LAND COVER, LAND USE AND HABITAT CHANGE IN VOLYN, UKRAINE: 1986-2011

by

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Abstract

Volyn Oblast in Western Ukraine has experienced substantial land use/land cover change over the last 25 years as a result of a change in political systems. Remote sensing provides a framework to quantify this change without extensive field work or historical land cover records. In this study, land change is quantified utilizing a post-classification change detection technique comparing Landsat imagery from 1986-2011(Post-Soviet era began 1991). A variety of remote sensing classification methods are explored to take advantage of spectral and spatial variation within this complex study area, and a hybrid scheme is ultimately utilized. Land cover from the CORINE classification scheme is then converted to the EUNIS habitat classification scheme to analyze how land cover change has affected habitat fragmentation. I found large scale agricultural abandonment, increases in forested areas, shifts towards smaller scale farming practices, shifts towards mixed forest structures, and increases in fragmentation of both forest and agricultural habitat types. These changes could have several positive and negative on biodiversity, ecosystems, and human well-being.

Table of Contents

List of Figures

List of Tables

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Chapter 1 - Introduction and Literature Review

Earth's land surface is changing at an unprecedented pace, magnitude and spatial extent (Lambin et al. 2001). Humans alter land cover (biophysical attributes of earth's surface) and land use (human use of earth's surface) for a variety of reasons, and these changes can have persistent effects on ecosystems (Sala et al. 2000), climate (Chase et al. 1999), and human well-being in general (Foley et al. 2005, Vitousek et al. 1997). Understanding land use/land cover (LULC) change patterns are therefore a key challenge for researchers (Turner et al. 2007). To gain greater understanding of land change it is important to link observed changes to their underlying socioeconomic and political causes (Geist & Lambin, 2002).

Human actions are often constrained partially or fully by laws, regulations, or policies brought about by political systems (Sieber et al. 2013). This is especially true in areas where strict policies are in place, limiting individuals in making decisions on how to use the land. Such limitations were common in the Soviet Union, and the consequences of Soviet-era land management practices are still relevant in areas formerly under Soviet control (Lerman 1999). During the Soviet Era, many eastern European countries operated under a collectivized farmland structure, in which decision making was centralized, and agricultural production intensified (Lerman 2004).When the Soviet Union fell in the early 1990's there were rapid changes in political systems, and as a result, LULC changed dramatically as it went from government controlled to local market driven decisions as to how land would be divided and managed (Hostert et al. 2011, Kuemmerle et al. 2006). This shift had impacts on LULC as well as ecosystems in areas formerly under the control of the Soviet Union.

While socio-economic disturbances can cause major hardships for local populations, they also present opportunities to understand how humans affect the landscape (Hostert et al. 2011). As human technology advances, so does the ability to change the earth's surface, LULC caused directly by humans is increasingly affecting biodiversity, biogeography, biophysics, and biochemistry of the Earth's surface and atmosphere (Pielke et al. 2011), with far reaching but only partially understood consequences on human well-being (Turner et al. 2007). Our scientific understanding of the extent, rates, drivers, patterns, and consequences of land cover change is often limited (Giri et al. 2013). Understanding the distribution and dynamics of the world's land cover is essential to better understand the Earth's fundamental characteristics and processes

(DeFries 2008). As populations increase, environmental stresses increase, and available land decrease, resource managers and planners need reliable mechanism to assess these consequences by detecting, monitoring, and analyzing land cover changes quickly and efficiently (Green et al. 1994).

Remote sensing data and techniques play an important role in the monitoring and analyzing LULC changes (Shalaby and Tateishi 2007). Remotely sensed data analysis can provide information on land change, habitat change, degradation and fragmentation as well as temporal analysis of change characteristics (Muchoney and Williams 2010). Additionally, use of remote sensing techniques allows for rapid, semi-automated assessment of the spatial patterns of land change over large areas and long periods of time (Coppin et al. 2004, Cihlar 2000). Implementation of remote sensing and its various data analysis techniques are valuable for land change investigations as they provide an effective and efficient way to track trends and change (Berlanga-Robles and Ruiz-Luna 2001, Dimyati et al. 1996).

Knowledge and understanding of processes and trends of the past allows for more effective environmental management in the present and the future (Coppin et al. 2004). Habitat and classification maps derived from remote sensing techniques serve a wide range of applications including: landscape planning, zoning, delineation of protection zones, habitat connection corridor planning/ biotope linkage, environmental impact assessment, and other Government/environmental agency guideline planning (Weiers et al 2004). Proper planning and implementation of conservation strategies present opportunities for natural ecosystems to recover which may have a wide variety of positive impacts on an ecosystem (Hostert et al. 2011). Better understanding of LULC aides in understanding of how humans have affected the landscape, and may provide insight into how to mitigate future impacts.

This thesis examines how a change in political systems affected LULC in the Volyn oblast, a province in northwest Ukraine. Change has undoubtedly occurred within this region; this study quantifies how LULC has changed and how this has affected potential habitat distribution a fragmentation in Volyn. Remote sensing and other geospatial technologies have proven to be effective tools for quantifying changes (Berlanga-Robles and Ruiz-Luna 2002, Cakir et al. 2008) and will serve as an essential tool for analysis in this study. Data and information generated within this study using the geospatial techniques will certainly provide greater knowledge to decision makers managing the land in Volyn, as they asses the LULC

patterns and formulate future policies. In general this study is aimed at understanding, in hopes of guiding future land management decisions.

An important first step in any study is to look at the history, trends, techniques, and methods that are relevant in the analysis. Evaluation of previous work utilizing similar methodologies is important for selection of appropriate techniques, methods, and data. To do this, I will review literature in several critical areas. First, I will review events in recent history that have affected current LULC trends, and examine works that have focused on landscape changes in former Soviet states. This review will provide context in which to place this analysis. Next, I will examine why this work is important and valuable for ecological applications. Finally, a variety of change detection techniques, remote sensing data acquisition systems, and classification schemes that have been used to quantify and evaluate change will be reviewed. These techniques, data, and schemes will be assessed for selection of appropriate methodology in my study.

1.1 LULC Change in Ukraine and former Soviet States

In 1991, due primarily to economic struggles and pressure from the general public, the Soviet Union dissolved (Zaleski 1991). The dissolution of the USSR was the ultimate cause for widespread change in historical land use practices. While under the control of the Soviet Union, land use planning was centralized (Baumann et al. 2011). Arable land, for example, was completely state owned and managed by large agricultural enterprises. The same was true for forests (Ash 1998). The collapse of the socialist governments in the former Soviet republics was a drastic socio-economic change, resulting in the creation (or re-creation) of a number of new independent states. Within these states, there was often a shift from a state-command to a market-driven economy (Prishchepov et al. 2012). This change in political systems from the Soviet to the post-Soviet era is said to have led to 'the most widespread and abrupt episode of land change in the 20th century' (Henebry 2009). Due to the change in political regimes, the fall of the Soviet Union is a crucial turning point in the history of Eastern Europe, as this event led to rapid land use and land cover change (Bicik et al. 2001, Kuemmerle et al. 2007). When societies and institutions change rapidly, opportunities arise to better understand the drivers and processes of land-use change (Prishchepov et al. 2012). There are vast research opportunities in areas formerly under Soviet influence to better understand how a change in political system can affect the land.

Based on previous LULC change work in Ukraine and other formerly Soviet states, it is expected that all Volyn land cover classes and its landscape in general, have shown substantial changes. Shierhorn et al. (2013) and Kuemmerle et al. (2007) studied land changes across regions of the former Soviet Union and found consistently high rates of land transition in both forests and agriculture. Kuemmerle et al. (2008) compared land abandonment rates between three Eastern European countries and found Ukraine to have the highest abandonment rates in areas with elevation less than 300 meters. Kuemmerle et al. (2006) studied the differences in land cover and landscape patterns in Eastern Europe, including an area of the Ukraine. They found significant differences in land cover and landscape patterns, suggesting that separate countries reacted differently to political change after the collapse of the Soviet Union. It has also been suggested that Ukraine was most strongly affected by post-Soviet changes relative to surrounding eastern European countries after the fall of the Soviet Union. Considering the consistently high rates of change found throughout former Soviet regions of Eastern Europe, the entirety of my study area at low altitudes, and the high rates of change found in Ukraine relative to other countries, widespread changes were expected.

1.1.1 Agricultural trends

In Ukraine, as in most former Soviet states, agriculture is the most widely studied of all land uses. This is not surprising, as much of the former Soviet Union was devoted to agricultural land use and agricultural lands are particularly prone to change under economic or market forces. In the post-Soviet period, guaranteed markets disappeared, subsidies ended, and foreign competition drove many people to abandoned tracts of land previously used in agriculture (Lerman and Shagaida 2007). With widespread political change, former Soviet states provide prime examples of regions with extensive land abandonment (Baumann et al. 2011).

Although, agricultural land abandonment is commonly studied in former Soviet states, rates of abandonment vary considerably. Rates vary from lows of less than 10% to highs greater than 40%. This is likely due to the fact that study area, terminology, time frames and methods vary greatly for tracking land abandonment. Hostert et al (2011) mapped farmland, forest, grassland and water in central Ukraine. They then used a support vector machine classification algorithm to delineate change and they suggest 36% land abandonment. Baumann et al. (2011) mapped farm land for two separate periods and then used a multi-temporal classification approach to map change in western Ukraine and suggests 30% land abandonment. Kuemmerle et

4

al. (2008) also utilized multi-temporal change detection in the western Carpathian region of Ukraine and suggest 13.3%. Schierhorn et al. (2013) used global land cover data and agricultural inventories to estimate abandonment across the whole country of Ukraine and suggests 8%. Some studies outside of Ukraine, such as Prishchepov et al. (2012), suggest rates as high as 60% in some parts of Russia.

Although land abandonment rates are commonly quantified, the restructuring or fragmentation of agricultural landscapes is less often studied. Kuemmerle et al. (2006) suggests that fragmentation in agricultural lands may be increasing, and suggests this may be due to arable land being subdivided, specifically for subsistence farming, leading to high levels of agricultural fragmentation in some areas. Similarly, Kuemmerle et al. (2008) notes that much former state owned land was converted to household plots, for people who now depend on subsistence farming. While agricultural fragmentation and restructuring are recognized, it is rarely quantified. The recognition that a shift from a centrally planned toward market economies resulted in a profound restructuring of Eastern Europe's agricultural sector provides opportunity for quantitative research (Lerman 1999).

1.1.2 Forest trends

Forests are another commonly studied LULC type in former Soviet states. Forests are particularly important to understand because they have widespread effects on biodiversity, ecosystem services, and provide important feedback to climate change and human welfare (Bonan 2008). Naturally, forest cover in Western Ukraine is estimated at 75% of land cover (Kuemmerle et al. 2011). Under Soviet influence, Ukraine had low forest cover, high proportion of coniferous forests, and high forest fragmentation (Kuemmerle et al. 2006). Reforestation, illegal logging, and overall weak forest management drove forest change in the transition period characterized by economic hardship and weakened institutions (Elbakidze & Angelstam 2007). Due to the fact that forests are important for ecosystems and are known to have been widely effected by the fall of the Soviet Union, forests changes and fragmentation have been studied across Ukraine and other former Soviet states.

Although studies do not always agree about the rate or patterns, forests have certainly changed following the fall of the Soviet Union. Baumann et al. (2012) studied forest changes across several Soviet states and found slight decreases after 1991, followed by periods of forest regrowth after 2000, and especially after 2005. Kuemmerle et al. (2009) studied forest cover

5

change in the Ukrainian Carpathians and documented both forest losses through logging and forest increases through reforestation on abandoned farmland. They concluded that overall forest areas slightly increased.

Although slight forest increases are an overall trend, restructuring and fragmentation of forests is less clear. Kuemmerle et al (2007) and Kuemmerle et al. (2009) suggest increases in disturbances and fragmentation between 1978 and 2000. Alternatively, Boentje and Blinnikov (2007) looked at forest fragmentation near Moscow as a result of the fall of the Soviet Union and found that it had decreased. Additionally, it has been suggested that forest increases can relate to fragmentation; Reforestation on abandoned agricultural lands can reconnect previously separated forest fragments, defragmenting forests (Prishchepov et al. 2012).

In summary, landscape changes in post-Soviet Union states has been moderately explored in academic research and often is focused on only one land cover class. Specifically, agricultural and forest changes are commonly recognized and studied independently of one another. My study looks at the landscape more holistically in hopes to quantify land changes in western Ukraine. While general land cover change trends in Eastern Europe are recognized, detailed spatial data on these trends are lacking (Kuemmerle et al. 2006). Understanding changes and trends is important as they hold a wide variety of consequences for landscapes, ecosystems, and humans (Rindfuss et al. 2004).

1.2 Remote Sensing in Ecology/Biogeography

Landscapes and their associated species are at the mercy of human decisions, which have profound effects on ecosystems and the organisms that inhabit them (Kerr and Ostrovsky 2003). Land-use change strongly affects ecosystems, their services and biodiversity, and ultimately human well-being (Foley et al. 2005). For example, McKinney (2002) showed that where intensive land development has already occurred, native animal biodiversity can be increased by revegetation with a diversity of native plant species. Protecting revegetated habitat from disturbance allowed ecological succession that not only enhance plant and animal diversity, but also tend to reduce the diversity of nonnative species (McKinney 2002). A number of positive or adverse effects can arise when landscape patterns change, and with proper quantitative landscape analysis positive management strategies can be developed (Mairota et al. 2013).

Transitioning towards sustainable habitat structures requires up-to date accounting of land cover structures, which is often done through computerized mapping (Kuemmerle et al.

2009). Traditional approach, such as digitizing habitats by hand, can be time consuming and subjective to several different digitizers interpretation (Schindler et al. 2008). Alternatively, remote sensing can play a key role in characterizing and mapping habitats quickly and efficiently for further use in a variety of applications (Nagendra et al. 2013). Remote sensing techniques provide a synoptic vision of the Earth that is not possible to obtain other than by exhaustive and expansive field evaluation (Berlanga-Robles and Ruiz-Luna 2002).

Remote sensing techniques have been adopted in ecology, to better understand habitat distribution and changes. In a relatively short time period, remote sensing analysis has become a common tool for ecologists, conservationists, and biologists to better understand landscape changes and dynamics (Roughgarden et al. 1991). There are a number of research studies that utilize or analyze remote sensing to understand the ecology or distribution of various species (Buermann et al. 2008, Debinski et al. 1999, Simone et al. 2010, Wiens et al. 2009, Rushton et al. 2004, Cauter et al. 2005). Each of these studies uses remotely sensed data in various ways but the conclusions are similar: remote sensing is an efficient and effective ecological tool that can quickly categorize large areas of land.

Products of remote sensing image processing techniques are often a fundamental first step in further analysis; specifically classification maps derived from remote sensing techniques are commonly used for fragmentation or landscape dynamics analysis (Kuemmerle et al. 2006, Boentje and Blinnikov 2007). In ecology, fragmentation involves the breaking up of habitats and ecosystems into smaller parcels, and has been shown to have adverse effects on habitats and species distributions (Fahrig and Meriam 1994, Salek et al. 2013). Fragmentation effects isolation of habitats, endangered species population dynamics, and species richness (Cakir, Sivrikaya and Keles 2008). Fragmentation also has effects on habitat connectivity and mobility of the ecological processes inside a landscape (Pearson 1994). Connectivity is considered a structural component of the landscape and its reduction is associated with reduction of species diversity and energy flow (Goossens et al. 1993). Landscape fragmentation, through the disruption of habitat connectivity, can impact species dispersion, habitat colonization, gene flow, population diversity, species mortality, and reproduction; thus, quantitative analyses of changes in landscape structure are needed to provide early warning signs of habitat degradation (Nagendra et al. 2013). In summary, fragmentation analysis on land cover maps, produced through remote sensing techniques, provide greater understanding as to how habitat distribution

and quality have changed through time, and ultimately assist in management (Nagendra et al. 2013).

1.3 Analyzing LULC Change

Understanding how the earth is changing as a result of both natural and a human interaction could be considered a grand challenge. Accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making (Lu et al. 2003). Change detection and remote sensing in general, are relatively young but may provide the most effective and efficient means of detecting temporal changes in landscapes over large scale; alternative methods such as, air photo interpretation, can be expensive and not easily repeatable (Coppin et al. 2004). Like much of remote sensing, change detection has subjective elements, where each analyst determines the techniques they will use and how they will assess their final products. Unfortunately, there is still no universally accepted method of detecting change or of assessing the accuracy of change detection map products (Jensen 2005).

