Khlong Pra Tu	-0.0513	-0.1202	-0.0643	-0.0767	-0.0067	-0.0241	-0.0051
8. Khlong Wa	-0.0566	-0.1321	-0.0688	-0.0892	-0.0268	-0.0877	-0.0225
9. Khlong Wat/Khlong Tam	-0.1095	-0.1900	-0.1335	-0.1468	-0.0811	-0.0496	-0.0861
10. Klong Bang Klam	-0.0633	-0.1466	-0.0804	-0.1045	-0.0458	-0.0514	-0.0404

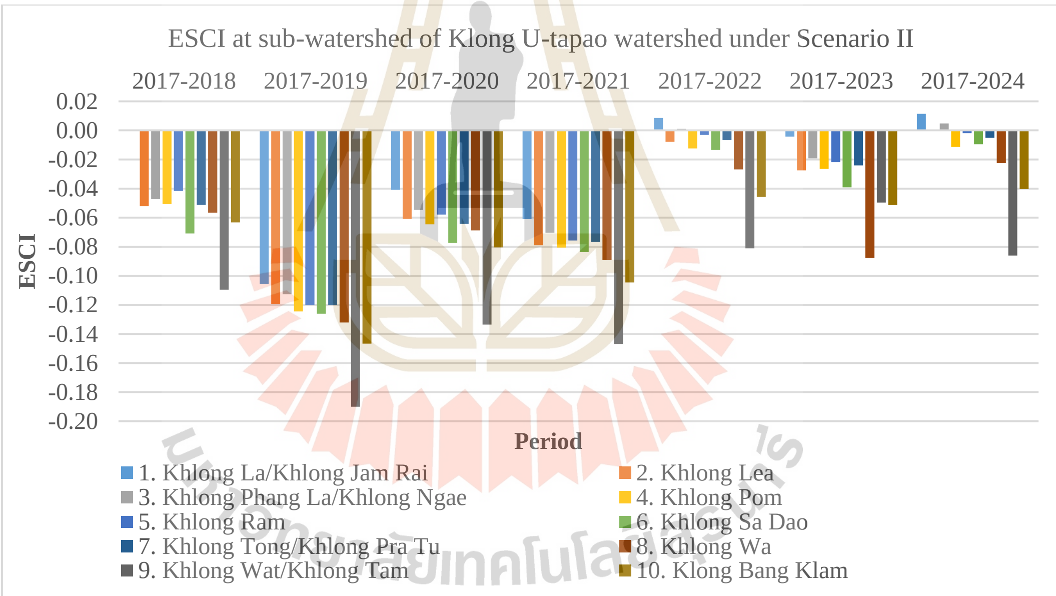


Figure 8.4 ESCI of water yield (runoff) at sub-watershed level of Khlong U-Tapao watershed under Scenario II.

As results, most of the ESCI values of all sub-watershed during 2017 to 2024 provide negative ecosystem service (loss) on runoff except some period of some sub-watersheds. Herein, Khlong La/Khlong Jam Rai sub-watershed will provide positive ESCI value of 0.0085 and 0.0114 in period of 2017-2022 and 2017-2024, respectively. Likewise, Khlong Lea sub-watershed will provide positive ESCI value of 0.0002 in period of 2017-2024 and Khlong Phang La/Khlong Ngae sub-watershed will provide positive ESCI value of 0.0010 and 0.0048 in period of 2017-2022 and 2017-2024, respectively. These results also suggest the effect of the predictive LULC change at sub-watershed level on predictive water yield (runoff) under Scenario II.

8.1.3 Ecosystem service change on water yield of Scenario III

At Khlong U-Tapao watershed, ecosystem service on water yield (runoff) of Scenario III: Agriculture production extension and its ESCI is summarized in Table 8.5 and is comparatively displayed in Figure 8.5.

As results, it reveals that according to predictive LULC and climate data between 2018 and 2024, the lowest runoff volume of Scenario III will also occur in 2019 with value of 1,619,029,718.35 m^3 and the highest runoff volume of Scenario III will occur in 2024 with value of 1,834,815,601.78 m^3.

Besides, the ESCI which provides the lowest cumulative ecosystem service loss on water yield under this scenario will occur in 2019 with value of -0.1313. In contrast, the ESCI which provides the highest cumulative ecosystem service loss on water yield under this scenario will occur in 2024 with value of -0.0155. The pattern of ESCI under Scenario III is also consistent with Scenario I and II. The temporal change of annual predictive rainfall also plays significant role on the predictive water yield (runoff) under this scenario.

Table 8.5 Ecosystem service on water yield (runoff) and its ESCI value in Klong U-Tapao watershed under Scenario III.

Year	Water yield volume (m^3)	ESCI	Period
2017	1,863,795,714.87		
2018	1,756,375,718.37	-0.0576	2017-2018
2019	1,619,029,718.35	-0.1313	2017-2019
2020	1,730,702,036.99	-0.0714	2017-2020
2021	1,700,840,701.27	-0.0874	2017-2021
2022	1,828,995,825.16	-0.0187	2017-2022
2023	1,799,989,836.18	-0.0342	2017-2023
2024	1,834,815,601.78	-0.0155	2017-2024
	Average	**-0.0595**	

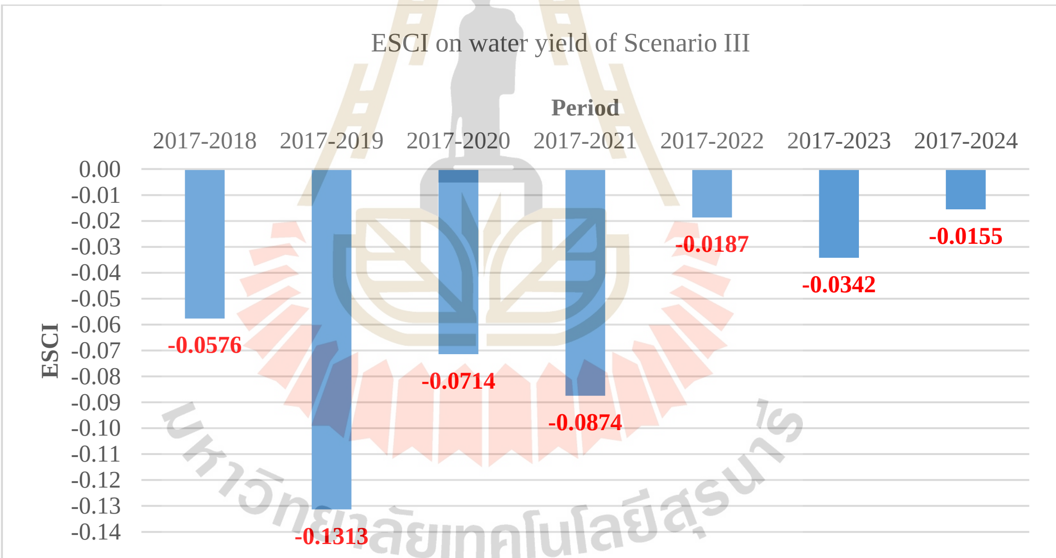


Figure 8.5 ESCI on water yield (runoff) in Klong U-Tapao under Scenario III.

Furthermore, ecosystem service on water yield (runoff) of Scenario III: Forest conservation and prevention and its ESCI at sub-watershed level of Khlong U-Tapao watershed is summarized in Table 8.6 and comparatively displayed in Figure 8.6.

Table 8.6 Ecosystem service on water yield (runoff) and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario III.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	-0.0220	-0.1042	-0.0388	-0.0586	0.0120	-0.0003	0.0160
2. Khlong Lea	-0.0520	-0.1191	-0.0598	-0.0768	-0.0030	-0.0213	0.0089
3. Khlong Phang La/Khlong Ngae	-0.0465	-0.1110	-0.0524	-0.0673	0.0050	-0.0149	0.0099
4. Khlong Pom	-0.0505	-0.1242	-0.0641	-0.0801	-0.0116	-0.0256	-0.0105
5. Khlong Ram	-0.0412	-0.1195	-0.0566	-0.0739	-0.0004	-0.0188	0.0022
6. Khlong Sa Dao	-0.0705	-0.1251	-0.0759	-0.0818	-0.0109	-0.0364	-0.0064
7. Khlong Tong/Khlong Pra Tu	-0.0508	-0.1192	-0.0627	-0.0750	-0.0044	-0.0215	-0.0018
8. Khlong Wa	-0.0570	-0.1326	-0.0693	-0.0895	-0.0268	-0.0361	-0.0224
9. Khlong Wat/Khlong Tam	-0.1091	-0.1893	-0.1327	-0.1458	-0.0797	-0.0948	-0.0842
10. Klong Bang Klam	-0.0635	-0.1464	-0.0804	-0.1045	-0.0457	-0.0512	-0.0407

