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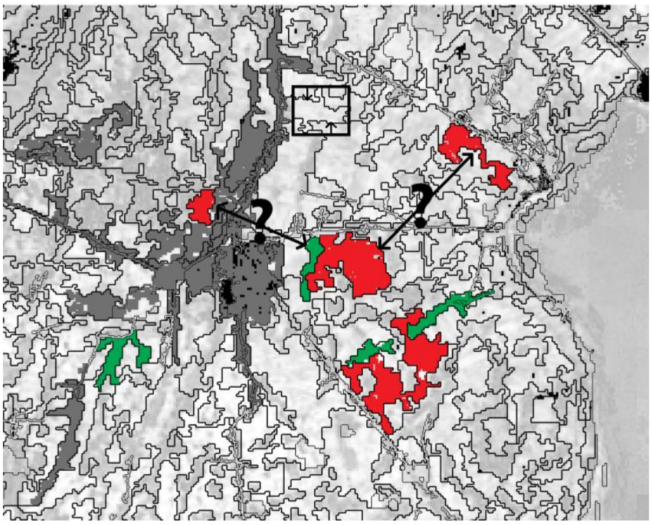
DETECTING SHIFTS IN AGRICULTURAL LANDSCAPE PATTERNS OF HAWASSA, ETHIOPIA

An Assessment of Land Cover Change Between 1984 – 2014 Using Object-Based Image Analysis and Landscape Metrics

Kristin Abraham



May 2015

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An assessment of land cover change between 1984-2014 using object-based image analysis and landscape metrics

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Abstract

South Ethiopian landscapes have undergone rapid and mostly uncontrolled landscape change in the last few decades with high social, economic and ecological impact. Changes in cropland composition are of particular interest to explain the link between landscape and potential natural pest control. We assessed landscape change in the Hawassa area in terms of land cover and land structure in the last three decades (1984, 1998, 2014) using Landsat TM and Landsat OLI/TIRS imagery. Eleven classes were assessed utilizing a hybrid approach of OBIA and pixel-based classification. Annual and perennial crops were separated using NDMI differencing, producing overall accuracies of 77 % (1984) and 75 % (2014). The results showed high dynamics and a clear shift in cropland cultivation towards perennial crops. Largest changes in the study area were seen in rising proportions of perennial crop and built up (+204 %, +616%) and decrease of annual crop, grassland and bare soil (-77 %, -82 %, -74 %). Natural land cover was thereby replaced by cropland. A large east-west difference was observed and substantiated by using landscape metrics Simpson Diversity, Contagion, Proximity Index, Number of patches and Edge density. Western areas showed least crop diversity in 1984 with strong dominance of annual crops. The introduction of perennial crops resulted in a shift of dominance towards mixed crop classes. Eastern areas were most diverse and fragmented in 1984, but showed trends in higher aggregation as perennial crop is strongly increasing towards 2014. Rising population pressure and cash cropping can be possible explanations of the observed change. The combination of OBIA and Landscape Ecology is promising, but requires a good data choice. Landsat data is not able to detect rapid small-scale changes of the Ethiopian landscape due to the relatively large pixel size compared to small field sizes. Thus, mixed crops were created to acknowledge the presence of mixed pixels. The use of OBIA was neither effective nor feasible for the purpose of cropland classification in our study. We suggest the use of VHR data to further assess the fragmentation of the landscape and other ecologically important landscape elements such as hedgerows and tree patches. The results of this study can help understanding impacts of landscape change on biodiversity and driving forces of pest incidence in the study area.

Keywords: Land Cover Change**,** Landscape Assessment, Object-based Image Analysis, Landscape Ecology, Perennial Cropland, Annual Cropland, Ethiopia

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List of Abbreviations

AOI	Area of Interest
DN	Digital Number
ESP	Estimation of Scale Parameter
LS	Landsat
LULC	Land Use/Land Cover
NBR	Normalized Burn Ratio
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
OBIA	Object Based Image Analysis
OLI	Operational Land Imager
ROI	Region of Interest
SWIR	Short Wave Infrared
NIR	Near Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
VHR	Very High Resolution

1 Introduction

1.1 Context and Background: Landscape change, population pressure and Ethiopian agriculture

The research of this thesis report is set in Hawassa, Ethiopia. The landscape is known to have changed rapidly and in a mostly uncontrolled way within the last three decades, which has large social, economic and ecological impacts. The goal of this study is to trace landscape changes in the Hawassa area. This shall help in linking observed agricultural practices and pest pressure to landscape composition and configuration. The recent landscape as well as the historic land cover and land structure will be assessed. Landscape is a very broad term and commonly used in many different disciplines. We will continuously use the terms landscape, land cover and land structure in this report. Therefore, we will start with clarifying how these terms are used before setting the scene.

Alexander von Humboldt defined “landscape” as one of the first as the “total character of a region” (Farina 2006). Green et al. (1996) describe it more precisely as “a particular configuration of topography, vegetation cover, land use and settlement pattern which delimits some coherence of natural and cultural processes and activities”. In the context of this study the latter definition shall be adopted. Land cover is commonly used to describe the physical appearance of the earth. Depending on the scale of interest a land cover type is formed as a class of objects with similar physical characteristics (Aplin 2004a).

Land or landscape structure takes into account the composition of the landscape as well as its configuration (Gustafson 1998). Pickett and Cadenasso (1995) begin their analysis of spatial heterogeneity by stating that “all landscapes are mosaics […] composed of discrete, bounded patches that are differentiated by biotic and abiotic structure or composition”. Therefore, the term structure takes into account patterns formed by various elements of the same or different land cover types (Forman & Godron 1986).

This thesis aims to connect observations in land cover, which is typically assessed with Remote Sensing, to land structure that is typically assessed with Landscape Ecology. Therefore, this thesis is also aiming to combine methods and perspectives of both disciplines.

Remote Sensing experts tend to see land cover as detached blocks of information. But land cover is in fact part of an ecological system, providing and connecting habitat of plants and animals. A relevant example of landscape change in the 21^{st} century is the simplification of landscape caused by the intensification of agriculture (Meehan et al. 2011). When fields become larger and the productivity of the crops higher, it often affects the existence of other plants that are habitat to certain species and ecological corridors that allow species to travel and exchange between habitats. In the particular scenario of observing insect pests in a landscape, the structure of the landscape can have implications for biocontrol services provided by natural enemies of insect pests. Decreasing landscape diversity is associated with increased pest pressure because of an absence or reduction of habitat for predator species in and around agricultural fields (pest habitat). Research has shown that diverse landscapes are necessary to remain biodiversity and sustain natural pest control (Brévault et al. 2014, Woltz et al. 2012, Meehan et al. 2011, Gardiner et al. 2009, Landis et al. 2008, Poveda et al. 2008, Bianchi et al. 2006, , Tscharnke et al. 2005).

Ethiopian landscapes have seen an extensive increase in farmlands with small scale agriculture, but uptake of space for natural vegetation on the contrary (Assefa & Berk 2014, Dessie and Kleman 2007, Sonneveld & Keyzer 2003, Shiferaw 2011).

Generally spoken, African agriculture is extensive and often characterized by low crop productivity (Nkamleu 2011). Lambin et al. (2003) report an increased food production through both agricultural intensification (better input, higher output) and extensification (increasing cropland sizes) in most African tropical states. A phenomenon that is also seen by Reid et al. (2000), who observed a dramatic increase of land cover conversion from grassland and forest to cropland and pasture. These observations are strongly connected to an ongoing global process: the growth of urban population that results in rapid land use change (Lambin et al. 2001).
Ethiopia is experiencing the effects of high population pressure on the landscape with population growth rates of 2.6 % per year (World Bank 2015). An increased population size not only means that less land is available to everyone; it also implies the use of less suitable land and a decline of privately owned field sizes. Land property is usually inherited and equally divided by the male descendants of the land owner (Sonneveld &Keyzer 2003, Grepperud 1996). As private field sizes are decreasing, many households can't live from selling food crops anymore. Therefore, they need to rethink their livelihood strategies and find other sources of income. A livelihood can roughly be described as all activities, capabilities and assets required to sustain a living (Rakodi 1999). Common strategies to improve livelihood under high population pressure are either to move to the city to find work or to diversify the income by carrying out more than one occupation or cultivating multiple kinds of crops (Barrett et al. 2001, Ellis 1999). It is common practice for households in rural Ethiopia to grow nutritious food crops on the one hand, but other non-food crops that reach high market prices on the other hand. Often these crops are referred to as cash crops (Poulton et al. 2001, Maxwell &Fernando 1989). Relevant examples for cash crops on the Ethiopian market are coffee (Rapsomanikis et al. 2001) or khat (Lemessa 2001). Common food crops are barley, wheat, maize, teff and sorghum (Benson et al. 2014). Especially with rising proportions of cash crops and increasing population size a higher performance of food crops is essential to sustain food security of the population.

Maize is a major crop in Ethiopia, with approx. 3.4 Mt supplied by domestic farmers in 2013 (Benson et al. 2014). However, despite increasing maize yields up to an average of 2.8 t/ha, they are still far below the global average of 5.5 t/ha (CSA 2013, Edgerton 2009 in: De Valença 2014). One of the key reasons for low maize productivity is the infestation by stem borers, a moth common in Africa whose larval stage is most harmful to the crop. Much research has been undertaken to explain stem borer control at field level. However, understanding the effects of agricultural land use needs a landscape perspective since pest population dynamics are likely to be affected at larger spatial scales (Dale et al. 2013, Tscharnke et al. 2005).

Therefore, WUR PhD-Candidate Yodit Kebede is investigating the influence of local management practices on stem borer incidence in the Hawassa area at the farm/landscape level. Her hypothesis is that complex landscapes, which contain a lower proportion of host plants (maize) for stem borers and provide shelter for their natural enemies, hold potential for sustainable suppression of this pest. Thus, it is hypothesised that pest pressure is inversely related to landscape diversity (Kebede 2013). Deffointaines et al. (1995) emphasise that agricultural landscapes can be better understood and modelled when landscape structure is the starting point of research. Identifying and understanding long term changes in the local landscape context of Hawassa is one of the very first steps to gain a deeper understanding of driving forces of pest incidence in the study area. This will help perceiving how farming systems can be intensified in a more sustainable way.

1.2 Problem definition

The landscape in the Hawassa area is known to have experienced dramatic changes throughout the last four decades (Wondrade et al. 2014). These might have been caused by a land reform in 1975 and a change in the political system in 1991. Other influencing factors are amended access to agricultural technologies since the 1990s and an increasing demand for cash crops and perennial food crops (Woyessa 2014). Wondrade et al. (2014) found that within the last four decades the study area has seen remarkable changes in the horizontal expansion of rain-fed agriculture replacing existing woody vegetation and grasslands. Causes have been found to be demographic factors, soaring prices of wooden products and urbanization. Indeed, Ethiopia is one of the most populous countries in Africa, experiencing rapid land-use/land-cover (LULC) dynamics from natural to agricultural and urban land use (Assefa & Berk 2014, Kindu et al. 2013).

Understanding the complexity of LULC change is an important step to sustainably manage natural resources (Wondrade et al. 2014). It is widely acknowledged that land cover and land use refer to different aspects. As stated before land cover describes the physical appearance of the earth which' components directly interact with electromagnetic radiation (Aplin 2004a). Land use on the other hand is a socioeconomic variable describing how humans utilize the earth's surface (Comber 2008, Jansen & Di Gregorio 2002). The interactions between land use and land cover are complex. Remote Sensing, as a single tool, is only able to determine land cover, which is therefore the focus of this study. We do not seek to make inferences on land use. This would be subject to on-site research, as for example carried out by WUR student Kassahun Lemi Woyessa (2014) who analysed trajectories of maize-based farming systems with participatory methods.

Although it is known that the landscape in the study area has changed in a rapid and mostly uncontrolled way, the extent and nature of change remain unknown. In particular changes in cropland composition are of interest, which have not been assessed until now as LULC studies in this area address agriculture as one class without further distinction (Kindu et al. 2013, Meshesha et al. 2012). Also the land cover analyses have not been linked to landscape patterns, yet. However, knowledge of landscape descriptors such as patch sizes and landscape fragmentation can give valuable hints on suitable pest and predator habitats. Insight in changing cropland composition can help to understand the impact of farming systems on pest pressure and natural pest control. Therefore, the change of land cover and structure shall be assessed quantitatively and qualitatively to help understand developments in this area. The results of the landscape change analysis will then be further used and discussed within the research of Kebede, who is seeking to understand the link between landscape composition and pest pressure (Kebede 2013). This connection has been studied before with varying results, of affirming landscape diversity to have a positive effect on natural biocontrol services but also stating that the formation of landscape elements such as forest and road verges play an important role (Schellhorn et al. 2014, Gardiner et al. 2009, Bianchi et al. 2008, Landis et al. 2008, Poveda et al. 2008, Bianchi et al. 2006). However, precise knowledge about the effects and importance of landscape on natural pest control is still missing (Tscharnke et al. 2005).

1.3 Research objectives and research questions

The main objective of this research is to understand landscape change dynamics in Hawassa, Ethiopia, within the last 30 years using object based image analysis of Landsat satellite data. Specific focus will lie on assessing the change of cropland cover, which will give insight into potential pest occurrence and spread in and between annual crops such as maize.

This will be approached with the following three research questions:

(i) *Which land cover types have undergone most change and in which period?*

(ii) *How does the cropland composition change and can this reflect changes in farmers' livelihood strategies?*

(iii) *How does land cover change affect landscape structure in terms of landscape configuration, diversity and annual to perennial crop distance?*

Second objective is the evaluation of the effectiveness of an object-based method, which is addressed in the following two research questions:

(iv) *How reliable are estimated change rates and trends based on the accuracies of the land cover classification?*

(v) *How well does an object-based classification approach perform to describe landscape change in the study area compared to pixel-based approaches?*

1.4 Outline

The following chapter gives a review, showing how landscape ecology and remote sensing can complement each other and presents the state of the art in object-based image classification.

Thereafter the study area will be introduced and the methodology will be explained in chapter 3. The methodology consists out of three parts: land cover classification, land cover change and land structure change. The results of each part will be presented in chapter 4. The discussion follows in chapter 5 and will aim to answer the research questions in consecutive order by reflecting on the results on the one hand and the methodology on the other. Chapter 6 provides a conclusion and gives recommendations for further research.

2 Literature Review

2.1 Linking Landscape Ecology and Remote Sensing

Land cover and structure are both variable. Their change can be monitored and examined by utilizing the principles of landscape ecology. As broad as the term 'landscape' itself, as ambiguous is the field of 'landscape ecology', which is claimed by various disciplines such as geography, biology, landscape architecture and environmental planning (Kirchhoff et al. 2012). Relevant for this study is the definition based on Forman's and Godron's (1986) topological ecology that explains landscape as mosaics, which are composed of spatial elements with characteristic patterns. The authors distinguish between three recurring elements: *patch*, a homogeneous area that differs from its surrounding and is habitat to a species; *matrix*, the concerning surrounding environment that has a different species composition; and *corridors*, which connect patches and therefore enable functional flows and movements through the landscape (Forman 1995). Landscape ecology is a suitable concept to consider and quantify landscape change and sustainability because it provides measurements to capture the essentials of an environment through patch mosaic, connectedness and heterogeneity (Dale et al. 2013, Deffontaines et al. 1995). Riitters et al. (1995) state that through rapid technological developments "the potential now exists to begin landscape monitoring and assessment by combining remote satellite imagery of landcover, geographic information system (GIS) technology, and recent advances in the science of landscape ecology."

Within this study we will combine the two research fields of Remote Sensing and Landscape Ecology. Remote Sensing provides repetitive spatially explicit measurements of the earth's surface regarding vegetation cover, biomass, vegetation community structure and landscape heterogeneity (Lambin et al. 2013). It is therefore able to highlight the spatial and temporal complexity of a landscape. The extent and rate of change can be determined with high certainty (Meshesha et al. 2014). The capabilities of air- and space-borne sensors to observe and monitor land change have improved over the past two decades by better spatial and temporal resolutions resulting in almost seamless global data of land cover (Turner et al. 2007). In addition, Remote Sensing is compared to other quantifitative methods, such as field studies, relatively inexpensive and able to give detailed insights while covering large areas (Kindu et al. 2013, Pettorelli et al. 2014, Wondrade et al. 2014).

Despite increasing interest in how both disciplines can complement each other, "the relationship between remote sensing and ecology is not particularly well-defined and is almost certainly under-exploited" (Gulinck et al. 2000 in: Aplin 2004b). A combination of both science domains holds the potential for understanding mechanisms determining current biodiversity patterns. Therefore, the integration of Remote Sensing and Landscape Ecology is clearly beneficial to both disciplines (Aplin 2005, Pettorelli et al. 2014). A few studies applied landscape pattern metrics on Remote Sensing based classifications in order to improve the classification result (Frohn 2006, Frohn & Hao 2006, Herold et al. 2002, Jiao et al. 2012). This is interesting, as those attempts are using texture and shape metrics which are very similar to methods now used by object-based classification approaches which will be explained later in this chapter. More often Remote Sensing has been applied in order to improve the understanding of ecological processes. The main fields of integration are hereby (1) identification of vegetation types and habitat through land cover classification, (2) ecosystem measurements as estimates of ecosystem function by deriving biophysical parameters, and (3) ecological monitoring through change detection (Aplin 2005). Although there is a clear interest amongst researchers to understand how Remote Sensing can

benefit biodiversity research, most research is often conducted within their own discipline, either Remote Sensing or Ecology, and is therefore not truly interdisciplinary (Pettorelli et al. 2014).
Another issue that complicates the combination of the two is the difference in scale practised by both research fields. Ecologists often deal with relatively small areas at resolutions of a few meters and temporal resolutions of days to years. Remote Sensing on the other hand is often utilized at landscape or global scales for years to decades. This circumstance is seen as added value within this study, as we seek to 're-built' trajectories of land cover change within the last 30 years covering not only field, but landscape scale.

Landscape patterns are caused by complex relationships between multiple factors such as climate, soils and physical relief. Especially the way in which humans interfere are key drivers to landscape patterns (Turner 2005).
The ecological extent for thesis is framed within the analysis of pest pressure in maize fields. When assessing locations of invasive species, mapping habitat fragmentation can be an important part of the research (MacLean & Congalton 2015). Quite frankly the occurrences of pest insects are determined by the existence of maize crops. The size, shape and configuration of fields is important in determining the habitat size of the pest and the probability of natural predator occurrence.
Fragmentation programs describe the state of landscape based upon LULC maps, which show landscapes of current and past state. Therefore land cover classes should be created to benefit a landscape analysis. Since the emergence of landscape ecology in the 1980s, many metrics to describe landscape were developed (Gustafson 1998). The qualification of spatial heterogeneity should aim to give insights on relationships between ecological processes and spatial patterns. Hence, Turner (2005) explicitly demands that spatial analysis should be used as a tool and not as a goal of its own. However, determining which types of metrics should be used to describe landscape diversity and fragmentation can be difficult (MacLean & Congalton 2015). A landscape cannot be adequately captured by using a single metric only. To avoid misclassifications multiple and each other complementing metrics should be used (Eiden et al. 2000, Turner 2005).

Landscape composition is quantified by the number of classes in a scene and the proportion of each class. Both aspects, also known as richness and evenness, are incorporated in diversity metrics such as Shannon or Simpson diversity. Configuration is assessed with patch-based metrics such as patch size, density or edge size; or with neighbourhood-based metrics describing relations between patches like the interspersion or juxtaposition index (Gustafson 1998).
O'Neill et al. (1988) presented a set of three metrics that were able to describe the most important dimensions of landscape. Those are *contagion*, which measures whether the landscape is clumped or aggregated; *fractal dimension*, which measures shape complexity of a patch and *dominance*, a measure to assess if a certain land cover type dominates the landscape. It is the complement of evenness. These metrics have thereafter been further developed and diversified (e.g. Baskent & Jordan 1995, Gustafson & Parker 1992, LaGro 1991, McGarigal & Marks 1995).

Various fragmentation programs for landscape assessment exist. The most commonly used software is Fragstats which was introduced by McGarigal and Marks in 1995 (MacLean & Congalton 2015, Turner 2005). It is providing capabilities to assess the landscape at patch, field and landscape level with numerous sets of metrics to choose from. In a comparison of five fragmentation softwares for identifying possible invasive plant species locations by MacLean and Congalton (2015) Fragstats created prediction maps with the highest accuracies.

Given the common use of Fragstats in the field of landscape ecology (e.g. Cushman et al. 2008, Tischendorf 2001, Terzioğlu 2010, Weng 2007) this program is a suitable choice for assessing landscape changes based on land cover maps created within our own research.

2.2 Change detection and object-based image classification

The quantification of LULC changes is one of today's major challenges. LULC change is known to affect a wide range of processes and cycles such as the global carbon cycle, local evapotranspiration, ecosystem goods and services, biodiversity and soil functionality (Haines-Young 2009, Lambin et al. 2013). Sala et al. (2000) argue that by 2100 the impact of LULC change on biodiversity is likely to be more significant than that of climate change, nitrogen deposition, species introductions and changing atmospheric concentrations of carbon dioxide. Hence, land cover change can have far reaching social, political and economic consequences (Meshesha et al. 2014). The topic of land change has been receiving so much attention from various research communities during the past years, that Turner et al. (2007) refer to 'land change science' as a "fundamental component of global environmental change and sustainability research". They proclaim an urgent need for an interdisciplinary effort to observe and monitor land changes and understand them in a coupled human-environment system.

Remote Sensing is able to monitor the earth over a long period of time and thus able to capture long term change because it holds the advantage of continuous and repetitive data acquisition. Various applications exist, such as monitoring of LULC change, forest and vegetation change, deforestation, wetland change or urbanization (Lu et al. 2004). There are multiple change detection techniques, many were summarized and reviewed (e.g. Jensen et al. 1997, Lu et al. 2004, Singh 1989, Tewkesbury et al. 2015). The choice of the optimal change detection technique depends on the purpose of research, but also on the unit of analysis, which can be pixel, kernel, image object or vector polygon for example (Tewkesbury et al. 2015). Change detection methods can be grouped into approaches using: algebra, transformation, classification, advanced models, GIS approaches, or visual analysis. Output of these analyses is in most cases a change map indicating magnitude and/or type of change. Within each group there are again multiple options for classification techniques of which only a few shall be named. An example for an algebra technique is image differencing, a subtraction of two subsequent images based on their pixel values. Transformation techniques are e.g. principal component analysis or tasselled cap. Classification based techniques use the thematic information of two classified images, e.g. in post-classification change, an overlay of two classification maps (Lu et al. 2004, Tewkesbury et al. 2015).
To quantify change in an adequate way Lu et al. (2014) recommend to take into account four things: area change and change rate, spatial distribution of change types, the change trajectory of land cover types and an accuracy assessment of the change detection results.

Because this report is dedicated not only to the department of Geo-Information and Remote Sensing, but also to the Farming System Ecology group, we will shortly summarize basic principles of Remote Sensing and introduce common terms, which will be used again later in this report.
There are various sensing and classification techniques. Optical Remote Sensing commonly measures reflected sunlight in wavelengths between 0.4 to 12 µm. Objects can be identified in the image due to the fact that every object has its very own characteristic of reflecting and absorbing light, it's fingerprint so to say. Radar Remote Sensing on the other hand uses a different approach of actively sending out energy of a known wavelength and measuring its return. In this thesis we will use optical Remote Sensing data.

Most classification approaches are pixel based (PBC), which means that the class membership is solely determined per pixel by means of spectral characteristics. For lower spatial resolution this holds the risk of misclassification because of ‘mixed pixels’. Those are pixels containing more than one object and therefore a mix of spectral information. In addition, some object classes have very similar fingerprints which can result in confusion between classes (Meshesha et al. 2012). Confusion is measured in accuracy assessments where the number of correctly classified pixels is counted and contrasted by the number of false positives (commission error) and false negatives (omission error) per class. Again, there are different techniques to perform pixel-based classifications. However, those shall not be further explained within this context. There are many studies on LULC change conducted in Ethiopia, especially in the Ethiopian highlands, utilizing PBC. Most of them stated the loss of natural vegetation like grassland and forests on advantage of cropland and residential areas (Bewket 2002, Dwivedi et al. 2005, Meshesha et al. 2012, Meshesha 2014, Rembold et al. 2000, Shiferaw 2011). The resulting accuracies of those classifications have been ranging between 67 to 87 %. These results are within a satisfying range, but they also show room for improvement.

Better results could be achieved by using a relatively new classification approach: object-based image analysis (OBIA). Other than PBC, OBIA performs first a clustering method to determine groups of pixels that belong together. After this segmentation step, the resulting objects are classified (Aplin 2011, Frohn et al. 2007, Baatz et al. 2008). The strength of this technique as compared to pixel based techniques is that it is able to combine spectral with spatial information of target features (Hay & Castilla 2006). This helps to determine object classes more accurately than when relying on spectral characteristics only. Frohn et al. (2007), for example, applied an object-oriented classification on Landsat 7 ETM+ data of wetlands in Florida. The produced overall accuracy was with 90.2 % more than 10 % higher than those of traditional PBC (78.4 %). In addition, OBIA has the advantage of providing image objects that are more likely to resemble landscape patches than pixels (Aplin 2011, Laliberte et al. 2004). Additionally object-based software packages use similar metrics to describe objects as landscape ecologists, e.g. size, border length, shape index or border index, which indicates fractal dimension. Also number of classes within a super-object or texture can be assessed, metrics similar to as those for landscape richness and configuration. This is why OBIA seems to be a good technique to represent ecological landscape components such as patch, matrix and corridors. Consequently, we hypothesise that it is also better suitable to identify patterns in landscape structure than PBC.

OBIA is mostly carried out for high or very high resolution (VHR) data, which provide spatial resolutions of few meters. It becomes difficult to classify VHR images with traditional pixel-based approaches, because the spectral variety between pixels is high which often results in an oversampling of the scene (Chen et al. 2011, Malinverni et al. 2011). Clustering pixels to objects as initial step provides a better basis for classification.
This technique is especially profitable in urban environments, where the level of geometry is high (e.g. O’Neil-Dunne et al. 2013, Owojori & Xie 2005, Potuckova et al. 2010). Shape parameters of objects like houses, streets or trees can be used for more accurate classification results that better resemble real world objects (Aplin 2011).

Little research has been carried out using OBIA in Ethiopia or comparable landscapes so far, but the results were promising. Kindu et al. (2013) performed OBIA to determine land cover change in the Ethiopian highlands based on Landsat and RapidEye data. Again, their results showed higher accuracies (85.7 – 93.2 %) than comparable studies using PBC. Wondrade et al. (2014) used a hybrid approach to map land cover changes in the Lake Hawassa Watershed, which comprises parts of the study area of this thesis. They partitioned the image based on visually homogeneous land cover types in a GIS environment and then classified the segments in Erdas Imagine by an unsupervised algorithm first, followed by a supervised classification to reduce spectral confusion. The overall accuracies of the produced LULC maps ranged from 82 to 85 %. OBIA can be performed with eCognition, a software environment enabling the user to perform the above mentioned steps in one process. However, the segmentation process is a black box, as the outcome cannot be perceived beforehand, which might be why the authors have chosen to use their own algorithm. But eCognition also holds the advantage of determining classes more accurately due to the use of other, non-spectral, features. Therefore, it is expected that an analysis of the study area using OBIA can be more effective than using PBC.

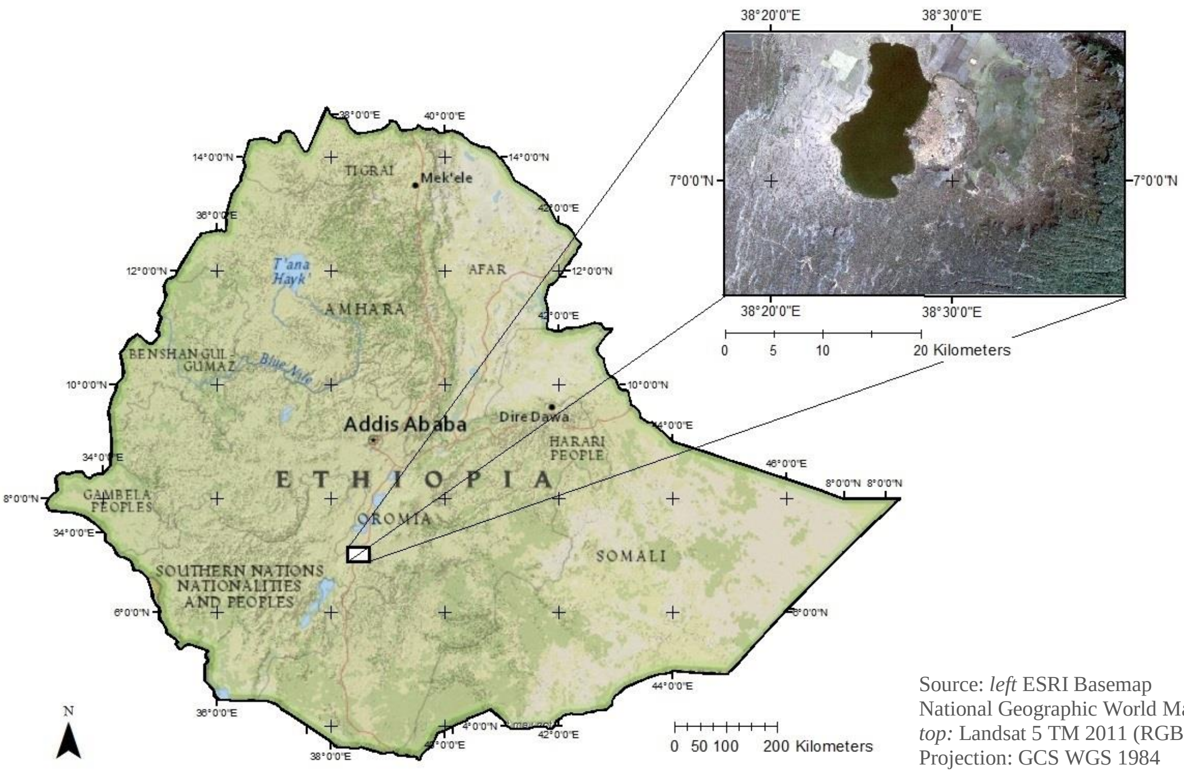
3 Methodology

3.1 Study Area

Figure 1 shows the study area, which is located in the region of Hawassa at the border of the provinces ‘Southern Nations, Nationalities and Peoples’(SNNPR) and ‘Oromia’, Ethiopia. The city is situated at the eponymous lake, which is part of the African eastern rift valley. Next to urban area and water, the area is mainly characterized by agricultural land use (Wondrade et al. 2014). The quality of soils is mostly poor, with arid and acid soil types such as xerosols, eutric nitosols and ferric acrisols dominant (FAO/UN). The area can further be distinguished by different levels of diversity (Kebede 2013). The spatial quantification of landscape diversity will be one of the objectives of this study.

The city of Hawassa was founded in 1959 and is the capital of SNNPR since 1995. Ever since its foundation a continuous population growth is seen. In 1978 the population size was estimated at 10.740, in 2006 it was 130.028 (Wolde et al. 2013).

The agricultural landscape in the region is a mosaic of annual crops, mainly maize, and perennial crops, mainly enset (false banana), coffee, khat and sugar cane (DeValenca 2014). Prior to 1991 especially maize, coffee and enset crops have been of importance (Woyessa 2014).



Source: *left* ESRI Basemap
National Geographic World Map
top: Landsat 5 TM 2011 (RGB 3-2-1)
Projection: GCS WGS 1984

Figure 1 Geographic location of the study area: Hawassa, Ethiopia.

3.2 Data

The classification is based on Landsat 8 OLI/TIRS, data for the year 2014 and Landsat 5 TM data for the years 1984 and 1998. All images are required by the USGS in L1T level, implying geometric correction. The Landsat series provides one of the longest continuous records of satellite-based observations, since the first satellite of this series was launched in 1972 (Chander et al. 2009). It is one of the most valuable data-sets for studying land cover change (Zhu & Woodcock 2012). Landsat TM and OLI sensors allow comparison of their imagery as the sensors have similar temporal, spectral and geometric resolutions (30 x 30 m). Only the radiometric resolution differs, as Landsat 5 has a radiometric resolution of 8 bit, Landsat 8 provides a 16 bit resolution.
The USGS also allows free download of processed Landsat data. As such, NDMI images of wet season and dry season state were acquired for each year of interest. Additionally cloud masks were downloaded to facilitate cloud masking of wet season imagery. Dry season images on the other hand were acquired in cloud-free condition.

For the purpose of scrub classification and for the exclusion of runoff in the classification process a SRTM elevation model was acquired, which offers a spatial resolution of 90 x 90 m.

Validation of classification map of 1984 is achieved by using topographic maps of 1979 and 1988 and aerial images of 1972. Aerial images have been geo-referenced with a basemap in ArcMap.
For the map of 2014 GPS ground truthing data was acquired in December 2014 and March 2015.

Table 1 Data characteristics

Purpose	**Data**	**Acquisition Date/ Source**	**Resolution/ scale**	**Used in *step***
Classification	Landsat 8 OLI/TIRS Path/raw	2014 USGS	30 m pixel, 15 m PAN	A2
	Landsat 5 TM Path/raw	1984, 1998 USGS	30 m pixel	A2
	NDMI	1984, 1998, 2014 USGS	30 m pixel	A3
	Cloud/Shadow Mask	1984, 1998 USGS	30 m pixel	A2
	SRTM Elevation	2000 USGS	90 m pixel	A2, A3
Validation	Aerial photo 133ET1 (51-54), 133 ET3 (8-10, 82-86), 133 ET4 (104-106)	Nov-Dec 1972 Ethiopian Mapping Agency	1:50000	A5.2
	Topographic maps ETH4 0638 A2 (Ed. 1 EMA/DOS 1979), ETH4 0638 B1 (Ed. 1 EMA 1988)	1979, 1988 Ethiopian Mapping Agency	1:50000	A5.2
	GPS Garmin eTrex	Nov 2014, March 2015 Manual acquisition Y. Kebede	Std. accuracy ± 3m	A5.1

3.3 Landscape Assessment

3.3.1 Methodological Overview

The study area is analysed on three moments in time: 1984, 1998 and 2014. The time span was chosen to represent the landscape before and after the political change in Ethiopia in 1991 by assessing three images of comparable time steps. The political break from a communist to democratic system is known to have had large effects on land distribution regulations and the economic situation (Holden &Yohannes 2002). Goal of this study is to assess both, land cover and landscape structure in order to understand change dynamics of the landscape. Therefore the methodology consists of three parts, which are visualized in Figure 2. The symbols at the bottom of the boxes indicate the software package that has been used for each step. Every box represents one processing step to which more detail will be given in the following sub-chapters. Rulesets and models mentioned in this chapter are fully presented in the Appendix and on the data DVD that is handed in with this thesis report.

Part A serves to assess the imagery of each time step by producing classified images. This part is the most extensive as it prepares the data for further re-use. However, the output of the classification itself is not yet meaningful. It will gain value as an input for change analysis in part B and C, which serve to analyse the change within the landscape regarding its cover and structure. Therefore, part B aims to answer research question i and ii, quantifying land cover and cropland changes, part C answers research question iii, assessing changes in landscape configuration. Research question iv, estimating the map reliability, will be answered in regard to the obtained classification accuracies of part A.

Research question v, the effectiveness of OBIA as a method, will be assessed after the landscape change analysis in the discussion chapter, by comparing the results to similar pixel-based studies and discussing part of the outcome of part B, as further described in section 3.3.9.

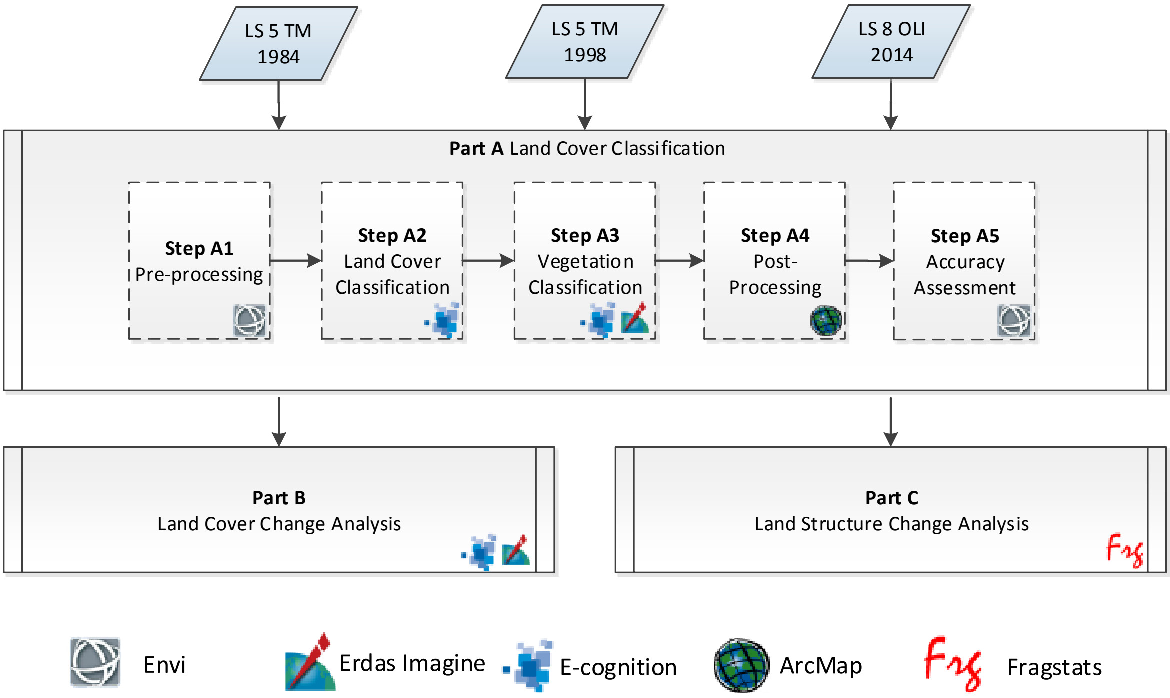


Figure 2 Landscape assessment in three main parts

3.3.2 Pre-processing (A1)

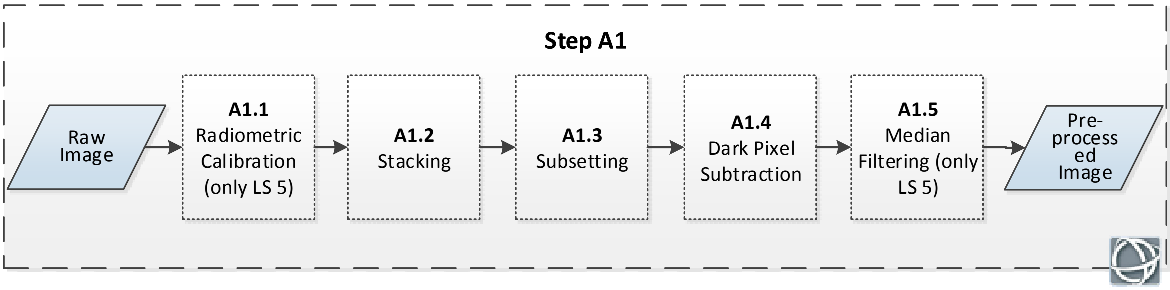


Figure 3 Pre-processing steps for Landsat 5 and 8 data

As described in chapter 3.2 Landsat data was acquired as a L1T product. The imagery has been terrain corrected by the USGS, providing a systematic radiometric accuracy and geometric accuracy by incorporating ground control points and a DEM (USGS 2013a).
To achieve a state of imagery that enables accurate classification and allows comparison between the results, a series of pre-processing steps is carried out, as presented in Figure 3.

