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# CHANGE DETECTION IN LAND USE LAND COVER (LULC) IN MEĐIMURJE COUNTY, CROATIA, BETWEEN 1978, 1992 AND 2007 USING LANDSAT SATELLITE IMAGERY

by

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Čakovec, January 28, 2012

## Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my thesis and I have always indicated their origin.

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## Abstract

Timely and precise information about Land Use Land Cover (LULC) change detection of the Earth's surface is extremely important for understanding relationships and interactions between human and natural phenomena for better management of decision making. This study evaluates LULC changes in Međimurje County, Croatia, between 1978, 1992 and 2007 using Landsat satellite images. Spatial dynamics of LULC changes were quantified using three Landsat satellite images: MSS, TM and ETM$^+$. Three series of the LULC maps of 1978, 1992 and 2007 were produced. A post classification technique was used based on a hybrid classification approach comprised of unsupervised classification based on "hill climbing" cluster algorithm, supervised classification based on the Maximum Likelihood Clasifier (MLC) and introduction of human-knowledge from field experience. Careful manual delineation on the topographic maps 1:25,000 and high aerial photographs were done around all urban areas of Međimurje County. The urban areas were clipped out of the image data later and classified separately from other data with an unsupervised classification. Based on the Anderson classification system, the land-use and land-covers are classified as: water bodies, forest land, barren land, agricultural land and urban built up land. Error matrices were used to assess classification accuracy. The overall accuracies, user's and producer's accuracies, and the Kappa statistics were derived from the error matrices. The overall accuracies for 1978, 1992 and 2007 were, respectively, 87.67%, 88.96% and 90.84%. Kappa statistics were 80%, 84% and 83%. User's and producer's accuracies of the individual classes were relatively high, ranging from 74% to 94% which indicates a good agreement between the thematic maps generated from images and the reference data. The results of the analysis showed that from 1978 to 2007 the urban area increased approximately 53%, while the agricultural land decreased 12%. Water, forest and barren land also increased 14%, 5% and 49% respectively. The derived LULC changes maps of Međimurje County provide good general information about land changes during the study period.



**Key words***: Land Use, Land Cover, Change Detection, Remote Sensing, Landsat Satellite Imagery, Međimurje County, Hybrid Classification.*

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## List of Acronyms and Abbreviations

| | |
|---|---|
| $ETM^+$ | Enhanced Thematic Mapper Plus |
| FOSS | Free Open Source Software |
| GIS | Geographic Information System |
| GLCF | Global Land Cover Facility |
| GLS | Global Land Survey |
| GPS | Global Positioning System |
| LULC | Land Use Land Cover |
| LULCC | Land Use Land Cover Change |
| MLC | Maximum Likelihood Classifier |
| MSS | Multi-spectral sensor |
| NASA | National Aeronautics and Space Administration |
| NDVI | Normalized Difference Vegetation Index |
| PCA | Principal Component Analysis |
| RS | Remote Sensing |
| SAGA | System for Automated Geoscientific Analyses |
| SGA | State Geodetic Administration |
| TM | Thematic Mapper |
| USGS | United States Geological Survey |
| UTM | Universal Transverse Mercator |

# 1. INTRODUCTION

## 1.1. Background to the Study

It is well known that there are only few places on the Earth that are still in their natural state and that have not been affected by human activity in some way. These human activities result in significant land use changes at regional and local scales together with ecological, socio-economic and aesthetical impacts.

Timely and precise information about LULC change detection of the earth's surface is extremely important for understanding relationships and interactions between human and natural phenomena for better management of decision making (Lu *et al.* 2004). Determining the effects of land use change on the Earth system especially biodiversity depends on the understanding of past land use practices, current land use patterns, and projections of future land use, as affected by human institutions, population size and distribution, economic development, technology, and other factors (Jingan *et al*. 2005). Viewing the Earth from space is crucial to the understanding of the influence of human activities and human impacts on land use changes over time. Information on Land Use/Land Cover (LULC) at regional scales derived with observations of the earth from space provides objective information of human utilization of the landscape. Such information is required to support environmental policy, physical planning purposes and sustainable land use and land development.

Remote sensing at regional and local scales has become an essential tool in wide areas. The classification of multi-spectral images has been a successful application that is used for classification of land cover maps (Lunetta and Balogh, 1999, Oettera *et al*. 2000, Yuan *et al*. 2005, ), urban growth (Yeh and Li, 1997, Zhang *et al*. 2002), forest change (Vogelmann and Rock, 1988, Hall *et al*. 1991, Coppin and Bauer, 1994), monitoring change in ecosystem condition (Lambin 1998, Weng 2002), monitoring assessing deforestation and burned forest areas (Potapov *et al*. 2008), agricultural expansion (Woodcock *et al*. 1993, Pax-Lenney *et al*. 1996), mapping corn (Maxwell *et al*. 2004), real time fire detection (Dennison and Roberts, 2009), estimating tornado damage areas (Myint *et al*. 2008), estimating water quality characteristics of lakes (Lillesand *et al*. 1983, Lathrop *et al*. 1991, Dekker and Peters, 1993), geological mapping (Mostafa and Bishta, 2004, Bishta 2010), estimating crop acreage and production (Liu *et al*. 2005), monitoring of environmental pollution (Zhu and Basir, 2005), monitoring and mapping mangrove ecosystem (Kuenzer *et al*. 2011).

### 1.2. Approaches Used in the Study

Three Landsat satellite images, as the primary data source, from 1978, 1992 and 2007 were used to determine these LULC changes. The post classification technique was used based on a hybrid classification approach comprised of unsupervised classification based on “hill climbing” cluster algorithm, supervised classification based on the Maximum Likelihood Classifier (MLC) and introduction of human-knowledge from field experience.

In this study careful manual delineation on the topographic maps 1:25,000 and high aerial photographs were done around all the urban areas of the Međimurje County. More than 150 polygons greater than 100 contiguous pixels, (with size of the surface larger than 9 ha), was obtained. The obtained urban areas then were clipped out of the image data and classified separately from the other data with an unsupervised classification. Pixels classified as low or high density urban were masked out of the others Landsat data, while the non-urban pixels were „put back“ into the Landsat image data for further supervised classification.

Based on the Anderson LULC classification system, the land-use and land-covers are classified as water bodies, forest land, barren land, agricultural land and urban built up land. The LULC maps of 1978, 1992 and 2007 were produced. These three, directly comparable lands cover data sets, allow us to look at, and quantify LULC changes in Međimurje County over the period of 29 years.

Error matrices were used to assess classification accuracy. Overall accuracies, user's and producer's accuracies, and the Kappa statistics were derived from the error matrices. For the accuracy assessment simple random sampling was adopted. A total of 146, 163 and 131 randomly pixels from the classified images 1978, 1992 and 2007 respectively without any consideration of informational class was selected. Aerial photographs, digital LULC maps, and topographic maps were utilized to assess classification accuracy.

The results for each land cover class are derived, and the total area of each land cover class for the entire study was compared using the three classified images from 1978, 1992 and 2007. The barren land was merged into the agricultural land cover class. Generally, from 1978 to 2007, the urban area increased approximately 53%, while the agricultural area decreased 12%. Water, forest and barren land also increased 14%, 5% and 49% respectively.

## 1.3. Statement of the Problem, Aim and Objectives of the Study

### 1.3.1. Statement of the Problem

Međimurje County, the northernmost and the most densely populated county in the Republic of Croatia has witnessed remarkable expansion, growth and development activities such as significant buildings construction, construction of two reservoir lakes on the Drava river and construction of a highway through the central part of the county. Such a rapid increase of land consumption and modifications on land use and land cover changes resulted in lack of attempt to map and evaluate these changes. Therefore, the aim of this study was to identify and analyze general trends in LULC changes taking place in Međimurje County over a period of 29 years using Landsat Satellite Imagery and GIS based technique.

### 1.3.2. Aim

This study will identify and analyze general trends in Land Use/Land Cover Change (LULCC) taking place in Međimurje County over a period of 29 years using Landsat Satellite Imagery and GIS based technique.

### 1.3.3. Objectives

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

- To create a Land use/Land cover classification scheme,
- To produce Land Use/Land Cover maps of Međimurje County at different years in order 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.

## 1.4. Research Questions

In order 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 the Međimurje County between 1978, 1992 and 2007?
- What is the nature of LULC changes that have taken place during the periods observed in this study?
- Whether Landsat satellite imagery can be applied successfully to mapping LULC changes in the study area?
- Whether the approach used in this study, consisting of unsupervised classification of the isolated urban areas in combination with the supervised classification of other areas, can improve the classification accuracy?

## 1.5. Overall Expectations from the Study

The findings of this study are assumed to provide analysis of landscape structure and change detection in Međimurje County using multi temporal imageries. Also, results of this research can be utilized as a land use land cover change maps for the region of Međimurje to quantify the extent and nature of development change which is relevant and critical for regional analyses, formulating effective environmental policies and resource management decisions. Thus, findings from this study about land use land cover and change detection over the period from 1978 to 2007 may be useful to the responsible persons in Međimurje County Departments for spatial planning, statistics, agriculture and environmental protection.

### 1.6. Structure of the Thesis

The thesis study is divided into six chapters (Figure 1). Chapter 1 primarily gives the aim and the objectives of the present research work as well as the organization of the paper. Chapter 2 presents in detail the Landsat program and examines the existing literature on the change detection techniques. Chapter 3 is allocated for the study area and data used for the present study as well as the software used in the thesis work. In Chapter 4 the methodology used to achieve the objectives of the study are presented. Chapter 5 concludes the research work, deals with the data analysis consisting of the nature and the rate of the LULC change maps, as well as discussion of the findings of the study. Finally, summary, conclusions and recommendation are presented in Chapter 6.

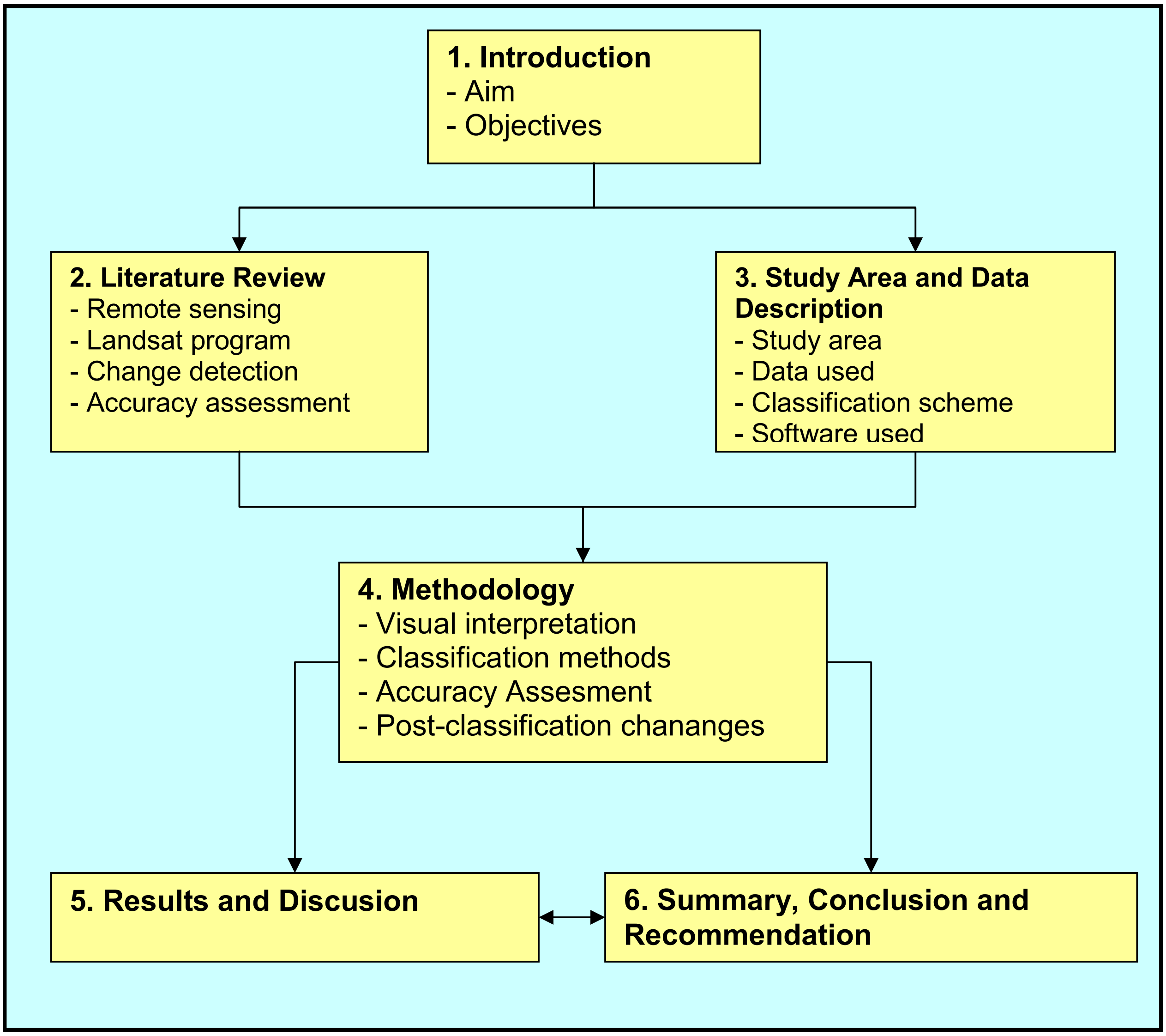



Figure 1: Thesis Workflow.

# 2. LITERATURE REVIEW

In order to analyze land use land cover changes it is important to review historical background, concepts and related works done so far. This chapter highlights review of related literature focusing on remote sensing, GIS and the Landsat program.

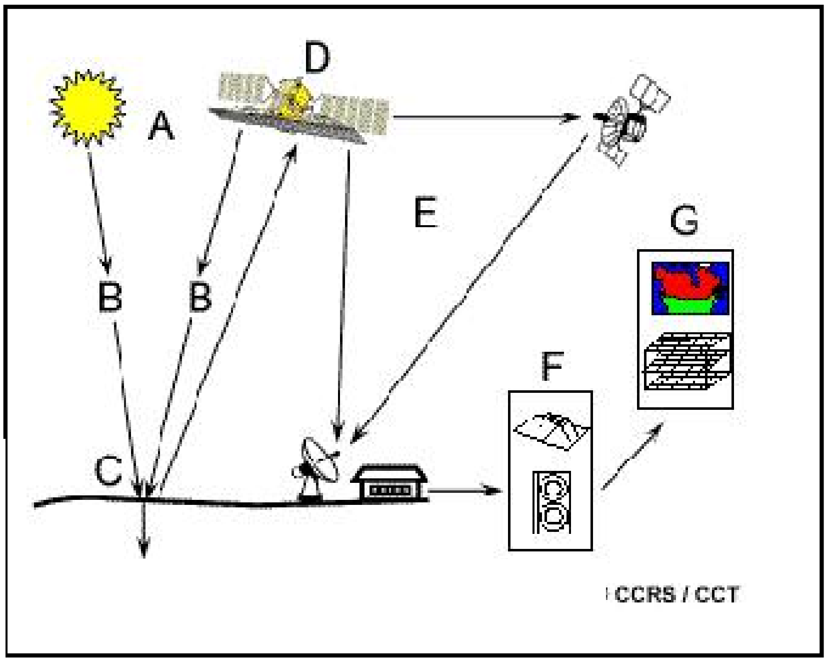
## 2.1. Remote Sensing as a Tool for Change Detection

Almost every day we can see that the surface of the earth is changing rapidly due to various reasons at local and regional scales with significant repercussions for people and for environment. To better understand, analyzing and predicting these changes, remote sensing satellite imagery are an inexhaustible source of useful information. Remotely sensed satellite observations from the space have fundamentally changed the way in which scientists study the atmosphere, oceans, land, vegetation, glaciers, sea ice, and other environmental aspects of the Earth's surface. Half a century of the satellite observations of the Earth have provided dramatic pictures and they are the basis for a new scientific paradigm: earth-system science (Tatem *et al*. 2008).

Congalton and Green (1999) note that the most basic remote sensing devices are the eyes and ears. There are many different ways to define remote sensing. One of the better explanations for remote sensing is: „Remote sensing is the science and the art of obtaining information about an object, area or phenomena through the analysis of data acquired by device that is not contact with the object, area or phenomena“ (Lillesand and Kiefer, 1994, pp. 1). A formal and comprehensive definition of applied remote sensing comes from Goddard Space Flight Centre, NASA, (URL 1): “Remote Sensing in the most generally accepted meaning refers to instrument-based techniques employed in the acquisition and measurement of spatially organized (for the Earth, most commonly geographically distributed) data/information on some property(ies) (spectral; spatial; physical) of an array of target points (pixels) within the sensed scene (anywhere in the Universe) that correspond to classes, features, objects, and materials, doing this by applying one or more recording devices not in physical, intimate contact with the item(s) under surveillance (thus at a finite distance from the observed target, in which the spatial arrangement is preserved); techniques involve amassing knowledge pertinent to the sensed scene (target) by utilizing electromagnetic radiation, force fields, or acoustic energy sensed by recording cameras, radiometers and scanners, lasers, radio frequency receivers, radar systems, sonar, thermal devices, sound detectors, seismographs, magnetometers, gravimeters, scintillometers, and other instruments". Definition of remote sensing from Canada Centre for Remote Sensing (CCRS 2007): "Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information". Generally, we can say that any method of observing the Earth's surface without being directly in contact with it can be under the definition of remote sensing.

Remote sensing images have four different types of resolutions: spectral, spatial, radiometric and temporal (Jensen, 1996). Spatial resolution is limited by pixel size and refers to the size of the smallest object on the ground which means that the smallest resolvable object cannot be smaller than the pixel size. In this study all three series of the Landsat data images were re-sampled to the common nominal spatial resolution of 30 meters. Spectral resolution is defined as the number and wavelength of bands of electromagnetic energy detectable by a given sensor. A Landsat multispectral image consists of seven bands (green, red, near-IR bands, two SWIR bands and a thermal IR band). Each band represents an image acquired at a particular wavelength for band. The temporal resolution specifies the revisiting frequency of a satellite sensor for a specific location. The temporal resolution of the Landsat satellite images used in this study is 16 days. The all process of remote sensing is illustrated in Figure 2 and consists of the following elements (CCRS, 2007):

**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 2: The all Process of Remote Sensing adopted from CCRS, 2007, pp. 5-6, available at: http://www.nrcan.gc.ca/sites/www.nrcan.gc.ca.earth-sciences/files/pdf/resource/tutor/fundam/pdf/fundamentals_e.pdf.

## 2.2. Remote Sensing and GIS

Remote sensing and geographic information systems (GIS) comprise the two major components of geographic information science (GISci), an overarching field of endeavour that also encompasses global positioning systems (GPS) technology, geodesy and traditional cartography (Goodchild 1992, Estes and Star, 1993, Hepner *et al*. 2005). The statement from twenty years ago „The integration of remotely sensed data (RS) and geographic information system (GIS) technology is one of the great ideas whose time has come"(Faust *et al*. 1991) is today extremely relevant, while the another statement from that year „Remotely sensed images have been shown to be a cost effective means for update GIS data"(Faust *et al*. 1991) is today clearly demonstrable.

Today RS, GIS, GPS, spatial analyses and data visualisations are a central part of the LULC characterization and analysis. There are many studies dealing with the remote sensing and GIS data integration (Ehlers 1991, Lauer *et al*. 1991, Hinton 1996, Tsou 2004, Merchant and Narumali, 2010). Rogan and Miller (2006) summarized four ways in which GIS and remote sensing data can be integrated: (1) GIS can be used to manage multiple data types, (2) GIS analysis and processing methods can be used for manipulation and analysis of remotely sensed data (e.g. neighbourhood or reclassification operations), (3) remotely sensed data can be manipulated to derive GIS data, and (4) GIS data can be used to guide image analysis to extract more complete and accurate information from spectral data. Remote sensing in conjunction with Geographical Information Systems (GIS), because of its ability to interrelate multiple types of various information and data obtained from a range of source, has been widely recognized as powerful tools to derive accurate and timely information on the spatial distribution of LULC changes.

## 2.3. The Landsat Program

### 2.3.1. A Brief History of the Landsat Program

The Landsat Program was established in 1969 through a joint initiative of the U.S. Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA). NASA develops remote-sensing instruments and spacecraft, then launches and validates the satellites. The USGS then assumes ownership and operation of the satellites, in addition to managing all ground-data reception, archiving, product generation, and distribution. The result of this program (Headley, 2010) is a visible, long-term record of natural and human-induced changes on the global landscape (Figure 3).