A wide variety of change detection methods within remote sensing have been developed and examined over the last several decades. Lu et al. (2003) comprehensively reviewed a number of different change detection techniques commonly found in remote sensing literature and summarized them into seven groups: algebra, transformation, classification, advanced models, GIS approaches, visual analysis, other/hybrid approaches. They concluded that although image differencing, post-classification and Principle Components Analysis (PCA) are the most widely used, change detection techniques should be selected based on study goals. Almutairi and Warner (2010) compared post-classification, direct classification, image differencing, PCA, and change vector analysis (CVA). They concluded that although no single change detection method consistently produced the best results, post-classification and direct classification generally produced the highest accuracies and were the most consistent, while PCA was the least consistent. Coppin et al. (2004) examined post-classification, composite, differencing, ratioing, linear data transformation, CVA, regression, spectral mixture analysis, and feature space analysis. They conclude that although remote sensing can be effective in detecting and monitoring changes in ecosystems, the remote sensing research community needs to develop an improved understanding of the change detection process and how to match applications and change detection methods. Although a wide variety of techniques have been developed and

successfully implemented, even a consistent terminology is still lacking (Coppin et al. 2004). While reviewing the literature it becomes quickly apparent that there are no strict guidelines or best practice guidelines for conducting change detection, and no one method is appropriate for all situations.

Change detection techniques are often grouped into two categories, depending on when the change detection is actually performed (Coppin et al. 2004). In pre-classification change detection, a transformation (e.g. image differencing, image ratioing, principle components analysis, artificial neural network, etc.) is applied to imagery prior to performing any classification. Alternatively, in post-classification change detection, the remotely sensed imagery is first submitted to some classification algorithm, and then change detection is performed on the classified output. Post-classification techniques are valuable as they show areas of change, areas of no change, and also make it possible to generate a "from-to" cross tabulation information table; Post-classification comparisons of derived thematic maps go beyond simple change detection and quantify the nature of the change that is occurring (Shalaby and Tateishi 2007). Alternatively, pre-classification techniques apply various algorithms to single or multiple spectral bands in order to generate "change" vs. "no-change" maps (Yuan et al. 2005). These techniques locate changes but do not provide information on the nature of change (Singh 1989). An additional advantage of post-classification comparison is that atmospheric correction and/or sensor calibration, which must be done in pre-classification techniques, is unnecessary (Song et al. 2001). Finally, classification before comparison minimizes errors caused by phenological variability between images collected at different dates (Lu et al. 2004). Post-Classification does, however, have a few drawbacks. The main disadvantage of post-classification change detection is that there is a need for two separate classifications, the classifications need to be very accurate to limit error propagation, and the final product is highly dependent on the accuracy classification (Yuan et al. 2005, Coppin et al. 2004). Another potential issue of this method is the importance of producing consistent classifications for each of the independent classifications (Almutairi and Warner 2010). Although there are a few things to carefully consider, there are many papers that utilize post-classification change detection because of its advantages over pre-classification techniques.

Post-classification change detection has proven to be a reliable and easily interpretable means of tracking change at various landscape scales. Shalaby and Tateishi (2007) used post-

classification change detection to map land cover changes in the northwestern coast of Egypt between 1987 and 2001. They reasoned this change detection technique as the most obvious method because they could avoid normalization of atmospheric and sensor differences between the two dates, especially because the two images were gathered more than ten years apart. Jensen et al. (1993) used post-classification change detection in his evaluation of wetland habitats and adjacent uplands in South Carolina. Post-classification was the selected change detection technique in this study because it yielded the best accuracy as opposed to other change detection techniques, and this was in large part due to high accuracies in the original input classifications. This technique has been widely used in previous LULC change research with varying goals, spatial extent, and study objectives. Yuan et al. (2005), Choi and Han (2013), and Berlanga-Robles and Ruiz-Luna (2002) utilized post-classification change detection to monitor urban growth in Minnesota, reclamation effects in Korea, and changing coastal zones in Mexico respectably, displaying the versatility of this method. As long as classification is objective, accurate, and consistent, this method provides an efficient and effective means of tracking landscape changes.

1.4 LULC Classification Schemes

An important first step in any remote sensing exercise is selecting or developing an appropriate classification scheme. While classification schemes are often developed based on specific study needs or locations, a number of standardized systems have been developed for a broad range of land cover or land uses (Kerr and Ostrovsky 2003). Land cover is defined as the observed physical layers which cover the surface of the earth while land use is the human induced socioeconomic function or use of land (Martinez and Mollicone 2012). The difference between land use and land cover makes defining a single classification scheme difficult. Fortunately, several classification schemes (e.g. Anderson, CORINE, International Global Biosphere Program Land Cover Classification System) can readily incorporate land use and/or land cover data obtained by the interpretation of remotely sensed data (Chen 2002). A commonly used land cover and land use classification guide used in Europe is the Coordination of Information on the Environment (CORINE) scheme. This scheme was developed within the CORINE land cover project of the European Union's European Environmental Agency (Weiers et al 2004). The CORINE classification scheme has been used in a variety of research applications, including research focused on land change (Osborne et al. 2001). Although the

CORINE scheme provides a systematic guide to map countries across Europe, including areas to the east, it has not been formally implemented in Ukraine.

The CORINE scheme has proven to be a versatile LULC scheme, capable of being implemented across scales and study regions. Yilmaz (2010) analyzes land cover change by classifying Landsat data from two separate dates to the CORINE scheme, and then comparing the classifications. This study was in Turkey, outside of the area for which the classification scheme had been developed. Alternatively, Radovic et al. (2011) utilized maps previously classified to the CORINE scheme to analyze habitat for endangered bird fauna in Croatia. Classifying land cover data to this scheme has proven to help decision makers, resource managers, ecologists, and other scientists studying across Europe (Han and Champeaux 2004).

Transitioning from LULC to habitat classification is often a difficult process requiring field information and expert knowledge (Negendra et al. 2013). Fortunately, the European Environmental Agency has developed a systematic way to transfer data classified in the CORINE scheme to the European Nature Information System (EUNIS), which is a habitat mapping scheme. Although a habitat is a species specific concept, habitat mapping schemes are generalized to provide a common and easily understood framework for mapping purposes. In the EUNIS habitat mapping scheme habitat is defined as: "plant and animal communities as the characterizing elements of the biotic environment, together with abiotic factors (soil, climate, water availability and quality, and others), operating together at a particular scale" (Moss 2008).

Similarly to the CORINE scheme, classification performed to the EUNIS habitat level can provide a key starting point for a variety of studies including monitoring biodiversity (Martinez, Ramil, and Chuvieco 2010), conservation (Barbera et al. 2012), invasive species tracking (Vila, Pino, and Font 2007), and vegetation monitoring (Cakan et al. 2011). The CORINE and EUNIS mapping schemes have shown to be robust and versatile for a variety of studies, and are the most widely implemented schemes in Europe. Additionally, they have proven to be valuable across various spatial extents and studies utilizing a variety of sensors.

1.5 Remote Sensing Imagery

There are several remotely sensed datasets that have been used to monitor the earth's surface and land changes such as SPOT, Landsat, AVHRR, MODIS (Kerr and Ostrovsky 2003). Landsat satellites are the most commonly utilized and are well suited to assess land change (Baumann et al. 2011). Numerous studies have utilized Landsat data to produce accurate

landscape change maps, change statistics, or other quantifiable change metrics for monitoring LULC change (Sieber et al. 2013, Shalaby and Tateishi 2007, Yuan et al. 2005). Landsat data have proven to be versatile in application and especially effective in the monitoring LULC change.

Landsat data is utilized in this study for a number of reasons. First, there is a large archive of Landsat imagery from before and after the fall of the Soviet Union, with sufficient temporal resolution to ensure a cloud free image. Second, the imagery has sufficient spectral resolution for multispectral analysis and the imagery is available free of charge (Cohen and Goward 2004). Although there may be finer spatial resolution data available (e.g., SPOT) Landsat data have been found to be more useful, in certain studies, because of their spectrally important thermal infrared bands (Gao 1999). Finally, for studies at a regional scale that cover a large area, Landsat data are appropriate. Weiers et al. (2004) suggests that for studies at regional to European scales (~1:200,000-1:100,000) Landsat data is appropriate imagery to use. The Volyn oblast is similar in size to one full Landsat image, and I can obtain all my data from a few downloaded images. Landsat data is an effective tool for large scale land cover classifications, regional time series analysis, and also for larger regional development/conservation strategies (Cohen and Goward 2004). For these reasons a vast majority of studies have used Landsat images to assess changes throughout the world, highlighting the continued utility of these data and the invaluable historical record that now covers a period of four decades (Nagendra et al. 2013).

Landsat data are not without limitation, however, and there are several important factors to consider. The most fundamental issue is most likely the revisit rate of this satellite. Images are gathered less frequently (16 day repeat cycle) relative to several other coarse resolution satellites making it occasionally difficult to obtain cloud free imagery or multi-date imagery within the same year (Giri et al. 2013). This relatively long revisit period leads to less opportunity for cloud free imagery (Baumann et al. 2012). Additionally, Landsat data can often be too coarse for studies of fine spatial extent, or too fine for larger spatial extent studies, depending on the nature and objectives of the study. Overall, however, Landsat is often the satellite of choice as the benefits are often greater than the weaknesses.

1.6 General Relevance of Research

The goal of this study is to provide recent perspectives of land cover and habitat changes in Volyn Oblast, Ukraine, that have taken place in the last 25 years, since the fall of the Soviet Union. Although, agricultural land abandonment and forest changes are recognized across the Ukraine and Eastern Europe, no quantitative land change analysis has been done within Volyn that I am aware. Additionally, very little work quantifies or considers agricultural/forest restructuring, or fragmentation of habitats. Restructuring in the agricultural class refers to shifts in land use from large collective style agriculture to small scale, subsistence style agriculture. For forests, restructuring refers to intra-categorical forests changes. Previous research is also often focused either forest or agricultural dominated landscapes. The Volyn Oblast is a more evenly distributed landscape allowing for an examination of interspecific and intra-categorical landscape changes as a result of political change. This study fills a gap in research and furthers knowledge, relevant to other studies, of how political events transform landscapes within and between countries, fragment the landscape, and cause restructuring or changes in land use. Understanding how landscapes evolve is important as changes can lead to alterations in soil stability, water quality, carbon sequestration, biodiversity, and other environmental and organic characteristics of the landscape (Kuemmerle et al. 2008). Understanding is a crucial first step to assist local land managers and decision makers in developing sustainable policy or strategies of land use.

Additional to aiding decision makers, scientists or others interested in quantifying land change in the study area, my research also contributes in the advancement of knowledge of change detection for both land cover and habitats. Although there are several techniques each of which has its own strengths and weaknesses, research of change detection techniques is still an active field of study (Lu et al. 2003). The identification of a robust change-detection methodology is essential for dealing with multi-date data and could ultimately expedite research processes in the future (Mas 1999). Utilizing the specific techniques in this study will add to the existing body of knowledge about the effectiveness of post-classification change detection.

A final area of contribution is in the analysis of remote sensing as an ecology tool. Monitoring national or regional changes in species distributions through field surveys cannot realistically keep pace with the rate of agricultural and infrastructure development (Osborne et al. 2001). Additionally, field surveys generally cover a small scale, are very subjective to the researchers' opinion, and expensive in terms of time, labor, and money (Lucas et al. 2007).

Relative to getting in field, the scheme implemented in this study will hopefully reinforce and illustrate how remote sensing can be an accurate and cost efficient method of monitoring habitat characteristics and change through time.

1.7 Research Question and Hypotheses

My research will address the following questions: How has the Volyn landscape changed or restructured in the last 20 years following a change in political systems? Specifically how have the forest and agricultural landscapes changed or been restructured and what effect have these changes had on the distribution and fragmentation of habitat types?

To address these questions, I propose the following hypotheses:

1) There will be a decrease and restructuring in the land cover class agriculture due to a change in political systems. 1a) I expect greater than 20% farmland abandonment based on previous studies of farmland abandonment in areas formerly under Soviet influence. 1b) There will be a shift towards complex smaller scale farming rather than large homogeneous agricultural production practices due to a shift from state controlled to market driven production policies. 1c) Increased fragmentation in agricultural habitats due to increased land abandonment and shifts towards smaller scale farming agricultural practices

2) Forested areas will increase and restructure as a result of farmland abandonment. 2a) Forested cover will increase as a result of losses in agricultural land cover. 2b) Due to less intensive forest management practices, there will be a shift from coniferous towards more of a mixed forest structure 2c) Decreased fragmentation in forest habitats as forests regenerate after a period of intensive management.

Chapter 2 - Study Area

2.1 Physical Landscape

The study area is the Volyn oblast located in Western Ukraine (Figure 2.1). Volyn oblast is one of 24 oblasts into which the Ukraine is divided. This oblast or province is located in the north-west corner of the Ukraine and is further subdivided into 16 rayons or districts. Oblasts are the first political subdivision in Ukraine, and are somewhat analogous to U. S. states, but without the autonomy of a state. Rayons are equivalent to a US county, in that they are a secondary political subdivision. The study area is roughly 20,000 km² and generally shows little elevation change. Slightly higher elevations in the south west gradually slope to the lowlands in the north east portion of the study area. Elevations range from approximately 125 to 290 m above sea level. The Bug River boarders the study area to the west and serves as a natural border between Ukraine and Poland. Belarus borders the oblast to the north, and to the east and south of the study area are the Rivne and Lviv oblasts respectively.

Figure 2.1 The study area is the full extent of the Volyn oblast which is outlined in gray (a) and is located in North-West Ukraine, near the border of Poland and Belarus (b).

Volyn is in the Palearctic biogeographic realm and in the temperate broadleaf and mixed forest biome. This biome is traditionally home to 400+ species of birds and mammals and is considered a critical/endangered biome (Olsen et al. 2001). Complex vegetation patterns are present within the study area, but a majority of the land cover is dominated by forest and agricultural. Wetlands are located mainly in the North West corner of Volyn but also appear along the Bug River and in other low-lying areas. Drainage ditches and canals are located throughout the study area, presumably to reclaim land for agricultural use during the Soviet era. The landscape changed drastically under the influence of the former Soviet Union as agricultural land expanded greatly putting marginal land into production (Hostert et al. 2011), forest structures changed as fast growing species, such as conifers replaced natural stands (Turnock et al. 2002).

2.2 Population and Climate

Volyn ranks 22 of 24 oblasts in total population at approximately 1,040,000 people. There are four cities with population greater than 30,000: Lutsk (~203,000), Kovel (~66,000), Novovolyns'k (~54,000), and Volodymyr-Volyns'kyi (~38,000). A majority of the settlements are smaller farming towns and villages. The climate is warm summer continental (Köppen Dfb). January has the lowest average temperature at approximately -5°C, and July typically has the warmest average temperature of 19°C. Rainfall varies from a high of about 94mm in July to a low of 33mm in December (hydrometeorological service of Ukraine http://meteo.gov.ua/en/).

2.3 Historical Land Use/Land Cover

2.3.1 Forests

The forests within Volyn have experienced significant anthropogenic induced changes, especially in the last 100 years. Before human settlement this area was dominated by mixed broadleaf and conifer forests (~75% of the landscape) due to past glaciation and uniform topography (Kuemmerle et al. 2011). Forests had been excessively exploited under Soviet rule, resulting in high fragmentation, loss of old growth forests, and widespread plantations of fast growing coniferous stands (Turnock 2002). After the fall of the Soviet Union, control of forests was decentralized and privatized resulting in both regeneration and illegal logging (Kuemmerle et al. 2009). Today there are deciduous, coniferous, and mixed forest structures present,

especially in the eastern area of study, where elevations are low relative to the rest of the study region. Naturally, broadleaved and mixed forests dominate the study area. Pedunculate oak (*Quercus robur*) and sessile oak (*Quercus petrea*) mixed with European beech (*Fagus sylvatica*), linden (*Tilia cordata*), hornbeam (*Carpinus betulus*), and ash (*Fraxinus excelsior*) (Kuemmerle et al. 2007). Strict forest management has changed the forest composition in many areas and led to widespread replacement of natural forests with coniferous species including Norway spruce and Scots pine monocultures (*Pinus sylvestris*).

2.3.2 Agriculture

Agricultural in Volyn has also experienced substantial historical changes. Under the Austro-Hungarian Empire control, large tracks of forests were cleared for agricultural production as technology advanced and human demands increased (Turnock 2002). More recently, during socialist rule, great efforts were made to intensify agricultural production. All land was owned and managed by the state in large-scale agricultural enterprises, known as collectives or state farms in the Soviet era (Kuemmerle et al. 2008). After the fall of the Soviet Union, agricultural land was distributed among the former workers of the agricultural enterprises (Lerman et al. 2004) or to residents of nearby villages. This agricultural history has resulted in a complex agricultural structure today; past social and political policies have shaped the Ukraine into an intricate mixture of farmed, abandoned, pastures and mixed fields. Today, agricultural activity includes dairy, meat, and various crops including cereals, vegetables and melons, fruits and nuts, oilseed crops, root/tuber crops, sugar crops, and flower crops.

