UNIVERSITÄT BAYREUTH

Remote sensing-based analysis of land cover detrimental for ecosystem services in fragile lands of Ethiopia

Dissertation

to attain the academic degree of Doctor of Natural Sciences (Dr. rer. nat.)
of the Bayreuth Graduate School of Mathematical and Natural Sciences
(BayNAT) of the University of Bayreuth

presented by

Yohannes Zergaw Ayanu
born 22 September 1980
in Bale (Ethiopia)

Bayreuth, March 2015

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This doctoral thesis was prepared at the Department of Earth Sciences, Professorship of Ecological Services, University of Bayreuth, 95440 Bayreuth, Germany, between December 2009 and March 2015. It was supervised by Prof. Dr. Thomas Koellner, Prof. Dr. Christopher Conrad and Prof. Dr. Anke Jentsch.

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Abstract

Fragile lands such as mountainous regions and drylands are highly vulnerable for land degradation and subsequent decline in productivity resulting from anthropogenic and natural causes. In developing countries of the tropics like Ethiopia, the human-induced impact is aggravated by the increasing population of subsistence farmers living in these areas. Land use/land cover type mainly determines the sustainability of supplies of ecosystem services and biodiversity supported. Land use decisions made without caution often deteriorate ecosystems in fragile lands and have detrimental impacts on supplies of ecosystem services. Therefore, continuous monitoring and assessment of land use/land cover types in fragile lands is essential to ensure sustainable supplies of ecosystem services in such environments that are liable for deterioration. Remote sensing provides fast and recurrent data for assessing land cover and ecosystem services. The main objective of the dissertation is identifying the potentials and limitations of remote sensing for assessing ecosystem services and map two major land cover types detrimental for ecosystem services in fragile lands of Ethiopia. Ethiopia was chosen for the case studies due to the ongoing pressure on fragile lands of the country which is triggered by population growth, large-scale agricultural land acquisition and problems arising from invasive species. The thesis is organized in series of chapters described below.

Overview of the thesis highlighting the research questions, methods and major findings is presented in *Chapter 1*. Following the general overview (*Chapter 1*), potentials and limitations of remote sensing in quantifying and mapping ecosystem services are reviewed (*Chapter 2).* The review showed that there is uncertainty involved in quantifying and mapping ecosystem services with remote sensing data which calls for more research to find the link between ecosystem services and image spectra. Moreover, while selecting remote sensing data, factors such as resolution, sensor types, and financial and technical capacity of users need to be considered. In *Chapter 3*, the trends in *Prosopis juliflora* invasion of the Awash basin of Ethiopia were mapped using Landsat ETM + and ASTER images for the years 2000, 2005, 2010 and 2013, and potential impacts on ecosystem services were assessed. Results showed that over the past decade *P. juliflora* spread rapidly and has had negative impacts on the supplies of ecosystem services such as provisioning and cultural services. Further research is needed to

understand drivers of *P. juliflora* invasion, quantify its impacts on ecosystem services and identify controlling mechanisms. *Chapter 4* discusses undercover cropland inside forests of the Bale Mountains of Ethiopia and its influential factors. Land use/land cover classes were derived by classifying RapidEye images using Random Forests classification approach. Undercover cropland was mapped using Boosted Regression Trees on field observed percent cover, topographic and location and parameters. The influential factors of undercover cropland are elevation, distance to settlements, slope, East aspect and distance to national park with elevation being the most important factor. Therefore, ecosystem management efforts in such mountainous areas should be based on the relative importance of these influential factors. In the last section (*Chapter 5*), the studies in the thesis are synthesized and presented. Besides, recommendations about monitoring of fragile lands and ecosystem services, management of invasive species, mountain regions, and future prospects of remote sensing in ecosystem services assessment are provided.

Zusammenfassung

Fragile Landschaften wie Gebirgsregionen und Trockengebiete sind sehr anfällig für Landdegradierung und dem daraus resultieren den Rückgangder Produktivität, ausgelöst durch verschiedene natürliche und anthropogene Einflussfaktoren. In tropischen Entwicklungsländern wie Äthiopien werden insbesondere vom Menschen verursachte Effekte durch die stetig steigende Zahl von Subsistenzlandwirten verstärkt. Die Art der Landbedeckung und Landnutzung bestimmt dabei in erster Linie die Nachhaltigkeit von Ökosystemleistungen sowie den Erhalt von Biodiversität. Unbedachte und voreilige Landnutzungsentscheidungen führen oft zur Schädigung von Ökosystemen mit negativen Konsequenzen für die Bereitstellung von Ökosystemleistungen. Die kontinuierliche Beobachtung und Bewertung von Landbedeckung und Landnutzung ist deshalb außerordentlich wichtig, um die nachhaltige Verfügbarkeit dieser Ökosystemleistungen zu gewährleisten, insbesondere in empfindlichen Landschaften, die besonders anfällig für Degradierung sind. Methoden der Fernerkundung liefern dabei schnelle und periodisch verfügbare Informationen, um Landbedeckung und Ökosystemleistungen bewerten zu können. Hauptziel dieser Dissertation ist es, die zwei wichtigsten Landbedeckungstypen räumlich zu erfassen, die sich schädigend auf die Ökosystemleistungen von fragilen Landschaften in Äthiopien auswirken. Äthiopien wurde als Fallstudienregion ausgewählt aufgrund des anhaltend hohen Drucks, der insbesondere durch Bevölkerungswachstum, großangelegte Landaneignungen sowie dem Eindringen invasiver Arten auf fragile Landschaften ausgeübt wird. Die Arbeit ist in fünf Kapitel unterteilt, welche im Folgenden erläutert werden.

Kapitel 1 gibt einen allgemeinen Überblick, beleuchtet die Fragestellungen der Arbeitund fasst die Methoden und wichtigsten Ergebnisse zusammen. In Kapitel 2 werden die Möglichkeiten und Grenzen der Fernerkundung für die Quantifizierung und Kartierung von Ökosystemleistungen diskutiert. Die Analyse zeigt, dass die Quantifizierung und Kartierung von Ökosystemleistungen mithilfe von Fernerkundungsdaten mit deutlichen Unsicherheiten verbunden ist und zusätzlicher Forschungsbedarf bei der Verknüpfung von Spektraldaten mit Ökosystemleistungen besteht. Darüber hinaus sind auch andere Faktoren, wie Auflösung, Sensortypen sowie finanzielle und technische Kapazitäten bei der Auswahl von geeigneten

Fernerkundungsdaten entscheidend. In Kapitel 3 werden die Ausbreitungstrends von *Prosopis juliflora* im Awash-Becken in Äthiopien mithilfe von Landsat ETM+ und ASTER Aufnahmen aus den Jahren 2000, 2005, 2010 und 2013 beschrieben und deren potentielle Auswirkungen auf Ökosystemleistungen bewertet. Die Ergebnisse zeigen, dass sich *P. juliflora* innerhalb des letzten Jahrzehnts rasant in der Region ausgebreitet hat, mit negativen Konsequenzen insbesondere für bereitstellende und kulturelle Ökosystemleistungen. Weiterer Forschungsbedarf besteht insbesondere im Hinblick auf die Treiber der Ausbreitung von *P. juliflora*, die Quantifizierung der Effekte auf Ökosystemleistungen sowie zu möglichen Kontrollmechanismen. Kapitel 4 diskutiert verdeckte landwirtschaftliche Anbauflächen innerhalb der Wälder der Bale Mountains in Äthiopien und deren Einflussfaktoren. Mithilfe eines Random Forest Klassifikationsverfahrens wurden Landbedeckungs und Landnutzungsklassen aus RapidEye Satellitenaufnahmen abgeleitet. Die verdeckten Anbauflächen konnten mittels Boosted Regression Trees und Feldbeobachtungen zu Bedeckungsgrad, Topographie und standortspezifischen Parametern kartiert werden. Als Einflussfaktoren für das Vorhandensein verdeckter Anbauflächen wurden Höhenlage, Entfernung zu Siedlungen, Hangneigung, östliche Exposition sowie die Entfernung zum Nationalpark identifiziert, wobei die Höhenlage den größten Einfluss hatte. Bewirtschaftungsmaßnahmen von Ökosystemen in diesen Gebirgsregionen sollten demnach an der relativen Bedeutsamkeit dieser Einflussfaktoren ausgerichtet werden. In Kapitel 5 werden die einzelnen Studien dieser Arbeit noch einmal zusammenfassend präsentiert sowieHandlungsempfehlungen zur Überwachung fragiler Landschaften und Ökosystemleistungen und zur Kontrolle invasiver Arten und zur Bewirtschaftung vonGebirgsregionen gegeben. Darüber hinaus werden die Zukunftsperspektiven von Methoden der Fernerkundung zur Bewertung von Ökosystemleistungen diskutiert.

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Table of contents

List of figures

List of tables

Chapter 1

Synopsis

Chapter 1 Synopsis

1.1 Fragile lands, cover and ecosystem services

Gow et al. (1987) defined the term 'fragile lands' as *"lands liable for deterioration and are under common agricultural, silvicultural, and pastoral use systems and management practices"*. These lands are characterized by declining productivity resulting from prevalent degradation (Gow et al. 1987, Jodha 1991, Bebbington et al. 1993, Osuji et al. 2010). Once disturbed by anthropogenic and natural causes their recovery is very slow (Liu et al. 2010, Bakr et al. 2012).

Fragile lands include drylands, forests and generally upland ecosystems that are less favored for intensive agriculture (Scherr and Hazell 1994, Liu et al. 2003, Barbier 2010). These lands are highly liable for degradation due to high concentrations of human population whose livelihood is largely dependent on agriculture (Barbier 2012). In developing countries, population in fragile lands doubled during the period 1950–2003 (The World Bank 2003). The high poverty rate in the rural areas of these countries forces the inhabitants to mainly depend on subsistence agriculture (Karsenty and Ongolo 2012, Pritchett and de Weijer 2011, Besley and Persson 2011, Baliamoune-Lutz and McGillivray 2011). Given the rapidly growing rural population and apparent poverty, the pressure on fragile ecosystems has increased over the past decades (Le et al. 2012).

The land use/land cover (LULC) type in fragile lands largely influences the ecosystem services that are supplied (Figure 1). Human decisions introduce land cover types that are beneficial or detrimental to supplies of ecosystem services. The type of LULC and the location where it is practiced may imply its detrimental impacts. For instance, croplands introduced to mountainous steep slopes can be detrimental cover types in those regions. Likewise, new plant species introduced to drylands could turn to be invasive and become detrimental for supplies of ecosystem services. Similarly, tea and palm tree plantations that involve conversion of natural forests are detrimental for forest ecosystem services.

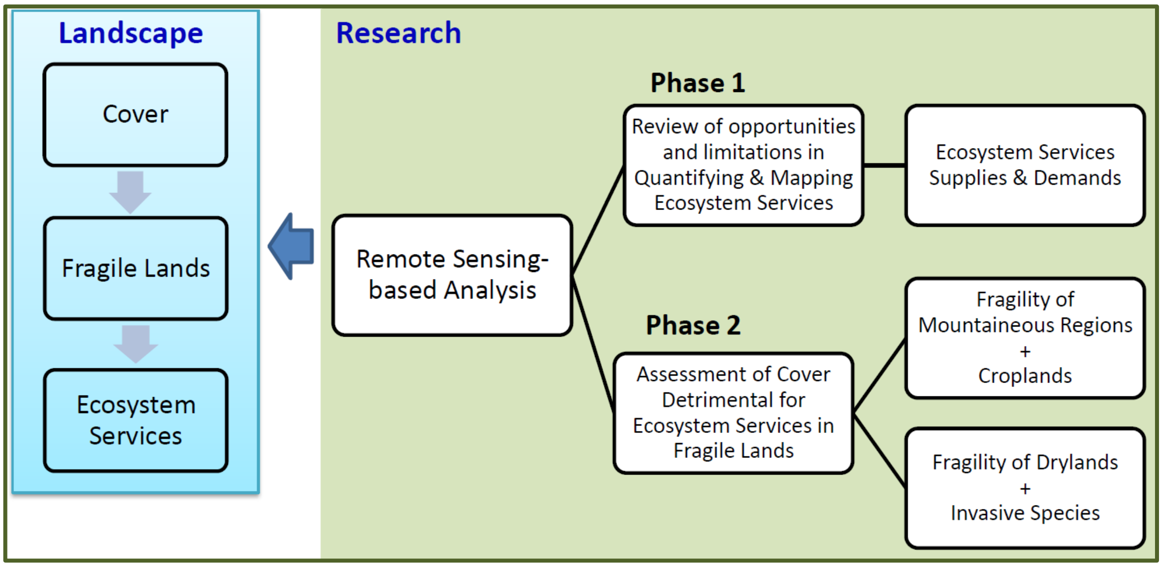

Figure 1 General concept and the different phases of the dissertation.

In this study two major examples of fragile lands (mountain region and drylands) are analyzed and discussed in relation to the detrimental impacts of selection of land cover types that improperly suit to these vulnerable lands. The general framework of concepts considered and the different phases in the dissertation are illustrated in Figure 1. In Phase 1 opportunities and challenges in the application of remote sensing for assessing ecosystem services were analyzed based on literature review. In phase 2 two major LULC types were mapped and their detrimental impacts on ecosystem services was assessed and discussed.

1.1.1 Fragility of mountain regions and detrimental effects of croplands

Nearly 27 percent of the earth's surface are mountains and support about 22 percent of the world's population (cf. Rodríguez-Rodríguez et al. 2011). Globally, these land masses are less accessible marginal and highly fragile areas (Jodha 2000, Oyonarte et al. 2008, Platts et al. 2011). Ecosystems in these regions support high biodiversity and supply various services such as provisioning (food, water, timber, fiber and fodder), regulatory (erosion control, flood control and water purification) and cultural (recreation, aesthetic and tourism) (MA 2005, TEEB 2010, Marquis et al. 2012, Rodríguez-Rodríguez et al. 2011, Grêt-Regamey et al. 2012). The origins of most of the rivers in our planet are the mountain regions (Liniger et al. 2005, Viviroli and Weingartner 2008). More than 50 percent of the water used for home consumption, irrigation, hydropower, and industries globally comes from mountain areas (Messerli et al. 2004, Liniger et. al 2005, Viviroli et al. 2007).

In developing countries like Africa, the rural poor people are directly dependent on natural resources for their livelihoods especially for provisioning services (Egoh et al. 2012).

Although mountain ecosystems are sources of multiple services and biodiversity, they are highly fragile and vulnerable to rapid global development (Grêt-Regamey et al. 2012, Pauli et al. 2005, Lama and Devkota 2009, Messerli et al. 2004, Messerli 2012). In the past decades, the low capacity, access to resources, and insufficient awareness of the people living in mountain regions, may have aggravated the impact of global changes (Jodha 2000). Moreover, indigenous knowledge is often ignored and new concepts are externally imposed on the local communities (Marquis et al. 2012). Mountain regions are often exploited with the aim of maximizing short-term benefits without considering their fragility and threatening impacts on the sustainable supplies of ecosystem services and conservation of biodiversity (Rodríguez-Rodríguez et al. 2011).

Agriculture constitutes a large portion of the global land cover with agroecosystems comprising about 40% of the earth's surface (Power 2010). Globally, potential arable land with low constraints is 12.6 percent (Blum and Swaran 2004). Growth in agricultural sector is usually considered as a fundamental step in reducing poverty especially in developing countries (Adhikari et al. 2013). In mountainous areas, agricultural land expansion is one of the leading driving forces of land degradation (Shrestha et al. 2014). Being triggered by the growing demand for food production, where there is shortage of land for growing crops, agricultural land expansion often involves conversion of other land covers such as forests and pasture lands (Foley et al. 2005). For instance, in the tropical regions, expansion of agricultural land during the 20th century was made possible mainly through deforestation of natural forests (Lambin and Meyfroidt 2011).

In principle, cultivation of crops in mountain regions should be adapted to the local situation in order to minimize the negative impacts on the environment (Marquis et al. 2012). However, especially in developing countries this is often not met and agricultural practices frequently end up in soil erosion and land degradation thereby declining productivity of the ecosystem (Liu et al. 2012, Sun et al. 2014, Shrestha et al. 2014).

In mountainous regions, adverse environmental effects such as high reservoir sediment deposition, water pollution and floods in lowlands are usually results of conversion of upland forests to croplands (Liniger et al. 2005, Ellison et al. 2012, Neris et al. 2013). Generally, land users face tradeoffs between maximizing crop production and supplies of other ecosystem services such as water provision, erosion control, sediment retention, nutrient retention and flood regulation in the fragile ecosystems of the mountainous regions (Chazdon 2008, Polasky et al. 2011, Marquis et al., 2012). Not only mountainous areas but often also drylands, because of their problematic socio-economic and bio-physical conditions are fragile ecosystems in developing countries.

1.1.2 Fragility of drylands and detrimental effects of invasive plant species

Drylands are defined as "*areas with a ratio of average precipitation to potential evapotranspiration of less than 0.65*" (Middleton and Thomas 1992). They cover over 40 percent of the terrestrial land and about 35 percent of the global population lives in these areas (MA 2005, cf. Frankl et al. 2013). Productivity of ecosystems in the drylands is largely constrained by moisture and soil degradation (Maia et al. 2007, Carberry et al. 2011, Silva et al. 2011, cf. Huang et al. 2012, cf. Frankl et al. 2013).

Fragility of land in arid and semi-arid areas is mainly manifested in the form of desertification which results from anthropogenic impacts in combination with climate change (Gow 1987, Slegers and Strosnijder 2008, Mganga et al 2010, Zhao et al. 2004, Zhao et al. 2005, Cui and Shao 2005, Zhang et al. 2008). Nevertheless, the major cause of change in ecosystems in tropical regions (e.g. the Sahel) is anthropogenic although climatic factors have their own share (Brandt et al. 2014). Ecosystems in dryland areas are highly fragile and more than 20 percent is already affected by desertification (MA 2005, Maia et al. 2007, Jing et al. 2010, John et al. 2009). Repeated drought and expanding desertification hamper sustainable resource use and management in these areas (Frankl et al. 2013, Solh and Ginkel 2014).

Drylands are highly vulnerable to degradation due to adverse human-induced and natural factors (van Walsum et al. 2014, Sterzel et al. 2014, cf. Huang et al. 2012). Loss of vegetation due to drought and human activities in drylands triggers soil erosion and land degradation (Vásquez-Méndez et al. 2010, Moiwo et al. 2010, Wang et al. 2010, John et al. 2009, Ravi et al. 2009). Coupled with moisture shortage, land degradation limits vegetation growth and agricultural production in drylands (Maia et al. 2007, Ravi et al. 2009, Adhikari 2013). Thus, degradation of drylands has potential to decline the supplies of ecosystem services such as water, carbon sequestration, food, forage, fuel, and flood regulation (John et al. 2009, Moiwo et al. 2010, Vogt et al 2011). Report on global assessment of land degradation and improvements shows that about 22 percent of drylands are degraded (cf. Adhikari 2013). In spite of this, about 70% more food should be produced by 2050 to feed the rapidly increasing global population (Carberry et al. 2011). Since drylands cover larger portion of our planet earth (MA 2005), they also need to contribute to the increment in agricultural production. This has been realized worldwide and drylands are recently highly exploited for irrigated agriculture mostly for food and commodity production (Maia et al. 2007, Carberry et al. 2011, Daftary 2014). However, this requires protection and/or rehabilitation of drylands against desertification and land degradation.

In the past decades, attempts made to cope with the arising problems of desertification and land degradation include development interventions such as introduction of fast growing plant species (Hooke and Sandercock 2012, Shelef et al. 2014). However, introduction of plant species has been a critical problem in the host areas with detrimental effects on the supplies of ecosystem services. Introduction of new species usually forms a new pattern of the host ecosystem in which introduced and native species interact (Didham et al. 2007, Thomas and Reid 2007, Belnap et al. 2012). The newly introduced plant species have potential to overtake the native species and eventually become invasive (Kizito et al. 2006, John et al. 2009, Callaway and Aschehoug 2000, Murrell et al. 2011, Coutts et al. 2011).

The competitiveness of invasive plants results from the fact that the species are away from their natural enemies and have developed mechanisms that enable them suppress the native species (Callaway and Aschehoug 2000, Pintó-Marijuan and Munneé-Bpsch 2013). Coutts et al. (2011) stated that the main drivers for the spreading of invasive species are dispersal, demography and formation of landscapes. The characteristics of the habitats in the origin of a species and host areas define the patterns and extent of invasions (Müller-Schärer et al. 2004, Hejda et al. 2014). Species that are adaptive to wide range of habitats have potential to become highly invasive (Prentis et al. 2008, Matzek 2011, Palacio-López and Gianoli 2011, Müller-Schärer et al. 2004, Hejda et al. 2014). These plants have capacity to reduce biodiversity and ecosystem services in the invaded areas (Le Maitre et al. 2011, Palacio-López and Gianoli 2011, Hejda et al. 2014).

Woody plants invasion of drylands has been widely increasing and become a threat to ecosystems around the globe (Huxman et al. 2005). For instance, *Acacia pycnantha* was introduced from Australia to South Africa where it became highly invasive (Ndlovu et al. 2013, Le Roux et al. 2011). The key invasive woody plant species in drylands of East Africa include *Lantana camara*, *Psidium guajava*, *Prosopis juliflora*, *Prosopis pallida*, *Opuntia ficus indica*, *Senna spectabilis*, *Caesalpinia decapetala*, *Acacia mearnsii*, *Acacia polyacantha*, and *Acacia farnesiana* (Obiri 2011). The detrimental impacts of these species include loss of grazing lands, fodder, farm lands, native species, and poisoning of livestock (Vilà et al. 2011, Obiri 2011, Powell et al. 2013, Vicente et al. 2013, Fei et al. 2014).

1.1.3 Remote sensing of land cover and ecosystem services in fragile lands

Management of fragile lands is becoming a growing concern globally since it affects the supplies of ecosystem services and biodiversity conservation. Thus, the need for robust methodologies for monitoring land cover in fragile lands has already been realized to ensure sustainable land use (Vogt et al 2011). Remote sensing has become one of the main sources of data for mapping land cover and assessing ecosystem services. With limited ground data available, high resolution remote sensing data provides an option for large scale mapping of land cover and monitoring of ecosystem services (Koch 2014).

Remote sensing data can be used for quantifying and mapping ecosystem services in three major ways (Figure 2). Firstly, remote sensing-based indicators can be directly used to quantify and map ecosystem services (e.g. Krishnaswamy et al. 2009). This approach involves identification of ecosystem services' indicators that can be derived from image spectra. It requires establishing a link between ecosystem services (e.g. biomass provision) and remotely sensed data such as vegetation indices (e.g. NDVI, EVI). Since there is no direct connection between image spectra and ecosystem services, the approach demands intensive field data collection of indicators of ecosystem services and linking them with image spectra through statistical analysis (e.g. regression).

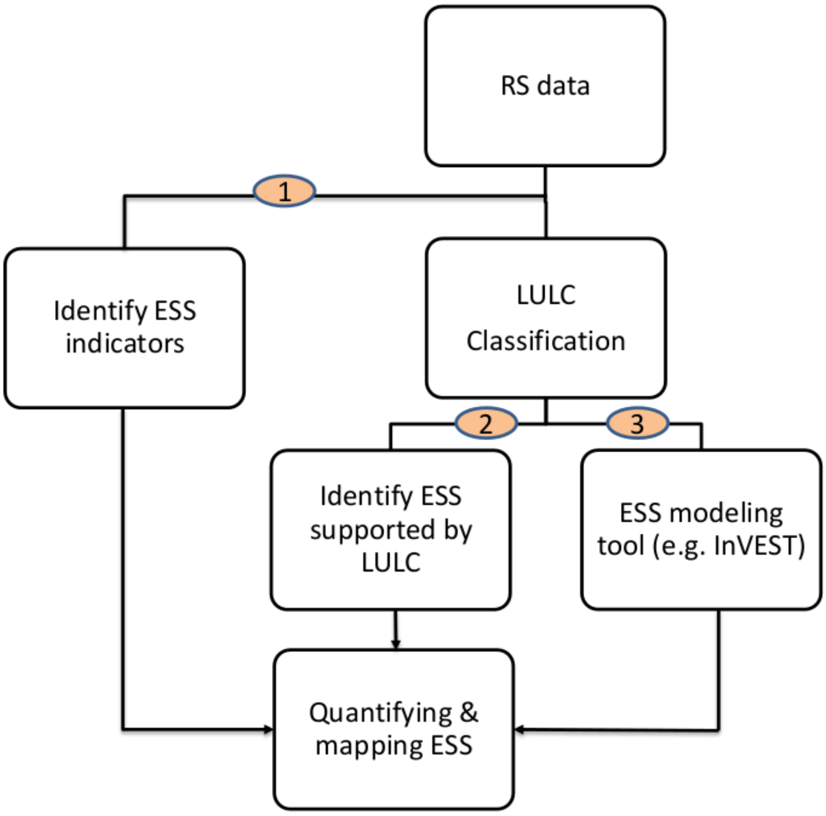

Figure 2 Commonly used approaches for quantifying and mapping ecosystem services using remote sensing data: 1 directly using image spectra 2 and 3 using LULC as proxies.

Secondly, LULC maps derived from classification of remote sensing images are used as proxies for ecosystem services. Quantifying and mapping ecosystem services in this case is usually done by identifying capacity of the LULC classes to support ecosystem services. In the past decade, several researchers used LULC as a proxy for quantifying ecosystem services (e.g. Sutton and Costanza 2002, Zhao et al. 2004, Li et al. 2007, Maes et al. 2011, Liu et al. 2012). For instance, Maes et al. (2011) quantified and mapped ecosystem services of Europe based on key indicators identified from LULC classes. Figure 3 shows examples of the relative capacity of some LULC classes as key indicators for quantifying and mapping ecosystem services. Obviously, croplands have high capacity for food production while they have no contribution for timber production unlike forests (Figure 3). Following identification of the capacity of LULC classes, spatially-explicit ecosystem services maps are produced. Although using LULC classes as a proxy for quantifying and mapping ecosystem services is simplistic and requires less data, it has some limitations

(Eigenbrod et al. 2010; Tianhong et al. 2010). Classification of remote sensing data involves a series of multivariate statistical analyses to obtain discrete classes from the images. The thematic level of detail i.e. number of classes of the LULC depends on properties of the remote sensing data available and/or selected for classification. The accuracy of assessment of ecosystem services thus depends on accuracy of the classification.

Thirdly, the LULC classes derived from remotely sensed data can be used as an input for scenario-based quantification of ecosystem services using modelling suits such as the InVEST tool (Nelson et al. 2009). Similarly, the accuracy of ecosystem services quantified using a modelling tool depends on accuracy of image classification as well as the model accuracy that relies on the algorithm, parameters considered, and data used for calibration and parameterization.

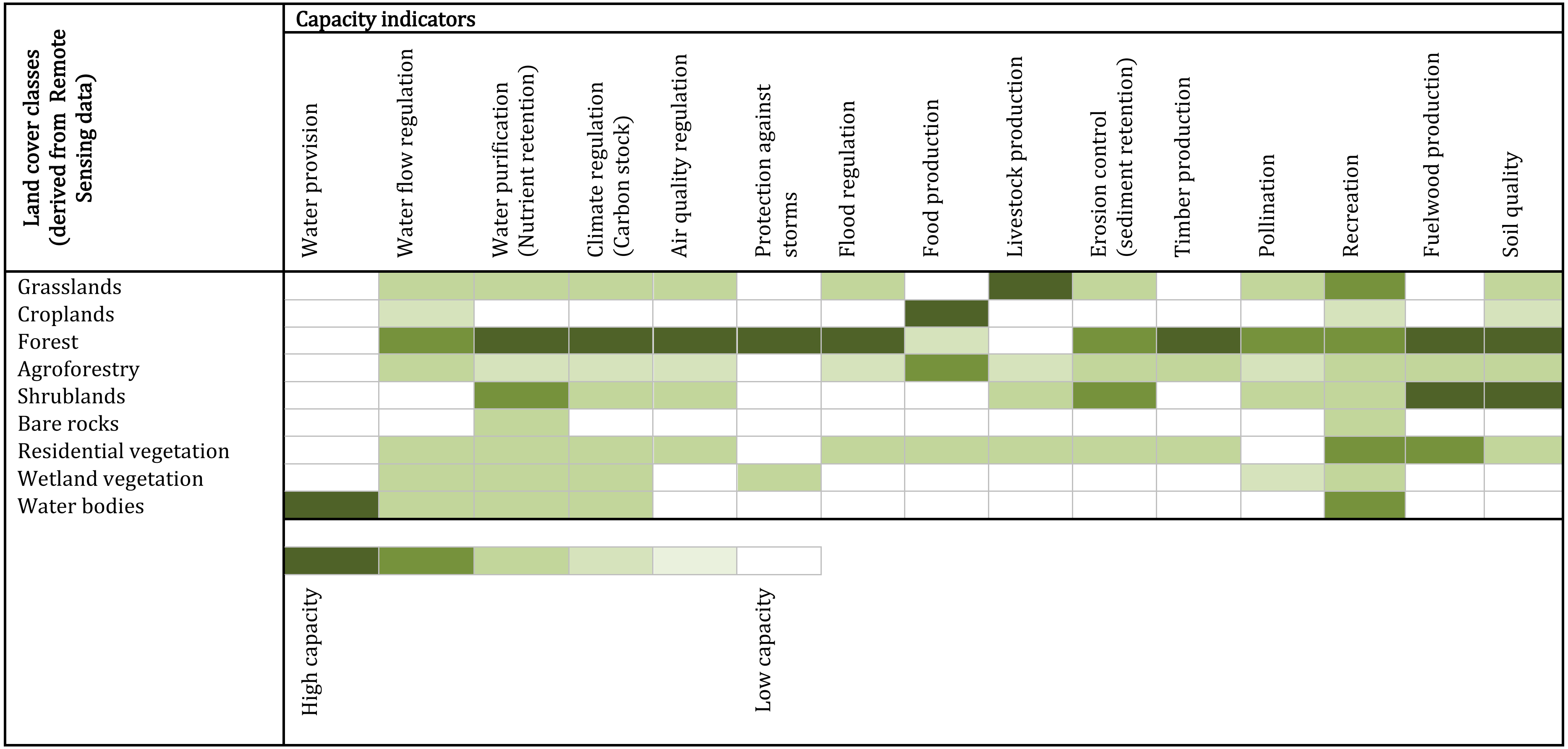

Figure 3 Capacity of land cover classes to support ecosystem services (adapted from Maes et al. 2011)

1.2 Objectives

Studying fragile land cover is essential since it increases awareness and reveals the formation mechanism of those lands (Jiang et al. 2011). The combined impact of agricultural land expansion and invasive plant species threatens the sustainable supplies of ecosystem services. The impact is highly aggravated in fragile lands in steep mountainous areas and drylands since the people living in these areas are highly vulnerable and have low capacity to respond to environmental hazards. Therefore, assessing cover types that are detrimental for sustainable supplies of ecosystem services in fragile lands is timely and relevant to recommend solutions for sustainable land management.

