CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

FACULTY OF ENVIRONMENTAL SCIENCES

DEPARTMENT OF ECOLOGY

Diploma Thesis

Land Use and Land Cover Change Surrounding the Rimov Reservoir in South Bohemia, Czech Republic

Supervisor: Ing. Zdeněk Keken, Ph.D.

Author: Laurin Wongibe Chambo

2021 CULS Prague

CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Environmental Sciences

DIPLOMA THESIS ASSIGNMENT

B.Sc. Chambo Wongibe, BSc

Engineering Ecology
Nature Conservation

Thesis title

Land Use And Land Cover Change Surounding The Rimov Reservoir In South Bohemia,Czech Republic

Objectives of thesis

The main objective of this study is to determine if Landsat satellite imagery and GIS techniques can be used monitor Land Use/Land Cover changes for the past 35 years since the creation of the Rimov Reservoir in South Bohemia, Czech Republic.

Methodology

The first step is Obtaining Landsat satellite Images of the Study area surrounding the Reservoir for the past years which from 1984 to 2019. This Images are then converted into GIS files and classified into 5 Land use Distinctive classes which are Agricultural Land, Bare Land, Built-Up areas, Grassland and Water Bodies. From this Classification, I will then be able to calculate the total area of all the total study area and area of each of the classes of the 5 satellite Images. With this information, it is possible to calculate the total change and accuracy assessment for the classes as well. In the study, Land satellite Images from 1984,1990,2000,2010 and 2019 will be used and each of these years will be represented by a Map showing all the five classes, Tables of their total area size, Charts to represent the results and accuracy classification data. The study will also show changes in the Reservoir size 1984- to 2019.

The proposed extent of the thesis

50 pages

Keywords

Land Use and Land Cover, GIS, Accuracy Assessment, Detection Change, Remote Sensing, Satellite Image, Kappa Coefficient, LULC classification

Recommended information sources

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Expected date of thesis defence

2020/21 SS – FES

The Diploma Thesis Supervisor

Ing. Zdeněk Keken, Ph.D.

Supervising department

Department of Applied Ecology

Electronic approval: 18. 3. 2021

prof. Ing. Jan Vymazal, CSc.

Head of department

Electronic approval: 18. 3. 2021

prof. RNDr. Vladimír Bejček, CSc.

Dean

Prague on 18. 03. 2021

Declaration

I declare that I have worked on my diploma thesis titled " Land Use and Land Cover Change Surrounding the Rimov Reservoir in South Bohemia, Czech Republic " by myself and I have listed all sources used to acquire the information included in this thesis.

In Prague on 25.03.2021 Laurin Wongibe Chambo

Acknowledgement

My primary gratitude goes to my supervisor Ing. Zdeněk Keken, Ph.D and as well as my consultant Ing Kobe Ismael for reading and correcting my work and bringing out what was needed to be added and also for his guidance towards the realization of this Thesis. My profound gratitude also goes to Mrs. Wongibe Rose Mary, Chambo Fritz and Chambo Cassandra for their enormous services during the publication of this project. This piece of work is dedicated to Mama Kewir Immaculate McBride of Blessed Memory. Finally, I would like to thank to my family and friends for their moral support during this time.

Abstract

Land use and land cover changes at regional scales has become an important subject that urgently needs to be addressed in the study of global environmental change. The aim of this study is to produce maps of land use and land cover of the Rimov Reservoir and Surroundings on previous years to monitor the possible changes that may occur since the creation of the dam site and to assess the trends of land use and land cover change. LULC changes were investigated using remote sensing data with the help of Google Earth Engine and GIS software. Geographic information system and remote sensing technologies was used to identified land cover changes detection; remote sensing data, satellite imagery and image processing techniques was done within five dates of 1984,1990 ,2000, 2010 and 2019 using Land sat TM and Landsat OLI of 30 m resolution images. Google Earth Pro and Arc GIS 10.8 soft wares were used to identify the changes. The classification was done using five land cover classes (agricultural land, bare land, built-up areas, grassland, and water bodies). Rimov reservoir size was measured and calculated separately from the water bodies. Preprocessing and classification of the images were analyzed carefully, and accuracy assessment was tested separately using the kappa coefficient. A total of 125 accuracy sampling points were randomly selected making it 25 points for each class of the allocated year. The results showed that overall accuracy for all five selected years range from 79.2% to 88% and kappa coefficient ranged from 74% to 85%. This study indicated that in the last 35 years period, built-up areas significantly increased from 13% in 1984 to 25% in 2019, agricultural land from 29% in 1984 to 38% in 2019 and bare land reduced from 27% in 1984 to 11% in 2019. Changes in the reservoir size ranged between 1.42km^2 to 1.93km^2 signifying a minimal change in reservoir size over the years. So, it is however important to conclude that GIS and Remote Sensing techniques could be used and recommend for LULC change studies.

Keywords: Land Use and Land Cover, GIS, Accuracy Assessment, Detection Change, Remote Sensing, Satellite Image, Kappa coefficient, LULC classification.

Abstrakt

Land Use a Land Cover v regionálním měřítku se staly důležitým tématem při studiu globálních změn životního prostředí, kterému je třeba naléhavě věnovat pozornost. Cílem této studie je analyzovat Land Use a Land Cover krajiny v okolí přehrady Římov s cílem sledovat možné změny, které mohou nastat od vytvoření přehrady. Změny LULC byly zkoumány pomocí dat dálkového průzkumu Země pomocí softwaru Google Earth Engine a Geografických informačních systémů. K identifikaci detekci změn krajinného pokryvu byl použit software GIS a technologie dálkového průzkumu Země; Data dálkového průzkumu Země, satelitní snímky byly z následujících časových úseků 1984, 1990, 2000, 2010 a 2019 získané z Land sat TM a Landsat OLI o rozlišení 30 m. K identifikaci změn byly použity Google Earth Pro a Arc GIS 10.8. Klasifikace byla provedena do pěti tříd krajinného pokryvu (zemědělská půda, holá půda (bez porostu), zastavěné plochy, louky a travní trvalé travní porosty a vodní útvary).

Velikost nádrže Římov byla měřena a počítána odděleně od ostatních vodních útvarů. Zpracování a klasifikace snímků bylo pečlivě analyzováno a hodnocení přesnosti bylo testováno samostatně pomocí koeficientu kappa. Celkem bylo náhodně vybráno 125 vzorkovacích bodů, což představuje 25 bodů pro každou kategorii v daném roce. Výsledky ukázaly, že celková přesnost se u všech pěti vybraných let pohybuje v rozmezí od 79.2 % do 88 % a koeficient kappa se pohybuje od 74 % do 85 %. Tato studie naznačila, že za posledních 35 let se zastavěné plochy výrazně zvýšily z 13 % v roce 1984 na 25 % v roce 2019, zemědělská půda z 29 % v roce 1984 na 38 % v roce 2019 a holá půda se snížila z 27 % v roce 1984 na 11 % v roce 2019. Změny velikosti nádrže se pohybovaly mezi 1,42 km^2 až 1,93 km^2, což znamená minimální změnu velikosti nádrže v průběhu let. J Studie prokazuje, že lze použít techniky GIS a dálkového průzkumu Země a doporučit je pro studie zaměřené na změny LULC.

Klíčová slova: Land Use, Land Cover, GIS, hodnocení přesnosti, detekce změny, dálkový průzkum země, satelitní snímky, Kappa koeficient, LULC klasifikace.

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LIST OF ABREVIATIONS

LUCC:	Land Use and Climate Change
LULC:	Land Use Land Cover
LULCC:	Land Use Land Cover Change
GIS:	Geographic Information Systems
ID:	Image Differencing
RADAR:	Radio Detection and Ranging
LIDAR:	Light Detection and Ranging
MSS:	Multi Spectral System
TM:	Thematic Mapper
OLI:	Operational Land Imager
EEA:	European Economic Area
CA:	Consumers Accuracy
PA:	Producers Accuracy
NDVI:	Normalized Difference Vegetation Index
USGS:	United States Geological Survey
KML:	Keyhole Markup Language
ES:	Ecosystem Services
ESV:	Ecosystem Service Valuation
GMES:	Global Monitoring for Environment and Security
INSPIRE:	Infrastructure for Spatial Information in the European Community

1. INTRODUCTION

Understanding the dynamics of land-use and land-cover (LULC) is one of the key concepts in global environmental change research (Meyer et al., 1996; Alcamo et al. 1998; Lambin et al., 2001; Petit & Scudder 2001). LULC changes have direct influence on the vegetation morphology (Defries et al., 2002), biodiversity, land degradation and climatic conditions of an area. The landcover changes occur naturally in a progressive and gradual way, however sometimes it may be rapid and abrupt due to anthropogenic activities. LULC changes especially those caused by human activities is the most important component of global environmental change with impacts possibly greater than the other global changes (Turner et al., 1994; Jensen, 2005). Land cover change is occurring from the conversion of forests to agricultural lands and built-up lands (Delang 2002; Duram et al., 2004; Shalaby & Tateishi 2007; Turner et al., 2007; Munoz-Villers & Lopez Blanco 2008). Land use and land cover analysis can be done from processed aerial photographs, Satellite images (Landsat image, Quick bird image) and Google Earth (Dash, 2005). Since remote sensed data from the earth orbit can be obtained repeatedly over the same area, they have been very useful to monitor and analyze LUCC in various regions of the earth and greatly contribute to planning and management of available resources, especially in the developing countries where other kinds of background data are often lacking (Dash, 2005; Fakeye et al., 2015). LULC change is possibly the most obvious form of global environmental change visible at spatial and temporal scales having great relevance to our daily life (CCSP, 2003). Technically, LULC change is directly related with the mean quantitative changes in spatial extent (increase or decrease) for a specified type of land cover and land use respectively. Both anthropogenic and environmental forces largely affect the behavior of changes in land use and land cover (Liu et al., 2009). In the last five decades, agriculture and forested landscapes have been transformed by economic and social development (Gaughan, 2006; Lambin & Geist, 2003; Walker, 2004; Wright, 2005). These transformations are important components of land cover disturbance and global environmental change (Foley et al., 2005; Moran, 2005; Rindfuss et al., 2004). The most rapid and significant include deforestation as a consequence of urbanization, agricultural expansion, logging and pastoral expansion (Boori & Ferraro, 2012; Lambin & Geist, 2003). Von Thunen model (Mather, 1986) explained the use of natural resources by the tourism industry. It explains that resource extraction increases with decreasing urbanization distance due to transportation cost (Chaplin & Brabyn, 2013). This evidence is outdated for developed world (Sinclair, 1967) due to improved infrastructure.

In most European countries including Czech Republic land use/land cover changes differ region by region. Changes in the landscape over the past 150 years (before 1999) in the Czech Republic, in particular the social forces, were analyzed recently (Bičík et al., 2001; Opršal et al., 2013), which revealed that social forces had a great effect on land-use changes during the period of the study. Lipský (2010) argues that the use of rural landscape is becoming more unequal both on local and regional levels. At the local level patches of abandoned arable and agricultural land emerge and these are again being inhabited by a number of species: a new “wilderness” comes into existence (Lipský 2010). On the other hand, the current agricultural subsidies channeled to less favored areas have a similar effect as subsidies under the centrally planned economy had in land use terms the existing structure (relatively high share of agricultural and arable land) is being conserved also in regions with less favorable natural conditions (Jančák, Bičík 2006). Due to this, the use of landscape moves towards large regional units with similar land use structure. In Czech Republic, this process is distinctive due to a strong concentration of agricultural businesses that had started already 50 years ago and that to a certain extent still exist till date.

The changes in LULC have rapidly been increasing in Czech Republic. As in other Eastern European countries, the Czech Republic has encountered substantial land cover change and land-use intensification over the past decades, resulting mainly from socio-political causes (Lorencová et al., 2013). The fastest growing landscape areas are urban regions. Therefore, it's important to own accurate and relevant information about the status and changes in LULC in these dynamically developing areas (Kasenko et al., 2006 & Feranec et al.,2007). After 1990, the new political conditions and economic transformation have led to substantial increase in urban fabric, industrial and commercial areas and grasslands (Bicík et al.,2001). These particular LULC changes are even more substantial within the European nation than in most of the Eastern European countries (EEA, 2006, LEAC, 2014). There are several studies assessing Land Use and Landcover change within Czech Republic and this research is one of them which focuses on the surroundings around the Rimov Reservoir in South Bohemia. .

2. AIMS AND OBJECTIVES

2.1 Aim

This study aims to identify and analyze general trends in Land Use/Land Cover Change (LULCC) taking place in Rimov area over a period of 35 years using Landsat Satellite Imagery and GIS based technique.

2.2 Objectives

The following objectives will be pursued in order to achieve the aim of this study.

- To create a Land use/Land cover classification blueprint,
- To produce Land Use/Land Cover maps of Rimov reservoir and surroundings at different years to detect changes,
- To determine the trend, magnitude, nature, and location of Land Use/Land Cover changes using Landsat satellite imagery and change detection technique.

2.3 Research Questions

To address the stated objectives, this study was focused on answering the following research questions:

- To what extent and rate of LULC changes have occurred in Rimov area due to the creation of the dam between 1984,1990,2000, 2010 and 2019?
- What is the nature of LULC changes that have taken place during the periods observed in this study within the years intervals?
- Whether Landsat satellite imagery can be applied successfully to mapping LULC changes in the study area?
- Whether classification accuracy plays an important part in LULC classification?

