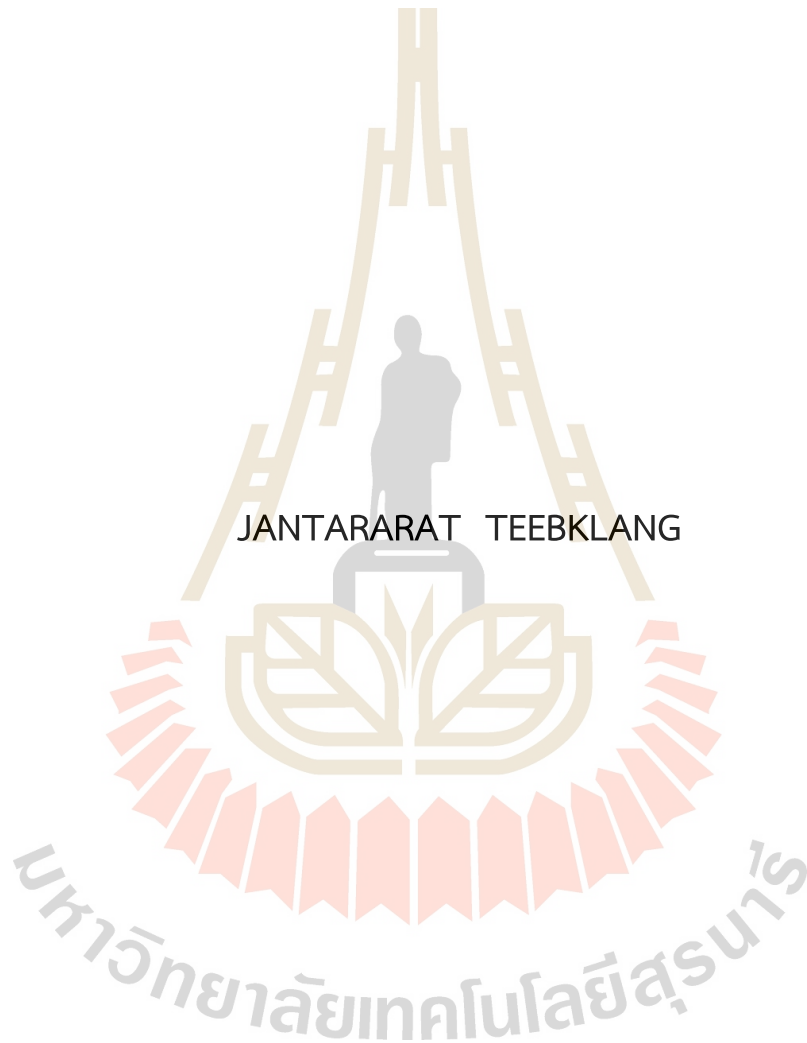


IMPACTS OF LAND USE AND LAND COVER CHANGE ON
ECONOMIC CROPS AND ECOSYSTEM SERVICE VALUES
AT LAM TAKHONG WATERSHED, THAILAND



A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Master of Science in Geoinformatics
Suranaree University of Technology
Academic Year 2024

ผลกระทบของการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดิน
ต่อมูลค่าพืชเศรษฐกิจและการให้บริการทางระบบนิเวศ
ในพื้นที่ลุ่มน้ำลำตะคอง ประเทศไทย



นางสาวจันทรัตน์ ตีบกลาง

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต

สาขาวิชาภูมิสารสนเทศ

มหาวิทยาลัยเทคโนโลยีสุรนารี

ปีการศึกษา 2567

IMPACTS OF LAND USE AND LAND COVER CHANGE ON ECONOMIC
CROPS AND ECOSYSTEM SERVICE VALUES
AT LAM TAKHONG WATERSHED, THAILAND

Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for a Master's Degree.

Thesis Examining Committee

Sura Au.

(Assoc. Prof. Dr. Sura Pattanakiat)

Chairperson

Suwit Ong.

(Assoc. Prof. Dr. Suwit Ongsomwang)

Member (Thesis Advisor)

S. Dasananda

(Assoc. Prof. Dr. Songkot Dasananda)

Member

Tanakorn Sritarapipat

(Asst. Prof. Dr. Tanakorn Sritarapipat)

Member

Yupaporn Ruksakulpiwat

(Assoc. Prof. Dr. Yupaporn Ruksakulpiwat)

Vice Rector for Academic Affairs

and Quality Assurance

Santi Maensiri

(Prof. Dr. Santi Maensiri)

Dean of Institute of Science

จันทรรัตน์ ตีบกกลาง : ผลกระทบของการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินต่อมูลค่าพืชเศรษฐกิจและการให้บริการทางระบบนิเวศในพื้นที่ลุ่มน้ำลำตะคอง ประเทศไทย (IMPACTS OF LAND USE AND LAND COVER CHANGE ON ECONOMIC CROPS AND ECOSYSTEM SERVICE VALUES AT LAM TAKHONG WATERSHED, THAILAND)
อาจารย์ที่ปรึกษา : รองศาสตราจารย์ ดร.สุวิทย์ อ่องสมหวัง, 100 หน้า.

คำสำคัญ: มูลค่าพืชเศรษฐกิจ/ มูลค่าการให้บริการทางระบบนิเวศ/ แบบจำลอง CLUE-S/ แบบจำลอง PRESENT VALUE/ SIMPLE BENEFIT TRANSFER METHOD/ ลุ่มน้ำลำตะคอง

ในช่วงหลายทศวรรษที่ผ่านมา การใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินในลุ่มน้ำลำตะคองเปลี่ยนแปลงอย่างรวดเร็วจากกิจกรรมของมนุษย์ เช่น การก่อสร้างอาคาร การก่อสร้างถนน การตัดไม้ทำลายป่า และกิจกรรมจากมนุษย์อื่นๆ ดังนั้น การทราบถึงปัจจัยขับเคลื่อนการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดิน การคาดการณ์การเปลี่ยนแปลงใช้ประโยชน์ที่ดินและสิ่งปกคลุมดิน และผลกระทบของการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินต่อมูลค่าพืชเศรษฐกิจและการให้บริการทางระบบนิเวศเป็นสารสนเทศสำคัญสำหรับนักจัดการที่ดินและนักวางแผนการใช้ประโยชน์ที่ดินเพื่อบรรเทาผลกระทบในอนาคต วัตถุประสงค์ของการวิจัยคือ (1) เพื่อระบุปัจจัยขับเคลื่อนการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินด้วยการวิเคราะห์การถดถอยแบบโลจิสติกแบบไบนารี (binary logistic regression analysis) (2) เพื่อคาดการณ์การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินระหว่างปี พ.ศ. 2567 ถึง ปีพ.ศ. 2582 ด้วยแบบจำลอง CLUE-S และ (3) เพื่อประเมินมูลค่าพืชเศรษฐกิจและมูลค่าการให้บริการทางระบบนิเวศและการเปลี่ยนแปลง

ผลการศึกษา พบว่า ปัจจัยขับเคลื่อนการเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินที่สำคัญที่สุด ได้แก่ ระดับความสูง ปริมาณน้ำฝนรายปีและเขตพื้นที่ชลประทาน ในขณะเดียวกัน ปัจจัยขับเคลื่อนที่สำคัญต่อพืชเศรษฐกิจ (ข้าว ข้าวโพด อ้อย และมันสำปะหลัง) ได้แก่ ระดับความสูง ความลาดชัน ปริมาณน้ำฝนรายปีและเขตพื้นที่ชลประทาน ผลการคาดการณ์การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินระหว่างปี พ.ศ. 2567 ถึง ปีพ.ศ. 2582 บ่งชี้ว่า พื้นที่เมืองและสิ่งก่อสร้าง อ้อย ไม้ยืนต้นและไม้ผล พื้นที่เกษตรกรรมอื่น ๆ แหล่งน้ำและที่ดินที่ไม่มีการใช้ประโยชน์มีเนื้อที่เพิ่มขึ้น ในขณะเดียวกัน พื้นที่นาข้าว ข้าวโพด มันสำปะหลัง ป่าไม้ ทุ่งหญ้าและพื้นที่ลุ่มมีเนื้อที่ลดลง สำหรับการประเมินมูลค่าทางเศรษฐกิจและการเปลี่ยนแปลง มูลค่าของพืชเศรษฐกิจ 4 ชนิดเพิ่มขึ้นอย่างต่อเนื่องในระหว่างปี พ.ศ. 2567 ถึง ปีพ.ศ. 2582 อย่างไรก็ตาม สัดส่วนมูลค่าทางเศรษฐกิจของข้าวและมันสำปะหลังจะลดลง แต่มูลค่าทางเศรษฐกิจของข้าวโพดและอ้อยจะเพิ่มขึ้นใน

ช่วงเวลาเดียวกัน สำหรับการประเมินมูลค่าการให้บริการทางระบบนิเวศและการเปลี่ยนแปลง พบว่ามูลค่าโดยรวมลดลงอย่างต่อเนื่องในระหว่างปี พ.ศ. 2567 ถึง ปีพ.ศ. 2582 อย่างไรก็ตาม หากพิจารณามูลค่าการให้บริการทางระบบนิเวศตามหน้าที่ พบว่า การควบคุมก๊าซ การควบคุมสภาพภูมิอากาศ การก่อดิน การปกป้องความหลากหลายทางชีวภาพ การผลิตอาหาร และวัตถุดิบลดลงเพียงเล็กน้อย แต่หน้าที่อื่น ได้แก่ การบำบัดของเสีย การประปา สันทนาการและวัฒนธรรมเพิ่มขึ้นเล็กน้อยในอนาคต

จากผลการศึกษาที่ได้รับทั้งหมด สามารถสรุปได้ว่า การเปลี่ยนแปลงการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินมีผลกระทบต่อมูลค่าพืชเศรษฐกิจและมูลค่าการให้บริการทางระบบนิเวศในแต่ละประเภทและหน้าที่ในลุ่มน้ำลำตะคอง โดยเฉพาะอย่างยิ่ง การเปลี่ยนพื้นที่นาข้าวและป่าไม้ไปเป็นการใช้ประโยชน์ที่ดินและสิ่งปกคลุมดินประเภทอื่นในอนาคต



สาขาวิชาคณิตศาสตร์และภูมิสารสนเทศ
ปีการศึกษา 2567

ลายมือชื่อนักศึกษา จิณรัตน์ อภิบาล
ลายมือชื่ออาจารย์ที่ปรึกษา [Signature]

JANTARARAT TEEBKLANG : IMPACTS OF LAND USE AND LAND COVER CHANGE ON ECONOMIC CROPS AND ECOSYSTEM SERVICE VALUES AT LAM TAKHONG WATERSHED, THAILAND. THESIS ADVISOR : ASSOC. PROF. SUWIT ONGSOMWANG, Dr. rer. Nat. 100 PP.

Keywords: ECONOMIC CROPS VALUE/ ECOSYSTEM SERVICE VALUE/ CLUE-S MODEL/ PRESENT VALUE MODEL/ SIMPLE BENEFIT TRANSFER METHOD/ LAM TAKHONG WATERSHED

During the past decades, land use and land cover (LULC) in the Lamtakhong watershed were rapidly changed by human activities such as building, road construction, deforestation and many other anthropogenic activities. Therefore, knowing the driving factors of LULC change, predicting LULC change and the effects of LULC change on economic crop and ecosystem service values in the future is very important for land managers and land use planners to mitigate such impacts. Research objectives are (1) to identify driving factors on LULC change using binary logistic regression analysis, (2) to predict LULC changes from 2024 to 2039 using the CLUE-S model and (3) to evaluate economic crops and ecosystem service values and changes.

As a result, the most significant driving factors on land use and land cover change were elevation, annual rainfall, and irrigation area. Meanwhile, the significant driving factors on economic crops (rice, corn, sugarcane, and cassava) were elevation, slope, annual rainfall, and irrigation. The predicted land use and land cover data between 2024 and 2039 indicated the increase of urban and built-up areas, sugarcane, perennial trees and orchards, other agriculture, water bodies, and unused land. Conversely, there were decreases in paddy fields, corn, cassava, forest land, rangeland, and marsh and swamp. For economic value evaluation and its change, the values of four economic crops in total were continuously increasing between 2023 and 2039. Still, the contribution of economic value from rice and cassava will decrease, but the economic value from corn and sugarcane will increase in the same period. For ecosystem service value evaluation and its change, the ecosystem service value in total continuously will decrease between 2023 and 2039. However, considering

ecosystem service value by its function, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions will be marginally decreased from 2023 to 2039. Still, waste treatment, water supply, and recreation and culture functions will be slightly increasing in the future.

In conclusion, land use and land cover change impacts economic crop value and ecosystem service value in each category and function in the Lam Takhong watershed, especially the conversion of paddy fields and forest land into other LULC types in the future.



School of Mathematical Sciences
and Geoinformatics
Academic Year 2024

Student's Signature ฉัตรชัย อังคาร
Advisor's Signature Swit Ong.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Assoc. Prof. Dr. Suwit Ongsomwang, my advisor, for his invaluable guidance, kind support, and continuous encouragement throughout my studies at Suranaree University of Technology. Without his dedication and unwavering support, this thesis would not have been possible.

I would also like to extend my sincere thanks to the chairperson and all members of the thesis committee, namely Assoc. Prof. Dr. Sura Pattanakiat, Assoc. Prof. Dr. Songkot Dasananda, and Asst. Prof. Dr. Tanakorn Sritarapipat, for their insightful comments and constructive suggestions which greatly contributed to the improvement of this research.

In addition, I am deeply grateful to Suranaree University of Technology for providing me with a scholarship, as well as to the administrative staff and my fellow students in the Geoinformatics Program for their kind assistance and support throughout my studies here.

Finally, I wish to express my heartfelt appreciation to my family for their financial support, unconditional love, care, and patience, which have been my greatest motivation and strength during my academic journey.

Jantararat Teebklang

มหาวิทยาลัยเทคโนโลยีสุรนารี

CONTENTS

	Page
ABSTRACT IN THAI.....	I
ABSTRACT IN ENGLISH.....	III
ACKNOWLEDGEMENTS	V
CONTENTS	VI
LIST OF TABLES	IX
LIST OF FIGURES	XI
LIST OF ABBREVIATIONS	XIII
CHAPTER	
I INTRODUCTION	1
1.1 Background problems and significance of the study.....	1
1.2 Research objectives	2
1.3 Scope and limitations of the study.....	2
1.3.1 Scope of the study	2
1.3.2 Limitation of the study	3
1.4 Study area.....	3
1.5 Benefits of the study	4
II RELATED CONCEPTS AND LITERATURE REVIEWS	5
2.1 Driving factor for LULC change	5
2.1.1 Biophysical factors	5
2.1.2 Economic and technological factors.....	6
2.1.3 Demographic factors.....	7
2.1.4 Institutional factors	8
2.1.5 Cultural factors	9
2.2 Modeling LULC change	10
2.2.1 Spatial versus non-spatial	10
2.2.2 Dynamic versus Static	11

CONTENTS (Continued)

	Page
2.2.3 Descriptive versus prescriptive	11
2.2.4 Deductive versus Inductive	12
2.2.5 Agent-Based versus Pixel-Based Representations	12
2.2.6 Global versus Regional Models	12
2.3 CLUE-S Model	13
2.3.1 CULE-S module structure	13
2.4 Ecosystem Services Evaluation	17
2.4.1 Concept of ecosystem services	17
2.4.2 Simple benefit transfer method	19
2.5 Applications of driving factor for LULC change	21
2.6 Applications of CLUE-S model	22
2.7 Applications of ecosystem services evaluation	23
III RESEARCH METHODOLOGY	26
3.1 Data collection and preparation	28
3.2 Identification of driving factors on LULC change	31
3.3 LULC prediction using CLUE-S model	31
3.3.1 Validation of CLUE-S model parameter for LULC prediction	31
3.3.2 LULC prediction between 2024 and 2039	32
3.4 Evaluation of economic value and ecosystem service value and change	33
3.4.1 Economic value evaluation and change	34
3.4.2 Ecosystem service value evaluation and change	34
IV RESULTS AND DISCUSSION	37
4.1 Data collection and preparation	37
4.1.1 LULC data in 2015, 2019 and 2023	37
4.1.2 Thematic accuracy assessment of LULC in 2023	41
4.1.3 Driving factor for LULC prediction	43

CONTENTS (Continued)

	Page
4.2 Identification of driving factors on LULC change.....	46
4.2.1 Multicollinearity test.....	46
4.2.2 Binary logistics regression analysis.....	46
4.3 LULC prediction using CLUE-S model.....	59
4.3.1 Validation of CLUE-S model parameter for LULC prediction	59
4.3.2 LULC prediction between 2024 and 2039	64
4.4 Evaluation of economic and ecosystem services and change	75
4.4.1 Evaluation of economic crop value between 2023 and 2039 ...	75
4.4.2 Change of economic crop value between 2023 and 2039.....	78
4.4.3 Evaluation of ecosystem service value between 2023 and 2039	80
4.4.4 Change of ecosystem service value between 2023 and 2039 ...	88
V CONCLUSION AND RECOMMENDATION.....	89
5.1 Conclusion.....	89
5.2 Recommendation.....	91
REFERENCES	92
CURRICULUM VITAE.....	100

LIST OF TABLES

Table	Page
2.1 Biophysical factors of forest, dryland, and cropland changes.....	6
2.2 Economic and technological factors of forest, dryland, and cropland changes	7
2.3 Demographic factors of forest, dryland, and cropland changes	8
2.4 Institutional factors of forest, dryland, and cropland changes	9
2.5 Cultural factors of forest, dryland, and cropland changes	10
2.6 Classification of ecosystem services	18
3.1 Lists data collection and preparation for data analysis in the study.	28
3.2 Reclassified land use and land cover classification in 2015, 2019 and 2023.	29
3.3 Driving factors on LULC change.	30
3.4 Coefficient value of different LULC types for ESV estimation.....	35
3.5 Definition of ecosystem services function.....	36
4.1 Area and percentages of LULC data in 2015.....	39
4.2 Area and percentages of LULC data in 2019.....	40
4.3 Area and percentages of LULC data in 2023.....	40
4.4 Error matrix and accuracy assessment of the reclassified LULC data in 2023.....	42
4.5 Basic statistical data on driving factors for LULC prediction.....	43
4.6 Multicollinearity diagnostic test of driving factors on LULC change.	47
4.7 Identified the driving factors for each LULC type allocation as equation form with AUC using binary logistic regression analysis.....	48
4.8 Elasticity of LULC change for predicting LULC in 2023.	60
4.9 Conversion matrix of possible LULC change between 2019 and 2023.....	60
4.10 Annual land requirement with annual rate for predicting LULC in 2023.....	61
4.11 Error matrix and accuracy assessment between reclassified LULC	

LIST OF TABLES (Continued)

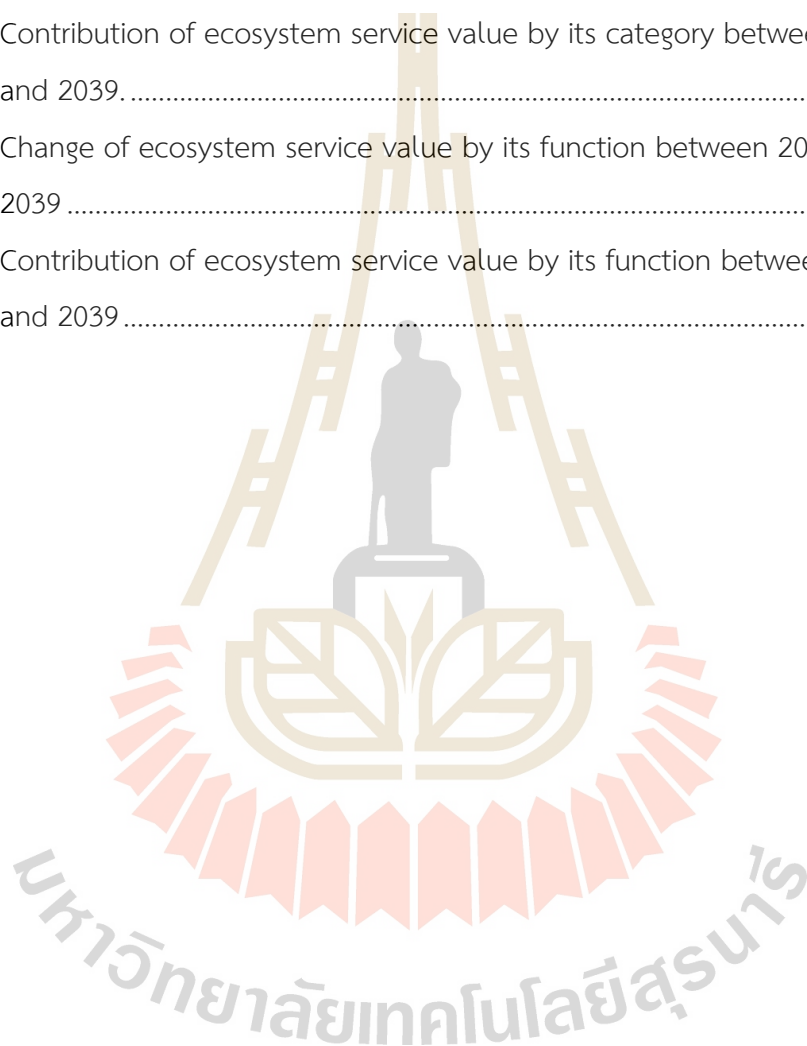
Table	Page
in 2023 and predicted LULC in 2023.	62
4.12 The matrix of the transition area between 2015 and 2023.	70
4.13 Annual land requirement of each LULC type LULC for LULC prediction between 2024 and 2039.	66
4.14 Area of predicted LULC type between 2024 and 2039.	69
4.15 Percentage of predicted LULC type between 2024 and 2039.	70
4.16 Simple comparison of LULC changes between 2023 and 2039.	71
4.17 Change detection matrix of LULC change between 2023 and 2039.	73
4.18 Present economic crop value in 2023.	76
4.19 Future economic crop value between 2024 and 2039.	77
4.20 Economic value change between 2023 and 2039 by ESCI.	79
4.21 Coefficient value for different LULC types for ESV estimation.	81
4.22 Area of each LULC type for ESV estimation between 2023 and 2039.	82
4.23 Ecosystem service value by its category and its total between 2023 and 2039.	83
4.24 Ecosystem service value by its function and its total between 2023 and 2039.	86
4.25 Ecosystem services values change between 2023 and 2039.	88

LIST OF FIGURES

Figure	Page
1.1 Study area.....	4
2.1 Generalized model structure of spatially explicit land-use change models....	11
2.2 Overview of the modeling procedure.	14
2.3 Overview of the information flow in the CLUE-S model.....	15
2.4 Illustration of translating a hypothetical land use change sequence into a land use conversion matrix.	16
2.5 Example of a land use conversion matrix with the different options implemented in the model.....	16
2.6 Supply and demand curves show cost definitions, net rent and consumer surplus for normal goods (a) and some essential ecosystem services (b).....	20
3.1 The overview of the research methodology framework.	27
3.2 Schematic workflow of optimum local parameter for LULC prediction and LULC prediction of two periods using CLUE-S model.....	33
4.1 Spatial distribution of LULC in 2015.	38
4.2 Spatial distribution of LULC in 2019.	38
4.3 Spatial distribution of LULC in 2023.	39
4.4 Comparison of each LULC type area in 2015, 2019 and 2023.....	41
4.5 Driving factors on LULC change.	44
4.6 Comparison of spatial LULC distribution in 2023: (a) classified LULC from LDD and (b) predicted LULC by the CLUE-S model.....	63
4.7 Spatial distribution of predicted LULC data between 2024 and 2039.	67
4.8 Percent of change of each LULC type in the study.	72
4.9 Change of future economic crop value between 2023 and 2039.	77
4.10 Contribution of the future economic value of four crops between 2023 and 2039.....	78

LIST OF FIGURES (Continued)

Figure	Page
4.11 Change of ecosystem service value by its category between 2023 and 2039	84
4.12 Contribution of ecosystem service value by its category between 2023 and 2039.	84
4.13 Change of ecosystem service value by its function between 2023 and 2039	87
4.14 Contribution of ecosystem service value by its function between 2023 and 2039	87



LIST OF ABBREVIATIONS

AUC	=	Area under curve
BOT	=	Bank of Thailand
CDD	=	Community Development Department
CLUE-S	=	Conversion of Land Use and its Effects at Small regional extent
DOPA	=	Department of Provincial Administration
ESV	=	Ecosystem service value
FV	=	Future Value
GIS	=	Geographic Information System
LDD	=	Land Development Department
LULC	=	Land use and land cover
MEA	=	Millennium Ecosystem Assessment
OAE	=	Office of Agricultural Economics
OCSB	=	Office of the cane and sugar board.
ONWR	=	Office of the National Water Resources
PV	=	Present Value
RID	=	Royal Irrigation Department
SRTM	=	Shuttle Radar Topography Mission
TMD	=	Thai Meteorological Department
TOL	=	Tolerance
VIF	=	Variance Inflation Factor

CHAPTER I

INTRODUCTION

1.1 Background problems and significance of the study

Economic crops generate income and drive the agricultural economy domestically and internationally, a food source, raw material sources for bio-energy production and consumption of humans and animals. Economic crops are divided into upland, horticultural, and economic plants. The main crops for export are rice, rubber, fresh fruit, cassava, maize, orchids, beans, tobacco leaves, cashew nuts, coffee, cotton, sugarcane etc., which can create a lot of economic value. (Ministry of Commerce, 2024) But at present, the main economic crops, cassava, corn, rubber, pineapple, longan, and rambutan, encountered problems of insufficient production to support the industry. The cost of production is higher than that of competitors, prices fluctuate, and large buyers choose to import products from competitors because of the low price. As a result, agricultural products in the country are low in price. (Office of Agricultural Economics, 2023) Such problems have greatly affected farmers.

Meanwhile, the evaluation of ecosystem services in specific areas has been conducted at national and international levels after the global initiative in 1999 by the Millennium Ecosystem Assessment (MEA), such as Kindu, Schneider, Teketay, and Knoke, 2016; Mamat, Halik, and Rouzi, 2018; Ongsomwang, Pattanakiat, and Srisuwan, 2019; Shuangao, Padmanaban, Mbanze, Silva, Shamsudeen, Cabral, and Campos, 2021; Karki, Kumar, and Baniya, 2022; and Mamat et al., 2024. Every ecosystem has a different capacity to provide ecosystem services, depending on its structure and condition (Nelson et al., 2009). The change in land use and land cover (LULC) would affect human well-being (MEA, 2005).

The Lam Takhong watershed is a crucial water resource for Nakhon Ratchasima province and the Northeast region of Thailand. In the past decades, rapid land use and land cover changes (Chaiyawannakarn, 2017), driven by human activities, including

urban expansion, road construction, deforestation, and other anthropogenic factors, have significantly altered the landscape (Ruamkaew, 2011). These changes have impacted the economic value of crops and led to a decline in ecosystem services within the watershed.

Therefore, knowing the driving factors of LULC change and predicting LULC change in the future is very important. Moreover, the effects of LULC change on economic crop and ecosystem service values are essential information for land managers and land use planners to mitigate such impacts.

1.2 Research objectives

The research aims to evaluate the impacts of LULC change on economic crops and ecosystem services values in the Lam Takhong watershed. Specific research objectives are as follows:

- (1) To identify driving factors on LULC change using binary logistic regression based on land use data from 2015, 2019, and 2023.
- (2) To predict LULC changes from 2024 to 2039 using the CLUE-S model.
- (3) To evaluate economic crops and ecosystem service value change.

1.3 Scope and limitations of the study

1.3.1 Scope of the study

(1) LULC data of Land Development Department (LDD) in 2015, 2019, and 2023 will be reclassified into twelve classes, including (1) urban and built-up area, (2) paddy field, (3) corn, (4) sugarcane, (5) cassava, (6) perennial trees and orchards, (7) other agriculture, (8) forest land, (9) water body, (10) rangeland, (11) marsh and swamp, and (12) unused land, for LULC change prediction.

(2) Driving factors for LULC change, including physical, proximity, and socio-economic factors, will be identified by multicollinearity test and binary logistic regression analysis and further applied to predict LULC change.

(3) Local driving factors and parameters of the CLUE-S model are validated by comparing the predicted LULC in 2023 from the CLUE-S model with the reclassified LULC in 2023 of LDD using wall-wall accuracy assessment.

(4) Four dominant agricultural crops in Nakhon Ratchasima, including rice, corn, sugarcane and cassava, are selected as economic crops for the evaluation of economic crop value and change in the future using the present value (PV) model.

(5) The evaluation of ecosystem service value and change are evaluated using the simple benefit transfer method.

1.3.2 Limitations of the study

The LULC data between 2024 and 2039 are predicted based on the historical land use evolution in the study area, extracted based on LDD land use data in 2015 and 2023 using the Markov Chain model and driving factors on LULC change. So, the accuracy of prediction data relies on the original collected land use data and driving factors on LULC change.

1.4 Study area

The Lam Takhong watershed spans 3,315.07 square kilometers (2,071,918 Rai) and is located between latitude 14° 22' to 15° 4' N and longitude 101° 16' to 102° 15' E. The watershed covers parts of multiple districts in Nakhon Ratchasima province, including Pak Chong, Wang Nam Khiao, Sikhiu, Dan Khun Thot, Sung Noen, Pak Thong Chai, Kham Thale So, Mueang Nakhon Ratchasima, and Chaloem Phra Kiat. Additionally, it extends into Mueang Nakhon Nayok district in Nakhon Nayok province (Ruamkaew, 2011), as displayed in Figure 1.1.

