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Analysis land use and land cover changes and the driving forces: A case study in Kaysone Phomvihan District, Laos

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Dissertation of Master in Geographic Information Systems and Spatial Planning

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Co-supervisor: Patrícia Catarina dos Reis Macedo Abrantes

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Declaration of honor

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Porto, 16/07/2018

Bandit Mienmany

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Resumo

As alterações no uso e ocupação do solo (LULCC) causadas por actividades humanas directas e indirectas têm consequências a nível local e global. No Laos, com destaque para as áreas urbanas, as práticas de uso do solo relacionadas com expansão da agricultura, urbanização e desflorestação afectam o o solo enquanto recurso finito, e contribuem para a degradação dos recursos naturais. No distrito de Kaysone Phomvihan, uma das principais cidades do Laos, verifica-se uma forte degradação e um ritmo intenso de conversão do solo associado aocrescimento económico e urbano ao longo das últimas décadas.

Este estudo parte do pressuposto que o entendimento dos padrões de LULCC e das suas forças motrizes são imprescindíveis para projectar os processos de LUCC e suas tendências espaciais para futuro no sentido de fornecer pistas e conhecimentos relevantes para a tomada de decisão. Portanto, o estudo tem como objectivo analisar alterações no uso e ocupação do solo e as suas forças motrizes para um período de vinte anos, entre 1997 e 2017. Tem ainda como objectivo complementar simular os padrões de uso e ocupação do solo para o anode 2022, num cenário BAU. A área de estudo é o distrito de Kaysone Phomvihan, onde se irão aplicar dados resultantes de detecção remota e fontes estatíticas, e combinar métodos provenientes de detecção remota, sistemas de informação geográfica e estatística, afim de aplicar um modelo de análise de forças motizes e de simulação do uso e ocupação do solo.

Os resultados revelam que as forças próximas do uso e ocupação do solo longo do período de vinte anos foram a conversão da floresta em vegetação herbácea e/ou arbustiva e a vegetação herbácea e/ou arbustiva convertida área da urbana e em área para agricultura. A área florestal teve a maior diminuição e a área construída teve o maior aumento. Além disso, variáveis biofísicas e socioeconómicas também contribuíram significativamente para as estas conversões, nomeadamenteo declive, a temperatura, a densidade populacional, a distância ao urbano, as estradas e à rede hidrográfica.

A tendência espacial da expansão urbana foi principalmente o oeste do distrito. As tendências espaciais da expansão agrícola e as conversões florestais foram a sul e a leste do distrito. Finalmente, o modelo simulado para 2022 evidencia que os padrões de uso e

ocupação do solo de 2017 para 2022 são ligeiramente diferentes. A área florestal terá ainda maior perda devido à conversão para área agrícola e para área urbana.

Palavras-chave: alterações de uso/ocupação do solo, forças motrizes, detecção remoto, sistemas de informação geográfica, análise estatística, modelação e simulação espacial, Kaysone Phomvihan.

Abstract

Land use and land cover changes (LULCC) caused by direct and indirect human activities have a wide range of consequences at local and global level. In Laos and its main cities, land use practices related to agriculture expansion, urbanization and deforestation have an effect on land use and natural resource degradation. Kaysone Phomvihan district is one of the main city in Laos that is facing with land use degradation from those practices due to an economic and urban growth over decades in the district that resulted in land use conversion and land concession widely.

Since, understanding in LULCC patterns and the driving forces are needed to project LULCC processes and their spatial trends, which will provide relevant knowledge that is a useful guideline for policymakers and civil society. Therefore, this research aims to analyze LULCC and the driving forces in the period 1997-2017 in order to simulate LULCC patterns for the year 2022 in Kaysone Phomvihan district by using remote sensing data, geographic information systems combined with statistical analysis and LULCC model.

The results revealed that the proximate drivers of LULCC over the 20 years were forest conversion to shrubland, and shrub area converted to agriculture and urban areas, which forest area was the highest decrease and built-up area was the highest increase. Moreover, both biophysical and socio-economic variables had significantly contributed to LULC conversions such as slope, temperature, population density, proximate to town, roads and to water sources.

Since, the spatial trend of urban expansion was mostly in the western of the district. For the spatial trends of agriculture expansion and forest conversions were in the southern to the eastern part of the district.The simulated LULCC model in 2022 found that LULC patterns of 2017 and 2022 were slightly different. Forest area still was the highest loss due to the conversion to agriculture and built-up areas that had driven by economic and urban growth in the district.

Keywords: LULCC, driving forces, remote sensing, geographical information systems, statistical analysis, LULCC model, Kaysone Phomvihan district.

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Abbreviations

ATCOR: Atmospheric and Topographic Correction

ASTER: Advanced Spaceborne Thermal Infrared Emission and Reflectance Radiometric

AUC: Area Under Curve

CA: Cellular Automaton

CEC: Cation Exchange Capacity

DHUP: Department of Housing and Urban Planning

DN: Digital Number

DBH: Diameter Breast Height

DEM: Digital Elevation Model

EIA: Environmental Impact Assessment

EWEC: East-West Economic Corridor

EO: Earth Observation

ETM+: Enhance Thematic Mapper Plus

FPR: False Positive Rate

GDP: Gross Domestic Product

GDEM: Global Digital Elevation Map

ISRIC: International Soil Reference and Information Center

JICA: Japanese International Cooperation Agency 2015

Lao PDR: Lao's People Democratic Republic

LFA: Land Forest Allocation

LST: Land Surface Temperature

LULC: Land Use and Land Cover

LULCC: Land Use and Land cover changes

LR: Logistic Regression

MPWT: Ministry of Public Works and Transport

MBLR: Multi Binary Logistic Regressions

MOLUSCE: Modules for Land Use Change Evaluation

NIR: Near Infrared

NUSS: National Urban Sector Strategy

OLI: Operational Land Imager

ODA: Official Development Assistance

PDPI: Provincial Department for Planning and Investment

PLMO: Provincial Land Management Office

RS: Remote Sensing

ROC: Receiver Operating Curve

RGB: Red Green Blue

SEDAC: Socioeconomic Data and Application Center

SPSS: Statistical Package for Social Sciences

SSSEZ: Savan-Seno Special Economic Zone

SSEZ: Special-Specific Economic Development Zone

SEDP: Socio-Economic Development Plan

SWI: Short Wave Infrared

TB: At-satellite Brightness Temperatures

TM: Thematic Mapper

TOA: Top of Atmosphere

TPR: True Positive Rate

USGS: United States Geological Survey

UTM: Universal Transverse Mercator

VIF: Variance Inflation Factor

WGS: World Geodetic System

Chapter 1 - Introduction

1.1. Background of the study

Land use and land cover (LULC) system are a fundamental part of the Earth's surface, and LULC changes (LULCC) has significant impacts on human society, climate, biodiversity, hydrological cycles, biogeochemical processes (Baldyga et al., 2008; Lambin et al., 2001; Were et al., 2014). LULCC are the intended employment and management strategy that placed on the land by human agents or land managers to exploit the land use and reflects human activities such as industrial and residential zones, agricultural fields, grazing, deforestation, and mining among many others that have affected on land and natural resources at local and global level (Chrysoulakis et al., 2004; Zubair, 2006).

Since 1950, the world population increased exponentially and this growth is producing major changes in LULC. In some countries, intensive agriculture is producing massive deforestation while in cities, unplanned or inadequately managed urban expansion is leading to rapid sprawl, pollution, and environmental degradation, together with unsustainable production and consumption patterns (Montgomery et al., 2004).

Over the last fifty years, LULC has undergone dramatic changes (FAO, 2005). LULCC are being mostly influenced by government policies for economic development that promotes the expansion and promotion of agricultural production as well as the infrastructure and urban growth (Fujita et al., 2007; Meyfroidt and Lambin, 2008). In Laos, the development projects although benefit the country’s economy. In the practical, sometimes they resulted in natural resources an environmental impacts (Baird and Shoemaker, 2005; Cornford, 1999).

Baird and Shoemaker (2005) reported that although economic and development policies have good intentions in upgrading local livelihood and descending the poverty. In the practical, sometimes they contribute to a long-term poverty, land and environment degradation and increasing social conflict.

Thus, LULC in Laos has changed dynamically over decades, especially forest areas. In 1982 forest cover was 11,636,900 ha (49%), in 1992 it was 11,168,000 ha (47%) and in 2002 it was 9,824,700 ha (41. %). This reflects a rapid decrease from 1992 to 2002 by 1,343,300 ha (5.5%), while from 1982 to 1992 it was only 468,900 ha (2%) (see Table 1.1). Most of these changes are due to unsustainable harvesting, commercial logging, wood extraction, and urban and infrastructure development (Boutthavong et al., 2016).

Table 1.1: Land use group and type with the percentage of distribution (Source: Boutthavong et al., 2016).

Land use group and land use type	**Distribution %**			**Change in %**		
	1982	**1992**	**2002**	**1982-02**	**1992-02**	**1982-02**
1. current forest	**49.142**	**47.162**	**41.49055**	**-1.980**	**-5.672**	**-7.652**
Dry dipterocarp	5.216	5.095	0.563	-0.121	0.468	0.347
Lower dry evergreen	0.374	0.361	0.237	-0.013	-0.124	-0.137
Upper dry evergreen	4.670	4.481	5.861	-0.189	1.380	1.191
Lower mixed deciduous	3.771	3.651	3.720	-0.120	0.069	-0.051
Upper mixed deciduous	32.907	31.463	23.224	-1.444	-8.239	-9.683
Gallery forest	0.383	0.370	0.119	-0.013	-0.251	-0.264
Coniferous	0.584	0.557	0.376	-0.027	-0.181	-0.208
Mixed coniferous	1.237	1.184	2.221	-0.053	1.037	0.984
Tree plantation	-	-	0.169	-	-	0.169
2. Potential forest	**36.141**	**37.971**	**47.095**	**1.667**	**9.496**	**10.971**
Bamboo	6.153	6.469	2.276	0.316	-4.193	-3.877
Unstacked	27.448	28.680	42.636	1.232	13.956	15.188
Shifting cultivation area	2.523	2.642	2.183	0.119	-0.459	-0.340
3. other wooded area	**6.526**	**6.098**	**1.210**	**-0.428**	**-4.888**	**-5.316**
Savannah/open woodlands	4.113	3.853	0.399	-0.260	-3.454	-3.714
Heath, shrub forest	27.448	2.245	0.811	-0.186	-1.434	-1.602
Sum of all forest area	**91.8**	**91.1**	**89.8**	**-0.741**	**-1.246**	**-2**
4. Permanent agriculture	2.993	3.588	5.068	0.595	1.480	2.075
Rice paddy	2.780	3.334	4.070	0.554	0.736	1.290
Agriculture plantation	0.063	0.075	0.916	0.012	0.841	0,853
Other agriculture land	0.150	0.179	0.082	0.029	-0.097	-0.068
5. Other non-forest area	5.215	5.361	5.137	0.146	-0.224	-0.078
Barren land, rock	0.464	0.490	0.976	0.026	0.486	0.512
Grassland	3.397	3.475	2.446	0.078	-1.029	-0.951
Urban land	0.464	0.356	0.517	0.009	0.215	0.224
Swamps	0.347	0.149	0.215	0.009	0.066	0.071
Water	0.114	0.891	0.929	0.005	0.038	0.066
Sum of all non-forest area	8.208	9.949	10.205	0.028	1.246	2
Total	100	100	100	0	0	0

According to FAO (2000), the LULCC related to agriculture expansion, urbanization and deforestation in Laos have caused land use and natural resource degradation, with 84% of the soils moderately degraded. In addition, agriculture and urban expansion are among important causes of the deforestation and LULC conversion in the potential or nearby cities in Laos. Thus, the deforestation and LULC conversion in this region have become a major issue in environmental change.

The knowledge and understanding of LULCC in Laos are still sparse. There are lacks in spatial perception about LULCC and in data acquisition to support LULC dynamic and the future changes analysis. These are main obstacles to provide the essential solutions for the spatial planning and decision-making.

In fact, most of LULC research in Laos focus on the change patterns and the driving forces context but without spatial context in predicting and modelling the future changes. Since LULCC model in the future is a new approach for the study area, which is important for giving the spatial planning information and land use planning. Only a few LULC research were referred (ADB, 2015; ELSA, 2015; PDPI, 2009; Nolintha and Masami, 2011), but they did not apply spatial prediction because the prediction of the future LULCC is a more difficult task as it requires comprehensive knowledge of the interaction between the driving forces(Riebsame et al., 1994).

Thus, an understanding of the spatial-driven relationships related to LULCC will help to address pertinent questions that are related to location and quantity changes such as: where are LULC changes taken place? What is the rate of change likely progress? And what is the future process? (Pontius Jr and Schneider, 2001).

This dissertation will focus on Kaysone Phomvihan district in order to analyze LULCC and the driving forces. Kaysone Phomvihan district is the main city in Savannakhet province that is the second largest province and most intensive population in Laos after Vientiane Capital.

This study area was chosen because few studies spatially related with LULCC were implemented for this area, and also because Kaysone Phomvihan district is one of the major cities in Laos that is currently having a strong economic development and urban growth that have an impact on LULCC (UNDP, 2011).

In fact, the economic and urban development over last decades in the district has influenced land resource demands and land concession widely, which is also causing a problem in land use management and planning in the district (Luanglatbandith, 2007). According to ADB (2012), the core problem in urbanization of Kaysone Phomvihan district is taking place with minimal coordination, inadequate infrastructure and insufficient concern for environmental impacts. This results in disorganized growth, inefficient land use, damage and loss of natural resources and inadequate access to urban services. These problems can be attributed to poor urban management, and spatial planning, poor connectivity between urban planning and environmental management, and insufficient investment in infrastructure and community services. Understanding land use patterns and changes as a major importance in this context. Since, accurate and timely information of land use change is highly necessary to many related spatial planning sectors and actors for estimating levels and rates of deforestation, urbanization, wetland and soil degradation and many other landscape-level phenomena (Vogelmann et al., 2001).

Remote sensing data coupled with geographic information systems (GIS) and statistical analysis are effective tools to identify, analyze and understand LULCC patterns (DeFries et al., 2010; Long et al., 2007; Serneels and Lambin, 2001; Verburg et al., 2004). Many studies have proved to achieved a good spatial modeling and prediction of the future LULCC through the several models such as logistic regression, Cellular Automata and Agent-based (Swart, 2016; Araya and Cabral, 2009; Serneels and Lambin, 2001; Jaimes et al., 2010; Lambin and Geist, 2006; Serra and Pons, 2008; Seto and Kaufmann, 2003; Were et al., 2014).

Therefore, this study focuses on applying remote sensing data and GIS technique integrated with the statistical approach and LULCC model to analyze the LULCC patterns and the driving forces in Kaysone Phomvihan, Savannakhet province over 20 years from 1997-2017 in order to predict LULCC in 2022.

This will provide relevant knowledge and data, which are useful guidelines for the local government and civil society in formulating the strategies and master plans to ensure that it will contribute to address the land use issues and to achieve sustainable development.

1.2. Research objectives and questions

The main objective of this research is to analyze the LULCC and the driving forces over 20 years from 1997-2017 in Kaysone Phomvihan district. From this complementary objective is to simulate LULCC for the future. The specific objectives are the following:

1. To analyze the LULCC patterns of forest area, permanent agriculture area, built-up area, shrub area and water bodies in the years 1997, 2003, 2007, 2013 and 2017.
2. To identify the proximate drivers and spatio-temporal trends of the changes, and quantify underlying drivers that have influenced LULCC.
3. To apply multi binary logistic regression method in analyzing the spatial relationship between the dependent and independent variables of LULCC.
4. To simulate LULCC for the year 2022.
5. To give spatial information to support land use planning and decision-making.

In order to achieve these objectives, the research questions were formulated as the following:

1. What are the LULCC patterns of forest, permanent agriculture, built-up, shrub and water? And what are the proximate and underlying drivers, and their spatial trends?
2. What are the relationships between the dependent and the independent variables?
3. Does the simulated LULCC model achieve the accurate result to predict LULCC in the future? And what are the future LULCC?
4. What the spatial planning will be considered on the LULCC in the study area?

1.3. Method

Figure 1.1 describes the methodology in this study in order to achieve the research objectives and questions. The methodology is divided into four phases as the following:

Phase 1: The objectives are to classify the satellite images by a supervised algorithm in order to analyze LULCC in the periods of 1997-2003, 2003-2007, 2007-2013 and 2013-2017. Then, the main LULC conversions and their spatial trends were identified as the proximate drivers (dependent variables) of LULCC. Since, the proximate drivers will be utilized for multi binary logistic regression analysis.

Phase 2: The aims are quantifying the underlying drivers and preparing the independent variables for multi binary logistic regression. The underlying drivers in this study include biophysical and socio-economic variables (Geist and Lambin, 2002; Kissinger et al., 2012).

Phase 3: The objective is to analyze the spatial relationship between the dependent variables (proximate drivers) and the independent variables (underlying drivers) in order to explain the probability of LULC conversions.

Phase 4: The objectives are applying LULCC model to estimate the predictive ability and the accuracy of the model, and then validating the result. If the result achieved acceptable accuracy, then the LULC simulation for 2022 will be conducted.

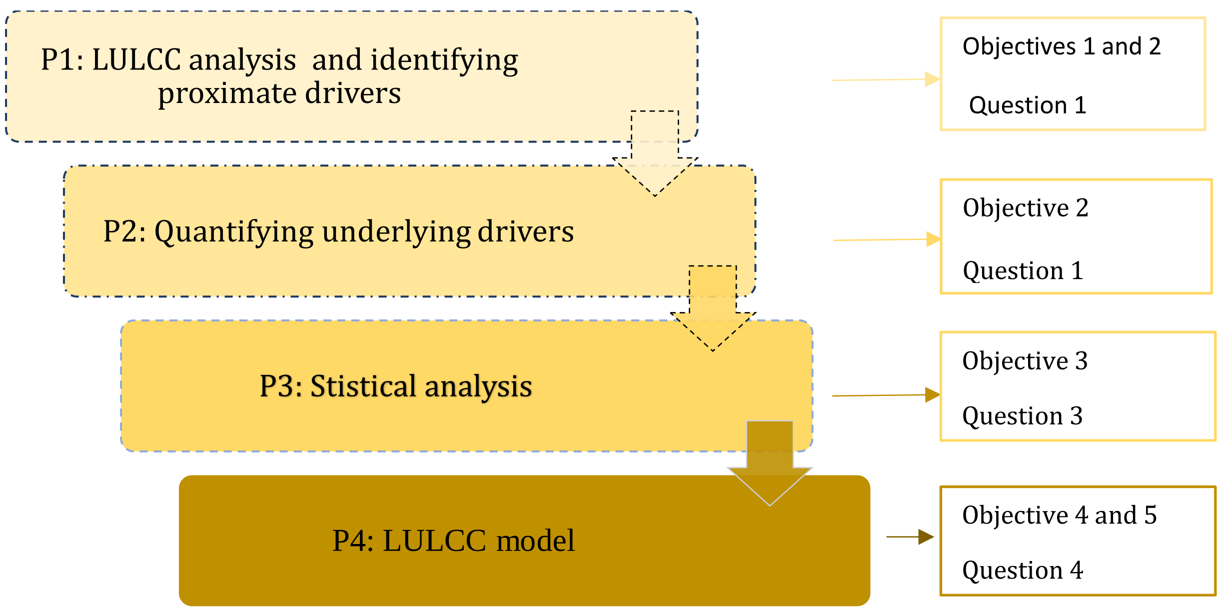


Figure 1.1: Methodology of this research to achieve research objectives and questions.

1.4. Thesis organization

This thesis has been divided into seven chapters. The first chapter is an introduction that presents an overview of the thesis: the research background, objectives, questions and the thesis outline. The second chapter is the literature review on the related theoretical framework and documents that can be formed the research methodology and investigation. The third chapter is an introduction to the study area and related information such as geographical location, background, socio-economic and relevant research in the study area.

The fourth chapter corresponds to the data and methodological part. This chapter introduces the study approach in each stage, the specific methods, data and material used, especially introducing the analysis process to achieve the research objectives and questions. The fifth chapter describes the main results of satellite image classifications, the proximate and underlying drivers, as well as the results of multi binary logistic regression and simulated LULCC model. These results were reviewed and discussed in the sixth chapter that explains the main findings related to the relevant studies and research. Finally, the seventh chapter presents the main conclusions and recommendations. In this section, key findings and critical points that need further treatment have been forwarded as a recommendation for related sectors and future work.

Chapter 2 - Literature review

2.1. LULC concept

The expression of "land use" and "land cover" are very frequent and can be easily confused. However, both definitions are important. According to Lambin et al. (2001), land cover points to the biophysical attributes of the Earth's surface whereas land use is the human purpose or intent applied to these attributes on the way the land cover is used.

According to NOAA (2017), land cover indicates a region that is covered by forests, wetlands, impervious surfaces, agriculture, and other land and water types. Land cover can be identified by analyzing satellite and aerial imagery. Land use is how people use the landscape whether for development, conservation, or mixed uses, the different types of land cover are managed or used differently by human agent, policy and interest.

Land use is the intended employment and management strategy placed on the land use by human agents, or land managers to exploit the land use and reflects human activities such as industrial and residential zones, agricultural fields, grazing, logging, and mining among many others (Chrysoulakis et al., 2004; Zubair, 2006).

According to FAO (1998), land use "is characterized by the arrangements, activities and people that undertake in a certain land cover type to produce, change or maintain it". Thus, this expression "establishes a direct link between land cover and the actions of people in their environment". Similarly, Lambin and Geist (2006) defined land use as "the purpose for which humans exploit land cover" that includes "both the manner in which biophysical attributes of the land are manipulated and the intent underlying that manipulation, i.e., the purpose for which the land is used".

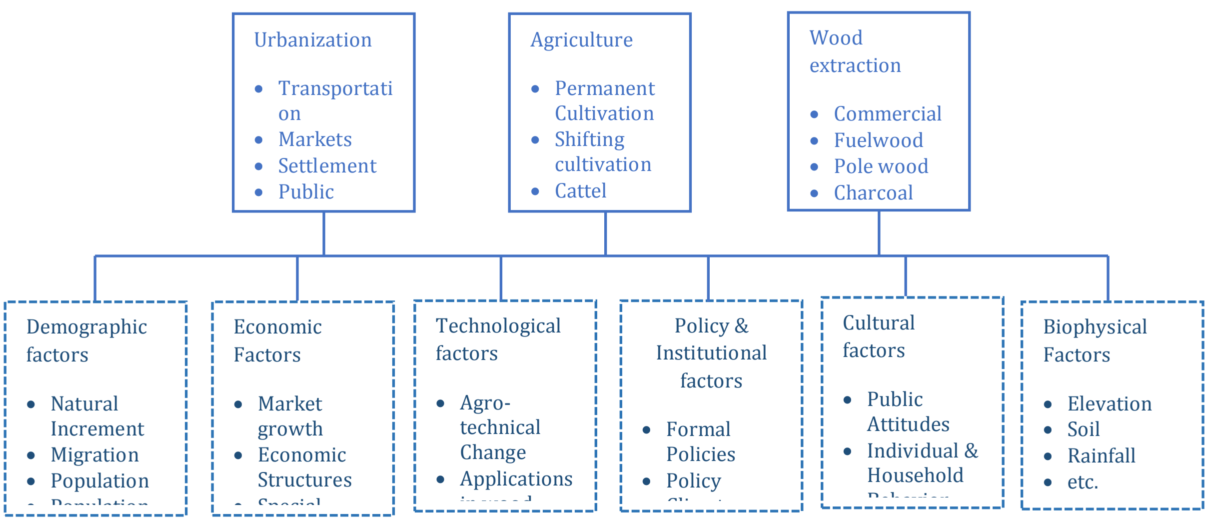
In this research, the data used were the classified satellite images to analyze land cover classes and integrate with the spatial data included biophysical and socio-economic variables in order to analyze the change patterns and how land is used in the study area. Therefore, the terms "land use and land cover" (LULC) was used in this research.

2.2. Drivers of LULCC

LULCC can be caused by several factors related to the complex interaction between social, political, economic, technological and biophysical variables (Geist and Lambin, 2002). Thus, considerable research has been conducted to identify the drivers of LULCC: from urban processes of land use change (Lambin et al., 2001; Seto and Kaufmann, 2003) to deforestation in tropical regions (DeFries et al., 2010; Geist and Lambin, 2002; Houghton, 2012) and to agricultural expansion and land use changes in mountainous ecosystems (Alexander et al., 2015; Mottet et al., 2006; Serra and Pons, 2008).

According to several authors, the causes of LULCC can be categorized as direct (proximate) or indirect (underlying) drivers (see Figure 2.1). The direct causes comprise human activities that could arise from the continuous use of land and directly alters driven forces for instance urbanization, deforestation, agriculture expansion, wood extraction. On the other hand, indirect causes are fundamental forces that strengthen more direct causes of LULCC include economic, biophysical, political/institutional, socio-cultural and technology (Geist and Lambin, 2002; Lambin et al., 1999; Turner II et al., 1995).

Proximate drivers



Underlying drivers

Figure 2.1: Proximate/direct drivers and underlying/indirect drivers of LULCC (Geist and Lambin, 2002; Lambin et al., 1999; Turner II et al., 1995).

2.2.1. Proximate drivers

The proximate or direct drivers are the human activities and actions that have a direct effect on LULCC (Geist and Lambin, 2002; Jaimes et al., 2010; Kissinger et al., 2012). The urbanization, agriculture expansion, deforestation and infrastructure development are among the drivers of LULCC.

In terms of urbanization, it has an impact to agricultural and forest lands that are generally accompanied by an increase in energy use, high demand of natural resources and food that lead to urban growth and land concessions (Braimoh and Onishi, 2007). The urban areas account for only 2% of the Earth's surface but over half of the world's population nowadays resides in cities (UN, 2014). These exert tremendous pressures on land and its resources, especially in developing countries. According to Weier (2002), over the next century, urbanization is predicted to move at a rapid pace. It is estimated that worldwide migration towards the cities increases at three times the rate of population growth. In addition, FAO (2011) estimated that in 2050, 100 million hectares of land would be transformed for residential, industrial and infrastructure purposes, and more than 90% of lands in less developed countries.

The development of infrastructure is correlated with urban growth and also leads LULC conversion, especially in Latin America, Asia and Africa (Geist and Lambin, 2002; Hosonuma et al., 2012; Kissinger et al., 2012). Since, better access to markets is correlated with land use conversion by infrastructure can trigger market development, cash crop adoption and economic growth. Infrastructure extension can be a component of rural development and settlement policies that drive market integration (Kissinger et al., 2012).

In the context of agricultural expansion has tremendous impacts on habitats, biodiversity and land use changes. Foley (2011) estimates that worldwide agriculture land has already cleared or radically transformed 70% of the world's prehistoric grasslands, 50% of savannas, 45% of temperate deciduous forests and 25% of tropical forests. Agriculture is mainly expanding in the tropical region where it is estimated that about 80% of new croplands are replacing forests (Geist and Lambin, 2002).

Multiple studies argue that agriculture expansion causes forest conversion and it results in deforestation: the development of subsistence or commercial agriculture can cause forest loss (Alexander et al., 2015; Kissinger et al., 2012; Hosonuma et al., 2012). Global food demands increase agriculture production and agricultural cropland expansion, which lead land use change associated with the deforestation: the forest conversion to permanent cropland, cattle ranching and shifting cultivation. These have an influence on the deforestation, especially in mainland Asia, Latin America and Africa (Kissinger et al., 2012). In case of shifting cultivation, the deforestation was driven by slash-and-burn agriculture is more widespread in upland zones of Asia than elsewhere (Kissinger et al., 2012; Geist and Lambin, 2002).

Another factor that explains deforestation can be the extraction of wood (for either commercial use or fuelwood for domestic use) (Hosonuma et al., 2012). The commercial wood extraction is frequent in both mainland and insular Asia. In Africa, the harvesting of fuelwood by individuals for domestic uses are associated with wood extraction and deforestation (Geist and Lambin, 2002).

2.2.2. Underlying drivers

The underlying drivers are fundamental (social) processes that underpin the proximate causes and either has an indirect impact on local and national or global level (Geist and Lambin, 2002). Kissinger et al. (2012) stated that there are complex interactions of social, economic, political, cultural and technological processes that affect the proximate drivers. Several studies mention an extra group of environmental or biophysical drivers as explaining forces for LULC (Aguiar et al., 2007; Jaimes et al., 2010; Were et al., 2014). Thus, these underlying drivers can be divided into environmental or biophysical, economic, demographic, policy, technological, cultural, and institutional drivers (see Figure 2.1). They can be considered as interconnected concepts, all linked to each other and operating in multiple scales (Geist and Lambin, 2002).

Economic growth: Economic drivers are essential to consider when explaining land use changes (DeFries et al., 2010; Geist and Lambin, 2002; Kissinger et al., 2012). Market growth, rising income of population, commercialization or change in poverty rates can all have an influence on the conversion of land use (Aguiar et al., 2007; Geist and Lambin, 2002). Other research mentioned that economic growth based on the export of primary commodities and increasing demand for timber and agricultural products in the global economy is identified as the main indirect drivers of deforestation and degradation across the tropical countries (Kissinger et al., 2012).

Population growth: Population growth and density are extensively discussed as an important driver for land use change (Kissinger et al., 2012; Alexander et al., 2015). The growth of urban population places pressure on rural landscapes for commercial agriculture (DeFries et al., 2010). Mutoko et al. (2014) argued that population growth increase the demand for food, and leads to agricultural intensification in developing countries.

Policy: The policy framework has an influence on how land is used to change regulations that can have enormous effects on land use. There is a number of developing countries that suffer from a causation link between rural poverty, land degradation and deforestation such as poor rural households abandoning degraded land to frontier forested lands, cropping in poor soils lead to further degradation, and finally, it leads to land abandonment and land conversion (Barbier, 2000).

Biophysical: Usually refers to catastrophic factors that lead to sudden shifts in the human-environment condition (Geist and Lambin, 2001). It comprises the natural processes of the environment such as climatic variations, topography, drainage, soil type and geomorphic processes. Verburg (2004) noted that biophysical factors mostly do not drive land use change directly, they can cause LULCC (through climate change) and they influence land use allocation decisions (soil quality).

Socio-cultural: Cultural factors often affect economic and policy drivers, public attitudes, values and beliefs toward the environment are important that how land is used in terms of socio-culture aspect (Geist and Lambin, 2002). Understanding values and beliefs of communities are essential in particular towards people and the future generations that can contribute to land use management and planning (Geist and Lambin, 2002).

Technological: Technological progress also fosters growth in individual city size because of knowledge accumulation leads to enhance urban scale economy or improving the ability to manage cities through transport technologies that have increased access to land and greater access to markets that have an impact to land use and finally, the conversion (Gruber and Peckham, 2009).

2.2.3. Identifying LULCC Drivers in Laos

Few studies identified LULCC drivers in Laos, Thongmanivong et al. (2006) examined land use change patterns and the driving forces of socio-economic development by farmer's decisions regarding changing land use in areas along the new North-South Economic Corridor that passes through Luang Namtha and Bokeo provinces in northwestern Laos over the period 1995 -2005. This research found that one of the reasons for the rapid expansion is increasing trade and investment with neighboring countries. This driver is quite complex and includes large land concessions, medium to small-scale investments, as well as household based activities.

Okamoto et al. (2014) studied LULCC in a village of the Vientiane municipality, the results found that there were two different processes and causality linkages from urban process to forest degradation and fragmentation due to commercial logging and wood extraction are significant processes with more than one third of the study area converted to shrubland and degraded forest.

For the forest loss caused by urbanization and development in Laos were explained by Mabbitt (2006) that the most basic factors are high demand for wood and non-wood forest products in wood-deficient markets in some countries, shifting cultivation practices and forest fires are still the main causes as well as the conversion of forest land to permanent agricultural land and infrastructure development. However, a reason for this agriculture expansion is the fact that increased population and economic growth that led farmers to change their future view from subsistence agriculture to economy perspective (Fujita et al., 2007).

Another study has pointed out that other factors of forest loss in Laos are due to: 1) unsustainable wood extraction from forest; 2) pioneering shifting cultivation; 3) agricultural expansion; 4) industrial tree plantation; 5) mining; 6) hydropower development; 7) infrastructure development; 8) fire and 9) urban expansion (Kulik, 2014).

Therefore, the driver of LULCC in Laos can be referred as the direct drivers (proximate) that alter from human activities include urbanization, land concession, deforestation. The indirect drivers increased LULCC that have an influenced by socio-economic process:

urbanization due to the economic and population growth, change subsistence agriculture to commercial agriculture production that leads forest and shrub lands conversion, and wood extraction and shifting cultivation lead to the deforestation.

2.3. Remote sensing for LULCC classification

Maktav et al. (2005) stated that traditional data collection methods such as demographic data, census and sample maps were not satisfactory for the purpose of urban land use management. The accurate information of LULCC is therefore highly essential to many sectors. To achieve this, remote sensing data can be used and it provides LULC useful information.

Remote sensing (RS) refers to the science or art of acquiring information of an object or phenomena in the Earth's surface without any physical contact with it. Moreover, this can be done though sensing and recording of both reflected or emitted energy and then the information is processed, analyzed and applied to a given problem (Campbell, 2002) (see Figure 2.2).

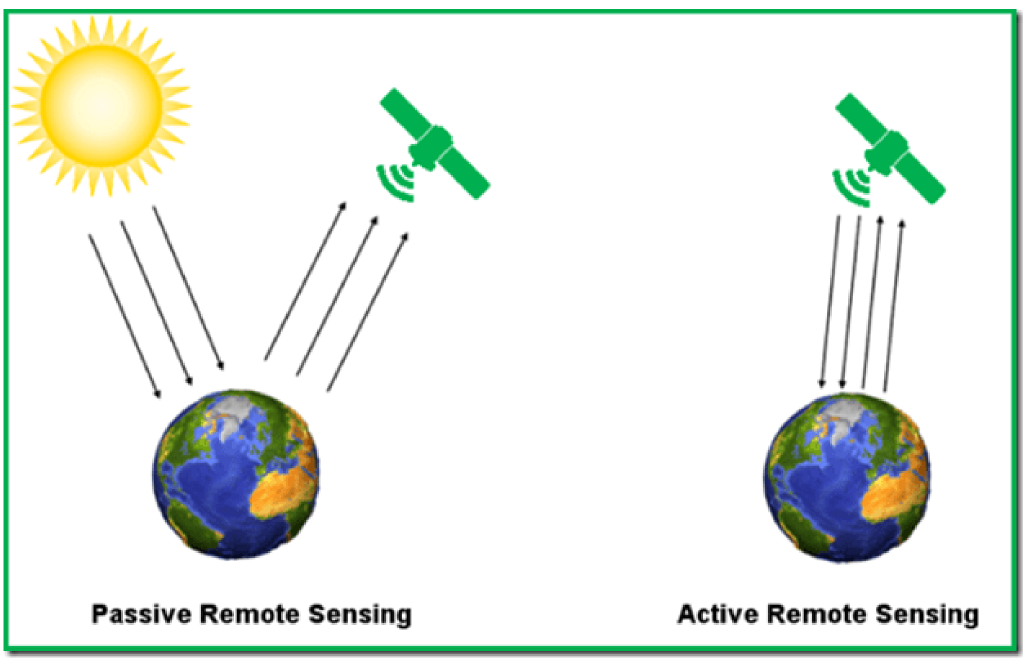


Figure 2.2: Passive sensor (reflected energy) and active sensor (emitted energy) (source: GrindGIS).

RS provides an efficient approach to monitor and detect land cover changes. The RS data are one of the primary sources extensively used for change detection in recent decades (Lu et al., 2004). The RS is important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation and many other landscape phenomena (Campbell, 2002).

The number of RS applications for urban studies has showed the potential to map and monitor urban land use and infrastructure. Herold and Menz (2001) mentioned that urban land use information with high thematic, temporal and spatial accuracy that derived from remote sensing data is an important condition for decision support to city planners, economists, ecologists and resource managers. Generally, LULCC have a wide range of impacts on environmental and landscape attributes that include the quality of water, land and air resources, ecosystem processes and functions (Rimal, 2011). Therefore, the use of RS data and image processing techniques provide accurate, timely and information for detecting and monitoring changes in LULC.