3.LITERATURE REVIEW

3.1 Land Use and Land Cover Change

3.1.1 Concepts and Framework of Landcover and Land Use

The terms land use and land cover have been used interchangeably in many publications despite the difference between these two terms. In general land cover refers to natural biophysical covers such as forest, water bodies and barren land, while land use refers to the human utilization of land for different purposes like agriculture and settlements, which lead to altering biogeochemical, physiographical and hydrological conditions (Di Gregorio & Jansen, 2000). Land cover refers to the surface cover on the ground like vegetation, urban infrastructure, water, bare soil etc. Identification of land cover establishes the baseline information for activities like thematic mapping and change detection analysis. Land use refers to the purpose the land serves, for example, recreation, wildlife habitat, or agriculture. Mapping LULC is presently the standard method and most common approach to monitor land use changes and developments (Mancino et al., 2014). Land use/land cover (LULC) changes play an essential role in the studies of regional, local and global environmental change (Gupta & Munshi, 1985; Mas, 1999). Land cover refers to how the Earth's surface is covered by forests, wetlands, impervious surfaces, agricultural, and other types of land and water (Prakasam, 2010). Land use refers to how humans use the landscape, whether for development, conservation, or mixed uses. Land use includes recreation areas, wildlife habitats, agricultural land, and built-up land (Reis, 2008). When the phrase Land Use / Land Cover (LULC) is used together ,it generally refers to the categorization or classification of human activities and natural elements on the landscape within a specific time frame based on established scientific and statistical methods of analysis of appropriate source materials .Especially when LULC classes and their spatial and temporal changes are to be determined for categories of small geographic extent in vast areas, high-resolution satellite images are needed (Reed et al., 1996).

LULC can be described as the most important environmental variable because involves all aspects and concepts of the environment such as Hydrology, Biodiversity, Sustainability, Climate, Natural disasters and so on. Information on these environmental variables is used worldwide by Research bodies, NGO's, the public as well as industrial purposes and development. LULC is recognized as one of the most important types of spatial data in two important European initiatives which are GMES (Global Monitoring for Environment and Security) and INSPIRE (Infrastructure for Spatial Information in the European Community). LULC is governed by as set of Policies and frameworks as seen in table 1.

Table 1. The need for LULC data. (Source: EEA)

EU Policy and legal framework	Information **requirement**
Water Framework directive (2006-2015+)	**Characterization of river catchment areas, prevention of groundwater pollution from diffuse and local soil contamination**
Community Biodiversity Strategy (2006 – 2010+) Habitats directive Natura2000, 2010 target	**Designated areas and habitats, change in ecosystems, fragmentation**
Common Agriculture Policy (agri-environmental Regulation; New guidelines for Rural Development; CAP evaluations 2007-2013)	**Landscape diversity and management, agriculture habitats, mapping rural area**
Community Structural Policies (European Spatial Development Perspective –Territorial Cohesion; 2007-13)	**Natural assets, land use conflicts, physical planning, territorial development**
Follow up European Strategy for ICZM (2006+)	**Land use and land cover change coastal zones**
European Thematic Strategy on Urban Environment and sustainable land use (2006+)	**Urban sprawl, rural-urban relationships**
European Thematic Strategy on Soil Protection (2006+)	**Soil degradation, protection and sealing**
...	**...**

3.1.2 What is Land?

In understanding what landcover and land use is all about, it is important to be able to distinguish between the various characteristics that they are made up of. The first important concept is understanding what land is about. Land as a resource is fixed in supply with variable demand (Briassoulis, 2000). Land can be defined as the foundation of the resources required for human activities as well as a platform on which the activities are performed. The use of land and its resources by mankind gives rise to "land use" which differs with the purposes it serves, whether for production of food, provision of housing, leisure, mining and handling of materials including the bio-physical features of land itself. The need of mankind coupled with ecological features and processes are the two major forces that influence land use.

Land can be described as a delineable area of the earth's terrestrial surface, embracing all attributes of the biosphere immediately above or below this surface. This includes

- near surface climate,
- soil and terrain forms,
- surface hydrology including shallow lakes, rivers, marshes and swamps,
- near-surface sedimentary layers and associated groundwater and geohydrological reserves,
- plant and animal populations,
- human settlement pattern and physical results of past and present human activity including terracing, water storage or drainage structures, roads, buildings and much more.

3.1.3 Importance of LULC

The growth of a society totally depends on its social and economic development. This is the basic reason why socio-economic surveys are carried out. This type of survey includes both spatial and non-spatial datasets. LULC maps play a significant and prime role in planning, management and monitoring programs at local, regional and national levels. This type of information, on one hand, provides a better understanding of land utilization aspects and on the other hand, it plays an important role in the formation of policies and programs required for development planning. For ensuring sustainable development, it is necessary to monitor the ongoing process on land use/land cover pattern over a period of time. In order to achieve sustainable urban development and to check the haphazard development of towns and cities, it is necessary that authorities associated with the urban development generate such planning models so that every bit of available land can be used in most rational and optimal way. This requires the present and past land use/land cover information of the area. LULC maps also help us to study the changes that are happening in our ecosystem and environment. If we have an inch-by-inch information about Land Use/Land Cover of the study unit we can make policies and launch programs to save our environment.

3.1.4 Applications of LULC maps

Land use and land cover maps are being used daily by millions of people. In the previous years, the maps were mostly analog but due to development and technology, most maps are now in mobile phones in digital formats making its usage and demand quite high and important. The application of LULC maps include:

- natural resource management,
- wildlife habitat protection,
- baseline mapping for GIS input,
- urban expansion / encroachment,
- routing and logistics planning for seismic / exploration/resource extraction activities,
- damage delineation such as tornadoes, flooding, volcanic, seismic, fire,
- legal boundaries for tax and property evaluation,
- target detection - identification of landing strips, roads, clearings, bridges, land/water interface.

3.2 Land Use and Land Cover Classification

Land cover classification is one of the most important remote sensing applications in the interests of identifying features such as land use by employing commonly multispectral satellite imagery (Osei et al., 2012). The use of multitemporal data as inputs has been reported to assist in improving classification accuracy, particularly for vegetation, due to the unique phenological characters of various kinds of vegetation (Zhu & Woodcock, 2014). However, using multitemporal data also may involve some problems when using conventional automated classification algorithms (Zhu & Woodcock, 2014). One of these problems is the difficulty in obtaining cloud-free images for some locations in particular years, especially when using data with a relatively low temporal frequency such as Landsat. Remote sensing is an attractive source of thematic maps such as those depicting land cover as it provides a map-like representation of the Earth's surface that is spatially continuous and highly consistent, as well as available at a range of spatial and temporal scales. Thematic mapping from remotely sensed data is typically based on an image classification. This may be achieved by either visual or computer-aided analysis. The classification may be one that seeks to group together cases by their relative spectral similarity (unsupervised) or that aims to allocate cases on the basis of their similarity to a set of predefined classes that have been characterized spectrally (supervised). In each situation, the resulting classified image may be treated as a thematic map depicting the land cover of the region.

LULC classification is one of the most widely used applications in remote sensing. The most used approaches include:

3.2.1 Unsupervised classification

This is done by a software calculated by software. This type of classification is based on the software analysis of an image without the user provided sample classes. This involves grouping of pixels with common characteristics. The computer uses techniques to determine which pixels are related and groups them into classes. The user can specify which algorithm the software will use and the desired number of output classes but otherwise does not aid in the classification process. There are three primary advantages to using this approach to classification. First, extensive knowledge of the area being classified is not required for the initial separation of image pixels. Second, there is less opportunity for human error as the analyst is not required to make as many decisions during the classification process. Third, unique classes in the data will be recognized by unsupervised classification, whereas they may be overlooked in a supervised classification. However, the user must have knowledge of the area being classified such as wetlands, developed areas, coniferous forests, and a lot more.

3.2.2 Supervised classification

Classified by human guide. Supervised classification involves the classification of pixels of unknown identity by means of a classification algorithm using the spectral characteristics of pixels of known informational class referred to as training areas identified by the analyst (Campbell, 2002). This is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites also known as testing sets or input classes are selected based on the knowledge of the user. The user also sets the bounds for how similar other pixels must be to group them together. These bounds are often set based on the spectral characteristics of the training area, plus or minus a certain increment often based on "brightness" or strength of reflection in specific spectral bands. The user also designates the number of classes that the image is classified into. Following are some of the LULC types and their respective classes.

Table 2: The land use classification system developed by Anderson et al., 1976.

Urban or Built-up Land	• Residential • Commercial and Services • Industrial • Communications and Utilities • Mixed Urban or Built-up Land • Other Urban or Built-up Land
Agricultural Land	• Cropland and Pasture • Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas • Confined Feeding Operations
Rangeland	• Herbaceous Rangeland • Shrub and Brush Rangeland • Mixed Rangeland
Forest Land	• Deciduous Forest Land • Evergreen Forest Land • Mixed Forest Land
Water	• Rivers • Streams and Canals • Lakes • Reservoirs • Bays and Estuaries
Wetland	• Forested Wetland • No forested Wetland
Barren Land	• Dry Salt Flats • Beaches • Sandy Areas Other than Beaches • Bare Exposed Rock • Strip Mines, Quarries, and Gravel Pits • Transitional Areas • Mixed Barren Land
Perennial Snow or Ice	• Perennial Snowfields • Glaciers

3.3 Land Use and Land Cover Change Detection

The earth's surface is changing as a result of natural phenomena or human activity, for example, wildfires, lightning strikes, storms, pests, agro-forestry, agricultural expansion, social, economic, technological, historical factors and urban growth (Borak, Lambin & Strahler 2000). Generally, the earth’s surface changes are divided into two categories: land use and land cover (Barnsley, Moller-Jensen & Barr, 2001). If the change detection of the earth’s surface is done timely and accurately then the relationship and interaction between natural phenomena and humans can be better analyzed and understood as a result of which better management and use of resources can be done. Change detection involves the application of multi-temporal datasets to quantitatively analyze the changes of land cover classes. Lambin & Ehrlich (1997), suggest that there are three major causes of land use/land cover changes that happen, with differing rates and on different scales: biophysical factors, technological and economic considerations, and institutional and political arrangements. Besides these, there are changes resulting from military conflicts. In order to be able to plan and implement meaningful policies and effective schemes to sustain regional development, there is a crucial need to know the land use/land cover patterns in a particular region (Lillesand, Keifer 1994; Lillesand, Kiefer & Chipman 2004, Lu et al., 2004).

Change detection has emerged as a significant process in managing and monitoring natural resources and urban development mainly due to provision of quantitative analysis of the spatial distribution of the population of interest. There are a lot of available techniques that serve purpose of detecting and recording differences and might also be attributable to change (Singh, 1989; Yuan et al., 1999). For detecting and analyzing the change on the earth’s surface, various techniques are employed. Before studying about various change detection techniques, it is necessary to know about the procedure of change detection. To detect the changes of the surface of the earth, six main steps are important as mentioned by Jensen which are as follows:

1.Nature of change detection problems.

2.Selection of remotely sensed data.

3.Image preprocessing.

4.Image processing or classification.

5.Selection of change detection algorithm.

6.Evaluation of change detection results.

There are various ways of approaching the use of satellite imagery for determining land use change in urban environments. Yuan, et al., (1998) divide the methods for change detection and classification into pre-classification and post-classification techniques. The pre-classification techniques apply various algorithms including image differencing and image rationing to single 13 or multiple spectral bands, vegetation indices (NDVI) or principal components, directly to multiple dates of satellite imageries to generate “change” vs. “no-change” maps. These techniques locate changes but do not provide information on the nature of change (Ridd & Liu, 1998; Singh, 1989; Yuan, et al., 1998). On the other hand, post classification comparison methods use separate classifications of images acquired at different times to produce difference maps from which “from-to” change information can be generated (Jensen, 2004).

The goal of change detection is to discern those areas on digital images that depict change in the feature of interest between two or more image dates. The reliability of the change detection process may be strongly influenced by various environmental factors that might change between image dates. Different change detection techniques which are commonly used are as follows:

A. Pre-classification Techniques:

Pre-Classification method analyses the change without classifying the image value. The most common and widely used pre-classification method is “Vegetation Index Differencing (NDVI)”. Many pre-classification techniques have been used and compared to assess and identify LULCC changes such as, Image Differencing (ID) (Hayes & Sader, 2001), Imp (Green, Kempka & Lackey, 1994), Band Image Differencing (Chavez, MacKinnon,1994) (Wen, Yang, 2009, Geun-Won Yoon, Young Bo Yun & Jong-Hyun Park 2003), Spectral Change Vector Analysis (Wen, Yang, 2009), Principal Component D (Chen et al., 2003) and others.

B. Post Classification Techniques

This method is also known as delta classification. The post classification method is proved to be the most popular approach in change detection analysis. It requires the comparison of independently produced classified image. The approach of this method is based on the rectification of the classified images independently then the thematic maps are generated which is followed by the comparison of corresponding labels to identify the areas where change has occurred. The post-classification comparison has been proven to be the most popular approach in change detection analysis (Foody, 2002). This approach is based on rectification of more than one classified image; where it involves the classification of each of the images independently, then the thematic maps are generated, followed by a comparison of the corresponding labels or themes to identify areas where change has occurred. The pixel-based classification process brings out small noisy appears in isolated pixel or small group of pixels of which classification process is different from its neighboring pixels (Huang, et al., 2004). The representation of classified map is usually a salt-and-pepper appearance (Lillesand, 2004, pp. 584), for instance, there are some very small spots existing and they are not suitable for analyzing. The post-classification processing can generate a smoother image. In Erdas, the common ways of post-classifications are to clump, sieve, eliminate and recode.

There are several advantages to this technique: it minimizes sensor, atmospheric, and environmental differences because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates and it provides a complete matrix of land cover change when using multiple images (Lu et al., 2004; Jensen, 2005; Naumann & Siegmund 2004; Teng et al., 2008).