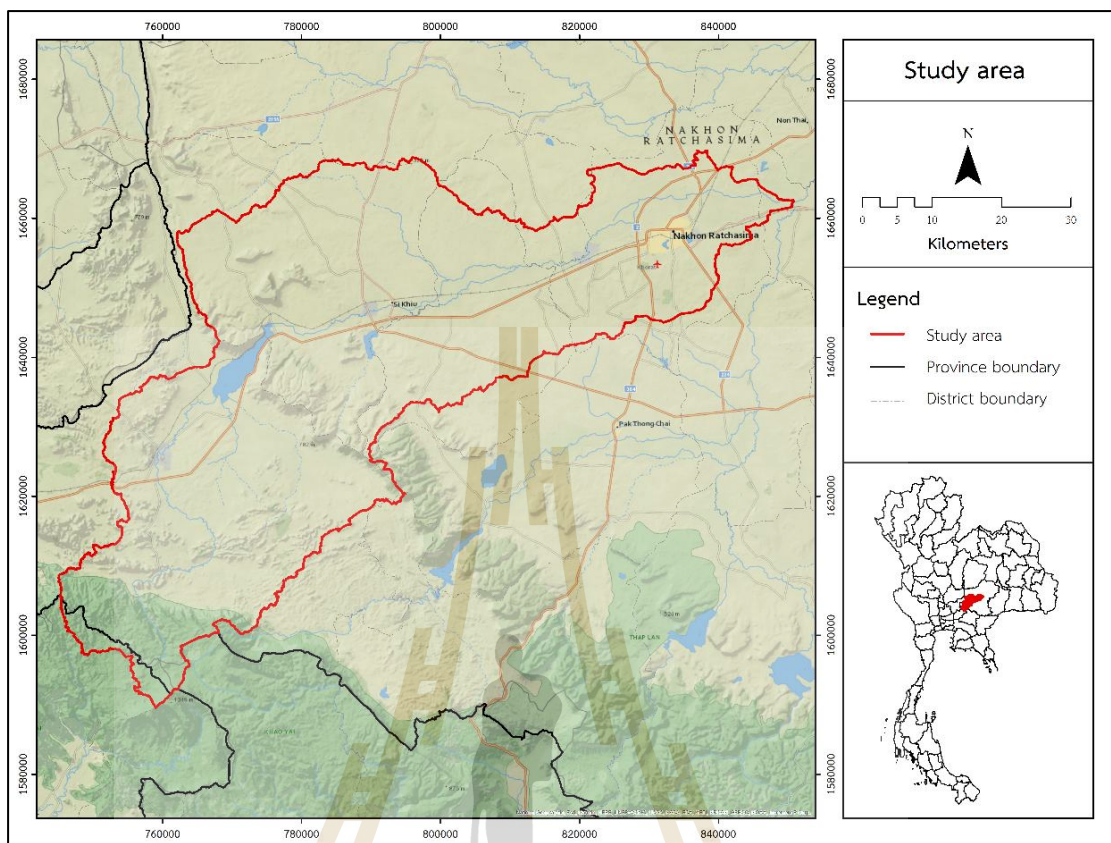


Figure 1.1 Study area.

1.5 Benefits of the study

The benefits of the study, which cover all research objectives, are as follows:

- (1) To know the driving factors affecting LULC changes in the Lam Takhong watershed
- (2) To understand LULC status in 2015, 2019, and 2023
- (3) To obtain LULC change information in the future (2024 to 2039) based on CLUE-S model
- (4) To obtain economic crop and ecosystem services values and change in the future

CHAPTER II

RELATED CONCEPTS AND LITERATURE REVIEWS

The essential concepts and literature reviews that are related to this research, including (1) Driving factors for LULC change, (2) Modeling LULC change, (3) CLUE-S Model, (4) Ecosystem Services Evaluation, (5) Applications of driving factor for LULC change, (6) Applications of CLUE-S model, and (7) Applications of ecosystem services evaluation, are separately summarized as follows:

2.1 Driving factor for LULC change

Lambin and Geist (2006) classified driving forces for LULC change into five groups: biophysical factors, economic and technological factors, demographic factors, institutional factors, and cultural factors. These groups of drivers are interconnected through the organization of the environment and human systems at two or more levels. Groups of drivers interact directly through responses and have joint effects (Lambin, Geist, and Lepers, 2003; Steffen et al., 2004).

Summary of each driving force based on the synthesis report of Geist, Lambin, Palm, and Tomich (2006) on causes and trajectories of land use land cover change are as follows:

2.1.1 Biophysical factors

Biophysical factors encompass both biological and non-biological elements that influence land characteristics, including climate, lithology, hydrology, vegetation, soil, topography, and relief. These factors vary across different locations, regions, and periods. The interaction between biophysical variability, natural environmental changes, and human-induced land changes plays a crucial role in shaping landscapes.

Additionally, natural variability can contribute to socio-economic instability. At a regional level, biophysical factors of forest, dryland, and cropland changes are summarized in Table 2.1.

Table 2.1 Biophysical factors of forest, dryland, and cropland changes.

Biophysical factors		
Forest change (Conversion and modification)	Land characteristics (Biophysical features)	<ul style="list-style-type: none"> ● Soil quality ● Slope. Topography ● Watercourse/Waterbody ● Vegetation
	Biophysical triggers	<ul style="list-style-type: none"> ● Soil-related ● Water, Climate ● Vegetation-related
Dryland change (land degradation)	Indirect impact (climatic variability)	<ul style="list-style-type: none"> ● High rainfall deficit ● Warmer, drier
	Direct impact (on land cover/surface vegetation)	<ul style="list-style-type: none"> ● Change in fire regime. ● More oscillations of dry/wet conditions ● Simple occurrence of drought
Cropland change (land use dynamics)		<ul style="list-style-type: none"> ● Precipitation variation ● Watercourse/Waterbody ● Soil properties

Source: Geist, Lambin, Palm, and Tomich (2006)

2.1.2 Economic and technological factors

Economic factors and related policies involve various processes that influence land management decisions and require distinct consideration. These factors directly affect land managers' choices through variables such as taxes, production and transportation costs, input and output prices, subsidies, credit access, trade, technology, and capital flows and investments (Barbier, 1997). Among these, taxes and subsidies play a crucial role in shaping land-use changes in land cover and ecosystems.

Technological factors shape the agricultural sector, as the effects of agricultural development on forest conversion depend on how new technologies influence labor markets and migration, the capital and labor demands of technologies,

the profitability of farming at the forest frontier, and the extent to which crops are marketed locally or globally (Angelsen and Kaimowitz, 2001).

At a regional level, economic and technological factors of forest, dryland, and cropland changes are summarized in Table 2.2.

Table 2.2 Economic and technological factors of forest, dryland, and cropland changes.

Economic and technological factors		
Forest change (Conversion and modification)	Dryland change (Land degradation)	Cropland change (Land use dynamics)
Market growth, commercialization <ul style="list-style-type: none"> • Sector market growth • Demand/Consumption 	Market growth, commercialization	Market access
Market failure	Economic depression, impoverishment	Standard of living
Urban-industrial growth	Innovative developments, introductions	Market demand
Foreign exchange	Deficiencies of technical applications	Off-farm employment
Special variables (low cost, price change)		Water provision program
Agrotechnological change		Infrastructure program
Poor timber/extraction techniques		

Source: Geist, Lambin, Palm, and Tomich (2006)

2.1.3 Demographic factors

Population growth and increasing pressure on land use have been key considerations in understanding the human-environment relationship. However, rather than absolute population numbers, factors such as household size and urbanization have emerged as the most significant aspects of population dynamics. These factors highlight the indirect or consumptive demands placed on land by a growing urban population (Lambin et al., 2001).

The effects of population change encompass mortality, fertility, and out-migration, which are influenced by factors such as technology, social organization,

culture, and consumption patterns. While population growth significantly contributes to land change, its impact is shaped by various factors, including the timing, location, and nature of the change, as well as who initiates and benefits from it. Research on demographic factors in land change is becoming increasingly sophisticated, requiring a nuanced and comprehensive population analysis. At a regional level, the demographic factors influencing forest, dryland, and cropland changes are summarized in Table 2.3.

Table 2.3 Demographic factors of forest, dryland, and cropland changes.

Demographic factors		
Forest change (Conversion and modification)	Dryland change (Land degradation)	Cropland change (Land use dynamics)
In-migration	Population growth, increased in size	Population numbers, density
Market failure	In-migration, rising population densities	Population composition
Growing population density	Innovative developments, introductions Deficiencies of technical applications	Settlement, migration Off-farm employment Water provision program Infrastructure program

Source: Geist, Lambin, Palm, and Tomich (2006)

2.1.4 Institutional factors

Institutional factors, including political, legal, economic, and traditional elements, are closely connected to economic and demographic factors and play a significant role in driving land use changes. Government policies universally influence land change, either as a direct cause or through mediation. These policies impact land use in various ways, such as infrastructure development, agricultural land management, forest conservation, conversion of farmland into residential areas, and population migration. Additionally, property rights are a critical institutional factor, as they determine land managers' ability to participate in and shape policy decisions. At a regional level, institutional factors of forest, dryland, and cropland changes are summarized in Table 2.4.

Table 2.4 Institutional factors of forest, dryland, and cropland changes.

Institutional factors		
Forest change (Conversion and modification)	Dryland change (Land degradation)	Cropland change (Land use dynamics)
Formal deforestation policies on land development	Malfunctioning common property regulation	Property regime
Formal deforestation policies on economic growth	New land tenure, land zoning measures	Government/NGO policy
Formal deforestation policies on credits/subsidies	Agricultural development policies	Income affecting program
Properties right issues		Infrastructure program
Policy failure		
Mismanagement		

Source: Geist, Lambin, Palm, and Tomich (2006)

2.1.5 Cultural factors

Cultural factors play a significant role in land use decision-making and must be considered alongside political and economic conditions. Inequalities in these areas, such as the status of women, ethnic minorities, and resource-poor households, impact access to resources and influence land use patterns. Land managers bring diverse motivations, experiences, and personal histories to their decisions, while individual attitudes, values, beliefs, and perceptions further shape land use choices (US National Research Council et al., 1999). Understanding the mental models of different stakeholders offers valuable insight into resource management, adaptive strategies, policy compliance or resistance, social learning, and societal responses to land-use changes (Lambin, Geist, and Lepers, 2003). At a regional level, institutional factors of forest, dryland, and cropland changes are summarized in Table 2.5.

Table 2.5 Cultural factors of forest, dryland, and cropland changes.

Cultural factors		
Forest change (Conversion and modification)	Dryland change (Land degradation)	Cropland change (Land use dynamics)
Public attitudes, values and beliefs	Public attitudes, values and beliefs	Regional/ethnicity
Public unconcern	Violent land conflict, war	Education
Missing basic values	Perception issues	
Individual/household behavior	Individual and household behavior	
Individual/household behavior	Individual and household behavior	
Situation-specific (especially rent-seeking)	Indifference	
Unconcern by individuals	Perceptual issues	

Source: Geist, Lambin, Palm, and Tomich (2006)

2.2 Modeling LULC change

Verburg, Rounsevell, and Veldkamp, (2006) categorized LULC models into six types as a summary in the following section.

2.2.1 Spatial versus non-spatial

The difference between spatial versus non-spatial is essential in choosing the type of model to use in the analysis. The spatial model focuses on presenting land use clearly in spatial terms, transformation, and various details will be specified by pixel-by-pixel changes in the raster or stored in other formats (Figure 2.1). Models can explore spatial variation and consider environmental and biophysical variations, such as the SLEUTH model, CLUE model, and GEOMOD (Pontius, Cornell, and Hall, 2001; Verburg, Soepboer, Limpiada, Espaldon, Mastura, and Veldkamp, 2002; Verburg, Schot, Dijst, and Veldkamp, 2004; Goldstein, Candau, and Clarke, 2004). In the group of non-spatial models, the focus is on modeling the rate and magnitude of land use change. Not focusing on spatial distribution by calculating the utility of land use to identify the most appropriate application at a time.

In the model structure, the difference in calculating the magnitude of land use change depends on the driving factors. The same factors but using different

models can affect the scale of land use change. Therefore, selecting driving factors is crucial to land use change simulation. There are various approaches, including (a) rule-based systems based on either theory or expert knowledge, (b) suitability maps based on empirical analysis, and (c) transition rules dependent on the land uses in the neighborhood (e.g., cellular automata).

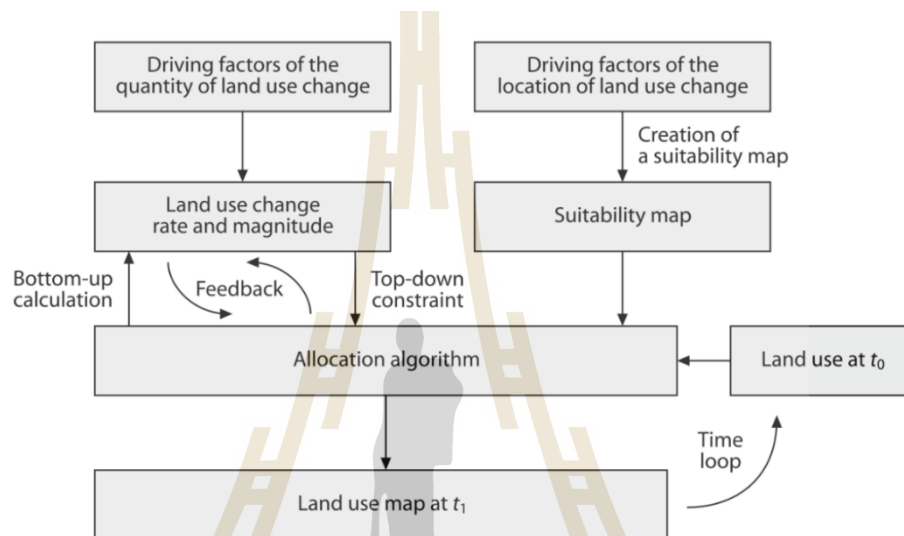


Figure 2.1 Generalized model structure of spatially explicit land-use change models. (Lambin and Geist, 2006)

2.2.2 Dynamic versus Static

Dynamic and static models are differentiated between models based on their temporal characteristics. The static model uses the coefficients of the regression model to describe the spatial distribution of land use changes. It is one of the functions of driving factors and is widely used.

The Dynamic model focuses on time to observe land use changes and can predict future occurrences based on the probability of driving factors such as GEOMOD, CLUE, and SLEUTH. (Lambin and Geist, 2006)

2.2.3 Descriptive versus prescriptive

The descriptive model is a model that aims to simulate the operation of a land use system and simulate a survey of near future land use patterns. The prescriptive model focuses on calculating land use as appropriately as possible

according to goals or policy plans. However, it does not use in-depth information about actual changes because the land use system is intended to be used according to the target. Therefore, deterministic models are used for policy and economic behavior but cannot explain social and cultural aspects. (Lambin and Geist, 2006)

2.2.4 Deductive versus Inductive

The main difference between deductive and inductive is the role of theory. Because the inductive analysis of land use change has requirements that depend on the statistical relationship between land change and a set of variables, multivariate statistics, change probabilities, and variable correlation tests are used to determine the conform to change. So, it makes the inductive method very popular. Inductive models range from models used to make decisions by specifying a set of relevant variables related to change and empirical models.

A deductive model is based on a theory that predicts patterns from the educational process. Using theory as a guideline to classify the relationship of variables to land use change or exploring the relationship of the variables themselves, but inductively using data that has already been analyzed or using statistics to measure the relationship. (Lambin and Geist, 2006)

2.2.5 Agent-Based versus Pixel-Based Representations

It is the difference in reference units of land use change. Pixel-based is the use of spatially explicit units of analysis stored in raster or other formats. Agent-based is based on units from independently defined agents such as population, density, or other agents to be used in connection with the objectives of interest. The choice of using an agent or pixel reference depends on the purpose of the research. (Lambin and Geist, 2006)

2.2.6 Global versus Regional Models

Regional models will vary according to the size of the study area. The focus is on analyzing land use problems or land cover changes, but the global model analyzes on a larger scale. It doesn't focus on land use problems, but it focuses on analysis of the weather, population, economy, or things that affect the environment. Global models often have limitations in analyzing land use changes, but regional models can connect relevant rules and analyze changes well. (Lambin and Geist, 2006)

2.3 CLUE-S Model

The Conversion of Land Use and its Effects (CLUE) model was developed to simulate land use changes by integrating empirical relationships between land use and its driving factors with dynamic modeling of competition among land use types (Veldkamp and Fresco, 1996; Verburg, De Koning, Kok, Veldkamp, and Bouma 1999). However, Verburg, (2010) noted that the CLUE model is not directly applicable at the regional scale. Consequently, it was modified into CLUE-S (Conversion of Land Use and its Effects at Small Regional Extent), specifically designed for spatially explicit land use change simulations. This model combines empirical location suitability analysis with dynamic simulations of competition and interactions among land use systems over time and space.

Significant characteristics of CLUE-S include: (1) CLUE-S module structure, (2) Spatial policies and restrictions, (3) Land use type-specific conversion settings, (4) Land use requirements and (5) Location characteristics and allocation procedures (Verburg, 2010), are summarized in the following:

2.3.1 CLUE-S module structure

The CLUE-S model consists of two primary modules, non-spatial and spatial modules (Figure 2.2). The non-spatial module estimates the annual land use demand for each type based on trend extrapolation. The spatial module then translates these demands into land use changes at specific locations using a raster-based system, incorporating spatial analysis and dynamic modeling (Verburg et al., 2002). The empirical analysis identifies relationships between land use distribution and key influencing factors, while the competition among land uses is simulated based on their relative advantages at each location.

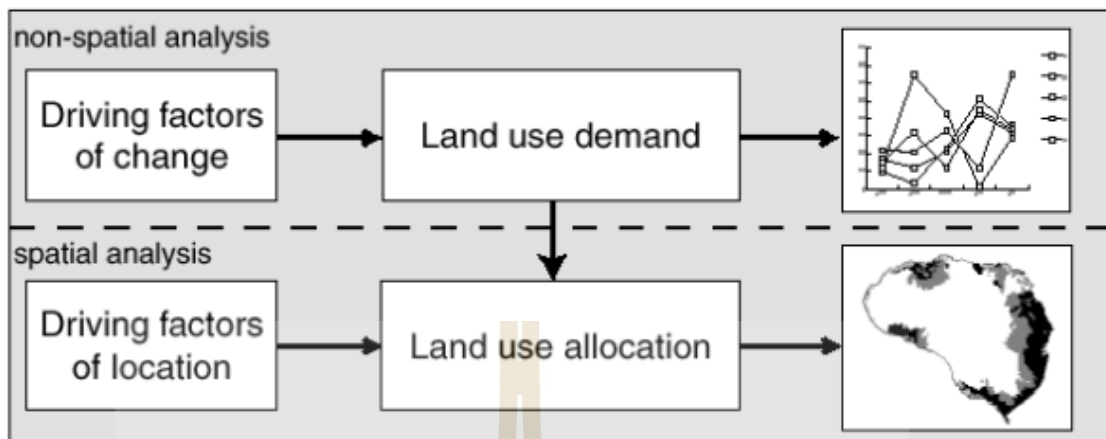


Figure 2.2 Overview of the modeling procedure. (Verburg, 2010)

(1) **Spatial policies and restrictions**

Spatial policies and restrictions can impose pressure on areas where land use changes are restricted by policies or tenure status (Verburg, Van de Steeg, and Schulp, 2005), such as a forest reserve policy resulting from a logging ban, species-specific habitat in a wildlife sanctuary, residential construction in designated agricultural areas, and permanent agriculture in the buffer zone of a nature reserve. These policies influence the land use conversion matrix, dictating which transformations are permissible. (Figure 2.3)

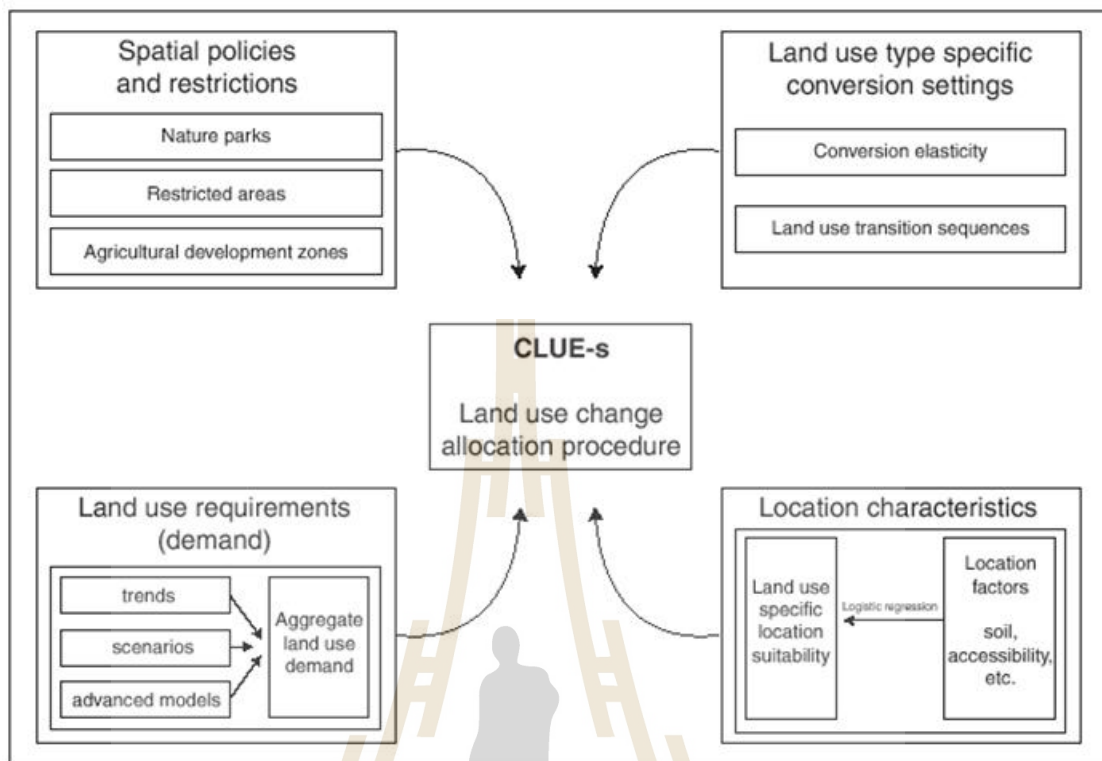


Figure 2.3 Overview of the information flow in the CLUE-S model. (Verburg, 2010)

(2) **Land use type-specific conversion settings.**

Conversion elasticities and land use transition sequences govern the temporal dynamics of land use changes:

The first parameter, conversion elasticities, relates to land use change between land use types. It must be specified as a relative elasticity value ranging from 0 (easy conversion) to 1 (not allowed). The user should determine this factor based on expert knowledge or observed historical behavior.

The second parameter defines the sequence and timing of land use changes, recorded in a conversion matrix (Figure 2.4). This matrix specifies conditions under which land use transformations can occur, including time constraints and spatial policies.

Additionally, Verburg (2010) suggested that the timeframe for land conversion should be specified in the conversion table. This timeframe is influenced by land use pressure and location-specific conditions (Figure 2.5).

(3) Land use requirements (demand)

The total area assigned to each land use type depends on land use requirements or demand, determined based on historical trends, policy objectives, or integrated modeling approaches (Verburg and Overmars, 2009; Verburg, 2010). The demand depends on the perspective of policy or population change or advanced model to communicate with the CLUE-S model such as SAMBA (Castella, Kam, Quang, Verburg, and Hoanh, 2007), LEITAP (Perez-Soba, Verburg, Koomen, Hilferink, Benito, Lesschen, and Banse, 2010), and SD model (Zheng, Zhao, Xiang, Li, Lv, and Yang, 2012).

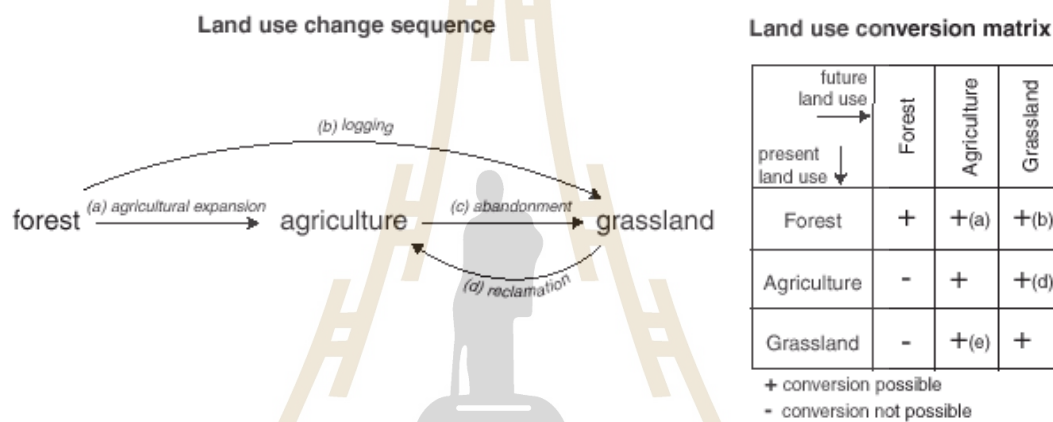


Figure 2.4 Illustration of translating a hypothetical land use change sequence into a land use conversion matrix. (Verburg, 2010)

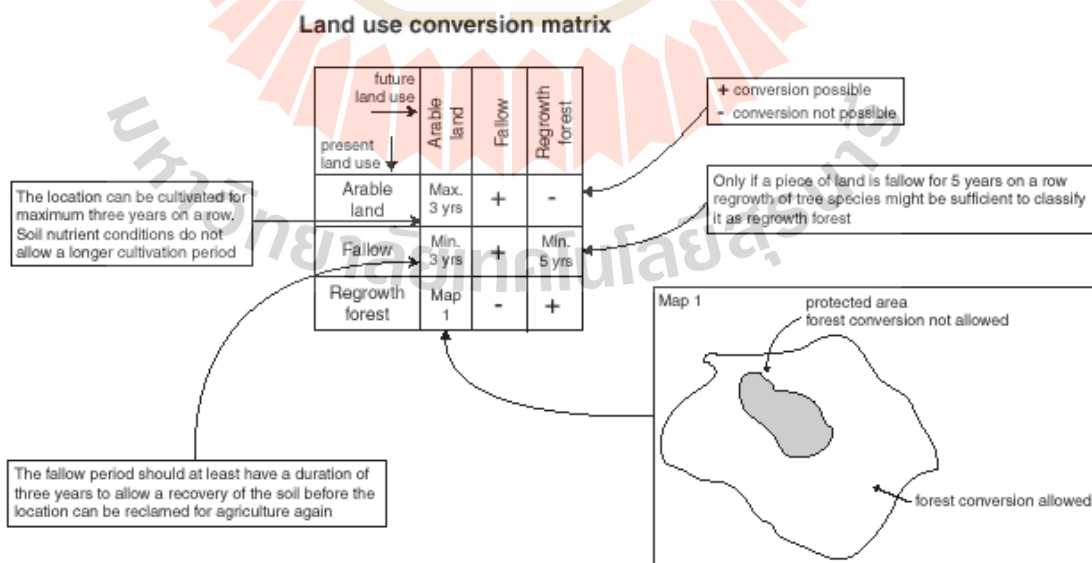


Figure 2.5 Example of a land use conversion matrix with the different options implemented in the model. (Verburg, 2010)

(4) Location characteristics

Land use conversions occur where preference for a specific type is highest, based on biophysical and socio-economic factors (Verburg, 2010; Trisurat, Alkemade, and Verburg, 2010). The preference is calculated using:

$$R_{ki} = a_k X_{1,i} + b_k X_{2,i} + \dots + n_k X_{n,i} \quad (2.1)$$

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

Since preference cannot be directly observed, it is estimated probabilistically using a statistical model, typically with a binomial logit approach as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \dots + \beta_n X_{n,i} \quad (2.2)$$

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

2.4 Ecosystem Services Evaluation

2.4.1 Concept of ecosystem services

The Millennium Ecosystem Assessment (MEA) (2005) popularized the concept of ecosystem services, defining them as "the benefits people obtain from ecosystems." These include both goods and services. The MEA categorized ecosystem services into four types: supporting, provisioning, regulating, and cultural services (Table 2.6). The ability of an ecosystem to provide these services varies based on its structure, condition (Nelson et al., 2009), and the complex interactions between physical and biological factors, as well as land use and management practices (Guswa, Brauman, Brown, Hamel, Keeler, and Sayre, 2014).

Table 2.6 Classification of ecosystem services.

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

Source: Millennium Ecosystem Assessment (2005).

The MEA (2005) highlights the degradation of global ecosystems and observes that, among the 24 ecosystem services reviewed, only four, i.e., crop production, livestock production, aquaculture production, and carbon sequestration, have improved. In contrast, the remaining 20 have degraded or declined.