In order to analyze LULCC, image classification results with high accuracy are mandatory. Image classification refers to the extraction of different classes or themes that usually were categorized from the satellite image classification (Weng, 2012). The classification using RS techniques have attracted the attention of research community as the results of the classification are the backbone of environmental, social and economic applications (Rimal, 2011). Lu and Weng (2007) categorized the image classification methods into supervised, unsupervised, parametric, nonparametric, subpixel, and many others. Some image classification methods are discussed as follows:

Supervised classification method: land cover classes are defined. The reference data are available and used as training samples. The signatures generated from the training samples are then used to train and classify the spectral data into a thematic map (Lu and Weng, 2007).

Unsupervised classification method: clustering-based algorithms are used to partition the spectral image into a number of spectral classes that is based on the statistical information inherent in the image. This method has no prior definitions of the classes are used. The analyst is responsible for labelling and merging the spectral classes into meaningful classes (Lu and Weng, 2007).

Parametric method: Gaussian distribution is assumed, the parameters (e.g. mean vector and covariance matrix) are often generated from training samples. When the landscape is complex, parametric classifiers often produce 'noisy' results. Another of the major drawback is that it is difficult to integrate ancillary data, spatial and contextual attributes, and non-statistical information are needed for the classification procedure (Lu and Weng, 2007).

Non-parametric method: without an assumption about the data is required. Non-parametric classifiers do not employ statistical parameters to calculate class separation. This method is especially suitable for incorporation of non-remote-sensing data into a classification procedure (Lu and Weng, 2007).

2.4. LULCC model

A way to understand LULCC dynamics and their drivers is to model LULCC. Several studies showed that the models of LULCC can be divided into two broad categories: non-spatial and spatial (Jaimes et al., 2010; Lambin and Geist, 2006; Serneels and Lambin, 2001; Serra et al., 2008; Seto and Kaufmann, 2003; Were et al., 2014). The first category models analyze the magnitude and rate of LULCC, without considering a spatial variation. The second, on the other hand, focuses on LULCC at a specific spatial level (for instance administrative units) and detects spatial variation of LULCC in the biophysical, socioeconomic and policy context (Seto and Kaufmann, 2003; Huang et al., 2007).

The spatial LULCC models are important for understanding LULCC processes. The knowledge of drivers in time and space is needed, in order to do this, the identification of proximate drivers is necessary for the spatial change prediction whenever insight the underlying drivers is essential for predicting the future drivers of LULCC (Serneels and Lambin, 2001). Specifically, detecting historical trends of the drivers help to construct future scenarios because it broadens knowledge about past and recent drivers (Kissinger et al., 2012; Veldkamp and Lambin, 2001). For instance, information about the development of an underlying driver such as population growth is useful for predicting the future of LULCC (continuous population growth keeps on affecting land use) (Kissinger et al., 2012).

Lambin et al. (2001) distinguished several categories of LULCC models: empirical-statistical, stochastic, optimization, dynamic (process-based) and integrated models (see Table 2.1).

Empirical-statistical models identify explicitly the causes of LULCC by using multivariate analysis of possible exogenous contributions to empirically derived rates of the changes (Lambin et al., 2000).

Stochastic models for LULCC consist mainly of transition probability models that describe stochastically processes that move in a sequence of steps through a set of states. The transition probabilities can be statistically estimated from a sample of transitions that occurs during the time interval (Hägerstrand, 1968).

Optimization models techniques originate from the land rent theory that are mostly used in economic context (Kaimowitz and Angelsen, 1998). The models are based either linear programming at the microeconomic level, and general equilibrium models at the macroeconomic scale (Kaimowitz and Angelsen, 1998; Lambin et al., 2000).

Dynamic (process-based) simulation models have been developed to analyze LULCC processes and their evolution. The simulation models emphasize the interactions among all components that are based on a prior understanding of the driving forces in LULCC systems and processes (Lambin et al., 2000).

Integrated models are based on combining elements of the different modelling techniques. Therefore, these types of the models are referred to as integrated models, although in many cases they are better described as hybrid models (Wassenaar et al., 1999; Lambin et al., 2000).

No matter which model type is used, modelling of LULCC tries to address at least one of the following questions: 1) Which one of the socio-economic and biophysical variables contribute most to an explanation of LULCC and why? 2) Which locations are affected by LULCC? 3) What rate do LULCC progress and when? (Lambin et al., 2001). The LULCC models that were used in this study are discussed as the following sections.

Table 2.1: Categories and subtype of LULCC model (Lambin et al., 2001).

Category of models	Representative models
Statistical models	• Linear Regression Models • Econometric Models • Multinomial Logit Models • Canonical Correlation Analysis Models
Stochastic models	• Natural-Sciences Oriented Model Approaches • Markow Modeling of land use • GIS-Based Modeling of Land use change • Cellular Automata • Agent-based
Optimization models	• Linear Programming Models. Single and Multi-Objectives • Dynamic Programming • Goal Programming, Hierarchical Programming, Linear and Quadratic Assignment problem, Bonlinear Programming Models • Utility-Maximization Models • Multi-Objective/Multi-Criteria Decision-Making Models
Spatial interaction models (Dynamic models)	• Potential models • Intervening opportunities models • Gravity/spatial models
Integrated models	• Gravity-spatial interaction based and Lowery type integrated models • Simulation integrated models ➢ Urban/Metropolitan level simulation models ➢ Regional Level simulation Models ➢ Global Level Simulation Models • Input-Output-Based Integrated Models.

2.4.1 Logistic regression model

Logistic regression (LR) quantifies the relationship between the drivers and probability of LULCC. LR model has been used to project the future LULCC, which are based on the past trends and drivers that determine the conversions between the different categories of LULC (Millington et al., 2007; Were et al., 2014). LR measures the probability of particular LULCC process from the given drivers (Rossiter and Loza, 2012). Moreover, it can estimate the direction and intensity of the independent variables (explanatory variables) by predicting the probability outcome associated with each category of the dependent variable that can be used to map where the probability occurred on LULC conversion.

The LR has been used in deforestation analysis (Geoghegan et al., 2001; Pontius Jr and Schneider, 2001), agriculture (Serneels and Lambin, 2001), and urban growth model (Allen, 2003; Landis and Koch, 1997; Wu, 1997). In many cases, the LR model fits with the spatial process analysis, and the outcomes are reasonably well (Irwin and Geoghegan, 2001). Allen (2003) also highlighted the use of LR to identify which variables are most appropriate to represent the urban change process and LR had a good explanation of the spatial relationship. Since, as LR is widely used and the satisfactory model for LULCC study. Therefore, LR was considered the proper model for this study in order to quantify the spatial relationship between drivers and explain how the drivers influence LULCC.

2.4.2. Cellular Automata model

Cellular Automata (CA) provides the powerful tool for the dynamic modelling of LULCC that is a method to take spatial interactions into account. The roots of CA in geography can be traced in ”A Monte Carlo approach to diffusion” by (Hagerstand,1965). The CA estimates the taken time in transition that can generate complex spatial patterns from the simple set of rules and predicts LULCC in the future (Singh, 2003).

The CA essentially comprises the following elements: 1) a cell space or lattice, 2) a finite set of cell states, 3) a definition of a cell's neighborhood, 4) a set of transition rules to compute a cell's state change and 5) time steps in which all cell states are simultaneously updated (White and Engelen, 2000) (see Figure 2.3). The CA model also requires GIS-based input as image format such as land use maps, road maps, protected areas, etc.

The CA are many has the ability to perform the spatial dynamics and time explicitly. CA can be incorporated with the spatial component and it addresses dynamism with simple rules that increases computational efficiency. Since the computational efficiency of CA leads it becomes favorite LULCC modeller (Singh, 2003). Besides, the ability of CA that represents the complex systems with spatial and temporal behaviours from a set of simple rules and states that made this technique very interesting for geographers and urban researchers (Alkheder and Shan, 2005). Wagner (1997) mentioned that CA can be considered as the analytical engine of GIS.

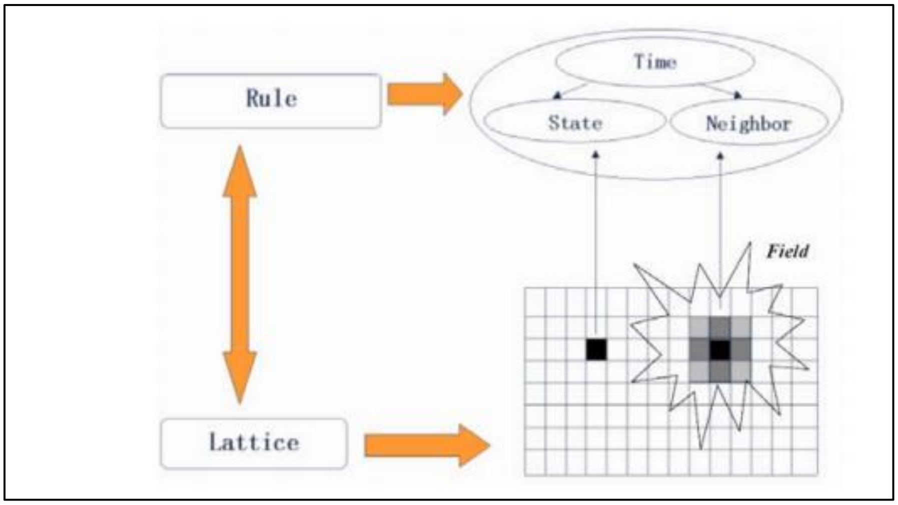


Figure 2.3: Five components of CA: lattice, cell state, neighbor, transition rule and time (White and Engelen, 2000).

Chapter 3 - Study area

3.1. Geography

Kaysone Phomvihane district is the capital city of Savannakhet province. The district is located between latitude 16° 26' 33" N and 16° 44' 53" N, and between longitude 105° 01' 26" E and 106° 44' 10" E. It has a total area of 701.18 km^2.

In terms of climate, the district has a tropical savanna climate with little subtropical climate characteristics as the city located 16.4° north of equator. The hottest month is April with a temperature varying from 29.5 °C to 35.2 °C while the coolest month is December with the temperature from 15.2 °C to 28.7 °C. The city experiences dry season during winter months and wet season during summer months due to activation of monsoon. The driest month is December with a precipitation total 2.0 millimeters (0.079 in), while the wettest month is August with precipitation total 323.1 millimeters (12.72 in) (Reid, 2015). In what concerns landscape, the district has 90% of large flat areas and 10% are hills. The large flat areas are mainly covered by agricultural activities and important forest areas as well as the settlement area in the western district and along the Mekong River (see Figure 3.1).

Kaysone Phomvihan district is the second-largest city in Laos after Vientiane Capital and the district is along the Mekong River-front in the western that shares the border with Moukdhan province, Thailand (LNBSS, 2015) (see Figure 3.1). The district has a favorable position. Since, it is considered as the crossroad between the northern and southern Laos. This marks a geographical advantage in the opportunity to attract foreign investment into the district (Nolintha and Masami, 2011). Especially, the second Lao-Thai friendship bridge is currently booming economy that has brought the new commercial development in the northern part of Kaysone Pomvyhan town (LNBSS, 2015).

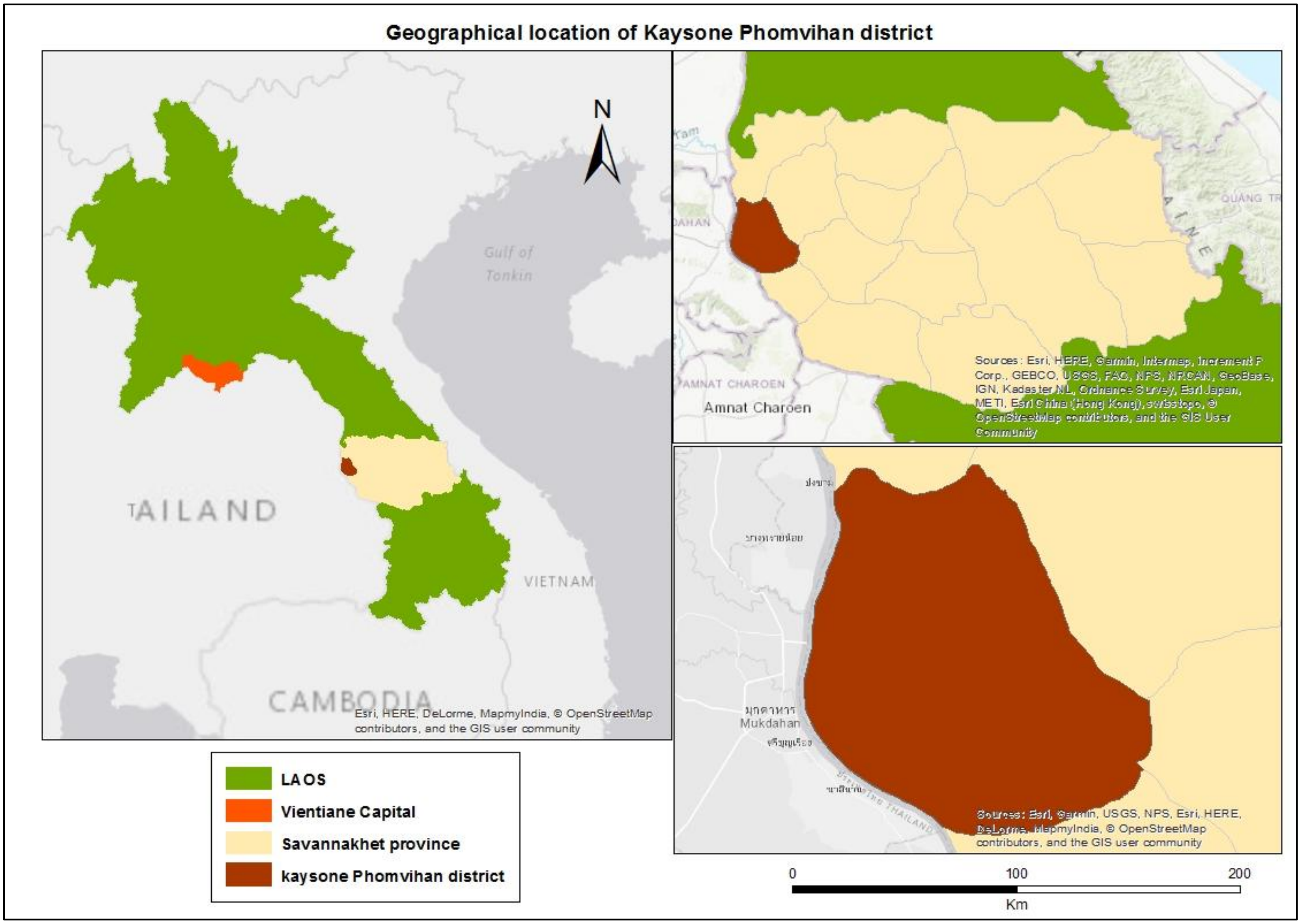


Figure 3.1: Geographical location of Kaysone Pmomvihan district (source: NGD Laos).

3.2. Socio-economic and demographic context

Fidloczky (2002) studied urban land use development in Laos and the result found that the urban expansion results mainly from strong socio-economic development and increased population in urban centers, which is partially due to immigration trends from rural towards urban areas. In relation, urban areas in Laos have increased in size since 1992 from 84,000 ha to 135,000 ha in 2002. This equals an average increase around 5000 ha per year and this trend is likely to continue.

Based on the 2015 Population and Housing Census (National Statistics Center, NSC), the population of Kaysone Phomvihan district was approximately 90,900 and a total number of households was 12,252, which gives an average household size of 5.8. In terms of sex distribution, the female population was 38,914 and accounting for 51% of the total population that was slightly higher than the male population of 37,991(49%) (ADB, 2015). The population density of the district is 17 people /ha but the city center of Kaysone Phomvihan district has a relatively high population density of 75 people/ha. The Japanese International Cooperation Agency (JICA) projected populations to 2030 by that time the population of the district is expected to increase of 128,200 by 2030 (ADB, 2015) (see Table 3.1).

Table 3.1: The population census in Kaysone Phomvihane district (source: Japanese International Cooperation Agency JICA 2015).

Year	Total Population
2010	78,900
2015	90,900
2020	101,700
2025	114,500
2030	128,200

In 2010, about 60% of households in the district are engaged in the commercial and service sectors that reflect an increasing number of medium and large trading and commercial enterprises in the district. Over 38% of the households are engaged in agriculture including small-holder farming, rice production, livestock and poultry raising and fish farming. Only a small proportion of the households is involved in handicraft making and home-based activities (ADB, 2015) (see Table 3.2).

Table 3.2: The proportion of the population engaged in each sector in 2010 by (Source: JICA 2015).

Sector	% of HHs
Agriculture and forestry	38.3
Handicraft	1.3
Commerce and service	59.9

Based on the gross domestic product (GDP), over the last three year periods 2007 to 2010, the economy of Kaysone Phomvihane district grew from 9.4% to 9.8%. The GDP per capita increased from US$712 in 2006 to US$1,027 in 2010 and reached to US$1,464 in 2014. Three main sectors contributed to this growth, namely agriculture sector (with a share of 20.9% of GDP in 2006 to 20.3% in 2010), service sector (GDP share reducing from 48.2% in 2006 to 46.6% in 2010) and industrial-commercial sectors (its share of GDP with 30.8%) (ADB, 2015).

These GDP growths can be due to the strategic positioning of the district at the crossroads between the EWEC (East-West Economic Corridor) connecting to Thai and Vietnamese road networks, and the Mekong River by second Lao-Thai friendship bridge (see Figure 3.2-3.4). In fact, after the second Lao-Thai friendship bridge was completed, the number of foreign and joint-venture companies in the district is doubled in the province between 2005 and 2008 from 30 projects in 2005 to 70 projects in 2008.

It is noteworthy that 12 projects have a major impact to land use in the northern city area that is near to the bridge and only three projects are in the historical city center (see Figure 3.5). Especially, Savan-Seno Special Economic Zone (SSSEZ), the SSSEZ has showed dynamism that influences urban land use, the initial plan is identified two sites, and then this plan has been modified to 600 hectares with four sites: Savan City (A), Logistic Park (B), Savan Park (C) and a resettlement site (D). All these sites are located in the northern urban area that is near the bridge (site A), along route number 9 (sites C and D), except site B located in Seno district (ELSA, 2015; ADB, 2012, 2015) (see Figure 3.5).

Figure 3.2: The East-West Economic Corridor route between Myanmar, Thailand, Laos and Vietnam (source: ADB 2012).

Figure 3.3: The East-West Economic Corridor route through three districts: Kayson Phomvihan, Phine and Dansavan (source: ADB 2012).

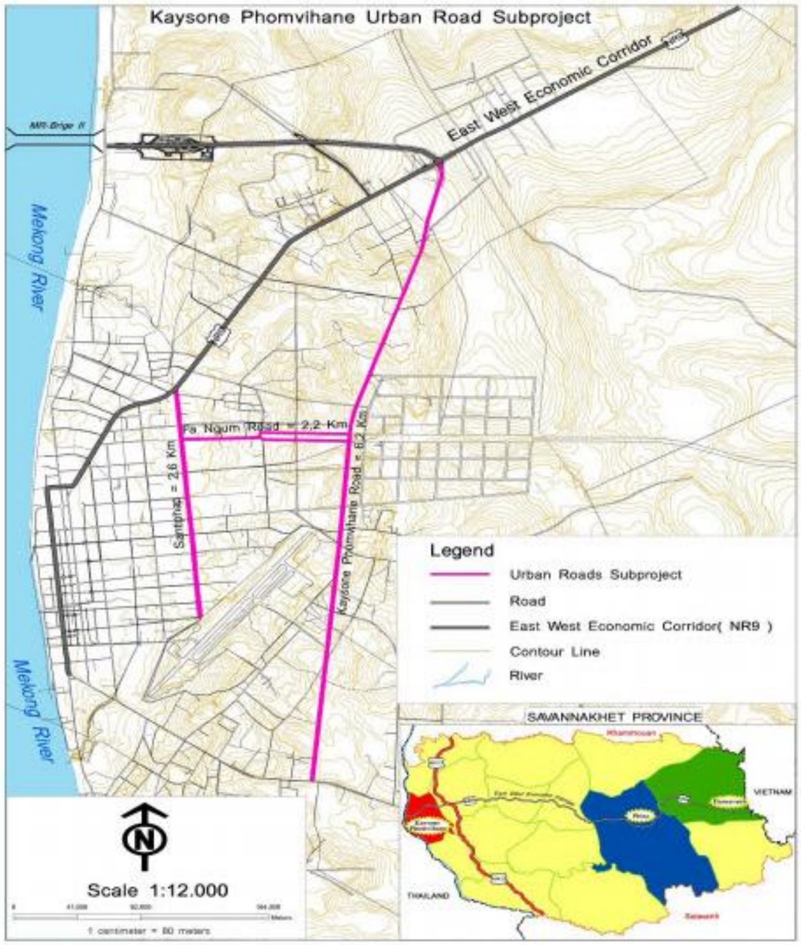


Figure 3.4: Road network in Kaysone Phomvihan district connects with East-West Economic Corridor and Lao-Thai Friendship Bridge (Source: ADB 2012).

3.3. Land use planning and urban development in Laos

Over the last two decades, considerable investments have been made in urban areas in Lao PDR by the government itself and through the assistance of development partners. These have resulted in significant improvements to urban environments and living conditions in many small, medium, and large urban centers (ADB, 2012).

According to ADB (2015), the National Urban Development agenda is contained in the draft of National Urban Sector Strategy (NUSS) that was prepared by the Department of Housing and Urban Planning (DHUP) of the Ministry of Public Works and Transport (MPWT). The NUSS sets out a range of objectives, policies and programs to develop all urban areas from the provincial capital to village clusters. It intends to strengthen the capacity of urban management authorities and create favorable conditions for civil society and private sector to actively participate in urban planning, management and sustainable development.

The Provincial Government of Savannahket gives special emphasis on the provision of essential infrastructure in the urban center where the majority of the local population resides (PDPI, 2009). The provision of infrastructure gives priority for improving and upgrading of the urban roads and drainage systems, installation of wastewater treatment facilities and expansion of sewerage/sanitation systems, and riverside embankment works for both protection and provision of tourism facilities.

Kaysone Phomvihave Urban Master Plan was approved in 2001. The Master Plan included the land use plan, road network planning, facility system and building regulation. Most of the current urban development activities such as road network improvements, land use management and city organization being undertaken in Kaysone Phomvihane district that is based on the Master Plan (ADB, 2015; Nolintha and Masami, 2011). The updated Kaysone Phomvihane socio-economic development plan (SEDP) identified key land management and infrastructure projects for the priority investments. These include the essential urban development projects such as residential areas, road network improvements, industry zone and natural protected areas. The plan also included the priority to support the development and environmental protection (ADB, 2015).

The Official Development Assistance (ODA) and foreign private investments were the main actors of the urban transformations through three important projects in Kaysone Phomvihan district. Before these transformations, the district was organized on the north-south axis, along the Mekong River and parallel streets that gathered administrative buildings, equipment, residential areas, main market and temples (Nolintha and Masami, 2011). Three main construction projects had later an impact on city organization and functional zone (see Figure 3.5). The first project is the displacement of the fresh products market from the city center to the north of the urban perimeter in 1998. The second project that changed the city organization under the Secondary Towns Project in 1998. Since, most of the administrative buildings that spread along the Mekong River have been relocated to a new-built neighbourhood on the east side of the city. The last project also has a specific function; it is the construction of the stadium in 2005 in the northern city to host the 7th National Games. These three projects aim to establish new functional centers in the district that is outside the perimeter of the historical city center (Nolintha and Masami, 2011; ADB, 2015). These new city centers have been designated along the East-West Economic Corridor, which is envisioned to be the future centers of economic activities for the district (see Figure 3.5). These locations are considered for the expanding commercial and business establishments such as supermarkets and shopping malls, restaurants and hotels. These will serve as the tourist destination in the district and province.

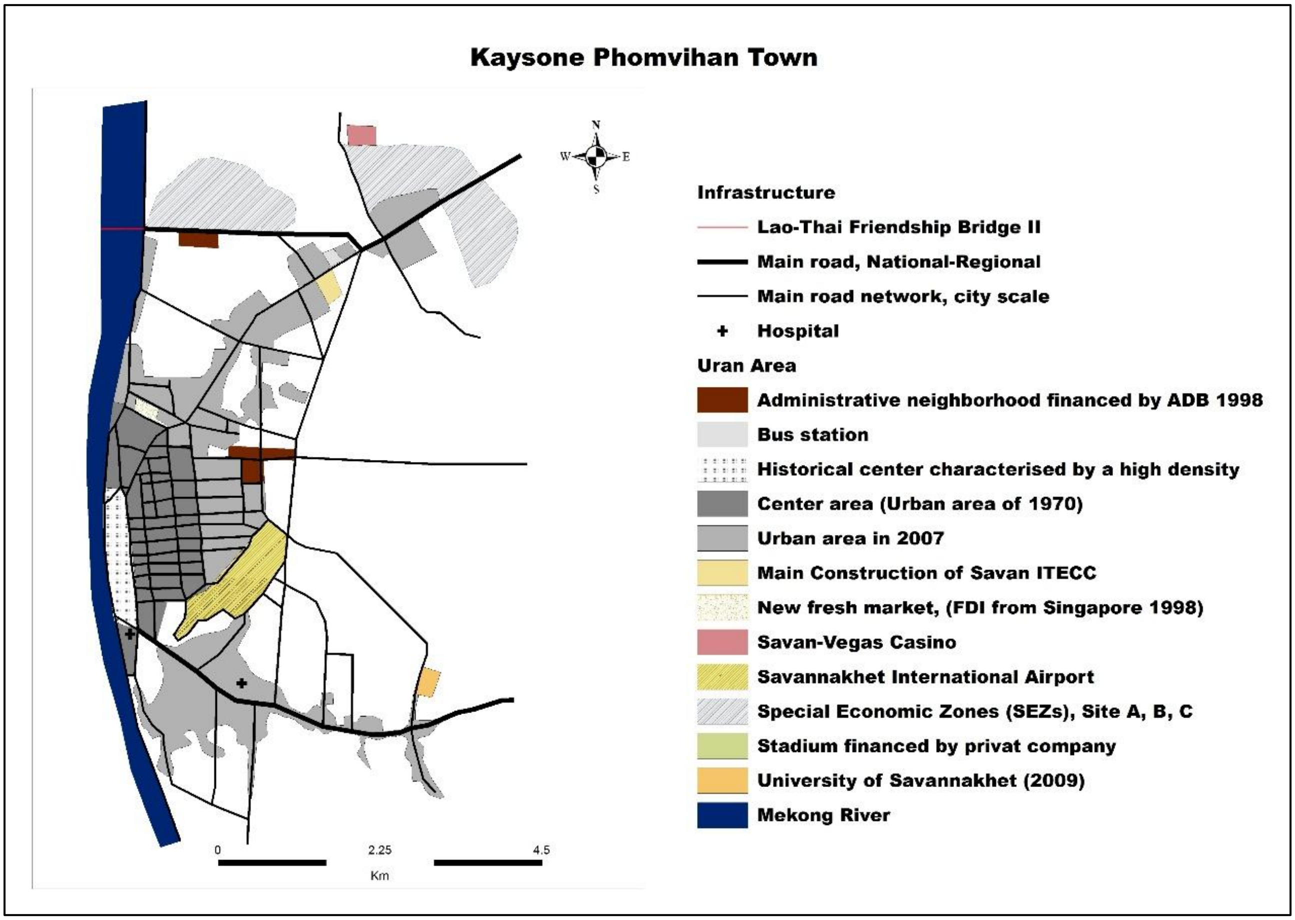


Figure 3.5: Kaysone Phomvyhan urban zone, three main construction projects and Special Specific Economic Zone sites (A, B, C) are in Kaysone Phomvyhan district except site C is in Seno district (S) (source:ADB: 2015).

The urban area is a major related to the spatial planning and development policy in Laos but in terms of forest and agriculture management, the Land and Forest Allocation program (LFA) developed in 1999 aims to allocate forestlands to communities, and agricultural land to families and individuals (GoL, 2005). This program set out that degraded land is for rehabilitation through plantations and tree crops. Forest is allocated that is based on the need to protect natural resources and provide for non-timber forest products and other traditional uses. Villagers of the district are required to set 5-10% of their land to accommodate future population growth (ADB, 2012, 2015; GoL, 2005). The LFA program has been implemented within three relevant laws:

1) Law of Forest (2007) that defines various forest categories in utilizing for business operations and traditional uses that includes the use of forest for tourism, recreational sites, logging and harvesting forest or forest products for commercial purposes. An investor wishes to engage in business operations in the forest must seek approval from the Forest sector and relevant sectors. All persons or organizations utilizing forests for business purposes shall avoid any negative impacts on forest and forest production areas, nature, the environment and society (GoL, 2005, 2007).

2) Agriculture Law (1998) defines the use for agricultural production land must seek approval from relevant sectors for allowing investment in agricultural activities such as investment in cultivation, animal husbandry and fishery to undertake agricultural production or agricultural business. This law determines the scale of production and business of agricultural lands regarding environmental protection, and also set out the obligation for individuals and organizations in undertaking agricultural production to protect the environmental and natural resources (GOL, 1998).

3) Environmental Protection Law (1999) that sets out the development projects and operations that have or will have the potential to affect the environment shall submit an Environmental Impact Assessment (EIA) report to accordance sectors who are responsible for environmental management and monitoring, and issue an Environmental Compliance.

In chapter 6 will discuss the relevance of these laws taking into account the results that were obtained through this study.

Chapter 4 – Data and Methodology

This chapter will describe the data and methodology used in this study. First, the study framework will be briefly introduced. The remote sensing data and classification algorithm, as well as identifying the proximate drivers of LULCC will be explained. Then, the pre-processing of the underlying drivers and independent variables will be discussed. In the last section, an explanation of the multi binary logistic regression analysis and the LULCC model will be performed.

4.1. Study framework

Based on the study framework presented in figure 4.1, the satellite image classification and LULCC were firstly analyzed in Erdas Imagine 2015 and ArcMap v.10.3.01 (HG, 2015; ArcGIS, 2014). Then, the preparation of independent variables included biophysical and socioeconomic factors were carried out in ArcMap. For the statistical analysis through logistic regression was computed in SPSS v.19 and the LULCC model was conducted in QGIS v.2.18 (IBM, 2010; QGIS, 2016). Figure 4.2 presents the preparing and analysis processes of the proximate driver (dependent variables) and underlying drivers (independent variables) for further analysis of MBLR and LULC simulation for 2022.

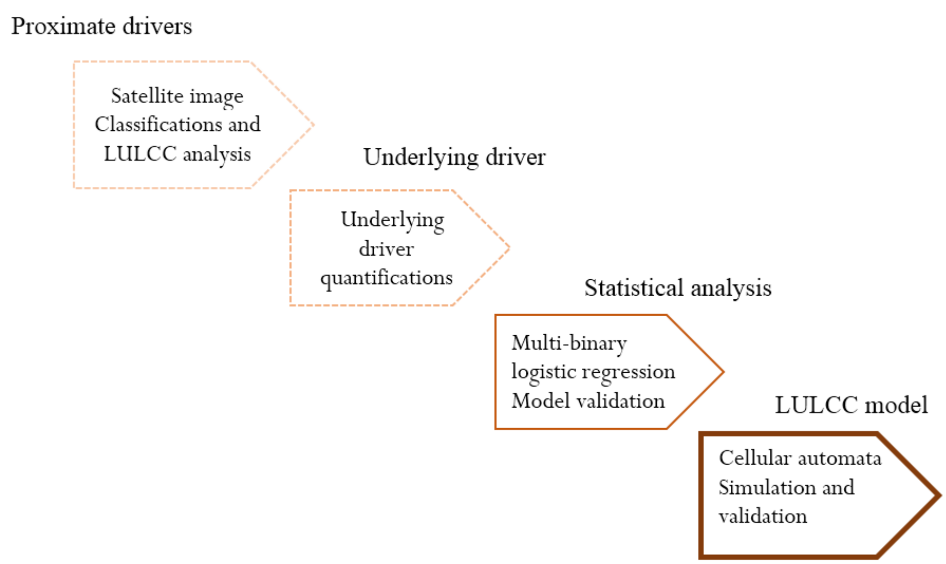


Figure 4.1 Study framework applied in this study.

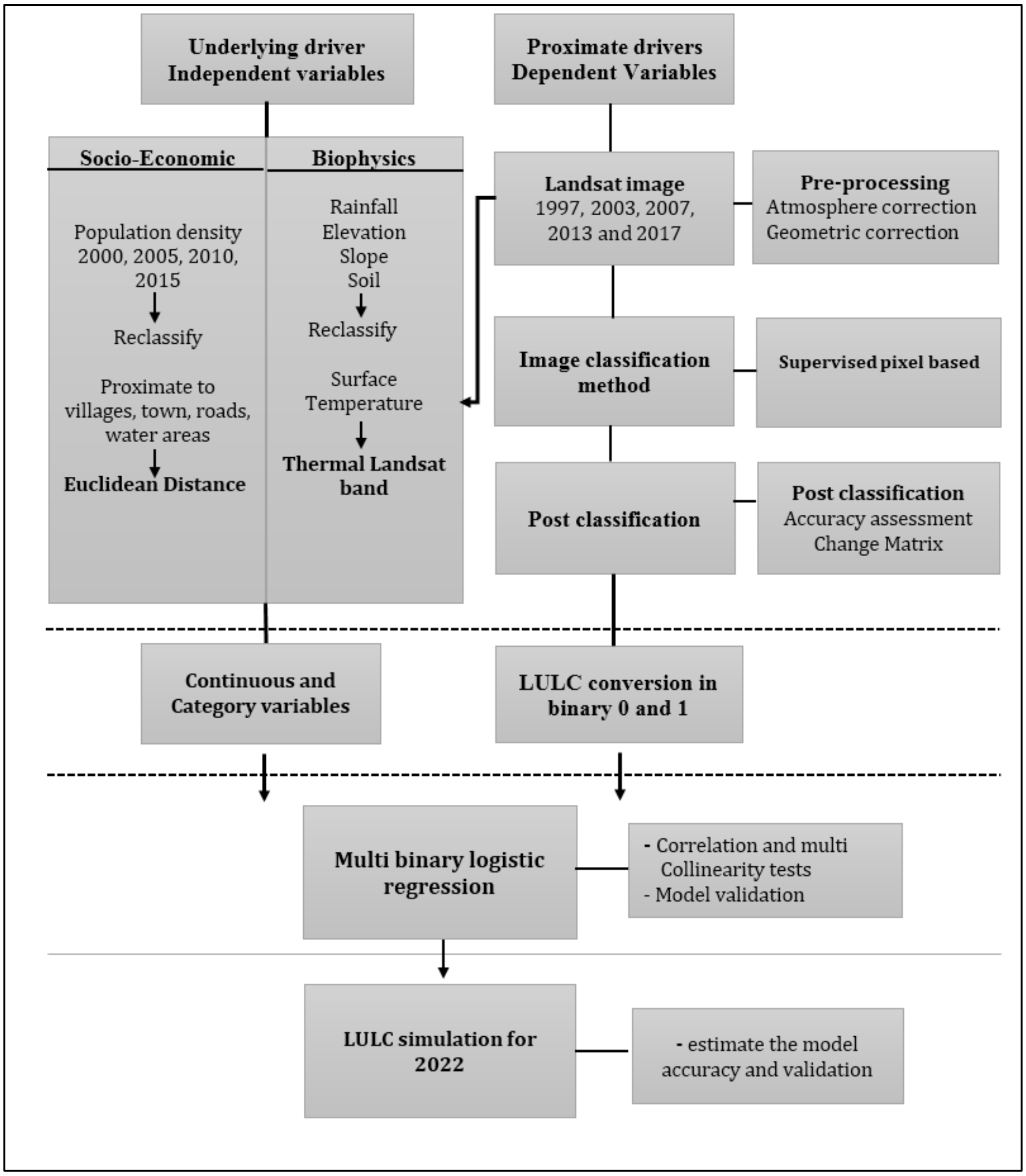


Figure 4.2: Data analysis processes in this research.