3.3.1 Factors influencing Change Detection

Generally speaking, to select a suitable method of detecting change is very significant because there is no single method that is can be efficiently applied to all study areas. Selection of an appropriate change-detection technique, in practice, often depends on the nature of the change detection problem under investigation, which considers a critical step in change detection studies, the requirement of information, application , the data sets availability and quality, time and cost constraints of the data sets, analysis skill and experience, and registration of multiple image data sets (Macleod, Congalton, 1998; Johnson, Kasischke, 1998; Nielsen, Conradsen & Simpson, 1998; Cracknell, 1998; Dai, Khorram, 1998). The appropriate technique for the change detection can be selected by determining the object of change detection study. Techniques like image differencing and image ratioing can be used only when the change and no-change information is required. If a detailed matrix is required, techniques such as post classification will have to be adopted. The size of the study area and spatial resolution plays a vital role in the selection of a particular change detection technique.

Regardless of the technique used, the success of change detection from imagery can be affected by many factors: the quality of image registration between multi-temporal images, the atmospheric conditions, acquisition times, illumination, viewing angles, soil moisture, noise, shadow present in the images (Singh, 1989a), vegetation phenological variability or differences (Lu et al., 2002; Rogan, Franklin & Roberts, 2002); sensor calibration (Lillesand, Keifer, 1994). In addition to the landscape and topography characteristics of the study areas, analyst's skill and experience, selection of the change detection technique, besides, the different steps during the implementation of change detection procedure that can produce problems and errors and affect the success of change detection, for example, image pre-processing (Lu et al., 2004; Jensen, 2005).

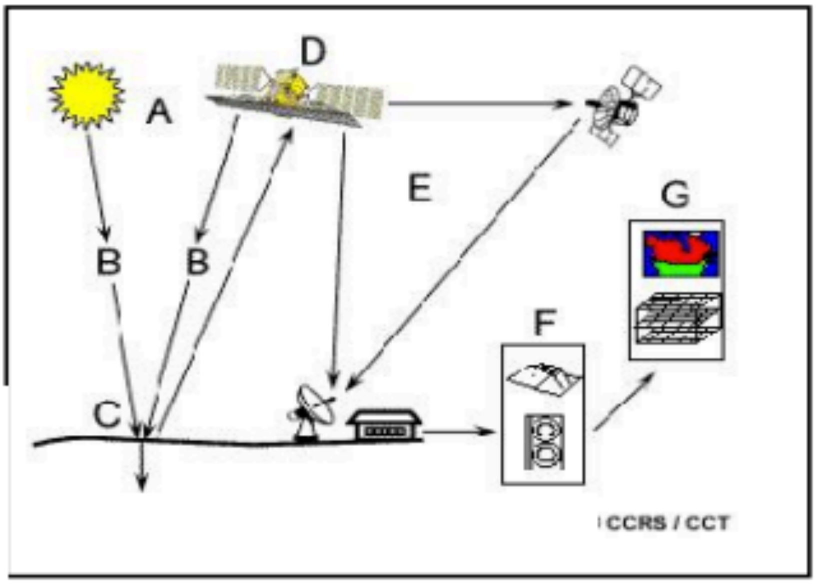
3.4 Remote Sensing and GIS in Land use and Land Cover Change

Remote sensing is defined as the science and art of obtaining information about an object, area or phenomena through the analysis of data acquired by a device that is not in contact with the object, area, or phenomena under investigation. The term "remote sensing," first used in the United States in the 1950s by Ms. Evelyn Pruitt of the U.S. Office of Naval Research. Remote Sensing (RS) is now commonly used to describe the science and art of obtaining information about an object, area, or phenomenon under investigation by a device that records the spectral properties of surface materials on the earth from a distance (Singh, 1989a; Rogan & Chen, 2004). Remote sensing is of two types: active remote sensing and passive remote sensing. The active remote sensing emits their own electromagnetic radiation which interacts with the object or area for example RADAR and LIDAR. The passive remote sensing system uses the radiation from the sun for the illumination of object or area under observation. The energy which is radiated or emitted back from the surface or object is recorded by the sensors. These sensors can be air based or space based. Numerous methods have been developed by many researchers to review changes in the LULC (Jwan Al-doski, 2013; Singh, 1989) including multi-temporal composite image change detection (Carmelo et al., 2012; Eastman & Fulk, 1993). on-screen digitization of change (Sreedhar et al., 2016), vegetation index differencing (Shanmugam & Rajagopalan, 2013), and post-classification change detection (Belal & Moghanm, 2011; Courage et al., 2013; Kafi et al., 2014).

Recently, multispectral and multi-temporal high-and medium-spatial-resolution satellite data have emerged as essential tools for estimating aspects such as the vegetation cover, forest degradation, and urban expansion (Mustafa et al., 2007). Remote sensing and GIS technology provide a platform for studying landscape transformations throughout the surface of the Earth (Estoque & Murayama, 2015). However, changes in land cover and in the way, people use the land have become recognized over the last 15 years as important global environmental changes in their own right (Turner, 2002). To understand how LULC change affects and interacts with global earth systems, information is needed on what changes occur, where and when they occur, the rates at which they occur, and the social and physical forces that drive those changes (Lambin, 1997)

The data obtained from remote sensing system is in the form of aerial photographs, satellite image, spatial data set and other data.

1. Energy Source or Illumination (A) – the first requirement for remote sensing is to have an energy source which illuminates or provides electromagnetic energy to the target of interest.



2. Radiation and the Atmosphere (B) – as the energy travels from its source to the target, it will come in contact with and interact with the atmosphere it passes through. This interaction may take place a second time as the energy travels from the target to the sensor.

3. Interaction with the Target (C) - once the energy makes its way to the target through the atmosphere, it interacts with the target depending on the properties of both the target and the radiation.

4. Recording of Energy by the Sensor (D) - after the energy has been scattered by, or emitted from the target, we require a sensor (remote - not in contact with the target) to collect and record the ectromagnetic radiation.

5. Transmission, Reception, and Processing (E) - the energy recorded by the sensor has to be transmitted, often in electronic form, to a receiving and processing station where the data are processed into an image (hardcopy and/or digital).

6. Interpretation and Analysis (F) - the processed image is interpreted, visually and/or digitally or electronically, to extract information about the target which was illuminated.

7. Application (G) - the final element of the remote sensing process is achieved when we apply the information we have been able to extract from the imagery about the target in order to better understand it, reveal some new information, or assist in solving a particular problem. These seven elements comprise the remote sensing process from beginning to end.

Figure 1. Process of Remote Sensing (Source: CCRS, 2007)

Remote Sensing presents a useful tool for understanding and managing earth resources and LULC change detection (Matinfar et al., 2007). Enormous efforts have been made to delineate LULC on a local scale as well as global scale by applying different multi-temporal and multi-source remotely sensed data from both airborne and space borne sensors. Medium resolution satellite imagery such as Landsat satellite data, are the most widely used data types of monitoring and mapping land cover changes (Williams, Goward & Arvidson, 2006). They have been successfully utilized for monitoring LULC changes especially in the land that has been affected by human activity to various degrees, for example, Lu Junfeng et al., (2011) used Landsat Multi-Spectral System (MSS), Landsat TM and ETM+ remote-sensing data for land cover changes. Remote sensing images can effectively record land use situations and provide an excellent source of data, from which updated LULC information and changes can be extracted, analyzed and simulated efficiently through certain means (Pradhan et al., 2008; Singh et al., 2017). Therefore, remote sensing is widely used in the detection and monitoring of land use at different scales (Hua et al., 2017; Mishra et al., 2016).

Lu et al., (2004) generalized the change detection methods into seven types, namely, arithmetic operation, transformation, classification comparison, advanced models, GIS integration, visual analysis and some other methods. Change information obtained may be either in the form of simple binary change (i.e., change vs. no change as in the case of image differencing, image rationing, etc) or detailed from-to change as in the case of using post-classification comparison (Im et al., 2007).

3.5 Accuracy Assessment in LULC

Accuracy assessment is an important part of any classification project. It compares the classified image to another data source that is considered to be accurate or ground truth data. Ground truth can be collected in the field; however, this is time consuming and expensive. Segmentation and classification are two steps to create objects in classification result (Hay, 2008). The segmentation gives an object a region of space (Carleer, 2005) and the classification gives the object the attribute (Castilla, 2008). Ground truth data can also be derived from interpreting high-resolution imagery, existing classified imagery, or GIS data layers. It is the final step in the analysis of remote sensing data which help us to verify how accurate our results are. It is carried out once the interpretation/classification has been completed.

In a statistical context, accuracy comprises bias and precision and the distinction between the two is sometimes important as one may be traded for the other (Campbell, 1996; Maling, 1989). In thematic mapping from remotely sensed data, the term accuracy is used typically to express the degree of 'correctness' of a map or classification. A thematic map derived with a classification may be considered accurate if it provides an unbiased representation of the land cover of the region it portrays. In essence, therefore, classification accuracy is typically taken to mean the degree to which the derived image classification agrees with reality or conforms to the 'truth' (Campbell, 1996; Janssen & van der Wel, 1994; Maling, 1989; Smits et al., 1999). A classification error is, thus, some discrepancy between the situation depicted on the thematic map and reality.

Accuracy of image classification is most often reported as a percentage correct and is represented in terms of consumer's accuracy and producer's accuracy. The consumer's accuracy (CA) is computed using the number of correctly classified pixels to the total number of pixels assigned to a particular category. The Accuracy Assessment producer's accuracy (PA) informs the image analyst of the number of pixels correctly classified in a particular category as a percentage of the total number of pixels actually belonging to that category in the image. Producer's accuracy measures errors of omission. In other words, the term consumer's accuracy is used when a classified image is examined from the user's point of view. Producer's accuracy is used when same is viewed from analyst's perspective.

The history of accuracy assessment outlined above, however, relates mainly to mapping investigations that have focused on local to regional scales. The methods used may not be transferable to coarser scales (Merchant et al., 1994). The confusion matrix is currently at the core of the accuracy assessment literature. As a simple cross-tabulation of the mapped class label against that observed in the ground or reference data for a sample of cases at specified locations, it provides an obvious foundation for accuracy assessment (Campbell, 1996; Canters, 1997).

3.5.1 Need for Accuracy Analysis

Accuracy becomes a critical issue while working in a Geographical Information System (GIS) framework where you use several layers of remotely sensed data. In such cases, it would be very important to know the overall accuracy which is dependent upon knowing the accuracy of each of data layers. There are a number of reasons why assessment of accuracy is so important. Some of them are given below:

- accuracy assessment allows self-evaluation and to learn from mistakes in the classification process,
- it provides quantitative comparison of various methods, algorithms and analysts,
- it also ensures greater reliability of the resulting maps/spatial information to use in decision-making process.

A map using remotely sensed or other spatial data cannot be regarded as the final product without taking necessary steps towards assessing accuracy or validity of that map. A number of methods exist to investigate accuracy/error in spatial data including visual inspection, non-site-specific analysis, generating difference images, error budget analysis and quantitative accuracy assessment.

3.5.2 Sources of Errors

Classification error occurs when a pixel or feature belonging to one category is assigned to another category. Errors of omission occur when a feature is left out of the category being evaluated. Errors of commission occur when a feature is incorrectly included in the category being evaluated. For example, errors of omission are the allotment of errors of barren land on the ground to the agricultural land category on the map. This has caused the removal of an area of real barren land on the ground from the map.

3.5.3 Calculation of Classification Accuracy

First way of calculating the classification accuracy is considering the Error Matrix.

A. Error Matrix

Error matrix is a very effective way to calculate map accuracy. Overall accuracy is the sum of the major diagonal which is the number of correctly classified sample units divided by the total number of sample units. Producer's and user's accuracy are computed for individual category accuracy by dividing the total number. A commission error represents an area in a category which it does not belong to that category. An omission error reveals the excluded area from the category to which it belongs to. Producer's accuracy plus omission error equals 1and user's accuracy plus commission error equals 1(Conggalton, 2008). Once a classification exercise has been carried out, there is a need to determine the degree of error in the end product which includes identified categories on the map. Errors are the result of incorrect labeling of the pixels for a category. The most commonly used method of representing the degree of accuracy of a classification is to build a k×k array, where k represents the number of categories. Error matrix is a set array (rows and columns) that can be used to evaluate the degree of correctness of classified image. According to Campbell (1987), it is a method of reporting site-specific error. It is derived from a comparison of two types of maps such as a standard reference map and a classified map.

For generation of the error matrix, you require two images namely, classified image which is image under evaluation and a standard or reference map derived from field survey. Sometimes, high resolution images are also used in the absence of a reference map. The classifier also keeps a count of the numbers of cells or pixels in each reference category as they are assigned to categories on the created image.

- **Interpretation of Errors**

Off-diagonal elements represent misclassified pixels or the classification errors, that is the number of ground truth pixels that ended up in another class during classification. The off-diagonal row elements represent ground truth pixels of a certain class which were excluded from that class during classification. Such errors are also known as errors of omission or exclusion. The off-diagonal column elements represent ground truth pixels of other classes that were included in a certain classification class. Such errors are also known as errors of commission or inclusion.