Chapter 3 - Data and Methods

3.1 Datasets

3.1.1 Satellite Images

Landsat 5 TM data were utilized in this study to map land cover and analyze changes between 1986 and 2011. Although the Soviet Union collapsed in 1991, 1986 was selected as the first year of analysis as this was the most recent year with sufficient cloud free imagery prior to 1991. 2011 was selected as it was the most recent date available with a cloud free image. In order to maximize spectral contrast between LULC classes, paired winter and summer images were used for each year of the analysis (Lucas et al. 2007). Coppin et al (2004) supports the use of summer and winter imagery and suggests they are the best seasons for change detection because of their phenological differences and overall stability. Additionally, winter imagery used in conjunction with summer imagery, for the purpose of classification, has been shown to improve classification accuracy (Baumann et al. 2012). For the year of 1986 two cloud free images were available, one in the summer and one in the winter. In 2011 there was only one cloud free image which represented the winter season. 2007 was the most recent year with a cloud free summer image available, so it was mosaicked with the 2011 image. Where cloud cover is a limiting factor, mosaicking images from different years to represent one distinct time period is often necessary. Mosaicking images from different years has been utilized in previous studies where multidate imagery was desired but not available in a single year; specifically, this method has been used in Eastern Europe and Ukraine where cloud cover is often problematic (Baumann et al. 2011 and Kuemmerle et al. 2009).

Eight TM images were used in the analysis. Two images for each date were needed to cover the full extent of the study area from path/row 185/24 and 185/25 (Table 3.1). Images were stacked, mosaicked and clipped to the extent of the Volyn oblast. The visible bands 1-3, near-infrared bands 4 and 5, and middle-infrared band 7 were utilized in this study. The thermal band 6 was not used. This band is commonly omitted due to the 30 vs. 120 meter spatial resolution which can affect classification (Oguz and Zengin 2011, Yu and NG 2006). Images were gathered from the USGS Earth Explorer and were orthorectified with a root mean squared error ranging from .15 to .51 pixels (Tucker et al. 2004).

3.1.2 Ground Truth and Training Data

Field work was conducted from September 9-20, 2013. A GPS was used for *in-situ* collection of ground truth point locations, land cover and land use attributes, species information, and other general notes. Points were taken in homogeneous areas of the landscape, away from edges, in order to avoid possible confusion in training or accuracy assessment. Photographs were also captured and linked to ground truth data through a GIS geodatabase. Ground truth data was gathered across the entire study region, representing all land cover classes as evenly as was practical. Water and wetlands were underrepresented in this field survey as the terrain near these classes made surveying impractical. Forest, agriculture, and urban classes were surveyed extensively.

The *in-situ* collected data was supplemented by a set of randomly generated points selected from the study imagery. This dataset was partially stratified to ensure that each class received a minimum of 15 ground truth points. Several iterations were needed to achieve this minimum, and points that were near edges or were difficult to interpret were discarded. In total 500 points were generated. Randomly generated points were assigned a land cover class through a combination of expert knowledge, evaluation of Landsat imagery and spectral signatures, unsupervised clustering, and analysis of high spatial resolution Quickbird images within Google Earth™. Google Earth has been used widely by remote sensing scientists for gathering of ground truth data (Baumann et al. 2011, Kuemmerle et al. 2009, Choi and Han 2013) especially when field work is not possible or limited. unsupervised classification was also used as a preliminary step for finding spectrally homogeneous clusters of pixels. Yu and NG (2006) utilized this method to aid in assigning values to ground truth data and finding training locations for supervised classification approaches

A total of 835 ground truth points were gathered through field work and generation of the stratified random sample. These points were used in both training for supervised classification and accuracy assessment of LULC maps. Careful consideration was taken to ensure that no ground truth point used in training was used in accuracy assessment, and vice-versa.

Table 3.1 The eight Landsat 5 TM images used to derive land cover maps for the years 1986 and 2011. These images were orthorectified to WGS84/UTM zone 35U.

Date	Path	Row	RMSE	GCP	Description
23-Apr-11	185	24	0.28	1706.00	30 m spatial resolution, bands 1-5, 7
23-Apr-11	185	25	0.32	1476.00	30 m spatial resolution, bands 1-5, 7
17-Jul-07	185	24	0.15	2123.00	30 m spatial resolution, bands 1-5, 7
17-Jul-07	185	25	0.28	1302.00	30 m spatial resolution, bands 1-5, 7
12-Nov-86	185	24	0.41	1521.00	30 m spatial resolution, bands 1-5, 7
12-Nov-86	185	25	0.51	985.00	30 m spatial resolution, bands 1-5, 7
20-May-86	185	24	0.28	1717.00	30 m spatial resolution, bands 1-5, 7
20-May-86	185	25	0.31	1281.00	30 m spatial resolution, bands 1-5, 7

3.2 Classification Scheme

Classifications were carried out using a slightly modified form of the CORINE Land Use/Land Cover classification scheme (Table 3.2). The CORINE system is a 3-level hierarchical classification system, with 5 classes at level one (the coarsest level) and 44 classes at the third and most detailed level. The first and third levels were desired as the first level provides a scheme for general LULC mapping, and the third level has much more detailed classes, such as mixed, coniferous, and deciduous rather than just forests. In summary, level 1 was the most general classification available, and level 3 was the most detailed level available within the CORINE scheme.

Classification LULC maps at the first and third CORINE levels were desired for several reasons. The level 1 classification is a very general LULC classification allowing for the examination of inter-categorical land changes. The level 3 classification is a much more detailed classification, and allows for the examination of intra-categorical changes within the landscape. The level 3 map was valuable as intra-categorical changes have not been quantifiably examined in former Soviet states to my knowledge. Finally, the level 1 classification was a natural first step preceding the level 3 classification; building a mask from the level 1 classification was used to isolate agriculture and forest for classification to level 3.

There are two classes that need further clarification within the third level of the scheme, pasture (231) and complex cultivation patterns (242). Natural grassland (class 321) and class 231 were combined in this classification, since it was nearly impossible to tell what was natural from what was being grazed regularly. Through field work and analysis of imagery, we determined

these classes could be combined into 231. Pasture, in this exercise, is a broad class of minimally or unmanaged grasslands. Another class needing clarification is the two actively tilled agricultural classes of 211 and 242. While reviewing the CORINE land cover nomenclature guide, it is not easy to distinguish the difference between arable land (211) and class 242. Both classes contain many of the same crops, are commonly in rotations, and have arable land within their definitions. The definition of 242 goes beyond arable land and uses the wording such as complexity of field patterns, juxtaposition of small parcels, and very fine textured agricultural patterns with no single unit larger than 25 hectare. LULC with this small, complex, juxtaposition of agricultural land was quite obvious while we conducted field work and examined aerial photography. Although 211 and 242 are, for most practical purposes, the same land cover I suggest they are different land use. I decided to separate them as 211 is more of a commercialized structure, while 242 is more of a local or subsistence style of agriculture. I utilized the area of 25 hectares to separate these two classes.

Table 3.2 The three level hierarchical classification scheme which was derived from CORINE land cover project.

Level 1 Classification	Level 3 Classification	Definitions
1 Artificial surfaces	1.1.1 Continuous urban fabric	Most of land is covered by: Buildings, roads and artificially surfaced area cover almost all the ground. Includes Non-linear areas of vegetation and bare soil.
2 Agricultural Areas	2.1.1 Non-irrigated arable land	Cereals, legumes, fodder crops, root crops and fallow land. Includes flower and tree (nurseries) cultivation and vegetables, whether open field, under plastic or glass (includes market gardening). Excludes pastures.
	2.3.1 Pastures	Dense, predominantly graminoid grass cover, of floral composition, not under a rotation system. Mainly used for grazing, but the fodder may be harvested mechanically. Includes areas with hedges (bocage).
	2.4.2 Complex cultivation patterns	Juxtaposition of small parcels of diverse annual crops, pasture and/or permanent crops.
3 Forest Natural Areas	3.1.1 Broad-leaved forest	Vegetation formation composed principally of trees, including shrub and bush understories, where broad-leaved species predominate (75%).
	3.1.2 Coniferous forest	Vegetation formation composed principally of trees, including shrub and bush understories, where coniferous species predominate (75%).
	3.1.3 Mixed forest	Vegetation formation composed principally of trees, including shrub and bush understories, where broad-leaved and coniferous species co-dominate.
4 Wetland	4.1.1 Inland marshes	Low-lying land usually flooded in winter, and more or less saturated by water all year round.
5 Water Bodies	5.1.2 Water bodies	Natural or artificial stretches of water.

3.3 Classification to CORINE Level 1

A hybrid classification technique combining supervised, unsupervised, and object-oriented classification techniques was used to generate LULC maps (Figure 3.1). Hybrid approaches bear significant potential for accurate classification, however no standard procedure exists, and approaches have to be adjusted based on data availability and study goals (Kuemmerle et al. 2006). The images were classified first to level one of the CORINE system using a hybrid supervised and unsupervised approach. After several attempts with both supervised and unsupervised approaches, using a variety of input parameters, water and wetlands where found to be most accurately classified using an unsupervised Iterative Self-Organizing Data Analysis (ISODATA) approach (Memarsadeghi et al. 2007). Input parameters for the unsupervised classification were 75 classes, 2500 minimum pixels per class, and 20 iterations. ISODATA was particularly useful as training data for wetlands was limited and this approach has proven to be effective in both mapping wetlands and finding areas of spectrally similar clusters (Long and Giri 2011). Wetlands and water classes had accuracies of 97 and 100 percent, repeatedly. However, ISODATA performed poorly for separating urban, forest, and agriculture. There were several confused classes which made conversion to information classes difficult, resulting in user/producer accuracies commonly below 70%. Due to low accuracy, water and wetlands were masked out and supervised approaches were pursued. Several supervised approaches were attempted, utilizing a variety of classifiers, training locations, and number of training sites. The maximum likelihood classifier with 30 training sites ultimately worked best for separating urban, forests, and agricultural lands. The supervised approach utilized yielded higher accuracy for urban, forests, and agriculture compared to the unsupervised approach. Training sites were selected from ground truth data gathered through the field survey outlined in section 3.1.2.

3.4 Classification to CORINE Level 3
3.4.1 Forest Classification

After assessment of the level 1 classification accuracies were deemed acceptable, classifications was carried out to level 3 of the CORINE system. Acceptable in this context was

accuracy higher than 90% overall with all classes having user/producers accuracy near 80% or higher. Water, wetlands and urban were accurately classified based on the guidelines listed in section 3.3. Forests were isolated by masking out all other classes. Forests were then classified to deciduous, coniferous, and mixed classes using a maximum likelihood supervised techniques. Training sites were carefully selected in this step using training data gathered in the field, as outlined in section 3.1.2. Where sufficient in situ data was lacking, supplemental training sites were taken from the randomly generated ground truth data set. When this was the case, spectral signatures were carefully evaluated to ensure consistent classification. Multidate imagery was essential for differentiating these forests types, especially for the interpretation of the 1986 image, which had no ground truth data. A band combination of 5 from the winter image and bands 4 and 1 from the summer image was found to be particularly useful. This combination was utilized in visual and spectral interpretation to differentiate the three forest types.

3.4.2 Agriculture Classification

As with forest, agriculture was classified to level 3 via stratification (using the Level 1 classification), using a supervised approach. This supervised approach did well separating pastures from the other two agricultural classes. Multidate imagery was again deemed essential as pastures did not change drastically throughout the year and the other two classes did. A band combination of 7,4,2 was useful to differentiate pastures from actively tilled classes. Band 7 was from the winter image, and band 4 and 2 were from the summer image. This combination maximized visual differences between pastures and the other two classes, which aided in training site selection and classification. However, supervised techniques did a poorer job of separating larger arable fields (CORINE class 211) from smaller complex fields (CORINE class 242). The same crops were grown in both class 211 and 242, so spectrally they were similar. An object-oriented approach was implemented to take advantage of size differences of fields within these two classes. Object based approaches first delineate objects, also known as segments in this analysis, that are made up of one or several pixels, and then utilize spectral and/or contextual information in an integrative way to aid in classification (Blaschke 2010). Object based approaches have proven valuable in remote sensing, and often can improve classification from traditional per pixel approaches (Yu et al. 2006). An edge based segmentation technique was used with a scale factor of .8 with no merging (Figure 3.2). Edge-detection methods are a common approach for the production of segments and are used to derive the initial boundaries

23

and delineate areas of contrast (Wang et al. 2004). A supervised approach with the selection of 50 training samples was then used to classify the image. Training fields were located by both calculating the area within the segmented images and referencing the ground truth data set. Classification involved the use of a support vector approach based on area size of each segment produced. The object based technique produced higher accuracy than either supervised or unsupervised approaches by taking advantage of spatial factors rather than purely spectral properties. After the classifications were complete, individual classifications were mosaicked together, and then a 3x3 lowpass filter was applied. Post classification filtering is a common approach for noise reduction and accuracy improvement within classified images (Zukowskyj et al. 2001). This procedure removes isolated pixels and is useful when there is interest in gross tonal variations rather than details (Berlanga-Robles and Ruiz-Luna 2002).
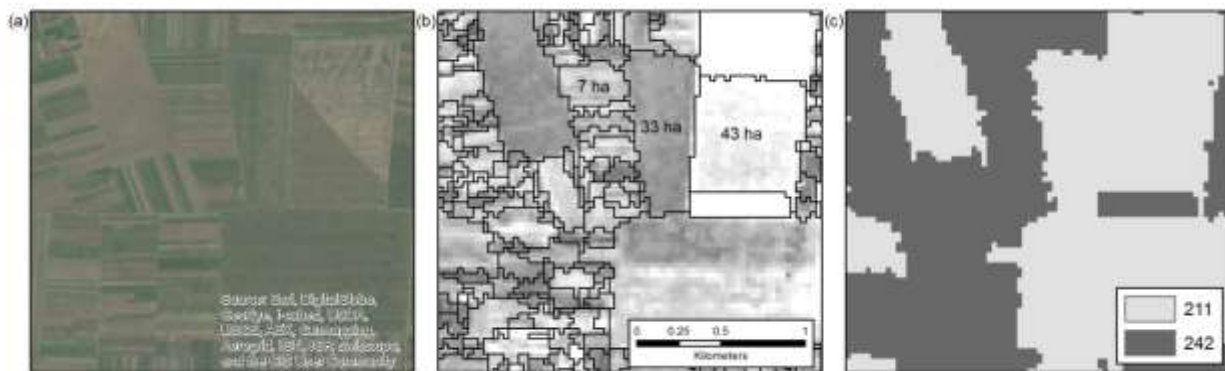
Figure 3.1 (a) High resolution 2011 image. (b) Result of segmentation overlain on band 3 of the 2011 Landsat image utilized in this study. Fields less than 25 ha were classified as 242 and fields greater than 25 ha were classified as 211. (c) Result after supervised classification was performed on the segmentation.
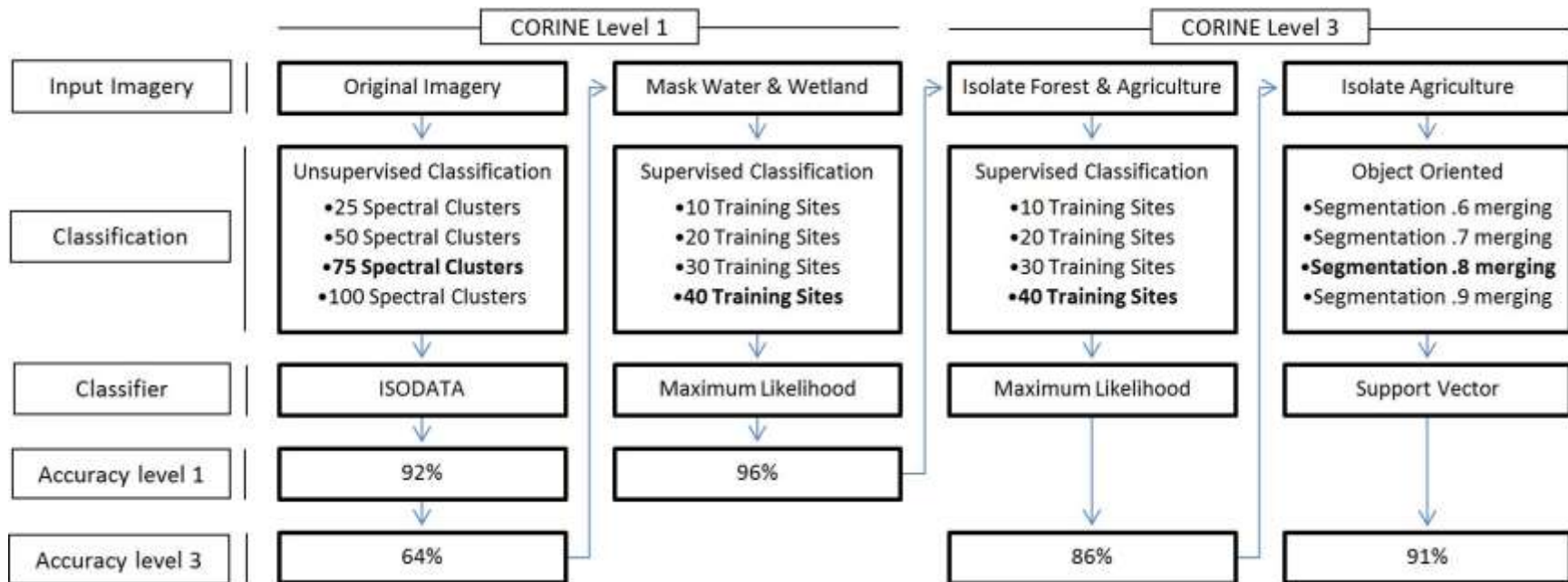
Figure 3.2 Simplified classification workflow, see text for details. In the classification row, the option that had the highest accuracy is highlighted; the highlighted option was utilized in final classification.