As stated by USGS (2013d) Landsat data is not yet rescaled to Top of Atmosphere (TOA) radiance or reflectance. A rescaling removes variation between images due to sensor differences, different Earth-sun distances and solar zenith angles (Bruce & Hilbert 2006). Therefore, a recalculation to TOA radiance is carried out in step A1.1 utilizing the radiometric correction function of envi. This step has been missed out on with Landsat 8 data for a lack of knowledge. Only at a later stage of this research we realized that the data have not been radiometrically corrected yet. A later change of DN values to corrected DN values would have resulted in a change of all thresholds applied in step A2, which is why a calibration on Landsat 8 data has not been carried out subsequently. However, it has been done consistently for Landsat 5 TM data. Therefore, comparability of the results of 1984 and 1998, which both are based on Landsat 5 TM data, is guaranteed. Landsat 8 OLI provides a radiometric resolution of 16 bit. Thus, the radiometric comparability between the two sensors is limited and does not depend on rescaling to TOA. To keep the advantage of using the higher DN range of Landsat 8 data with 16 bit resolution, we decided to not rescale the data to reflectance but to radiance. This increases the contrast and allows better class separation for the year of 2014.

Following the radiometric correction the data is prepared by stacking all bands into one file (*A1.2*) and subsetting the acquired tile to the size of the research area (*A1.3*). Additionally, the scene is atmospherically corrected by using a dark object subtraction method (*A1.4*). As reference for a 'dark' area an area of interest (AOI) situated in the middle of Lake Awassa was chosen. This method is recommended by many researchers (e.g. Schroeder et al. 2006, Song et al. 2001) as well as by the USGS itself (USGS 2013b). It is an image-based technique that corrects for the additive scattering effect of the atmosphere (Chavez et al. 1996). Schroeder et al. (2006) recommend it for its simplicity and ability to produce a consistent common scale for image time series.

Landsat TM 5 data of both years, 1984 and 1998, was affected by impulse noise (IN). The term describes artefacts in the imagery which are generally seen as isolated coloured pixels that occur in random patterns. It is usually caused by digitizing the data from an earlier format (USGS 2013c). This corruption is consistent and incorrectable. The most prominent method to decrease the effect of IN is the application of a Median Filter (Geoffrine & Kumarasabapathy 2011). It is able to remove local peaks and brightness drops by replacing the value with the median value of its

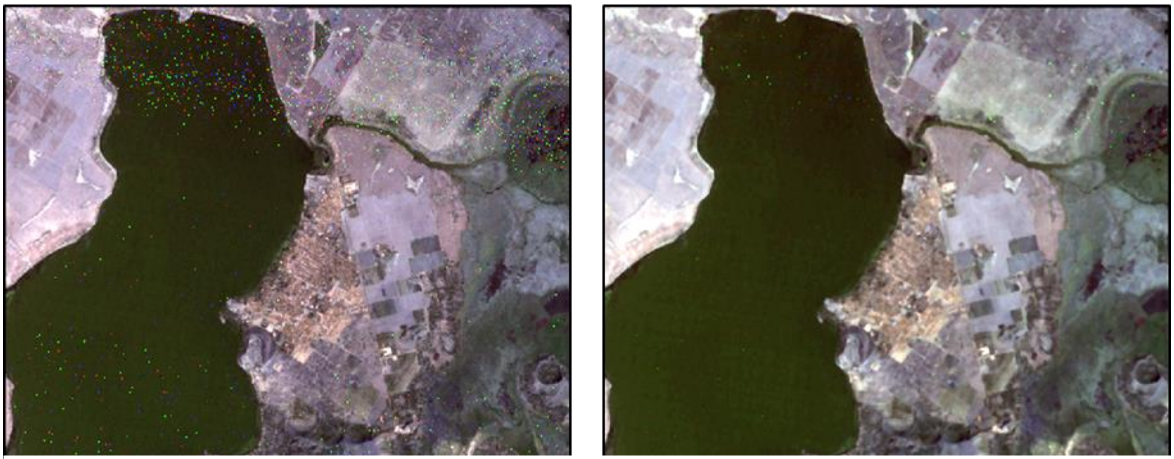


Figure 4 Effect of Impulse Noise on Landsat Scene before (*left*) and after median filtering (*right*)

neighbourhood without changing the overall appear of the image. Consequently, in *step A1.5* a Median Filter was applied to all Landsat TM 5 data with a window size of 3x3 pixels.
On the downside the filter is applied to all pixels, also those that are uncorrupted. Therefore, it should not be applied if discrete pixel values are of higher importance. This is stated because the effect of Impulse Noise is not only visible in the acquired raw data but also in NDMI images, which were also acquired directly from USGS and not calculated based on the filtered image. Because the filtering process affects all pixel values those images have not been filtered since discrete NDMI values will become relevant in *step A3*.

3.3.3 Object-based Land Cover Classification (A2)

The identification of land cover types is carried out in two steps (*A2* and *A3*). Step *A2* serves to create subsets of the landscape, create objects and carry out a classification of water, built up areas and vegetation. Step *A3* serves to identify specific types of vegetation and will be explained in more detail in the next sub-chapter. Figure 5 gives an overview of all classes that are created within the process. The class symbols have also been incorporated into the following methodological graphs to show when a class is created and further used.

The object-based classification is carried out using eCognition. It is an object-based software package that performs a clustering method first to determine groups of pixels that belong together (objects). After a segmentation step, the resulting objects are classified (Blaschke 2010). As described in chapter 2 the strength of this technique as compared to pixel based techniques is that it is able to combine spectral and spatial information of target features.
For *step A2* an image representing the dry season state or an in-between state is used as input. The reasoning for using a dry season image instead of a wet season image lies in the observation that in wet season the state of greenness is too high. As a result, a separation of sparsely vegetated and intensely vegetated areas which will become relevant in *step A2.1* is not feasible. Also it can be the case that smaller roads are less visible because they are partly covered by tree canopy.
The classification is carried out for each year of interest, starting with the most recent one going back in time. The year 2014 has been chosen as the starting point of analysis, because our knowledge about land cover is most accurate for this year. Additionally Landsat 8 provides higher contrast with a 16 bit resolution and a higher spatial resolution of 15 m for the panchromatic channel. This channel has been used for road classification in *step A2.3*.

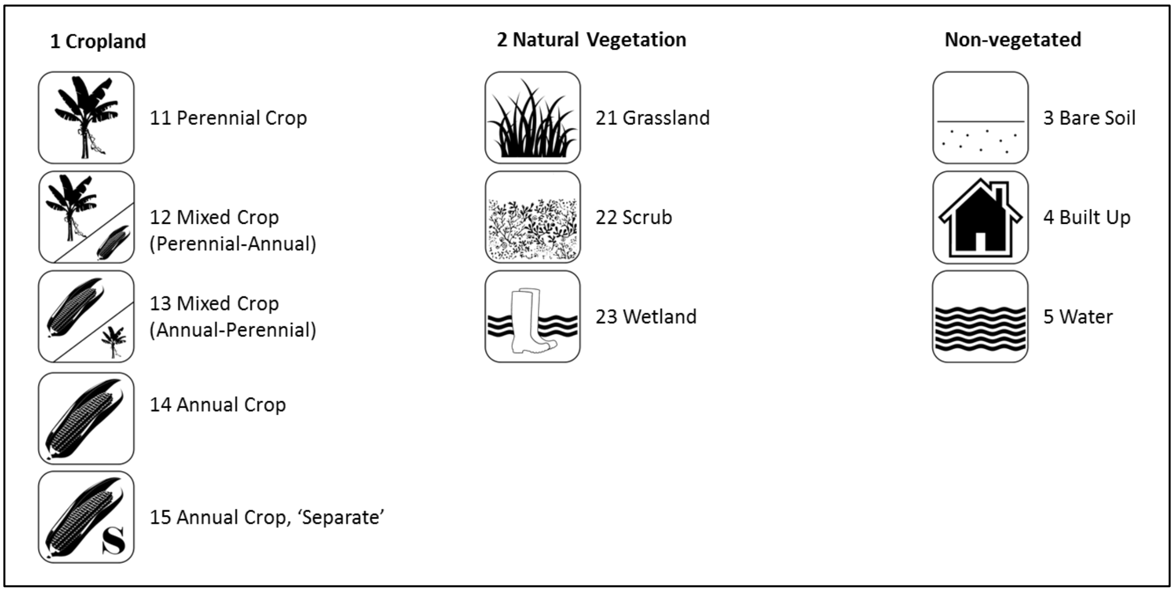


Figure 5 Typology for classes that are created within landscape assessment.
Class 15 is comparable to class 14, but based on different classification criteria.

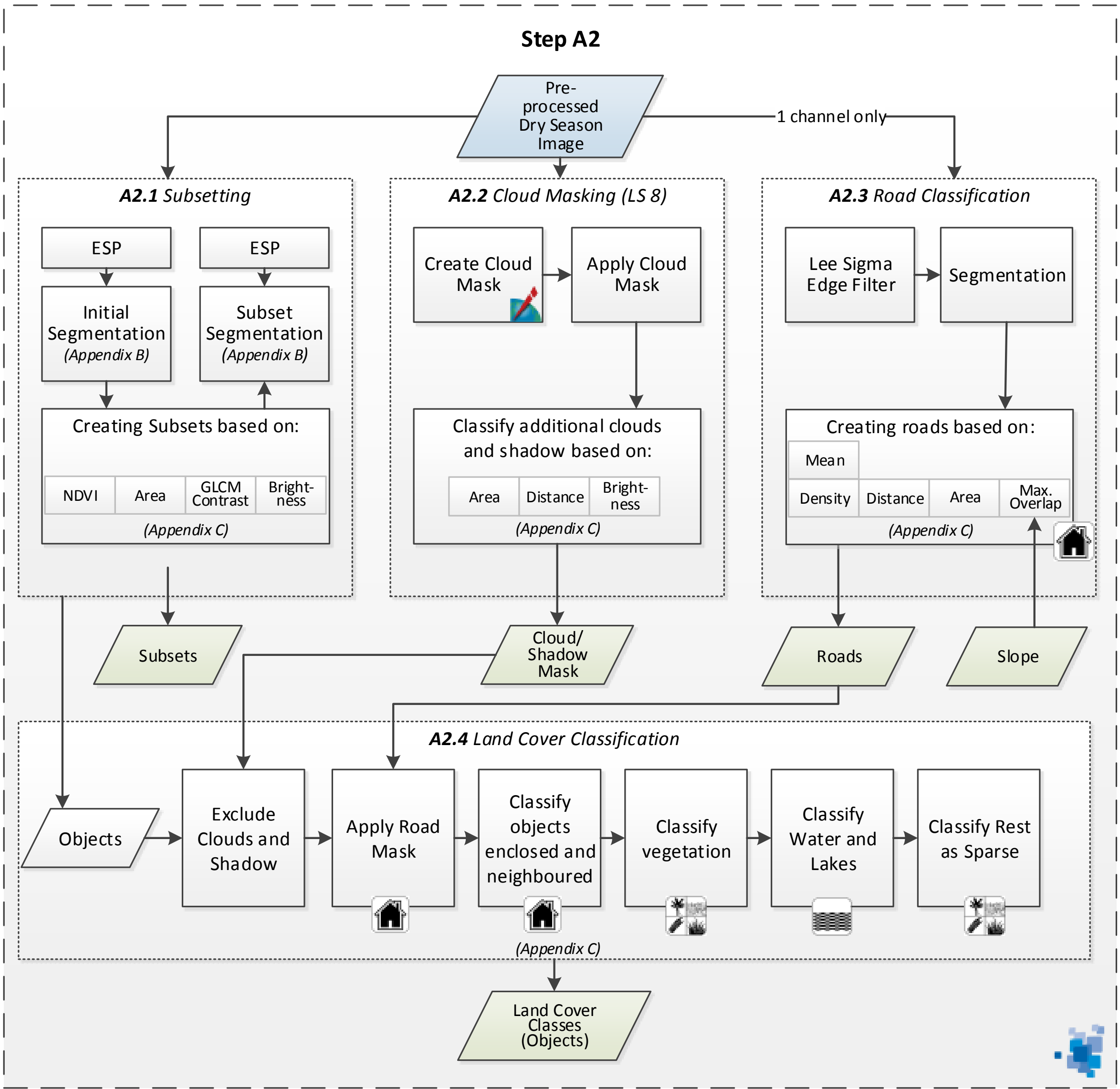


Figure 6 Object-based land cover classification

Figure 6 displays the sub-steps of the land cover classification. The colour of the input/output parallelograms refers to the data format. Blue indicates raster format, green indicates vector format, which is typically an output format of eCognition.

Pre-processed images of *step A1* serve as input for the land cover classification of *A2* and *A3*. The only difference is that as stated before, *step A2* uses one image of a dry season state only, whereas *step A3* uses multiple images of one year representing dry season and wet season state. Further explanation will be given within the description of step *A3.* A description on images used within both steps is presented in Table 2.

Before the actual classification is performed, two other projects have to be applied first, which deliver input datasets for the classification process. These are cloud and shadow masking (*A2.2*) and road classification (*A2.3*).
For *step A2.2* a cloud and shadow mask is produced which can be used to identify those during the classification process. For Landsat 5 TM data a cloud and shadow mask from the automatic cloud cover assessment (ACCA) by USGS is used as a thematic layer that is direct input for *step A2.4*. For Landsat 8 OLI the mask was produced by ourselves to increase the accuracy. The reason hereof is that the automatically derived cloud masks do not detect all, in particular small, clouds. A problem also observed by Zhu and Woodcock (2012), who significantly increased the accuracy of the ACCA by using brightness temperature and an object-based detection of cloud shadow. eCognition makes it especially easy to identify cloud shadows in approximation to their distance from clouds and relative darkness. In *step A2.2* a cloud mask is created using a threshold of DN below 23000 in thermal band 1 (LS 8 TIRS), which was enhanced in eCognition searching for high brightness values, and classifying large dark objects close to classified cloud objects as shadow. The produced classes are exported as vector dataset and inserted to the project of *A2.4* as described for Landsat 5 TM data before. The ruleset is available in Appendix C.

The identification of roads requires a different set of segmentation parameters than the creation of landscape objects, which are created in *step A2.1*. ECognition has strong restrictions on how to create levels of different sized objects that make it hard to apply more than one segmentation ruleset on one image without changing previously created objects. Therefore, *step A2.3* was performed in a separate project. It serves to identify roads which are usually long, but narrow objects.
The input for the road classification stays the same, with the difference that only one channel is used. For Landsat 8 this is the panchromatic channel, which provides the advantage of a higher spatial resolution of 15 m. For Landsat 5 a panchromatic channel is not available, instead the green channel was chosen because it provided more contrast between vegetation and non-vegetation than the red channel. Since many roads are gravel roads, they show high confusion with the bare soil class. That's why spectral information is not considered to give more knowledge on the road class, which is why one channel is enough as an input. In the first step of *A2.3* this channel is edge filtered by applying a Lee Sigma Filter of Sigma 30. This increases the contrast of roads to their environment, but also shows positive effects at the lake shore and the edges of the image itself. The Sigma filter smoothens image noise by averaging neighbourhood pixels, only preserving intensities within a fixed sigma probability of the Gaussian distribution. "Consequently, image edges are preserved, and subtle details and thin lines such as roads are retained" (Lee 1983).
Afterwards, objects are formed using a segmentation algorithm. The two different sensors showed different contrast in filtered images, which is why different segmentation algorithms were applied. The filtered channel based on Landsat 8 data showed more contrast and was segmented using a

multiresolution segmentation with a scale of 50 and shape and compactness values of 0.1 each. A multiresolution segmentation of filtered Landsat 5 data did not give the same result. Therefore, it was segmented using a contrast split algorithm with a tile size of 10. Roads are then identified as bright, long and narrow objects in the filtered image. Large and wide areas can instantly be excluded. Furthermore, the results are refined by connecting neighbouring road objects at their corners; searching for less bright, but long and narrow objects within close distance; and excluding lake shores, image edges and runoff using slope as an indicator. The referring ruleset is shown in Appendix C. The created road dataset is exported as vector layer and inserted as thematic layer into the project of *step A2.4*.

The segmentation of the image is the first and most crucial step of object-based image analysis as it will determine the following classification (Neubert & Herold 2008, Kavzoglu & Yildiz 2004, Wang et al. 2004). In *step A2.1* a multiresolution segmentation was applied. A problem within this step is that parameters determining object size are subjectively chosen, often with a trial-and-error method (Drăguţ et al. 2010, Kim et al. 2008). To facilitate a more objective decision on an appropriate segmentation scale the Estimation of Scale Parameter (ESP2) method developed by Drăguţ et al. (2014) was used. It is a new automated approach to test different scale parameters with fixed shape and compactness values on an image, producing graphs of local variance plotted against the rate of change. These can help to indicate appropriate scale. The programme also automatically recommends three scale levels to the user at the end of the procedure.

However, the outcome of the initial segmentation was not satisfying despite the use of ESP as it did not represent real world objects very well. This was caused by the fact that a segmentation of the whole image results in a compromise between all elements present in the scene. Therefore, objects are partly over-segmented whereas others are under-segmented. To avoid this undesirable effect the study area is further divided into subsets. We decided to create subsets internally, based on the image itself, instead of using secondary data such as Globcover, which was created in a different year and with a different spatial resolution. Internally created subsets showed a better resemblance of scene characteristics. Subsets shall indicate different landscape types containing objects of similar characteristics. Thus, subsets provide the advantage that objects can be formed within a smaller context. Therefore, segmentation parameters can differ per subset, allowing objects of different sizes and shapes to be present within the whole image.
The described procedure is visualised in *step A2.1.* An initial segmentation results in relatively large and fuzzy objects. These objects are classified and summarized to landscape classes by using area, texture, brightness and greenness thresholds. The output of this step is a dataset containing six subsets that represent water, homogenous green areas, sparsely vegetated areas, areas of intense agriculture, urban and marshland areas. Many studies recommend the use of a hierarchical classification, where multiple levels are used to reproduce differently sized objects such as forests and trees (Kavzoglu & Yildiz 2013, Kindu et al. 2013, Moskal & Jakubauskas 2013, Drăguţ et al. 2010). Yet, the approach of assembling multiple object sizes and shapes in one level is new.
Step A2.1 was carried out only for the first classification, which was the classification of the year 2014. Afterwards the subsets created for 2014 have been used as an input for all years to a second ESP analysis and segmentation. Consequently, segmentation parameters differ per year, but are applied in the same spatial context.

The actual classification is then performed in step *A2.4* where cloud objects and road objects are incorporated and classified. Water is classified as an area of negative NDVI. Additionally, objects of low NDVI with a relative border to water higher than 50 % and shallow water bodies are classified. Shallow waters are difficult to identify because they look very similar to soil in real-colour combination. To classify those we used a HUE parameter in SWIR-NIR-Red combination. In this combination shallow lakes appear as being azure blue. This is caused by a high amount of suspended sediment, which results in remotely sensed data peaks in green/red wavelengths of approx. 550-650 nm (Novo et al. 1991 and 1989 in: Liu et al. 2003). In contrast to soil, the amount of reflection in NIR and SWIR bands is low in shallow waters, which is why the layer combination is suitable to separate the two classes, as visualized in Figure 7.

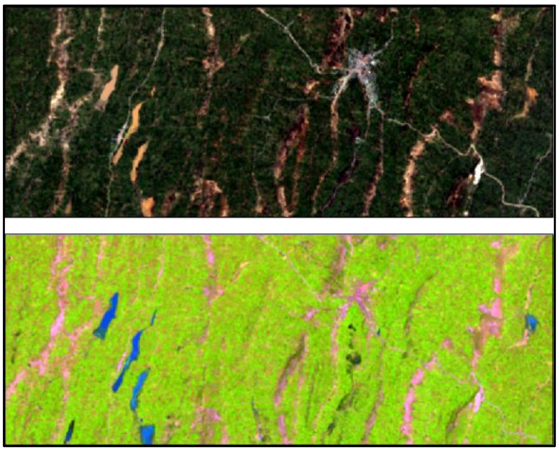


Figure 7 Identification of shallow waters using SWIR-NIR-Red Combination *(bottom)* compared to a real colour composite *(above)*

Urban areas are classified using inserted road objects. Objects fully enclosed by roads or with more than 5 neighbouring road objects have been classified as built up. This way highly agglomerated areas have been taken into account as ‘cities’. Vegetation is classified based on its greenness with a NDVI value above 0.35 (range -1 to 1). Other areas that do not fall under the criteria of the named classes were classified as sparsely vegetated objects that contribute to the vegetation mask as well. These objects hold higher potential of containing bare soil and annual cropland classes. The classification of 2014, which was carried out first, was more extensive than the following. It involved a creation of more object classes and usage of more object characteristics than described in the text. A diagram of the original classification is presented in Appendix C. A larger ruleset was motivated by the idea of classifying object change. However, during the process it became clear that objects were too big for cropland classification, which is why the methodology had to be changed. *Step A3* classifies at pixel level. Consequently, a larger ruleset was not needed any longer for the classification of the other images. Therefore, the rulesets for Landsat 5 TM classification were shortened to only classify water, built up, green vegetation and sparse vegetation as described. All classes have been created with a threshold-driven approach. This means that instead of creating samples and training a classification algorithm on selected sample objects, the objects are strictly classified by parameter descriptions. The reasoning for this decision is that ground truthing data are only available for the 2014 image not for previous years. Therefore, a sample-based approach would have resulted in a subjective selection of sample objects, strongly influenced by our own interpretation of the image. Samples for the previous years would have therefore solely been selected based on our own interpretation. Using a threshold-driven approach on the other hand holds the advantage that the same ruleset can be used with only minor changes for each year. Thresholds had to be changed for example, when applying the ruleset that was developed for Landsat 8 on Landsat 5 data, caused by the different radiometric resolution.
Outputs of this step are the land cover classes water, built up and a vegetation mask, which will be further used in the next step (*A3).*

3.3.4 Separate Vegetation Analysis (A3)

The vegetation mask from the previous step is further classified into vegetation types such as perennial and annual crop, grassland, scrub and non-vegetated areas of bare soil. An application of the vegetation mask excludes water and built up classes from the analysis of this step because they do not need to be further assessed.

Figure 8 Pixel Size compared to field sizes in west of study area *(above)* and east of study area *(bottom).* Image Coverage of Google Earth 19.12.2014 and 17.01.2014, respectively.

A problem occurring with Landsat data in this research area is that the provided spatial resolution of 30 x 30 m is often slightly larger or just as large as local field sizes. This is especially the case in agricultural areas in the south and east of the study area where fields typically range between 20 to 30 m. Figure 8 shows field sizes in relation to the pixel size of Landsat data. It can be seen that fields in the west of the study area are usually longer, typically in ranges of 100 to 200 m length, but still narrow, with widths of approx. 30 to 40 m. In conclusion, fields can only be classified at sub-pixel level. For this reason objects previously created cannot be used during this step, as they are simply too large to represent fields. However, the assessment of cropland types is of high importance to give insights in landscape development. The presence or absence of crop types such as maize might give valuable knowledge on the presence and possible movements of pests, e.g. stem borers. The spectral and spatial resolution of Landsat data is not suitable to detect specific crop types. By using a time series, however, we are able to distinguish annual and perennial crop types. Annual crops in the study area are mainly maize. Earlier also grains such as barley and wheat have been cultivated. Perennial crops on the other hand are often enset, khat and sugar cane (De Valenca 2014, Woyessa 2014).

The idea of the cropland classification is to assess the change in greenness of each pixel within a year. Annual cropland classes are vegetated during wet season but bare after harvest. Therefore, a change in greenness will be visible when comparing wet season to dry season state.
Perennial crops on the other hand are green throughout the whole year and thus show hardly any change in greenness. Phenology based classification of vegetation is widely used to separate different vegetation types based on their temporal growing characteristics (Wang et al. 2011). A suitable measure for greenness is a vegetation index. Multiple indexes have been assessed, including NDVI, NDMI, NBR and tasselled cap. We found the NDMI most useful because it does not saturate as easily as NDVI (Wilson & Sader 2002). Therefore, especially in wet season it distinguishes better between vegetation types. In contrast to NDVI NDMI does not only use the NIR dimension of the electromagnetic spectrum to distinguish vegetation from non-vegetation but also information of SWIR, as seen in the formula below:

$$NDMI = \frac{\text{NIR (760−900 nm)−SWIR(1550−1750 nm)}}{\text{NIR+SWIR}}$$

This gives an indication on plant structure, leaf moisture and crop canopy physiological status (Ji et al., 2011). Hais et al. (2009) state that spectral indices based on NIR and SWIR are commonly used to assess forest disturbance caused by harvesting. Thus, NDMI seems to be a good solution to separate harvested from non-harvested fields. Tasseled Cap Wetness (TCW) also seemed to be a suitable indicator, as it uses almost the same band combination as NDMI, but based on a transformation of data to three dimensions (including wetness) (Wilson & Sader 2002, Crist et al.

1986). A paper by Jin and Sader (2005) showed that NDMI and TCW are highly correlated and detect forest disturbance with nearly equal accuracy. An additional advantage of NDMI is that processed images can be downloaded from USGS directly, whereas tasseled cap has to be calculated separately. Therefore, NDMI images have been acquired through USGS directly to avoid influences of our own pre-processing. Those images are based on a calibration to surface reflectance, so that they are assumed to be suitable for comparison between multiple years.

For cropland classification one NDMI image of dry season state and one of wet season state is required. However, if we want to apply the vegetation mask of *step A2* one pre-processed Landsat image should be included in the project as well. This does not need to be used during classification,

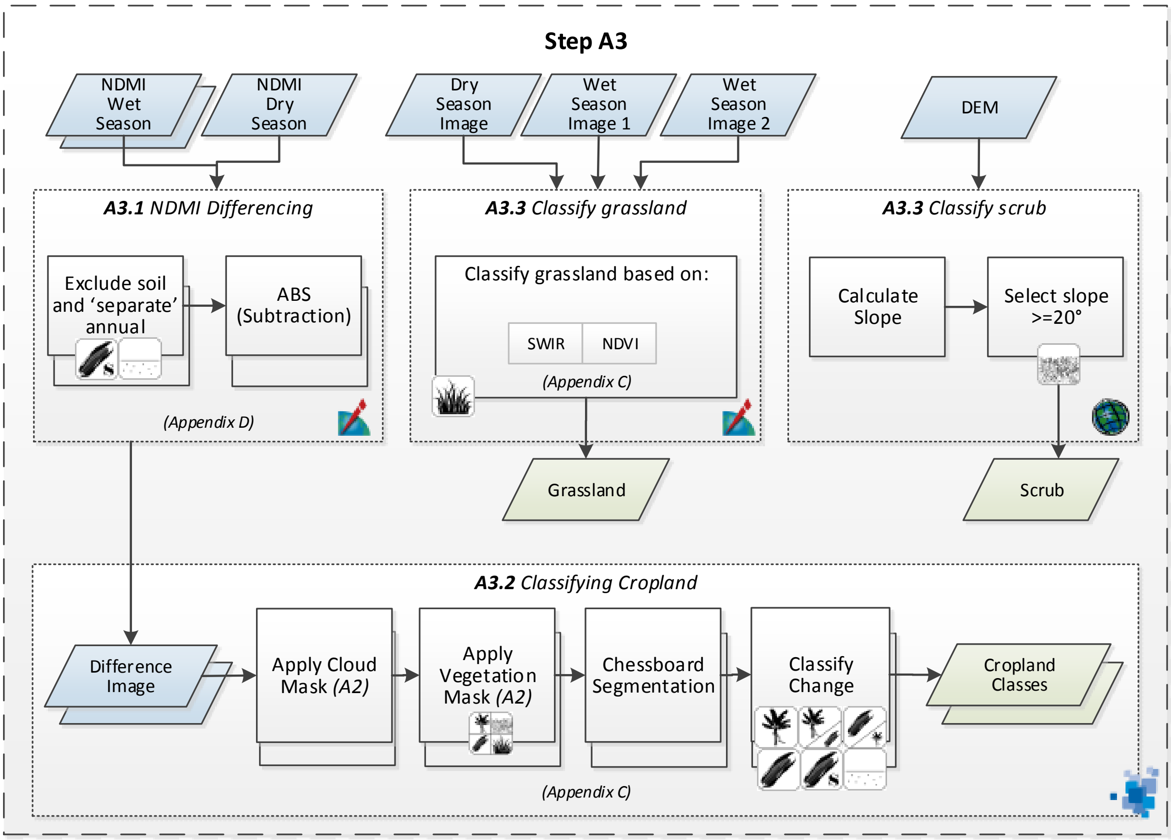


Figure 9 Identification of vegetation types

Table 2 Applied Image Datasets for Land Cover Classification

Classified year	Sensor	Acquisition Date	Layer used for road classification	Used in step
2014	LS 8 OLI/TIRS	17.10.2014	Layer 8 (Pan)	A2
	LS 8 OLI/TIRS	27.06.2014		A3-wet season
	LS 8 OLI/TIRS	30.08.2014		A3-additional
	LS 8 OLI/TIRS	04.12.2014		A3-dry season
1998	LS 5 TM	25.01.1999	Layer 2 (Green)	A2, A3-dry season
	LS 5 TM	15.06.1998		A3-wet season
	LS 5 TM	27.03.1998		A3-additional
1984	LS 5 TM	17.12.1984	Layer 2 (Green)	A2, A3-dry season
	LS 5 TM	27.08.1984		A3-wet season
	LS 5 TM	21.04.1984		A3-additional

but it is necessary to provide overlap with vegetation objects. The reason hereof is that the cell centre slightly shifts during the calculation of surface reflectance by the USGS. Thus, objects do not overlap 100 % with pixels of NDMI images, which makes a classification of objects harder.

Figure 9 presents the overall procedure of the vegetation analysis. In the first step (*A3.1*) a difference image is produced as the absolute of the subtraction of NDMI values of wet and dry season state. Small changes in greenness shall later be classified as perennial crop, large changes as annual crop. One limitation of this method is that areas of bare soil that are never vegetated throughout the whole year are also showing small change. Consequently, those areas would be misclassified as perennial crops. However, as these areas show no greenness they can be excluded from the subtraction because they do not exceed NDMI values of 0 (range -1 to 1) in both images. Regarding pixels are marked as -9999, which will be used as a classification criteria for bare soil in *step A3*.2.The difference image is then inserted to an eCognition project in *step A3.2* where pixels are classified according to change thresholds. This is achieved with a chessboard segmentation of tile size 1. Thus, each pixel gets treated as a separate object. A threshold for perennial classes (low change) was chosen according to ground truthing points of 2014. Perennial classes have been seen to not exceed a change in NDMI of more than 0.15 (range 0 to 1). Every pixel above this threshold is considered as annual crop. Many fields are smaller than the 30 x 30 m pixel size, which is why a pixel could potentially contain more than one cropland type. To acknowledge the presence of mixed pixels the annual crop class has been further divided. Thresholds for those mixed classes have been chosen subjectively and have not been assessed with field data. Therefore, they do not represent a certain percentage of crop type present in the pixel, but allow more interpretation on the annual cropland class. Pixels with changes larger than 0.5 are considered purely annual. Pixels with an intermediate change are represented by mixed classes. Thresholds for cropland classes are presented in Table 3. The whole procedure of *step A3.1* and *A3.2* is carried out again afterwards using a different wet season image. A repetition is necessary because no wet season image was available that was 100 % cloud free. Therefore, the results of the second difference image will be used to replace cloud covered areas of the first. The combination will be carried out during post-classification in *step A4.*

In addition the class ‘Annual, S’ has been created within the classification of the years 1984 and 1998, which is an exceptional class. It shows annual crop, but has a potential of showing confusion with bare soil and was therefore kept separate (‘s’).

The class is created based on a lowered threshold for bare soil, which has originally been a NDMI value of less than 0. An exception was created for the wet season image of 1998 and the additional wet season image of 1984. 1998 was a very dry year, with 52 mm rain in June being less than half compared to other years (111 mm in 1997 and 99 mm in 1999; National Meteorological Agency, 2010) causing a crop failure in the region (Quinlan et al. 2014). This results in less green and less dense vegetation, represented by lower NDMI values. To take this fact into account the bare soil threshold of the dry season image has been lowered to -0.3 to also consider pixels that contain a higher proportion of soil than during a usual vegetation period. If these pixels are showing values in the range of -0.3 to 0 during wet season and values below 0 during dry season they are marked as -1111, which will be classified as annual ‘s’ in *step A3.2*. Perennial classes would have regained greenness again in dry season. Therefore, the potential misclassification of this class is mainly with bare soil.

The additional image of 1984 showed a similar problem because it was acquired at the start of the vegetation period. Therefore, greenness was not as strong as during full growing season. The same threshold as before was used to create the separate annual class. Additionally, a minimum threshold of NDVI >= 0.2 is taken into account, to decrease the probability of misclassifying bare soil. Because NDMI is a measure for plant structure and leaf moisture it is less sensitive to detecting young plants. NDVI on the other hand is highly sensitive to any green element. Therefore, it is better suitable to detect plants at early growing stages (White et al. 2009). Models created in Erdas Image are presented in Appendix D.

The output of *step A3.2* are cropland classes of mixed and pure character and bare soil. However, the results indicated that other classes were still present in the image biasing the results. Grassland shows similar characteristics as annual crops, since they are greenest during wet season, but drying out later in the year. Scrub shows similarity with perennial classes because most bushes hold the same state of greenness throughout the whole year and thus show low change.
To avoid a contribution of these classes to the estimated cropland areas, they have been classified in additional projects and will be excluded from cropland areas in the following step (*A4)*.
Grassland is identified in *step A3.3* using a combination of SWIR and NDVI thresholds. Grassland has a different vegetation structure than other plants because it is dense but short. Therefore, the SWIR channel can be used. In combination with NDVI the greenness is taken into account as well, that has been seen to show values between 0.45 to 0.6.
Scrub is identified in *step A3.3.* This class did not show specific spectral or textual characteristics that enabled classification. Yet within the most recent year of 2014 scrub was present in uninhabited areas only. These areas on the other hand, due to the high population pressure, only occur in regions of high slope. Therefore, we instrumentalized slopes of higher than 20° as an indicator for scrub presence. The threshold was visually assessed with Google Earth (Figure 10).

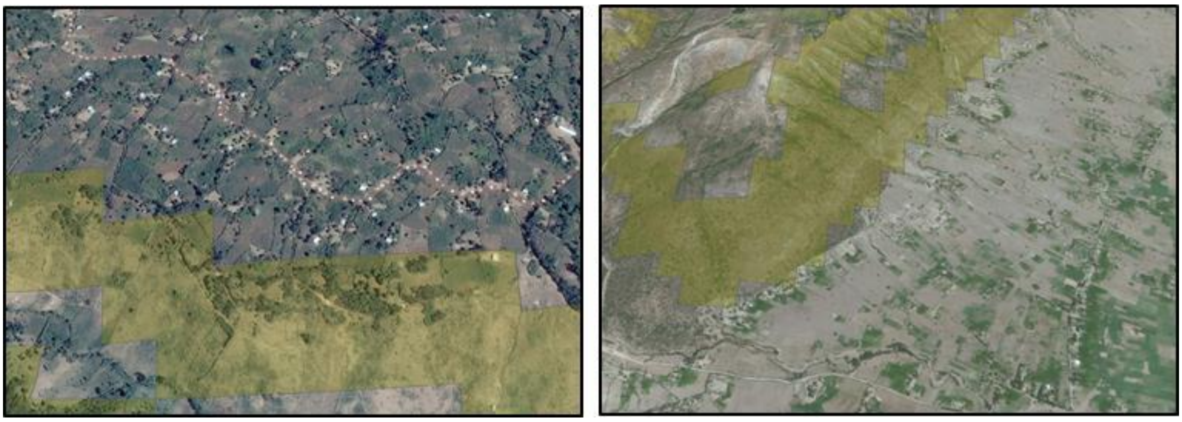


Figure 10 Scrub class at slopes greater than 20 ° (yellow) shown in Google Earth coverage

Table 3 Change Thresholds of NDMI between dry and wet season within a year for cropland classification

Class	Change Threshold	Other Threshold (Marker)
Perennial	< = 0.15	
Annual, of which:	> 0.15	
Perennial – Annual	> 0.15 <= 0.3	
Annual – Perennial	> 0.3 <= 0.5	
Annual	> 0.5	
Annual ‘Separate’	-	-1111
Bare Soil	-	-9999

3.3.5 Post-Classification (A4)

The output of eCognition is a vector dataset. When exporting an object with class properties the class is not inherited in the object itself but its membership to each class is saved with a value of 0 or 1 for every object. For further re-use with conventional Remote Sensing software a conversion to raster format is necessary. This conversion requires each pixel to contain one discrete class value only. Therefore, the output of *A2* and *A3* is post-processed in ArcMap, which is a suitable software environment for handling shapefiles. Four ArcMap models were created, which are represented as sub-steps in Figure 11 and applicable in Appendix E.

Objects of one class are selected by querying membership values of 1 for each class. Class names and numerical codes (see Figure 5) are assigned to objects of the same class. Also the area of a class is calculated.

In *step A4.1* this procedure is applied on cropland and bare soil classes of *A3*. This step is carried out twice because as described in the previous sub-chapter the vegetation classification had to be applied on two wet season images due to cloud cover. In this step, cloud covered area of the first wet season image is identified and replaced by objects of the additionally classified image. Classes of both images are merged and dissolved after the selection process.