- **Producer's Accuracy**

Producer's accuracy is defined as the probability that any pixel in that category has been correctly classified. It is the values in column accuracy (producer's accuracy) present the accuracies of the categories in the classified image

$$\text{Accuracy (Producer's Accuracy)} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., row total)}}$$

- **User's Accuracy**

User's accuracy is defined as the probability that a pixel classified on the image actually represents that category on the ground. The figures in row reliability (user's accuracy) present the reliability of classes in the classified image

$$\text{Reliability (User's Accuracy)} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived from the reference data (i.e., column total)}}$$

- **Overall Accuracy**

It is also desirable to calculate a measure of accuracy for the entire image across all classes present in the classified image. The collective accuracy of map for all the classes can be described using overall accuracy, which calculates the proportion of pixels correctly classified. The overall accuracy is calculated as given below:

$$\text{Overall accuracy} = \frac{\text{Sum of the diagonal elements (as shown in bold letters in Table 14.1)}}{\text{Total number of accuracy sites (pixels)}}$$

B. Kappa Analysis

The Kappa coefficient is a measure of overall agreement of a matrix. In contrast to the overall accuracy — the ratio of the sum of diagonal values to total number of cells counts in the matrix — the Kappa coefficient takes also non-diagonal elements into account (Rosenfield & Fitzpatrick, 1986). It is a discrete multivariate technique used to assess classification accuracy from an error matrix. Kappa analysis generates a kappa coefficient or Khat statistics, the values of which range between 0 and 1. Kappa coefficient (Khat) is a measure of the agreement between two maps taking into account all elements of error matrix. The Kappa coefficient was introduced to the remote sensing community in the early 1980s (Congalton & Mead, 1983; Congalton et al., 1983) and has become a widely used measure for classification accuracy. It was recommended as a standard by Rosenfield & Fitzpatrick-Lins (1986). It is defined in terms of error matrix as given below:

$$\boldsymbol{K_{hat}} = \mathbf{(Obs - exp)/(1 - Exp)}$$

Where:

Obs = Observed correct, it represents accuracy reported in error matrix (overall accuracy)

Exp = Expected correct, it represents correct classification.

Accuracy assessment is still relatively new and is an evolving area in remote sensing. The effectiveness of different methods and measurement are still being explored and debated.

3.5.4 Sample Design for Accuracy Assessment

Sample Design Assessing the accuracy of maps derived from remote sensing data is both time and money consuming. Due to the fact that it is not possible to check whole mapped areas, sampling becomes the means by which the accuracy of land-cover maps can be derived (Congalton, 1988a). As stated by Ginevan (1979) any sampling scheme should satisfy three criteria:

1. It should have a low probability of accepting a map of low accuracy.

2. It should have a high probability of accepting a map of high accuracy.

3. It should require a minimum number, N, of ground truth samples.

Therefore, researchers have published formulas to calculate the numbers of sample plots which are dependent on the objectives of the project (van Genderen and Lock, 1977; Rosenfield, Fitzpatrick-Lins and Ling 1982; Rosenfield, 1982; Congalton, 1991). Common Sampling methods are:

- Simple Random Sampling (SRS),
- Stratified Random Sampling (STRAT),
- Systematic Sampling (SYS),
- Stratified Systematic Unaligned Sampling (SSUS),
- Cluster Sampling (CLUSTER).

These different sampling methods can be seen in the figure below

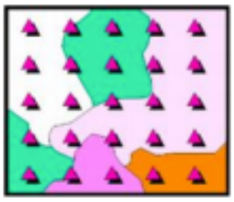
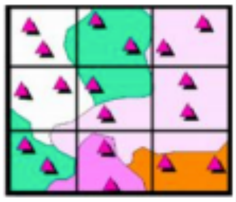
Simple Random Sampling	Systematic Sampling	Stratified Random Sampling	Systematic Non-Aligned Sampling	Cluster Sampling
				
Observations are randomly placed	Observations are placed at equal intervals	In each class a minimum number of observations are randomly placed	Randomly placed centroids are used as a base of nearby observations	A grid provides even of randomly placed observations

Figure 2. Methods for collecting ground reference data, (Source http://www.forestry.oregonstate.edu)

Congalton (1991) suggested a combination of stratified and random sampling. The stratified sampling can be done in conjunction with training data collection in an early phase of the project.

After the first classification results, stratified random sampling completes the data collection necessary for accuracy assessment. Fen Stermaker (1991) proposes a multistage sample approach for large area sampling. The number of samples is a compromise between the effort to minimize the costs of field sampling and the requirement of a minimum sample size to be representative and statistically sound. In general, the larger the sample size, the greater the confidence one can have in assessments based on that sample (Dicks & Lo, 1990). Depending on the goal of the accuracy assessment the number of sample plots can be calculated with different methods.

Basic sampling designs, such as simple random sampling, can be appropriate if the sample size is large enough to ensure that all classes are adequately represented. The adoption of a simple sampling design is also valuable in helping to meet the requirements of a broad range of users (Stehman & Czaplewski, 1998) although the objectives of all users cannot be anticipated (Stehman et al., 2000).

3.6 LULC and Climate Change

Climate and land-use changes are two major global ecological changes predicted for the future. Heretofore, causes and consequences of human-induced climate change and land-use activities have largely been examined independently (but see Turner et al., 1993). However, climate change and land use affect each other. It is widely believed that climate change and increased climatic variability will impact land use through affecting different economic sectors such as agriculture, housing, nature and ecosystems, and by changing the water resources system (Commissie Waterbeheer 21e eeuw, 2000; IPCC, 2001; Verbeek, 2003). Land-use activity contributes to climate change, and changes in land-cover patterns are one way in which the effects of climate change are expressed. Obviously, climate change is not the only factor driving land-use change. Socio-economic developments are another major driving force. In fact, these developments interact with climatic changes (Dale, 1997; Watson et al., 2000). For example, economic and population growth cause increased emission of greenhouse gasses, which influence the global climate. As a result, changes in annual regional rainfall patterns could impact agricultural production or cause the tourist industry to migrate to other regions.

Land-use effects on climate change include both implications of land-use change on atmospheric flux of CO^2 and its subsequent impact on climate and the alteration of climate change impacts through land management. Effects of climate change on land use refers to both how land use might be altered by climate change and what land management strategies would mitigate the negative effects of climate change. The largest climate sensitive sector is agriculture. Both natural science experiments and economic analyses suggest that crop yields have a hill-shaped relationship with temperature and precipitation. There is an ideal temperature and precipitation level for every crop. Locations that are either cooler or warmer than the ideal, or drier or wetter, have lower productivity. Some crops are more valuable than others. The temperature and precipitation levels that produce the most valuable crop will lead to the most net revenue. If a farm is either cooler or warmer than that ideal, or drier or wetter, it may be forced to grow a lower-valued crop. Consequently, net revenue also has a hill-shaped relationship with temperature and precipitation (Mendelsohn, Nordhaus & Shaw, 1994).

The ecological literature suggests that warming will increase plant productivity and lead to a widespread movement of ecosystems toward the poles (Mellilo et al., 1993, Neilson et al., 2005). Land uses, such as forestry and grazing, that depend on specific ecosystems will be affected. Productivity will change and the mix of land uses in different regions will change. This process is dynamic and progresses as climate changes. Climate change may also have an indirect effect as it changes hydrological systems, affecting flows of water available to landowners. Insect and disease vectors may change, thereby affecting farms and forests with new pest problems. Finally, sea-level rise will affect land uses along the coast.

3.7 LULC and Human Influence

There are basically a lot of human activities which have an influence of Land-use Cover and change (Table 1). Early analysts of climate impacts identified five sectors of the economy that are sensitive to climate change: agriculture, forestry, water, coastal, and energy (Pearce et al., 1996). Agriculture and forestry are key land uses. Water is important to land because its availability affects the viability of agriculture through irrigation. In the coastal sector, sea level rise might alter the land available along the coasts for urban and other uses.

Table 3. Human Causes and Consequences of LULCC. Source; Turner et al., 1993

Human causes and consequences of land-cover change.

Causes†	Consequences: Typical land-cover changes	Consequences: Typical activities that modify land cover	Consequences: Ecological characteristics affected
Population growth	Forest harvesting	Irrigation	Biodiversity
Affluence	Agricultural expansion	Fertilization	Habitat
Technology	Urbanization	Forest degradation (thinning, coppicing, gathering wood)	Soil quality
			Productivity
Political economy	Second home development	Introduction of exotics	Extractable resources
Political structure	Flooding	Landscape fragmentation	Water quality
Attitudes and values			Regional and global climate

Land use/cover (LULC) is the most prominent form of the global environmental change phenomenon occurring at spatial and temporal scales. Land cover is the physical and biological cover of the surface of the land, whereas land use is the indicator of complex human activities that alter land surface processes (Foley et al., 2005). The conversion of natural land to anthropogenic landscapes represents the form of human impact on the environment (McGranham et al., 2005).

Roughly 40 % of the earth's land surface is under agriculture and 85 % has some level of anthropogenic influences (Sanderson et al., 2002).

Urbanization is a process through which the productive agricultural land, forests and surface water bodies are being irretrievably decreasing. Rapid growth of cities has posed a threat to their Central Business District (CBD). This is evident from the growing eagerness of the people to seek accommodation in rural-urban fringe areas (Tali, 2012). For the period from 1990 to 2000, Angel et al., (2005: 56) estimated that the annual increase in built-up areas in developing countries was around 3.6%, whereas it amounted to only 2.9% on average in industrialized countries. In Europe, the annual growth of urban land is expected to range between a maximum of 2% in rapidly growing areas and nearly zero in remote rural regions (EEA, 2006). As the surface physical, chemical, and biological characters vary greatly across regions, the climatic influences of urbanization and land-use change vary correspondingly (Deng et al., 2013). Due to the lack of data and knowledge, it has been widely recognized that this issue is of great importance for further exploration and discussion (Feddema et al., 2005).

3.8 LULC and Ecosystems

Land use and land cover (LULC) changes alter structures and functions of ecosystems and influences the supply of ecosystem services (Hu, Liu & Min, 2008; Kreuter et al., 2001; Yirsaw et al., 2017). The ecosystem is directly affected by changes in land use/land cover (LULC). However, due to the development of society and the rapid increase in population, the speed, degree, and intensity of LULC changes are now faster compared to the past, and a large number of landscapes on Earth are getting disturbed (Lambin et al., 2011). For instance, in the tropics, more than 55% of new agricultural land was at the expense of intact forests, while 28% was associated with disturbed forests from 1980–2000 (Gibbs et al., 2010). Changes in LULC influence ecosystem services by increasing the availability of certain services while reducing other services that influence the ability of the biosystem to support human needs, further impacting ecological degradation (Polasky et al., 2011).

4. METHODOLOGY

4.1 Study Area of Rimov, South Bohemia and Characteristics

Rimov is a municipality and village in České Budějovice District in the South Bohemian Region of the Czech Republic. It has about 900 inhabitants and located on left bank of the Malše River about 14 km south of České Budějovice. South Bohemia has a high landscape value as well due to the absence of large industrial facilities. Proof of this is the great number of protected areas. South Bohemia is a region of countless fishponds, pine forests and extensive peat bogs, enhanced by outlines of cities and rural churches that harmonize beautifully with the snow-white marshland farmsteads. This is the typical South Bohemian scenery around České Budějovice, Třeboň and Veselí nad Lužnicí.

The South Bohemia Region has more than 627 000 inhabitants in 7 districts with a total of 623 municipalities, 45 of which are towns. The largest town and the centre of the Region is České Budějovice with 95 000 inhabitants. The other big towns are Tábor, Písek, Strakonice, and Jindřichův Hradec. One-third of the South Bohemian inhabitants live in these five towns and only 4.3% live in municipalities with up to 200 inhabitants. The South Bohemia Region is not rich in raw materials and raw material resources for energy are negligible. Its main raw material are sands, gravel sands, clay, gravel, and glass sands. The most important of the other resources is peat, and in some localities also limestone, diatomaceous earth, gneiss, granite, and graphite. The important natural resources include the vast coniferous, spruce, and pine forests, especially in the Šumava and Novohradské Mountains. Agriculture is focused on plant production, mainly cereals, oleipherous plants, and potatoes. Cattle and pig breeding are dominant in livestock production. The Region accounts for some 11% of the agricultural production of the Czech Republic and has a long tradition in fish farming. The total area of its ponds comprises around 25 000 hectares.

The climate in South Bohemia is of a transitional Central European type. It is affected alternatively by an oceanic influence from the west, and a continental influence from the east. Therefore, the weather can be variable. Most of the South Bohemian region belongs to the mild, warm and wet zone and at altitudes above 750 m this passes to mild and cool. The warmest month is usually July, with temperatures averaging between 17 and 18 °C in valley areas. In higher localities (over 900 m) the temperatures can drop below 14 °C.