3.5 Accuracy Assessment

Accuracy was assessed for each classification using a confusion matrix, which was used to compute a number of accuracy metrics. A confusion matrix (also referred to as error matrix) is an n x n matrix (where n is the number of classes), commonly used for generating accuracy statistics and performing classification evaluation (Congalton and Green 1999). This matrix is arranged such that class membership determined by ground truth values are along the x-axis, and class membership determined by image classification is along the y-axis. When arranged this way, correct values fall along the major diagonal of the matrix. Incorrectly classified values lie in the off-diagonal areas of the matrix, such that it is apparent which class they are confused with. It has been suggested that a minimum of 50 sample points for each land-use/land-cover category in the error matrix be collected for the accuracy assessment of any image classification (Congalton, 1991). In total 500 of the 835 ground truth points were utilized for accuracy assessment (the other 335 were used in training). Ground truth points used in accuracy assessment accurately represent the distribution of land cover classes within the study area. For example there were 175 ground truth points in the forest class which is about 34.9% of the total ground truth points. The actual distribution in this class of forest in the level 1 land cover map was close to that number with as forests composed 32.5% of the total land cover. Agriculture ground truth points were a bit underrepresented as compared to the actual distribution within the field (50.2% compared to 60.6%). This is due to the fact that I stratified the sample so the relatively small classes of water, wetland, and urban had at least 15 ground truth points. Ground truth points were assigned values based on methods outlined section 3.1.2. Points were carefully selected to ensure no single ground truth point was used in both training of unsupervised classifications and accuracy assessment. The ground truth points were overlain on the land cover maps, the land cover value was extracted. After values were extracted a confusion matrix was generated for accuracy assessment.

The confusion matrix was used for several accuracy calculations including user/producer error, overall percent accuracy and the Kappa statistic. Overall accuracy is produced by dividing the sum of the major diagonal by the total number of ground truth points. The Kappa statistic was also calculated from the error matrix (Foody 2002). Kappa is a categorical comparison metric that quantifies how much better a classification is compared to random chance. Finally,

errors of omission (producer's accuracy) and commission (user's accuracy) were calculated. Errors of commission are produced when a pixel is assigned to a different category, in the classification process, than it belongs. Errors of omission are produced when a pixel is excluded from the category to which it belongs (Congalton and Green 1999). In statistics, an error of commission would be equivalent to a Type I error, while an error of omission would be equivalent to a Type II error.

The 1986 classifications did not have aerial photographs or field data for validation, so it is assumed that a similar accuracy is achieved using the same methods from the 2011 image. This assumption has been utilized in previous research, where no field data or aerial photography was available (Berlanga-Robles and Ruiz-Luna 2002, Li et al. 2004). One important thing to remember here is that post-classification change detection techniques require very accurate classifications. If inaccurately classified maps are compared there is a significant probability that changes between maps may be caused by misclassification rather than by actual differences in land cover (Green et al. 1994). For this reason accuracy results of roughly 90% were needed.

3.6 Change Detection from LULC classifications

Change was evaluated by overlaying classified maps from each year to create a composite change map, followed by quantitative assessment of categorical change. The change map shows areas of change and, since attributes could also be joined, it is possible to quantify the extent to which specific changes have occurred. A to-from cross tabulation chart or transition matrix was also produced, which provided a useful tool for analyzing detailed land change. Creation of a cross tabulation chart is common in post-classification land use change analysis in order to quantify change (Li et al. 2004, Yu and Ng 2006). The transition matrix gives detailed, quantifiable information about the nature and rate of change between and within classes. From this information several graphs, charts and maps can be produced to aid in visualization of change. One concern in change detection analysis is that both position and attribute errors can propagate through the multiple dates (Yuan et al. 2005). The change map accuracy is determined by multiplying the individual classification map accuracies to estimate the expected accuracy of the change map (Yuan et al. 1998). For this research, accuracy was assessed by this multiplication method.

3.7 Conversion from LULC to Habitat Maps

Classified maps were converted to the EUNIS habitat classification scheme in order to demonstrate how LULC change has affected habitat distribution in the study area (Table 3.3). The methodology for this conversion is detailed in guidelines published by the European Environmental Agency, which provides guidelines for converting land cover classes to habitat types (http://www.eea.europa.eu/). Transformation from the CORINE classification scheme to the EUNIS habitat scheme was straight forward in this study. All CORINE classes belonged to only 1 EUNIS class, which was carried out using spatial analysis software.

Table 3.3 Name, description, and CORINE level 3 classes from which each of the EUNIS habitats were derived for fragmentation analysis.

CORINE Level 3	Eunis Habitat Types	Description
5.1.2.	C Freshwater aquatic habitats	Inland surface waters are non-coastal above-ground open fresh or brackish waterbodies (e.g. rivers, streams, lakes and pools, springs), including their littoral zones.
4.1.1.	D Wetland Habitats	Wetlands, with the water table at or above ground level for at least half of the year, dominated by herbaceous or ericoid vegetation.
2.3.1.	E Grassland habitats	Non-coastal land which is dry or only seasonally wet (with the water table at or above ground level for less than half of the year) with greater than 30% vegetation cover. The vegetation is dominated by grasses and other non-woody plants, including mosses, ferns, sedges and herbs.
3.1.1., 3.1.2., 3.1.3.	G Woodland/forest habitats/other wooded areas	Woodland and recently cleared or burnt land where the dominant vegetation is, or was until very recently, trees with a canopy cover of at least 10%. Trees are defined as woody plants, typically single-stemmed, that can reach a height of 5 meters.
2.1.1., 2.4.2.	I Regularly/recently cultivated habitats or garden	Habitats maintained solely by frequent tilling or arising from recent abandonment of previously tilled ground such as arable land and gardens. Includes tilled ground subject to inundation.
1.1.1.	J Constructed industrial/ other arificail habitats	Primarily human settlements, buildings, industrial developments, the transport network, waste dump sites.

3.8 Fragmentation Analysis

Landscape fragmentation analysis metrics were used to determine structural changes in habitat between the two dates of 1986 and 2011. Fragmentation analysis offers a means to analyze categorical maps with more than 50 landscape metrics and more than 60 class metrics (Li et al. 2004). Many of these metrics are redundant so it is important to select only a few metrics (Riitters et al. 1995). Previous research has acknowledged this redundancy and suggested a core set of metrics may be possible across scale and space (Schindler et al. 2008). Leitao and Ahern (2002) proposed 9 core landscape metrics that are most useful and relevant for landscape

analysis. Several studies analyzed utilize the same 6-8 metrics in study sites located in Eastern Europe, southern Europe, western Asia, and central Asia suggesting these metrics can be applied in varying regions and spatial scales (Kadiogullari 2012, Keles et al. 2008, Li et al. 2004, Mairota et al. 2013, Oguz and Zengin 2011, Schindler et al. 2008, Yu and NG 2006). I selected 8 metrics that are commonly used for fragmentation analysis and understanding landscape changes in general. Selection of metrics was based on the previously mentioned literature and the metrics proposed by Leitao and Ahern (2002).

      Two groups of landscape metrics were used: one at the class level and one at the landscape level. The class level metrics analyze each individual class type, while the landscape metrics considers the study area as a whole. The specific metrics chose for this analysis were class area (CA), percentage of land (PLAND), number of patches (NP), mean patch size (MPS) and largest patch size (LPI) at the class level (Table 3.4). At the landscape level number of patches (NP), mean patch size (MPS), mean-nearest neighbor distance (MNN), Contagion Index (CONTAG) and Shannon's Diversity Index (SHDI) were utilized. Each fragmentation metric applies to the landscape level, the class level, or both. Understanding these metrics aids in interpret of how habitats and/or land cover classes are fragmented currently, how this has changed through time, and also provide a baseline for future analysis.

      At the class level I wanted to understand not only how the landscape was composed but also how the fragmentation has changed through time. CA and PLAND provide a basic summary of the landscape, can show an indication of dominance, and can be used to quantitatively show how a landscape has changed through time (Tyler and Peterson 2004). MPS was used as it is arguably the most important indication of fragmentation (McGarigal and Marks 1995). Other indicators are often used in conjunction with MPS to indicate fragmentation, specifically NP and CONTAG (Yu and Ng 2006). It has been suggested that NP and MPS should be used complementarily since high NP and low MPS values suggest fragmentation (Keles et al. 2008, Leitao and Ahern 2002, Matsushita et al. 2006, Yu and NG 2006). LPI has been shown to reinforce or be associated with changes in MPS (Keles et al. 2008) thus giving an indication of fragmentation. LPI also gives indication of dominance within a landscape, which gives indication of changes in landscape homogeneity (Yu and Ng 2006). In summary, statistics generated at the class level were useful for understanding changes through time and general fragmentation patterns.

To more fully understand landscape changes within Volyn, landscape level statistics were desired. Landscape metrics aid in not only understanding of fragmentation, but also composition and connectivity, which have been shown to be important for species distribution (Salek et al. 2013). SHDI is a diversity index (Li et al. 2004, Yu and Ng 2006) and is particularly useful in studying landscape patterns as it is very sensitive to changes (Mairota et al. 2013). In this study SHDI provides a quantitative measure of how many different types of habitats are in the landscape, and how evenly these habitats are distributed. CONTAG is an adjacency index (Li et al. 2004) and has also been used as a fragmentation index (Yu and Ng 2006). SHDI and CONTAG are commonly used together as they give indication of landscape fragmentation and heterogeneity (Li et al. 2004, Mariota et al. 2013). CONTAG has also been shown to be the best landscape index for differentiating landscape patterns (Remmel and Csillag 2003). MNN is a measure of isolation and is important to understand as it quantifies the mean distance between patches (Li et al. 2004). This may affect the ability of species to disperse between patches, interact, and maintain relationships between populations (Tyler and Peterson 2004). In summary, statistics generated at the landscape level go beyond fragmentation patterns, and show diversity, adjacency and isolation. Diversity, adjacency, and isolation have been shown to have important implications for ecosystems (Mariota et al. 2013, Schindler et al. 2008).

Throughout this thesis, geospatial analysis, image classification, and fragmentation analysis were done using ENVI 5 (Exelis Visual Information Solutions 2013), ArcGIS 10.2 (ESRI 2013), and Fragstats 4.2 (McGarigal and Marks 1995).

Table 3.4 Acronym, metric name, and description of the landscape metrics used in this study. There is also an indication as to whether the index was calculated for the class level, the landscape level, or both.

Acronym	Metric name	Level	Description
CA	Class/Total Area	Class	Total Area of all patches per class
PLAND	Percentage of Landscape	Class	Percentage the landscape comprised by certain class
LPI	Largest Patch Index	Class	Area of largest patch in landscape divided by landscape area
NP	Number of Patches	Both	Number of patches per class/landscape
MPS	Mean Patch Size	Both	Average size of patches
MNN	Mean Nearest-Neighbor Distance	Landscape	Sum of distances to nearest neighboring patch of same type
CONTAG	Contagion Index	Landscape	Measure of adjacency, dissagrigation
SHDI	Shannon's diversity Index	Landscape	Measure of diversity within landscape

Chapter 4 - Results

4.1 CORINE Level 1 Classification, Accuracy, and Change

4.1.1 Classification Results

The first two classifications contained 5 classes from the CORINE level 1 classification scheme and represent the years of 1986 and 2011(Figure 4.1). These two land cover maps are essential first steps in this study as they are inputs for change detection and fragmentation analysis. These maps can also provide some quantifiable and qualitative (visual interpretation) indication of landscape structure. The agriculture class dominates the majority of landcover in both 1986 and 2011, representing 65.8% and 60.6% of the total land cover respectively. This class is most prevalent in areas of higher elevation, specifically areas to the south west portion of the study area. Forest is the next most prevalent class in each image representing 28.8% of the land cover in 1986 and 32.5% of the land cover in 2011. Forests become more prevalent throughout the central and especially the eastern portions of Volyn. The northeast corner of Volyn is dominated by wetlands, which follows the general elevation pattern within the study area (In general, highest elevations in the southwest slope to lower elevations in the northeast). The classes of wetland, water and urban cumulatively represent only about 5.5% of the 1986 image and 6.9% of the 2011 image.

4.1.2 Accuracy Results

Classifications to level 1 of the CORINE scheme proved to be highly accurate (Table 4.1). Overall accuracy and the kappa statistic were both over 95%, with user and producer accuracies over 97% for all classes except urban. Unsupervised techniques were the most accurate method of identifying the wetland and water classes. After water and wetland were masked out, a supervised technique, improved accuracy in the urban, agriculture, and forest classes.

While overall accuracy within the landscape is high, urban land cover accuracies are relatively low. When examining the error matrix and the Producers/Users Accuracy table (Table 4.1), it is apparent this was a difficult class. User's accuracy of this class is 81.25, indicating that a sample from the urban class is actually a different class about 19% of the time. The producer's accuracy is a low relative to the other classes as well. Producer's accuracy indicates that there is about a 13% more urban area than was actually mapped. Overall this means that the urban class

was slightly overestimated. From the field work survey, it was apparent that agriculture and settlements were intricately mixed. This juxtaposition increases difficulty of separating urban and agriculture, and could be the cause of relatively low accuracy of the urban class. Although accuracy is low within the urban class, this is a relatively small class which was not of particular interest in this study.
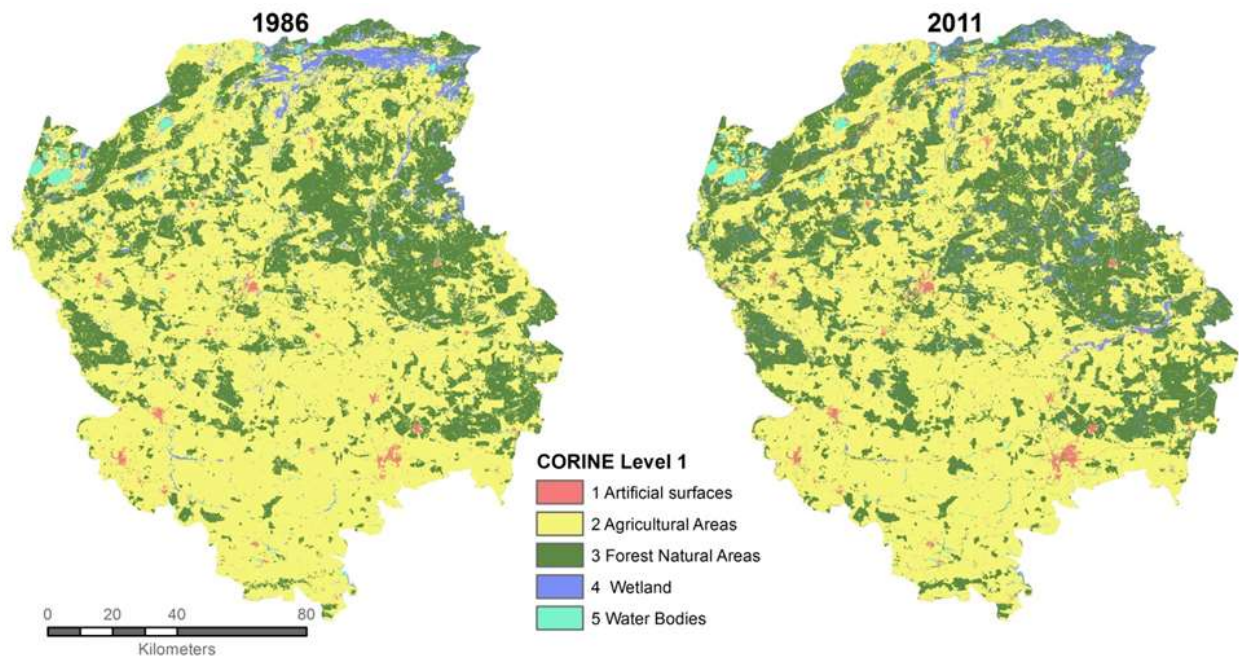

Figure 4.1 Land cover maps generated to level 1 of the CORINE classification scheme for 1986 and 2011.

Table 4.1 Confusion matrix generated for CORINE level 1 accuracy assessment. Producer's and user's accuracy for each class, overall accuracy and Kappa accuracy are also included.