The Tenth Meeting of the Conference of Parties (COP10) in 2010 formulated a strategic plan for biodiversity (2011–2020) and established 20 targets to reduce habitat loss and mainstream conservation efforts. The long-term goal, "living in harmony with nature," aims to conserve, restore, and sustainably use biodiversity to maintain essential ecosystem services. Despite ongoing challenges, these targets emphasize the need for communication, education, institutional reform, and incentives to combat biodiversity loss.

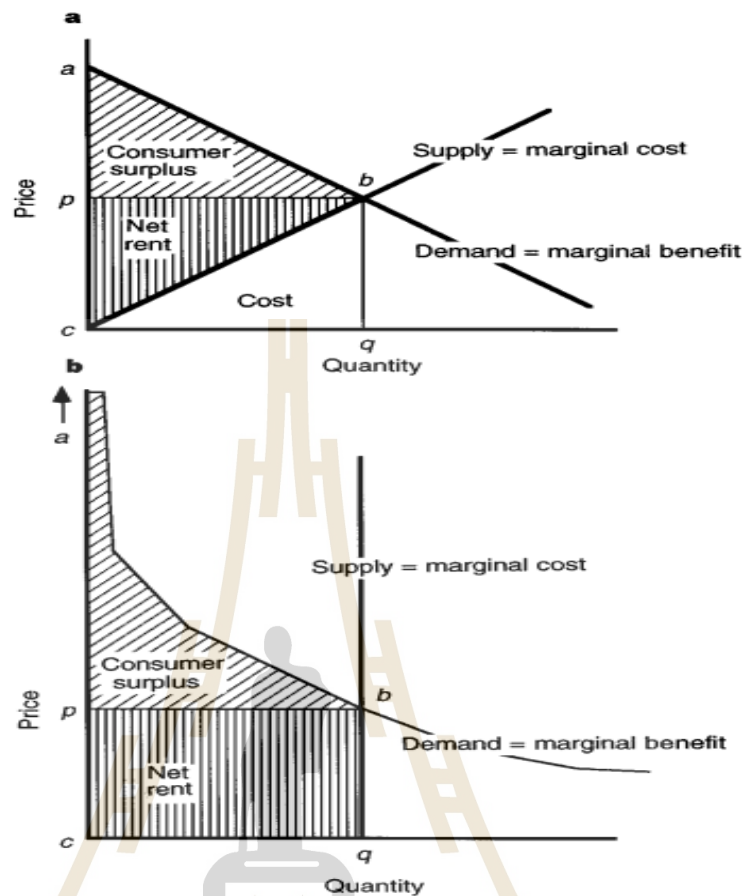
Ecosystem services directly influence human well-being, which in turn impacts ecosystems through drivers like population growth, technology, and land use practices (MEA, 2005). For instance, increased timber demand can lead to deforestation

and heightened flood risks. Decision-makers must balance environmental, economic, and social factors to ensure sustainable land use and ecosystem management.

Fu, Li, Hou, Bi, and Zhang (2017) argue that integrating ecosystem services into land use planning enhances decision-making by making trade-offs transparent. Spatially explicit assessments help quantify relationships between land use patterns and ecosystem services (Hu, Fu, Lu, and Zheng, 2014). However, many ecosystem services lack market value, making economic quantification challenging. The rise of ecosystem services valuation (ESV), after the publication of the MEA (2005) has increased recognition of ecosystem services in policy frameworks, ultimately supporting conservation and sustainable development.

2.4.2 Simple benefit transfer method

Costanza et al. (1997) estimated the per-unit area value of each ecosystem service for different ecosystem types. To determine this "unit value," they applied one of the following methods in order of preference: (1) the sum of consumer and producer surplus, (2) net rent (or producer surplus), or (3) price multiplied by quantity as a proxy for the service's economic value. Their approach assumed that the demand curve for ecosystem services resembles Figure 2.6b more than Figure 2.6a, making the area "pbqc" a conservative underestimate of the area "abc." Finally, they multiplied the unit values by the surface area of each ecosystem to calculate global totals.



Source: Costanza et al., 1997.

Figure 2.6 Supply and demand curves show cost definitions, net rent and consumer surplus for normal goods (a) and some essential ecosystem services (b).

Su, Xiao, Jiang, and Zhang (2012) suggested that the ecosystem service values, using a simple benefit transfer method, are calculated as follows:

$$ESV = \sum(A_k \times VC_k) \quad (2.3)$$

Where ESV is estimated ecosystem service value; A_k is area of land use category k ; VC_k is value coefficient for land use category k .

In practice, LULC datasets for each reference year are prepared as proxies for measuring ESVs, with the corresponding area in hectares summarized within a GIS environment. During the ecosystem service estimation process, value coefficients are assigned to each LULC type based on those used by Costanza et al. (1997). The total ecosystem service value for each LULC type is then calculated by multiplying its

area in hectares by the corresponding value coefficients (Kindu, Schneider, Teketay, and Knoke, 2016).

2.5 Applications of driving factor for LULC change

Ongsomwang and lamchuen (2015) studied the integration of geospatial models for optimal land use allocation in three scenarios within the Upper Lam Phra Phloeng watershed, Nakhon Ratchasima province, Thailand, using the CLUE-S model to predict LULC changes. The driving factors considered included slope, annual rainfall, soil drainage, watershed land use capability, population density, and proximity to roads, with population density being the most influential.

Zhang, Liu, Wu, Yao, Wu, and Chen (2019) conducted a study on multiple intra-urban land use simulations and driving factor analysis in Huicheng, China. They developed and applied a Random Forest algorithm-based Cellular Automata (RF-CA) model to simulate intra-urban land use changes and identify key driving factors influencing these changes. The study incorporated four categories of driving factors, traffic location, public services, population, and natural factors, to predict LULC. The results showed that the RF-CA model achieved a Kappa hat value of about 73% and an overall accuracy of about 89%.

Li, Feng, Biswas, Su, Niu, and Cao (2020) studied driving factors and future land use and cover change prediction in Gansu Province, China. The study identified the major driving factors behind LUCC patterns and predicted land use and cover using satellite remote sensing data and the LCM model. Fifteen driving factors were considered: temperature, precipitation, elevation, aspect, slope, distance to water bodies, distance to roads, distance to residential areas, GDP change, GDP per capita, agricultural outputs, industrial outputs, tertiary industry outputs, livestock numbers, and population change. The study found that the significant factors driving changes in land use across all six types were elevation, precipitation, and distance to residential areas. Additionally, other factors also influenced land use changes.

Gharaibeh, Shaamala, Obeidat, and Al-Kofahi (2020) enhanced the modeling of land-use change predictability by integrating Artificial Neural Network (ANN) with the Cellular Automata-Markov Chain (CA-MC) model. This integration aims to improve the

accuracy of predicting changes in land use by incorporating various driving factors that significantly impact land-use changes. Driving factors in predicting land use include elevation, slope, land fertility, population density, distance to roads, distance to urban centers, and distance to commercial areas. The result shows validation of the ANN-CA-MC model showed an accuracy of about 90%, outperforming the original CA-MC model, which had an accuracy of about 86%. This improvement in accuracy suggests that incorporating driving forces through ANN was essential for more precise predictions of land-use changes.

Cui, Zhu, Liang, Qin, Li, and Liu (2022) studied land use/land cover change and its driving factors in the Yellow River Basin of Shandong Province, utilizing Google Earth Engine (GEE) from 2000 to 2020. The objective was to analyze the changes in land use and land cover in the region during this period and the factors influencing these changes. The study identified eight driving factors: population density, gross domestic product (GDP), temperature, rainfall, elevation, slope, aspect, and soil type. The analysis was carried out using Google Earth Engine technology (GEE), Random Forest (RF), and Geographical Detector (GD) methods, resulting in overall accuracy and kappa coefficient of the LULC category exceeding 86%. The study found that the urbanization of building areas increased sharply from 19.42% to 29.77% during the studied period.

2.6 Applications of CLUE-S model

Zhou, Zhang, Ye, Wang, and Su (2016) developed the CLUE-S model to simulate future land use changes and urban growth in Xinzhuang Town, Changshu City, China, from 2009 to 2027. In their study, the authors designed three scenarios based on different spatial policies: current trends, urban planning, and ecological protection. The model incorporated 11 driving factors of land use change using logistic regression to identify preferences for specific land use types. A pixel-based comparison between the simulated and actual 2009 land use maps was conducted to evaluate the accuracy of the model. The results showed that the ROC value was greater than 0.7 for all land use types, and the accuracy of classifying land use types ranged from 77.3% to 83.1%, demonstrating the effectiveness of the model in predicting land use change.

Zare, Nazari Samani, Mohammady, Salmani, and Bazrafshan (2017) applied the CLUE-S model to simulate land use in the Kasilian watershed of Iran, predicting LULC maps for five scenarios based on the LULC maps from 1986, 2000, and 2011. Nine driving factors were used to indicate land use preferences through the logistic regression model. The results showed that the AUC value exceeded 0.8 for all land use types, indicating good accuracy in assessing the driving forces for LULC prediction. Consequently, the authors concluded that the CLUE-S model is well-suited for modeling future land use transitions.

Liu, Jin, Li, Li, He, Huang, and Yao (2017) examined the impact of government policy on land use change to develop effective strategies for sustainable land use in the Lijiang River Basin, Guangxi Zhuang Autonomous Region, southern China. They simulated two scenarios: natural growth and government intervention. The findings showed distinct differences in land use change patterns between the two scenarios.

Srichaichana, Trisurat, and Ongsomwang (2019) applied the CLUE-S model to predict LULC in the Klong U-Tapao watershed, Songkhla province, Thailand. Using LULC maps from 2010 and 2017, their study predicted LULC changes from 2018 to 2024 under three scenarios. The results revealed that the most significant driving factor for all LULC changes was the distance to settlements, followed by the distance to water bodies and the road network. Moreover, the authors concluded that the LULC predictions derived from the three scenarios in the CLUE-S model provided realistic results, as expected.

Sun, Zhang, Shen, Randhir, and Cao (2019) assessed the effects of land use change on multiple ecosystem services in the Kaihua watershed of China using CLUE-S and InVEST models. Their simulations highlighted optimal strategies for balancing urban growth and ecosystem preservation.

2.7 Applications of ecosystem services evaluation

Kindu, Schneider, Teketay, and Knoke (2016) analyzed changes in ecosystem service values in response to land use and land cover (LULC) dynamics in the Munessa–Shashemene landscape of the Ethiopian highlands. Using both globally developed value coefficients and modified conservative values specific to the studied landscape,

they found a decline in ecosystem service values over the past decades (1973–2012). The total value decreased from 130.5 million USD in 1973 to 118.5 million USD in 1986, 114.8 million USD in 2000, and 111.1 million USD in 2012.

Mamat, Halik, and Rouzi (2018) analyzed the impact of land-use changes on ecosystem service values (ESV) in the Kashgar region, Northwest China, from 1986 to 2015. Using multi-temporal Landsat data, they classified land use into nine categories and assessed changes over time. ESV was estimated using the Simple Benefit Transfer approach, with coefficients adapted from Costanza and Xie's studies. The findings revealed significant land-use changes, including an increase in cultivated land and a decline in grassland, leading to fluctuations in total ESV. Sensitivity analysis showed that ESV estimates were relatively inelastic to variations in value coefficients, confirming the robustness of the results.

Ongsomwang, Pattanakiat, and Srisuwan (2019) assessed land use and land cover (LULC) changes and their impact on ecosystem services in Khon Kaen City, Thailand, from 2006 to 2016, while also predicting future changes for 2026 under different scenarios. The study employed LULC assessment, scenario-based predictions, and ecosystem service evaluation using multiresolution segmentation of Landsat images and the standard nearest neighbor classification. Ecosystem service values were estimated using the benefit transfer method with coefficients from existing studies. Land use was categorized into urban, agricultural, and natural areas. The results indicated significant urban expansion and the conversion of agricultural land, leading to a decline in ecosystem services. The study emphasized the importance of monitoring LULC changes and assessing their impact to support sustainable urban planning and policymaking.

Shuangao et al. (2021) assessed the impact of land use changes on ecosystem services and their economic values in the Tarim Basin, Northwest China, using satellite image fusion. The study aimed to evaluate how land use changes influenced ecosystem services and their valuation. The methodology involved using InVEST software to quantify ecosystem services, while ESV calculation and classification followed the benefit transfer method with coefficients from relevant studies. Land use was categorized into cultivated land, forest, grassland, water bodies, construction

areas, and unused land. The results showed that land use changes significantly affected ecosystem services, with declines in water quality and biodiversity but improvements in climate regulation services between 2005 and 2009. The study concluded that this approach could effectively monitor ecosystem services and support policy decision-making.

Karki, Kumar, and Baniya (2022) evaluated the economic value of ecosystem services in Nepal and examined their response to land use changes and climate change from 2000 to 2020. The study covered the entire country, including its seven provinces and three ecological regions: Terai, Hills, and Mountains. The methodology incorporated land use data from FRTC, ICIMOD, and ESA Sentinel-2, along with temperature and precipitation data from DHM and CRU TS4.0. Ecosystem service values (ESVs) were estimated using the Simple Benefit Transfer approach, referencing ESV coefficients from the Tibetan Plateau study due to their ecological similarity to Nepal. Land use categories included water bodies, glaciers, snow, forests, barren land, cropland, grasslands, and shrubland. The results showed a decline in Nepal's total ESV from 2010 to 2020. While forests and barren land experienced an increase in ESV, glaciers, croplands, and grasslands saw a decline. Rising temperatures and decreasing precipitation further influenced land use and ESV variations across different regions of Nepal.

CHAPTER III

RESEARCH METHODOLOGY

The overview of the research methodology framework, which consists of four components: (1) data collection and preparation, (2) identification of driving factors on LULC change, (3) LULC prediction using the CLUE-S model, and (4) evaluation of economic value and ecosystem service value and change, is displayed in Figure 3.1. Details of each component are described below.



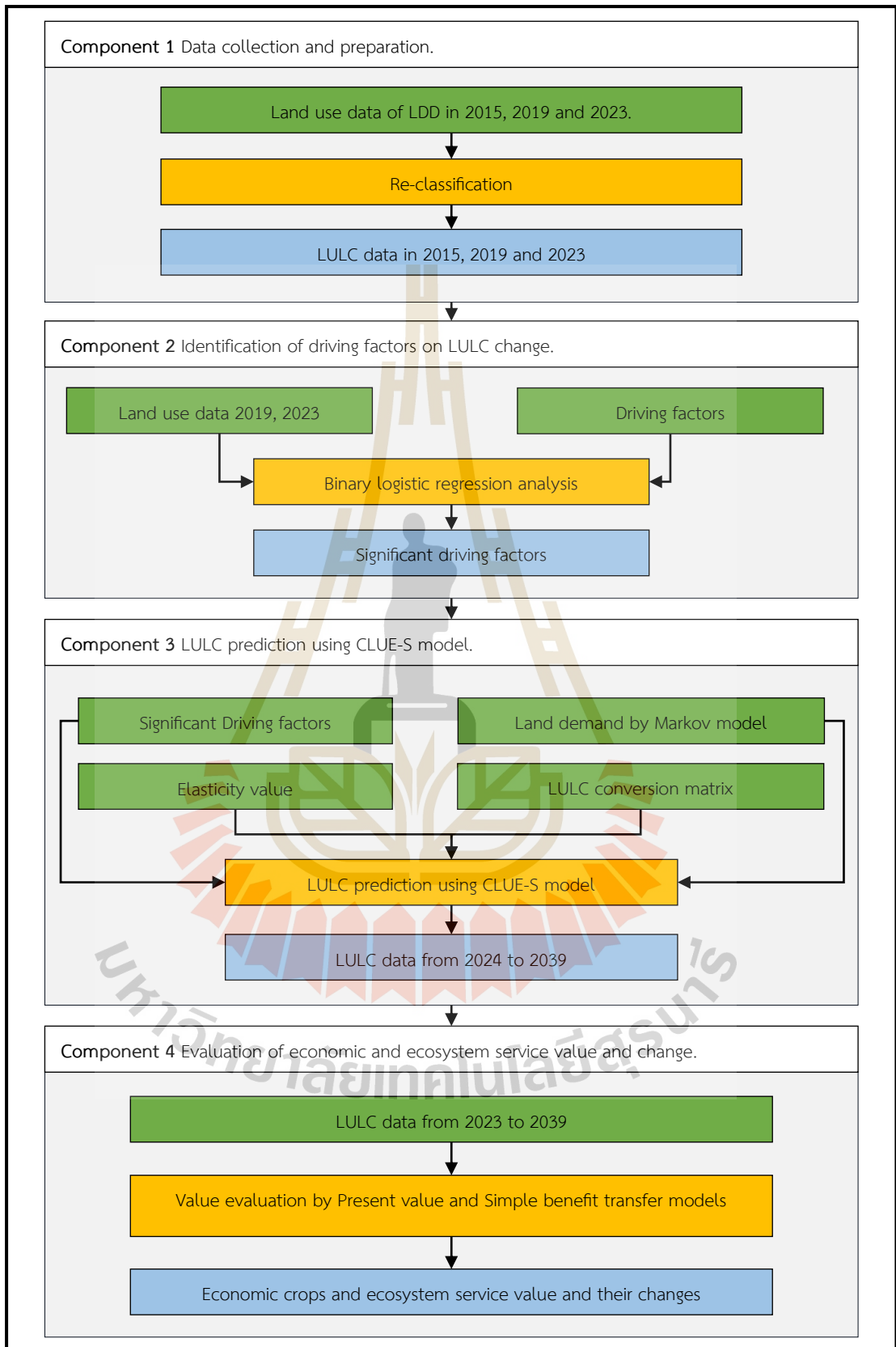


Figure 3.1 The overview of the research methodology framework.

3.1 Data collection and preparation

The relevant input data for the study were collected and prepared in advance as a summary in Table 3.1.

For land use data, land use datasets of LDD in 2015, 2019 and 2023 were reclassified into twelve LULC classes, including (1) urban and built-up area, (2) paddy field, (3) corn, (4) sugarcane, (5) cassava, (6) perennial trees and orchards, (7) other agriculture, (8) forest land, (9) water body, (10) rangeland, (11) marsh and swamp, and (12) unused land. The reclassified LULC classification system is modified for evaluating ecosystem service according to a coefficient of ecosystem service value, as suggested by Mamat, Halik, and Rouzi (2018). The description of the reclassified LULC classification system is reported in Table 3.2. Besides, the LULC in 2023 map was assessed for thematic accuracy based on the 757 stratified random points from the very high spatial resolution image of Google Inc. in 2023.

For the driving factor on LULC change, the collected driving factors on LULC change, which were reviewed from research papers, were prepared and reclassified for binary logistics regression analysis, as shown in Table 3.3.

Table 3.1 Lists data collection and preparation for data analysis in the study.

Data Collection	Data Preparation	Source	Component
Land use in 2015	Reclassify using the Reclassify function of ESRI ArcGIS	LDD	2-4
Land use in 2019	Reclassify using the Reclassify function of ESRI ArcGIS	LDD	2-4
Land use in 2023	Reclassify using the Reclassify function of ESRI ArcGIS	LDD	2-4
Sub-district boundary	-	LDD	2-4
Watershed boundary	-	ONWR	2-4
Irrigation area	Reclassify using the Reclassify function of ESRI ArcGIS	RID	2 & 3
Road network	Calculate distance to the road network in 2019 and 2023 using Euclidean Distance function of ESRI ArcGIS	NOSTRA	2 & 3
Stream and Waterbody	Calculate the distance to stream and waterbody in 2019 and 2023 using the Euclidean Distance function of ESRI ArcGIS.	LDD & NOSTRA	2 & 3
Railway	Calculate the distance to the railway using Euclidean Distance function of ESRI ArcGIS	NOSTRA	2 & 3
Elevation	Extract from SRTM DEM	SRTM	2 & 3

Table 3.1 (Continued).

Data Collection	Data Preparation	Source	Component
Slope	Extract from SRTM DEM using the Slope function of ESRI ArcGIS	SRTM	2 & 3
Urban area	Calculate distance to existing urban areas in 2019 and 2023 using Euclidean Distance function of ESRI ArcGIS	LDD	2 & 3
Average annual rainfall	Interpolate average annual rainfall data (1975-2019) and 1975-2023) using the IDW function of ESRI ArcGIS.	TMD	2 & 3
Population density	Population density at sub-district level in 2019 and 2023	DOPA	2 & 3
Income per capita	Income per capita at sub-district level in 2019 and 2023	CDD	2 & 3
the average interest rate	Calculate the average from the interest rate of 12-month fixed deposits in 2023.	BOT	4
Prices of agricultural products	Average prices of rice, corn, sugarcane, and cassava in 2023.	OAE	4
Harvest of Agricultural products	Harvest data of rice, corn, sugarcane, and cassava in 2023.	OAE & OCSB	4

Note: LDD: Land Development Department; ONWR: Office of the National Water Resources; RID: Royal Irrigation Department; SRTM: Shuttle Radar Topography Mission; TMD: Thai Meteorological Department; DOPA: Department of Provincial Administration; CDD: Community Development Department; BOT: Bank of Thailand; OAE: Office of Agricultural Economics, OCSB: Office of the cane and sugar board.

Table 3.2 Reclassified land use and land cover classification in 2015, 2019 and 2023.

No	LULC type	Description	LDD Code
1	Urban and built-up area	All classes under urban and built-up areas at level 1: U	Level 1: U
2	Paddy field	Paddy field under agricultural land (A) at level 2: A1.	Level 2: A1
3	Corn	Corn under agricultural land (A) at level 3: A202.	Level 3: A202
4	Sugarcane	Sugarcane under agricultural land (A) at level 3: A202.	Level 3: A203
5	Cassava	Cassava under agricultural land (A) at level 3: A202.	Level 3: A204
6	Perennial trees and orchards	Perennial trees and orchards under agricultural land (A) at level 2: A3 and A4, respectively.	Level 2: A3 and A4
7	Other agriculture	Other classes under agricultural land (A) exclude paddy fields, corn, cassava, cassava, perennial trees and orchards.	Level 1: A, excluding A1, A202, A203, A204, A3 and A4
8	Forest land	All classes under forest land at level 1: F	Level 1: F
9	Water body	All classes under water body at level 1: W	Level 1: W

Table 3.2 (Continued).

No	LULC type	Description	LDD Code
10	Rangeland	Rangeland under miscellaneous land (M) at level 2: M1.	Level 2: M1
11	Marsh and swamp	Marsh and swamp under miscellaneous land (M) at level 2 M2.	Level 2: M2
12	Unused land	Other classes under miscellaneous land (M) exclude rangeland marsh and swamp.	Level 1: M, excluding M1 and M2

Table 3.3 Driving factors on LULC change.

Categories	Driving factors	Unit
Physical factor	- Elevation	Meter
	- Slope	Percent
	- Annual rainfall	Millimeter
Socio-economic factor	- Average income per capita at the sub-district level	Bath/year
	- Population density at the sub-district level	Persons/sq.km
Proximity	- Irrigation area	-
	- Distance to the road network	Meter
	- Distance to the railway	Meter
	- Distance to the existing urban areas	Meter
	- Distance to stream and water body	Meter

Source: Modified from Phinyoyang (2021) and Allan et al. (2022)

3.2 Identification of driving factors on LULC change

The selected driving factors on LULC change were first normalized using Equation 3.1 since the measured units of factors are different, as reported in Table 3.3.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (3.1)$$

After that, the normalized driving factors of LULC change are examined the multicollinearity using the tolerance (TOL) or variance inflation factor (VIF) values to prevent the correlation among driving factors. The general rule of thumb, the TOL values should be more than 0.10 or the VIF values should not exceed 10. The TOL and VIF value is calculated (O'Brien, 2007) as:

$$\text{TOL} = 1 - r^2 \quad (3.2)$$

$$\text{VIF} = \frac{1}{1 - r^2} \quad (3.3)$$

Where, r^2 is associated with the regression of the independent variable on all other independent variables.

Finally, driving factors without multicollinearity problems were applied to identify significant driving factors by binary logistics regression analysis. In this study, multiple linear regression of binary logistic regression analysis was conducted with Python programming. The significant identified driving factors were further applied for LULC prediction with the local parameters under the CLUE-S model.

3.3 LULC prediction using CLUE-S model

Two significant steps were undertaken for LULC prediction using the CLUE-S model: (1) validation of the CLUE-S model parameter for LULC prediction and (2) LULC prediction for the period 2024 to 2039.

3.3.1 Validation of CLUE-S model parameter for LULC prediction

In this study, the basic parameters of the CLUE-S model, which include (1) identified driving factors for LULC allocation, (2) elasticity value, (3) LULC conversion matrix, and (4) land requirement of each LULC type in 2023, were first applied to predict LULC in 2023.

After that, the predicted LULC in 2023 was compared with the reclassified LULC in 2023 from land use data of LDD using wall-to-wall thematic accuracy assessment, with overall accuracy and Kappa hat coefficient values. The thresholding values of overall accuracy and Kappa hat coefficient values for validation CLUE-S model parameter for LULC prediction are equal to or more than 80%.

3.3.2 LULC prediction between 2024 and 2039

The identified significant driving factors, elasticity value, LULC conversion matrix, and land requirement of each LULC type from 2024 to 2039, which are extracted using the Markov Chain model based on LULC data in 2015 and 2023, were applied to predict LULC data. The predicted LULC data between 2024 and 2039 were further applied to evaluate economic crops and ecosystem services values and change in the next component.

The workflow of optimum local parameters for LULC prediction and LULC prediction between 2024 and 2039 using CLUE-S is displayed in Figure 3.2.

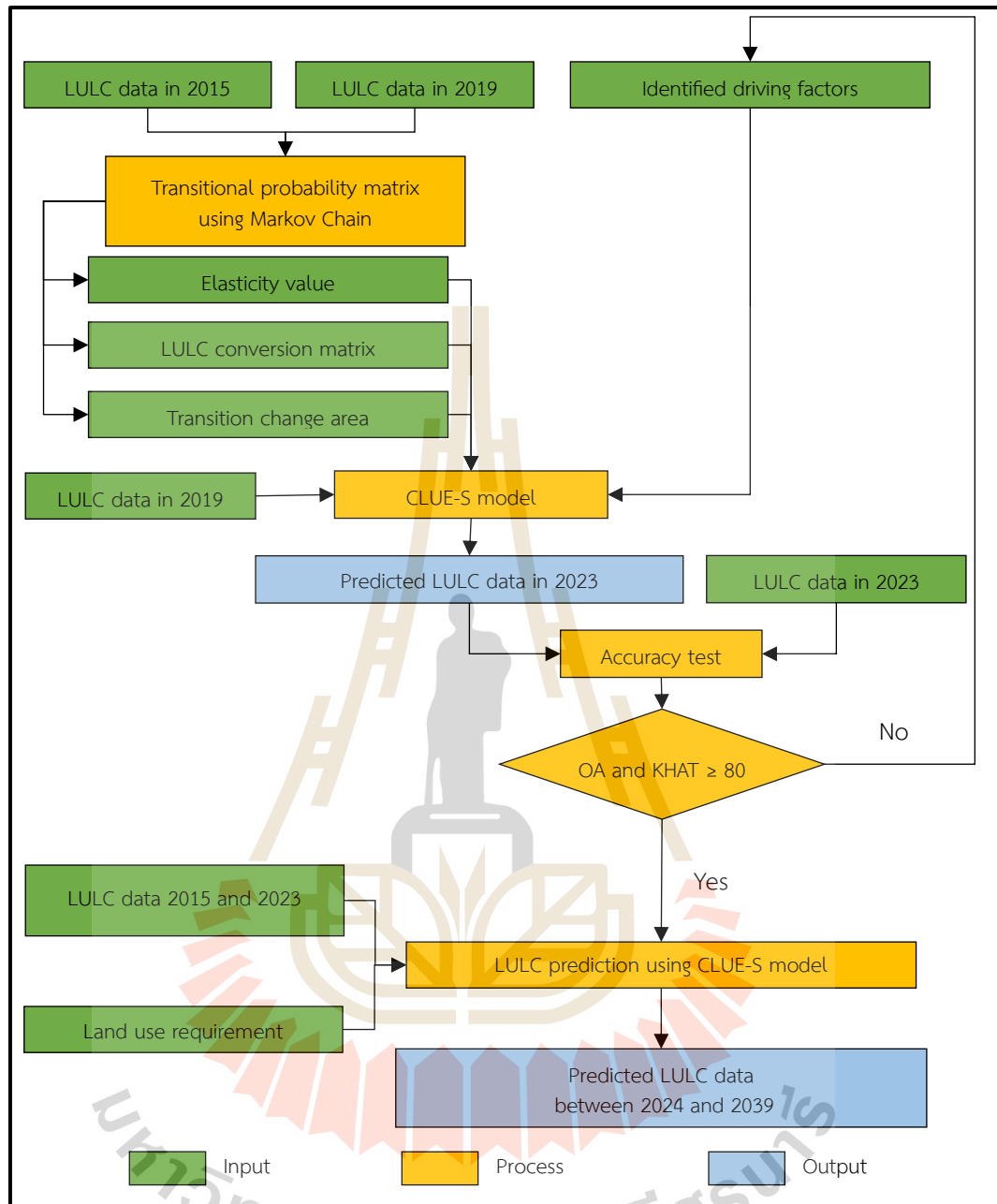


Figure 3.2 Schematic workflow of optimum local parameter for LULC prediction and LULC prediction of two periods using CLUE-S model.