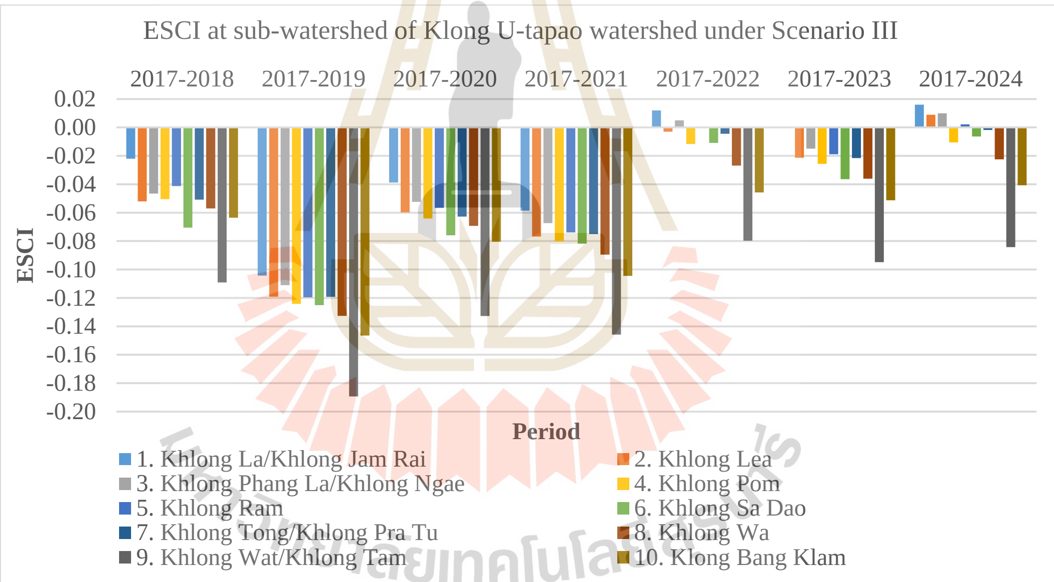


Figure 8.6 ESCI of water yield (runoff) at sub-watershed level of Khlong U-Tapao watershed under Scenario III.

As results, most of the ESCI values of all sub-watershed during 2017 to 2024 provide negative cumulative ecosystem service (loss) on runoff except some periods of sub-watershed. Herein, Khlong La/Khlong Jam Rai sub-watershed will provide positive ESCI value of 0.0120 and 0.0160 in period of 2017-2022 and 2017-

2024, respectively. Likewise, Khlong Lea sub-watershed will provide positive ESCI value of 0.0089 in period of 2017-2024 and Khlong Phang La/Khlong Ngae sub-watershed will provide positive ESCI value of 0.0050 and 0.0099 in period of 2017-2022 and 2017-2024, respectively. Likewise, Khlong Ram sub-watershed will provide positive ESCI value of 0.0022 in period of 2017-2024. These results also suggest the effect of LULC change at sub-watershed level on predictive water yield under Scenario III.

8.1.4 Optimum water yield ecosystem service of LULC scenario

The calculated ESCI values on water yield (runoff) and its average from three different scenarios in Khlong U-Tapao watershed were here compared to identify LULC scenario for optimum water yield ecosystem service as shown in Table 8.7 and Figure 8.7.

As results, it was found that LULC of Scenario I generates the least runoff in every year during 2018 to 2024 among three LULC scenarios and the cumulative ESCI values on runoff ecosystem service of this scenario is also the lowest with average ESCI value of -0.0627. Therefore, LULC of Scenario I: Historical LULC evolution is here chosen for optimum water yield (runoff) ecosystem service to mitigate flood risk in Khlong U-Tapao watershed. Herewith, average ESCI of three different LULC scenarios were tested the difference of mean using t-Test statistics. The result demonstrations that there are significant different among average ESCI values on water yield ecosystem service of three different scenarios at 95% confidential level as shown details in Table 8.8.

Table 8.7 Water yield (runoff) and ESCI value and its average of three different scenarios.

Year	Period	Scenario-I		Scenario-II		Scenario-III	
		Water yield (m³)	ESCI	Water yield (m³)	ESCI	Water yield (m³)	ESCI
2017		1,863,795,714.87		1,863,795,714.87		1,863,795,714.87	
2018	2017-2018	1,755,154,110.51	-0.0583	1,755,799,564.77	-0.0579	1,756,375,718.37	-0.0576
2019	2017-2019	1,616,257,946.91	-0.1328	1,617,767,874.74	-0.1320	1,619,029,718.35	-0.1313
2020	2017-2020	1,726,525,208.33	-0.0737	1,728,733,356.91	-0.0725	1,730,702,036.99	-0.0714
2021	2017-2021	1,695,370,640.42	-0.0904	1,698,139,630.56	-0.0889	1,700,840,701.27	-0.0874
2022	2017-2022	1,820,993,958.11	-0.0230	1,824,878,523.67	-0.0209	1,828,995,825.16	-0.0187
2023	2017-2023	1,790,466,081.66	-0.0393	1,795,291,837.77	-0.0368	1,799,989,836.18	-0.0342
2024	2017-2024	1,823,490,354.39	-0.0216	1,829,037,584.00	-0.0186	1,834,815,601.78	-0.0155
		Average	**-0.0627**		**-0.0611**		**-0.0595**

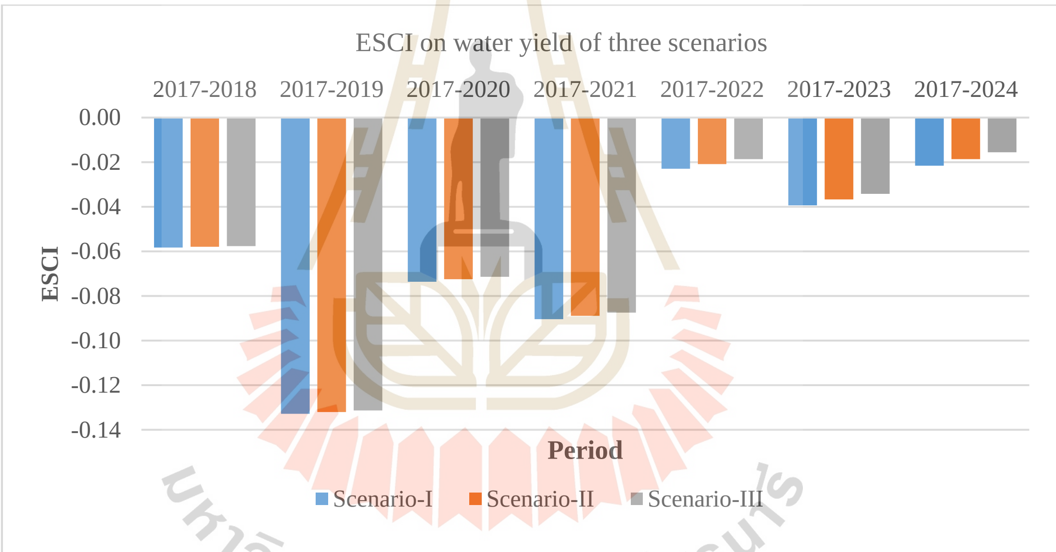


Figure 8.7 Comparison of ESCI on water yield of three different scenarios.

Table 8.8 Details of t-Test for average ESCI values on water yield service among three different scenarios.

Pairwise of Scenario	Mean		Variance		df	t- Stat	t Critical 2-tail
	Variable 1	Variable 2	Variable 1	Variable 2			
I and II	-0.0627	-0.0611	0.0016	0.0017	6	-268,522.62*	2.4469
I and III	-0.0627	-0.0594	0.0016	0.0017	6	-127,913.00*	2.4469
II and III	-0.0611	-0.0594	0.0017	0.00177	6	-244,188.26*	2.4469

8.2 LULC scenario for optimum sediment retention ecosystem service

Characteristics of ESCI on sediment retention of three different scenarios at watershed and sub-watershed levels are firstly reported and then compared to identify LULC scenario for optimum sediment retention ecosystem service.

8.2.1 Ecosystem service change on sediment retention of Scenario I

At Khlong U-Tapao watershed, ecosystem service on sediment retention of Scenario I: Historical LULC evolution and its ESCI is summarized in Table 8.9 and comparative displayed in Figure 8.8.

As results, it reveals that according to predictive LULC, terrain and climate data between 2018 and 2024, the highest sediment retention of Scenario I will occur in 2022 with amount of 8,392,356.57 tons and the lowest sediment retention of Scenario I will occur in 2019 with amount of 7,349,843.49 tons. Additionally, it was found that all predictive sediment retention between 2018 and 2024 of Scenario I is higher than sediment retention of actual LULC 2017 as base year data. This result indicates the increasing ecosystem service on sediment retention in the future of Scenario I during 2018 and 2024 when it was compared with sediment retention of base year data in 2017 (see Table 8.9 and Figure 8.8).

In addition, the ESCI which provides the lowest cumulative ecosystem system gain on sediment retention under this scenario during 2017 to 2024 will occur in 2019 with amount of 0.0561. In contrast, the ESCI which provides the highest cumulative ecosystem service gain on sediment retention under this scenario during 2017 to 2024 will occur in 2022 with amount of 0.2059. These findings show effect of annual predictive rainfall and predictive LULC change on sediment retention prediction under this scenario as mentioned in Section 7.3 of Chapter VII, particularly, influence of temporal change of annual predictive rainfall on predictive sediment retention during 2018 to 2024.

Table 8.9 Ecosystem service on sediment retention and its ESCI value in Klong U-Tapao watershed under Scenario I.