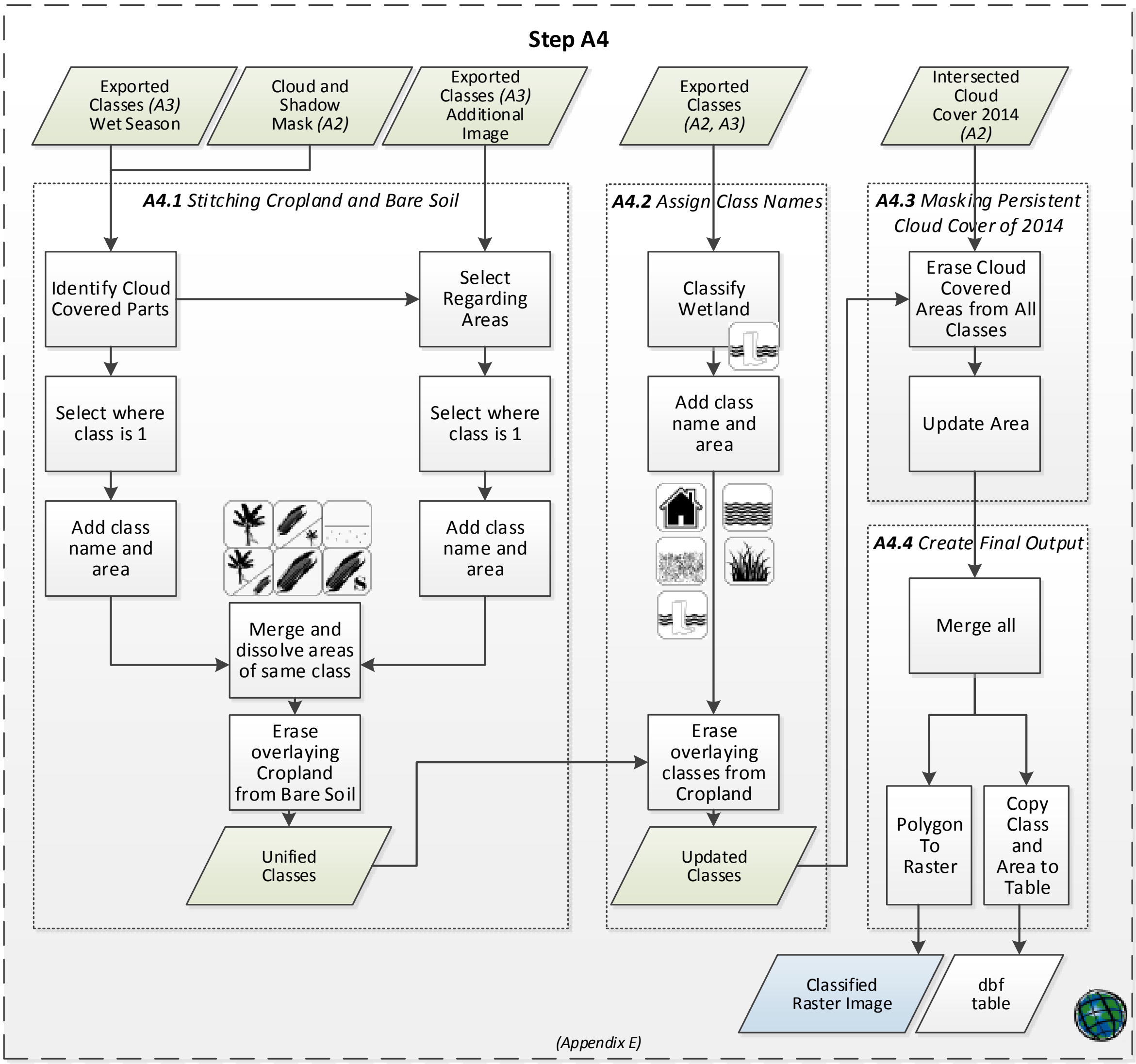


Figure 11 Post-classification

There is a possibility that bare soil has been classified in one of the images but not in the other. However, if it was vegetated in one of the two images it should be classified as cropland. Consequently, bare soil pixels are erased from the class if they overlap with cropland.

In *step A2.2* other classes, which were exported as separate classes, are dissolved, assigned class names, numerical code and area. Wetland is created as a class by querying a change in water coverage from 1984 to 1998 or 2014. Areas that have changed from water to a different class are therefore classified as wetland. In addition, cropland objects that overlap with other classes are erased from the cropland class. This is applicable for overlap with wetland, grassland and scrub because these have been created after cropland classification.

Step A4.3 involves an additional masking process where all objects within the cloud mask of persistent cloud cover are erased from their classes. This step is necessary as a result from the vegetation analysis (*A3*) of 2014. Both wet season images that were used in the process showed areas of persistent cloud cover. Therefore, not all covered areas could be filled in the first post-processing step (*A4.1*). To enable adequate comparison between the results of all three years regarding areas have been masked.
A different image (e.g. from April 2014) could have been used as additional wet season image, in order to avoid persistent cloud cover. However, this would have meant using an image representing the start of growing season, whereas now both images are in the peak of growing season (June and August). An earlier image of e.g. March or April would have resulted in the creation of a separate annual class again. As 2014 is the year where we have most knowledge on, we did not want to add the uncertainty associated with the annual 's' class.

Afterwards class areas are updated. As a last step all classes are merged in one dataset in *A4.4* and transformed to raster format with each cell holding a numerical class code. Additionally a table is created that holds information on each class and is easily accessible with Microsoft Excel to read out the results.

3.3.6 Accuracy Assessment (A5)

The accuracy of the images is checked at the start (1984) and the end (2014) of the time series.
For the imagery of 1998 no reference dataset was available. Thus, the error of 1998 cannot be assessed.

Figure 12 visualises the validation process, which is carried out as a last step in the land cover classification of block A.

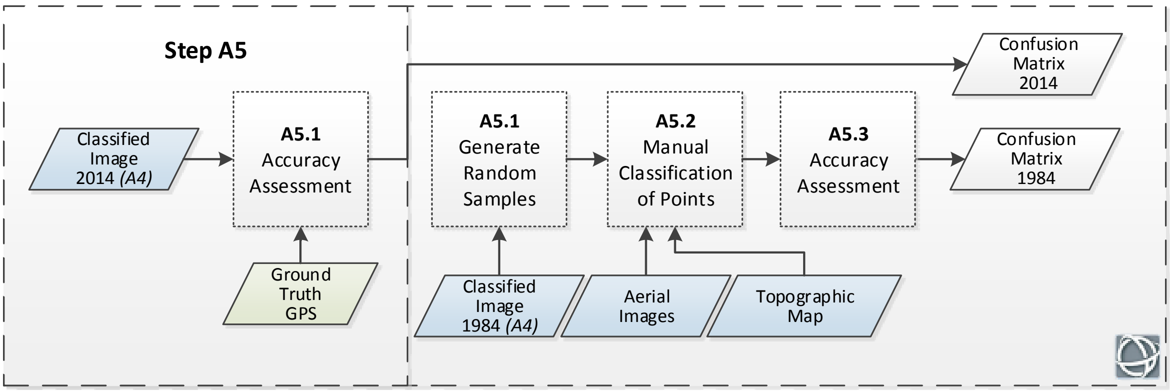


Figure 12 Accuracy Assessment of Land Cover Maps 2014 (*left)* and 1984 *(right)*

For the most recent classification result of 2014, ground truth was taken via GPS (Garmin eTrex) in late November 2014 and March 2015. Because of limited accessibility ground truth for the class water was taken via Google Earth. 30 sample points were acquired for each class but mixed cropland classes, wetland and scrub, resulting in a total of 180 samples.
For the image of 1984, aerial images of 1972 and a topographic map of 1988 were used as reference. 210 sample points are generated from the classified image, 30 points per class except mixed cropland and wetland classes. Those are then manually classified using the reference imagery. Additionally 30 points of the Annual 's' class are assessed to check confusion between annual cropland and bare soil within the class. Figure 14 shows examples of the visual appearance of each class that was used for interpretation during the manual classification. Also it shall be noted, that as seen in Figure 13 the reference imagery did not cover the outmost eastern part of the study area. Therefore, no sample points were generated in this area.
Output of the assessment is a confusion matrix stating omission and commission error per class and overall accuracy of the classified image.

As stated before, mixed classes of both classified images have not been assessed. Their assessment would require a more extensive sampling of 30 x 30 m plots that resemble the position of pixels to assess the percentage of cover per cropland type.
Also the wetland and scrub class are not checked in the 2014 image because those classes are built upon an assumption. Areas that have been classified as water in 1984 have been classified as wetland in later years subsequently. The decision to classify scrub is based on an observation in Google Earth that showed the presence of scrubs at slopes higher than 20°.

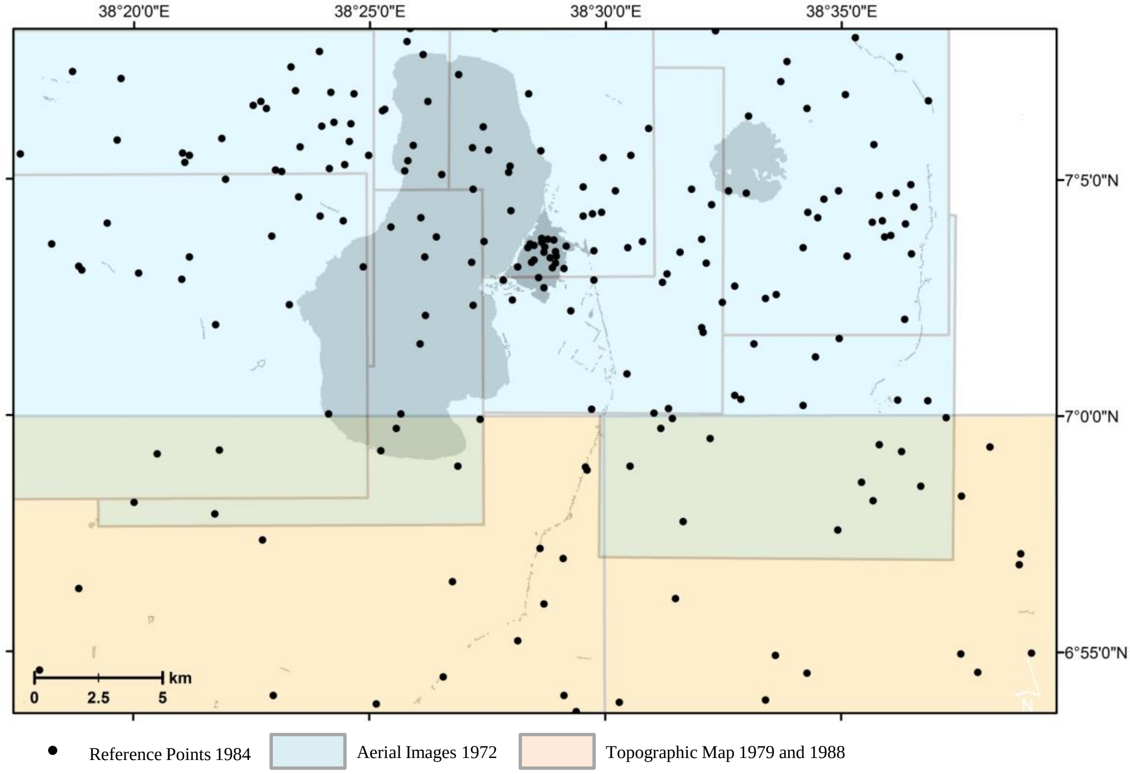
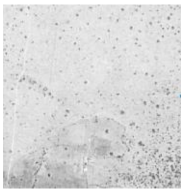


Figure 13 Spatial coverage of reference data for 1984

Class 3 – Bare soil

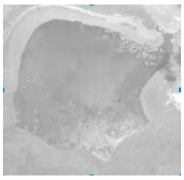


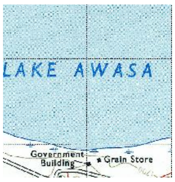
large plain areas with few single trees and no field borders

Class 4 – Built up

linear streets and agglomerated housing areas

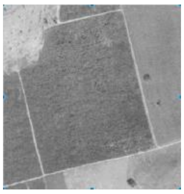
Class 5 – Water

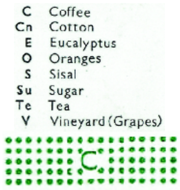




homogenous dark areas with mirroring reflectance

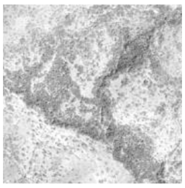
Class 11 – Perennial Crop

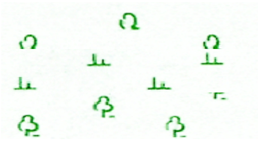




rectangular shaped fields with high texture

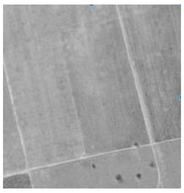
Class 22 – Scrub





plain areas with many trees and bushes and no field borders

Class 14 – Annual Crop



n.a.

rectangular shaped fields with low texture

Class 21 – Grassland

n.a.

homogeneous vegetated areas with intermediate texture and no field borders

Figure 14 Interpretation criteria of Reference Imagery for the Land Cover Map of 1984
Left image: aerial image, *right* image: topographic map, n.a.: not applicable.

3.3.7 Land Cover Change Detection (B)

The land cover change analysis is carried out with Erdas Imagine. It would be possible to create a ruleset in eCognition for this part as well, but then a lot of conditional statements would be needed. Erdas already provides a function to detect land cover change. Land cover change is assessed in two time steps: from 1984 to 1998; and from 1998 to 2014. These years serve as snapshots in time. Eventual change that happened in between such as seasonal fluctuations are not assessed and therefore do not contribute to associated change.

Land cover change assessed in three spatial contexts:

- *Step B1* assesses class change seen in the total scene.
- *Step B2* assesses class change seen within subsets of *A2*.
- *Step B3* assesses class change based on segmented objects of *A2*.

The goal is to identify land cover change by measuring the quantity of change (in ha and percent), the quality of change (change classes, e.g. from grassland to cropland) and to give more detail on the specific location of change. In conclusion, part B aims to answer research questions i and ii.

The first step (*B1*) simply identifies areas with no class change and areas in a post-classification change assessment. The change between the images is hereby assessed thematically based on a pixel-by pixel comparison of two consecutive land cover maps. This gives insight into which classes are decreasing or increasing over the years. The technique is one of many change detection techniques and was chosen because it minimizes the impact of atmospheric and sensor differences between multi-temporal images and provides a complete matrix of change information (Lu et al. 2004). Results are simple to analyse and to interpret. However, the user should be aware, that the change detection result is directly influenced by the accuracy of the classified input image of each date.

Spatially more specific insight is given in *step B2* where the output of *B1* is linked to previously created subsets (*A2.1*). This way it can be observed, whether some classes are more prominent within certain areas or whether certain regions are more affected by change than others. Additionally class properties are assessed in eCognition. Subset texture is measured on Grey Level Co-Occurrence Matrix (GLCM) contrast and orderliness. Classes form objects with specific shape properties. Mean length, area, shape index and border index are assessed per subset. These features can already indicate a change in landscape structure and shall therefore be linked to the outcome of part C to answer research question iii.
GLCM texture after Haralick et al. (1973) is used to analyse combinations of grey level occurrences considering the relationships of 2 neighbouring pixels. The matrix holds information on counts of co-occurrence combinations and is normalized by a division through the total number of counts in the image. Therefore, texture is comparable between subsets of different sizes. In this research we use GLCM contrast to measure diversity and dominance and GLCM Entropy and GLCM Angular Moment (ASM) to assess chaos and orderliness, respectively. The produced texture variables are based on a calculation in all directions.

While *Step B3* is not necessary for the understanding of land cover change, it serves to give insight on the usefulness of the method itself. It has been proposed to use an object-based approach for analysis. During the process of this thesis we found out that a better way to approach field level is

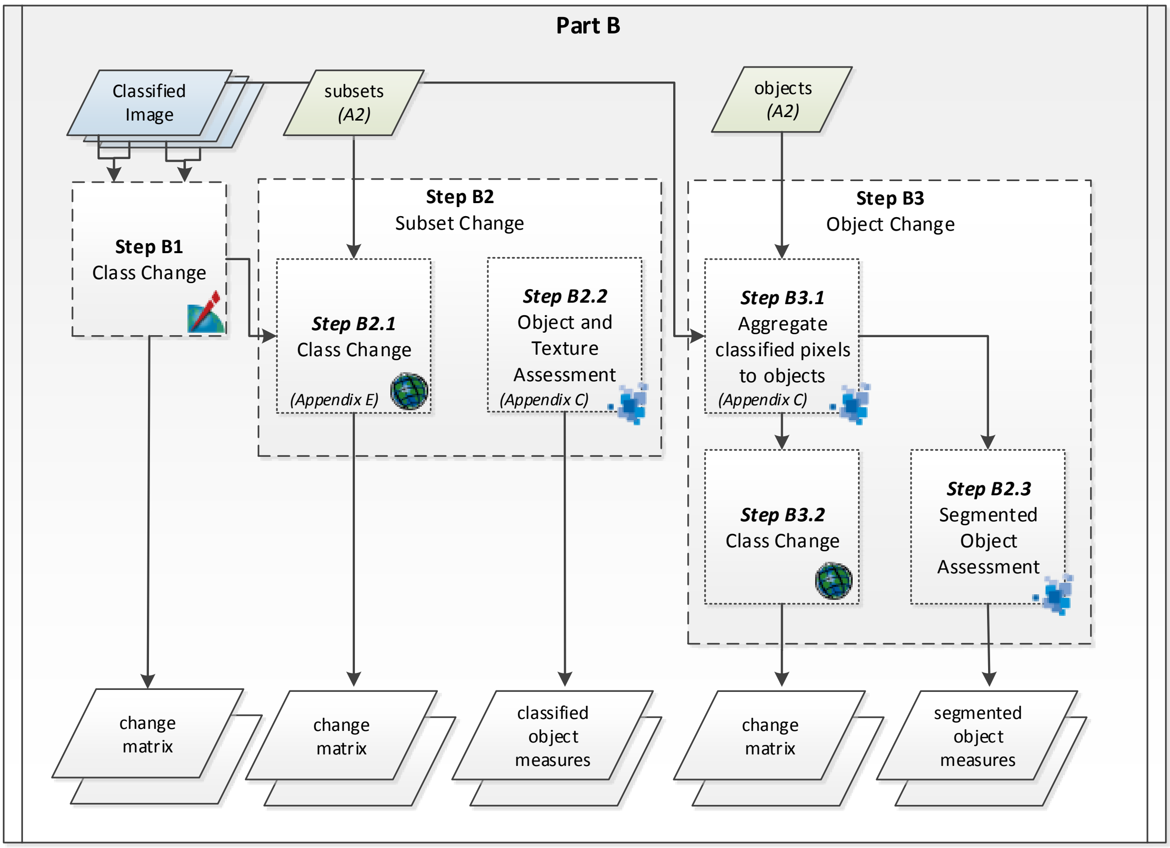


Figure 15 Post-classification Change Analysis

to use pixel classification due to the small field size and relatively large pixel size. Therefore, objects have only been used to classify built up and water.

In spite of this, objects have been created in step *A2.1*. To evaluate the meaningfulness of these objects, pixel-based classification results are aggregated to the size of exported objects of each year. These objects are than assessed as in *step B2* and their results being compared. Therefore, this step will help to answer research question v.

3.3.8 Land Structure Change (C)

Change in landscape structure shall be assessed in terms of landscape fragmentation and diversity.

The concept fragmentation originates from Godrons' and Formans' (1986) topological landscape ecology and is a measure of landscape heterogeneity or 'patchiness'. The definition of a patch is relatively vague as it can refer to structural, functional, resource or habitat patches (Farina 2006). In the context of this study we refer to patches as habitat patches. Annual cropland is considered to be habitat to pest insects, perennial elements as habitat to natural pest predators (De Valenca 2014). Other classified objects such as urban settlements and infrastructure also contribute to landscape fragmentation, which is why these elements have been taken into consideration, too. With increased fragmentation the following effects in landscape structure should be visible: decrease of habitat area, decrease of patch size, increase of distance and isolation and increase of edge effects (Forman & Godron 1986).

Landscape diversity on the other hand describes the relative abundance of land cover classes in a landscape. Therefore, a landscape can be highly fragmented without being highly diverse at the same time.

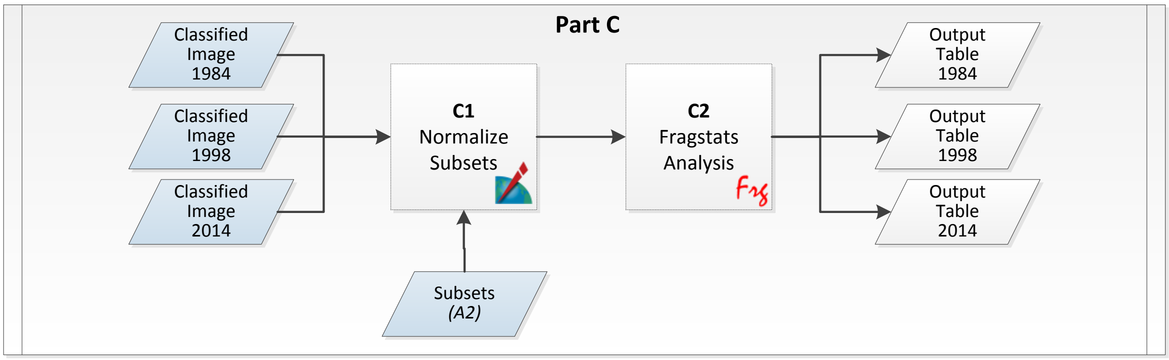


Figure 16 Land structure change

The analysis of part *C* follows a straightforward approach where the land cover maps of all years are analysed in Fragstats (Figure 16). To acknowledge the presence of differently diverse landscapes, the scene is subsetted again. The same subsets as in *step B2* are used (output of *step A2.1*).
Unlike texture measures after Haralick the size of the subset will influence the results of diversity and fragmentation because bigger regions have a higher potential for more diversity. Therefore subsets are normalized in *step C1* to a size of 2500 x 2500 m. Six regions were manually selected within all subsets but water. The size is chosen to represent landscape scale, which is a relevant scale for the research on pest pressure. Ecologically, scale is highly important because it determines observed patterns. What is sensible in one scale might not be observed in another (Turner 2005). Landscape scales in ecological studies are typically assessed at scales between 1 x 1 km (Hansen et al. 2015), or 5 x 5 km (Bianchi et al. 2015).

After normalization each tile is analysed for each year of interest in Fragstats, the most commonly used software for landscape assessment (Farina 2006, Turner 2005).
Fragstats provides a wide range of landscape metrics. Out of those five measures are chosen and assessed with an 8-cell neighbourhood rule and no sampling. Edge depth is not specified (Depth=0) due to the large pixel size of 30 x 30 m that is assumed to hold both, edge and core areas. At landscape level composition is assessed using Simpson Diversity. Configuration is assessed with Contagion and Proximity between annual and perennial cropland classes. At class level edge density and patch number is calculated. An overview of used metrics is applicable in Table 4.

An indication of the relevance of each measure to this research is given as followed.
Simpson Diversity can give insight in the relative abundance of patch types (classes) within a landscape. High diversity represents high numbers of different patch types (patch richness) that share similar proportions. Low diversity is associated with the dominance of one patch type (McGarigal & Marks 1995). In less diverse landscapes insect populations are determined by the patch types present in the landscape. If pest habitat is dominant, intrusion of natural pest predators is limited due to the absence of their habitat and ecological corridors.

Contagion is a measure for aggregation, showing how clumped patch types are (O'Neill et al. 1988). The higher contagion (aggregation), the larger is the core habitat. Predators are more likely to be present at patch edges than in patch cores (Bianchi et al. 2006). This means that in highly clumped pest habitats, natural pest enemies are less probable to interfere because edges are small.

Table 4 Landscape metrics of analysis of *part C*

Metric	Measure for	Level	Unit	Range	Relevance
Simpson Diversity Index	Proportional abundance of each patch type in landscape	Landscape	-	0-1	Composition, Dominance
Contagion	Aggregation of landscape patches within landscape	Landscape	%	0-100	Configuration, Dominance
Proximity Index	Neighbouring patches within specified distance	Landscape	-	≥0	Configuration
Edge Density	Length of patches of one class in proportion to area size	Class	m/ha	≥0	Configuration
Number of patches	Count of patches per class	Class	-	≥0	Configuration

and cores are big. Contagion is inversely related to Edge Density.

Proximity measures the closeness of patches by dividing the summed patch area by the nearest patch to patch distance. The mean is created for the whole landscape. This measure has been used only considering perennial (11) and annual (13,14,15) classes. A close proximity between the two class-sets can give insight on increasing potential of natural pest suppression because perennial elements are considered pest predator habitat. The closer their distance to annual crop the more probable is an exchange between insect populations.

The number of patches estimates the number of all habitats present. This measure is assessed for each class (habitat type) present in the landscape. It can give insight on either patch sizes (the larger, the less counts) and abundance of patch type (the fewer, the less counts). Diversity and Edge measures can facilitate a better interpretation.

Edge density or perimeter/area ratio assesses the relative length of a patch type (class), which is measured as total length of class divided by total landscape area. Edges are of high ecological importance. They are used as corridors on the one hand, but also facilitate the “Edge Effect” on the other hand. It describes the colonization and exchange of species within close distance to the patch border (Schellhorn et al. 2014). Therefore, a landscape with many edges holds a higher potential for exchange between insect populations.

3.3.9 Evaluation of Object-based Image Analysis

It has been hypothesised that object-based classification will produce higher accuracies than pixel-based classification due to its ability of detecting shape patterns. To evaluate this hypothesis the results of this study shall be compared to similar studies that used OBIA in South Ethiopian landscapes. The comparison will be literature based.

As a second part the effectiveness of an object-based classification approach for this research shall be evaluated by comparing the output of the analysis to itself. As described in section 3.3.7 classification results are aggregated to object level and then compared to the ‘original’ classification.

4 Results

4.1 Land Cover Classification of 1984, 1998, 2014

4.1.1 Land Cover

The following paragraphs give a description of land cover for the years 1984, 1998 and 2014 that shall guide the reader by highlighting relevant classes and giving hints on misclassifications or underlying landscape processes. The classification map is presented with a list of most prominent features. More detailed description on four to five selected features is given afterwards. A quantification of land cover change will be presented for the results of *part B* in chapter 4.2.

<u>1984</u>

Largest and smallest class:

- Largest area: cropland
- Within cropland: annual 's' (class 15) holds largest shares (28.34% of cropland), followed by mixed crop class 12 (26.77 % of cropland, Table A.1)
- These two classes roughly represent the west and the east of the study area.
- Smallest area: built up (class 4, 0.76 %)

Natural coverage:

- Grassland areas are extensive and many.
- They occur especially in the south and east of the study area.
- Largest grassland areas are situated in the centre of the image, east of Hawassa City.

Cropland coverage:

- Annual classes are mainly created based on an additional image of early growing season. This results in a high coverage of land cover class 15 (Annual, 's').
- Western areas show mainly coverage by annual crops (14 and 15) or mixed crop (13).
- Western areas show almost no pixels that belong to class 11 (Perennial).
- Eastern areas generally show more coverage by perennial crops.
- Coherent areas of perennial crops are small.
- Perennial crop is often neighbouring fields of mixed cropland status. This indicates that there is a large amount of small sized annual crops present.

Built-up:

- The city of Hawassa is relatively small. It is surrounded by large scale agricultural fields of mainly annual character.
- Only two roads were mapped. One road connects the city with the south; the other road expands through the east to the north. It is the road where the town Wondo Genet is situated today. Roads are hardly visible in the image, because they are often not wider than the size of 1 pixel.

Water:

- East of Lake Hawassa exists a second lake, Lake Cheleleka, with an area of 6,75 km².

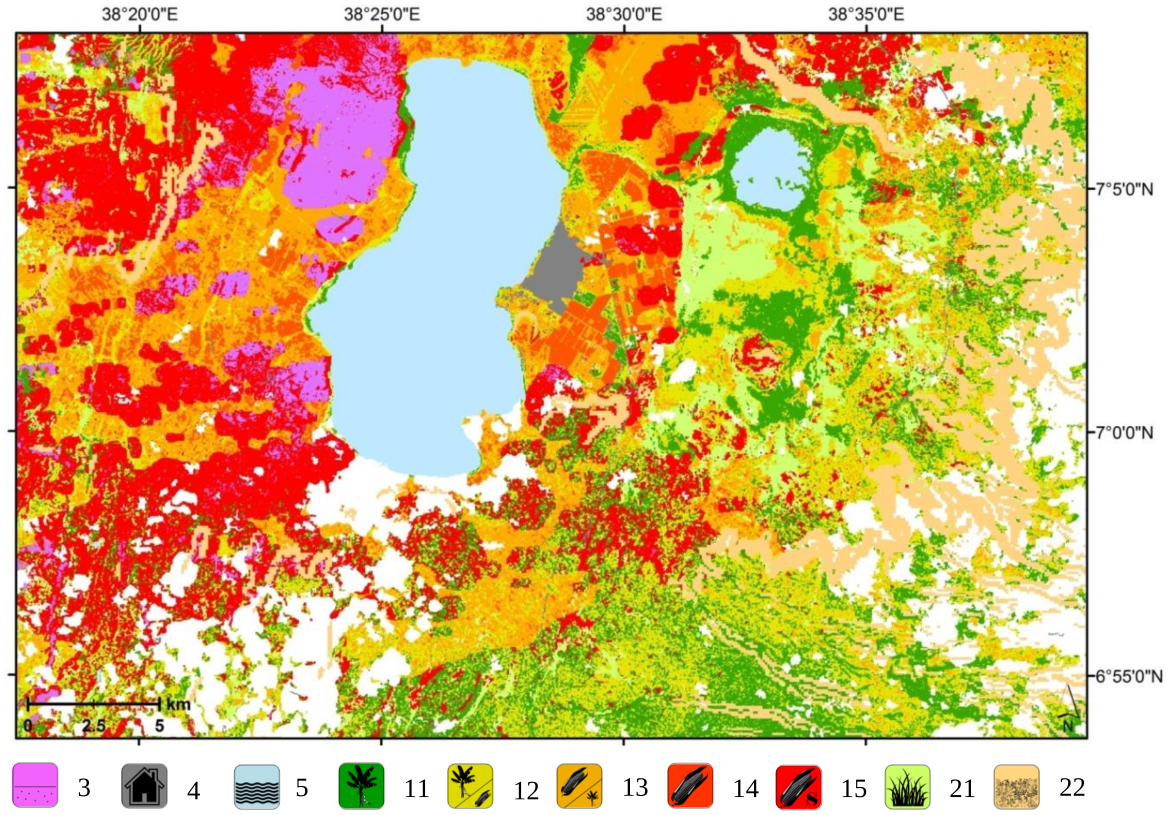


Figure 17 Land Cover Classification of 1984. White areas refer to No-Data due to masked cloud cover of 2014.

Especially interesting features are shortly described in more detail. Their position can be seen in Figure 18. The background of the overview image shows Lake Awassa and the class built up, for better orientation. Therefore, this image is also suitable to identify road networks which are hard to see in the overall classification image.

Remarkable in 1984 is the high amount of grassland that is present in eastern areas (Snapshot 1). Grassland is forming relatively large patches, neighboured by cropland. It is indicating low population pressure that allows part of the landscape to be unused or at least not used for agriculture. Also it is possible, that these patches were used as grazing areas for cattle.
The biggest grass patches are seen in an area further east of Hawassa city close to the Lake Cheleleka (snapshot 2). This area is different to others as until the year 2014 no cropland has been cultivated there (personal communication, Kebede 2015). The area is corresponding to a subset created in *step A2* that was initially called "Other- Wetlands". The name indicates that the region doesn't show similar characteristics as other areas, e.g. in greenness or brightness. Thus, the region was leftover during the classification process and later summarized as "other". It might be the case that soil characteristics are different in this region, which makes it unfavourable for agricultural use. Also it has been noticed that the eastern road is not passing through this area. Therefore, cropland classes in this region are most likely misclassified, which will be discussed during the Accuracy Assessment in chapter 4.1.2.

Another region that is remarkably different from surrounding cropland is a bare soil patch in the west (snapshot 3). It can be seen that these regions are surrounded by annual cropland class 15 (red).

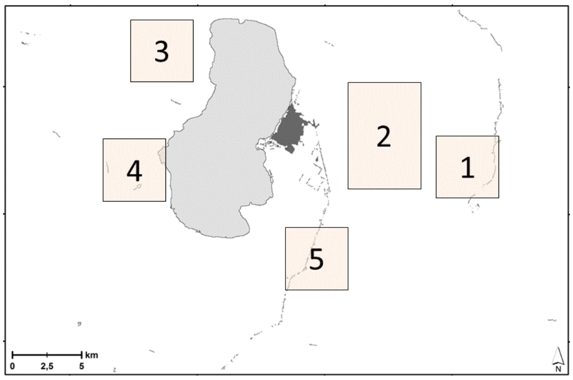
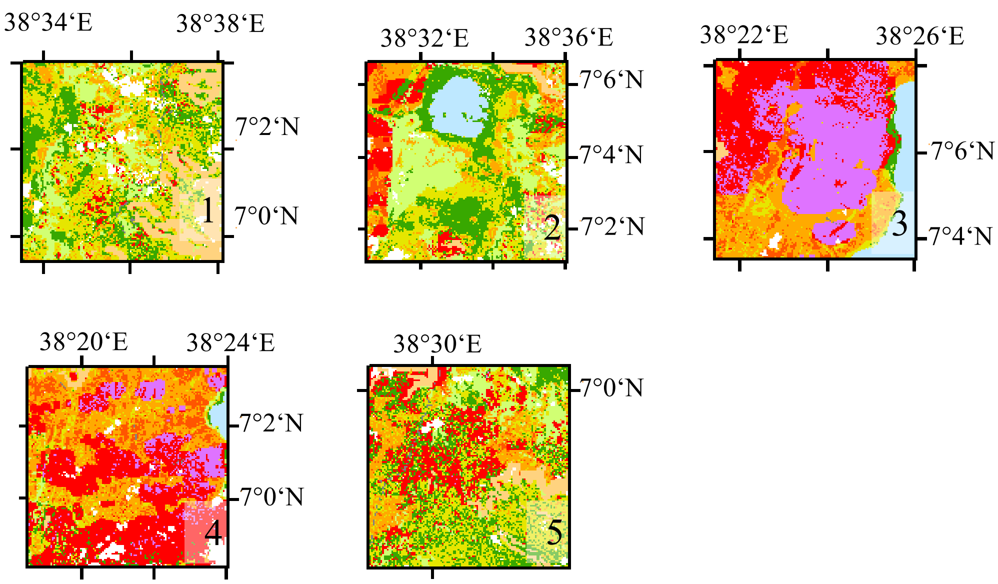


Figure 18 Overview of snapshots from LCC 1984. Background Lake Awassa and Class Built-up.

As wetlands described before, it can be speculated that soil characteristics are different to its surrounding as subsequent years also show bare soil in this region.
Very noticeable in the map of 1984 is the use of the additional image in *step A3*. This image represents an early stage in the growing season. Therefore classes are created based on a lowered NDMI and minimum NDVI threshold, which results in classification of class 15. Its appearance is very prominent in western areas as it represents the cloud pattern. The lowered threshold causes a direct classification of these areas as annual ‘s’. Neighbouring pixels of this class suggest that a classification as mixed crop might have better represented the area (snapshot 4). The annual‘s’ class shows highest potential of misclassification with bare soil, as further described in chapter 5. Red areas (class 15) in southern regions do not seem to fit in the classification pattern of the region and might therefore be misclassified bare soil patches (snapshot 5).



1998

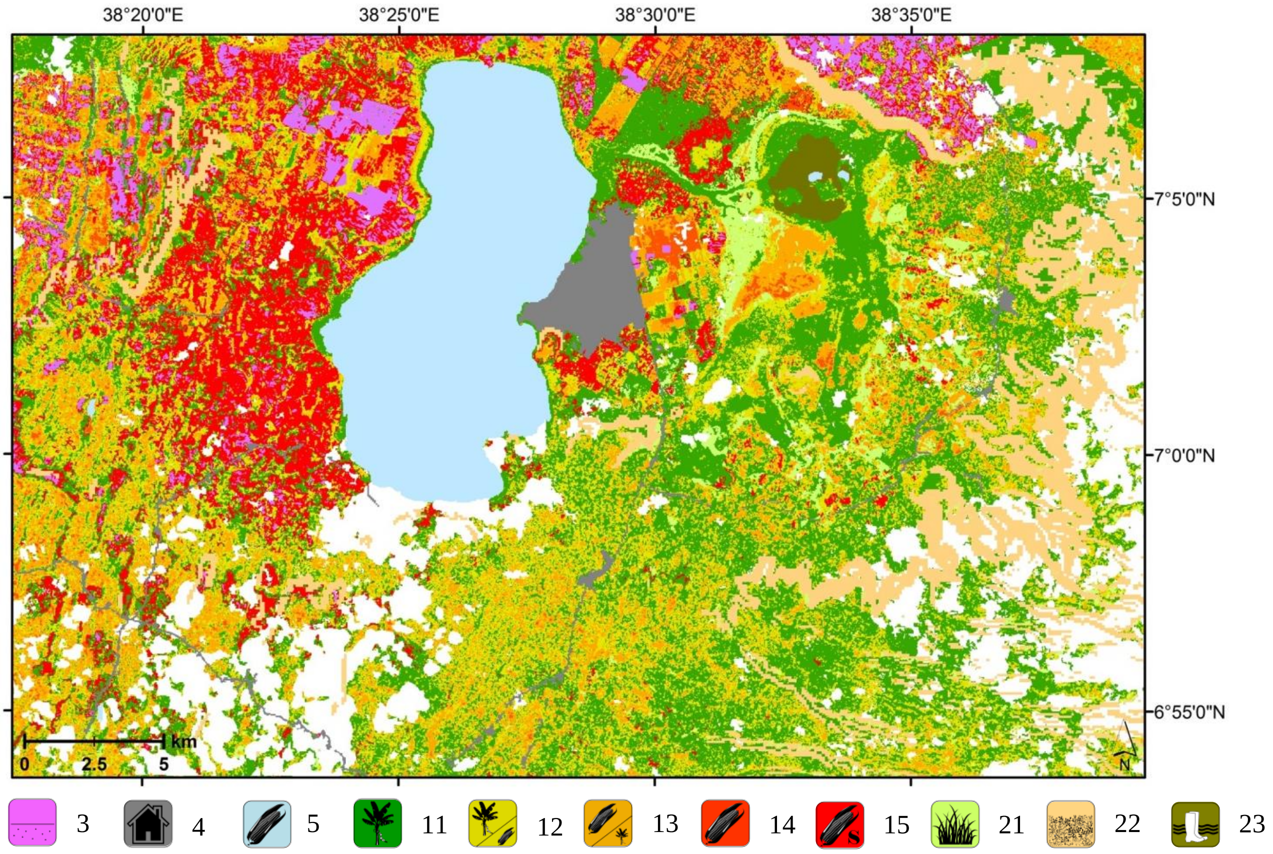


Figure 19 Land Cover Classification of 1998. White areas refer to no-data due to masked cloud cover of 2014.

Largest and smallest class:

- Largest area: cropland, of which 36.3 % class 11 (Perennial) and 28.97 % class 12 (mixed)
- Smallest area: class 23 (wetland), which replaced dried up areas of Lake Cheleleka

Natural Coverage:

- Grassland patches are small and few. Grassland can mainly be found in central regions close to wetland area and subset ‘Other-wetland’ (see Figure 28)
- Eminent influence of dry year. Dried up grassland patches in wetland areas were classified as mixed crop. Bare soil is mapped more often in cropland areas, e.g. Northeast.

Cropland:

- Increase of perennial crop in all areas.
- Increase of mixed crops in all areas.
- Western areas show high percentage of coverage with annual crops. But expansion of class 11 (perennial) and mixed cropland class 12 into western areas is seen, emerging from the south.
- Mixed crops and perennial crops in western areas form linear features, suggesting the existence of small roads.

Built-up:

- Hawassa city expanded to the edge of the road.
- Other cities (Wondo-Genet, Busa, Tula) emerge at north-eastern road.
- Existence of a new road connecting southern areas with the east.

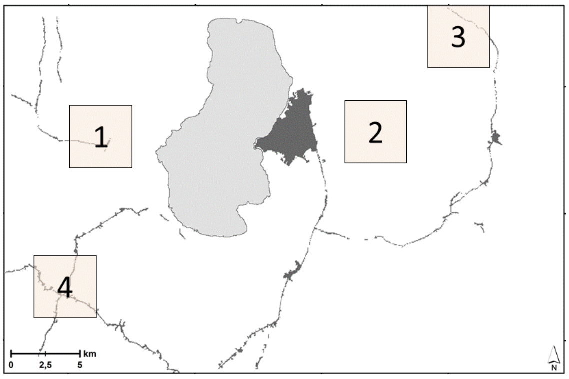


Figure 20 Overview of snapshots from LCC 1998.