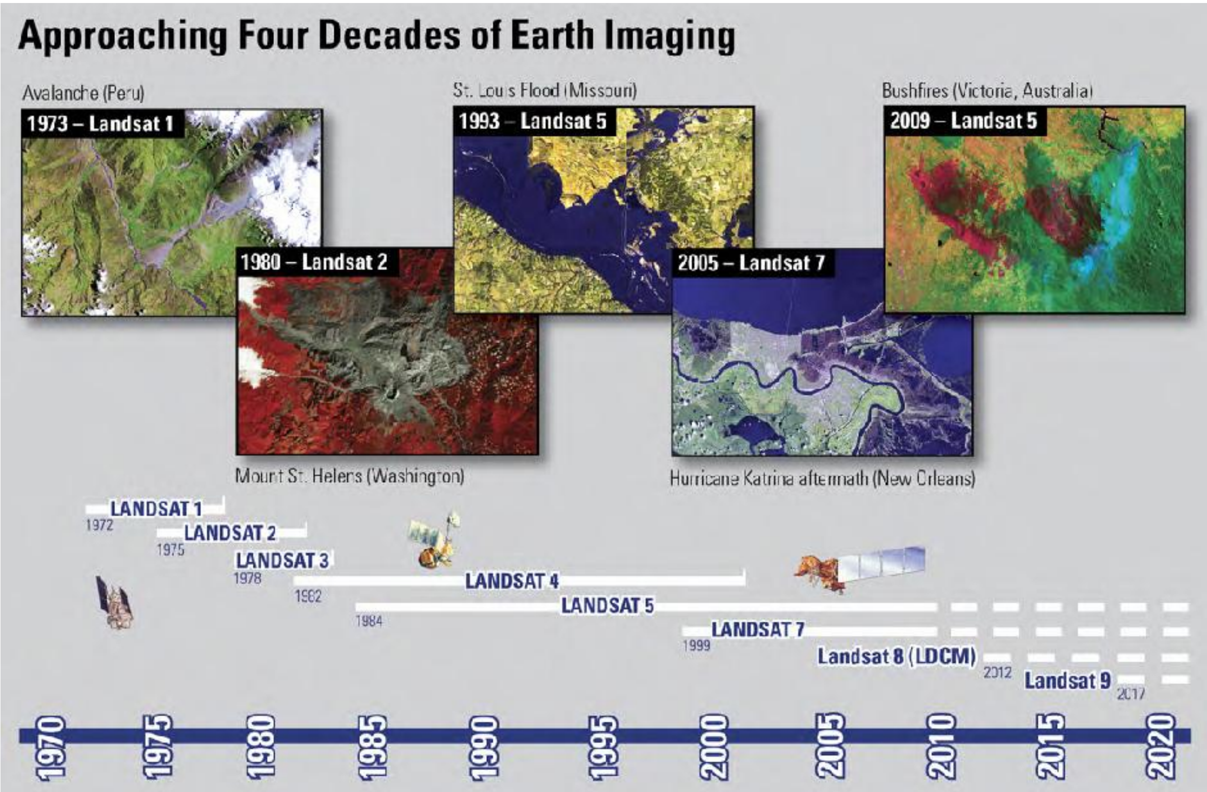



Figure 3: A Global Landsat-Imaging Project, Source: http://pubs.usgs.gov/fs/2010/3026 /pdf/FS2010-3026.pdf, (15.11.2011).

In July 1972, the first “land sensing satellite” (originally the Earth Resources Technology Satellite, later renamed Landsat 1) was launched. Landsat 1 was highly successful, and Landsats 2 and 3 were launched in 1975 and 1978, respectively. Landsat 1, 2 and 3 carry the *Multi-Spectral Scanner* (MSS) sensor which acquires imagery in four spectral bands that cover the blue, visible green, visible red and near infrared wavelengths. Each band has a radiometric depth of 7 bits. The resolution for all MSS bands is 79 meters, and the approximate scene size is 185 x 170 kilometres. Landsats 4 and 5, launched in 1982 and 1984, respectively, brought a new sensor to the Landsat program, the *Thematic Mapper* (TM). The *Thematic Mapper* collects seven bands that cover the blue, green, red, near-infrared, two mid-infrared and one thermal infrared wavelength. The resolution for all TM bands is 30 meters, and the approximate scene size is as well 185 x 170 kilometres. Unfortunately, the Landsat 6 satellite was lost on launch. Landsat 7 was successfully launched in April 1999. Till June 29. Landsat 7 was declared operational for data acquisition and product generation, and distribution to users began in mid-September 1999. The TM and ETM+ sensors are advanced, multi-spectral scanning devices designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity and greater radiometric accuracy and resolution than the MSS sensor. The wavelength of the TM and $ETM^+$ sensor ranges from the visible, through the mid-IR, into the thermal-IR portion of the electromagnetic spectrum. These sensors have a spatial resolution of 30 meters for bands 1 to 5, and band 7, and a spatial resolution of 120 meters for band 6 in TM. The ETM+ has an additional panchromatic band with 15 meters spatial resolution. This band may be used to increase the ground resolution of the 6 multi-spectral bands through image fusion (URL 2).

### 2.3.2. Who really uses Landsat Data?

Who really uses Landsat satellite imagery? In the first study of this kind U.S. Geological Survey scientists identified and surveyed broad cross-section of professional users in private, government and academic sectors in order to answer the question: who are the users, and how they use the Landsat imagery (Miller *et al.* 2011). The results of their survey revealed that respondents from multiple sectors use Landsat imagery in many different ways, and that the current level of use will be likely increase among these respondents, particularly as it becomes better known that the imagery is available at no cost. More than 2500 users of the Landsat satellite imagery, including almost 1400 current users of the Landsat imagery in private, academic, government and non-profit sectors participated in their 2009-2010 survey (Figure 4).

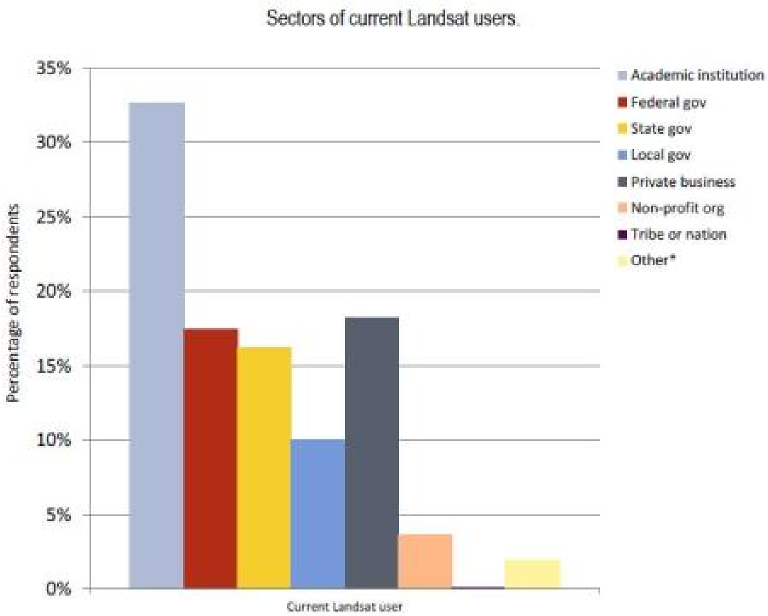



Figure 4: Sectors of current Landsat users (Miller *et al.* 2011, fig. 2, pp.8).

Generally, there are several major factors for using and analysing the Landsat satellite imagery data: rapid developments of work stations and personal computers based on high-speed processors with high capacity hard disk drives, development of sophisticated and powerful software packages, commercial and free, for combined image processing, Landsat images have become a free and easily accessible, Landsat images are unique in the sense that they are uninterrupted over 30 years, so they can effectively serve for „before and after“ comparison of the Earth's surface.

### 2.3.3. Esri-Landsat- *ChangeMatters*

Recently, working in close collaboration with the U.S. Department of the Interior, Esri announce the release of the Landsat image services. Jack Dangermond, president of Esri says: „These Landsat image services expand the ability to monitor landscape change to Internet users world wide. We're excited to show case this valuable government resource that users ArcGIS to rapidly deliver Landsat data so that it can be used to help users understand changes in the world“. This Esri's Web tool called *ChangeMatters* allows users to navigate around the globe and quickly view the GLS Landsat imagery both multi-spectrally (in different Landsat band combination) and multi-temporally (across epochs), and to conduct simple change detection analysis. *ChangeMetters* provides increased access of Landsat imagery to both scientific and non-scientific users (Green 2011). In the Figure 5 below is shown side by side comparison in *ChangeMatters* of the north part of Croatia from the 1990 and 2000 GLS epochs served in an infrared band combination. In the figure below far right, the change image is a multi-temporal image with the Normalized Difference Vegetation Index (NDVI) of the imagery from 1990 and the imagery from 2000.

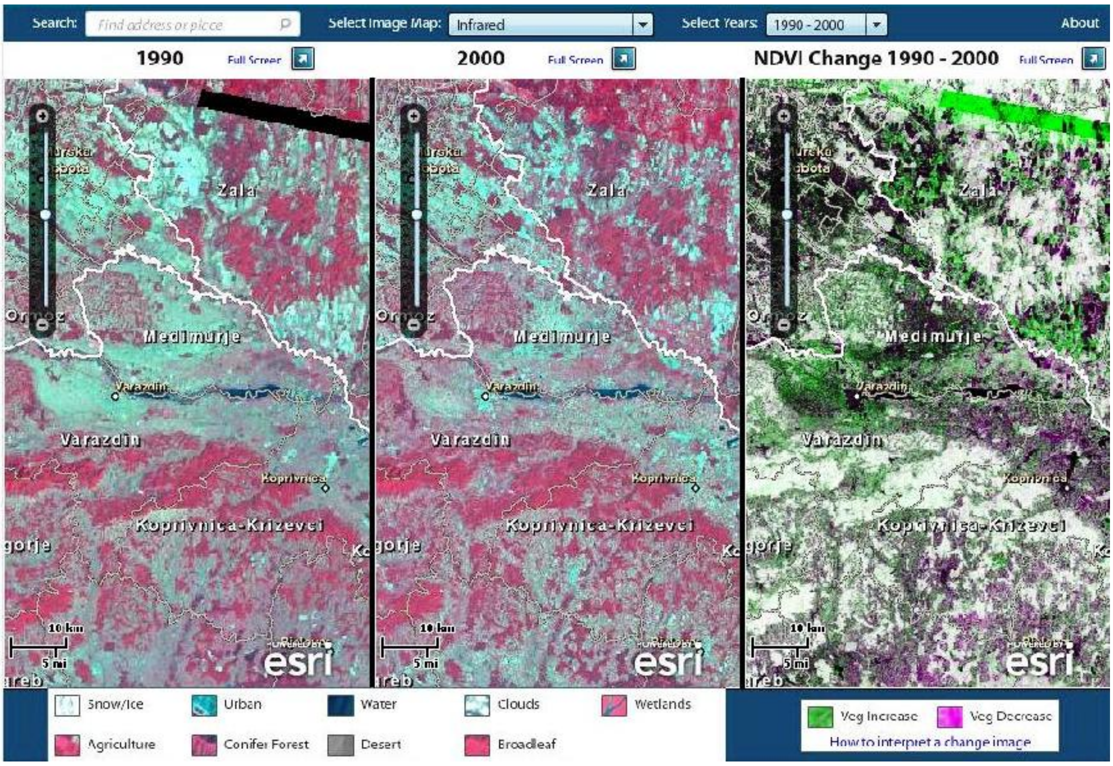



Figure 5: The change images from ChangeMatters in the Međimurje County, Source: http://www.esri.com/landsat-imagery/viewer.html (1.9.2011).

## 2.4. LULC in Croatia

Several authors in Croatia have been doing research using Landsat satellite images for a variety of purposes. For example, considering that topographic maps of the Republic of Croatia are more than 25 years old for some areas Javorović *et al.* (2002) are presented the interpretability of satellite images (panchromatic satellite image IRS-1C and the multi-spectral image Landsat TM) to be used in the topographic map updating. Using the Landsat $ETM^+$ satellite image a vegetation map of Žumberak – Samoborsko gorje Nature Park was created (Jelaska *et al.* 2005). Oluić and Oluić (1994) investigated the contribution of Landsat TM satellite images in geo-research areas of the Nature Park Papuk. Further, Vidović (2006) analyzed various possibilities of using landsat satellite images for urban and physical planners. Seletković *et al*. (2008) dealt with accuracy of high spatial resolution satellite images classification for forestry needs. The main objective of their work was to investigate, compare and find the best way of interpretation of IKONOS high resolution satellite images that were simple and acceptable for operational use.

Pernar and Šelendić (2006) explored the possibility of increasing the interpretation of aerial photographs and satellite images. The combination of black and white aerial photographs high spatial resolution of 0.5 m. and multi-spectral Landsat $ETM^+$ satellite images of spatial resolution of 30 m. joined together their mutual characteristics, combining different channels of Landsat and black and white images. Pernar and Šelendić (2006) argue that the achievement of that synergy provides better visual interpretation of images. The importance of cartography in remote sensing has been also proved by the analysis of articles published in the Bilten Vijeća za daljinska istraživanja i fotointerpretaciju HAZU (Lapaine and Frančula, 2001).

At the end of year 2000, the Ministry of Environmental Protection and Physical Planning of the Republic of Croatia started the project "Mapping the habitats of the Republic of Croatia". The three year project was carried out by Oikon Ltd. Institute for Applied ecology from Zagreb, and finished at the beginning of year 2004. On the terrestrial part of the Croatian territory data source for mapping were classified and interpreted Landsat ETM$^+$ satellite images with the minimum mapping area of 9 ha, as well as the results of the intensive fieldwork. The spring and the autumn set of the satellite images were simultaneously used (Antonić *et al.* 2004). Each Landsat ETM+ scene in this project was classified using supervised classification on the basic land cover units, after that each land cover unit, on the each scene, was classified on the subunits using unsupervised classification supported by the optimisation of the number of clusters.

The all above mentioned research in Croatia shows that the technology of remote sensing offers a practical and useful method for mapping, studying and monitoring broad areas. Since Landsat satellite program has a long history of dataset it is very helpful to map long-term land cover land use and study the LULC changes at regional scales to monitor the way areas have changed through time as proposed in this study.

### 2.5. Change Detection Technique

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Earth surface features are extremely important to understand relationships and interactions between human and natural phenomena in order to promote better decision making (Lu *et al*. 2004). With the availability of historical RS data, the reduction in data cost and increased resolution from satellite platforms, RS technology appears poised to make an even greater impact on monitoring land-cover and land-use change at a variety of spatial scales (Rogan and Chen, 2004). Successful use of RS for LULC change detection largely depends on an adequate understanding of the study area, the satellite imaging system and the various information extraction methods for change detection in order to fulfil the aim of the present study (Yang and Lo, 2002). LULC change detection analysis has become a major application of remote sensing technology in recent decades, because of repetitive coverage at short intervals and consistent image quality. Thus remotely sensed data represents a viable source of LULC information which can be efficiently and cheaply extracted in order to assess and monitor these changes effectively (Mas 1999).

Since the Remote Sensing data are usually used for change detection in recent decades, many change detection techniques have been developed. For example, six change detection procedures were considered and tested using Landsat Multi-Spectral Scanner (MSS) images for detecting areas of changes in the region of the Terminos Lagoon, a coastal zone of the State of Campeche, Mexico (Mas 1999). The change detection techniques considered and tested were: image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison.

Further, Lu *et al*. (2004) grouped the change detection techniques into seven categories: (1) Algebra, (2) Transformation, (3) Classification, (4) Advanced Models, (5) Geographical Information System (GIS) Approaches, (6) Visual Analysis and (7) Other Approaches (Table 1). Lu *et al*. (2004) also provided, for the first six change detection categories, the main characteristics, advantages and disadvantages, key factors affecting change detection results and some application examples. They concluded that image differencing, principal component analysis and post-classification comparison are the most common methods used for change detection, but in recent years some new techniques for change detection applications such as spectral mixture analysis, artificial neural networks and integration of GIS and RS have become important. Their conclusion is also that different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases.

| **Categories** | **Techniques** |
|---|---|
| 1. Algebra | Image differencing<br>Image regression<br>Image rationing<br>Vegetation index differencing<br>Change vector analysis<br>Background subtraction |
| 2. Transformation | Principal component analysis (PCA)<br>Tasseled cap (TC)<br>Gramm-Schmidt (GS)<br>Chi-square |
| 3. Classification | Post classification comparison<br>Spectral-temporal combined analysis<br>EM detection |

| | |
|---|---|
| | Unsupervised change detection<br>Hybrid change detection<br>Artificial natural networks (ANN) |
| 4. Advanced Models | Li-Strahler reflectance model<br>Spectral mixture model<br>Biophyisical parameter method |
| 5. Geographical Information System (GIS) Approaches | Integrated GIS and remote sensing method<br>GIS approach |
| 6. Visual Analysis | Visual interpretation |
| 7. Other Approaches | Measures of spatial dependence<br>Knowledge-based vision system<br>Area production method<br>Combination of three indicators<br>Change curves<br>Generalized linear models<br>Curve-theorem-based approach<br>Structure-based approach<br>Spatial statistics-based method |

Table 1: The change detection techniques (Lu *et al*. 2004).

According to Mas (1989) change detection procedures can be grouped under three broad headings characterized by the data transformation procedures and the analysis techniques used to delimit areas of significant changes: (1) image enhancement, (2) multi-date data classification and (3) comparison of two independent land cover classifications. Lu *et al.* (2004) suggested that before implementing change detection analysis, the following conditions must be satisfied: precise registration of multi-temporal images, precise radiometric and atmospheric calibration or normalization between multi-temporal images, similar phenological states between multi-temporal images and selection of the same spatial and spectral resolution images if possible).

Good change detection research should provide the following information: area change and change rate, spatial distribution of changed types, change trajectories of land cover types and accuracy assessment of change detection results (Lu *et al.* 2004). When implementing a change detection project, three major steps are involved: image pre-processing including geometrical rectification and image registration, radiometric, atmospheric and topographic correction if the study area is in mountainous regions, selection of suitable techniques to implement change detection analyses and accuracy assessment (Lu *et al.* 2004).

Some of the most common change detection techniques are: image differencing, principal component analysis (PCA) and post-classification comparison (PCA). Image differencing and PCA analysis can provide change/non-change information whereas post-classification comparison provides detailed 'from–to' change information. Visual interpretation, supervised and unsupervised classification of urban areas and post-classification change detection used in this study are described and discussed in the chapter of methodology.

### 2.6. Accuracy Assessment

After the classification has been completed it is very important to estimate the accuracy assessment of the achieved classified images. Accuracy assessment or validation is very important and has become a standard component of any land cover/land use map derived from remotely sensed data for understanding the developed results and employing these results for decision-makers (Foody 2002, Lu *et al.* 2004).

The error matrix is the most widely used approaches for image classification accuracy assessment and can be used to derive a series of descriptive and analytical statistics (Congalton and Mead, 1983, Hudson and Ramm,1987, Congalton 1991, Congalton and Green, 1999, Smits *et al.* 1999, Congalton and Plourde, 2002, Foody 2002, Liu *et al.* 2007). Generally, the error matrix compares the relationship between the reference field data (ground truth) and the corresponding results of a classification. In order to properly generate an error matrix, one must consider the following factors: ground truth data collection, classification scheme, sampling scheme, spatial autocorrelation and simple size and simple unit (Congalton and Plourde, 2002). Basically, there are two types of data collected in support of accuracy assessment: ancillary data and ground based data. The data should be taken as close as possible in the same vegetation season, i.e. as close as possible to the time of acquisition. Accuracy data should be collected consistently and should be independent of reference or ground truth data. Sampling schemes must include appropriate sample design. Special attention should be placed on the following issues: what kind of sample unit will be used, how big will it be, how many samples should be taken in order to be statistically valid, how should samples be chosen.

There are many ways to look at the accuracy assessment:

- overall accuracy,
- errors of omission,
- errors of commission,
- user's accuracy,
- producer's accuracy,
- Kappa statistics,
- fuzzy accuracy.

The meaning and calculation for terms above have been explained in detail in many studies (Lunetta *et al*. 1991, Congalton 1991, Kalkhan *et al*. 1997, Smits *et al*. 1999, Plourde and Congalton, 2003, Foody 2002).The user’s accuracy indicates the probability that a pixel on the image actually represents that class on the ground (Story and Congalton, 1986). It is calculated for each class by dividing the correctly classified pixels by the row total for that class. The producer’s accuracy is defined as the probability of a pixel being correctly classified and is mainly used to determine how well an area can be classified (Story and Congalton, 1986). The producer’s accuracy is calculated for each class by dividing the number of correct pixels by the column total for that class.

Over the past 15 years the Kappa statistics has became a standard part of evaluating classification accuracy. The Kappa statistics is a discrete multivariate technique used to evaluate the accuracy of change detection and classification maps by measuring the agreement between the two images (Story and Congalton, 1986). The Kappa statistics is a measure of the difference between the actual agreement between the reference data and an automated classifier and the chance agreement between the reference data and a random classifier.

$$\hat{K} = \frac{\text{observed accuracy - chance agreement}}{\text{1 - chance agreement}}$$

This statistics serves as an indicator of the extent to which the percentage correct values of an error matrix are due to “true” agreement versus “chance” agreement. As true agreement observed approaches 1 and chance agreement approaches 0, *k* approaches 1. This is the ideal case. In reality, *k* usually ranges between 0 and 1 (Lillesand and Kiefer, 2002).

There are five common methods to collect ground reference data for assessing the accuracy of classification results (Congalton and Green, 1999, Jensen 2005): (1) simple random sampling, (2) systematic sampling, (3) stratified random sampling, (4) systematic non-aligned sampling and (5) cluster sampling (Table 2).

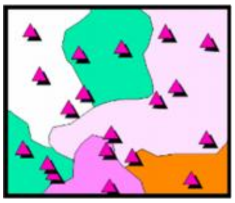
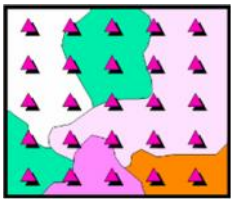
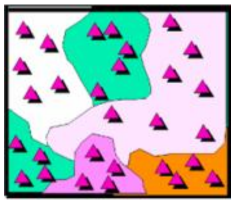
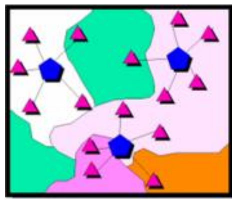
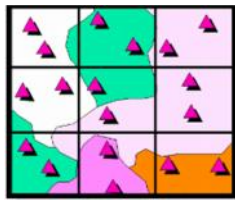
| Simple Random Sampling | Systematic Sampling | Stratified Random Sampling | Systematic Non-Aligned Sampling | Cluster Sampling |
|---|---|---|---|---|
|  |  |  |  |  |
| Observations are randomly placed | Observations are placed at equal intervals | In each class a minimum number of observations are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

Table 2: Methods for collecting ground reference data, Source: http://www.forestry.oregonstate.edu (1.10.2011)

# 3. STUDY AREA, DATA DESCRIPTION AND SOFTWARE USED

This chapter describes the area and data used for the study. Description of the study area is given with the characteristics of the area in terms of geography, changes in environment in the last 30 years and land use land cover. Then, it describes various data and software used in the study. The data can be subdivided into remote sensing data and ancillary data.