Year	Sediment retention (tons)	ESCI	Period
2017	6,959,665.62		
2018	7,967,995.96	0.1449	2017-2018
2019	7,349,843.49	0.0561	2017-2019
2020	7,786,660.83	0.1188	2017-2020
2021	7,752,227.81	0.1139	2017-2021
2022	8,392,356.57	0.2059	2017-2022
2023	8,162,308.49	0.1728	2017-2023
2024	8,313,835.49	0.1946	2017-2024
	Average	**0.1438**	

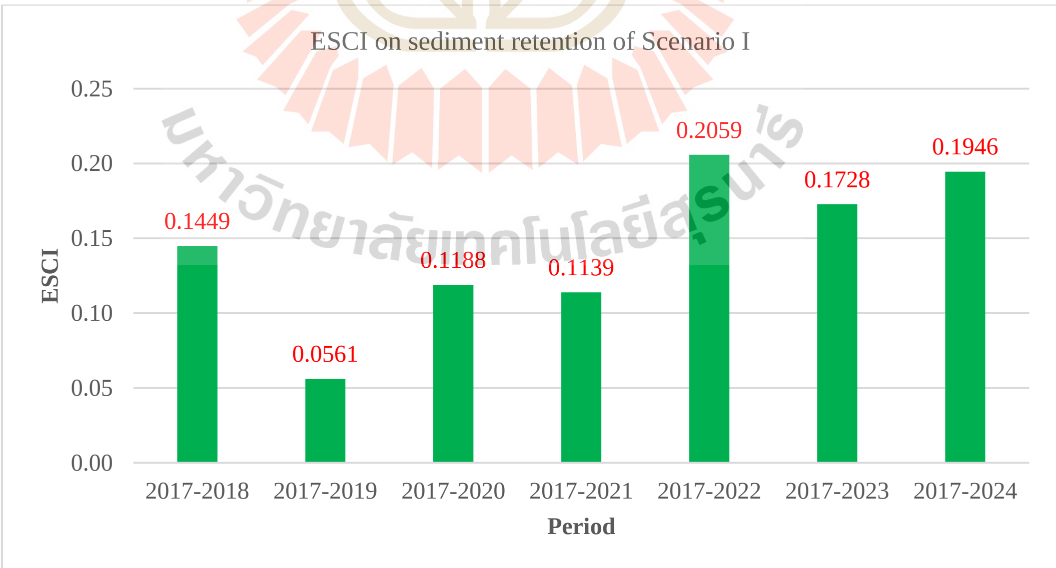


Figure 8.8 ESCI on sediment retention in Klong U-Tapao under Scenario I.

Furthermore, ecosystem service on sediment retention of Scenario I: Historical LULC evolution and its ESCI at sub-watershed level of Khlong U-Tapao watershed is summarized in Table 8.10 and comparatively displayed in Figure 8.9.

Table 8.10 Ecosystem service on sediment retention and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario I.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	0.3015	0.1887	0.2693	0.2544	0.3559	0.3260	0.3451
2. Khlong Lea	0.2634	0.1760	0.2519	0.2298	0.3241	0.2973	0.3336
3. Khlong Phang La/Khlong Ngae	0.0918	0.0194	0.0801	0.0710	0.1529	0.1252	0.1529
4. Khlong Pom	-0.2750	-0.3296	-0.2879	-0.2934	-0.2398	-0.2548	-0.2435
5. Khlong Ram	0.5464	0.4121	0.5059	0.4901	0.6200	0.5748	0.6021
6. Khlong Sa Dao	0.3031	0.2351	0.2882	0.3007	0.4004	0.3553	0.3984
7. Khlong Tong/Khlong Pra Tu	-0.1212	-0.1822	-0.1366	-0.1367	-0.0703	-0.0925	-0.0758
8. Khlong Wa	-0.4772	-0.5167	-0.4863	-0.4898	-0.4527	-0.4624	-0.4548
9. Khlong Wat/Khlong Tam	0.2550	0.1396	0.2120	0.2042	0.3138	0.2734	0.2868
10. Klong Bang Klam	-0.5277	-0.5693	-0.5370	-0.5475	-0.5175	-0.5209	-0.5156

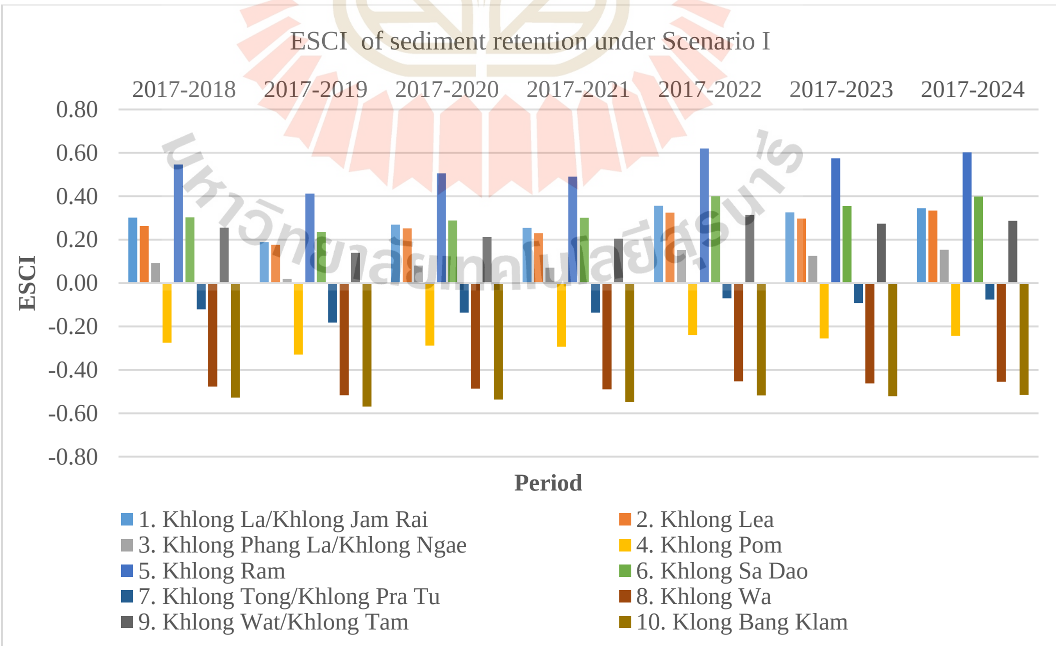


Figure 8.9 ESCI of sediment retention at sub-watershed of Khlong U-Tapao watershed under Scenario I.

As results at sub-watershed level, it was found that six sub-watersheds include Khlong La/Khlong Jam Rai, Khlong Lea, Khlong Phang La/Khlong Ngae, Khlong Ram, Khlong Sa Dao, and Khlong Wat/Khlong Tam can provide positive ESCI values (gain) on sediment retention in every periods during 2017 to 2024. On contrary, four sub-watershed includes Khlong Pom, Khlong Tong/Khlong Pra Tu, Khlong Wa and Klong Bang Klam delivery negative ESCI value on sediment retention in every periods (See detail in Table 8.10 and Figure 8.9). These results suggest the effect of predictive LULC change at sub-watershed level, particularly existing evergreen forest and characteristics of soil and terrain on predictive sediment retention under this scenario.

8.2.2 Ecosystem service change on sediment retention of Scenario II

At Khlong U-Tapao watershed, ecosystem service on sediment retention of Scenario II: Forest conservation and prevention and its ESCI is summarized in Table 8.11 and comparative displayed in Figure 8.10.

As results, it reveals that according to predictive LULC, terrain and climate data between 2018 and 2024, the highest sediment retention of Scenario II will occurs in 2022 with amount of 8,428,253.52 tons and the lowest sediment retention of this scenario will occur in 2019 with amount of 7,364,066.22 tons. Additionally, it was found that all predictive sediment retention between 2018 and 2024 of Scenario II is higher than sediment retention of actual LULC 2017 as base year data. This result indicates the increasing ecosystem service on sediment retention in the future of Scenario II during 2018 and 2024 when it was compared with sediment retention of base year data in 2017 (see Table 8.11 and Figure 8.10).

In addition, the ESCI which provides the lowest cumulative ecosystem system gain on sediment retention under this scenario during 2017 to 2024 will occur in 2019 with amount of 0.0581. In contrast, the ESCI which provides the highest cumulative ecosystem service gain on sediment retention under this scenario during 2017 to 2024 will occur in 2022 with amount of 0.2110. These findings also show effect of annual predictive rainfall and predictive LULC change on sediment retention prediction under this scenario, particularly, influence of temporal change of annual predictive rainfall on predictive sediment retention during 2018 to 2024.

Table 8.11 Ecosystem service on sediment retention and its ESCI value in Klong U-Tapao watershed under Scenario II.