4.2. Satellite images classification for LULCC analysis

4.2.1. Remote sensing data

The different Landsat sensors obtained via United States of Geological Survey source (USGS, year): Thematic Mapper (TM) for the years 1997 and 2007, Enhance Thematic Mapper Plus (ETM+) for the year 2003 and Operational Land Imager (OLI) for the years

2013 and 2017 were considered (see Table 4.1). All the images are from tropical areas, it is cloudy in monsoon season and selecting images are restricted to the period of December to March. It is also important to use a cloud-free scene and using images acquired almost or in the same season is a fundamental factor of LULC change study. This eliminates the effects of seasonal change when investigating year-to-year change. The same period of images is often used because it minimizes the discrepancies in reflectance caused by seasonal vegetation fluxes, climatic differences and sun angle differences (Singh, 1989).

Table 4.1: Landsat images used in this study from USGS site.

Landsat Sensor	Scene (Path-Row)	Date	Spatial Resolution
OLI 8	127/48	29 Dec 2017	30 x 30 m
OLI 8	127/48	18 Dec 2013	30 x 30 m
TM 4-5	127/48 127/49	16 Jan 2007 16 Jan 2007	30 x 30 m 30 x 30 m
ETM+ 7	127/48 127/49	29 Jan 2003 29 Jan 2003	30 x 30 m 30 x 30 m
TM 4-5	127/48	06 Dec 1997	30 x 30 m

4.2.2. Image-preprocessing

Multi pre-processing tasks were taken in Erdas Imagine 2015. All image layers of each Landsat sensor were combined such as Landsat OLI 2017 and 2013 from bands 1-7, Landsat ETM+ 2003 from bands 1-7 and Landsat TM 2007 and 1997 from bands 1-7, but excluded bands 8-11(OLI), bands 6 and 8 (ETM+) and band 6 (TM) (see Table 1.B in Appendix for all Landsat bands). The thermal infrared bands of each Landsat sensor were used to analyze land surface temperature (see section 4.4.2). Remote sensing data in a raw format generally contains flaws such as noise, haze effect etc. Therefore, following correction operations were performed on the data during the pre-processing stage: atmospheric and radiometric correction. For geometric correction, all data from Landsat OLI, Landsat ETM+ and Landsat TM are in Level 1 that has been already geometrically corrected (USGS).

Atmospheric correction

The atmospheric correction had employed ATCOR algorithm that is available in Erdas Imagine 2015. ACTOR enables correcting the multispectral remote sensing data over flat terrain (Raaba et al., 2015). This algorithm firstly removal haze from images before performing atmospheric correction knew as haze correction. Then, converting pixel values to physical reflectance, as measured above the atmosphere. It normalizes images based on radiance values and image acquisition times and then calculates the reflectance values at the surface to remove atmospheric effects in the satellite images, as well as preparing the images for further analysis under different atmospheric conditions (Geomatica, 2013). This method needs to construct the calibration file that the radiance of each band has to enter to values for C_0 and C_1, the respective values of bias (addictive value C_0) and gain (multiplicative value C_1) (Geosystems, 2014) (see Equation 4.1). The bias and gain values (C_0 and C_1) were computed based on the metadata files (MTL.txt) from Landsat 8 OLI, Landsat 7 ETM+ and Landsat TM (see Table 4.2 for calibration file of Landsat 8 OLI in 2017 and see Table B.2-7 in Appendix for Landsat ETM+ and Landsat TM).

C_0 = 0.1 * RADIANCE _ADD (Offset) and C_1 = 0.1* RADIANCE_MUILT (Gain) (4.2)

The factor 0.1 is required to convert the units used by Landsat [Watts/(m2 * sr * micron)] into the radiance unit employed by ATCOR in Erdas Imagine [$Mw/cm^2 * sr^1 * micron^1$] (Geosystems, 2014).

Table 4.2 Calibration file of Landsat OLI in 2007.

Landsat 8 OLI in 2017 path/row 127/48				
Band	**RADIANCE_ADD_BAND (C_0)**	**RADIANCE_MULT_BAND (C_1)**	**Cal-file (C_0)**	**Cal-file (C_0)**
1	-64.92003	1.2984E-02	-0.6492003	0.0012984
2	-66.47890	1.3296E-02	-0.6647890	0.0013296
3	-61.25974	1.2252E-02	-0.6125974	0.0012252
4	-51.65766	1.0332E-02	-0.5165766	0.0010332
5	-31.61191	6.3224E-03	-0.3161191	0.0006322
6	-7.86160	1.5723E-03	-0.7861600	0.0001572
7	2.64978	5.2996E-04	0.2649780	0.0000529

In order to proceed with the atmospheric correction, the process needs the information of acquisition period of satellite sensors that are related the date, month and year, as well as the solar zenith and sun elevation (see Table 4.3). These data can be found in metadata file of Landsat data.

Table 4.3: Landsat sensors information for calibration files.

Landsat Sensor	Path/Row	D/M/Y	Solar Zenith	Solar Azimuth	Sun Elevation
OLI	127/48	29 Dec 2017	57.25110854	148.33568	42.74889146
OLI	127/48	18 Dec 2013	56.56740677	150.26451	43.43259323
TM	127/48	16 Jan 2007	57.26410278	143.20348	42.73589722
	127/49	16 Jan 2007	56.23982326	142.14522	43.76017674
ETM+	127/48	29 Jan 2003	56.39264748	138.24314	43.60735252
	127/49	29 Jan 2003	55.47052817	137.08222	44.52947183
TM	127/48	06 Dec 1997	58.56260429	144.10757	41.43739571

Radiometric correction

The haze was removed in the previous process (atmospheric correction). The noise reduction was applied to all satellite images for the radiometric correction. The noise reduction algorithm is available in Erdas Imagine 2015 enables to reduce the amount of noise in the input raster images. This technique preserves the subtle details in an image such as thin lines while removing noise along edges and in flat areas (Erdas Imagine, 1997).

4.2.2. Satellite image classification

Image classification is a complex and time-consuming process. In order to improve the classification accuracy, the selection of appropriate classification method is required. This would also enable the analyst to detect changes successfully (Elnazir et al., 2004). There are different types of image classification techniques. However, in most cases, the researchers categorized them into 3 major types: supervised, unsupervised and hybrid (Campbell, 2002). In this study, the supervised classification was applied. It is a type of the classification that is based on the prior knowledge of the researcher of the study area. It requires the manual identification of point of interest areas as the reference (Ground Truth) within the images to determine the spectral signature of identified features.

Due to the different Landsat sensors used, the RGB band combinations for the image classification process considered as Landsat TM (1997 and 2007) and Landsat ETM+ (2003) were RGB 742 and in Landsat OLI (2013 and 2017) were RGB 753, which band 7 corresponds to SWIR, bands 4 and 5 correspond to NIR, and bands 2 and 3 correspond to visible green band. These combinations give the visualization of vegetation in green that helps to identify between forest class and other classes (see Figure 4.3). The LULC classes were classified as forest area, permanent agriculture area, built-up area, shrub area and water area. These LULC classes are based on Laotian Ministry of Agriculture and Forestry guideline (Thongphanh et al.2006) (see Table 4.4).

The image classification was performed considering Maximum Likelihood Algorithm. This is a parametric decision and its rule is based on the probability that a pixel belongs to a particular class (Eguavoen, 2007). The maximum likelihood classifier forms the power classification as it is implemented quantitatively to consider several classes and several spectral channels simultaneously. This classifier has been reported to provide the higher classification accuracy in LULCC study (Campbell, 2002). Therefore, this classifier was considered as the most suitable for LULCC analysis in this study.

Table 4.4: Criteria of land use classes based on the Laotian Ministry of Agriculture and Forestry.

National class	Definition
Forest	Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent. It does not include land that is predominantly under agricultural or urban land use.
Permanent agriculture lands	These are areas permanently being used for rice cultivation, areas of agricultural land being used for production of other crops and various kinds of vegetables, for fruit tree cultivation, for plantation with cash crops, such as coffee, tea, cocoa and etc, as well other agriculture lands, unless the tree cover exceeds 20%.
Built-up area	Includes all areas being used for permanent settlements such as villages, towns, public gardens, factory etc. It also includes roads having a width of more than 5 m and areas under electric high power lines. Any type of land under high power lines.
Shrub	This area is where the vegetation cover is mainly bushes and grass. Normally, a large tree is not presented. There are some small trees with diameter breast height (DBH) is less 10 centimeters and height is below 10 meters. This category could be found throughout the area especially around the active swidden field.
Water area	This area includes rivers, water reservoirs (i.e. ponds and dams for irrigation and hydropower) and lakes. Water reservoirs and lakes should have an area of 0.5 ha and rivers should be at least 10 m wide to be classified as Water.

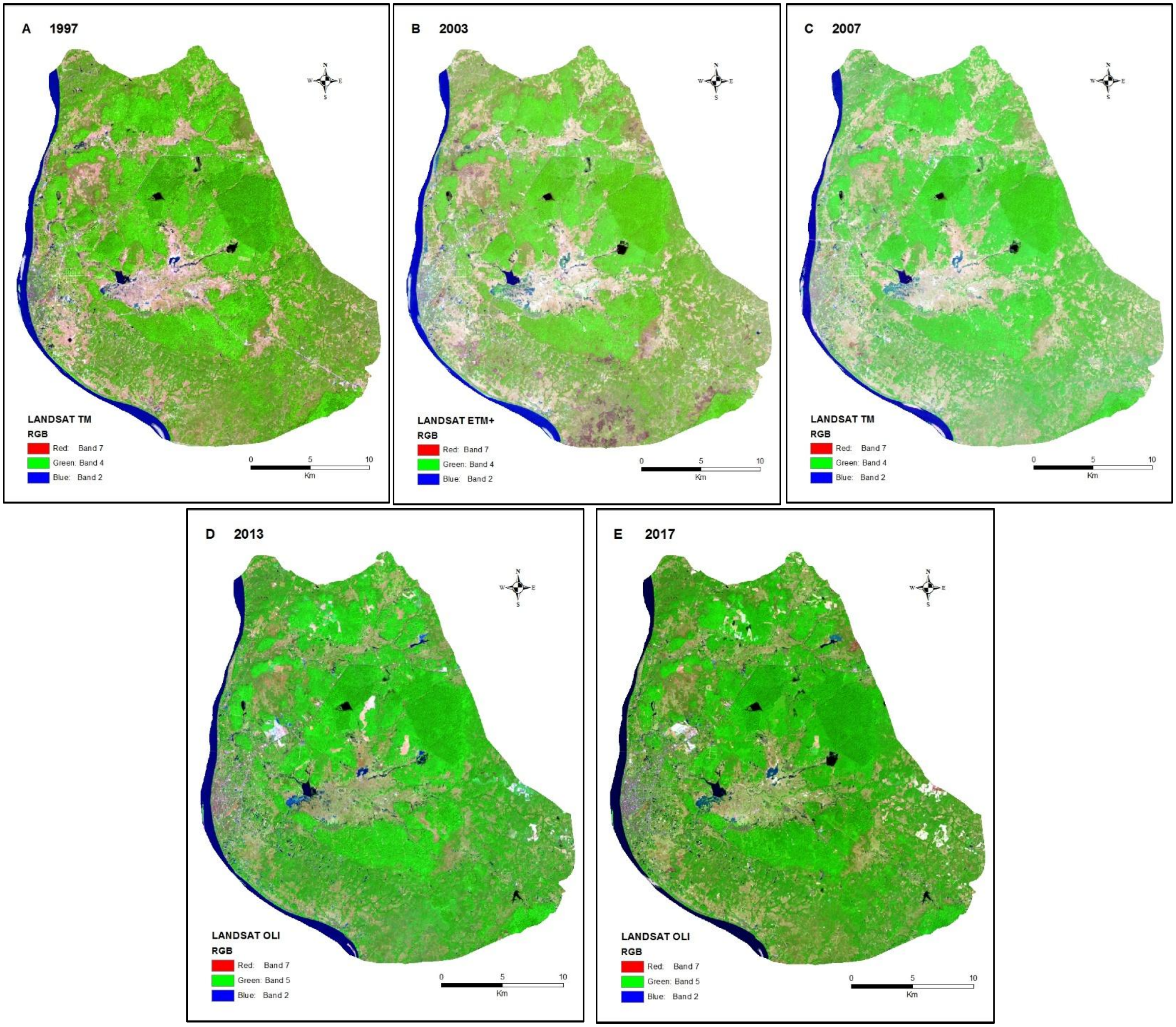


Figure 4.3: The RGB bands combination considered for the supervised classification of the years 1997 (A), 2003 (B), 2007 (C), 2013 (D) and 2017 (E).

4.2.3. Accuracy assessment

Accuracy assessment is a post-classification operation because the classified results were not thoroughly validated and the accuracy assessment is important. According to Foody

(2002), the accuracy assessment generated randomly training samples and analyzed the confusion matrix. The confusion matrix computed an overall accuracy (a measure of accuracy that considers the diagonal in the matrix), and producer's and user's accuracies. The producer's accuracy is related to omission error: the probability that a reference pixel is correctly classified. The user's accuracy represents the commission error: the probability that a pixel classified on the image actually is that land use on the ground (Foody, 2002). Kappa coefficient calculates error generated by the classification process and compared with an error of a completely random classification (Congalton, 1991) (see Equation 4.2):

$$K = \frac{(\text{overall classification accuracy} - \text{expected classification})}{(1 - \text{expected classification accuracy})} \quad (4.2)$$

The accuracy assessment process was carried out in Erdas Imagine 2015 by using classified images of the years 1997, 2003, 2007, 2013, 2017 and the Landsat images that correspond to each year of the classified images. Thus, the agreement and disagreement of the analysis were evaluated by using the error confusion matrix and simple descriptive statistics.

4.3. Identification of proximate drivers

4.3.1. Characterization of LULCC

All classified images were converted to shapefiles and reclassified in ArcMap software. Five LULC maps of the years 1997, 2003, 2007, 2013 and 2017 were computed (magnitude and rate of each class coverage in square kilometer and percentage). Then, these LULC maps were analyzed by change matrix to produce LULC conversion maps of five periods: 1997-2003, 2003-2007, 2007-2013, 2013-2017 and 1997-2017. These maps presented the conversions from class to class that can help to identify the main conversions and the proximate drivers of LULCC in each period. The proximate drivers are human activities that directly affect LULCC for instance, urbanization, agriculture expansion, deforestation, etc.(see section 2.2.1 in Literature Chapter). The proximate drivers will be selected as the dependent variables for the MBLR analysis.

4.3.2. Proximate drivers (Dependent variables)

Based on five LULC conversion maps from the previous analysis (see section 4.3.1), the produced maps were used to identify the foremost LULC conversions that will be considered as the proximate drivers. The large significant conversions were: forest to shrub conversion (deforestation), shrub to agriculture conversion (agriculture expansion) and shrub to built-up conversion (urban expansion). These three main LULC conversions were selected for the MBRL models because these three conversions dynamically changed over the study period, which can be used to explain the main LULCC processes in the study area. In order to apply these conversions to the models, three conversion maps were transformed to binary variables considering as 0 and 1, for instance, if the class is maintained the value 0 is considered, and if it changed the value 1 is then considered (see Table 4.5 and Figure 4.4 for example binary map).

Table 4.5: Binary code of LULC conversions.

LULC conversions	Binary code	
	Not change	changed
Forest to shrub conversion	0	1
Shrub to agriculture conversion	0	1
Shrub to built-up conversion	0	1

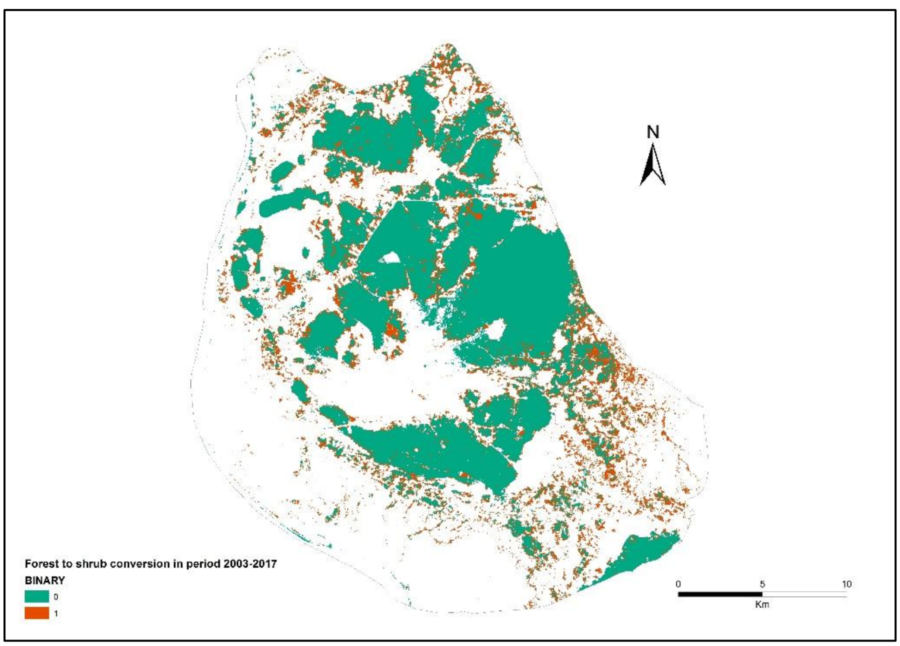


Figure 4.4: Binary map of forest to shrub conversion: 0 not changed and 1 changed.

4.4. Quantification of underlying drivers (Independent variables)

4.4.1. Independent variable dataset

The underlying drivers are the complex interaction of social, political, economic, technological and biophysical (Geist and Lambin, 2002). It is not possible to capture all these interactions due to this study scale and data available.

Therefore, this study only considered the biophysical and socio-economic variables, which were identified as the independent variables for MBLR (see Table 4.6). The biophysical variables considered rainfall, temperature, elevation, slope and soil types. For the socio-economic variables include the population density and proximate to roads, village, urban and to water sources, even though these variables are not directly as socio-economic but they can be identified as related factors that provide facilities to access market and economic development (Swart, 2016). The acquisition and preparation of the independent variables are discussed in the following sections.

Table 4.6: Biophysical and socio-economic variables for MBLR analysis.

Independent Variables				
Biophysical	**Type**	**Unit**	**Source**	**Coordinate system**
Rainfall	Continuous	mm	Worldclim.org	WGS 84 Zone 48N
Temperature	Continuous	ºC * 10	Landsat Images	WGS 84 Zone 48N
DEM	Continuous	m	ASTER GDEM	WGS 84 Zone 48N
Slope	Continuous	º	Dem extraction	WGS 84 Zone 48N
Soil type	Category	I-III	World Soil Information	WGS 84 Zone 48N
Socio-economic				
Population density 2015	Continuous	pers/km²	SEDAC	WGS 84 Zone 48N
Population density 2010	Continuous	pers/km²	SEDAC	WGS 84 Zone 48N
Population density 2005	Continuous	pers/km²	SEDAC	WGS 84 Zone 48N
Population density 2000	Continuous	pers/km²	SEDAC	WGS 84 Zone 48N
Proximate to villages	Continuous	Km	National Map	WGS 84 Zone 48N
Proximate to town	Continuous	Km	National Map	WGS 84 Zone 48N
Proximate to Roads	Continuous	Km	National Map	WGS 84 Zone 48N
Proximate to Water areas	Continuous	Km	National Map	WGS 84 Zone 48N

4.4.2. Biophysical

Rainfall

The rainfall dataset in Kayson Phomvihan district was obtained from WorldClim with the spatial resolution of 925x925m. This data presented the monthly precipitation (12 months) per millimeter in the period 1950-2000. The data was clipped to the study area and the average rainfall was calculated by cell statistic, and then resize the pixel resolution. The obtained average rainfall values were between 124-140 mm and a cell size of 30x30m resolution (see figure 4.5). The rainfall factor is expected to affect soil erosion including precipitation amounts and intensities. Increasing soil erosion reduce a vegetation cover loss and low fertilization areas for land use (Plangoen et al., 2003).

Temperature

The temperature was derived from the Land Surface Temperature (LST) extracted from the thermal infrared bands of Landsat TM (1997 and 2007) band 6, Landsat ETM+(2007) band 6 and Landsat OLI (2013 and 2017) bands 10 and 11. The processes of LST were computed in raster calculation and cell statistic in ArcMap by the following stages:

1) Conversion of the Digital Number (DN) to spectral radiance ($L\lambda$): every object emits thermal electromagnetic energy as its temperature is above absolute zero Kelvin. Following this principle, the signals received by the thermal sensors can be converted to at-sensor radiance. The thermal band data from TM, ETM+ and OLI were converted to Top Atmosphere (TOA) of spectral radiance (L_λ) by using the radiance rescaling factors provided in the metadata file (Landsat Project Science Office, 2002) (see Equation 4.3):

$$L_\lambda = M_L Q_{cal} + A_L \quad (4.3)$$

Where $L\lambda$ is the TOA spectral radiance (Watts / (m2 * srad * μm)), M_L is the band specific multiplicative rescaling factor from the metadata (RADIANCE_MULTI_BAND_X where x is the band number), A_L is the specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x where is the band number), and Q_{cal} is the quantized and calibrated standard product pixel values (DN).

2) Conversion of spectral radiance (L_λ) to At-satellite brightness temperatures (TB): the emissivity corrected surface temperature has been computed following (see Equation 4.4).

$$T = \frac{k_2}{\ln\left(\frac{k_1}{L\lambda} + 1\right)} \qquad (4.4)$$

Where T is the TOA brightness temperature (Kelvin), L_λ is the TOA spectral radiance (Watts / (m2 * srad * μm)), K_1 is the specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x where x is the thermal band number), and K_2 is the band specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x where is the band number).

3) Conversion of LST from Kelvin to degree Celsius: the derived LST unit of each Landsat sensor was converted to degree Celsius by using the relation of 0 ℃ equals 273.15 K. Then, the average temperature from the years 1997-2017 was computed by cell statistic. The average LST in Kayson Phomvihan District was between 19 and 27 ℃ with a cell size of 30x30m resolution (see Figure 4.5).

Altitude

The altitude was computed by considering the DEM that was downloaded from ASTER GDEM site and a cell size is 30x30m resolution. Then, it was clipped and value range from 104-242 m elevation in the study area (see Figure 4.5). This DEM was after used to create the slope map. According to Qasim et al. (2013), LULCC appear significantly related to geophysical factors such as slope and altitude. In the low elevation zone, an accessibility is a factor that is associated with agriculture and urban expansion.

Slope

The slope percentage was extracted from DEM. The value range between 5 and 15% where 5% presents the horizontality and 15% is steeper in the study area (see figure 4.5). The slope gives an indication of the different land use purpose for example forestlands are on the higher and steeper areas while construction land often moved to the flat areas with good traffic condition and water supplying (Buckley, 2010; Olaya, 2009).

Soil type

The soil data was downloaded from International Soil Reference and Information Center (ISRIC) that is the global dataset for soil type with a cell size of 1x1 km resolution. Then this data was clipped to the study area and resized the pixel resolution to 30x30m. The data present the main three soil types included Gleysols, Acrisols and Arenosols (see Figure 4.5).

Gleysols is generally considered fertile soil because of its fin soil texture and it has more organic matter, greater Cation Exchange Capacity (CEC), higher base saturation, and usually high level of phosphorus and potassium (ISRIC, 2015).

Acrisols often supports forested area and low fertility and toxic amounts of aluminium pose limitations to its agricultural use. Crops can be successfully cultivated, if the climate allows, which included tea, rubber tree, oil palm, coffee and sugar cane (FAO, 1970).

Arenosols soil is not appropriate for agriculture, most Arenosols in humid tropical regions are strongly leached soils with a low nutrient content and a very tight nutrient cycling between vegetation and surface soils (FAO, 1970).

Therefore, Acrisols and Gleysols were considered as suitable for agriculture and forest areas, but for Arensols with deposited sand was considered for urban area purpose.

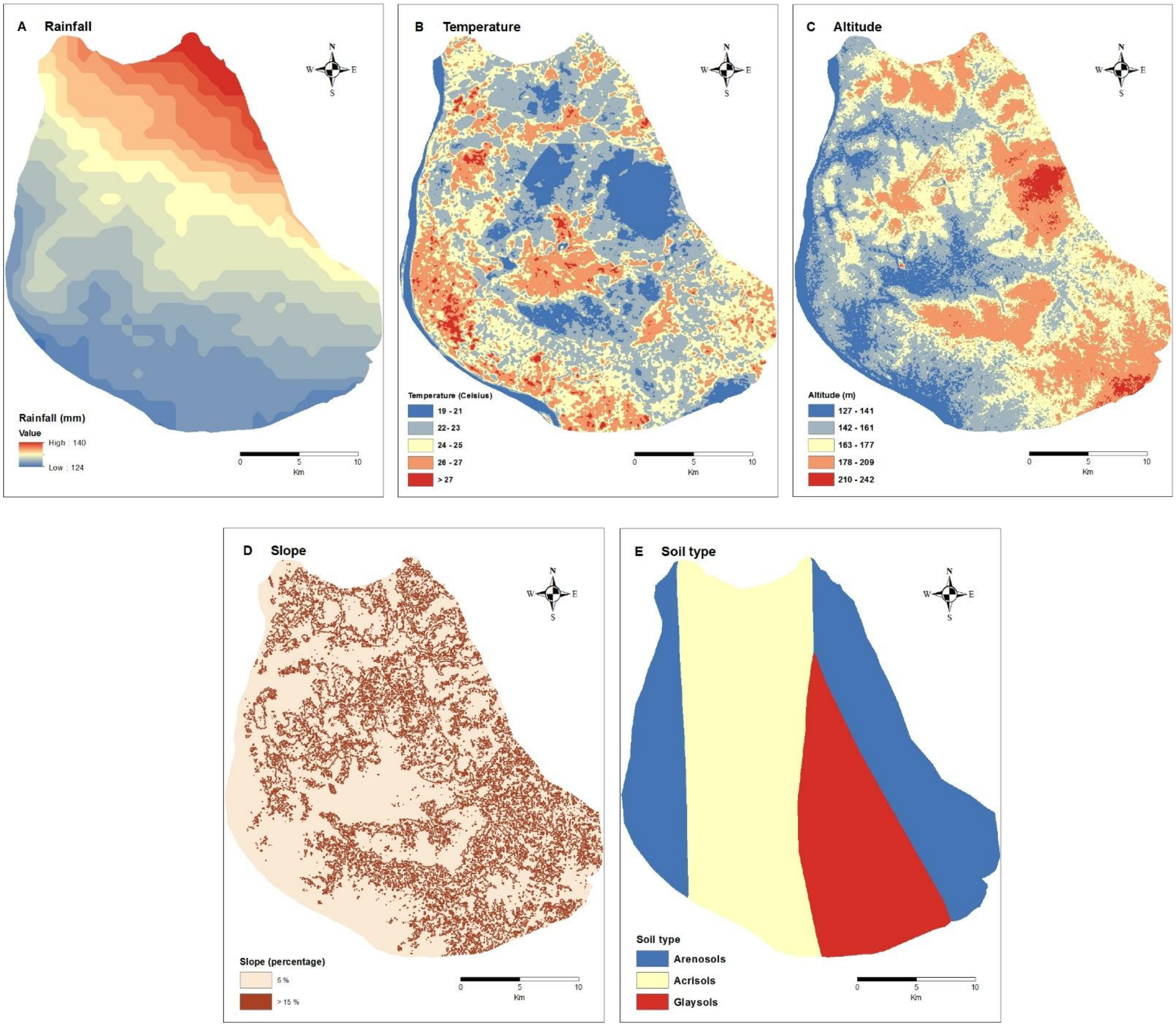


Figure 4.5: Biophysical variables that include rainfall(A), temperature (B), altitude (C), Slope(D) and soil type (E).

4.4.3. Socio-Economic

Population density

The population density is an important variable for LULCC analysis. Verburg et al. (2002) emphasized the importance of calculating the population density over larger areas. The population can affect land use, not only locally but also in particular over certain distances. It is difficult to find the population density data accurately because there is a limited source of the data in the study area. Therefore, the population density data was downloaded from Socioeconomic Data and Application Center (SEDAC site) for Global UN-Adjust Population Density in the years 2000, 2005, 2010 and 2015 with a cell size 1x1 km resolution (SEDAC, 2018). Then the data was clipped and resized to 30x30 resolution. This data is an estimation of the number population per square kilometer (see Figure 4.6). The population density is five years interval that corresponds to the periods of LULC conversion maps (see Table 4.7).

Table 4.7: The population density in Kayson Phomvyhan District.

Population density year	LULC conversion period
2000	1997-2003
2005	2003-2007
2010	2007-2013
2015	2013-2017

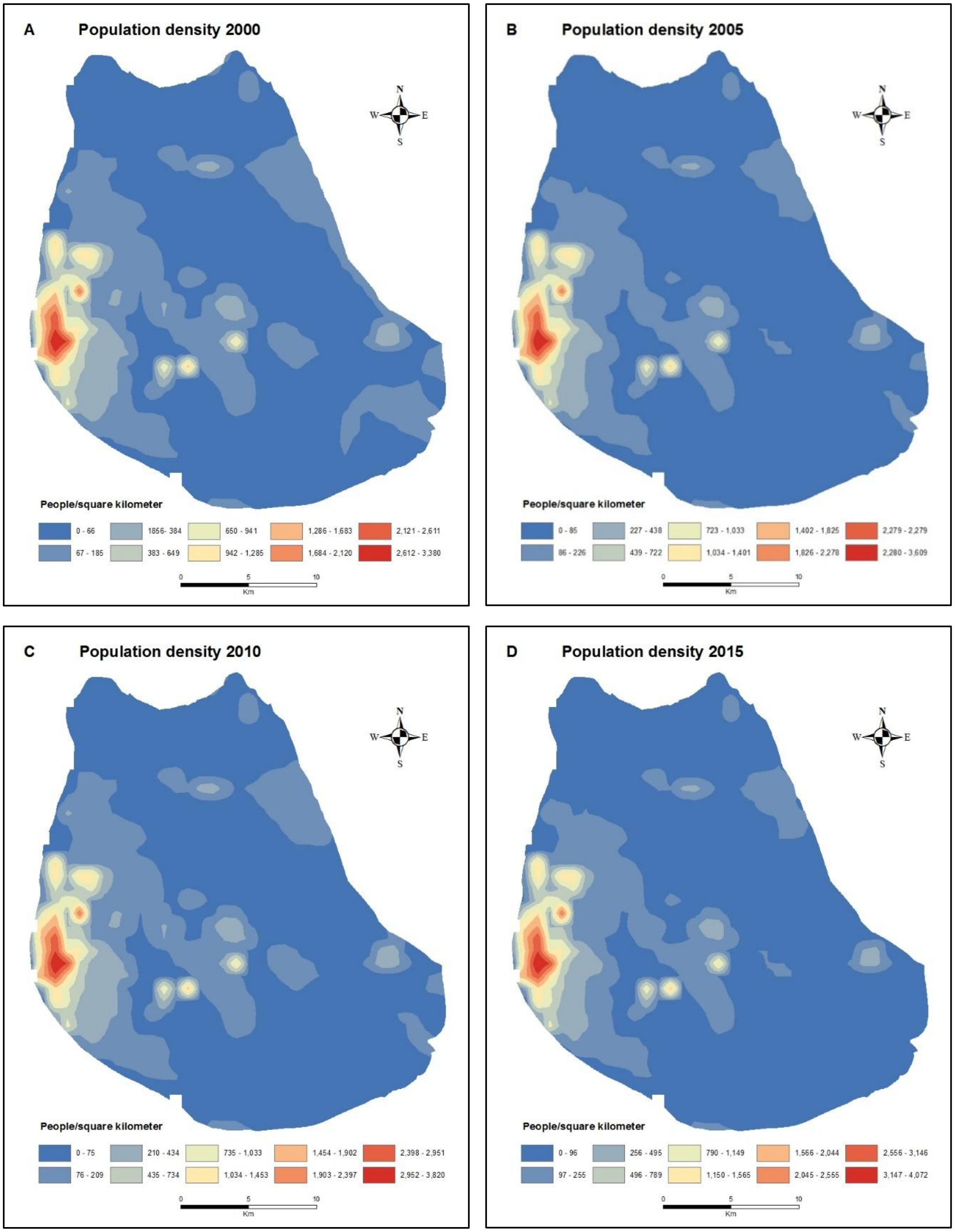


Figure 4.6: The population density of the years 2000 (A), 2005 (B), 2010(C) and 2015(D).

Proximate to town

The proximate to the town of Kayson Phomvihan district that is the capital city of the province that has very intensive population density was considered. The town is important to market, services, and economic development zone. The proximate to the town is an important explanatory variable in the model that has an influence LULCC over the last decades in the study area. Therefore, the proximate to the town was calculated by Euclidean distance from the nearest area to the town (see Figure 4.7).

Proximate to villages

The proximate to the nearest villages around the study area indicates the settlement and availability of markets in areas that can influence LULCC. This data was derived from National Map (National Geography Department) and then the data was calculated by Euclidean distance from the nearest area to villages with a cell size of 30x30 m resolution (see Figure 4.7).

Proximate to roads

The road data was derived from National Map and then it was clipped to the study area. This data included high way and small road network that indicates an accessibility by roads to the study area. The road network was calculated by Euclidean distance from the nearest area to road network with a cell size of 30x30 m resolution (see Figure 4.7).

Proximate to water sources

The proximate to water sources are an accessibility to permanent water areas that are highly important to the community, agriculture and life stock are needed regular access to water. Besides permanent rivers and other permanent water sources were also mapped. Temporary rivers and seasonal water points were not taken into account, as their seasonal importance are difficult to account for. This data was obtained from National Map and then it was calculated by Euclidean distance from the nearest area to water sources with the cell size of 30x30 m resolution (see Figure 4.7).

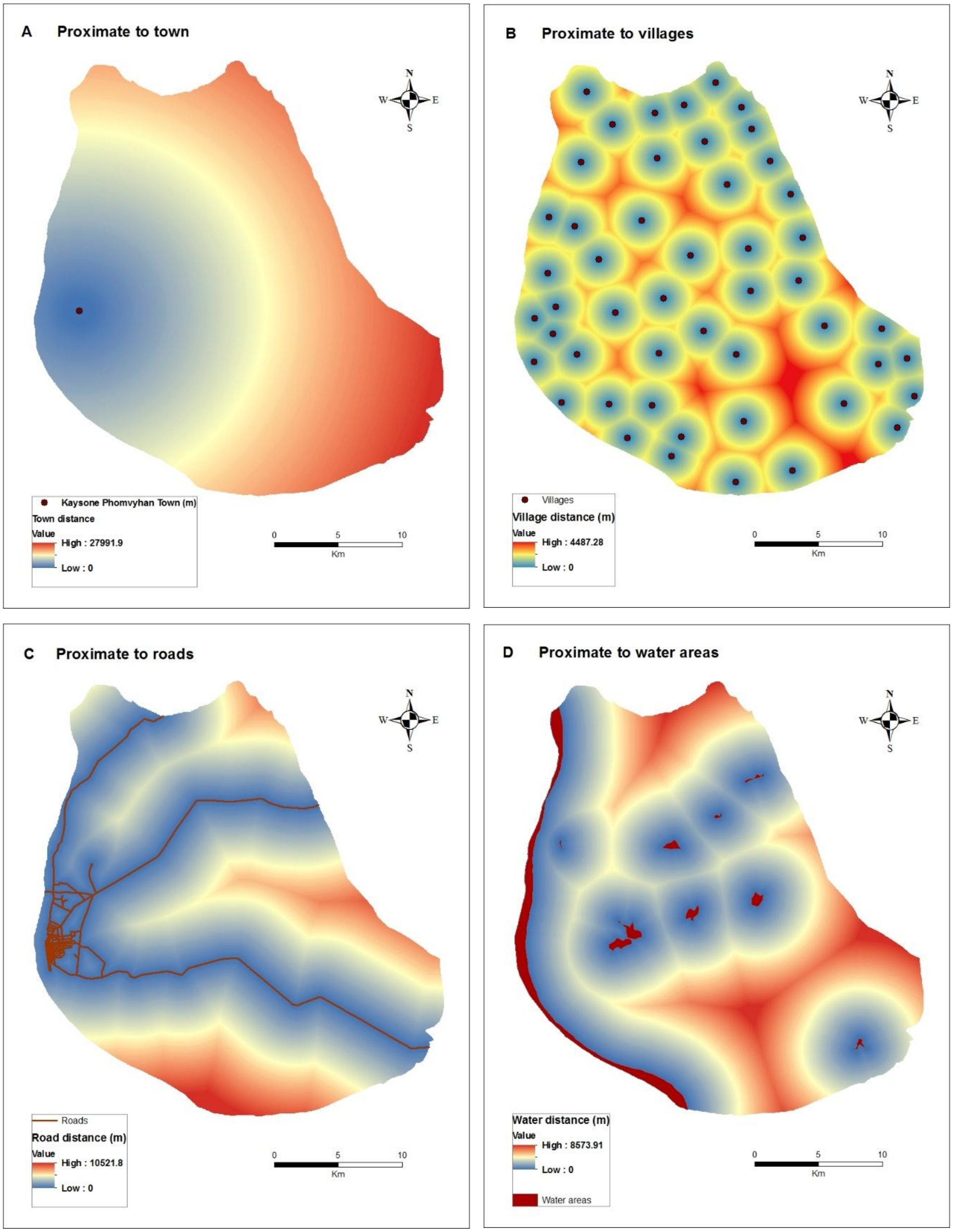


Figure 4.7: Proximate the nearest area to town (A), villages (B), roads (C) and to water Area (D).