## 3.1. Study Area

### 3.1.1. Location and Climate

Međimurje County (in Croatian: Međimurska županija) is a triangle-shaped county in the northern part of the Republic of Croatia (Figure 6).

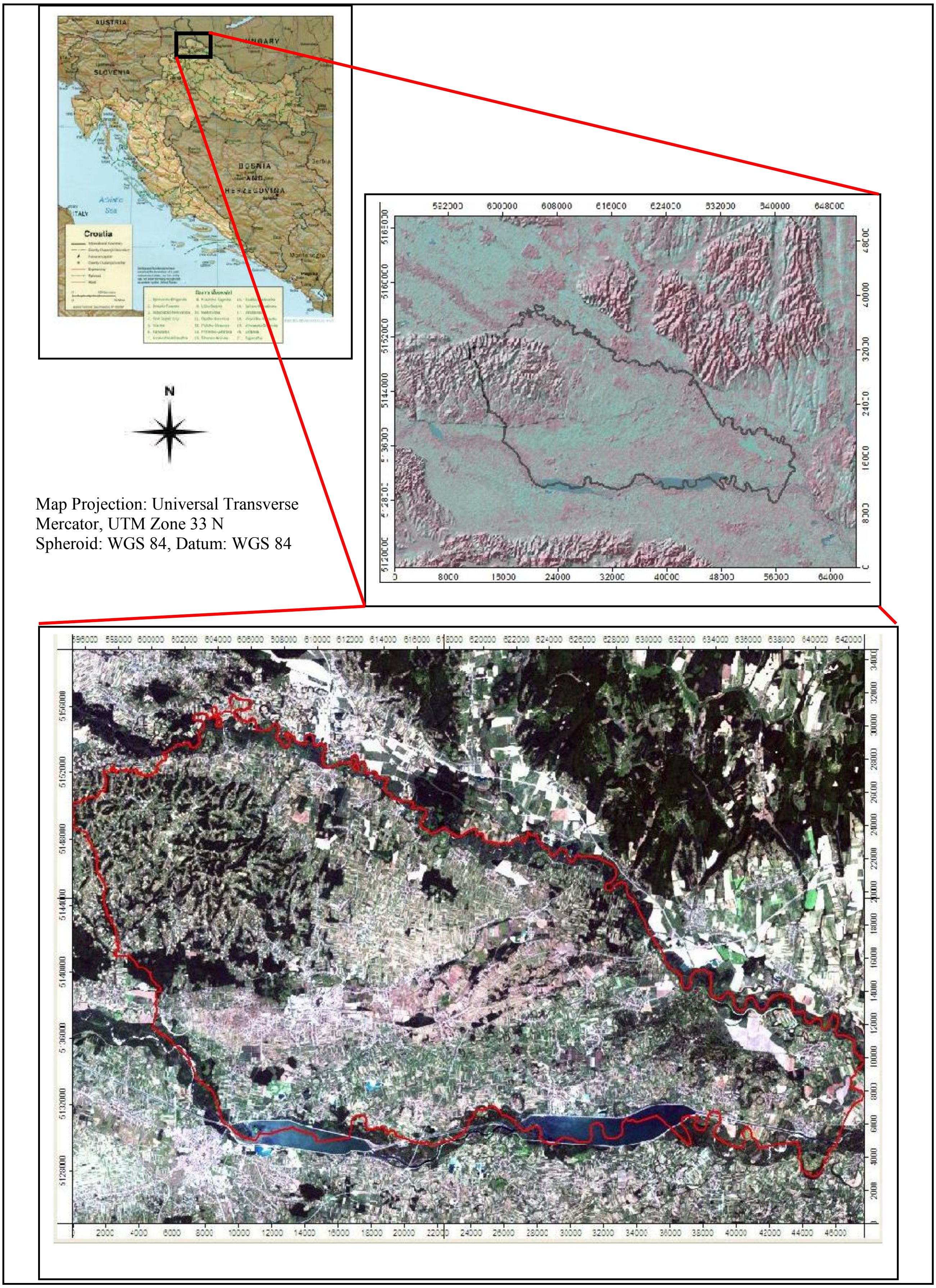



Figure 6: The geographic location of the study area.

Međimurje County covers the plains between two rivers – the Mura and the Drava. The elevation of Međimurje County ranges between 120 and 374 metres above the sea level. Total area of Međimurje is 729 km$^2$ and it is the most densely populated county in Croatia. Almost 120,000 inhabitants live on 729 km$^2$ in 3 towns and 22 municipalities, amounting to the population density of 164.2 people/km$^2$. However there are significant differences in population density between different parts of the County (Figure 7). The population of the Međimurje County accounts for 2,5% of the total population of The Republic of Croatia.

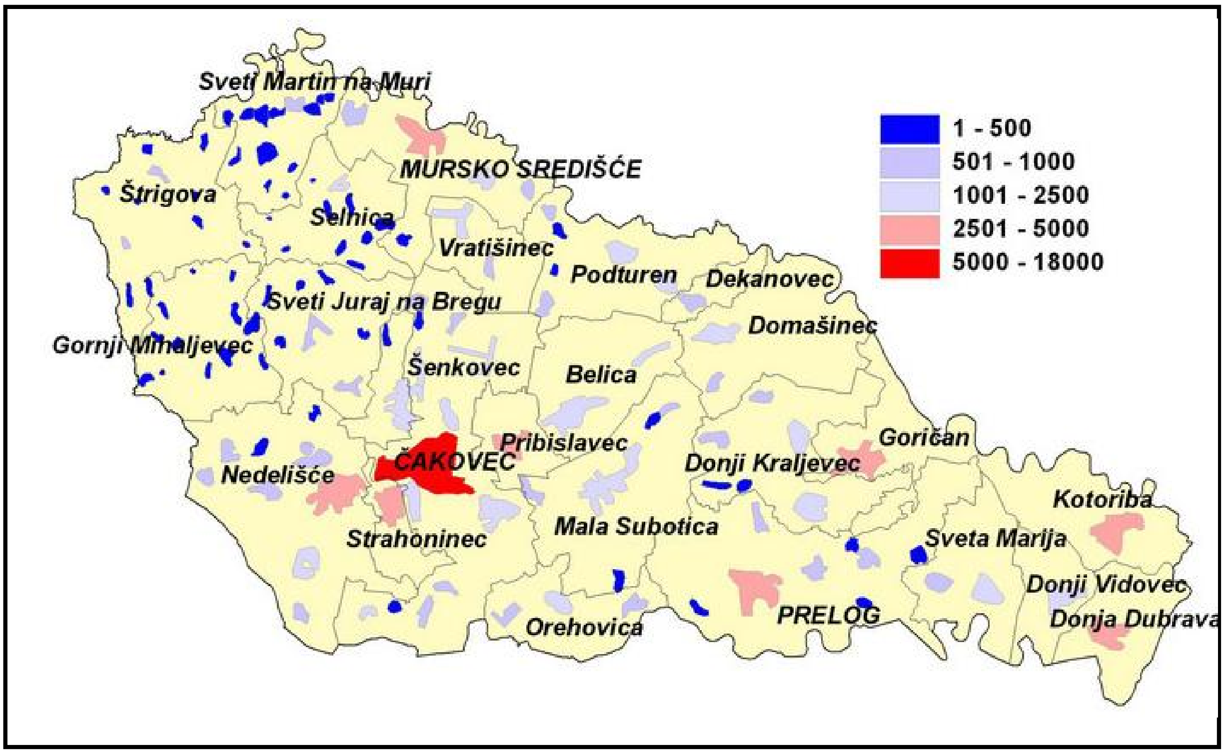



Figure 7: Population density in Međimurje County, Source: Regional Operative Programme of the Međimurje County for the period 2006-2013, available at: http://www.redea.hr/r_includes/sub_links/download/rop.pdf)

In the last 30 years there have been significant changes in environment such as:

- Construction of two reservoir lakes on the Drava river – Lake Varaždin and Lake Dubrava - both built to serve the two hydroelectric power plants.
- Construction of a highway through the central part of the Međimurje County.
- The rapid urbanization and industrialization, especially in the eastern part of the county.

Međimurje County is surrounded by two EU member countries - Slovenia and Hungary to the west, north and east, while its southern border is with Koprivnica-Križevci and Varaždin counties. The climate in Međimurje County is continental with hot summers, calm autumns and sometimes very cold winters. Until recently, two of the biggest rivers in this part of Europe the Drava and the Mura river flooded arable land, woodland and settled areas thus creating very good conditions for the development of agriculture, along with the high fertility of the land.

#### 3.1.2. Land Use/Land Cover

According to Meyer (1995) every parcel of land on the Earth's surface is unique in the cover it possesses. Land use and land cover are distinct yet closely linked characteristics of the Earth's surface. Land cover and Land use are sometimes used as terms with the same meanings. Actually they have different meanings. The mixing of the concepts of land cover and land use has been present for at least the last 25 years (Anderson *et al*. 1976). The difference in Land Use and Land Cover is acknowledged in many documents (Anderson *et al*.1976, Campbell 1981, Di Gregorio and Jansen, 2000, Cihlar 2000). Land cover is the physical material at the surface of the earth. It is the material that we see in direct interaction with electromagnetic radiation and causes the level of reflected energy that we observe as the tone or the digital number at a location in an aerial photograph or satellite image. Land use, by contrast to land cover, is a description of how people use the land. (Fisher *et al*. 2005). Land cover categories include: grass, asphalt, cropland, water, snow, deciduous forests, bare soil, wetlands and pasture. Examples of land use include: agricultural land, urban and recreation areas, grazing and mining.

Over half of Međimurje County is agricultural, but unfortunately, due to high population density, agricultural parcels are very small (Figure 8).

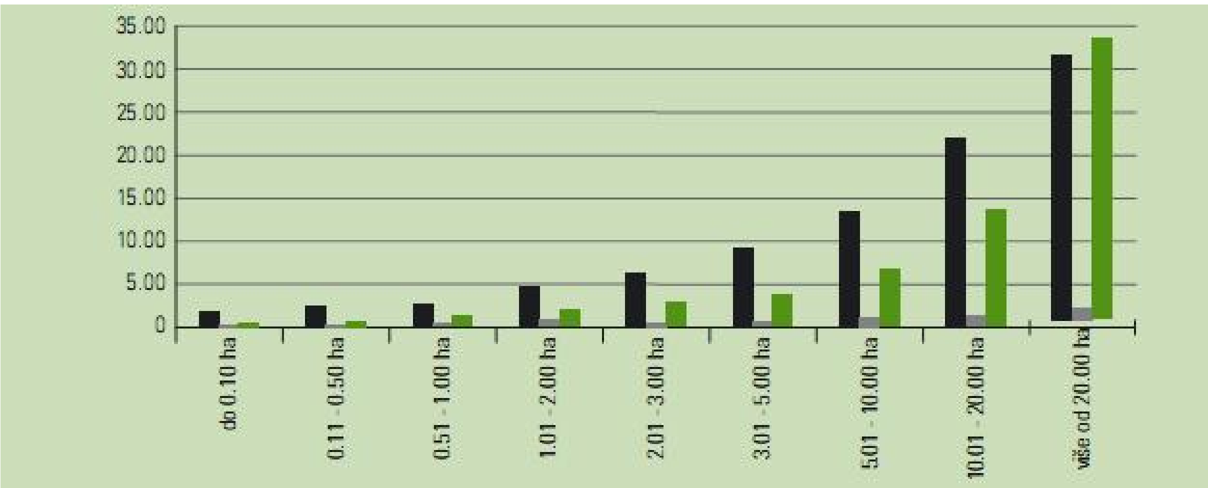


Figure 8: The average number of land parcels, the area of land parcels and the area of farms in the Međimurje County, Source: The agriculture census from 2003 (URL 4)

The agricultural land is divided into 21,000 parcels which mean that the average size of agricultural land is about 0,21 ha (Figure 9).

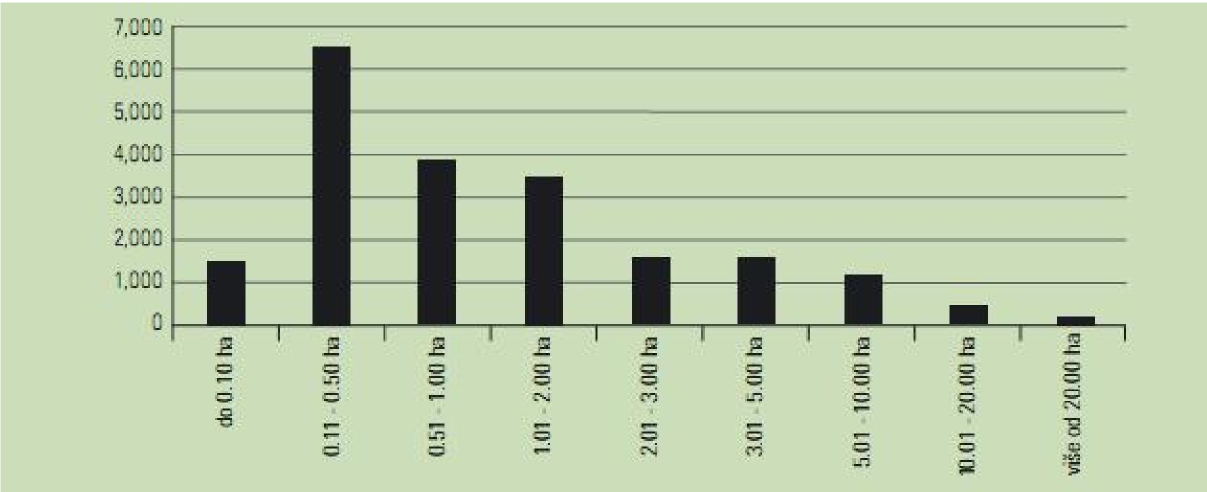


Figure 9: The distribution of land areas in Međimurje county, Source: The agriculture census from 2003 (URL 4.)

Although agricultural parcels are very small and fragmented, the dominant agricultural crops are wheat and corn, recently orchards and vineyards. The most widely represented agricultural product of Međimurje is potato, taking the County to the nationwide top spot with 18% of the total area under potato crops. The potato production usually is organized on private farms on small fields. In the west of the county are the slopes of the Alpine foothills and this part of the county is famous for its vineyards. In Figure 10 we can see typical LULC areas in Međimurje County.

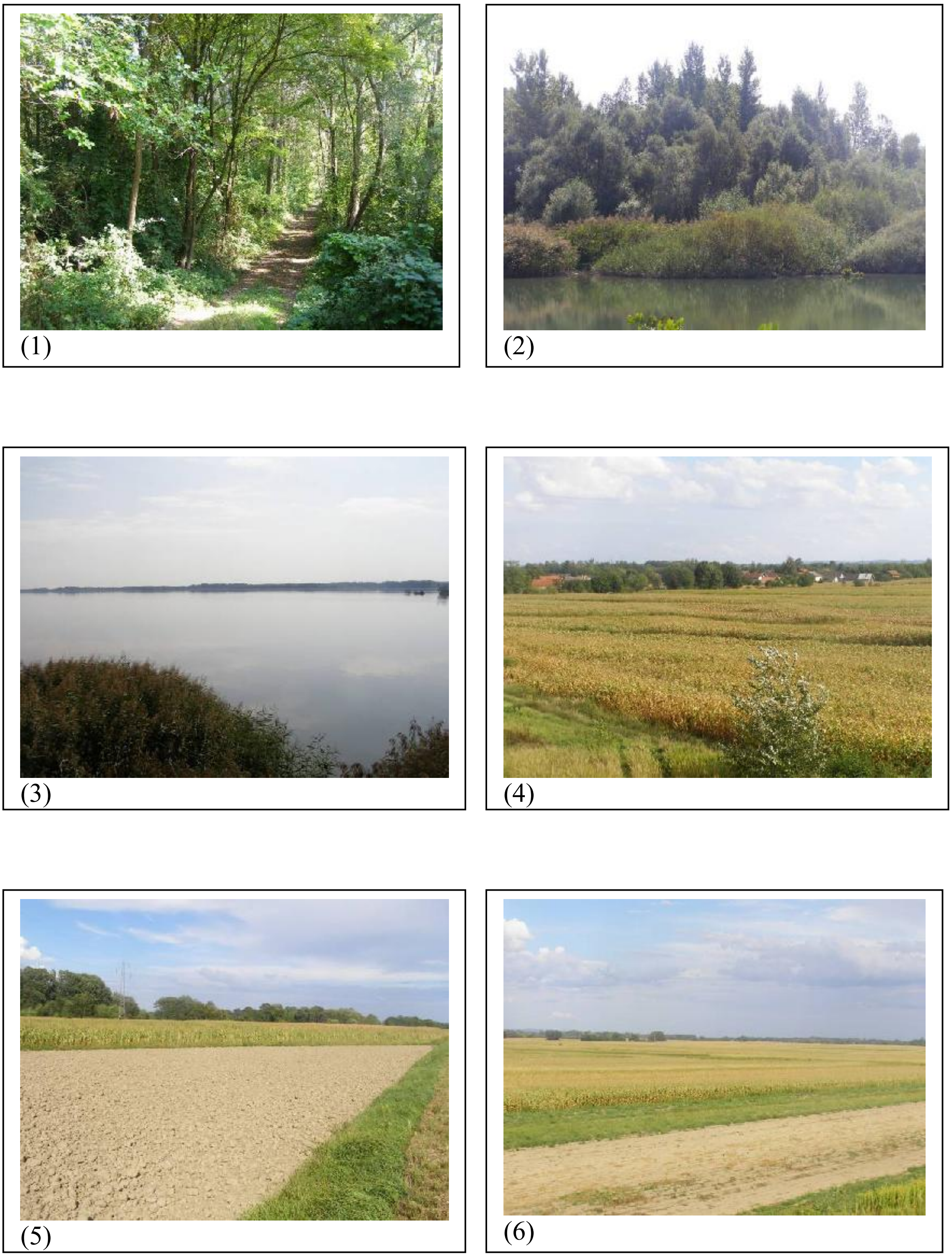



Figure 10: Photos showing (1) forest area, (2) mixed forest area, (3) Reservoir lake Dubrava, (4) ploughed area (5,6), bare soil.

## 3.2. Data

### 3.2.1. Landsat Data

For the purpose of this study the Landsat images of following were procured (Table 3): Landsat 4-MSS of August 23, 1978, Landsat 5-TM of August, 28 and Landsat ETM$^{+}$ of June 2007. The study area is contained within the Landsat path 204, row 028 for Landsat MSS and path 189, row 028 for Landsat TM and ETM$^{+}$. All three series of the Landsat data images are created into global data set - Global Land Survey (GLS). The U.S. Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) collaborated on the creation of four global land datasets using Landsat data. These global data sets were created from the primary Landsat sensors in use at the time: the Multispectral Scanner (MSS) in the 1970s, the Tematic Mapper (TM) in 1990, the Enhanced Thematic Mapper Plus (ETM+) in 2000 and a combination of the TM and ETM+, as well as EO-1 ALI data, in 2005 (URL 5). The Landsat data incorporated into GLS collections meet quality, cloud cover standards and are processed to the following specifications:

- Terrain Corrected,
- Universal Traverse Mercator (UTM) projection,
- WGS84 datum,
- Cubic Convolution (CC) resampling,
- GeoTIFF data format.

The dates of the Landsat images were chosen to be as closely as possible in the same vegetation season. The impact of the sun angle differences and the vegetation phenology differences may be partially reduced by selecting data belonging to the same time of the year (Singh 1989). All datasets were acquired within the time difference of one month and considering that all three Landsat imagery dataset are acquired in August in the growing seasons, so they are dominated by vegetation.

The Landsat data images were geometrically precision corrected by the EROS Data Centre (Sioux Falls, South Dakota) to less than ½ pixel root mean square error, registered to Universal Transverse Mercator coordinates, zone 33N, WGS84 Datum. To ensure consistency among Landsat satellite images, all three series of the Landsat data images were re-sampled to a common nominal spatial grid of 30 meters resolution using nearest neighbour technique to avoid altering the original values (Jensen 1996, Yang and Lo, 2002). All three Landsat satellite images series are downloaded from the Global Land Cover Facility at the University of Maryland. The Table 3 shows the full detail about the data including World Reference System (WRS), acquisition data, attribute and data type.

| ID | WRS:P/R | Acq. Date | Dataset | Producer | Attribute | Type |
|---|---|---|---|---|---|---|
| 231-497 | 1:204/028 | 1978-08-23 | MSS | USGS | Ortho, GLS1975 | GeoTIFF |
| 205-327 | 2:189/028 | 1992-08-28 | TM | USGS | Ortho, GLS1990 | GeoTIFF |
| 220-573 | 2:189/28 | 2007-07-21 | ETM+ | USGS | Ortho, GLS2005 | GeoTIFF |

Table 3: Detail characteristics of the Landsat satellite imageries used in this study

### 3.2.2. Characteristics of Landsat Data

Landsat satellite images are among the widely used satellite remote sensing data and their spatial, spectral and temporal resolution made them useful input for creating land use land cover maps and for change detection. The Landsat images used for this study are from three Landsat operations. The Tables 4, 5 and 6 shows technical details, spectral and spatial resolution details of the Landsat MSS, TM and ETM+.

| Band No MSS | Description | Spectral resolution (µm) | Spatial resolution (m) |
|---|---|---|---|
| MSS1 | Green | 0.5 – 0.6 | 57 |
| MSS2 | Red | 0.6 – 0.7 | 57 |
| MSS3 | Near-Infrared | 0.7 – 0.8 | 57 |
| MSS4 | Near-Infrared | 0.8 – 1.1 | 57 |

Table 4:  Spectral and spatial resolution for the Landsat MSS bands used in this study, Source: http://landsat.usgs.gov/about_landsat5.php, (1.11.2011).

| Band No<br>TM | Description | Spectral resolution<br>(µm) | Spatial resolution (m) |
|---|---|---|---|
| 1 | Blue | 0.45 – 0.52 | 30 |
| 2 | Green | 0.52 – 0.60 | 30 |
| 3 | Red | 0.63 – 0.69 | 30 |
| 4 | Near-Infrared | 0.76 – 0.90 | 30 |
| 5 | Near-Infrared | 1.55 – 1.75 | 30 |
| 6 | Thermal | 10.4 – 12.5 | 120 |
| 7 | Mid-Infrared | 2.08 – 2.35 | 30 |

Table 5: Spectral and spatial resolution for the Landsat $ETM^+$ bands used in this study, Source: http://landsat.usgs.gov/about_landsat5.php, (1.11.2011).

| Band No<br>$ETM^+$ | Description | Spectral resolution<br>(µm) | Spatial resolution (m) |
|---|---|---|---|
| 1 | Blue | 0.45 – 0.52 | 30 |
| 2 | Green | 0.52 – 0.60 | 30 |
| 3 | Red | 0.63 – 0.69 | 30 |
| 4 | Near-Infrared | 0.77 – 0.90 | 30 |
| 5 | Near-Infrared | 1.55 – 1.75 | 30 |
| 6 | Thermal | 10.4 – 12.5 | 60 |
| 7 | Mid-Infrared | 2.08 – 2.35 | 30 |
| 8 | Panchromatic | 0.52 – 0.90 | 15 |

Table 6:  Spectral and spatial resolution for the Landsat $ETM^+$ bands used in this study, Source: http://landsat.usgs.gov/about_landsat7.php, (1.11.2011).