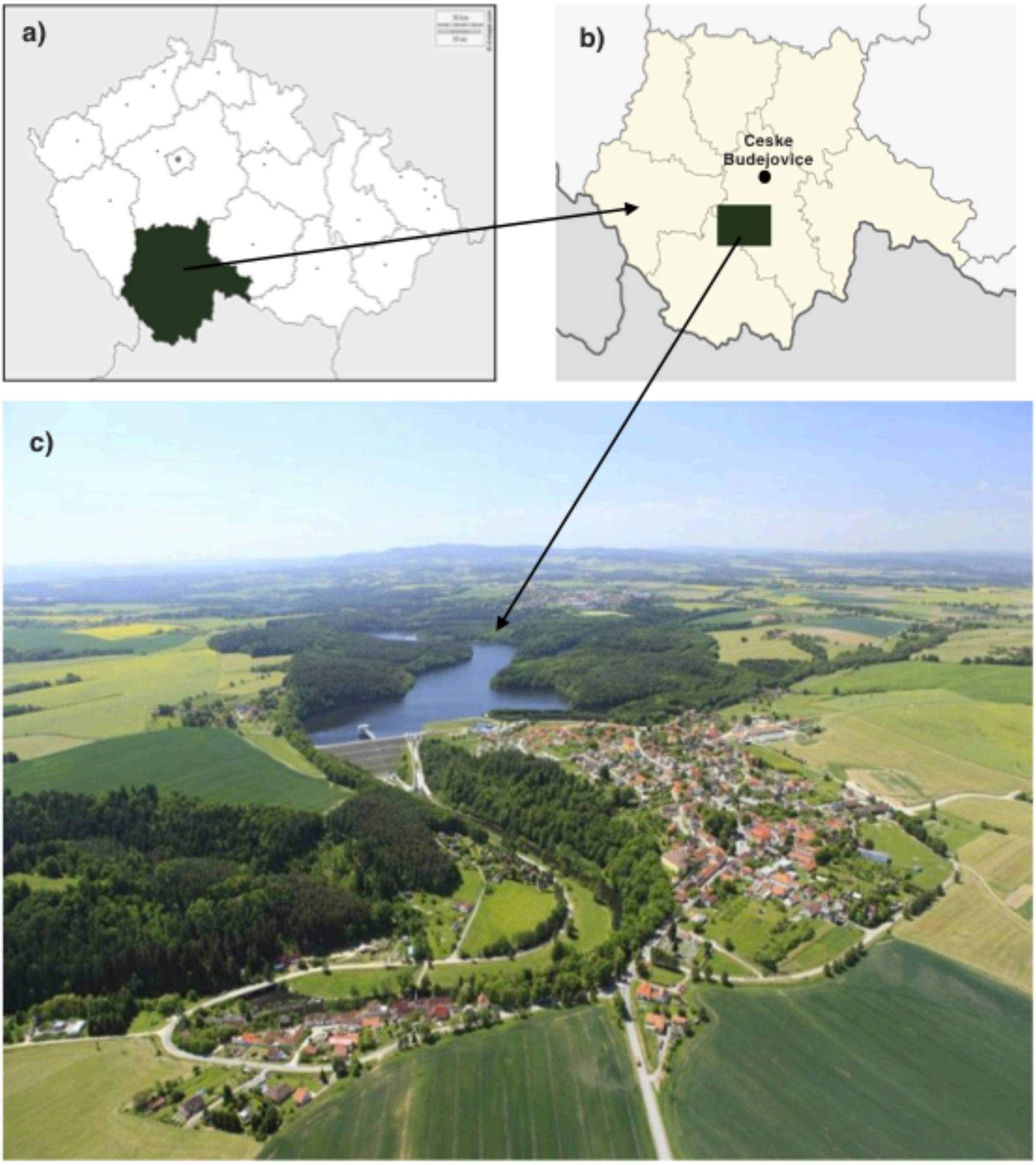


Figure 3. Selected study area used in this research. a) Map of Czech Republic, b) Map of south Bohemia and c) Aerial photo of the selected study site showing the different Types of Land Use and Land Cover Classes

4.1.1 Reservoir Characteristics

The Římov Reservoir (48○50’56” N, 14○29’26” E) is a dimictic, deep valley reservoir with a surface area of 2.06 km2. The total population in the area is 35 inhabitants per km2. It has the minimum altitude of 430 m a.s.l. and maximum altitude if 1111 m a.s.l. It was built in 1974–78 as a storage reservoir for drinking water supply by damming the River Malše, the main reservoir tributary accounting for 90% of the water inflow.The reservoir is filled by headwaters from a medium-sized hilly catchment (489 km2) covered mostly by forests and partly with arable land, pastures and meadows. The dam is 47m high and 290m long at its crest and is equipped with multilevel outlet and withdrawal structures. Water is discharged into the river via

(i) a gated spillway (466.1m a.s.l.)
(ii) two bottom outlets (430.5m a.s.l.)
(iii) a small shaft outlet with adjustable spot height of intakes from 440.5 to 471m a.s.l. and a capacity of 3.6 m3 s−1, which is also used by a small hydropower plant with a maximum capacity of 1 MW. Raw water for the drinking water plant (approx. 7km downstream from the dam) is withdrawn at different elevations (444.5, 450.5, 457 and 463.5m a.s.l.) in a tower situated near the dam. Maximum and mean depths are 43 and 17 m, respectively, theoretical retention time is 92 days, maximum volume 32 x 106m^3, and watershed area 488 km^2.

The trophic state of the reservoir is mesotrophic to eutrophic with well-developed thermal stratification during the summer. Dominant fish are common bream (Abramis brama Linnaeus, 1758), roach (Rutilus rutilus Linnaeus, 1758) and bleak (Alburnus alburnus Linnaeus, 1758). These species frequently occur in open water of the reservoir during the first year of life (Jůza et al., 2009, 2013).

4.2 Research Methodology

This section gives a broad overview the data and methods that were applied in data acquisition, preprocessing, image classification, presentation which aims to achieve the designed objectives and the research questions posed.

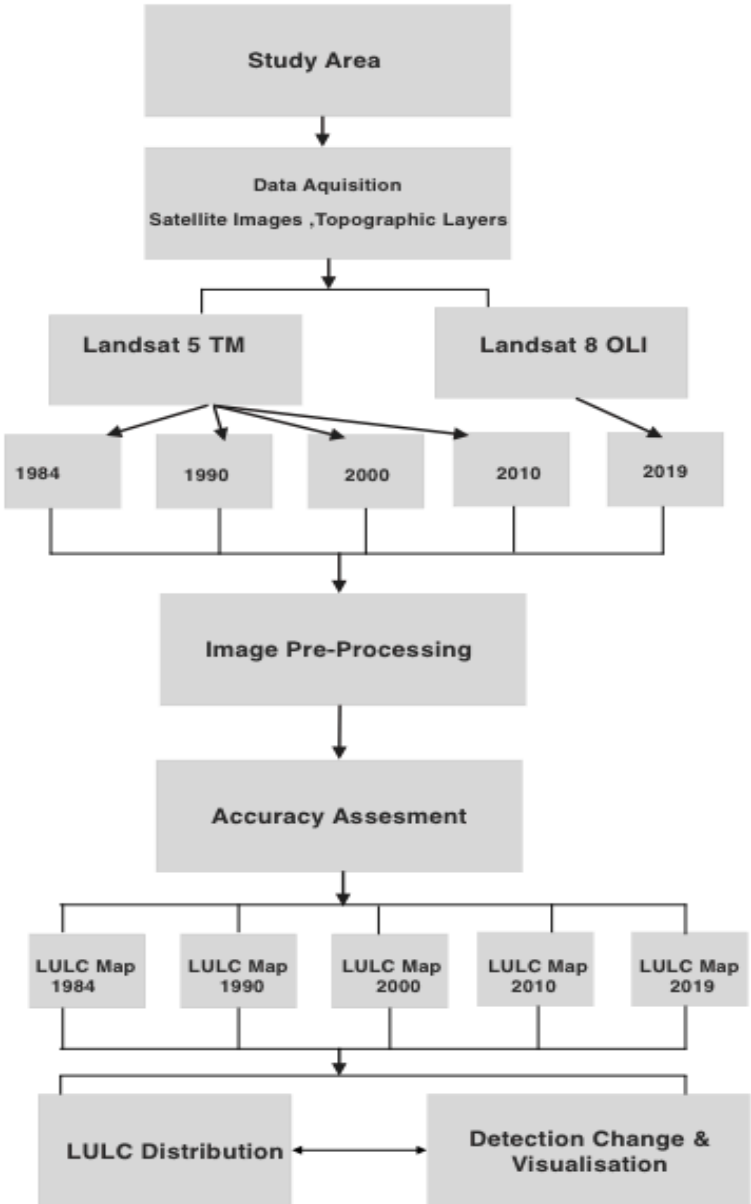


Figure 4. Overview of Research Methodology flowchart used in this study.

4.2.1 Data Acquisition

To achieve the objective of the present study, Landsat satellite images are obtained from USGS database that is an online resource where satellite images are freely available. Landsat Thematic mapper (TM) and Landsat Operational Land Imager (OLI) data are used to identify and analyze the land use/land cover around the Rimov reservoir of Czech Republic. These datasets have multi-temporal properties. The Landsat 4 and Landsat 5 images consist of seven spectral bands described in Table 4 with a spatial resolution of 30 meters from band 1 to 5 and 7. The Landsat 8 images consist of 11 bands with a spatial resolution of 30 meters from band 1 to 7 and 9 as described in Table 5.

Table 4. Description of Spectral bands of Landsat TM

Bands	Wavelength
Band 1 (Blue)	0.45 – 0.52
Band 2 (Green)	0.52 – 0.60
Band 3 (Red)	0.63 – 0.69
Band 4 (Near Infrared)	0.76 – 0.90
Band 5 (Shortwave infrared 1)	1.55 – 1.75
Band 6 (Thermal)	10.40 – 12.50
Band 7 (Shortwave Infrared 2)	2.08 – 2.35

Table 5. Description of Spectral bands of Landsat OLI

Bands	Wavelength
Band 1 (Aerosol)	0.43 – 0.45
Band 2 (Blue)	0.45 – 0.51
Band 3 (Green)	0.53 – 0.59
Band 4 (Red)	0.64 – 0.67
Band 5 (Near Infrared)	0.85 – 0.88
Band 6 (Shortwave infrared 1)	1.57 – 1.65
Band 7 (Shortwave Infrared 2)	2.11 – 2.29
Band 8 (Panchromatic)	0.50 – 0.68
Band 9 (Cirrus)	1.36 – 1.38
Band 10 (TIRS 1)	10.6 – 11.19
Band 11 (TIRS)	11.5 – 12.51

The images were taken for the time period of 35 years starting from 1984 to 2019 (Table 6). Images used in the study were chosen on the basis of data availability and suitability. Suitability in this case refers to the time series and image clarity. Images selected were between the months of July and September with less than 10% cloud cover. Landsat images for the year 1984, 1990,2000,2010 and 2019 were acquired from USGS website (USGS Earth Explorer) under the following link http://earthexplorer.usgs.gov.

Table 6. Landsat images used in this research.

Acquired Date	Spacecraft/Sensor	Path/Row	Pixel Size (m)	Coordinate System/Datum
1984-08-28	Landsat 5	191/026	30	UTM/WGS84
1990-09-30	Landsat 5	191/026	30	UTM/WGS84
2000-09-09	Landsat 5	191/026	30	UTM/WGS84
2010-09-21	Landsat 5	191/026	30	UTM/WGS84
2019-07-05	Landsat 8	191/026	30	UTM/WGS84

4.2.2 Softwares Used

The study utilized a number of software in analyzing the data above. These softwares included ArcGIS 10.8, Google Earth Pro, and Microsoft Excel. ArcGIS was used for both vector and raster analysis. Google Earth Pro complemented ArcGIS in the process of accuracy assessment for verifying of randomly generated points and creating KML files.

4.2.3 Image Pre-Processing

In cartography, georeferencing processes follow the identification of homologous points in the coordinate systems of two documents of different origin:

- the raster coordinates system of a digitized ancient map without geographic coordinates, and
- the coordinates system of a support map or reference cartography (Dávila-Martínez; Camacho-Arranz, 2012).

Typical pre-processing operations include applying the geometric correction technique that helps to bring the digital images into registration with the Earth’s surface which is georeferencing. Georeferencing involves image alignment in a coordinate system, and it is the stage at which the image becomes a form of spatial data, since they are characterized by reference to a coordinate system defined by parameters such as projection and point of origin. A first step in the pre-processing is to check all images any defects such as striping. Then, all images were clipped to focus on our study area. After that, all images were corrected geometrically and radiometrically. At last, all images were stacked and classified.

4.2.4 Image Classification

One of the prerequisite components in any LULC classification study is the selection of a classification system. The classification system is usually designed to cover the user's requirement, availability of reference samples and classification algorithms, and reproducibility at various scales (Lu & Weng,2007). The method of image classification was used for change detection purposes. Its major advantage is the ability to create a series of maps for land cover and land use. The maximum likelihood classification method was used for the time series of Landsat images which is based on the likelihood of each pixel belonging to a particular class. The method consists of choosing training samples for each desired class from the composite image. The Land-cover and Land-use maps for the study area were developed by performing supervised classification of Landsat TM and OLI images. The five LULC classes that were used are described in detail in Table 7 below.

Table 7: Types of LULC classes used in this study

LULC Classes	Description
Built-up Area	Consists of dense built-up like settlements and urban structures. The building materials for the built-up class include bricks, concrete, asphalt, cement, etc.
Agricultural Land	It consists of entire agricultural fields of that particular season.
Bare Land	Includes the area which lies barren year-round, this also includes the land cleared up for the construction projects for developing new housing societies and other construction activities.
Water	This class includes all the water bodies in the study area, from ponds and pools of identifiable sizes to canals.
Grassland	It includes the vegetative land cover like grasses, herbs, shrubs and trees

5. RESULTS

5.1 Accuracy Assessment

A classification is inadequate without assessing its accuracy and can be defined as the precision by which a classifier processes image classification with respect to the reference or truth ground data. Accuracy tables show the relationship between ground truth data and the corresponding classified data obtained through error matrix report. The overall classification accuracy = No. of correct points/total number of points. The accuracy assessment was carried out by taking 25 ground truth points for each class. The total ground truth points taken were 125 without any consideration of informational class was selected. The ground truth points were taken with the help of Google Earth Pro. These points were compared with the classification results in Arc Map software of ESRI. (Figure 5 & 6)

In this study accuracy assessment was performed for the classified maps for all steps. Error matrices were used to assess classification accuracy using four measures of accuracy: overall accuracy, user's accuracy, producer's accuracy and Kappa statistic. Achieved results for the accuracy of all five years are summarized in the table above showing. For the accuracy assessment in this study, stratified random sampling was adopted, and the pixels were verified with using ancillary data. The Kappa Coefficient can range from -1 to 1. A value of 0 indicated that the classification is no better than a random classification. A negative number indicates the classification is significantly worse than random. A value close to 1 indicates that the classification is significantly better than random.