The main objective of the dissertation is to assess two major land cover types detrimental for ecosystem services in fragile lands of Ethiopia. The main reason why Ethiopia was chosen for the case studies is due to the ongoing pressure on fragile lands of the country which is triggered by population growth, large-scale agricultural land acquisition and problems arising from invasive species. The specific objectives are: i) Explore opportunities and challenges of remote sensing applications in assessing ecosystem services ii) Map the extent of *Prosopis juliflora* invasion of the Awash Basin of Ethiopia and iii) Assess undercover cropland inside forests of the Bale Mountains of Ethiopia. To achieve the main goal of the research, three major studies were carried out.

Study 1 Identifying applications of remote sensing in quantifying and mapping ecosystem services

Globally, there is a growing interest by decision-makers and scientists to quantitatively estimate the benefits of nature to humans. Such quantitative assessments require fast and cost-effective tools that enable to generate reliable information at various scales. Remote sensing is one of such tools that is recently being realized for their applicability in quantifying and mapping ecosystem services (e.g. Krishnaswamy et al. 2009; Feng et al. 2010). Remote sensing technologies can thus be highly relevant in large-scale assessing of ecosystem services in fragile lands as well as any type of land which is of interest. Therefore, exploring the potential in using remote sensing for quantifying and mapping ecosystem services is a valuable contribution to the future developments of ecosystem services research. This study was mainly geared towards identifying remote sensing data and methods that can be used to quantify and map ecosystem services at different scales by systematically reviewing literature in the past. The major themes in this study are listed below.

- Identify remote sensing data and approaches that are used in quantifying and mapping ecosystem services;
- Identify important factors that need to be considered in selecting suitable remote sensing data and methods for quantifying and mapping ecosystem services; and
- Discuss examples of remote sensing applications for quantifying and mapping ecosystem services and identify research gaps that are relevant to the topic.

Study 2 Prosopis juliflora invasion and its impacts on ecosystem services

Exotic species are often introduced to a given locality for the benefits they provide to the society. However, introduction of a new species not always achieves the intended goals since a species could become invasive and threaten supply of ecosystem services. *P. juliflora* is one of such species was introduced to provide ecosystem services (e.g., breaks to stop wind erosion), but has widely become invasive in those regions, because of its characteristics (e.g. deep rooting system, fast germination and coppicing capacity). Thus, it is essential to map invaded areas with remote sensing and assess the potential impacts of invasion on ecosystem services. In this study the potential risks of introducing a species to new vicinity were explored using *P. juliflora* invasion in the fragile lands of the Afar Regional State of Ethiopia as an example. The main focuses of this study are:

- Quantifying & mapping of *P. juliflora* invasion and assess its temporal dynamics;
- Identify and discuss the impacts of the invasion on selected ecosystem services;
- Identify the major challenges in the management of *P. juliflora* invasion and recommend possible solutions.

Study 3 Undercover cropland inside forests: revealed with remote sensing and field observations

Being driven by the ever increasing global demand for food, cropland has been largely expanding worldwide. Recently, this is an ongoing process especially in tropical and subtropical countries particularly in the Sub-Saharan African countries. Large-scale agricultural land expansion is taking most of the flat-terrains that are suitable for mechanized agriculture which in turn led to shifting of the land that is used by local small-scale farmers. Since the produced crop from large-scale farms is mainly for export, small-scale cropland continued to expand to feed the increasing population to the extent fragile lands that were previously marginalized are nowadays cultivated.

Due to desperate need for growing crops new patterns of cropland expansion emerge and/or old traditional systems such as agro-forestry are adopted in new areas where they were previously not practiced. Where there is restriction in clearing of forest lands in mountainous areas, secretly growing of crops inside forests (undercover cropland) is becoming a common phenomenon. The hidden (undercover) cropland inside forests are not direct replicates of traditional agro-forestry systems since we assume that farmers use them just as a point of entry to own a new cropland by gradually and secretly degrading the forest which will finally be converted to agricultural land. To ensure sustainable resource use and management, understanding the patterns of such complex systems and the variables that influence them is essential.

In this study, the patterns of undercover/hidden cropland inside forests and its influential factors were assessed using combination of remote sensing and ground surveying data based on a case study site in the Bale Mountains of Ethiopia. The major issues addressed here are:

- to map the general patterns of cropland in the Bale Mountains of Ethiopia and identify the hotspots of cropland under forest canopies;
- identify explanatory variables of undercover cropland in the region, and
- discuss the emerging challenges and future prospects of the undercover cropland.

1.3 Research questions and hypotheses

To meet the overall goals of the study, the following research questions were considered in each of the individual case studies:

1. What are the opportunities and limitations of remote sensing in quantifying and mapping ecosystem services?

2. How did *Prosopis juliflora* invasion of the Awash Basin of Ethiopia changed over the past decade?

3. What are the influential factors of undercover cropland inside forests in the Bale Mountains of Ethiopia?

The three research questions outlined above are inter-linked. Research question 1 was used to identify to which extent remote sensing contributes to assessment of ecosystem services. The opportunities and challenges in the data availability as well as methods are explored based on review of past literature. This was an essential step to define the scope of the thesis based on resource and time limitations. Research questions 2 and 3 address the detrimental impacts of land cover in drylands and mountainous regions respectively. Based on research questions 2 and 3, the following hypotheses were defined for the individual case studies.

Hypothesis 1: *Prosopis juliflora* invasion of the Awash basin increased over the past decade and puts pressure on ecosystem services and local people's livelihood.

Hypothesis 2: Topographic parameters such as slope, elevation and aspect as well as location factors such as distance to settlements and the national park influence undercover cropland inside forests in the Bale Mountains of Ethiopia.

Hypotheses 1 and 2 above were tested in studies 2 and 3 respectively.

1.4 Study area

1.4.1 Background

In sub-Saharan Africa, most of the mountainous and dryland areas are highly fragile i.e. subjected to deterioration and show slow recovery after disturbance (Peng et al 2011). The majority of the population (65%) in the sub-Saharan Africa is rural poor whose livelihood is dependent on agriculture (Palm et al. 2009, Messerli 2012). So far, agriculture is the major sector in the economies of many countries in the region (Gibbs et al. 2010, Dile et al. 2013, Stevenson et al. 2014). With rapid population growth, increasing food production mainly involves increasing the size of arable lands including the fragile and marginal areas (Oyekale 2012). Land degradation is often aggravated in developing countries of the tropics in general and sub-Saharan Africa in particular especially where there is unequal access to the arable land which is suitable for growing crops (Gibbs et al. 2010, Anya 2013, Laurance et al. 2014). In the past decades, the sub-Saharan Africa is highly affected by deforestation and land degradation resulting from agricultural land expansion (Palm et al. 2009, Blay 2012, Rudel 2013).

Ethiopia is one of the oldest sub-Saharan African countries with highly fragile mountainous areas and drylands. Most of these fragile lands are highly affected by deforestation and land degradation that came mainly from agricultural land expansion. Ethiopia has a long history of agriculture with its livestock raring and growing of crops through "Ox-plow" tradition which dates back to 500-1000 B.C. (Butzer 1981, McCann 1995, cf. Bard et al. 2000, Tefera 2011, Assefa and Bork 2014). McCann (1995) stated that Cushitic people of the northern highlands invented "Ox-plow" although later it became the livelihood base for the Semitic peoples. It later spread to the rest of Ethiopia including pastoralist areas such as the Somali, Borana and Kereyu in the late 19th and 20th centuries (McCann 1995, Zeleke and Hurni 2001). Due to the wide range of agro-climatic zones, different crops are grown across Ethiopia (Bard et al. 2000). This was one of the major reasons for Italiy's failed attempt to colonize Ethiopia in the 1890s with the aim of exporting crops to the high food demand in Italy (McCann 1995). Crop and livestock production has been the livelihood and economic base for different kingdoms of Ethiopia for over 2000 years (McCann 1995, Boardman 1999).

During the era of the Axumite Kingdom (today's northern Ethiopia and Eritrea) with its capital, Axum, which was founded around 100 A.D., Ethiopia was known with ancient civilization and trade across the red sea with the Roman Empire and Ancient India (Connah 2013, Phillipson 2012). However, during the 7th and 8th centuries most of the agricultural land in the kingdom was highly degraded and rainfall become erratic which resulted in reduced productivity. Besides, due to entrance of Islam from the Arabian peninsula into the eastern part of Ethiopia, the kingdom become landlocked around 715 A.D. leading to the decline in trade and eventually downfall of Axum around the 800 A.D. (Butzer 1981). This later led to shift of power from the northern Ethiopia to the then fertile humid lands of central Ethiopia (Horvath 1969, Butzer 1981). The tradition of abandoning degraded lands and shifting to new fertile areas continued to be practiced by the royal families of the Zagwe and Solomonic dynasties of the northern and central Ethiopia. The capital cities of the Ethiopian empire have also been wandering depending on interest of the ruling dynasty until today's stable capital of the unified Ethiopia was found in 1890 by Emperor Menelik II (Table 1). The continuous movement and resettlement of the royal families in search of fertile lands for growing crops and raring livestock contributed to deforestation and degradation in the newly inhabited areas (McCann 1997) and yet continues to do so.

Table 1 Capitals in Ethiopian history (Taken from Horvath 1969).

Capital	Period
Axum and neighborhood	Unknown date B.C.–12th century A.D.
Lasta capitals	12th century –1268
Teguelat	1268 –1412
Roving capitals	1412 – 1636
Gondar	1636 – 1755
Regional capitals	1755 – 1855
Magdella	1855 – 1868
Mekele	1868 – 1890
Addis Ababa	1890 – present

Land reform during the 19th and 20th centuries has been a central problem of Ethiopia that hampered the country's sustainable development and resource management

(Lanckriet et al. 2014). Menelik II's occupation and unification of the independent states in the southern, eastern and western parts of Ethiopia, secured land tenure rights to the royal families of the Solomonic dynasty from the central highlands of Ethiopia. This shift in land ownership brought instability among the local farmers who entirely lost their land and become tenants which in turn has had impact on the management of land leading to increased deforestation and land degradation (Teka et al. 2013). The same trend continued also throughout the successor of Menelik II, Emperor Haile Selassie I, until the end of the Solomonic dynasty in 1974. During the Derg regime (1974–1991), land was given back to the peasants who till the soil through "Ox-plow" tradition. However, large-scale state-owned farms emerged and occupied vast flat areas suitable for agriculture, pushing many small-scale farmers to marginal and fragile lands. Under the current EPRDF regime, land is owned by the state which brought even more instability among the farmers. Due to rapid population growth (Figure 4a) and less developed technology that lasted for three millennia, agricultural land continued to expand to fragile marginal lands in the expense of remnants of forests and grazing lands (Josephson et al. 2014).

The Agriculture Development Led Industrialization (ADLI) policy of the current government of Ethiopia gave priority to maximizing commodity production from the sector (Headey et al. 2014). This is particularly realized over the past decade where many foreign investors have leased land for growing crops either by evacuating the small scale farmers or granting the sparsely populated pastoralist lands resulting in drastic increase of croplands (Figure 4b). The recently ongoing land grabbing to boost commercial agriculture raises concerns about its impacts on the local people and pressure on fragile lands (De Schutter 2011, Lavers 2012, Woodhouse 2012, Sparks 2012). Due to the growing global demand for agricultural land by foreign and local investors, the poor are usually forced to exploit fragile lands/ecosystems thereby accelerating land degradation (Blum and Eswaran 2004, Lambin and Meyfroidt 2011, Oyekale 2012, Anya 2013, Headey et al. 2014).

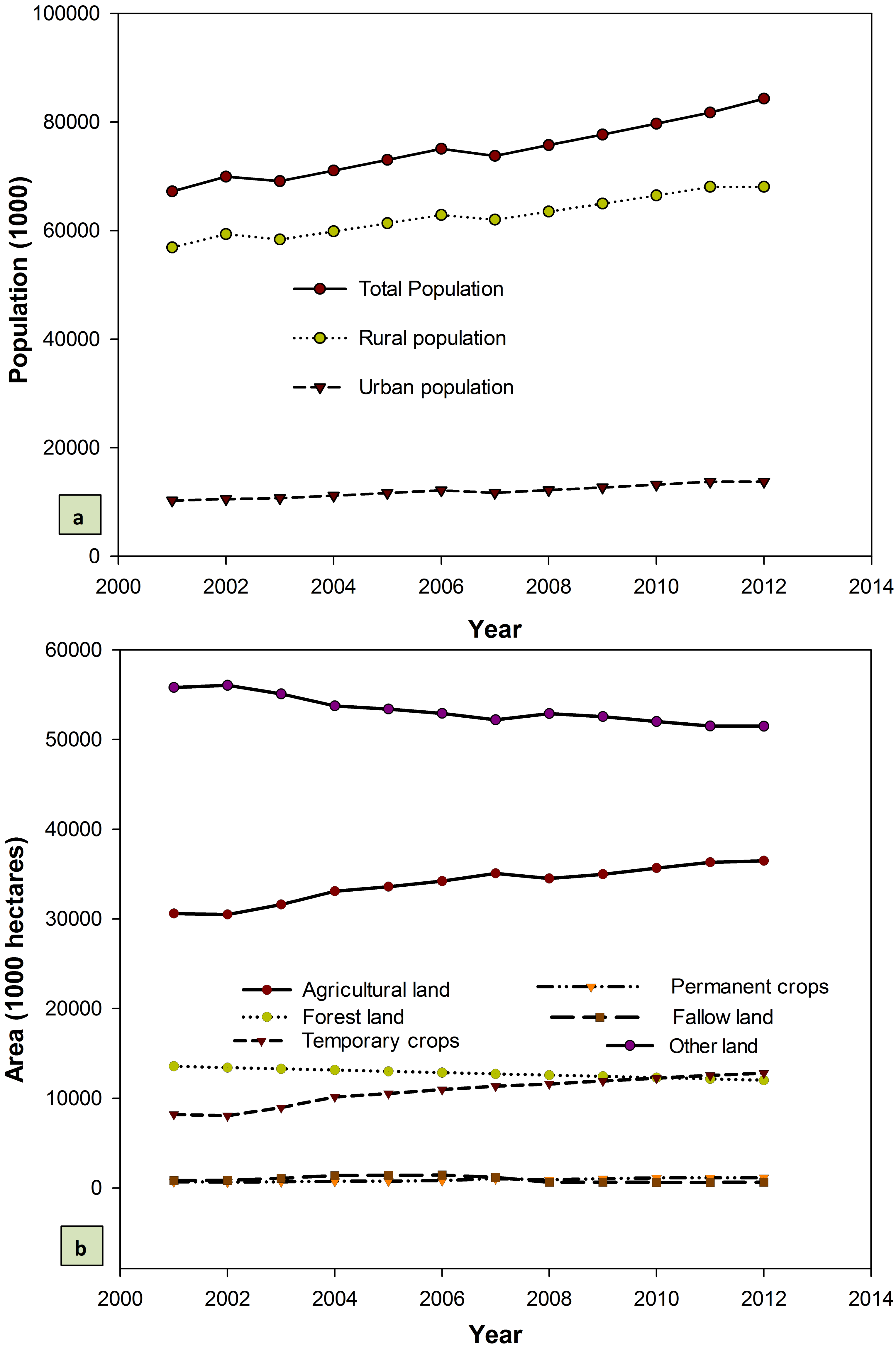

Figure 4 a) Ethiopia's population growth and b) distribution of land use in the past decade (Source: FAOSTAT 2014)

As a response to deforestation and land degradation in Ethiopia, introduction of fast growing exotic plant species was in the past considered as an alternative solution for supplying fuel wood, timber, and soil conservation. Several exotic tree and shrub species have been introduced in the 19th and 20th centuries for afforestation across different parts of the country (Senbeta et al. 2002, Lemma et al. 2006). This has been part of the government policy since 1974 as a solution for rehabilitation of degraded lands and boost supply of services such as timber and fuelwood (Poschen-Eiche 1987). Fast growing exotic tree species such as *Eucalyptus*, *Cupressus* and *Pinus* are important components of plantation forestry (cf. Lemma et al. 2006). Some of the introduced species are highly adapted to the environment of Ethiopia and become the preference of the people than the slow growing native species though their impact on the environment is a paradox. For instance, in humid climates Eucalyptus plantations are found almost in all cities, towns and villages throughout the country.

In the contrary to the positive aspects, some of the introduced exotic species have become highly invasive. Most of the exotic plant species introduced to Ethiopia in the past decades have become invasive and threatened biodiversity and ecosystem services (Fessehaie and Tessema 2014). The top 10 most influential invasive species in Ethiopia are presented in Figure 5.

Species	**Most affected ecosystems**							
	Cultivated land	Road side	Grazing lands	Uncultivated lands	Rural villages	Urban areas	River side	Forest areas
Parthenium hysterophorus	■	■	■	■	■	■	■	■
Prosopis juliflora	■	■	■	■	■	■	■	■
Opuntia ficus- indica			■	■	■	■		
Opuntia stricta			■	■	■	■		
Mimosa diplotricha	■	■	■	■	■	■	■	■
Mimosa pigra			■	■			■	
Cryptostegia grandiflora		■	■	■			■	■
Lantana camara	■	■	■	■	■	■	■	■
Acacia drepanolobium	■		■	■				
Acacia saligna		■	■	■	■			

Figure 5 Top 10 invasive plant species and ecosystems they mostly invade (Source: Fessehaie and Tessema 2014)

These plant species have invaded large areas in the country. For instance, woody plant species *Prosopis juliflora* has rapidly spread throughout Ethiopia invading wide range of habitats (Figure 6).

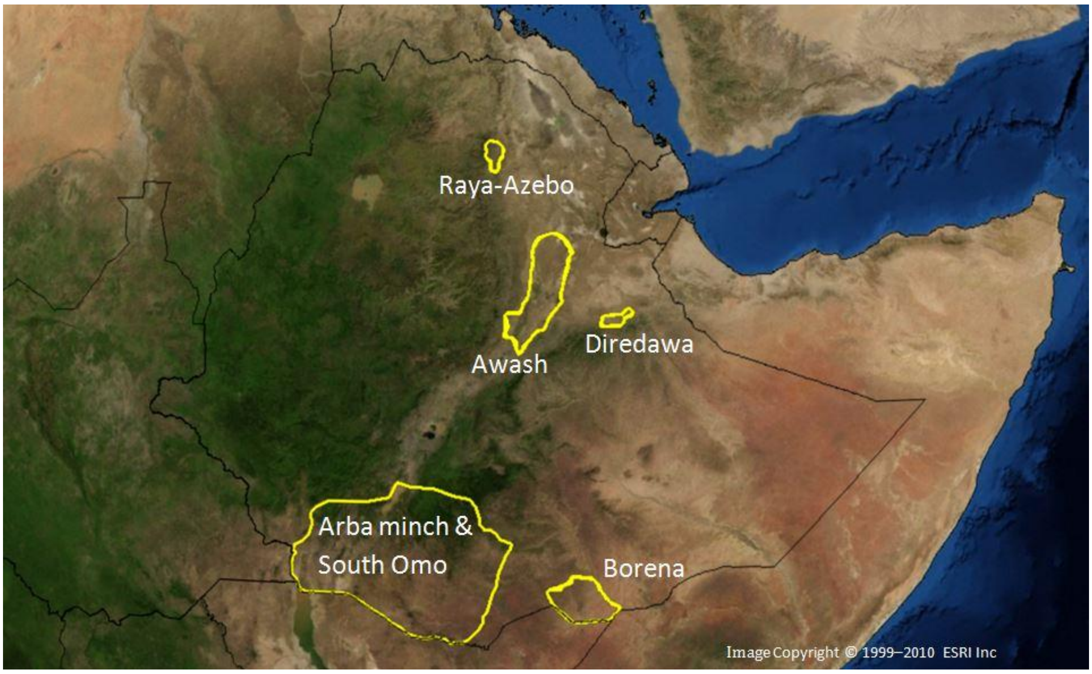

Figure 6 Major spreading areas of *P. juliflora* spreading in Ethiopia (Source: Fessehaie and Tessema 2014)

1. 4.2 Case study sites

The two major case studies in this thesis (Study 2 and Study 3) were carried out in two separate sites, Baadu-the Awash Basin and the Bale Mountains of Ethiopia respectively. These sites were selected because they represent fragile lands and land-cover related problems in two different agro-climatic conditions i.e. the lowland areas and high altitude mountainous areas.

i. Baadu

Baadu is part of the regional state of Afar and is located in the semi-arid part of the middle Awash River Basin of Ethiopia (Figure 7). It comprises an area of approximately 1500 km^2 and consists of flat floodplains at an altitude of 500m above sea level surrounded by upland dryland areas. The average rainfall in Baadu is estimated at 450 mm per annum. According to the definition by Middleton and Thomas (1992) the whole parts of Baadu (floodplains and drylands) fall under the category of drylands with ratio of precipitation to evapotranspiration below 0.65. Therefore, in this study, fragile drylands refer to these two categories of landscapes in Baadu.

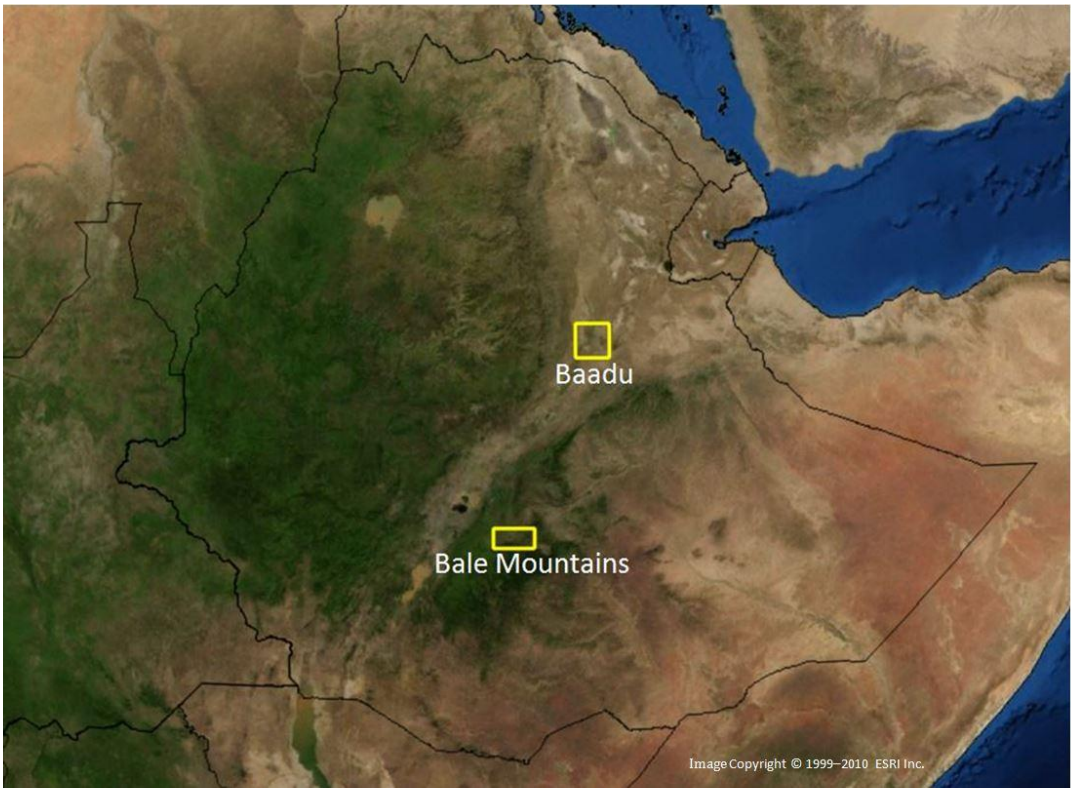

Figure 7 Map of Ethiopia showing case study sites

The Baadu area was selected as one important study site due to three distinct features. Firstly, the area has been of interest to state government in the past and the current government for large-scale irrigated agriculture. It has been considered as one of the bases for the agriculture-led economic development plan of the government of Ethiopia. Irrigation capacity of the Awash River and suitability of the land for mechanized agriculture attracts small and large-scale private investors as well as the government state farms. Secondly, due to availability of water from the Awash River, the Baadu area hosts more than twenty pastoral Afar clans who inhabit Baadu (Rettberg 2010). The seasonal inundations of the Awash River make water available year round enabling the grasslands of Baadu to serve as dry season pastures and drought retreat for Afar pastoralists. Thirdly, a new species, *Prosopis juliflora,* which was introduced to the area during 1980s for soil conservation and windbreaks has become highly invasive and problematic. *P. juliflora* is potentially threatening ecosystem services and livelihood of the Afar pastoralists and is also hindering the progress of small and large-scale investment in agriculture. This invasive plant species invaded most of the rangelands as well as the abandoned croplands in the flood plains of Baadu. Nowadays, *P. juliflora* is recognized world-wide as an invasive plant species that needs to be carefully managed and/or eradicated (Pasiecznik and Felker 2001; El-Keblawy and Al-Rawai 2007). Though Baadu is highly important for Afar pastoralists and is an area of high potential for irrigated agriculture, the damage caused by the invasive species *P. juliflora* continued to increase. Therefore, the study site is a typical example showing impacts of an invasive species in a fragile land shared by pastoralists, agro-pastoralists and irrigated agriculture simultaneously.

ii. Bale Mountains

The study site selected for study 3 is part of the Adaba, Dodola, Asasa and Dinsho districts of the Bale and Arsi zones of the Oromia Regional State in the Southeastern Ethiopia (Figure 7). It consists of total area of 2500 km^2 with elevation range of 2266 to 4059 meters above sea level and average annual rainfall of 1000-1400 mm. The Bale Mountains study site was preferably selected due to two major reasons. Firstly, the area is characterized by high ecological heterogeneity along various altitude ranges from valley bottoms to mountain tops (Yimer et al. 2006), which made it source of diversified ecosystem goods and services for local as well as national beneficiaries. For instance, provisioning services dominant in the Bale Mountains include supplies of food, water, timber, fuelwood, and fodder.

Secondly, location of the site makes it an important area that needs focus to find solutions for sustainable resource use and management. The site is adjacent to the Bale Mountains National Park (BMNP), which is known for its high biodiversity and insitu conservation of highly endangered mammals, birds, plants, and amphibians that are endemic to Ethiopia. Moreover, since the site is situated at the border of four districts mentioned above, it is under continuous pressure coming from growing population of the districts. The high population growth in the area increased the food demand by the local farmers, nearby villages and towns. The fact that pressure due to cropland expansion in this area is threatening the national park and the supplies of ecosystem services, makes it an interesting site for assessing the patterns of cropland.

Therefore, the study site was selected since it represents a fragile area under a continuous pressure due to multiple actors and growing population from the surrounding districts with potential threat to ecosystem services and the conservation areas.

1.5 Data and methods

Study 1 Applications of remote sensing for quantifying and mapping ecosystem services

In this study, literature was systematically reviewed to assess the applications of remote sensing in quantifying and mapping the supplies and demands of ecosystem services. The definition of ecosystem services used in this study is the Millennium Ecosystem Assessment (2005) that defines ecosystem services as "*benefits that ecosystems provide to support human well-being".* Ecosystem services were defined based on the TEEB classification (TEEB 2010). The review was limited to remote sensing applications in quantifying and mapping of selected provisioning and regulatory ecosystem services. The other ecosystem services were excluded from this review due to lack of literature dealing with such ecosystem services. Articles published from year 1990 to 2011 were collected from peer reviewed journals using key words from the ISI Web of Science (www.webofknowledge.com) and Google Scholar (www.googlescholar.com) as primary search engines. The publications were screened with respect to the ecosystem services considered. This review focuses particularly on literature that used remote sensing for quantifying and mapping ecosystem services.

Study 2 Prosopis juliflora invasion and its impacts on Ecosystem services

Detecting invasive plant species in drylands using remote sensing starts with understanding of the characteristics of the species and its seasonal variations in terms of aspects such as greenness. *P. juliflora* has distinct features that differentiates it from other species in the Baadu area. Unlike other vegetation in the area, it remains green throughout the year which makes it easily detectable specially during dry seasons. Figure 8 shows the seasonal changes of MODIS NDVI values comparing *P. juliflora* dominated pixels with dry upland vegetation.

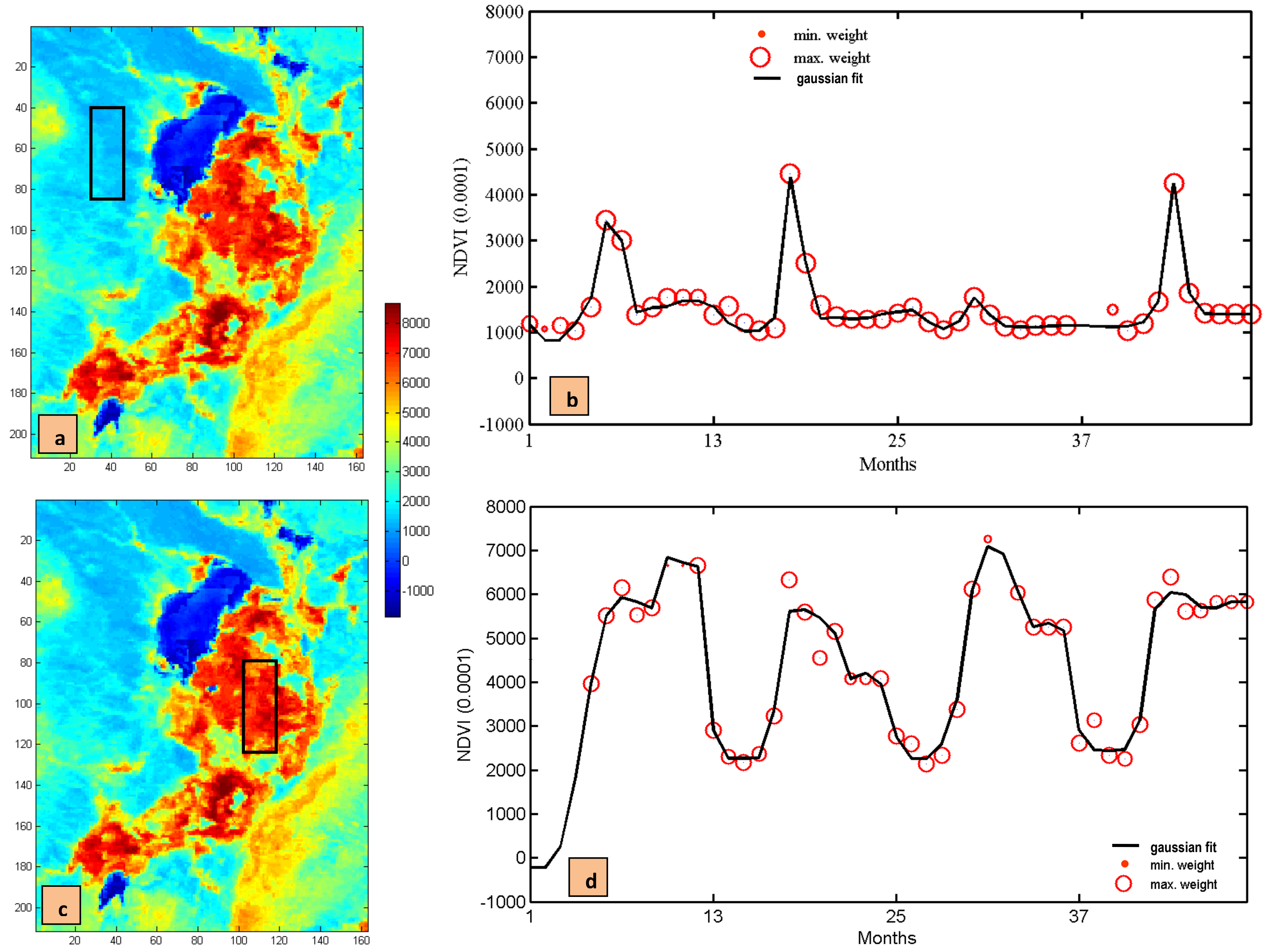

Figure 8 a) Map showing processing window for pixels located in dry uplands with sparse shrubs and grasses b) Monthly variations of MODIS NDVI as an indicator of greenness in the dry upland vegetation c) Map showing processing window for *P. juliflora* dominated pixels d) Monthly variations of MODIS NDVI as an indicator of greenness in the *P. juliflora* dominated pixels.