Classifiation→ Reference↓	Urban	Agriculture	Forest	Wetland	Water	Row	Producer's Accuracy
Urban	13	2	1	0	0	16	81.25%
Agriculture	2	243	3	1	0	249	97.59%
Forest	0	3	170	0	0	173	98.27%
Wetland	0	0	1	39	0	40	97.50%
Water	0	0	0	0	22	22	100.00%
Column	15	248	175	40	22	487	
User's Accuracy	86.67%	97.98%	97.14%	97.50%	100.00%		

Overall Accuracy = (13 + 243 + 170 + 39 + 22)/500 = 97.40%
Kappa Accuracy = 95.82%

4.1.3 Change Analysis

Overall, about 15% of the Volyn oblast has experienced some change from 1986-2011 for the level 1 classification (Table 4.3). In the transition map and the transition table, only the top 5 of a total of 20 possible combinations for transition are displayed (Figure 4.3). The top 5 are displayed in order to reduce confusion and due to the fact that these classes account for about ~83% of the change. Changes were also color coded to give not only the nature of the change (e.g. from agriculture to forest, forest to wetland, etc.) but also as an aid for visualizing the geographic location of the changes. The most dominate transition within the study area is from agriculture to forest (~1284 km²). This change seems to be consistent throughout the study area, especially near existing forest edges, within forests, and areas where forest and agriculture classes meet. The next most prevalent area of change was from forested areas to wetland. This change occurred most prevalently in the northeast area of Volyn, but also occurred in the east-central area which is dominated by forest. In general, the classes of agriculture, forest, and wetland experienced the most changes. Although the urban class experienced a noticeable amount of increase (almost doubled in area) it is a small class relative to agriculture, forest, and wetland, and accuracy of this class was questionable (see section 4.1.2). The water class remained relatively stable over the time period examined.

Table 4.2 CORINE level 1 land cover change matrix, 1986-2011 (km²)

| From-1986	TO-2011					1986 Total
	Urban	Agriculture	Forest	Wetland	Water	
Urban	101.63	45.16	10.16	2.36	0.81	160.13
Agriculture	199.94	11471.11	1284.71	178.60	26.30	13160.65
Forest	38.82	303.96	4987.72	417.64	2.79	5750.92
Wetland	7.55	280.80	208.20	246.56	11.92	755.03
Water	0.44	1.96	3.31	13.73	141.86	161.31
2011 Total	348.38	12102.99	6494.09	858.89	183.68	19988.04
Change	188.25	-1057.66	743.17	103.86	22.37	3039.15
Change (%)	54.04%	-8.74%	11.44%	12.09%	12.18%	15.20%
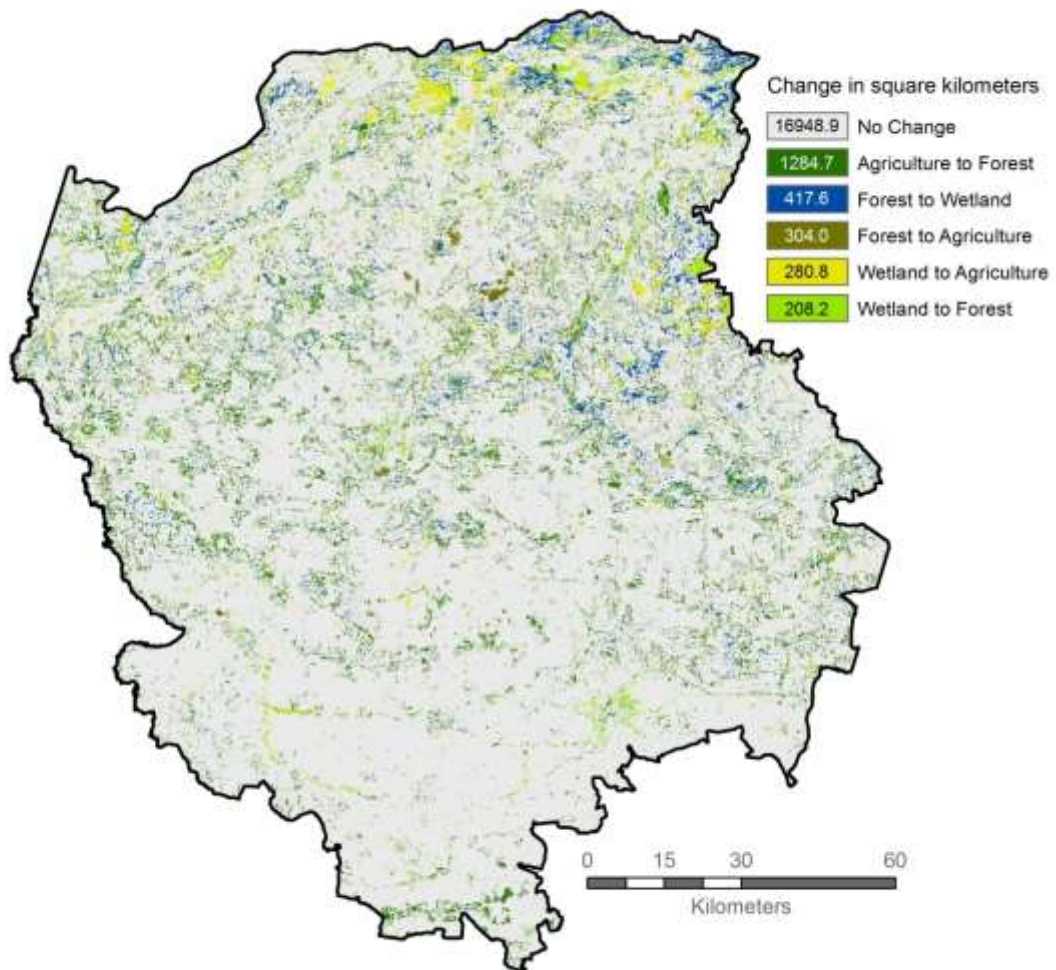
Figure 4.2 Top 5 CORINE level 1 change map, Volyn, 1986-2011.

4.2 CORINE Level 3 Classification, Accuracy, and Change

4.2.1 Classification Results

The level three classification subdivide the two largest classes, Agriculture and Forest, into six separate sub classes. Agriculture is split into large arable fields (211), pasture (231) and small complex fields (242) (see table 3.2 for a full list of land cover codes and definitions). Forests are divided into deciduous (311), coniferous (312) and mixed (313). While examining the two level 3 classifications clear visual signs begin to emerge of land cover changes that have taken place in Volyn. Within the agricultural class, class 211 has noticeably been replaced by class 231 and 242. Visually inspecting figure 4.2, class 211 is much less dominant, and classes 231 and 242, which are shown in brown and orange respectably, have replaced 211. Class 211 has decreased from 34% of the landscape to 11%. This has resulted in increases in other agricultural classes including an increase from 15% to 25% for class 231, and an increase from 16% to 25% for class 242. Changes in forests are less obvious and no immediate trends are apparent from strictly visual interpretation.

4.2.2 Accuracy Results

The level three CORINE classified map were above or very near the desired 90% accuracy for both overall and kappa statistic (Table 4.2). Of the 500 ground truth points gathered 456 were accurately classified resulting in an overall accuracy was 91.2%. The Kappa statistic indicates that the classification was 89.76% better than a random classification. Classes 111, 411, and 512 show the same accuracy as the level 1 classification as they were not reclassified. Classes 231, 242, 311, and 312 all had similarly high user and producer accuracy values, never falling below 88% accuracy. Accuracy in these four classes is particularly important, as they comprise about 75% of the study area. Class 211 showed a relatively low user's accuracy of 82.72 indicating that about 17% of the time a pixel that is classified as class 211 is actually a member of another class. Class 313 had the lowest value in the producer accuracy with a value of 79.31%. This indicates that slightly more than 20% of the time a pixel that was actually mixed forest was incorrectly classified to another class. Urban and Mixed classes have proved to be difficult to classify in past studies (Kuemmerle et al. 2006) and are considered problematic as borders need to be drawn artificially (Foody 2002).

Most of the inaccuracies in the error matrix are from within subclasses of the same level 1 class, for example, mixed forests confused with deciduous forests. For the three agriculture classes (211, 231 and 242) 21 of the 32 misclassified pixels where classified as another form of agriculture. Similar results are true for the forest classes, where greater than half of the misclassified pixels were within a different forest class. This is commonly the case in remote sensing as splitting land cover classes that are similar spectrally is difficult and often subjective to interpretation (Foody 2002, Kuemmerle et al. 2006).
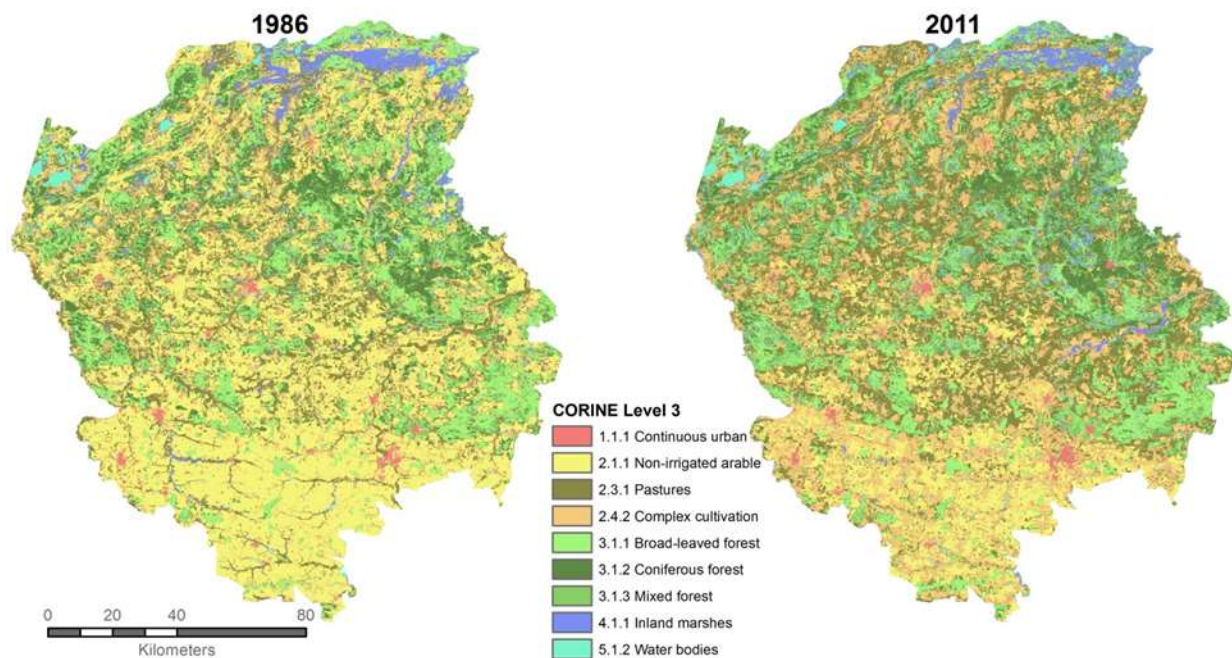

Figure 4.3 Land cover maps generated to level 3 of the CORINE classification scheme for 1986 and 2011.

Table 4.3 Confusion matrix generated for CORINE level 3 accuracy assessment. Producer's and user's accuracy for each class, overall accuracy and Kappa accuracy are also included.

Classifiation→ Reference↓	111	211	231	242	311	312	313	411	512	Total	Producer's Accuracy
111	13	-	1	1	-	1	-	-	-	16	81.3%
211	1	67	8	2	1	1	-	1	-	81	82.7%
231	-	-	98	3	1	-	-	-	-	102	96.1%
242	1	5	3	57	-	-	-	-	-	66	86.4%
311	-	-	-	2	68	-	-	-	-	70	97.1%
312	-	-	1	-	1	69	6	-	-	77	89.6%
313	-	-	-	-	3	-	23	-	-	26	88.5%
411	-	-	-	-	-	1	-	39	-	40	97.5%
512	-	-	-	-	-	-	-	-	22	22	100.0%
Total	15	72	111	65	74	72	29	40	22	456	
User's Accuracy	86.7%	93.1%	88.3%	87.7%	91.9%	95.8%	79.3%	97.5%	100.0%		

Overall Accuracy = (13 + 67 + 98 + 57 + 68 + 69 + 23 + 39 + 22)/500 = 91.20%
Kappa Accuracy = 89.76%

4.2.3 Change Analysis

According to the level three classifications, about 56% of the total study area has experienced change (Table 4.4). Transformation of the landscape has occurred throughout the study area, with the most changes occurring in the west, central, and southern regions of the study area. In the transition map and the transition table, only the top 7 of a total of 72 possible combinations for transition are displayed (Figure 4.4). The top 7 are displayed in order to reduce confusion and due to the fact that these classes account for about three quarters of the change.

The transition matrix shows that the most prevalent changes involved transitions within agricultural classes. Specifically class 211 showed a 220% decrease with a net loss of 4,692 km². Classes 231 and 242 showed the largest increases with gains of 1891 km² and 1744 km² respectably. The top 4 transitions involve changes to or from classes 211, 231, or 242. These changes involved large percentages of the landscape, resulting in widespread agricultural LULC change.

The next most prevalent changes occurred within the forest classes. The 5th and 6th largest transitions involved intra-categorical forest changes. Specifically class 313 showed an increase of 1200 km². This large increase is, for the most part, from previously homogeneous forest classes 311 and 312. Due to this transition, classes 311 and 312 both show decreases of ~10%.

However, class 311, has shown increases from other classes, specifically agricultural class 231. The forest class
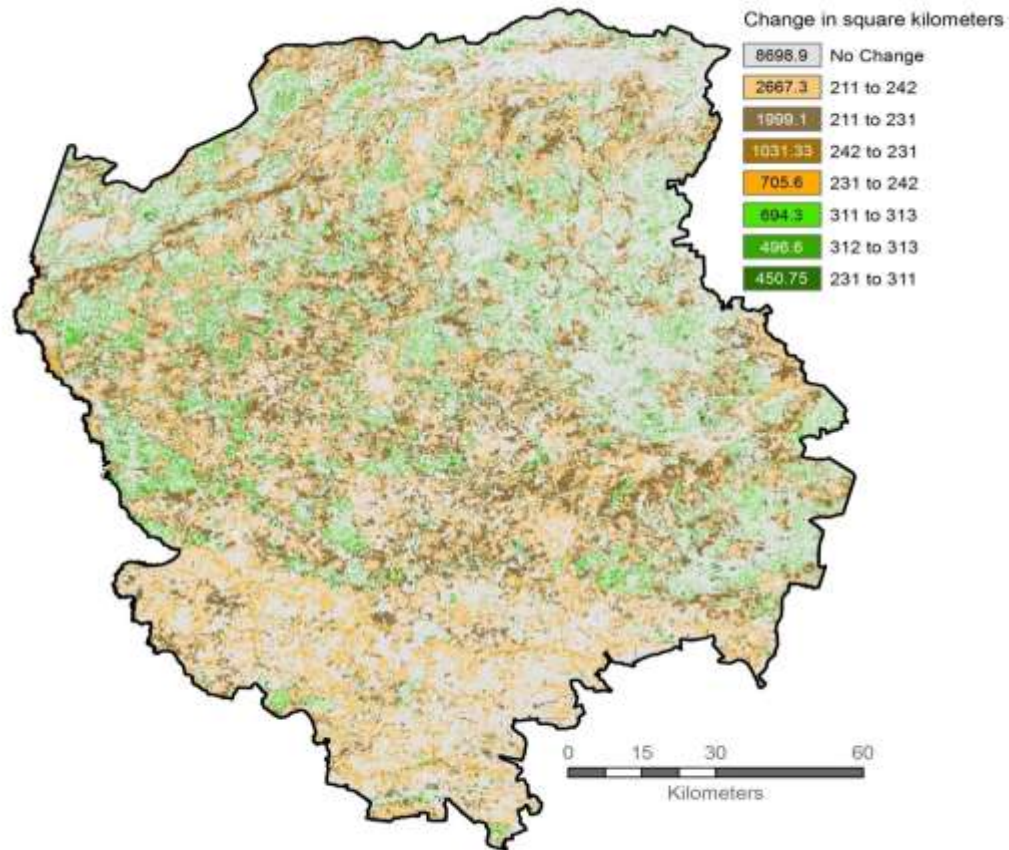

Figure 4.4 Top 7 CORINE level 3 change map, Volyn, 1986-2011. These top 7 represent ~75% of the change in this time period.