Year	Sediment retention (tons)	ESCI	Period
2017	6,959,665.62		
2018	7,975,689.42	0.1460	2017-2018
2019	7,364,066.22	0.0581	2017-2019
2020	7,809,244.04	0.1221	2017-2020
2021	7,779,992.81	0.1179	2017-2021
2022	8,428,253.52	0.2110	2017-2022
2023	8,202,220.40	0.1785	2017-2023
2024	8,359,998.44	0.2012	2017-2024
	Average	**0.1478**	

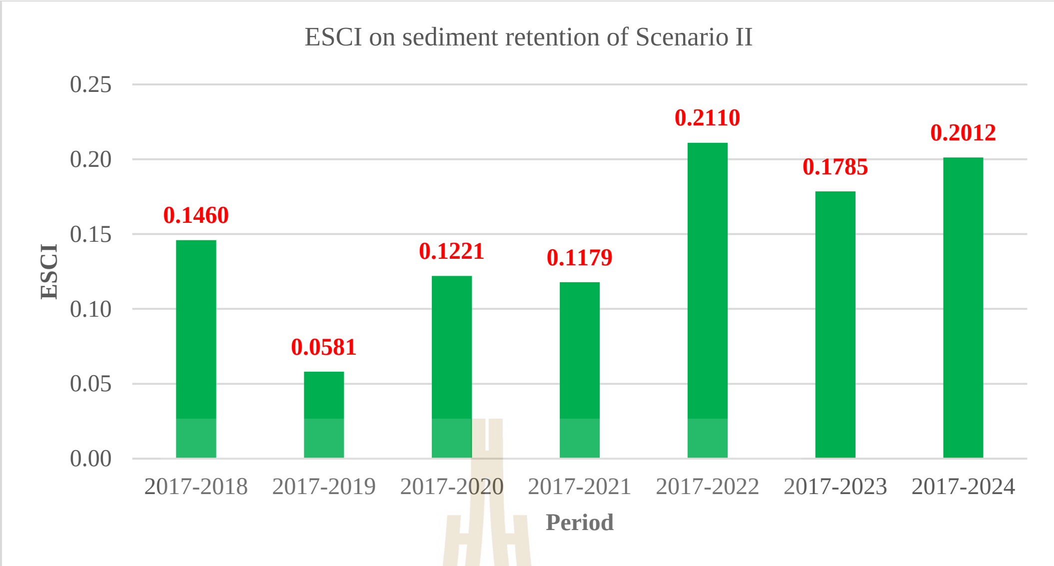


Figure 8.10 ESCI on sediment retention in Klong U-Tapao under Scenario II.

Furthermore, ecosystem service on sediment retention of Scenario II: Forest conservation and prevention and its ESCI at sub-watershed level of Khlong U-Tapao watershed is summarized in Table 8.12 and comparatively displayed in Figure 8.11.

Table 8.12 Ecosystem service on sediment retention and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario II.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	0.3029	0.1912	0.2733	0.2595	0.3626	0.3336	0.3541
2. Khlong Lea	0.2634	0.1762	0.2526	0.2312	0.3261	0.3008	0.3387
3. Khlong Phang La/Khlong Ngae	0.0944	0.0233	0.0862	0.0783	0.1618	0.1353	0.1646
4. Khlong Pom	-0.2738	-0.3273	-0.2840	-0.2884	-0.2331	-0.2476	-0.2355
5. Khlong Ram	0.5480	0.4145	0.5097	0.4946	0.6255	0.5810	0.6091
6. Khlong Sa Dao	0.3044	0.2376	0.2919	0.3053	0.4063	0.3616	0.4058
7. Khlong Tong/Khlong Pra Tu	-0.1188	-0.1777	-0.1304	-0.1293	-0.0610	-0.0824	-0.0647
8. Khlong Wa	-0.4759	-0.5143	-0.4827	-0.4854	-0.4472	-0.4562	-0.4479
9. Khlong Wat/Khlong Tam	0.2561	0.1410	0.2140	0.2066	0.3167	0.2766	0.2905
10. Klong Bang Klam	-0.5278	-0.5694	-0.5371	-0.5475	-0.5175	-0.5209	-0.5155

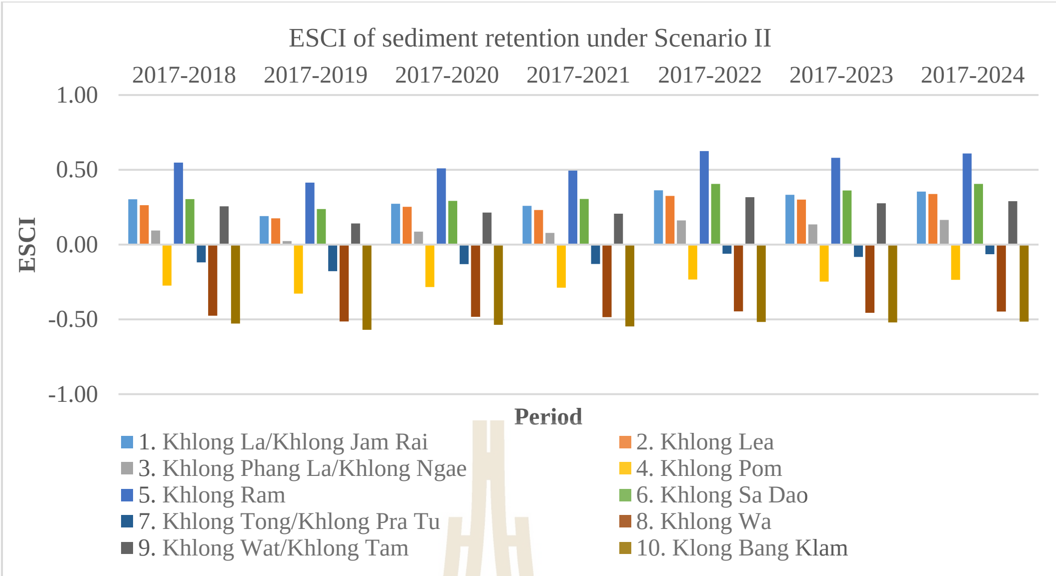


Figure 8.11 ESCI of sediment retention at sub-watershed of Khlong U-Tapao watershed under Scenario II.

As results at sub-watershed level, it was found that six sub-watersheds include Khlong La/Khlong Jam Rai, Khlong Lea, Khlong Phang La/Khlong Ngae, Khlong Ram, Khlong Sa Dao, and Khlong Wat/Khlong Tam can provide positive ESCI values (gain) on sediment retention in every periods during 2017 to 2024. On contrary, four sub-watershed includes Khlong Pom, Khlong Tong/Khlong Pra Tu, Khlong Wa and Klong Bang Klam delivery negative ESCI value on sediment retention in every periods (See detail in Table 8.12 and Figure 8.11). These results also suggest the effect of predictive LULC change at sub-watershed level, particularly existing evergreen forest and characteristics of soil and terrain on predictive sediment retention under Scenario II.

8.2.3 Ecosystem service change on sediment retention of Scenario III

At Khlong U-Tapao watershed, ecosystem service on sediment retention of Scenario III: Agriculture production extension and its ESCI is summarized in Table 8.13 and comparative displayed in Figure 8.12.

As results, it reveals that according to predictive LULC, terrain and climate data between 2018 and 2024, the highest sediment retention of Scenario III will occurs in 2022 with amount of 8,410,129.35 tons and the lowest sediment retention of this scenario will occur in 2019 with amount of 7,357,848.38 tons. Additionally, it was found that all predictive sediment retention between 2018 and 2024 of Scenario III is higher than sediment retention of actual LULC 2017 as base year data. This result indicates the increasing ecosystem service on sediment retention in the future of Scenario III during 2018 and 2024 when it was compared with sediment retention of base year data in 2017 (see Table 8.13 and Figure 8.12).

In addition, the ESCI which provides the lowest cumulative ecosystem system gain on sediment retention under this scenario during 2017 to 2024 will occur in 2019 with amount of 0.0572. In contrast, the ESCI which provides the highest cumulative ecosystem service gain on sediment retention under this scenario during 2017 to 2024 will occur in 2022 with amount of 0.2084. These findings also show effect of annual predictive rainfall and predictive LULC change on sediment retention prediction under this scenario, particularly, influence of temporal change of annual predictive rainfall on predictive sediment retention during 2018 to 2024.

Table 8.13 Ecosystem service on sediment retention and its ESCI value in Klong U-Tapao watershed under Scenario III.

Year	Sediment retention (tons)	ESCI	Period
2017	6,959,665.62		
2018	7,973,180.41	0.1456	2017-2018
2019	7,357,848.38	0.0572	2017-2019
2020	7,797,614.42	0.1204	2017-2020
2021	7,765,051.69	0.1157	2017-2021
2022	8,410,129.35	0.2084	2017-2022
2023	8,180,528.73	0.1754	2017-2023
2024	8,335,915.43	0.1977	2017-2024
	Average	**0.1458**	

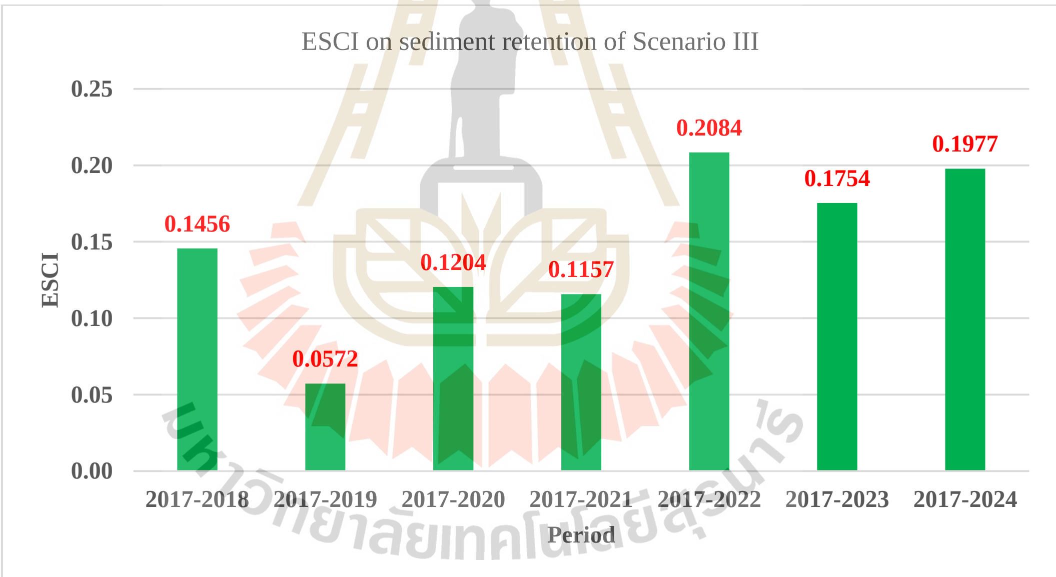


Figure 8.12 ESCI on sediment retention in Klong U-Tapao under Scenario III.