4.5. Statistical analysis

4.5.1. Statistical dataset

Fifteen datasets were organized in order to analyze the MBLR between the dependent variables (LULC conversions) and various independent variables (biophysical and socio-economic) (see Table 4.8). Firstly, each LULC conversion map was overlaid with the independent variable maps in ArcMap. The mean values of the independent variables per LULC conversion pixels were calculated by using zonal statistic, which the mean values of the independent variables were assigned to each pixel of LULC conversion map. Then, these raster maps were converted to shapefiles in the geodatabase that included 15 datasets from the five periods (1997-2003, 2003-2007, 2007-2013, 2013-2017 and 1997-2017).

Figure 4.8 indicates the example dataset of shrub to built-up conversion in period 1997-2003. The pixel values of the independent variables (soil type, rainfall, temperature, altitude, slope, proximate to roads, villages, water and town, and population density in 2000, 2005, 2010 and 2015) were assigned to each pixel value of the dependent variable (binary: 0 not change and 1 changed).

Then, the fifteen datasets were exported to excel files for the MBLR analysis in SPSS software.

Table 4.8: The dependent and the independent variables included in 15 datasets.

Variables			
Dependent Variables	**Type**	**Independent variables**	**Type**
Forest to shrub conversion 1997-2003	Binary (0-1)		
Forest to shrub conversion 2003-2007	Binary (0-1)	Rainfall	Continuous
Forest to shrub conversion 2007-2013	Binary (0-1)	Temperature	Continuous
Forest to shrub conversion 2013-2017	Binary (0-1)	DEM	Continuous
Forest to shrub conversion 1997-2017	Binary (0-1)	Slop	Continuous
Shrub to agriculture conversion 2007-2003	Binary (0-1)	Soil	Category
Shrub to agriculture conversion 1997-2003	Binary (0-1)	Population density 2015	Continuous
Shrub to agriculture conversion 2007-2013	Binary (0-1)	Population density 2010	Continuous
Shrub to agriculture conversion 2013-2017	Binary (0-1)	Population density 2005	Continuous
Shrub to agriculture conversion	Binary (0-1)	Population density 2000	Continuous
Shrub to built-up conversion 1997-2003	Binary (0-1)	Proximate to villages	Continuous
Shrub to built-up conversion 2007-2003	Binary (0-1)	Proximate to town	Continuous
Shrub to built-up conversion 2007-2013	Binary (0-1)	Proximate to roads	Continuous
Shrub to built-up conversion 2013-2017	Binary (0-1)	Proximate to water areas	Continuous

model1.vat

VALUE	Rowid	AB97_03	BINARY	Soil type	Rainfall	Temperature	Altitude	Slope	Distance to Road	Distance to village	Distance to Water	Distance to town	POP_Density_2000	POP_Density 2005	POP_Density 2010	POP_Density 2015
913	912	301	0	1	138	24	179	3	9	3	8	8	66	64	62	60
914	913	301	0	1	138	25	175	3	9	3	8	8	67	64	63	61
915	914	401	0	1	138	23	175	3	9	3	8	8	60	58	57	56
916	915	101	0	1	138	24	176	3	9	3	8	9	59	57	56	55
917	916	101	0	1	138	24	174	3	9	3	8	9	57	56	55	54
918	917	201	0	1	133	25	146	3	6	7	1	10	61	57	54	50
919	918	401	0	1	133	25	143	3	6	7	1	10	61	57	54	50
920	919	102	1	1	133	25	148	3	6	6	1	10	61	57	54	50
921	920	401	0	1	133	25	152	3	5	6	1	10	61	57	54	50
922	921	101	0	1	133	25	150	3	5	6	1	10	60	57	54	50
923	922	101	0	1	133	26	144	3	5	6	1	10	60	57	54	50
924	923	101	0	3	133	25	141	3	5	6	2	10	60	57	54	50
925	924	401	0	1	133	25	138	3	5	6	2	9	60	57	54	50
926	925	101	0	3	133	25	143	3	5	6	2	9	60	57	54	50
927	926	101	0	4	133	25	143	3	5	5	2	9	60	57	54	50
928	927	101	0	2	133	25	144	3	5	5	2	9	60	57	54	50
929	928	101	0	1	133	24	144	3	5	5	2	9	60	57	54	50
930	929	101	0	1	133	24	146	3	5	5	2	9	60	57	54	50
931	930	101	0	1	133	24	152	3	4	4	3	9	56	53	51	48
932	931	101	0	1	133	24	152	3	4	4	3	9	55	53	51	48
933	932	401	0	2	135	24	164	3	3	2	4	9	39	40	42	44
934	933	401	0	1	135	24	167	3	3	2	4	9	38	39	41	43
935	934	101	0	1	138	24	164	3	7	2	9	8	53	50	48	45
936	935	301	0	1	138	23	171	3	7	1	8	8	50	47	45	43
937	936	301	0	1	138	23	168	3	7	1	8	8	50	47	45	43
938	937	301	0	1	138	23	168	3	7	1	8	8	50	47	45	42
939	938	301	0	1	138	24	163	3	8	1	8	8	49	47	44	42
940	939	101	0	1	138	23	174	3	8	2	8	8	59	56	54	51
941	940	101	0	1	138	24	175	3	8	2	8	8	59	57	55	52
942	941	301	0	1	138	25	179	3	9	3	8	8	70	67	65	63
943	942	301	0	1	138	25	178	3	9	3	8	8	71	68	66	64
944	943	301	0	1	138	25	176	3	9	3	8	8	72	69	67	65
945	944	301	0	1	138	24	173	3	9	3	8	8	70	68	66	64
946	945	201	0	1	133	25	144	3	6	7	1	10	60	57	53	50
947	946	101	0	1	133	25	144	3	5	6	1	10	60	57	53	50
948	947	102	1	1	133	25	148	3	5	6	1	10	60	57	53	50
949	948	101	0	1	133	25	146	3	5	6	1	10	60	57	53	50
950	949	101	0	2	133	25	143	3	5	6	1	10	60	57	53	50
951	950	101	0	1	133	25	141	3	5	6	1	10	60	57	54	50
952	951	101	0	1	133	25	145	3	5	5	2	9	60	57	54	50
953	952	101	0	1	133	24	148	3	5	5	2	9	60	57	54	50
954	953	401	0	1	133	24	153	3	4	4	3	9	56	53	51	49
955	954	101	0	1	133	24	153	3	4	4	3	9	56	53	51	48
956	955	401	0	1	134	25	146	3	4	4	3	9	52	50	48	47

Figure 4.8: Example dataset of shrub to built-up conversion in period 1997-2003 that includes the Dependent variable (red color) and the independent variables (blue color).

4.5.2. Exploratory independent variables

The exported excel files from the previous stage were imported in SPSS software. Firstly, the data were tested for correlation and collinearity among the independent variables. Then the LR and the model validation were applied.

The collinearity between the independent variables can influence the result of RL analysis. When the independent variables are highly correlated, they influence predictive values of the variables (Ott and Longnecker, 2010). Several techniques have been proposed for detecting the multicollinearity such as examination of the correlation matrix and variance inflation factor (Paul and Bhar, 2012). In SPSS software, the correlation and collinearity were tested by bivariate correction and linear regression.

Bivariate correlation: Pearson's correlation was considered for testing the independent variables because it is appropriate for continuous variables (IBM, 2014). In this study, all independent variables are continuous except soil variable that is ordinal. Since, the soil variable was not included together with other variables in Pearson's correlation test. The correlation coefficient value range from -1 to +1, for –1 (a perfect negative relationship) and for + 1 (a perfect positive relationship. If the coefficient value is less than 0.29, it is a weak correlation; the value is between 0.30-0.49, it is a moderate correlation; and the value is between 0.50-1.00, it is a very strong correlation (IBM, 2014; Paul and Bhar, 2012). Therefore, in the LULC conversion models, for the variables that coefficient value exceeds 0.50 needs to be reconsidered.

Linear regression: computes the Variance Inflation Factor (VIF) and it is used as an indicator of the multicollinearity (Paul and Bhar, 2012; Daoud, 2017). In this study, Stepwise linear regression was used to compute the VIF. The Stepwise linear regression is regressing multi variables while simultaneously removing those that are not important and the weakest correlated variables. The VIF value range from 0-10, if the variable value is more than 5 is highly correlated and if it exceeds 10, it has to remove from the models (see Table 4.9).

Table 4.9: Variance inflation factor (VIF) scale.

VIF Value	Conclusion
VIF = 1	Not correlated
1 < VIF ≤ 5	Moderately correlated
VIF > 5	Highly correlated

4.5.3. Multi binary logistic regression

After the correlation and multi-collinearity tests were performed, the data were analyzed considering the LR. This study analyzes the relationship between binary dependent variables and multi independent variables that it is called “multi binary logistic regressions (MBLR)”. The MBLR estimate the parameters of the multivariate explanatory model in the situation where the dependent variable is dichotomous and the independent variables are continuous or categorical (Ott and Longnecker, 2010).

The MBLR identifies the role and intensity of independent variables Xn in predicting the probability of the dependent variable, which is defined as the categorical variables Y (Ott and Longnecker, 2010) (see Equation 4.5). Suppose X is the independent variable and p is the response probability of the model, and Y is the dichotomous dependent variable, for example, in case the forest to shrub conversion model, with $Y = 0$ meaning of the presence of forest and $Y = 1$ meaning of the forest conversion to shrub areas.

$$In\left(\frac{\rho\, x}{1-\rho(x)}\right) = +\,\beta 1X1 + \beta 2X2 + \cdots + \beta nXn \quad (4.5)$$

Odds ratio is an important interpretation of the MBLR. The odds ratio is a measure of association, which approximates how much more likely (or unlikely) of the independent variables in the model (Hosmer and Lemeshow, 1989). The odds ratio can be interpreted as the change in the odds can increase of one unit in variables. The estimated odds values are computed as the exponential of the parameter estimate values (Agresti, 1990; Hosmer and Lemeshow, 1989) (see Equation 4.6).

$$\text{Odd (p)} = \exp(\alpha\ +\ \beta 1X1\ +\ \beta 2X2\ +\cdots+\beta nXn) \quad (4.6)$$

4.5.4. Model Validation

Pseudo R-square

R-square measures the predictive power and it gives an indication about the model performance or how well the model can predict the dependent variable that is based on the independent variables and fitted model (Allison, 2013). However, in LR analysis it is not possible to compute an exact R-square, and therefore the pseudo R-square was used (it is called ‘pseudo’ because the measure looks similar as value range from 0 to 1) (Swart, 2016). Therefore, in this study pseudo R-square was tested with Cox and Snell’s R and Nagelkerke’s R. The Cox and Snell's R is based on the log likelihood for the model compared to the log likelihood for a baseline model. It has a theoretical maximum value of less than 1 for the perfect model.The Nagelkerke's R is an adjusted version of the Cox & Snell R that adjusts the scale of the statistic to cover the full range from 0 to 1.

Receiving operating curve and Area under curve

The Receiver Operating Curve (ROC) was tested. In case of true positive rate, the model correctly predicted change polygons, for the false positive rate is correctly predicted no changed polygons (Swart, 2016; Rossiter and Loza, 2012). The ROC graph shows on the y-axis for the true positive rate and on the x-axis for the false positive rate. The model is accurate if the curve is close to the left top border: it predicts most true positives with a few false positives. If the curve comes close to the diagonal line, the model is less accurate. For the curve at the diagonal line is the random case: the model predicts at random, the chances would be equally like to be true or false positive (Rossiter and Loza, 2012).

The Area Under Curve (AUC) was used to distinguish between alternative model specifications. The AUC value varies from 0.5 for the model that assigns the probability of LULCC at random, and for value 1 for the model that perfectly assigns LULCC to the empirically observed locations (Williams et al., 1999).

4.6. LULC simulation

The LULCC model was used to simulate LULC for 2022. It is important to estimate the predictive ability and reliable of the model. Therefore, simulated LULC in 2017 was conducted from the transitional potential of LULC map for time t1 (2007) and for time t2 (2013) to predict LULC for time t3 (2017). Then the result will be validated between the simulated LULC in 2017 and the reference map in 2017 (classified LULC map of 2017). Therefore, if the validated result achieved an acceptable accuracy, then the simulated LULC in 2022 will be conducted. However, if the result is less accurate, the simulation will not be implemented. The simulated LULCC in 2017 was carried out in QGIS MOLUSCE plugin (Model for Land Use Change Evaluation)(QGIS, 2016). The simulation processes are described in the following sections:

4.6.1 Model setting

The LULC maps of 2007 and 2013, and spatial variables (biophysical and socioeconomic variables) were input in the model. The LULC map of 2007 was assigned for the first period (time t1) and LULC map of 2013 was the second period (time t2). The spatial variables included rainfall, temperature, DEM, slope, soil type and the population density for the years 2000, 2005, 2010 2015, as well as proximate to villages, town, roads and to water sources. All these input variables have the coordinate system, spatial resolution and extent.

4.6.2. Transitional Potential model

The transitional potential method of the simulated LULC in 2017 was the LR method. This method analyzed the changed pixels between two LULC maps and spatial variables by sampling and training data. The sampling mode was defined as random. The model also needs to define maximum iteration and neighbor pixel. The maximum number of iteration considered was 1000 and the neighbor pixel size was 1, which means 9 cells (3x3 cells). The transitional potential result presented in form of coefficient values, standard deviations and p-values that are based on equation 4.7.

$$M((C - 1)(2N + 1)^2 + B(2N + 1)^2 + 1) \quad (4.7)$$

Where value C is the count of LULC categories, N is a neighbor pixel size as 1, B is summary band count of spatial variable rasters, M usually is counting of unique categories in the change map (C^2). M is the sampling mode of the model (NEXTGIS, 2012).

4.6.3. Cellular Automata simulation

The Cellular Automata simulation is based on the LR method from the transitional potential model that was implemented in the previous stage. The LR has the coefficients for every neighbor pixel and the coefficients affect the transitional potential of LULC classes (GISLAB, 2014). By using this rule, the simulation computed the transition potential map of each LULC category between 2007 and 2013 for predicting the LULC categories in 2017. The simulation also generated the probability map of 2017 that presented the percentage of transitional potential between LULC maps of 2007 and 2013.

4.6.4. Validation

The validation model allows evaluating the simulation accuracy. The process compares between the reference map of 2017 and the simulated LULC map of 2017. The validation result is based on Kappa statistic and error multi resolution.

Kappa statistic

The kappa statistic includes three types: kappa overall, kappa location and kappa histogram. Kappa overall is the total accuracy of the number pixel that correctly classified between the reference map and the simulated map, kappa location is the simulation’s ability to specify location perfectly between both maps, and kappa histogram is an estimation of the frequency distribution of pixels in the reference map and the simulated map (Landis and Koch, 1997).

Multi resolution

The mulit resolution is an error of the location and quantity information between the reference map and the simulated map (Pontius and Suedmeyer, 2004). In MOLUSCE, the location and quantity information are explained by 5 plots include: 1) No location information, no quantity information; 2) No location information, medium quantity information; 3) Medium location information, medium quantity information; 4) Perfect location information, medium quantity information; and 5)Perfect location information, perfect quantity information (GISLAB, 2014).

Chapter 5 - Results

5.1. Accuracy assessment of satellite image classification

The LULC classified maps were carried successfully (see Figure. A.1-5 in Appendix). The accuracy assessment indicated that the overall accuracies of classified LULC maps were higher than 80% (see Tables B.8-12 in Appendix). The classified LULC map of 2017 was the highest overall accuracy of 89.29% and kappa coefficient of 0.85, which the producer and user's accuracies of forest, built-up, permanent agriculture and shrub classes were higher than 60% but water class was the lowest producer's accuracy with 50% (see Table B.12 in Appendix). The classified LULC map of 2003 was obtained the lowest overall accuracy with 80.88% and kappa coefficient with 0.73. In this classified map, the producer and user's accuracies of water, forest, built-up and permanent agriculture were higher than 60%, only shrub class was the lowest producer's accuracy (see Table B.9 in Appendix).

For other classified LULC maps of 1997, 2007 and 2013, the overall accuracies were 83.33%, 85.79% and 89.04 %, and the kappa coefficients were 0.74, 0.79 and 0.84 respectively (see Tables B.8, B.10, B.11 in Appendix).

5.2. LULCC analysis

5.2.1. LULCC in magnitude and rate

The major dominant of LULC class in 2017 was shrub (30.55%), followed by forest (25.11%) and permanent agriculture (25.15%), built-up (16.37%) and water (2.95%) (see Table 5.1 and Figures 5.1 and 5.2).

The changes of LULC classes in km^2 and percentage in each period are showed in table 5.2. The built-up class had the highest increase area compared to other classes with a total of 99 km^2 (14.16%). The foremost increase of built-up was between 2007 and 2013 with 34.51 Km^2 (4.92 %). Permanent agriculture class also had a high increase with a total of 70 km^2 (10.03%). During 2007-2013, the permanent agriculture had a significant increase with 35.78 km^2 (5.10%) that corresponds to the highest increase period.

On the other hand, the decreases of LULC classes were in forest class with -113 km^2 (-18.98%), shrub class with -30.83 km^2 (-4.40%), and water class slightly decreased -5.69 km2 (-081%). The forest class had the highest decrease area in 1997-2003 with -56.45 km^2 (8.05%) Another important decrease was in the shrub class that had the highest loss in the period 2007-2013 with -52.40 km^2 (see Table 5.1 and 5.2).

From Table 5.2 and Figures 5.1 and 5.2 can be concluded that the built-up and permanent agriculture classes steadily increased over 20 years, especially during 2007-2013, the built-up and permanent agriculture had the highest increase areas. While the major decrease was in the forest class, particularly in the period 1997-2003 that had the highest forest loss. For the shrub class was quite lower decrease than the forest class but its number was still too much and the water can be noticed with very small number declined. All the classified LULC maps are showed in figure 5.3.

Table 5.1: LULC classes in km^2 and % in the year 1997, 2003, 2007, 2013 and 2017.

Land use and land cover in km^2 and Percentage										
Classes	1997		2003		2007		2013		2017	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Permanent Agriculture	105.08	14.99	114.82	16.38	117.76	16.79	153.54	21.90	175.40	25.01
Built-up	15.51	2.21	29.44	4.20	56.13	8.01	90.64	12.93	114.80	16.37
Forest	309.15	44.09	264.67	37.75	208.22	29.70	190.91	27.23	176.06	25.11
Shrub	245.07	34.95	269.39	38.42	296.79	42.33	244.39	34.85	214.24	30.55
Water	26.37	3.76	22.86	3.26	22.28	3.18	21.70	3.09	20.68	2.95
Total	701.18	100.00	701.18	100	701.18	100	701.18	100.00	701.18	100

Table 5.2: LULCC of the different classes in Km^2 and % for four periods.

Land use and land cover changes in Km^2 and percentage										
	1997-2003		2003-2007		2007-2013		2013-2017		Total	
	Km^2	%	Km^2	%	Km^2	%	Km^2	%	Km^2	%
Permanent Agriculture	9.74	1.39	2.94	0.42	**35.78**	**5.10**	21.86	3.12	70.32	10.03
Built-up	13.93	1.99	26.69	3.81	**34.51**	**4.92**	24.16	3.45	99.29	14.16
Forest	-44.48	-6.34	**-56.45**	**-8.05**	-17.31	-2.47	-14.85	-2.12	-133.09	-18.98
Shrub	24.32	3.47	27.4	3.91	**-52.40**	**-7.47**	-30.15	-4.30	-30.83	-4.40
Water	-3.51	-0.50	-0.58	-0.08	-0.58	-0.08	-1.02	-0.15	-5.69	-0.81

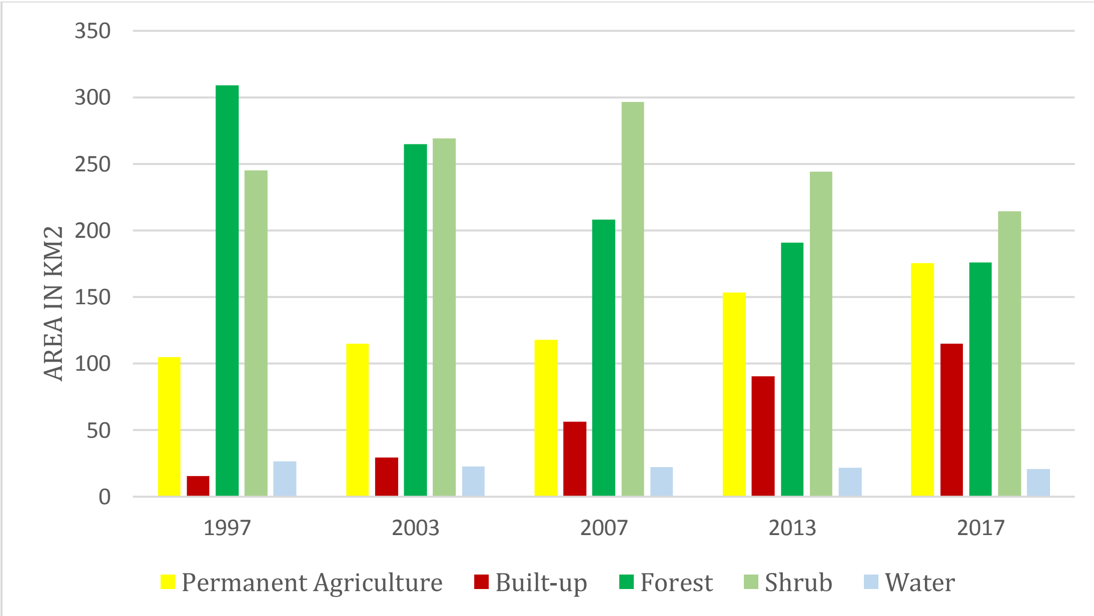


Figure 5.1: LULC classes of the year 1997, 2003, 2007, 2013 and 2017.

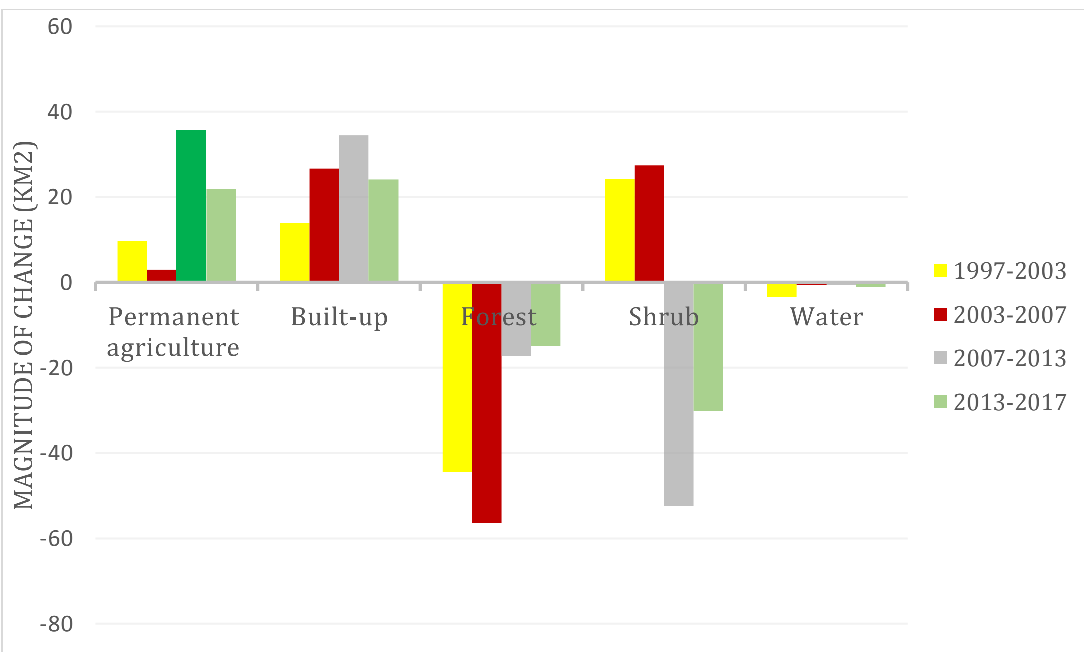


Figure 5.2: Changes of LULC classes in four periods.

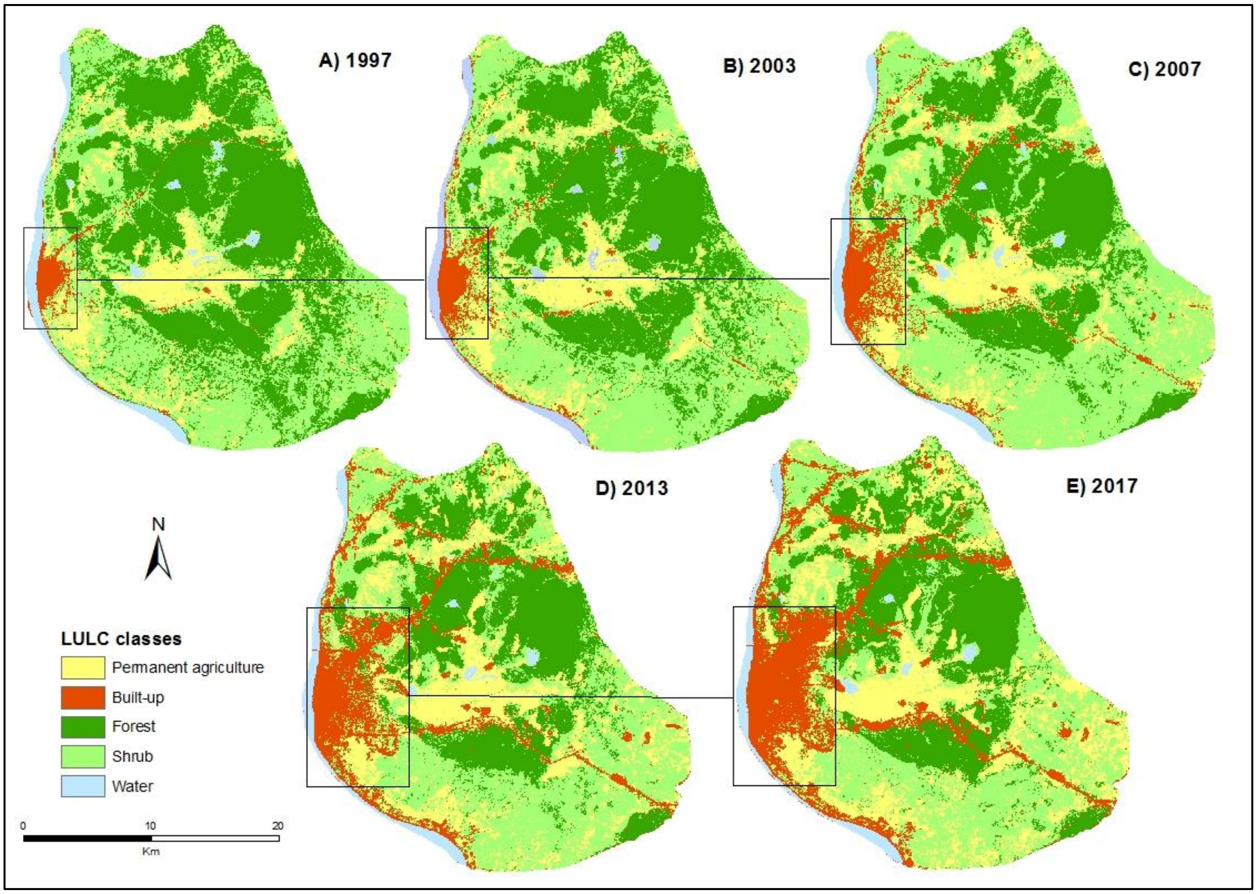


Figure 5.3: Classified LULC map in the years 1997(A), 2003(B), 2007(C), 2013(D) and 2017(E).

5.2.2. LULC conversions

In the first and second periods, forest presented the highest loss that had converted to shrub class with 61.53 km^2 (1997-2003) and 62.49 km^2 (2003-2007). The shrub class presented the highest total gain with more than 80 km^2 in these periods (see tables B.13-14 and figures A.7-8 in Appendix). In the third and fourth periods, the highest LULC loss was replaced by shrub class that converted to permanent agriculture and built-up classes with more than 50 km^2, especially the shrub class conversion to permanent agriculture reached to 49.16 km^2 (2007-2013) and 43.57 km^2 (2013-2017) (see Tables B.15-16 and Figures A.9-10 in Appendix).

The total loss and gain of LULC classes over 20 years are showed in table 5.3 and Figure 5.4. Forest presented the highest loss with a total of 146.54 km^2, next to the forest was shrub area with a total loss of 129.34 km^2. In contrast, built-up and permanent agriculture classes were the highest total gain areas that from the conversion of forest and shrub areas. The built-up gained 99.80 km^2 and permanent agriculture gained 97 km^2.

Three highest conversions of LULC classes are showed in table 5.3 and figure 5.5 including: 1) forest converted to shrub with 90.86 km^2; 2) shrub converted to agriculture with 67.93 km^2; and 3) shrub to built-up conversion was 48.52 km^2.

These three LULC conversions were considered as the main proximate drivers of LULC changes and these conversions will be used for the MBLR analysis. These three conversions are showed in figure 5.6 (see Figure A.11 in Appendix for all LULC class conversions between 1997-2017).

Table 5.3: LULC class conversions between 1997-2017.

	1997							
	Class	PA	B	F	S	W	Total	Gain
2017	PA	78.40	0.16	27.14	**67.93**	1.77	175.40	**97.00**
	B	18.95	15.00	28.47	**48.52**	3.86	114.80	**99.80**
	F	0.53	0.08	162.62	12.60	0.24	176.06	13.45
	S	6.59	0.12	**90.86**	115.73	0.94	214.24	98.51
	W	0.61	0.16	0.07	0.29	19.55	20.68	1.13
	Total	105.08	15.51	309.15	245.07	26.37	701.18	309.89
	Loss	26.68	0.51	**146.54**	**129.34**	6.82	309.89	619.77

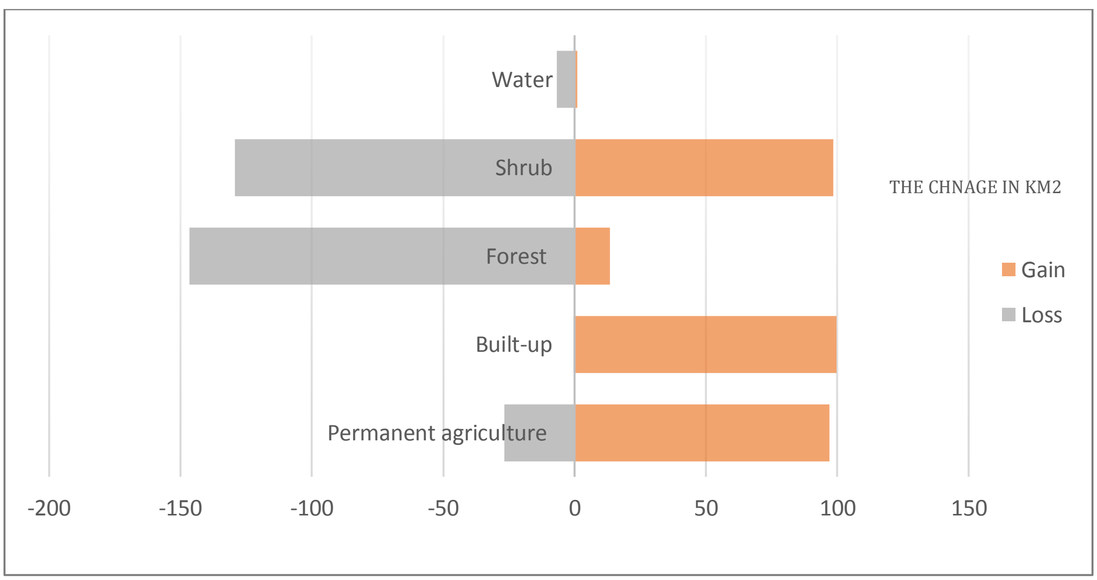


Figure 5.4: LULC classes in gain and loss over the study period.

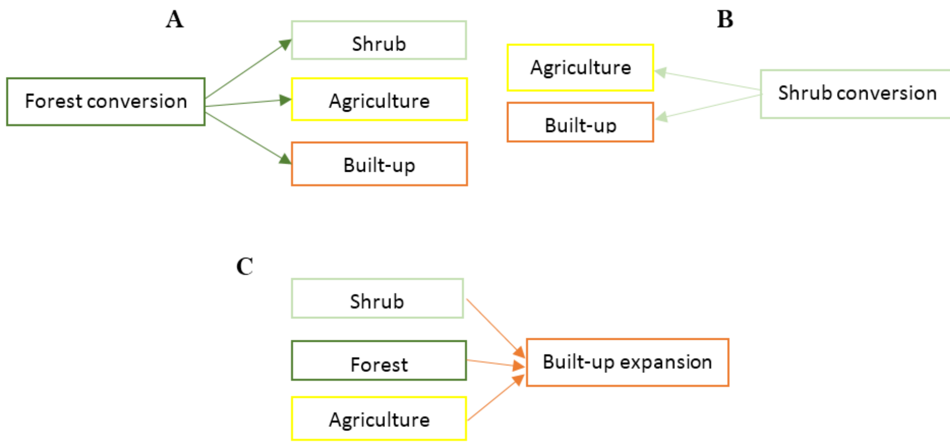


Figure 5.5: Three LULC conversions considered as the main proximate drivers of LULC changes over the study period.