The overview image alongside displays the newly built road that connects the south with the west of the study area. This connection displays a population increase that makes new routes of transportation necessary.

Higher population in western regions is also suggested by the formation of linear features by perennial crops (dark green) and mixed crops (orange) that intersperse annual cropland (red; snapshot 1). These features represent “home gardens”, small sized fields at the backyard of houses. Houses on the other hand are located along streets. Therefore, home gardens form characteristic linear features, indicating the presence of perennial crop cultivation and population increase.

Very visible in the map of 1998 is the effect of the dry year, which results in increased bare soil areas in the north (snapshot 3). The structure of the mapped area suggests, however, that they are cropland. Big grassland patches in the centre of the image are mapped as annual or mixed annual crop (snapshot 2) because they were too dry and did not fit the spectral characteristics of grassland for classification. Also most annual cropland is classified as class 15 (Annual ‘s’), based on a lowered threshold of NDMI for cropland classification to compensate for the dry year effect. This might cause misclassification in the south, where annual crop patches seem to not fit the surrounding classification (snapshot 4). It can be speculated that these patches are in fact bare soil or mixed crops.

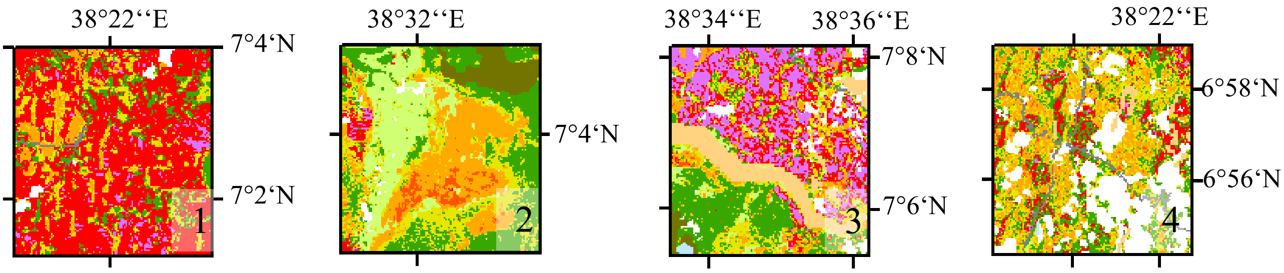
<u>2014</u>

Largest and smallest class:

- Largest area: cropland, of which 60.12 % class 11 (perennial)
- Smallest area: wetland, grassland, bare soil, annual crop; each represent approx.1% of total area

Natural coverage:

- Grassland areas are rare.
- Bare soil is restricted to very few areas north of the study area.



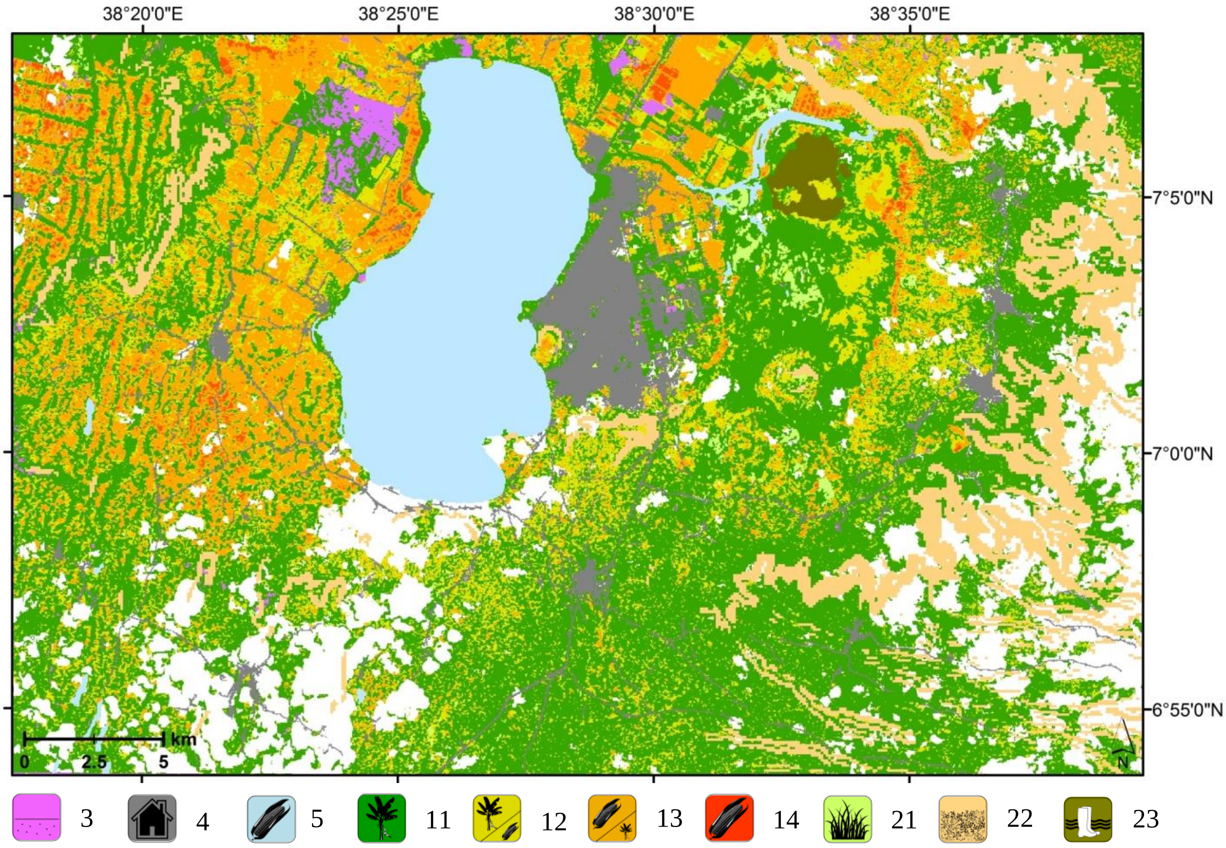


Figure 21 Land Cover Classification of 2014. White areas refer to no-data due to cloud cover.

Cropland:

- Eastern and southern areas are very much covered with perennial cropland, with neighbouring fields of mixed cropland status (mostly class 12). Western areas show higher coverage of annual crops, represented by mixed cropland class 13.
- Areas of pure annual class (14) are rare.
- Perennial crops in western areas form many linear features, suggesting existence of many small roads.

Built-up:

- City of Hawassa has largely expanded.
- All other cities, east and south have expanded, too.
- Emergence of new big city in the west of study area.
- Infrastructure has increased. Road network is detailed and intertwined. This suggests that not only more roads are build, but also wider roads and more concrete roads which can be better detected.

Water:

- Large water areas classified close to wetlands. This resembles river runoff, which has not been mapped in previous classifications.

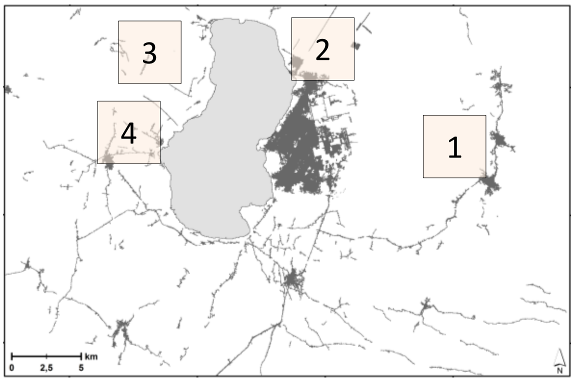


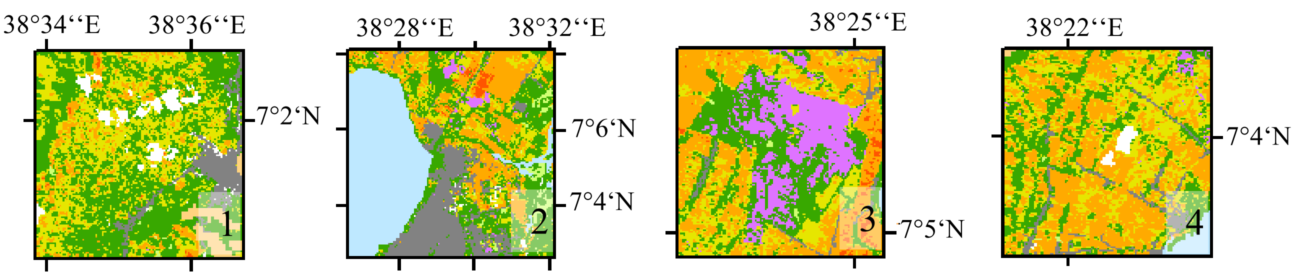
Figure 22 Overview of snapshots from LCC 2014. Background Lake Awassa and Class Built-up.

Figure 22 displays the detailed road network of 2014 that connects streets at multiple junctions. This is remarkable as earlier roads very linear, with only one or two junctions. It indicates a population increase in the study area that demands more transportation routes, not only to the city of Hawassa but also between smaller cities.

Eastern areas in 2014 show high texture contrast in cropland composition (snapshot 1), indicating that field sizes are very small on the one hand, but that crop cultivation is various on the other hand. Grassland patches are rare. Eastern regions were occupied by grassland in earlier years. The disappearance of grassland, together with the small field sizes, suggests high population pressure leading to conversion into cropland. However, it is known that the class grassland is under-estimated due to its very small patch size below 30 x 30 m resolution. These areas cannot be mapped, as they will be summed up with cropland areas. Also bare soil patches are rare and only seen in the northwest of the study area (snapshot 3). The bare soil patch is characterized by its very geometrical shape. Even in previous years soil was dominant in this area as described in Figure 18. In 2014, it is known that the region is being prepared for the building of a new international airport (personal communication, Kebede 2015). Therefore, bare soil patches with minimum vegetation cover have been misclassified as perennial crop.

Large scale agriculture is only remaining in northern regions (snapshot 2). Field sizes are relatively large and have distinct field borders, which makes them easy to identify. All other fields in 2014 are much smaller. Therefore, this northern region was mapped as a subset with own characteristic features in *step A2* (Figure 28). It is likely that the area is owned by a company or the government as it does not resemble the for the study area typical small scale agricultural pattern.

Linear features in western areas have increased and are very remarkable for the area (snapshot 4). In 2014, they are mostly classified as perennial crop instead of mixed crop, indicating increasing home garden proportions, higher population rates and the presence of many small roads. Composition of surrounding cropland is widely homogeneous, suggesting that field sizes in the west are larger than in the east.



4.1.2 Accuracy Assessment

1984

The land cover map of 1984 shows an overall accuracy of 77.14 % with a Kappa coefficient of 0.7333 (Table 5). Mixed cropland was not validated in this assessment. Highest accuracies are achieved for water (class 5) and built up (class 4). Commission error is highest for the perennial cropland class (11), 6 out of 30 pixels were misclassified grassland (class 21), another 5 pixels were misclassified scrub (class22). These pixels often refer to wetland areas in the centre of the image, which were described before (Figure 23). This observation confirms that wetland regions are a source for potential misclassification and might therefore be better masked from the classification result.

The omission error of perennial fields on the other hand is small with only 1 misclassified pixel that was classified as annual crop (class 14), resulting in a producer's accuracy of 96.67 % (Table 5). Omission error is highest for the scrub (class 22). 17 out of 45 pixels were misclassified. The scrub class was created based on slopes higher than 20°. In the methodology it was explained that this threshold was chosen based on an observation in 2014, where scrub was only seen in uninhabited areas. It is likely that scrub is present in lower slope areas in years before 2014 due to a lower population pressure. This assumption can be validated with the results of the accuracy assessment. Scrub is present not only in pixels classified as cropland, but also in those classified as bare soil and grassland. Thus, scrub cover is highly under-estimated in 1984.

The annual crop class (14) shows highest confusion with bare soil, grassland and scrub. Again this indicates, that cropland is over-estimated in the land cover classification of 1984, whereas natural cover is under-estimated. The confusion between the two cropland classes, however, is low.

An assessment of 'separate' annual cropland (class 15) has shown that annual crops are displayed by this class with 70 % accuracy (Table 6). There is some confusion with bare soil as assumed earlier. Nine out of 30 pixels were misclassified, 6 of them were bare soil, 2 were scrub and 1 was grassland.

2014

The land cover map of 2014 shows an overall accuracy of 75.76 % with a Kappa Coefficient of 0.7067 (Table 7). The accuracy is comparable to that of 1984. The low accuracy is mainly influenced by the classes bare soil (3) and grassland (21) which are under-estimated and show producer accuracies of 46.67 % and 40.00 %, respectively. This will be discussed further in chapter 5. Reference points of bare soil were partly taken in built up areas (Figure 24), because many roads and urban areas are still covered by soil instead of concrete. Apart from roads it is difficult to find reference points for bare soil because this class is mostly absent. Grassland (class 21) on the other hand forms very small patches, which are not visible in 30 x 30 m. Therefore sample points were confused with cropland.

Highest accuracies were achieved for water (class 5) and built up (class 4) as before in 1984. Cropland classes also showed good resemblance of ground truthing data. Out of 30 samples of perennial cropland, 19 corresponded to class 11, 6 to class 12, 2 to class 13. Based on the assumption that mixed cropland classes contain both annual and perennial crop, mixed crop results were counted as correctly classified. Annual crops resemble 14 pixels of class 12 and 11 pixels of class 13. The counts show that the proportion of annual crops within mixed classes is higher than the proportion of perennial crops, as assumed before the creation of these classes. Also it proves the presence of mixed pixels that contain more than one crop type, which require mixed crop classes. The result also indicates that there are almost no pure annual crop fields (class 14). Field sizes are generally small, which leads to more mixed pixels and intermediate NDMI change rates.

However, the annual class might have been underrepresented in the ground truth sampling. Figure 24 shows that only a few cropland samples have been taken in the western study area where a higher proportion of annual crops was observed in the land cover map.

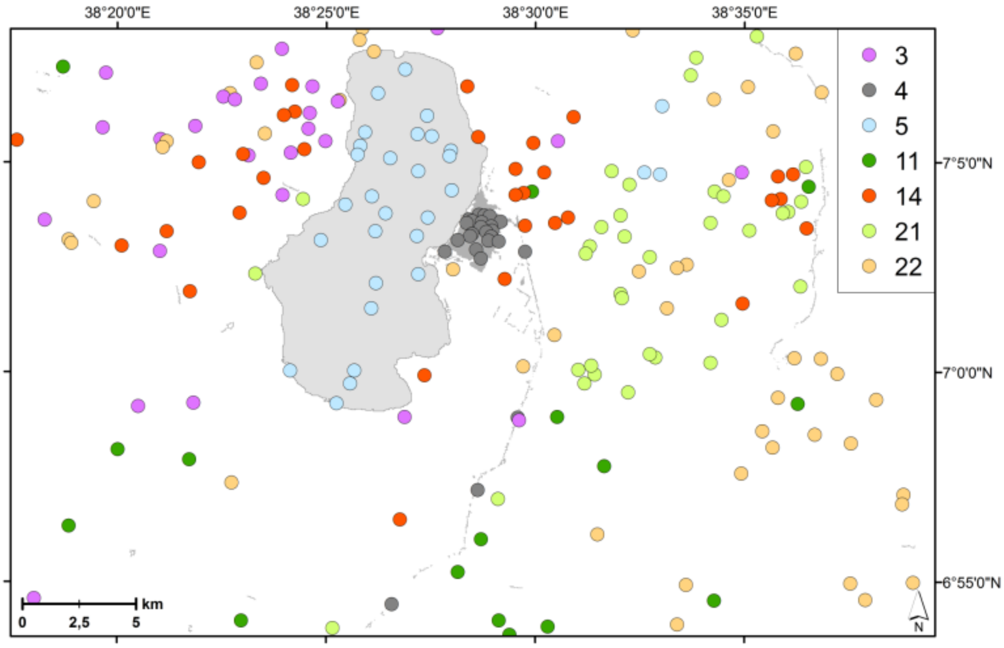


Figure 23 Ground truthing coverage for LCC 1984, based on randomly generated points

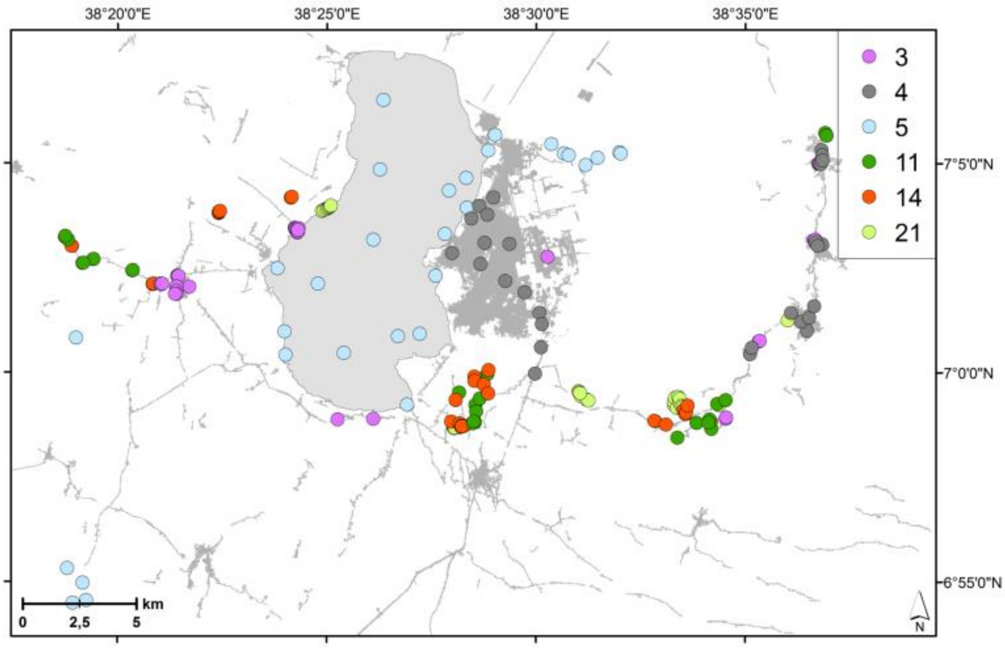


Figure 24 Ground truthing coverage for LCC 2014, based on collected GPS points

Table 5 Confusion Matrix 1984 in total pixels. Commission , omission error and accuracy in percent.

Overall Accuracy: 77.14 % , Kappa Coefficient: 0.7333

	Reference Points										
	#	3	4	5	11	14	21	22	Total	Com-mission	User Accuracy
Classified as	3	19	0	0	0	5	1	5	30	36.67	63.33
	4	1	26	0	0	1	1	1	30	13.33	86.67
	5	0	0	29	0	0	0	1	30	3.33	96.67
	11	1	0	1	15	2	6	5	30	50	50
	14	3	0	0	1	21	2	3	30	30	70
	21	1	0	0	0	3	24	2	30	20	80
	22	1	0	0	0	0	1	28	30	6.67	93.33
	Total	26	26	30	16	32	35	45	210		
	Omission	26.92	0	3.33	6.25	34.38	31.43	37.78			
	Producer Accuracy	73.08	100	96.67	93.75	65.63	68.57	62.22			

Table 6 Confusion of ‘Separate’ Annual Class 1984. Commission error and accuracy in percent.

Overall Accuracy: 70.00 %

	Reference Points										
	#	3	4	5	11	14	21	22	Total	Com-mission	User Accuracy
Classified as	15	6	0	0	0	21	1	2	30	30	70

Table 7 Confusion Matrix 2014 in total pixels. Commission, omission error and accuracy in percent.

Overall Accuracy: 75.76 %, Kappa Coefficient: 0.7067

	Ground Truth Points (GPS)									
	#	3	4	5	11	14	21	Total	Com-mission	User Accuracy
Classified as	3	14	0	0	0	0	0	14	0.00	100.00
	4	16	30	0	3	2	3	54	44.44	55.56
	5	0	0	28	0	0	0	28	0.00	100.00
	11	0	0	2	27*	3	8	40	32.50	67.50
	14	0	0	0	0	25**	7	32	0.00	78.13
	21	0	0	0	0	0	12	12	0.00	100.00
	Total	30	30	30	30	30	30	180		
	Omission	53.33	0	6.67	10.00	16.67	60.00			
	Producer Accuracy	46.67	100	93.33	90.00	83.33	40.00			

*class 11 of which: #11: 19 pixels, #12= 6 pixels, #13= 2 pixels
*class 14 of which: #12: 14 pixels, #13: 11 pixels

4.2 Land Cover Change

4.2.1 Class Change

Overview

Visual comparison of the land cover maps already indicated obvious changes in land cover such as in cropland composition and urban expansion. A more detailed analysis of change shall give a quantitative and qualitative insight in these changes. Within both steps almost all areas are affected by change (Figure 25). In total, slightly more change is measured in the period from 1984 to 1998 than from 1998 to 2014, where 56648 ha are affected by change compared to 51874 ha of non-changing areas (including cloud masked areas).

Within the period of study the area of perennial crops (class 11) is strongly increasing (Figure 26). Mixed cropland class 12 holds maximal coverage in 1998, decreasing in 2014. Mixed cropland class 13 is comparably stable throughout all years, whereas annual cropland classes 14 and 15 are strongly decreasing from 1984 to 2014. Also grassland and bare soil classes (21, 3) show high decrease in area coverage. Built up areas (class 4) grow drastically in both periods, especially between 1998 and 2014. This increase is even better visible when inspecting Figure 27. When only taking into account the change rate within the last 30 years, built up is the class that showed most pre-eminent changes. Considering the total amount of change, perennial classes showed the highest change. The increase in water (class 5) is caused by the mapping of the perennial river channel from former Lake Cheleleka to Lake Awassa in 2014.

Qualitatively, highest change is seen from annual cropland (class 15) changing to perennial, and mixed crop classes 12 and 13 (21%, 26 %, 20% of class area) in the period 1984-1998 (Table A.2). For period 1998-2014 most change is seen in change from mixed crop class 13 to perennial crop and mixed crop 12 (49%, 22% of class; Table A.3). But also changes from annual crop (15) to mixed crop class 13 and from perennial crop to mixed crop class 12 are high. This displays a loss in large annual cropland areas one the hand, but shows an increase in small scale farming of various crop types and small field sizes on the other hand.

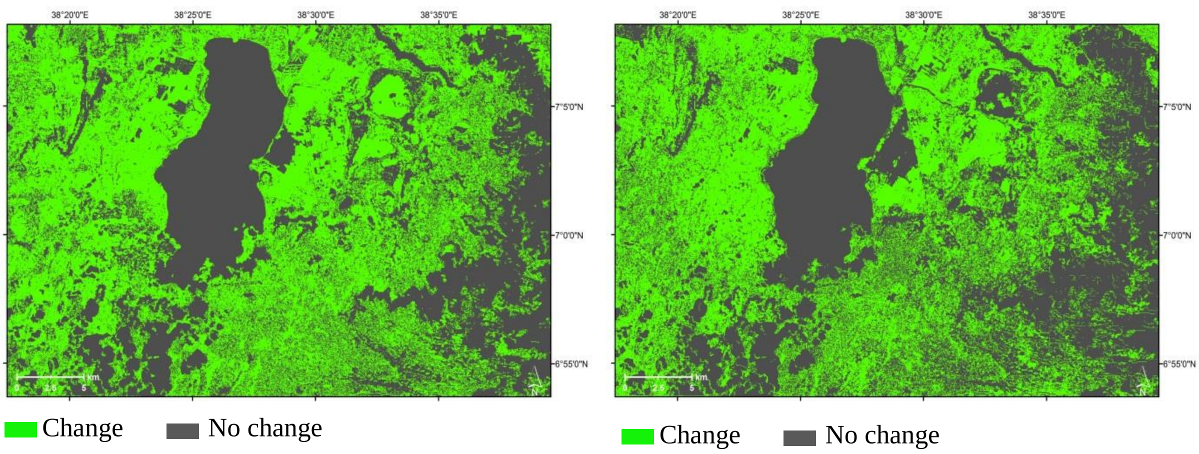


Figure 25 Areas affected by class change from 1984 to 1998 *(left)* and from 1998 to 2014 *(right)*

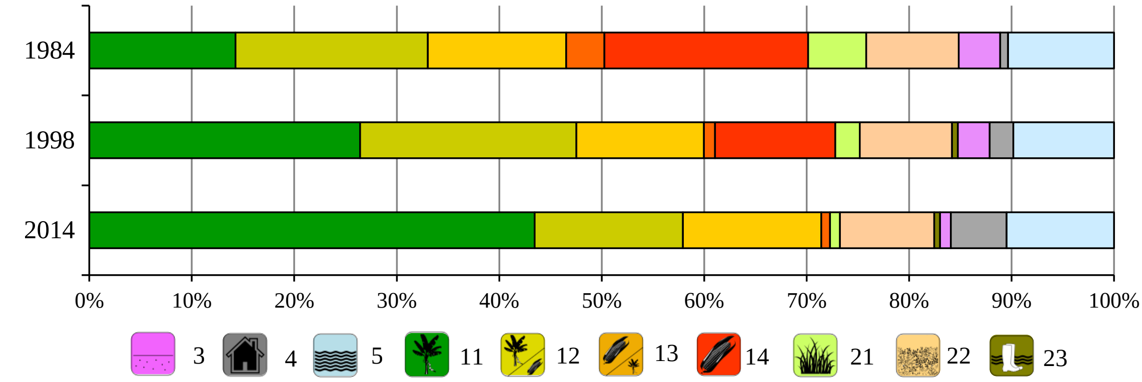
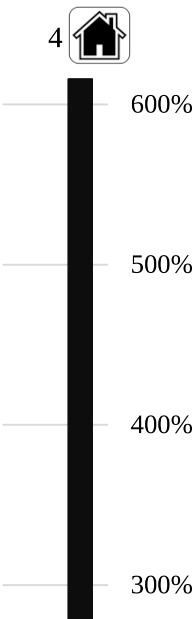


Figure 26 Comparison of land cover in percent per class and time step

<u>Cropland change</u>

In all years, cropland classes share the highest percentage of the area, slightly increasing from 1984 to 2014. Interesting is especially the change within the cropland class.

Approx. 16000 ha have changed from an annual or mixed crop status to perennial crop in 1998, and 21000 ha from 1998 to 2014 (Table A.4 in Appendix). The change from perennial class to annual or mixed class only affected 5000 ha in both years. This shows a clear transition of farming systems towards the cultivation of perennial crops. This trend begins earlier (1984-1998) in the eastern areas of the study area, gradually increasing to 2014. Western and southern areas experience these increases in the later time period from 1998 to 2014 (Figure A.1, Figure A.2 in Appendix).



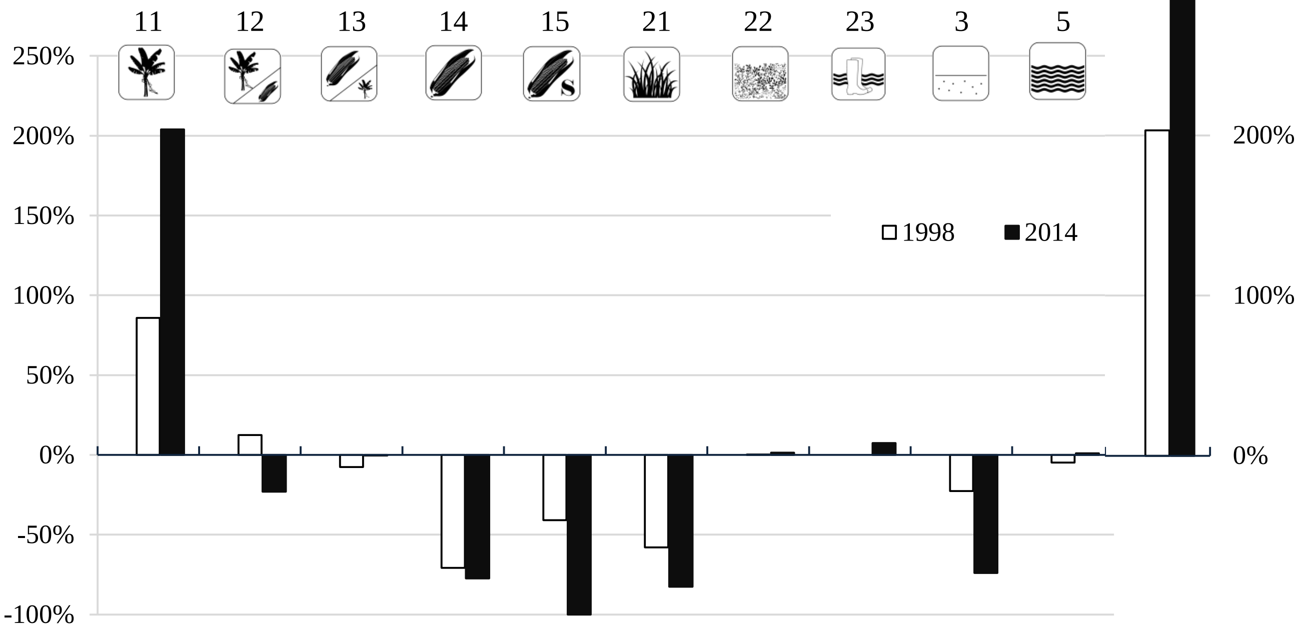


Figure 27 Land cover increase/decrease per class for 1998 and 2014, each compared to estimated areas in 1984

Change of natural land cover

Grassland and bare soil cover decreased remarkably over the period of study (-82%, -74%) in advantage of cropland with slightly more area decrease in the period 1984-1998 than 1998 -2014 (Table A.5). Whereas between 1984-1998 all crop types are expanding their area onto previously natural land cover, in the later time period especially perennial crop and mixed crop 13 are increasing on behalf of natural areas. The class built up did affect the transformation of grassland and bare soil to only small extents with 50 ha and 117 ha in 1998 and 2014, respectively. Therefore, cropland expansion can be considered the main driver in transformation of marginal land cover.

Spatially, there is a clear distinction between changing bare soil areas and changing grassland areas. Bare soil was mainly located in western regions. Grassland was mainly present in eastern regions (Figure A.3, Figure A.4 in Appendix). In 2014 both classes show only small area estimates.

4.2.2 Subset Change

Class Change

A large east-west difference was found in the study area by analysing subsets that were created in *step A2.1* (Figure 28).

The proportion of perennial crops is increasing in all subsets, indicating a general shift in cropland composition. Perennial crop is most dominant in southern and eastern part of the study area, where the majority (56%) is covered by perennial crop and the mixed cropland class 12 (16%) in 2014 (Figure 29). In 1998 and 1984 this subset shows high shares of perennial cropland that always exceed the amount of annual crops. The only other subset that shows similarly high proportions of perennial crop is the central 'other' subset. As described in the results section of part A these areas are wetland areas. Therefore, it can be discussed if the subset should be excluded from the classification result so that they do not contribute to the total estimate of cropland cover.

Annual croplands are declining in all subsets. Most evident is this process in western regions. This subset shows a tradition in annual crop farming, as 40% and 37% of the area contribute to class 14 and 15 in 1984 and 1998, respectively (Figure 29). A clear cut is visible in comparison to 2014 where only 2.2 % of the region is classified as annual crop. As a result the mixed cropland classes gained high importance. Reasons for the dramatic change could be a higher population pressure that causes field sizes to decline and the existence of home gardens containing more perennial crops. Decreasing bare soil amounts are mainly found in western areas. Grassland areas are decreasing in all subsets and time steps, most apparent in the south and east, where area estimates have declined from 3670 ha in 1984 to 356 ha in 2014 (Table A.7). This can indicate a loss of grazing area.

The increase in urban area is not only visible in the subset of the City Hawassa, but also in the western, south/eastern and northern subset. The increase in the first two subsets mentioned is likely to be associated with the emergence and expansion of smaller cities and new and better roads. The increase in the northern subset can be explained by an expansion of the city into the north. The urban class in the city subset itself has been growing towards the east and south, taking in cropland areas that existed in 1984 and 1998. Those were mostly of annual character.

Lake Awassa is the only subset without changes as it incorporates the water body only. However, a slight increase of 0.5 % of the lake area in this subset was observed, as border parts of the lake were partly classified as cropland and bare soil in 1984.

The assessment has shown that western regions have a tradition in annual cropland farming. Thus, increase of perennial crops results in strong decrease rates of annual cropland. Eastern areas have had large perennial crop proportions since 1984 already.

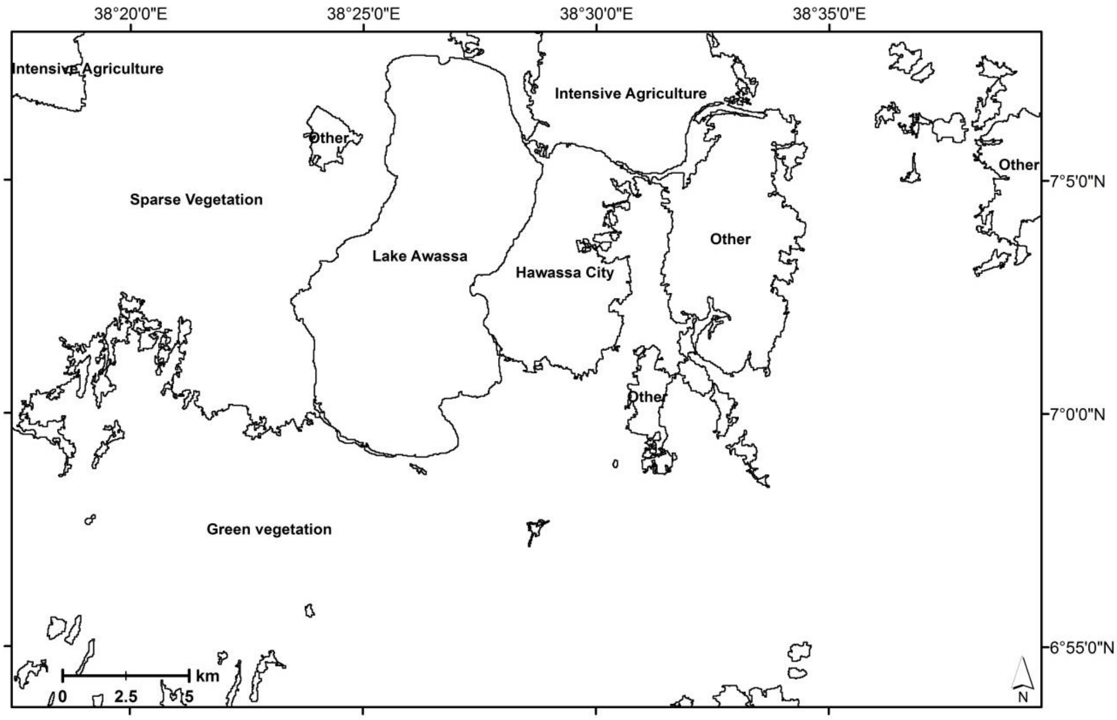


Figure 28 Subsets as output of the land cover classification of 2014, *step A2.1*
Names of the subset refer to their physical appearance in an October image of 2014, which was used for classification.

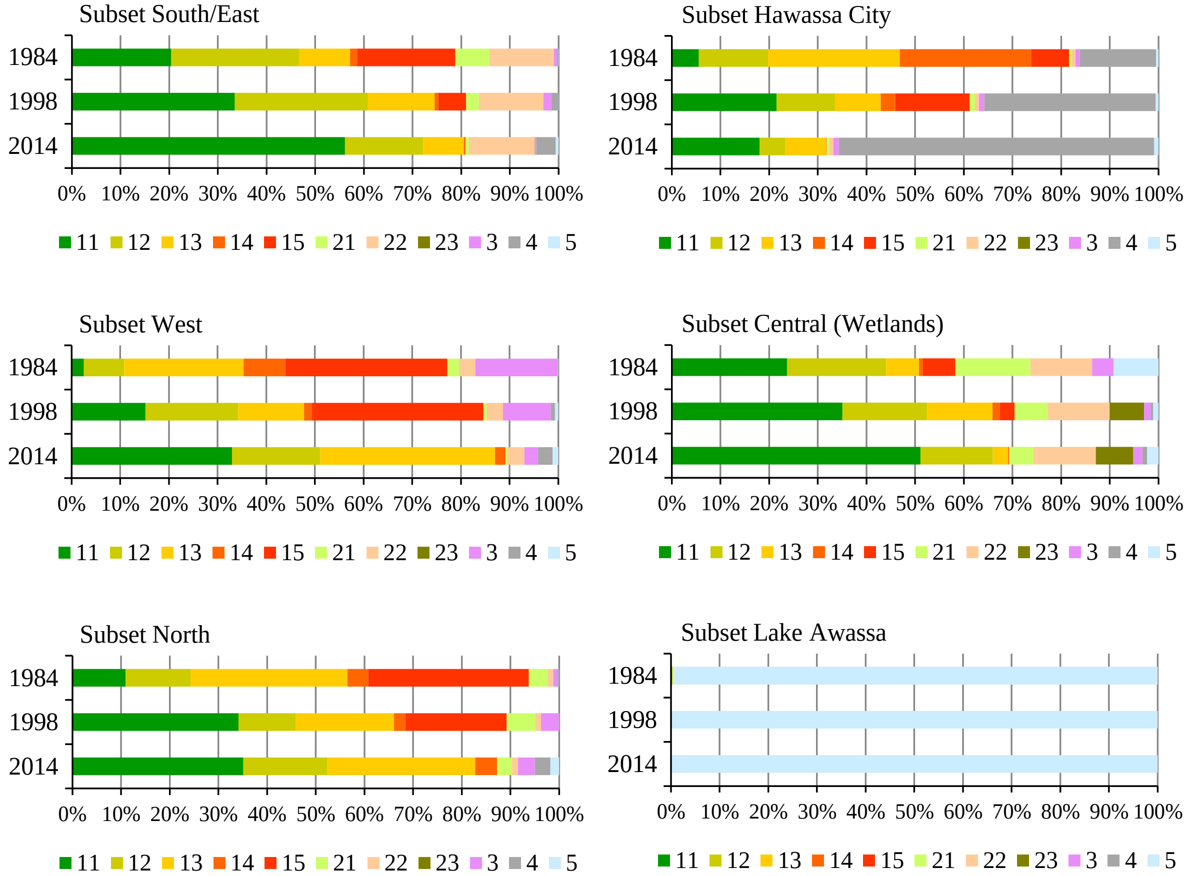


Figure 29 Land cover change in relative area per subset

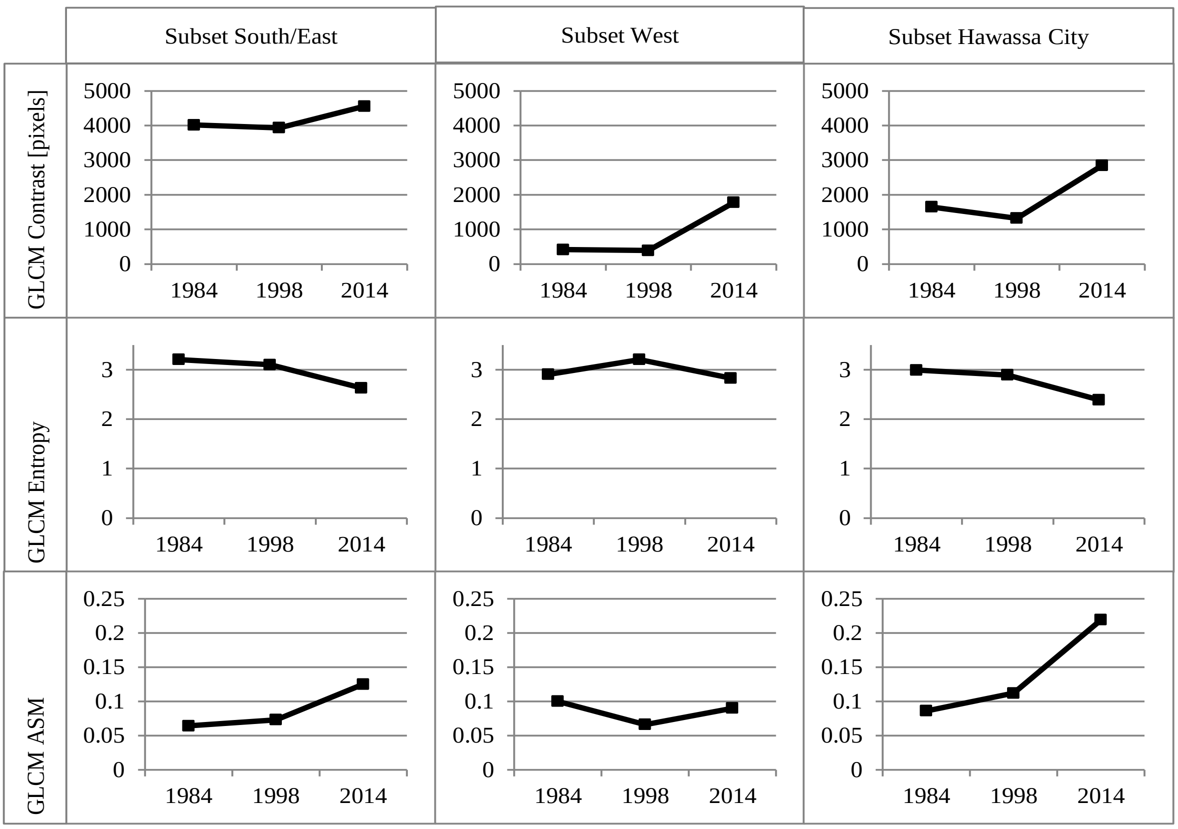


Figure 30 GLCM Texture Change for three subsets based on classification result (all directions)

Texture Change

Texture contrast has increased in all subsets, but most pronounced in the west and Hawassa city between 1998 and 2014 (Figure 30, Table A.8). This indicates that more classes are present in the subset within a small focal window because GLCM represents the count of co-occurrences of observed pixel combinations. The results suggest higher landscape diversity and the loss of a dominant class. Dominance can be seen in the western subset for years 1984 and 1998, where contrast is low. The overall level of contrast is remarkably higher in the south/east within all years.
GLCM entropy is decreasing in all subsets, showing that the scene is becoming less ‘chaotic’. This means that patches get more geometric and their alignment follows recurrent patterns. On the other hand this can also indicate that class areas increase, which results in homogeneity. Higher homogeneity was also implied by class change in east-southern subsets, where perennial classes were available in over 50 % of the area. GLCM Angular Second Moment (ASM) is a complementing metric that measures orderliness. It is therefore inversely correlated to Entropy. ASM shows strong increases in orderliness for the south-eastern subset and the City subset. The western subset shows highest order in 1984. This confirms the loss of one dominant class in this subset, which causes more patches to be ‘unordered’.