Furthermore, ecosystem service on sediment retention of III: Agriculture production extension and its ESCI at sub-watershed of Khlong U-Tapao watershed is summarized in Table 8.14 and comparatively displayed in Figure 8.13.

Table 8.14 Ecosystem service on sediment retention and its ESCI value at sub-watershed in Klong U-Tapao watershed under Scenario III.

Sub-watershed	Ecosystem Change Services Index (ESCI)						
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024
1. Khlong La/Khlong Jam Rai	0.3030	0.1908	0.2722	0.2575	0.3599	0.3301	0.3500
2. Khlong Lea	0.2628	0.1748	0.2506	0.2293	0.3267	0.3014	0.3422
3. Khlong Phang La/Khlong Ngae	0.0953	0.0245	0.0866	0.0782	0.1612	0.1335	0.1620
4. Khlong Pom	-0.2739	-0.3280	-0.2859	-0.2910	-0.2362	-0.2513	-0.2399
5. Khlong Ram	0.5476	0.4135	0.5077	0.4921	0.6226	0.5775	0.6054
6. Khlong Sa Dao	0.3041	0.2370	0.2907	0.3036	0.4041	0.3590	0.4028
7. Khlong Tong/Khlong Pra Tu	-0.1199	-0.1806	-0.1347	-0.1343	-0.0669	-0.0890	-0.0718
8. Khlong Wa	-0.4769	-0.5165	-0.4859	-0.4891	-0.4517	-0.4614	-0.4536
9. Khlong Wat/Khlong Tam	0.2558	0.1405	0.2132	0.2054	0.3154	0.2750	0.2887
10. Klong Bang Klam	-0.5272	-0.5686	-0.5364	-0.5470	-0.5170	-0.5206	-0.5152

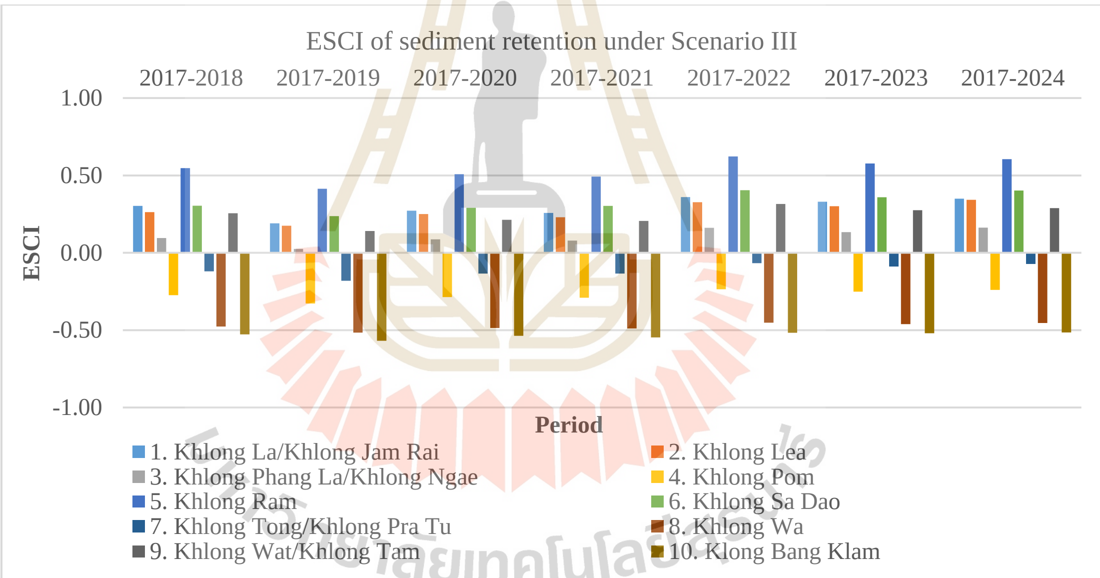


Figure 8.13 ESCI of sediment retention at sub-watershed of Khlong U-Tapao watershed under Scenario III.

As results, it was found that six sub-watersheds include Khlong La/Khlong Jam Rai, Khlong Lea, Khlong Phang La/Khlong Ngae, Khlong Ram, Khlong Sa Dao, and Khlong Wat/Khlong Tam can provide positive ESCI values (gain) on sediment retention in every periods during 2018 to 2024. On contrary, four sub-watershed includes Khlong Pom, Khlong Tong/Khlong Pra Tu, Khlong Wa and Klong

Bang Klam delivery negative ESCI value on sediment retention in every periods. (See detail in Table 8.14 and Figure 8.13). These results also suggest the effect of predictive LULC change at sub-watershed level, particularly existing evergreen forest and characteristics of soil and terrain on predictive sediment retention under Scenario III.

8.2.4 Optimum sediment retention ecosystem service of LULC scenario

The calculated ESCI values on sediment retention and its average from three different LULC scenarios in Khlong U-Tapao watershed were here compared to identify LULC scenario for optimum sediment retention ecosystem service as shown in Table 8.15 and Figure 8.14.

As results, it was found that LULC of Scenario II retains the highest sediment retention in every year during 2018 to 2024 among three LULC scenarios and cumulative ESCI values on sediment retention ecosystem service of this scenario is also the highest with average of 0.1478. Therefore, LULC of Scenario II: Forest conservation and prevention is here chosen for optimum sediment retention ecosystem service to reduce sediment export into Songkhla Lake. Herewith, average ESCI of three different LULC scenarios were tested the difference of mean using t-Test statistics. The result demonstrations that there are significant different among average ESCI values on sediment retention ecosystem service of three different scenarios at 95% confidential level as shown details in Table 8.16.

Table 8.15 Sediment retention and ESCI of three different scenarios.

Year	Period	Scenario-I		Scenario-II		Scenario-III	
		Sediment retention (tons)	ESCI	Sediment retention (tons)	ESCI	Sediment retention (tons)	ESCI
2017		6,959,665.62		6,959,665.62		6,959,665.62	
2018	2017-2018	7,967,995.96	0.1449	7,975,689.42	0.1460	7,973,180.41	0.1456
2019	2017-2019	7,349,843.49	0.0561	7,364,066.22	0.0581	7,357,848.38	0.0572
2020	2017-2020	7,786,660.83	0.1188	7,809,244.04	0.1221	7,797,614.42	0.1204
2021	2017-2021	7,752,227.81	0.1139	7,779,992.81	0.1179	7,765,051.69	0.1157
2022	2017-2022	8,392,356.57	0.2059	8,428,253.52	0.2110	8,410,129.35	0.2084
2023	2017-2023	8,162,308.49	0.1728	8,202,220.40	0.1785	8,180,528.73	0.1754
2024	2017-2024	8,313,835.49	0.1946	8,359,998.44	0.2012	8,335,915.43	0.1977
		Average	**0.1438**		**0.1478**		**0.1458**

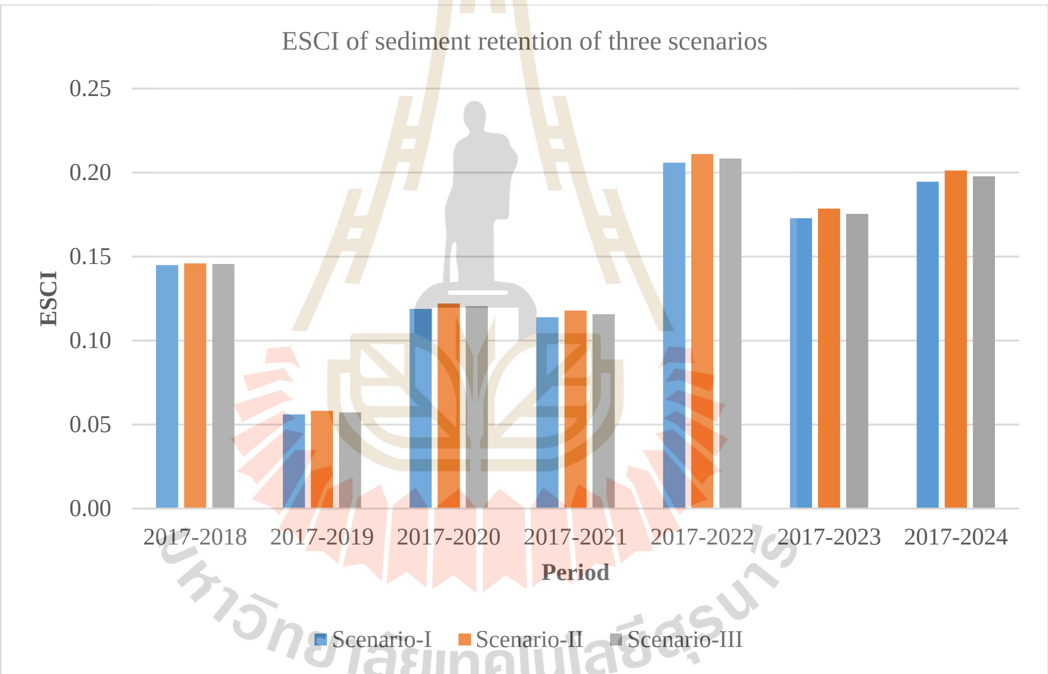


Figure 8.14 Comparison of ESCI on sediment retention of three different scenarios.