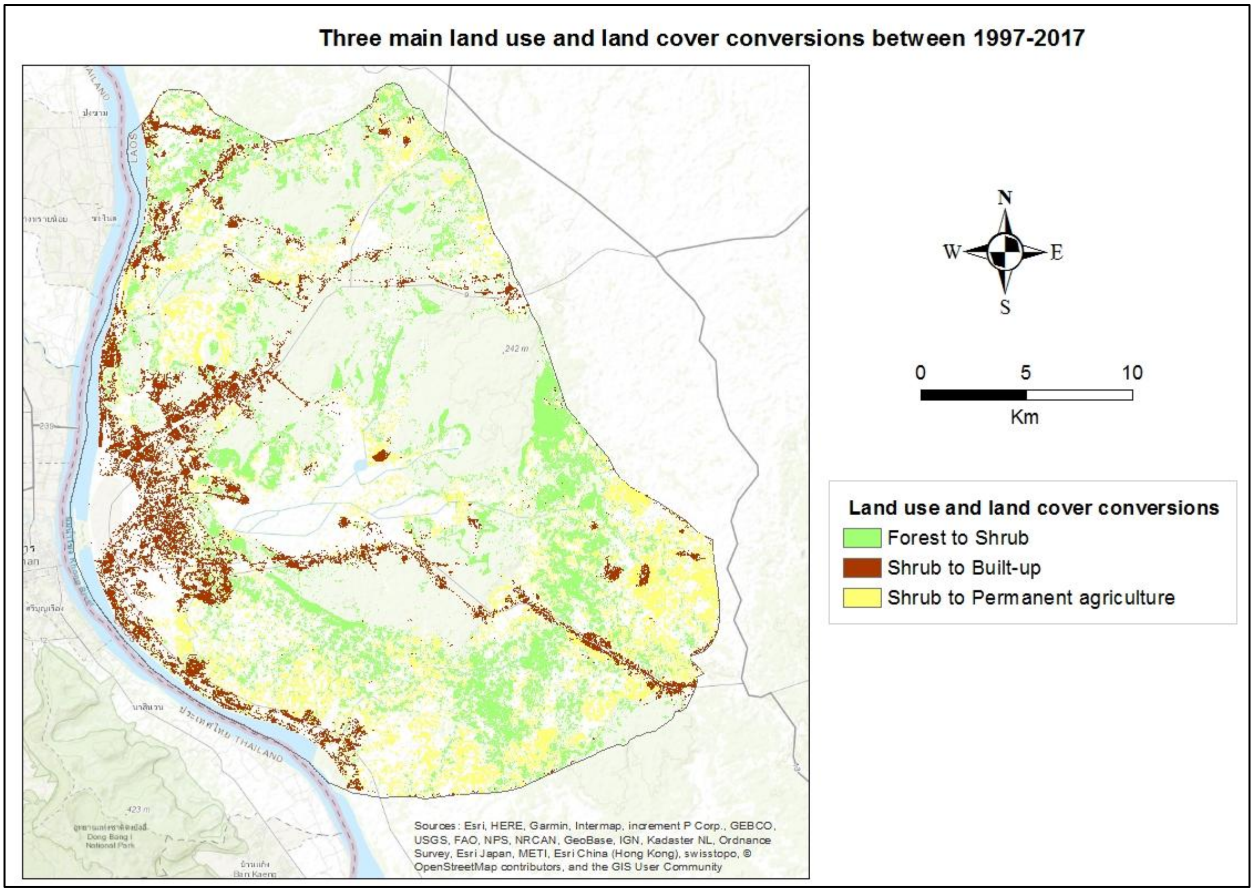


Figure 5.6: Three main LULC conversions map.

The three LULC conversions were used to analyze the spatial trends over 20 years that are showed in figure 5.7. The conversion trends were presented in polynomial order from the lowest to the highest value. A lower value means a less change and a higher value means that having more change (see Figure 5.7). The spatial trends of forest conversion to shrub areas were similar to shrub conversion to permanent agriculture areas, which the changes were mostly distributed from the southwest to the southeast of the study area where there were high forest and shrub coverages, as well as the changes also occurred in some parts of the northern study area. For shrub conversion to built-up areas, the spatial trend of the conversions was mostly inside and around the western part of the study area that is the main urban areas of Kaysone Phomvihan district.

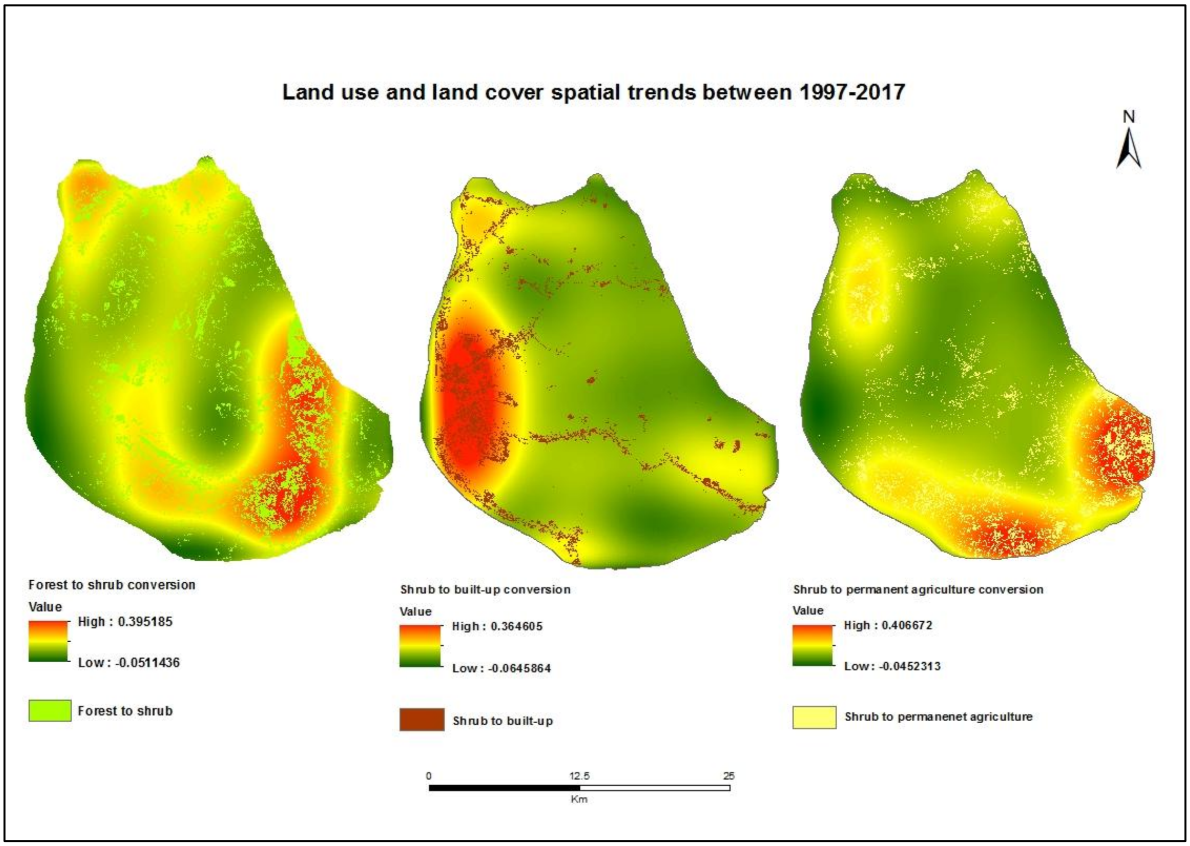


Figure 5.7: Spatial trends of the three LULC conversions map.

5.3. Multi binary logistic regression

5.3.1. Exploratory data

The correlation was tested by Pearson's correlation that showed the coefficient values of the independent variables with a low correlation but the population density in 2000, 2005, 2010 and 2015 had a high correlation with the coefficient values almost 1 (see Table 5.4). As mentioned in the Methodology chapter, the variables that have a correlation value between 0.50-1.00 will be excluded or not used together in each model of the MBLR. The moderately correlated coefficients were found in proximate to roads variable (-0.47 to -0,45), soil variable (-0.42 to -0.45) and proximate to town variable (-0.65 to -0.55). Therefore, the multicollinearity of the independent variables was tested by VIF in each model. If the VIF value of the variables exceeds 10, it will be removed from the models and for the variables are between 0-8, will be included in the models (see Table 5.5).

Table 5.4: Correlation test based on Pearson's rank.

	Pearson's rank												
Correlation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Population density 2000	1												
Population density 2005	**.922****	1											
Population density 2010	**.987****	**.931****	1										
Population density 2 015	**.893****	**.964****	**.901****	1									
DEM	-.27**	-.29**	-.24**	-.22**	1								
Rainfall	-.21**	-.21**	-.21**	-.22**	.264**	1							
Proximate to Roads	**-.47****	**-.46****	**-.46****	**-.45****	.15**	.343**	1						
Slop	-.01**	-.02**	-.01**	-.03**	.013*	-0.003	.011*	1					
Soil type	**-.42****	**-.42****	**-.43****	**-.45****	-.022**	.035**	.256**	.040**	1				
Temperature	.137**	.144**	.140**	.139**	-.143**	.036**	-.023**	-.015**	-.086**	1			
Proximate to town	**-.65****	**-.64****	**-.62****	**-.58****	**.550****	.356**	.160**	0.009	.251**	-.08**	1		
Proximate to villages	-.01**	-.01**	-.03**	-.02**	-.110**	-.159**	.017**	0.003	.189**	-.06**	-.059**	1	
Proximate to water source	-.28**	-.30**	-.27**	-.28**	.008**	.274**	.356**	-.015**	.205**	-0.006	.275**	-.024**	1

* Red color indicates that strong correlation between population density in 2000, 2005, 2010 and 2015
* Yellow color indicates that distance to roads variable has moderately correlated with population density 2000, 2005, 2010 and 2015
* Blue color indicates that soil variable has moderately correlated with population density 2000, 2005, 2010 and 2015
* Green color indicates that distance to town variable has moderately correlated with population density 2000, 2005, 2010 and 2015, and DEM variable

5.3.2. LULC conversion models

Coefficient and VTF value of the variables in each period that were significant to the three LULC conversion models are showed in Table 5.5. The odds ratios are when the independent variables increase, the probability of the dependent variables increase (LULC conversion) for example in period 1 showed the temperature increased 1 unit (in this case is mm), odds ratio increased 2.24 times of the probability that forest conversion to shrubland. For VTF values indicated a low multicollinearity between variables in each model that was less than 8 (see Table B.17-21 in Appendix for all statistical values).

The models were validated by considering pseudo R-square (Nagelkerke and Cox & Snell) (see Table 5.5), Receiver Operating Curve (ROC) and Area Under Curve (AUC) (see Figure 5.8). The pseudo R-square showed the percentage of the dependent variables that were explained by the independent variables. For ROC, if the curve is closer to left-top, the model is more accurate. The AUC indicated that a good fitting of the model. The following sections are an explanation of the three models in each period.

Forest to shrub conversion model

This model indicated that the most important periods were periods 4 and 3 that had more effect on the forest conversion to shrubland. In period 4, the variables that contributed to the conversion included temperature, population density, as well as proximate to town, roads and to water sources, which the conversion mostly occurred in the forest areas that are proximity to the highly populated urban areas, roads and water areas.

In period 3, the temperature, soil type, population density, proximate to urban and roads were significant in this model, especially the population density that increased 1.39 times of the conversion probability.

In periods 1 and 2 had the same variables such as temperature, proximate to urban and water sources. The temperature variables increased 2.24 times and 2.63 times the probability of the forest conversion. This happens because the temperature is climate determination of land use function that leads to the forest transition (MRC, 2009).

The overall period of this model can be concluded that the temperature, population density, proximate to town and water sources had contributed to the forest conversion. The proximate to the town and roads increased the probability with 2.17 and 2.05 times of the forest conversion. This means that good accessibility and infrastructure to the forest area had a higher probability of the conversion. Another important variable was the temperature that was included in all periods. The probability of forest to shrub conversion map over the study period that are based on logistic regression coefficients is showed in figure 5.9.

Shrub to agriculture conversion model

In this model indicated that the period 3 was the most important because the population density increased 2 times of the probability that shrub conversion to agriculture. Soil variable appeared in this period, which means that proper soil is important for agriculture activities, especially for industrial agriculture production in the study area such as rice, eucalyptus, vegetables (MRC, 2009).

In periods 1 and 2, the temperature variables increased 2.37 and 2.12 times the probability of shrub conversion. In period 4 was found that shrub areas that are near to roads and town with the high population density had the probability of the conversion.

The temperature, population density, as well as proximate to town, roads and water sources were important in the overall period of this model. Slope appeared in the overall period, which means that less steeper areas are important for agriculture purpose. The population density and accessibility (town, roads and water sources) increased the probability of agriculture expansion. The probability of shrub to agriculture conversion map over the study period is showed in figure 5.10.

Shrub to built-up conversion model

The most important periods were 3 and 4 that contributed to shrub to built-up conversion model. Both periods had the same variables such as climate conditions (temperature and rainfall), population density, and proximate to town and to water sources. In period 3, the temperature increased 1.16 times of the probability of shrub conversion to built-up areas. For the period 4, proximate to roads and temperature increased 1.64 times and 1.34 times of the probability of this conversion. Both periods have the same patterns of the conversions: the shrub areas that are near to the town and roads with high population density have the probability of built-up expansion.

In period 1, the proximate to town increased 1.7 times of the probability that shrub conversion to built-up areas that mostly occurred in the areas that are close to the city center (Kaysone Phomvihan district). For the period 2, the temperature increased 1.56 times the probability of the shrub conversion.

The overall period indicated that the climate condition (temperature and rainfall), population density and proximate to town, roads and to water sources (basic infrastructure) were important to the built-up expansion (see Figure 5.11 for shrub to built-up conversion). Slope variable appeared in the overall period, this might be related to flat areas in the study area are the purpose of urban expansion. The climate conditions (temperature and rainfall) are the determination of land use function, especially the sensitive climate areas had a higher risk of the forest and shrubland degradation and conversion (MRC, 2009). The infrastructure provides facilities and accessibilities to land use resources, which appear the proximate to town, roads and to water sources had highly contributed to built-up expansion in each period of this model. This can be referred to the development of infrastructure and accessibilities is correlated with urban growth and also leads LULC conversion (Geist and Lambin, 2002; Hosonuma et al., 2012; Kissinger et al., 2012). The better access to markets is correlated with land use conversion by infrastructure can trigger market development, cash crop adoption and economic growth. Infrastructure extension can be a component of rural development and settlement policies that drive market integration (Kissinger et al., 2012).

Table 5.5: Three LULC conversion models in each period.

Time Periods	Forest to shrub conversion model				Shrub to agriculture conversion model				Shrub to built-up conversion model			
	Variable	**Coefficient**	**Odds ratio**	**VTF**	**Variable**	**Coefficient**	**Odds ratio**	**VTF**	**Variable**	**Coefficient**	**Odds ratio**	**VTF**
1) 1997-2003	Temperature	0.80	2.24	1.87	Temperature	0.86	2.37	2.3	Temperature	0.53	1	2..28
	Proximate to town	0.20	1.23	1.16	Rainfall	0.02	1.02	1.24	Rainfall	0.03	1.03	1.24
	Proximate to villages	0.03	1.03	1.34	Population density 2000	0.01	1	1.62	Population density 2000	0.34	1	1.66
	Proximate to water sources	0.01	1.01	1.21	Proximate to town	0.01	1.01	1.1	Proximate to town	0.19	1.7	1.1
					Proximate to villages	0.04	1.04	1.57	Proximate to roads	0.05	1.	1.68
2) 2003-2007	Temperature	0.96	2.63	1.82	Temperature	0.75	2.12	2.26	Temperature	0.45	1.56	2.27
	Proximate to town	0.31	1.36	1.19	Population density 2005	0.54	1.08	1.5	Rainfall	0.04	1.06	1.25
	Proximate to water sources	0.08	1.09	1.28	Proximate to town	0.08	1	1.1	Proximate to town	0.08	1	1.11
					Proximate to roads	0.08	1.08	1.64	Proximate to villages	0.39	1.09	1.59
									Proximate to roads	0.45	1.02	1.7
									Proximate to water sources	0.06	1.06	1.19
3) 2007-2013	Temperature	0.33	1	1.98	Temperature	0.65	1.91	2.25	Temperature	0.15	1.16	2.18
	Soils	0.07	1.073	1.28	Soils	0.09	1.1	1.38	Rainfall	0.03	1.03	1.25
	Population density 2010	0.01	1.395	1.32	Population density 2010	0.67	2	1.42	Population density 2010	0.76	1	1.54
	Proximate to town	0.11	1.12	1.22	Proximate to town	0.06	1.06	1.11	Proximate to town	0.05	1	1.1
	Proximate to roads	0.04	1.04	1.28	Proximate to roads	0.03	1.03	1.58	Proximate to roads	0.01	1	1.61
					Proximate to water sources	0.11	1.01	1.24	Proximate to water sources	0.10	1.11	1.21
4) 2013-2017	Temperature	0.08	1.08	1.38	Temperature	0.61	1.85	1.27	Temperature	0.29	1.34	1.26
	Population density 2015	0.56	1	1.31	Proximate to town	0.08	1.09	2.2	Population density 2015	0.01	1	1.42
	Proximate to town	0.07	1.08	1.87	Proximate to roads	0.01	1.02	1.48	Rainfall	0.06	1.06	1.30
	Proximate to roads	0.08	1.08	1.25	Proximate to water sources	0.03	1.03	1.47	Proximate to town	0.01	1.04	2.141
	Proximate to water sources	0.07	1.08	1.32					Proximate to roads	0.44	1.64	1.50
									Proximate to water sources	0.02	1.02	1.48
Overall period (1997-2017)	Temperature	0.47	1.6	1.4	Temperature	0.97	2.65	1.25	Temperature	0.65	1.92	1.24
	Population density 2015	0.89	1.6	1.28	Population density 2015	0.23	1.06	1.3	Population density 2015	0.01	1	1.55
	Proximate to town	0.19	2.17	1.77	Slope	0.04	1.04	1.01	Rainfall	0.02	1.02	1.25
	Proximate to roads	0.05	2.05	1.27	Proximate to roads	0.01	1.01	1.51	Slope	0.18	1.2	1.01
	Proximate to water sources	0.03	1.03	1.29	Proximate to town	0.14	1.16	2.21	Proximate to town	0.08	1	2.13
					Proximate to water sources	0.01	1.01	1.49	Proximate to toads	1.09	1	1.58
									Proximate to water sources	0.13	1.13	1.14
	Nagelkerke R^2 = 0.160 Cox & Snell R^2 = 0.196				**Nagelkerke R^2 = 0.187 Cox & Snell R^2 = 0.275**				**Nagelkerke R^2 = 0.269 Cox & Snell R^2 = 0.428**			

From table 5.5 can be concluded that the most significant variable is a temperature that contributed to three LULC conversion models in each period. The temperature variable was extracted by LST from Landsat thermal infrared band (OLI, ETM+ and TM) over the study period, which is more accurate of the spatial resolution and land surface temperature in the study area. Zhou and Wang (2011) mentioned that LST derived from Landsat sensor is an accurate measurement of temperature and the LST result is a more reliable for LULCC because the derived temperature from Landsat sensor is an indication of the energy exchange balance between the atmosphere and the Earth that affected the surface attributes and is a good factor for explaining LULCC. The result of LULC conversion models was found the dependent variables (LULC conversion) were well explained by temperature in each model compared to other independent variables.

Many studies were also proved that LST derived from Landsat sensor is suitable and proper for LULCC studies, for instance, the study of urban heat island of Singapore (Winston and Matthias, 2006), urban heat island and shifting behavior in Delhi and Mumbai (Grover and Singh, 2015), the effect land use/cover change by LST in Netherlands (Youneszadeh et al., 2015), the impacts of LULCC on LST in the Zhujiang Delta (Qian et al., 2006).

Another important variable was the population density that significantly contributed to the models except for the periods 1 and 2 of the first model, the period 4 of the second model, and the period 2 of the third model, which the population density was not significant. This might be because of population density in 2000, 2005, 2010 and 2015 were highly correlated with other variables (see Table 5.4). When the independent variables are highly correlated, they influence predictive values of the variables and generate an uncertain of the model (Ott and Longnecker, 2010). Therefore, the overall period of each model was considered to include only one population density in order to avoid the correlation. Since, the result indicated that population density 2015 was significant in each overall period model (see Table 5.5).

5.3.3. Model validation

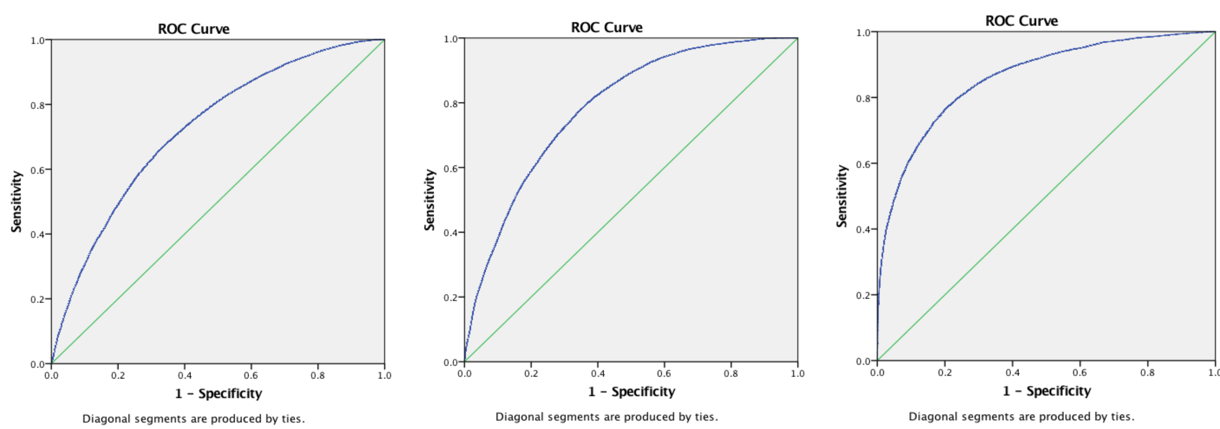
The model validation indicated that the most accurate model was in the third model (shrub to built-up conversion), the second model (shrub to permanent agriculture conversion) was moderate accurate and the first model (forest to shrub conversion) was less accurate.

In the third model showed R^2 (Nagelkerke R^2 and Cox & Snell R^2) with 26% and 43% of the dependent variable (shrub to built-up conversion) were explained by the independent variables (see Table 5.5). The AUC (0.87) indicated that the model was a good fitting and ROC curve was near to the left-top, which means the model was correctly classified between changed and not changed areas of the shrub conversion to built-up (binary 0= not change and 1= change)(see Figure 5.8).

The second model indicated R^2 of 18 % and 27%. The goodness fit of the model was satisfactory with AUC (0.78), and the ROC curve was between diagonal line and left top that presented the good model performance (see Table 5.5 and Figure 5.8).

The first model was the lowest in terms of R^2, AUC and ROC curve (see Table 5.5 and figure 5.8). The R^2 showed only 16% and 19% that were predicted by the independent variables. The AUC (0.72) indicated that the model was less accurate of the prediction between the dependent and independent variables. The ROC curve was closer to the diagonal line than left-top that presented the weak model.

A. Model 1 **B. Model 2** **C. Model 3**



AUC: 0.72 **AUC: 0.78** **AUC: 0.87**

Figure 5.8: The ROC and AUC of three LULC conversion models.

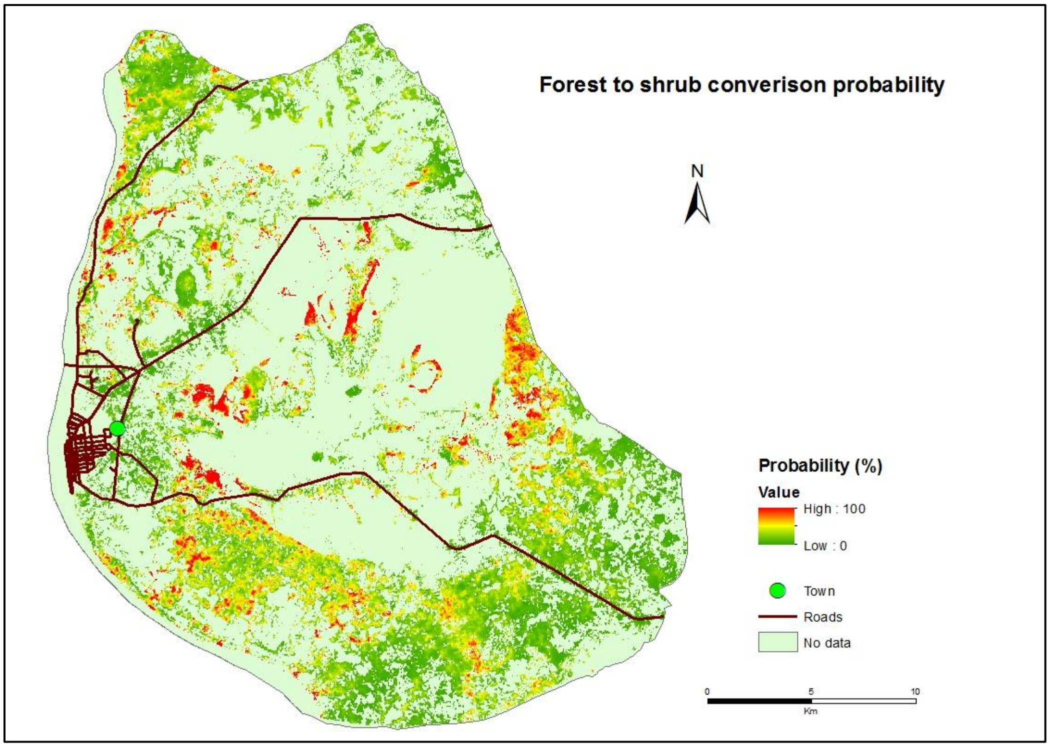


Figure 5.9: The probability of forest to shrub conversion over the study period.

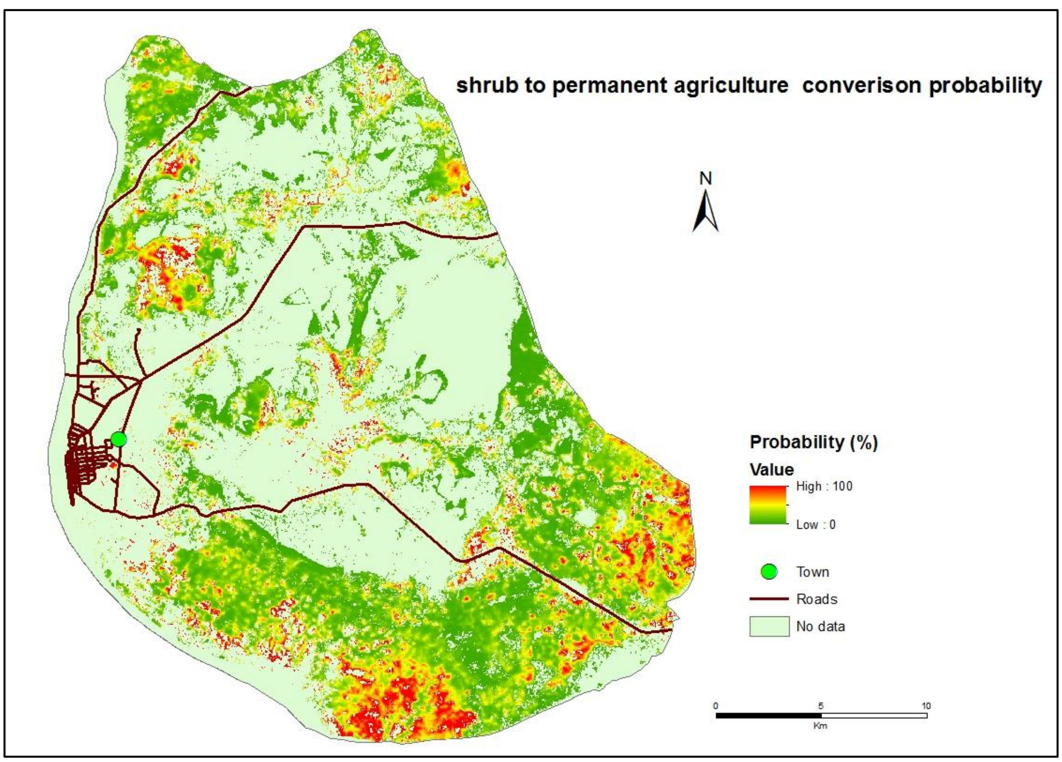


Figure 5.10: The probability of shrub to permanent agriculture conversion over the study period.

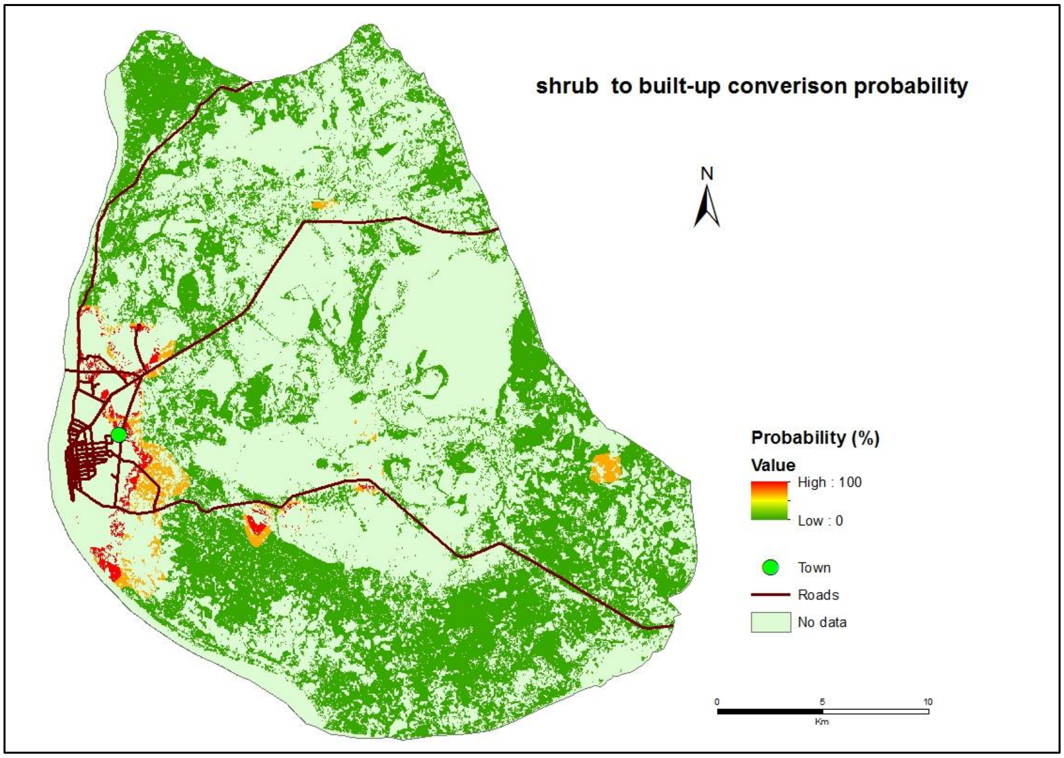


Figure 5.11: The probability of shrub to built-up conversion over the study period.

5.4. LULC simulation

5.4.1. Simulated LULC in 2017

As mentioned in Methodology Chapter (see section 4.6 in chapter 4) the simulated LULC of 2017 was conducted in order to estimate the accuracy and predictive ability of the model in forecasting LULC for 2022. The simulated LULC in 2017 was established from historical LULCC process by simulating LULC for time t1 (2007) and for time t2 (2013). The result was validated by comparing the simulated LULC map of 2017 and the reference LULC map of 2017 (classified LULC map in 2017). Therefore, if the validated result is accurate and reliable, then the LULC simulation for 2022 will be implemented.

The simulated LULC in 2017 was carried out in QGIS MOLUSCE plugin that is based on Cellular Automata, which analyzed the transitional potential of LULC between 2007 and 2013 to predict LULC patterns in 2017. In table 5.6 shows the differences of permanent agriculture and forest areas between the reference map of 2017 and the simulated map of

2017 that were 27 km^2 . For built-up and shrub areas were slightly different around 8.29 km^2 and 7.20 km^2 between both maps. As can be clearly seen in figure 5.12 that forest had increased in the simulated map of 2017. The increase of shrub areas occurred in small pixels that cannot be noticed on the map.

Table 5.6: Changed areas in km^2 and in % between the reference LULC map 2017 and the simulated LULC map 2017.

Classes	Reference LULC map 2017		Simulated LULC map 2017		Change detection
	Area km2	%	Area km2	%	Area Km2
Permanent agriculture	175.40	25.01	148.11	21.12	-27.29
Built-up	114.80	16.37	106.51	15.18	-8.29
Forest	176.06	25.11	203.45	29.014	27.39
Shrub	214.24	30.55	221.44	31.58	7.20
Water	20.68	2.95	21.70	3.094	1.02
Total	701.18	100.0	701.18	100	

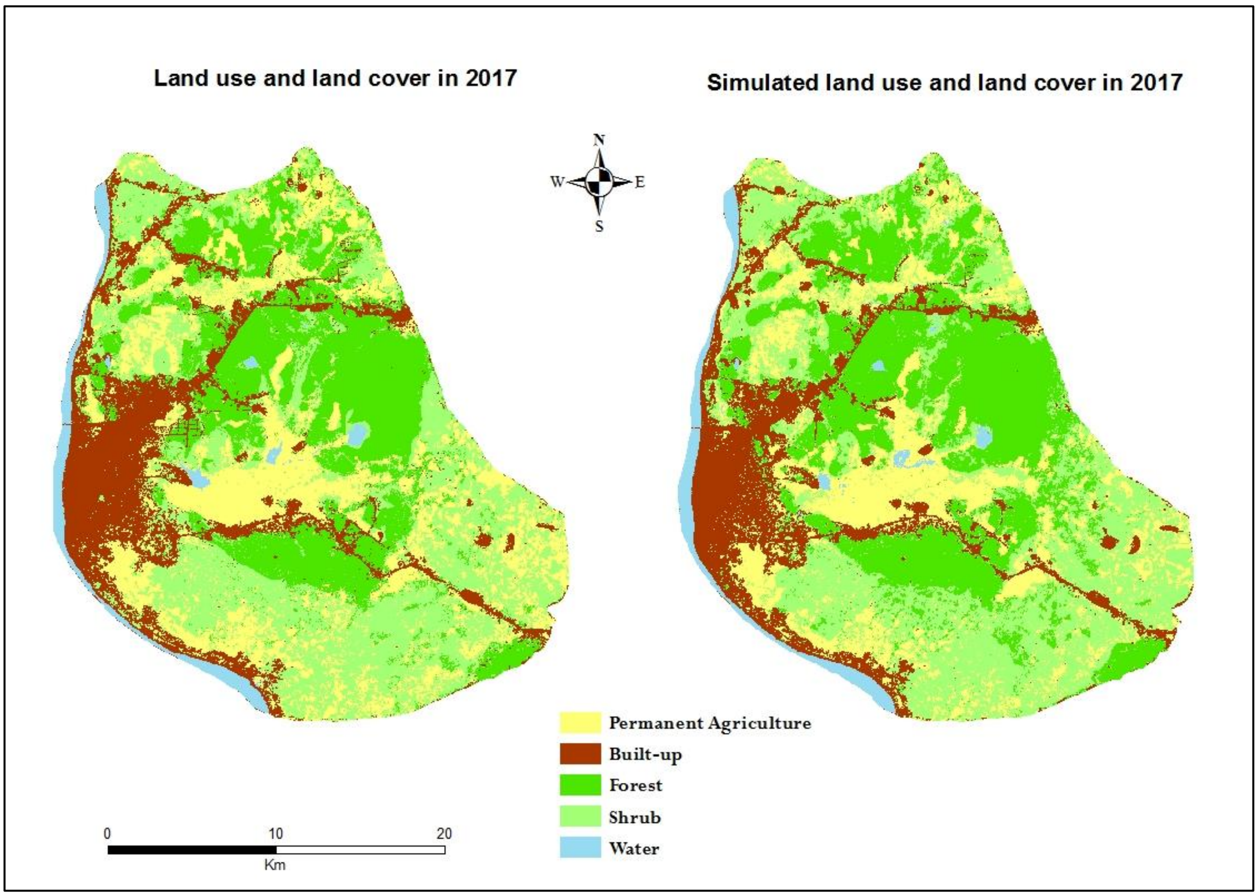


Figure 5.12: The Reference LULC map 2017 and the simulated LULC map 2017.