Object change (of classified areas) per subset

The mean area size per subset is measured, as well as mean object length, mean Shape Index and mean Border Index. All mean Border Index values are relatively small (<1.6; Figure A.5), indicating that highly complex shapes are rare. This suggests that fields are compact and small. Complex road shapes for example have been identified during road classification at Border Indexes of 8.
Object shapes get more complex from 1984 to 1998, therefore lose its geometric fit (Figure A.5). This can mean two things, on the one hand that object borders become less linear and that patch sizes become bigger on the other hand. Shape index values close to 1 are seen in eastern areas in 1984, which resemble almost perfect fit to the shape of a square (Figure A.5). It can be speculated that this is an effect of the pixel size.
The mean object area is strongly increasing in subset south/east between 1984 and 1998. This suggests a gain in homogeneity, which causes larger coherent areas of one class. As a direct effect of the area increase, the object length is increasing. This effect is also visible to a lesser extent in the western subset. Area sizes and object lengths in the west are comparably large throughout all years. It suggests that homogeneity is higher and patches are bigger in these regions.

The Subset of Hawassa City shows highest values in 1998 for all features. This indicates that the class composition has been most balanced during this year, when large crop fields and large built up areas were present to almost same extent but spatially divided in east and west.

Both, texture and object change, substantiated an east/west difference in the study area. It showed that not only cropland composition is different, but also that field sizes and change trajectories differ. Whereas eastern areas gained higher order, western areas became more chaotic.

4.2.3 Object Change

This section serves to validate segmented objects that were created during *step A2.1*. These objects have not been used because they were unable to resemble field sizes.

An aggregation of classified pixels to the extent of objects showed that these are not able to resemble the classification result. Large areas after the aggregation process remain unclassified (black; Figure 31), because the mean of all classes present in an object does not reflect a class value. Consequently, it will be unclassified. This is especially the case in southern and eastern parts of the study area, where too many different classes are present within an object. This implies that segmentation scale of objects was too high to produce similar sizes as observed in coherent class areas. Object sizes are particularly over-estimated in the year 2014. This can show that real world object sizes become smaller on the one side, but reflects a higher scale setting on the other side.

Mean size and length of segmented objects are continuously over-estimated compared to classified objects (Figure 32). The only exception are estimates for subset west, where segmented objects are smaller than coherent classified areas and therefore, over-segmented. It proves that field sizes in the west are larger than in other regions of the study area and therefore detectable as objects with OBIA.

Additionally, we tested if objects are generally too big, but in proportion to the classified objects. In this case their change would show the same trends despite the over-estimated size.
Results indicate that segmented objects show no relation to classified objects, as they are not able to show the same trends (Table 8). Exception is again the subset west where a significant difference between the area change and length change of classified and segmented objects was observed. It can be explained by the over-segmentation of these elements by OBIA. For the subset Hawassa City the area and length change was strongly correlated, indicating that built up features are better resembled by OBIA than other features.

Table 8 Correlation of shape development of three moments in time (1984, 1998, 2014) between classified and segmented objects per subset and measure

Subset	South/East	West	North	Hawassa City
Area	0.66	-0.99	-0.13	0.96
Length	0.69	-0.78	0.04	0.98
Shape Index	0.54	-0.01	0.10	0.66
Border Index	0.50	-0.09	-0.14	0.59

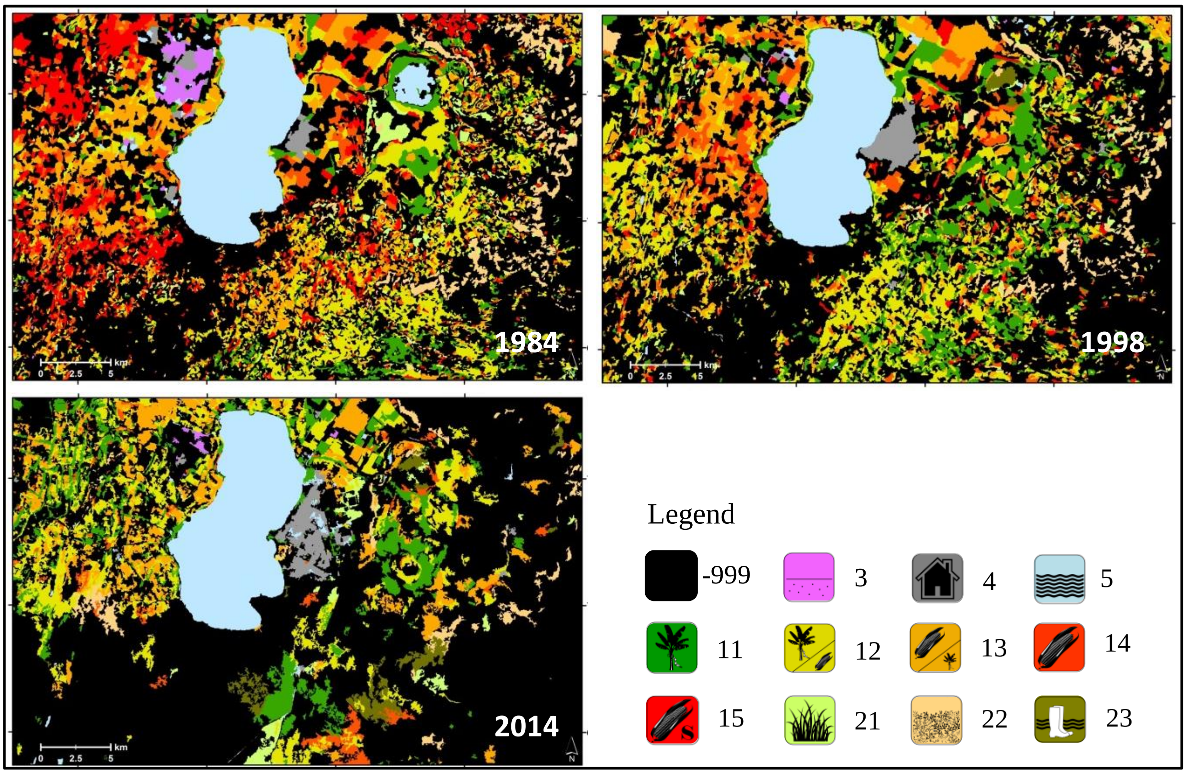


Figure 31 Aggregated classes for segmented objects of each year

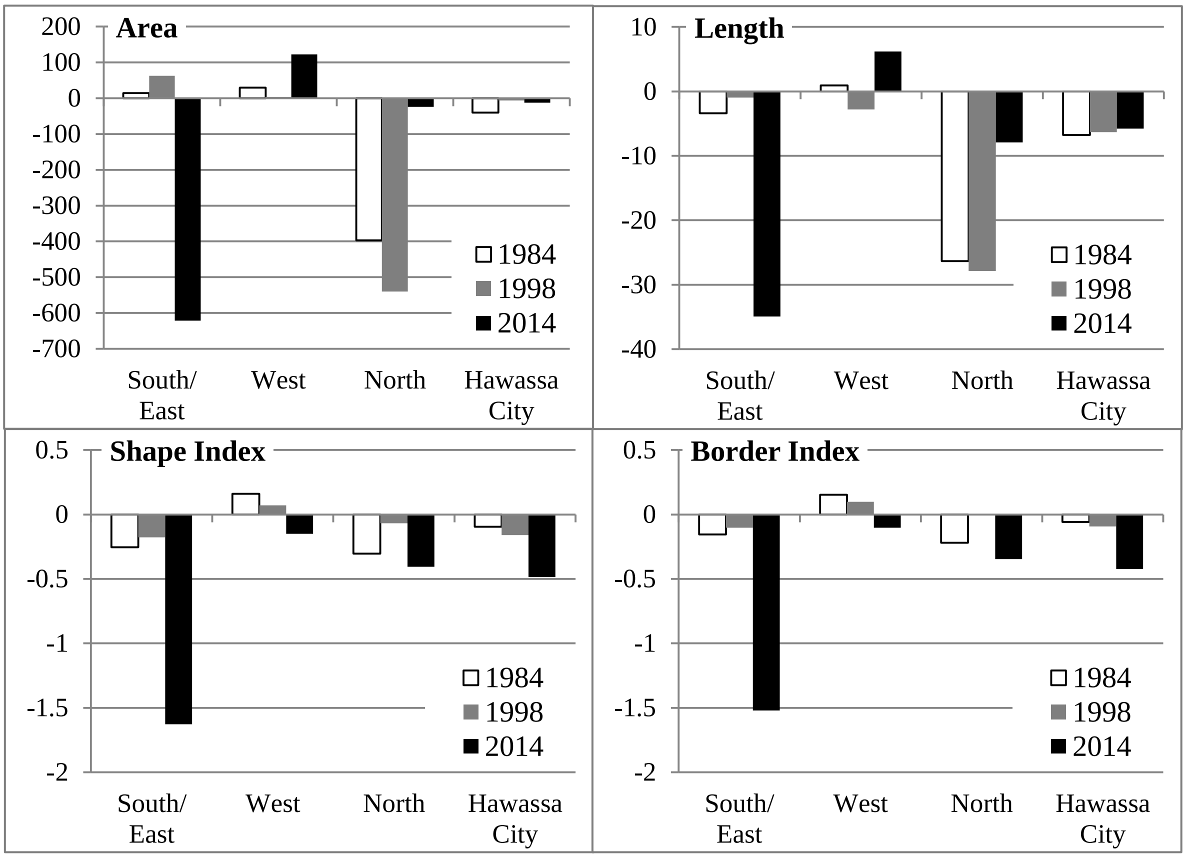


Figure 32 Direct comparison of classified objects (I) and segmented objects (II) as result of subtraction I-II

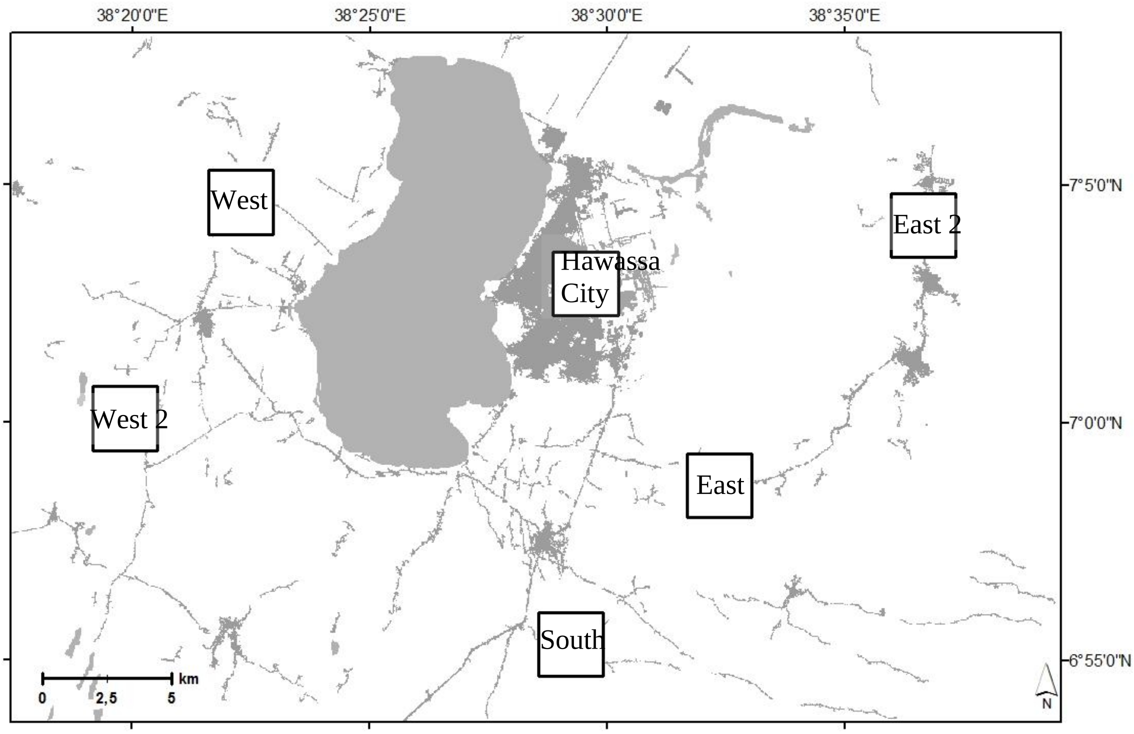


Figure 33 Tiles selected for representation of landscapes south, west, east and central

4.3 Changes in Landscape Diversity and Fragmentation

Landscapes are represented by 2,5 x 2,5 km tiles of the subsets created in *step A2.1*.
To ensure that a subset is adequately represented 2 tiles were selected within the western and 3 within the south/eastern subset. One tile was placed in the subset of Hawassa city (Figure 33).

The results show a clear east-west difference in the landscape in terms of dominant classes and Simpson Diversity. Southern tiles are more likely to resemble characteristics of the eastern landscape but with a more pronounced 1998-2014 change, as seen in western areas. In eastern tiles the change from 1984 to 2014 is seen to be more continuous without hard breaks. In general both eastern tiles show similar trends and characteristics with only few differences in class composition. Same applies for both western tiles. This indicates that the landscapes are resembled well by the initial creation of subsets.

Landscape diversity was highest in eastern landscapes and the city subset in 1984 (Figure 34). Since then a strong decrease in diversity has been noted. Likewise contagion is increasing, confirming that patch types get fewer and a few classes become more dominant. Contagion and diversity are inversely related. Dominant classes in the east and south in 1998 and 2014 are larger areas of perennial (11) with low number of patch habitats and high edge densities (Figure 35) and many medium sized mixed crop (12) patches. It shall be noted that the mixed crop class holds diversity in itself and also reflects high levels of fragmentation. Therefore low diversity levels combined with a dominance of mixed crop might indeed suggest the opposite. Generally, it is seen that edge densities of all classes are higher in the east and south than in the western regions. This indicates higher fragmentation levels and less geometric patches in eastern than in western regions.

Aggregation levels were relatively high in western tiles in 1984, showing the dominance of few classes, which are class 14 and 12 as seen in a high number of patches with large edge densities

(Figure 35). In2014, Simpson diversity is higher than in eastern areas, caused by the higher aggregation levels in the east. Diversity and contagion in the west are relatively stable throughout the whole time period. This can indicate that the overall proportions within the landscape stay constant. Combining these findings with other metrics shows a shift in class composition, however. It can be perceived by a decrease in distance between perennial and annual crops, as implied by the Proximity Index. This can indicate increased interspersion of annual and perennial crops, which is supported by rising patch numbers (Figure 35). A permanent change in cropland composition from annual towards mixed and perennial crops can be observed in a shift from high edge densities of classes 12-14 in 1984 to high densities of classes 11-13 in 2014. Perennial crops increased thereby first in number of patch habitats, which were small in size (1984-1998) then became larger, with higher edge densities (1998-2014).

In eastern and southern areas a general reduction in the patch abundance of annual crop is observed in decreasing number of patches and decreasing edge densities. Therefore, proximity index results in higher values. Again it shall be noted that mixed crop classes hold the highest level of proximity possible. Therefore, areas with dominating mixed crop status are assumed to hold highest potential for population exchange between pest habitat and pest predator habitat. This refers especially to the "East 2" tile (Wondo Genet) where the number of distinct patches of mixed crop class 12 is very high, complemented by relatively large edge densities.

The aggregation level in the city is highest (71 %) in 2014, showing an expansion of built up with only 4 discrete patches but a large edge density (Figure 35). Also it can be seen that number of patches and edge densities are relatively small in the city subset compared to other subsets, reflecting larger and more compact patches.

The landscape assessment substantiated an east-west difference in the landscape, implying that eastern areas lost class diversity, as dominance and aggregation of perennial class increased. Western areas have shown stable Simpson diversity and Contagion levels. A change in cropland composition can be perceived through decreasing Proximity Index values and a shift of patch count and edge densities from annual to mixed crops. The results imply that eastern landscapes were more fragmented in 1984 than western landscapes. Their change is mainly perceived in changing cropland composition. Western landscapes faced a more complex change of decreasing field sizes, which results in high aggregation of mixed crop and the introduction of perennial crops.

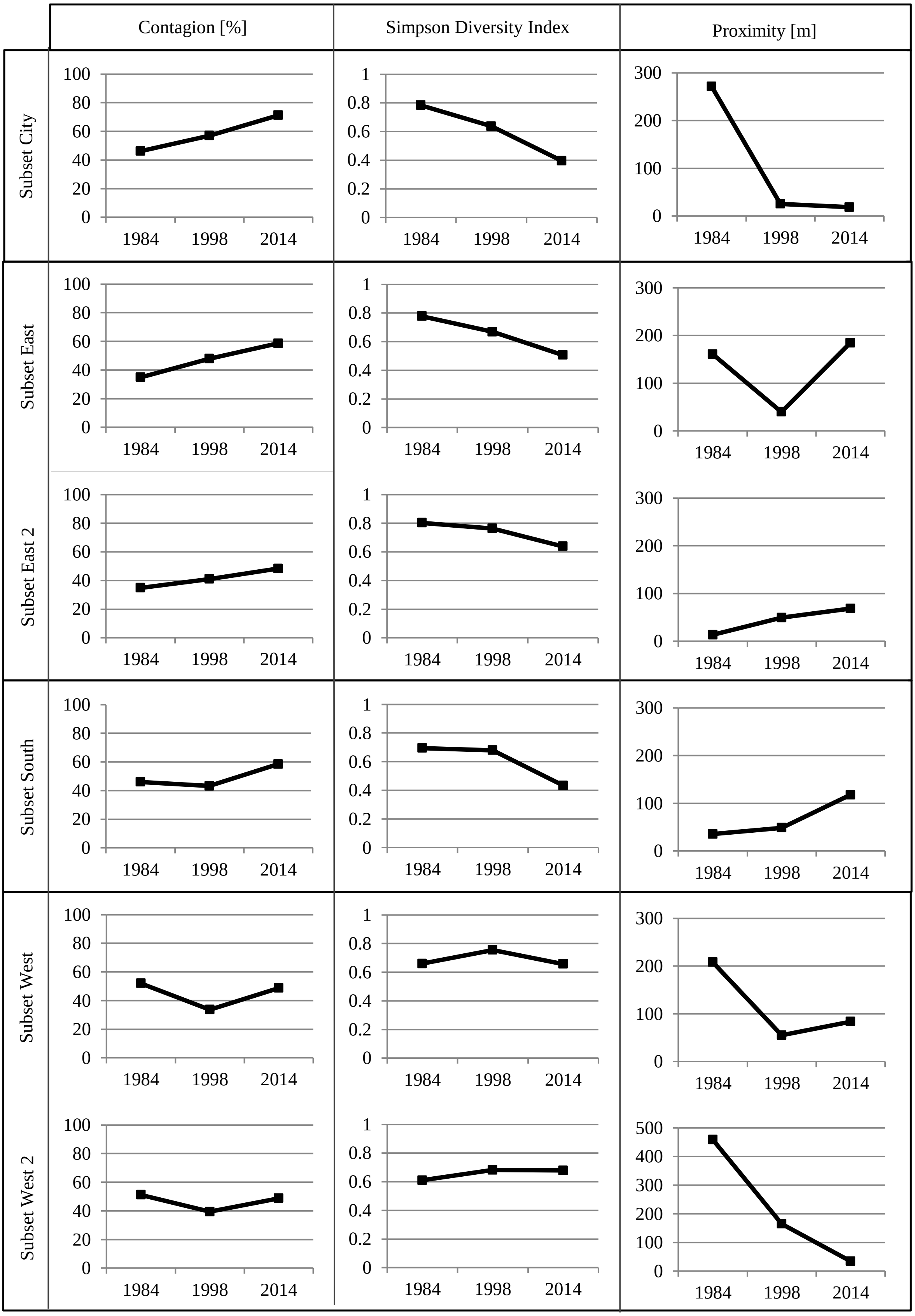


Figure 34 Landscape descriptors at landscape level for all tiles. Proximity is measured between class 11 and class 13/14/15.

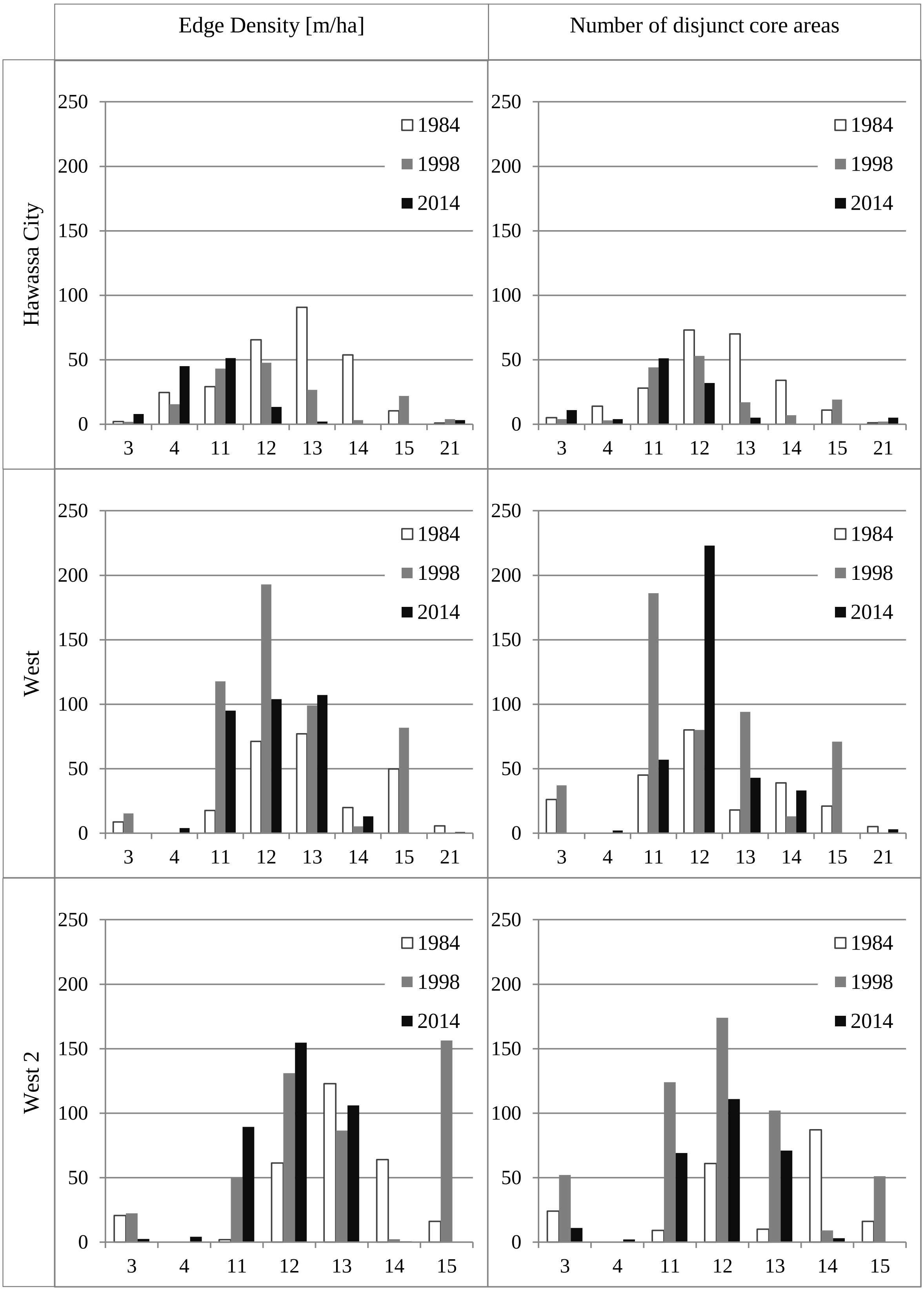


Figure 35 Landscape descriptors at class level for subsets City and West

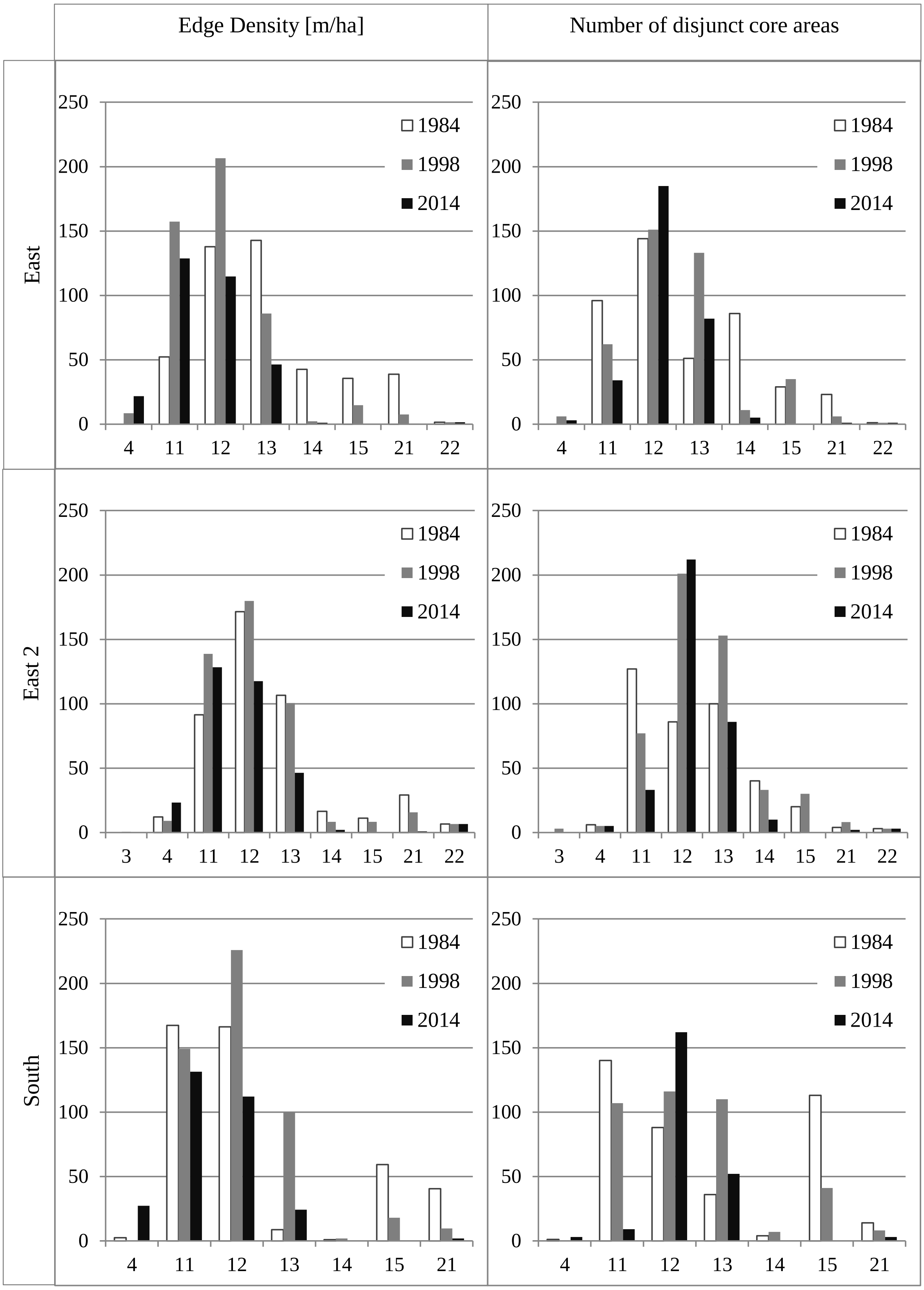


Figure 36 Landscape descriptors at Class Level for Subset East and South

5 Discussion

The discussion is divided in two parts. The first part is addressed to discuss the second objective, the effectiveness of the method. The second part is dedicated to reflect on the results and answer the research questions of the first objective, understanding landscape change and give an outlook on ecological implications.

5.1 Evaluation of Methodology

5.1.1 Research Question iv

How reliable are estimated change rates and trends based on the accuracies of the land cover classification?

Within our study we produced three thematic land cover maps (1984, 1998, 2014). For the first and last map we could acquire reference data for validation to determine overall accuracies of 77 % (1984) and 75 % (2014). For the intermediate map, reference data is missing. Therefore, the error of this image could not be assessed. The accuracy can be interpolated based on the class accuracies in the year before and after. If a class produced high accuracies in both years, it can be assumed reliable in 1998 as well because it was classified based on the same criteria. If it was seen less reliable in both years, its accuracy in 1998 should therefore also be assumed low. The map of 1998 saw another problem in the classification, which was pointed out in the result section of A (Figure 18). It was a very dry year, which caused a “famine” in the region of Boricha, south of our study area (Quinlan et al. 2014). Meteorological data proved that there was less precipitation than usual, which led to a crop failure, visible in no or scarce vegetation. To classify cropland despite its unusual appearance the bare soil threshold was adapted and the class “annual, separate” (15) was created. Those pixels were then excluded from the NDMI change analysis. This class holds higher potential to be misclassified with bare soil, because of the lowered threshold. This assumption was proven right in an accuracy assessment of class 15 for land cover in 1984, where 20 % of the sample pixels were seen to be soil instead of cropland. Another 6.67 % of the sample pixels were misclassified scrub. In the same year the commission error of annual class 14 on bare soil was a lot lower with 10 %, whereas another 10 % were misclassified scrub (Table 6).
For the image of 1984 the separate crop class 15 was created, too, because of the use of a wet-season image early in the growing season. It can be seen that this class holds large proportions of the scene in 1984 (19.88 %, Figure 26) and is present in all subsets (Figure 29). Therefore, it should be considered that annual crop in both years, 1984 and 1998, is over-estimated on behalf of under-estimated bare soil and scrub.

The accuracy assessment of 1984 revealed that scrub cover was present in all other classes and is therefore largely under-estimated. The omission error was with 38 % the highest amongst all classes. The user’s accuracy on the other hand was with 93 % very high, which proved that slope as a classification criterion is valid (Table 5). But the result suggests that in 1984 scrub is also present at lower slopes. This finding is proved by studies in the Hawassa area (Wondrade et al. 2014, Woyessa 2014, Kindu et al. 2013, Meshesha et al. 2012, Dessie & Kleman 2010), which all observe a reduction of scrub, bushland or natural forest. Also scrub and forest was reported to be present near the location of Hawassa city before it was built in 1959. Initially it was called Adare, which means home for cattle because it could find shelter underneath the trees (Wolte et al. 2010).

Another problem in land cover classification is the low producer's accuracy of grassland, which means that many pixels were not classified as grassland when in the reference data they were (omission). This was found for both years, 1984 and 2014, but probably for different reasons.
We believe that for 1984 our threshold, based on SWIR and NIR, did not capture the whole spectral variety of the class. Therefore, not enough grassland was excluded from the cropland classification. For 2014, grassland was covered a relatively low surface area Based on this image the thresholds were created, which were seen to work well with a user's accuracy of 100 % (Table 7). The omission in 2014 is believed to be caused by relatively small patch sizes of grassland that are smaller than the pixel size. Therefore, grass cannot be effectively separated from cropland.
Also bare soil patches were rare in 2014 and ground truthing points hard to find (personal communication, Kebede 2015). Most of the reference points were taken along streets and close to cities. These areas were therefore misclassified as built up. Not taking grassland and soil into account, which might be too small in size to be detected, the overall accuracy of 2014 would lie at 91.67 % with a Kappa Coefficient of 0.89. This indicates that the classification of cropland itself is of high accuracy. Indeed inter-crop confusion was low. However, mixed classes in 2014 were counted as correctly classified for perennial and annual crop because they are assumed to hold both classes. This contributes to the high accuracy values (Table 7).
Additionally, it shall be stated that the thresholds for mixed crops are made subjectively to represent different proportions of crop types. The threshold itself has not been assessed. Therefore, we recommend the classes to be interpreted as higher proportions of annual crop cover being present with higher class numbers within cropland classes 12 to14. The precise proportions, however, are unknown.

Wetland areas are contributing to an over-estimation of cropland in all three maps. We thereby do not mean the class wetland, but the subset "Other-Wetlands", which holds the former Lake Cheleleka and areas south of it. They are unsuitable for agriculture as discussed in the result section (Figure 18), not inhabited nor crossed by any streets. Therefore, they should be masked from the classification result or alternatively be defined as wetland class 23. An exclusion would result in lower area estimates of cropland classes, but does not have an effect on observed crop type proportions of the overall images.

Lastly, it shall be noted that the reference data itself might hold errors, too. Despite a subjective interpretation of the aerial images for 1984, the date might also cause errors. For 1984 we used aerial images of 1972 and topographic maps of 1979 and 1988 as validation data. These images are not representing the exact year of classification, which would be desirable. However, as these are the only data available for reference of the study area and in the time period, also used by other researches (Dessie & Kleman 2010, Rembold et al. 2000), they serve as the best estimate of land cover in 1984. The images were orthorectified based on an ArcGIS base map. The accuracy assessment was hence performed assuming perfect co-registration, which is an unrealistic assumption (Foody et al. 2002).

Overall it can be concluded that cropland cover is over-estimated in both images 1984 and 2014, and therefore probably in the image of 1998 as well. Wondrade et al. (2014) have measured an increase in cropland cover from 43 % in 1973 to 56,4 % in 2011. Our results show a smaller increase of 2 % between1984 and 2014 (Table A.1). This is due to a large under-estimation of the classes grassland and scrub in 1984, and a slight under-estimation of these classes in 2014. Hence, also the increase in cropland cover is underestimated. The inter-crop confusion, however, is low. Thus, depicted trends in changing cropland composition are valid and reliable.

5.1.2 Research Question v

How well does an object-based classification approach perform to describe landscape change in the study area compared to pixel-based approaches?

Our main finding concerning the use of an object-based approach is that object based image classification using Landsat imagery is neither effective nor feasible within our study area for the classification of cropland types.

The class water and built up are the only classes that were classified based on objects, although water was classified using NDVI which would have been feasible using a pixel-based approach as well. Built up is therefore the only class that was truly created with the special opportunities of eCognition using shape features. We did see this classification to perform very well, as a producer's accuracy of 100 % was achieved in both images (Table 5, Table 7). The higher commission in 2014 was mainly attributed by sample points close to streets that merged with the class in the used pixel size of 30 x 30 m. Also other studies have shown that roads are better detectable with OBIA using shape features instead of spectral features because of its specific geometry (Potuckova et al. 2010).

It was suggested to compare the results of an object-based classification of our research to those of pixel-based classifications of other researchers.
As most of the classes within our study are now pixel-based this comparison doesn't make sense anymore. However, we did segment image objects at the beginning of the process. Therefore, we can compare the classification result to itself by aggregating classified pixels to segmented objects, as done in *step B3*. It was shown that objects over-estimate the size of cohesive class areas by far (Figure 32) and thus, under-estimate the number of discrete objects (Table A.6, Table A.10). Largest differences between the shapes of classified and segmented objects were seen for objects of 2014. This can indicate that the segmentation process for Landsat 5 and Landsat 8 is different due to a different radiometric resolution. To increase the comparability of segmentation parameters it might have been better to rescale the data of both sensors to comparable units, such as reflectance. This is especially stated because, other than expected, the use of radiance did not result in any advantage over reflectance as in the end we used NDMI images for the main classification process.
Also it was shown that segmented objects are not only over-estimating the size of classified (real-world) objects, they were also not able depict change trends seen in the classification result. This was proven by a correlation between shape metrics of classified and segmented objects (Table 8). Therefore, it can be concluded that the objects created in the segmentation step are meaningless and are not able to depict real-world objects like fields in our study area.

It was suggested in chapter 2 that OBIA was able to produce higher classification accuracies than PBC. Our classification is with 75 % (2014, Table 7) and 77 % (1984, Table 5) accuracy comparable to the accuracies of other studies in Ethiopian landscapes using PBC that were seen to range between 67 to 87% (Meshesha 2014, Meshesha et al. 2012, Shiferaw 2011, Dwivedi et al. 2005, Bewket 2002, Rembold et al. 2000). The high accuracies that are promised by researchers using object-based approaches in South Ethiopian landscapes were not achieved, e.g. Kindu et al. 2013 (Landsat MSS, TM, ETM+, RapidEye; 85,7 % to 93,2 %), Wondrade et al. 2014 (Landsat MSS, TM; 82 to 85 %). This is indicating that for the right purpose in the right landscape and with the right sensor OBIA can be very effective.