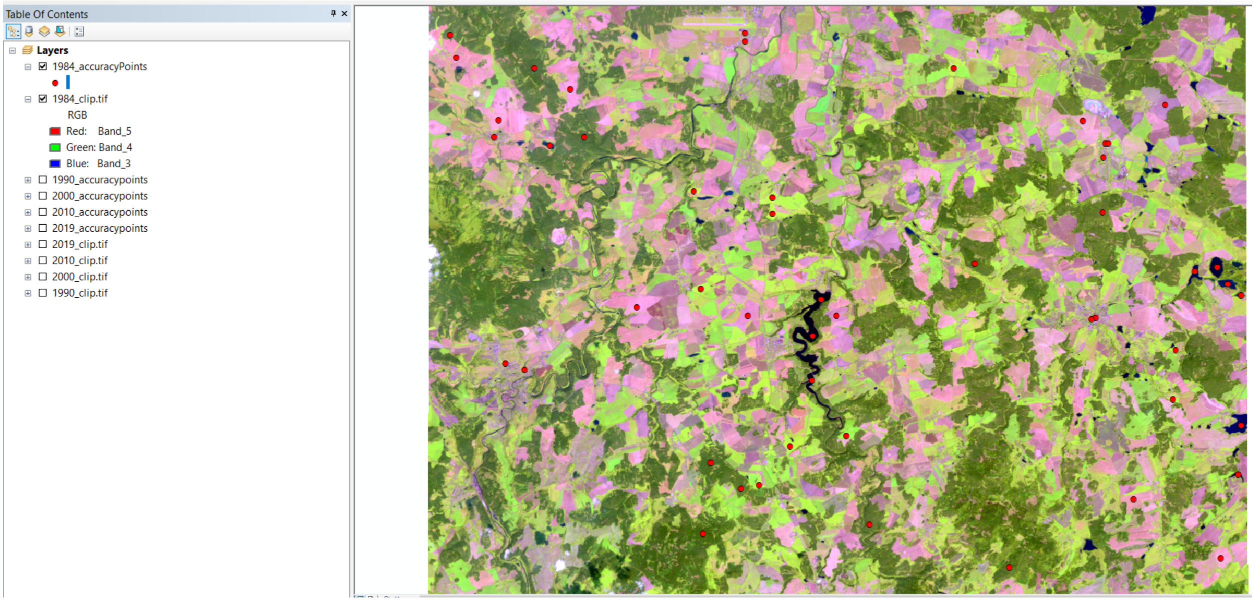


Figure 5. Simple Random Sampling for Accuracy Assessment in 1984

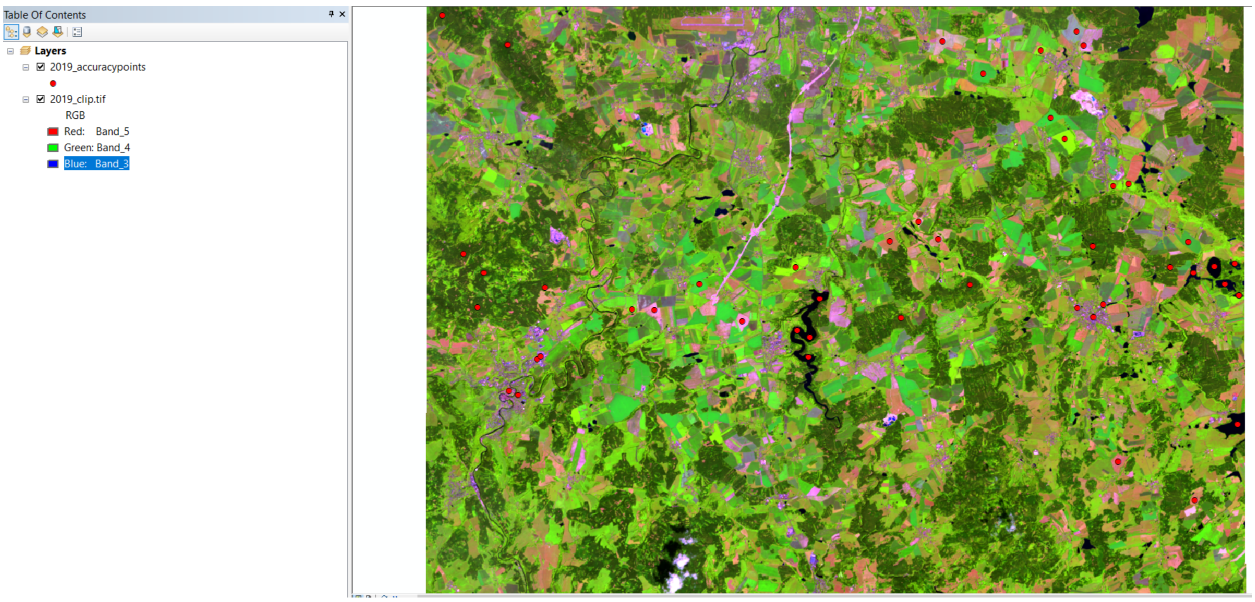


Figure 6. Simple Random Sampling for Accuracy Assessment in 2019

Table 8. Accuracy Assessment table showing the Producers accuracy, users' accuracy, overall accuracy, and kappa coefficients over the past years from 1984 – 2019.

LANDUSE/ LANDCOVER	1984		1990		2000		2010		2019	
Class Name	**Prod Acc**	**User Acc**	**Prod Acc**	**User Acc**	**Prod Acc**	**User Acc**	**Prod Acc**	**User Acc**	**Prod Acc**	**User Acc**
Agricultural Land	75	84	79.17	76	80.77	84	76.92	80	78.26	72
Bare Land	85.71	96	100	100	100	88	100	80	70.59	96
Built-up Area	72	72	84	84	83.33	80	92	92	90.9	80
Grassland	70.83	68	84	84	80.77	84	92	92	92	92
Water	95	76	76.92	80	85.19	92	82.76	96	100	84
Overall	79.2%		84.8%		85.6%		88%		85%	
Kappa Statistics	74%		81.8 %		82%		85%		81%	

The Kappa statistic was used to measure the agreement between two sets of categorizations of a dataset (Table 8). It is used to estimate the accuracy of predictive models by measuring the agreement between the predictive model and a set of field surveyed sample points (Moriasi et al., 2007). The results showed that the overall accuracy of 1984 (Table 8) was 79% while the producer's and user's accuracy range from 72 to 95 % and 68 to 96% respectively. Kappa statistics had calculated from the error matrix, and the coefficient of the classification for 1984 was 0.74. Thus, according to the classification scale given by (Moriasi et al., 2007), the classification lies in a substantial or very good range. 1990 showed a slight difference in accuracy classification. The overall classification for 1990 was 85% while the producers and user's accuracy range from 76.92

to 100% and 76 to 100% respectively. The Kappa Statistics after calculating the error matrices for 1990 was 0.82. This falls on the Almost category from the Kappa Statistics table signifying that it was more accurate in comparison to 1984. In 2000, the overall accuracy resulted at 86% while the producer and user's accuracy were between 80.77 to 100% and 80 to 92% respectively. With the use of the error matrices, the Kappa statistics test resulted at 0.82 and based on the criteria ratings, almost perfect. 2010 accuracy classification also resulted in an almost perfect criteria with the kappa statical test resulting at 0.85. The producer's accuracy user's accuracy ranges from 76.92 to 100% and 80 to 96 % respectively. In 2019, both the producers and user's accuracy ranges from 70.59 to 100% and 72 to 96% respectively and the kappa statistical test resulted to 0.81 which is Almost Perfect and had an overall accuracy of 85%. In general, the closer the statistical results are to 100% or closer to 1 for the kappa statistical test, the more accurate the pixel images were classified. This means none of the images and points where below 50% or had a negative number result so its however possible to accept the how accurate the maps are.

A Kappa coefficient equal to 1 means perfect agreement whereas a value close to 0 means that the agreement is no better than would be expected by chance. According to Landis & Koch (1977), categorization of Kappa statistic is widely referenced which is reproduced in Table 9 below

Table 9. Kappa Statistical Reference Table. Source: (Rwanga & Ndambuki : Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS, 2017)

Rating criteria of Kappa statistics.

S.No	Kappa statistics	Strength of agreement
1	<0.00	Poor
2	0.00 - 0.20	Slight
3	0.21 - 0.40	Fair
4	0.41 - 0.60	Moderate
5	0.61 - 0.80	Substantial
6	0.81 - 1.00	Almost perfect

5.2 Land Use and Land cover Distribution

The land use land cover classification of the area in 1984, showed that the majority of the study area is covered by Grassland which is 247.22 km^2 and contributes to 30% of the total study area (Table 10). Agricultural land and bare land cover an aerial size of 237.64 km^2 (29%) and 224.27 km^2 (27%) respectively. Built-up area covers 104.64 km^2 (13%) and water bodies covered the least which is 6.60 km^2 (1%). In1990, the recorded distribution of the total aerial sizes changed for some categories. The agricultural land decreased to 142.18 km^2 (17%) while the Grassland size increased to 275.91 km^2 (33%) as well as bare land to 275.70 km^2 (33%) respectively. An increase in land cover can also be seen in the Built-up areas 124.84 km^2 (15%) and water bodies size decreased a little to 5.57 km^2 (1%) which is not very significant. From all indications, the greatest change in 1990 was a loss in agricultural land from 29% in 1984 to 17% in 1990.

In 2000, there was a significant increase Agricultural land 243.13 km^2 (28%) and significant decrease in bare land 206.13 km^2 (24%). The change in built up area was insignificant 134.78 km^2 and remained at 15%. The grassland aerial size dropped by 1% which is 280.44 km^2 (32%) and water body size increased a little to 6.24 km^2 (less than 1%). 2010 recorded some changes as well especially in the land class Grassland at 325.16 km^2 (38%). There was a decrease in size of agricultural land and Bare land at 203.35 km^2 (24%) and 171.51 km^2 (20%) respectively. The recorded water bodies in. 2010 were seen to drop in size to 5.78 km^2which is also less than 1%.

2019 recorded some significant distribution different sizes as compared to 2010. Agricultural land and Built-up area greatly increased by 323.09 km^2 (38%) and 206.37 km^2 (25%) as compared to 24% and 17% respectively in 2010. The decrease in Grassland area size was recorded at 210.70 km^2 (25%) and bare land drastically reduced to 91.90 km^2 (11%). The water bodies increased a little to 8.53 km^2 but however still under 1%.

Table 10. Area (km^2) and percentages of different land cover types from the year 1984 to 2019.

LANDUSE/ LANDCOVER CATEGORY	1984		1990		2000		2010		2019	
Class Name	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**
Agricultural Land	237.64	29	142.18	17	243.13	28	203.35	24	323.09	38
Bare Land	224.27	27	275.7	33	206.13	24	171.51	20	91.9	11
Built-up Area	104.64	13	124.84	15	134.78	15	141.21	17	206.37	25
Grassland	247.22	30	275.91	33	280.44	32	325.16	38	210.7	25
Water	6.6	1	5.57	1	6.24	1	5.78	1	8.53	1
Total	820.37	100	824.2	100	870.72	100	847.01	100	840.59	100
***Rimov Reservoir**	1.93	0.23	1.60	0.19	1.62	0.19	1.42	0.17	1.68	0.20

In general, the most significant change is the loss of bare land from 27% in 1984 to 11% in 2019 and there was a great increase in Built up areas from 13% in 1984 to 25% in 2019.