Landsat MSS has four spectral channels with 57m. spatial resolution, Landsat TM has seven spectral channels and Landsat ETM+ has eight spectral channels; the thermal band has 60m spatial resolution and the panchromatic has 15m spatial resolution. In this study four Landsat MSS multispectral images (bands 1,2,3 and 4), and six Landsat TM and $ETM^+$ (bands 1,2,3,4,7) multispectral images were used. The thermal bands due to their coarser spatial resolution and weak signal to noise ratio were not employed in this study. More detail information about Landsat data is available at URL 2.

### 3.2.3. Ancillary Data

Ancillary data is often used to improve image classification and for the accuracy assessment. Analysts can choose to use ancillary data at any stage of image classification. Hutchinson (1982) described three different methods of combining Landsat and ancillary data to improve digital classification accuracy. He incorporated ancillary data before, during, and after classification. An example of using ancillary data before classification is the stratification of the data into smaller areas that can be then processed separately. Training and classification can be performed dependently on each area and the results merged together. In this study polygons around urban areas were used as ancillary data. Polygons were then clipped out of the image data and classified separately. If data are organized in form of additional layers and used jointly with the conventional spectral bands in a classifier we have an example of using ancillary data during the classification. Ancillary data can be used after classification to improve or to correct the results of the classification. For example, topographic information can be added in order to better discriminate between classes with a similar spectral response.

Jensen (1996) stated that any type of spatial or non-spatial information that may be of value in the image classification process, including elevation, slope, aspect, geology, soils, hydrology, transportation networks, political boundaries, and vegetation maps can be under the definition of ancillary data. For example, Franklin (1988) in his work concluded that remote-sensing studies of complex terrain phenomena can benefit greatly from careful application of digital ancillary data. These data may be obtained from maps (e.g. geological units, soil classifications, and political boundaries) or may be continuous variables (e.g. digital elevation models, aeromagnetic surveys and regional economic indicators). The following ancillary data (all from the State Geodetic Administration, SGA) were procured (Table 7): high resolution colour aerial photographs acquired between 2008 and 2009, black and white aerial photographs acquired in 1984 and 2002, topographic maps of 1:25,000 scales also published by the State Geodetic Administration acquired in 1967 and 2001 (Figure 11).

| Data | Date of Acquisition | Band/Colour | Resolution | Source |
|---|---|---|---|---|
| High resolution colour aerial photographs | 2008-2009 | GeoTIFF | 1:5,000 | State Geodetic Administration |
| Black and white aerial photographs | 1984<br>2002 | GeoTIFF | 1:5,000 | State Geodetic Administration |
| Topographic maps, black and white | 1967-1970<br>1995-1997 | GeoTIFF | 1:25,000 | State Geodetic Administration |
| Topographic maps, colour | 2001-2003 | GeoTIFF | 1:25,000 | State Geodetic Administration |

Table 7: Ancillary data, all published by SGA, used in this study.

All procured ancillary datasets were used for “ground-truth” information required for classification and accuracy estimation of classified MSS, TM and $ETM^+$ Landsat satellite images respectively.


(1)

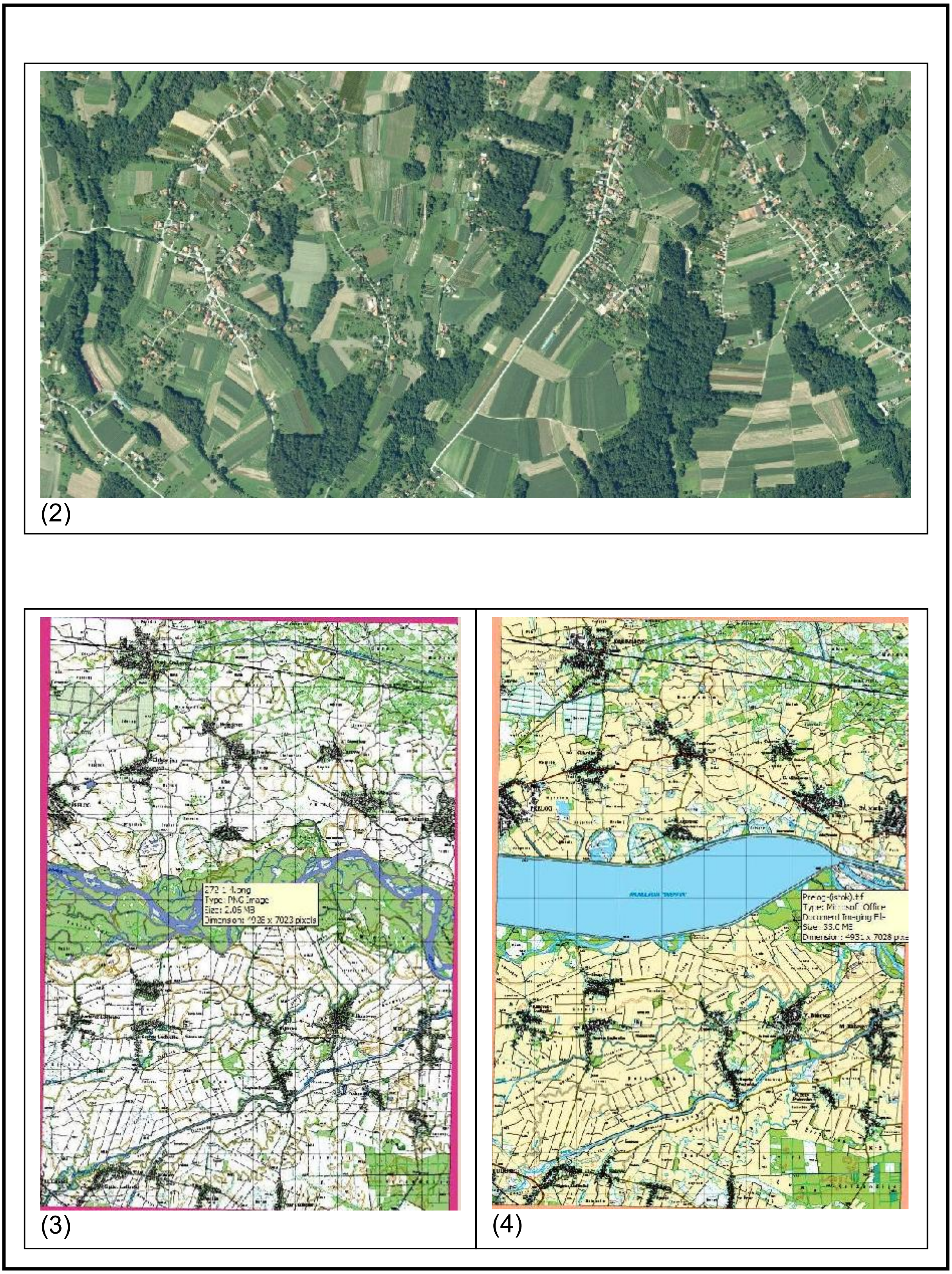



Figure 11: Ancillary data: (1) black and white aerial photograph, (2) high resolution colour aerial photograph, (3) topographic map from 1970 and (4) topographic map of the same area from 2002.

### 3.3. Software Used

There are numerous software programs available for image processing and image classification. Several programs are available as Free Open Source Software (FOSS), and can be downloaded from the Internet. Other programs are available through commercial vendors. In general, the various commercial programs and same FOSS programs available have many similar processing functions and there were just a minor difference in the programs interfaces, terminology functions and types of files that programs can read. Various software programs have been used in this study to process, quantify and analyze images.

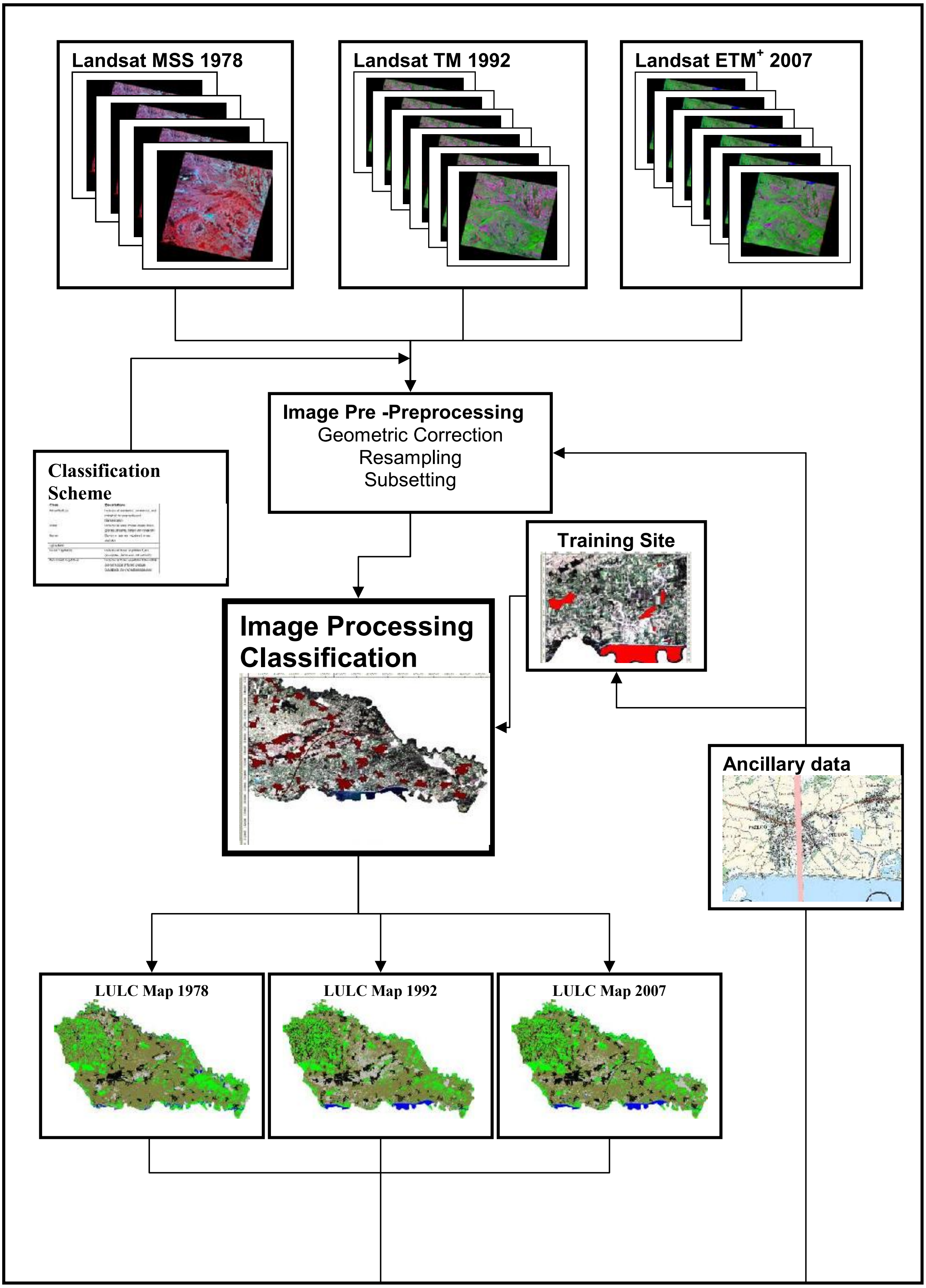
For the preliminary data processing, extracting the study area, unsupervised and supervised classification and producing change detection maps, System for Automated Geoscientific Analyses (SAGA) GIS software 2.0.7 version was used. SAGA is a Free Open Source Software (FOSS) for the analysis of spatial data and provides all basic functions of desktop Geographical Information System (GIS) software. The analytical and operational capabilities cover geostatistics, terrain analysis, image processing and various tools for vector and raster data manipulation (Conrad 2006). Georeferencing of the ancillary data used in this study was also performed in SAGA using Proj 4. cartographic projection library (Conrad 2006). Microsoft office (Excel and Word) was used for analysis, calculating error matrices and reporting.

### 3.4. Summary

In this chapter the location, climate and land use land cover characteristic of Međimurje County are described. Presented were also three series of the Landsat data images as basic data for image classification, as well as available ancillary data procured from SGA and used to improve image classification and accuracy assessment. Presented was also SAGA GIS software which was mainly used for data processing, classification and producing change detection maps.

# 4. THE METHODOLOGY

In this chapter a general review of the methodology for image classification along with the required pre-processing (geometric correction, re-sampling and sub-setting) used in the study have been described. The aim of this study is to identify and analyze general trends in Land Use/Land Cover Changes (LULCC) that have taken place in Međimurje County over a period of 29 years using Landsat Satellite Imagery and GIS based technique. The workflow diagram for the methodology used in this study is shown in Figure 12.


Landsat MSS 1978
Landsat TM 1992
Landsat ETM+ 2007
Image Pre -Preprocessing
Geometric Correction
Resampling
Subsetting
Classification
Scheme
Training Site
Image Processing
Classification
Ancillary data
LULC Map 1978
LULC Map 1992
LULC Map 2007

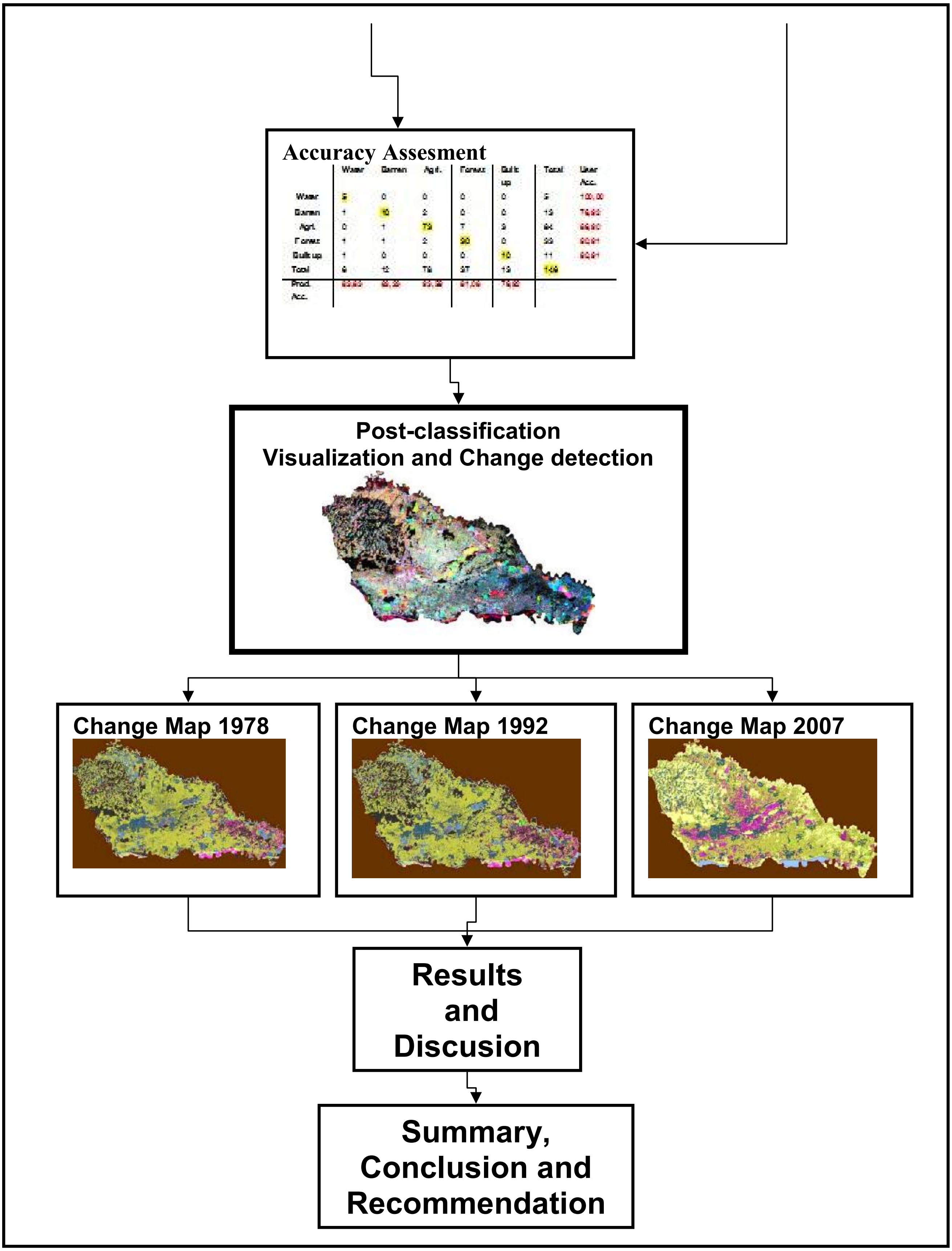



Figure 12: Workflow Diagram for Methodology of the Thesis

## 4.1. Data Pre-Processing

Before applying the classification of the remote sensed data, pre-processing of the data must be done to remove errors and to make the various data consistent. Typical steps of pre-processing of the data are: geometric, radiometric and atmospheric corrections, re-sampling and sub-setting.

Geometric correction of the data is critical for performing a change detection analysis. Once the various data have been obtained, they have probably different projections, and the next necessary step is to project it. Thus, all obtained spatial data sets of a study belong to one single coordinate system. In this study the geometric correction of the Landsat satellite data has not been performed because the data had already been orthorectified and georeferenced, as explained in Chapter 3.2., to the UTM Zone 33N coordinate system. Accordingly with that the Universal Transverse Mercator (UTM) projection, Zone 33N, Spheroid WGS84 and WGS84 Datum was used as the primary coordinate system in this study. Different situation we have with ancillary data obtained from SGA. Because the ancillary data are in three different coordinate systems to ensure consistency among the Landsat satellite images and ancillary data we have to make geometric correction of the ancillary data.

On the basis of the Law on State Survey and Real Estate Cadastre, the Government of the Republic of Croatia, made at its meeting on August the 4th 2004 the *Decree on Establishing New Official Geodetic Datums and Planar Map Projections of the Republic of Croatia* (NN 110/04). Coordinate system of the transverse aspect of Mercator's projection, with the main meridian 16° 30' and the linear scale on that meridian 0.9999, is defined to be the projection coordinate system of the Republic of Croatia for the field of cadastre and detailed state topographical cartography. The projection is based on GRS80 ellipsoid as a mathematical meaning Croatian Terrestrial Reference System (Lapaine and Tutić, 2007). However, most of the ancillary data used in this work are in the Gauss Krüger map projection, zone 5 and 6, and the ellipsoid datum Bessel 1841, the false easting of 5,500,000 for data in zone 5 (with central meridian set to 15°) and 6,500,000 for data in zone 6 (with central meridian set to 18°). The central meridian scale factor for both zones is 0.9999 (Table 8).

| | 5. zona E13$^0$ 30'- E16$^0$ 30' | 6. zona E13$^0$ 30'- E16$^0$ 30' | HTRS 96/TM |
|---|---|---|---|
| Projection | Transverse Mercator | Transverse Mercator | Transverse Mercator |
| Latitude of origin | 0$^0$ | 0$^0$ | 0$^0$ |
| Longitude of origin | 15$^0$ | 18$^0$ | 16,5$^0$ |
| Scale factor | 0.9999 | 0.9999 | 0.9999 |
| Units to meter scale | 1 | 1 | 1 |
| False East at origin | 5 500 000 m. | 6 500 000 m. | 500 000 m. |
| False north at origin | 0 m. | 0 m. | 0 m. |

Table 8: The projection coordinate system in Croatia

The geometric correction of all ancillary data that are used for this study has been done with SAGA and Proj 4. library. Proj 4. library work for raster and vector data and provide various projections for free definable cartographic parameters (Conrad 2006). After the geometric correction of ancillary data, visual comparisons with ground control point selected from topographic maps, as well as image-to-image comparisons showed that the images were geometrically correct.

Also, the Landsat scenes and ancillary datasets are much larger than the study area and it is beneficial to reduce the size of the image files to include in work process only the study area. This reduction of data is known as subsetting, and this reduction eliminates the extraneous data in the file and speeds up processing due to the smaller amount of data to process. The subsetting of all datasets has been done with SAGA as well.

### 4.2. Visual Analysis

Visual interpretation is the first step, from a technology perspective the simplest way to interpret an image, to distinguish various land covers and change information over the particular area by a human interpreter. The goal of visualisation is to identify image elements by recognizing the relationship between pixels and group of pixels.

However, visual interpretation cannot provide detailed change information, and the results of interpretation depend on the analyst's skill in image interpretation meaning that significant training and experience are needed to produce a skilled image interpreter (Lu *et al.* 2004, Campbell 2007).