The NDVI values from the *P. juliflora* dominated pixels remained high over all months ranging from about 0.60 in the dry seasons to above 0.8 during wet seasons. Whereas, the NDVI values in the dry upland vegetation ranges from 0.10 during dry periods to 0.50 during wet seasons. With high resolution images, *P. juliflora* can be identified from other wetland vegetations such as croplands and grasslands especially during the dry periods. Based on the aforementioned preliminary assessment of the characteristics of P. juliflora, images from dry seasons were selected for mapping invasion of the species.

Classification

To extract *P. juliflora* invaded layers from the Landsat ETM+ (30 m) and ASTER (15 m) satellite images, maximum likelihood supervised classification provided by Envi 5.0 software was used. Figure 9 illustrates the difference in spatial resolution between the satellite images.

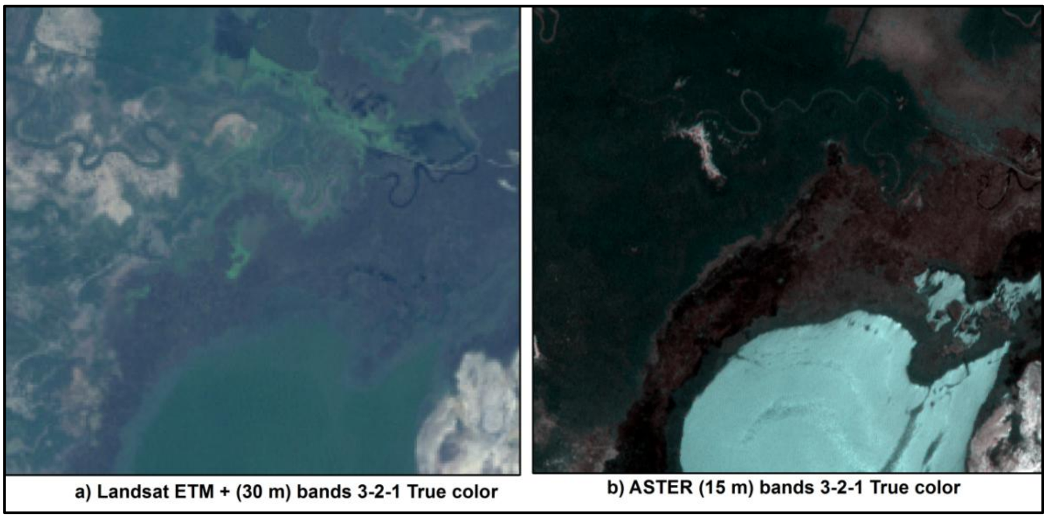

Figure 9 Example of difference in the resolution of the a) Landsat ETM+ and b) ASTER satellite images zoomed near a lake area in Baadu

Training areas representing different land cover classes were defined using data from field observations and Google earth images by digitizing polygon features that correspond to pixels in the satellite images. These training areas were used to guide the maximum likelihood classifier to classify the images into different land cover classes. This method is robust and has been widely used in the past for image classification and mapping of land cover (Erbek et al. 2004; Tuia et al. 2011; Behnia et al. 2012). An example of separation between *P. juliflora* and other land cover classes is presented in Figure 10.

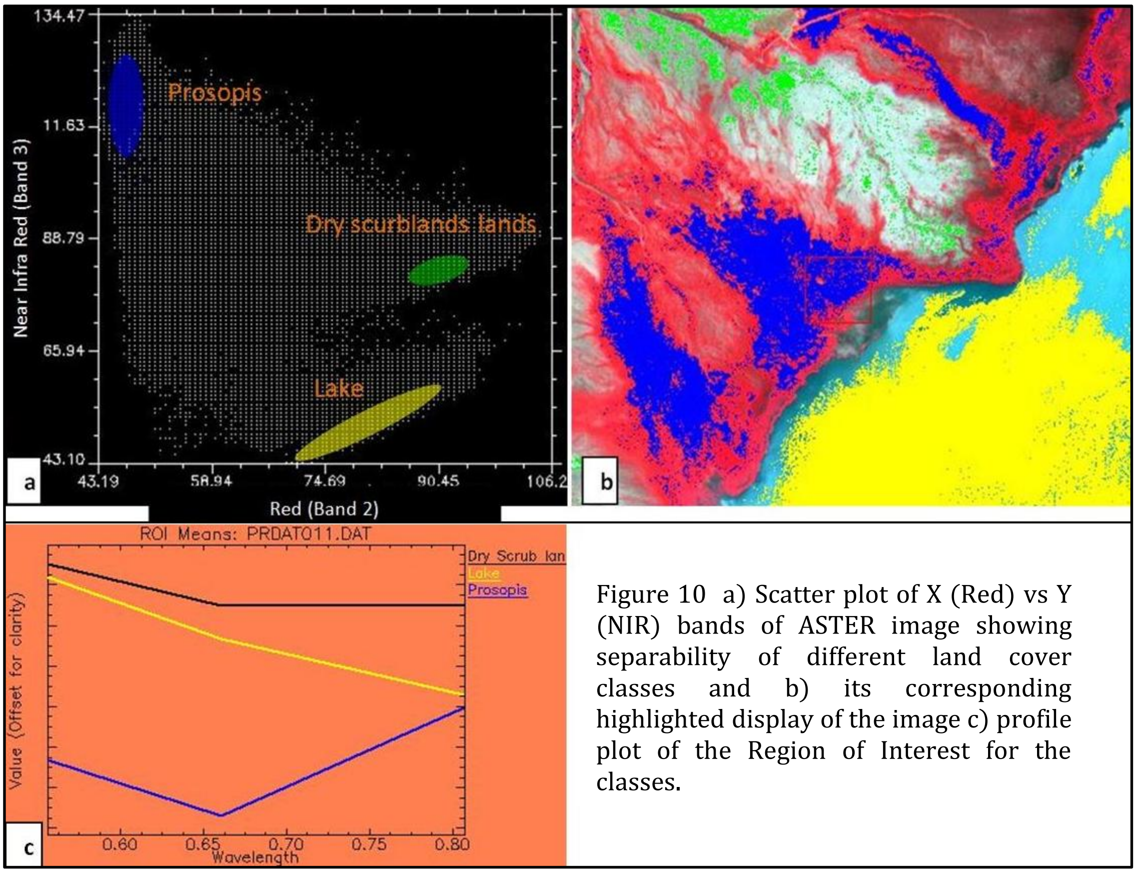

Figure 10 a) Scatter plot of X (Red) vs Y (NIR) bands of ASTER image showing separability of different land cover classes and b) its corresponding highlighted display of the image c) profile plot of the Region of Interest for the classes.

Maximum likelihood classifier assumes normal distribution for each band and calculates the probability that an individual pixel belongs to a given class (Paola and Schowengerdt 1995; Perumal and Bhaskaran 2010; Tuia et al. 2011). The term 'maximum likelihood' thus refers to using the maximum probability as a guideline to assign a pixel to a class. Pixels with probability below the set threshold will be left unclassified. In supervised classification, pixels are clustered into classes based on user-defined training areas (Richards 1999). The training areas (Region Of Interests, ROs) can be defined as multiple irregular polygons, vectors, and/or individual pixels. The accuracy of classification depends on separability between the ROIs (Oskouei and Busch 2012; Zhang et al. 2012). Hence, points within each ROI should be homogenous and tightly clustering together to avoid overlap between classes.

Assessing the impacts of P. juliflora on ecosystem services

The impact of the invasive species, *P. juliflora* on ecosystem services was analyzed by calculating the area of important land categories (wetlands, agricultural lands & dry lands) that is invaded by the species. Ecosystem services supplied by the above land categories were identified based on the Millennium Ecosystem Assessment, 2005 ecosystem services classification scheme in order to discuss potential loss of the services due to the invasion. For comparison, ecosystem services that can be supplied by *P. juliflora* itself were also identified to discuss potential gains in terms of ecosystem services supplies due to introduction of the invasive species in the area. In spite of these, the beneficiaries of ecosystem services that are affected by the invasion of *P. juliflora* were identified and discussed. In the end, the pros and cons of *P. juliflora* invasion were assessed and summarized based on the impacts on supplies of ecosystem services and the beneficiaries affected.

Study 3 Undercover cropland inside forests

Random Forest classification

For this study, level 3A RapidEye images were used to derive LULC classes for the study site. The images were corrected for atmospheric and topographic errors using ATCOR 2/3 software. Figure 11 shows an example of comparison between the original level 3A product and the image corrected for atmospheric and topographic errors.

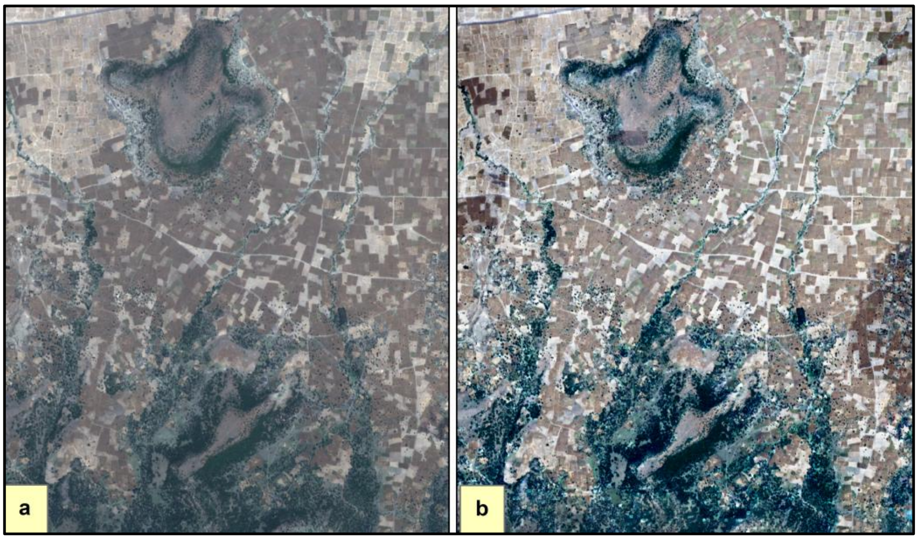

Figure 11 a) Rapideye image bands 3-2-1 before atmospheric and topographic correction b) after atmospheric and topographic correction using ATCOR 2/3

Random Forest (RF) classification method (Breiman 2001) was used to classify the RapidEye images. The method uses bootstrap samples derived from user-defined training samples for multiple binary decisions in order to randomly select variables at a each node of trees (Breiman 2001; Genuer et al. 2010). The final classification is thus the result of multiple decision trees (Figure 12).

Breiman (2001) expressed the RF classification as:

$\{h(X, \Theta_k), k = 1, ...\}$ ....eq. 1 where $h(X, \Theta_k)$ stands for the kth classifier, the $\{\Theta_k\}$ are independent identically distributed random vectors generated for the kth tree grown using the training set. X is an input vector for which a class is voted by each tree. The classification process involves random selection of input variables (*mtry*) at each node of the trees (*ntree*) to calculate the best split within this subset (Genuer et al. 2010; Gislason et al. 2006; Rodriguez-Galiano et al. 2012; Zhu et al. 2012). In Figure 12 the ends of $tree_1$, $tree_2$,... $tree_n$ result in decision for k_1, k_2, ...k_n which are later used in voting class k.

Since its introduction by Breiman (2001), it become highly popular and has been a widely used statistical method for classification (Biau et al 2012; Genuer et al. 2010). The RF method was preferably used for classification due to its multiple advantages over other classification approaches. For instance, Pal (2005) compared RF classifier with Support Vector Machines (SVMs) and found that R F requires less number of user defined parameters while it provides a comparable accuracy within similar training time with SVMs. The random selection of subsets of input variables minimizes correlation between classifiers (De'ath 2002; Rodriguez-Galiano et al. 2012). Gislason et al. (2006) stated that RF is able to handle large datasets since it is not sensitive to noise or overtraining. Besides, it provides estimates of relative importance of variables used in classification including the interaction between them (Rodriguez-Galiano et al. 2012; Zhu et al. 2012). Moreover, RF provides an option for internally estimating classification error (Breiman 2001; Rodriguez-Galiano et al. 2012).

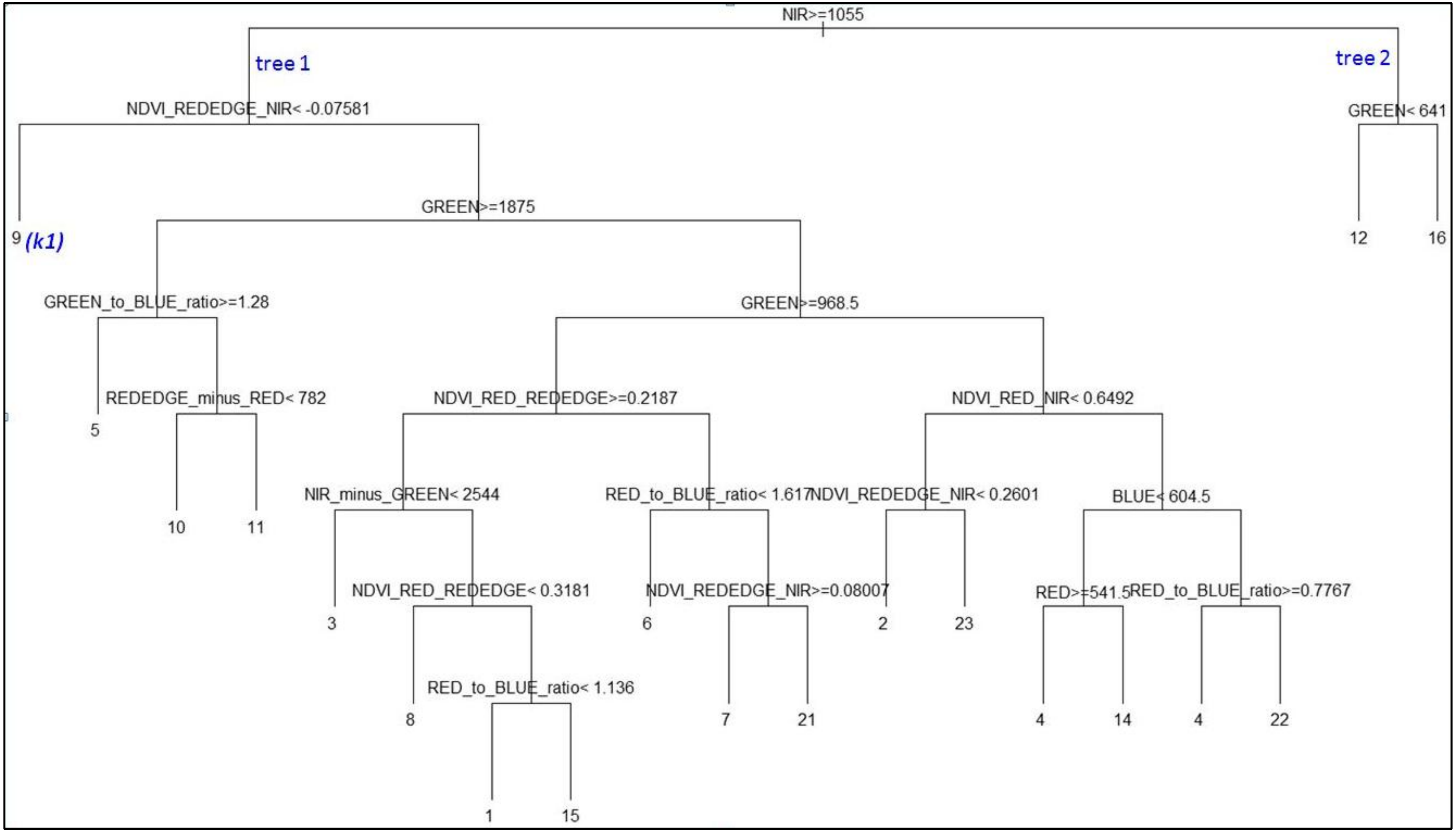

Figure 12 An example of a Random Forest classification tree structure (based on Breiman 2001). Numbers *k* values 1,2 ... 23 represent land cover classes.

Validation of the satellite image classification

The results of the satellite image classification were validated using three sets of data: high resolution Google earth images, reference LULC classes recorded at the centre of sample plots and GPS photos taken in North, East, West and South (NEWS) directions from the centre point. The GPS photos were converted to points using QGIS 2.0.1 software and LULC classes were identified on the photos. The GPS photos were merged with the sample points to validate the results of the image classification. The details of the steps used in the validation are provided in chapter 3 and 4.

Boosted Regression Trees

To identify influential variables for cropland area in the study site, Boosted Regression Trees (BRTs), a method for fitting statistical models was used (Leathwick et al. 2006; De'ath 2007; Elith et al. 2008). BRTs are combinations of algorithms of regression trees and boosting. Regression trees are models that use recursive binary splits to relate a response to their predictors while boosting is an adaptive method that improves predictive performance by combining multiple simple models (Elith et al. 2008). Thus, Boosted Regression Trees can be considered as an additive regression model that undergoes forward stagewise fitting without changing existing trees when the model enlarges (De'ath 2007). An example of BRTs decision tree structure is provided in Figure 13.

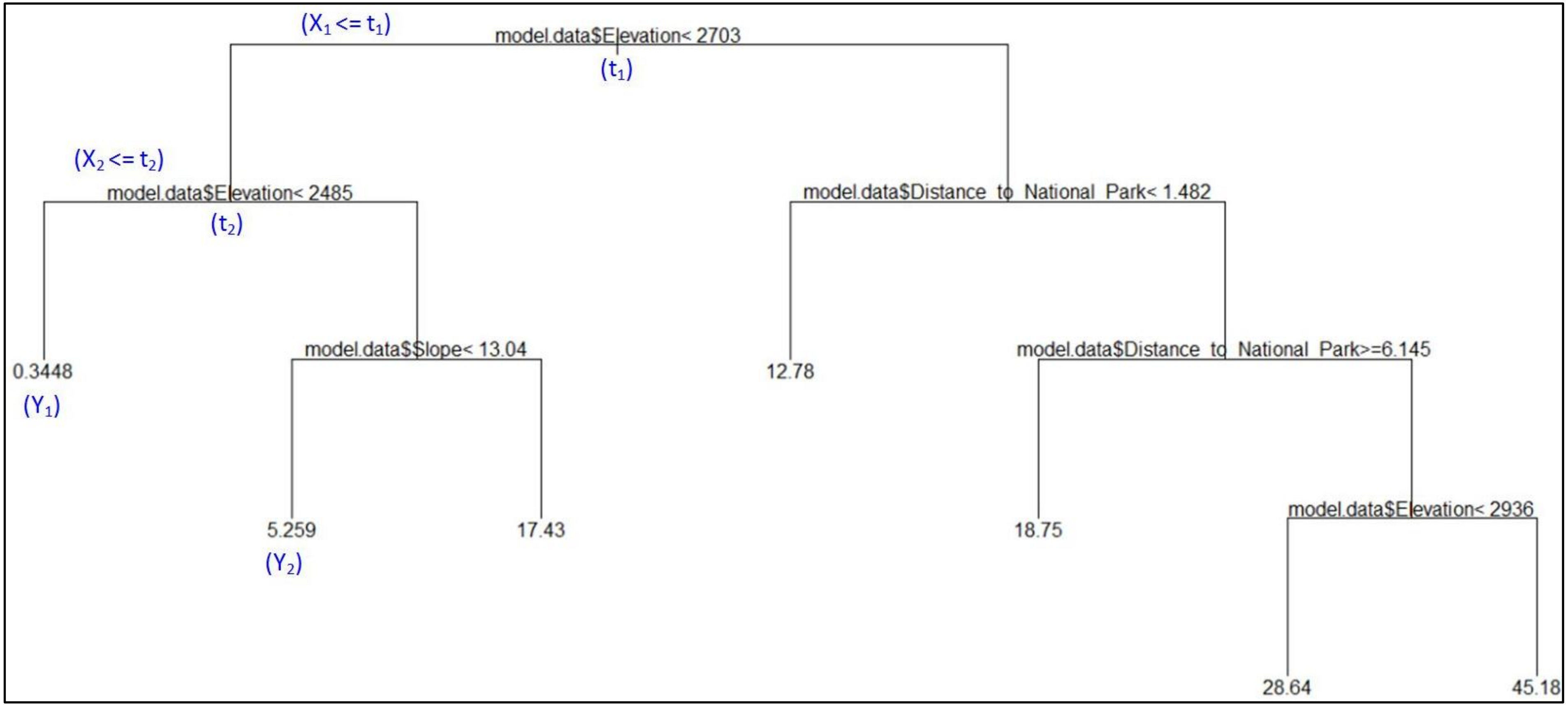

Figure 13 An example of decision trees with responses Y_n, predictors variables, X_m and split points t_k (based on Elith 2008). A single decision tree consists of response Yn and predictor Xm and split point tk where n is the number of response, m stands for the number of predictor variables and k is the number of split points.

1.6 Results and discussion

1.6.1 Remote sensing applications for quantifying and mapping ecosystem services

The review of remote sensing applications in "quantifying and mapping ecosystem services supplies and demands" provided the following insights. Quantifying ecosystem services using remote sensing requires establishing a theoretical link between the remote sensing data and the ecosystem in interest. However, there is no direct link between images and an ecosystem service. Hence, only proxies can be used to estimate ecosystem services (e.g. Carbon storage) based on indicators derived from remote sensing data. Remote sensing systems vary in their properties which make selection of the sensor system and the methodological prerequisites for deriving proxies of ecosystem services (Eigenbrod et al. 2010). The scale at which ecosystem services are quantified depend on the spatial, temporal, spectral and radiometric resolution of the remotely sensed data (Andrew et al. 2014). Even though indicators for extensive areas can be defined based on operationally available data and well-established methods, indicators useful for exact quantification of ecosystem services can be only derived experimentally at local scale.

Quantifying and mapping proxies of ecosystem services using remote sensing involves uncertainties that come from intrinsic sources of errors such atmospheric influences, geometric distortions and drifts in the calibration coefficients of the sensors. Though these sources of errors can be corrected to a certain degree, there will still be errors resulting from the statistical model used to establish link between an ecosystem services parameter (e. g. standing biomass) and the remote sensing data resulting in uncertainty of the final results. In general, the success in quantifying and mapping ecosystem services using remote sensing depends on the sensor types, resolution, and financial as well as technical capacity. Moreover, there are uncertainties involved when using remote sensing data for quantifying and mapping ecosystem services and they need to be identified and managed.

1.6.2 *Prosopis juliflora* invasion and its impacts on ecosystem services

In this section, the results of the analysis of *P. juliflora* invasion of Baadu, located in the Awash River Basin of Ethiopia, are highlighted. Even though *P. juliflora* was introduced to the area as an ecosystem engineer mainly for regulating soil erosion, it invaded lands that are crucial in supplying ecosystem services. The species continuously spread to new un-invaded areas and dense coppices of *P. juliflora* emerged after previously invaded areas were cleared. Trends in the invasion of *P. juliflora* in the past decade showed drastic increment in the invaded area of wetlands (flood plains) and agricultural lands (Figure 14). In the year 2000 from the 45000 ha total area of wetlands, 3600 ha was invaded which amounts to 8 % of the wetlands area. The invaded area increased to over 8000 ha in 2005 making the proportion of invaded area of wetlands about 18 %. In the year 2010 more than 13600 ha area (30 % of wetlands) was invaded. Analysis of the invasion in 2013 showed that 20000 ha of wetlands (40 % of the total area of wetlands) was invaded.

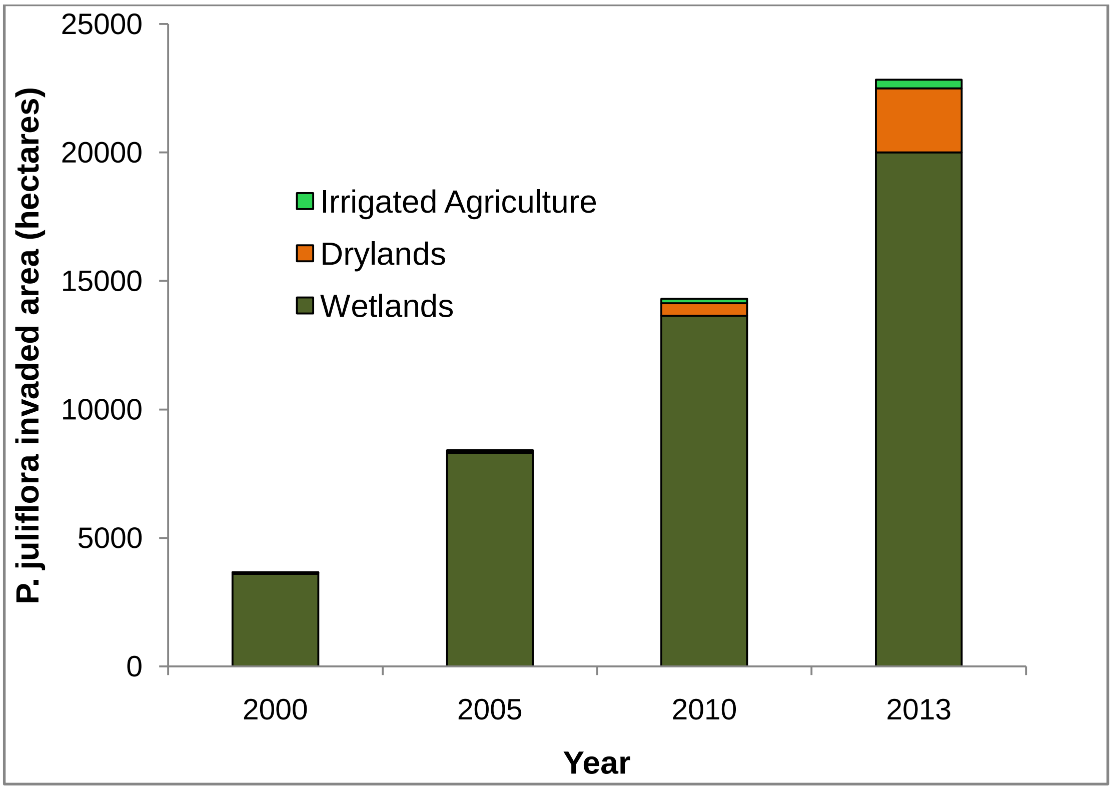

Figure 14 *P. juliflora* invasion over the last decade (year 2000 to 2013).

The area of drylands that is invaded by *P. juliflora* in the year 2000 was 60 ha which comprises < 1 % of the total area of 207000 ha. The invaded area was 20 ha in year 2005 while it increased to 490 ha and 2500 ha in the years 2010 and 2013 respectively with proportion of invaded area still < 1 % of the total area of drylands. Invaded area of irrigated agriculture land was 2 ha in the year 2000 (< 1 % of the total area of irrigated agriculture in the year 2000). It further increased to 76 ha, 166 ha and 327 ha in the years 2005, 2010 and 2013 respectively. The proportion of irrigated land invaded in these years ranges from 2-4 % of the total area of irrigated land during the same time period.

The findings demonstrated that wetlands of Baadu are the most affected with *P. juliflora* invasion and yet are the most useful sources of ecosystem services on which the livelihood of the Afar pastoralists depends on. The most threatened ecosystem services include provisioning services such as food and fodder, water, and loss of native tree species that supply timber, fuelwood and charcoal. The impacts of *P. juliflora on* the livelihood of people vary among different user groups such as mobile pastoralists, small-scale agro-pastoralists and large-scale farmers.

1.6.3 Undercover cropland inside forests

In the Bale Mountains of Ethiopia, cropland was found as an undercover inside the remnants of forests forming a belt in the upper escarpments though there is no undercover cropland in the upper most extremes of the site. Field observations confirmed that this belt is dominated with *J. procera* trees. The area of cropland per pixel of 250 m resolution grid ranges from 0 to 6 hectares. Cropland was observed inside *J. procera* forests including very steep terrains that were entirely covered with forest and/or with some open areas that were meadows previously used for livestock grazing. The undercover cropland forms vertical strata with cropland as an undergrowth and *J. procera* being the upper canopy. As it was observed in the field, the major crop cultivated inside the *J. procera* forest is wheat due to the high market demand for wheat and provision of improved seeds and fertilizer by government due to its recent plan to improve crop production.

The relative influence of different factors on undercover cropland area calculated from RapidEye images and field estimated percent cover was assessed using BRTs. The results of the BRTs model fitting demonstrated that the highly influential factors for undercover cropland area are elevation, distance to settlements, slope, East Aspect and distance to national park. Among all the factors tested the most influential is elevation which contributed to the highest values of deviance explained by the BRTs model. Undercover cropland area showed increment with increasing elevation, slope, distance to major settlements while it decreases with increasing distance from the national park. However, after certain limit the graph remains constant with a value of 0 showing that there is no undercover cropland above such limits. Similar patterns of the relationships between aspect and undercover cropland area were observed.

Finally, the details of the analysis, the results, discussion and specific conclusions of studies 1, 2 and 3 are presented in the manuscripts listed in section 1.7 and included in chapters 2 to 4 respectively. The research questions and hypotheses presented in section 1.3 are addressed by the first three manuscripts listed in section 1.8 below.

1.7 List of manuscripts and specifications of individual contributions

Manuscript 1

Title:	Quantifying and mapping ecosystem services supplies and demands: a review of remote sensing applications.
Author(s)	**Yohannes Ayanu**, Christopher Conrad, Thomas Nauss, Martin Wegmann and Thomas Koellner
Journal	Environmental science & technology
Status	published

Individual contributions:

Yohannes Ayanu	Major contributions to study design, methods, data collection, data analysis, discussion, manuscript writing and editing (corresponding and first author)
Christopher Conrad	Minor contributions to study design, methods, discussion and manuscript editing
Thomas Nauss	Minor contributions to study design, methods, discussion and manuscript editing
Martin Wegmann	Minor contributions to study design, methods, discussion and manuscript editing
Thomas Koellner	Minor contributions to study design, methods, discussion and manuscript editing

Manuscript 2

Title:	Ecosystem engineer unleashed: Prosopis juliflora threatening ecosystem services?
Author(s)	**Yohannes Ayanu**, Anke Jentsch, Detlef Müller-Mahn, Simone Rettberg, Clemens Romankiewicz and Thomas Koellner
Journal	Regional Environmental Change
Status	published

Individual contributions:

Yohannes Ayanu	Major contributions to study design, methods, data collection, data analysis, discussion, manuscript writing and editing (corresponding and first author)
Anke Jentsch	Minor contributions to study design, methods, discussion and manuscript editing
Detlef Müller-Mahn	Minor contributions to study design, methods, discussion and manuscript editing
Simone Rettberg	Minor contributions to study design, methods, discussion and manuscript editing
Clemens Romankiewicz	Minor contributions to study design, methods, data collection, data analysis, discussion and manuscript editing
Thomas Koellner	Minor contributions to study design, methods, discussion and manuscript editing

Manuscript 3

Title:	Unveiling undercover cropland inside forests using landscape variables: a supplement to remote sensing image classification.
Author(s)	**Yohannes Ayanu**, Christopher Conrad, Anke Jentsch and Thomas Koellner
Journal	PLoS One
Status	resubmitted after revision

Individual contributions:

Yohannes Ayanu	Major contributions to study design, methods, data collection, data analysis, discussion, manuscript writing and editing (corresponding and first author)
Christopher Conrad	Minor contributions to study design, methods, discussion and manuscript editing
Anke Jentsch	Minor contributions to study design, methods, discussion and manuscript editing
Thomas Koellner	Minor contributions to study design, methods, discussion and manuscript editing

List of manuscripts written during the study but are not part of the PhD thesis.