For our sensor, Landsat, in our landscape, small-scale African agriculture, and for our purpose, cropland classification, the use of OBIA is not feasible.

Therefore, it shall be remarked that Landsat data might not be the best data choice to detect land cover change in Ethiopian landscapes that are characterised by high population densities, high fragmentation and small farm sizes (Sonneveld & Keyzer 2003). VHR data, that allows better spatial resolutions, would be able to give more insight on these landscapes (Lung et al. 2013). They would also allow the classification of smaller landscape features such as hedgerows and small scrub areas, which are of high ecological importance.

With VHR data object-based classification would be more effective for cropland classification, as fields can be separated from each other. Despite the fact that OBIA did not work in our research project, we believe that it can be a great addition to landscape assessment if real world objects are large enough to be detected by the sensor that is used. The results of texture and object shape assessment (Figure 30, Figure A.5) showed that object descriptors are able to detect similar trends as landscape metrics of Fragstats. Therefore, the potential of OBIA to contribute to landscape analysis is high.

The strong advantage of Landsat over VHR data is that it is providing a continuous data series since 1972, which allows mapping of historic land cover. VHR data on the other hand is only available for the most recent year and not free of charge.

Despite the described problem regarding the relatively low spatial resolution of Landsat data, two other obstacles of OBIA were observed: segmentation is too important and incomparable; and the classification strongly depends on the knowledge and expectations of the user.

The segmentation step is crucial in the process of object-based classification. It determines the outcome of the classification to a large extent. The determination of the right segmentation scale, however, is very complicated and highly subjective as there is no unique solution. Also segmentation is image dependent and changes for every image. These problems have been noted by many researchers (Kavazoglu & Yildiz 2014, Baatz et al. 2008, Neubert & Herold 2008, Hay-Castilla 2006). There have been attempts to enhance decision making on the right segmentation scale by involving statistic measures for interpretation (Drăgut et al. 2014, Drăgut et al. 2012, Kim et al. 2008, Wang et al. 2004). However, these metrics are often difficult to interpret. Baatz et al. (2008) propose an object-oriented approach that overcomes the problem of a two-staged classification, first segmentation then classification, by the creation of flexible objects that are constantly altered. We used the ESP approach by Drăgut et al. (2014) in our research. It helped decision making to a large extent and the suggested scales seemed to resemble the visual appearance of image properties well. Because fields were classified on sub-pixel level and thus not detectible, we cannot judge its effectiveness. We noticed that it seemed to be less effective for Landsat 8.

The second problem observed for OBIA is that you can only classify what you expect. OBIA is certainly not able to produce unexpected results, as the user needs to define objects beforehand. Therefore, our own analysis was seen to work in a circular approach. We expected different levels of diversity in terms of crop composition and fragmentation in the landscape and thus, created subsets that we segmented with different segmentation parameters of scale, compactness and shape. Later on in the analysis, we proved that the landscape showed indeed different levels of diversity with using landscape metrics. The cropland composition was now based on pixel level. But assuming that we would have worked with objects, as planned, in a landscape where fields would have been larger, this would have only proven our assumptions to be right, but OBIA would have not helped to create new knowledge.

5.2 Understanding landscape change

5.2.1 Research Question i

Which land cover types have changed the most and in which period?

Key findings are an increase of perennial crop (+ 204 %) and a decrease of annual crop, grassland and bare soil (-77 %, -82 %, -74 %) in the whole study area between 1984 and 2014 (Figure 27). A qualitative analysis showed that natural areas were thereby replaced by cropland (Table A.2). A large east-west difference was found to be present in the scene, with more annual crop and bare soil proportions being observed in the west (Figure 29).
The loss of natural vegetation can be confirmed by many studies conducted on land cover change in Ethiopia (Assefa & Berk 2014, Kindu et al. 2014, Meshesha et al. 2014, Teferi et al. 2013, Meshesha et al. 2012, Shiferaw 2011), but also for our study area more specifically. Shewingazew & Micheal (2010) observed a loss of natural vegetation of 9 % within the years 1995-1998 in the Lake Awassa watershed. Wondrade et al. (2014) confirmed a horizontal expansion of agriculture replacing existing woody vegetation and grassland in Hawassa Zuria, an area south of Hawassa city. A loss in scrub or bushland cannot be evaluated in our study because over the period of study it was classified based on slopes larger 20°. Therefore, the class extent does not change. However, as described in chapter 5.1.1 scrub known to be present in lower slope areas, too, and thus largely under-estimated in 1984. In 2014 a visual check in Google Earth implied that scrub is not present at lower slopes (Figure 10). Therefore, it can be hypothesised that scrub cover in our research area is decreasing, too. Dessie and Kleman (2010) have studied deforestation at a study site close to Hawassa city and present a loss of natural forest of 82 % due to an expansion of small-scale agriculture, which strengthens our assumption.

Whereas land cover change has been studied in South Ethiopian landscapes with rising extent, the change of cropland composition has rarely been a target of research. Therefore, it is difficult to confirm our finding of decreasing annual and increasing perennial crops. Meshesha et al. (2014) reported an increase of perennial crops and decrease of annual crops in a study located in the Ethiopian highlands, which goes along with our findings. Most studies assessing cropland change have been based on qualitative approaches such as field surveys with locals (Woyessa 2014, Abebe & Kjørholt 2009). Our findings support the assumption that annual crops are losing their importance in the study area as a shift towards the cultivation of perennial or multiple crops can be observed. A more detailed discussion of cropland change will be given for research question ii.

The transition of natural vegetation to cropland implies that the landscape is under enormous population pressure which requires the population to use all land possible.
Grepperud (1996) summarizes the process of extensification and population increase as "forcing people on new land." When the demand on land for crops and livestock, building materials and fuel increase, it ultimately results in removal of original vegetation cover. People are moving onto new, less fertile land, which is less suitable for production and more erosion-prone (Sonneveld & Keyzer 2003, Grepperud 1996).

Perennial cropland increased the most in terms of total area (Figure 26), but the highest growing rates were depicted for class built up, that has gained more than 600 % from 1984 to 2014 (Figure 27). It is known that these rates are even under-estimating population growth as it does not take into account the presence of houses and farms within the landscape. An inspection in Google Earth (Figure 37) shows these buildings as white spots next to almost every field. In a 30 x 30 m resolution of Landsat their signal gets merged with the surrounding field information. The expansion of cropland and high proportion of mixed cropland, indicating small field sizes, gives reason to assume that the number of on-site farms is also growing. Additionally, the emergence of new rural cities and roads as well as the presence of linear perennial features observed in the western regions (Figure 38) encourages this thought. Increasing urban features were affirmed by many studies of LULC change in Ethiopia with high expansion rates of up to + 200 %, but at different time spans and study sites (Kindu et al. 2014, Meshesha et al. 2014, Wondrade et al. 2014, Meshesha et al. 2012, Shewangizew & Micheal 2010).

Lastly, a small change of + 0.5 % (100 ha) in the lake area was noted from 1984 to 2014 (Table A.7). This seemed unlikely and was thought to be caused by different classification settings for Landsat 5 and Landsat 8. Wondrade et al. (2014) and Shewangizaw & Micheal (2010) have made the same observation. They suggest that an expansion of lake size is caused by the salination of the smaller lake Cheleleka that was situated east of Hawassa city and increasing runoff due to deforestation in the eastern highlands. Lake Cheleleka served as a water and sediment trap. With its aridification it loses this function and water and sediments are directly transported to Lake Awassa via the perennial river Tikurewuha.

Concerning the moments of change, it can be noted that change was seen to proceed gradually from 1984 to 2014, but was slightly more pronounced in the time period 1984-1998. Especially losses in grassland and annual crop cover were seen within this time period (Table A.1). Land cover changes might be affected by the political change in 1991 that resulted in a transition of communal land to privately owned land (Woyessa 2014, Holden & Yohannes 2002). Therefore, everyone was able to buy land and free to cultivate the crop of their own choice. It followed an earlier land reform in 1975 that claimed all land as state property, but distributed it to farmers with only to use- right basis (Headey et al. 2014, Belete et al. 1991 in: Woyessa 2014). Between 1975 and 1991 commercial large-scale farming was promoted to the state farms (Headey et al. 2014, Zerihun 2009 in: Woyessa 2014).

For perennial and built up classes most change was seen in period 1998-2014. This could have different reasons. Built up increase was mainly seen in the subset of Hawassa city and the subset East/South (Figure 29). Therefore the increase is clearly connected to the expansion of Hawassa city and the emergence and growth of cities in the east (Wondo Genet, Busa) and south (Irba, Tula). A possible reason hereof could be that in the aftermath of the land reform in 1991 less land is available which causes people to move to the city to maintain and/or increase their income (Barrett et al. 2001). Another reason could be that Hawassa city has been designated capital of the South Nations, Nationalities and People’s state (SNNPR) in 1995, which brought a transition in almost all economic sectors, private investment, tourism, the service sector, industrial development, trade and commerce. Along with it new opportunities in the employment sector evolved (Wolde et al. 2013).

The increase in perennial crop between 1998 and 2014 can potentially be explained by a population increase in the western regions that promotes the formation of home gardens with higher proportions of perennial crops (Abebe 2005, Zemede & Ayele 1995). Also a new road was mapped in 1998, connecting the west with regions south and east of Lake Awassa. This reflects the population increase in the western regions that demands new and better ways of transportation. Also it displays the opportunity of better market access, which might trigger the production of more lucrative, perennial, crops.

5.2.2 Research Question ii

How does the cropland composition change and can this reflect changes in farmers' livelihood strategies?

A closer inspection of cropland change can be interesting, because it can provide us with hints on where to find more potential on sustainable pest suppression and can give insights into social and economic processes.

Research question i has presented that highest changes occur in increasing perennial crop cover and decreasing annual crop cover. This finding can be confirmed by studies of Ethiopian land cover and crop market change, which were mainly conducted by field surveys. Meshesha et al. (2014) made a study in the Ethiopian highlands on land degradation and found a decrease of annual crop with 29 % and increasing perennial crop shares of 42 % between 1985 and 2011. This supports our findings as the trend in cropland change is the same, despite a different land composition. Most land in their study area degraded to marshland. Feyisa & Aune (2003) found a rapid increase of the perennial crop khat especially between 1985 and 2000 in the Ethiopian highlands, also stating decreasing amounts of annual food crops. The most relevant study for our research area was carried out by Woyessa (2014), who interviewed the 49 participant of the local population in the Hawassa area to re-produce trajectories on land cover change. He reported a large difference in crop proportions before and after 1991. The proportion of maize strongly decreased, attributed to the relative increase in perennial crops enset and khat. This observation coincides with the results of the quantitative analysis of our research, where perennial crops more than doubled its size from 1984 to 2014 (Table A.1). Despite the fact that all studies indicate the same trends in decreasing maize proportions, yields of annual food crops have been seen to rise with 12 -14% throughout the last years (Benson et al. 2014). This seems to contradict our finding of a reduction of annual cropland cover. According to Benson et al. (2014) higher yields are mainly achieved through a governmental Agricultural Growth Program, helping farmers to improve their farming methods and intensify their production with the availability of improved inputs, such as seeds and fertilizer. Therefore, it seems that the increase in maize productivity is achieved by intensification only because our results suggest that an extensification of annual crop is not taking place. At least not in the Hawassa area. However, concrete numbers on yield production in this area are missing.

In our research mixed crop classes have been created in addition to annual and perennial crop. They were created because of a relatively large pixel size of 30 x 30 m and therefore, to acknowledge the presence of mixed pixels, containing more than one crop type. The development of mixed crop classes showed the same process of increasing perennial crop proportions. Therefore, a decrease in annual crop type was observed as a shift towards mixed crop class 13 and 12 first.

Figure 29 has shown that a large difference between the west and east of the study area exists. It leads especially to differences in the importance of mixed crop classes. Whereas the overall amount of mixed crop is decreasing, its proportion in the west of the study area is increasing over the period of study. This difference can reflect that there are different underlying processes in both landscapes that are causing changes in cropland composition.

The western region showed a tradition in the cultivation of annual crop, which has been dominating this area in 1984, shown in low diversity and high aggregation values. From 1984 to 1998 diversity levels increased in western regions with decreasing contagion, implying less aggregation and less dominance of annual crops (Figure 34).Also the proximity index showed that distances between annual and perennial crop became smaller throughout the years, indicating the introduction of perennial crops to the region.

The eastern areas were seen to be more diverse in 1984 then western regions, but also showed small field sizes. This can be assumed from the high amount of mixed crop observed in 1984 (Table A.7). Already then a high proportion of perennial crop was present. As the importance of perennial crops increased this led to a loss of mixed crop fields and resulted in overall higher proportions of perennial crops (over 50 % in 2014). On the contrary in the west perennials were newly introduced to the area after 1991 (Woyessa 2014) and thus, a decrease in annual crop and increase in perennial crop mainly resulted in higher proportions of mixed crop.
A reason for the observed west/east difference could be explained historically. High aggregation rates and low number of patches indicated relatively large field sizes of annual crops in the west. It can be speculated that this farm land was determined by state demands on food supply. After the political change a change in settling patterns was observed. Especially the formation of more geometric and linear feature (Figure 38) implies that this area was "colonized" at a later time and in an organized way. The east showed small field sizes and high fragmentation in all years. This suggests that this region has grown from itself over a longer period of time and in a more unorganized way (Figure 37).
Summarizing, it can be stated that a shift in crop cultivation towards a higher rate of perennial crops can be observed in landscapes east and west of Lake Awassa. This results in a higher proportion of perennial crop class in the east and higher proportions of mixed crop class in the west in 2014.

Next to an increase in perennial crops also a decrease in field sizes was indicated by mixed crop shares. Woyessa states that in his survey enset and maize was present in 90 %, khat in 57,5 % and coffee in 32,5 % at the farms. These numbers indicate that many farmers cultivate more than one crop, of both perennial and annual character. They are present on spatially small scale as farm land sizes in South Ethiopia commonly range between an average of 0.6 -2 ha (Woyessa 2014, Abebe & Kjørholt 2009, Shiferaw & Holden 1999). Therefore, our hypothesis of mixed pixels, containing more than one crop type can be assumed right.
Another phenomenon promoting the cultivation of mixed crops, which can be used to explain higher perennial crop proportions, is the presence of home gardens. These have been studied before in South Ethiopia (Zemede & Ayele 1995) and our study area (Abebe et al. 2010, Abebe 2005). Home gardens are characterised by a wide variety of different crops growing spatially close to each other. Zemede & Ayele (1995) found a range of 162 different species in a survey of 111 home garden sites, with enset and maize being the most frequent. Abebe (2005) made similar findings in a survey in the Sidama province, of which Hawassa is capital. In a study on home garden diversity he found 78 different species within 144 farms. Enset and coffee were the most dominant perennial crops and maize the most frequent annual crop. Within recent years these crops have been gradually replaced by khat and pineapple, which are financially more attractive (Abebe et al. 2010, Abebe & Kjørholt 2009). These crops are considered cash crops.
In our study area perennial crops are especially khat, coffee and enset (De Valenca 2014,Woyessa 2014). Enset is used as a food crop but also for its by-products such as fibre (Abebe 2010). It has an advantage over other cereal grains because it can support a higher density of population, offers a high caloric yield per unit and is more drought resistant (Abebe &Kjørholt 2009). Whereas enset has been an important crop for home consumption already in the past (Woyessa 2014, Bezenuh 1966), khat production has rapidly expanded within the last years and is one of Ethiopia's largest export items. It is grown partly for home consumption, but largely for sale on regional or national markets. About a third of the production was exported to Djibouti and Somalia in 2000 (Feyisa & Aune 2003). Woyessa (2014) reported especially an increase in khat production in Wondo Genet, a region in the east of our study area that was addressed as tile "east 2" in the result section of *part C*.

The observation of Woyessa is substantiated by our study, which found lowest diversity rates and a high dominance of perennial crop within this area in 2014.

Can an increase in perennial crop production reflect changes in livelihood strategies? Yes, changes in livelihood strategies in the study area are very likely. Increasing shares of cash crops such as khat, positively affects the households income. It enables them to obtain more food than by producing their own food crops, but also has seen to have positive effects on all other aspects of consumption, as well as education (Poulton et al. 2001, Maxwell & Fernando 1989).

Households aim for livelihood with resilience, low sensitivity to shock and stress (Rakodi et al.1999), which can be achieved through cash crops on the one hand but diversification on the other hand (Ellis 1999). Maize has been an unstable food source for farmers in the Hawassa region because of recurring droughts and pest infestations (Woyessa 2014), which was also seen in our own research when water scarcity resulted in crop failure in 1998. However, diversification of crop types is also important, as global market prices change quickly. Coffee, which is also sold as a cash crop is a relevant example. In 1998 coffee prices were sharply declining on the global market due to an expansion in supplies, but stable demands (Hallam 2003). This can explain increasing proportions of khat as an alternative after 1998 within the perennial crop class (Feyisa & Aune 2009).

A change in livelihood strategies becomes even more likely considering the dramatic population growth in the area, which was discussed in research question i. Higher population densities ultimately result in land scarcity and forces people to find new and stable sources of income. Thus, Poulton et al. (2001) state that shifts on greater reliance on cash cropping are inevitable as population increases.

The higher production of cash crops and population increase might be a coupled process since both processes seem to have high influence on the local cropland composition and configuration. Therefore, the conclusion of Woyessa (2014) that the production of perennial cash crops are key drivers in the change of farming systems in the Hawassa area can be strongly supported by our results.

Figure 37 On-site farms in rural areas between Busa and Colaris *(left)* and south of Awassa Lake *(right)* in January and December 2014. Source: Google Earth.

Figure 38 Home gardens in the western areas *(above left)* and south-western areas *(below left)*. Characteristic formation of linear features due to home gardens along streets in the west *(right)* in December 2014. Source: Google Earth.

5.2.3 Research Question iii

How does land cover change affect landscape structure in terms of landscape configuration, diversity and annual to perennial crop distance?

Our results have confirmed a west-east difference in the study area that showed different levels of class diversity, which can have large ecological impacts. Possible implications of landscape configuration on natural pest control will be discussed at the end of this chapter. Eastern areas were most fragmented and most diverse in 1984, western areas showed low diversity, high aggregation and dominance of one class (annual crop). Southern areas show characteristics of both areas, with high fragmentation on one side, but higher aggregation and dominance of annual crops on the other (Figure 34). In the past 30 years eastern regions have lost class diversity, approaching levels of western areas with high dominance of perennial crop. Diversity levels in western areas stayed almost the same, despite a loss in aggregation.

Solely from these findings it seems as though only eastern areas experience a land structure change. But as Turner (2005) points out "no single metric can capture the pattern on a given landscape" It needs a palette of complementing measures to explain landscape change (Eiden et al. 2000).
Adding the proximity index to the palette shows that the western area is indeed also experiencing changes in landscape configuration as the distance between annual and perennial crop is drastically decreasing (Figure 34). A closer look at number of patches and edge densities per class identifies a clear shift from annual cropland towards mixed cropland. Whereas in 1984 a few large fields of annual classes14 and 15 and mixed crop 13 dominate the area, the number of mixed crop 13, 12 and perennial crop patches increase in 1998 and 2014. Thereby the number of patches was seen to increase first, which afterwards gain in size in 2014. One problem that was neglected during the land structure assessment was the existence of class 15, which held annual crop as separate class due to different classification settings.
It is important to keep this class separate to acknowledge the higher potential of misclassification and allow better interpretation of the area. However, it is considered to hold annual crops and should therefore be treated as such in the analysis. This means that class 14 and 15 should have been merged. This has not taken place, which might explain almost consistent levels of diversity and aggregation. We suggest that indeed those metrics would have resulted in lower class diversity and higher aggregation if class 14 and 15 had been one class. This affects also the analysis of *B2.2* where we assessed texture and object shapes.
However, the proximity index assessed annual class as a merged class of class 13, 14 and 15. Class 13 was involved because it is assumed to hold large proportions of annual crop. Therefore, measuring its distance to purely perennial features is also relevant.

Another aspect that might lead to misinterpretation of the data is the presence of mixed crop. It is assessed as one compact class, when in reality it is meant to hold more than one crop type. Therefore mixed crops hold highest crop diversity and fragmentation levels already in itself. This should be considered in the analysis of the data. Especially eastern landscapes that have shown decreasing diversity levels and hold high proportions of large mixed crop patches (class 12), which was shown in 2014 in the highest number of patches for class 12 with intermediate edge density at the same time (Figure 36). Therefore, fragmentation and crop diversity in the eastern regions are higher than indicated by the levels of Simpson's Diversity Index (Figure 34). One the other hand, the data also showed that the number of perennial patches is decreasing while edge densities grow. This implies that the overall importance of perennial crops in the east is rising and large, compact areas of this crop type are present. This observation could be interpreted as an increase in field sizes, which is known to not be true from observations made on satellite data and on-site knowledge (DeValenca 2014, Woyessa 2014, Kebede 2013). However, for eastern regions we cannot see this from our data because of the large pixel size of 30 x 30 m that is not able to depict field edges. Also the combination of number of patches and edge densities requires more interpretation on the relation between patch sizes and patch number. Another complimentary landscape metric such as area-to-edge ratio might have made this interpretation easier.

The metrics in our assessment were chosen especially to complement the work of Kebede in assessing pest pressure in maize crops. Her hypothesis is that a higher proportion of perennial crops, which is habitat to natural pest predators, in the landscape can help sustainable pest suppression. A diversified agricultural mosaic in the landscape with many patches and especially edges can sustain diversity of natural enemies (Bianchi et al. 2006). Edges are ecologically very important because they hold higher concentration of biodiversity, as populations move along edges (Bianchi et al. 2006).

Therefore, edge density is an important measure in our assessment. The more edges are available per ha the higher is the potential for exchange (Debinsky & Holt 2000, Landis et al. 2000). Now it was measured per class, to complement the interpretation of number of habitat patches. However, it might have been more interesting to explain edge densities on landscape level instead of on class level because one discrete number would have improved a comparison between different landscapes and point out areas of higher potential for natural pest control.

The number of habitat patches is an important measure to assess potential predator and pest habitat. Especially interesting is the size of a patch. The bigger the patch, the bigger becomes the core area which is where habitat for one species but can be hostile for others (Bianchi et al. 2006). Predators are known to mainly colonize pest habitat along its edges. Therefore, it can be speculated that bigger annual crop patches are more affected by pests than small fields (Poveda et al. 2008). Based on the stated, we can speculated, that for our study area pest pressure was the highest in western regions, where large annual crop fields were present and edge densities of these classes were low (Figure 35). The potential for natural pest suppression was highest in eastern areas, where the opposite was seen. We do not have past or current data on pest pressure to validate these assumptions. Therefore, a validation will follow within the work of Kebede, who is currently collecting these kinds of data.

To assess the potential of natural pest control the distance between perennial and annual landscape elements was measured. It is hypothesised that the closer these elements are, the higher is the potential of colonization of pest habitat by natural pest predators (De Valenca 2014, Kebede 2013). The data have shown that the proximity decreases in western areas, but rises in the south and east. This can be explained through an introduction of perennial crops to the western areas, especially along new built streets in home gardens, which results in decreasing distances between the 2 crop types. In the east proportions of annual crop are largely decreasing, which results in rising distances.

We tried to achieve an approximation of the landscape dynamics by using the Proximity Index. However, the classification is based on a 30 x 30 m pixel size. A pixel might incorporate hedgerows which are of high ecological importance (Schellhorn et al. 2014, Vialette et al. 2007, Bianchi et al. 2006, Forman & Baudry 1984), because they enable functional flows through the landscape and have been found to be predator habitat in our study area (DeValenca 2014). Information on hedgerow presence and length would be very interesting, but is not feasible when using Landsat data. VHR data or Radar data can be recommended as suitable data choices to gain more insight on hedgerow occurrence.

Another problem when indicating distances between pest and predator habitat is that now only perennial crop is considered as pest habitat. But is it known that scrub can also serve as predator habitat. This has not been considered because scrub area is inflexible in our analysis. Therefore, an assessment of scrub and annual class distance would have meant a correlation between crop cover and relief, on which the scrub class is based on. For 2014, this correlation might be valid, because scrub was seen to not occur on lower slopes. In this case the eastern areas hold the highest potential on natural pest control, because it is more mountainous and comprises many steep slopes. Southern regions and regions close to the lake hold the least potential for natural pest control based on scrub cover, because high slopes and therefore scrubs are missing. However, as discussed in research question i and iv, we assume that scrub cover was also present at lower slopes in 1984. Therefore, the influence of scrub presence on natural pest control in earlier years cannot be adequately assessed.

In result section *B2* texture and object shapes were assessed. Texture measures were seen to support the results of the land structure analysis on landscape level. GLCM contrast was seen to compliment diversity, whereas GLCM Orderliness (Entropy and ASM) were related to Contagion. The texture measure implied the same trends of increasing aggregation in the east and more or less stable aggregation and diversity in the west. GLCM contrast in the eastern areas on the other hand was seen to be increasing (Figure 30), whereas the Simpson's Diversity Index showed the opposite. This is most likely caused by the different spatial context. GLCM measurements were based on subsets, for which eastern and southern areas were assessed in one subset. The diversity analysis was based on normalized subsets of a tile size of 2,5 x 2,5 km. Therefore, the subset east/south was represented by three tiles (East, East2, South; Figure 33)

The object measures of shape, mean area and length, can be correlated to the measurements of number of patches and edge density. Both combinations can give more knowledge on patch sizes.

Shape index and border index are comparable to the landscape metric "fractal dimension", which usually is used to indicate human impact (Feng & Liu 2015, Trimble 2014). Especially with small field sizes and high diversity this metric was largely affected by the pixel size, which it resembles (Figure A.5). Therefore, fractal dimension was not assessed in *part C.*

The good resemblance of landscape patterns with measurements derived by OBIA proves this method to be a valid addition to landscape analysis. It was able to show similar patterns as landscape metrics of Fragstats. But the accuracy and reliability of Fragstats metrics have been analysed to a large extent already (Fan & Myint 2014, Cushman et al. 2008, Tischendorf 2001, Riitters et al. 1995), which enables easier interpretation of these metrics and better comparison. Also, within in our own study an assessment of texture and object shape did not add more information on landscape then already achieved with Fragstats. Therefore, this step was redundant.

6 Conclusion and Recommendations

Identifying and understanding long term changes in the local landscape context of Hawassa, Ethiopia is one of the very first steps to gain a deeper understanding of driving forces of pest incidence in the study area. Of particular interest are changes in cropland composition that can help to understand the impact of farming systems on pest pressure and natural pest control. Understanding patterns and trajectories of maize cultivation, for example, can be linked to the occurrence of stem borer infestation.

In this study the land cover of the Hawassa area was examined using available long term Landsat time series for three moments in time, 1984, 1998 and 2014. Eleven relevant land cover classes were classified: bare soil, built-up, water, perennial crop, two annual crop classes, two mixed crop classes, grassland, scrub and wetland.

The developed method could achieve overall accuracies of 77 % (1984) and 75 % (2014), which are comparable to those of other studies in our research area using pixel-based classification.
We used an object-based image analysis for detecting the classes water and built-up. Due to locally very small field sizes that are often below the pixel size of 30 x 30 m, cropland, grassland, bare soil and scrub were classified based on pixel level. Vegetation was assessed by using NDMI as a measure for greenness and assessing its change between wet season and dry season state. Annual crop and perennial crop were separated using a change threshold of <0.15 for perennials. Additionally, mixed crop classes were created to acknowledge the presence of mixed pixels and thus, pixels containing more than one crop type. Bare soil was classified as being not green in both wet and dry season images. Grassland and scrub were excluded from the cropland classification by using NDVI and SWIR; and slope as classification criteria, respectively. Accuracies were assessed using aerial images and topographic maps for 1984 and ground truthing GPS data for 2014 as validation.

Object based image classification of Landsat data was found to be neither effective nor feasible within our study area for the purpose of cropland classification.
Created objects were meaningless and not able to depict trends in land cover change. This can be explained by a relatively low resolution of Landsat data that is not useful to detect small scale agriculture. Therefore, Landsat data might not be the best data choice to detect current landscape patterns at field level in Ethiopian landscapes or other 3rd world countries that experience high population pressure. However, it is the only global data source that allows long-term monitoring of land cover change.

The landscape change revealed a clear increase of perennial crop at the cost of annual crops with a large difference between the eastern and western part of the study area.
More specific, our results showed an increase of perennial crop (+204 %) and built up (+616 %) and a decrease of annual crop, grassland and bare soil (-77 %, -82 %, -74 %) in the whole study area between 1984 and 2014. A qualitative analysis showed that natural areas were thereby replaced by cropland. A large east-west difference was noticed in higher annual crop and bare soil proportions in western regions. This led especially to a difference in the importance of mixed crop. Eastern areas already showed high proportions of perennial crop and mixed crops in 1984, whereas perennial crop classes have been introduced to western areas only after 1984. A shift in crop cultivation towards a higher rate of perennial crop was observed in higher proportion of perennial

crop class in the east and higher proportions of mixed crop classes in the west in 2014. Change was seen to proceed gradually from 1984 to 2014, but was slightly more pronounced in the time period 1984-1998, which might be related to a political change in 1991. The results can give insights on underlying social and economic changes such as rising population pressure and a change in livelihood strategies towards the cultivation of multiple crops and cash crops. The depicted trends in changing cropland composition were found to be valid and reliable, despite the fact that the total amount of cropland is over-estimated. This is especially the case in 1984, where scrub and grassland areas are largely under-estimated.

Land structure assessment showed that eastern areas lost most crop diversity on behalf of higher aggregation rates of perennial crops within the last 30 years. Western areas became more fragmented through the introduction of perennial crops. Dominance has shifted towards mixed crops.

The west-east difference was substantiated using the landscape metrics Simpson Diversity, Contagion and Proximity Index. In specific, eastern areas were most fragmented and most diverse in 1984, western areas showed low diversity, high aggregation and dominance of annual crop at the time. Southern areas showed characteristics of both areas, with high fragmentation on one side, but higher aggregation and dominance of annual crops on the other. In the past 30 years eastern regions have lost class diversity, approaching levels of western areas. Changing perennial crop proportions in the western areas resulted in lower distances between crop types, higher edge densities and less aggregation. Mixed crop classes are of special importance as they hold high fragmentation and crop diversity in themselves.

It can be speculated that changing annual-to-perennial crop distance and higher edge densities in western areas result in increased amount of predator habitat and thus, higher potential of pest suppression. The potential for the occurrence of natural pest enemies is highest in the eastern parts of the landscape through to the higher availability of perennial and mixed crops that serve as pest habitat. Mixed crops also indicate small patch sizes of annual crop, which result in smaller core areas for pest species and thus, higher potential for colonization by natural enemies.

<u>Recommendations:</u>

- Other satellite data, such as VHR data, is better suitable for depicting field level in Ethiopian landscapes than Landsat as a higher spatial resolution is demanded to detect crop patches. Additionally, other ecologically important features such as hedgerows, tree groups or allies and scrub would be visible. Radar could also be useful data in that sense.

- Landscape assessment is highly scale dependent. We have now assessed landscape at a spatial scale of 2,5 x 2,5 km within the land structure assessment. Other studies used different higher scales, e.g 5 x 5 km (e.g. Bianchi et al. 2014, Fan & Myint 2014). Considering the fact, that pest predators can fly this might also be an interesting scale, especially for the assessment of perennial-to-annual crop distance and edge density. Edge density assessment was carried out on class level. One discrete density number at landscape level might be more interesting to allow comparison between different parts of the landscape.

- Object based image analysis is a great tool for accurate mapping if used for the right purpose and with the right data. A crop type classification can be feasible in landscapes with larger fields, detectable by Landsat. If used in Ethiopian landscapes, VHR data should be used as a data source or the classification should be limited to the separation of basic land cover types, such as soil, water, built up and vegetation.

- The combination of OBIA and landscape assessment for landscape ecology is high. Further research should be carried out to define the relation between objects and patches and explain the usefulness of shape variables for landscape assessment. This can be achieved, e.g in a comparison of shape and object variables to existing metrics as used in Fragstats.

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A Appendix: Supporting Results

A Land Cover Classification

Table A.1: Output Step A Coverage per class in ha and percent per year

Class	Name	1984		1998		2014	
		[ha]	[%]	[ha]	[%]	[ha]	[%]
1	Cropland	67297.61	70.16	69952	72.81	69121.83	72.29
11	Perennial crop	13670.30	14.25	25394.10	26.43	41555.7	43.46
12	Perennial-Annual Crop	18013.40	18.78	20265.20	21.09	13838.5	14.47
13	Annual-Perennial Crop	12960.50	13.51	11980.30	12.47	12917.9	13.51
14	Annual Crop	3582.81	3.74	1043.10	1.09	809.73	0.85
15	'Separate' Annual Crop	19070.60	19.88	11269.30	11.73	-	-
2	Natural Vegetation	14092.02	14.69	11477.43	11.95	10279.98	10.75
21	Grassland	5430.78	5.66	2286.09	2.38	942.39	0.99
22	Scrub	8661.24	9.03	8667.27	9.02	8774.73	9.18
23	Wetland	-	-	524.07	0.55	562.86	0.59
3	Bare Soil	3893.49	4.06	3006.99	3.13	1011.87	1.06
4	Built Up	724.86	0.76	2197.71	2.29	5189.22	5.43
5	Water	9914.04	10.34	9443.16	9.83	10019.3	10.48
	TOTAL	95922.02	100.00	96077.29	100.00	95622.20	100.00
	Cloud Cover	12773.61		12618.27		13073.49	

B1 Land Cover Change (all)

Table A.2: Change Classes from 1984 to 1998 in pixel and percent

Class	to 3	4	5	11	12	13	14	15	21	22	23
from 3	7704 18%	200 0%	46 0%	4191 10%	6399 15%	4722 11%	288 1%	19606 45%	104 0%		
4	14 0%	6230 77%	15 0%	765 9%	450 6%	168 2%	1 0%	217 3%	26 0%		
5		10 0%	102845 93%	1257 1%	115 0%	84 0%	17 0%	1 0%			5823 5%
11	732 0%	1995 1%	616 0%	79505 52%	44656 29%	16929 11%	1037 1%	2990 2%	3423 2%		
12	1733 1%	3798 2%	409 0%	94165 47%	60163 30%	25434 13%	1490 1%	8619 4%	4328 2%		
13	5821 4%	4649 3%	114 0%	37670 26%	36454 25%	24581 17%	1800 1%	30902 21%	2013 1%		
14	2270 6%	1630 4%	4 0%	6250 16%	8201 21%	6439 16%	990 2%	13712 34%	311 1%		
15	13862 7%	3955 2%	208 0%	44888 21%	54141 26%	41537 20%	4603 2%	46685 22%	2011 1%		
21	1274 2%	426 1%	292 0%	13459 22%	14583 24%	13212 22%	1363 2%	2478 4%	12312 20%	939 2%	
22									872 1%	95364 99%	

Table A.3 Change Classes from 1998 to 2014 in pixel and percent

Class	to 3	4	5	11	12	13	14	21	22	23
from	3814	478	3	5991	6438	14596	1661	119	48	
3	11%	1%	0%	18%	19%	44%	5%	0%	0%	
4	93	16073	52	5549	1087	520	12	32	13	
	0%	66%	0%	23%	4%	2%	0%	0%	0%	
5	57	67	104093	300	47	26	4	3	1	243
	0%	0%	99%	0%	0%	0%	0%	0%	0%	0%
11	1567	14148	3319	197275	37322	17171	1134	2929	1329	156
	1%	5%	1%	70%	13%	6%	0%	1%	0%	0%
12	1547	9602	1163	133671	43954	27248	1190	2255	575	23
	1%	4%	1%	59%	20%	12%	1%	1%	0%	0%
13	991	4240	521	65093	29856	26410	1612	2244	149	7
	1%	3%	0%	49%	22%	20%	1%	2%	0%	0%
14	109	333	126	4174	2504	3548	418	218	4	1
	1%	3%	1%	36%	22%	31%	4%	2%	0%	0%
15	2997	7930	61	33008	26265	50247	2680	734	273	
	2%	6%	0%	26%	21%	40%	2%	1%	0%	0%
21	41	717	1304	11388	4722	3493	280	1918	1121	0
	0%	3%	5%	45%	19%	14%	1%	8%	4%	0%
22	20	27		1757	208	41		17	92877	0
	0%	0%		2%	0%	0%		0%	96%	0%
23										5823
										100%

Table A.4: Cropland Change Only

Class	LCC 1984 to 1998 [ha]		LCC 1998 to 2014 [ha]		LCC 1984 to 2014 [ha]	
	was	changed to	was	changed to	was	changed to
11	5905.08	16467.6	5006.43	21235.15	2708.64	27203.4
12	8474.85	5905.08	12030.4	5006.43	12434.3	2708.64
13	3390.31		5858.37		5307.75	
14	562.52		375.66		844.66	
15	4039.92		2970.72		8616.69	
Total	22372.68		26241.58		29912.04	

Table A.5: Change of Natural Vegetation

Class	LCC 1984 to 1998 [ha]		LCC 1998 to 2014 [ha]	
	was	changed to	was	changed to
1		7359.75		4585.68
11		1701.63		1749.24
12		1898.73		1027.35
13		1621.62		1634.04
14		150.12		175.05
15		1987.65		
21	4097.25		1891.53	
22			116.01	
3	3186.63		2648.43	
4		57.24	47.43	117.72
5	133.01			
Total	7416.99		4703.4	

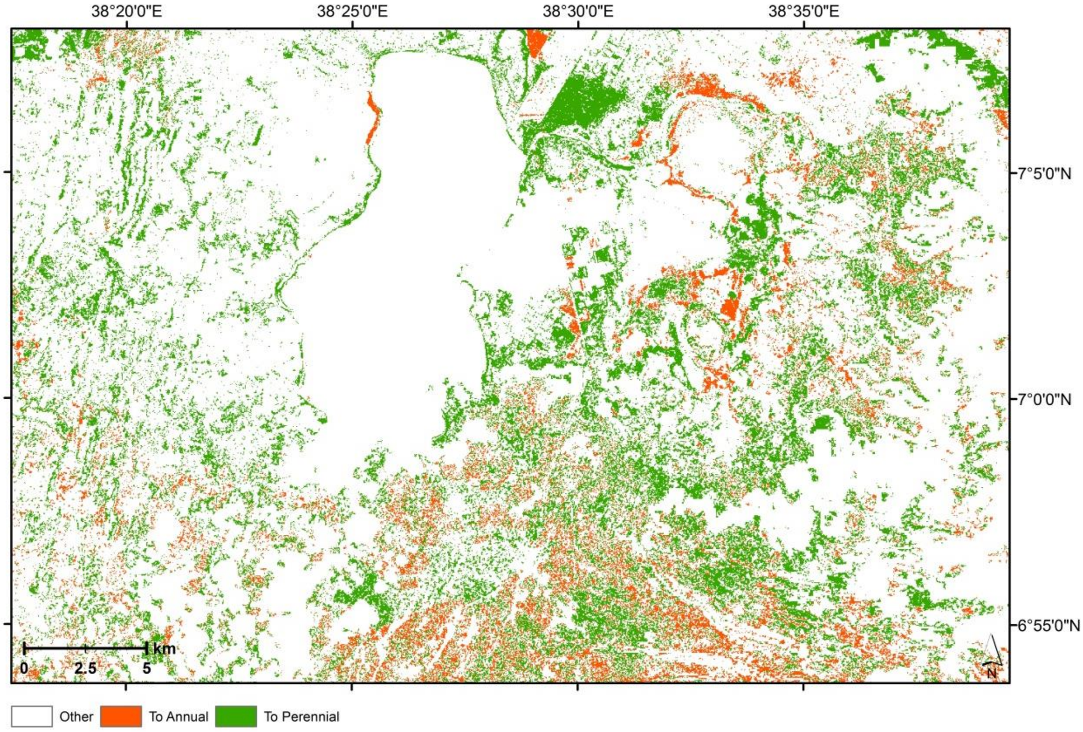


Figure A.1 Change in cropland composition 1984-1998 to Annual (#12,13,14,15) or Perennial Crop (#11)