For validating the output of the simulated LULC map in 2017, two maps were compared the reference LULC map of 2017 and the simulated LULC map of 2017. The validation was based on kappa statistic and multiple-resolution. The kappa statistic is showed in table 5.7 that includes kappa histogram (0.932) that is an estimation of frequency distribution of the simulation, Kappa location (0.754) that is the simulation's ability to perfectly specify location between the reference map and the simulated map, and Kappa overall (0.703) that is the total accuracy of the number pixel correctly classified between the reference map and simulated map. All of these Kappa values can be referred to Landis and Koch (1997), which explained the kappa value range. The value between 0.61-0.80 corresponds to a moderate agreement between the reference map and the simulated map, the value between 0.81-1 corresponds to almost perfect agreement in both maps. For the total correctness value is 77.72%, which indicates that the moderate accuracy of the simulated LULC map in 2017.

The multiple resolution is the accuracy in location and in quantity of the reference map and the simulated map that correspond to the agreement and disagreement component between two maps (Pontius and Suedmeyer, 2004). In figure 5.13 appears 4 types of the plots but the most important plot is "perfect location, medium quantity inform" where the plot is almost 1 (back color line in figure 5.7). This presents the perfect location and medium quantity information are almost 100% between both maps. According to Pontius and Suedmeyer (2004), the perfect location is a grid cell level information of the reference map that has a perfect location in the simulated map and for the medium quantity is the reference map that has the same quantity as the simulated map. So, the perfect location and medium quantity information are considered as a good agreement for the simulated map in 2017. Both Kappa statistics and multi resolutions of the simulated LULC map in 2017 are acceptable accuracies and good predictive ability of the LULCC model. Therefore, the simulated LULC in 2022 was implemented (see section 5.4.2).

Table 5.7: Kappa and correctness of the simulated LULC map in 2017.

Simulated LULC map in 2017	
Correctness	77.72 %
Kappa (overall)	0.703
Kappa (histogram)	0.932
Kappa (location)	0.754

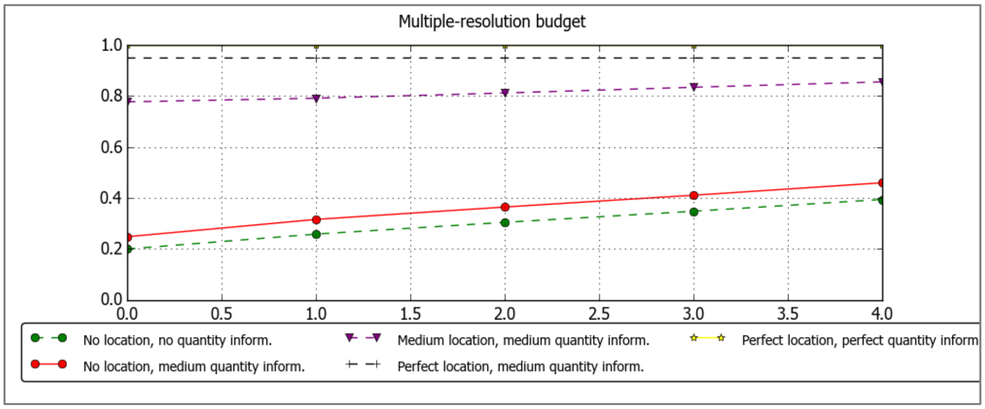


Figure 5.13: Multi-resolution included 4 plots of simulated LULC in 2017.

5.4.2. LULC simulation for 2022

The simulated LULC in 2022 was done through the Cellular Automata simulation of LULC transitional potential between 2013 and 2017 to predict LULC for the next five years (2022). The result of LULC simulation in 2022 is showed in table 5.8. The dominant area is shrub class (220.55 km^2), followed by forest (171 km^2), agriculture (167.13 km^2), built-up (122.12 km^2) and water (20.32 km^2).

The built-up and shrub classes in 2022 are estimated to increase 7.32 km^2 and 6.31 km^2 (1.04% and 0.9%) but the agriculture and forest classes are estimated to decrease -8.27 km^2 and -5.06 km^2 (-1.18% and -0.72%). When comparing LULC maps of 2017 and 2022, there are slightly different between them. The built-up areas present a pronounced change as can be clearly seen in figure 5.14. The built-up areas expanded inside and around the urban areas and road network, which mean that the expansion was mostly affected by these spatial variables such as proximate to roads, town and the population density. For other changed areas are a smaller scale that cannot be noticed on the map.

Table 5.8: Changed areas in km^2 and % between LULC in 2017 and LULC in 2022.

Classes	LULC in 2017		LULC in 2022		Change	
	km2	%	Km2	%	Km2	%
Permanent Agriculture	175.40	25.01	167.13	23.84	-8.27	-1.180
Built-up	114.80	16.37	122.12	17.42	7.32	1.044
Forest	176.06	25.11	171.00	24.39	-5.06	-0.722
Shrub	214.24	30.55	220.55	31.46	6.31	0.900
Water	20.68	2.95	20.32	0.24	0.36	0.051
Total	701.18	100.0	701.18	30.1	27.32	10.34

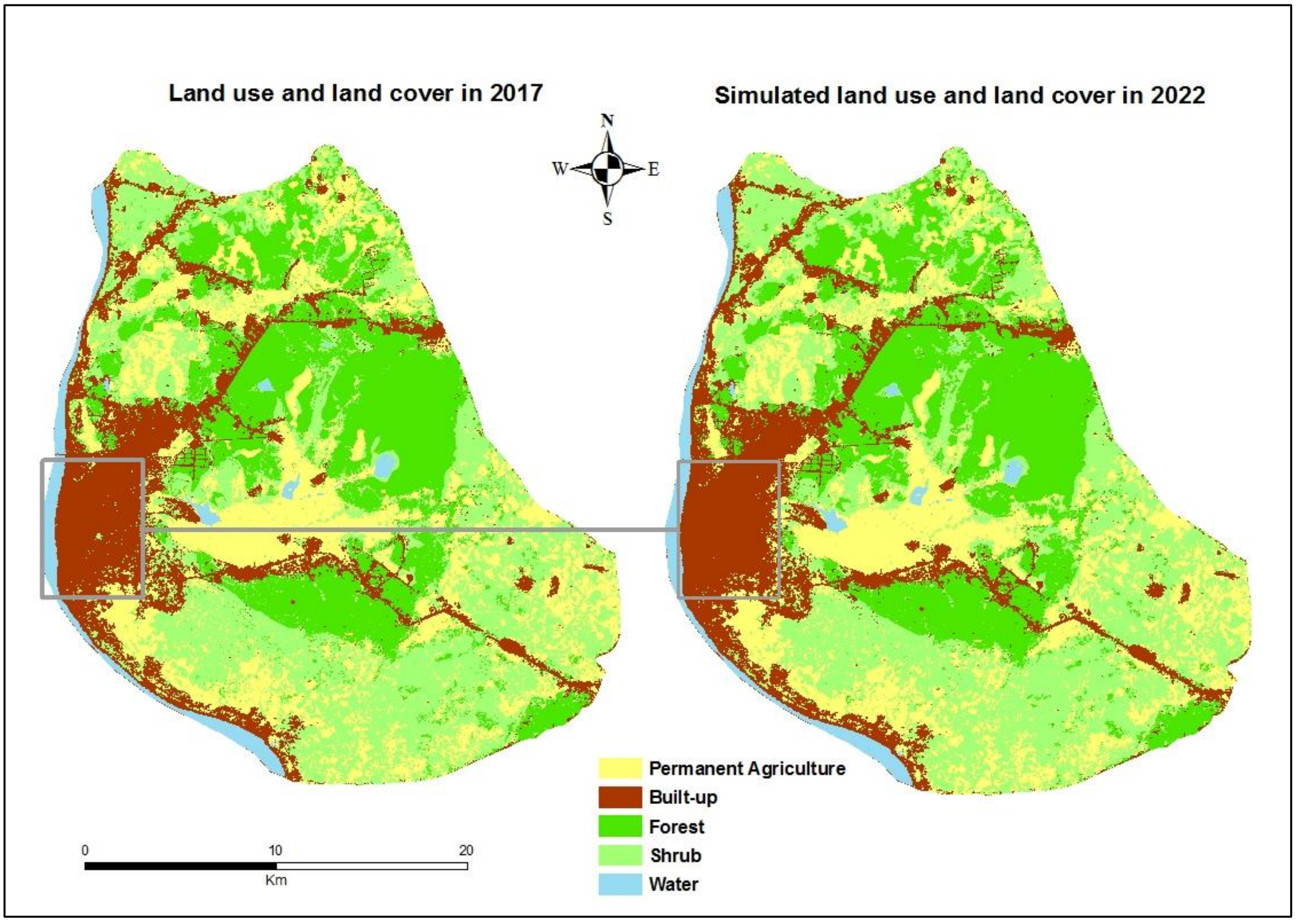


Figure 5.14: LULC map 2017 and simulated LULC map 2022.

The result of LULC transitional potential between 2017 and 2022 is showed in table 5.9 and figure 5.15. Large LULC conversions are similar to the overall study period that included shrub to agriculture conversion with 43.57 km^2, forest to shrub conversion with 30.90 km^2, shrub to built-up conversion with 13.31 km^2 (see table 5.9). These mean that in responding to economic growth and urban process in 2022, the potential forest and shrub areas will be converted to multi land use functions, especially for agriculture and built-up purposes that may affect to land use and natural resource in the future.

Moreover, figure 5.16 presents the probability percentage of LULC conversions. According to Mkrtchian and Svidzinska (2016), a lower percentage is an uncertain area on the time of simulation and has the probability to the conversion, and for a higher percentage is the certain area on the time of simulation and lower probability of the change. Therefore, from figure 5.16 can be concluded that the areas with low percentage have a high probability of the change, and for high percentage areas mean less probability of the conversion in the simulated LULC of 2022.

Table 5.9: LULC class conversions between 2017-2022 in km^2.

	2017					
	Classes	PA	BU	F	S	W
2022	PA	**124.98**	0.88	5.20	**43.57**	0.83
	BU	7.20	**87.58**	5.85	**13.31**	0.87
	F	3.40	0.82	**148.93**	22.88	0.05
	S	3.40	1.29	**30.90**	**164.38**	0.38
	W	0.73	0.08	0.03	0.26	**19.57**

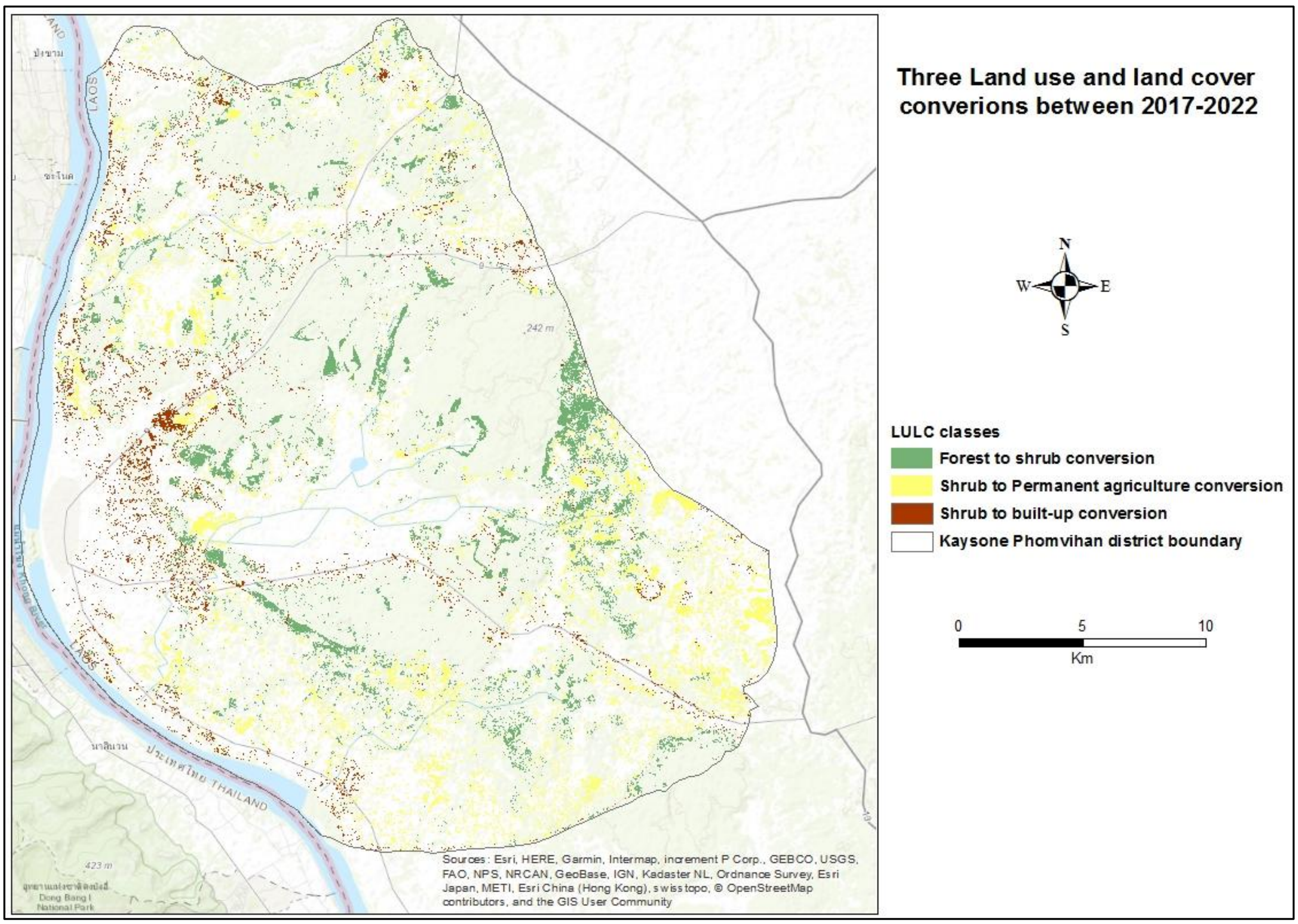


Figure 5.15: Three main LULC conversions map between 2017-2022 based on Cellular Automata simulation.

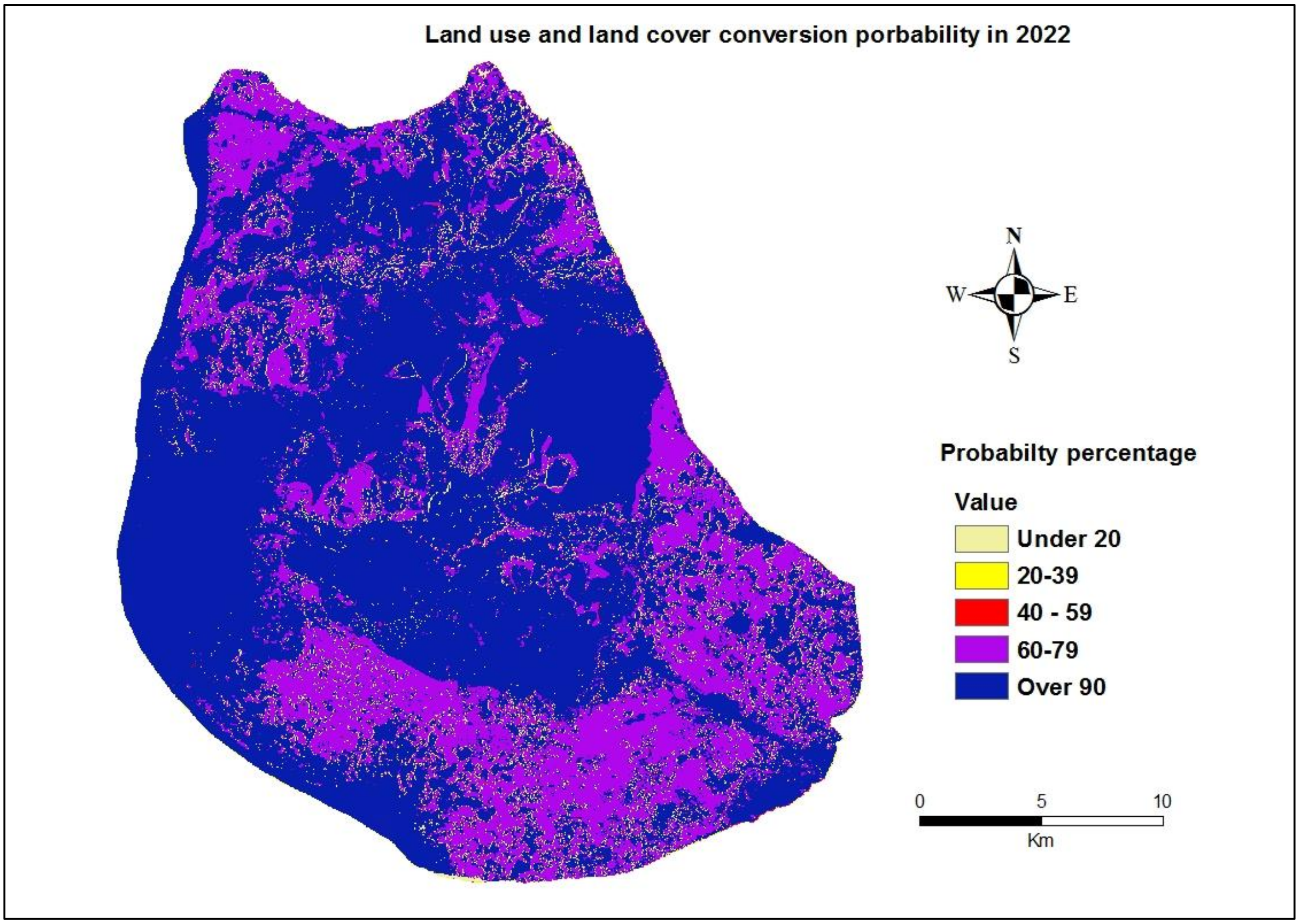


Figure 5.16: LULC conversion probability 2022 indicates in percentage from the highest (certain areas) to the lowest (uncertain areas).

Chapter 6 - Discussion

6.1. Satellite image classification

This thesis analyzed LULCC the in Kaysone Phomvihan district by utilizing satellite images classification (Landsat data). In which, uncertainties generated at different stages in a procedure have influenced the classification accuracy and area estimation of LULC classes (Canters, 1997; Friedl et al., 2001; Dungan, 2002). Another impact is the spatial resolution that affects in the classification method and accuracy (Chen et al. 2004). This study used Landsat images from the different sensors: TM, ETM+ and OLI that have a medium spatial resolution (930x930m). Strahler et al. (1986) explained that H- and L-resolution (high and low-resolution) have an impact in the classification process. In the fact that, the scene elements in the H-resolution images are larger than the resolution cell and can, therefore, be directly detected. In contrast, the elements in the L-resolution image are smaller than the resolution cells and are not detectable. For the medium spatial resolution data such as Landsat TM/ETM + and OLI are attributed to the L-resolution images. Mixed pixels are common in these data that can lead to inaccurate classification results.

This study found that permanent agriculture and built-up were the most of LULC classes that had the mixed pixels. The agriculture class did not show an explicitly spatial pattern, which it was mixed with other class pixels. According to Václavík and Rogan (2009), the category of agriculture is normally the most problematic class at the medium spatial resolution because it represents a mixture of various crops in different periods as well as bare soil (plowed fields). The built-up class had no obvious pattern and most areas were mixed with other classes such as forest, permanent agriculture and shrub. According to Zhou et al. (2009), mapping accurate pattern of the urban area is a challenge. Using high spatial resolution images from satellite sensors such as IKONOS and QuickBird are more accurate.

For the reliable classification results, the accuracy assessment was performed. Lu et al. (2004) noted that the accuracy of change detection results highly depends on many factors such as the complexity of landscape of the study area, the change detection methods or algorithms, and availability and quality of ground truth data. However, the accuracy assessment in this study was implemented without the ground truth data from the fieldwork and it was computed with random sampling points. Since the built-up, agriculture, shrub and water classes of each image had sampling point less than 20 pixels, which made the results not statistically validated (Congalton and Green, 2008). For the overall accuracy, as mentioned by Anderson et al. (1976), the minimum overall accuracy value computed from an error matrix should be 85%. However, some authors mentioned lower values of overall accuracy (e.g., 75%). The overall accuracy of the first and second classified LULC maps in this study were lower than 85% that less accurate results and the rest classified LULC maps were higher 85% with acceptable results.

6.2. LULCC drivers

6.2.1 Proximate drivers

This study found that forest and shrub areas presented the highest losses with 146.54% and 129% in the overall study periods but the built-up and agriculture presented the highest increase areas with 97% and 99% respectively. The foremost LULC conversions were: forest to shrub conversion; shrub to agriculture conversion; and shrub to built-up conversion. These conversions were identified as the proximate driver of LULCC in the study area.

The forest in Kaysone Phomvihan district had the highest loss of 56.45% during 2003-2007 due to the conversion to shrub areas. This corresponded to the total forest loss in the whole Savannakhet province that was about 60% of a total area in 2005. The loss of forest land use mainly occurred in these districts: Kaysone Phomvihan, Champhone, Outhoumphone, Xayboury, Atsaphangthong, Sephonh and Songkhone (UNDP, 2011). According to PDPI (2009), Savannakhet has experienced forest and rich forest losses, and poorly stocked areas due to deforestation and wood industry, especially deforestation are the main cause of the forest and natural resource degradation. As explained by Geist and Lambin (2001), the tropical deforestation is caused by multiple proximate factors that are the combination of wood extraction, agricultural expansion and infrastructure expansion, particularly commercial wood expansions in mainland Asia and Southeast Asia are fluently reported. Therefore, in case of the forest conversion to shrubland in the study area was identified that caused by the deforestation.

Shrub to agriculture conversion increased over 20 years from 9.77% in 1997 to 21.86% in 2017. This result is related to agriculture production expansion and investment in the district such as rice, maize, vegetable, and industrial crops like sugarcane, rubber, acacia and eucalyptus. According to UNDP (2011), agriculture was the main economic sector in Savannakhet province that contributed to 52.32% of the total economic sectors in during 2000-2010, especially agriculture production from Kaysone Phomvihan, Outhoumphone and Songkhon. This can be concluded that the shrub conversion is mainly caused by agriculture expansion that is one of the proximate drivers of LULC changes in the study area.

Shrub to built-up conversion is related to the urban expansion because of the built-up areas dynamically increased more than 10 times compared from the year 1997 (15.51 km^2) to the year 2017(114.80 km^2). The built-up areas were expanded around Kaysone Phomvihan district, alongside the Mekong River and road network. This was proved by the research of Nolintha and Masami (2011) that Kaysone Phomvihan's urban transformation on the north-south axis, along the Mekong River and parallel streets that gathered administrative buildings, equipment, residential areas, main market and temples.

6.2.2. The underlying drivers

The underlying drivers have an influence in LULCC, which resulted from the complex interaction of social, political, economic, technological and biophysical variables (Geist and Lambin, 2002). It is not possible to capture all of these interactions, especially the social, economic, political, and technology due to this study timeline and scale. Therefore, this study only considered biophysical and socio-economic variables.

The biophysical variables were rainfall, temperature, elevation, slope and soil types. The socio-economic variables included the population density and proximate to roads, urban areas and water sources, even these variables are not directly as socio-economic but can be identified as the related factors that provide facilities to access market and economic development (Swart, 2016).

Multi binary logistic regression was applied to analyze the relationship between LULC conversions and the independent variables in three different models: forest to shrub conversion (deforestation); shrub to agriculture conversion (agriculture expansion); and shrub to built-up conversion (built-up expansion).

The pseudo R-square revealed that all models presented weak performances. The lowest pseudo R-square presented for the first model where only 16% and 19% of the dependent variable (forest to shrub conversion) were explained by the independent variables (biophysical and socio-economic). The highest pseudo R-square was obtained in the third model with 26% and 42% were explained between both variables. These weak performances can be explained by the poor data quality of both the dependent and the independent variables such as less inaccurate of the LULC classification (as discussed in section 6.1) and the quantification of the biophysical and socio-economic variables was difficult due to the data limitation and unavailability. For instance, the population density is an estimation of population number that not corresponding to real population figure in the study area, as well as road network, water sources data that were not updated over the times.

According to Swart (2016), the drivers cannot be incorporated in the models because of the absence of spatial data and the difficulties of quantifying some variables and some missing variables such as poverty, technological changes, environmental governance and policies, international drivers and behaviour of people. The economic, social, cultural and political drivers have influenced each other, they interact and do not operate independently in the model (Geist and Lambin, 2001).

6.3. LULC conversion models

6.3.1. Forest to shrub conversion

This model indicated that the socio-economic variables had more contribution to the conversion than the biophysical variables. The socio-economic variables significantly contributed to this model such as proximate to town and population density increased 2.17 times and 1.6 times the probability of the forest conversion that caused by the deforestation. Geist and Lambin (2005) mentioned that socio-economic factors are prominent underlying forces of tropical deforestation. Commercialization and growth of mainly timber markets (as driven by national and international demands) have driven the deforestation. Moreover, the population growth and economic development lead to land use and natural resource demands that play a role as the drivers of deforestation and forest degradation.

Temperature variable was the only one of the biophysical factors that contributed to forest conversion due to Kaysone Phomvihan district is located at the hottest area in Laos. High temperature has an impact in the fertilization of forested areas and led to the conversion. In Laos, an increase of annual temperature is predicted to impacts environmental change and ecosystem service, especially in the Mekong river basin, an increases temperature have affected to land degradation and soil erosion as well as changes of vegetable cover type from forest to grassland shrubland and agriculture land that occurred in large landscapes of the Mekong River basin (MRC, 2009).

6.3.2. Shrub to agriculture conversion

Both biophysical and socio-economic factors played a role in shrub conversion to agriculture. The socio-economic was pronounced factors to drive agriculture expansion such as population density, proximate to town and water sources were significant to the model, and they increased the probability of shrub conversion. Serneels and Lambin (2001) pointed out that the conversion to agriculture is controlled by the proximity to the market, as a proxy for transportation costs, and agro-climatic potential. The accessibility to main roads and proximity to markets (urban areas) are important variables in explaining agriculture expansion in Kaysone Phomvihan district (Nolintha and Masami, 2011; UNDP, 2011).

Slope and temperature variables were the biophysical factors that contributed to agriculture expansion. The slope relates to flat areas in Kaysone Phomvihan district is the purpose of agriculture expansion because of easier access to facilities such as markets, water supply, etc. For each unit of temperature increases, it increased 2.65 times of the probability of shrub conversion to agriculture. This can be explained by shrub land modification is influenced by the sensitivity to climate fluctuations and determining land use functions (Serneels and Lambin, 2001).

6.3.3. Shrub to built-up conversion

Shrub to built-up conversion revealed that high population areas that are near to the town, roads and water sources were converted into built-up areas. These areas are likely urban areas of Kaysone Phomvihan district that have the high population density and are close to the Mekong River. This can refer that the expansion of settlements is controlled by land concession such as proximity to permanent water, location near an economic development center, tourism market and vicinity to town that can access to social services and facilities (health clinics, schools, local market) (Serneels and Lambin, 2001). In case of Kaysone Phomvihan district is the city center that includes Special-Specific Economic Zone, commercial center and facilities such as Center hospital, University, schools and others). The slope increased 1.2 times the probability of shrub conversion, which means that flat areas in the western district are the urban expansion purpose.

6.4. LULC simulation.

The LULC simulation for 2022 was based on the Cellular Automata. The validation of the model accuracy is needed, in order to achieve acceptable accuracy, this study had employed an approach to simulate LULC of 2017 (time t3) from the historical LULCC process for time t1 (2007) and for time t2 (2013) and then the simulated result was compared to the reference LULC map of 2017 (classified LULC map 2017). Since, the reference map is usually considered more accurate in the study area at time t3 (Dushku and Brown, 2003; Ponstius and Chen 2006). The simulated LULC in 2017 was successful in both correctness value and multi resolution. The correctness value was 77.72% that is a good agreement between the reference map and the simulated map. The multi resolution indicated the perfect location and medium quantity information between the reference map and the simulated map, which means that the historical LULCC process from 2007 to 2013 is accurate and reliable to predict LULC patterns in 2022. However, the validation of the simulated map is a challenge because there is no criterion to assess the performance of the different LULCC models. Another problem is parameters to indicate the overall accuracy, parameters for comparing different modelling results and the minimum accuracy standard (Pontius and Chen, 2006). Therefore, this research was considered to simulate LULC for short-time period

(2017-2022) because as Araya and Cabral (2009) mentioned that short-term prediction is more reliable than long-term due to is not easy to assess the accuracy of the long-term simulation.

The result of simulated LULC in 2022 showed a number of the areas in each LULC class were slightly different compared to the years 2017. The built-up and shrub areas increased 7.32% and 6.31%. The forest and agriculture areas decreased -5.06% and -8.27%. These indicate that in 2022, natural forest and agriculture areas will decrease. This has corresponded to reporting from Savannakhet PDPI that forest is decreasing and has been converted to other lands illegally and legally. The agricultural is shrinking because of agriculture sector is being replaced with industry and service sectors (ADB, 2012).

The built-up areas trend to increase over the time because the local government is making the fundamental factors for the future development and population flow from rural villages to the sub-urban areas that are vicinity of the town center because over next decades (2020-2030). Kaysone Phomvihane district envisions are becoming the international and regional core city for increasing trade and flows of people, goods and services along the East-West Economic Corridor (EWEC) (ADB, 2012).

6.5. LUCC and spatial planning challenges

From the result of LULCC analysis over the study periods indicated that forest and shrublands had the highest losses and built-up and agriculture are the highest increase areas, which encourage land use planners to have more concern on land use management and planning.

Urban planning terms may have been concerned more on land use changes because of ADB (2012) mentioned that the core problem in urbanization of Kaysone Phomvihan district is inadequate infrastructure and insufficient concern for environmental impacts. This results in disorganized growth, inefficient land use, damage and loss of natural resources and inadequate access to urban services. Therefore, land use management and planning should be focused on both contexts of urbanization, and environmental and natural resource protection in the district.

In terms of the urban planning, the Urban Master Plan was approved in 2001 and The updated Kaysone Phomvihane SEDP (see section 3.3 in chapter 2) are established to provide sufficient urban infrastructure, and formulate a planned development to meet the demands from increasing trade and traffic flows along EWEC of the district (ADB, 2015; Nolintha & Masami, 2011). Their development visions are to become “a socially responsible, environmentally friendly and economically successful town” in order to be the economic center for increasing trade and investments in the East-West Economic Corridor road. All of these through the provision of adequate urban and infrastructure and essential services to facilitate growth and increase urbanization (ADB, 2015; Nolintha & Masami, 2011; Reid, 2015). The urbanization has corresponded to the result of the spatial trends of urban expansion occurred in the western of the district alongside Mekong River and road network. Especially, in SSSEZ and around the Thai-Lao friendship bridge, the development projects covered the 600 ha over past decade, and land use around these projects are being converted to economic and residential zone. In responding to the urban growth, local government has set out the different land use zone categories for agricultural production, industrial zones, commercial and residential areas in the updated urban master plan (Reid, 2015).

However, this urban plan does not cover the natural land use context, even the study found that forest and shrub lands are close to urban areas increased the probability of urban expansion. Since, the urban land concession of local people leads them to access a new land likely richer forest and shrub lands, which make further issues of land use conversion.

In terms of natural forest and shrub land uses have been protected through Land and Forest Allocation program (LFA) and the relevant law such as Law of forest and Environmental protection Law, but it seems these laws are not compliant with forest management because the study indicated that forest and shrub lands still have high rates of losses and their trends of losses are still increasing in 2022. According to Tong (2007), the LFA achievement is limited and various obstacle policy because of LFA is constraint of Lao policies are oriented towards economic development such as land concessions, timber extraction, commercial agriculture explanation and forest production that highly benefit to national economic development, which leads the LFA has not enough attention in the practical context.

Therefore, the different of land use management context between urban and natural land use, as well as the inefficiency of law enforcement in the study area can lead the gap in administrative level and inefficiency of land use management between local government and community in the study areas. In which, it has encouraged policy makers to reconsider on their land use planning and the laws that are more appropriate in the practical terms for sustainable land use management.

Chapter 7 - Conclusions and Recommendations

7.1. Conclusions

The changes of LULC caused by direct and indirect human activities have a wide range of consequences at spatial and temporal scales. Understanding LULCC patterns and the driving forces are needed to project LULCC processes and spatial trends, which will provide relevant knowledge that is a useful guideline for decision-makers at the national and local government, and civil society. This study was conducted to analyze LULCC and the driving forces over 20 years (1997-2017), as well as simulating LULCC for the year 2022 in Kaysone Phomvihan district by using RS data and GIS combined with statistical analysis and LULCC model.

This research started with the satellite image classification for the years 1997, 2003, 2007, 2013 and 2017 into five LULC classes: permanent agriculture, built-up, forest, shrub and water. Then, characterizing LULCC and spatio-temporal trends of the proximate drivers, and quantifying the underlying drivers of biophysical and socio-economic variables for further analysis. MBLR was applied in order to analyze the relationship and interaction between the proximate and underlying drivers in terms of cause and effect over the study period. The last section corresponds to the analysis of spatial transitional potential and LULCC prediction for 2022 through Cellular Automata simulation.

Based on LULCC analysis over 20 years was found that forest and shrub areas had the highest losses. Built-up and permanent agriculture areas had the highest increases. The highest conversions of LULC classes were: forest to shrub conversion (deforestation); shrub to agriculture conversion (agriculture expansion); and shrub to built-up conversion (urban expansion). These three conversions were considered as the proximate driver of LULCC.

The spatio-temporal trends of deforestation and agriculture expansion occurred from the southwestern to the southeastern areas of Kaysone Phomvihan district where there is high coverage of the forest and shrub areas. For built-up expansion's trends occurred in the western of the district alongside the Mekong river, as well as on the areas that are close to the road network.

The MBLR revealed that both biophysical and socio-economic factors had significantly influenced the three LULC conversion models that can be concluded that: 1) forest to shrub conversion the socio-economic factors had an effect on the forest conversion that identified as the deforestation that occurred in the areas that are vicinity to road network and town with high population density. In which, good accessibility to forest areas and had a high risk of the deforestation; 2) shrub to agriculture conversion had an impact from both factors that caused from agriculture expansion, especially in the areas that can access to markets, transportation, water sources and labor (population) are mostly converted to agriculture croplands; 3) shrub to built-up conversion had been driven by both factors to urban expansion because the population and economic growth over few decades in Kaysone Phomvihan district, which led to establishing new urban areas and infrastructure development (roads, schools, hospitals etc.) that occurred mostly in the areas where proximate to the western district that is landscape and high potential economic development.

The LULC simulation for 2022 was carried out and the result was satisfactory. In 2022, forest and permanent agriculture areas will decrease -1.18% and -0.72% compared to LULC in 2017, but built-up and shrub areas will slightly increase 1.04 % and 0.9%.

The transitional potential in 2022 indicated that forest loss is mainly due to the forest conversion to shrubland that will consequence from the deforestation. Agriculture land loss will result from the urban expansion (permanent agriculture to built-up conversion) Both LULC losses imply that high economic growth and land demands for urban developments in the district is due to in responding to the Government policy in ”Turning lands to capital” this is needed policy-makers to reconsider on land use planning, especially improving urban master plan that covered both urban and natural land use context, as well as increasing the efficiency of the relevant laws enforcement for sustainable land use management in the future.

7.2. Limitations and recommendations

7.2.1. Limitations

The main limitations of this study are related to data acquisition and analysis process. Most of the data were based on online sources such as satellite images and spatial data. The main limitations are:

1) Data of the proximate driver: LULC maps were produced from Landsat satellite images classification that are the medium spatial resolution sensors and the study area is small scale, which gives the mixed pixels in each LULC class. Since, the mixed pixels create a problem in the medium spatial resolution image, based-pixel classifier has difficulty dealing with them, as well as uncertainties generated in each step of the classification method have influenced the result. Validating the results were difficult due to lacking reference maps and absence of the fieldwork. Therefore, the accuracy assessment is only based on satellite image references.