Title:	Crop production versus surface water regulation services: assessing trade-offs for land use scenarios in the Tat Hamlet Watershed of Vietnam.
Author(s)	**Yohannes Ayanu**, Carsten Marohn, Thanh Nguyen and Thomas Koellner
Journal	International Journal of Biodiversity Science, Ecosystem Services & Management
Status	published

Title:	Weakening the Brazilian legislation for forest conservation has severe impacts for ecosystem services: A case study from the Atlantic Southern Forest.
Author(s)	Gisele Alacorn, **Yohannes Ayanu**, Alfredo Fantini, Joshua Farley, Abdon Schmitt Filho and Thomas Koellner
Journal	Land Use Policy
Status	accepted

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Chapter 2

Quantifying and mapping ecosystem services supplies and demands: a review of remote sensing applications

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Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications

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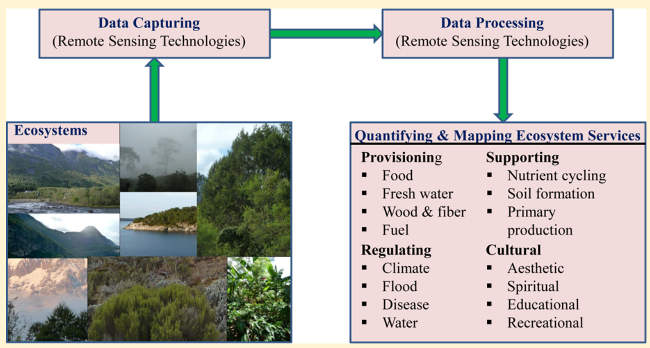
S Supporting Information

ABSTRACT: Ecosystems provide services necessary for the livelihoods and well-being of people. Quantifying and mapping supplies and demands of ecosystem services is essential for continuous monitoring of such services to support decision-making. Area-wide and spatially explicit mapping of ecosystem services based on extensive ground surveys is restricted to local scales and limited due to high costs. In contrast, remote sensing provides reliable area-wide data for quantifying and mapping ecosystem services at comparatively low costs, and with the option of fast, frequent, and continuous observations for monitoring. In this paper, we review relevant remote sensing systems, sensor types, and methods applicable in quantifying selected provisioning and regulatory services. Furthermore, opportunities, challenges, and future prospects in using remote sensing for supporting ecosystem services' quantification and mapping are discussed.



■ INTRODUCTION

Many landscapes worldwide show mixed patterns of natural ecosystems and intensively managed and anthropogenically modified land cover, e.g. agricultural land and urban settlement, from which human well-being is supported.[1,2] To optimize between nature conservation and management of ecosystems for various uses, decision-making should be based on concrete information about the potential and actual timely benefits obtained from different ecosystems.[3−6] Quantifying and mapping ecosystem services is therefore necessary to periodically determine the response of ecosystem processes and the services to global change, e.g. climate and land cover change.[7−14] Moreover, continuous monitoring of ecosystem services is crucial in nature conservation.[15−20]

To achieve efficient monitoring of ecosystem services, fast and low-cost tools that provide reliable information are needed. For such applications remote sensing provides single scene and frequent multitemporal data.[21−24] Remote sensing has advantages in that it enables large scale mapping of ecosystem services with relatively low cost. In addition, remote sensing is a useful source of data for areas inaccessible for ground surveying. It provides consistent time series of data and real-time data for monitoring ecosystem services. Therefore, exploring historical, present, and future development of remote sensing applications is useful within the context of monitoring ecosystem services. A few authors attempted to review the trends of remote sensing applications in quantifying and mapping ecosystem services.[3,4] However, a more systematic analysis showing the remote sensing systems and methods suitable for quantifying specific ecosystem services remains unaddressed.

In this article, we review the application of remote sensing in quantifying and mapping the supplies and demands of ecosystem services. Following this introduction, the scope of this study and the methods used for literature selection are described. Furthermore, we give an overview of remote sensing approaches commonly used in quantifying and mapping ecosystem services. We discuss also important factors that need to be considered in selecting suitable remote sensing techniques for quantifying ecosystem services. Afterward, examples of remote sensing applications will be presented and we conclude with the identification of research gaps related to this topic.

Scope of the Review. The term "ecosystem service" has been used interchangeably with concepts like ecosystem functions,

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environmental services, ecological functions, and environmental functions.[5,6] In this article we adopt the definition by Millennium Ecosystem Assessment that defines ecosystem services as "*benefits that ecosystems provide to support human well-being*".[1] We used the TEEB classification[7] as a basis to identify the ecosystem services. In TEEB classification, provisioning services include food, water, raw materials, and genetic, medicinal, and ornamental resources. Regulatory services include regulation of air quality, climate, erosion, water quality, soil fertility, extreme events, water flows, pollination, and biological control. Other ecosystem services in TEEB classification are habitat services like maintenance of life cycles of migratory species (e.g., nursery services) and maintenance of genetic diversity (e.g., gene pool protection). The fourth category of ecosystem services in TEEB classification is the cultural and amenity services like aesthetic information, opportunities for recreation and tourism, inspiration for culture, art and design, spiritual experience, and provision of information for cognitive development.

Due to availability of a sufficient number of publications in the past decades that proved suitability of remote sensing for their quantification and mapping, we focus on the provisioning services (timber and food production) and regulatory services (air quality, climate, extreme events, waste treatment, erosion, and soil fertility). On the other hand, ecosystem services like "Maintenance of genetic diversity" are excluded because the topic of biodiversity alone is too wide to include in this type of review where our ultimate goal is to enlighten readers with the possibilities of using remote sensing for quantifying and mapping ecosystem services. The indicators used for quantifying the ecosystem services, suitable remote sensing data sets, and the relevant methods are identified and discussed. Within the aforementioned groups of ecosystem services, only those indicators which were reported to be quantifiable with remote sensing are selected for this review. For more details, please refer to the Supporting Information (SI) Tables S1 and S2.

Literature Selection. The articles were mainly collected from peer reviewed journals using the ISI Web of Science (www.webofknowledge.com) and Google Scholar (www.googlescholar.com) as primary search engines. The year 1990 was taken as a starting point for the search and relevant literature was retrieved until the year 2011. Keywords used in searching the databases included "ecosystem services", "quantifying and mapping ecosystem services", "ecosystem assessment", "modeling ecosystem services", "remote sensing of ecosystem services", "remote sensing indices", "remote sensing of ecosystems", "radiative transfer models", "proxy-based methods for quantifying ecosystem services", and "methods for quantifying and mapping ecosystem services". Besides these, to account for the fact that many studies were not conducted in the explicit context of ecosystem services, more specific keywords like "carbon mapping", "biomass estimation", "flood risk mapping", "quantifying erosion", "soil fertility mapping", and "water quality assessment" were used.

From a total of 548 studies identified between 1990 and 2011, we selected 297 papers that are primarily relevant to remote sensing applications in quantifying ecosystem services. The publications were screened with respect to the ecosystem services considered. Figure 1 presents the breadth of the literature in the past two decades for quantifying various types of ecosystem services although the term "ecosystem services" was not directly used. This review focuses particularly on literature that used remote sensing for quantifying and mapping ecosystem services. Part of the literature was used in this article and the remaining articles can be found in the Supporting Information.

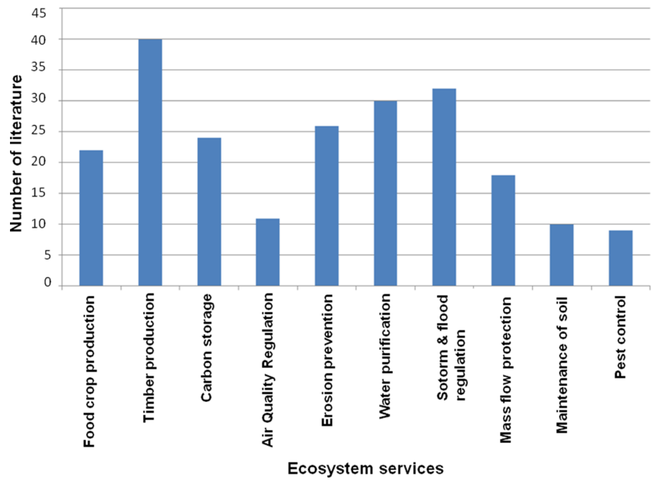

Figure 1. Identified literature between years 1990 and 2012 that used remote sensing for quantifying ecosystem services and their indicators.

■ REMOTE SENSING-BASED APPROACHES FOR QUANTIFYING ECOSYSTEM SERVICES

Remote sensing can be defined as "*the art and science of acquiring information about an object without being in direct physical contact with the object*".[8] Hence, remotely sensed information is usually a physically more or less direct measurement of the properties of an object through its interference, i.e. scattering, reflection, and absorption/emission with electromagnetic radiation as the primary carrier of the information signal. A detailed introduction to remote sensing is beyond the scope of this review and the reader is referred to ref 8.

In general, the quantification of ecosystem services is a 2-fold indirect procedure. The remotely sensed information is used as a proxy for some kind of variable (e.g., biomass) which in turn is used as a proxy for the actual ecosystem service (e.g., carbon storage). Based on the literature selected, two categories of commonly used approaches can be identified for deriving biophysical variables like biomass.[4] The first category directly uses the remotely sensed radiation signal and includes statistical regressions and/or radiative transfer models. The second approach uses remote sensing data to generate land use/land cover classifications which are subsequently linked to ecosystem services and also serve as input layers within biophysical models of ecosystem services.

Regression Models. In this type of approach, the quantification of ecosystem services is achieved by linking remotely sensed information to a limited number of in situ observations using semiempirical linear or nonlinear regression models.[9−12] For example, vegetation indices derived from the near-infrared and red proportion of the electromagnetic spectrum can be linked to in situ biomass measurements to derive a proxy for timber production.[13] Irrespective of the regression type, the statistical relationship between the sensor signal and the data derived from field observations is affected by the sensor characteristics like spectral, spatial, and temporal resolution (cf. 14). Moreover, multiple boundary conditions like time of the day and year, actual state of ecosystem components, and the atmosphere also affect the statistical relationship and reduce its validity for monitoring and spatial transfers to other study areas (cf. 14).

Radiative Transfer Models. Unlike the empirical relations just mentioned above, canopy radiative transfer models allow a physically more direct derivation of biophysical parameters. They describe the interaction of electromagnetic radiation with atmospheric and land-cover constituents like aerosols, clouds, gases, canopy leafs, and soil surface, and account for scattering, absorption, and emission characteristics.[15,16] Neglecting atmospheric influences, the sensor signal can be modeled as a function of the sensor characteristics and sampling conditions, and the physical or biochemical plant canopy properties like leaf density and photosynthetic physiology. In addition, the properties of the underlying earth surface, namely the soil characteristics and the understory vegetation patterns (cf. 14) can be taken into account. The proxy variables are finally derived from an inverted radiative transfer approach, i.e. by iterating the vegetation parameters used within the radiative transfer model to align the modeled sensor signal to the actual remotely sensed measurements.[36−38] Radiative transfer models are affected by our understanding of vegetation, land processes, and their interaction which increases uncertainty in the robustness and accuracy of ecosystem services quantification.[17] The lack of a priori knowledge about land cover and phenology also hampers the retrieval of biophysical and biochemical variables useful for quantifying ecosystem services like timber biomass.[18]

Land Use/Land Cover. Land use/land cover has been widely used as a proxy for the quantification and mapping of ecosystem services. This mostly involves assigning of ecosystem services values to the different land use/cover types.[6,19,20] Remote sensing provides useful data for land use/land cover classification. The classification techniques involve a series of multivariate statistical analysis to obtain discrete classes from the remotely sensed data.[21] Mostly supervised classification is used and its accuracy depends on the training areas set. The thematic level of detail, i.e. number of classes of the land use/land cover, depends on properties of the remote sensing data available and/or selected for classification.[22] The accuracy of quantification of ecosystem services thus depends on the accuracy of the classification and the number of the land use/cover classes.[23]

Provision of Input Data for Biophysical Models. Remote sensing provides valuable input data for biophysical models that are used for the subsequent simulation of ecosystem services. Biophysical models provide an explicit connection between ecosystem services to be quantified and the remotely sensed parameters. For instance, the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) is one of these tools used for quantifying and mapping ecosystem services like carbon storage, sediment deposition, pollination, timber, and water purification.[24] InVEST requires area-wide information on land use/land cover, evapotranspiration, precipitation, and topography which can be derived from remote sensing data.[25,26] The parameterization of InVEST undergoes assigning of numerical data to different land use/cover types. For instance, carbon model uses above-ground, below-ground, dead organic materials, and soil carbon pool data as an input for quantifying carbon storage and sequestration which varies with the land use/cover types.[27] Similarly, land use/cover is used as an input in mapping pollination services because different land use/cover types have different nesting and flowering potential.[27] Though multiple ecosystem services can be quantified and mapped using biophysical models, this is limited by the complexity and accuracy of the models.[28]

SELECTING SUITABLE REMOTE SENSING TECHNIQUES AND APPROACHES FOR QUANTIFYING AND MAPPING ECOSYSTEM SERVICES

The properties of remote sensing systems vary significantly among each other making selection of the sensor system and the optimal methodology prerequisites for an accurate delineation of the proxies for ecosystem services. For instance, many indicators can be delineated for extensive areas within a clearly defined range of uncertainty based on operationally available data and well-established methods.[29] Other indicators useful for exact quantification of ecosystem services can be only derived experimentally at local scale.

The success of remote sensing application therefore depends on careful selection of the data from which the relevant parameters are derived for the chosen indicators of ecosystem services.[30] Some of the factors that need to be considered while choosing suitable remote sensing systems and approaches for quantifying and mapping ecosystem services are presented in Table 1 and discussed in this section.

Resolution. The properties of remote sensing systems can be described by their spatial, temporal, spectral, and radiometric resolution. Spatial resolution refers to the area of ground observed with a picture element, i.e. pixel, and determines the level of details captured by the image.[30] Due to calculation time and storage requirements, the potential size of the study area generally decreases with increasing spatial resolution and vice versa. Very high (pixel size below 30 m) and high (pixel size below 1000 m) resolution sensors are therefore typically used for an in-depth analysis of areas below 100 km^2 which is subsequently referred to as landscape scale. Medium resolution sensors (pixel size up to 1 km) are typically used for larger regions like subcontinental areas and define the data source for regional scale analysis. Finally, low resolution sensors (pixel size around and above 1 km) form the basis for global scale analysis.

The temporal resolution of a system indicates how often the sensor records imagery from a particular area.[30,31] For instance, geostationary sensors like the Meteosat system offer a temporal resolution of 15 min. Polar orbiting platforms have much lower temporal resolutions, typically in a range between days and weeks or even months. The temporal resolution of polar orbiting platforms can be enhanced if the swath width, i.e. the width across-flight scan line, is increased which in turn generally decreases the spatial resolution. The spectral resolution is characterized by the number of specific wavelength intervals of the electromagnetic spectrum to which the sensor is sensitive.[8] Such wavelength intervals are also referred to as channels or bands. The radiometric resolution describes sensitivity of the sensor and quantifies the accuracy at which the incoming radiation can be recorded.[32]

The quantification of ecosystem services is limited by the respective resolution of the remote sensing system. While multispectral data (e.g., Landsat, MODIS) have been widely used (see Table 2 and SI Tables S1 and S2), the retrieval of some variables is limited by the rather poor combination of spatial and spectral resolution.[33] Thus, utilizing high resolution hyperspectra, radar and LiDAR sensors would be desirable. With respect to the current status of these sensors, the derivation of ecosystem parameters such assoil clay mineralogy,[34] belowground biomass,[35] or water quality indicators like

Table 1. Commonly Used Sensors and Their Key Attributes with Respect to Scale of Application, Costs, and Availability by Remote Sensing Type[a]

satellite/sensor	sensor type[c]	spatial resolution	number of bands	temporal resolution	revisit time in days[d]	maximum swat width at nadir (km)	scale of application[f]	costs	availability	source
						passive				
multispectral										
SeaWiFS	SB	4.5 km, 1.1 km	8	16 days	daily	2801	R−G	yes	1997---	http://oceancolor.gsfc.nasa.gov/SeaWiFS/
SEVIRI	SB	3 km, 1 km	12	15 min	daily	2330	R−G	yes	2002---	http://www.esa.int/msg/pag4.html
NOAA −AVHRR-1(2,3)	SB	1.1 km	4 (5,6)	daily	1−2	2800	R−G	free	1978---(1981, 1998)	http://edc2.usgs.gov/1KM/avhrr_sensor.php
SPOT VGT	SB	1 km	4	26 days	2−3	2200	La−R	free	1998---	http://www.spot-vegetation.com/
Terra/Aqua MODIS	SB	1 km, 500 m, 250 m	36	daily	1−2	2330	R−G	free	1999/2002---	http://modis.gsfc.nasa.gov/
Terra MISR	SB	275 m	4	9 days	2−9	360	La−G	yes	1999---	http://www-misr.jpl.nasa.gov/
Landsat MSS	SB	80 m	4	16 days	16	185	La−G	free	1972−1992	http://landsat.gsfc.nasa.gov/images/
Landsat TM	SB	30 m	7	16 days	16	185	La−G	free	1984---	http://landsat.gsfc.nasa.gov/images/
Landsat ETM+	SB	15−60 m	8	16 days	16	185	La−G	free	1999---2003[b]	http://landsat.gsfc.nasa.gov/images/
ASTER	SB	90 m, 30 m, 15 m	14	4−16 days	16	60	La−G	yes	1999---	http://asterweb.jpl.nasa.gov/
IRS LISS-III	SB	23.5 m	4	24 days	24	140	La−R	yes	1995---	http://www.isro.org/satellites/allsatellites.aspx
SPOT 1, 2, 3	SB	20 m, 10 m	4	26 days	2−3	2200	La−R	yes	1986---	http://www.spotimage.com/web/en/1285-spotmaps.php
SPOT 4	SB	20 m, 10 m	5	26 days	2−3	2200	La−R	yes	1998---	http://www.spotimage.com/web/en/1285-spotmaps.php
SPOT 5	SB	10 m, 5 m, 2.5 m	5	26 days	2−3	2200	La−R	yes	2002---	http://www.spotimage.com/web/en/1285-spotmaps.php
RapidEye	SB	5 m	5	1−5.5 days	daily	77	La−R	yes	2009---	http://www.rapideye.de/
IKONOS	SB	4 m	4	3−5 days	3	11	La−R	yes	1999---	http://www.satimagingcorp.com/satellite-sensors/ikonos.html
QuickBird	SB	2.44 m, 2.88 m	4	1−3.5 days	1−3.5	16.5	La−R	yes	2001---	http://www.satimagingcorp.com/satellite-sensors/quickbird.html
hyperspectral										
EO-1 Hyperion	SB	30 m	220	16 days	16	7.5	La−G	yes	2001---	http://eo1.gsfc.nasa.gov/
ER-AVIRIS	AB	20 m	224	flight per request	NA	10.5	La−R	yes	1987---	http://geo.arc.nasa.gov/sge/coral-health/airborne_missions
HyVista-HyMap	AB	10−2 m	126	flight per request	NA	18	La−R	yes	1998---	http://www.hyvista.com/
HyEurope-HyMap	AB	10−2 m	126	flight per request	NA	18	La−R	yes	2009---	http://www.hyvista.com/
CASI (1−3)	AB	2−1 m	288	flight per request	NA	2	La	yes	1990---	http://arsf.nerc.ac.uk/instruments/casi.asp
ERS-SAR	SB	30 m	2 (L, C)	3,35, 336 days	35	80.4	La−R	yes	1995---	http://earth.esa.int/ers/instruments/sar/
						active				
radar, LiDAR										
TerraSAR-X	SB	1 m, 2 m, 3 m, 18 m	1 (X)	11 days	2	100	La−R	yes	2007---	http://www.spotimage.com/web/en/684-terrasar-x.php
ICEsat/GLAS	SB	175−76 m	2 (L, C)	8, 91, 183 days	33	NA	G	yes	2003---	http://nsidc.org/data/icesat/

[a]The resolution in space (spatial) and time (temporal) as well as spectral resolution (number of bands) vary among the sensors. The area coverage (spatial extent) determines the scale of application and also varies among sensors. [b]Since 2003 malfunction, serious quality problems. [c]SB = Spaceborne, AB = Airborne. [d]NA= Not applicable. The air craft can fly any convenient time as per request for data. [e]L = Limited area coverage, M = medium area coverage, W = wide area coverage. [f]La = Landscape, R = Regional, G = Global, La−R = Landscape to regional, La−G = Landscape to global, R−G = Regional to global.

chlorophyll-*a* content, nitrogen, and phosphorus loading[36,37] is primarily restricted to experimental landscape scale studies.

Sensor Types. Two types of sensors can be distinguished, active and passive sensors. They can be mounted on platforms on the ground, airplanes, or satellites.

Passive Sensors. These are sensors that receive radiation emitted from an external source such as reflected sunlight and emitted thermal radiation from the earth. Most passive sensors are optical systems, i.e. multispectral, which record data with a small number of broad bands, or hyperspectral, which record a

Table 2. Application of Data from Commonly Used Sensors in Mapping Selected Ecosystem Services, by Remote Sensing Type[a]

satellite/sensors	provisioning services: food (potential production of agro-ecosystems)	provisioning services: raw material (timber)	regulatory services: climate regulation (carbon storage)	air quality regulation	erosion prevention (potential of ecosystems to retain soil and to avoid erosion)	waste water treatment (water purification)	water storm protection and flood prevention	wind storm protection	mass flow protection	maintenance of soil fertility	biological control (pest control)
passive											
multispectral											
SeaWiFS	×	×	×	×	×	★	★	×	×	×	×
SEVIRI	×	×	×	★	×	×	×	×	×	×	×
NOAA -AVHRR	★	★	★	★	★	★	★	×	×	×	×
Terra/Aqua MODIS	★	★	★	★	−	★	★	★	−	★	★
Terra MISR	×	★	×	×	×	×	×	×	×	×	×
Landsat MSS	★	★	×	×	★	×	×	×	★	×	★
Landsat TM	★	★	×	×	★	×	×	×	★	×	★
Landsat ETM+	★	★	×	★	★	★	×	★	★	★	★
ASTER	×	★	★	×	−	−	−	−	−	★	−
IRS LISS-III	×	×	★	×	×	×	★	×	×	×	×
SPOT 1- 5	★	−	−	×	−	★	−	−	★	★	−
SPOT VGT	★	★	×	×	×	×	×	×	×	×	×
RapidEye	−	★	★	−	★	−	★	−	−	−	★
IKONOS	★	★	★	×	×	★	×	★	★	★	★
Quickbird	★	★	★	×	×	★	×	★	★	★	★
hyperspectral											
EO-1 Hyperion	×	×	×	×	×	★	★	×	×	×	×
ER-2 AVIRIS	×	×	★	×	★	×	×	×	×	★	×
HyVista-HyMap	★	−	−	−	−	−	−	−	−	★	−
HyEurope-HyMap	★	★	★	−	★	★	★	−	−	★	★
CASI (1−3)	★	★	×	×	×	★	×	×	×	×	×
active											
ERS-SAR	★	★	★	×	★	×	★	×	★	×	×
TerraSAR- × *	★	★	★	×	★	×	★	×	★	×	×
ICEsat/GLAS	★	★	★	×	★	×	×	×	×	×	×

[a]Key: ★ = recommended, × = less recommended, − = unknown.

large number of narrow spectral bands. Various multispectral systems are designed to provide data with high spatial resolution but limited area coverage (e.g., ASTER, SPOT) or moderate spatial resolution but global coverage within one or two days (e.g., AVHRR, MODIS). However, since many of the technically advanced systems have been launched just recently, they are inappropriate for long time series analysis. The only exceptions are the Landsat and NOAA-AVHRR sensor families which were launched in the early 1970s, and for which data are continuously stored in cost-free archives permitting easy access.[38]

Compared with multispectral sensors, hyperspectral sensors provide more details on the type and state of the observed ecosystems.[39,40] However, their potential is not yet fully exploited because most of these sensors are in an experimental stage and mainly mounted on airplanes making the data acquisition rather expensive. In addition, although the spatial resolution is very high, up to <1 m, they have limited area coverage. With respect to spaceborne systems, there are only a few experimental instruments available yet which provide hyperspectral near real-time data with an acceptable aerial coverage at landscape scale.[41,42]

Active Sensors. Active sensors include radar and laser scanners that are emitting signals and receiving the backscattering electromagnetic radiation. Under extreme weather and dense vegetation conditions, radar is a prime alternative for optical systems[43] due to the potential to penetrate clouds, haze, and vegetation canopy.[44] Radar can reach into the upper few centimeters of soils though intensive data processing techniques are required.[45] Besides radar, LiDAR has proved to be very promising for mapping vegetation parameters but so far, these sensors are primarily airborne which results in the same limitations as mentioned for the hyperspectral sensors.[46] However, these restrictions can be overcome by spaceborne laser scanners which are emerging just recently.[47]

Most often different sensors are combined for quantification of ecosystem services. Nevertheless, this approach is complicated since it involves combining categorical data with different projections and different grids with different or the same pixel size. Moreover, often data of different years are combined, which is not always easy as land conversion happens all the time.

Uncertainty. Even though remote sensing provides a prime alternative for quantifying and mapping ecosystem services, uncertainties have to be considered. The primary intrinsic sources of errors are atmospheric influences, geometric distortion, and drifts in the calibration coefficients of the sensors. While these influences can be corrected to a sufficient degree, errors related to the retrieval model, e.g. statistical relationships between vegetation indices and ecosystem parameters like biomass production are much harder to quantify, and the error propagation within the retrieval approach has to be investigated.[48,49]

Image classification itself is also a potential error source, because the spatiotemporal variability of biophysical measures cannot be fully reflected within the classes and this affects the accuracy of land use based approaches for quantifying ecosystem services.[62−64] Though input data for biophysical models can be derived from remotely sensed images, the estimation of ecosystem services is affected by accuracy of the data besides the model uncertainties and magnitude of errors during parameterization and calibration.[23]

In general, sufficient knowledge about the magnitude of errors or uncertainties in the data, approaches, and processing methods is necessary for reliable quantification of ecosystem services. Therefore, in situ measurements are needed for validation when using remote sensing data.[50] Quality information assigned to biophysical parameters like the standardized MODIS products on global scale,[51] are helpful for corrections and adaptations prior to the analysis.

Financial and Technical Capacity. Remote sensing data acquisition and processing requires financial, technological, and professional capacity. Even though there are some freely available data sets (see Table 1), the quantification of broad categories of ecosystem services cannot be achieved with these data sets alone. Acquiring the commercially available satellite images (e.g., QuickBird) incurs higher costs[52] which also applies to the current hyperspectral, RADAR, and LiDAR sensors.[39] Data acquisition from these sensors is usually upon request by the users which creates inconvenience in obtaining data from a specific area (see Table 1). Besides the acquisition, processing and analysis of data like hyperspectral images demands a very high technical capacity and computers with storage capacities up to tens of Terrabytes or even Petabytes.[53]

APPLICATIONS OF REMOTE SENSING FOR QUANTIFYING AND MAPPING ECOSYSTEM SERVICES

Quantifying Supplies of Provisioning Services. Remote sensing data sets can be used for quantifying production capacity of agro-ecosystems and forests using biomass as an indicator. Biomass estimation for many forest types is challenging due to the fact that most existing data mainly contain properties of the vegetation canopy but not of understory vegetation.[54] Passive systems mainly record the interaction of light with the most upper leaf layers. Hence, single multispectral data, for instance, are less applicable to detect the structure of a dense forest because the woody parts of the vegetation like stems or branches, and sub-canopy layers like shrubs are hardly visible in the spectral signature of forests.[55]

Despite single sensors, combining data from multiple sensors provides more accurate estimation of biomass due to the benefits from the fused properties of the data sets. For instance, nonlinear regression analysis on a combination of Landsat and WiFS images provides a reliable estimate of aboveground biomass.[56] In addition, using multidate satellite imagery by averaging over several scenes could reduce the bias resulting from radiometric calibration uncertainties and improves biomass estimation.[38] Hyperspectral sensors can also improve forest biomass estimation because they enable distinguishing vegetation composition much better than the multispectral sensors.[57]

In complex story forests, biomass estimations will be more accurate if stands are stratified as marginal and within-stand areas.[58] In such type of forests, radiation penetrating the canopy is practically more useful.[59] The scattering of low-frequency radar (L-band, minor C-band) retrieves more detailed information about the forest composition.[60] However, satellite systems having such advantageous properties are still rare, and existing airborne options require an optimum balance between costs and area under investigation. Radar wavelengths are well adapted to monitor biomass overtime since the C-band (5.3 GHz) scattering signal is sensitive to the water content of vegetation canopy.[61] Moreover, since C-band wavelengths are rather insensitive to cloud cover, radar data are more useful in quantifying biomass during the rainy growing season.[61]

Besides radar data, airborne laser scanners (ALS) are widely used for retrieving biomass from complex story forest stands since clouds of concentrated laser beams permit very accurate three-dimensional delineation of the forest structure.[60,62] A statistical link can be established through regression between the scanning signal of the ALS and biomass.[63] Because of local effects on the ALS, field measurement within sample plots distributed over the entire area would be needed for applications in regional or national biomass monitoring projects.[63] LiDAR data provide a good estimate of timber production because they enable accurate tree-height measurement.[47] Moreover, detection of suppressed tress is possible from height models based on laser scanning data.[47,64]

Though most studies that have mapped food production in the past used the readily available national statistics census data from FAO, remote sensing could be highly applicable where such data are not sufficient. Most often the census data is combined with remotely sensed data to estimate crop production in terms of biomass and yield. The useful spatially explicit data sets include statistical census data, land use/cover data, satellite imagery, biophysical crop suitability assessments, population density, and distance to urban centers.[65] For instance, combinations of the aforementioned data sets were used to develop a model that enables spatial disaggregation of crop production through pixel-scale allocation of statistical census data of crop production.[65] Statistical census of cropped area and production and weather data were synthesized to estimate rice yield at district level which was further extrapolated to pixel level yield values over larger areas using MODIS NDVI.[66]

Estimating biomass of agricultural crops with remote sensing is less complex in the view of having mainly one vegetation layer with a comparatively low woody fraction. Hence, data from optical remote sensing systems especially vegetation indices are highly suitable for estimating biomass and yields of many crop types.[67] One typical variable derived as proxy for crop growth and biomass production is the leaf area index (LAI). The LAI can be retrieved either from inverse radiative transfer models for crops (leaf and canopy models) or correlation with reflectance values or vegetation indices.[68] In case of annual crops, there is seasonal change in biomass production from bare soil before sowing to the maturity stages, which is followed by harvest. Biomass estimation for annual crops often utilizes multitemporal observations utilizing radiation budget based models due to seasonal changes in biomass production.[69] Often, fraction of absorbed photosynthetically active radiation (fPAR) derived from reflectance serves as a key input parameter for such models.[70]

In addition to scale and area extent, information about field sizes and crop diversity are useful for selecting the most adequate sensor. For large field sizes, medium resolution multispectral data are useful for predicting crop biomass and yield to assist prognosis of regional availability of food crops such as corn and soybean.[71,72] For instance, MODIS data with 250-m resolution are adequate to monitor homogeneous crop fields greater than 25 ha.[73] Integrating multispectral images with field-measured biomass data enables more accurate estimation of crop yield.[88−90] Moreover, utilization of phenologically tuned time series of vegetation indices like NDVI is more appropriate in predicting crop production anomalies.[73] In landscapes with high crop diversity, hyperspectral sensors are more appropriate than the multispectral systems in identifying crop types and precise estimation of biomass and/or yield.[74] However, since only a few experimental hyperspectral systems are launched just recently, they are not fully exploited in precision agriculture though there appears huge potential in the future. Finally, for more details on remote sensing applications in forest and crop biomass estimation, the underlying assumptions, and methods, please refer to SI Table S1.