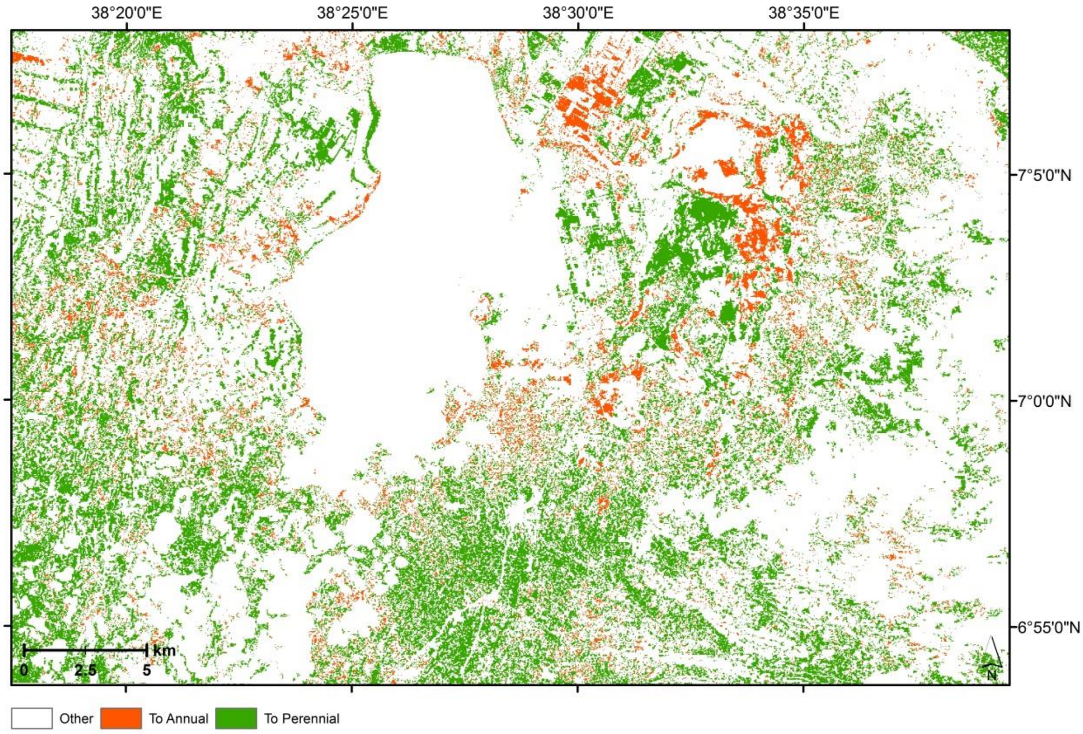


Figure A.2 Change in cropland composition 1998-2014 to Annual (#12,13,14,15) or Perennial Crop (#11)

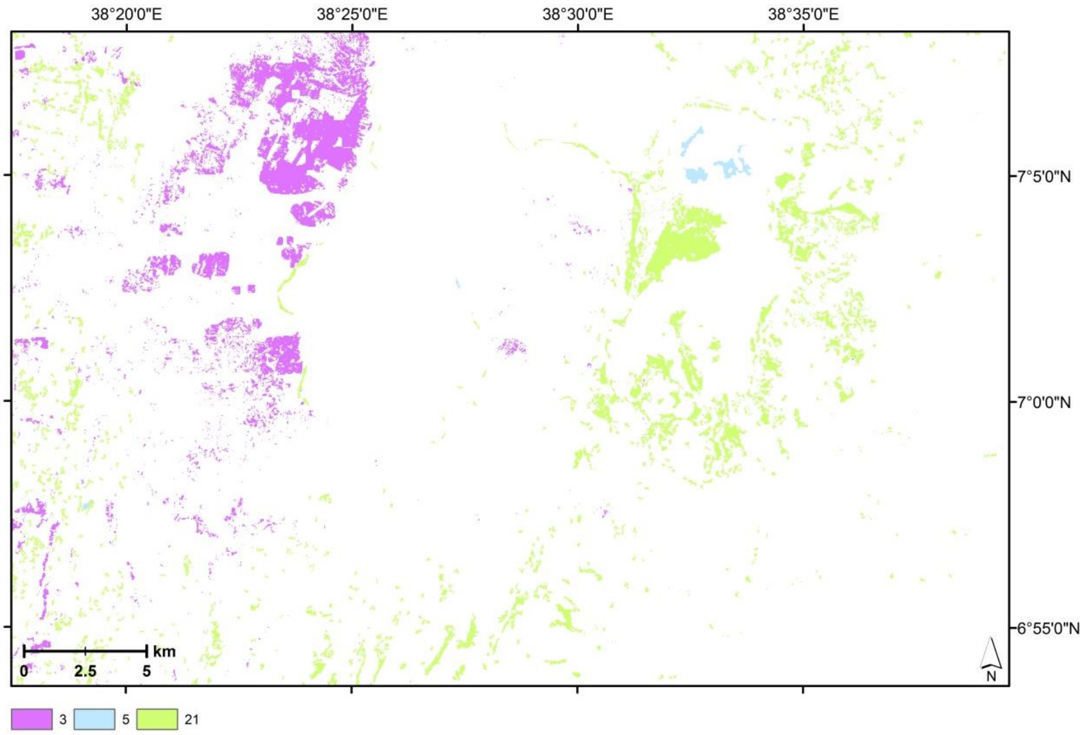


Figure A.3 Areas and classes affected by change in natural cover from 1984 to 1998

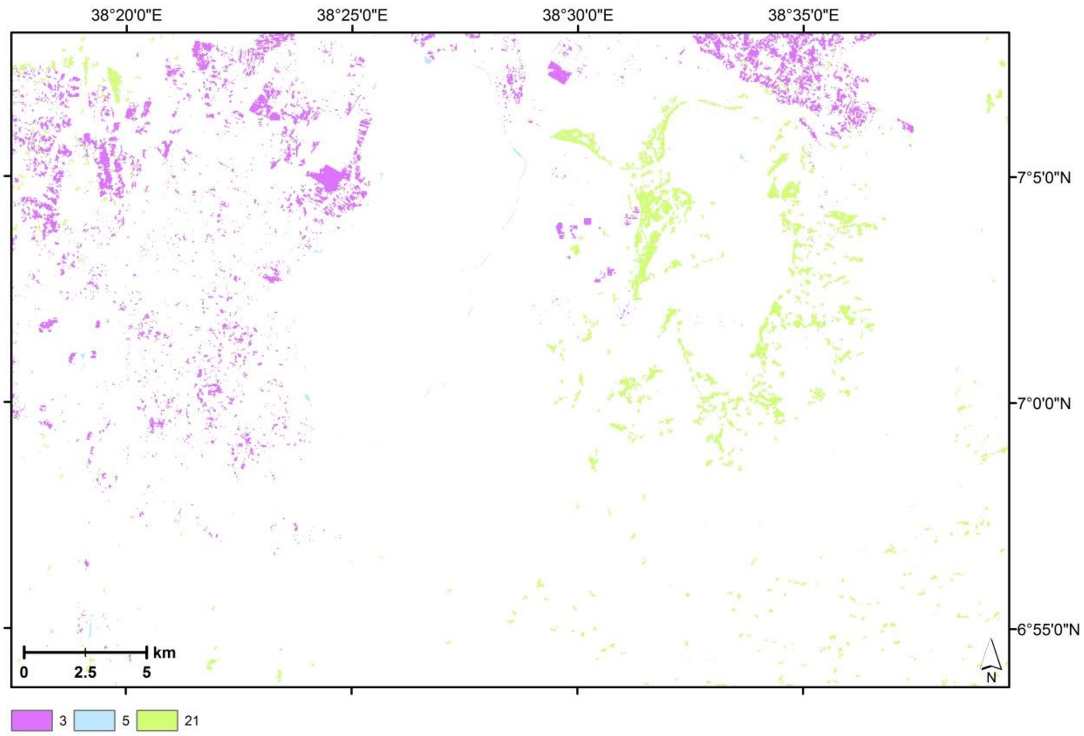


Figure A.4 Areas and classes affected by change in natural cover from 1998 to 2014

B2 Land Cover Change (subset)

Table A.6: Number of classified sub-objects per subset

Subset	1984	1998	2014
Green Vegetation (south, east)	42079	46772	33257
Sparse Vegetation (west)	9068	17558	13046
Intensive Agriculture (north)	97	4135	2992
Other (Hawassa City; wetlands)	1408;463	2059;1787	2059;502
Water (Awassa Lake)	1	1	1

Table A.7: Classes present per subset, area in ha

class	Green vegetation (south, east)			Sparse Vegetation (west)		
	1984	1998	2014	1984	1998	2014
11	10766.6	17695.5	29491.3	472.1	2839.9	6158.0
12	13869.9	14454.8	8434.3	1545.3	3565.4	3385.7
13	5516.8	7240.1	4385.6	4584.3	2526.3	6703.2
14	771.5	410.0	189.9	1603.2	308.3	407.8
15	10638.3	3025.7		6228.4	6580.2	
21	3668.1	1384.1	356.1	441.4	116.1	72.3
22	7015.9	7014.9	7105.6	628.3	628.7	640.7
23		0.4	0.7			
3	344.5	870.1	160.2	3149.4	1838.8	527.5
4	131.3	730.2	2098.9	16.6	159.9	558.6
5	33.5	19.3	306.7	14.5	125.0	216.7
class	Intensive Agriculture (north)			Hawassa City		
	1984	1998	2014	1984	1998	2014
11	461.5	1443.6	1481.2	198.3	775.1	647.3
12	564.6	497.2	729.0	509.6	433.4	189.0
13	1365.9	855.6	1279.4	967.3	337.7	301.5
14	179.3	97.6	189.3	965.8	108.9	3.8
15	1396.1	880.7		278.9	552.1	
21	161.9	247.6	131.0	17.7	37.4	18.7
22	51.0	51.0	51.1	28.9	28.9	30.1
23						
3	42.6	156.6	145.2	33.0	39.6	39.2
4	7.7	0.2	136.4	558.7	1269.1	2322.4
5	0.2	0.2	74.5	17.6	20.5	33.5
class	Other- Wetlands			Awassa Lake		
	1984	1998	2014	1984	1998	2014
11	1743.8	2594.6	3753.8	19.8	15.2	
12	1496.0	1289.0	1089.6	10.1	0.9	
13	500.3	988.8	230.9	2.5	0.5	
14	59.5	114.9	18.3	0.0	0.3	
15	491.3	221.9		0.2	0.2	
21	1129.4	500.5	362.8	7.2		
22	936.9	943.5	945.5	0.2		0.3
23		523.7	562.2			
3	318.6	99.5	136.7	0.1		
4	9.3	38.4	72.9	1.2		
5	674.6	79.3	171.0	9173.5	9198.9	9217.0

Table A.8: GLCM Texture Measurements (all directions) based on Land Cover Classification

Measure		Green Vegetation (south, east)	Sparse vegetation (west)	Intensive Agriculture (north)	Hawassa City	Wetlands
Contrast	1984	4016.47	415.36	340.21	1647.17	484.42
	1998	3935.56	390.47	278.34	1323.80	479.64
	2014	4555.10	1776.33	361.83	2849.37	879.81
Entropy	1984	3.205	2.905	2.549	2.992	2.547
	1998	3.099	3.205	3.062	2.891	2.635
	2014	2.632	2.830	2.786	2.389	2.123
ASM	1984	0.064	0.1	0.143	0.086	0.119
	1998	0.073	0.066	0.075	0.112	0.125
	2014	0.125	0.09	0.104	0.219	0.22
Mean	1984	53.91	14.91	14.95	17.96	14.67
	1998	51.48	14.58	14.28	14.33	15.88
	2014	54.42	20.56	13.18	17.38	16.63

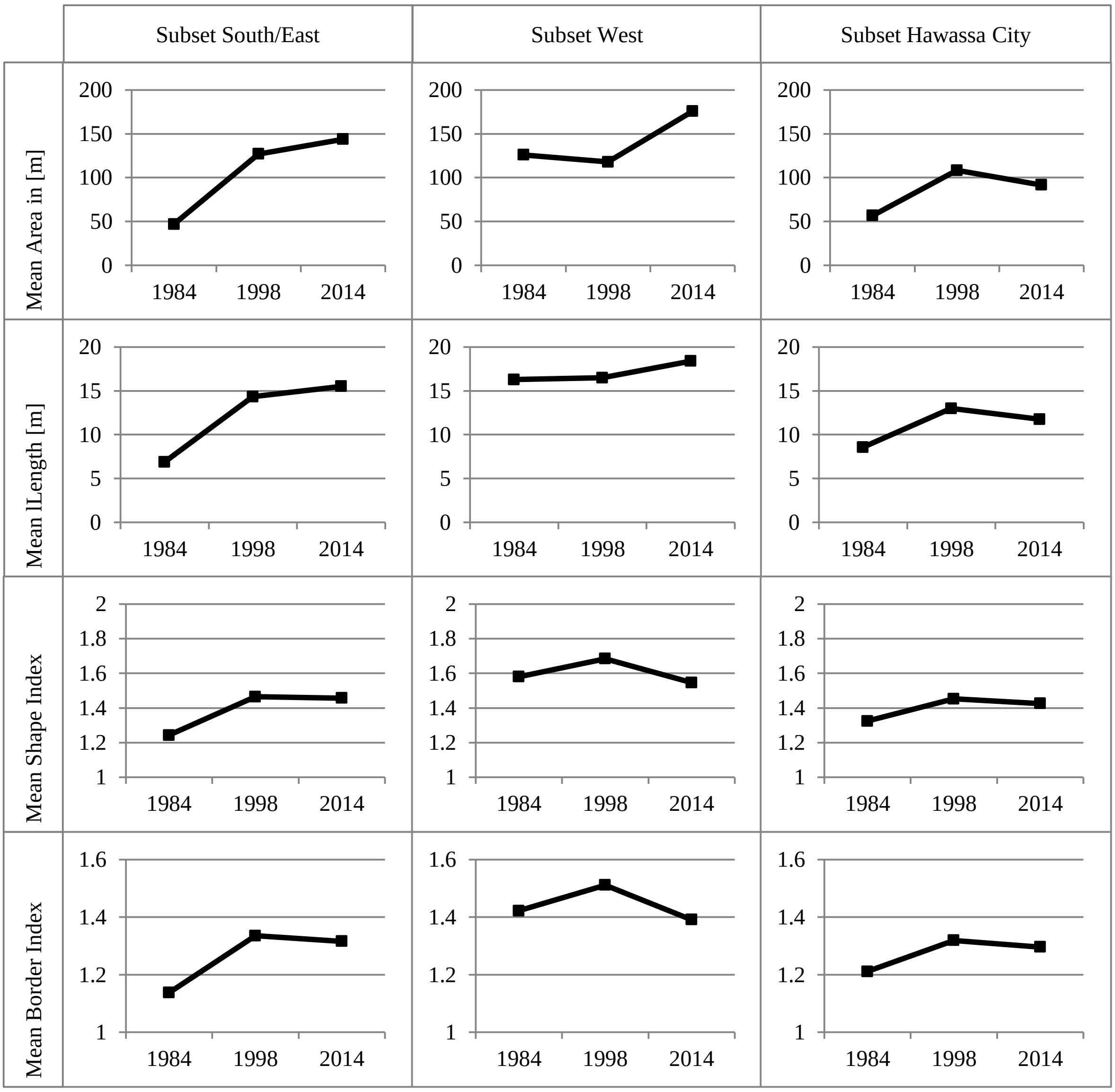


Figure A.5 Description of mean object shapes for three subsets based on land cover maps of 1984, 1998, 2014

Table A.9: Object measures for classified objects per subset

Parameter		Green Vegetation (south, east)	Sparse vegetation (west)	Intensive Agriculture (north)	Hawassa City
Area	1984	46.95	125.86	102.88	56.68
	1998	126.95	117.93	162.61	108.21
	2014	143.74	175.66	163.16	91.63
Length	1984	6.895	16.28	12.6	8.56
	1998	14.33	16.49	18.39	12.99
	2014	15.51	18.38	17.07	11.75
Shape index	1984	1.243	1.58	1.412	1.324
	1998	1.465	1.684	1.66	1.453
	2014	1.457	1.546	1.547	1.426
Border index	1984	1.137	1.422	1.301	1.211
	1998	1.335	1.511	1.499	1.319
	2014	1.316	1.391	1.386	1.296

B3 Land Cover Change (Object)

Table A.10 Number of segmented objects per subset

Subset	1984	1998	2014
Green Vegetation (south, east)	21881	11098	938
Sparse vegetation (west)	2173	1828	3973
Intensive Agriculture (north)	97	69	259
Other (Hawassa City; wetlands)	177; 187	233;231	525;270
Water (Hawassa Lake)	1	1	1

Table A.11: B3 Object measures for segmented objects per subset

Parameter		Green Vegetation (south, east)	Sparse vegetation (west)	Intensive Agriculture (north)	Hawassa City
Area	1984	32.81	96.44	499.57	96.44
	1998	64.68	114.64	702.29	114.64
	2014	765.27	52.75	187.1	104.31
Length	1984	10.3	15.35	38.92	15.35
	1998	15.31	19.29	46.25	19.29
	2014	50.46	12.21	24.96	17.54
Shape index	1984	1.498	1.419	1.715	1.419
	1998	1.642	1.613	1.727	1.613
	2014	3.084	1.697	1.952	1.91
Border index	1984	1.291	1.269	1.521	1.269
	1998	1.438	1.412	1.506	1.412
	2014	2.837	1.493	1.732	1.719

C Landscape Structure Change

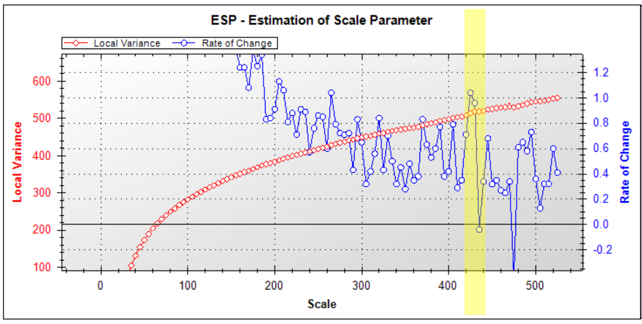
Table A.12: Landscape metrics at landscape level

Tile		Contagion [%]	Simpson Diversity [-]	Proximity Index [-]
City	1984	46.2211	1.7131	271.4742
	1998	56.9571	1.4122	25.471
	2014	71.2326	0.8096	18.3759
East	1984	34.9025	1.6895	160.8476
	1998	47.8938	1.3424	39.9211
	2014	58.6179	1.021	184.5178
East2	1984	34.8962	1.8255	13.2855
	1998	41.029	1.6757	49.3234
	2014	48.341	1.3636	68.3262
South	1984	46.0282	1.3373	35.3402
	1998	43.1414	1.2662	48.4912
	2014	58.4528	0.8581	117.7522
West	1984	52.0362	1.3497	207.8721
	1998	33.6877	1.5358	54.9104
	2014	48.7735	1.2333	83.4019
West2	1984	51.1525	1.2581	458.6867
	1998	39.4194	1.3751	164.8544
	2014	48.7886	1.2243	34.3274

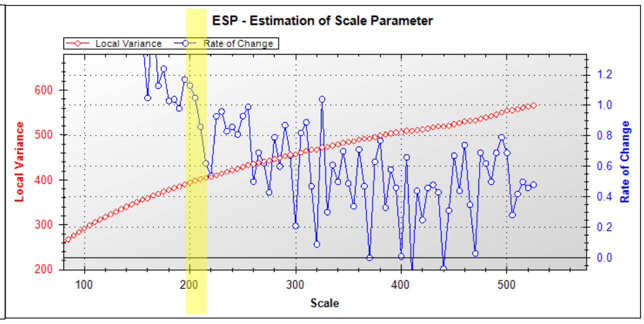
B Appendix: ESP Analysis

Table B.1: Segmentation Parameters of multiresolution segmentation per subset and year. Scale (Colour, Compactness).

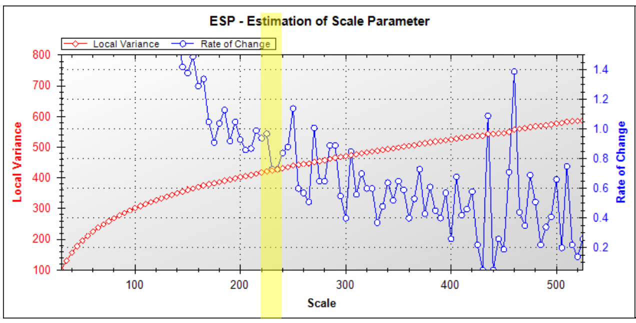
Subset	1984	1998	2014
Green Vegetation (south, east)	3 (0.1, 0.1)	5 (0.1, 0.1)	430 (0.1, 0.5)
Sparse vegetation (west)	5 (0.1, 0.6)	7 (0.1, 0.5)	250 (0.1, 0.5)
Intensive Agriculture (north)	14 (0.3, 0.3)	20 (0.3, 0.3)	165 (0.4, 0.9)
Other (Hawassa City; wetlands)	10 (0.2, 0.3)	10 (0.2, 0.3)	200 (0.2, 0.5)
Water (Hawassa Lake)	-	-	-



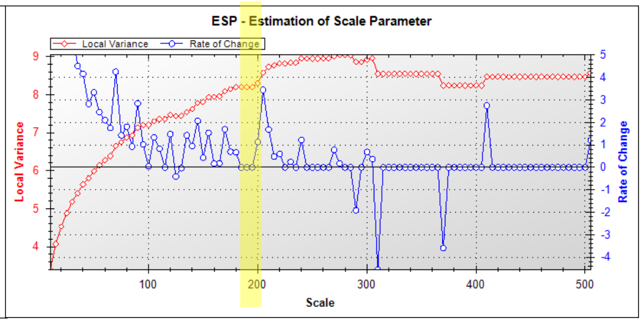
Subset East/South - “Green Vegetation”



Subset North - “Intensive Agriculture”



Subset West- “Sparse Vegetation”



Subset Central- “Other”

Figure B1 ESP2 Output of 2014, Graphs showing Local Variance against Rate of Change. Yellow bars indicate suggested scale.

C Appendix: E-cognition rulesets

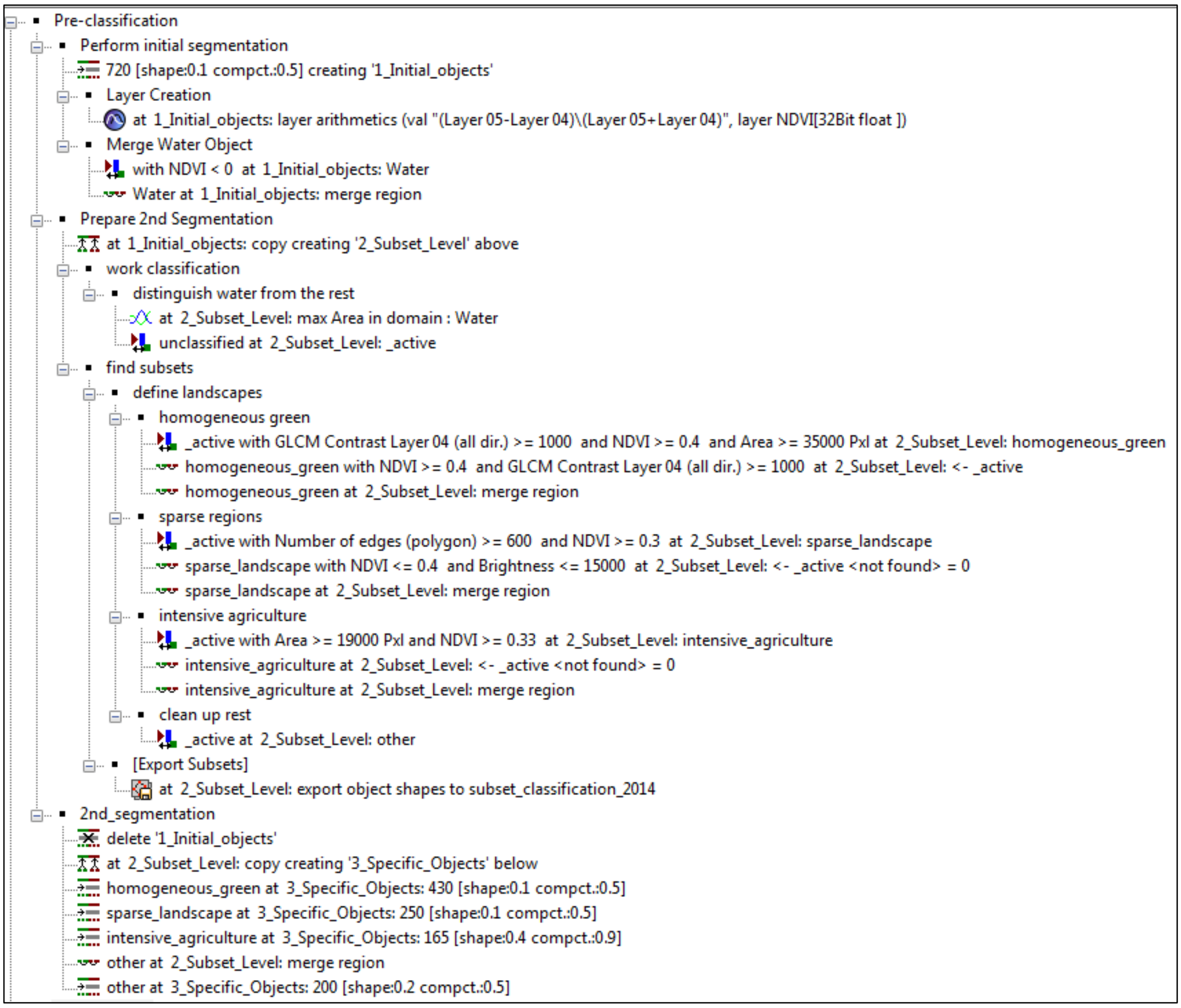


Figure C.1 Ruleset of *step A2.1*, creating subsets

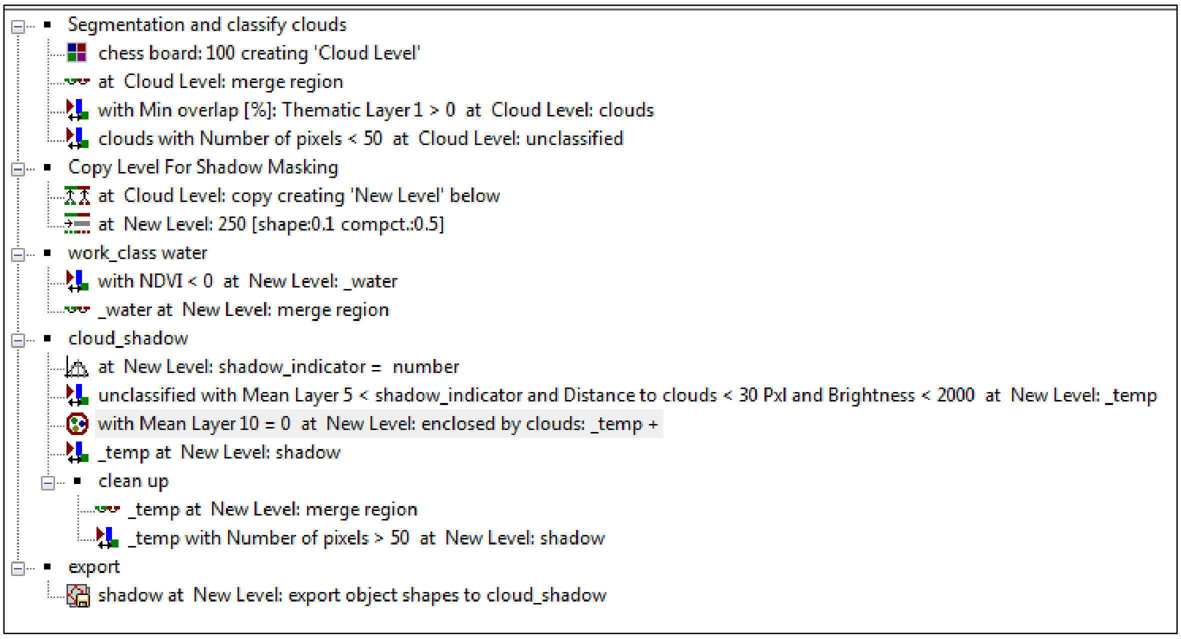
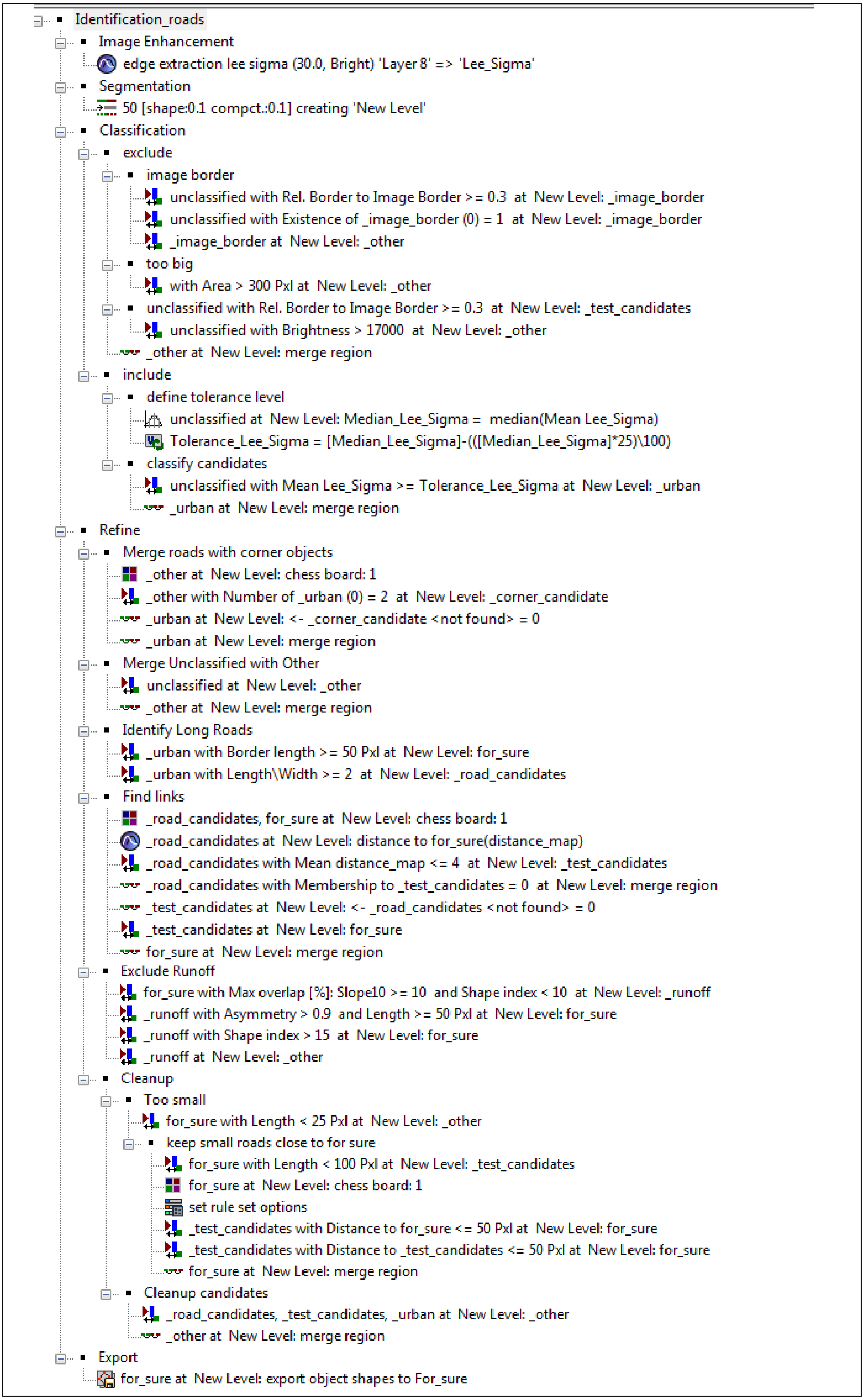


Figure C.2 Ruleset of *step A2.2*, cloud masking



- Identification_roads
  - Image Enhancement
    - edge extraction lee sigma (30.0, Bright) 'Layer 8' => 'Lee_Sigma'
  - Segmentation
    - 50 [shape:0.1 compct.:0.1] creating 'New Level'
  - Classification
    - exclude
      - image border
        - unclassified with Rel. Border to Image Border >= 0.3 at New Level: _image_border
        - unclassified with Existence of _image_border (0) = 1 at New Level: _image_border
        - _image_border at New Level: _other
      - too big
        - with Area > 300 Pxl at New Level: _other
      - unclassified with Rel. Border to Image Border >= 0.3 at New Level: _test_candidates
        - unclassified with Brightness > 17000 at New Level: _other
      - _other at New Level: merge region
    - include
      - define tolerance level
        - unclassified at New Level: Median_Lee_Sigma = median(Mean Lee_Sigma)
        - Tolerance_Lee_Sigma = [Median_Lee_Sigma]-(([Median_Lee_Sigma]*25)\100)
      - classify candidates
        - unclassified with Mean Lee_Sigma >= Tolerance_Lee_Sigma at New Level: _urban
        - _urban at New Level: merge region
  - Refine
    - Merge roads with corner objects
      - _other at New Level: chess board: 1
      - _other with Number of _urban (0) = 2 at New Level: _corner_candidate
      - _urban at New Level: <- _corner_candidate <not found> = 0
      - _urban at New Level: merge region
    - Merge Unclassified with Other
      - unclassified at New Level: _other
      - _other at New Level: merge region
    - Identify Long Roads
      - _urban with Border length >= 50 Pxl at New Level: for_sure
      - _urban with Length\Width >= 2 at New Level: _road_candidates
    - Find links
      - _road_candidates, for_sure at New Level: chess board: 1
      - _road_candidates at New Level: distance to for_sure(distance_map)
      - _road_candidates with Mean distance_map <= 4 at New Level: _test_candidates
      - _road_candidates with Membership to _test_candidates = 0 at New Level: merge region
      - _test_candidates at New Level: <- _road_candidates <not found> = 0
      - _test_candidates at New Level: for_sure
      - for_sure at New Level: merge region
    - Exclude Runoff
      - for_sure with Max overlap [%]: Slope10 >= 10 and Shape index < 10 at New Level: _runoff
      - _runoff with Asymmetry > 0.9 and Length >= 50 Pxl at New Level: for_sure
      - _runoff with Shape index > 15 at New Level: for_sure
      - _runoff at New Level: _other
    - Cleanup
      - Too small
        - for_sure with Length < 25 Pxl at New Level: _other
        - keep small roads close to for sure
          - for_sure with Length < 100 Pxl at New Level: _test_candidates
          - for_sure at New Level: chess board: 1
          - set rule set options
          - _test_candidates with Distance to for_sure <= 50 Pxl at New Level: for_sure
          - _test_candidates with Distance to _test_candidates <= 50 Pxl at New Level: for_sure
          - for_sure at New Level: merge region
      - Cleanup candidates
        - _road_candidates, _test_candidates, _urban at New Level: _other
        - _other at New Level: merge region
  - Export
    - for_sure at New Level: export object shapes to For_sure

Figure C.3 Ruleset of *stepA2.3* for 2014, Road Classification

- Identification_roads
  - Image Enhancement
    - edge extraction lee sigma (30.0, Bright) 'Layer 9' => 'Lee_Sigma2'
  - Segmentation
    - edge ratio split Lee_Sigma [0-255:+1] :10-> [creating 'New Level', _urban,unclassified]
  - Find Objects with high Lee Sigma
    - _urban with Mean Lee_Sigma < 1.5 at New Level: unclassified
    - _urban at New Level: merge region
    - _urban with Mean Lee_Sigma > 2 or Length > 10 Pxl at New Level: for_sure
  - Refine
    - Merge roads with corner objects
      - unclassified at New Level: chess board: 1
      - unclassified with Number of for_sure (0) = 2 at New Level: _corner_candidate
      - for_sure at New Level: <- _corner_candidate <not found> = 0
      - for_sure at New Level: merge region
    - Exclude Runoff
      - create\modify project
      - for_sure with Max overlap [%]: Slope10 >= 10 and Shape index < 10 at New Level: _runoff
      - _runoff with Asymmetry > 0.85 and Length >= 25 Pxl at New Level: for_sure
      - _runoff with Shape index > 15 at New Level: for_sure
      - _runoff at New Level: _other
    - Cleanup
      - Cleanup candidates
        - _test_candidates at New Level: for_sure
        - for_sure with Area < 10 Pxl at New Level: unclassified
        - _other, _runoff, _urban, unclassified at New Level: merge region
      - for_sure at New Level: merge region
  - Export
    - for_sure at New Level: export object shapes to For_sure 1984