Table 8.16 Details of t-Test for average ESCI values on sediment retention service among three different scenarios.

Pairwise of Scenario	Mean		Variance		df	t- Stat	t Critical 2-tail
	Variable 1	Variable 2	Variable 1	Variable 2			
I and II	0.1439	0.1478	0.0027	0.0029	6	-126,326.77*	2.4469
I and III	0.1438	0.1458	0.0027	0.0028	6	-291,255.00*	2.4469
II and III	0.1439	0.1458	0.0027	0.0028	6	-221,909.00*	2.4469

8.3 LULC scenario for optimum water yield and sediment retention ecosystem services

The calculated average ESCI values of water yield (runoff) and sediment retention ecosystem services from three different LULC scenarios in Khlong U-Tapao watershed were simultaneously compared to identify LULC scenario for optimum water yield (runoff) and sediment retention ecosystem services as summary in Table 8.17 and Figure 8.15.

As results, it was found that at watershed level, an average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem services from LULC of Scenario II: Forest conservation and prevention can provide the highest average ESCI value of 0.0434 among three different LULC scenarios. Therefore, LULC of Scenario II: Forest conservation and prevention is here chosen for optimum water yield (runoff) and sediment retention ecosystem services in Khlong U-Tapao watershed. This LULC scenario can mitigate flooding event in Khlong U-Tapao watershed and reduce sediment export in Songkhla Lake.

Table 8.17 Average ESCI values of ecosystem service on water yield and sediment retention service among three different scenarios.

Period	Ecosystem Change Services Index (ESCI)								
	Scenario I			Scenario II			Scenario III		
	Water yield	Sediment retention	Average	Water yield	Sediment retention	Average	Water yield	Sediment retention	Average
2017-2018	-0.0583	0.1449	0.0433	-0.0579	0.1460	0.0441	-0.0576	0.1456	0.0440
2017-2019	-0.1328	0.0561	-0.0384	-0.1320	0.0581	-0.0370	-0.1313	0.0572	-0.0371
2017-2020	-0.0737	0.1188	0.0226	-0.0725	0.1221	0.0248	-0.0714	0.1204	0.0245
2017-2021	-0.0904	0.1139	0.0118	-0.0889	0.1179	0.0145	-0.0874	0.1157	0.0142
2017-2022	-0.0230	0.2059	0.0915	-0.0209	0.2110	0.0951	-0.0187	0.2084	0.0949
2017-2023	-0.0393	0.1728	0.0668	-0.0368	0.1785	0.0709	-0.0342	0.1754	0.0706
2017-2024	-0.0216	0.1946	0.0865	-0.0186	0.2012	0.0913	-0.0155	0.1977	0.0911
Average			**0.0406**			**0.0434**			**0.0432**

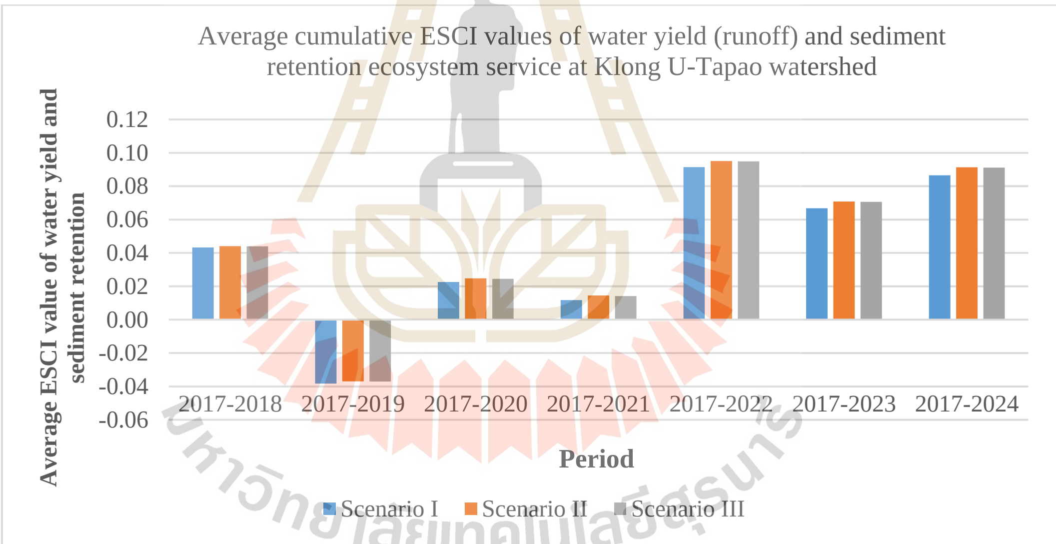


Figure 8.15 Comparison of average ESCI value on water yield and sediment retention ecosystem service among three different scenarios.

In addition, the calculated an average ESCI values on water yield (runoff) and sediment retention ecosystem services at sub-watershed in Khlong U-Tapao watershed from three different LULC scenarios were simultaneously compared to identify LULC scenario for optimum water yield (runoff) and sediment retention ecosystem services as summary in Table 8.18.

As result, it was also found that at sub-watershed level, an average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem services in term of gain and loss from LULC of Scenario II: Forest conservation and prevention can provide the highest average value of -0.009470 among three different LULC scenarios. Therefore, LULC of Scenario II is here again chosen for optimum water yield (runoff) and sediment retention ecosystem services in Khlong U-Tapao watershed.

Table 8.18 Comparison of an average ESCI on water yield (runoff) and sediment retention ecosystem service from three difference scenarios at sub-watershed level of Klong U-Tapao watershed during 2018 and 2024.

Sub-watershed	Average ESCI value (Gain or loss)		
	Scenario I	Scenario II	Scenario III
1. Khlong La/Khlong Jam Rai	0.1303	0.1331	0.1334
2. Khlong Lea	0.1092	0.1102	0.1118
3. Khlong Phang La/Khlong Ngae	0.0282	0.0318	0.0332
4. Khlong Pom	-0.1641	-0.1615	-0.1623
5. Khlong Ram	0.2449	0.2472	0.2470
6. Khlong Sa Dao	0.1330	0.1352	0.1353
7. Khlong Tong/Khlong Pra Tu	-0.0827	-0.0795	-0.0809
8. Khlong Wa	-0.2705	-0.2709	-0.2692
9. Khlong Wat/Khlong Tam	0.0569	0.0646	0.0613
10. Klong Bang Klam	-0.3076	-0.3049	-0.3046
	-0.012240	-0.009470	-0.009500

Details of an average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem service at sub-watershed from three different scenarios in different periods is summarized in Tables 8.19 to 8.21. In the meantime, comparison of an average ESCI of water yield (runoff) and sediment retention in term of gain or loss at sub-watershed among three different scenarios is displayed in Figure 8.16.

Table 8.19 An average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem service at sub-watershed of Scenarios I in different periods.

Sub-watershed	Average ESCI value (Gain or loss)							
	2017-2018	**2017-2019**	**2017-2020**	**2017-2021**	**2017-2022**	**2017-2023**	**2017-2024**	**Average**
1. Khlong La/Khlong Jam Rai	0.1394	0.0416	0.1142	0.0966	0.1820	0.1606	0.1778	**0.1303**
2. Khlong Lea	0.1056	0.0283	0.0955	0.0754	0.1581	0.1349	0.1669	**0.1092**
3. Khlong Phang La/Khlong Ngae	0.0222	-0.0467	0.0126	0.0003	0.0769	0.0530	0.0789	**0.0282**
4. Khlong Pom	-0.1630	-0.2272	-0.1764	-0.1871	-0.1262	-0.1408	-0.1276	**-0.1641**
5. Khlong Ram	0.2524	0.1459	0.2239	0.2072	0.3084	0.2763	0.3000	**0.2449**
6. Khlong Sa Dao	0.1161	0.0545	0.1054	0.1085	0.1935	0.1581	0.1945	**0.1330**
7. Khlong Tong/Khlong Pra Tu	-0.0861	-0.1510	-0.1001	-0.1063	-0.0380	-0.0578	-0.0399	**-0.0827**
8. Khlong Wa	-0.2672	-0.3251	-0.2784	-0.2904	-0.2411	-0.2509	-0.2404	**-0.2705**
9. Khlong Wat/Khlong Tam	0.0721	-0.0268	0.0369	0.0257	0.1122	0.0835	0.0946	**0.0569**
10. Klong Bang Klam	-0.2959	-0.3588	-0.3103	-0.3284	-0.2853	-0.2907	-0.2835	**-0.3076**

Table 8.20 An average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem service at sub-watershed of Scenarios II in different periods.