2) The underlying drivers: only were considered socio-economic and biophysical variables because LULCC processes are complex and difficult to capture all the drivers. Even analyzing two variables are still limited because of availability and accessibility of these data. For example, only the road network, water sources and administrative boundary data were obtained from an official source, but these data were not updated over the times. The population density used the global data that is an estimation of the population number, which is less inaccurate and not corresponding to the real population figure in the study area. Rainfall data acquired from online sources, the data is an average precipitation over the 50 years from 1950-2000.

7.2.2. Recommendations

This thesis addressed the potential of GIS, RS and modelling tools for analyzing LULCC and the relationship between the drivers in order to predict LULCC in the future. Therefore, based on the findings of this study, these followings are recommended to:

Implementer

1) The current trends of urban land use and on-going economic development will have remarkable impacts on the surrounding land resources. These results will assist policy makers and decision makers to reconsider on their current and future economic development plans to integrate with land use management, especially improving urban master plan on the infrastructure development for East-West Economic Corridor project in Kaysone Phomvihan district in order to avoid future of urban sprawl.

2) These results can be used as a guideline for the environmentalist to investigate impacts of land use change and urban growth to natural resources and ecological service systems, as well as an effect to people's livelihood for natural and land resources management in the future.

For future research

1) The future research should have a good understanding and comprehensive context of LULCC processes and the interactions of the drivers such as economic, policy, technology, institution and biophysical, which will help to identify the drivers and improve LULCC model performance.

2) The proper satellite image resolution and classification process should be considered. High spatial resolution images are needed such as QuickBird and IKONOS will provide good quality of LULC maps because urban areas have complex and heterogonous features, the high spatial resolution image provides better information to map land use areas. If the medium spatial resolution image, subpixel features such as fraction images of spectral mixture analysis or fuzzy membership information are considered as the classification method. Moreover, the accuracy and updated data of underlying drivers are important such as socio-economic, biophysical, etc. that will provide a more accurate result and predictive ability for the LULCC model.

3) The qualitative assessment is highly recommended as visiting study area, conduct a fieldwork and interview in order to obtain expert knowledge and validating of the data analysis. It is essential to have knowledge of the study area context because in this way it is easier to identify and understand LULCC processes and the spatial relationships.

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Appendices

Appendix A

Figure A.1: Land use and land cover map of 1997.

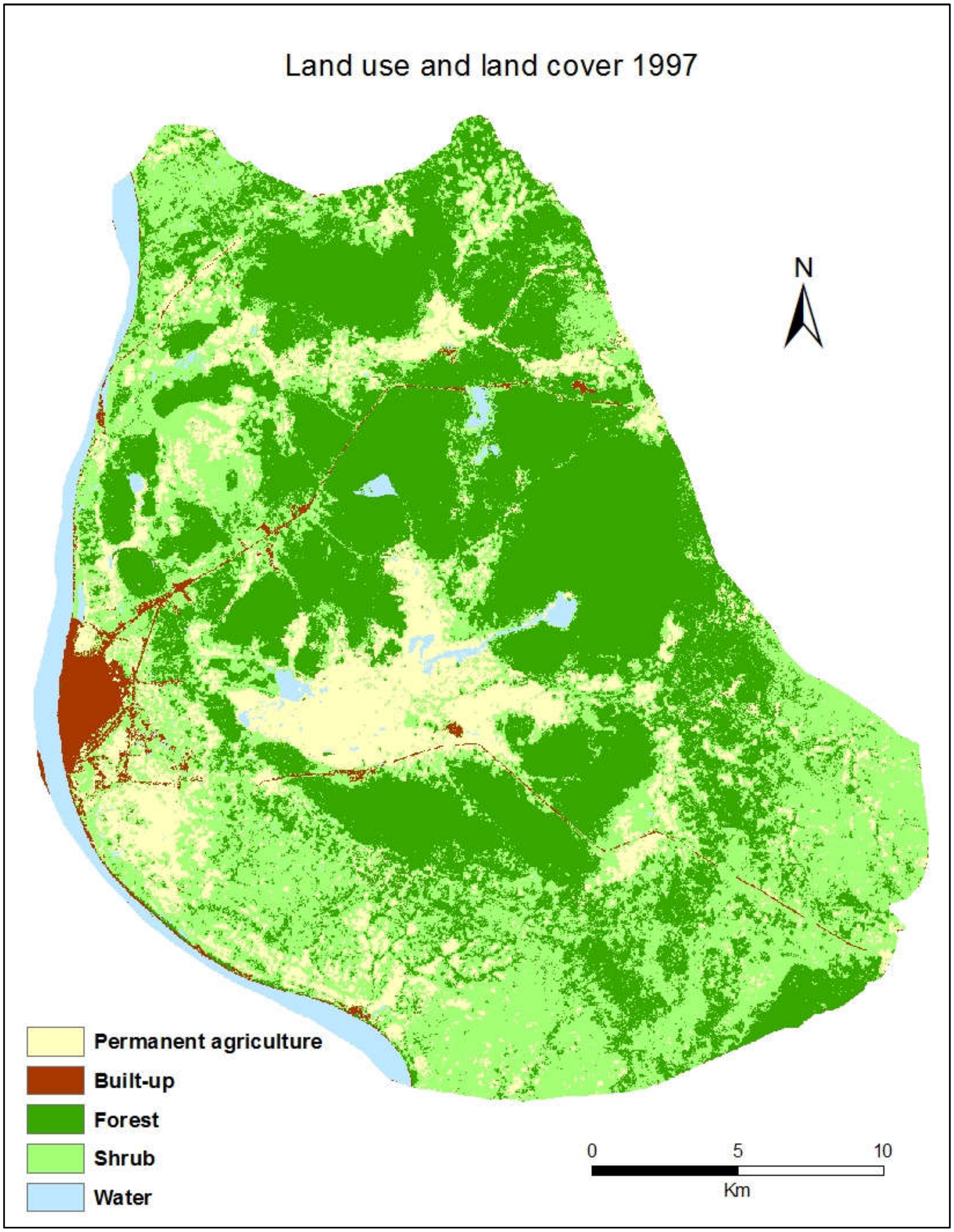


Figure A.2: Land use and land cover map of 2003.

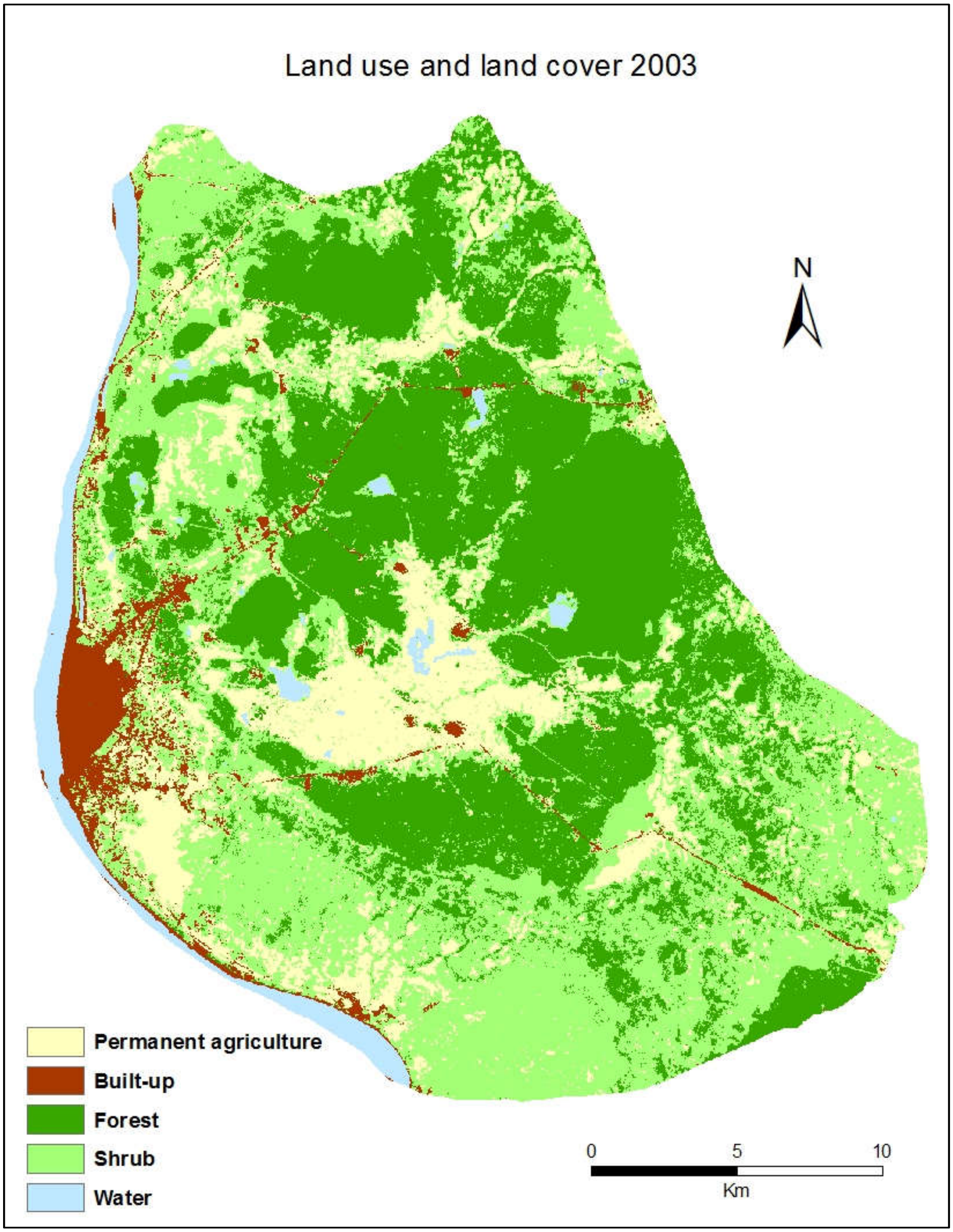


Figure A.3: Land use and land cover map of 2007.

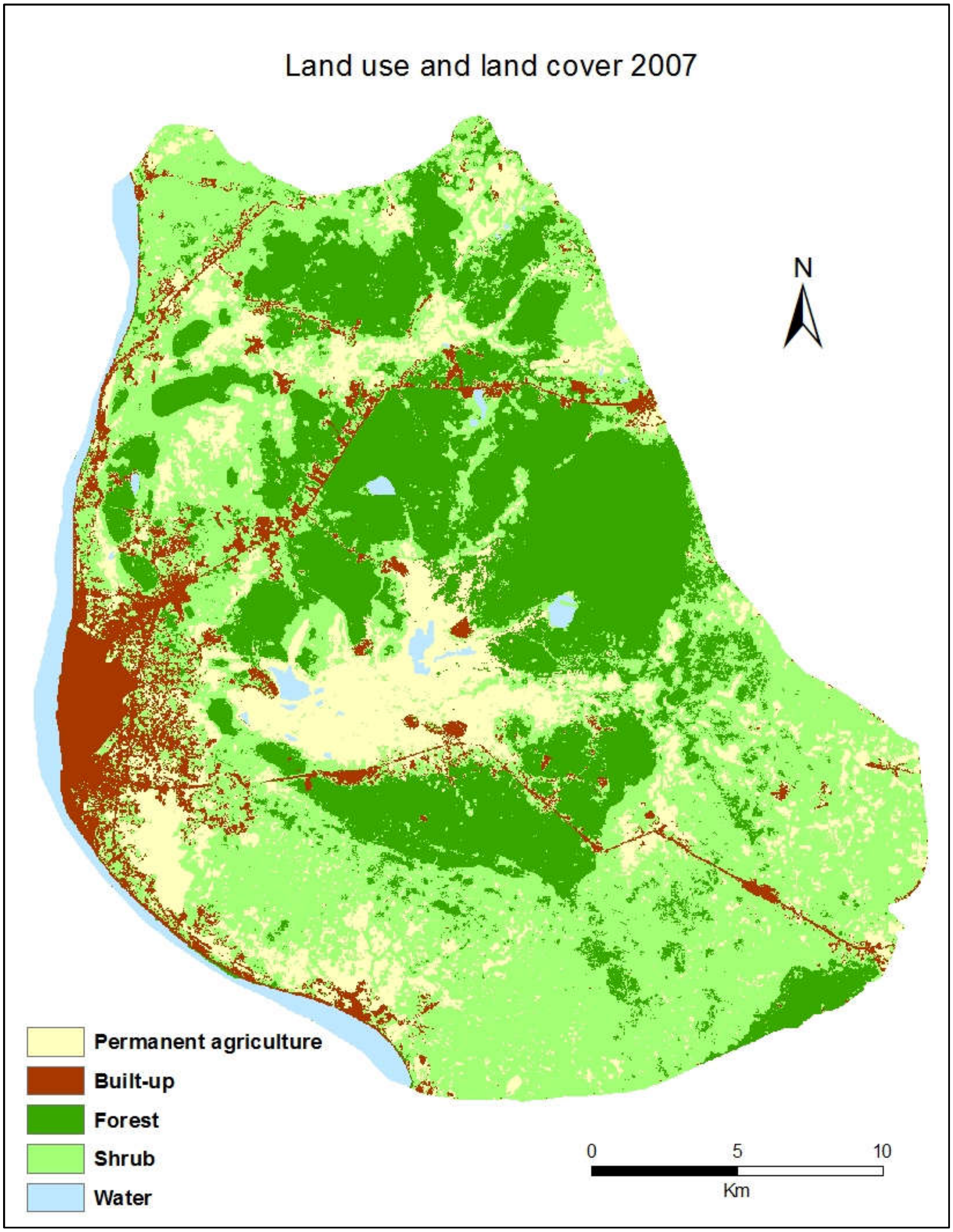


Figure A.4: Land use and land cover map of 2013.

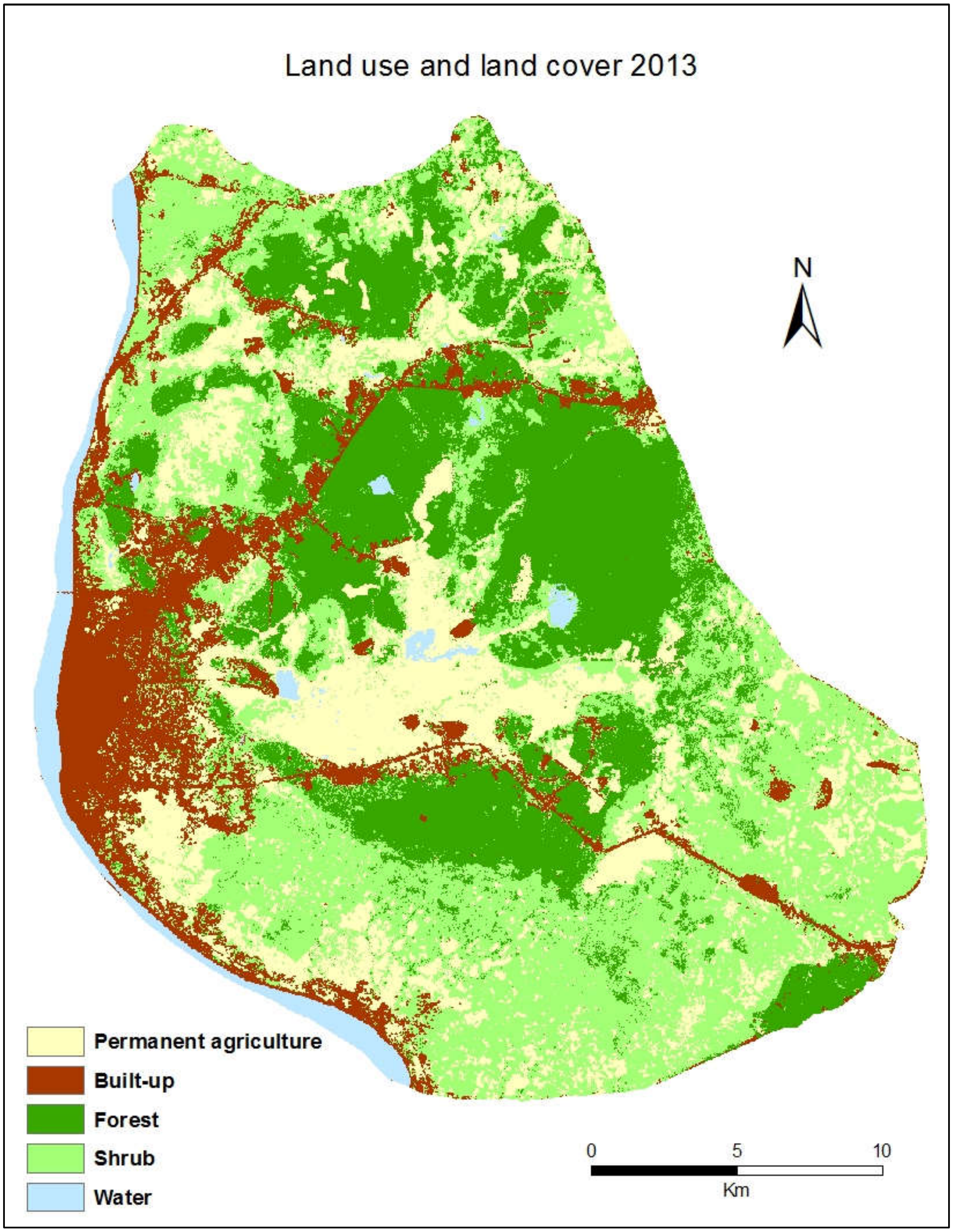


Figure A.5: Land use and land cover map of 2017.

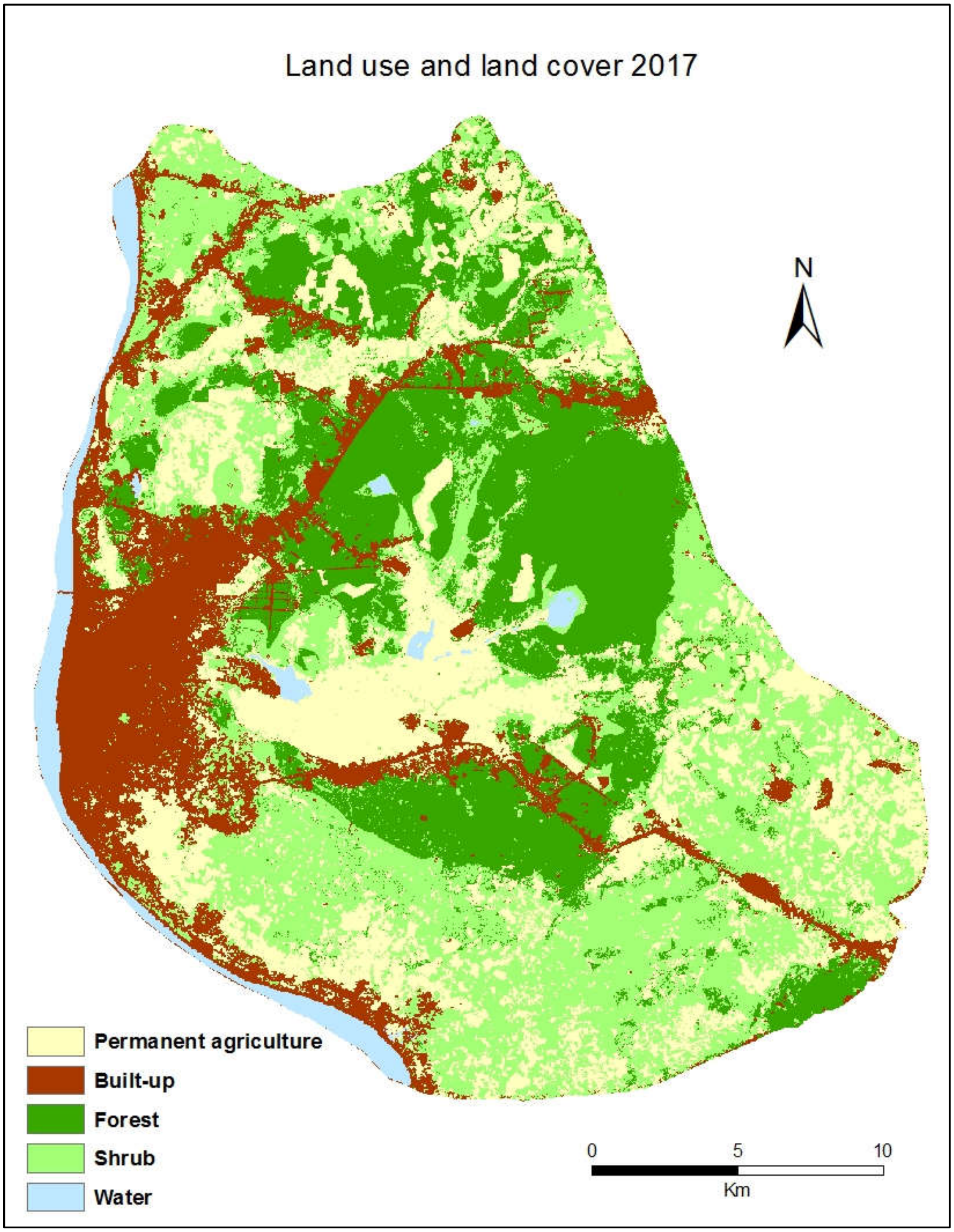


Figure A.6: Land use and land cover map of 2022.

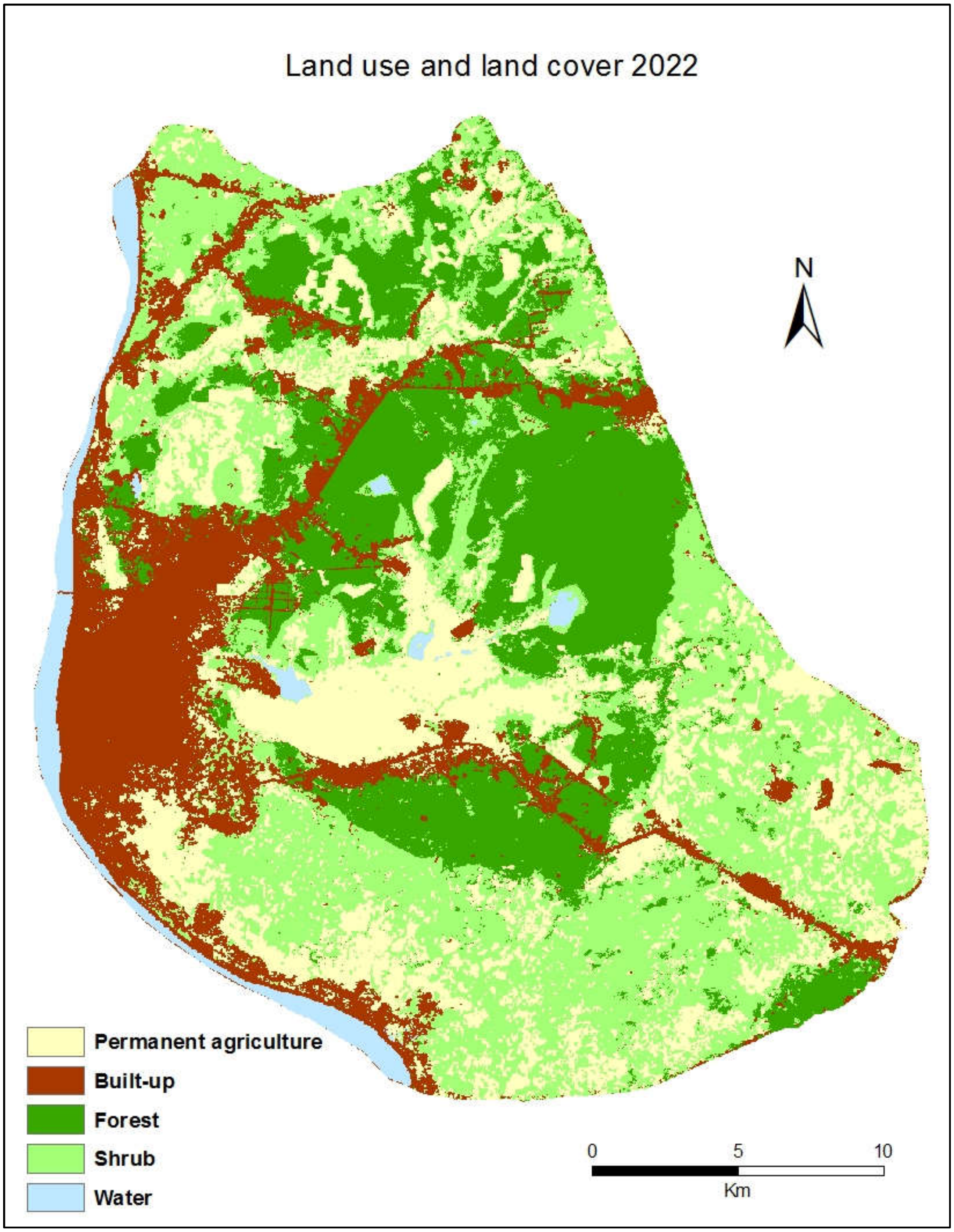


Figure A.7: Land use and land cover conversions between 1997 and 2003.

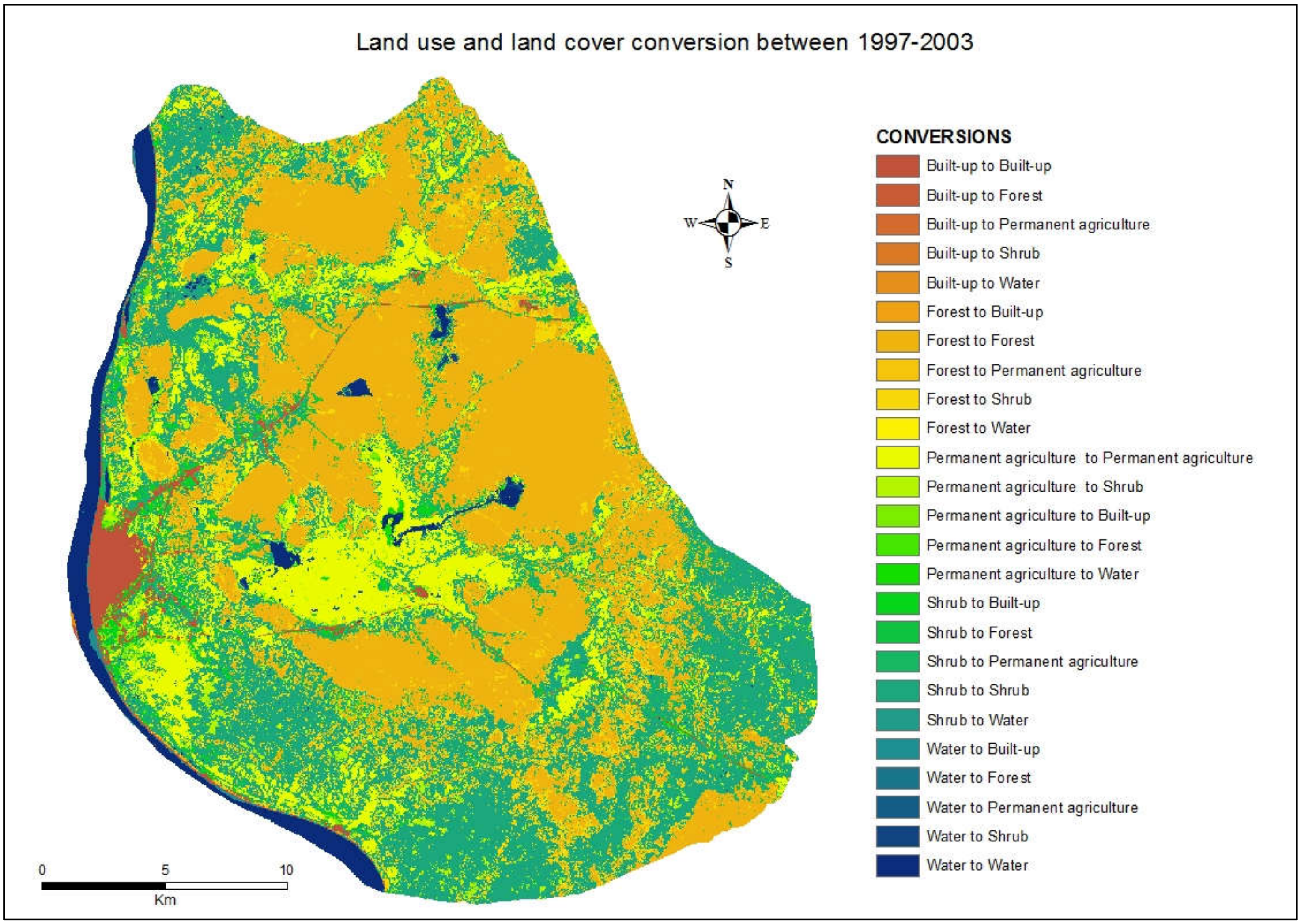


Figure A.8: Land use and land cover conversions between 2003 and 2007.

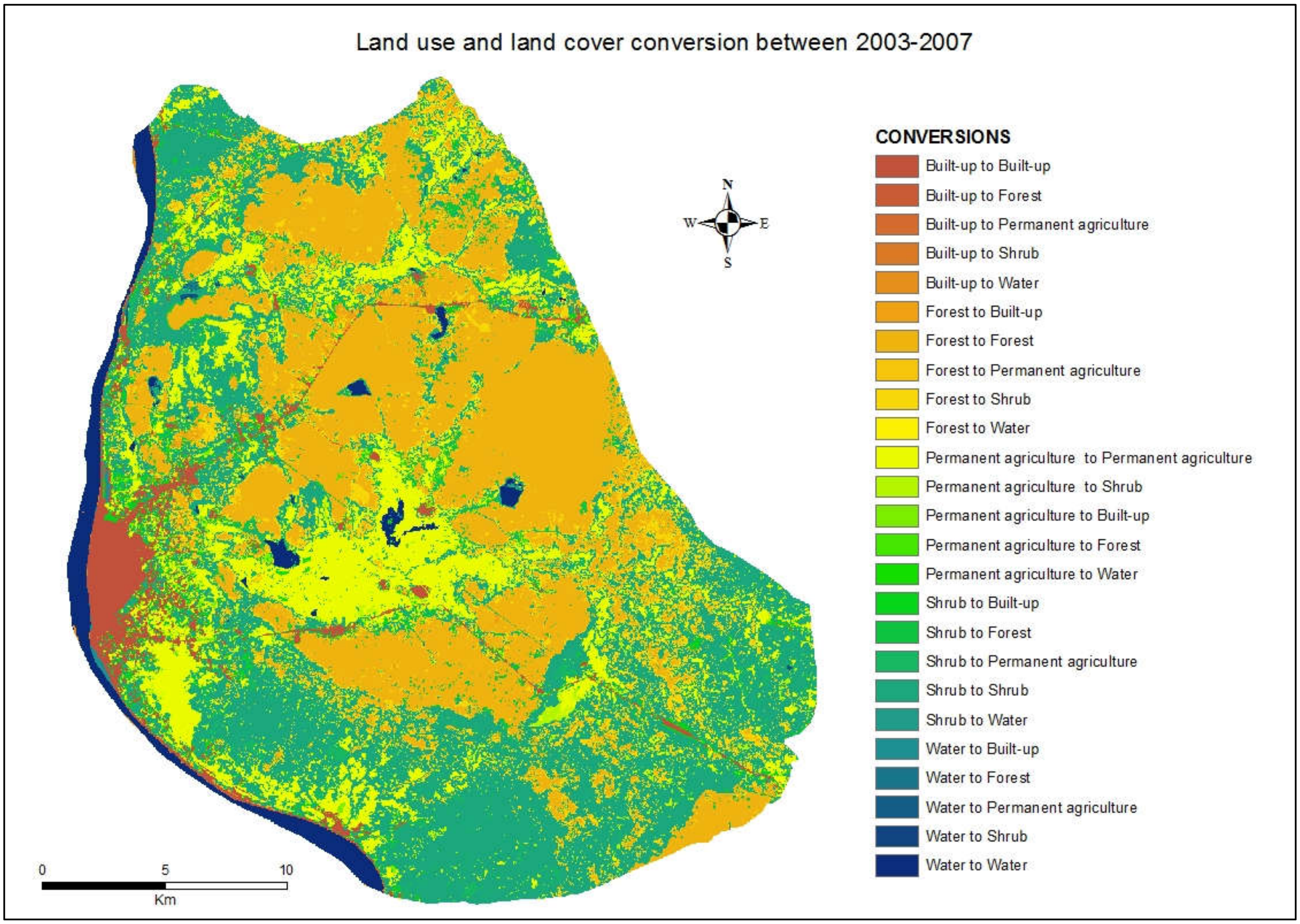


Figure A.9: Land use and land cover conversions between 2007 and 2013.

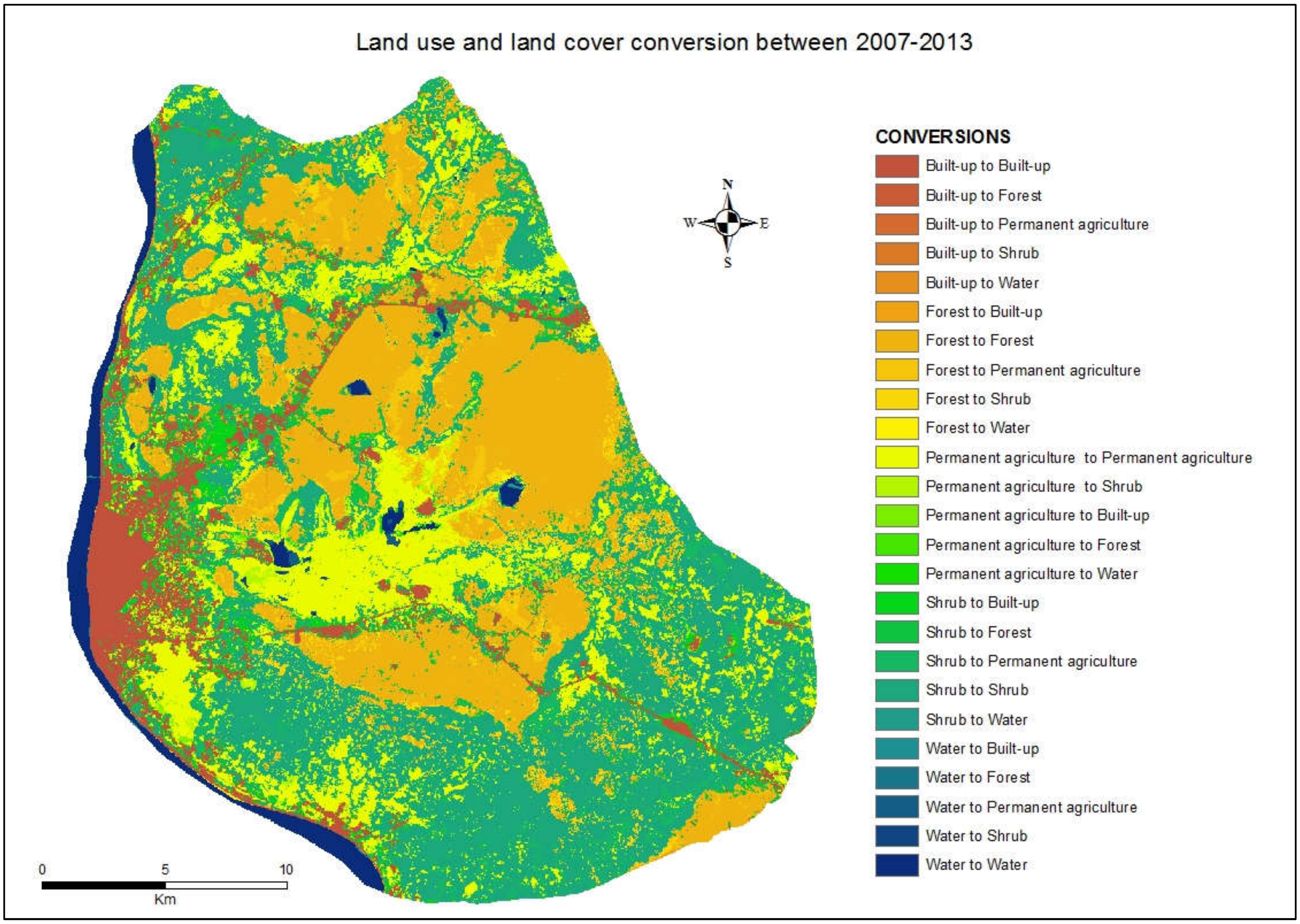


Figure A.10: Land use and land cover conversions between 2013 and 2017.