Table 4.4 CORINE level 3 land cover change matrix, 1986-2011 (km²)

	TO-2011									
From-1986	1.1.1.	2.1.1.	2.3.1.	2.4.2.	3.1.1.	3.1.2.	3.1.3.	4.1.1.	5.1.2.	1986 Total
1.1.1.	101.63	1.79	6.47	36.90	1.98	6.03	2.15	2.36	0.81	160.13
2.1.1.	63.51	1857.66	1999.14	2667.33	97.97	63.61	52.89	20.35	7.87	6830.33
2.3.1.	20.39	118.92	1521.72	705.55	450.75	49.86	87.14	122.76	8.80	3085.89
2.4.2.	116.03	144.46	1031.33	1425.00	201.04	149.27	132.19	35.48	9.62	3244.42
3.1.1.	4.83	2.29	89.32	30.84	1717.49	80.59	694.34	379.22	1.31	3000.24
3.1.2.	32.37	1.90	119.44	29.32	71.27	1253.41	496.62	14.15	1.09	2019.58
3.1.3.	1.62	0.07	27.20	3.57	51.91	188.55	433.53	24.26	0.39	731.11
4.1.1.	7.55	10.50	181.25	89.06	147.90	27.28	33.02	246.56	11.92	755.03
5.1.2.	0.44	0.16	0.97	0.84	2.02	0.95	0.34	13.73	141.86	161.31
2011 Total	348.38	2137.74	4976.85	4988.40	2742.33	1819.55	1932.22	858.89	183.68	19988.04
Change	188.25	-4692.60	1890.96	1743.98	-257.91	-200.03	1201.11	103.86	22.37	11289.18
Change (%)	54.04%	-219.51%	38.00%	34.96%	-9.40%	-10.99%	62.16%	12.09%	12.18%	56.48%

4.3 Habitat Classification and Fragmentation Analysis

Following classification, the level 3 CORINE maps were used to produce EUNIS habitat maps (Figure 4.5). Essentially this involved collapsing several classes, recode the raster grid, and renaming the classes. CORINE class 311, 312 and 313 collapsed into EUNIS class G, Woodland/forest habitats/other wooded areas (see figure 3.4 for detailed information on CORINE to EUNIS conversion). CORINE class 211 and 242 collapsed into EUNIS class I, Regularly/ recently cultivated habitats or gardens. The main point for the production of these maps was to perform fragmentation statistics (Tables 4.5 and 4.6). While examining the fragmentation statistics, there appears to be substantial changes at both the class and the landscape level.

Agricultural habitats are the most dominant habitat type located in Volyn for both years studied, followed by forests and then grasslands. Agricultural habitats show a decrease from 10075 km² to 7152 km² or from 50% to 36% of the landscape. Grassland habitats show the greatest increase from one time to the next. In 1986 the composed 15% of the landscape and by 2011 that number had jumped to 25%. The rest of the habitat types remained relatively stable in terms of CA and PLAND from 1986 to 2011. However, there are large increases in NP, and decreases in MPS for all habitat types.

The landscape level statistics also reveal change over the time period studied. Looking at the EUNIS habitat maps, this is not surprising, as visually the landscape appears different. NP and SHDI both show increases, while MPS, MNN, and CONTAG all show decreases. All statistics calculated at the landscape level have changed substantially.
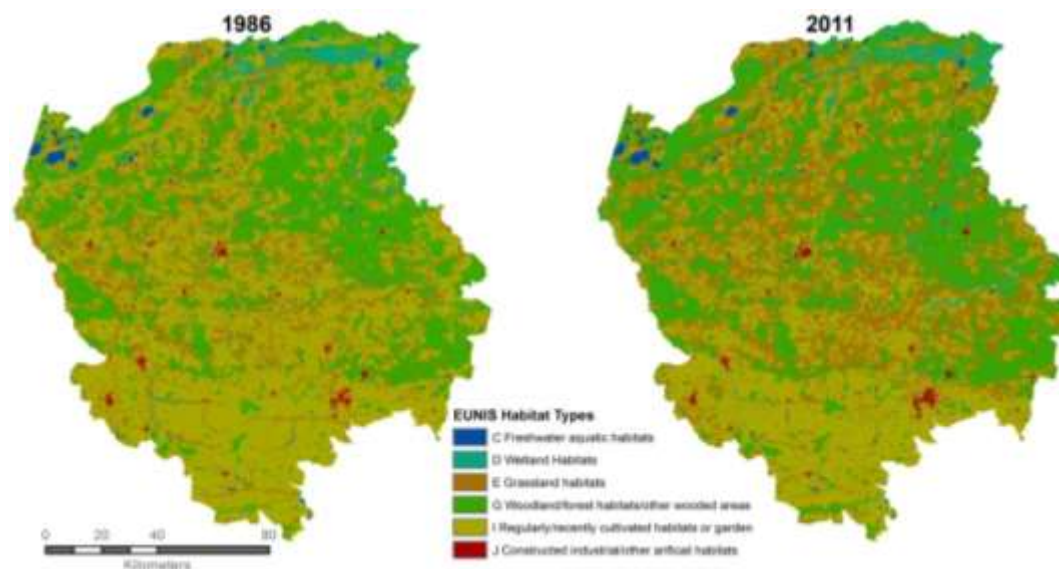
Figure 4.5 Maps produced after conversion to EUNIS habitat scheme.

Table 4.5 Landscape metrics change in class level, Volyn, 1986-2011

EUNIS Habitat Class	CA (km²)		PLAND		NP		LPI (km²)		MPS (ha)	
	1986	2011	1986	2011	1986	2011	1986	2011	1986	2011
C Freshwater aquatic habitats	161.31	183.21	0.81	0.92	599	973	0.13	0.13	26.93	18.83
D Wetland Habitats	755.03	842.17	3.78	4.21	8040	10608	1.06	0.71	9.39	7.94
E Grassland habitats	3085.89	4963.16	15.44	24.83	18202	30493	0.22	0.91	16.95	16.28
G Woodland/forest habitats/other wooded areas	5750.92	6527.78	28.77	32.66	5698	10326	8.08	8.66	100.93	63.22
I Regularly/recently cultivated habitats or garden	10074.76	7151.58	50.40	35.78	11927	15225	35.51	17.65	84.47	46.97
J Constructed industrial/other arificial habitats	160.13	320.04	0.80	1.60	3971	7237	0.09	0.11	4.03	4.42

Table 4.6 Landscape metrics change in landscape level, Volyn, 1986-2011

Year	NP	MPS(ha)	MNN	CONTAG(%)	SHDI
1986	48437	41.266	253.0129	59.2405	1.1935
2011	74826	26.7126	215.98	54.61	1.3218

Chapter 5 - Discussion

The fall of the Soviet Union is recognized as one of the most significant socio-economic changes in recent history, with widespread effects on the landscape (Prishchepov et al. 2012). Like other former Soviet states, Volyn has felt the effect of this political change. Although there is widespread change, I utilized the land cover maps, transition matrix, and fragmentation statistics to look specifically at 1) agricultural changes and 2) forest changes. For each of these two classes 1) changes in areal extent, 2) restructuring, and 3) habitat changes were examined to get a better overall picture of landscape changes. Agriculture and forests classes were selected for closer examination as they make up the largest percentage of the landscape, they are the most widely studied in this region of the world, and these classes are known to be important for various ecosystem functions.

5.1 Agriculture Changes

5.1.1 Agricultural Land Abandonment

Arable land was completely state owned and managed by large agricultural enterprises in the former Soviet Union (Ash 1998). While some of the agricultural land still operate in a collective or co-op style (Ash 1998), the transition from a subsidized, centrally planned agricultural economy to a market-drive economics has resulted in large scale land abandonment of unproductive land (Baumann et al. 2011). Several former soviet states in Eastern Europe show this large scale land abandonment trend and the Volyn oblast is no exception (Prishchepov et al. 2012).

Examination of the land cover maps, transition matrix, and fragmentation metrics suggest widespread changes within the agricultural class. The level 1 transition matrix shows that agricultural land use decreased from 66% of the total landscape in 1986 to 61% in 2011, or a decrease from roughly 13,160 km² to approximately 12,100 km². The most common transition was from the agricultural class to the forest class (1200 km²) which I consider as one indication of abandonment. Transition from agriculture to forest was three times greater than any other change in the level 1 map. From the level three transition analysis, two of the top three transitions in terms of total area are from actively cultivated agricultural classes (class 211 and 242) to pasture (class 231), accounting for over 3000 km² of land transition. Additionally about 450 km² of land was converted from class 231 to 311, the largest inter-categorical transition.

41

These two changes represent the largest indication of abandonment as land transitions from currently farmed fields to grassland and eventually to forest. Another indication of abandonment could be derived by looking at the fragmentation statistics. Regularly cultivated habitats decline from 50% to only 35% of the landscape, while grassland habitats increased from 15% to 25%. Additionally Shannon's diversity increases from 1.19 to 1.35 showing that the landscape became more heterogeneous and evenly distributed. The landscape is no longer dominated by regularly cultivated habitats, suggesting land has transitioned most likely through abandoned.

While the transition matrices and fragmentation statistics suggest abandonment, a more narrowly defined abandonment rate is needed to put this research in context of previous work. Past studies have defined abandonment in a variety of ways, such as transition from fields and pastures that reverted to forests (Sieber et al. 2013), from farmland to fallow (Baumann et al. 2011) and/or the sum of fallow and reforested divided by total agricultural land (Kuemmerle et al. 2008). I will define abandonment rate as changes from either class 211 or 242 in 1986, which are active agricultural classes, to class 231, 311, 312 or 313, or from class 231 to 311, 312, or 313 (see table 3.2 for a full list of land cover codes and definitions). Using the aforementioned definition of abandonment produces a 33% abandonment rate, or 4336 km² of 13,160.6 km². I feel it is important not to consider the 33% abandonment rate without the context of agricultural gains over the same time period. The level 3 transition matrix (table 4.4) shows that 992 km² were gained by classes 211 and 242. Most of this gain, 706 km² of 992 km², was from 231 to 242. This suggests an agricultural net loss of 26%, less than the abandonment rate of 33%, from 1986 to 2011.

When mapped, widespread land abandonment across the entire study region becomes visually apparent (Figure 5.1). One thing noticeable about change is that it does not appear to be even across the oblast. Areas to the south of the study area tended to remain in the agricultural classes. As you traverse north, abandonment is widespread. I believe this difference has to do with elevation, and wetness. Elevation is highest in the southern third of the oblast (200-290 m), where land abandonment visually appears to be lowest. The northern two thirds of the study area have low elevations (125-200 m) and contain more wetlands. I suggest abandonment is more widespread in the northern two thirds of the study region due to low elevations and poor drainage.

A net abandonment rate of 26% fits well with previous land abandonment research in Eastern Europe, and suggests an average rate of abandonment in the 25 year transition period. A few selected studies suggest abandonment rates of 16.1% (Kuemmerle et al. 2008), 30% (Baumann et al. 2011), 39.89% (Sieber et al. 2013) all the way to 55.4% (Hostert et al. 2011), however these studies vary in terms of time periods, study area, elevation, methodologies, and terminology for defining abandonment.

Drivers of this change can be attributed to a variety of reasons. In Soviet times, subsidies and capital investment by the state led to increases in agricultural and farmed lands, often on highly marginal lands (Turnock 1998). The ending of subsidies and capital investment let to declining profitability in agriculture under free markets, restructuring of the agricultural sector, and societal changes; these reasons can be used to generalize the drivers of agricultural changes (Kuemmerle et al. 2006). Additionally, many large scale agricultural enterprises went bankrupt after the political systems change (Ash 1998). Access to machinery was limited and farmers could only cultivate small portions of the potentially available land (Kuemmerle et al. 2006).

Area in square kilometers
- 8566 — Not Agriculture
- 992 — Agriculture Gains
- 6094 — Agriculture Consistent
- 4336 — Agriculture Loss
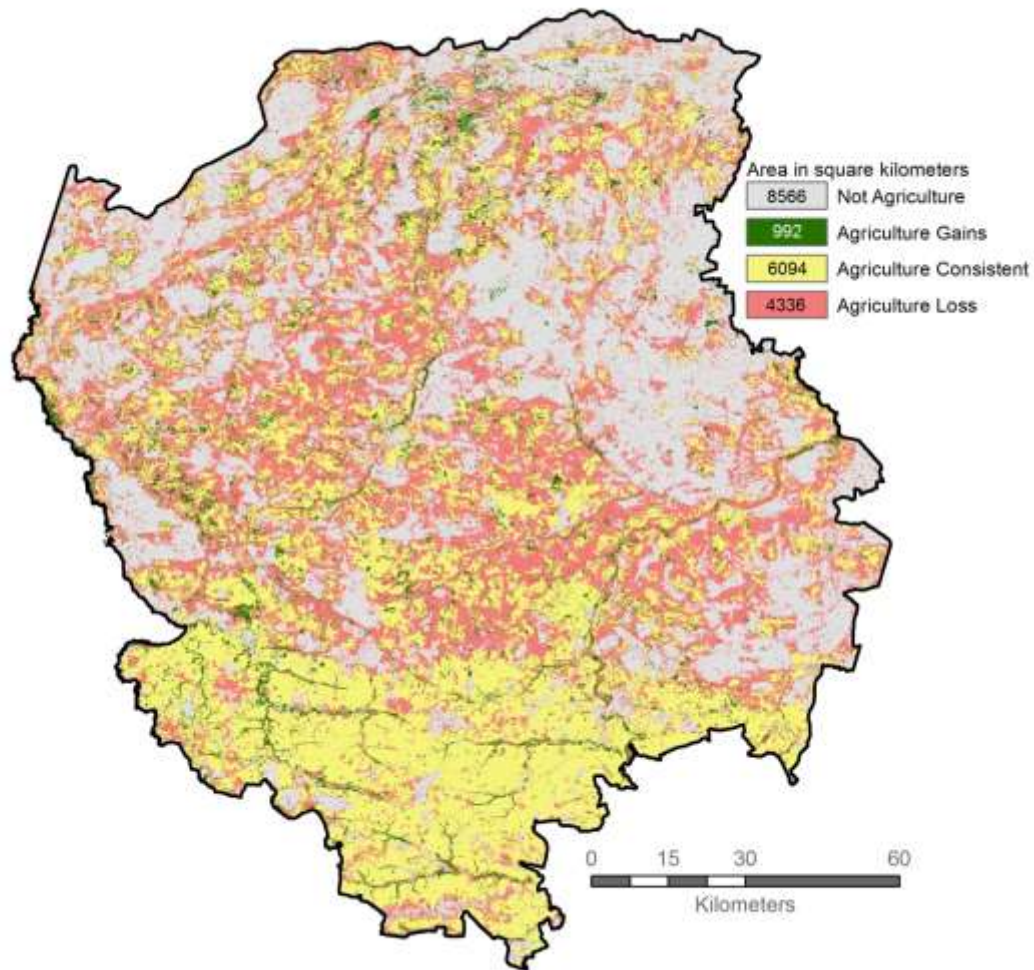
Figure 5.1 Map of agricultural land abandonment in Volyn, 1986-2011.

5.1.2 Changes in agricultural land use

Examination of the segmentation process, transition matrix, and classification statistics reveal that the agricultural landscape has changed dramatically. The first sign of restructuring resulted from the segmentation process used in classification. Segments were produced to separate agricultural class 211 from 242 before classification (figure 3.2). Using the exact same methods, the segmentation resulted in the production of 402,301 segments in 1986 and 592,318 segments for the 2011 image. The large increase in number of segments is profound considering agricultural land decreased from 1986 to 2011, from 10074 km² to 7126 km². The average field size halved from 1986 to 2011, declining from .25 km² or 6.18 acres to .012 km² or 2.97 acres.

44

Other signs of reorganization within the agricultural class are apparent when examining the transition matrix. The largest single transition within the level 3 transition matrix was from class 211 to class 242 (table 4.4). 2667 km² or 13% of the total study area made this transition, suggesting a large portion of the study area has been converted from large scale homogenous collective or co-op style agriculture to smaller scale heterogonous family style agriculture. When examining the proportions each of these classes make to the actively tilled agricultural class (211+242), it becomes apparent that agricultural production has underwent restructuring or shifted toward 242 (Figure 5.2). In 1986, class 211, accounted for roughly 70% of actively tilled agriculture. By 2011, this proportion had flipped and small, complex fields were the agricultural land use.

Drivers of agricultural land use change from 211 to 242 are difficult to determine within Volyn. Although many studies recognize and acknowledge agricultural land abandonment (Kuemmerle et al. 2009, Hostert. et al 2011), few comment on agricultural restructuring (Kuemmerle et al. 2006, Baumann et al. 2011). Suli-Zakar (1998) acknowledges that the regime change has given rise to structural change in agriculture with small farms providing food and income to a transitional population. Additionally, declining profitability of agriculture may be deterring large scale farming practices for production of cash crops, in favor of small local production for consumption and possibly local sale, which may be why we see the pattern that has emerged.

This shift in agricultural land use may have profound impacts on the local environment. Shifting away from intensive agricultural land use may decrease infectious diseases, improve air and water quality, increase carbon sequestration, increase forests, and preserve habitats and biodiversity (Foley et al. 2005). Furthermore, a shift away from intensive agricultural land use, such as monocultures, may be beneficial for local and global environments as intensive agricultural use is responsible for a wide range of negative impacts (Tilman 1999).