3.4 Evaluation of economic value and ecosystem service value and change

Under this component, the reclassified LULC in 2023 and predicted LULC data between 2024 and 2039 were applied to evaluate the economic crops and ecosystem service values and their changes.

3.4.1 Economic value evaluation and change

The present value of four economic crops (paddy field, corn, sugarcane, and cassava) in 2023 was first calculated based on the statistical report of relevant government agencies, including the Office of Agricultural Economics and the Office of the Cane and Sugar Board. Later, the future value of economic crops between 2024 and 2039 was calculated based on the predicted area of crops in the corresponding year with the average interest rate in 2023 of the Bank of Thailand using the PV model (Eq. 3.4) as suggested by Rossiter (1994).

$$PV = FV \cdot \left[\frac{100}{100 + IR} \right]^Y \quad (3.4)$$

Where PV is the present value, FV is the future value, IR is the interest rate in percent, and Y is the number of years from the present, counting from zero.

After that, the time-series economic value changes due to LULC change were assessed using the ecosystem services change index (ESCI) (Mansoor, Marty, Eric, and Lanier, 2013) as:

$$ESCI_x = \left[\frac{ES_{FutureX_i} - ES_{BaseyearX_j}}{ES_{BaseyearX_j}} \right] \quad (3.5)$$

Where, $ESCI_x$ is the Ecosystems Services Change Index of service X, $ES_{FutureX_i}$ and $ES_{BaseyearX_j}$ are the current and predicted ecosystem service state values of service X at times j and i, respectively.

3.4.2 Ecosystem service value evaluation and change

The ecosystem service value (ESV) was first calculated based on LULC data between 2023 and 2039 using a simple benefit transfer method (Costanza et al., 1997) using Equation 2.3 according to the coefficient value for different LULC types for ESV calculation as shown in Table 3.4. Each ecosystem service function used in the calculation is defined in Table 3.5

After that, the time-series ecosystem service value changes due to LULC change were assessed using the ESCI (Eq. 3.5)

Table 3.4 Coefficient value of different LULC types for ESV estimation.

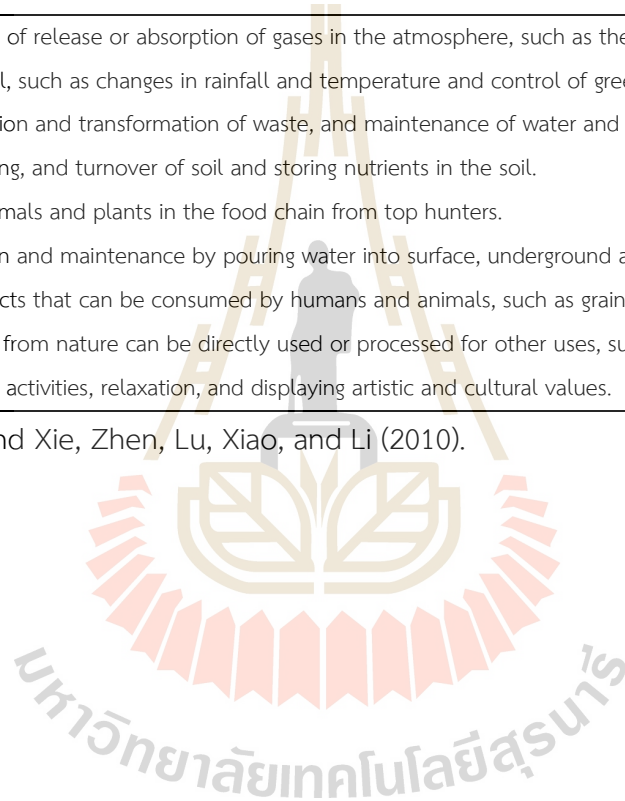
Ecosystem services category	Ecosystem services function	Ecosystem Services Value (USD/ha/year)							
		Urban and built-up area	Paddy field	Field crop	Forest land	Water body	Rangela nd	Marsh and swamp	Unused land
1. Regulating services	1.1 Gas regulation	0	74.7	74.7	299.4	0	104	268.9	4.2
	1.2 Climate regulation	0	133	133	282.1	68.7	108	2,554.70	9
	1.3 Waste treatment	0	245	245	119.2	2,719.00	91.5	2,716.00	18
2. Supporting services	2.1 Soil formation	0	218.1	218.1	278.6	1.5	155	255.5	11.8
	2.2 Biodiversity protection	0	106.1	106.1	312.6	372	130	373.5	27.7
3. Provisioning services	3.1 Water supply	0	89.6	89.6	283.5	3,047.70	105	2,315.60	4.8
	3.2 Food production	0	149.4	149.4	22.9	14.9	29.8	44.8	1.4
	3.3 Raw materials	0	14.9	14.9	206.5	1.5	25	10.5	2.8
4. Cultural services	4.1 Recreation and culture	12.7	1.5	1.5	144.2	648.4	60.3	829.2	16.6
Total		12.7	1,032.30	1,032.30	1,949.00	6,873.70	808.6	9,368.70	96.3

Source: Modified from Mamat, Halik, and Rouzi (2018)

Table 3.5 Definition of ecosystem services function.

Ecosystem service function	Definition
Gas regulation	Maintaining the balance of release or absorption of gases in the atmosphere, such as the release of gases by living things or plant absorption.
Climate regulation	Regional climate control, such as changes in rainfall and temperature and control of greenhouse gas emissions.
Waste treatment	Waste disposal, absorption and transformation of waste, and maintenance of water and air quality through biodegradation.
Soil formation	Accumulation, weathering, and turnover of soil and storing nutrients in the soil.
Biodiversity protection	Control and protect animals and plants in the food chain from top hunters.
Water supply	Water storage, allocation and maintenance by pouring water into surface, underground and reservoirs.
Food production	Plant and animal products that can be consumed by humans and animals, such as grains, fruits, and fish.
Raw materials	Raw materials obtained from nature can be directly used or processed for other uses, such as wood, fuel, rocks, and minerals.
Recreation and culture	A space for recreational activities, relaxation, and displaying artistic and cultural values.

Source: Modified from Costanza et al. (1997) and Xie, Zhen, Lu, Xiao, and Li (2010).



CHAPTER IV

RESULTS AND DISCUSSION

Results of the study, which include (1) data collection and preparation, (2) identification of driving factors on LULC change, (3) LULC prediction using the CLUE-S model and (4) evaluation of economic and ecosystem services and change, are separately described and discussed below.

4.1 Data collection and preparation

Three significant data preparations of the collected data are summarized, including (1) LULC data in 2015, 2019 and 2023, (2) thematic accuracy assessment of LULC in 2023 and (3) driving factor for LULC prediction.

4.1.1 LULC data in 2015, 2019 and 2023

The results of the LULC in 2015, 2019, and 2023 from the reclassified land use data of LDD into 12 classes are shown in Figures 4.1 to 4.3. Area and percentages of the LULC data in 2015, 2019, and 2023 are reported in Tables 4.1 to 4.3. The comparison of each LULC type area in 2015, 2019 and 2023 is displayed in Figure 4.4.

As a result, urban and built-up areas, sugarcane, perennial trees and orchards, water bodies, and unused land tend to increase in the future. In contrast, paddy fields, cassava, forest land, and rangeland tend to decrease in the future. Meanwhile, corn, other agriculture, and marsh and swamp are fluctuating.

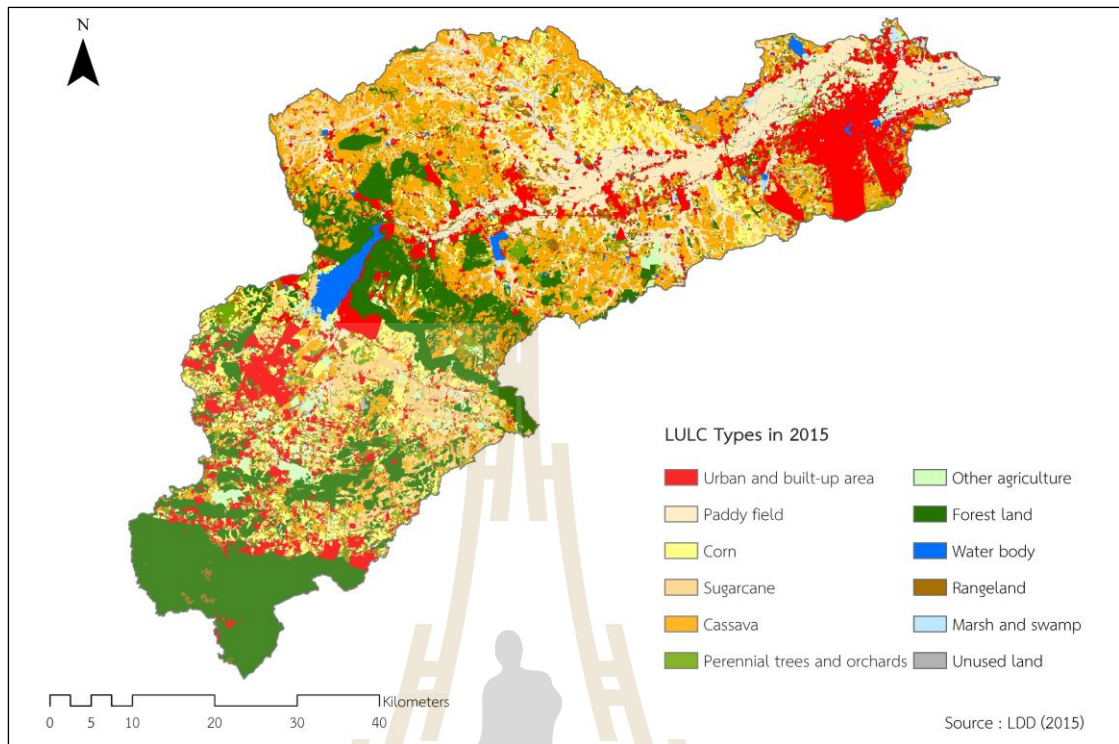


Figure 4.1 Spatial distribution of LULC in 2015.

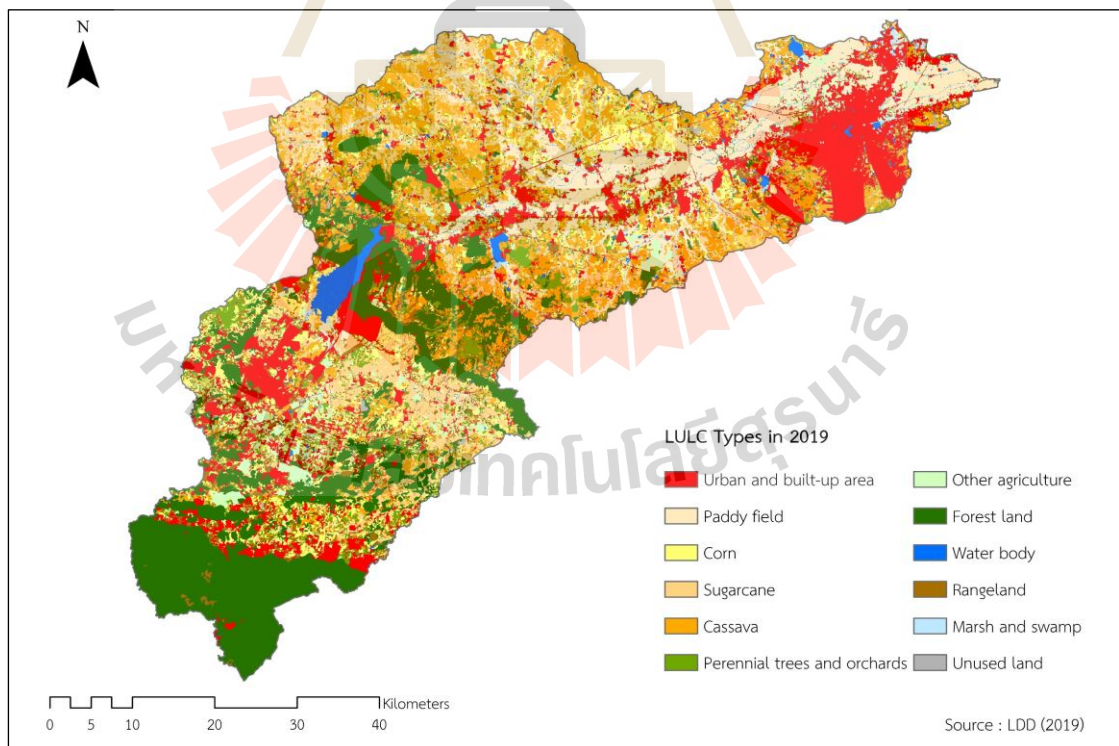


Figure 4.2 Spatial distribution of LULC in 2019.

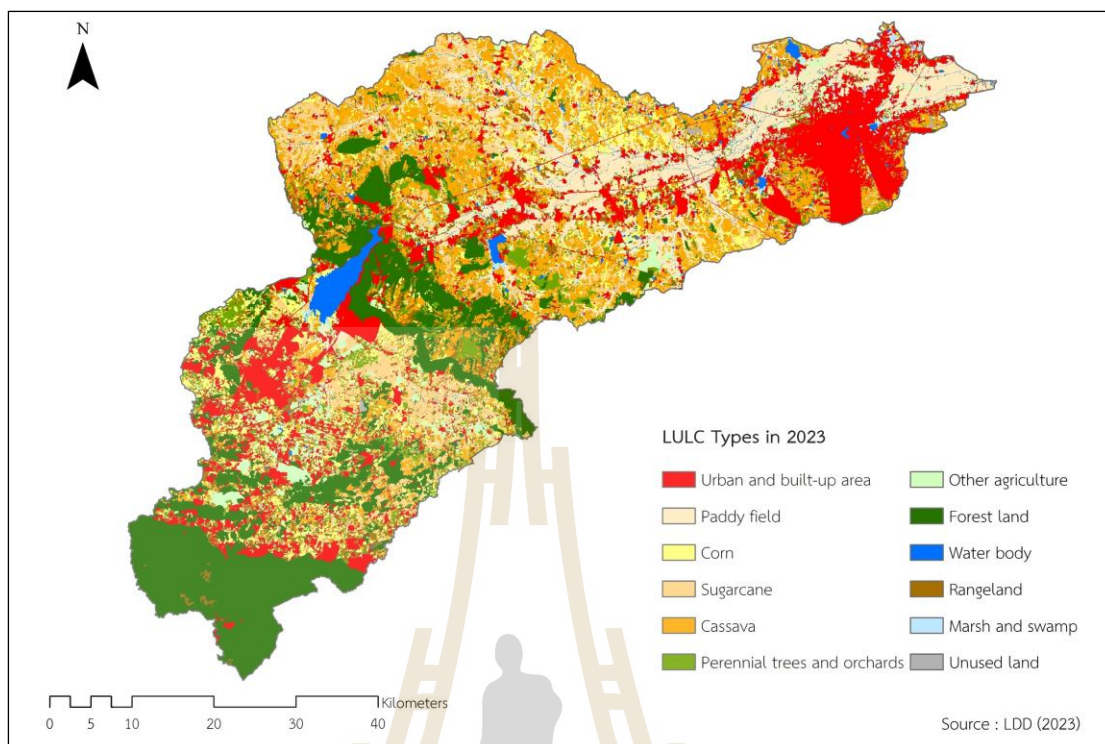


Figure 4.3 Spatial distribution of LULC in 2023.

Table 4.1 Area and percentages of LULC data in 2015.

Area and percentages of LULC data in 2015		
LULC type	Sq. km	Percentage
Urban and built-up area	505.15	15.07
Paddy field	477.81	14.25
Corn	267.56	7.98
Sugarcane	217.03	6.47
Cassava	649.37	19.37
Perennial trees and orchards	162.58	4.85
Other agriculture	133.20	3.97
Forest land	646.86	19.29
Water body	67.66	2.02
Rangeland	199.51	5.95
Marsh and swamp	14.32	0.43
Unused land	11.60	0.35
sum	3352.64	100

Table 4.2 Area and percentages of LULC data in 2019.

Area and percentages of LULC data in 2019		
LULC type	Sq. km	Percentage
Urban and built-up area	571.75	17.05
Paddy field	399.65	11.92
Corn	295.23	8.81
Sugarcane	276.47	8.25
Cassava	590.88	17.62
Perennial trees and orchards	184.51	5.50
Other agriculture	117.76	3.51
Forest land	614.48	18.33
Water body	72.78	2.17
Rangeland	198.63	5.92
Marsh and swamp	11.08	0.33
Unused land	19.42	0.58
sum	3352.64	100

Table 4.3 Area and percentages of LULC data in 2023.

Area and percentages of LULC data in 2023		
LULC type	Sq. km	Percentage
Urban and built-up area	599.64	17.89
Paddy field	388.42	11.59
Corn	267.11	7.97
Sugarcane	281.82	8.41
Cassava	574.98	17.15
Perennial trees and orchards	190.18	5.67
Other agriculture	135.31	4.04
Forest land	613.12	18.29
Water body	78.62	2.35
Rangeland	191.05	5.70
Marsh and swamp	12.71	0.38
Unused land	19.69	0.59
sum	3352.64	100

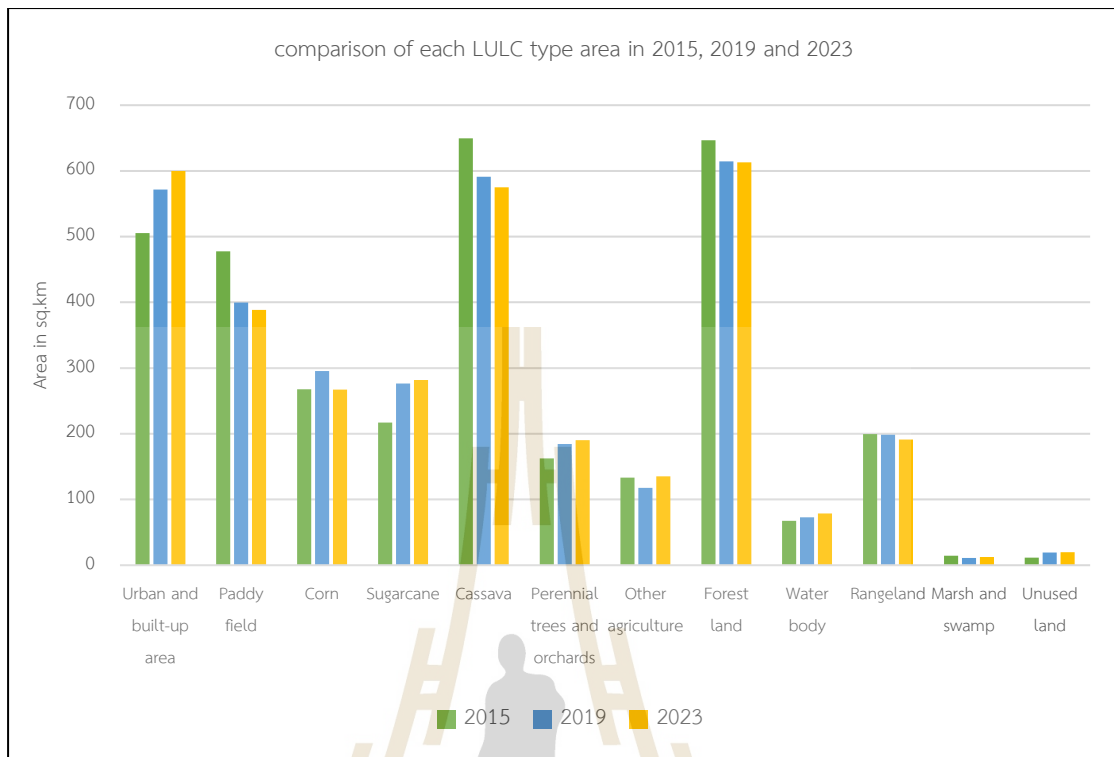


Figure 4.4 Comparison of each LULC type area in 2015, 2019 and 2023.

4.1.2 Thematic accuracy assessment of LULC in 2023

The result of the thematic accuracy assessment of LULC data in 2023 from the reclassified land use of LDD with an error matrix with 757 stratified random points based on reference data from Google Map satellite is reported in Table 4.4.

The overall accuracy and Kappa hat coefficient values of the LULC data in 2023 were 89.04% and 87.56%, respectively. The producer's accuracy of 12 LULC types varied from 46.67%-100.00%. Meanwhile, the user's accuracy of 12 LULC types varied from 63.64%-100.00%.

As a result, the LULC map in 2023 with twelve classes can be accepted for identifying local parameters for LULC prediction with the CLUE-S model since the overall accuracy is more than 85% (Anderson, Hardy, Roach, and Witmer, 1976) and Kappa hat coefficient value over 80% represents strong accuracy between the reclassified and reference data (Fitzpatrick-Lins, 1981 and Rosenfield and Fitzpatrick-Lins, 1986).

Table 4.4 Error matrix and accuracy assessment of the reclassified LULC data in 2023.

LULC types	Google map satellite												Total
	UR	PD	CO	SU	CA	PT	AR	FO	WB	RL	MS	UN	
Urban and built-up area (UR)	107	1	3	1	2		1	5	4	1		2	127
Paddy field (PA)	1	77		1	2	1	1					2	85
Corn (CO)		1	48	3	4	2	1	1				1	61
Sugarcane (SU)			1	59	2	2							64
Cassava (CA)			1	2	112	3	3					1	122
Perennial trees and orchards (PT)			1		1	42						1	45
Other agriculture (AR)					1	1	30		1	1			34
Forest land (FO)								126		4			130
Water body (WB)									23				23
Rangeland (RL)	1		3		2		2	3			34		45
Marsh and swamp (MS)											9	1	10
Unused land (UN)			1	2				1				7	11
Total	109	79	58	68	126	51	38	136	28	40	9	15	757
Producer's accuracy (%)	98.17	97.47	82.76	86.76	88.89	82.35	78.95	92.65	82.14	85.00	100.00	46.67	
User's accuracy (%)	84.25	90.59	78.69	92.19	91.80	93.33	88.24	96.92	100.00	75.56	90.00	63.64	
Overall accuracy (%)	89.04%												
Kappa hat coefficient (%)	87.56%												

4.1.3 Driving factor for LULC prediction

The driving factors collected for LULC prediction 2020-2023 and 2024-2039 were ten factors. The basic statistical data of driving factors with different units before normalization is summarized in Table 4.5. The spatial driving factors for LULC prediction after normalization from 2020 to 2023 and from 2024 to 2039 are displayed in Figure 4.5.

As a result, four driving factors, including elevation, slope, irrigation area, and distance to the railway, are static and they are applied for LULC prediction in two periods (2015-2019 and 2015-2023). Meanwhile, other factors, including annual rainfall, average income per capita at the sub-district level, population density at the sub-district level, distance to the road network, distance to the existing urban areas, and distance to stream and water body dynamic are dynamic, and they are applied for LULC prediction in the corresponding period. For example, annual rainfall between 1975 and 2019 will be used for LULC prediction from 2020 to 2023, while annual rainfall between 1975 and 2023 will be used for LULC prediction from 2024 to 2039.

Table 4.5 Basic statistical data on driving factors for LULC prediction.

Driving factors	Minimum	Maximum	Remark
Elevation (m)	145	1351	Static
Slope (%)	0	209.43	Static
Annual rainfall between 1975 and 2019 (mm)	955.94	1,947.87	Dynamic
Annual rainfall between 1975 and 2023 (mm)	979.79	1,912.25	Dynamic
Average income per capita at the sub-district level in 2019 (Bath)	49,909.10	184,151.00	Dynamic
Average income per capita at the sub-district level in 2023 (Bath)	67,987.03	258,963.50	Dynamic
Population density at the sub-district level in 2019 (Persons/sq.km)	29.70	4,261.26	Dynamic
Population density at the sub-district level in 2023 (Persons/sq.km)	30.41	3,898.59	Dynamic
Irrigation and non-irrigation areas	0	1	Static
Distance to the road network in 2019 (m)	0	8,287.94	Dynamic
Distance to the road network in 2023 (m)	0	8,287.94	Dynamic
Distance to the railway (m)	0	32,754.24	Static
Distance to the existing urban areas in 2019 (m)	0	8,746.43	Dynamic
Distance to the existing urban areas in 2023 (m)	0	8,746.43	Dynamic
Distance to stream and water body in 2019 (m)	0	8,013.11	Dynamic
Distance to stream and water body in 2023 (m)	0	8,013.11	Dynamic

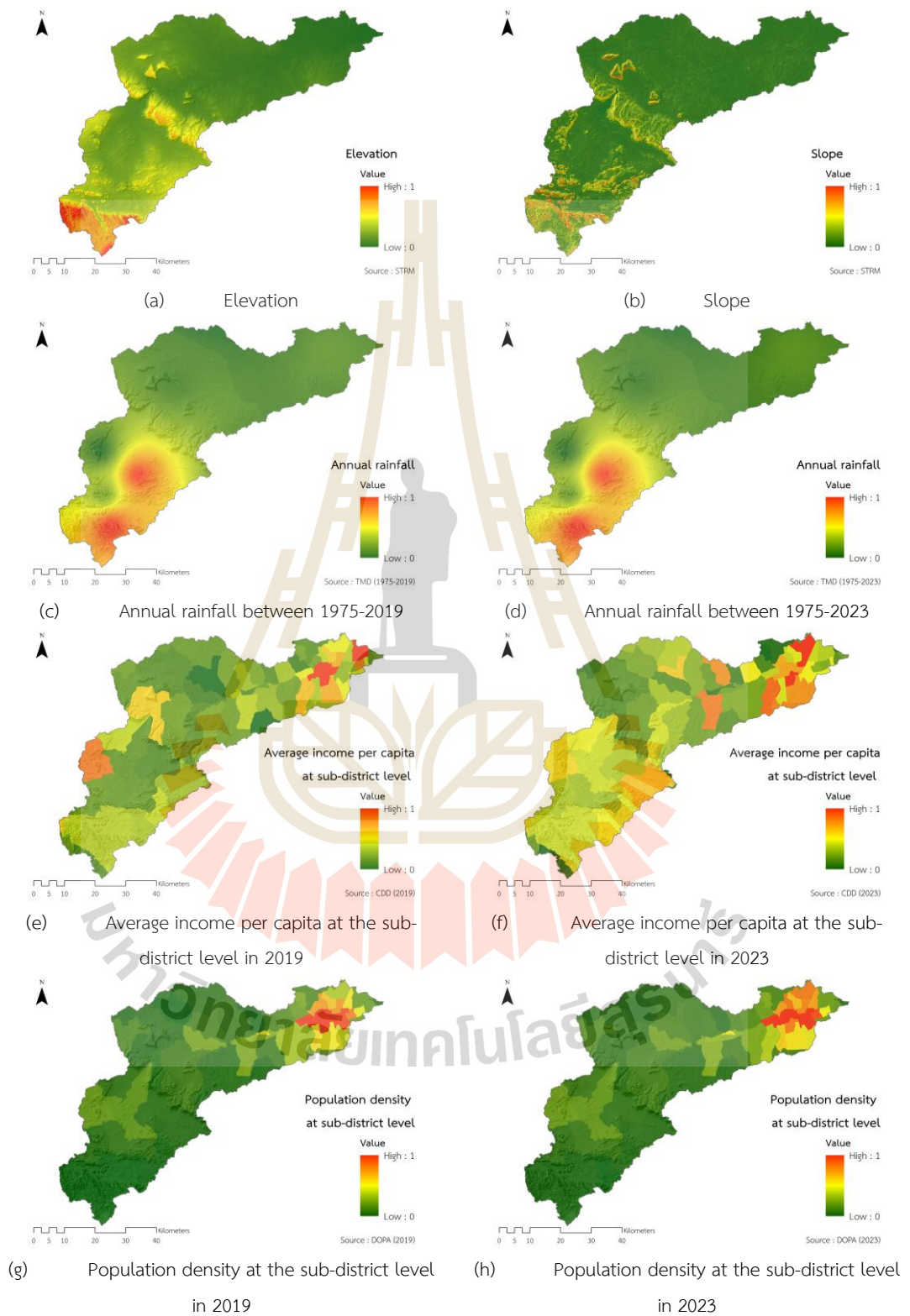


Figure 4.5 Driving factors on LULC change.