One band from image 1 as red, the same band from date 2 images as green and the same band from date 3 images as blue if available can help for visual interpretation the colour composite to identify the changed areas (Lu *et al*. 2004). In the Figure 13 is shown combination of 1978 MSS band 1 as red, 1992 TM band 1 as green and 2007 ETM+ band 1 as blue. In Figure 13 we can see, for example, the red areas which represent the changes that have occurred over the study time.

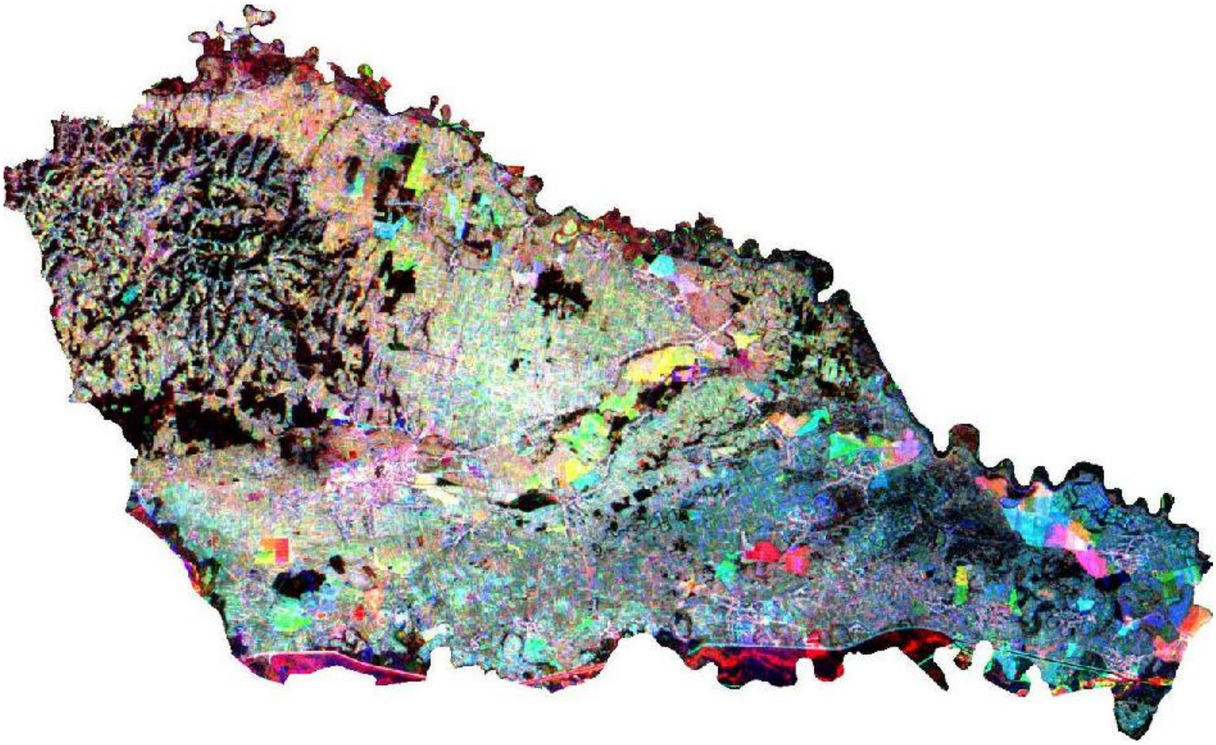


Figure 13: The combination of 1978 MSS band 1 as red, 1992 TM band 1 as green and 2007 ETM+ band 1 as blue for visual interpretation.

The six primary elements of visual interpretation are: tone or colour, size, shape, texture, shadow and pattern (Estes and Simonett, 1975). Tone refers to the relative brightness of colour of the object in an image or to the lightness or darkness of a region within an image. Shape refers to the general form, structure or outline of individual objects. Manmade and natural features often have shapes. Size of objects in an image is a function of scale. For example, large buildings in an image (factories or warehouses) suggest that the property is commercial, whereas small buildings in an image suggest that there is residential use. Further, the relative size of an object related to other objects gives the interpreter a sense of scale. Pattern refers to the spatial arrangement of visibly discernible objects. Texture refers to the arrangement and frequency of tonal variation in particular areas of an image. Shadow may reveal information about the size and shape e.g. may provide an idea of the profile and relative height of a target which may facilitate identification.

### 4.3. A Brief Introduction of Classification Methods used in this Study

Image classification is considered an important process to recognize the geographical features in the digital remotely sensed images. It is the process of categorizing all pixels into classes (Campbell 2007). There are many classification methods which have improved by scientists over the years. Jensen (2005, pp. 338) stated, "No pattern classification method is inherently superior to any other." It is up to the analyst, using his/her knowledge of the problem set, the study area, the data sources, and the intended use of the results, to determine the most appropriate, efficient, time and cost-effective approach. Very similar about classification stated Campbell (2007), "None of the strategies are the best and it is vital that the analyst understand the classification strategies to select the most appropriate method for the task".

Generally, image classification can be separated into two main types; supervised and unsupervised classification. In both classifications, previous knowledge of the imaged scene is highly desirable. When the classifier shares the characteristics of both supervised and unsupervised methods the classification is called a hybrid classification (Campbell 2007).

Remote-sensing classification is a complex process and requires consideration of many factors. The major steps of image classification may include determination of a suitable classification system, selection of training samples, image pre-processing, feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment (Lu and Weng, 2007).

Classification results are often greatly influenced by a variety of factors, including (1) ground truth data and ancillary data available; (2) the complexity of landscape and analyst's knowledge about the study area; (3) image band selection and processing; and (4) the classification algorithm and analysts experience with the classifiers used. In practice, it is difficult to identify a suitable approach for a given study area, but using a suitable classifier is of considerable importance in improving land-cover classification accuracy (Lu *et al*. 2004).

### 4.4. Unsupervised Classification and Hill Climbing Cluster Algorithm

Unsupervised Classification (Clustering) is the identification of natural groups, or structures, within multi-spectral data by the algorithms programmed into the software. After the identification of pixels was made, each pixel is assigned to one of the class cluster. Knowledge of the region that is required for unsupervised classification is not needed, analyst may specify only the number of desired categories, and the opportunity for human error is minimized. Classified maps then require knowledge of the study area in order to determine what each class represent in the real world. In this study used was the "hill climbing" Cluster algorithm (Rubin 1967). This "hill climbing" algorithm is an iterative local-search partitioning algorithm that allows the user to define the number of clusters to which the cells of the yield map will be assigned. For each resulting zone, the mean zone value in each source layer and a total variance are also produced. The essential steps in "hill climbing" cluster algorithm are: (1) find some initial partition of the *n* objects into *g* groups; (2) calculate the change in clustering criterion produced by moving each object from its own to another group; (3) make the change which leads to the greatest improvement in the value of the clustering criterion; (4) repeat the previous two steps until no move of a single objects causes the cluster criterion to improve (Rubin 1967).

### 4.5. Supervised Classification and Maximum Likelihood Classifier (MLC).

Supervised Classification depends on using samples of known identity pixels to classify unknown identity pixels. These samples, training areas, are selected by the analyst under his supervision. Supervised classification involves three steps:(1) training stage, identifying representative training areas and developing a numerical description of the spectral attributes of each land cover type in the scene, known as training set or training areas; (2) classification stage, each pixel in the image data set is categorized into the land cover class; (3) output stage: the process consists of a matrix of interpreted land cover category types (Lillesand and Kiefer, 2002). In general, supervised classifications are more accurate than unsupervised, provided that the classes are correctly identified by the analyst, which means that a significant knowledge and skills of the analyst are required. Also, the process of the supervised classification is user-controlled.

In this study used was Maximum likelihood classifier (MLC). MLC represent a conventional classification method, but MLC is still the most widely parametric classification algorithm used because of its theory and availability, in many commercial and free processing software. MLC requires sufficient number of representative training samples for each class to accurately estimate the mean vector and covariance matrix needed by the classification algorithm (Landgrebe 1980, Michelson *et al*. 2000, Tso and Mather, 1999). MLC is a parametric statistical method where the analyst supervises the classification by identifying the training areas. These training areas are then described numerically and presented to the computer algorithm. The computer algorithm than classifies the pixels of the entire scene on which we do classification into the spectral class that appears to be most alike. During classification all unclassified pixels are assigned class membership based on the relative likelihood of the pixel occurring within each class probability density function (Lillesand *et al*. 2004). The Maximum Likelihood classifier may have difficulty distinguishing the pixels that come from different land cover classes but have very similar spectral properties, and consequently, complex landscape environment will increase the possibility on existing of mixed pixel in the image. A detailed description of MLC is explained in many books (Richards and Jia 1999, Lilesand and Kiefer, 2002, Jensen 2005).

## 4.6. Classification Criteria and Classification Scheme

### 4.6.1. Classification Criteria

According to Anderson (1971) a land use and land cover classification system, which can effectively employ orbital and high-altitude remote sensor data should meet the following criteria:

1. The minimum level of interpretation accuracy in the identification of land use and land cover categories from remote sensor data should be at least 85 percent.
2. The accuracy of interpretation for the several categories should be about equal.
3. Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another.
4. The classification system should be applicable over extensive areas.
5. The categorization should permit vegetation and other types of land cover to be used as surrogates for activity.
6. The classification system should be suitable for use with remote sensor data obtained at different times of the year.
7. Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensor data should be possible.
8. Aggregation of categories must be possible.
9. Comparison with future land use data should be possible.
10. Multiple uses of land should be recognized when possible.

### 4.6.2. Classification Scheme

Definition of a classification scheme is an initial step in any classification project. No matter what classification scheme is selected, each class must be well defined and documented. Defining own mapping classes is often an iterative process. There must be a balance between the desired classes and the classes that can be accurately and economically delimited. If we use existing classification system, advantage is that the classes are already defined and the map we produce can be easily compared with other maps using the same system.

There are a large number of classification schemes used for land use and land cover maps throughout the world and numerous countries can have diverse classification system. Some of the more common schemes are listed in Table 9.

| **Classification name** | **URL** |
|---|---|
| Anderson | http://landcover.usgs.gov/pdf/anderson.pdf |
| National Land Cover Data | http://landcover.usgs.gov/classes.php |
| FAO Land Cover Classification System | http://www.africover.org/LCCS.htm |
| CORINE Land use/cover classification system | http://www.ec-gis.org/document.cfm?id=426&db=document |

Table 9: The more common classification schemes for creating LULC

Today is widely used the land use classification system developed by Anderson *et al*. (1976). The hierarchical system provided by Anderson *et al*. (1976) has four levels. The categories in the first two higher levels (Table 10) we can usually identify using space images such as Landsat images, whereas for levels III and IV required are aerial photos with higher resolution. Considering that to determine LULC changes in Međimurje County Landsat satellite images were used, this classification system seems appropriate to determine the final classification scheme for this study. The scheme needs to be hierarchical because a large number of classes may lead to misclassification among cover types, while too few classes may not meet the user's information needs.

| **Level I** | **Level II** |
|---|---|
| 1 Urban or Built-up Land | 11 Residential<br>12 Commercial and Services<br>13 Industrial<br>14 Transportation, Communications, and Utilities<br>15 Industrial and Commercial Complexes<br>16 Mixed Urban or Built-up Land<br>17 Other Urban or Built-up Land |
| 2 Agricultural Land | 21 Cropland and Pasture<br>22 Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural |

| | |
|---|---|
| | Areas<br>23 Confined Feeding Operations<br>24 Other Agricultural Land |
| 3 Rangeland | 31 Herbaceous Rangeland<br>32 Shrub and Brush Rangeland<br>33 Mixed Rangeland |
| 4 Forest Land | 41 Deciduous Forest Land<br>42 Evergreen Forest Land<br>43 Mixed Forest Land |
| 5 Water | 51 Streams and Canals<br>52 Lakes<br>53 Reservoirs<br>54 Bays and Estuaries |
| 6 Wetland | 61 Forested Wetland<br>62 Nonforested Wetland |
| 7 Barren Land | 71 Dry Salt Flats.<br>72 Beaches<br>73 Sandy Areas other than Beaches<br>74 Bare Exposed Rock<br>75 Strip Mines Quarries, and Gravel Pits<br>76 Transitional Areas<br>77 Mixed Barren Land |
| 8 Tundra | 81 Shrub and Brush Tundra<br>82 Herbaceous Tundra<br>83 Bare Ground Tundra<br>84 Wet Tundra<br>85 Mixed Tundra |
| 9 Perennial Snow or Ice | 91 Perennial Snowfields<br>92 Glaciers |

Table 10: The land use classification system (Level I and II) developed by Anderson *et al*. (1976).

### 4.7. Urban versus rural Classification

Urban surface is heterogeneous and typically composed of a complex combination of features that are smaller than the spatial resolutions of the sensors (buildings, roads, grass, tress, soil, water), (Jensen 2000). This characteristic of urban landscapes makes mixed pixels a common problem in medium spatial resolution data (between 10 to 100 m spatial resolutions) such as Landsat MSS, TM and ETM$^+$. Such a mixture becomes especially prevalent in residential areas where buildings, trees, lawns, concrete, and asphalt can all occur within a pixel (Lu and Weng, 2005). Nevertheless, in practice we can see that Landsat satellite imagery, in spite of the mentioned mixed pixel problem, is still the most commonly used data for urban classification. In order to improve urban classification accuracy with Landsat satellite imagery different approaches have been used (Jensen and Toll, 1983, Lu and Weng, 2005, Myint and Lam, 2005, Van de Voorde *et al*. 2008, Lu *et al*. 2011, Moran 2011). Lu and Wang (2005) these approaches grouped into four categories: (1) use of sub-pixel information, (2) data integration of different sensors or sources, (3) making full use of the spectral information of a single sensor and (4) use of expert knowledge. Characteristics of the study area, due to high population density and the existence of many scattered small settlements with mixed pixels with mixtures of vegetation, water, impervious and other surfaces, will inevitably cause spectral confusion between classes, so it could be a critical step in this study. Furthermore, at the time of the year when the Landsat satellite images for this study were captured many of the agricultural fields have already been harvested and tilled thereby exposing bare soil. Due to the similar reflectance values of the urban and the built up areas, this class was mixed up with the sand and the barren land classes.

In this study, approach recommended by Robinson and Nagel (1990), Harris and Ventura (1995), Reese *et al.* (2002) was used. With this approach the urban areas, due to confusion with the bare soil, can be classified more accurately if it is done separately from the rural areas. For this reason, careful manual delineation on the topographic maps 1:25,000 and high area photographs was done around all urban areas of the Međimurje County (Figure 14). More than 150 polygons greater than 100 contiguous pixels, (with size of the surface larger than 9 ha) was obtained. Obtained urban areas were then clipped out of the image data and classified separately from other data with an unsupervised classification. Pixels classified as low or high density urban were masked out of the others Landsat data, while non-urban pixels were „put back" into the Landsat image data for further supervised classification.

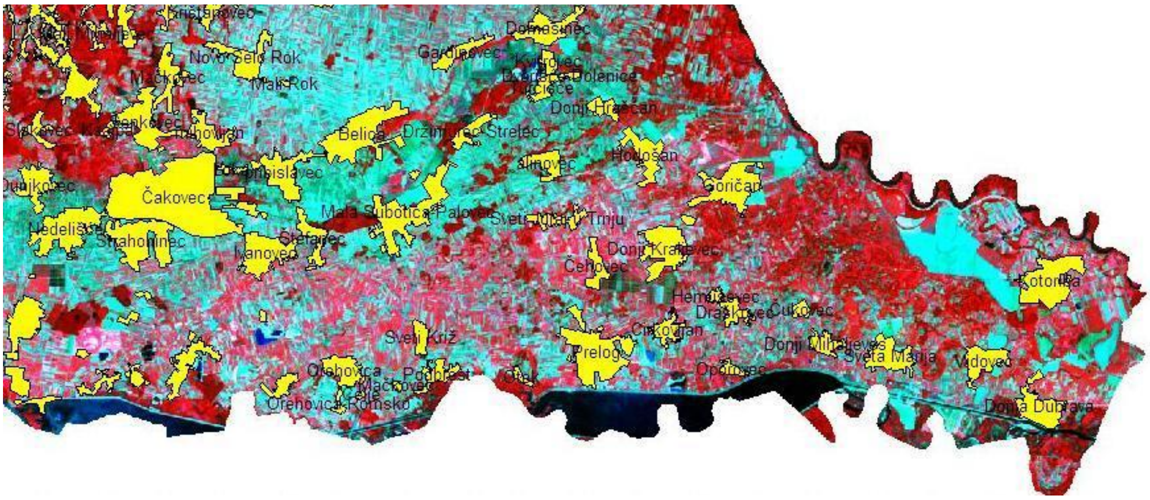



Figure 14: Manual delineation for urban areas

## 4.8. Post-Classification Change Detection

There are four important aspects of change detection for monitoring natural resources: (1) Detecting if a change has occurred, (2) Identifying the nature of change, (3) Measuring the aerial extent of change and (4) Assessing the spatial pattern of change (Macleod and Congalton, 1998). As stated in Chapter 2.5 many change detection techniques have been developed in recent decades. Post-classification detection, in a variety of studies, is considered to be one of the most suitable and commonly used methods for change detection (Singh 1989, Mas 1999, Jensen 1996, Peterson *et al*. 2004). Post-classification change detection can be used when data are available from similar or comparable satellite sensor which can be used to examine change detection over a long period of time when one type of remotely sensed data is not available. Post-classification is a term describing the comparative analysis of spectral classifications for different dates produced independently (Singh 1989). This method involves comparing two independent classified land use/land cover maps from images of two different dates. The principal advantage of post-classification lies in the fact that the two dates of imagery are separately classified; thereby minimizing the problem of radiometric calibration between dates (Coppin *et al*. 2004).

# 5. RESULTS AND DISCUSSION

This chapter presents the results and discussion of the generated Land use Land Cover maps from classification of Landsat images. There are 3 major steps required for accurately measuring Land Use Land Cover change using satellite imagery: (1) image pre-processing, (2) selection of change detection method, and (3) accuracy assessment (Lu *et al*. 2004). Each of these steps, used for this study, is described in detail below.

## 5.1. Visualisation

The most important LULC changes that have occurred in the Međimurje County over the study period from 1978 to 2007 were first analyzed by visual interpretation. The visual interpretation, as discussed in Chapter 4.2 can give a general idea about the LULC changes over the time period of 29 years.

Using the Landsat satellite images natural (Figure 15) and false colour (Figure 16) composite images were generated. Natural and false colour composites were chosen as a very easy, but very useful technique to visually extract information from Landsat satellite images and to achieve a general description of LULC changes in the study area. For Landsat TM and $ETM^+$ data, band 3 (red), band 2 (green), and band 1 (blue) were used to create a normal colour composite. Landsat MSS data do not have a blue band, and therefore they cannot be used to generate a true normal colour composite. However, the normal colour composite can be simulated. For the Landsat MSS, the simulated normal colour composite can be created using the following formula: Red=MSS2, Green=(MSS1*3 + MSS2) / 4 and Blue=MSS1.

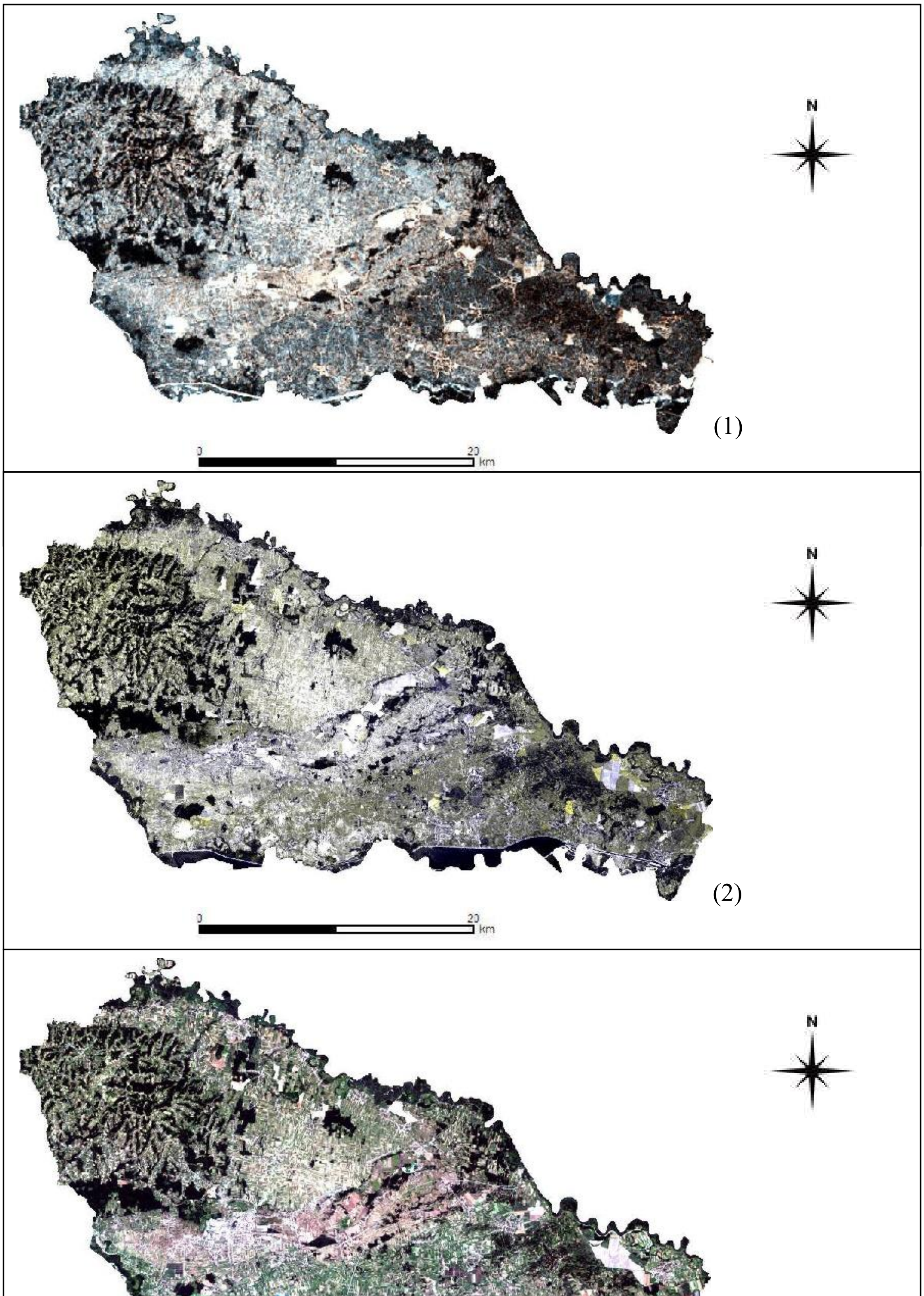


Figure 15: Međimurje County, imaged in (1) 1978, (2) 1992 and (3) 2007 by Landsat MSS, TM and ETM* bands 3, 2, 1 (RGB), Natural colour composite.