Besides ecosystem services that are linked with vegetation structure, freshwater availability (e.g., water for drinking and irrigation), which is one of the provisioning services, can also be tracked and mapped from space. Remote sensing enables accurate monitoring of fresh water through assessment of changes in the volume of water stored and flowing in rivers, lakes, and wetlands.[75] The extent and condition of natural freshwater habitats can be mapped with remote sensing.[76] Hydraulic models (e.g., SWAT) that use remotely sensed data as input are often applied in quantifying and mapping fresh water.[77,78] Fresh water discharge was estimated at global scale as a measure of global water budget using ocean−atmosphere mass balance and land−atmosphere water balance models.[79] Moreover, satellite-based estimation of interannual variability and emerging trends in continental freshwater discharge was plausible at global scale.[80] Remote sensing has been used also in assessing water footprint for crops since it provides physically based consistent worldwide spatial information.[81] Parameters estimated from remote sensing data to map water footprint for crops include evapotranspiration, precipitation, water storage, and runoff. The volume of irrigation applied, and green and blue evapotranspiration components can be calculated from remote sensing data to estimate water footprint for crops.[81]

Quantifying Supplies of Regulatory Services. Ecosystem services like air quality cannot be directly detected with remote sensing. However, the pollutants (disservices) and ecosystems retaining pollutants (services) can be mapped to assess air quality. For instance, the capacity of ecosystems to regulate air quality can be estimated through the assessment of their potential to remove or retain dust and reduce airborne pollutants.[82,83] In this context remote sensing is useful for detecting and mapping dust particles and vegetation structure. Overlaying vegetation structure maps with dust particles maps enables the contribution of ecosystems in protecting areas such as settlements, waterbodies, and susceptible agricultural lands. High spectral resolution images are needed for distinguishing dust and nondust particles but spatial resolution is rather less relevant.[84] Since factors determining air quality change with time, high temporal resolution images are needed for frequent monitoring of air quality.[85,86] Multispectral images like MODIS aerosol data are applicable in differentiating between dust and nondust particles.[87,88] Combination of data from multiple sensors, e.g. SEVIRI and GERB instruments on Meteosat-8, provides a powerful tool for detecting aerosols and estimating their radiative effect.[89] Application of multilinear regression on thermal infrared channels of satellite data also improves the performance in detecting dust.[89]

Ecosystems' capacity to influence climate can be estimated using carbon storage and sequestration as an indicator which is dependent on fluxes, emission, and aboveground storage of carbon. Basically all previously described remote sensing based methods to quantify biomass production can be translated to carbon storage or sequestration. In addition, the net ecosystem exchange (NEE) of carbon flux can be derived from multispectral images and used as proxy for carbon.[90] For instance, CO_2 fluxes can be predicted using AVHRR-NDVI data collected during the growing seasons.[90] Combining data from different sensors such as QuickBird and ASTER improves the estimation of above ground carbon (AGC).[91] Carbon emission due to fire can be predicted by integrating remote sensing data with carbon flux cycles.[92] Hyperspectral sensors like AVIRIS have also proved to be a useful source of data for quantifying carbon fluxes.[93] Due to its capacity to detect forest structure, LiDAR is also applicable in quantifying forest carbon storage.[94] Multisensor satellite data can also be used for more robust and accurate estimation of carbon storage. For instance, Woods Hole Research Center (WHRC) developed a national level carbon stock data set from combinations of MODIS and ground measured vegetation height data. This can be accessed from the WHRC Web site at http://www.whrc.org/mapping/nbcd/index.html. In addition the WHRC used colocated field measurements of vegetation heights with satellite data such as MODIS, GLAS-LiDAR, and NASA-Shuttle Radar Topography Mission (SRTM) for quantifying aboveground woody carbon density for pantropical ecosystems.[95]

Remote sensing is useful for estimating the capability of ecosystems to provide protection against extreme events such as storm, flood, and mass movements.[96] Classification of cloud-free images taken before, during, and after extreme events is useful for detecting the changes and estimating impacts of the events as well as capacity of ecosystems to provide protection against them. For such applications, especially, a high temporal resolution of suitable sensor systems appears more relevant.

Multispetral images such as SeaWiFS and MODIS sensors are suitable to map the extent and direction of storms that originate from river discharge and wind effects or Tsunamis in coastal areas.[105−107] On the other hand, laser scanners and LiDAR have proved to be other useful data sources for quantifying damage by storms.[97]

Flood risk can be predicted directly through monitoring of inundation events using high temporal resolution images.[98] Multispectral images like MODIS time series data are useful to detect and monitor flood inundation events.[99] However, since passive sensors are affected by clouds, the best alternatives are radar sensors that penetrate clouds and record flood events from space.[100] For instance, time series of SAR data sets are applicable in mapping flood temporal dynamics.[101] Indirect monitoring of flood risk is usually through quantification of damage to vegetation and infrastructure as well as mapping flood-prone areas and protective structures such as dams, drains, diversions, and river beds.[102]

Ecosystems such as forests in mountainous areas provide protection against mass movements from landslides and avalanches.[114−118] Remote sensing helps in mapping areas prone to or affected by mass flows.[103,104] In this context, multispectral images, e.g. SPOT 5, can be used in combination with terrain parameters such as slope, soil type, and aspect.[105] In addition, hyperspectral sensors like AVIRIS and Hyperion are useful sources of data to detect and map flow of debris caused by, e.g., earthquakes due to availability of large number bands that enable distinguishing debris from land surface and vegetation.[106] Radar technologies, e.g. JERS-1 SAR, have also proved their potential use in mapping mass flows.[107] Besides preventive investigations, remote sensing can be used for pre- and postextreme events change detection to estimate the impact of mass flows.[108]

Water purification is one of the regulatory services provided by ecosystems. Quality of surface water is mostly described in terms of parameters such as chlorophyll-*a* concentration, colored dissolved organic matter, salinity, turbidity, and sediment nitrogen and phosphorus loading.[37,45,109,110] Hyperspectral sensors like hyperion are useful to estimate water purification through quantification of these key indicators.[111,112] Supported with field data, multispectral images also enable detection of water quality indicators. For instance, surface water parameters can be derived from MODIS, Landsat, and SeaWiFS at visible and near-infrared wavelengths.[122]

Natural ecosystems like forests and grasslands prevent water erosion by retaining sediments, and protect against wind erosion through provision of cover for soils. The conversion of these ecosystems for expansion of agriculture usually leads to soil erosion, implying the loss of soil protection services with the increase in commodities like crop yield.[113] Erosion can be detected directly using satellite data through identification of individual large erosion features and detection of eroded areas or damage occurred due to major erosion events.[114] To estimate sedimentation, the elevation of a riverbed can be calculated by establishing a relationship between imagery data like SPOT5 with water depth measurements.[115] In addition, reflectance properties of surfaces are determined by the lithologic composition, grain size, and moisture content of sediments, and these properties can be detected with remotely sensed images.[116]

Besides using images from single sensors alone, combination of sensors such as Landsat-TM and ERS-1 improves estimation of erosion by enabling discrimination of eroded and noneroded areas.[117] In agricultural fields, spectral reflectance of crop residues and bare soils can be differentiated to map spatial variability of residue cover to estimate wind and water erosion risk.[118] For such applications hyperspectral sensors, e.g. Probe-1, perform better than multispectral sensors like IKONOS.[119] Erosion and sediment deposition can be detected and mapped also using LiDAR data by assessing multitemporal changes in elevation.[120]

Ecosystems ensure maintenance of soil fertility which is characterized by key indicators determining the production potential of soils such as soil nutrient content, mineralogy, salinity, contamination, and structure.[54] Passive sensors can be used to directly assess the change in soil quality as a result of these indicators or indirectly by monitoring structural and functional properties of the vegetation.[133] Nevertheless, these sensors can only measure the indicators in the uppermost layer of soil. Hyperspectral sensors are more efficient than multispectral sensors because they provide large number of bands that enable one to distinguish and quantify the aforementioned key indicators of soil quality.[121] Alternatively, active radar sensors are preferable for soils covered with vegetation and to assess below ground soil properties because they can penetrate the vegetation and top-soil layer.[122,123]

Demands for Ecosystem Services. While quantifying and mapping the supplies of ecosystem services provides information about the status and availability in the production areas, quantifying the demands considers the beneficiaries and factors determining their status.[124,125] It is usually described in terms of the distribution, size, and location of the beneficiaries.[126] Beneficiaries are human beings utilizing nearby and/or far-located infrastructure, settlements, farmlands, recreational areas, parks, and related ecosystems.[2] See Figure 2.

Therefore, estimating the size and distribution patterns of beneficiaries involves direct estimation of human population and indirectly through mapping of settlements, infrastructure, and other ecosystems like valuable croplands.[127,128] See Figure 2. Mapping beneficiaries using settlements and population distribution as proxy is feasible by using nighttime light emissions, DMSP-OLS data.[129] Regression model can be used to establish an empirical relationship between emissions in the visible and near-infrared electromagnetic spectrum and census data.[129]

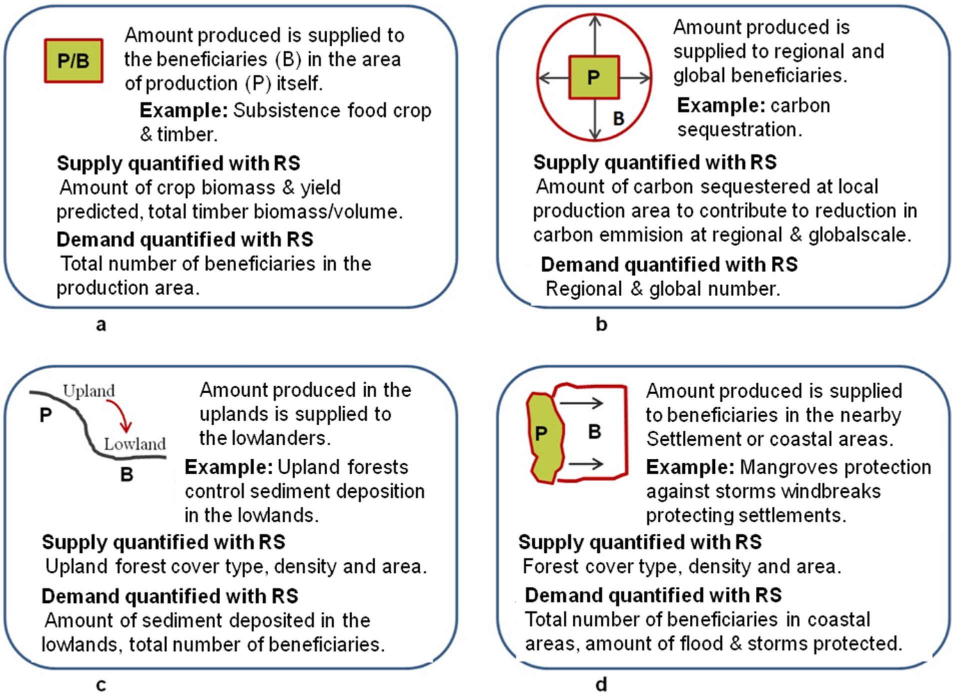

Figure 2. Application of remote sensing in mapping and quantifying spatial relationships between supplies and demands of ecosystem services: *a* = supply in the production area, *b* = supply at larger spatial scale, *c* = upland−lowland linkages, *d* = protection of adjacent areas (adapted from Fisher et al., 2009[2]).

A similar approach can be used by combining data from other sensors (e.g., MODIS) with DMSP-OLS to estimate population size which is an indicator for demands.[130] However, this approach can only be applied with the assumption that the infrastructure exists for the emissions of light which cannot be postulated for large areas like Africa.

Alternatively, an indirect way of monitoring the demands is mapping the spatial location of human settlements and properties with remote sensing data to assess the need for a particular ecosystem service, e.g. protection against hazards like floods and avalanches.[131,132] If very high resolution sensors like QuickBird are used, the protection demand can be even further described by spatially and thematically graduated information. Examples include mapping locations of expensive buildings, open spaces, and vegetation types within the respective settlements.[133]

In a nutshell, the examples presented in this section demonstrate the potential for using remote sensing to quantify the supplies and demands of provisioning and regulatory services. However, some data sources, e.g. HyMAP hyperspectral sensors, are developed very recently and are just at experimental phase to be used in actual research projects. Hence, there are limited numbers of articles that deal with their application. Thus, it should be noted that the application of data from these sensors may not be limited to what we presented here. Table 2 is synthesized from what has been discussed above and SI Tables S1 and S2, with some examples of data from commonly used sensors.

■ RESEARCH OUTLOOK

This review confirmed that there is uncertainty involved when using remote sensing data for quantifying and mapping ecosystem services. Therefore, further research is needed to provide guidelines that assist in validating the reliability of the results obtained by using remote sensing in quantifying and mapping ecosystem services. Further studies are needed to find approaches that are useful in checking the validity of remote sensing-based proxies in estimating the indicators of ecosystem services. Developing systematic approaches for the validation of remote sensing-based findings with field-measured data and/or model-based approaches call for further research in this field.

■ ASSOCIATED CONTENT

Supporting Information

Tables S1 and S2 provide a critical review of other relevant remote sensing data sources and their properties; detailed description of methods and assumptions with examples on remote sensing application for quantifying and mapping ecosystem services. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

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Quantifying and Mapping Ecosystem Services Supplies and Demands: A Review of Remote Sensing Applications

Supporting Information

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Table S1: Provisioning services: food, raw materials

	Ecosystem service Indicator(s) *(1)*	Remote sensing data	Assumptions and methods to quantify the ecosystem service indicators	Satellite/Sensors
Food (Potential production of agro-ecosystems & livestock)	Expected crop production in tons ha^{-1} $year^{-1}$, total area of cropland, Area of grasslands suitable for grazing, Gross Primary Production (GPP)	Vegetation indices (e.g. NDVI, EVI, fPAR, LAI)	NDVI, EVI, fPAR and LAI are considered as indicators of productivity in a crop growing season because they show phenology and photosynthetic potential of crops and help identify the cropping cycle and growth; stepwise multiple regression and correlation of crop biomass with these indices to estimate yield and or fodder productivity (*(2)*, *(3)*, *(4)*, *(5)*, *(6)*, *(7)*, *(8)*, *(9)*, *(10)*, *(11)*, *(12)*, *(13)*, *(14)*, *(15)*, *(16)*, *(17)*, *(18)*, *(19)*). High biomass production (e.g. crop yield, fodder) is expected in areas with high values of NDVI, EVI, fPAR and LAI.	AVHRR, MODIS, Landsat, Quickbird, SPOT 5, MERIS
		GPP	GPP is the first component of the carbon cycle and is significant in understanding the effects of crop management on food production and can be used as indicator of crop yield and/or fodder biomass (*(20)*, *(21)*, *(22)*).	MODIS, MERIS
Raw materials (Forest capacity to produce timber)	Expected total biomass production (average dry matter productivity in forests in m^3 $year^{-1}$)	Vegetation indices (e.g. NDVI, fPAR, LAI)	Variations in NDVI, fPAR and LAI are considered as key indicators of forest productivity since the photosynthetic capacity of forests can be capture with these indices. Multiple regression of forest biomass with these indices to estimate timber production (*(23)*, *(24)*, *(25)*, *(26)*, *(27)*, *(28)*, *(29)*, *(30)*, *(31)*, *(32)*, *(33)*, *(34)*, *(35)*, *(36)*, *(37)*, *(38)*). In addition, inversion of radiative transfer models is another method for estimating forest biomass (*(39)*, *(40)*, *(41)*, *(42)*, *(43)*).	Landsat, MODIS, IRS-LISS III, ASTER, SPOT, IKONOS, AVIRIS, MISR
		LiDAR data	Forest biomass can be directly estimated from space borne and airborne laser scanners data once relationship is established (e.g. regression models) between measured biomass and LiDAR point data due to the ability of laser scanners to collect point data representing the vegetation structure (*(44)*, *(45)*, *(46)*, *(47)*, *(48)*, *(49)*, *(50)*).	Laserscanners
		RADAR data	Radar data can be used to estimate forest biomass productivity because backscattering radar coefficient derived from radar data is sensitive to biomass production per plant species. Thus, relating radar backscattering coefficient with biomass production by applying inversion techniques enables prediction of forest productivity (*(51)*, *(52)*, *(53)*, *(54)*, *(55)*).	JERS-1 SAR, InSAR

Table S2: Regulatory Services: regulation of biophysical conditions (Climate regulation e.g. capacity of ecosystems to influence global climate through carbon storage & sequestration; air quality regulation; erosion prevention; water purification; moderation of extreme events like floods, massflow; maintenance of soil fertility, biological control)

	Ecosystem service indicator (s) *(1)*	Remote sensing data	Methods and assumptions to quantify the ecosystem service	Satellites/Sensors
Climate regulation (Carbon storage)	CO_2 flux (Net Primary Production: NPP), Net Ecosystem Exchange: NEE, Above Ground Carbon storage (AGC), Above ground biomass	Vegetation indices (e.g. NPP, NDVI, PRI, WBI, EDVI)	Carbon storage and sequestration can be estimated through quantification of NEE of CO_2 flux (NPP) because NEE determines amount of atmospheric carbon stored in an ecosystem (*(56)*, *(57)*, *(58)*, *(59)*, *(60)*, *(61)*, *(62)*). Time integrated NDVI (iNDVI) data to estimate CO_2 flux (NPP). Combination of vegetation indices such as NDVI, PRI, EDVI and WBI are considered indicators of net CO_2 flux (NPP)..Correlating insitu measured CO_2 fluxes with NDVI over smaller area and upscaling for a larger area (NPP). Moreover, suitable predictors can be determined based on regression of field measured AGC data against spectral information from the vegetation indices (*(63)*, *(64)*, *(65)*, *(66)*, *(67)*). Above Ground Carbon (AGC) estimation through stepwise multiple regression on spectral information of satellite bands. CO_2 emission indicates the amount of carbon released to the atmosphere from ecosystems (e.g. burning forest or agricultural land) and affects the carbon balance and thus, it can be used as indicator of carbon storage (*(68)*, *(69)*, *(70)*, *(71)*, *(72)*, *(73)*).	Landsat AVHRR, MODIS, AVIRIS, HJ-1A/B, Quickbird, ASTER
		LiDAR data	Point cloud LiDAR data enables direct estimation of AGC through calculation of Digital canopy height model (DCHTM) and digital terrain model (DTM). AGC estimation from DCHM and DTM derived from LiDAR data (*(74)*, *(75)*, *(76)*,, *(77)*, *(78)*, *(79)*).	Laserscanners
Air quality regulation	Total amount of pollutants removed via dry deposition on leaves in tons ha-1 year -1 (dust, airborne pollutants: NO_2, CO, HCHO, SO_2 concentrations)	Aerosol data, infrared and thermal infrared data	Trace gases and aerosols (O_3, NO_2, CO, HCHO and SO_2) can be used as indicators of air quality because aerosol data enable the source of dust polluting air to be discerned. Moreover, the change in the amount of dust accumulation in the air changes the spectral reflectance of objects and pollutants can be detected from reflectance data (*(80)*, *(81)*, *(82)*, *(83)*, *(84)*, *(85)*). Therefore, correlating insitu air quality parameters (e.g. dust) with remote sensing measurements of aerosol optical thickness data and regression analysis of field observed dust accumulation data with remotely sensed spectral reflectance data enables to assess air quality.	AVHRR, Landsat, MODIS, ERS-2, SEVIRI, MERIS, MetOp-IASI

Table S2 Continued

	Ecosystem service indicator (s) *(1)*	Remote sensing data	Assumptions and methods to quantify the ecosystem service	Satellites/Sensors
Erosion Prevention (Potential of ecosystems to retain soil and to avoid erosion: area of forest in vulnerable zones)	Total amount of soil retained in tons ha-1 year-1 (Eroded area, ground cover, deposited sediment).	Vegetation indices (e.g. NDVI, SR) Crop Residue Index Multiband (CRIM), Antecedent Precipitation Index (API), Cellulose Absorption Index (CAI).	Constituents of sediments such as the lithologic composition, grain size, and moisture content change reflectance properties of surfaces and this enables detection of eroded land and material deposition (*(86)*, *(87)*, *(88)*, *(89)*, *(90)*, *(91)*, *(92)*, *(93)*). Surfaces covered with vegetation and/or plant residue are less prone to erosion and thus detecting and mapping variability in surface conditions (e.g. vegetation cover change) based on spectral reflectance captured by vegetation indices such as NDVI and SR is a useful method in predicting risk of erosion (*(94)*, *(95)*, *(96)*, *(97)*).	Landsat, ERS-1, IRS, IKONOS, MODIS
		LiDAR data	Point cloud LiDAR (Laser scanning) data enables detection of eroded land and deposited soil material because it helps to detect change in topographic characteristics of the eroded and sediment deposition area (*(98)*, *(99)*, *(100)*, *(101)*, *(102)*, *(103)*, *(104)*).	Laser Scanners
Waste treatment (Water purification)	Water clarity; Total amount of pollutants removed annually in tons ha-1 year-1, total amount of water purified (quantifying chlorophyll concentration, dissolved organic matter, salinity, turbidity, suspended sediment concentrations, water surface temperature and heat flux).	Light attenuation (Reflectance data)	Light attenuation is a measure of turbidity and clarity of water as a function of changes in phytoplankton pigments, organic matter, and suspended sediments (*(105)*, *(106)*, *(107)*, *(108)*, *(109)*, *(110)*). Thus, correlating satellite derived reflectance data with insitu measured light attenuation data enables assessment of water clarity and hence water purification capacity of ecosystems.	AVHRR, EO-1 ALI
		Brightness (Reflectance data)	Brightness of reflectance data from a water body is an indicator of water clarity. Water quality determines the spectral reflectance from the water body (*(111)*, *(112)*, *(113)*, *(114)*, *(115)*, *(116)*). Correlating reflectance data from water body with field observed insitu measurements of water clarity indicators (brightness).	Landsat, SeaWiFS, QUickBird, IKONOS
		Chlorophyll content	Amount of chlorophyll-a, suspended minerals and dissolved organics are indicators of water quality. Quantifying phytoplankton chlorophyll-a content, suspended minerals, and dissolved organic matter from remote sensing data (*(117)*, *(118)*, *(119)*, *(120)*, *(121)*, *(122)*, *(123)*, *(124)*, *(125)*, *(126)*, *(127)*, *(128)*, *(129)*, *(130)*, *(131)*, *(132)*, *(133)*).	Landsat, SPOT, MODIS, Hyperion, CASI

Table S2 continued

		Ecosystem service indicator (s) *(1)*	Remote sensing data	Methods and assumptions to quantify the ecosystem service	Satellites/Sensors
Moderation of extreme events	Water storm and flood regulation	Total number of storms mitigated, protected infrastructure (Flooded area, flood prone area, flood events/inundation)	Hydrological flux derived from vegetation indices (e.g. NDVI), Water surface fraction	Reflectance properties vary with change in water flux that can be quantified from vegetation indices (e.g. NDVI). Thus, inundation processes can be detected and modelled from vegetation indices and surface water body is extracted to predict flood extent (*(134)*, *(135)*, *(136)*, *(137)*, *(138)*, *(139)*, *(140)*). Storm from rainfall and fresh water runoff can be detected using sea spectral reflectance data because reflectance properties of sea changes with the events of storms (*(141)*). Detecting the extent and direction of plumes that originate from river discharge using channels of normalized water leaving radiance to estimate extent of storms since plumes are useful indicators of storms prevalence(*(142)*, *(143)*).	AVHRR, Landsat, IRS-LISS III, SSM/I, SeaWiFS, SeaWiFS, MODIS
			LiDAR data	Damages caused by storms indicate the extent of storms in a given area and can be used as a clue to quantify the contribution of vegetation like Mangroves in regulating storms and floods. point cloud LiDAR data are useful in mapping damage of mangroves caused by water storms due to capacity of laser scanners to collect point data of vegetation structure and topography of the surface (*(144)*, *(145)*, *(146)*, *(147)*, *(148)*, *(149)*, *(150)*, *(151)*).	Laserscanners
			RADAR data	In flood plain areas vegetation faces flood stress and this can be used to assess flood dynamics indirectly by assessing change in vegetation structure. Temporal series of backscattering radar data provides accurate information about vegetation structural and functional conditions and hence suitable to monitor flood dynamics as a function of impact on the nearby vegetation (*(152)*, *(153)*, *(154)*, *(155)*, *(156)*, *(157)*, *(158)*).	ENVISAT-SAR RADARSAT-1, TerraSAR-X
	Wind storms regulation	Protected infrastructure, croplands due to vegetation in the nearby area		Detecting dust storms to estimate capacity of ecosystems to protect the surrounding infrastructure and croplands using high spatial resolution satellite data because remote sensing provides real-time, accurate and for large scale assessment of wind storms (*(159)*, *(160)*, *(161)*). Besides these, wind disturbance and damage severity can be quantified to assess the capacity of ecosystems to regulate wind storms since extent of damage to vegetation and infrastructure varies with the wind speed and strength (*(162)*, *(163)*, *(164)*).	MODIS, AMSR-E, IKONOS, NSCAT, QuickSCAT, Landsat
	Mass flow protection	Protected infrastructure, croplands, water bodies due to vegetation in the nearby area (e.g. protection against landslides, debris, avalanches).	Reflectance data	Potential mass flow can be derived from elevation and spectral data because digital surface models enable detection of change in topography due to material flows and the spectral reflectance properties of surface change when there is mass flow (*(165)*, *(166)*, *(167)*, *(168)*, *(169)*, *(170)*).	SEBASS, SPOT 4/5, Landsat, ASTER, Hyperion, AVIRIS, Landsat TM, Beijing-1 Microsatellite, IKONOS, QuickBird
			LiDAR data	Analysis of LiDAR derived topographic information for characterizing and differentiating mass movements (e.g. landslides) because material flow changes the topographic characteristics of a landscape that can be detected with laser scanners (*(171)*, *(172)*, *(173)*, *(174)*, *(175)*, *(176)*).	Laserscanners
			RADAR data	RADAR backscattering data to map mass movements because radar data can provide 3D terrain models and enables evaluation of susceptibility of land surfaces to hazards (*(177)*, *(178)*, *(179)*, *(180)*, *(181)*).	InSAR, ERS-SAR, TerraSAR-X, ALOS

Table S2 continued

	Ecosystem service indicator (s) (*(1)*)	Remote sensing data	RS[1] data, methods and assumptions to quantify and map ESS[2]	Satellites/Sensors
Maintenance of soil fertility	Nutrients: nitrogen (N), Phosphorus(P), Potassium (K), organic carbon, Soil nutrients, salinity, heavy metal contamination, mineralogy, water content, soil crusts	Vegetation indices e.g. Non-Photosynthetic vegetation (NPV), Green Vegetation (GV), NDVI, EVI	Vegetation structure and functions are determined by soil fertility (nutrients: N,P,K contents). Thus, correlating insitu measurements of soil fertility indicators (soil nutrients: N,P,K, salinity, iron oxide content, mineralogy, water content, heavy metal contamination) with vegetation indices such as Non-Photosynthetic vegetation (NPV), Green Vegetation (GV) and soil (derived from spectral mixture analysis), and the NDVI is a useful method in quantifying soil fertility status (*(182)*, *(183)*, *(184)*). Salinity, mineralogy (e.g. smectite, illite, kaolinite), iron-oxide content, and heavy metal contamination change the reflectance properties of the soils on bare lands and of vegetation in covered areas. Hence, correlating field observed data with bare soil reflectance data for smaller areas and calibration of the satellite imagery data for up-scaling over larger landscapes helps in quantifying the status of soils (*(185)*, *(186)*, *(187)*, *(188)*, *(189)*, *(190)*).	Landsat, ASTER, MODIS, SPOT, AVIRIS, HyMap
Biological control (Pest control)	Avoided damage of crops by pests due to availablity of insects that feed on the pests.	Vegetation indices (e.g. NDVI, EVI, NDII, NDWI, EWDI, G:R ratio, LAI)	Enhanced Wetness Difference Index (EWDI) is considered as indicator of plant water stress and can be used in detecting pest outbreak with stepwise regression analysis because it shows changes in vegetation moisture status before and after pest attack (*(191)*). Reduction in photosynthetic activity causes defoliation and can be used as an indicator of pest attack which can be mapped using indices such as NDVI LAI, EVI, NDWI, and G:R (*(192)*, *(193)*, *(194)*, *(195)*, *(196)*, *(197)*, *(198)*, *(199)*).	Landsat, MODIS, QuickBird, SpecTIR VNIR, AVIRIS, HyMap

Abbreviations

AISA	**A**irborne **I**maging **S**pectrometer
ALS	**A**irborne **L**aser **S**canner
AMSR-E	**A**dvanced **M**icrowave **S**canning **R**adiometer
ASE	**A**utonomous **S**cientific **E**xperiment
ASTER	**A**dvanced **S**paceborne **T**hermal **E**mission and **R**eflection **R**adiometer
AVHRR	**A**dvanced **V**ery **H**igh **R**esolution **R**adiometer
AVIRIS	**A**irborne **V**isible **I**nfrared **I**maging **S**pectrometer
BRDF	**B**idirectional **R**eflection **D**istribution **F**unction
CASI	**C**ompact **A**irborne **S**pectrographic **I**mager
DAIS	**D**igital **A**irborne **I**maging **S**pectrometer
DMSP-OLS	**O**perational **L**inescan **S**ystem of the **D**efense **M**eteorological **S**atellite **P**rogram
EOS	**E**arth **O**bserving **S**ystem
ERS	**E**uropean **R**emote-sensing **S**atellite
ETM^+	**E**nhanced **T**hematic **M**apper
GERB	**G**eostationary **E**arth **R**adiation **B**udget
GLAS	**G**eosciences **L**aser **A**ltimeter **S**ystem
IRS	**I**ndian **R**emote-sensing **S**atellite
IS	**I**maging **S**pectroscopy
JERS	**J**apanese **E**arth **R**esources **S**atellite
LiDAR	**Li**ght **D**etection **A**nd **R**anging
MISR	**M**ulti-angle **I**maging **S**pectro **R**adiometer
MODIS	**MOD**erate **R**esolution **I**maging **S**pectroradiometer
MSS	**M**ulti-**S**pectral **S**canner
NIRS	**N**ear-**I**nfrared **R**eflectance **S**petroscopy
ROSIS	**R**eflective **O**ptics **S**ystem **I**maging **S**pectrometer
RADAR	**RA**dio **D**etection **A**nd **R**anging
SAR	**S**ynthetic **A**perture **R**adar
SeaWiFS	**Sea**-viewing **Wi**de **F**ield-of-view **S**ensor
SEVIRI	**S**pinning **E**nhanced **V**isible and **I**nfrared **I**mager
SOC	**S**urface **O**ptics **C**orporation
SPOT	**S**atellite **P**our l'**O**bservation de la **T**erre
SRTM	**S**huttle **R**adar **T**opographic **M**ission
TM	**T**hematic **M**apper

Glossary of selected remote sensing based vegetation parameters

AGC	**A**bove-**G**round **C**arbon
API	**A**ntecedent **P**recipitation **I**ndex
CAI	**C**ellulose **A**bsorption **I**ndex
CHQ	**C**anopy **H**eight **Q**uantile
CRIM	**C**rop **R**esidue **I**ndex **M**ultiband
ECD	**Ê**co-**C**limatic **D**istance
EDVI	**E**nhance **D**ifference **V**egetation **I**ndex
EVI	**E**nhanced **V**egetation **I**ndex
EWDI	**E**nhanced **W**etness **D**iffeence **I**ndex
fAPAR	**f**raction of **A**bsorbed **P**hotosynthetically **A**ctive **R**adiation
G:R	**G**reen to **R**ed ratio
GPP	**G**ross **P**rimary **P**roductivity
GV	**G**reen **V**egetation
LAI	**L**eaf **A**rea **I**ndex
LUE	**L**ight **U**se **E**fficiency
NDII	**N**ormalized **D**ifference **I**nfrared **I**ndex
NDVI	**N**ormalized **D**ifference **V**egetation **I**ndex
NDWI	**N**ormalized **D**ifference **W**ater **I**ndex
NEE	**N**et **E**cosystem **E**xchange
NPV	**N**on-**P**hotosynthetic **V**egetation
PAM	**P**lant **A**vailable **M**oisture
PAR	**P**hotosynthetically **A**ctive **R**adiation
PRI	**P**hotochemical **R**eflectance **I**ndex
SIPI	**S**tructure **I**nsensitive **P**igment **I**ndex
SR	**S**imple **R**atio
WBI	**W**ater **B**and **I**ndex

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Chapter 3

Ecosystem engineer unleashed: *Prosopis juliflora* threatening ecosystem services?