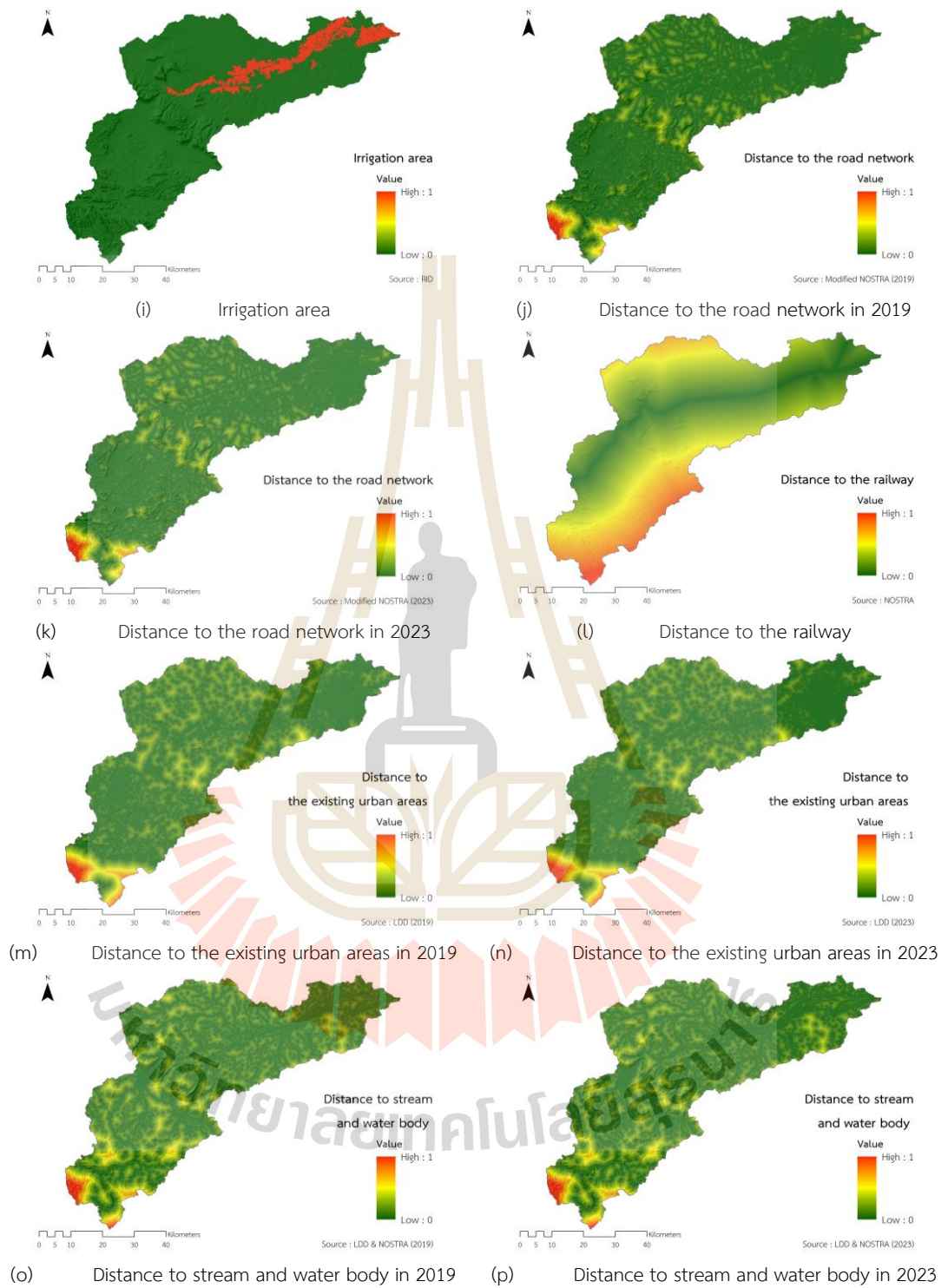


Figure 4.5 (Continued)

4.2 Identification of driving factors on LULC change

Two main results under this section include (1) multicollinearity test and (2) binary logistics regression analysis.

4.2.1 Multicollinearity test

The result of the multicollinearity test among independent variables using VIF and TOL is summarized in Table 4.6. The result demonstrated that all the tolerance (TOL) values of driving factors were more than 0.10, and all the variance inflation factors (VIF) values of driving factors were less than 10. These values indicate that the driving factors are not correlated, making them suitable for binary logistic regression analysis for specific LULC type allocation (Shrestha and Shrestha, 2017; Liang et al., 2020).

4.2.2 Binary logistics regression analysis

The result of binary logistics regression analysis, which consists of multiple linear regression equations for each LULC type allocation under the CLUE-S model and their area under the curve (AUC) values, is reported in Table 4.7. Brief information on driving factors for each LULC type allocation is summarized in the following sections.



Table 4.6 Multicollinearity diagnostic test of driving factors on LULC change.

Driving factor	Unstandardized Coefficients		Standardized Coefficient	t-test	Sig.	TOL	VIF
	Beta	Std. error					
Elevation (X ₁)	6.496	0.061	0.300	106.985	0.000	0.231	4.326
Slope (X ₂)	11.427	0.097	0.195	117.596	0.000	0.659	1.518
Annual rainfall (X ₃)	0.221	0.025	0.018	8.867	0.000	0.430	2.323
Average income per capita at the sub-district level (X ₄)	0.000	0.000	-0.001	-0.460	0.645	1.000	1.000
Population density at the sub-district level (X ₅)	0.000	0.000	0.000	0.057	0.955	1.000	1.000
Irrigation area (X ₆)	-1.334	0.016	-0.123	-85.862	0.000	0.883	1.132
Distance to the road network (X ₇)	-0.681	0.095	-0.021	-7.200	0.000	0.218	4.590
Distance to the railway (X ₈)	-0.470	0.026	-0.036	-18.338	0.000	0.475	2.106
Distance to the existing urban areas (X ₉)	5.952	0.079	0.210	75.089	0.000	0.231	4.329
Distance to stream and water body (X ₁₀)	-4.773	0.061	-0.163	-77.892	0.000	0.414	2.414



Table 4.7 Identified the driving factors for each LULC type allocation as equation form with AUC using binary logistic regression analysis.

LULC type	Driving factors											AUC
	Constant	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	
Urban and built-up areas (UB)	1.865	-1.737	n. s.	n. s.	n. s.	1.441	-2.029	-11.043	-0.891	-245.424	2.211	0.98
Paddy field (PD)	-0.185	-14.685	-41.237	-3.517	n. s.	n. s.	3.051	8.409	2.497	n. s.	-13.091	0.92
Corn (CO)	-2.046	0.841	-13.105	0.619	n. s.	n. s.	-2.750	-9.618	n. s.	3.188	-0.684	0.69
Sugarcane (SU)	-2.755	-5.722	-33.576	0.993	n. s.	n. s.	-0.750	n. s.	4.723	1.933	-2.293	0.80
Cassava (CA)	-0.860	-0.709	-14.748	-3.675	n. s.	n. s.	-2.390	-0.960	1.977	3.054	n. s.	0.80
Perennial trees and orchards (PO)	-3.048	4.926	-12.026	-0.300	0.324	n. s.	-0.440	-4.785	n. s.	n. s.	-1.097	0.65
Other agriculture (OA)	-3.146	n. s.	-18.131	2.221	n. s.	n. s.	0.648	-16.770	-0.958	3.038	0.926	0.73
Forest land (FO)	-5.323	7.105	34.689	1.480	n. s.	n. s.	n. s.	8.735	-1.115	4.498	n. s.	0.97
Water body (WB)	0.164	-5.716	-19.122	1.105	n. s.	n. s.	-3.797	14.025	-3.290	n. s.	-191.884	0.98
Rangeland (RL)	-2.535	3.620	-5.299	0.934	n. s.	n. s.	-1.776	n. s.	-1.501	-3.642	-3.132	0.68
Marsh and swamp (MS)	-2.192	-46.695	n. s.	6.288	n. s.	n. s.	-2.471	9.782	-2.761	n. s.	-15.009	0.91
Unused land (UN)	-4.083	-6.230	n. s.	1.926	n. s.	n. s.	-0.265	-10.708	-2.038	n. s.	n. s.	0.89

Remark: All explanatory variables are significant at $p < 0.05$ error level; n. s. is insignificant at 0.05 level; AUC is the area under the curve.

(1) Driving factors for urban and built-up area allocation

The multiple linear equation of the binomial logit regression model for allocating urban and built-up areas is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = 1.865 - 1.737X_1 + 1.441X_5 - 2.029X_6 - 11.043X_7 - 0.891X_8 - 245.424X_9 + 2.211X_{10} \quad (4.1)$$

Where

- X_1 is Elevation,
- X_5 is Population density at the sub-district level,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway,
- X_9 is Distance to the existing urban areas, and
- X_{10} is Distance to stream and water body.

According to Eq. 4.1, it was found that five driving factors, including elevation, irrigation area, distance to the road network, distance to the railway, and distance to the existing urban areas, have a negative relationship with the probability of urban and built-up area allocation. However, two driving factors, population density at the sub-district level and distance to stream and water body, positively correlate with the probability of urban and built-up area allocation. These findings suggest that urban and built-up areas tend to be located at lower elevations, characterized by high population density at the sub-district level, outside irrigation areas, and in proximity to road networks, railways, and existing urban areas, while being farther from streams and water bodies.

Additionally, the allocation of urban and built-up areas shows an excellent fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.98 (Pontius and Schneider, 2001).

(2) Driving factors for paddy field allocation

The multiple linear equation of the binomial logit regression model for allocating the paddy field is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = 0.185 - 14.685X_1 - 41.237X_2 - 3.517X_3 + 3.051X_6 + 8.409X_7 + 2.497X_8 - 13.091X_{10} \quad (4.2)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway, and
- X_{10} is Distance to stream and water body.

According to Eq. 4.2, it was found that four driving factors, including elevation, slope, annual rainfall, and distance to stream and water body have a negative relationship with the probability of paddy field allocation. Meanwhile, three driving factors, including irrigation area, distance to the road network, and distance to the railway, positively correlate with the probability of paddy field allocation. These findings suggest that paddy fields tend to be located at lower elevations, on gentler slopes, and in areas with lower annual rainfall, within irrigation areas, farther from road networks and railways, but closer to streams and water bodies.

Additionally, the allocation of paddy fields shows an excellent fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.92 (Pontius and Schneider, 2001).

(3) Driving factors for corn allocation

The multiple linear equation of the binomial logit regression model for allocating corn is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = - 2.046 + 0.841X_1 - 13.105X_2 + 0.619X_3 - 2.750X_6 - 9.618X_7 + 3.188X_9 - 0.68X_{10} \quad (4.3)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,

- X_6 is Irrigation area,
 X_7 is Distance to the road network,
 X_9 is Distance to the existing urban areas, and
 X_{10} is Distance to stream and water body.

According to Eq. 4.3, it was found that four driving factors, including slope, irrigation area, distance to the road network, and distance to stream and water body have a negative relationship with the probability of corn allocation. Meanwhile, three driving factors, elevation, annual rainfall, and distance to the existing urban areas, positively correlate with the probability of corn allocation. These findings suggest that corn tends to be located at higher elevations, on gentler slopes, in areas with higher annual rainfall, outside irrigation areas, and in proximity to road networks, streams, and water bodies but farther from existing urban areas.

Additionally, the allocation of corn shows a poor fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.69 (Pontius and Schneider, 2001).

(4) Driving factors for sugarcane allocation

The multiple linear equation of the binomial logit regression model for allocating sugarcane is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = -2.755 - 5.722X_1 - 33.576X_2 + 0.993X_3 - 0.750X_6 + 4.723X_8 + 1.933X_9 - 2.293X_{10} \quad (4.4)$$

Where

- X_1 is Elevation,
 X_2 is Slope,
 X_3 is Annual rainfall,
 X_6 is Irrigation area,
 X_8 is Distance to the railway,
 X_9 is Distance to the existing urban areas, and
 X_{10} is Distance to stream and water body.

According to Eq. 4.4, it was found that four driving factors, including elevation, slope, irrigation area, and distance to stream and water body, have a

negative relationship with the probability of sugarcane allocation. Meanwhile, three driving factors, including annual rainfall, distance to the railway, and distance to the existing urban areas, positively correlate with the probability of sugarcane allocation. These findings suggest that sugarcane tends to be located at lower elevations, on gentler slopes, but in areas with higher annual rainfall, outside irrigation areas, farther from the railway and existing urban areas, but closer to streams and water bodies.

Additionally, the allocation of sugarcane shows a good fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.80 (Pontius and Schneider, 2001).

(5) Driving factors for cassava allocation

The multiple linear equation of the binomial logit regression model for allocating cassava is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = -0.860 - 0.708X_1 - 14.748X_2 - 3.675X_3 - 2.390X_6 - 0.960X_7 + 1.977X_8 + 3.054X_9 \quad (4.5)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway, and
- X_9 is Distance to the existing urban areas.

According to Eq. 4.5, it was found that five driving factors, including elevation, slope, annual rainfall, irrigation area, and distance to the road network, have a negative relationship with the probability of cassava allocation. Meanwhile, two driving factors, including distance to the railway and distance to the existing urban area, positively correlate with the probability of cassava allocation. These findings suggest that cassava tends to be located at lower elevations, on gentler slopes, in areas with lower annual rainfall, outside irrigation areas, and in proximity to the road network but farther from the railway and existing urban areas.

Additionally, the allocation of cassava shows a good fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.80 (Pontius and Schneider, 2001).

(6) Driving factors for perennial trees and orchards allocation

The multiple linear equation of the binomial logit regression model for allocating perennial trees and orchards is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = - 3.048 + 4.926X_1 - 12.026X_2 - 0.300X_3 + 0.324X_4 - 0.440X_6 - 4.785X_7 - 1.097X_{10} \quad (4.6)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,
- X_4 is Average income per capita at the sub-district level,
- X_6 is Irrigation area,
- X_7 is Distance to the road network, and
- X_{10} is Distance to stream and water body.

According to Eq. 4.6, it was found that five driving factors, including slope, annual rainfall, irrigation area, distance to the road network, and distance to stream and water body, have a negative relationship with the probability of perennial trees and orchards allocation. Meanwhile, two driving factors, including elevation and average income per capita at the sub-district level, positively correlate with the probability of perennial trees and orchards allocation. These findings suggest that perennial trees and orchards tend to be located at higher elevations, on gentler slopes, in areas with lower annual rainfall, characterized by high average income per capita at the sub-district level, outside irrigation areas, in proximity to the road network, streams, and water bodies.

Additionally, the allocation of perennial trees and orchards shows a poor fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.65 (Pontius and Schneider, 2001).

(7) Driving factors for other agriculture allocation

The multiple linear equation of the binomial logit regression model for allocating other agriculture is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = - 3.146 - 18.131X_2 + 2.221X_3 + 0.648X_6 - 16.770X_7 - 0.958X_8 + 3.038X_9 + 0.926X_{10} \quad (4.7)$$

Where

- X_2 is Slope,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway,
- X_9 is Distance to the existing urban areas, and
- X_{10} is Distance to stream and water body.

According to Eq. 4.7, it was found that three driving factors, including slope, distance to the road network, and distance to the railway, have a negative relationship with the probability of other agriculture allocation. Meanwhile, four driving factors, including annual rainfall, irrigation area, distance to the existing urban areas, and distance to stream and water body, positively correlate with the probability of other agriculture allocation. These findings suggest that other agriculture tends to be located on gentler slopes, in areas with higher annual rainfall, within irrigation areas, and in proximity to the road network and railway, but farther from existing urban areas, streams, and water bodies.

Additionally, the allocation of other agriculture shows an acceptable fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.73 (Pontius and Schneider, 2001).

(8) Driving factors for forest land allocation

The multiple linear equation of the binomial logit regression model for allocating forest is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = - 5.323 + 7.105X_1 + 34.689X_2 + 1.480X_3 + 8.735X_7 - 1.115X_8 + 4.498X_9 \quad (4.8)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway, and
- X_9 is Distance to the existing urban areas

According to Eq. 4.8, it was found that one driving factor, the distance to the railway, has a negative relationship with the probability of forest land allocation. Meanwhile, five driving factors, including elevation, slope, annual rainfall, distance to the road network, and distance to the existing urban areas, positively correlate with the probability of forest land allocation. These findings suggest that forest land tends to be located at higher elevations, on steeper slopes, in areas with higher annual rainfall, farther from the road network and existing urban areas, but closer to the railway.

Additionally, the allocation of forest shows an excellent fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.97 (Pontius and Schneider, 2001).

(9) Driving factors for water body allocation

The multiple linear equation of the binomial logit regression model for allocating water bodies is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = 0.164 - 5.716X_1 - 19.122X_2 + 1.105X_3 - 3.797X_6 + 14.025X_7 - 3.290X_8 - 191.884X_{10} \quad (4.9)$$

Where

- X_1 is Elevation,
- X_2 is Slope,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway, and

X_{10} is Distance to stream and water body

According to Eq. 4.9, it was found that five driving factors, including elevation, slope, irrigation area, distance to the railway, and distance to stream and water body, have a negative relationship with the probability of water body allocation. Meanwhile, two driving factors, including annual rainfall and distance to the road network, positively correlate with the probability of water body allocation. These findings suggest that water body tend to be located at lower elevations, on gentler slopes, in areas with higher annual rainfall, outside irrigation areas, in proximity to the railway, streams, and water bodies, but farther from the road network.

Additionally, the allocation of the water body shows an excellent fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.98 (Pontius and Schneider, 2001).

(10) Driving factors for rangeland allocation

The multiple linear equation of the binomial logit regression model for allocating rangeland is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = -2.535 + 3.620X_1 - 5.299X_2 + 0.934X_3 - 1.776X_6 - 1.501X_8 - 3.642X_9 - 3.132X_{10} \quad (4.10)$$

Where

X_1 is Elevation,

X_2 is Slope,

X_3 is Annual rainfall,

X_6 is Irrigation area,

X_8 is Distance to the railway,

X_9 is Distance to the existing urban areas, and

X_{10} is Distance to stream and water body

According to Eq. 4.10, it was found that five driving factors, including slope, irrigation area, distance to the railway, distance to the existing urban areas, and distance to stream and water body, have a negative relationship with the probability of rangeland allocation. Meanwhile, two driving factors, including elevation and annual rainfall, positively correlate with the probability of rangeland allocation. These findings

suggest that rangeland tends to be located at higher elevations, on gentler slopes, in areas with higher annual rainfall, outside irrigation areas, and in proximity to the railway, the existing urban areas, streams, and water bodies.

Additionally, the allocation of rangeland shows a poor fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.68 (Pontius and Schneider, 2001).

(11) Driving factors for marsh and swamp allocation

The multiple linear equation of the binomial logit regression model for allocating marsh and swamp is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = -2.192 - 46.695X_1 + 6.288X_3 - 2.471X_6 + 9.782X_7 - 2.761X_8 - 15.009X_{10} \quad (4.11)$$

Where

- X_1 is Elevation,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway,
- X_{10} is Distance to stream and water body

According to Eq. 4.11, it was found that four driving factors, including elevation, irrigation area, distance to the railway, and distance to stream and water body have a negative relationship with the probability of marsh and swamp allocation. Meanwhile, two driving factors, including annual rainfall and distance to the road network, positively correlate with the probability of marsh and swamp allocation. These findings suggest that marsh and swamp tend to be located at lower elevations, in areas with higher annual rainfall, outside irrigation areas, and in proximity to the railway, streams, and water bodies but farther from the road network.

Additionally, the allocation of marsh and swamp shows an excellent fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.91 (Pontius and Schneider, 2001).

(12) Driving factors for unused land allocation

The multiple linear equation of the binomial logit regression model for allocating unused land is as follows:

$$\text{Log} \left(\frac{P_i}{1 - P_i} \right) = - 4.0825 - 6.23038X_1 + 1.92649X_3 - 0.26527X_6 - 10.70817X_7 - 2.03766X_8 \quad (4.12)$$

Where

- X_1 is Elevation,
- X_3 is Annual rainfall,
- X_6 is Irrigation area,
- X_7 is Distance to the road network,
- X_8 is Distance to the railway,

According to Eq. 4.12, it was found that four driving factors, including elevation, irrigation area, distance to the road network, and distance to the railway, have a negative relationship with the probability of unused land allocation. Meanwhile, one driving factor, annual rainfall, positively correlates with the probability of unused land allocation. These findings suggest that unused land tends to be located at lower elevations, in areas with higher annual rainfall, outside irrigation areas, and in proximity to the road network and railway.

Additionally, the allocation of unused land shows a good fit between the predicted and actual LULC transition, as indicated by an AUC value of 0.89 (Pontius and Schneider, 2001).

In summary, the most significant driving factors for LULC allocation are elevation, annual rainfall, and irrigation area. Meanwhile, the driving factors influencing the LULC allocation of economic crops (paddy fields, corn, sugarcane, and cassava) include elevation, slope, annual rainfall, and irrigation area. The specific driving factors for each LULC type preference, identified through binary logistic regression, are further applied to allocate LULC types for predicting LULC changes under the CLUE-S model.

4.3 LULC prediction using CLUE-S model

Two significant results include (1) validation of the CLUE-S model parameter for LULC prediction and (2) LULC prediction for the period 2024 to 2039.

4.3.1 Validation of CLUE-S model parameter for LULC prediction

The local parameters for predicting LULC in 2023, including elasticity value, LULC conversion matrix, and land requirement in 2023, which were extracted based on LULC in 2015 and 2019 with the Markov chain model, are summarized in Tables 4.8 to 4.10. Additionally, the maximum average difference in demand allowed and maximum individual difference in demand allowed parameters were set to 0.35% and 3%, respectively, which are the default parameters of the CLUE-S model.

The result of the accuracy assessment for local parameters of CLUE-S model validation is reported in Table 4.11. The spatial LULC distribution between the reclassified LULC data in 2023 from LDD and the predicted LULC data in 2023 from the CLUE-S model is displayed in Figure 4.6.

Table 4.8 Elasticity of LULC change for predicting LULC in 2023.

LULC type	Resistance value
Urban and built-up area (UB)	0.9965
Paddy field (PD)	0.8069
Corn (CO)	0.5622
Sugarcane (SU)	0.6546
Cassava (CA)	0.6687
Perennial trees and orchards (PO)	0.7051
Other agriculture (OA)	0.6065
Forest land (FO)	0.9487
Water body (WB)	0.9789
Rangeland (RL)	0.7626
Marsh and swamp (MS)	0.6239
Unused land (UN)	0.6197

Table 4.9 Conversion matrix of possible LULC change between 2019 and 2023.

LULC type in 2019	Possible change in 2023												
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	
Urban and built-up area (UB)	1	0	0	0	0	0	0	0	0	0	0	0	
Paddy field (PD)	1	1	1	1	1	1	1	0	1	0	1	1	
Corn (CO)	1	0	1	1	1	1	1	0	1	0	0	1	
Sugarcane (SU)	1	0	1	1	1	1	1	0	1	0	0	1	
Cassava (CA)	1	0	1	1	1	1	1	0	1	0	0	1	
Perennial trees and orchards (PO)	1	0	1	1	1	1	1	0	1	0	0	1	
Other agriculture (OA)	1	1	1	1	1	1	1	0	1	0	0	1	
Forest land (FO)	1	0	1	1	1	1	1	1	1	1	0	1	
Water body (WB)	0	0	0	0	0	0	0	0	1	0	1	1	
Rangeland (RL)	1	0	1	1	1	1	1	0	1	1	0	1	
Marsh and swamp (MS)	0	0	0	0	0	0	1	0	1	0	1	1	
Unused land (UN)	1	1	1	1	1	1	1	1	1	0	0	1	

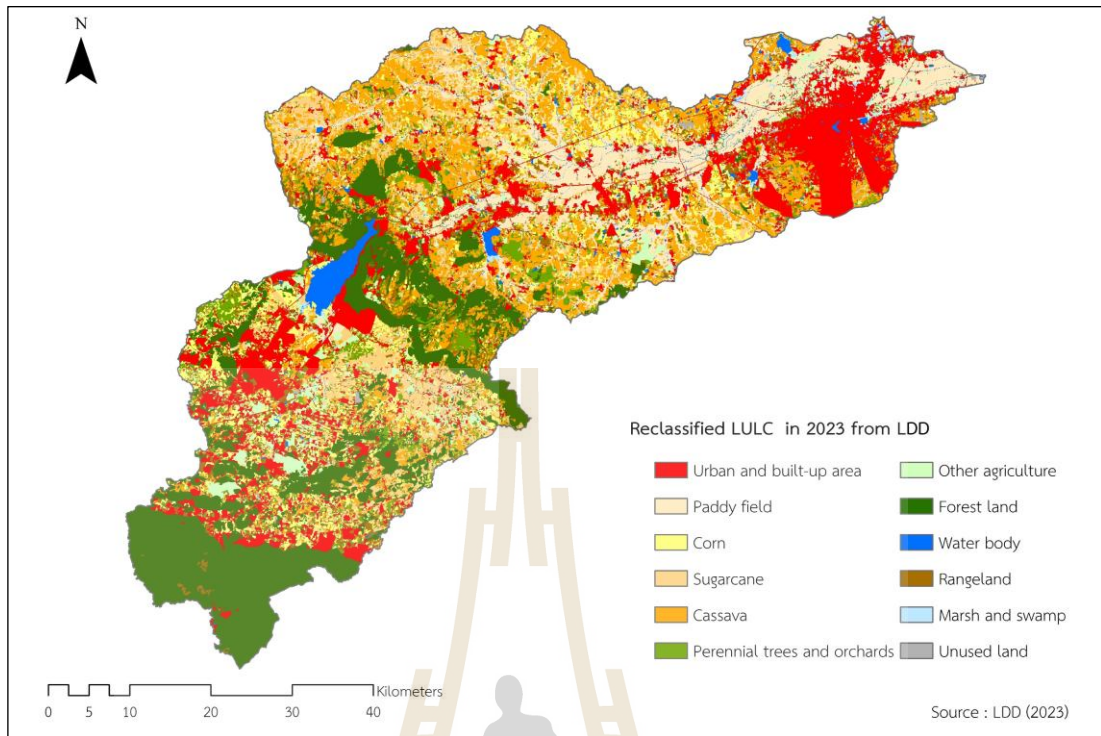
Table 4.10 Annual land requirement with annual rate for predicting LULC in 2023.

Year	LULC type (sq.km)												
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	Total
2019	571.75	399.65	295.23	276.47	590.88	184.51	117.76	614.48	72.78	198.63	11.08	19.42	3,352.64
2020	588.38	383.80	297.99	283.96	584.60	188.14	115.57	606.80	73.93	198.46	10.54	20.45	3,352.64
2021	605.00	367.96	300.76	291.45	578.33	191.76	113.39	599.13	75.07	198.30	10.01	21.48	3,352.64
2022	621.63	352.12	303.52	298.94	572.06	195.39	111.21	591.45	76.22	198.13	9.48	22.51	3,352.64
2023	638.26	336.27	306.28	306.43	565.79	199.01	109.03	583.78	77.36	197.96	8.94	23.53	3,352.64
Annual rate	16.63	-15.84	2.76	7.49	-6.27	3.63	-2.18	-7.68	1.14	-0.17	-0.53	1.03	

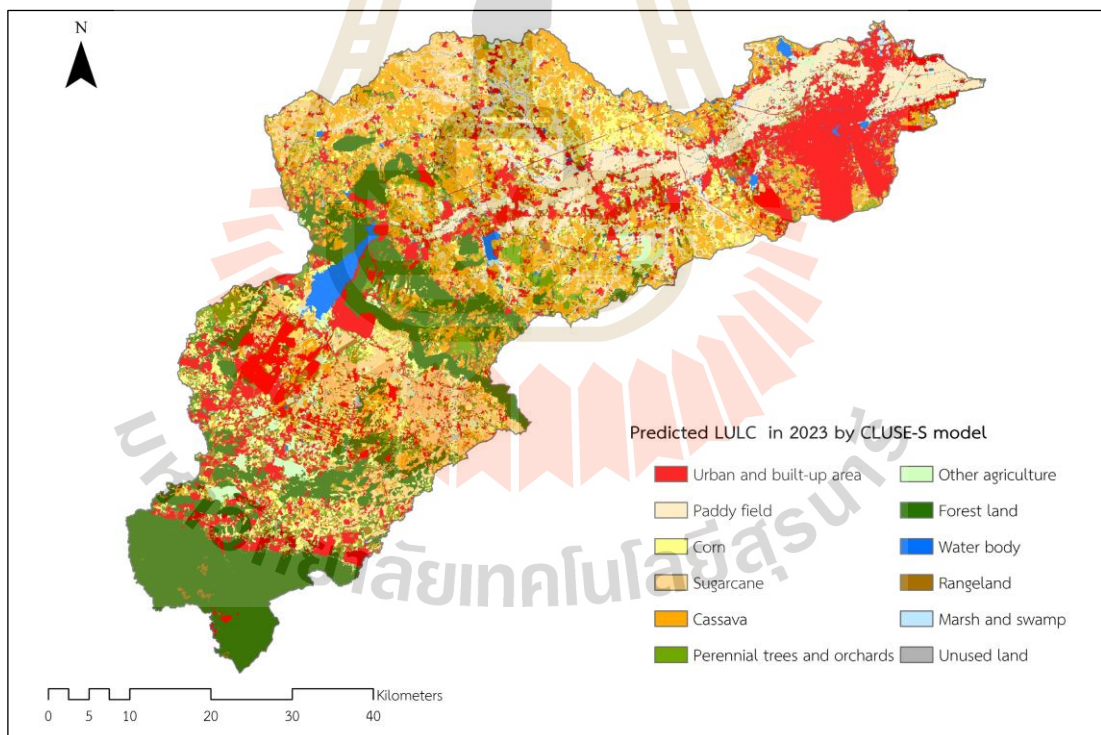


Table 4.11 Error matrix and accuracy assessment between reclassified LULC in 2023 and predicted LULC in 2023.