Figure C.4 Ruleset of *stepA2.3* for 1984 and 1998, Road Classification

- Classification
  - Create new map
    - on main : copy map to 'classification'
    - on classification at 3_Specific_Objects: remove classification
  - Classify
    - vegetation
      - on classification unclassified with Mean NDVI >= 0.35 at 3_Specific_Objects: Vegetation
    - clouds_and_co
    - missed water
      - close to lake
        - on classification with Mean NDVI < 0.3 and Rel. border to Water > 0.4 at 3_Specific_Objects: _missed_water
      - Shallow, soily water
        - on classification unclassified with HSI Transformation Hue(R='Layer 06',G='Layer 05',B='Layer 04') >= 0.3499 at 3_Specific_Objects: _missed_water
      - on classification Water at 3_Specific_Objects: <- _missed_water <not found> = 0
      - on classification _missed_water at 3_Specific_Objects: Water
      - Water at 3_Specific_Objects: merge region
    - bare soil
      - on classification unclassified with Mean Layer 02 < Mean Layer 03 and Mean Layer 03 < Mean Layer 04 and Mean Layer 04 < Mean Layer 05 and Brightnes
      - on classification : manual classification (brush: 5) -> Bare_soil
    - built-up area
      - Edit Thematic Layer Roads
        - copy map to 'Temp'
        - on Temp at 3_Specific_Objects: copy creating 'Test_level' below
        - on Temp at Test_level: chess board: 100
        - on Temp at Test_level: merge region
        - on Temp at Test_level: assign class by thematic layer using "ID"
        - on Temp Road at Test_level: merge region
        - on Temp Road with Rel. border to Water > 0.1 at Test_level: _temp
        - on Temp Road with Rel. border to Bare_soil > 0.3 at Test_level: Bare_soil
        - on Temp Road at Test_level: export object shapes to Road
        - on Temp : delete map
        - save project state
        - show warning: "automated load of edited roads as thematic layer"
        - create\modify project
      - Create road objects
        - at 3_Specific_Objects: copy creating '4_Classified_objects' below
        - at 4_Classified_objects: chess board: 100
        - on classification at 4_Classified_objects: merge region
        - at 4_Classified_objects: assign class by thematic layer using "ID"
        - Road with Rel. border to Bare_soil >= 0.8 at 4_Classified_objects: Bare_soil
      - spaces in between roads
        - unclassified at 4_Classified_objects: enclosed by Road: Built-up +
      - other urban
        - unclassified with Number of Road (0) >= 5 and Area < 300 Pxl and Mean NDVI < 0.3 at 4_Classified_objects: Built-up
        - unclassified with Mean Layer 02 >= 10000 and Mean NDVI < 0.2 at 4_Classified_objects: Built-up
        - unclassified at 4_Classified_objects: enclosed by Built-up: Built-up +
    - Objects with Field Character
      - unclassified with Mean Layer 05 > 20000 at 4_Classified_objects: Potential_crop
      - Potential_crop at 4_Classified_objects: merge region
      - Potential_crop with Area < 500 Pxl at 4_Classified_objects: unclassified
      - unclassified with Rectangular Fit > 0.7 and Density > 1.8 and Mean NDVI > 0.3 and Roundness < 0.6 at 4_Classified_objects: Potential_crop
      - unclassified with Existence of Potential_crop (0) = 1 and Rectangular Fit > 0.75 at 4_Classified_objects: Potential_crop
    - Other
      - Long Objects
        - unclassified with Length > 50 Pxl and Density < 1 at 4_Classified_objects: _temp
        - _temp with Existence of Water (0) = 1 at 4_Classified_objects: Water
        - _temp with Existence of Bare_soil (0) = 1 at 4_Classified_objects: Bare_soil
        - _temp with Existence of Road (0) = 1 or Mean NDVI < 0.3 at 4_Classified_objects: Road
        - _temp at 4_Classified_objects: unclassified
      - very dark
        - unclassified with Mean Layer 08 < 8500 at 4_Classified_objects: _temp
        - _temp with Mean NDVI > 0.3 at 4_Classified_objects: Potential_Bushland
        - _temp with Mean NDVI < 0.2 at 4_Classified_objects: Water
        - _temp at 4_Classified_objects: Marshland
      - Objects with soil charcter
        - unclassified with Area > 50 Pxl at 4_Classified_objects: Sparse Vegetation
      - Leftovers
        - unclassified with Mean NDVI > 0.3 at 4_Classified_objects: Vegetation
        - unclassified with Existence of Built-up (0) = 1 at 4_Classified_objects: Built-up
        - unclassified at 4_Classified_objects: Sparse Vegetation
- Export class objects
  - Water at 4_Classified_objects: export object shapes to water
  - Bare_soil at 4_Classified_objects: export object shapes to Bare_soil
  - Built-up, Road at 4_Classified_objects: export object shapes to built_up
  - on classification Marshland at 4_Classified_objects: export object shapes to Marshland
  - on classification Sparse Vegetation at 4_Classified_objects: export object shapes to Sparse
  - on classification Potential_Bushland at 4_Classified_objects: export object shapes to Bushland_10_2014
  - on classification Vegetation at 4_Classified_objects: export object shapes to vegetation_10_2014
- Export object shapes
  - at 3_Specific_Objects: export object shapes to ObjectShapes14_2

Figure C.5 Ruleset of *step A2.4* in 2014, Land Cover Classification

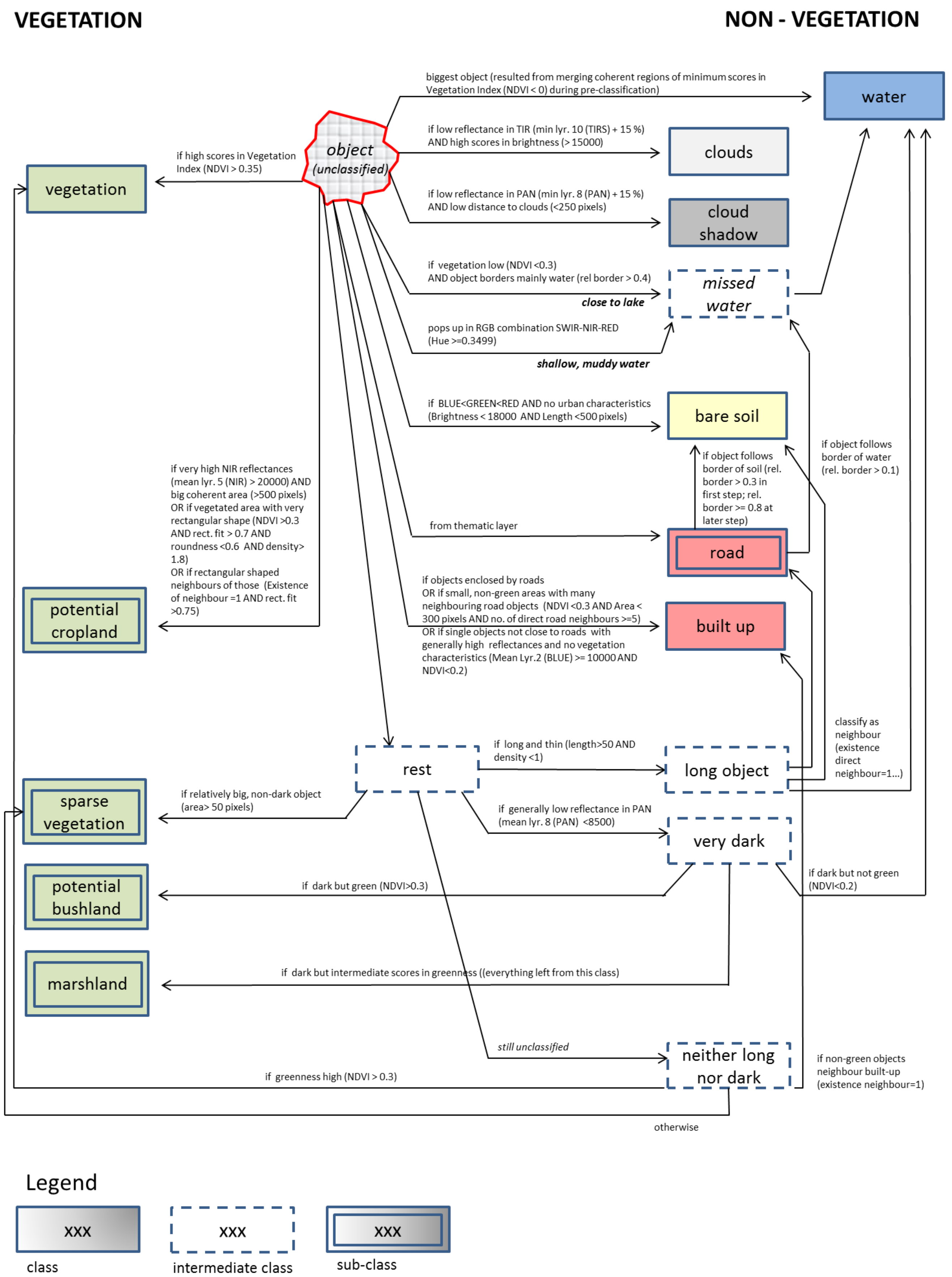


Figure C.6 Overview of Classification process of *step A2.4* for 2014

- Copy Classified Landscapes from shp
  - quadtree: 60 creating '1_Initial_objects'
  - at 1_Initial_objects: merge region
  - create\modify project
- prepare 2nd Segmentation
  - at 1_Initial_objects: copy creating '2_Subset_Level' above
  - with "Sub": Subsets = "water" at 2_Subset_Level: Water
  - with "Sub": Subsets = "hom_green" at 2_Subset_Level: homogeneous_green
  - with "Sub": Subsets = "int_agri" at 2_Subset_Level: intensive_agriculture
  - with "Sub": Subsets = "other" at 2_Subset_Level: other
  - with "Sub": Subsets = "sparse" at 2_Subset_Level: sparse_landscape
- 2nd_segmentation
  - at 2_Subset_Level: copy creating '3_Specific_Objects' below
  - delete '1_Initial_objects'
  - homogeneous_green at 3_Specific_Objects: 5 [shape:0.1 compct.:0.1]
  - sparse_landscape at 3_Specific_Objects: 7 [shape:0.1 compct.:0.5]
  - intensive_agriculture at 3_Specific_Objects: 20 [shape:0.3 compct.:0.3]
  - other at 2_Subset_Level: merge region
  - other at 3_Specific_Objects: 10 [shape:0.2 compct.:0.3]
- Classification
  - Create new map
    - on main : copy map to 'classification'
    - on classification at 3_Specific_Objects: remove classification
  - Classify
    - missed water
      - close to lake
        - on classification with Mean NDVI_lyr < 3000 and Rel. border to Water > 0.4 at 3_Specific_Objects: _missed_water
      - Marshland_water
        - unclassified with Mean Layer 01 <= 1 and Mean Layer 03 <= 1 and Mean Layer 05 < 0 at 3_Specific_Objects: _missed_water
      - Shallow, soily water
        - [on classification unclassified with HSI Transformation Hue(R='Layer 05',G='Layer 04',B='Layer 03') >= 0.3499 at 3_Specific_Objects: _missed_water]
        - [manual classification -> _missed_water]
      - on classification Water at 3_Specific_Objects: <- _missed_water <not found> = 0
      - on classification _missed_water at 3_Specific_Objects: Water
      - Water at 3_Specific_Objects: merge region
    - vegetation
      - on classification unclassified with Mean NDVI_lyr >= 3500 at 3_Specific_Objects: Vegetation
    - built-up area
      - Create road objects
        - create\modify project
        - at 3_Specific_Objects: copy creating '4_Classified_objects' below
        - at 4_Classified_objects: chess board: 100
        - on classification at 4_Classified_objects: merge region
        - at 4_Classified_objects: assign class by thematic layer using "ID"
        - Road at 4_Classified_objects: merge region
      - spaces in between roads
        - unclassified at 4_Classified_objects: enclosed by Road: Built-up +
      - other urban
        - Road with Border index > 3 and Length < 50 Pxl at 4_Classified_objects: _temp
        - Road with Border index > 5 at 4_Classified_objects: _temp
        - unclassified with Number of _temp (0) >= 2 at 4_Classified_objects: Built-up
        - unclassified with Area < 250 Pxl and Number of _temp (0) >= 1 at 4_Classified_objects: enclosed by Built-up, Road, Vegetation: Built-up +
        - Vegetation, unclassified with Area < 300 Pxl and Number of _temp (0) >= 1 at 4_Classified_objects: enclosed by Built-up, Road, Vegetation: Built-up +
        - Vegetation, unclassified at 4_Classified_objects: enclosed by Built-up, Road: Built-up +
        - _temp at 4_Classified_objects: Road
    - Other
      - unclassified at 4_Classified_objects: Sparse Vegetation
- Export class objects
  - Water at 4_Classified_objects: export object shapes to water1998
  - Built-up, Road at 4_Classified_objects: export object shapes to built_up 1998
  - on classification Sparse Vegetation at 4_Classified_objects: export object shapes to Sparse1998
  - on classification Vegetation at 4_Classified_objects: export object shapes to vegetation_01_1999
- Export object shapes
  - at 3_Specific_Objects: export object shapes to ObjectShapes98

Figure C.7 Ruleset of *step A2.4* in 1984 and 1998, Land Cover Classification

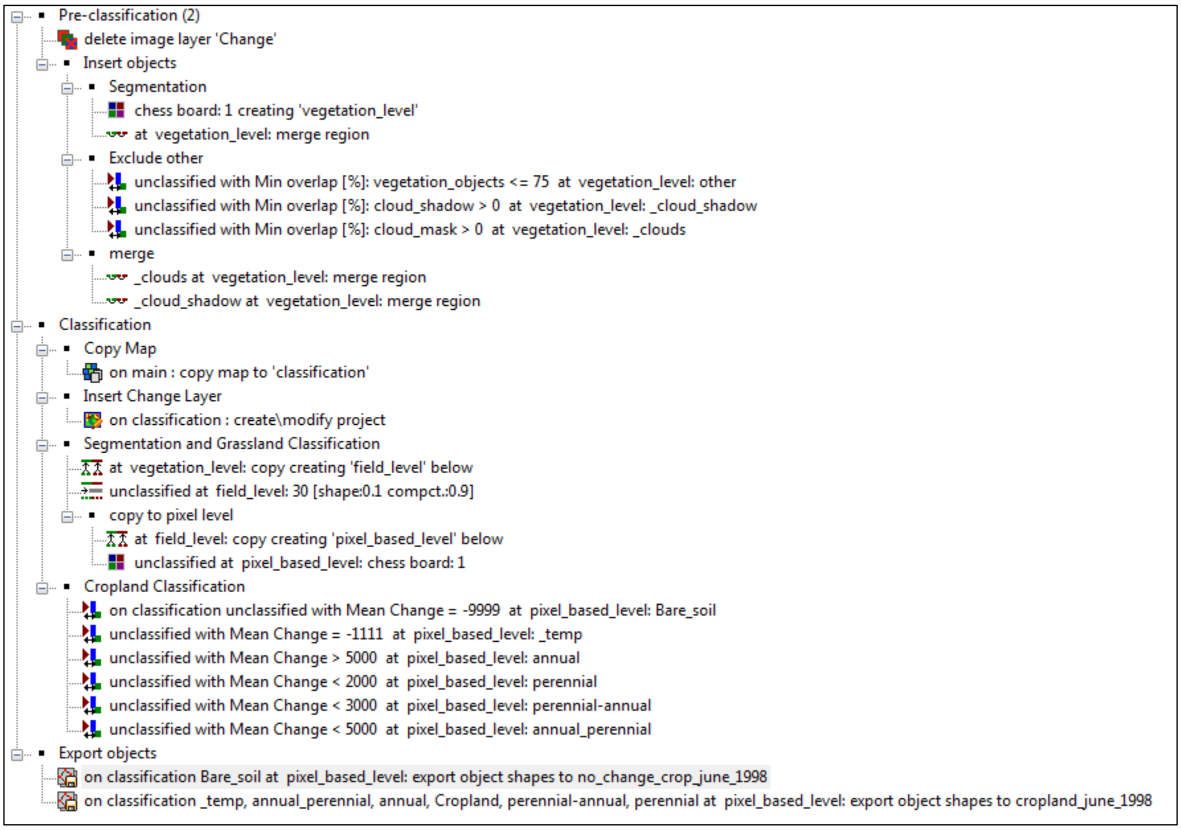


Figure C.8 Ruleset of *step A3.2*, cropland classification based on NDMI Change Thresholds

- Creating Levels and Maps
  - Segmentation of Subsets
    - quadtree: 60 creating '1_Initial_objects'
    - at 1_Initial_objects: merge region
  - Subset as Superobjects
    - at 1_Initial_objects: copy creating 'Subset_Level' above
    - with "Sub": Subsets = "water" at Subset_Level: Water
    - with "Sub": Subsets = "hom_green" at Subset_Level: homogeneous_green
    - with "Sub": Subsets = "int_agri" at Subset_Level: intensive_agriculture
    - with "Sub": Subsets = "other" at Subset_Level: other
    - with "Sub": Subsets = "sparse" at Subset_Level: sparse_landscape
  - Classes as Subobjects
    - delete '1_Initial_objects'
    - 1984
      - copy map to '1984'
      - on 1984 at Subset_Level: copy creating 'Class_level_1984' below
      - on 1984 at Class_level_1984: 10 [shape:0.1 compct.:0.5]
    - 1998
      - copy map to '1998'
      - on 1998 at Subset_Level: copy creating 'Class_level_1998' below
      - on 1998 at Class_level_1998: 10 [shape:0.1 compct.:0.5]
    - 2014
      - copy map to '2014'
      - on 2014 at Subset_Level: copy creating 'Class_level_2014' below
      - on 2014 at Class_level_2014: 10 [shape:0.1 compct.:0.5]
- Analysis
  - Subset Texture see Object Variables
  - Mean Object Information
    - 1984
      - mean object area
        - on 1984 homogeneous_green at Class_level_1984: hom area 84 = mean(Area)
        - on 1984 sparse_landscape at Class_level_1984: sparse Area 84 = mean(Area)
        - on 1984 intensive_agriculture at Class_level_1984: int Area 84 = mean(Area)
        - on 1984 other at Class_level_1984: other Area 84 = mean(Area)
      - mean object length
        - on 1984 homogeneous_green at Class_level_1984: hom length 84 = mean(Length)
        - on 1984 sparse_landscape at Class_level_1984: sparse length 84 = mean(Length)
        - on 1984 intensive_agriculture at Class_level_1984: int length 84 = mean(Length)
        - on 1984 other at Class_level_1984: other length 84 = mean(Length)
      - mean object shape index
        - on 1984 homogeneous_green at Class_level_1984: hom shape 84 = mean(Shape index)
        - on 1984 sparse_landscape at Class_level_1984: sparse shape 84 = mean(Shape index)
        - on 1984 intensive_agriculture at Class_level_1984: int shape 84 = mean(Shape index)
        - on 1984 other at Class_level_1984: other shape 84 = mean(Shape index)
      - mean object border index
        - on 1984 homogeneous_green at Class_level_1984: hom border 84 = mean(Border index)
        - on 1984 sparse_landscape at Class_level_1984: sparse border 84 = mean(Border index)
        - on 1984 intensive_agriculture at Class_level_1984: int border 84 = mean(Border index)
        - on 1984 other at Class_level_1984: other border 84 = mean(Border index)
    - 1998
      - mean object area
      - mean object shape index
      - mean object length
      - mean object border index
    - 2014
      - mean object area
      - mean object shape index
      - mean object length
      - mean object border index

Figure C.9 Ruleset of *step B2.2*, Creating Variables for Object Metrics

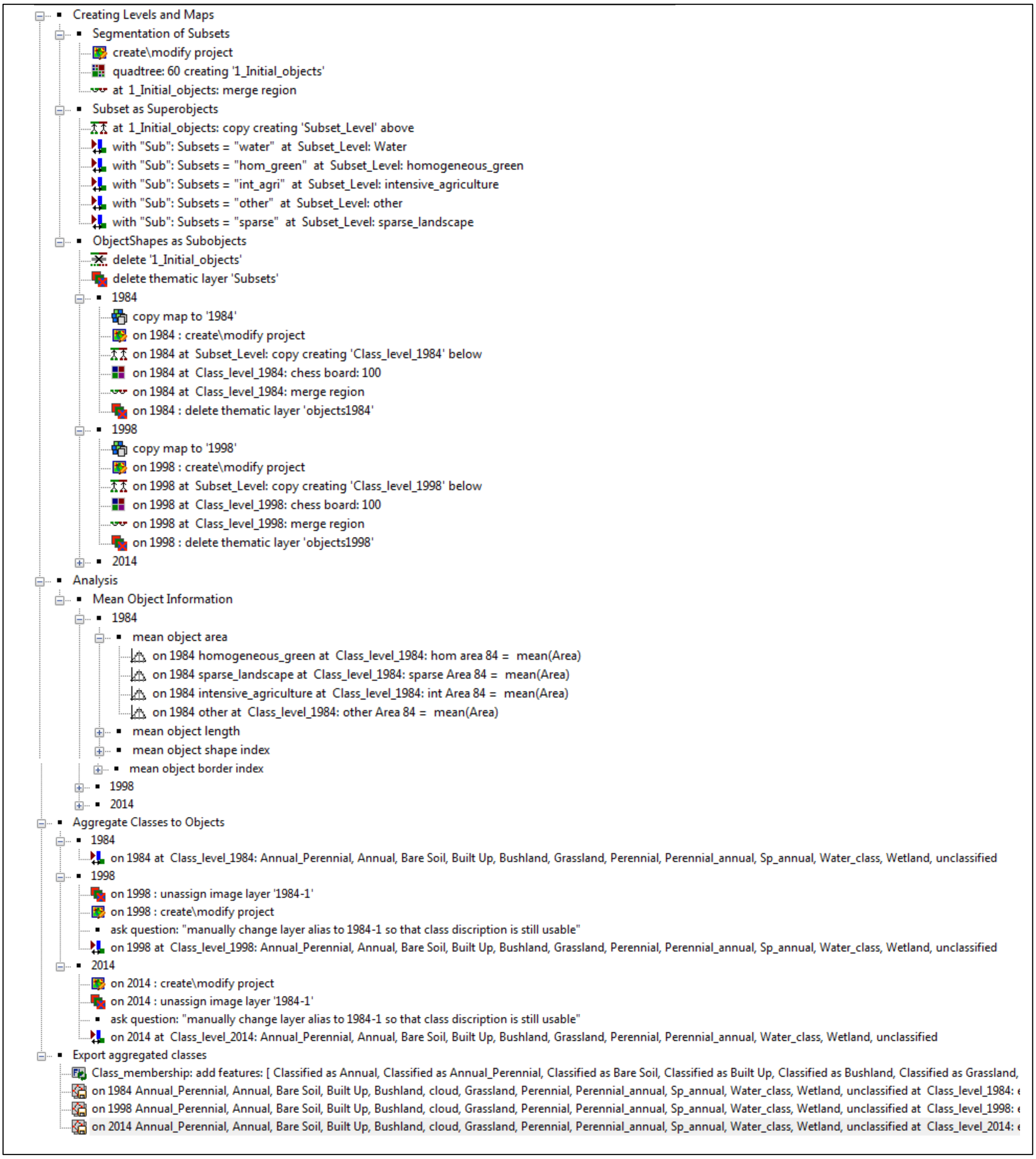


Figure C.10 Ruleset of *step B3.1*, aggregation classification results to segmented objects

D Appendix: Erdas Imagine Models

Figure D.1 NDMI Differencing for Wet Season /Dry Season Comparison

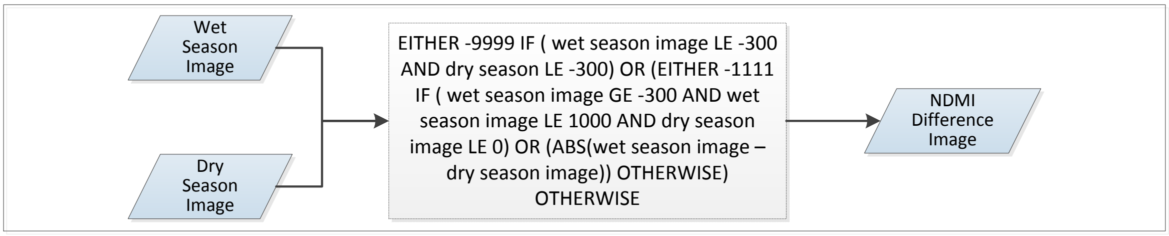


Figure D.2 NDMI Differencing for Wet Season /Dry Season Comparison, Exception June 1998

Figure D.3 NDMI Differencing for Wet Season /Dry Season Comparison, Exception April 1984

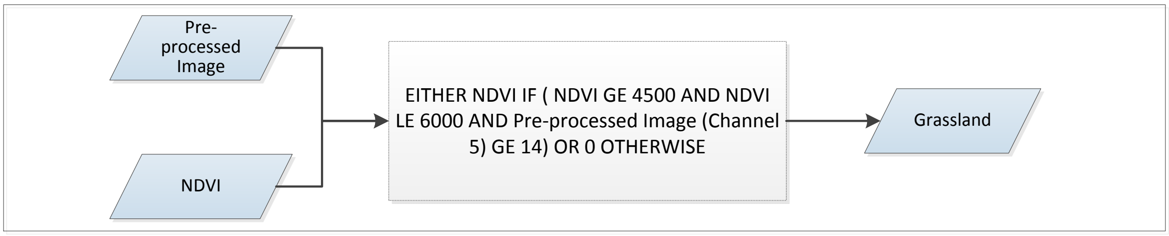


Figure D.4 Grassland Classification Thresholds

E Appendix: ArcGis Models

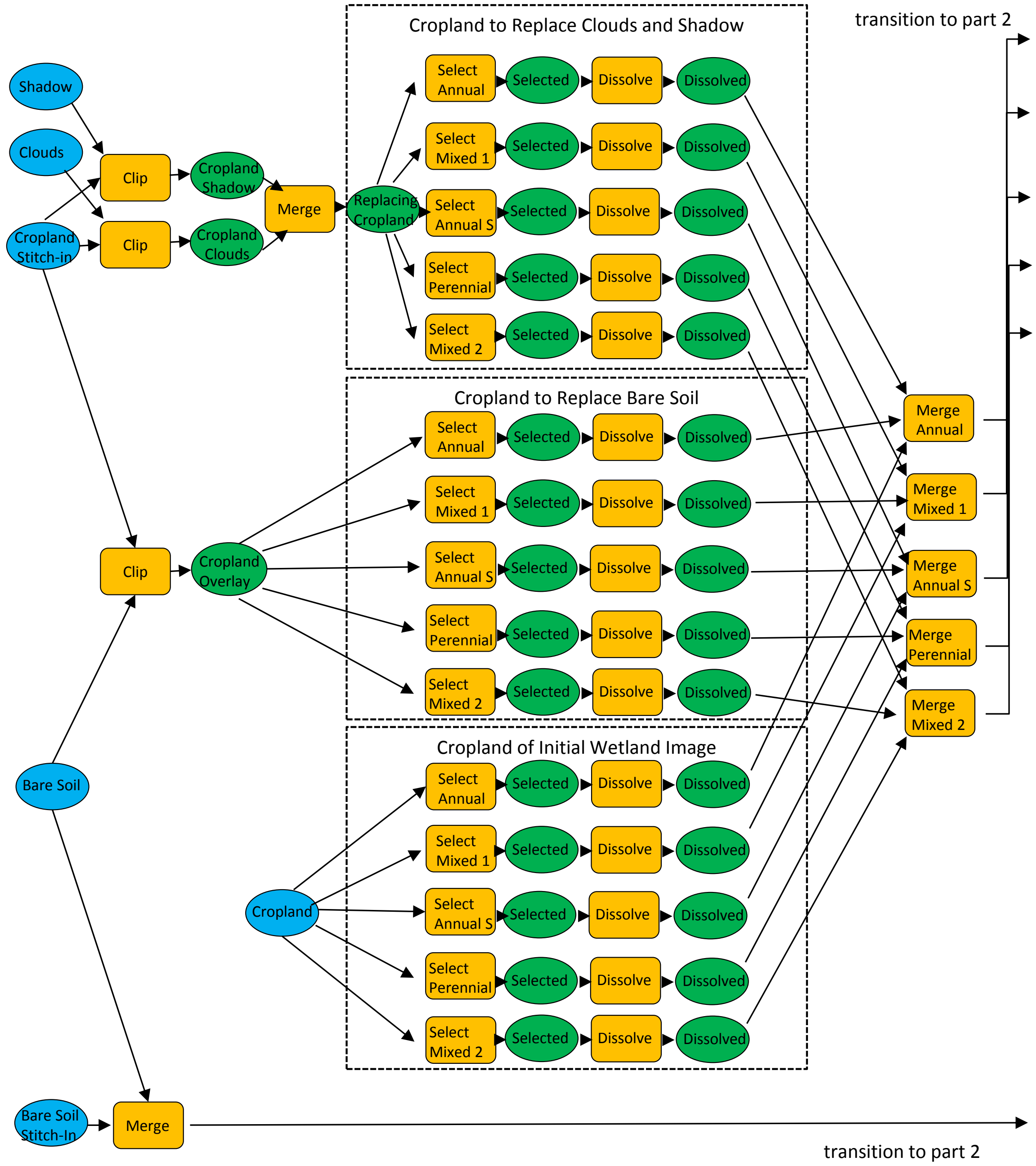
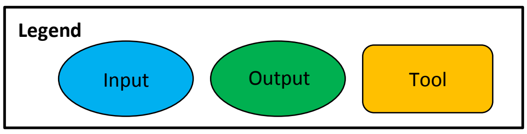


Figure E.1 ArcMap Model for *Step A4.1*, Filling Cloud Covered Areas of the wet season image with data from an additional wet season image, part 1



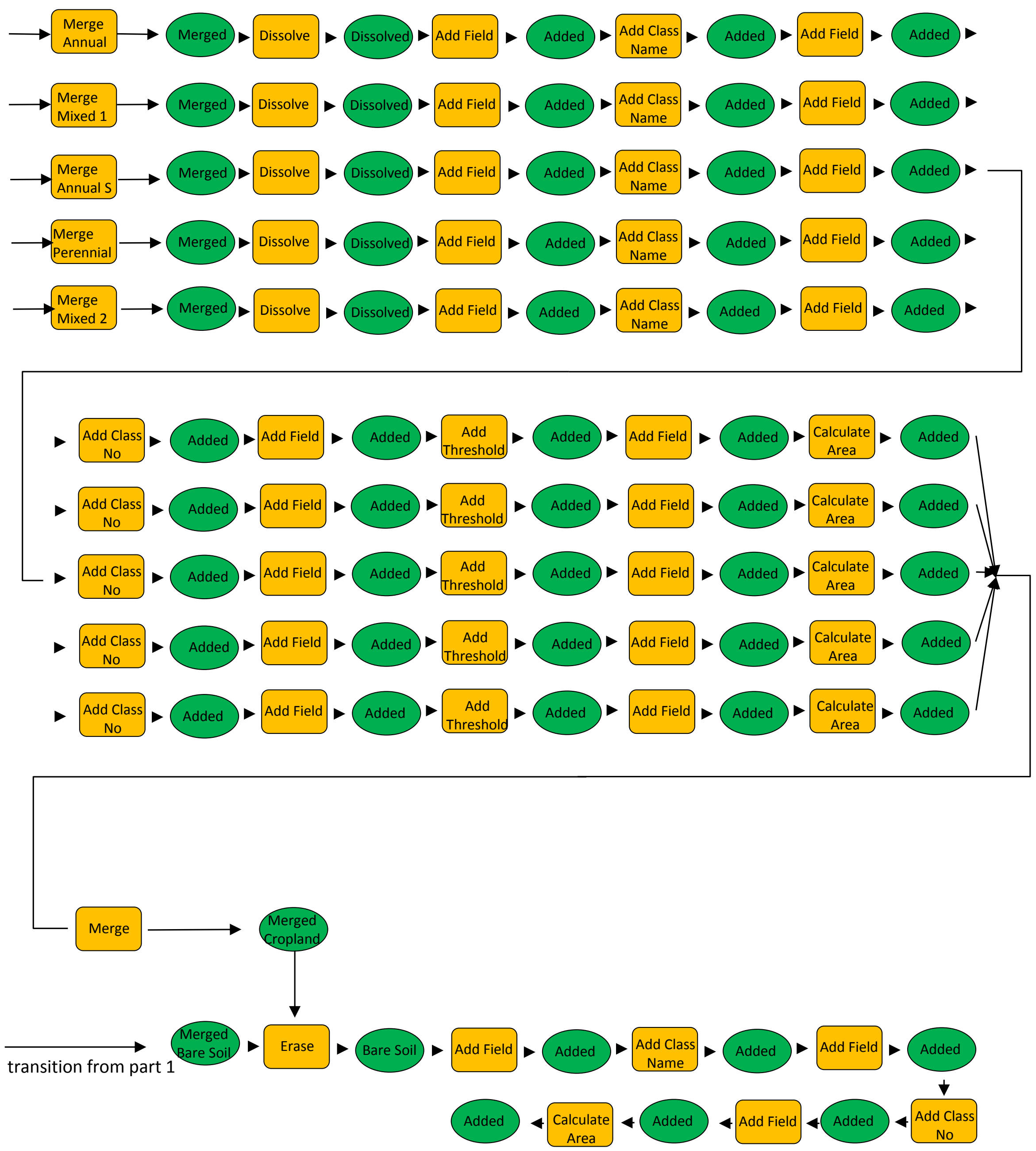
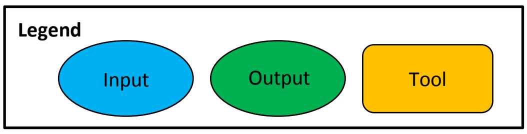


Figure E.2 ArcMap Model for *Step A4.1*, Filling Cloud Covered Areas of the wet season image with data from an additional wet season image, part 2



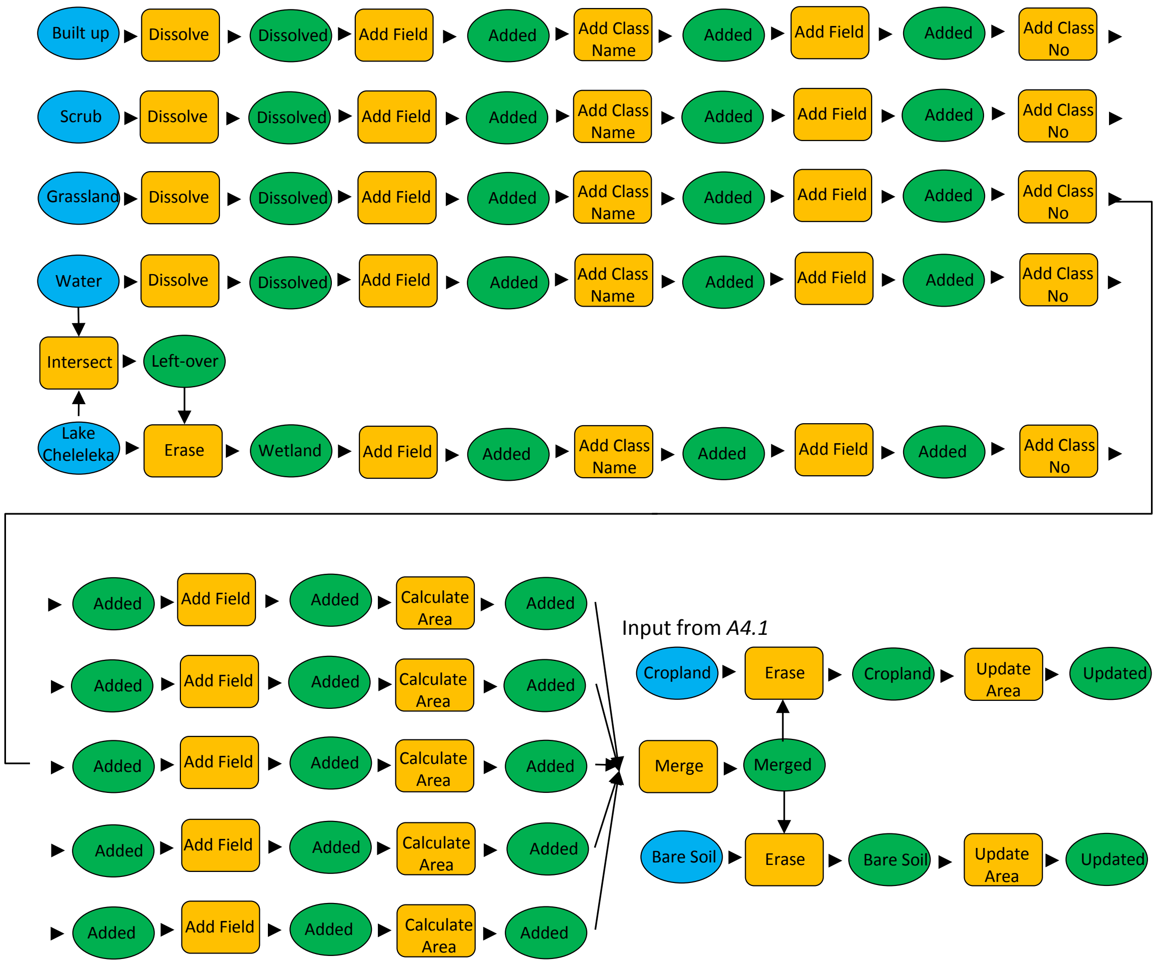


Figure E.3 ArcMap Model for *step A4.2*, Adding Class Details and Erasing Overlay

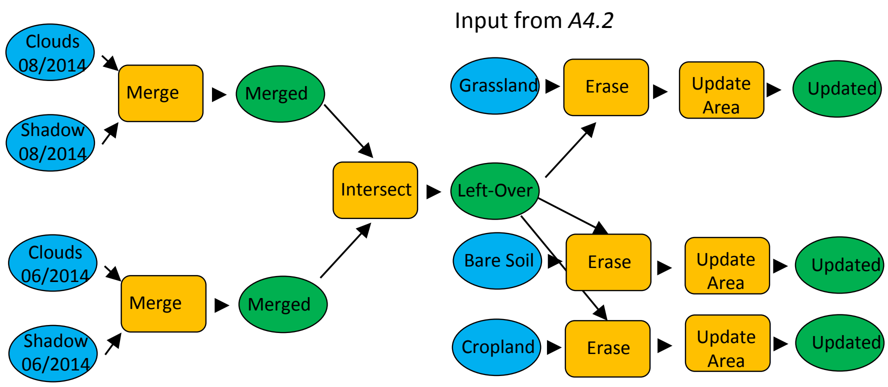
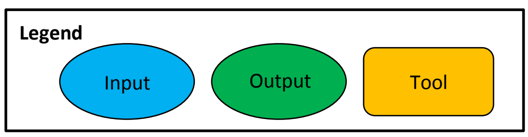


Figure E.4 ArcMap Model for *step A4.3*, Erasing Cloud Covered Areas of 2014



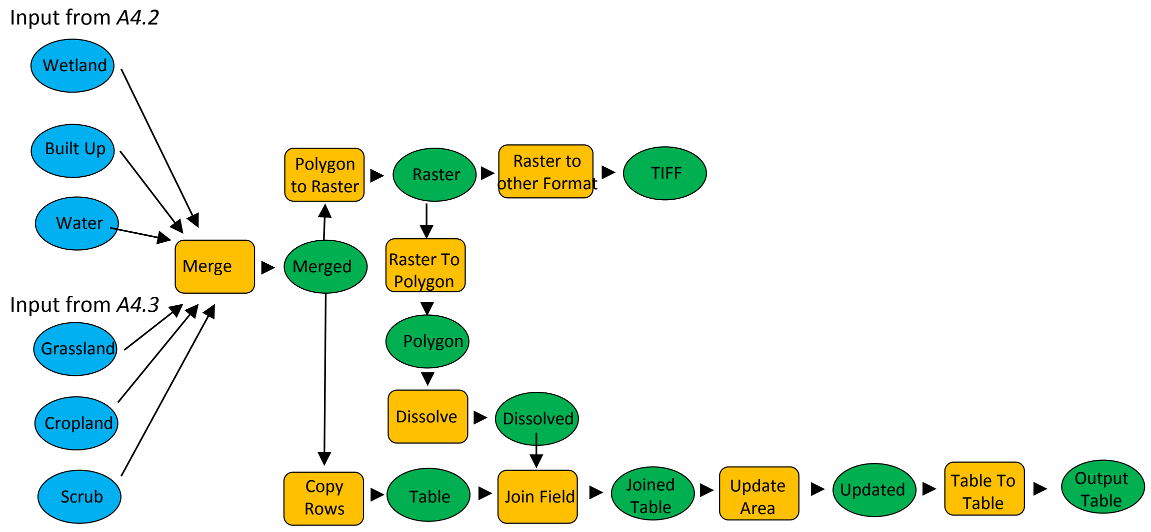


Figure E.5 ArcMap Model for *step A4.4*, Transformation to Raster and Output Table