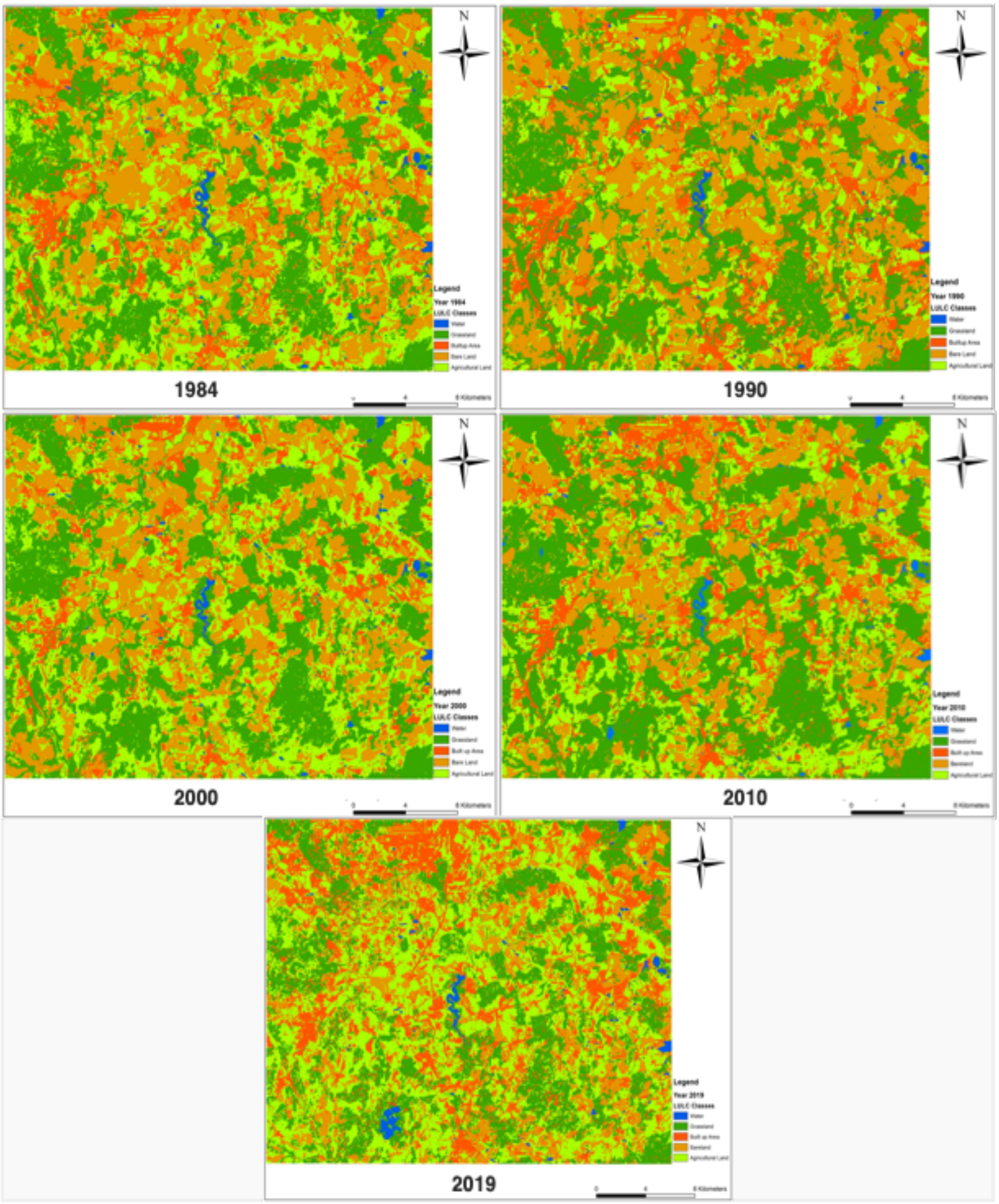


Figure 7. Classified maps of the study area based on supervised classification of 1984, 1990,2000, 2010, and 2019 Landsat imageries.

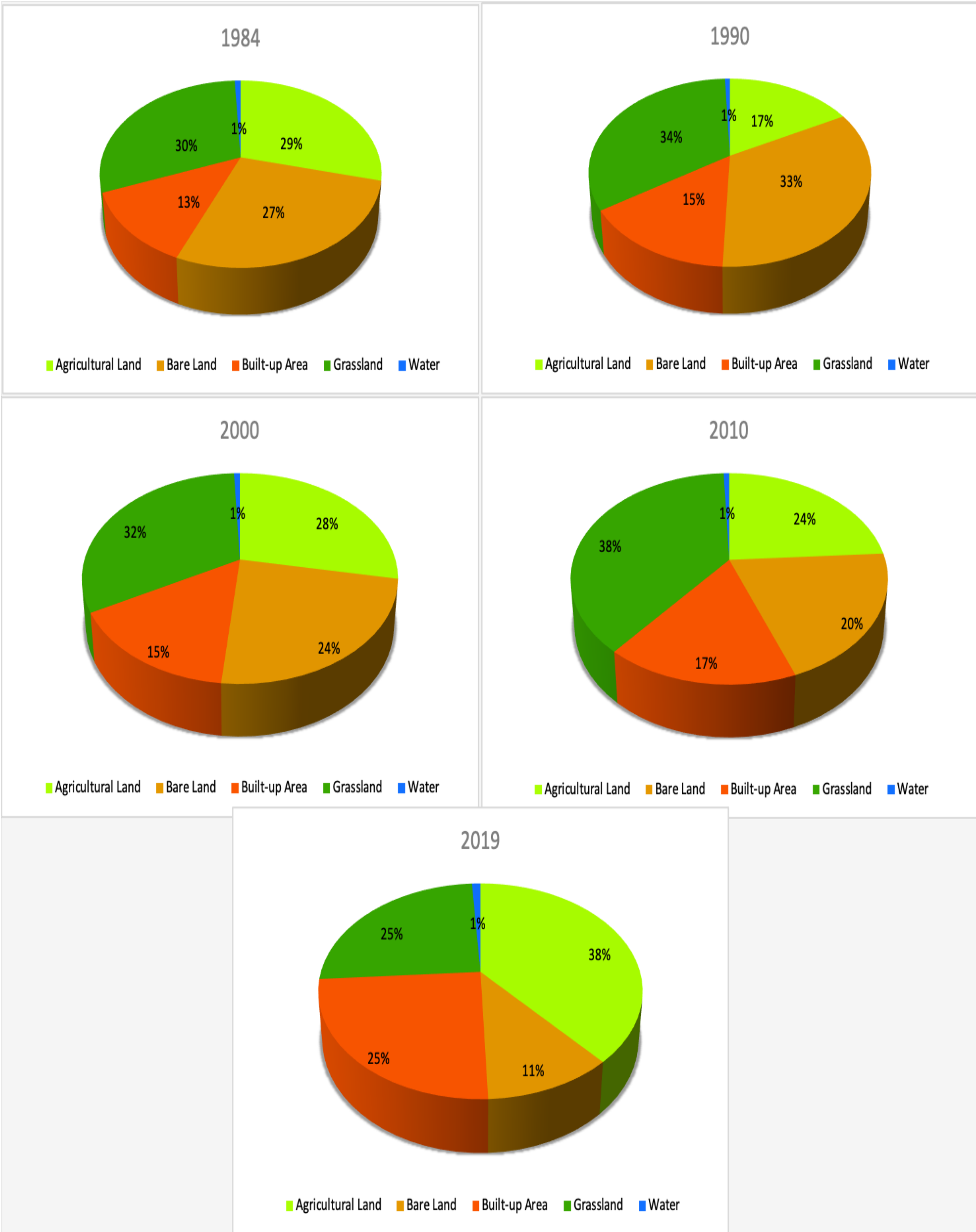


Figure 8. Percentage LULC from the total area in 1984,1990, 2000, 2010, and 2019

5.3 Land Use and Land cover Detection change

The land use and land cover change detection based on remote sensing images have been widely applied in research for LUCC, natural resource management and environment monitoring & protection (Zhang et al., 2014). The percentage area of each land cover class had derived from supervised classified images for each year separately with Arc GIS. This explains how stable or unstable the total area has been changing. From 1984-1990, the most unstable category was Agricultural land which we found reduced at 40% or -95.46 km^2. Second most unstable category is water bodies which reduced at 16%, or -1.03 km^2 while Bare land was found to increase at 23% or 51.43 km^2. Built up areas and Grassland areas also increased by 19% (20.2 km^2) and 12% (28.69 km^2).

Table 11. LULC change in the selected study area in South Bohemia from 1984 to 2019.

LAND USE/LAND COVER CATEGORY	**1984 - 1990**		**1990- 2000**		**2000 -2010**		**2010 - 2019**	
	Area Change		**Area Change**		**Area Change**		**Area Change**	
Class Name	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**	**km^2**	**%**
Agricultural Land	-95.46	-40	100.95	71	-39.78	-16	119.74	59
Bare Land	51.43	23	-69.57	-25	-34.62	-17	-79.61	-46
Built-up Area	20.2	19	9.94	8	6.43	5	65.16	46
Grassland	28.69	12	4.53	2	44.72	16	-114.46	-35
Water	-1.03	-16	0.67	12	-0.46	-7	2.75	48
***Rimov Reservoir**	-0.33	-17.18	0.03	1.84	-0.21	-12.91	0.26	18.54

Change from 1990-2000 was also measured and it was noted that Bare land had the most negative change by -25% (-69.57 km^2) and Agricultural land had the most significant positive change with an increase by 71% (100.95 km^2). Built up areas, Grasslands and water bodies all increased by 8% (9.94 km^2),2% (4.53 km^2) and 12% (0.67 km^2) respectively. From 2000 to 2010, the most significant negative change was in bare land where there was a loss in 17% of the bare land from -69.57 km^2 between 1990-2000 to -34.62 km^2 between 2000-2010. There was a 16% (-39.78 km^2) loss in Agricultural land 7%(-0.46km^2) loss in Water bodies in the total study area. Positive changes in LULC between 2000-2010 resulted in Grassland and Built-up areas at 16% (44.72 km^2) and 5% (6.43 km^2) increase respectively. From 2010 to 2019, the most significant positive change was the increase in Agricultural land, water bodies and built-up areas by 59% (119.74 km^2), 48% (2.75 km^2) and 46% (65.16 km^2) respectively. The bare land size was lost by 46% and Grassland by 35%.

5.4 Trends of LULC Rimov Reservoir

Over the years, the size of the reservoir has been changing with the highest recorded in 1984 at 1.93 km^2 and the lowest recorded in 2010 at 1.42 km^2. The greatest change calculated seen in drop in reservoir when the total size reduced from 1.93 km^2 in 1984 to 1.60km^2 in 1990. From 1984 to 1990, the reservoir lost 17.18% (-0.33 km^2) of its total size as seen in the figure above. The changes from 1990 to 2000 were minimal with an increase in size by 1.84%(0.03km^2). From 2000 to 2010, another significant loss in reservoir size by 12.91% (-0.21 km^2) and recorded as the second highest change after the significant change between 1984 and 1990. From 2010 to 2019, the reservoir size increased by 18.54 %(0.26km^2) and it is the most significant increase in the with regards to the reservoir change detection. The table below shows how the changes in reservoir size over the past years and area measured in Km^2

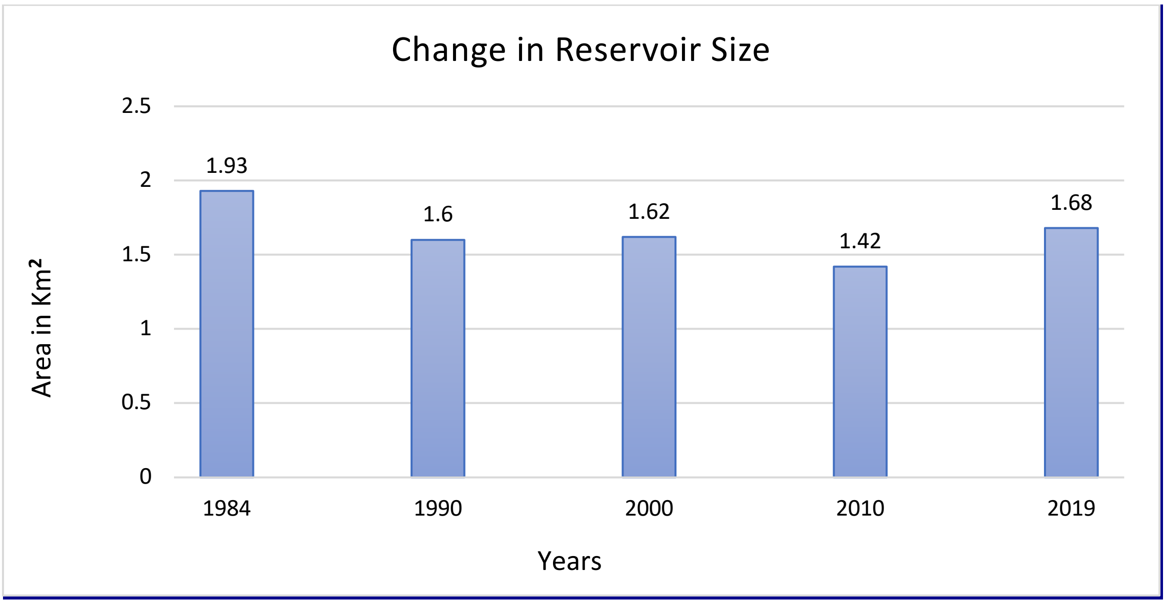


Figure 9. Trends and changes in Rimov Reservoir (km^2) from 1984 to 2019

6. DISCUSSION
6.1 Accuracy Analysis

Accuracy assessment is quite important in LULC studies because it gives a clear analysis of how truth ground data can be represented on a map. It gives detailed assessment of how effectively the pixels were sampled into the correct land cover classes. The results from accuracy assessment showed an overall accuracy obtained from the random sampling process for the images were 79.2%, 84.8%, 85.6%, 88%, 85% for 1984, 1990, 2000, 2010 and 2019 respectively. According to (Anderson, 1976), the minimum accuracy value for reliable land cover classification is 85 %. On the other hand, accuracy levels are accepted by users may not be acceptable by other users for a certain task (Geremew, 2013).

The accuracies for the individual classes were relatively high, ranging from 70.59% to 100% for the producer's accuracy and 68% to 100% for the user's accuracy which indicates a good agreement between thematic maps generated from images and the reference data. The water mapping accuracy of all five years for producer's and user's accuracies were ranging from 76% to 100% due to better spectral differentiation from other classes. The producer's and user's accuracies of all five years for agricultural land and grassland ranged from 75% to 84% and 68% to 92% respectively. The reason for this low obtained accuracy is due to the fact that many agricultural lands have patches of shrubs and short trees which are characteristics of grasslands and grasslands are made up of grasses which look like cultivated crops. The built-up areas had accuracies ranging from 72% to 92% for both the producer and users' accuracies. This is because within the built-up areas, there are little zones characterized by trees and vegetation but not as much as between grasslands and agricultural lands. The bare lands had relatively high accuracies with most of the accuracies at 100% but ranging from 70.59 to 100%. This is because the bare lands are exposed and covered with soil making it easier to identify the brown soil color and differentiate it from the green colors of grassland and agricultural land. Accuracies reflects the reliability of the classification based on the use, so grassland in 1984 was found to be most unreliable with 68 % of user accuracy while bare land in 2019 could was also the most unreliable with 70.59 % for the producer's accuracy. Classification is not complete until its accuracy is assessed using the known

Kappa statistics (Forkuor & Cofie, 2011) and in this research, the Kappa statisitics was calculated for all five years.