LULC types	Predicted LULC in 2023 (pixel)												Total
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	
Urban and built-up area (UB)	227,102	6443	3880	1125	6803	1351	3156	3053	135	1555	121	562	255,286
Paddy field (PD)	1236	128,810	227	934	323	349	843	8	775	240	528	244	134,517
Corn (CO)	2056	5,883	94,999	3,591	6643	2281	2126	2766	395	1657	1	88	122,486
Sugarcane (SU)	1183	5,761	1,409	98,870	5587	1,358	2510	4610	375	740	0	150	122,553
Cassava (CA)	1414	747	3698	7222	207524	1850	1759	340	497	1046	5	190	226292
Perennial trees and orchards (PO)	1085	4456	1215	325	1631	67,601	829	1735	76	637	3	51	79,644
Other agriculture (OA)	558	333	212	162	356	531	40,712	102	77	379	103	62	43,587
Forest land (FO)	1027	3	262	87	143	96	109	231,497	38	174	0	56	233,492
Water body (WB)	170	1161	20	54	169	40	88	160	28,635	144	287	10	30,938
Rangeland (RL)	3453	203	879	341	638	565	1924	931	263	69,680	109	191	79,177
Marsh and swamp (MS)	95	11	0	6	5	7	2	0	35	1	3,400	2	3,564
Unused land (UN)	477	1558	41	11	168	43	65	45	147	166	527	6,270	9,518
Total	239,856	155,369	106,842	112,728	229990	76,072	54,123	245,247	31,448	76,419	5,084	7,876	1,341,054
Producer's accuracy (%)	94.68	82.91	88.92	87.71	90.23	88.86	75.22	94.39	91.06	91.18	66.88	79.61	
User's accuracy (%)	88.96	95.76	77.56	80.68	91.71	84.88	93.40	99.15	92.56	88.01	95.40	65.88	
Overall accuracy (%)	89.86												
Kappa hat coefficient (%)	88.35												



(a)



(b)

Figure 4.6 Comparison of spatial LULC distribution in 2023: (a) classified LULC from LDD and (b) predicted LULC by the CLUE-S model.

As a result, the overall accuracy and Kappa hat coefficient values of the predicted LULC in 2023, when compared with reclassified LULC in 2023 of LDD, were 89.86% and 88.35%, respectively. Both values are higher than the thresholding value, with equal or more than 80%. Therefore, the predefined local parameters of the CLUE-S model can be accepted for LULC prediction between 2024 and 2039.

4.3.2 LULC prediction between 2024 and 2039

The predefined local parameters of the CLUE-S model from the previous section were adopted to predict LULC data between 2024 and 2039. The specific land requirements based on change rate between 2015 and 2023, which were calculated from the transition area of the Markov Chain model, are summarized in Tables 4.12 and 4.13.

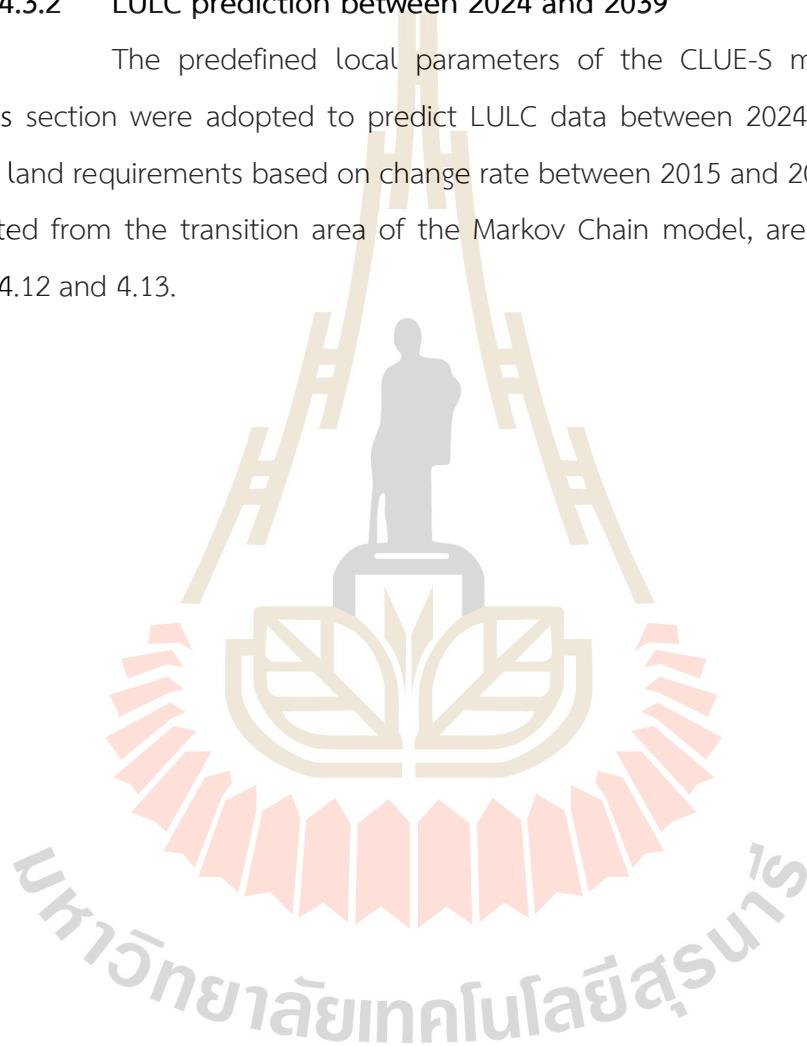


Table 4.12 The matrix of the transition area between 2015 and 2023.

LULC type	LULC in 2023 (Area in sq.km)											
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN
Urban and built-up area (UB)	591.26	0.21	0.95	0.30	0.97	0.83	1.30	0.57	0.18	2.73	0.17	0.19
Paddy field (PD)	10.92	302.62	7.32	31.04	12.31	3.98	7.54	0.04	3.91	4.03	1.96	2.77
Corn (CO)	18.11	1.68	132.12	25.86	45.74	16.70	12.99	1.48	1.39	10.12	0.03	0.91
Sugarcane (SU)	5.87	1.92	20.11	170.76	54.40	11.18	11.02	0.28	1.13	4.32	0.16	0.68
Cassava (CA)	18.61	4.05	67.77	63.77	365.22	24.94	13.05	0.74	1.90	12.11	0.33	2.50
Perennial trees and orchards (PO)	9.84	0.82	12.70	5.78	24.36	125.71	4.66	0.43	0.54	4.59	0.07	0.68
Other agriculture (OA)	8.96	4.16	8.39	4.25	12.79	8.36	79.74	0.24	0.54	6.65	0.42	0.82
Forest land (FO)	7.61	0.18	4.12	0.72	8.58	8.83	1.22	576.41	0.28	4.41	0.00	0.77
Water body (WB)	0.65	0.31	0.10	0.06	0.15	0.23	0.35	0.02	75.93	0.38	0.13	0.32
Rangeland (RL)	13.97	2.07	8.37	3.74	14.96	5.38	3.79	1.21	1.37	133.32	0.43	2.44
Marsh and swamp (MS)	1.46	0.61	0.56	0.10	0.06	0.04	0.37	0.00	0.82	0.84	7.54	0.32
Unused land (UN)	4.05	0.26	0.05	0.04	0.95	0.37	0.46	0.10	0.46	1.75	0.18	11.03

Table 4.13 Annual land requirement of each LULC type LULC for LULC prediction between 2024 and 2039.

Year	LULC type (sq.km)												Total
	UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	
2023	599.64	388.42	267.11	281.82	574.98	190.18	135.31	613.12	78.62	191.05	12.71	19.69	3,352.64
2024	611.10	379.73	266.53	284.89	570.66	192.22	135.45	609.17	79.85	190.32	12.55	20.16	3,352.64
2025	622.56	371.04	265.96	287.97	566.35	194.27	135.60	605.21	81.08	189.60	12.39	20.62	3,352.64
2026	634.01	362.35	265.39	291.04	562.04	196.31	135.75	601.26	82.30	188.87	12.22	21.09	3,352.64
2027	645.47	353.65	264.82	294.11	557.72	198.36	135.89	597.31	83.53	188.15	12.06	21.55	3,352.64
2028	656.93	344.96	264.25	297.18	553.41	200.40	136.04	593.36	84.76	187.42	11.90	22.02	3,352.64
2029	668.39	336.27	263.68	300.26	549.10	202.45	136.18	589.41	85.99	186.70	11.74	22.49	3,352.64
2030	679.84	327.58	263.11	303.33	544.79	204.49	136.33	585.45	87.21	185.97	11.58	22.95	3,352.64
2031	691.30	318.88	262.54	306.40	540.47	206.54	136.48	581.50	88.44	185.25	11.42	23.42	3,352.64
2032	702.76	310.19	261.97	309.48	536.16	208.58	136.62	577.55	89.67	184.52	11.25	23.88	3,352.64
2033	714.22	301.50	261.40	312.55	531.85	210.63	136.77	573.60	90.90	183.80	11.09	24.35	3,352.64
2034	725.67	292.81	260.83	315.62	527.53	212.67	136.91	569.65	92.12	183.07	10.93	24.82	3,352.64
2035	737.13	284.11	260.26	318.69	523.22	214.72	137.06	565.70	93.35	182.35	10.77	25.28	3,352.64
2036	748.59	275.42	259.69	321.77	518.91	216.76	137.20	561.74	94.58	181.62	10.61	25.75	3,352.64
2037	760.05	266.73	259.12	324.84	514.60	218.81	137.35	557.79	95.81	180.90	10.44	26.21	3,352.64
2038	771.50	258.04	258.55	327.91	510.28	220.85	137.50	553.84	97.03	180.17	10.28	26.68	3,352.64
2039	782.96	249.34	257.98	330.99	505.97	222.90	137.64	549.89	98.26	179.45	10.12	27.15	3,352.64
Annual rate	11.46	-8.69	-0.57	3.07	-4.31	2.04	0.15	-3.95	1.23	-0.73	-0.16	0.47	

The spatial distribution of the predicted LULC data between 2024 and 2039 is presented in Figure 4.7. Meanwhile, the area and percentage of predictive LULC types between 2024 and 2039 are summarized in Tables 4.14 to 4.15, respectively.

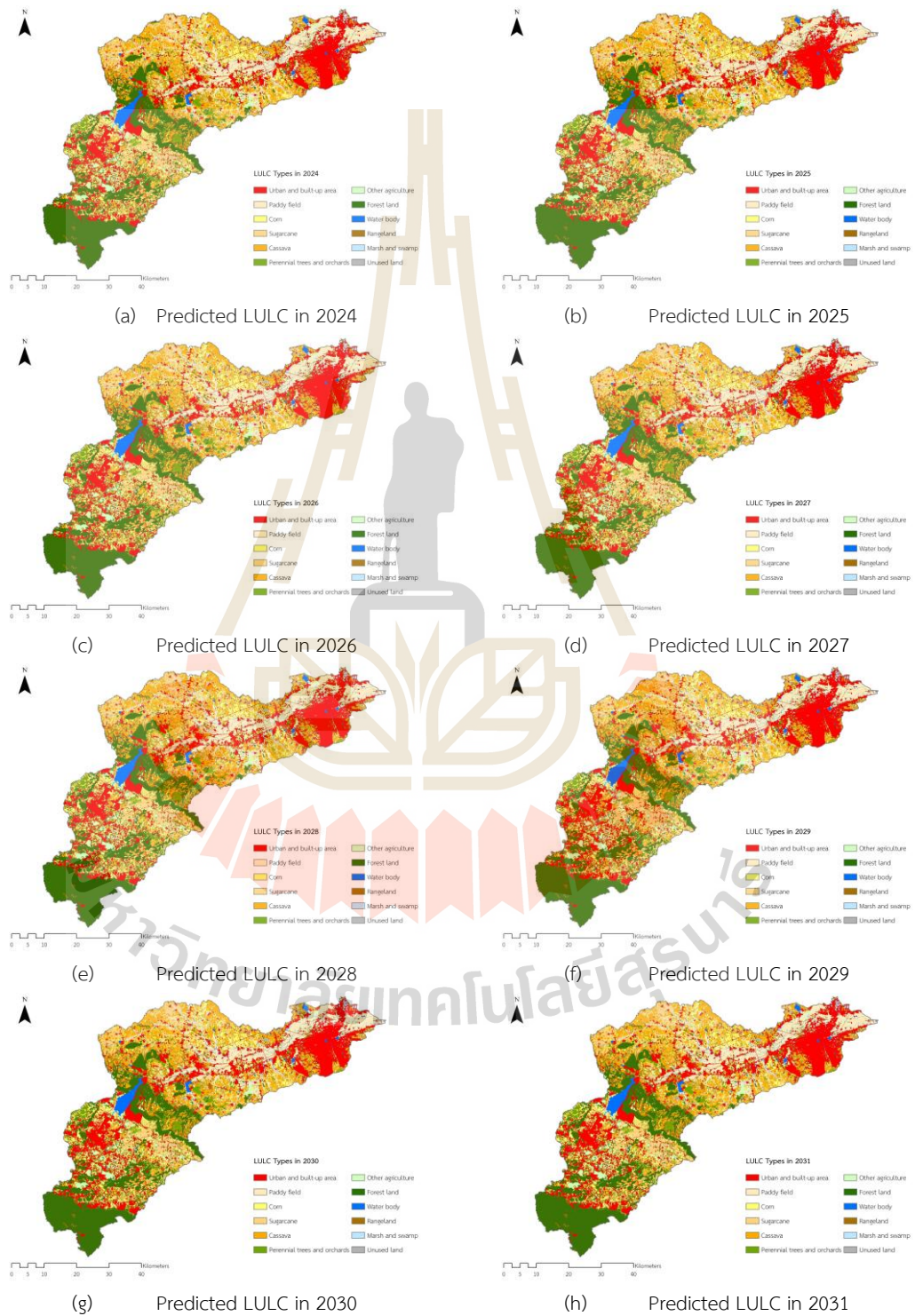


Figure 4.7 Spatial distribution of predicted LULC data between 2024 and 2039.

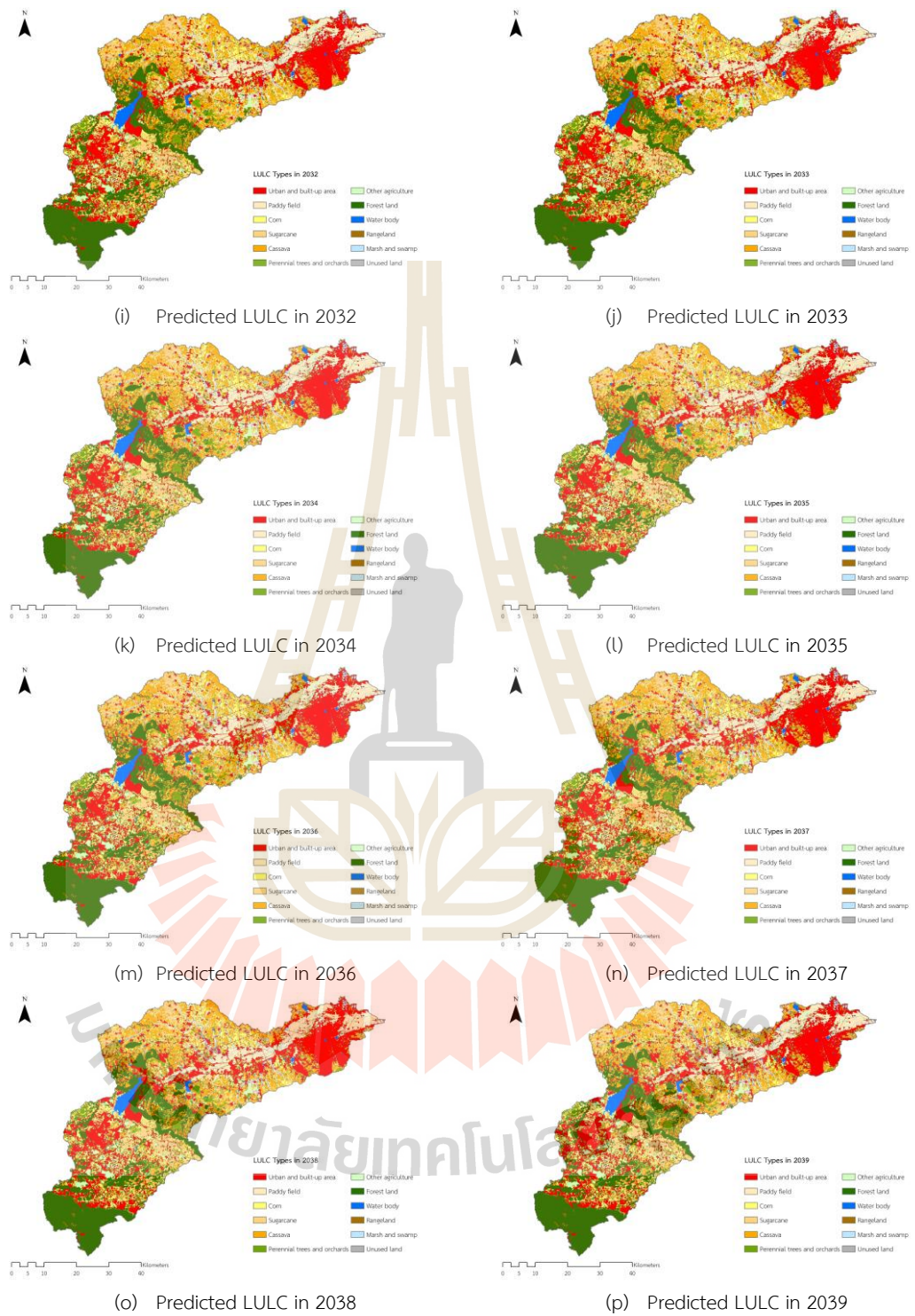


Figure 4.7 (Continued)

Table 4.14 Area of predicted LULC type between 2024 and 2039.

LULC types	Area of predicted LULC type in sq.km															
	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
Urban and built-up area (UB)	611.20	622.51	633.97	645.47	656.88	668.42	679.82	691.31	702.73	714.17	725.63	737.08	748.57	760.03	771.47	782.96
Paddy field (PD)	379.51	370.88	362.33	353.53	344.92	336.27	327.54	318.84	310.17	301.47	292.77	284.09	275.38	266.70	258.00	249.31
Corn (CO)	266.66	265.82	265.37	264.80	264.19	263.44	263.02	262.56	261.94	261.37	260.79	260.22	259.65	259.09	258.51	257.94
Sugarcane (SU)	285.16	288.14	291.01	294.10	297.16	300.27	303.31	306.40	309.43	312.51	315.59	318.66	321.73	324.81	327.89	330.95
Cassava (CA)	570.77	566.37	561.99	557.77	553.38	549.14	544.75	540.48	536.12	531.81	527.50	523.19	518.85	514.56	510.25	505.93
Perennial trees and orchards (PO)	191.84	194.11	196.28	198.32	200.36	202.46	204.47	206.52	208.56	210.60	212.65	214.67	216.72	218.78	220.82	222.86
Other agriculture (OA)	135.30	135.47	135.73	135.92	136.02	136.24	136.30	136.49	136.62	136.80	136.93	137.13	137.29	137.32	137.46	137.59
Forest land (FO)	609.67	605.80	601.21	597.31	593.35	589.44	585.43	581.50	577.52	573.57	569.62	565.67	561.72	557.76	553.80	549.84
Water body (WB)	79.75	81.06	82.30	83.59	84.75	86.06	87.21	88.46	89.65	90.86	92.09	93.31	94.54	95.80	97.04	98.24
Rangeland (RL)	190.44	189.49	188.81	188.19	187.39	186.75	185.95	185.25	184.48	183.76	183.03	182.30	181.58	180.85	180.14	179.41
Marsh and swamp (MS)	12.67	12.67	12.59	12.38	12.26	12.02	11.92	11.73	11.59	11.42	11.26	11.09	10.92	10.76	10.59	10.39
Unused land (UN)	19.67	20.33	21.06	21.28	21.98	22.14	22.92	23.10	23.84	24.32	24.78	25.23	25.71	26.20	26.68	27.22
Total	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64	3,352.64



Table 4.15 Percentage of predicted LULC type between 2024 and 2039.

LULC types	Area of predicted LULC type in sq.km															
	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039
Urban and built-up area (UB)	18.23	18.57	18.91	19.25	19.59	19.94	20.28	20.62	20.96	21.30	21.64	21.99	22.33	22.67	23.01	23.35
Paddy field (PD)	11.32	11.06	10.81	10.54	10.29	10.03	9.77	9.51	9.25	8.99	8.73	8.47	8.21	7.95	7.70	7.44
Corn (CO)	7.95	7.93	7.92	7.90	7.88	7.86	7.85	7.83	7.81	7.80	7.78	7.76	7.74	7.73	7.71	7.69
Sugarcane (SU)	8.51	8.59	8.68	8.77	8.86	8.96	9.05	9.14	9.23	9.32	9.41	9.50	9.60	9.69	9.78	9.87
Cassava (CA)	17.02	16.89	16.76	16.64	16.51	16.38	16.25	16.12	15.99	15.86	15.73	15.61	15.48	15.35	15.22	15.09
Perennial trees and orchards (PO)	5.72	5.79	5.85	5.92	5.98	6.04	6.10	6.16	6.22	6.28	6.34	6.40	6.46	6.53	6.59	6.65
Other agriculture (OA)	4.04	4.04	4.05	4.05	4.06	4.06	4.07	4.07	4.07	4.08	4.08	4.09	4.09	4.10	4.10	4.10
Forest land (FO)	18.18	18.07	17.93	17.82	17.70	17.58	17.46	17.34	17.23	17.11	16.99	16.87	16.75	16.64	16.52	16.40
Water body (WB)	2.38	2.42	2.45	2.49	2.53	2.57	2.60	2.64	2.67	2.71	2.75	2.78	2.82	2.86	2.89	2.93
Rangeland (RL)	5.68	5.65	5.63	5.61	5.59	5.57	5.55	5.53	5.50	5.48	5.46	5.44	5.42	5.39	5.37	5.35
Marsh and swamp (MS)	0.38	0.38	0.38	0.37	0.37	0.36	0.36	0.35	0.35	0.34	0.34	0.33	0.33	0.32	0.32	0.31
Unused land (UN)	0.59	0.61	0.63	0.63	0.66	0.66	0.68	0.69	0.71	0.73	0.74	0.75	0.77	0.78	0.80	0.81
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00



As results in Tables 4.14 and 4.15, the predicted LULC data between 2024 and 2039 indicates increases in areas of urban and built-up areas, sugarcane, perennial trees and orchards, other agriculture, water body, and unused land. Conversely, there are decreases in areas of paddy field, corn, cassava, forests, rangeland, and marsh and swamp. The area and percentage of LULC prediction obtained from the CLUE-S model are strongly aligned (decrease or increase) with the annual rate for land requirement projections derived from the Markov chain model.

In addition, a simple LULC change detection by comparing the area of each LULC type in 2023 and 2039 is reported in Table 4.16 and Figure 4.8. As a result, the top three increasing LULC types in 2039 are urban and built-up area, sugarcane, and perennial trees and orchards, while the top three increasing LULC types in 2039 are paddy field, cassava and forest land.

Furthermore, LULC change detection between 2023 and 2039 by post-comparison detection algorithm, which provides from-to-change information (Jensen, 2005), is reported in Table 4.17.

Table 4.16 Simple comparison of LULC changes between 2023 and 2039.

LULC types	Area in sq.km			% of change in the study area	Remark
	LULC in 2023	LULC in 2039	Changed area		
Urban and built-up area (UB)	599.64	782.96	183.32	5.47	Increase
Paddy field (PD)	388.42	249.31	-139.11	-4.15	Decrease
Corn (CO)	267.11	257.94	-9.17	-0.27	Decrease
Sugarcane (SU)	281.82	330.95	49.13	1.47	Increase
Cassava (CA)	574.98	505.93	-69.05	-2.06	Decrease
Perennial trees and orchards (PO)	190.18	222.86	32.68	0.97	Increase
Other agriculture (OA)	135.31	137.59	2.28	0.07	Increase
Forest land (FO)	613.12	549.84	-63.28	-1.89	Decrease
Water body (WB)	78.62	98.24	19.62	0.59	Increase
Rangeland (RL)	191.05	179.41	-11.64	-0.35	Decrease
Marsh and swamp (MS)	12.71	10.39	-2.32	-0.07	Decrease
Unused land (UN)	19.69	27.22	7.53	0.22	Increase

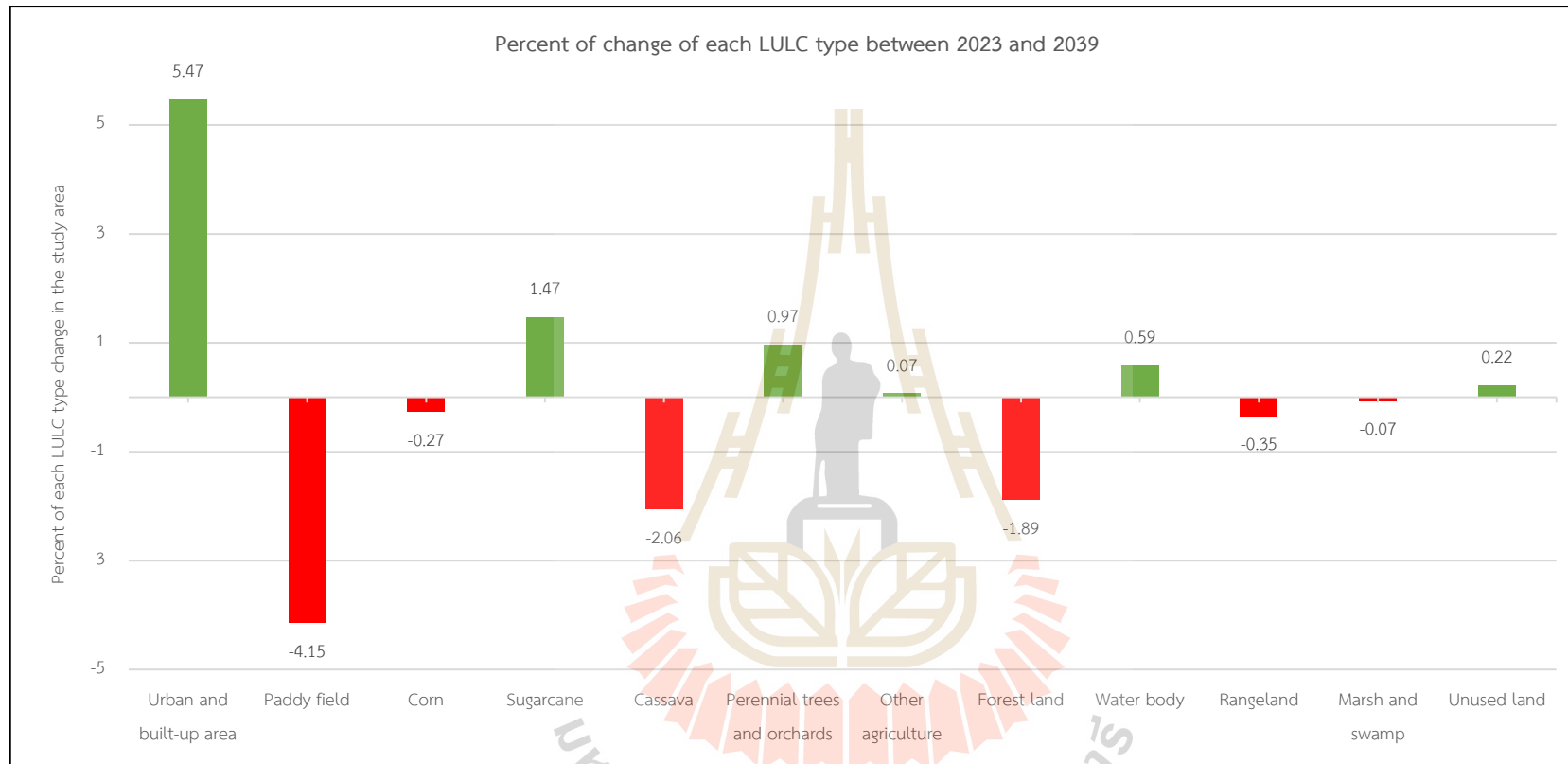
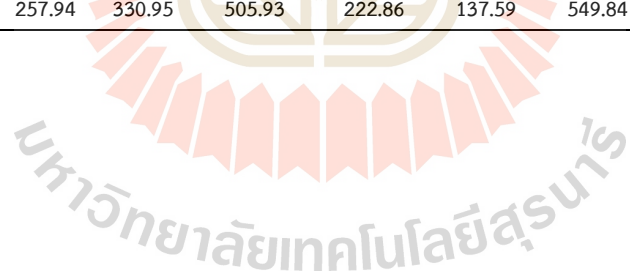


Figure 4.8 Percent of change of each LULC type in the study.

Table 4.17 Change detection matrix of LULC change between 2023 and 2039.