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Ecosystem engineer unleashed─ *Prosopis juliflora* threatening ecosystem services?

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Abstract

The introduction of fast-growing plant species has been a strategy worldwide to combat problems arising from land degradation. *Prosopis juliflora* is an ecosystem engineer that was introduced to Ethiopia in the 1970s to address erosion problems but has subsequently become an important invader. This paper analyzes the spread of *P. juliflora* in Baadu, located in the middle Awash Basin of Ethiopia, qualitatively assesses its impacts on ecosystem services and identifies research needs and challenges for sustainable land management. The plant was introduced in 1983 around cotton farms in the case study region to provide erosion regulation. By the year 2013, *P. juliflora* had invaded 20,000 ha (40 % of wetlands). It partly invaded also the riverbanks and agricultural lands and is expanding into adjacent dryland areas. The negative impacts of this invasion are partially offset by provisioning of firewood and charcoal. However, the difficulties to control its rapid spread indicate that the threats it poses to ecosystem services, people's livelihoods and lifestyles may exceed its benefits. We argue for an integrated research approach that considers both the services and disservices, as well as the social discourse among different groups of actors to appropriately address this issue and identify options for sustainable action.

Key words: Invasive species, Land use, Remote sensing, Pastoralism, Livelihoods, Mapping

Introduction

The practice of introducing new plant species as ecosystem engineers has often been used for restoring degraded ecosystems and combating the problems that arise from deforestation. Worldwide, fast-growing exotic species are often introduced for purposes such as soil and water conservation or fuelwood and timber production. Various species introduced around the world in the last few decades for use in horticulture, food production, and agro-forestry are now some of the most widespread organisms (Richardson and Rejmánek 2011). Some species are introduced for horticultural use by nurseries, botanical gardens, and individuals (Reichard and White 2001). The ecological ranges of many plant species have been extended by human activities in the past centuries. Aside from the introduction of species for commodity production in agriculture and forestry, an important reason for introducing a species is for its utilization as an ecosystem engineer for soil and water conservation, windbreaks, and rehabilitation of degraded lands. Jones et al. (1994) defined ecosystem engineers as "organisms that directly or indirectly modulate the availability of resources to other species by causing physical state changes by biotic or abiotic materials." In doing so, ecosystem engineers modify, maintain, and create habitats. Ecosystem engineers (e.g., exotic shrub or tree species) can alter the hydrological cycle, nutrient cycles, soil stability, humidity, temperature, and light infiltration. For example, nitrogen-fixing plants enhance nitrogen input, soil fertility, and productivity, though they may outcompete native species in nutrient-limited systems (Ehrenfeld et al. 2001).

The strategy of introducing engineering species can backfire if they become invasive in the host areas (Kumschick and Richardson 2013; Pejchar and Mooney 2009). Thus, this practice has had ecological and economic impacts around the globe, with the severity of the impact varying depending on the vulnerability of the host ecosystem and the stability of its ecosystem services (Gallien et al. 2010; Pyšek and Richardson 2010; Robinson et al. 2008; Vilà et al. 2011). Though species introduced to a new vicinity face a new environment, they often outcompete and replace the native species (D'Antonio and Meyerson 2002; Allendorf and Lundquist 2003). Once established, these invasive plant species transform ecosystems both above- and belowground, especially when their functional traits differ from the native flora (Stromberg et al 2007; Wardle et al. 2011).

Prosopis juliflora, native to South and Central America and the Caribbean, is a woody species growing to a height of 5–10 m with a deep-root system that is also able to fix nitrogen. Due to these traits, it was brought to different parts of the world for ecosystem engineering purposes such as reclaiming degraded lands (Pasiecznik et al. 2001). For instance, the species was introduced to Sudan in 1917 through afforestation programs intending to combat desertification and to provide fuelwood (Elfadl and Luukkanen 2006). However, its aggressive invasive nature affected agricultural lands, mainly irrigated fields. Arab Gulf regions used the plant for the greening of landscapes in order to reduce wind erosion and combat desertification (El-Keblawy and Al-Rawai 2007). The species was brought to India in the late nineteenth century for the rehabilitation of sodic lands to supply of fuelwood, fodder, timber, and fiber, but it later began to spread and became invasive (Mishra et al. 2003; Sharma and Dakshini 1996). Likewise, to alleviate fuelwood shortage due to a loss of native species through deforestation, *P. juliflora* was planted around Lake Baringo, Kenya, in the 1980s (Mwangi and Swallow 2005). The introduction of *P. juliflora* to the arid and semi-arid regions of Ethiopia in the 1970s and 1980s mainly aimed at soil and water conservation (Tegegn 2008). However, the species invaded larger areas than intended and became problematic (Tegegn 2008). A good example of this situation is found in Baadu, an area in the middle of the Awash basin of Ethiopia, where the species has been highly invasive since the 1990s (Admasu 2008), generating ecosystem disservices to the local people living in this region.

Previous research on *P. juliflora* in the Awash Basin mainly focused on changes in the social-ecological system of the Afar pastoralists, specifically how the invasion is perceived by different social groups (Müller-Mahn et al. 2010; Rettberg 2010; Rettberg and Müller-Mahn 2012). But these studies did not explicitly link *P. juliflora* to the concept of ecosystem services. Seid (2012) discussed the impacts of *P. juliflora* on pastoral livelihood diversification strategy based on household perception surveys without mapping its spatial distribution or considering broad classes of ecosystem services. Tessema (2012) described ecological and socioeconomic dimensions of *P. juliflora* but focused on biodiversity and policy challenges in the management of the species without quantitative analysis of the invasion. Though Rettberg and Müller-Mahn (2012) mapped the distribution of *P. juliflora* in Awash basin for the years 2000 and 2007, only the human–environment interaction was assessed. Nigussie et al. (2013) used Landsat images to map the rate of *P. juliflora* invasion in Amibara, lower Awash, for the years 1973, 1987, 1999, and 2004 but failed to include recent years. Moreover, the authors focused on how this plant species affects biodiversity, human health, and livestock production, without providing details of its impact on other ecosystem services.

In this article, we use remote sensing data to map the rate of *P. juliflora* invasion in the years 2000, 2005, 2010, and 2013 and discuss its impacts on multiple ecosystem services. The objectives of this paper are threefold: first, to map the temporal dynamics of *P. juliflora*; second, to identify the impacts of the invasion on provisioning ecosystem services (fodder and grass, crop production, fuelwood, charcoal, and water), regulatory services (erosion regulation, flood regulation, water purification, and soil salinity regulation), and cultural services (secured land and mobility); and third, to identify challenges in *P. juliflora* management and further research needs.

Methodology

Description of the case study site

Baadu is located in the mid-Awash River Valley in the regional state of Afar in Ethiopia (Fig. 1). It comprises an area of approximately 1,500 km^2 and consists of seasonally inundated floodplains (wetlands) in the flat areas, at an altitude of 500 m above sea level, surrounded by upland dryland areas. The Awash River originates in the central highlands of Ethiopia (Ayenew and Legesse 2007) and flows through Baadu floodplains (wetlands). The Baadu wetlands extend along the Awash River forming about 25 % of the total area of Baadu. The spatial extent of these floodplains slightly varies seasonally depending on the amount of water coming down from the River. A small portion of the wetlands, which varies annually from 2 to 16 %, is used for irrigated agriculture, while most of the area is used for grazing during dry seasons. The major area of Baadu are drylands that account for more than 75 % of the total Baadu area.

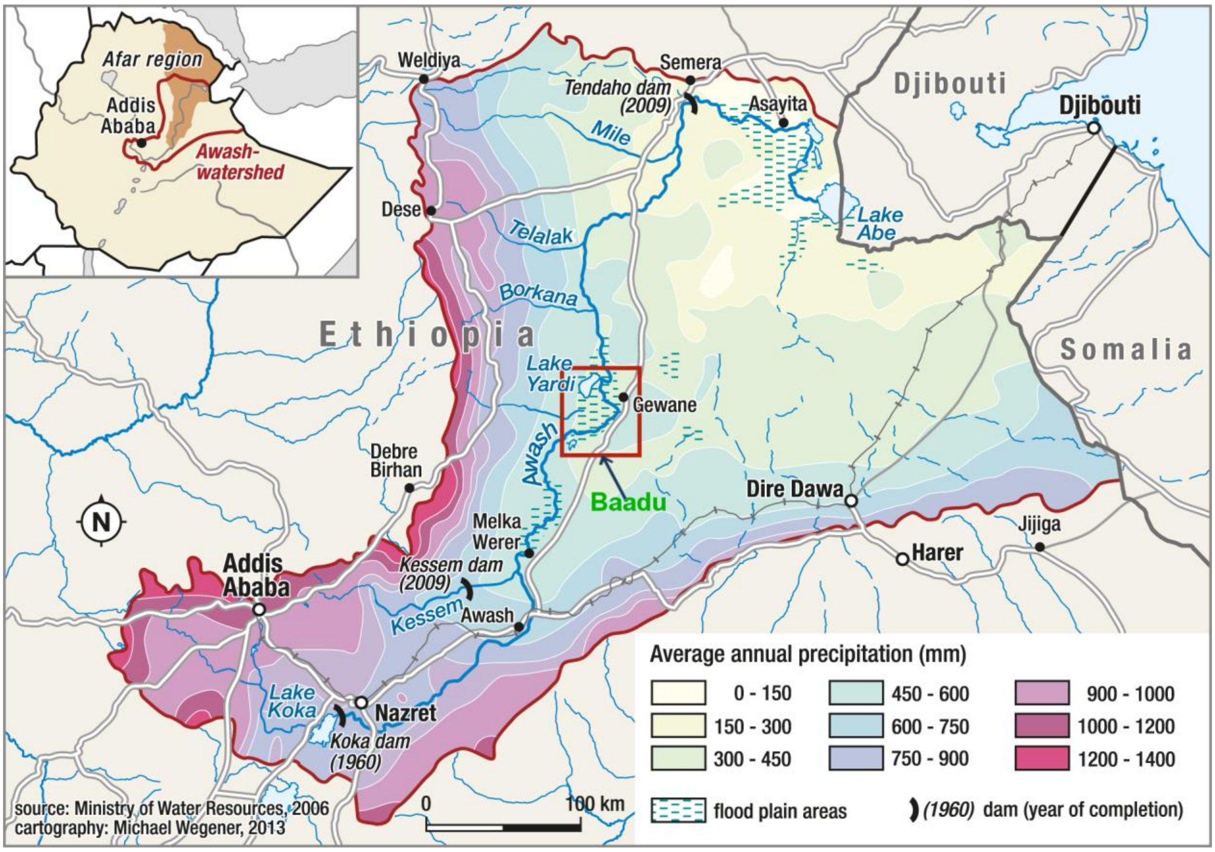


Fig. 1 Location of Baadu case study site

Prior to the invasion by *P. juliflora*, the wetlands hosted an abundance of native grasses, important sources of fodder for cattle, while different types of acacia trees (*A. tortilis, A. senegal, A. mellifera*) covered the surrounding hills. With an average annual rainfall of 450 mm, the Awash River basin is of a critical resource for more than twenty pastoral Afar clans who inhabit Baadu (Rettberg 2010). The grasslands of Baadu served as dry season pastures and drought retreats for Afar pastoralists due to the seasonal inundations of Awash River that make water available year round in the wetlands.

Mapping the *P. juliflora* invasion and assessing its impacts on Ecosystem services

Remote sensing provides useful data for assessing and mapping ecosystems at different scales (Ayanu et al., 2012). In this study, cloud-free Landsat ETM+ (30m resolution) and ASTER (15m resolution) satellite images taken during the dry seasons (October- March) of 2000, 2005, 2010 and 2013 were used to map the *P. juliflora* invasion. Details of the remote sensing data used, and the band combinations for classification, is presented in Table 1.

Table 1 Satellite images used for land use/cover classification

Sensor	Spatial resolution	Band combination	Date when image was taken
Landsat ETM+	30m	4-3-2	17.03.2000
ASTER	15m	3-2-1	01.01.2005
ASTER	15m	3-2-1	01.01.2010
ASTER	15m	3-2-1	31.10.2013

Since the spread of *P. juliflora* and its negative impacts have become more pronounced in the last decade, we compared the extent of its invasion over the years 2000, 2005, 2010 and 2013. In order to compare the results of the classification from the different years, the Landsat ETM+ images were resampled to 15m resolution prior to classification.

Data from field observations and Google earth were used to identify land cover types and training areas were defined by digitizing polygon features in the satellite images. The images were classified using maximum likelihood supervised classification method provided by Envi 5.0 software. The classification results were validated by using Google earth high resolution images and 130 ground truth points collected using Trimble Juno 3B GPS. See Figure S1 in the electronic supplementary material provided for the distribution of the GPS sample points. Ground truth points collected during February-March 2014 were used to validate the classification results of October 2013 images. The field data from year 2014 were used because of difficulty in acquiring ASTER images for February/March 2014, and there was no field visit in the year 2013 due to lack of resources. We found it reasonable to use these data since the months October–March are in the dry season, which provide comparable information regarding the spread of *P. juliflora*. The previous years (2000, 2005, and 2010) were validated using Google Earth high-resolution images from the same time period because there were no ground truth points collected in these years and the field data from year 2014 could not be used due to drastic change in *P. juliflora* invasion over a time period of 4-10 years . In addition, ground truth points collected in areas where *P. juliflora* invasion prevailed over the past decade was also used to supplement the validation from Google Earth images. A confusion matrix was calculated using ground truth Region Of Interests (ROIs) to determine accuracy of the image classification for the *P. juliflora* invasion. Details of the steps in image classification are provided in Fig. 2a.

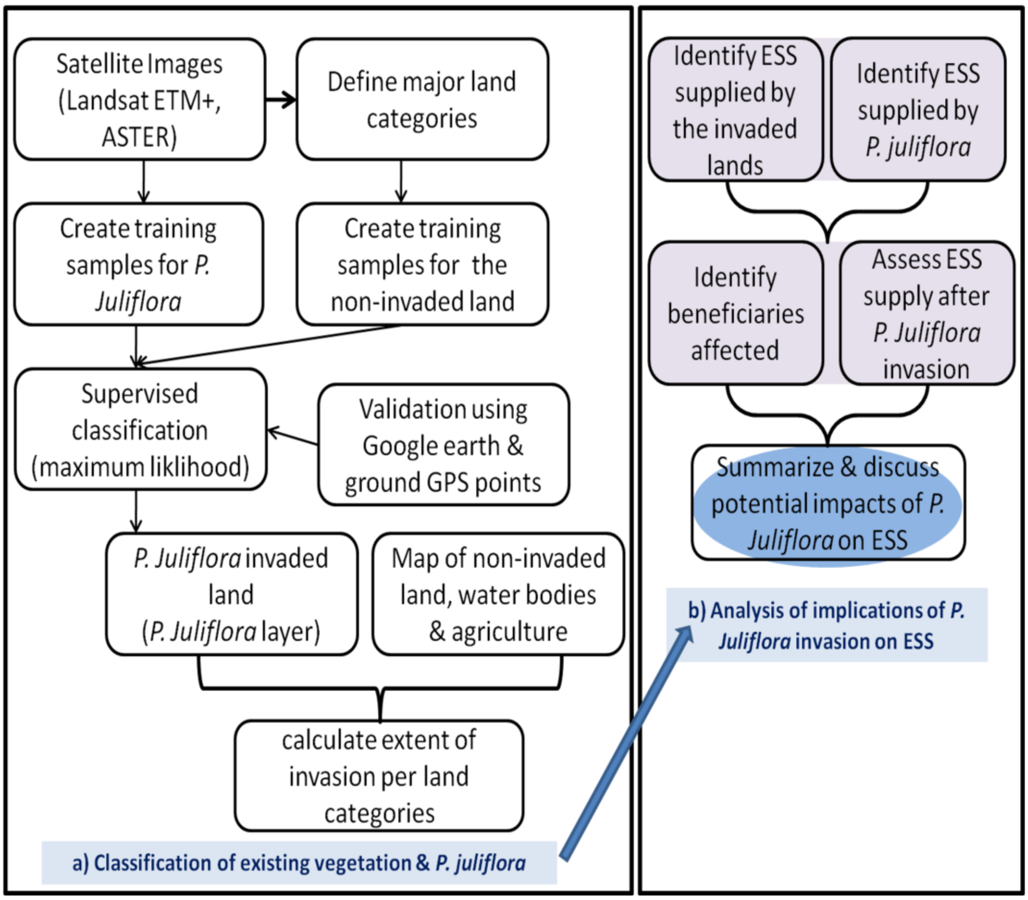


Figure 2 General workflow for a) mapping *P. juliflora* invasion b) analysis of the implications of *P. juliflora* invasion on ecosystem services and their beneficiaries.

Given spatial resolution of 15 and 30 m, the P. juliflora vegetation that can be detected in the satellite images is mainly the dense thickets and forests that could easily be identified in the floodplains of Baadu. Single trees and shrubs of small size that are sparsely distributed across the landscape cannot be detected with such resolution. Moreover, in the drylands of Baadu, *P. juliflora* is in its initial stage of invasion and is found mixed with other native species which makes it difficult to detect with spatial resolution of 15–30 m. Therefore, these limitations need to be taken into consideration while interpreting the results of the classification.

The impact of this invasive plant on ecosystem services was assessed by identifying the ecosystem services supplied by different land categories (Fig. 2b). The major ecosystem services that are supplied by the wetlands, drylands and agricultural lands were identified based on the Millennium Ecosystem Assessment, 2005 ecosystem services classification scheme (MEA 2005). The ecosystem services supplied by *P. juliflora* were also identified, and their extent was estimated. The negative impacts of *P. juliflora* and beneficiaries of ecosystem services affected were also identified. Finally, the pros and cons of the Prosopis invasion regarding the supply and demand of ecosystem services were assessed.

Results

Spreading patterns of *P. juliflora* in Baadu

In the initial years following 1983, when the government first introduced *P. juliflora* to areas around irrigated farms and the permanent settlements in Baadu, its spread was rather slow (Fig. 3). In the mid-1980s, no significant spread and invasiveness of *P. juliflora* were noted since the species was in its early stage of adaptation to the new environment in the host area. After the Derg regime collapsed in 1991, a lack of resource management and changes in land use contributed to the increased vulnerability of the landscape, resulting in the accelerated spread of *P. juliflora* throughout the 1990s and 2000s (Rettberg and Müller-Mahn 2012). The downfall of the Derg regime halted the agricultural activities on the state farms in Awash, allowing *P. juliflora* to invade the abandoned agricultural lands.

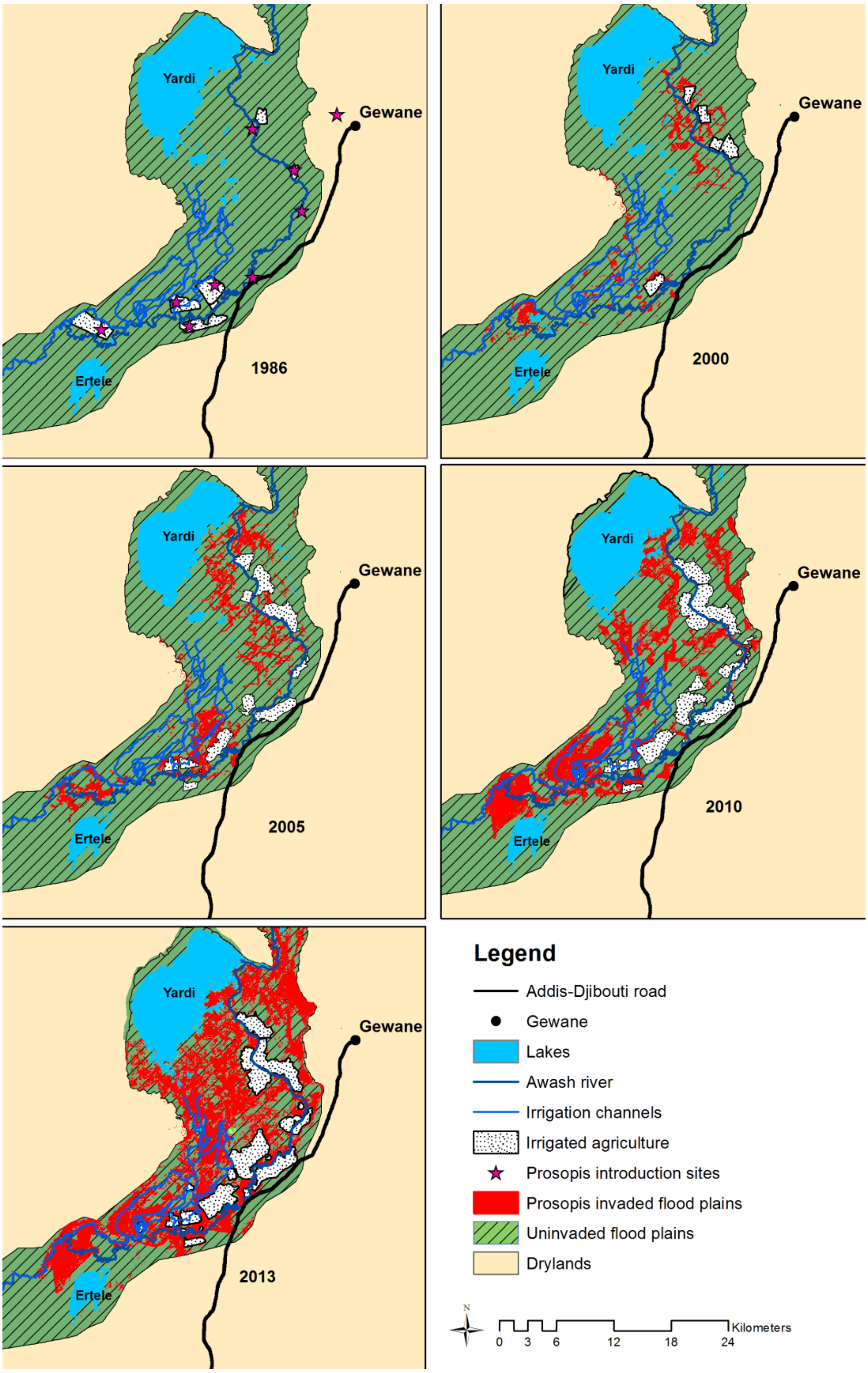


Figure 3 Spread of *P. juliflora* in Baadu during the years 2000 to 2013. *P. juliflora* was introduced in 1983 around cotton farms in Baadu but gradually spread to other parts of the Awash Valley.

Proportion of land invaded by *P. juliflora*

In the last decade, from the year 2000 to 2013, among the land categories in Baadu, wetlands were the most affected ones by the invasion of *P. juliflora* (Table 2). By the year 2000, *P. juliflora* covered 3,600 ha, invading about 8 % of the total area of wetlands in Baadu. Five years later, in 2005, the area covered by *P. juliflora* had increased to over 8,000 ha, accounting for 18 % of the wetland area. By the year 2010, *P. juliflora* had already invaded over 13,000 ha, which is about 30 % of the total area of the Baadu floodplains. Almost 40 % of the wetlands in Baadu was invaded at the end of 2013 which is about a 10 % increment over a period of 3 years when compared with year 2010. Only 2 ha (<1 %) of agricultural land was invaded in 2000, but the invaded area increased to 76 ha in 2005 (4 %). In the year 2010, the total area of agricultural land invaded by *P. juliflora* increased to 166 ha (2 % of the total area of agricultural land in the same year). In the year 2013, the area of agricultural land invaded increased to 327 ha (4 %), resulting in reduction in agricultural land mainly due to some investors who abandoned their farmland in the same year. The agricultural land area increased in the past decade due to increasing demand for cropland and a government program encouraging investors into agriculture. The slow invasion of agricultural lands is mainly due to frequent clearing of *P. juliflora* annually to ensure cultivation which would otherwise result in the abandoning of agricultural land. This was the case with the state farms that were abandoned during the downfall of the Derg regime.

Table 2 The rate of *P. juliflora* invasion as a proportion of invaded lands

Year	Wetlands (Total Area 45000 ha)		Drylands (Total Area 207000 ha)		Irrigated Agriculture (Total Area 2000: 1187 ha; 2005: 2044 ha; 2010: 7205 ha; 2013: 6926 ha)	
	Area invaded (ha)	Proportion of invasion (%)	Area invaded (ha)	Proportion of invasion (%)	Area invaded (ha)	Proportion of invasion (%)
2000	3600	8	60	< 1	2	< 1
2005	8312	18	20	< 1	76	4
2010	13645	30	490	< 1	166	2
2013	20000	40	2500	<1	327	4

Field observations and interviews made in 2011 and 2012 indicated that *P. juliflora* recently began to spread into the higher-lying dryland areas too. In 2013 the total area of drylands invaded by *P. juliflora* was 2500 hectares (< 1 % of the total area of the drylands in Baadu). As it was observed during the field visit, drylands with relatively less fertile and insufficient moisture content appear unfavorable for the growth of *P. juliflora.* For further understanding of the extent of the *P. juliflora* invasion in Baadu, please, refer to Table S1 and Figure S 2 provided in the electronic supplementary material.

Validation of the image classification results of the *P. juliflora* invasion

The accuracy assessment results calculated using the post classification function of Envi 5.0 software is presented in Table 3. All the images from the different years were classified with an overall accuracy above 80% and kapa coefficient above 0.24 which are acceptable values for a supervised classification. Validation of image classification results of the year 2013 using ground truth GPS points gave an overall accuracy of 95.23 % and kapa coefficient of 0.90 Whereas, the values obtained using Google earth images were 86.40 % overall accuracy and 0.73 kapa coefficient implying the improvement in accuracy when ground truth GPS points were used. However, in general, the results of accuracy assessment using Google Earth images of the same time period are also quite acceptable which shows that high resolution Google Earth images can be used for validating image classifications where there is no available field collected data.

Table 3Confusion matrix showing the accuracy assessment of the classification of *P. juliflora* invasion.

a) Year 2000 Overall accuracy[a] = (152034/179636) 84.63%; Kapa Coefficient[b] = 0.25

Ground truth[c]				Commission[d]& Omission [e]		Accuracy	
Class	Prosopis invaded (%)	Not invaded (%)	Total	Commission (Pixels)	Omission (Pixels)	Producer accuracy[f] (%)	User Accuracy[g] (%)
Prosopis invaded	16.82	0.10	3.16	153/5552	27449/33001	16.82	97.32
Not invaded	83.18	99.90	96.74	27449/173931	153/146635	99.90	84.22
Total	100	100	100				

b) Year 2005 Overall accuracy = (153557/154774) 92.89 %;Kapa Coefficient = 0.55

Ground truth				Commission & Omission		Accuracy	
Class	Prosopis invaded (%)	Not invaded (%)	Total	Commission (Pixels)	Omission (Pixels)	Producer accuracy (%)	User accuracy (%)
Prosopis invaded	43.47	0.81	5.64	1217/9508	10781/19072	43.47	87.20
Not invaded	56.53	99.19	94.36	10781/159135	1217/149571	99.19	93.23
Total	100	100	100				

c) Year 2010 Overall accuracy = (58554/64944) 90.16%; Kapa Coefficient = 0.79

Ground truth				Commission & Omission		Accuracy	
Class	Prosopis invaded (%)	Not invaded (%)	Total	Commission (Pixels)	Omission (Pixels)	Producer accuracy (%)	User accuracy (%)
Prosopis invaded	99.08	21.49	65.44	6052/42502	338/36788	99.08	85.76
Not invaded	0.92	78.51	34.56	338/22442	6052/28156	78.51	98.49
Total	100	100	100				

d) Year 2013 Overall accuracy = (39130/41082) 95.23 %; Kapa Coefficient = 0.90

Ground truth				Commission & Omission		Accuracy	
Class	Prosopis invaded (%)	Not invaded (%)	Total	Commission (Pixels)	Omission (Pixels)	Producer accuracy (%)	User accuracy (%)
Prosopis invaded	95.00	4.63	33.86	1287/13911	665/13289	95.00	90.75
Not invaded	5.00	95.37	66.14	665/27171	1287/27793	95.37	97.55
Total	100	100	100				

Key (adapted from Envi 5.0 User's Guide: Exelis Visual Information Solutions, 2013):
[a] Overall accuracy is the ratio of the sum of pixels correctly classified and the total number of pixels.
[b] Kappa coefficient = (total number of pixels in all ground truth classes * sum of confusion matrix diagonals)-(sum of ground truth pixels in a class * sum of classified pixels in that class summed over all classes)/(total number of pixels squared - the sum of ground truth pixels in that class)* the sum of the classified pixels in that class summed over all classes.
[c] Percent ground truth shows the class distribution for each ground truth class. In a matrix, it is calculated by dividing the number of pixels in each ground truth column by the total number of pixels in a given class.
[d] Commission refers to pixels that belong to 'Not invaded' class but are classified as 'Prosopis invaded' class and vice versa.
[e] Omission pixels are pixels that belong to ground truth class but are omitted by the classifier and are not assigned to the proper class.
[f] Producer accuracy indicates the probability that the classifier has labeled a pixel into 'Prosopis invaded' class given that the ground truth is 'Prosopis invaded' class. The same applies to the 'Not invaded' class.
[g] User accuracy indicates the probability that a pixel is in 'Prosopis invaded'class given that the classifier has labeled the pixel into 'Prosopis invaded class'. The same applies to the 'Not invaded' class.