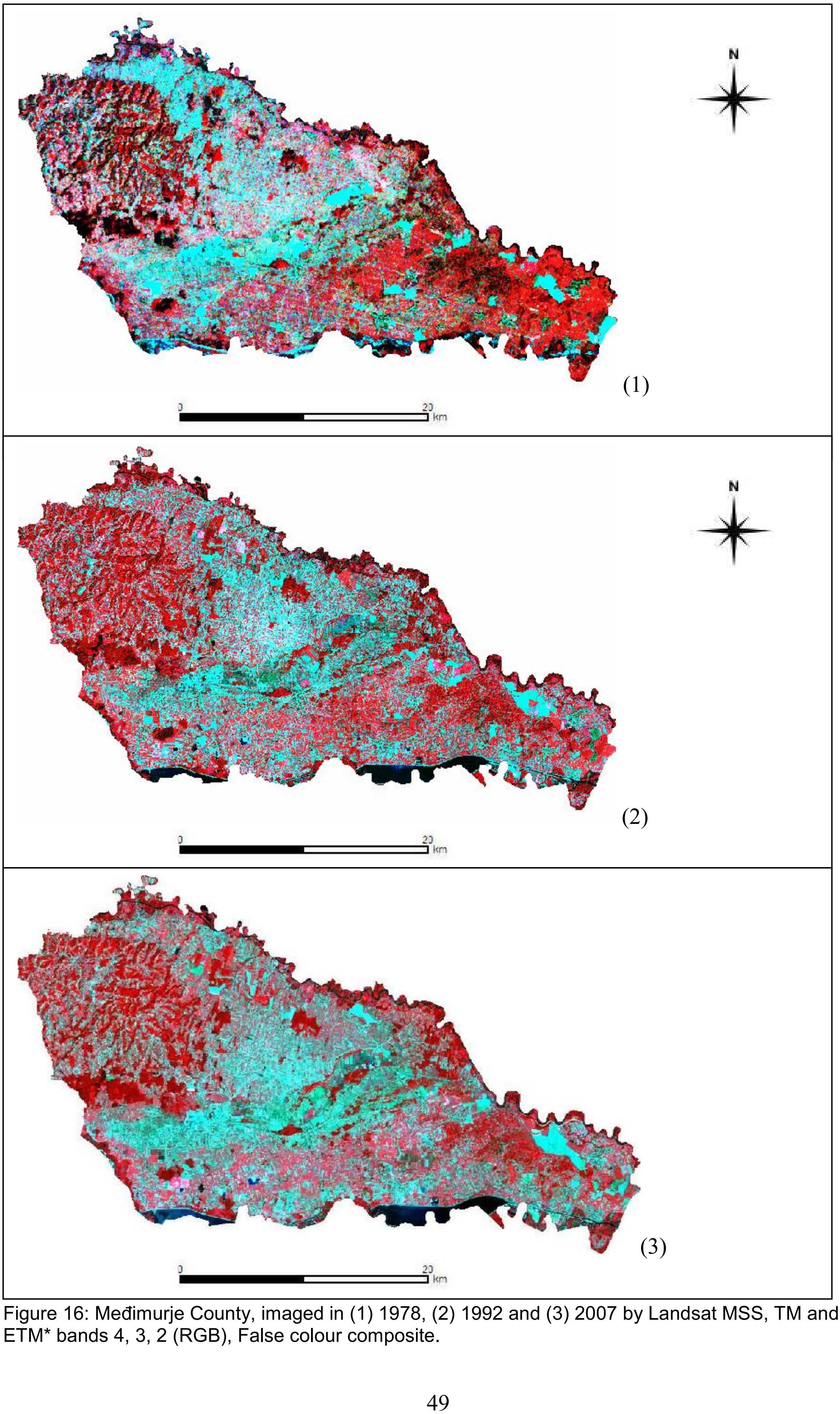



Figure 16: Međimurje County, imaged in (1) 1978, (2) 1992 and (3) 2007 by Landsat MSS, TM and ETM* bands 4, 3, 2 (RGB), False colour composite.

Band 3 detects chlorophyll absorption in vegetation, band 2 detects the green reflectance from vegetation and band 1 differentiates between soil and vegetation and is suited for penetration in water. Healthy vegetation is green; unhealthy brown and yellow, roads are grey. For standard „false colour“ composite, which is similar to traditional colour infrared aerial photography, band 4 (Visible Near Infra Red), band 3 (red) and band 2 (green) were used for Landsat TM and ETM+ data, while for Landsat MSS band combination 421 was used. In band 4 is detected the high reflectance peak from vegetation, so that band enables discrimination of numerous vegetation types and water. Vegetation appears as red tones, soils range from white to greens or browns, water appears blue and urban areas appear cyan blue towards grey.

For example, by comparing the three composite images from 1978, 1992 and 2007 we can see how the urban areas grow for the cities Prelog (Figure 17) and Čakovec (Figure 18). Further, in Figure 19 we can see the conversation of bare ground (image from 1978) to the gravel (image from 1992), as well as the expansion of the water surface due to the exploitation of the gravel over the years (images 1992 and 2007). By comparing the three composite images, in Figure 20, some of the agriculture and barren lands in the 1978 image have been taken over by orchard in the 1992 and 2007 images. On the time series of the three composite images (Figure 21) we can see the construction of reservoir lake on the Drava river built to serve the hydroelectric power plant Čakovec. All these changes detected by visual interpretation show us that there have been significant changes in LULC over the investigated time.

1978 1992 2007

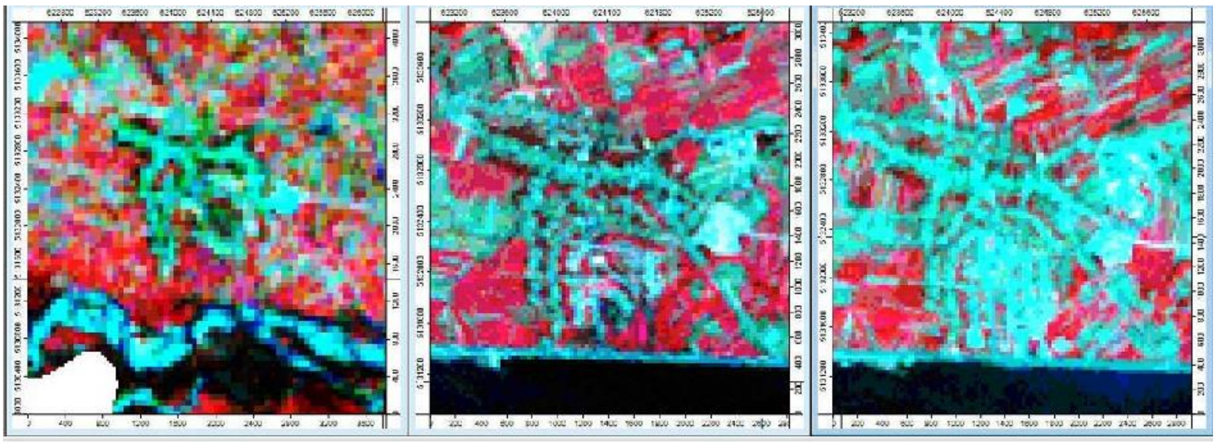


Figure 17: Urban growth for the city of Prelog.

1978 1992 2007

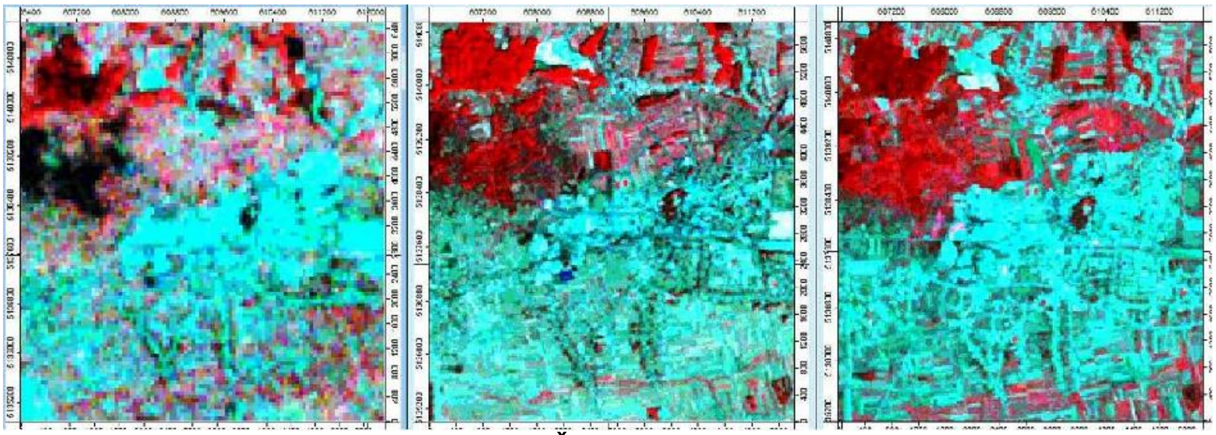


Figure 18: Urban growth for the city of Čakovec.

1978 1992 2007

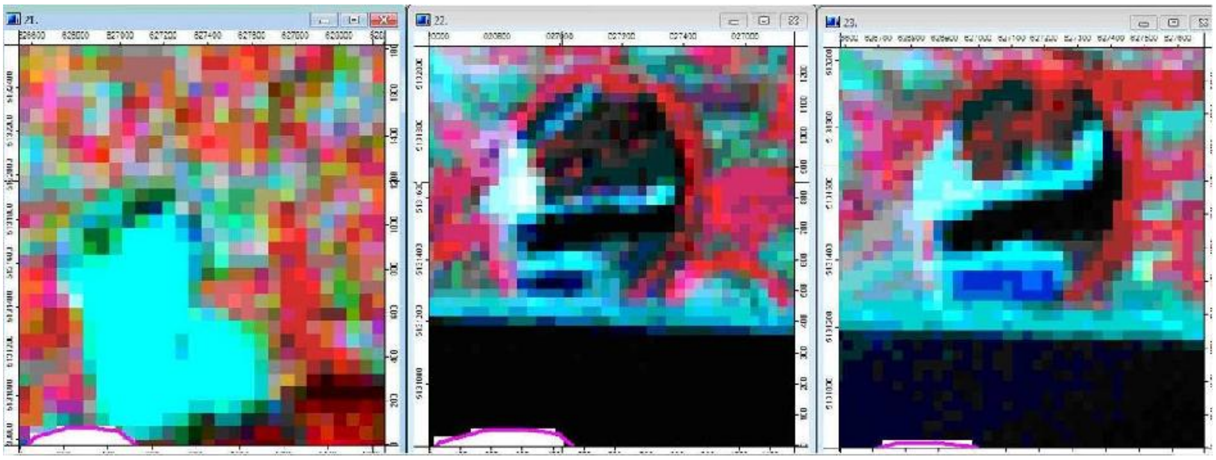


Figure 19: Conversation of agricultural and bare lands to the gravel.

1978 1992 2007

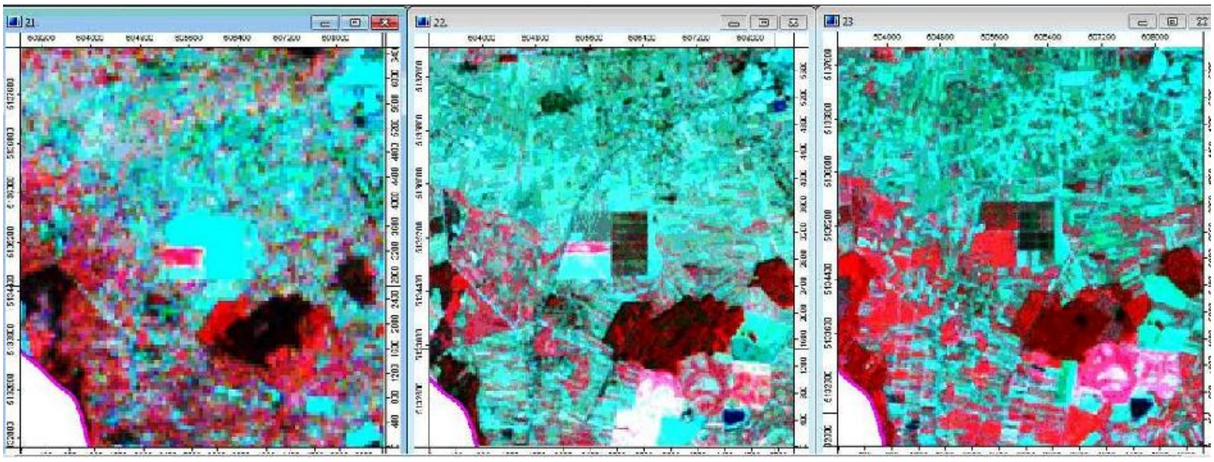


Figure 20: Agriculture and barren lands to orchard.

1978 1992 2007

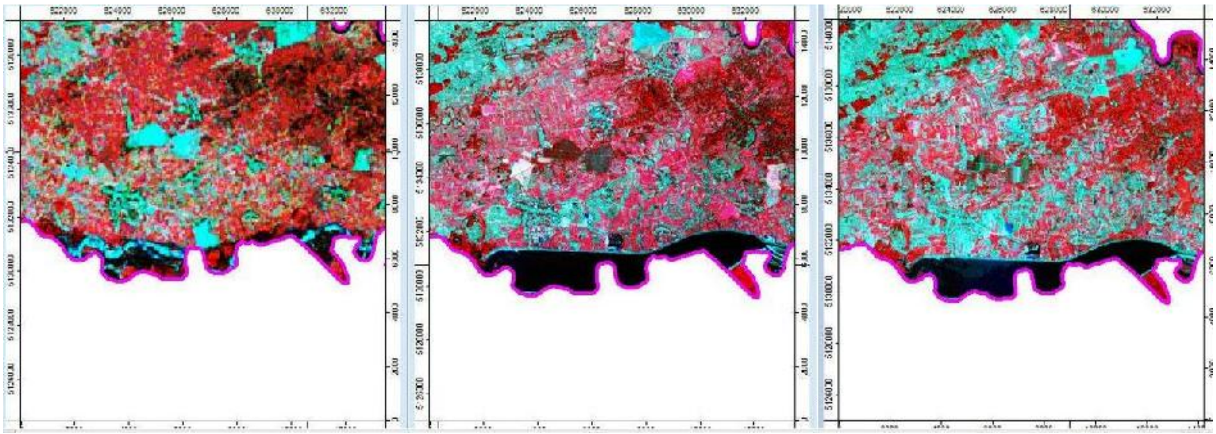


Figure 21: The construction of reservoir lake on the Drava river.

## 5.2. Training Areas

Training area selection is an important step of the classification. Training areas must be homogeneous and represent LULC classes. There are many ways to collect training data which include: collecting from field information (ground survey), on screen selecting training data as polygons, and on screen seeding of training data (Jensen, 2005).

Richards and Jia (1999) concluded that there are several different sources that can be used in collecting training pixels including in situ data, ancillary data such as topographic maps, aerial photographs or satellite imagery. They also suggested fieldwork that develops knowledge of the area with interviews, photography of characteristics surfaces, spectral measurements and collecting of ground truth data in order to validate a classification. To obtain a more reliable accuracy assessment and to keep the effects of LULC changes over time it is very important and it is recommended that ground truth data are obtained within the same time of data acquisition or, at least, within the time that the environmental condition does not change.

In this study obtained ancillary data, aerial photographs and topographic maps, were used during the selection of training samples for „ground truth" information required for classification, and for accuracy assessment of achieved classified LU/LC maps. Also, the training areas were based on the author's good knowledge of the study area, and on visual comparison of the natural and false colour composite images. Areas depicting the various defined land covers were heads-up digitized from that aerial photography and topographic maps.

As explained before in Chapter 4.7 the determination of training areas for urban built up class was not done because of confusion with urban and bare soil (Figure 22). In the middle of the figure below we can see the small black areas classified as urban areas but in fact this area represents bare soil.

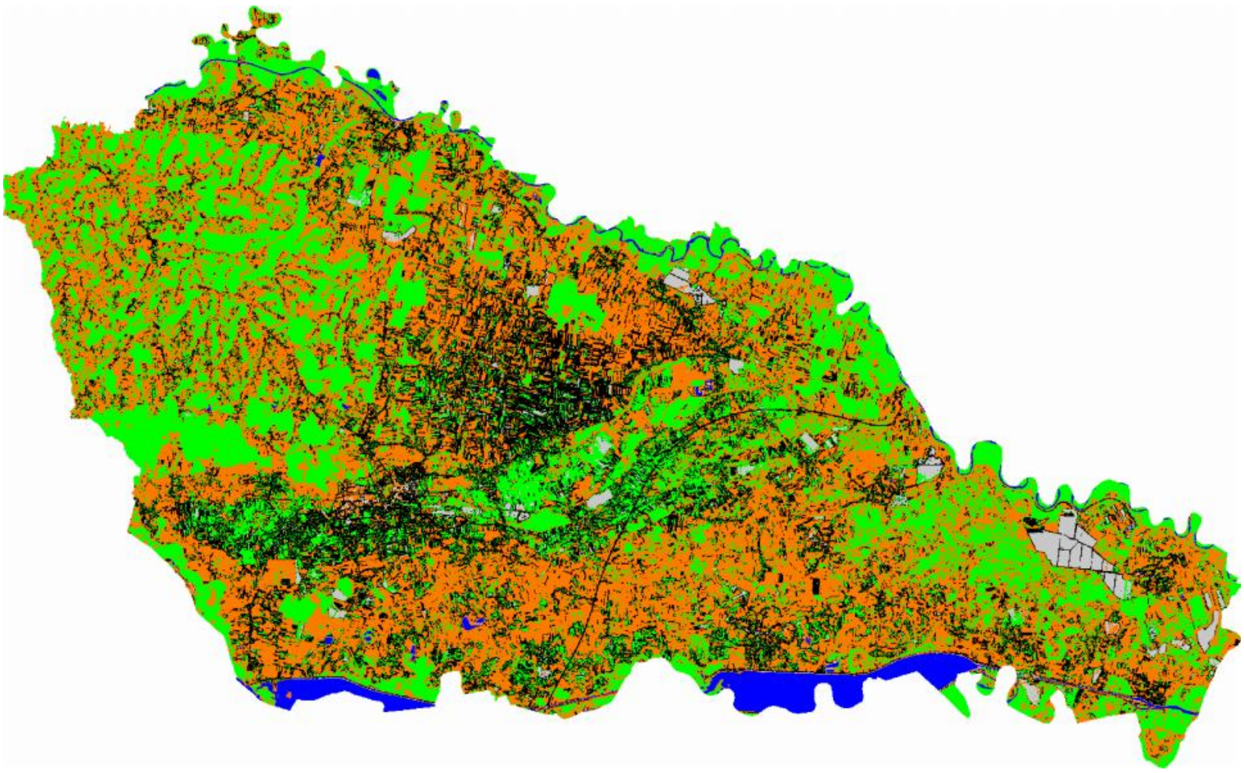


Figure 22: Confusion urban-bare soil

Typically 10 times the number of bands used dictates the number of training pixels that should be collected to represent each class, but the more training pixels collected the higher the accuracy will be (Jensen, 2005). At least 25 training areas for the defined classes (except for urban areas) were created for the 1978, 1992 and 2007 Landsat MSS, TM and ETM+, respectively to train the images for supervised classification in this study. It is obvious that collecting ground truth data through aerial photographs has an advantage over conventional method of survey because of its speed, accuracy, and cost effectiveness.

### 5.3. Classification Scheme for the Study

The primary classification scheme used for this study was based on the Anderson *et al*. (1976) land-use/cover classification system for a level one classification and author's good knowledge of the terrain. The derived final land-use and land covers classification scheme for producing general LULC maps for 1978, 1992 and 2007 and for exploration changes that occurred between these periods utilized five classes: Urban Built up, Water, Barren, Agricultural and Forest and can be seen in Table 11.

| Class | Descriptions |
|---|---|
| Urban/Built-Up | Includes all residential, commercial, and industrial developments and transportation. |
| Water | Includes all water bodies (rivers, lakes, gravels, streams, canals and reservoirs. |
| Barren | Includes barren or sparsely vegetated areas, stubbles. |
| Agricultural | Includes all agricultural lands |
| Forest | Includes all forest vegetation types (evergreen, deciduous and wetland), and non-forest vegetation futures that are not typical of forest (pasture grasslands and recreational grasses. |

Table 11: The final classification scheme for this study based on the Anderson *et al.* (1976) land-use/cover classification system.

### 5.4. Classification Accuracy

The acceptable minimum level of interpretation accuracy in the identification of LULC categories from remote sensing data should be at least 85%. (Anderson *et al*. 1976). In this study accuracy assessment was preformed for the classified maps of all three time steps. Error matrices, as discussed in Chapter 2.6., 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 three years are summarized in Tables 12, 13 and 14.

For the accuracy assessment in this study, simple random sampling was adopted. A total of 146, 163 and 131 randomly pixels from the classified images 1978, 1992 and 2007 respectively without any consideration of informational class was selected. The pixels were verified with using ancillary data (Figure 23).