		LULC type in 2039 (sq.km)													
LULC change 2023-2039		UB	PD	CO	SU	CA	PO	OA	FO	WB	RL	MS	UN	Total	
LULC type in 2023 (sq. km)	Urban and built-up areas (UB)	599.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	599.64	
	Paddy field (PD)	54.13	249.31	4.84	33.50	1.19	24.03	1.58	0.00	11.74	0.00	0.00	8.12	388.42	
	Corn (CO)	14.90	0.00	250.69	0.24	0.00	0.00	0.00	0.00	1.28	0.00	0.00	0.00	267.11	
	Sugarcane (SU)	4.28	0.00	0.00	277.33	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	281.82	
	Cassava (CA)	57.05	0.00	0.00	5.36	504.55	0.69	3.95	0.00	3.38	0.00	0.00	0.00	574.98	
	Perennial trees and orchards (PO)	7.37	0.00	0.00	0.00	0.00	182.80	0.00	0.00	0.02	0.00	0.00	0.00	190.18	
	Other agriculture (OA)	6.03	0.00	0.00	0.00	0.00	0.00	129.27	0.00	0.01	0.00	0.00	0.00	135.31	
	Forest land (FO)	25.40	0.00	2.41	14.53	0.19	15.35	2.13	549.84	1.00	1.65	0.00	0.62	613.12	
	Water body (WB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	78.62	0.00	0.00	0.00	78.62	
	Rangeland (RL)	12.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	177.76	0.00	0.00	191.05	
	Marsh and swamp (MS)	0.03	0.00	0.00	0.00	0.00	0.00	0.67	0.00	1.38	0.00	10.39	0.24	12.71	
	Unused land (UN)	1.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.24	19.69	
	Total		782.96	249.31	257.94	330.95	505.93	222.86	137.59	549.84	98.24	179.41	10.39	27.22	3,352.64



As a result, in Table 4.17, urban and built-up areas and water body in 2023 are not changed into any LULC type in 2039. In contrast, paddy fields, corn, sugarcane, cassava, perennial trees and orchards, other agriculture, forest land, rangeland, marsh and swamp and unused land in 2023 are changed into other LULC types in 2039.

In detail, the increasing extent of urban and built-up area in 2039 comes from other LULC types in 2023, except water body. Meanwhile, the increasing area of sugarcane in 2039 comes from paddy field, corn, cassava, and forest land in 2023. the increasing extent of perennial trees and orchards in 2039 comes from paddy field, cassava, and forest land in 2023. The increasing area of water body in 2039 comes from other LULC types in 2023, except urban and built-up area and unused land in 2023. The slightly increasing extent of other agriculture in 2039 comes from paddy field, cassava, forest land, and marsh and swamp in 2023. The slightly increasing area of unused land in 2039 comes from paddy fields, forest land, and marsh and swamp in 2023.

On the contrary, paddy field in 2023 is changed into urban and built-up area, corn, sugarcane, cassava, perennial trees and orchards, other agriculture, water body, and unused land in 2039. Likewise, corn in 2023 is changed into urban and built-up area, sugarcane and water body in 2039. Sugarcane in 2023 is changed into urban and built-up area and water body in 2039. Cassava in 2023 is changed into urban and built-up area, sugarcane, perennial trees and orchards, other agriculture, and water body in 2039. Perennial trees and orchards in 2023 will be changed into urban and built-up area and water body in 2039. Other agriculture in 2023 is changed into urban and built-up area and water body in 2039. Forest land in 2023 is changed into urban and built-up area, corn, sugarcane, cassava, perennial trees and orchards, other agriculture, water body, rangeland, and unused land in 2039. Rangeland in 2023 is changed into urban and built-up area and water body in 2039. Marsh and swamp in 2023 are changed into urban and built-up area, other agriculture, water body and unused land in 2039. Unused land in 2023 is changed into urban and built-up area in 2039.

The extracted LULC change patterns between 2023 and 2039 will play an essential role in the evaluation of economic crop value and ecosystem service value and change in the watershed.

4.4 Evaluation of economic and ecosystem services and change

Two significant results included (1) evaluation of economic crop value and its change between 2023 and 2039 and (2) evaluation of ecosystem service value and its change between 2023 and 2039, are separately described in the following sections.

4.4.1 Evaluation of economic crop value between 2023 and 2039

The present economic values (PV) of four economic crops (rice, corn, sugarcane, and cassava) in 2023 were calculated based on the reports of the Office of Agricultural Economics (2023) and the Office of the Cane and Sugar Board in 2023 are summarized in Table 4.18.

The future economic values (FV) of four crops (rice, corn, sugarcane, and cassava) between 2024 and 2039, which were calculated using the PV model (Eq. 3.4) with the average general inflation rate from the Bank of Thailand in 2023, which is equal to 1.23, are reported in Table 4.19 and Figures 4.9 and 4.10.

As a result in Table 4.19, the future economic value of four crops in total is continuously increasing from 2023 to 2039. However, the future value of rice will decrease between 2023 and 2039 (Figure 4.9) since the area of paddy field will decrease during this period. Conversely, the future value of sugarcane will increase between 2023 and 2039 since the area of sugarcane will increase in the same period.

Meanwhile, the future value of corn and cassava is also increasing, even their area will decrease in the same period. This finding indicates the effect of the future value of corn and cassava.

In addition, by considering the contribution of economic crop value between 2023 and 2039, as shown in Figure 4.10, the most important crop in the watershed is cassava since it contributes about 39% of the total future economic crop value in this period.

These findings indicate the impact of LULC change on economic crop value in the future, especially the conversion of paddy fields into other LULC types.

Table 4.18 Present economic crop value in 2023.

LULC type	Price (Baht/ton) ¹	Yield (ton/sq.km)	Present value (Baht/ sq.km)
Rice ¹	13,527.00	317.19	4,290,629.13
Corn ¹	9,210.00	500.00	4,605,000.00
Sugarcane ²	1,185.00	6,312.50	7,480,312.50
Cassava ¹	2,720.00	2,081.25	5,661,000.00

Source: ¹Office of Agricultural Economics: OAE (2023), ²Office of the cane and sugar board: OCSB (2023).

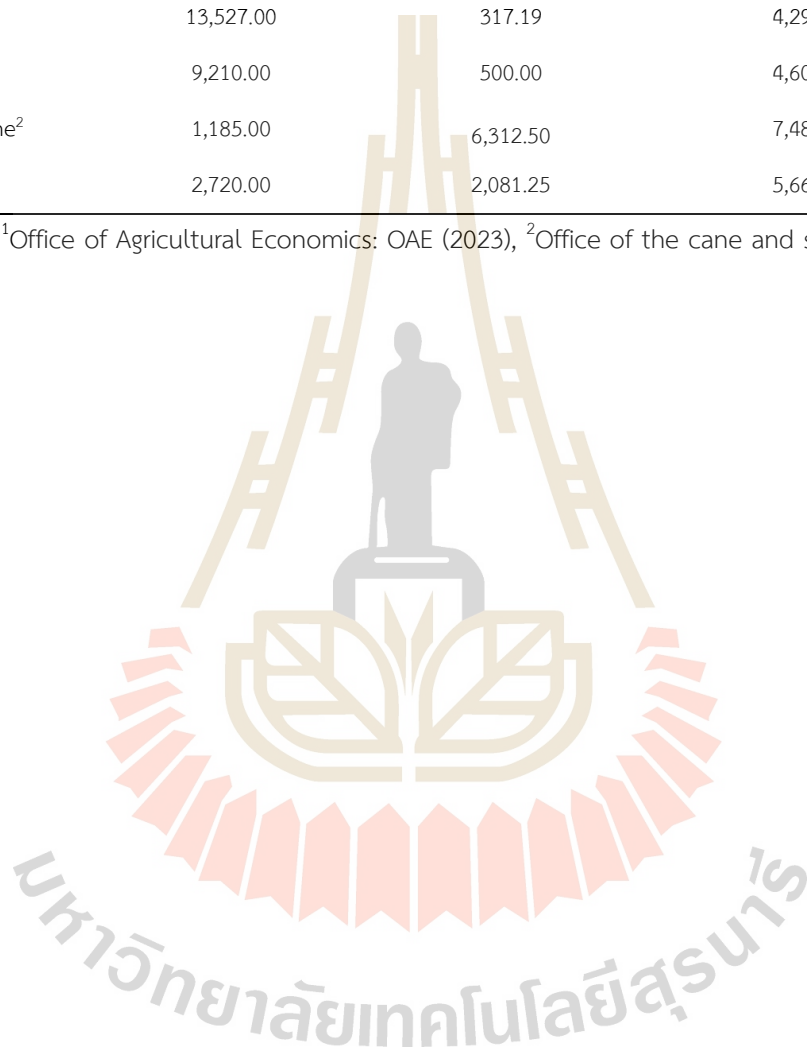


Table 4.19 Future economic crop value between 2024 and 2039.

Future economic value of economic crops from 2024 to 2039 (million Bah)					
Year	Paddy	Corn	Sugarcane	Cassava	Total value
2023	1,666.57	1,230.04	2,108.10	3,254.96	8,259.67
2024	1,648.37	1,243.07	2,159.32	3,270.87	8,321.63
2025	1,630.70	1,254.40	2,208.73	3,285.58	8,379.40
2026	1,612.70	1,267.68	2,258.16	3,300.27	8,438.81
2027	1,592.88	1,280.51	2,310.21	3,315.78	8,499.39
2028	1,573.21	1,293.28	2,362.96	3,330.14	8,559.59
2029	1,552.62	1,305.47	2,417.06	3,345.27	8,620.42
2030	1,530.91	1,319.42	2,471.56	3,359.35	8,681.24
2031	1,508.58	1,333.31	2,527.45	3,374.01	8,743.35
2032	1,485.61	1,346.53	2,583.84	3,387.96	8,803.93
2033	1,461.70	1,360.12	2,641.65	3,402.06	8,865.53
2034	1,436.97	1,373.80	2,700.50	3,415.99	8,927.27
2035	1,411.52	1,387.65	2,760.31	3,429.76	8,989.25
2036	1,385.08	1,401.65	2,821.18	3,443.14	9,051.05
2037	1,357.92	1,415.83	2,883.22	3,456.67	9,113.64
2038	1,329.78	1,430.03	2,946.36	3,469.88	9,176.06
2039	1,300.79	1,444.43	3,010.44	3,482.82	9,238.48

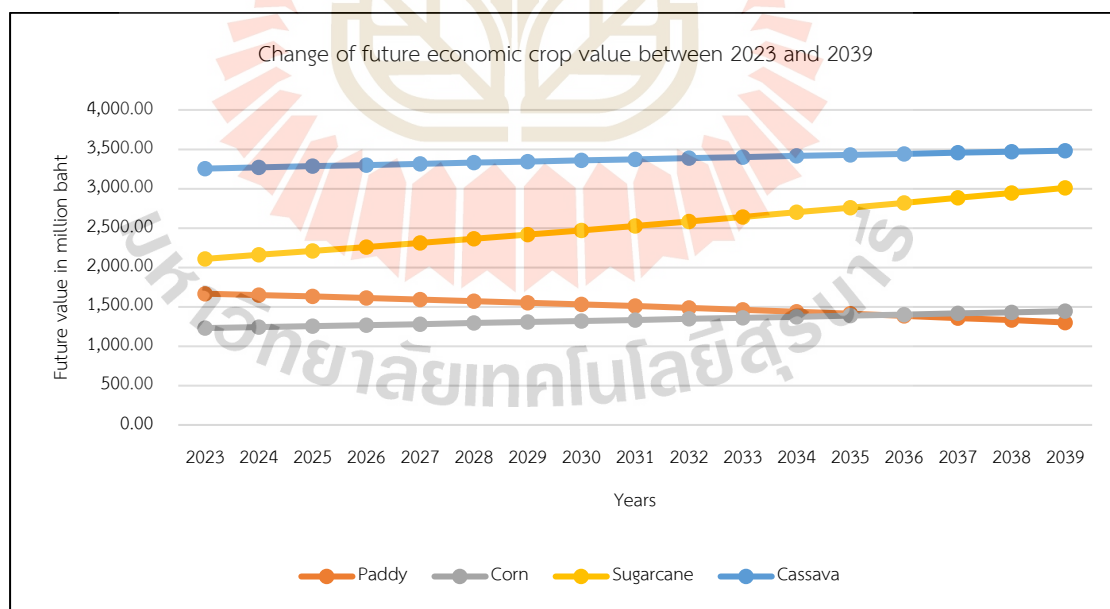


Figure 4.9 Change of future economic crop value between 2023 and 2039.

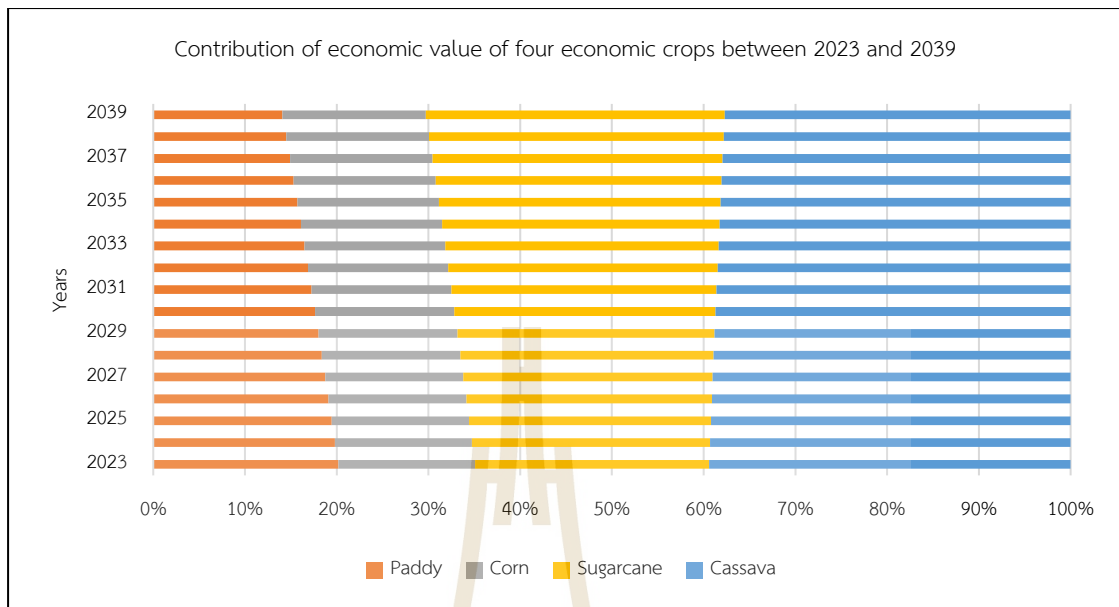


Figure 4.10 Contribution of the future economic value of four crops between 2023 and 2039.

4.4.2 Change of economic crop value between 2023 and 2039

The results of economic value change from 2023 (base year) to 2039 using ESCI, Eq. 8, are reported in Table 4.20. As a result, the total economic value of four crops is continuously increasing from 2023 to 2039. Also, it can be observed that economic value change will increase about 1 percent per period, from the first period (2023-2024), with a value of 0.75% until the last period (2023-2039), with a value of 11.85%

Table 4.20 Economic value change between 2023 and 2039 by ESCI.

Year	EV Total	Economic value change		
		Period	By index	By percentages
2023	8,259.67	Y2023	0.00000	
2024	8,321.63	Y2023-Y2024	0.00750	0.75
2025	8,379.40	Y2023-Y2025	0.01450	1.45
2026	8,438.81	Y2023-Y2026	0.02169	2.17
2027	8,499.39	Y2023-Y2027	0.02902	2.90
2028	8,559.59	Y2023-Y2028	0.03631	3.63
2029	8,620.42	Y2023-Y2029	0.04368	4.37
2030	8,681.24	Y2023-Y2030	0.05104	5.10
2031	8,743.35	Y2023-Y2031	0.05856	5.86
2032	8,803.93	Y2023-Y2032	0.06589	6.59
2033	8,865.53	Y2023-Y2033	0.07335	7.34
2034	8,927.27	Y2023-Y2034	0.08083	8.08
2035	8,989.25	Y2023-Y2035	0.08833	8.83
2036	9,051.05	Y2023-Y2036	0.09581	9.58
2037	9,113.64	Y2023-Y2037	0.10339	10.34
2038	9,176.06	Y2023-Y2038	0.11095	11.09
2039	9,238.48	Y2023-Y2039	0.11851	11.85



4.4.3 Evaluation of ecosystem service value between 2023 and 2039

The evaluation results of ecosystem service value between 2023 and 2039, which were calculated using Eq. 2.3, based on the coefficient value of different LULC types for ESV estimation and the area of each LULC type between 2023 and 2039 (Tables 4.21 and 4.22), are reported in Table 4.23. As a result, the ESV in total in the Lam Takhong watershed is continuously decreasing between 2023 and 2039.

By considering ecosystem service value by its category, as shown in Table 4.23 and Figure 4.11, the regulating, supporting, and provision of services are continuously decreasing between 2023 and 2039. Still, cultural service is continuously increasing in the same period. The increase of cultural services caused by the increasing of urban and built-up areas in this period,

Meanwhile, the contribution of ecosystem service value in each category is displayed in Figure 4.12. As a result, the most important ecosystem service category is regulating service since it contributes about 49% of the total ecosystem service value in the watershed. This ESV category plays an important ecosystem service function in gas and climate regulations.



Table 4.21 Coefficient value for different LULC types for ESV estimation.

Ecosystem services category	Ecosystem services function	Coefficient value for different LULC types (million Baht/sq.km/year)								total
		Urban and built-up area	Paddy field	Field crop	Forest land	Water body	Rangeland	Marsh and swamp	Unused land	
1. Regulating services	1.1 Gas regulation	0.00	0.26	0.26	1.03	0.00	0.36	0.92	0.01	2.83
	1.2 Climate regulation	0.00	0.46	0.46	0.97	0.24	0.37	8.75	0.03	11.27
	1.3 Waste treatment	0.00	0.84	0.84	0.41	9.32	0.31	9.31	0.06	21.08
2. Supporting services	2.1 Soil formation	0.00	0.75	0.75	0.95	0.01	0.53	0.88	0.04	3.90
	2.2 Biodiversity protection	0.00	0.36	0.36	1.07	1.27	0.45	1.28	0.09	4.89
3. Provisioning services	3.1 Water supply	0.00	0.31	0.31	0.97	10.44	0.36	7.93	0.02	20.34
	3.2 Food production	0.00	0.51	0.51	0.08	0.05	0.10	0.15	0.00	1.41
	3.3 Raw materials	0.00	0.05	0.05	0.71	0.01	0.09	0.04	0.01	0.95
4. Cultural services	4.1 Recreation and culture	0.04	0.01	0.01	0.49	2.22	0.21	2.84	0.06	5.87
Total		0.04	3.54	3.54	6.68	23.55	2.77	32.10	0.33	72.54

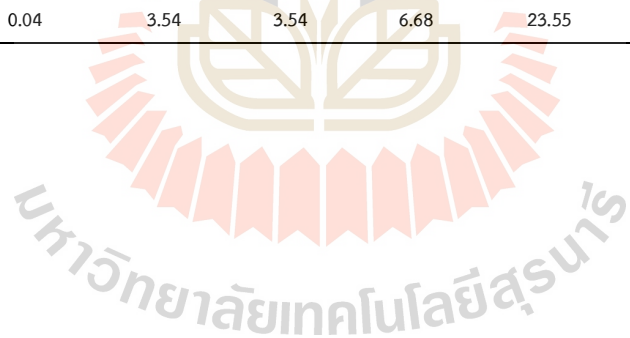


Table 4.22 Area of each LULC type for ESV estimation between 2023 and 2039.

Year	Area of LULC types for ESV estimation (Sq.km)							
	Urban and built-up area	Paddy field	Field crop	Forest land	Water body	Rangeland	Marsh and swamp	Unused land
2023	599.64	388.42	1,449.40	613.12	78.62	191.05	12.71	19.69
2024	611.20	379.51	1,449.73	609.67	79.75	190.44	12.67	19.67
2025	622.51	370.88	1,449.91	605.80	81.06	189.49	12.67	20.33
2026	633.97	362.33	1,450.38	601.21	82.30	188.81	12.59	21.06
2027	645.47	353.53	1,450.91	597.31	83.59	188.19	12.38	21.28
2028	656.88	344.92	1,451.11	593.35	84.75	187.39	12.26	21.98
2029	668.42	336.27	1,451.55	589.44	86.06	186.75	12.02	22.14
2030	679.82	327.54	1,451.85	585.43	87.21	185.95	11.92	22.92
2031	691.31	318.84	1,452.45	581.50	88.46	185.25	11.73	23.10
2032	702.73	310.17	1,452.67	577.52	89.65	184.48	11.59	23.84
2033	714.17	301.47	1,453.09	573.57	90.86	183.76	11.42	24.32
2034	725.63	292.77	1,453.46	569.62	92.09	183.03	11.26	24.78
2035	737.08	284.09	1,453.87	565.67	93.31	182.30	11.09	25.23
2036	748.57	275.38	1,454.24	561.72	94.54	181.58	10.92	25.71
2037	760.03	266.70	1,454.56	557.76	95.80	180.85	10.76	26.20
2038	771.47	258.00	1,454.93	553.80	97.04	180.14	10.59	26.68
2039	782.96	249.31	1,455.27	549.84	98.24	179.41	10.39	27.22

Table 4.23 Ecosystem service value by its category and its total between 2023 and 2039.

Year	Ecosystem services category				Total
	Regulating services	Supporting services	Provision services	Cultural services	
2023	5,515.08	3,600.33	3,709.78	589.78	13,414.96
2024	5,502.88	3,584.57	3,707.46	590.80	13,385.71
2025	5,492.08	3,568.18	3,706.57	592.09	13,358.91
2026	5,478.22	3,550.76	3,703.48	592.71	13,325.18
2027	5,463.75	3,534.30	3,700.95	593.39	13,292.38
2028	5,449.24	3,517.48	3,697.45	594.00	13,258.17
2029	5,434.43	3,501.00	3,694.90	594.63	13,224.96
2030	5,420.06	3,484.10	3,691.37	595.25	13,190.78
2031	5,405.70	3,467.67	3,688.62	595.87	13,157.85
2032	5,391.02	3,450.79	3,685.22	596.49	13,123.52
2033	5,376.32	3,434.14	3,682.03	597.08	13,089.57
2034	5,361.93	3,417.46	3,679.06	597.73	13,056.19
2035	5,347.34	3,400.82	3,675.97	598.34	13,022.46
2036	5,332.74	3,384.12	3,672.93	598.97	12,988.76
2037	5,318.56	3,367.43	3,670.24	599.70	12,955.93
2038	5,304.06	3,350.76	3,667.30	600.35	12,922.46
2039	5,288.56	3,333.93	3,663.67	600.82	12,886.98

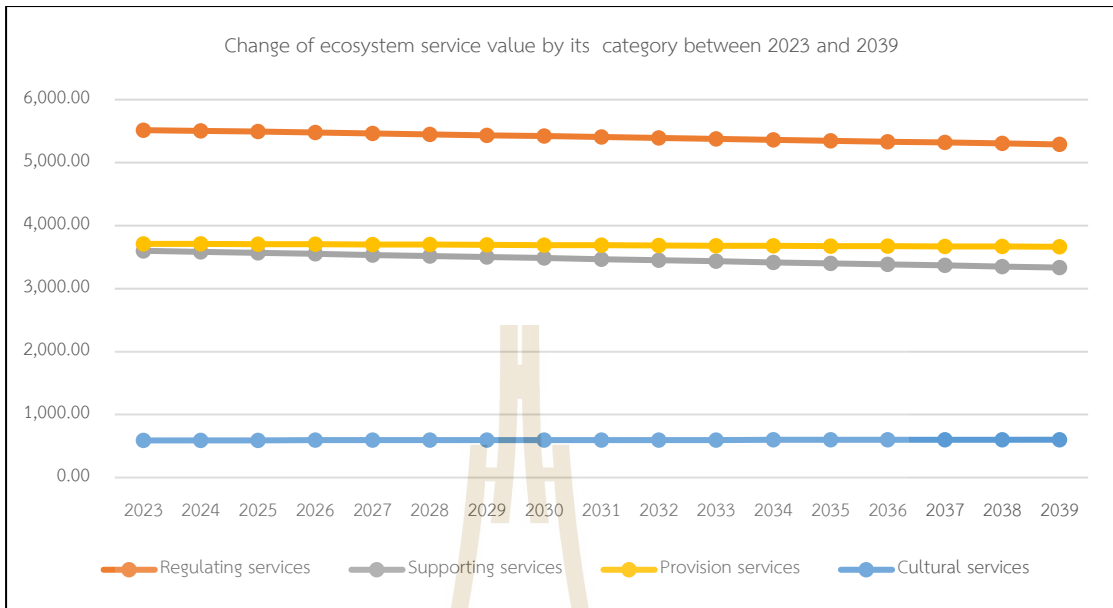


Figure 4.11 Change of ecosystem service value by its category between 2023 and 2039.

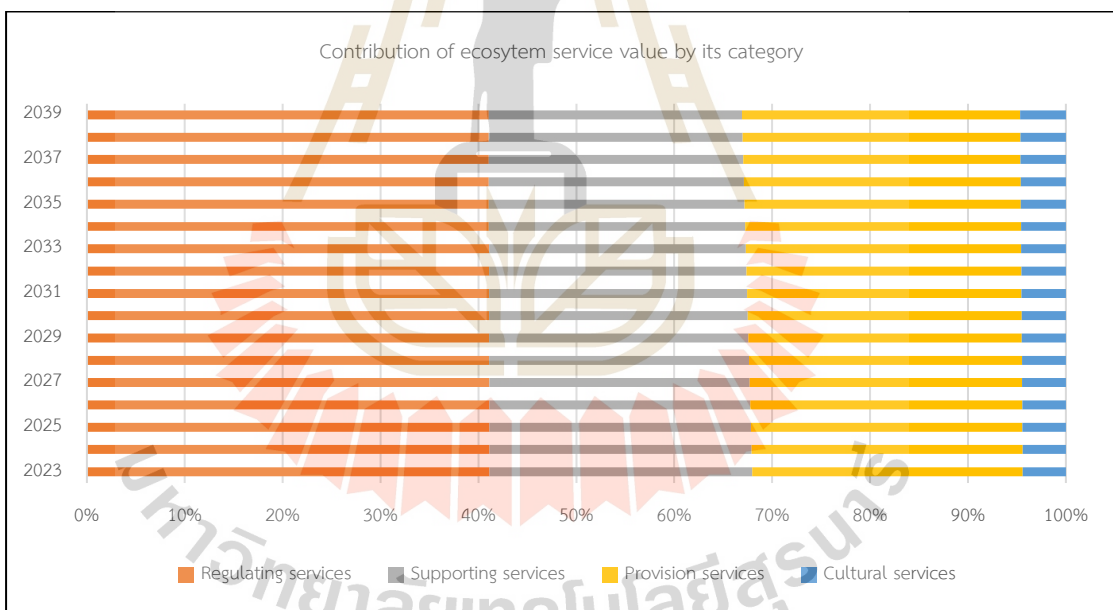


Figure 4.12 Contribution of ecosystem service value by its category between 2023 and 2039.

Furthermore, by considering ecosystem service value by its function (gas regulation, climate regulation, waste treatment, soil formation, biodiversity protection, water supply, food production, raw materials, recreation and culture), as a result shown in Table 4.24 and Figure 4.13. As a result, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions marginally decreased from 2023 to 2039, but waste treatment, water supply, and recreation and culture functions slightly increased in the same period.

The contribution of ecosystem service value in each function is displayed in Figure 4.14. As a result, the most important ecosystem service function is waste treatment since it contributes about 30% of the total ecosystem service value in the watershed.

These findings indicate the impact of LULC change on ecosystem service value in each category and function in the watershed. For example, the areas of the water body, which play an important role with high coefficient value in waste treatment, water supply and recreation and culture function, will be increasing from 78.62 sq. km in 2023 to 98.24 sq. km in 2039. So, the increasing water body between 2023 and 2039 induces the increasing ecosystem service value in waste treatment, water supply and recreation and culture functions in the same period.

On the contrary, the areas of the forest land, which serve an important role in ecosystem service with high coefficient value in gas regulation, climate regulation, soil formation, biodiversity protection, and raw material, will be decreasing from 613.12 sq. km in 2023 to 549.84 sq. km in 2039. Thus, the decreasing forest land between 2023 and 2039 makes the decreasing ecosystem service value in gas regulation, climate regulation, soil formation, biodiversity protection, and raw material functions in the same period. See detail in Table 4.24.

Table 4.24 Ecosystem service value by its function and its total between 2023 and 2039.