While the impacts of large scale farming is well research and mostly understood to be environmentally and socially detrimental, little research has been done on the impacts of small scale farming practices. However, one study indicates that there is a positive and statistically significant relationship between small farms and sustainable impacts (Tavernier and Tolomeo 2008). Additionally, Sarris et al. (1999) suggests that small-scale farming has major yet unexploited economic and production potential for local populations. The shift in agricultural

land use within Volyn from 211 to 242 may have wide reaching positive impacts for the people and the environment.
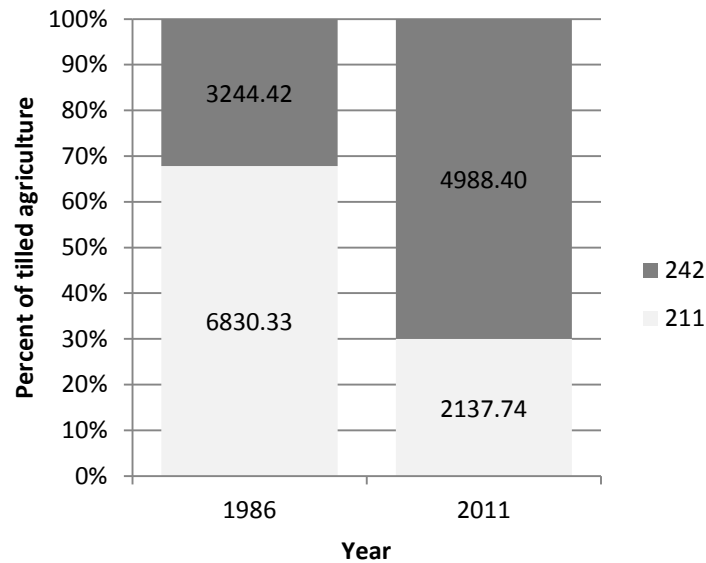

Figure 5.2 Tilled agriculture restructuring, Volyn, 1986-2011.

5.1.3 Agricultural Habitat Fragmentation

Agricultural fragmentation has been shown to be high where state farms have dissolved and land was thus made available to the people (Kuemmerle et al. 2006). Agricultural land abandonment has, in turn, resulted in fragmentation of the agricultural landscape, as active parcels become interspersed with abandoned ones (Kuemmerle et al. 2008). This undoubtedly affects species that rely on agricultural lands for habitat. For instance, *Mustela eversmanii* or steppe polecat, a species in decline in Europe, has adopted agricultural habitats consisting of mosaic grassland and small fields (Salek et al. 2013). Understand landscape metrics and structures can aid in prioritizing research, provide baselines, and promote intervention allowing for more effective landscape management (Mairota et al. 2013)

When examining the fragmentation statistics it becomes apparent that agricultural habitats have changed (see table 4.5). First the percentage of landscape that agriculture habitats occupy has decreased from 50.4% to 35.7%. This drastic decrease contributes to a large increase from 15.4% to 24.8% in grassland habitats, which were in the agricultural class in the CORINE level 3 classifications. The number of agricultural habitat patches has increased from 11,927 to 15,225, the largest patch index has decreased from 3.6 to 1.8 km², and the mean patch size has

decreased from 8.5 to 4.7 km². Figure 5.3 shows that the number patches less than 1 hectare (approximately 10 Landsat pixels) has tripled. The increase in number of patches, decrease in largest patch index, decrease in mean patch size, and large increase in number of patches under 1 hectare suggest increased fragmentation in agricultural habitats.

My findings fit well with a few studies in Eastern Europe that have analyzed fragmentation. Kuemmerle et al. (2006) suggests that agricultural fragmentation was highest where private land ownership was allowed during socialist times (Poland) and where state farms were dissolved and land was made available to the people (Ukraine). The study also suggests that before the fall of the Soviet Union, Ukraine agricultural structure was similar to Slovakia in that there were large fields, and today it is transitioning to a fragmented agricultural landscape, similar to the findings within my study.

While patterns of agriculture fragmentation after the fall of the Soviet Union are recognized in academic literature, drivers are sparsely explained. The high degrees of arable landscape fragmentation may be a result of a shift towards subsistence farming and increases in agricultural land abandonment, in the post-Soviet era (Kuemmerle et al. 2006). Although there is no clear answer from the literature, it appears that as farmland was abandoned it converted to grassland, which divided and isolated agricultural habitat patches. Therefore increased agricultural fragmentation is likely a result of farmland abandonment.
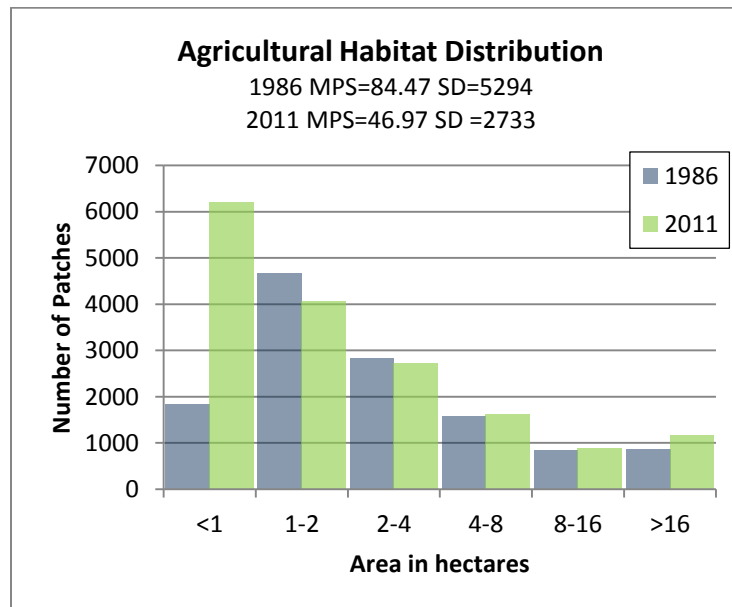

Figure 5.3 Distribution of agricultural patches based on area, Volyn, 1986-2011.

It is relevant to talk about landscape level changes when examining the agricultural habitat as this habitat composed over half of the Volyn landmass in the 1986 image. The landscape has seen an increase in the number of patches from 48,437 to 74,826 and a decrease in mean patch size from 41.27 to 26.71 ha². The Contagion index, which ranges from 0 to 100, decreased from 59.2 to 54.6 which is an indication of a disaggregation tendency and also a sign that the whole landscape has become more complicated and fragmented (Yu and Ng 2006). At the surface, these statistics suggest that the landscape has become more fragmented, however I suggest they represent a more heterogeneous landscape with high diversity. This statement is backed by the fact that the mean nearest neighbor distance has decreased from 253 to 216 and Shannons diversity index has increased from 1.19 to 1.32. The decrease in mean nearest neighbor distance suggests a less isolated landscape (Li et al. 2004) and the increase in Shannon's Index suggests a more equally distributed landscape (Figure 5.4) (Yu and NG 2006). Although the statistics at the landscape level are likely skewed due to many small patches in the agricultural and grassland, the agricultural dominated landscape transitioned to a more equally distributed landscape of agriculture, grassland, and forested habitats. A more heterogeneous landscape is a good goal of conservation policies (Fahrig 2001) as it may haves positive implications for species and landscapes (Gustafson and Gardner 1996).

While landscape indices provide a quantifiable means for understanding and comparison of spatial processes, they are not without limitation. In a study using a simulated binary landscape, Remmel and Csillag (2003) showed how very different landscapes can produce the same landscape pattern indicies. Furthermore, the statistical distribution properties of landscape metrics are not well known, meaning that expected values and variances are not readily usable for statistical comparison (Hess and Bay 1997, and Remmel and Csillag 2003). In summary, while results may look significant, they may in fact be misleading.
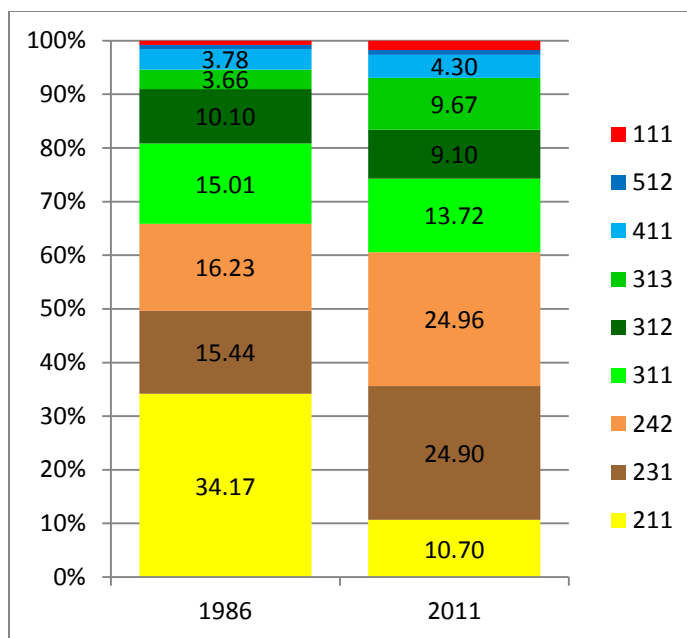
Figure 5.4 Distribution of landcover by class, Volyn, 1986-2011.

5.2 Forest Changes

5.2.1 Increase in Forest Land Cover

From 1986 to 2011, forests within Volyn have increased in areal extent. Forest show an expansion from 28.8% of the land cover in 1986 to 32.5% in 2011, which is an increase from about 5751 km² to roughly 6494 km². Approximately 1500 km² of land were gained in the forest class, while approximately 750 km² were lost in the time period studied (Figure 5.5). The most significant increases (~1285 km² or ~90%) came from the agricultural class. The largest decreases were changes from forest to agriculture representing 304 km². Far and away the largest gains in forest were specifically to deciduous forests with a gain of approximately 900 km². Coniferous and mixed forests both showed a gain on formerly unforested lands of about 300 km². Relative net change was calculated, as outlined by Baumann et al. (2012) to be 12% between 1986 and 2011.

Large increases in forests are likely a result of agricultural land abandonment, but this switch also could represent recovery from Soviet era practices of large scale clear cut logging. The largest increases in forest land cover came from the agricultural class, which fits well with the idea of land abandonment or forest regeneration from clear cut. Relative net change is slightly higher than previous research reviewed near Ukraine on forest change (Baumann et al. 2012, Kuemmerle et al. 2009). However, these studies were in areas where forest cover was

historically a much higher percentage of the landscape, and there was less agricultural land that could be abandoned.

In Soviet times, Ukrainian forests were overexploited (Kuemmerle et al. 2011) and heavily managed for timber production. After the collapse of the Soviet Union forests were largely unmanaged resulting in a period of forest decreases through the early 1990's (Kuemmerle et al. 2007). Additionally, it has been suggested that there was a period of slight expansion in the late 1990's through the early 2000's, and strong forest expansion through the first decade of the 21st century (Baumann et al. 2012, Kuemmerle et al. 2011). This fits well with what my study shows, as there is a relatively high rate of forest regrowth. It has also been suggested that abandoned farmland, which was widespread in this study, will ultimately revert back to forests in this ecosystem without anthropogenic effects (Rudel et al. 2005) so forest expansion was anticipated.

Gains in forest are not surprising as Ukraine has taken important steps towards sustainable forestry in recent years, and reporting and forest monitoring have improved significantly (Kuemmerle et al. 2009). Additionally, demand for forestry products has been thought to have decreased considerably in the Ukraine (Kuemmerle et al. 2007). Formerly state funded forest enterprises could not afford to modernize or buy new equipment (Turnock 2002). Observed increases in forests are likely due to improvement in management of existing forests, agricultural land abandonment leading to natural succession, and the relative expense of logging in general.
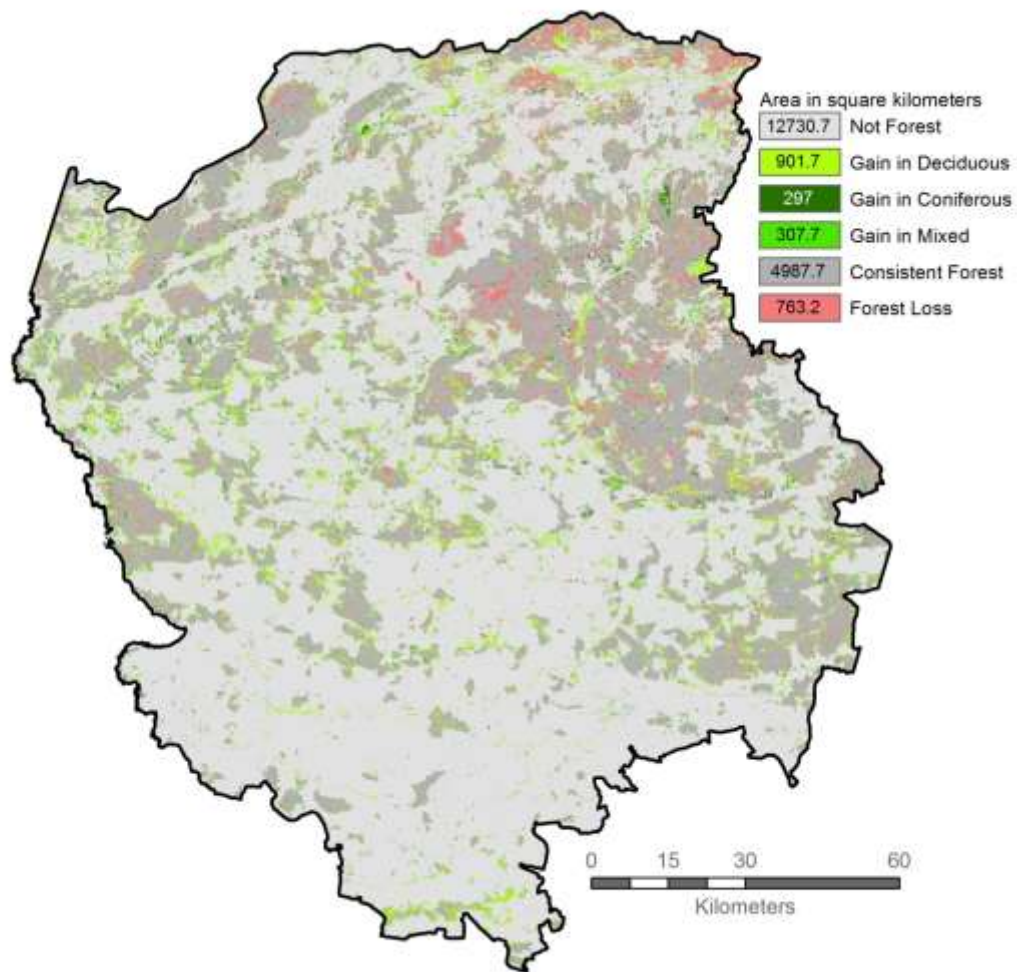
Figure 5.5 Map of forest changes in Volyn, 1986-2011.

5.2.2 Restructuring within Forests

Within class forests, there have been substantial changes within Volyn. In this study the most prevalent changes, within the forest class, were from deciduous and coniferous forests to a mixed forest structure. In 2011 the forest distribution was 42% deciduous, 28% coniferous, and 30% mixed, which is a large shift from 52% deciduous, 35% coniferous, and 13% mixed from the 1986 image (Figure 5.6). According to the transition matrix, mixed forests expanded from 731 km² to 1932 km², while pure deciduous and coniferous forests decreased by 250 km² and 200 km², respectably. A raise in mixed forests and slight decreases in coniferous and deciduous forests make sense in light of less strict forest management practices today, which may be

allowing the system to return to a more natural mixed forest structure. From the level 3 transition matrix, two of the top six transitions involve forest classes. The top four all involved agricultural changes but the 5th and 6th largest transitions were intra-specific changes, specifically, from deciduous forests to mixed forests (694 km²) and from coniferous forests to mixed forests (497 km²). In summary, forests have shifted from a pure coniferous and deciduous dominated landscape to a more evenly distribution between the three forests types, with the largest gains being in the mixed forests, and the largest decreases in coniferous forests.

Kuemmerle et al. (2006) suggests pure coniferous forests found in Ukraine do not occur naturally; rather they are due to anthropogenic and legacy effects of socialist forest management practices. In Ukraine, Soviet forest management resulted in widespread replacement of natural forest communities with coniferous forests (Kuemmerle et al. 2006). The collapse of the Soviet Union resulted in a return to semi-natural vegetation across large areas (Hostert et al. 2011). There are a few studies that show general or intra-categorical forest changes through time (Baumann et al. 2012, Kuemmerle et al. 2009). There are no studies, to my knowledge, that show intra-specific change through time within the forest category, in areas of Eastern Europe.
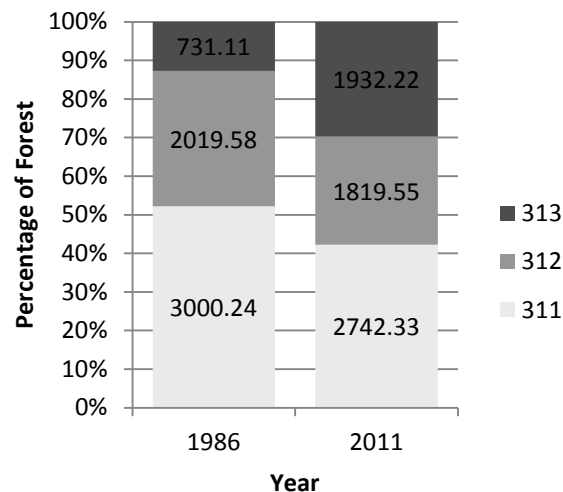

Figure 5.6 Forest restructuring within Volyn, 1986-2011. Each classes area is included in km²

While the forest does show noticeable restructuring, there are a few important points to remember when evaluating the classifications. I had very good training data for the 2011 image, and could confidently select training sites for the supervised classification. However, for the

52

1986 image, no such data was available, causing me to rely solely on expert knowledge of the study area and forest canopy reflectance values. Additionally, classification of mixed classes has been shown to be somewhat problematic because class boarders are drawn artificially (Foody 2002). I did find a band combination of band 5 from the summer image, and bands 4 and 1 from the winter images, which illuminated differences between the three forests types. Along with spectral profile analysis, and field work, the 5, 4, 1 combination was used for training in the classification of both images, allowing high accuracies to be achieved. Although there are important considerations and limitations with discerning deciduous, coniferous, and mixed forests in previous research, I am confident in this classification and the trends are too widespread to ignore.