Sub-watershed	Average ESCI value (Gain or loss)							
	2017-2018	**2017-2019**	**2017-2020**	**2017-2021**	**2017-2022**	**2017-2023**	**2017-2024**	**Average**
1. Khlong La/Khlong Jam Rai	0.1401	0.0428	0.1163	0.0992	0.1856	0.1647	0.1827	**0.1331**
2. Khlong Lea	0.1057	0.0284	0.0959	0.0761	0.1591	0.1367	0.1695	**0.1102**
3. Khlong Phang La/Khlong Ngae	0.0236	-0.0447	0.0158	0.0040	0.0814	0.0581	0.0847	**0.0318**
4. Khlong Pom	-0.1622	-0.2259	-0.1743	-0.1845	-0.1227	-0.1370	-0.1235	**-0.1615**
5. Khlong Ram	0.2532	0.1472	0.2259	0.2094	0.3112	0.2795	0.3036	**0.2472**
6. Khlong Sa Dao	0.1168	0.0558	0.1073	0.1108	0.1964	0.1612	0.1981	**0.1352**
7. Khlong Tong/Khlong Pra Tu	-0.0851	-0.1489	-0.0973	-0.1030	-0.0338	-0.0533	-0.0349	**-0.0795**
8. Khlong Wa	-0.2662	-0.3232	-0.2757	-0.2873	-0.2370	-0.2719	-0.2352	**-0.2709**
9. Khlong Wat/Khlong Tam	0.0733	-0.0245	0.0403	0.0299	0.1178	0.1135	0.1022	**0.0646**
10. Klong Bang Klam	-0.2955	-0.3580	-0.3087	-0.3260	-0.2817	-0.2861	-0.2780	**-0.3049**

Table 8.21 An average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem service at sub-watershed of Scenarios III in different periods.

Sub-watershed	Average ESCI value (Gain or loss)							
	2017-2018	2017-2019	2017-2020	2017-2021	2017-2022	2017-2023	2017-2024	Average
1. Khlong La/Khlong Jam Rai	0.1405	0.0433	0.1167	0.0994	0.1859	0.1649	0.1830	**0.1334**
2. Khlong Lea	0.1054	0.0278	0.0954	0.0762	0.1619	0.1401	0.1755	**0.1118**
3. Khlong Phang La/Khlong Ngae	0.0244	-0.0433	0.0171	0.0055	0.0831	0.0593	0.0859	**0.0332**
4. Khlong Pom	-0.1622	-0.2261	-0.1750	-0.1856	-0.1239	-0.1385	-0.1252	**-0.1623**
5. Khlong Ram	0.2532	0.1470	0.2256	0.2091	0.3111	0.2793	0.3038	**0.2470**
6. Khlong Sa Dao	0.1168	0.0560	0.1074	0.1109	0.1966	0.1613	0.1982	**0.1353**
7. Khlong Tong/Khlong Pra Tu	-0.0853	-0.1499	-0.0987	-0.1046	-0.0357	-0.0553	-0.0368	**-0.0809**
8. Khlong Wa	-0.2669	-0.3246	-0.2776	-0.2893	-0.2393	-0.2488	-0.2380	**-0.2692**
9. Khlong Wat/Khlong Tam	0.0733	-0.0244	0.0402	0.0298	0.1178	0.0901	0.1022	**0.0613**
10. Klong Bang Klam	-0.2954	-0.3575	-0.3084	-0.3257	-0.2814	-0.2859	-0.2780	**-0.3046**

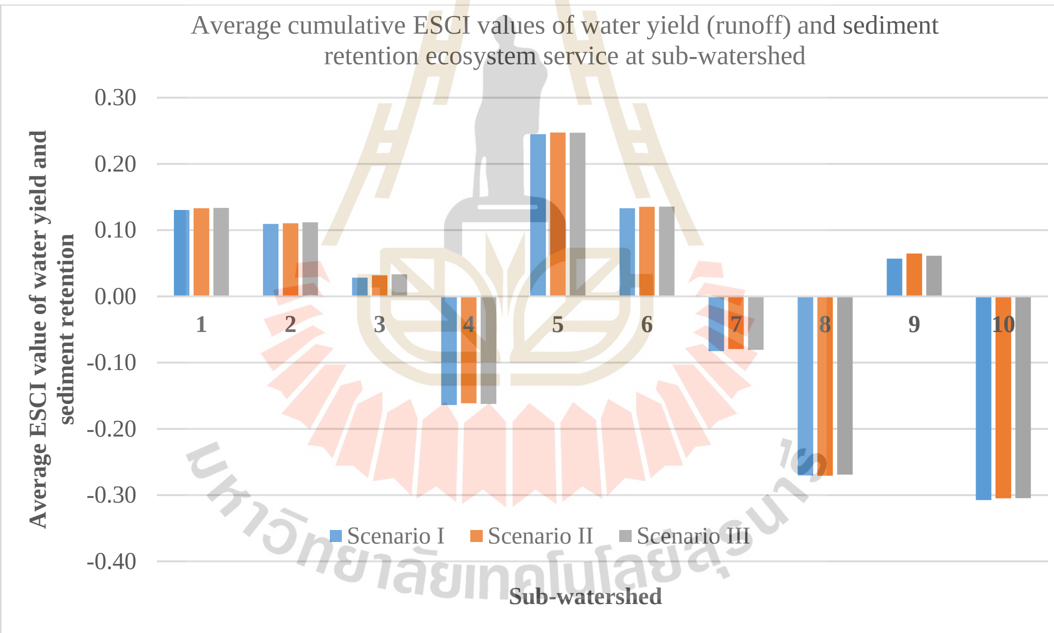


Figure 8.16 Comparison of an average ESCI of water yield (runoff) and sediment retention in term of gain or loss at sub-watershed among three different scenarios.

According to Tables 8.19 to 8.21 and Figure 8.16, it can be observed that at sub-watershed level, six sub-watershed include (1) Khlong La/Khlong Jam Rai, (2) Khlong Lea, (3) Khlong Phang La/Khlong Ngae, (4) Khlong Ram, (5) Khlong Sa Dao and (6) Khlong Wat/Khlong Tam can provide an average positive ESCI value (gain) of water yield and soil retention during 2018 to 2024. In contrast, four sub-watershed include (1) Khlong Pom, (2) Khlong Tong/Khlong Pra Tu, (3) Khlong Wa, and (4) Klong Bang Klam deliver an average negative ESCI value (loss) of water yield and soil retention during 2018 to 2024. These sub-watershed should be considered as critical sub-watershed to reduce surface runoff and increase sediment retention for flood mitigation and sediment export in the near future by increasing forest area.

CHAPTER IX

CONCLUSION AND RECOMMENDATIONS

In this chapter, five main results, which were reported according to research objectives of the study in the previous chapters including (1) land use and land cover assessment and its change, (2) land use and land cover prediction of three different scenarios, (3) water yield assessment, (4) sediment retention assessment, and (5) land use and land cover scenario for optimum water yield and sediment retention ecosystem services, are concluded and recommendations for future research and development are suggested.

9.1 Conclusion

9.1.1 Land use and land cover assessment and its change

The main LULC types in 2010 as the historical record and recent LULC data in 2017, which were classified by RF classifier from Landsat 5 TM and Landsat 8 OLI data, consisted of (1) urban and built-up area, (2) paddy field, (3) rubber plantation, (4) oil palm plantation, (5) perennial tree and orchard, (6) aquatic culture area, (7) evergreen forest, (8) mangrove forest, (9) marsh and swamp, (10) water body, and (11) miscellaneous land (bare land and abandoned mine). The major increasing areas of LULC types between 2010 and 2017 were rubber plantation and urban and built-up area. On the contrary, the major decreasing areas of LULC classes between 2010 and

2017 were evergreen forest and miscellaneous. In addition, the derived overall accuracy and Kappa hat coefficient for accuracy assessment of the thematic LULC map in 2010 and 2017 were 91.36% and 84.00% and 94.32% and 87.00%, respectively.

9.1.2 Land use and land cover prediction of three different scenarios

Prediction of LULC change of three different scenarios: Scenario I: Historical LULC evolution; Scenario II: Forest conservation and prevention; and Scenario III: Agriculture production extension during 2018 to 2024 were successfully implemented using CLUE-S model.

In this study, 8 driving factors on LULC change included elevation, slope, soil fertility, distance to road, distance to settlement, distance to water bodies, population density at sub-district level and average household income at sub-district level were applied to analyze for specific LULC type allocation using binomial logistic regression analysis. The most significant driving factor for all LULC types allocation was distance to the settlement and the derived multiple linear equations from binomial logistic regression analysis provided AUC values from 0.7239 (fair fit) to 0.9957 (excellent fit). Additionally, the deviation values between the required land area and the predicted area of each LULC type under three different scenarios varied from -0.1008% to 0.1290% or -10.08 km^2 (under estimation) to 12.89 km^2 (over estimation).