Year	Ecosystem service function values between 2023 and 2039 (million Baht)									
	Gas regulation	Climate regulation	Waste treatment	Soil formation	Biodiversity protection	Water supply	Food production	Raw materials	Recreation and culture	Total
2023	1,179.31	1,631.03	2,704.74	2,072.23	1,528.10	2,150.45	1,014.34	544.99	589.78	13,414.96
2024	1,173.32	1,623.47	2,706.09	2,062.17	1,522.40	2,155.72	1,009.67	542.07	590.80	13,385.71
2025	1,166.86	1,615.86	2,709.36	2,051.69	1,516.49	2,162.72	1,005.02	538.83	592.09	13,358.91
2026	1,159.78	1,607.10	2,711.34	2,040.88	1,509.88	2,167.86	1,000.50	535.12	592.71	13,325.18
2027	1,153.25	1,597.81	2,712.69	2,030.48	1,503.82	2,173.12	995.94	531.89	593.39	13,292.38
2028	1,146.65	1,589.10	2,713.49	2,019.92	1,497.56	2,177.57	991.28	528.60	594.00	13,258.17
2029	1,140.09	1,579.55	2,714.79	2,009.52	1,491.48	2,182.80	986.74	525.36	594.63	13,224.96
2030	1,133.45	1,570.96	2,715.65	1,998.92	1,485.18	2,187.26	982.08	522.03	595.25	13,190.78
2031	1,126.93	1,561.85	2,716.92	1,988.59	1,479.08	2,192.25	977.59	518.78	595.87	13,157.85
2032	1,120.29	1,552.95	2,717.78	1,977.98	1,472.81	2,196.84	972.91	515.47	596.49	13,123.52
2033	1,113.71	1,543.90	2,718.71	1,967.52	1,466.62	2,201.50	968.33	512.20	597.08	13,089.57
2034	1,107.13	1,534.92	2,719.88	1,957.02	1,460.44	2,206.42	963.72	508.92	597.73	13,056.19
2035	1,100.55	1,525.88	2,720.91	1,946.56	1,454.26	2,211.18	959.14	505.65	598.34	13,022.46
2036	1,093.96	1,516.81	2,721.97	1,936.05	1,448.07	2,216.03	954.53	502.37	598.97	12,988.76
2037	1,087.36	1,507.81	2,723.39	1,925.52	1,441.91	2,221.25	949.91	499.08	599.70	12,955.93
2038	1,080.76	1,498.75	2,724.55	1,915.02	1,435.74	2,226.20	945.30	495.80	600.35	12,922.46
2039	1,074.12	1,489.39	2,725.05	1,904.47	1,429.46	2,230.48	940.67	492.52	600.82	12,886.98

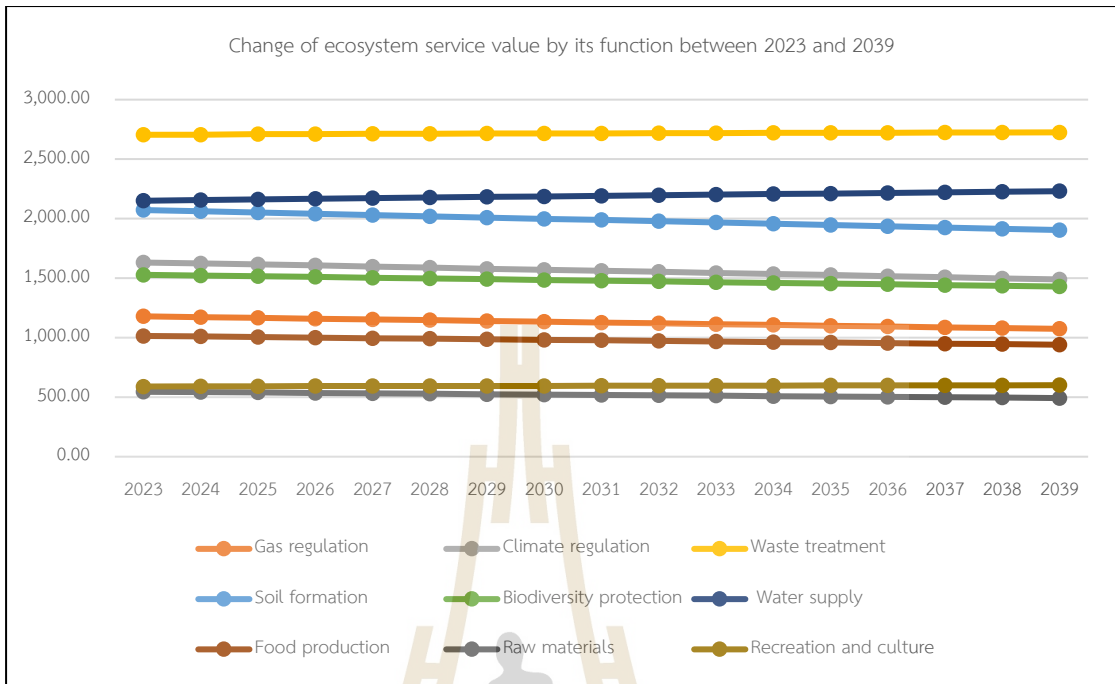


Figure 4.13 Change of ecosystem service value by its function between 2023 and 2039.

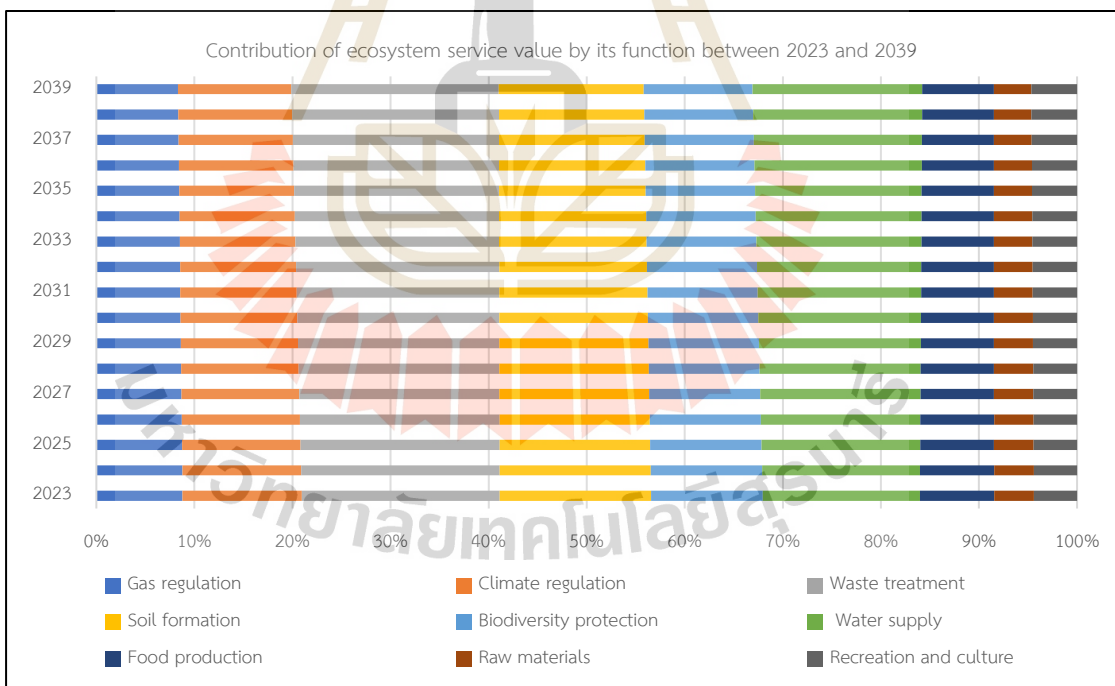


Figure 4.14 Contribution of ecosystem service value by its function between 2023 and 2039.

4.4.4 Change of ecosystem service value between 2023 and 2039

The results of ecosystem service value change between 2023 (base year) and 2039 using ESCI are reported in Table 4.25. As a result, the total ecosystem service value in the watershed will continuously decrease from 2023 to 2039.

The simple linear equation of ecosystem service value change in the future, with the R^2 of 0.9997, is

$$Y = 13456 - 33.309X \quad (4.13)$$

Where X is year, and Y is ESV value.

In addition, the change of total ESV based on ESCI in 16 periods is slightly decreasing and with marginally different between consequent periods.

Table 4.25 Ecosystem services values change between 2023 and 2039.

Year	ESV Total (million Baht)	Ecosystem services values Change		
		Year of change	By index	By percentages
2023	13,414.96	Y2023		
2024	13,385.71	Y2023-Y2024	-0.00218	-0.22
2025	13,358.91	Y2023-Y2025	-0.00418	-0.42
2026	13,325.18	Y2023-Y2026	-0.00669	-0.67
2027	13,292.38	Y2023-Y2027	-0.00914	-0.91
2028	13,258.17	Y2023-Y2028	-0.01169	-1.17
2029	13,224.96	Y2023-Y2029	-0.01416	-1.42
2030	13,190.78	Y2023-Y2030	-0.01671	-1.67
2031	13,157.85	Y2023-Y2031	-0.01917	-1.92
2032	13,123.52	Y2023-Y2032	-0.02172	-2.17
2033	13,089.57	Y2023-Y2033	-0.02426	-2.43
2034	13,056.19	Y2023-Y2034	-0.02674	-2.67
2035	13,022.46	Y2023-Y2035	-0.02926	-2.93
2036	12,988.76	Y2023-Y2036	-0.03177	-3.18
2037	12,955.93	Y2023-Y2037	-0.03422	-3.42
2038	12,922.46	Y2023-Y2038	-0.03671	-3.67
2039	12,886.98	Y2023-Y2039	-0.03936	-3.94

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study on the impacts of land use and land cover change on economic crops and ecosystem service values at Lam Takhong Watershed, Thailand, was conducted based on the integration of geospatial models and methods. In brief, the Binary logistics regression model was applied to identify significant driving factors for land allocation under the CLUE-S model. The CLUE-S model, as a spatial model for predicting land use and land cover change, was applied to predict land use and land cover change in the future (2024-2039). The present Value model was applied to evaluate the future economic value of four crops, including rice, corn, sugarcane, and cassava. Likewise, the simple benefit transfer method was used to evaluate the future ecosystem service value in the watershed. The ecosystem service value change index was applied to characterize the change in economic value and ecosystem service value in the future. The significant results and findings are summarized below:

1. The result of the thematic accuracy assessment of land use and land cover data in 2023 based on 757 stratified random points reference points from Google Map satellite provided the overall accuracy and Kappa hat coefficient values, with a value of 89.04% and 87.56%, respectively. As a result, the land use and land cover data in 2023 with twelve classes can be accepted for identifying local parameters for LULC prediction with the CLUE-S model since the overall accuracy is more than 85 percent and the Kappa hat coefficient value is more than 80 percent.

2. Based on binary logistics regression analysis, the most significant driving factors on land use and land cover change were elevation, annual rainfall, and irrigation area. Meanwhile, the significant driving factors on economic crops (rice, corn, sugarcane, and cassava) were elevation, slope, annual rainfall, and irrigation.

3. The result of the validation of the local parameters for land use and land cover prediction with the CLUE-S model was accepted since the accuracy of the predicted LULC in 2023 was higher than the thresholding value, with overall accuracy and Kappa hat coefficient value equal to more than 80%.

4. The predicted land use and land cover data between 2024 and 2039 indicated the increase of urban and built-up areas, sugarcane, perennial trees and orchards, other agriculture, water body, and unused land. Conversely, there were decreases in paddy fields, corn, cassava, forest land, rangeland, and marsh and swamp.

5. The land use and land cover prediction results obtained from the CLUE-S model were strongly aligned (decrease or increase) with the annual rate for land requirement projections derived from the Markov chain model.

6. According to the result of land use and land cover change detection between 2023 and 2039 using the post-classification comparison algorithm, urban and built-up area and water body in 2023 will not be converted into any land use and land cover type in 2039. In contrast, paddy field, corn, sugarcane, cassava, perennial trees and orchards, other agriculture, forest land, rangeland, marsh and swamp and unused land in 2023 will be converted into other LULC types in 2039.

7. For economic value evaluation, the values of four economic crops in total were continuously increasing between 2023 and 2039. Still, the contribution of economic value from rice and cassava will decrease, but economic value from corn and sugarcane will increase in the same period.

8. For ecosystem service value evaluation, the ecosystem service value in total continuously decreased between 2023 and 2039.

9. By considering ecosystem service value by its category, the regulating, supporting, and provision of services will be continuously decreasing between 2023 and 2039. Still, cultural service will continue to increase in the same period. The most important ecosystem service category is regulating service since it contributes about 49 percent of the total ecosystem service value in the watershed. The regulating service category plays an important role in the ecosystem service function in gas and climate regulations.

10. By considering ecosystem service value by its function, gas regulation, climate regulation, soil formation, biodiversity protection, food production, and raw material functions will be marginally decreased from 2023 to 2039, but waste treatment, water supply, and recreation and culture functions will be slightly increasing in the future. The most crucial ecosystem service function is waste treatment since it contributes about 30 percent of the total ecosystem service value in the watershed.

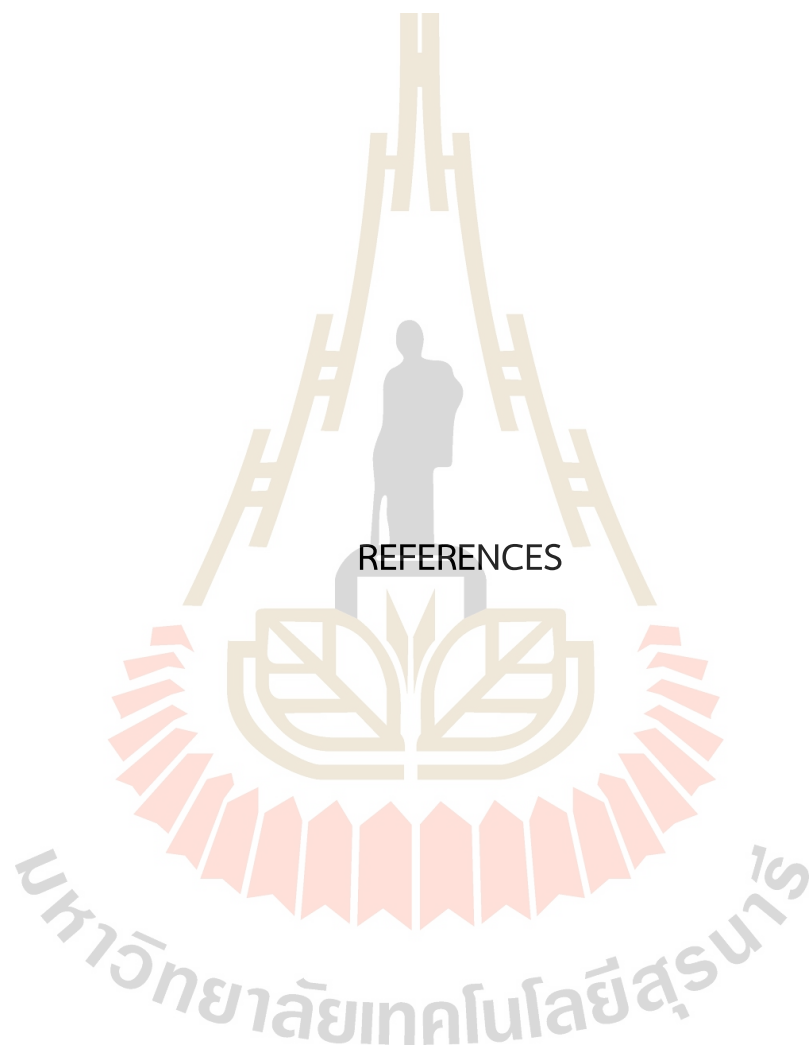
In conclusion, land use and land cover change impacts economic crop value and ecosystem service value in each category and function in the Lam Takhong watershed, especially the conversion of paddy fields and forest land into other LULC types in the future.

5.2 Recommendation

Three main objectives were successfully conducted in this study. Still, the possible expected recommendations and implications could be made as the following.

1. According to the results of this study, land use and land cover change impacts economic crop value and ecosystem service value in each category and function in the Lam Takhong watershed. So, the Government should set up specific policies or interventions to prevent land use and land cover change in the Lam Takhong watershed. The Land Development Department should implement land use planning. Meanwhile, the Royal Forest Department and Department of National Parks, Wildlife and Plants Conservation Department should be preventing illegal forest encroachment in the watershed. Additionally, the encroached national reserve forest areas should be reforested to increase forest land in the watershed.

2. The study found that the coefficient for calculating the value of ecosystem services should have specific values for each region studied in order to obtain values that are consistent with the actual land use in that region. Therefore, it is recommended to survey to determine the coefficient for valuing ecosystem services in Thailand in order to use in calculating the value of ecosystem services that will increase or decrease in the future.



REFERENCES

REFERENCES

- Allan, A., Soltani, A., Abdi, M. H., and Zarei, M. (2022). Driving Forces behind Land Use and Land Cover Change: A Systematic and Bibliometric Review. *Land*, 11(8), 1222. <https://doi.org/10.3390/land11081222>
- Angelsen, A., and Kaimowitz, D. (Eds.) (2001) *Agricultural technologies and tropical deforestation*. Wallingford, Oxon, UK: CABI Publishing in association with CIFOR. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Anderson, J. R., Hardy, E. E., Roach, J. T., and Witmer, R. E. (1976). *A land use and land cover classification system for use with remote sensor data* (964). Retrieved from <https://pubs.usgs.gov/publication/pp964>
- Barbier, E. (1997). The Economic Determinants of Land Degradation in Developing Countries. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 352, 891-899. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Castella, J.-C., Kam, S. P., Quang, D. D., Verburg, P. H., and Hoanh, C. T. (2007). Combining top-down and bottom-up modelling approaches of land use/cover change to support public policies: Application to sustainable management of natural resources in northern Vietnam. *Land Use Policy*, 24(3), 531-545. doi:<https://doi.org/10.1016/j.landusepol.2005.09.009>
- Chaiyawannakarn, N., Tangtham, N., and Tokrisna, R. (2017). Application of Life Cycle Assessment to Assess Impact of Lamtakong Basin's Land Management. *Journal of Food Health and Bioenvironmental Science*, 10(2), 133-151. Retrieved from <https://li01.tci-thaijo.org/index.php/sdust/article/view/178703>

- Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., ... van den Belt, M. (1997). The value of the world's ecosystem services and natural capital. *Nature*, 387(6630), 253-260. doi:10.1038/387253a0
- Cui, J., Zhu, M., Liang, Y., Qin, G., Li, J., and Liu, Y. (2022). Land Use/Land Cover Change and Their Driving Factors in the Yellow River Basin of Shandong Province Based on Google Earth Engine from 2000 to 2020. *ISPRS International Journal of Geo-Information*, 11(3). doi:10.3390/ijgi11030163
- Fitzpatrick-Lins, K. (1981). Comparison of sampling procedures and data analysis for a land-use and land cover map. *Photogrammetric Engineering and Remote Sensing*. 47(3), 343–351.
- Fu, Q., Li, B., Hou, Y., Bi, X., and Zhang, X. (2017). Effects of land use and climate change on ecosystem services in Central Asia's arid regions: A case study in Altay Prefecture, China. *The Science of the total environment*, 607-608, 633-646. doi:10.1016/j.scitotenv.2017.06.241
- Geist, H., Lambin, E., Palm, C., and Tomich, T. (2006). Agricultural transitions at dryland and tropical forest margins: actors, scales and trade-offs. In: Brouwer F, McCarl BA . (Eds). *Agriculture and climate Beyond 2015: A New Perspective on Future Land Use Patterns*. (Environment & policy, Vol. 46, pp. 53–73). Dordrecht: Springer. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Gharaibeh, A., Shaamala, A., Obeidat, R., and Al-Kofahi, S. (2020). Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. *Heliyon*, 6(9), e05092. doi:10.1016/j.heliyon.2020.e05092
- Goldstein, N., Candau, J. T., and Clarke, K. (2004). Approaches to simulating the “March of Bricks and Mortar”. *Computers, Environment and Urban Systems*, 28(1), 125-147. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Guswa, A. J., Brauman, K. A., Brown, C., Hamel, P., Keeler, B. L., and Sayre, S. S. (2014). Ecosystem services: Challenges and opportunities for hydrologic modeling to

- support decision making. *Water Resources Research*, 50(5) , 4535- 4544. doi:<https://doi.org/10.1002/2014WR015497>
- Hu, H., Fu, B.-J., Lu, Y., and Zheng, Z. (2014). SAORES: a spatially explicit assessment and optimization tool for regional ecosystem services. *Landscape Ecology*, 30. doi:10.1007/s10980-014-0126-8
- Karki, J., Kumar, P., and Baniya, B. (2022). Estimation of Land Use Based Ecosystem Service Values and Its Response to Climate Change in Nepal. *Applied Ecology and Environmental Sciences*, 10, 730-737. doi:10.12691/aees-10-12-5
- Kindu, M., Schneider, T., Teketay, D., and Knoke, T. (2016). Changes of ecosystem service values in response to land use/land cover dynamics in Munessa–Shashemene landscape of the Ethiopian highlands. *Science of The Total Environment*, 547, 137-147. doi:<https://doi.org/10.1016/j.scitotenv.2015.12.127>
- Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006
- Lambin, E. F., Geist, H., and Lepers, E. (2003). Dynamics of Land-use and land-cover change in tropical regions. *Annu. Rev. Environ. Resour*, 28, 205–241. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Lambin, E. F., Turner, B., Geist, H. J., Agbola, S., Angelsen, A., Bruce, J. W., . . . Xu, J. (2001). The causes of land-use and land-cover change: Moving beyond the myths. *Global Environmental Change-Human and Policy Dimensions* 11 (2001). - ISSN 0959-3780, 11(4), 261–269. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Li, K., Feng, M., Biswas, A., Su, H., Niu, Y., and Cao, J. (2020). Driving Factors and Future Prediction of Land Use and Cover Change Based on Satellite Remote Sensing Data by the LCM Model: A Case Study from Gansu Province, China. *Sensors (Basel)*, 20(10). doi:10.3390/s20102757

- Liu, G., Jin, Q., Li, J., Li, L., He, C., Huang, Y., and Yao, Y. (2017). Policy factors impact analysis based on remote sensing data and the CLUE-S model in the Lijiang River Basin, China. *Catena*, 158, 286-297. doi:10.1016/j.catena.2017.07.003
- Mamat, A., Halik, Ü., and Rouzi, A. (2018). Variations of Ecosystem Service Value in Response to Land- Use Change in the Kashgar Region, Northwest China. *Sustainability*, 10(1), 200. Retrieved from <https://www.mdpi.com/2071-1050/10/1/200>
- Mamat, A., Saydi, M., Wang, J., Pang, Z., Long, X., Zhang, X., . . . Yisimayili, A. (2024). Evolution and Driving Forces of Ecological Service Value in Response to Land Use Change in Tarim Basin, Northwest China. *Remote Sensing*, 16(13), 2311. Retrieved from <https://www.mdpi.com/2072-4292/16/13/2311>
- Millennium Ecosystem Assessment (2005) *Ecosystems and human well-being: Synthesis*. Washington DC: Island Press. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D. R., . . . Shaw, M. (2009) . Modeling Multiple Ecosystem Services, Biodiversity Conservation, Commodity Production, and Tradeoffs at Landscape Scales. *Frontiers in Ecology and the Environment*, 7, 4. doi:10.1890/080023
- Office of Agricultural Economics (2023). *Agricultural economic situation in 2023 and trends in 2024*. Retrieved from https://www.oae.go.th/assets/portals/1/fileups/bappdata/files/Outlook_2566_2567.pdf
- Office of Agricultural Economics (2023). *Exports structure*. Retrieved from <https://traderreport.moc.go.th/Report/Default.aspx?Report=MenucomTopNCountry&Option=1&Lang=Th&ImExType=1>
- Ongsomwang, S., and lamchuen, N. (2015). Integration of geospatial models for optimum land use allocation in three different scenarios. *Suranaree J. Sci. Technol*, 22(4), 377-396.

- Ongsomwang, S., Pattanakiat, S., and Srisuwan, A. (2019). Impact of Land Use and Land Cover Change on Ecosystem Service Values: A Case Study of Khon Kaen City, Thailand. *Environment and Natural Resources Journal*, 17(4), 43-58.
- Pérez-Soba, M., Verburg, P., Koomen, E., Hilferink, M., Benito, P., Lesschen, J. P., and Banse, M. (2010). *Land use modelling - implementation; Preserving and enhancing the environmental benefits of land-user services*.
- Phinyoyang, A. (2021). *Optimized land use and land cover allocation for flood mitigation with goal programming, Mueang Chaiyaphum district, Chaiyaphum province, Thailand*. (Doctoral dissertation, Suranaree University of Technology). Retrieved from <http://sutir.sut.ac.th:8080/jspui/handle/123456789/8985>
- Pontius, R. G., Cornell, J. D., and Hall, C. A. S. (2001). Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agriculture, Ecosystems & Environment*, 85(1), 191-203. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Pontius, Jr. R. G., and Schneider, M. (2001). Location bias in land use modeling. *Agriculture, Ecosystems & Environment*, 82(1-3), 163-177.
- Rosenfield, G. H., and Fitzpatrick-Lins, K. (1986). A coefficient of agreement as a measure of thematic classification accuracy. *Photogrammetric Engineering and Remote Sensing*, 52(2), 223-227.
- Ruamkaew, S. (2011). *Assessment and prediction of agricultural and forest landscape sustainability in Lamtakhong watershed, Nakhon Ratchasima province, Thailand*. (Doctoral dissertation, Suranaree University of Technology). Retrieved from <http://sutir.sut.ac.th:8080/jspui/handle/123456789/4222>
- Shuangao, W., Padmanaban, R., Mbanze, A. A., Silva, J. M. N., Shamsudeen, M., Cabral, P., and Campos, F. S. (2021). Using Satellite Image Fusion to Evaluate the Impact of Land Use Changes on Ecosystem Services and Their Economic Values. *Remote Sensing*, 13(5), 851. Retrieved from <https://www.mdpi.com/2072-4292/13/5/851>
- Srichaichana, J., Trisurat, Y., and Ongsomwang, S. (2019). Land Use and Land Cover Scenarios for Optimum Water Yield and Sediment Retention Ecosystem

- Services in Klong U-Tapao Watershed, Songkhla, Thailand. *Sustainability*, 11(10), 2895-2916.
- Steffen, W., Sanderson, A., Tyson, P. D., Jäger, J., Matson, P. A., Moore, B. III., ... Wasson, R. J. (2004) *Global change and the Earth system: A planet under pressure. (The IGBP Series)*. Berlin Heidelberg: Springer, 336 pp Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Su, S., Xiao, R., Jiang, Z., and Zhang, Y. (2012). Characterizing landscape pattern and ecosystem service value changes for urbanization impacts at an eco-regional scale. *Applied Geography*, 34, 295–305
- Sun, X., Zhang, Y., Shen, Y., Randhir, T. O., and Cao, M. (2019). Exploring ecosystem services and scenario simulation in the headwaters of the Qiantang River watershed of China. *Environmental Science and Pollution Research*, 2019, 1-19.
- Trisurat, Y., Alkemade, R., and Verburg, P. (2010). Projecting land use change and its consequences for biodiversity in Northern Thailand. *Environmental Management*, 45, 626-639.
- US National Research Council, Committee on Global Change Research, Board on Sustainable Development, Policy Division (1999) *Global environmental change: Research pathways for the next decade*. Washington DC: National Academy Press, 595 pp. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006.
- Veldkamp, A., and Fresco, L. O. (1996). CLUE: A Conceptual Model to Study the Conversion of Land Use and Its Effects. *Ecological Modeling*, 85(2-3), 253-270.
- Verburg, P. H. (2010). *The CLUE model Hands-on exercises*. Amsterdam: Institute for Environmental Studies, University Amsterdam.
- Verburg, P. H., De Koning, G. H. J., Kok, K., Veldkamp, A., and Bouma, J. (1999). A spatial explicit allocation procedure for modeling the pattern of land use change based upon actual land use. *Ecological Modeling*, 116(1), 45-61.

- Verburg, P. H., and Overmars, K. P. (2009). Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. *Landscape Ecology*, 24(9), 1167-1181.
- Verburg, P. H., Rounsevell, M. D. A., and Veldkamp, A. (2006) Scenario-based studies of future land use in Europe. *Agric Ecosyst Environ*, 114, 1–6. Quoted in Lambin, E. F., and Geist, H. (2006). *Land-Use and Land-Cover Change Local Processes and Global Impacts*. Germany: © Springer-Verlag Berlin Heidelberg 2006
- Verburg, P. H., Schot, P. P., Dijst, M. J., and Veldkamp, A. (2004). Land Use Change Modelling: Current Practice and Research Priorities. *GeoJournal*, 61(4), 309-324.
- Verburg, P. H., Soepboer, W., Limpiada, R., Espaldon, V., Mastura, S. S., and Veldkamp, A. (2002) Land use change modelling at the regional scale: The CLUE-S model. *Environ Manage*, 30, 391–405.
- Verburg, P. H., Van de Steeg, J., and Schulp, N. (2005). *Manual for the CLUE-Kenya application*. Wageningen: Department of Environmental Sciences, Wageningen University.
- Zare, M., Nazari Samani, A. A., Mohammady, M., Salmani, H., and Bazrafshan, J. (2017). Investigating effects of land use change scenarios on soil erosion using CLUE-s and RUSLE models. *International Journal of Environmental Science and Technology*, 14(9), 1905-1918. doi:10.1007/s13762-017-1288-0
- Zhang, D., Liu, X., Wu, X., Yao, Y., Wu, X., and Chen, Y. (2019). Multiple intra-urban land use simulations and driving factors analysis: a case study in Huicheng, China. *GIScience & Remote Sensing*, 56(2), 282-308. doi:10.1080/15481603.2018.1507074
- Zheng, X-O., Zhao, L., Xiang, W-N., Li, N., Lv, L-N., and Yang, X. (2012). A coupled model for simulating spatio-temporal dynamics of land-use change: A case study in Changqing, Jinan, China. *Landscape and Urban Planning*, 106(1), 51-61.
- Zhou, R., Zhang, H., Ye, X. Y., Wang, X. J., and Su, H. L. (2016). The Delimitation of Urban Growth Boundaries Using the CLUE-S Land-Use Change Model: Study on Xinzhuang Town, *Changshu City, China. Sustainability*, 8(11).

CURRICULUM VITAE

Name Miss Jantararat Teebklang

Date of Birth January 23, 2000

Place of Birth Nakhon Ratchasima Province, Thailand

Education 2018 Bachelor of Technology in Urban Planning Technology (Second Class Honor), Program of Urban Planning Technology, Faculty of Architecture and Creative Arts, Rajamangala University of Technology Isan.

Grant and Fellowships SUT kittibandit scholarship, Suranaree University of Technology.



มหาวิทยาลัยเทคโนโลยีสุรนารี