6.2 Classification and Distribution of LULC

With the economic development and the influence of human activities, the regions land use has experienced substantial changes since the 1980s. In this study, Landsat5 TM and Landsat8 OLI image data were used to obtain land use maps for 1984, 1990,2000,2010 and 2019. This is the most common approach to change detection (Jenson, 2004). The post classification approach provides "from-to" change information and the kind of landscape transformation that have occurred can be easily calculated and mapped. According to the results of the classification, the agricultural land, grassland and bare land coverage rate of the study area was high in 1984. The area was inhabited by fewer people because built up area had just 13% of the total study area and vast bare land. Six years later in 1990, the changes in distribution could be widely observed especially with agricultural land.12% the agricultural land was lost as compared to 1984 and distributed to grassland, bare land and built-up areas. 10 years later, the total built up areas and water bodies do not change and remain at 15% and 1% respectively. It could be observed that over the years, the inhabitants practiced agriculture and converted a large portion of the bare land to agricultural land. In 2010, both the agricultural land bare land reduced in size while grassland and built-up areas in increased at 38% and 17% respectively. Built up areas and agricultural lands significantly increased in 2019 at 25% and 38% respectively. Human activities which are mainly driven by socio-economic factors bring out changes in non-built-up and built-up land despite restrictions by physical conditions (Long et al. 2007). Land use change, including land transformation from one type to another and land cover modification through land use management, has altered a large proportion of the earth's land surface. The bare land and grasslands reduced over the years. In General, the bare land witnessed the most significant loss from 224.27km^2 in 1984 to 91.9km^2 in 2019. Significant changes in bare land may also further contribute to an increase in mass movement and soil erosion (Yu et al.,2007; Qasim,et al; 2011,Nandy et al.,2011) during the rainfall season around the reservoir area.

Built up areas increased from 104.64km^2 to 206.37 km^2 in 1984 to 2019 respectively while agricultural land 237.64km^2 to 323.09km^2 in 2019. However, this analysis could not be 100% accurate because the data and satellite Images were obtained once in some cases 5 years and some cases after 10 years. The classified satellite images showed that there is a change in Land Use and Land cover.

6.3 Trends and Changes in the Study area

According to the results obtained, the changes were increasing and decreasing for all the LULC classes. The only class which had a steady increase was the Built-up area which did not experience a drop in size over the years from 1984 to 2019. To visualize the changes that occurred in that period, a simple technique (El-Hattab, 2015a) was used to create a final change image for each land cover class, representing the areas of change, either positive or negative, in addition to the areas that showed no change. The most significant negative change was within the grassland class between 2010 and 2019 with a loss of 114.46km^2 of its size and the highest positives change was within the agricultural land class between 2010 and 2019 with an increase 119.74km^2 of its previous size. In the Czech Republic, this has been mainly a result of changes in the system of agricultural subsidies (Bicík et al. 2015). However, it is important to note that 2010 to 2019 the most outstanding changes in total area for the various classes. The reservoir experienced its greatest change and loss in size from 1984 to 1990 where it lost 17.18% of its initial size. From 2010 to 2019, it gained 18.54% of its size which makes the greatest increase over the years. From all indications and predictions, there is a high chance that the built-up areas and agricultural land will keep on increasing simultaneously because the more people that live in an area, the more agricultural activities that will be practiced. It is noted that over the years, the built-up area size was never greater than the agricultural land but due to urbanization, there is a possibility that in the next 30 to 50 years, the built-up area might be larger than the agricultural land due to its steady growth and increase in size. With the minimal precipitation rates, it is possible to say that the reservoir size will not experience a significant change in the future years as well as the water bodies in the region because from 1984 to 2019, the water bodies size did not exceed 1% of the total study area.

7. SUMMARY AND CONCLUSION

Remote sensing is very important for the production of Land Use / Land Cover maps which can be done through a method called image classification. Images from Remote sensing are the most important data source for research in ES, and LULC is the most widely used variable for assessment in ESV (Song, 2018). However, the limitations of global land cover data arise from the product generation process, including satellite sensor characteristics such as spectral, temporal and spatial resolutions, definition and classification methods of land cover. This method had made huge improvements over the past decades. Sustainable assessment of LULC changes provide environmental, social, and economic dimensions. Based on the results from the study, it is possible to address the aims and objects and it is clearly evident that GIS and other softwares can be used to determine Land use Change and Land use Cover.

In this thesis, two kinds of classification approaches and post classification was performed to generate reliable and accurate classified maps of land use and land cover in South Bohemia.
The mean Kappa Coefficient from the study for all five years is 0.8076 and 84.44% for the Overall Accuracy which rated as substantial and hence the classified image found to be fit for further research. This indicates that the integration of visual interpretation with supervised classification of remote sensing data is useful to identify the changes of land use and land cover in this study. To be able to get the classification, the error matrix for each of the land use was randomly sampled and calculated. Obtaining a reliable confusion matrix is, therefore, a weak link in the accuracy assessment chain (Smits et al., 1999), yet it remains central to most accuracy assessment and reporting. The major drivers of land-use changes are human population, affluence, technology, political economics, political structure, attitudes, and values (Turner et al., 1993). The results and findings of this research show that the mean area of land use and land cover transition over the years around the Rimov area, south Bohemia was 840.58 km^2, which included five investigated land-use types. The general pattern of LULC in this region included agricultural land, built-up land, bare land, Grassland and water bodies. The transition of Grassland and bare land to built-up and agricultural land have been the dominant LULC Change patterns over the past 35 years in the selected study site. Built-up is the dominant land-use type because it has been increasing over the

past years consistently from 1984 to 2019. This shows that most of the bare land from 1984 to 2019 have been converted to either agricultural land or built-up areas. On the other hand, the water bodies size does not experience a significant change as the total average recorded over the years were still below 1%. Within agricultural lands, there are some changes depending on the particular condition in each region, (Zomeni et al., 2008 & Mottet et al., 2006). In agricultural lands, improper farming management could have long-term effects on natural resources. Economic benefit is also a main factor to induce farmers to change the type of their farm. Consequently, further environmental conditions, especially ecological factors within the areas, are affected. However, green areas are still maintained as per the land use classification.

So, in order to address, the Aim and objectives of the thesis report, our findings identified and analyze and the trends in Land Use/Land Cover Change (LULCC) taking place in Rimov area and can conclude that GIS and Landsat Imagery could be used as a good tool for Land use and Landcover analysis. The Land Use/Land Cover maps of Rimov reservoir and surroundings were produced, the LULC classification analyzed, and the trends and magnitude of change assessed in this region of south Bohemia, so it is suitable to say the Aims and Objectives of the thesis were met. To answer the research questions, it is evident that there have been some changes in study area and the rate of LULC changes has been significant for some classes (Built-up areas, agricultural land) and insignificant for some classes (water bodies) as explained and analyzed in the previous chapter. Landsat Satellite imagery can be successfully applied to mapping LULC changes in the area because it makes it possible to extract and calculate the actual changes which occur on the earth surface and in the case of the Rimov area and surroundings, it was possible to monitor these changes with the satellite imagery and information. The use of classification accuracy is very important in LULC research because it is able to categorize the data on the ground and makes this possible with the use of pixel sampling. For instance, in this research, it was possible to distinguish between agricultural land and bare land with the use of accuracy classification because they both have similar characteristics, but the accuracy assessment comes in with the error matrix to classify the pixel based on its allocated color. So, our findings conclude that Accuracy Classification is important in LULC studies.

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9.APPENDIX

The five tables show the accuracy statistics for the classified results from the classification of year 1984,1990, 2000 ,2010 and 2019. The accuracies of producer and user are given in percentage values.

A. Accuracy Assessment with Error Matrices for year 1984

	Grassland	Water	Built up Area	Bare Land	Agricultural Land	Total	User Acc
Grassland	21	4	0	0	0	25	84
Water	1	24	0	0	0	25	96
Built up Area	0	0	18	7	0	25	72
Bare Land	0	0	7	17	1	25	68
Agricultural Land	6	0	0	0	19	25	76
Total	28	28	25	24	20	125	
Producer Acc	75	85.71	72	70.83	95		
Overall Classification accuracy	79%						
Kappa Statistics	74%						

B. Accuracy Assessment with Error Matrices for year 1990

	Grassland	Water	Built up Area	Bare Land	Agricultural Land	Total	User Acc
Grassland	19	0	0	0	6	25	76
Water	0	25	0	0	0	25	100
Built up Area	0	0	21	4	0	25	84
Bare Land	0	0	4	21	0	25	84
Agricultural Land	5	0	0	0	20	25	80
Total	24	25	25	25	26	125	
Producer Acc	79.16	100	84	84	76.92		
Overall Classification accuracy	85%						
Kappa Statistics	82%						

C. Accuracy Assessment with Error Matrices for year 2000

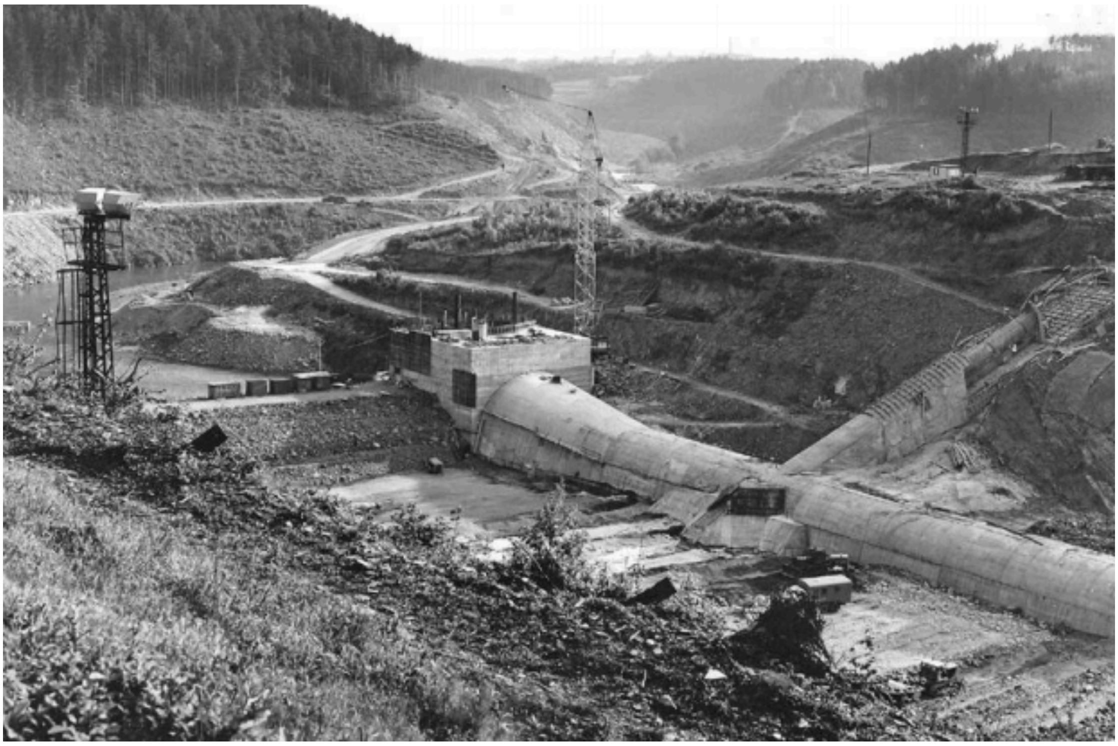
	Grassland	Water	Built up Area	Bare land	Agricultural Land	Total	User Acc
Grassland	21	0	0	0	4	25	84
Water	3	22	0	0	0	25	88
Built up Area	0	0	20	5	0	25	80
Bare land	0	0	4	21	0	25	84
Agricultural Land	2	0	0	0	23	25	92
Total	26	22	24	26	27	125	
Producer Acc	80.76	100	83.33	80.76	85.18		
Overall Classification accuracy	86%						
Kappa Statistics	82%						

D. Accuracy Assessment with Error Matrices for year 2010

	Grassland	Water	Built up Area	Bare land	Agricultural Land	Total	User Acc
Grassland	20	0	0	0	5	25	80
Water	5	20	0	0	0	25	80
Built up Area	0	0	23	2	0	25	92
Bare land	0	0	2	23	0	25	92
Agricultural Land	1	0	0	0	24	25	96
Total	26	20	25	25	29	125	
Producer Acc	76.92	100	92	92	82.75		
Overall Classification accuracy	88%						
Kappa Statistics	85%						

E. Accuracy Assessment with Error Matrices for year 2019

	Grassland	Water	Built up Area	Bare Land	Agricultural Land	Total	User Acc.
Grassland	18	7	0	0	0	25	72
Water	1	24	0	0	0	25	96
Built up Area	0	3	20	2	0	25	80
Bare Land	0	0	2	23	0	25	92
Agricultural Land	4	0	0	0	21	25	84
Total	23	34	22	25	21	125	
Producer Acc.	78.26	70.58	90.9	92	100		
Overall Classification accuracy	85%						
Kappa Statistics	81.00%						



G. The Římov Reservoir – construction of the dam, 1974–1975. (Source: Znachor, P et al 2016).

H. The Římov Reservoir – construction of the dam 1977 (Source: Znachor, P et al 2016).

I. The Římov Reservoir – present day aerial view of then reservoir from the dam (Source: Znachor, P et al 2016).