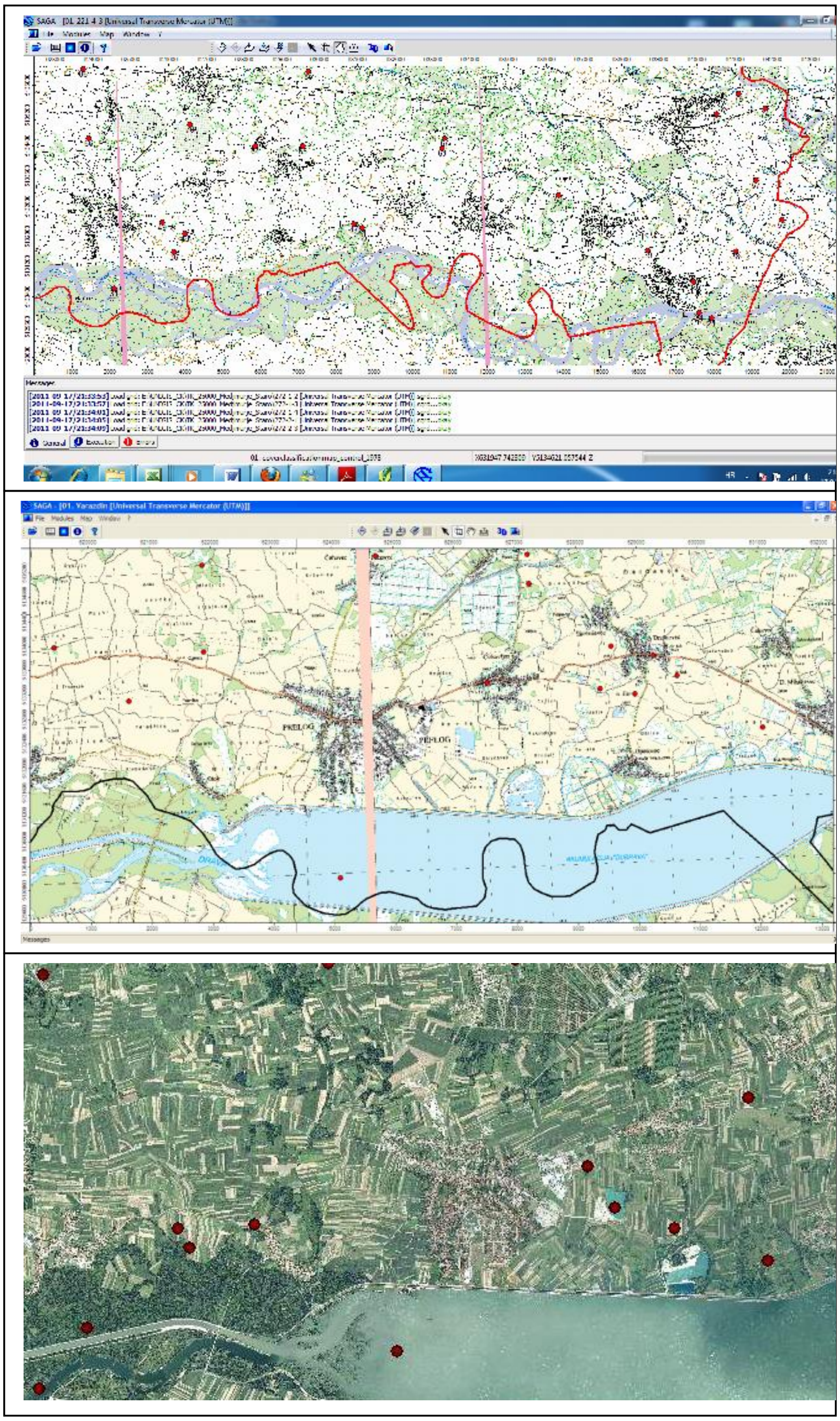



Figure 23: Simple random sampling and ancillary data

The overall accuracies for 1978, 1992 and 2007 were, respectively, 87.67%, 88.96% and 90.84%. Kappa statistics were 80%, 84% and 83%. User's and producer's accuracies of individual classes were relatively high, ranging from 74% to 94% which indicates a good agreement between thematic maps generated from images and the reference data. The water mapping accuracy of all three time steps referred to producer's and user's accuracies were ranging from 83.33% to 100.00% due to better spectral discrimination from other classes. That was followed by agricultural, forest and built up class which accuracies were ranging from 76.92% to 91.67%. The barren mapping accuracy of all three time steps referred to producer's and user's accuracies ranging from 73.91% to 80.95%. This accuracy was the lowest achieved accuracy apparently due to the presence of many small agricultural parcels after ploughing and harrowing, scattered throughout the study area and surrounded by other, larger agricultural parcels. However, bare soil in this study should be considered as agricultural land, because only small parts of that land presents bare soil around the gravel pit or around the river flows. The achieved accuracies of classification turned out to be better than expected.

| | **Water** | **Barren** | **Agricultural** | **Forest** | **Built up** | **Total** | **User Acc.** |
|---|---|---|---|---|---|---|---|
| **Water** | 5 | 0 | 0 | 0 | 0 | 5 | 100,00 |
| **Barren** | 1 | 10 | 2 | 0 | 0 | 13 | 76,92 |
| **Agricultural** | 0 | 1 | 73 | 7 | 3 | 84 | 86,90 |
| **Forest** | 1 | 1 | 2 | 30 | 0 | 33 | 90,91 |
| **Built up** | 1 | 0 | 0 | 0 | 10 | 11 | 90,91 |
| **Total** | 6 | 12 | 78 | 37 | 13 | 146 | |
| **Prod. Acc.** | 83,83 | 83,33 | 93,59 | 81,08 | 76,92 | | |
| **Overall classification accuracy: 87,67** | | | | | | | |
| **Kappa statistics:** | | | | **80 %** | | | |

Table 12: The achieved accuracies of classification for 1978

| | Water | Barren | Agricultural | Forest | Built up | Total | User Acc. |
|---|---|---|---|---|---|---|---|
| **Water** | 7 | 1 | 0 | 0 | 0 | 8 | 87,50 |
| **Barren** | 1 | 17 | 3 | 0 | 0 | 21 | 80,95 |
| **Agricultural** | 0 | 1 | 75 | 4 | 1 | 81 | 92,59 |
| **Forest** | 0 | 4 | 0 | 31 | 0 | 35 | 88,57 |
| **Built up** | 0 | 0 | 3 | 0 | 15 | 18 | 83,33 |
| **Total** | 8 | 23 | 81 | 35 | 16 | 163 | |
| **Prod. Acc.** | 87,50 | 73,91 | 92,59 | 88,57 | 93,75 | | |
| **Overall classification accuracy: 88,96** | | | | | | | |
| **Kappa statistics:** | | | **84 %** | | | | |

Table 13: The achieved accuracies of classification for 1992

| | Water | Barren | Agricultural | Forest | Built up | Total | User Acc. |
|---|---|---|---|---|---|---|---|
| **Water** | 6 | 0 | 0 | 0 | 0 | 6 | 100,00 |
| **Barren** | 0 | 7 | 2 | 0 | 0 | 9 | 77,78 |
| **Agricultural** | 1 | 1 | 78 | 2 | 2 | 84 | 92,86 |
| **Forest** | 0 | 0 | 3 | 17 | 0 | 20 | 85,00 |
| **Built up** | 0 | 0 | 1 | 0 | 11 | 12 | 91,67 |
| **Total** | 7 | 8 | 84 | 19 | 13 | 131 | |
| **Prod. Acc.** | 85,71 | 87,50 | 92,86 | 89,47 | 84,62 | | |
| **Overall classification accuracy: 90,84** | | | | | | | |
| **Kappa statistics:** | | | **83 %** | | | | |

Table 14: The achieved accuracies of classification for 2007

### 5.5. Classification, Change Maps and Statistics

The LULC classification maps of 1978, 1992 and 2007 were generated (Figure 25, 26 and 27). In all classification methods, especially in a traditional per-pixel classification as we have in this study, the resulting images of the classification are probably speckled, which means that individual, isolated pixels of one class are surrounded by pixels of another class, and classified images usually have to be post-processed before integration into a geographic information system (GIS). For this reason, filters are usually applied to smooth or generalize the final classification images. With majority filter each pixel is recoded to the majority class of a neighbourhood defined by the filter (Stuckens *et al*. 2000). Majority filter reduce the "salt-and-paper" effect typical for traditional per-pixel classifiers (Figure 24).

However, final classification accuracies do not necessarily improve dramatically. Some authors, Thunnissen *et al*. (1992) for example, report an improvement of only 2% compared to a pure per-pixel classifier. In this study majority filter was used and applied for all three classification maps. An improvement of 3.47% compared to a per-pixel classifier was achieved.

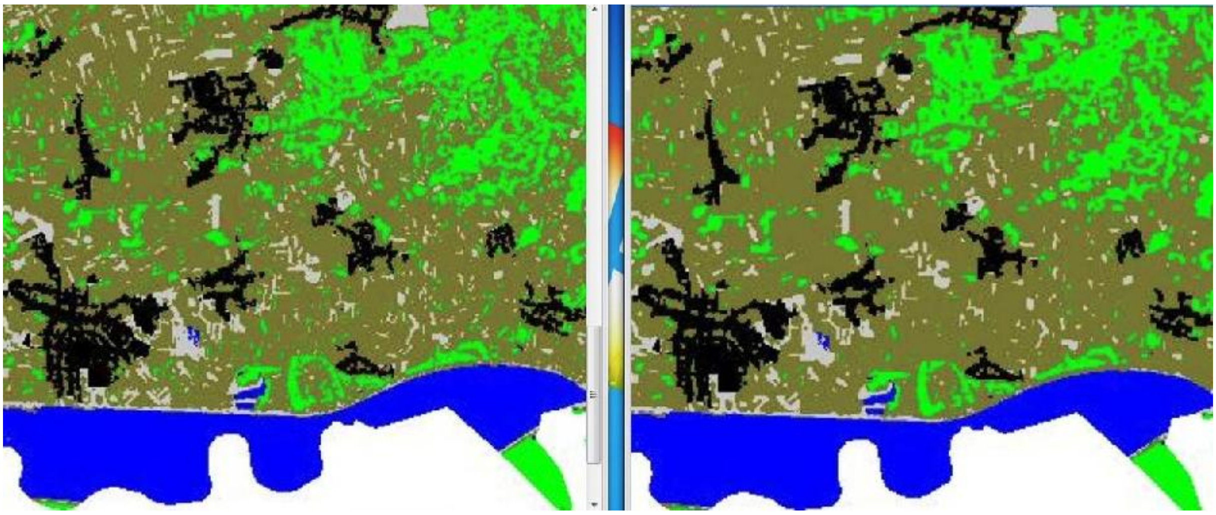


Figure 24: Left-classification image, right-image with majority filter.

Results for each land cover class are found in Table 15.

| Land Use/Land Cover Categories | 1978 Land use/cover | | 1992 Land use/cover | | 2007 Land use/cover | |
|---|---|---|---|---|---|---|
| | (ha) | % | (ha) | % | (ha) | % |
| **Water** | **1617,30** | **2,22** | **1776,42** | **2,44** | **1843,74** | **2,53** |
| **Barren** | **4679,28** | **6,42** | **9698,85** | **13,31** | **6979,77** | **9,58** |
| **Agricultural** | **46456,47** | **63,77** | **40520,61** | **55,61** | **40685,94** | **55,84** |
| **Forest** | **15425,01** | **21,17** | **13973,49** | **19,18** | **16180,38** | **22,21** |
| **Built up** | **4676,13** | **6,42** | **6891,66** | **9,46** | **7170,57** | **9,84** |
| **Total** | **72854,19** | **100** | **72861,03** | **100** | **72860,40** | **100** |
| **Agricultural and Barren** | **51135,75** | **70,19** | **50219,46** | **68,92** | **47665,71** | **65,42** |

Table 15: Land Use/Land Cover Distribution (1978, 1992, 2007).

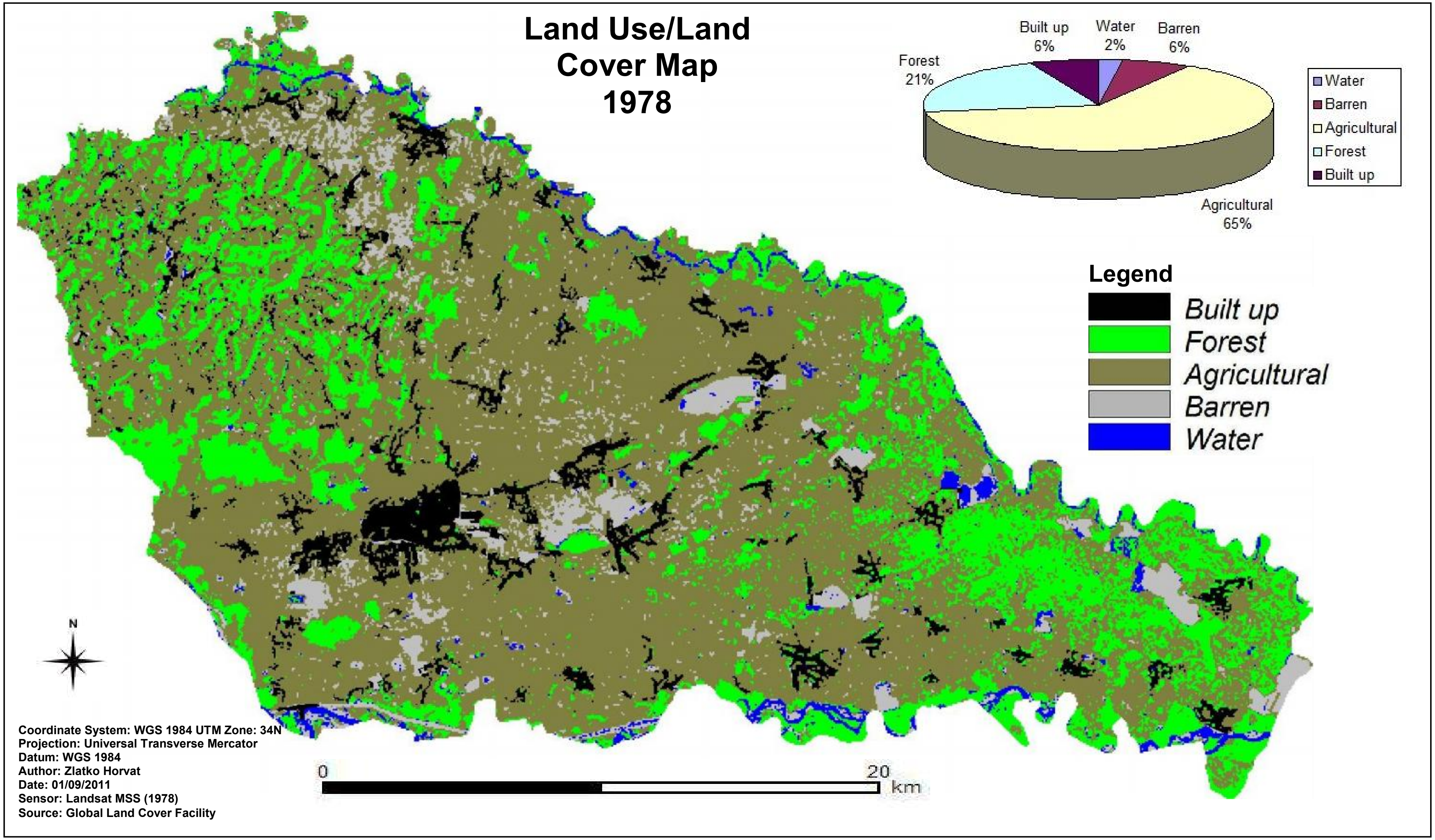



Figure 25: Land Use Land Cover map of the Međimurje County (1978).

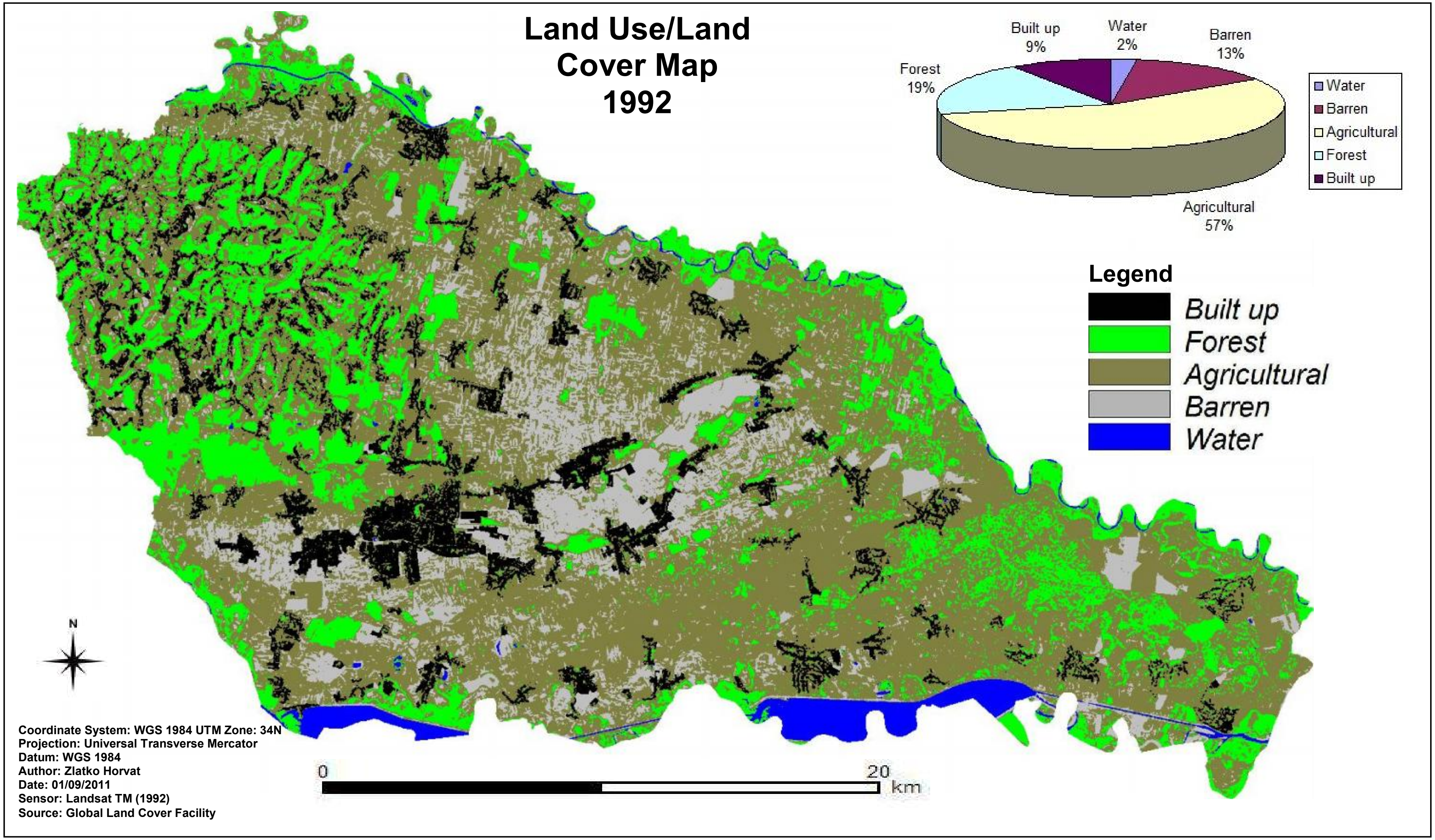


Figure 26: Land Use Land Cover map of the Međimurje County (1992).