Impact of *P. juliflora* invasion on ecosystem services

The wetlands of Baadu are sources of wide range of ecosystem goods and services. The major ecosystem goods and services that are supplied from these floodplains include provisioning services such as fodder/grass for livestock, food and cash crops, water for irrigation and home use, fuelwood, and timber. Ecosystems in these wetlands also supply regulatory services such as flood and erosion regulation. The cultural services provided by the floodplains include secured land, mobility and refuge during dry periods.

The *P. juliflora* invasion and associated loss of native wetland vegetation in Baadu has had major impacts on the supplies of a broad range of ecosystem services, including regulating (e.g. erosion control), provisioning (e.g. fodder/grass, food, fuelwood, water), and cultural (e.g. secured land and mobility) services. Different social groups' use of these services depends on their livelihood systems, resource requirements, and resource availability. Thus, the benefits or risks of *P. juliflora* tend to vary among the major user groups, such as the mobile pastoralists, sedentary small-scale agro-pastoralists, and large-scale farmers.

Regulating services

In the Awash Valley, *P. juliflora* was mainly used on large, state-run cotton farms to provide regulating services such as soil-erosion control and to function as windbreaks (Tegegn 2008) due to its fast growth, dense ground coverage, and deep root system (El-Fadl 1997). *P. juliflora* is also useful in the restoration of salinized soils (Bhojvaid et al 1998, Goel and Behl 2001).Yet some of the capabilities of the species became driving factors in its invasion process. For instance, the salt-tolerant nature of *P. juliflora* facilitated its rapid spread across abandoned governmental farms during the 1990s, after the collapse of the Derg regime.

Provisioning services: Food and Fodder

In the past decade, provisioning services in Baadu and the surroundings were drastically affected by the invasion of *P. juliflora*. The livelihood of the mobile Afar pastoralists depends highly on livestock production, which in turn is dependent on grass and fodder availability (Tsegaye et al. 2013). Therefore, the reduction of grasslands within the wetlands due to the spread of *P. juliflora* affects the livelihood and food security of nomads and agro-pastoralists tremendously (Admasu 2008; Amdihun *et al* 2010). Many of the traditional dry-season grazing areas have been taken over by thickets of *P. juliflora* (Figure 4a). This has been especially devastating for the pastoralists, whose cattle depend on the grasslands as a primary fodder resource.

Although the pods of *P. juliflora* contain high levels of protein and are available twice per year, pastoralists in Baadu complain that the pods negatively impact the health of their livestock. This may be due to the fact that the animals also browse on the unpalatable leaves, which leads to indigestion and dental problems. In some cases, some ruminants are spontaneously poisoned and intoxicated by pods of *P. juliflora* (Câmara et al 2011). The low digestibility of the leaves and pods of *P. juliflora* is mainly associated with the presence of harmful substances such as tannins, glucosinolate, cyanogens, alkaloids and nitrates (Chaturvedi and Sahoo 2013; Leonard 2011). The ethanolic leaves of *P. juliflora* could have toxic effects on some livestock, so the level of toxicity needs to be evaluated before feeding these leaves to animals (Leonard 2011, Silva et al 2013, Wamburu et al 2013). Chaturvedi and Sahoo (2013) found that the dried leaves of *P. juliflora* cannot be included in the feed of livestock since they suppresses feed intake and nutrient availability. On the other hand, alkaloid-enriched extracts from *P. juliflora* hinder microbial activity and could be a potential feed additive to help decrease gas production during ruminal digestion (dos Santos et al 2013).

Figure 4 a) *P. juliflora* invaded grazing lands; b) *P. juliflora* invasion along the Awash River c) *P. juliflora* spread to acacia forests as an undergrowth d) Dense stands of *P. juliflora* after becoming dominant over the native acacia forest.

Provisioning services: Water

Water-provisioning services are also affected by the invasion of *P. juliflora*, because it becomes invasive primarily where water is abundant (Elfadl and Luukkanen 2006; Tromble 1977). This explains its enormous spread in the seasonally-flooded area of Baadu, which is vital due to its importance as pasture and cropland. The dense growth and large thorns of *P. juliflora* prevent pastoralists’ and agro-pastoralists' access to water wells and the river, especially along the Awash River and irrigation channels (Figure 4b). Moreover, the species has the capacity to modify the hydrological regime at the landscape scale and lower the groundwater table (Dzikitiet al. 2013; Gallaher and Merlin 2010). *P. juliflora* produces more biomass in the irrigated floodplains, where it grows at the expense of high water consumption, than in the drylands (Singh *et al* 1990). This limits the availability of water for pastoralists, agro-pastoralists, and large-scale farms in the wetlands of Baadu. In addition, due to its high transpiration rate, *P. juliflora* substantially decreases the amount of available surface water and stream flows (cf. Charles and Dukes, 2007).

Provisioning services: Fuelwood, charcoal, and timber

Following its invasion, *P. juliflora* suppressed the growth of the native tree species, which has left the invasive species as the only alternative source of wood in the affected areas (Berhanu and Tesfaye 2006; Yohannes et al., 2011). In forested areas, *P. juliflora* spread as an undergrowth shrub (Figure 4c), and later formed dense stands (Figure 4d) that resulted in the loss of the native tree species. Contrary to its negative impacts on the native species, *P. juliflora* itself provides wood for multiple uses to the local communities living in Awash Valley and the surrounding areas. Well-established forests of *P. juliflora* with trees up to 10m high are the main sources of wood for fuelwood, charcoal, fence, and house construction (Figure 5a and b). Charcoal production from *P. juliflora* (Figure 5b) has recently become a new, major source of income for pastoralists living in the affected areas (Rettberg and Müller-Mahn 2012).

Figure 5 a) Fuelwood collected from *P. juliflora* forest prepared for sell along the main road to the surrounding towns b) Charcoal production from *P. juliflora* forest by the local people in Baadu c) Clearing and burning of *P. juliflora* stand from invaded grazing lands d) Coppices sprouting from stems of *P. juliflora* plants after clearing and burning.

Cultural services

Cultural services are understood as non-material benefits of ecosystems (Seid 2012). The invasion of *P. juliflora* has affected several cultural services which play an important role in the livelihood of the local pastoralists. Secured grazing lands and mobility are important cultural identity markers for the Afar pastoralists (Rettberg 2010). *P. juliflora* has turned the floodplains into an impassable dense shrubland and formed impenetrable thickets that block human and herd mobility and hinder the traditional nomadic life style. The loss of grazing lands therefore causes a feeling of insecurity among the pastoralists. The introduction of *P. juliflora* was solely based on government policy with the underlying perception that pastoralism is a backward production and livelihood system. Thus, pastoralists in Baadu consider the loss of their land to *P. juliflora* as an autocratic governmental intervention that disregarded their interests.

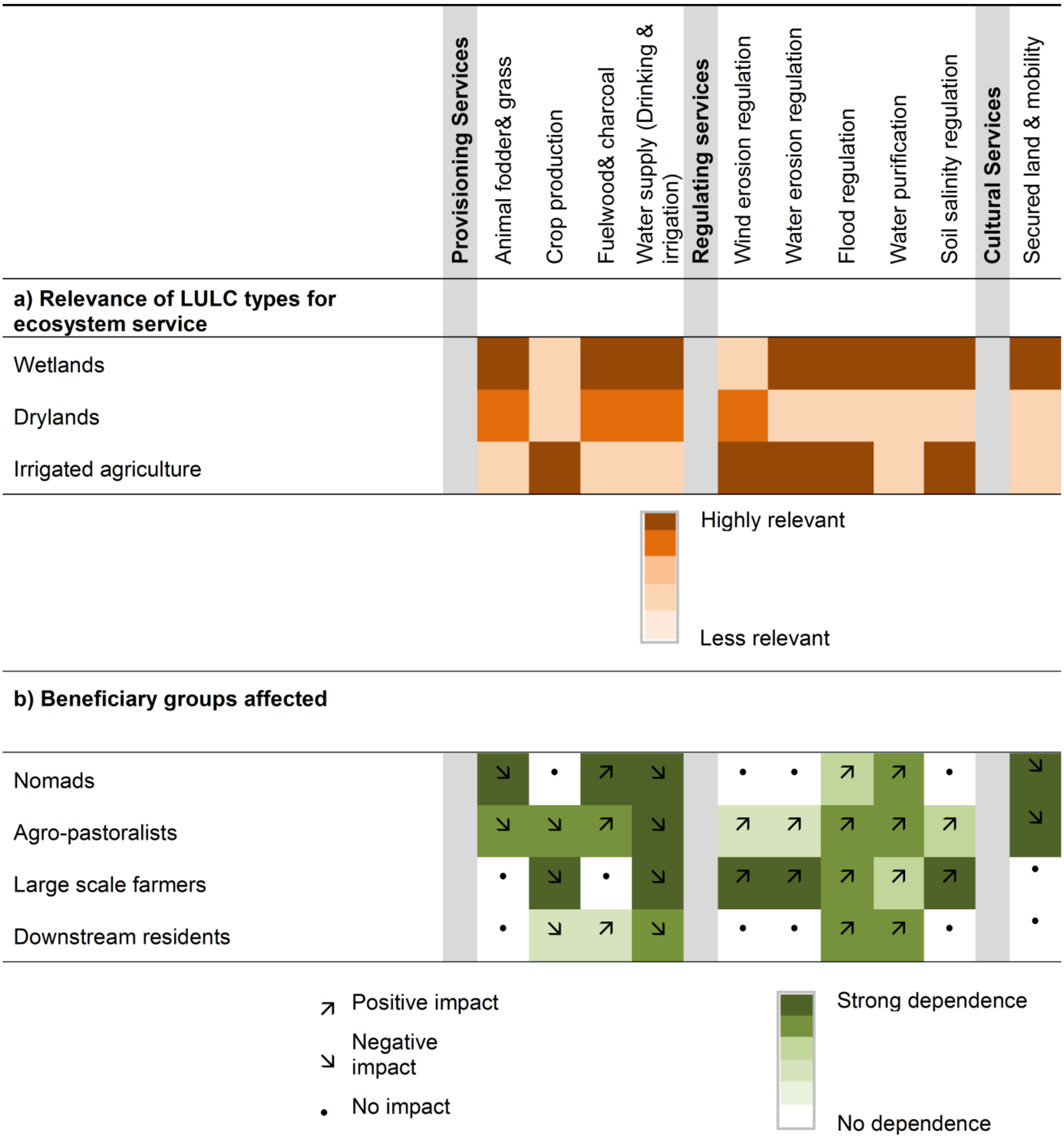
The loss of the aforementioned ecosystem services due to *P. juliflora* invasion is one among several factors resulting in the widespread impoverishment of pastoralists. Following the last severe drought in 2003, many pastoralists did not have the capacity to recover due to lack of grazing opportunities. Thus, they were forced to give up their pastoralist activities and way of life, and had to become sedentary (Müller-Mahn et al. 2010).

Discussion

Synthesis of the pros and cons of *P. juliflora* invasion

The likely impacts of *P. juliflora* on supplies of selected ecosystem services are presented in Table 4. Negative impacts of *P. juliflora* include decreased livestock productivity due to the loss of grazing land. The most affected social groups here are nomads, who are completely dependent on the native vegetation, followed by agro-pastoralists. *P. juliflora* also reduces yields by invading cropland, thus raising concerns for large-scale farmers and agro-pastoralists. Negative impacts related to decreased water availability for drinking and irrigation purposes apply to all people in Baadu and downstream residents.

Table 4: **a**) Relevance of land use/cover types (LULC) for ecosystem service in Baadu **b**) Impact of *P. juliflora* invasion on beneficiary groups and their dependence on nature's services for their well-being.



The positive aspects of *P. juliflora* are predominantly associated with regulatory services such as soil erosion regulation, rehabilitation of sodic soils, flow regulation, and water purification (Tripathi and Singh 2010). The dense shrubs of *P. juliflora* provide physical protection to soils against wind erosion during dry periods and against heavy rains during the rainy seasons, thus reducing runoff where grasses are not available to cover the soil. In addition, during rainy seasons and when the Awash River overflows, the dense structures of the *P. juliflora* shrubs stabilize the soil, regulate the flow of water, and promote the infiltration of water into the soil. Although the existence of a *P. juliflora* forest alone may not ensure flood regulation (Calder and Aylward 2006), the flow regulation provided by *P. juliflora* is an important benefit especially in protecting surrounding farmlands and settlements. The retention of soil by *P. juliflora* also results in a reduced sediment-and pollutant-load in the river and lakes, and therefore indirectly contributes to the improvement of water quality. Apart from its regulatory services, *P. juliflora* serves as a resource for fuelwood, timber, and charcoal. Even though *P. juliflora* is useful for provision of the aforementioned services, the functions of this exotic species would also have been supplied by the native species in the area (e.g. Acacia species and grasses), almost certainly with less harm to the natural ecosystem, farmlands, and water resources.

Challenges in the management of *P. juliflora* invasion

The management and control of an exotic species can be controversial, especially concerning eradication of the species since its removal may result in unforeseen negative consequences for ecosystems and benefits previously provided by the species could be lost (D'Antonio and Meyerson 2002; Wittenberg 2004). The introduction of *P. juliflora* to the Awash Basin has led to landscape level consequences and is increasingly perceived as a problem by large scale farmers, nomads, and agro-pastoralists. In order to ensure the successful management of *P. juliflora*, three critical challenges need to be addressed.

Firstly, the functional properties of *P. juliflora* foster its adaptability and support the invasion of the species. *P. juliflora* has distinct features that contribute to its invasiveness across various agro-ecosystems including wetlands, drylands, and irrigated agricultural lands (Shiferaw *et al* 2004). Its fast growth, drought tolerance, high seed yield, and vigorous coppicing gave *P. juliflora* competitive advantages over the native species in the arid and semi-arid regions of Ethiopia (Berhanu and Tesfaye 2006; Singh et al. 2012). Moreover, *P. juliflora* is salt-tolerant, which allows the species to dominate in the salt-affected irrigated lands of the Awash Basin. In addition, its seeds pass through the digestive system of animals that feed on the pods, enter the soil through animal feces, and form a seedbank that is ready to germinate when conditions are favorable (Berhanu and Tesfaye 2006; Shiferaw *et al* 2004). Typically, such seedbanks are difficult to manage and may persist longer than individual lifetimes of the organism itself (Hastings et al. 2007). Accumulated evidence suggests that the negative impacts of invasive nitrogen-fixers on ecosystem functions show time lags (Crook 2011; Essl et al. 2011; Vitousek et al 1987). As a nitrogen-fixer, *P. juliflora* transforms ecosystems both above and belowground, and drives ecosystem processes, particularly because its functional traits differ from native flora (Wardle et al. 2011). This might push the ecological system into a trajectory of *P. juliflora* invasion, which is irreversible and can no longer be controlled by the people in the region.

Secondly, the social discourse regarding *P. juliflora* will determine the successful management of the species. The need to control the fast spread of *P. juliflora* is undisputed among stakeholders in Ethiopia. However, there are controversial discussions between those who favor complete eradication of the species (e.g. pastoralists and agro-pastoralists) and those (e.g. NGOs, scientists) who point towards the not fully exploited benefits of the plant as a source of timber, charcoal, and feed for animals (Seid 2012). Selling fuelwood, timber, and charcoal products extracted from *P. juliflora* has recently become an important alternative source of income for the local people. There is a varied perception of *P. juliflora* amongst various stakeholders, which clearly has impacts on management of the species (Nigussie et al. 2013). Therefore, these dilemmas and conflicts of interest among stakeholders involved in the management of *P. juliflora* need to be thoroughly investigated and addressed in order to derive applicable management methods.

Finally, failed past attempts to control *P. juliflora* indicate the infeasibility of the invasion control given the functional properties of the species and difference in the perception of stakeholders in the Awash Valley. In order to control the invasion, the government of Ethiopia has legalized the eradication of *P. juliflora* by allowing the local people to intensively exploit it for the production of charcoal and fuelwood. Nevertheless, it is apparent that the utilization of the species for its various benefits will not ensure sustainable management over long-term period. For instance, new sprouts of *P. juliflora* will not get thick enough to produce quality charcoal and hence, harvesting likely results in the formation of thickets that are even more difficult to control. Furthermore, non-governmental organizations such as Farm Africa have introduced various methods for controlling the affected areas. These include the mobilization of the local communities to uproot seedlings from newly invaded areas, cutting of mature trees for charcoal production, removal the plant roots 10-30 cm below ground to reduce coppicing, and seed collection and crushing before feeding to livestock, in order to prevent further dispersal via animals (Admasu 2008). Eradication trials by means of cutting and burning (Figure 5c) proved to be extremely labor-intensive and expensive. Despite the high level of effort, this procedure appears to be ineffective considering the rapid regrowth of *P. juliflora* that produces numerous sprouts shortly after clearing (Figure 5d). Therefore, the species continues to invade new areas and forms inaccessible, dense thickets. In general, most of the control measures undertaken were only partially successful in smaller areas such as irrigated fields, but failed when applied at larger scales.

Conclusions

The story of *P. juliflora* highlights the consequences of unsustainable land use practices with ecosystem engineering approaches. Although *P. juliflora* was introduced to Ethiopia as an ecosystem engineer mainly for regulating soil erosion, it became invasive and ironically resulted in unforeseen negative impacts on the supply of provisioning and cultural ecosystem services. These impacts vary according to the land-use/land-cover types considered. The trends in invasion of *P. juliflora* also showed change in the spatial distribution due to efforts in the past that only involved the clearing of invaded irrigated croplands and grasslands. Since complete eradication was not possible, the species continued to spread to new areas that were not previously invaded. Moreover, dense coppices of *P. juliflora* emerged after previously invaded areas were cleared. Positive and negative impacts on ecosystem services differ among social groups depending on the impact of the species on their livelihoods. An analysis of ecosystem services and their socio-economic impact has to take into account social differentiation. Further research is needed to understand the *P. juliflora* invasion and its impact on ecosystem services, as well as to identify appropriate approaches for controlling the spread of *P. juliflora*. Modeling, for example with the InVEST tool (e.g. Nelson et al 2009), or LUCIA (e.g. Ayanu et al. 2011), with the explicit inclusion of longer time scales and broader spatial scales is required in order to assess the impact of *P. juliflora* on ecosystem services at the landscape level. In this context, it will be essential to distinguish between beneficiaries (nomads, agro-pastoralists, large scale farmers, and downstream residents) in order to specify in which way their well-being is affected by *P. juliflora*. Management practices for *P. juliflora* invasion control should be planned and implemented only after considering the invasive characteristics of the species and its perception by social groups in the regions.

Supplementary Information

Electronic supplementary material (Table and Figures) are provided with this article for further details in the analysis of the invasion of *P. juliflora*.

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Ecosystem engineer unleashed–
Prosopis juliflora threatening ecosystem services?
Supplementary Information

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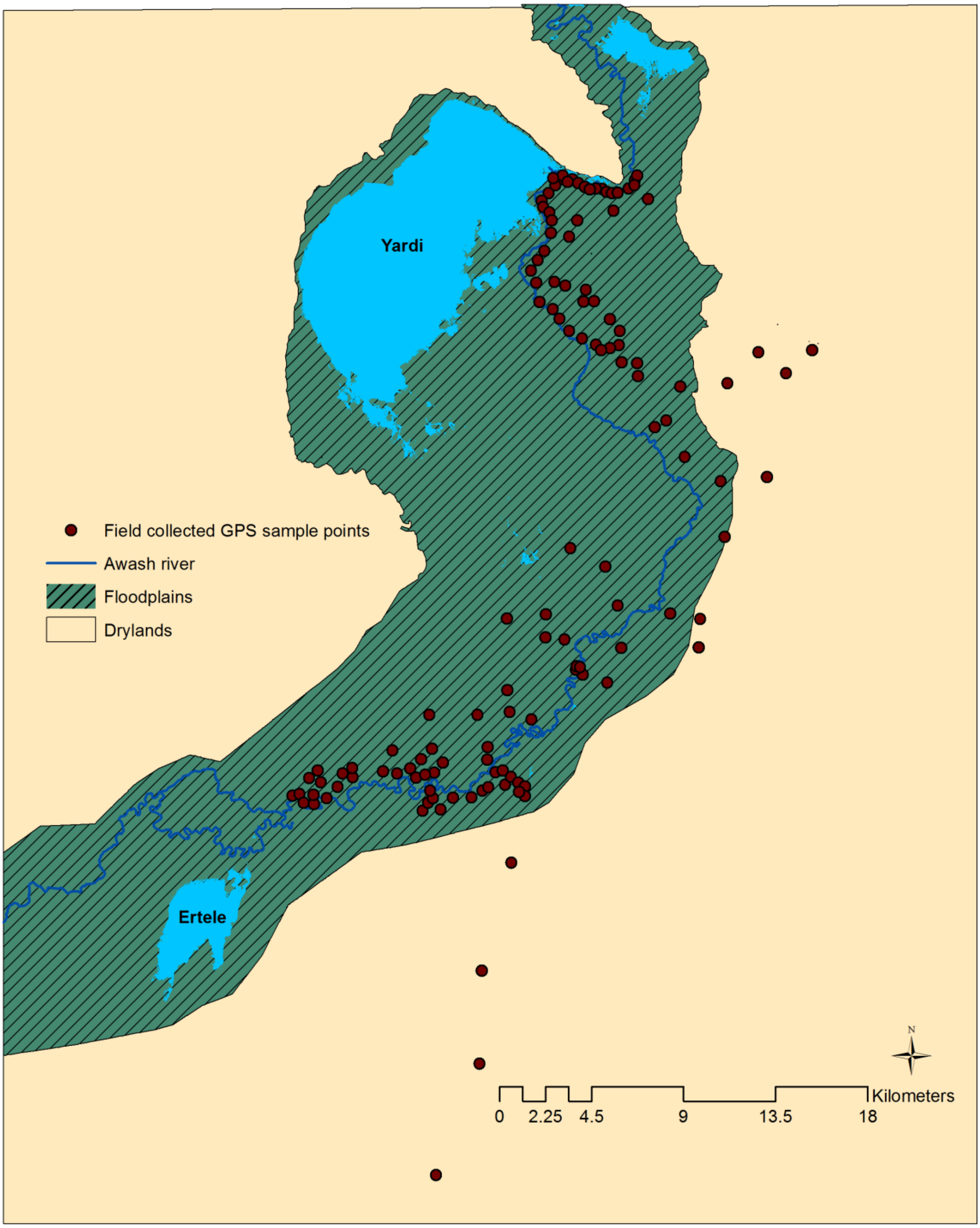

Figure S1 Distribution of the GPS sample points taken in February-March 2014. A total of 130 sample points were used for validating the classification of ASTER images for October 2013.

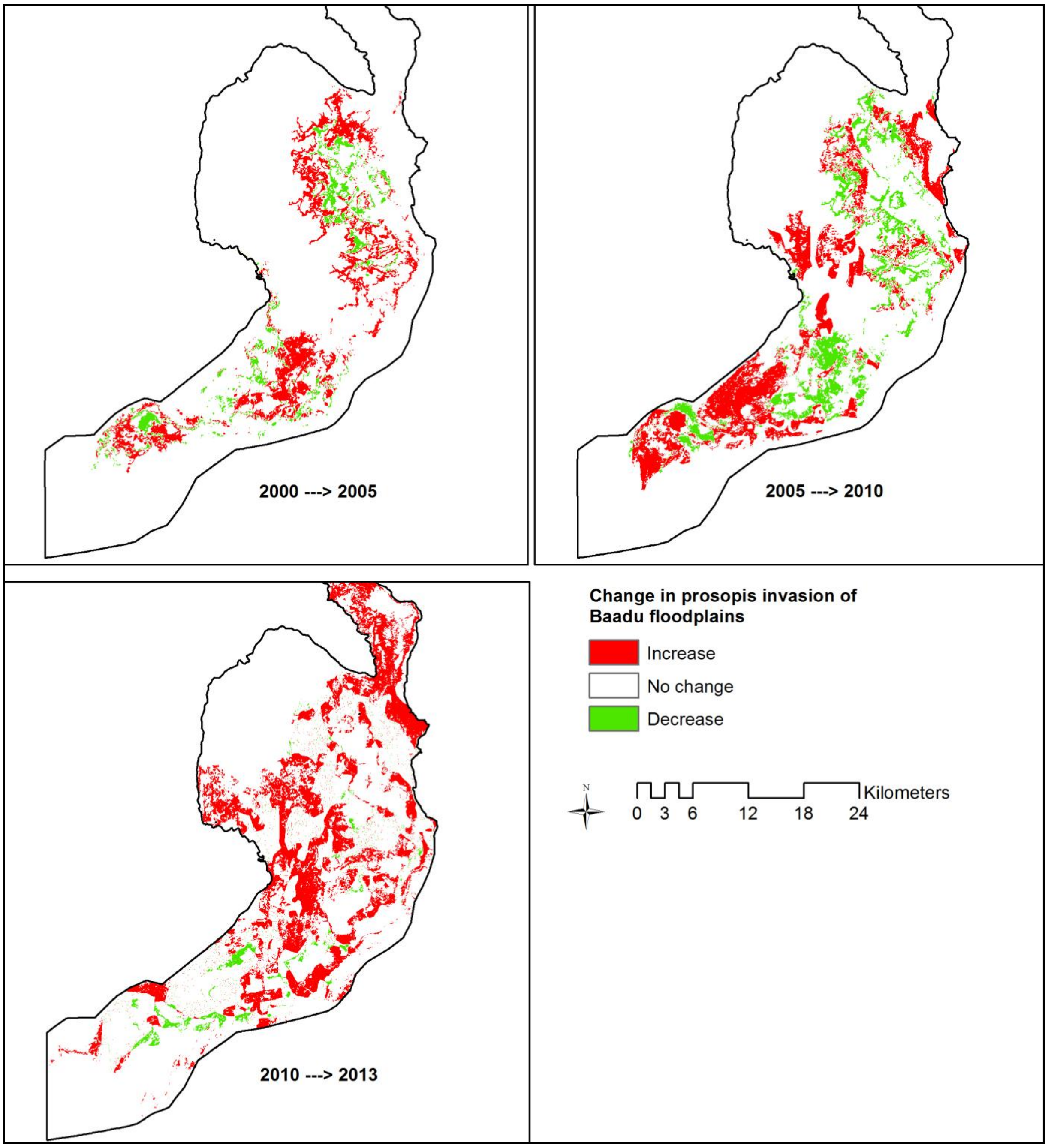

Figure S2 Change detection maps showing areas with increased, decreased or no change in *Prosopis juliflora* invasion status over the period of 2000 to 2013.

Table S1 Change detection statistics (area in square kilometers) for *Prosopis juliflora* invaded and no-invaded land, comparing different years over the period of 2000 to 2013.

		Initial state (year 2000)			
		Prosopis invaded	Not invaded	Row total	Class total
Final state (year 2005)	Prosopis invaded	11.82	69.93	82.08	83.17
	Not invaded	23.73	682.75	706.48	706.48
	Class total	36.22	752.68		
	Class changes	24.07	69.93		
	Image difference	46.95	-46.19		
		Initial state (year 2005)			
		Prosopis invaded	Not invaded	Row total	Class total
Final state (year 2010)	Prosopis invaded	51.99	266.66	318.65	318.65
	Not invaded	30.04	439.82	469.86	469.86
	Class total	82.03	706.48		
	Class changes	31.18	266.66		
	Image difference	235.48	-236.62		
		Initial state (year 2010)			
		Prosopis invaded	Not invaded	Row total	Class total
Final state (year 2013)	Prosopis invaded	118.96	156.17	275.13	275.20
	Not invaded	13.11	499.92	513.03	520.60
	Class total	132.07	656.44		
	Class changes	13.11	156.52		
	Image difference	143.13	-135.84		

Key (adapted from Envi 5.0 User's Guide: Exelis Visual Information Solutions, 2013):

- The 'Class total' rows indicates the total number of pixels in the initial state class i.e. years 2000, 2005 and 2010.
- The 'Class total' column stands for the total number of pixels in each final state class i.e. years 2005, 2010 and 2013.
- The 'Row total' column is a class-wise summation of all final state pixels that fell into the selected initial state classes.
- The 'Class changes' row refers to the total number of pixels changed from the initial state class
- The 'Image difference' row refers to the difference in the total number of equivalently classed pixels in the two images which is computed as by subtracting initial state class total from the final state class. Positive values indicate increment in the class size while negative values show decrement in the class size.

Chapter 4

Unveiling undercover cropland inside forests using landscape variables: a supplement to remote sensing image classification

PLOS ONE

Unveiling undercover cropland inside forests using landscape variables: a supplement to remote sensing image classification

--Manuscript Draft--

Manuscript Number:	PONE-D-14-52434R1
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Corresponding Author:	Yohannes Ayanu University of Bayreuth Bayreuth, GERMANY
Keywords:	Land use, forests, ecosystem services, random forests, conservation, degradation, deforestation
Abstract:	The worldwide demand for food has been increasing due to the rapidly growing global population and agricultural lands increased to produce more food crops. The pattern of cropland varies among different regions depending on the traditional knowledge of farmers and availability of uncultivated land. Satellite images can be used to map cropland in open areas but have limitation for detecting undergrowth inside forests. Classification results are often biased and need to be supplemented with field observations. Undercover cropland inside forests in the Bale Mountains of Ethiopia was as-sessed using field observed percent cover of land use/land cover classes, and topographic and loca-tion parameters. The most influential factors were identified using Boosted Regression Trees and used to map undercover cropland area. Elevation, slope, east aspect, distance to settlements, and distance to national park were found the most influential factors determining undercover cropland area. Under restricted rights for clearing forest, when there is very high demand for growing food crops, cultivation could take place inside forests as an undercover. Further research on the impact of undercover cropland on ecosystem services and challenges in sustainable management is thus es-sential.
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Opposed Reviewers:	
Response to Reviewers:	Dear editor in chief, Thank you very much for considering our manuscript for resubmission to PLoS One after major revision. Following the comments by the reviewers, in this revised version we have rewritten the sections and added new paragraphs and sentences where necessary. We made changes where required and replied to some of the comments where we could not address within the scope of this paper. We responded to each of the detailed questions (queries) by the reviewers and included it in this document under the heading Response to Reviewers' comments. The major changes in the manuscript are highlighted with yellow and page numbers and line numbers are indicated. All the other changes can be seen in the track mode of MS Word. We believe that the manuscript is now improved and fits to the goals and requirements of PLoS One and hope that you consider it for publication. Best regards, Yohannes Ayanu, corresponding author

Unveiling undercover cropland inside forests using landscape variables: a supplement to remote sensing image classification

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Abstract

The worldwide demand for food has been increasing due to the rapidly growing global population and agricultural lands increased to produce more food crops. The pattern of cropland varies among different regions depending on the traditional knowledge of farmers and availability of uncultivated land. Satellite images can be used to map cropland in open areas but have limitation for detecting undergrowth inside forests. Classification results are often biased and need to be supplemented with field observations. Undercover cropland inside forests in the Bale Mountains of Ethiopia was assessed using field observed percent cover of land use/land cover classes, and topographic and location parameters. The most influential factors were identified using Boosted Regression Trees and used to map undercover cropland area. Elevation, slope, east aspect, distance to settlements, and distance to national park were found the most influential factors determining undercover cropland area. Under restricted rights for clearing forest, when there is very high demand for growing food crops, cultivation could take place inside forests as an undercover. Further research on the impact of undercover cropland on ecosystem services and challenges in sustainable management is thus essential.