5.2.3 Forest Habitat Fragmentation

Fragmentation statistics show widespread changes in current and formerly forested habitats. The class level fragmentation statistics calculated show that forest habitats have increased in area and thus, they make up a larger percentage of the land; In 1986 forest made up ~29% of the land and in 2011 they made up ~33% of the landscape. There is also a large jump in the number of patches from one period to the next from 5698 to 10326, and subsequently the mean patch size has decreased 100.93 to 63.22, which are associated with increased fragmentation (Li et al. 2004). It has been suggested that mean patch size is likely the most important indicator of fragmentation (McGarigal and Marks 1995), therefore I suggest fragmentation has increased

The statistics suggest increased fragmentation since the socialist period. One reason for this increased fragmentation may be changes in logging patterns. Today it appears that logging is done over relatively smaller tracts, which give forests a 'swiss cheese' or perforated pattern as shown in figure 5.7. Kuemmerle et al. (2006) suggests high forest fragmentation, within Ukraine, and attributed this trend to lack of management and presumed illegal forest harvesting (Turnock 2002). The perforated pattern observed may be due to this lack of management and illegal logging as well.

Another possible explanation for increased fragmentation may be forest regeneration. Abandonment of large tracts of agricultural land has allowed forests to regenerate, creating small isolated patches of forest throughout the landscape (figure 5.8). This pattern of young forest growth in apparently abandoned fields was commonly observed while conducting field work

within Volyn (figure 5.8f). Kuemmerle et al. (2006) suggests fragmentation may partially be caused by successional forests. Additionally, Hostert et al. (2011) acknowledges that forests have regrown on many former farm fields. These small isolated patches, a result of regeneration, have likely contributed to fragmentation of forests within Volyn.

While some research in areas under former Soviet influence suggests no change or defragmentation, previous research in Ukraine generally agrees with increased fragmentation. In Romania, forest cover and fragmentation were found to be stable between 1990 and 2005. Stability was due to forest institutions and policies that were in place in the transition period, which prevented large-scale logging (Kuemmerle et al. 2009). Ukraine did not have similar policies or stability in the transition period. Kuemmerle et al. (2007) suggests increased fragmentation after the socialist regime, likely due to ownership changes, worsening economic conditions, and weakening of governing institutions. Similarly, Kuemmerle et al. (2006) and Kuemmerle et al. (2009) suggest fragmentation within Ukraine may be high, but they do not quantifiably analyze fragmentation through time. In summary, the combination of current forest harvesting practices and regeneration on formerly agricultural habitats are likely causes of the forest fragmentation observed. The trends observed are important as fragmentation of forests have been found to have profound impacts on ecosystems (Boentje and Blinnikov 2007).

Figure 5.7 (a) **2011 imagery (b) map of forested (green) and not forested (grey) area for 2011 (c) indication of where frames a, b, c, d are located (d) 1986 imagery (e) map of forested(green) and not forested(grey) area for 1986 (f) image taken illustrating selective harvesting patterns which may be contributing to increased fragmentation.**
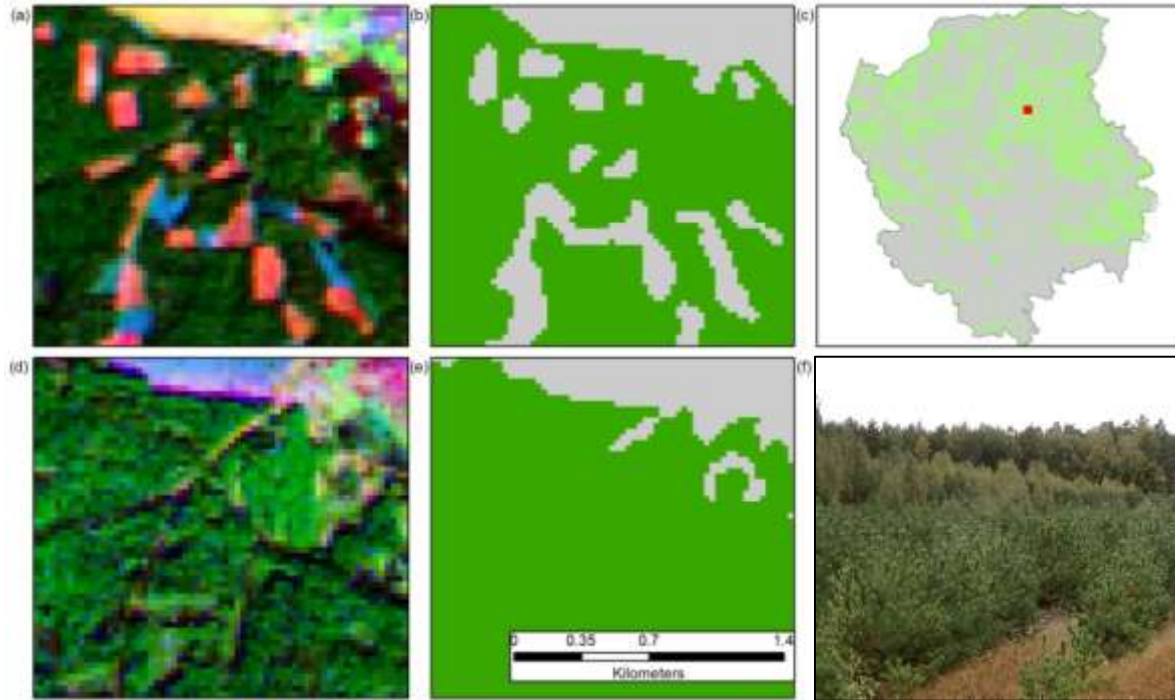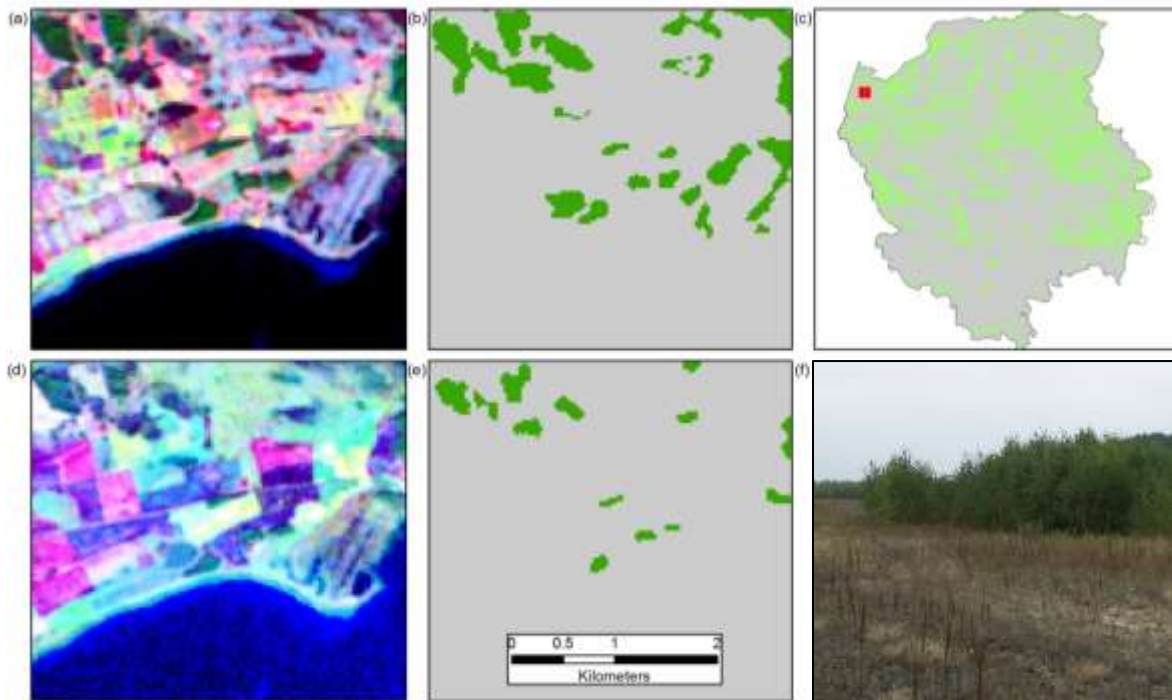
Figure 5.8 (a) 2011 imagery (b) map of forested (green) and not forested (grey) area for 2011 (c) indication of where frames a, b, c, d are located (d) 2986 imagery (e) map of forested(green) and not forested(grey) area for 1986 (f) image taken illustrating regrowth of young forest on abandoned lands.

Chapter 6 - Conclusion

This research quantifies how the Volyn landscape changed or restructured in the last 20 years following a change in political systems. In the agricultural classes we see decreases in agricultural lands, a shift towards smaller field structures, and increased fragmentation in agricultural habitats. In forests, I observed increases in areas, shifts in composition towards a mixed structure, and an increase in fragmentation. Five of the six hypotheses proposed were supported (see section 1.7 for list of hypotheses).

Hypothesis 1a is supported by the net abandonment rate of 25% calculated as a result of classification and post-classification change detection. Hypothesis 1b is supported by both the result of the segmentation that revealed that the size of fields had more than halved. Additionally, classification and post-classification change detection revealed that class 242, small complex fields contributed to 70% of actively tilled agricultural land use, a shift from 30% in 1986. Hypothesis 1c was also supported by the fragmentation statistics that show increased fragmentation over the two years studied. Additionally, most of the land lost by actively tilled agricultural classes (~3000 of 4000 km²) is now pasture, or grassland habitats. This shift or abandonment has resulted in large increases in small patches of agricultural habitats, thus, increased fragmentation.

 It is widely agreed that agricultural changes are a result of post-Soviet institutional changes and economic shock (Kuemmerle et al 2008, Bauman et al. 2011, Prishchepov et al. 2012). Land was abandoned as profitability of agriculture decreased, the agricultural sector restructured, and societal changes occurred in Eastern Europe's landscape (Kuemmerle et al. 2008) all of which lead to agricultural land decreases. Much arable land was also subdivided for subsistence farming (Kuemmerle et al. 2006) thus a shift towards smaller field sizes. Land abandonment and the observed shift in the farming landscape patterns undoubtedly contributed to increased agricultural habitat fragmentation, and an increase in grassland habitats. Finally, there was an observed shift from agricultural dominated habitat structure, to a more even distribution of habitat types.

Hypothesis 2a is supported by the Level 1 transition matrix which shows that most of the gains in forest cover (1,285 of 1500 km² or ~85%) were from agricultural land cover. The Level 3 transition matrix shows that about half of the gain observed, from agriculture to forest, was

from the class 231 or pasture category. Hypothesis 2b is supported by the evaluation of the Level 3 transition matrix, which shows that that the coniferous forest class has experienced the largest decrease, in terms of percentage of the landscape, of the three forest cover types. Finally, hypothesis 2c is not supported as the fragmentation statistics show an increase in fragmentation, as opposed to the decrease that was hypothesized.

The changes in forests are also widely accepted as results of economic changes in the post-socialist era. Farmland abandonment is thought to be the main driver for increases in forest (Kuemmerle et al. 2009, Baumann et al. 2012) and this study agrees. I believe shifts in forest composition are primarily due to a lack of current management relative to the socialist era. In the former Soviet Union, coniferous forests were desired as they grew quickly, and increased timber production. Today very little is done in the way of management relative to the Soviet era, and this has caused a shift away from pure coniferous forests, which are not natural in this region of the world, to a more mixed structure. Increases in forest fragmentation are likely also due to lack of management which allows local actors to log small pockets forest (Griffiths et al. 2012). Additionally, increases in small patches are observed, as agricultural lands revert to forest, likely increasing fragmentation. Kuemmerle et al. (2007) attributed increased fragmentation in southwestern Ukraine to ownership changes, worsening economic conditions, and weakening of institutions. These factors likely contributed to increased forest fragmentation in Volyn as well.

Understanding LULC changes is paramount to effective future landscape management. LULC information helps us understand the spatial distribution of land uses and land cover; with this knowledge proper strategies and policies can be developed and applied in various professions including land use planning, environmental monitoring, and disaster prevention (Choi and Han 2013). Change analysis has many applications for ecologists, conservation biologists, policy makers, protected area managers, conservation consultants and other experts (Nagendra et al. 2013). While land cover and change analysis data can be used to further knowledge and understanding of changes in the landscape, which are known to have impact on biodiversity, this analysis also allow for long-term planning for restoration of habitats (e.g., establishment of corridors, regeneration) and planning for protection from the adverse effects of climate change (Jones et al. 2009). Data derived from studies such as my research provide land managers and decision makers with spatial and temporal information on the extent and condition

58

of habitats, and knowledge as to how landscapes response to political change over time (Nagendra et al. 2013).

This research compares landscapes through time using remote sensing, GIS, and fragmentation analysis. For a more thorough understanding of changes, land cover was examined in three different ways including a general land cover classification (CORINE level 1), a more detailed land cover classification scheme (CORINE level 3) and a habitat classification (EUNIS). After analyzing the results it becomes obvious that the Volyn oblast has experienced drastic change over the last 25 years. However, it is important to acknowledge that this study only considered two specific points in time. Any change observed could be largely influenced by a high disturbance event just before image acquisition, which may largely affect results. I have no reason to believe that such an event has occurred, but it is an important consideration nonetheless.

Every land cover class has experienced a change in spatial extent or spatial distribution to some extent. With such drastic changes occurring in a relatively short period of time, coinciding with the collapse of the Soviet Union, I suggest the changes can be attributed to large-scale changes in socioeconomic and political regimes. No study to date has studied land cover change in Volyn specifically, to my knowledge. Additionally most studies in this region of the world focus specifically on land abandonment (Kuemmerle et al. 2008, Baumann et al 2011) or forest changes (Boentje and Blinnikov 2007, Kuemmerle et al. 2009) in the post-Soviet era. This study examines landscape change dynamics holistically giving a more complete view of how the landscape has changed and an idea as to how the overall ecosystem has changed.

The Global Terrestrial Observing System identified land cover as one of the five highest priority essential climate variables along with biomass, glacier and ice caps, soil moisture, and permafrost (Giri et al 2013). The fact that sustainability has become a primary objective in present-day ecosystem management has as one of its consequences the continuous need for accurate and up to date monitoring of land surfaces (Coppin et al. 2004). Remote sensing using a hybrid classification scheme and the post classification change detection technique utilized in this study proved to be effective and efficient means of understanding landcover and landscape changes. I would suggest that a hybrid approach, especially with multidate imagery, is beneficial in any study that requires highly accurate classification, such as post-classification change detection. The post classification technique utilized was valuable as it showed consistent changes

relative to other studies in the area, and opened more questions which may have significant implications for Volyn's landscape and habitats. For example, urban areas were shown to have expanded, and wetlands experienced changes in spatial distribution. Wetlands are known to provide a variety of ecosystem services, including groundwater recharge, flooding risk reduction and increased dry season flows, as well as possible benefits for biodiversity and human welfare in general (Bullock and Acreman 2003). To my knowledge these changes have not been adequately studied in Eastern Europe and may provide direction for future research.

This research quantifies how profound an impact a political regime changes can have on a landscape. The observed changes in Volyn, including widespread farmland abandonment and subsequent forest regrowth, may have important implications for the ecosystem. Decreases in agriculture and increases in forests have been shown to lead to increased soil stability (Tasser et al. 2003), improved water quality (Kramer et al., 1997), increase biodiversity (Baur et al. 2006, Bowen et al. 2007) and increased carbon sequestration (Post and Kwon 2000). Conversely, increases in fragmentation have been shown to have a number of negative effects on ecosystems. For example, increases in fragmentation have been linked to increases in infectious diseases, ultimately influencing human health (Allen et al. 2003).

The future of Ukraine is largely uncertain, and the trends observed may change rapidly again soon. If adequately supported by policy, positive effects could be realized. For example, forest expansion on former farmland could help mitigate climate change, benefit sustainable development and conserve biodiversity (Kuemmerle et al. 2011). Conversely, if agricultural land use intensifies on presently abandoned lands, a wide variety of negative impacts may result including loss of biodiversity, degradation of water and soil, and decreased carbon sequestration (Stoate et al. 2001). There are vast opportunities for conservation and implementation of effective land-use policies to guide future land cover and land use trajectories.

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