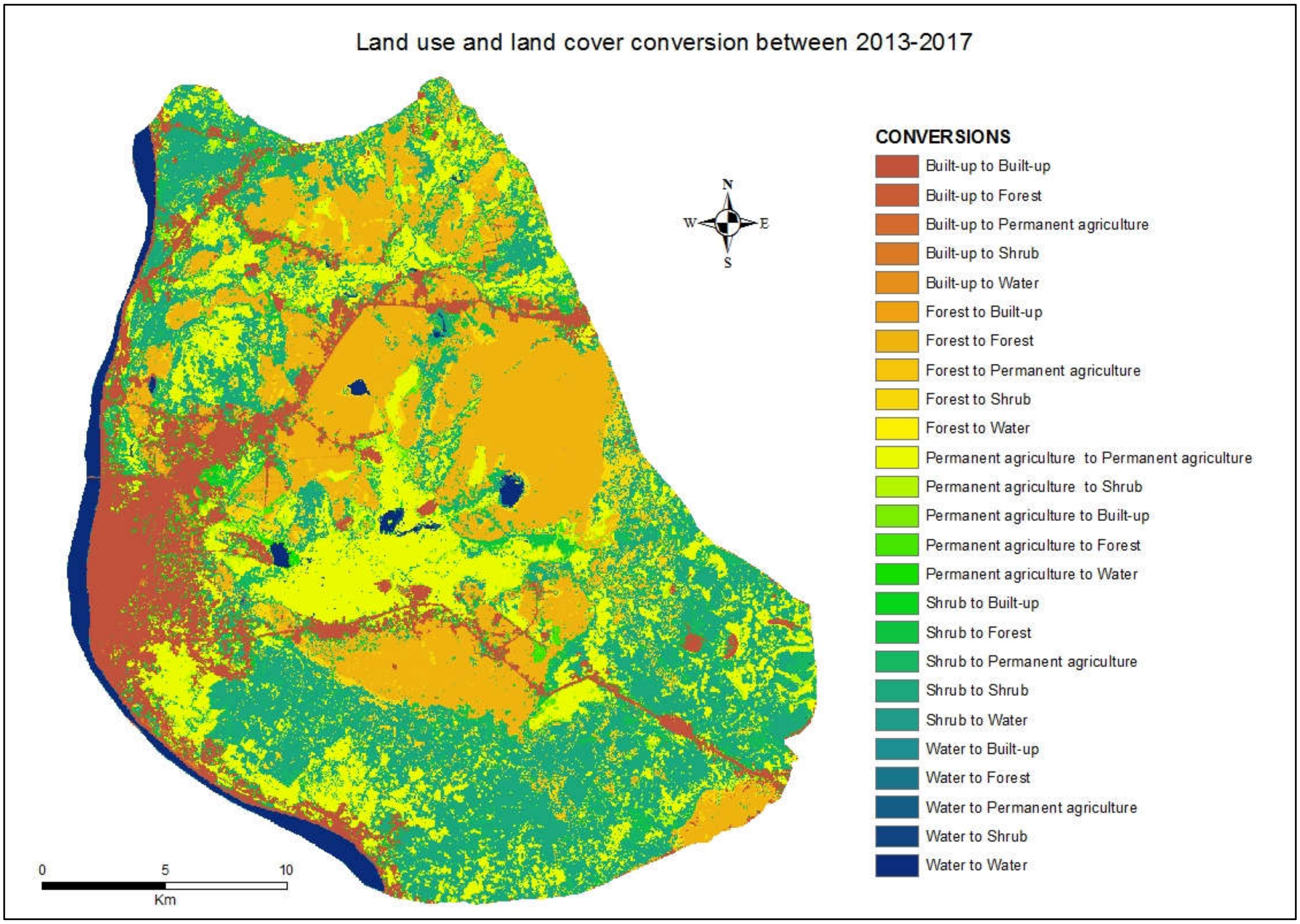


Figure A.11: Land use and land cover conversions between 1997 and 2017.

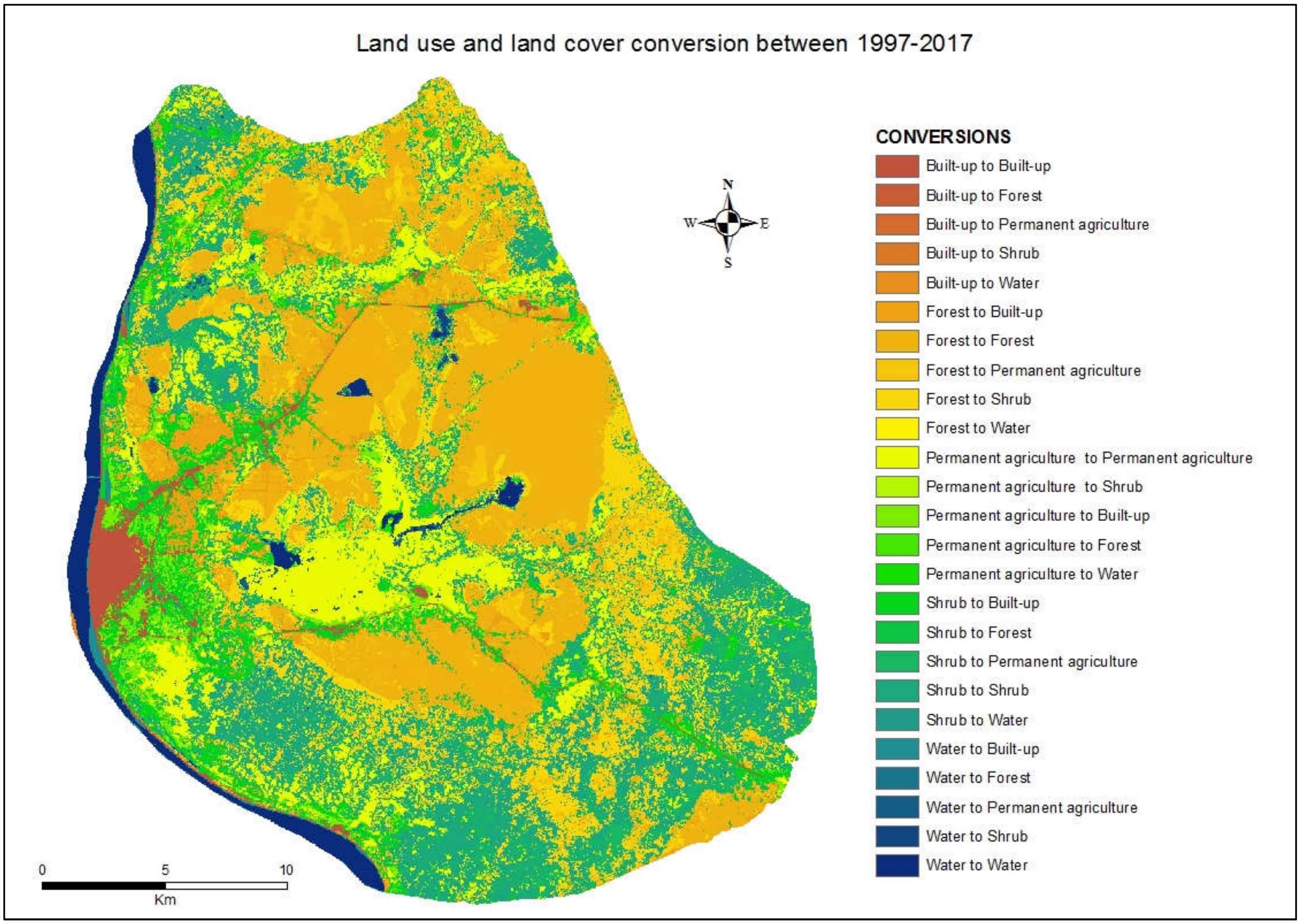
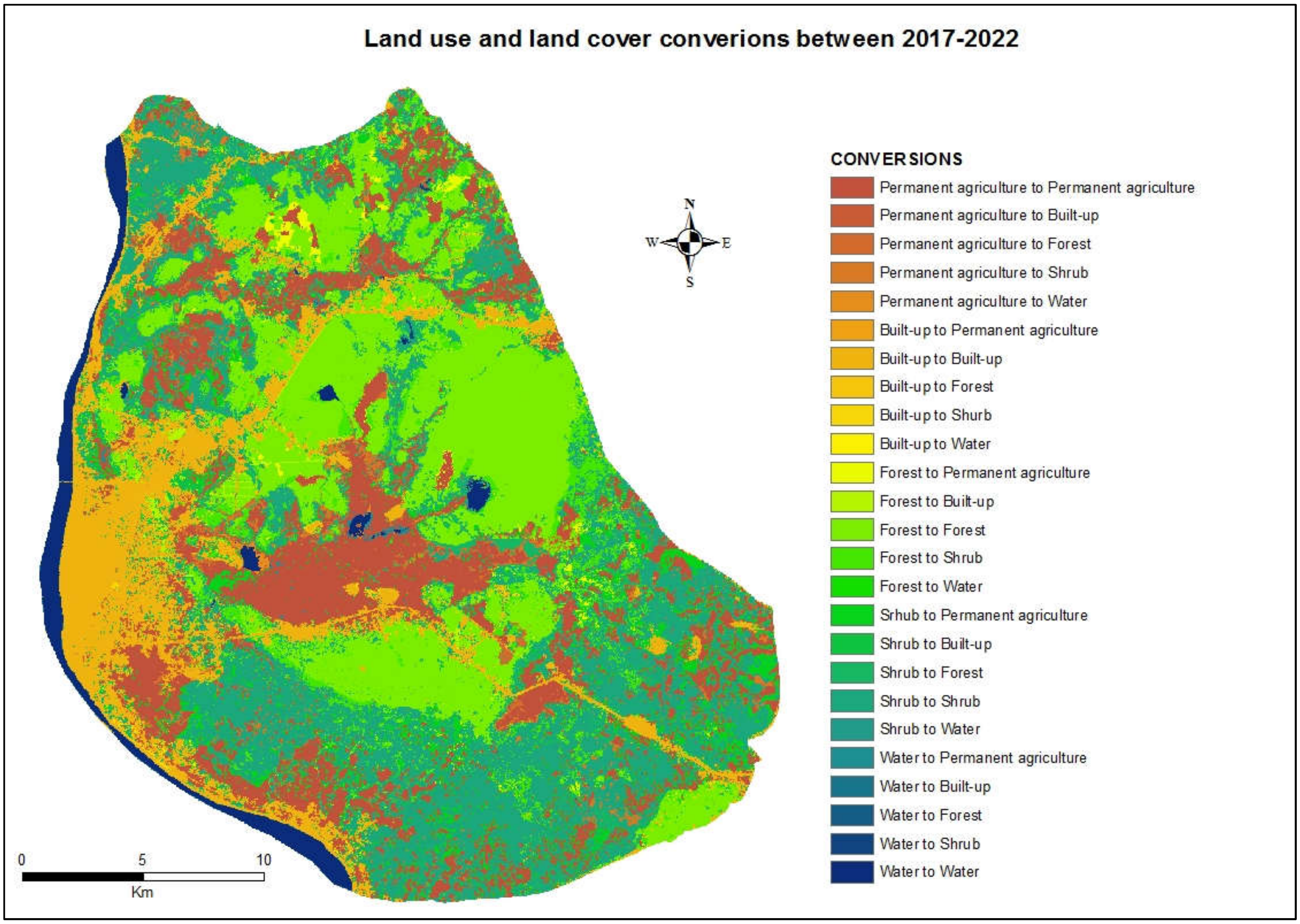


Figure A.12: Land use and land cover conversions between 2017 and 2022.



Appendix B

Table 1.B: Landsat sensor wavelength.

Landsat	Band	Wavelength	Resolution (m)
Landsat TM 199 and 2007	Band 1 - Blue	0.45-0.52	30
	Band 2 - Green	0.52-0.60	30
	Band 3 - Red	0.63-0.69	30
	Band 4 - Near Infrared (NIR)	0.76-0.90	30
	Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
	Band 6 - Thermal	10.40-12.50	120* (30)
	Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	30
Landsat 2003	Band 1 - Blue	0.45-0.52	30
	Band 2 - Green	0.52-0.60	30
	Band 3 - Red	0.63-0.69	30
	Band 4 - Near Infrared (NIR)	0.77-0.90	30
	Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
	Band 6 - Thermal	10.40-12.50	60 * (30)
	Band 7 - Shortwave Infrared (SWIR) 2	2.09-2.35	30
	Band 8 - Panchromatic	.52-.90	15
Landsat 2013 and 2017	Band 1 - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
	Band 2 - Blue	0.452 - 0.512	30
	Band 3 - Green	0.533 - 0.590	30
	Band 4 - Red	0.636 - 0.673	30
	Band 5 - Near Infrared (NIR)	0.851 - 0.879	30
	Band 6 - Shortwave Infrared (SWIR) 1	1.566 - 1.651	30
	Band 7 - Shortwave Infrared (SWIR) 2	2.107 - 2.294	30
	Band 8 - Panchromatic	0.503 - 0.676	15
	Band 9 - Cirrus	1.363 - 1.384	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Table B.2: Landsat OLI in 2013 calibration file.

Landsat 8 OLI in 2013 path/row 127/48				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	- 64.84140	1.2968E-02	-0.6484140	0.0012968
2	-66.39838	1.3280E-02	-0.6639838	0.0013280
3	-61.18554	1.2237E-02	-0.6118554	0.0012237
4	-51.59509	1.0319E-02	-0.5159509	0.0010319
5	-31.57362	6.3147E-03	-0.3157362	0.0006314
6	-7.85207	1.5704E-03	-0.7852070	0.0001570
7	-2.64657	5.2931E-04	-0.2646570	0.0000529

Table B.3: Landsat TM in 2007 calibration file.

Landsat TM in 2007 path/row 127/48				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	-2.28583	7.6583E-01	-0.228583	0.76583
2	-4.28819	1.4482E-01	-0.428819	0.14482
3	-2.21398	1.0440E-01	-0.221398	0.10440
4	-2.38602	8.7602E-01	-0.238602	0.87602
5	-0.49035	1.2035E-01	-00.49035	0.12035
7	-0.21555	6.5551E-01	-0.021555	0.65551

Table B.4: Landsat TM in 2007 calibration file.

Landsat TM in 2007 path/row 127/49				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	-2.28583	7.6583E-01	-0.228583	0.76583
2	-4.28819	1.4482E-01	-0.428819	0.14482
3	-2.21398	1.0440E-01	-0.221398	0.10440
4	-2.38602	8.7602E-01	-0.238602	0.87602
5	-0.49035	1.2035E-01	-00.49035	0.12035
7	-0.21555	6.5551E-01	-0.021555	0.65551

Table B.5: Landsat ETM+ year 2003 calibration file.

Landsat ETM+ in 2003 path/row 127/48				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	-6.97874	7.7874E-01	-0.697874	0.077874
2	-7.19882	7.9882E-01	-0.719882	0.079882
3	-5.62165	6.2165E-01	-0.562165	0.062165
4	-6.06929	9.6929E-01	-0.606929	0.096929
5	-1.12622	1.2622E-01	-0.112622	0.012622
7	0.39390	4.3898E-02	0.039390	0.004389

Table B.6: Landsat ETM+ in 2003 calibration file.

Landsat ETM+ in 2003 path/row 127/49				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	-6.97874	7.7874E-01	-0.697874	0.077874
2	-7.19882	7.9882E-01	-0.719882	0.079882
3	-5.62165	6.2165E-01	-0.562165	0.062165
4	-6.06929	9.6929E-01	-0.606929	0.096929
5	-1.12622	1.2622E-01	-0.112622	0.012622
7	0.39390	4.3898E-02	0.039390	0.004389

Table B.7: Landsat TM in 1997 calibration file.

Landsat TM in 1997 path/row 127/48				
Band	RADIANCE_ADD_BAND (C_0)	RADIANCE_MULT_BAND (C_1)	Cal-file (C_0)	Cal-file (C_0)
1	-2.28583	7.6583E-01	-0.228583	0.0765837
2	-4.28819	1.4482E+00	-0.428819	1.448200
3	-2.21398	1.0440E+00	-0.221398	1.044000
4	-2.38602	8.7602E-01	-0.238602	0.087602
5	-0.49035	1.2035E-01	-0.049035	0.012003
7	-0.21555	6.5551E-02	-0.021555	0.0065551

Table B.*8*: Confusion matrix of Landsat images classification in 1997.

Confusion Matrix 1997								
Class	W	F	BU	PA	S	Total	Producer's Accuracy	User's Accuracy
Water	**2**	0	0	0	0	**2**	66.67 %	100 %
Forest	1	**31**	0	0	6	**38**	100 %	81.58
Built-up	0	0	**1**	0	0	**1**	25 %	100 %
Permanent Agriculture	0	0	1	**12**	0	**13**	85.71 %	92.31%
Shrub	0	0	2	2	**14**	**18**	70%	77.78 %
Total	**3**	**31**	**4**	**14**	**20**	**72**		
Overall Accuracy = 83.33 % Kappa = 0.74								

Table B.9: Confusion matrix for Landsat image classification in 2003.

Confusion Matrix 2003								
Class	W	F	BU	PA	S	Total	Producer's Accuracy	User's Accuracy
Water	**2**	0	0	0	0	**2**	66.67 %	100 %
Forest	0	**25**	1	0	2	**28**	96.15 %	89.29 %
Built-up	1	1	**3**	0	0	**5**	60 %	60 %
Permanent Agriculture	0	0	1	**9**	0	**10**	56.25 %	100 %
Shrub	0	0	0	7	**16**	**23**	88.89 %	66.67 %
Total	**3**	**26**	**5**	**16**	**18**	**68**		
Overall Accuracy = 80.88 % Kappa = 0.73								

Table B.10: Confusion matrix of Landsat image classification in 2007.

Confusion Matrix 2007								
Class	W	F	BU	PA	S	Total	Producer's Accuracy	User's Accuracy
Water	**1**	0	0	0	0	**1**	100 %	100 %
Forest	0	**27**	1	1	1	**30**	100 %	90 %
Built-up	1	1	**3**	1	0	**6**	42.86 %	75 %
Permanent Agriculture	0	0	2	**10**	0	**12**	71.43 %	83.33%
Shrub	0	0	1	2	**13**	**16**	92.86 %	81.86%
Total	**2**	**28**	**7**	**14**	**14**	**65**		
Overall Accuracy = 85.71 % Kappa = 0.79								

Table B.11: Confusion matrix of Landsat image classification in 2013.

Confusion Matrix 2013								
Class	W	F	BU	PA	S	Total	Producer's Accuracy	User's Accuracy
Water	**3**	0	0	0	1	**4**	100 %	75 %
Forest	0	**20**	0	0	1	**21**	100 %	95.24 %
Built-up	0	0	**6**	0	2	**8**	100 %	75 %
Permanent Agriculture	0	0	0	**12**	2	**14**	85.71 %	85.71%
Shrub	0	0	0	2	**24**	**26**	80 %	92.31 %
Total	**3**	**20**	**6**	**14**	**30**	**73**		
Overall Accuracy = 89.04 % Kappa = 0.84								

Table B.12: Confusion matrix of Landsat image classification in 2017.

Confusion Matrix 2017								
Class	W	F	BU	PA	S	Total	Producer's Accuracy	User's Accuracy
Water	**1**	0	0	0	0	**1**	50 %	100 %
Forest	0	**22**	0	0	1	**23**	95.65 %	95.65 %
Built-up	1	0	**9**	0	4	**14**	100 %	62.29 %
Permanent Agriculture	0	0	1	**18**	2	**21**	100 %	90%
Shrub	0	1	0	0	**25**	**26**	78.13 %	96.15 %
Total	**2**	**23**	**10**	**18**	**32**	**85**		
Overall Accuracy = 89.29 % Kappa = 0.85								

Table B.13: LULC class conversions between 1997 and 2003 in km^2

		1997						
	Classes	PA	Built-up	Forest	Shrub	Water	Total	Gain
2003	PA	80.35	0.83	3.03	**29.50**	1.11	114.82	34.47
	B	3.89	13.44	1.08	**9.12**	1.92	29.44	16.00
	F	0.88	0.29	243.46	**19.77**	0.27	264.67	21.21
	S	19.04	0.82	**61.53**	186.10	1.90	269.39	**83.29**
	W	0.93	0.13	0.06	0.57	21.17	22.86	1.69
	Total	105.08	15.51	309.15	245.07	26.37	701.18	156.67
	Loss	24.73	2.07	**65.69**	**58.97**	5.20	156.67	313.35

Table B.14: LULC class conversions between 2003 and 2007 in km^2

		2003						
	Class	PA	B	F	S	W	Total	Gain
2007	PA	89.40	0.12	2.26	**25.56**	0.42	117.76	28.36
	B	7.33	28.28	5.18	**14.65**	0.68	56.13	27.84
	F	0.91	0.44	194.69	11.93	0.26	208.22	13.53
	S	16.85	0.09	**62.49**	216.89	0.47	296.79	**79.90**
	W	0.34	0.51	0.04	0.36	21.03	22.28	1.25
	Total	114.82	29.44	264.67	269.39	22.86	701.18	150.89
	Loss	25.42	1.16	**69.98**	**52.50**	1.83	150.89	301.77

Table B.15: LULC class conversion between 2007 and 2013 in km^2

		2007						
	Class	PA	B	F	S	W	Total	Gain
2013	PA	92.09	0.56	10.71	**49.16**	1.01	153.54	**61.44**
	B	8.29	54.90	3.77	**23.26**	0.42	90.64	35.74
	F	0.45	0.07	163.99	26.31	0.09	190.91	26.92
	S	16.31	0.58	**29.39**	197.74	0.38	244.39	46.65
	W	0.62	0.02	0.37	0.32	20.38	21.70	1.32
	Total	117.76	56.13	208.22	296.79	22.28	701.18	172.07
	Loss	25.67	1.22	44.23	**99.05**	1.90	172.07	344.15

Table B.16: LULC class conversions between 2013 and 2017 in km^2

		2013						
	Class	PA	B	F	S	W	Total	Gain
2017	PA	124.92	0.87	5.20	**43.57**	0.83	175.40	**50.48**
	B	7.20	87.58	5.85	**13.31**	0.87	114.80	27.23
	F	3.40	0.82	148.93	22.88	0.05	176.06	27.14
	S	17.29	1.29	**30.90**	164.38	0.38	214.24	49.86
	W	0.73	0.08	0.03	0.26	19.57	20.68	1.10
	Total	153.54	90.64	190.91	244.39	21.70	701.18	155.81
	Loss	28.61	3.06	41.98	**80.01**	2.13	155.81	311.61

Table B.17: LULC conversion model in period 1997-2003.

LULC conversion models in 1997-2003					
Forest to shrub conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-0.915	0.4	0.073	0.511	
Population density 2015	**-0.001**	**0.999**	0	0	1.448
DEM	**-0.03**	**0.97**	0	0.001	1.791
Rainfall	**-0.105**	**0.9**	0	0.003	1.304
Roads	**-0.069**	**0.934**	0	0.005	1.377
Slope	-0.023	0.977	0.107	0.014	1.009
Soils	**-0.029**	**0.972**	0.019	0.012	1.351
Temperature	**0.808**	**2.244**	0	0.012	1.871
Distance to town	**0.207**	**1.231**	0	0.007	1.165
Distance to villages	**0.033**	**1.034**	0	0.006	1.341
Distance to water areas	**0.011**	**1.011**	0.017	0.005	1.212
Nagelkerke $R^2 =$ 0.167 Cox & Snell $R^2 = 0.237$					
Shrub to agriculture conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-23.388	0	0	0.578	
Population density 2015	0.01	1	0	0	1.62
DEM	**-0.011**	**0.989**	0	0.001	1.929
Rainfall	**0.026**	**1.027**	0	0.004	1.247
Roads	**-0.025**	**0.976**	0	0.006	1.644
Slope	**-0.086**	**0.918**	0	0.018	1.014
Soils	**-0.04**	**0.96**	0.003	0.014	1.498
Temperature	**0.865**	**2.375**	0	0.011	2.307
Distance to town	**0.018**	**1.018**	0.037	0.008	1.103
Distance to villages	**0.04**	**1.04**	0	0.007	1.573
Distance to water areas	**-0.028**	**0.972**	0	0.006	1.142
Nagelkerke $R^2 = 0.105$ Cox & Snell $R^2 = 0.187$					
Shrub to built-up conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-17.729	0	0	1.175	
Population density 2015	**0.34**	**1.007**	0	0	1.663
DEM	0	1	0.823	0.002	1.876
Rainfall	**0.03**	**1.031**	0	0.008	1.248
Roads	**0.056**	**1.006**	0	0.021	1.682
Slope	0.012	1.012	0.689	0.03	1.013
Soils	**-0.194**	**0.824**	0	0.024	1.543
Temperature	**0.535**	**1**	0	0.019	2.283
Distance to town	**0.192**	**1.707**	0	0.015	1.104
Distance to villages	**-0.086**	**0.009**	0	0.012	1.599
Distance water areas	**-0.076**	**0.927**	0	0.014	1.153
Nagelkerke $R^2 = 0.098$ Cox & Snell $R^2 = 0.29$					

Positive and increase odds ratio of probability in land use conversion

Negative and decrease odds ratio of probability in land use conversion

Table B.18: LULC conversion model in period 2003-2007.

LULC conversion model in 2003-2007					
Forest to shrub conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-3.132	0.044	0	0.585	
Population density 2015	0	1	0.141	0	1.361
DEM	**-0.023**	**0.978**	0	0.001	1.756
Rainfall	**-0.119**	**0.888**	0	0.004	1.343
Roads	**-0.077**	**0.926**	0	0.005	1.298
Slope	-0.019	0.982	0.239	0.016	1.007
Soils	**-0.197**	**0.821**	0	0.014	1.296
Temperature	**0.967**	**2.631**	0	0.014	1.82
Distance to town	**0.312**	**1.366**	0	0.009	1.193
Distance to villages	**-0.047**	**0.954**	0	0.007	1.312
Distance water areas	**0.087**	**1.091**	0	0.005	1.281
Nagelkerke $R^2 = 0.196$ Cox & Snell $R^2 = 0.267$					
Shrub to agriculture conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-15.987	0	0	0.609	
Population density 2015	**0.54**	**1**	0	0	1.509
DEM	**-0.021**	**0.979**	0	0.001	1.966
Rainfall	0.002	1.002	0.565	0.004	1.249
Roads	**0.08**	**1.083**	0	0.007	1.643
Slope	**-0.145**	**0.865**	0	0.019	1.011
Soils	-0.003	0.997	0.813	0.015	1.414
Temperature	**0.756**	**2.129**	0	0.012	2.266
Distance to town	**0.081**	**1**	0	0.009	1.109
Distance to villages	**-0.045**	**0.956**	0	0.007	1.557
Distance to water areas	**-0.093**	**0.911**	0	0.007	1.135
Nagelkerke $R^2 = 0.10$ Cox & Snell $R^2 = 0.186$					
Shrub to built-up conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-15.504	0	0	0.799	
Population density 2015	**0**	**1**	0.54	0	1.623
DEM	**-0.006**	**0.994**	0	0.001	1.873
Rainfall	**0.042**	**1.006**	0	0.005	1.258
Roads	**0.457**	**1.022**	0	0.012	1.708
Slope	0.012	1.012	0.603	0.023	1.011
Soils	**-0.305**	**0.737**	0	0.018	1.475
Temperature	**0.45**	**1.568**	0	0.014	2.275
Distance to town	**0.081**	**1**	0	0.01	1.111
Distance to villages	**0.39**	**1.09**	0.001	0.009	1.595
Distance to water areas	**0.064**	**1.066**	0	0.008	1.193
Nagelkerke $R^2 = 0.105$ Cox & Snell $R^2 = 0.235$					

Positive and increase odds ratio of probability in land use conversion

Negative and decrease odds ratio of probability in land use conversion

Table B.19: LULC conversion model in period 2007-2013.

LULC conversion model in 2007-2013					
Forest to shrub conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-1.057	0.348	0.133	0.703	
Population density 2015	**0.011**	**1.395**	0	0	1.322
DEM	**-0.012**	**0.988**	0	0.001	1.857
Rainfall	**-0.044**	**0.957**	0	0.004	1.424
Roads	**0.045**	**1.046**	0	0.006	1.289
Slope	**-0.107**	**0.899**	0	0.018	1.006
Soils	**0.07**	**1.073**	0	0.016	1.283
Temperature	**0.333**	**1.001**	0	0.016	1.928
Distance to town	**0.114**	**1.121**	0	0.01	1.223
Distance to villages	0.003	1.003	0.661	0.008	1.321
Distance to Water areas	0.002	1.002	0.771	0.007	1.294
Nagelkerke R^2 = 0.003 Cox & Snell R^2 = 0.05					
Shrub to agriculture conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-15.431	0	0	0.51	
Population density 2015	**0.67**	**2**	0.023	0	1.42
DEM	**-0.011**	**0.989**	0	0.001	2.011
Rainfall	0.003	1.003	0.278	0.003	1.268
Roads	**0.031**	**1.031**	0	0.005	1.58
Slope	**-0.078**	**0.925**	0	0.015	1.009
Soils	**0.097**	**1.102**	0	0.013	1.385
Temperature	**0.651**	**1.917**	0	0.01	2.25
Distance to town	**0.066**	**1.068**	0	0.008	1.117
Distance to villages	0.008	1.008	0.164	0.006	1.515
Distance to water areas	**0.113**	**1.013**	0.008	0.005	1.246
Nagelkerke R^2 = 0.095 Cox & Snell R^2 = 0.145					
Shrub to built-up conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-7.874	0	0	0.712	
Population density 2015	**0.76**	**1**	0	0	1.547
DEM	**-0.002**	**0.998**	0.033	0.001	1.881
Rainfall	**0.037**	**1.038**	0	0.005	1.254
Roads	**0.002**	**1.003**	0	0.01	1.614
Slope	0.028	1.028	0.163	0.02	1.009
Soils	**-0.104**	**0.902**	0	0.017	1.428
Temperature	**0.152**	**1.164**	0	0.013	2.186
Distance to town	**0.05**	**1.006**	0	0.009	1.109
Distance to villages	**-0.045**	**0.956**	0	0.008	1.535
Distance to water areas	**0.108**	**1.114**	0	0.007	1.219
Nagelkerke R^2 = 0.144 Cox & Snell R^2 = 0.265					

Positive and increase odds ratio of probability in land use conversion

Negative and decrease odds ratio of probability in land use conversion

Table B.20: LULC conversion model in period 2013-2017.

LULC conversion model 2013-2017					
Forest to shrub conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	18.448	0	0	0.714	
Population density 2015	**0.560**	**1**	0	0	1.313
DEM	**-0.017**	**0.983**	0	0.001	1.935
Rainfall	**-0.141**	**0.868**	0	0.004	1.437
Roads	**0.085**	**1.089**	0	0.006	1.256
Slope	**-0.1**	**0.904**	0	0.019	1.008
Soils	**-0.351**	**0.704**	0	0.016	1.346
Temperature	**0.082**	**1.086**	0	0.016	1.382
Distance to town	**0.079**	**1.082**	0	0.01	1.876
Distance to villages	**-0.027**	**0.974**	0	0.007	1.244
Distance to water areas	**0.077**	**1.08**	0	0.006	1.328
Nagelkerke $R^2 = 0.058$ Cox & Snell $R^2 = 0.087$					
Shrub to agriculture conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-9.691	0	0	0.52	
Population density 2015	0	1	0.607	0	1.326
DEM	**-0.002**	**0.998**	0.027	0.001	2.061
Rainfall	**-0.042**	**0.958**	0	0.003	1.293
Roads	**0.019**	**1.02**	0	0.005	1.488
Slope	**-0.056**	**0.946**	0	0.016	1.009
Soils	**-0.118**	**0.889**	0	0.013	1.353
Temperature	**0.619**	**1.857**	0	0.01	1.275
Distance to two	**0.088**	**1.092**	0	0.008	2.207
Distance to villages	**-0.053**	**0.948**	0	0.006	1.12
Distance to water areas	**0.034**	**1.035**	0	0.005	1.479
Nagelkerke $R^2 = 0.09$ Cox & Snell $R^2 = 0.136$					
Shrub to built-up conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-15.29	0	0	0.799	
Population density 2015	**0.001**	**1.001**	0	0	1.425
DEM	0.002	1.002	0.087	0.001	1.932
Rainfall	**0.063**	**1.065**	0	0.005	1.3
Roads	**0.447**	**1.64**	0	0.01	1.503
Slope	-0.041	0.96	0.08	0.023	1.01
Soils	**-0.303**	**0.739**	0	0.019	1.368
Temperature	**0.293**	**1.34**	0	0.015	1.264
Distance to town	**0.018**	**1.004**	0	0.011	2.141
Distance to villages	-0.003	0.997	0.769	0.009	1.127
Distance to water areas	**0.028**	**1.028**	0.001	0.009	1.487
Nagelkerke $R^2 = 0.125$ Cox & Snell $R^2 = 0.248$					

Positive and increase odds ratio of probability in land use conversion
Negative and decrease odds ratio of probability in land use conversion

Table B.21: LULC conversion model in period 1997-2017 .

LULC conversion model 1997-2017					
Forest to shrub conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	14.126	1363984.04	0	0.555	
Population density 2015	**0.891**	**1.6**	0	0	1.286
DEM	**-0.022**	**0.978**	0	0.001	1.898
Rainfall	**-0.164**	**0.848**	0	0.003	1.346
Roads	**0.057**	**2.059**	0	0.005	1.275
Slope	-0.026	0.974	0.076	0.015	1.008
Soils	**-0.309**	**0.734**	0	0.013	1.337
Temperature	**0.473**	**1.605**	0	0.012	1.406
Distance to town	**0.196**	**2.17**	0	0.008	1.778
Distance to villages	**-0.044**	**0.957**	0	0.006	1.195
Distance Water areas	**0.039**	**1.039**	0	0.005	1.295
Nagelkerke $R^2 = 0.160$ Cox & Snell $R^2 = 0.196$					
Shrub to agriculture conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-16.226	0	0	0.506	
Population density 2015	**0.234**	**1.061**	0.003	0	1.309
DEM	**-0.01**	**0.99**	0	0.001	2.079
Rainfall	**-0.049**	**0.952**	0	0.003	1.261
Roads	**0.014**	**1.014**	0.011	0.005	1.511
Slope	**0.04**	**1.041**	0.008	0.015	1.01
Soils	**-0.091**	**0.913**	0	0.013	1.353
Temperature	**0.975**	**2.65**	0	0.011	1.256
Distance to town	**0.148**	**1.16**	0	0.008	2.214
Distance to villages	**-0.041**	**0.96**	0	0.006	1.113
Distance to water areas	**0.016**	**1.016**	0.003	0.005	1.498
Nagelkerke $R^2 = 0.187$ Cox & Snell $R^2 = 0.275$					
Shrub to built-up conversion					
Variables	**B**	**Odds ratio**	**Sig.**	**S.E.**	**VIF**
Constant	-17.631	0	0	0.645	
Population density 2015	**0.001**	**1**	0	0	1.553
DEM	-0.001	0.999	0.165	0.001	1.883
Rainfall	**0.025**	**1.025**	0	0.004	1.252
Roads	**1.09**	**1**	0	0.009	1.58
Slope	**0.186**	**1.204**	0	0.018	1.01
Soils	**-0.298**	**0.742**	0	0.016	1.437
Temperature	**0.653**	**1.922**	0	0.012	1.241
Distance to town	**0.084**	**1.002**	0	0.009	2.138
Distance to villages	**-0.05**	**0.951**	0	0.007	1.109
Distance to water areas	**0.13**	**1.138**	0	0.006	1.149
Nagelkerke $R^2 = 0.269$ Cox & Snell $R^2 = 0.428$					

Positive and increase odds ratio of probability in land use conversion
Negative and decrease odds ratio of probability in land use conversion