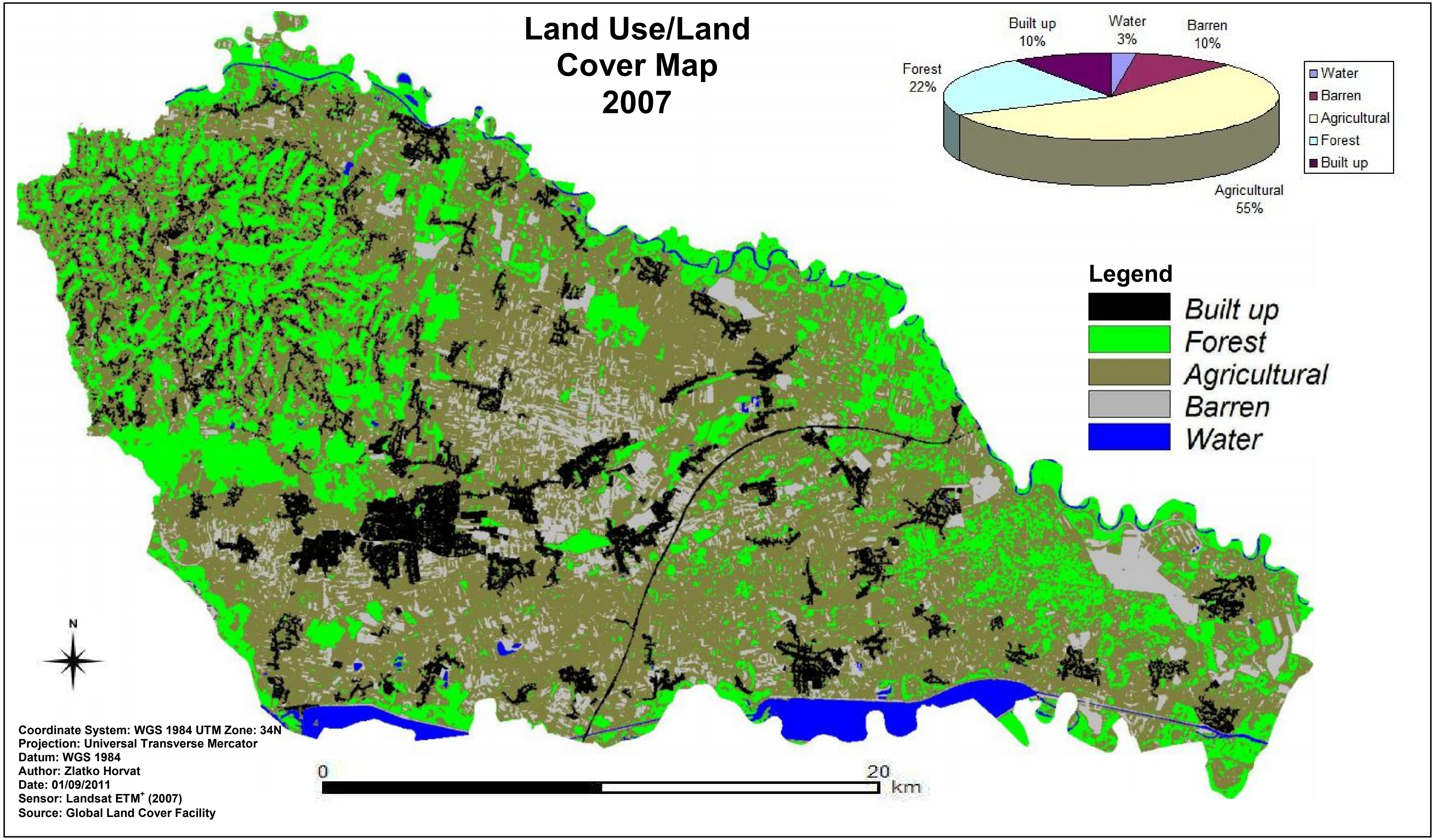


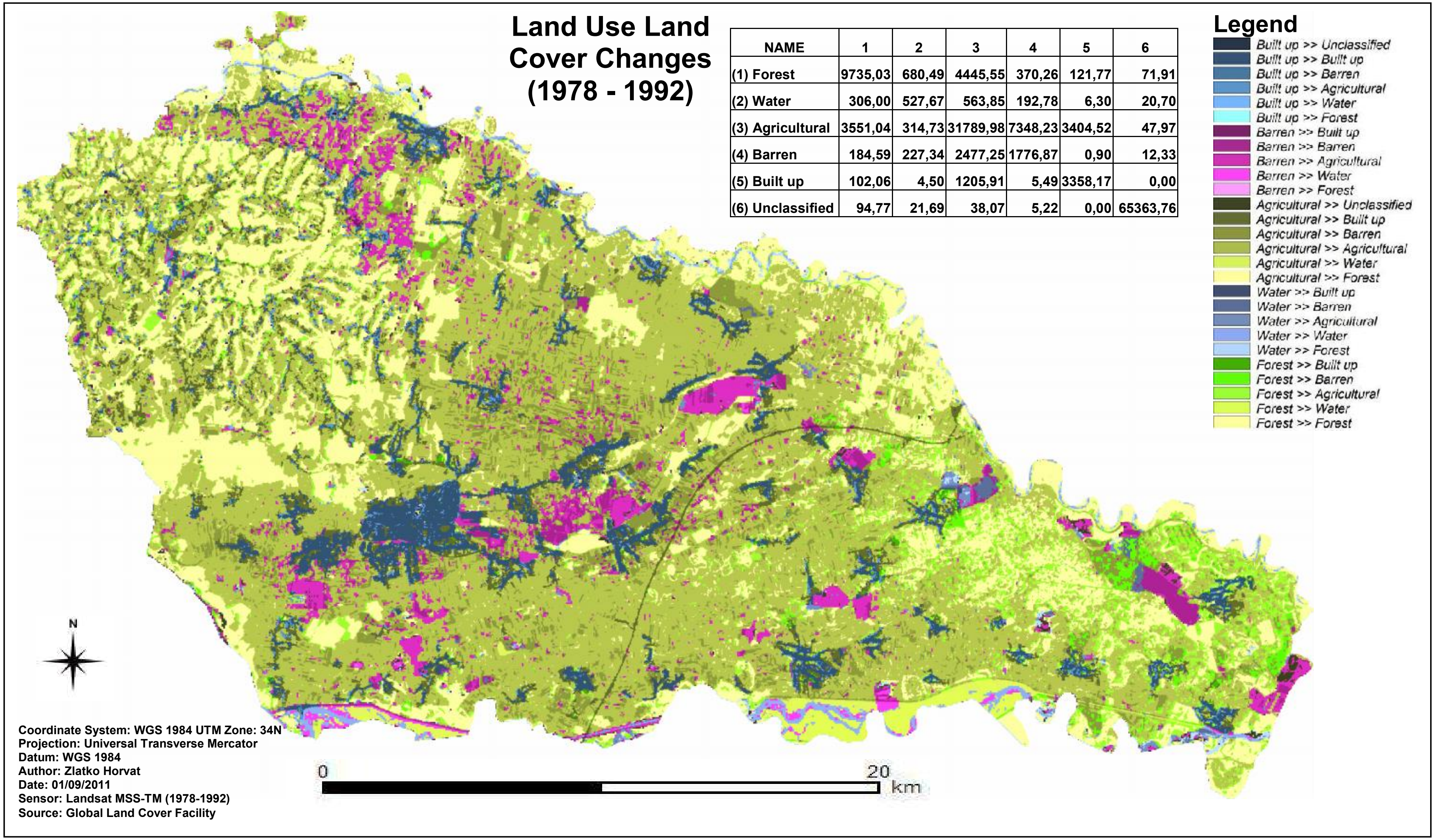

Figure 27: Land Use Land Cover map of the Međimurje County (2007).

### 5.6. Change Detection

The post classification technique was used based on a hybrid classification approach comprised of unsupervised classification based on “hill climbing” cluster algorithm, supervised classification based on the Maximum Likelihood Classifier (MLC) and introduction of human-knowledge from field experience to determine the amount of change over the study period. LULC maps for 1978-1992, 1992-2007 and 1978-2007 were derived (Figure 28, 29 and 30). The total area of each land cover class for the entire study was compared in Table 16, using three classified images from 1978, 1992 and 2007.

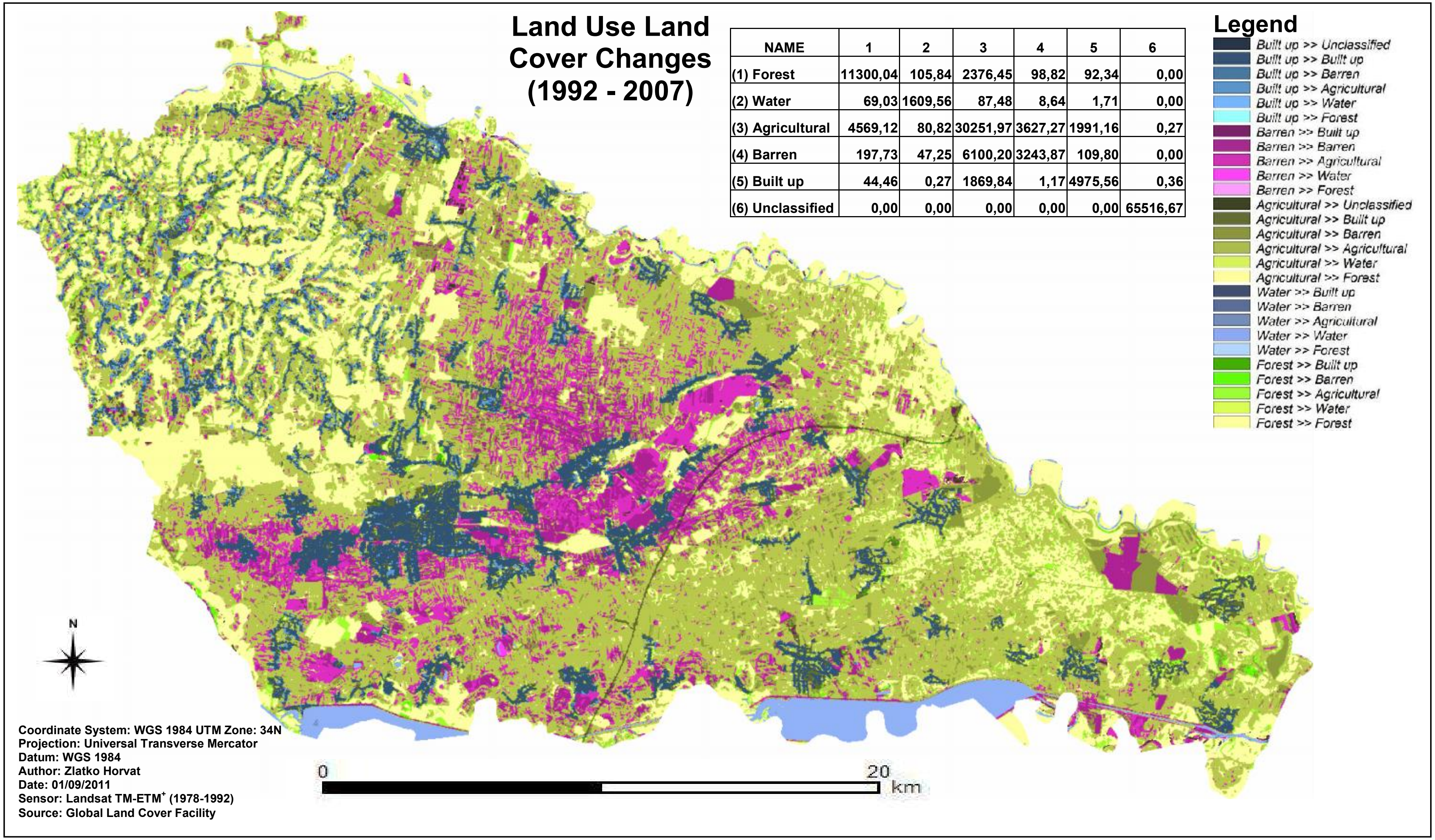
| **Land Use/Land Cover Categories** | **1978-1992** | | **1992-2007** | | **1978-2007** | |
|---|---|---|---|---|---|---|
| | **Area change** | | **Area change** | | **Area change** | |
| | **(ha)** | **%** | **(ha)** | **%** | **(ha)** | **%** |
| **Water** | **159,12** | **10** | **67,32** | **4** | **226,44** | **14** |
| **Barren** | **5019,57** | **107** | **-2719,08** | **-28** | **2300,49** | **49** |
| **Agricultural** | **-5935,86** | **-13** | **165,33** | **0** | **-5770,53** | **-12** |
| **Forest** | **-1451,52** | **-9** | **2206,89** | **16** | **755,37** | **5** |
| **Built up** | **2215,53** | **47** | **278,91** | **4** | **2494,44** | **53** |
| **Agricultural and Barren** | **-916,29** | **-2** | **-2553,75** | **-5** | **-3470,04** | **-7** |

Table 16: LULC changes of the Međimurje County (1978, 1992 and 2007).



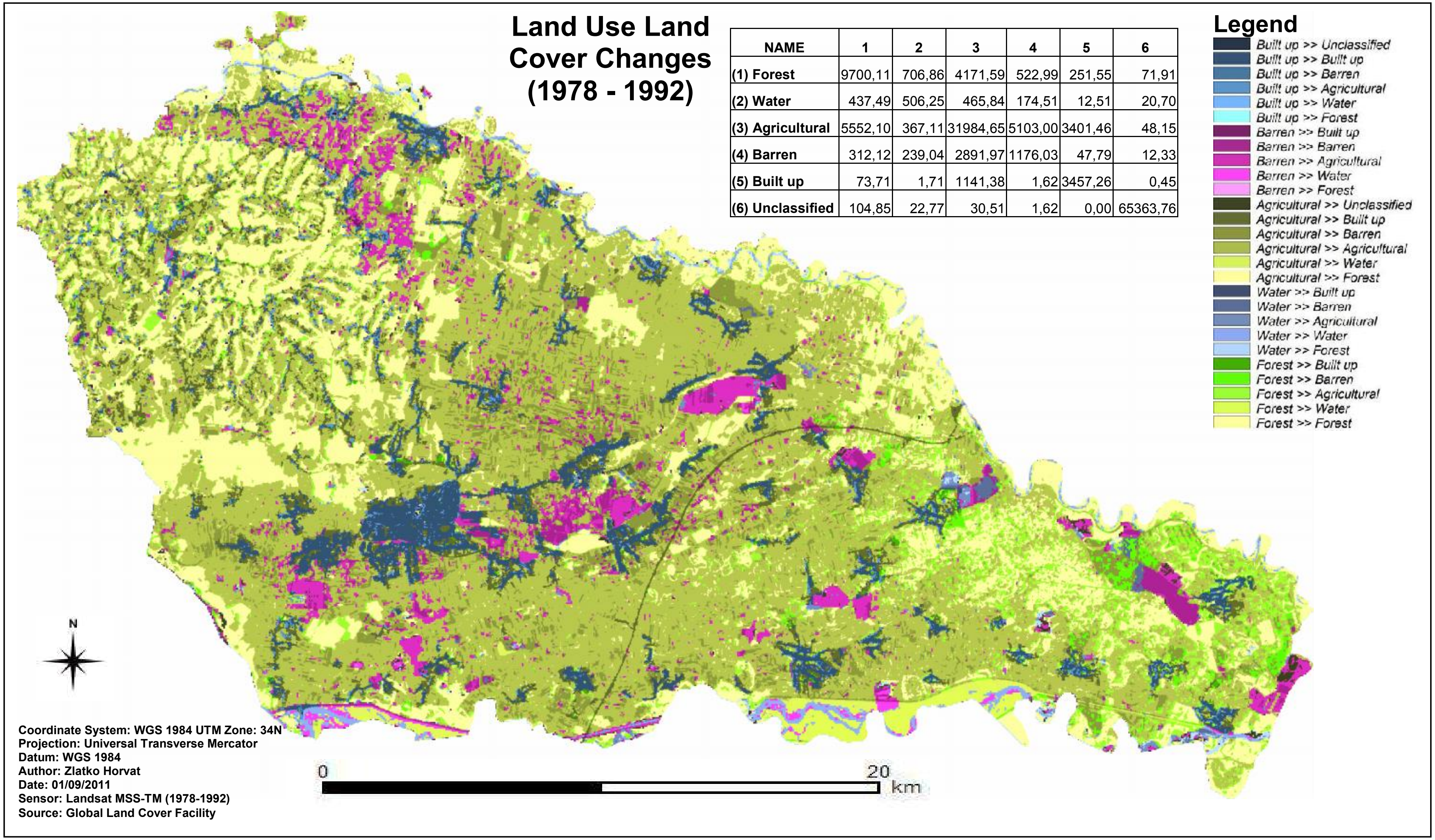

| NAME | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| (1) Forest | 9735,03 | 680,49 | 4445,55 | 370,26 | 121,77 | 71,91 |
| (2) Water | 306,00 | 527,67 | 563,85 | 192,78 | 6,30 | 20,70 |
| (3) Agricultural | 3551,04 | 314,73 | 31789,98 | 7348,23 | 3404,52 | 47,97 |
| (4) Barren | 184,59 | 227,34 | 2477,25 | 1776,87 | 0,90 | 12,33 |
| (5) Built up | 102,06 | 4,50 | 1205,91 | 5,49 | 3358,17 | 0,00 |
| (6) Unclassified | 94,77 | 21,69 | 38,07 | 5,22 | 0,00 | 65363,76 |

Figure 28: LULC change map 1978-2007.




| NAME | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| (1) Forest | 11300,04 | 105,84 | 2376,45 | 98,82 | 92,34 | 0,00 |
| (2) Water | 69,03 | 1609,56 | 87,48 | 8,64 | 1,71 | 0,00 |
| (3) Agricultural | 4569,12 | 80,82 | 30251,97 | 3627,27 | 1991,16 | 0,27 |
| (4) Barren | 197,73 | 47,25 | 6100,20 | 3243,87 | 109,80 | 0,00 |
| (5) Built up | 44,46 | 0,27 | 1869,84 | 1,17 | 4975,56 | 0,36 |
| (6) Unclassified | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 65516,67 |

Figure 29: LULC change map 1978-2007.




| NAME | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| (1) Forest | 9700,11 | 706,86 | 4171,59 | 522,99 | 251,55 | 71,91 |
| (2) Water | 437,49 | 506,25 | 465,84 | 174,51 | 12,51 | 20,70 |
| (3) Agricultural | 5552,10 | 367,11 | 31984,65 | 5103,00 | 3401,46 | 48,15 |
| (4) Barren | 312,12 | 239,04 | 2891,97 | 1176,03 | 47,79 | 12,33 |
| (5) Built up | 73,71 | 1,71 | 1141,38 | 1,62 | 3457,26 | 0,45 |
| (6) Unclassified | 104,85 | 22,77 | 30,51 | 1,62 | 0,00 | 65363,76 |

Figure 30: LULC change map 1978-2007.

Generally, from 1978 to 2007, urban area increased approximately 53%, while agriculture decreased 12%, whereas water, forest and barren land also increased 14%, 5% and 49% respectively. Achieved LULC change maps showed that urban land area increased 53% due to urbanization that resulted from high speed economic development, especially in period from 1978 to 1992, water increased 14% mainly due to the construction of reservoir lakes on the Drava river and land conversion in the gravels. Consequently, forest area decreased 9% from 1978 to 1992, but increased from 1992 to 2007, especially along the border of the existing forest areas. Since early nineties, the share of agricultural population is constantly decreasing, and therefore there were more abandoned land which, after a while, becomes a forest. In total, the forest land in the study area has increased by slightly less than 1000 ha. Increase in urban and forest areas resulted in a substantial reduction in the area of agricultural land. Looking at the barren and agricultural land as a single class, total agricultural land decreased by 2% during 1978-1992 and significant decrease by 5% was from 1992-2007. Total reduction over study period in agricultural land was 7% indicating a permanent reduction of agricultural land in Međimurje County.

# 6. SUMMARY, CONCLUSION AND RECOMMENDATION

## 6.1. Summary

The aim of this study was to identify and analyze general trends in Land Use/Land Cover Changes (LULCC) that have taken place in Međimurje County over a period of 29 years using Landsat Satellite Imagery and GIS based technique. The key findings of this study are as follows:

- The relationship between the LULC classes was identified and investigated and three thematic maps for year 1978, 1992 and 2007 were developed. Međimurje County is predominantly a rural region - over half of the county is used for agriculture. In the study periods covered, the major land use land cover classes of Međimurje County identified includes agriculture, forest, barren land, built up areas and water.

- Significant buildings construction, construction of the reservoir lakes on the Drava river and construction of a highway were major drives of land use land cover changes in Međimurje County over the study period from 1978 to 2007. This study showed a continuous decrease in agricultural lands in Međimurje County. Consequently, the urban built-up area and the water area increased.

- The remarkable changes of land use classes have occurred from 1978 to 1992, but the changes were not so significant during 1992 to 2007.

- The remote sensing and classifications of the Landsat satellite imagery can be used as economical and accurate way to produce accurate land use land cover change maps in the Međimurje County that can be used as inputs for regional analyses, formulating effective environmental policies and resource management decisions as useful up-to date information.

### 6.2. Conclusion

An effective approach for making LULC maps and detecting changes in Međimurje County over the period of 29 years was presented in this study without using a complex methodology such as fuzzy classification or object-based methodology. Basically, the use of the traditional per-pixel based classification in combination with a separate classification of urban areas approach, i.e. with dividing barren agricultural fields from built-up areas, a good knowledge of the research area, GIS tools, availability of the quality ancillary data (aerial photographs and topographic maps) for the selection of training samples for „ground truth“ information required for classification, and for accuracy assessment of achieved classified LU/LC maps, demonstrate the potential of multi-temporal Landsat satellite imagery to provide accurate LULC maps and to analyze changes in LULC that can be used as inputs to land management and policy decisions, to the development of sustainable urban land use planning decisions and for governmental or non-governmental organizations in a variety of purposes as up-to-date information.

Based on the results of this study, there is a strong evidence that changes in the land use land cover occurred in the Međimurje County during the last three decades. In this study land use land cover types were grouped into five major groups; namely built-up (all residential, commercial and industrial developments and transportation), water (all water bodies), barren (barren or sparsely vegetated areas and stubbles), agriculture (all agricultural lands) and forest (evergreen, deciduous, wetland, pasture grasslands and recreational grasses). The changes in land use were determined for Međimurje County as follows: Increase in water body areas by 10% from 1978-1992 and by 4% from 1992-2007; Significant decrease in agricultural land by 13% from 1978-1992, and very small increase from 1992-2007; Increase in barren land by 107% from 1978-1992, and decrease by 28% from 1992-2007; Constant increase in built-up by 10% from 1978-1992, and by 4% from 1992-2007; Decrease in forest by 9% from 1978-1992 but increase by 16% from 1992-2007.

Furthermore, as the purpose of this study was to provide a general LULC characterization and change analysis instead of detailed mapping, the spatial resolution of using Landsat satellite imagery was appropriate for a regional land use scale. Derived land cover classification maps have good overall accuracy (more than 85%) which makes them suitable for use as an input for many natural resource applications, as well as for various environmental monitoring and planning applications. The results achieved in this study demonstrate that classifications of the Landsat satellite imagery can be used as economical and accurate way to produce accurate land use land cover change maps in the Međimurje County over time that can be used as inputs in a variety of purposes as very useful up-to-date information.

### 6.3. Recommendation

One of the most interesting questions when considering future work is the usefulness of high-resolution (spatial and spectral) satellite and airborne sensors, for detailed map and research of LULC changes. For the future work it would be very interesting to use a combination of high resolution remote sensing imagery such as Quickbird and IKONOS, GIS and Landsat satellite imagery in order to improve the mapping, to detect changes in Međimurje County and for creating detailed land use land cover maps. Area of the northern part of Republic of Croatia (counties Varaždin, Međimurje and Koprivnica) has more or less the same characteristics of the terrain. Land cover mapping of such large area with medium-resolution imagery is costly and often constrained by lack of good training and validation data. The idea and recommendation for further work is to classify the neighbouring Landsat scenes using the land cover classification of the scene used in this study as an initial classification. Validate the results of such rapid classification in order to see whether the method is good enough to produce satisfactorily accurate LULC maps and to determine trend and location of LULC changes for such large area with similar spectral features.

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