Under Scenario I, the LULC change during 2018 to 2024 was dictated by the historical LULC change between 2010 and 2017 that represents socioeconomic development in the study area. The significant LULC types with increasing area of this scenario were urban and built-up area, oil palm plantation, perennial trees and orchards, and water bodies whereas the dominant LULC types with decreasing area were paddy field, evergreen forest, marsh and swamp, and miscellaneous land.

Meanwhile, under Scenario II, the significant LULC types with increasing area were urban and built-up area, perennial trees and orchards, and evergreen forest but the dominant LULC types with decreasing area were rubber plantation, and miscellaneous land. The LULC change under this scenario was dictated by policy on forest conservation and prevention transformation, particularly the increasing forest area by the reforestation program on the illegal rubber plantation in the protected forest area.

In the meantime, the significant LULC types with increasing area under Scenario III were urban and built-up area, oil palm plantation, and evergreen forest while the dominant LULC types with decreasing area were rubber plantation, marsh and swamp and miscellaneous land. The LULC change under this scenario was dictated by policy on agriculture production extension, particularly the increasing of oil palm plantation and the decreasing of rubber plantation.

9.1.3 Water yield assessment

Estimation of water yield of actual LULC in 2017 and the predictive LULC of three different scenarios at Khlong U-Tapao watershed and its sub-watershed were successfully implemented based on water balance model by using water yield model of InVEST software suite. Water yield volume in 2017 in Khlong U-Tapao watershed was about 1,863,795,715 m^3 whereas at sub-watershed level, top three dominant sub-watersheds which provided the highest water yield were Khlong Wat/Khlong Tam, Khlong La/Khlong Jam Rai, and Khlong Wa. Likewise, the dominant LULC types which delivered high average water yield were marsh and swamp, evergreen forest and rubber plantation. The validation result of water yield estimation with observed data from hydrological station of RID at X90 (Khlong U-Tapao) provided a good to far fit for water yield estimation with NSE of 0.8132 and a high correlation between the observed and estimated water yield with R^2 of 0.8739.

Meanwhile, it revealed that dynamic pattern of water yield in three different scenarios during 2018 and 2024 dictated by annual rainfall data, which were here extracted from NCAR GIS Program, USA. Additionally, the significant different of annual water yield volume of three different scenarios depended on the predictive LULC change of three scenarios, and Scenario I provided the lowest annual water yield volume during 2018 to 2024. In fact, LULC of Scenario I was solely predicted based on annual rate of LULC change from transition area matrix between 2010 and 2017, it did not represent dramatic LULC change under this scenario. The contribution of each LULC type on water yield was insignificant. Herewith, the increasing LULC classes under this scenario were urban and built-up area, rubber plantation, oil palm plantation, perennial tree and orchard, aquatic cultural area, mangrove forest, and water body while the decreasing LULC classes were paddy field, evergreen forest, marsh and swamp and miscellaneous land. In contrast, LULC of Scenario II and Scenario III were predicted based on transformation of Government policy in forestry and agriculture sectors. Under Scenario II, increasing LULC classes were urban and built-up area, oil palm plantation, and evergreen forest, decreasing LULC classes were rubber plantation, and miscellaneous land, and other LULC types including paddy field, perennial tree and orchard, aquatic cultural area, mangrove forest, marsh and swamp, and water body were fixed during 2018 to 2024. Likewise, under Scenario III, increasing LULC classes were urban and built-up area and oil palm plantation, decreasing LULC classes were rubber plantation, marsh and swamp and miscellaneous land, and other LULC types including paddy field, perennial tree and orchard, aquatic cultural area, evergreen forest, mangrove forest and water body were fixed during 2018 to 2024. The contribution of LULC from Scenario II and III higher reflected on water yield than Scenario I.

9.1.4 Sediment retention assessment

Estimation of sediment retention of actual LULC in 2017 and the predictive LULC of three different scenarios at Khlong U-Tapao watershed and its sub-watershed were successfully implemented based on RUSLE and soil delivery ratio (SDR) using sediment delivery ratio model of InVEST software suite and three derivative outputs included soil erosion, sediment retention, and sediment export. Herein, only sediment retention as selected ecosystem services in this study is summarized.

For actual LULC in 2017, amount of sediment retention in Khlong U-Tapao watershed was about 6,959,666 tons whereas at sub-watershed level, Khlong Sa Dao retained the highest average sediment retention while Klong Bang Klam retained the lowest average sediment retention. Likewise, the dominant LULC type which retained the highest average sediment retention was evergreen forest while marsh and swamp retained the lowest average sediment retention.

At Klong U-Tapao watershed, the highest total sediment retention during 2018 to 2024 under Scenario I was 8.39 million tons occurring in 2022 while the lowest total sediment retention in this period was 7.35 million tons occurring in 2019. Likewise, under Scenario II, the highest total sediment retention was 8.43 million tons occurring in 2022 while the lowest total sediment retention was 7.36 million tons occurring in 2019. Similarly, under Scenario III, the highest total sediment retention was 8.41 million tons occurring in 2022 while the lowest total sediment retention was 7.36 million tons occurring in 2019. These results indicate the influence of dynamic factor of RUSLE model, which includes rainfall erosivity (R), soil erodibility (K), slope length-gradient factor (LS) and cover factor (C) and practice factor (P) for erosion control practice from LULC data on soil erosion as a budget of sediment retention and sediment export.

Meanwhile, at sub-watershed level, it was found that in three different scenarios the highest average sediment retention during 2018 to 2024 always occurred at Khlong Sa Dao and the lowest average sediment retention in the same period constantly occurred at Klong Bang Klam. This finding suggest that dynamic pattern of predictive annual rainfall during 2018 to 2024 plays more important role than the predictive LULC of three different scenarios on soil erosion (as budget of sediment retention and sediment export).

By comparison sediment retention information among three different scenarios, the predictive LULC between 2018 and 2024 of Scenario II retained the highest annual sediment retention with an average value of 3,320.18 tons/km^2, since this scenario generated the lowest soil erosion with an average value of 8,403.54 tons/km^2. In contrast, the predictive LULC between 2018 and 2024 of Scenario I retained the lowest sediment retention with an average value of 3,307.81 tons.

9.1.5 Land use and land cover scenario for optimum water yield and sediment retention ecosystem services

Based on an average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem service from three different scenarios at watershed level, it was found that LULC of Scenario II: Forest conservation and prevention provided the highest average ESCI value of 0.0434 among three different LULC scenarios. Therefore, LULC of Scenario II was chosen for optimum water yield (runoff) and sediment retention ecosystem services in Khlong U-Tapao watershed. This LULC scenario can mitigate flooding event in Khlong U-Tapao watershed and reduce sediment export in Songkhla Lake. Likewise, at sub-watershed level, an average cumulative ESCI values of water yield (runoff) and sediment retention ecosystem services in term of gain and loss from LULC of Scenario II provided the highest average value of -0.009470 among three different LULC scenarios. Consequently, LULC of Scenario II was also chosen for optimum water yield (runoff) and sediment retention ecosystem services in Khlong U-Tapao watershed.

In conclusion, it can be here concluded that integration of remote sensing technology with advance classification method (Random Forests) and geospatial models (CLUE-S model, Water yield and Sediment delivery ratio models of InVEST software suite) can be used as an efficient tools to identify an optimum water yield and sediment retention ecosystem services from different scenarios.

9.2 Recommendations

Many objectives were here investigated including LULC assessment and its change, simulation of LULC under three difference scenarios, water yield and sediment retention assessment and LULC scenario for optimum water yield and sediment retention ecosystem services in Klong U-Tapao watershed, Songkhla, Thailand. The possible expected recommendations and implication could be made for further studies as follows.

(1) The RF classifier can be easily apply to classify LULC from Landsat data and it can proved high accuracy. In the current study, the derived overall accuracy and Kappa hat coefficient of LULC map in 2010 and 2017 were 91.36% and 84.00% and 94.32% and 87.00%, respectively.

(2) According to LULC change prediction using CLUE-S model, it delivers 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, particularly Scenario II and III. These predicted scenarios were set up based on government policy as top-down approach. Hence, bottom-up approach for LULC change prediction based the requirement of local people or local government organization by a participatory approach should be examined in the future.

(3) To operate sediment deliver ratio (SDR) model for soil loss, sediment retention and sediment export estimation, an important parameters includes threshold flow accumulation, Borselli (kb), Borselli (IC_0) and max SDR values should be more calibrate to fit with local physical characteristics of the study area instead of applying default values. In principle, IC_0 and kb are calibration parameters that define the relationship between the index of connectivity and the sediment delivery ratio (SDR). Vigiak et al. (2012) mentioned that IC_0 is landscape independent and it is more sensitive to kb.

(4) Varieties of ecosystem services models are available to evaluate the impact of land use change on ecosystem services under the InVEST software suite. Therefore, additional ecosystem services models, such as nutrient retention (provision services), carbon storage (regulating services), and habitat quality (supporting services) can be examined in the future by researchers who are interest in ecosystem service evaluation. For example, Arunyawat and Shrestha (2016) used a set of ecosystem services including sediment retention, water yield, carbon stock, and habitat quality to quantify the impact of land use on ecosystem services in northern Thailand.

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