Key words: Land use, forests, ecosystem services, random forests, conservation, degradation

1. Introduction

Cropland expansion is one of the major anthropogenic factors causing loss of major natural ecosystems around the globe (Phalan et al. 2013, Gibbs et al. 2010). With the recently increasing global population and demand for food, cropland continued to expand and resulted in 'land grabbing', large-scale acquisition of agricultural land, mostly in developing countries of the tropics (Sankhayan and Hofstad 2001, Phalanet al. 2013, Dereje et al. 2013, Rulli et al. 2012). Vast areas of land in sub-saharan African countries such as Sudan, Ethiopia and Kenya are leased to local and global investors for large scale agriculture (Lavers 2012, Phalan et al. 2013). In most cases, local small-scale farmers are displaced when their land is needed for investment (Häberli and Smith 2014). Thus, with growing population, poor technology and increasing 'land grabbing', local farmers in the sub-Saharan Africa are often forced to look for unoccupied marginal lands in the mountains that are not optimal for growing crops due to extremely rugged topography. These ecosystems are generally threatened by global land use/land cover (LULC) change and are under continuous pressure due to cropland expansion to feed the rapidly growing global population (Ayanu et al 2011, Grêt-Regamey et al 2012). Meanwhile, mountainous areas provide diverse ecosystem services such as water, sediment retention, erosion control, flood regulation and recreation and are hotspots of biodiversity (Körner 2004, Briner et al. 2013, Viviroli et al. 2011). In the long-term, conversion of forests and grasslands to croplands may lead to degradation of fragile mountainous (Estoque et al. 2012, Lambin et al. 2013). This impact has been realized worldwide and protection of mountain ecosystems has gained attention (Denniston 1995, Crabtree and Bayfield 1998, Kasperson J. X. and Kasperson R. E. 2013). However, in regions with slow industrial development and the majority of the population being subsistence farmers, the past efforts in protecting forests in mountainous areas only shifted the patterns and distribution of cropland instead of slowing its rate.

Agroforestry systems that combine multipurpose trees with crops have been effectively practiced in the past across different parts of the world. For instance, in India, wheat has been planted with *Eucalyptus* and *Poplar* plantation trees (Kohli and Saini 2003, Gill et al. 2009, Singh et al. 1993, Singh et al. 1998, Sharma 1992). In western Himalaya, rice and wheat are intercropped with tree species such as *Grewia optiva*, *Morus alba* and *Eucalyptus* (Khybri et al. 1992). In China, over two million hectares area was an intercrop of wheat and *Paulownia* trees during the 1990's (cf. Li et al. 2008). Multipurpose trees such as *Ginkago biloba* have been grown in southern China with broad beans and wheat mixtures (Cao et al. 2009).

In Ethiopia, agroforestry systems (e.g. combining fruit trees, coffee, crops and vegetables as multi-story vegetation) have been traditionally practiced for hundreds of years (Negash et al. 2012). However, this was mainly limited to flat to moderate slope areas of the southern and south western parts of Ethiopia. In the past, researchers have been investigating the potential for the adoption of agroforestry systems in the mountainous areas of the Ethiopian highlands (Aerts et al. 2011, Jamnadass et al. 2011, Negash et al. 2012). However, the transfer of agroforestry knowledge from the southern and southwestern to the mountainous regions of Ethiopia showed limited success. In most cases, tree-crop combinations in the mountainous areas of Ethiopia lasted only for short time until the forest land is fully converted to cropland. One example of such patterns is undercover cropland inside forests in mountainous areas. In this study we define the term 'undercover cropland' as cultivation and growing of crops under forest canopies without future plans for transforming the forest into a multistory agroforestry system. To ensure sustainability of such complex systems where multistory vegetation types form an ecosystem, detailed analysis and assessment of its influential factors and emerging land management challenges is essential.

Remote sensing provides fast and reliable data for large scale assessment of vegetation cover. In principle, airborne and spaceborne remote sensing data are suitable for LULC classification (Chan et al. 2008, Seppelt et al. 2011, Cord et al. 2010, Hansen et al. 2013). However, due to their property of being a reflectance measure, these datasets are mainly based on canopy structure visible from above. Consequently undercover cropland cannot be fully detected. Most of the global land cover classifications in the past used coarse resolution data and provided only broad classes such as cropland-woodland and cropland-grassland mosaics. Thus, detailed analysis to capture the hidden cropland inside forests requires supplementing the remote sensing data with field surveying in order to obtain reliable results.

In this study, we assess undercover cropland area and its explanatory variables in the hilly terrains of the Bale Mountains of Ethiopia by analyzing field observed percent cover in combination with topographic and location factors using Boosted Regression Trees. The study is based on the hypothesis that topographic parameters such as slope, elevation and aspect as well as location factors such as distance to settlements and the national park influence undercover cropland inside forests in the Bale Mountains of Ethiopia. The main objectives are to i) map LULC and identify hotspots of cropland under forest canopies; ii) identify explanatory variables and map undercover cropland area; iii) assess the emerging challenges and future prospects of undercover cropland in the region.

2. Materials and Methods

2.1 Study site

Situated in the southeastern part of Ethiopia, the Bale Mountains are characterized by enormous ecological heterogeneity and steep gradients of altitudinal zones (Figure 1a). The site we selected for data sampling is part of the Adaba, Dodola, Asassa and Dinsho districts of the Arsi and Bale zones of the Oromia regional state of Ethiopia. It is adjacent to the boundary of Bale Mountains National Park (BMNP), which is known for its enormous biodiversity and insitu conservation of highly endangered mammals, birds, plants, and amphibians endemic to Ethiopia (Gower et al. 2013, Johansson 2013, Kidane et al. 2012, Le Saout et al. 2013).

The region supplies diversified ecosystem goods and services to local and national beneficiaries. For instance, provisioning services dominant in the Bale Mountains and the surroundings include food, water, timber, fuelwood, and fodder. Regulatory services include flood regulation, erosion control and water purification. Due to the availability of tourist attraction sites in the area, aesthetic and recreational values are the other important services supplied by ecosystems in the Bale Mountains. The high population growth in the area increased demand for food by local farmers, nearby villages and towns. In the past, crop production in the area is used to concentrate in the lower escarpments and flat areas. However, with increased population, the open grasslands and forest areas are nowadays intensively cultivated (Mamo et al. 2010). Besides, recent undercover cropland expansion under forest canopies is becoming an ongoing practice. Local farmers expand croplands in the uplands where forest clearing is restricted by the local government. Such increasing shift in the patterns of land cover indicates potential for tradeoffs in the supplies of various ecosystem services such as provisioning and regulatory services.

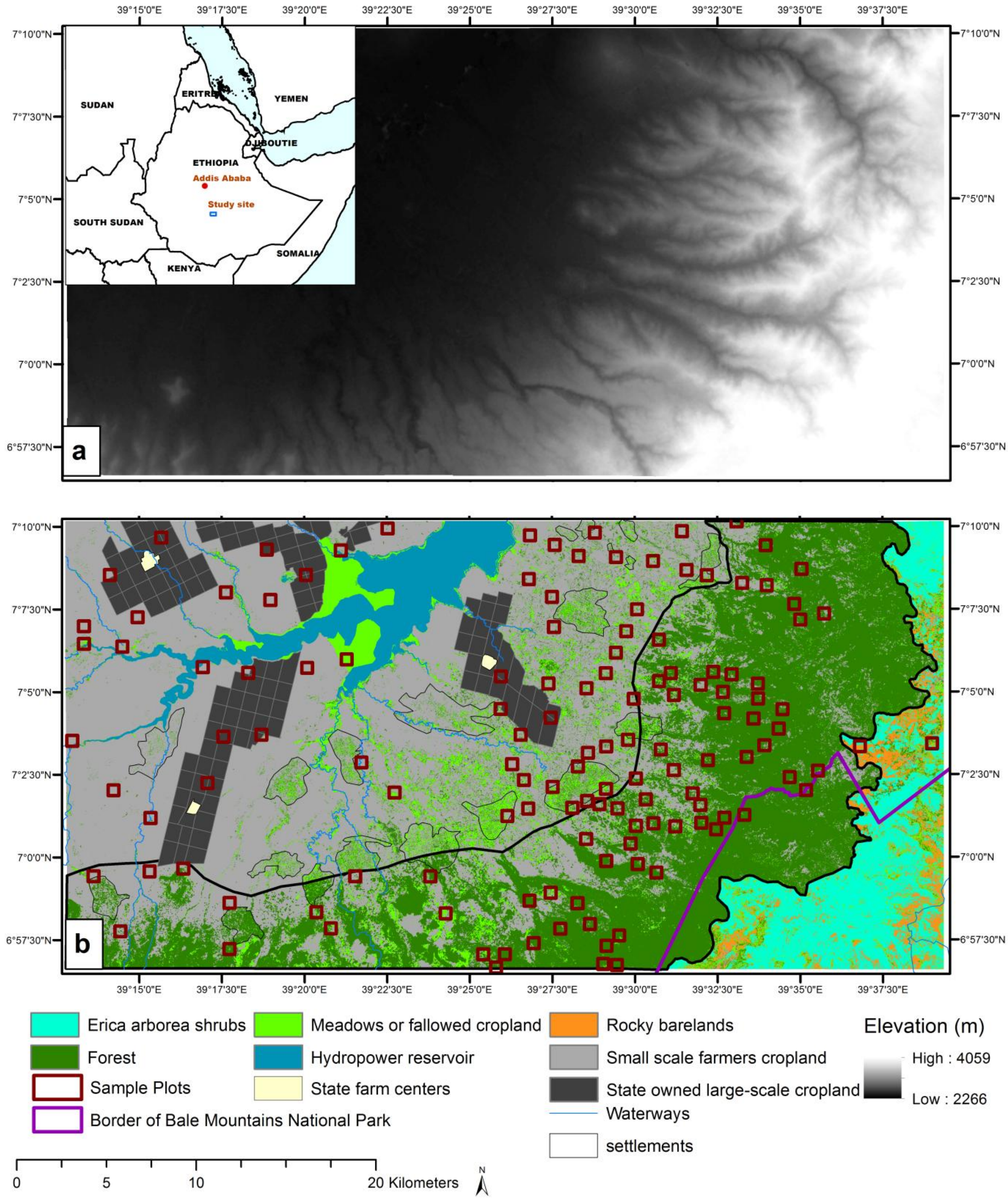

Figure 1 Study site and land use/land cover classes a) Location of the study site and distribution of sample plots b) Major land use/land cover types derived using Random Forest classification of RapidEye images. Field estimated percent cropland per plot is overlaid on the land use/land cover map.

The area is under continuous pressure from different actors and a growing population in the surrounding districts. This poses a threat to the conservation areas, the BMNP. The fact that the area is adjacent to the national park, being at the border of the four districts mentioned above, and varying altitudinal gradient makes it interesting for assessing the LULC, especially the patterns of cropland expansion.

2.2 Remote Sensing data

In this study, RapidEye images (Tyc et al. 2005) taken during dry periods (December 2012) were used for the LULC classification. The images were orthorectified 3A products with spectral bands Blue (440-510 nm), Green (520-590 nm), Red (630-685 nm), Red Edge (690-730 nm) and Near Infrared (760-850 nm). Each image had a resolution of 5 meters and covered a total ground area of 625 km^2 (25x25 m image dimension). The level 3A products are geometrically corrected for sensor-related effects using sensor telemetry. The bands are co-registered and spacecraft-related effects are corrected using attitude telemetry and best available ephemeris data. These products are further orthorectified using ground control points (GCPs) and Digital Elevation Models (DEMs).

The two scenes were mosaicked using the ENVI 5.0 (Exelis Visual Information Solutions, 2013) georeferenced mosaicking function. Atmospheric and topographic corrections were performed using ATCOR 3 software (Richter 1998). ATCOR 3 was preferably used for our largely mountainous study site since it provides algorithms for correcting images taken from rugged topography (Richter 1998, Richter and Schläpfer 2002). ATCOR 3 corrects changes in spectral reflectance of objects, removes haze and reduces the effects of shadow in mountainous terrains (Richter 1998, Richter and Schläpfer 2002).

2.3 Field data sampling

A field visit in the study site was carried out between October and December 2012, thus in the same season in which the RapidEye satellite images were taken. Land use/land cover related data was collected with the official permission of Adaba, Dodola, Asassa and Dinsho districts of Ethiopia, the local village leaders and private land owners in the area. Since part of the site is inside the boundary of the Bale Mountains National Park, permission to collect land cover related data was granted by the head of the national park. However, the study does not involve animals for experimenting and we confirm that the field studies did not involve endangered or protected species. A total of 136 sample plots were laid out randomly at varying intervals based on heterogeneity of LULC and accessibility of the landscape (see Figure 2 for details of steps in field sampling). The interval between the sample plots was long (up to 5 kilometres) in homogenous areas while it was short (1-2 kilometres) in heterogeneous landscapes. The sample plots were laid out with a distance of 300 m from the centre point in four directions, North, South, East, and West (NEWS) with each having an area of 0.36 km^2 (Figure 2a). The sampling of data was carried out for each plot and recorded in the worksheets prepared for field surveying.

Trimble Juno-3B GPS was used to measure the coordinates at the centre of the sample plots to identify the spatial location where the data was recorded. Percentage cover of different LULC classes was estimated for each plot taking the GPS centre point as a reference. The percent cover for each LULC class was estimated visually in a range of 0 to 100. The visual estimation was made relative to the total area of the plot i.e. 0.36 km^2. For this, discontinuous LULC classes (e.g. forest patches, meadows, croplands) were assumed to be as continuous relative to the plot area to assign total percent cover per plot. As a visual guideline the area covered by 1% of the LULC class as a percentage of 0.36 km^2 which is equivalent to 0.0036 km^2. Thus, one percent cover of LULC is equivalent to a square land with dimensions of 0.06 x 0.06 km. Besides the percentage cover per plot, LULC classes at the GPS points were recorded for later use in the validation of classification results. To further support validation of results from the satellite image classification, photographs were also taken in four directions from the GPS centre point using the built-in Trimble Juno 3B camera.

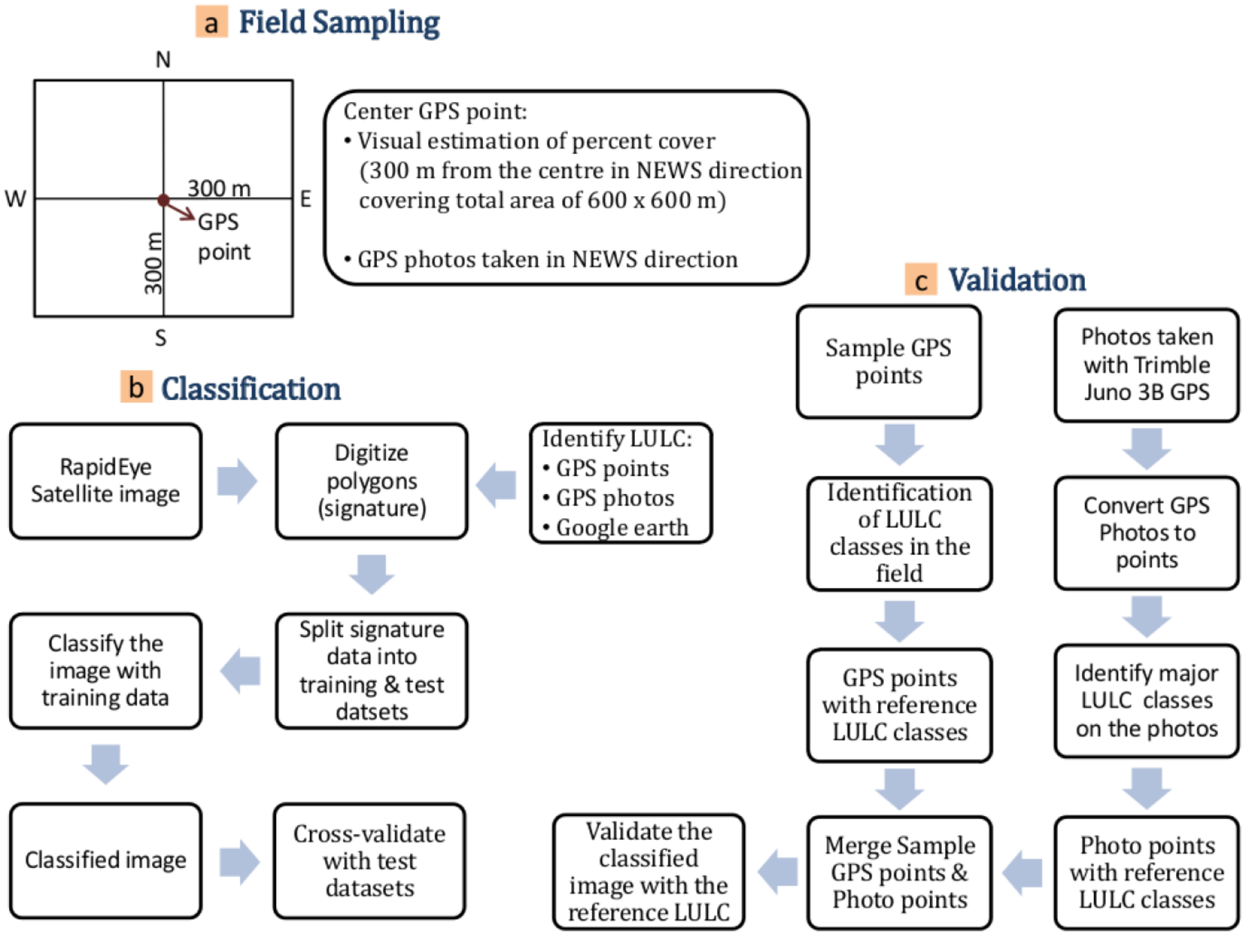

Figure 2 General workflow of a) Field data sampling b) Image classification c) Validation of classification results

2.4 Land use/land cover classification

The Random Forest (RF) classifier (Breiman 2001) was used to classify the RapidEye images in order to derive LULC classes using R 3.0.2 statistical software package (R Development Core Team 2008). This method uses an ensemble of tree-like classifiers similar to Bagging Trees in which bootstrap samples are drawn to construct multiple trees (Breiman 2001). Breiman (2001) stated that RF is a refinement of Bagging Trees, since it improves bagging by "de-correlating" the trees. With RF a large number of trees (500 to 2,000) are grown. Unlike Bagging Trees, in RF each tree is grown with a randomized subset of predictors from which the name random forests is derived. Trees are grown to maximum size without pruning, and are aggregated by averaging to select only the best split among a random subset at each node (Breiman 2001).

Random Forest classifier searches a random subset of features from the total number of predictors to find the best split at each tree node in order to minimize the correlation between classifiers in the ensemble. The classifier ensembles are based on the concept that a set of classifiers performs better than individual classifiers (Breiman 1996). Since the resampling is not based on weighting, the RF classification method is not sensitive to noise or overtraining (Gislason et al. 2006). Moreover, the method has been widely used for classification since it provides high classification accuracy (Gislason et al. 2006, Prasad et al. 2006, Rodriguez-Galiano et al. 2012, Zhu et al. 2012, Conrad et al. 2014).

For the purpose of classification, eleven major LULC classes (see Table 1) were identified based on field observation of the study site. Accordingly, sample polygons (ESRI shape files) representing each class were digitized based on LULC data collected at 136 field sample plots and georeferenced GPS photographs taken at the centre of the plots. For each LULC class, 250 samples (pixels) were randomly extracted from the list of image features (Figure S1 in File S1) and split into training (63 %) and testing (37 %) datasets. Each tree is grown on the training datasets using the bootstrap sampling process. The number of trees in the forest (n_{tree}) and the number of random subsets of features tried at each node (m_{try}) were set to 1000 and 3, respectively. For the LULC classification, the five bands and indices calculated from the RapidEye images were evaluated for their importance in identifying different LULC classes. In RF, the importance of a feature is determined based on how often the feature was used in the tree construction process. Figure S1 in File S1 illustrates the relative importance of the features evaluated for the RF classification showing the most used and least used features.

After classification into the eleven classes, similar LULC types were grouped into major classes such as cropland, forest, meadows or fallowed cropland, shrubs and barelands. From classes listed in Table 1, classes 1(dense forest) and 2 (single scattered trees) were grouped into forest since they represent different types of forest. Similarly, classes 3 to 7 were grouped as cropland because they all represent areas of land used for growing crops. The boundaries of state farms and major settlement areas were digitized manually from the RapidEye images from high resolution Google Earth images and GPS points recorded during the field observation and overlaid on the produced LULC map.

2.5 Validation

For validation of the RF classification, as a cross-validation step, error measurements used were of twofold: errors calculated from the Out-Of-Bag (OOB) subset and that calculated from the test subset. Firstly, performance of the RF classifier was evaluated using cross-validation during the model training process. Each tree is grown using a bootstrapping technique that involves sampling in which some of the data are left out i.e. the Out-Of-Bag (OOB) sample, while some others are repeated in the sample (Breiman 2001). In the training process, 2/3 of the training data was actually used for tree construction leaving 1/3 as OOB. Since the OOB data was not used for tree construction, in parallel with the training step, the OOB samples were used for cross-validation. Secondly, independent test datasets were used to assess the performance of RF algorithm by calculating the proportion of test elements that were incorrectly predicted. Finally, confusion matrices were calculated for each predicted class and its corresponding reference class as well as the OOB and test error rates. The steps in the cross-validation of the classification result are shown in Figure 2b.

Besides the cross-validation step, reference LULC classes collected at the centre of the sample plots were used in combination with reference LULC classes identified from GPS photos taken in NEWS directions (Figure 2a). The GPS photos were converted to points using QGIS 2.0.1 software and the reference LULC classes were assigned to the points based on the photos. The sample GPS points were merged with the photo points and were used to validate the major LULC such as cropland, forest and meadows or fallowed croplands (Figure 2c). A total of 611 (120 GPS points taken at the center of the plot and 491 points extracted from GPS photos taken in four directions from the center point) were used for the accuracy assessment.

2.6 Identifying factors influencing undercover cropland area

Boosted Regression Trees (BRTs) (Leathwick et al. 2006; De'ath 2007; Elith et al. 2008), an ensemble method used for fitting statistical models was used to identify influential variables for cropland area. At each sample plot, undercover cropland area was calculated as the product of area of the sample plot and field estimated percent undercover cropland. Boosted Regression Trees combine algorithms of regression trees that use recursive binary splits to relate a response to their predictors and boosting that combines simple models to improve predictive performance (Elith et al. 2008). Moreover, BRTs are preferred since they capture complex structures that arise from spatial autocorrelation within a dataset. In contrast, with simpler modeling approaches, results are highly influenced by spatial autocorrelation in datasets (Crase et al. 2012). De'ath (2007) described BRTs as an additive regression model that undergoes stagewise fitting without changing existing trees when the model enlarges.

Boosted Regression Trees were constructed using R 3.0.2 statistical software package (R Development Core Team 2008) to identify the relationship between undercover cropland area and potential influential factors. The factors considered include elevation, slope, east aspect, west aspect, north aspect, south aspect, distance to the national park, and distance to settlement areas. Slope and aspect maps were derived from digital elevation model, while distance to the national park and distance to settlements were calculated from sample plot centers to the boundaries of the national park and settlement areas. These factors were selected for analysis since they often dictate agricultural activities in mountainous regions (Stage and Sales 2007, Yimer et. al 2006). The four aspect raster layers were extracted from aspect map as dummy values of 0 and 1. All the raster layers were rescaled to a grid size of 10 pixels.

Values of all the influential factors were calculated for the sample plots where undercover cropland area was estimated. The BRTs model was set with Gaussian error distribution, tree complexity of 2, learning rate of 0.008 and bag fraction of 0.75 while the maximum number of regression trees specified was 3000. The results of the relationship between the influential factors and undercover cropland area estimated in the field were plotted and visualized as fitted functions showing the relative importance of each influential factor as a percentage. In addition to the undercover cropland inside forests, influential variables were predicted for total cropland area per plot both from field estimated data and the RapidEye images for further understanding of factors determining the general patterns of cropland expansion in the region. See Elith et al. (2008) for details about Boosted Regression Trees and the model settings.

2.7 Prediction and mapping of the undercover cropland

The raster layers of influential variables tested using BRTs model in section 2.6 were used to predict and map the percentage cover of undercover cropland. Field estimated percentage undercover cropland data from 136 sample plots were used to predict the undercover cropland from the most influential factors such as elevation, slope and east aspect using Boosted Regression Trees. To obtain reliable result, the prediction was done using 16-fold cross-validation of the data. Hence, the final predicted undercover map is the result of the 16-fold cross-validation. Furthermore, the predicted map of undercover cropland was overlaid with the forest layer derived from the classification of RapidEye images to produce the final map of undercover cropland.

3. Results

3.1 Land use/cover types

The major LULC classes in the case study site are presented in Figure 1b. The major LULC types in the area include small-scale croplands and the state owned large-scale croplands. Forests are the other LULC types situated in the upper escarpments of the area. The upper most escarpments adjacent to the forest are *Erica arborea* shrublands. These shrublands are found mixed with rocky barelands in extremely rugged topography. Settlement areas consist of built-up areas mixed with croplands, meadows or fallowed croplands, and scattered trees. In the study site, there is a large reservoir that belongs to Melka Wakena hydropower station and is used by the government of Ethiopia to generate electricity. The area is near the BMNP and cropland has extended to parts of the national park shrinking the area which was previously part of the national park (Figure 1b).

3.2 Accuracy of classification

The OOB and test error rates of the RF classification for each LULC class are presented in confusion matrix in Table 1a and Table 1b respectively. Most of the LULC types were classified with an OOB error rate of 4.87% and test set error rate of 4.22%. The error rate in each class shows the proportion of misclassified observations in that class, whereas the average test error rate shows the proportion of misclassified observation for the entire dataset. The mean test error rate per class ranges from 0 to 10.77.

The OOB error value computed from the left out data during the training process showed a very good performance of the RF model with an average model accuracy of 95%. The calculated test set errors imply that all the LULC types were classified with an average accuracy above 95%. The numbers in the matrix show the number of samples from the actual class (reference class) that is correctly or wrongly predicted. For instance, in the training set, class 1 has 128 samples of which 121 (94%) are correctly classified while 7 (6%) are misclassified as class 2. In the test set, class 1 has 122 samples of which the 113 (92%) are correctly classified and 9 (8%) samples are misclassified as class 2. The values in confusion matrix of Table 1 for the rest of the classes can be also interpreted in a similar way. The matrices indicate major confusion between the "dense forest" and "single scattered tree" classes, but also between the class "single scattered trees" and "recently grown green crops". These overlaps are very well known and can be attributed to the spectral similarity among green vegetation classes.

Table 1a) Confusion matrix showing the error rate of the training dataset (OOB error rate)

		Predicted											
	LULC_ID	1	2	3	4	5	6	7	8	9	10	11	Class error
Reference	1	121	7	0	0	0	0	0	0	0	0	0	0.05
	2	4	124	5	5	0	1	0	0	0	0	0	0.11
	3	0	2	108	1	0	0	3	6	0	0	0	0.10
	4	0	2	0	120	0	0	0	0	0	0	0	0.02
	5	0	0	0	0	123	0	0	0	0	0	2	0.02
	6	0	0	0	0	1	123	1	0	0	0	0	0.01
	7	0	0	1	0	0	1	111	0	0	0	0	0.02
	8	0	0	1	1	0	0	0	130	0	0	0	0.02
	9	0	0	0	0	0	0	0	0	121	1	0	0.01
	10	0	0	0	0	3	0	0	0	1	117	9	0.08
	11	0	0	0	1		3	1	0	0	5	107	0.11
Average OOB estimate of the error: 4.87%													

Table 1b) Confusion matrix showing the error rate of the test dataset

		Predicted											
	LULC_ID	1	2	3	4	5	6	7	8	9	10	11	Class error
Reference	1	113	9	0	0	0	0	0	0	0	0	0	0.07
	2	5	101	3	1	0	0	1	0	0	0	0	0.09
	3	0	11	116	1	0	0	0	2	0	0	0	0.11
	4	0	0	0	128	0	0	0	0	0	0	0	0.00
	5	0	0	0	0	119	0	0	0	0	0	3	0.02
	6	0	0	0	0	0	125	1	0	0	0	0	0.01
	7	0	0	0	0	0	0	137	0	0	0	0	0.00
	8	0	0	1	1	0	0	0	116	0	0	0	0.02
	9	0	0	0	0	0	0	0	0	128	0	0	0.00
	10	0	0	0	0	0	1	0	0	0	118	4	0.04
	11	0	1	1	0	4	2	0	1	0	5	116	0.11
Average estimate of the error rate for the test dataset: 4.22%													

Key:

LULC_ID	**Description of classes**	**Broad category**
1	Dense forest	Forest
2	Single scattered trees	Forest
3	Recently grown green crops	Cropland
4	Close to ripening green crops	Cropland
5	Ripened crops or recently harvested land	Cropland
6	Cultivated land_dark colored wet soils	Cropland
7	Cultivated land_grey colored dry soils	Cropland
8	Meadows and fallowed croplands	Meadows or fallowed croplands
9	Reservoirs	Reservoirs
10	Shrublands	Erica arborea shrubs
11	Bare rocks	Rocky barelands

* LULC_ID: Land use/land cover ID

However, the high resolution of RapidEye data may be one reason that mixed pixel problems have less influence on classification accuracies as observed e.g. by Cord et al. (2010) who used ASTER 15 m datasets for classification of Savannah landscapes in West-Africa. Minor confusion between

"*Erica arborea* shrubs" and "bare rocks" can be explained by the topography, because both classes mainly occur in rugged terrain where shadows occur which can cause uncertainty during classification. The validation results for the three major categories of LULC classes (Cropland, forest, meadows or fallowed croplands) is presented in Table 2. These LULC were considered for further validation besides the cross-validation step since they are central focus of the research about the undercover cropland.

Table 2 Accuracy assessment of classification results for dominant land cover classes in the study site.

	Ground truth points					
	LU_Name	Croplands	Forests	Meadows or fallowed croplands	Total	Class accuracy (%)
Predicted	Croplands	**379**	8	16	403	94.04
	Forests	8	**111**	6	125	88.80
	Meadows or fallowed croplands	4	8	**71**	83	85.54
	Total	391	127	93	611	
	Sum of correct predictions				561	
	Overall Accuracy				91.82	
	Kappa Coefficient				0.84	

Cropland and forest were classified with accuracy of 94 % and 89 % respectively. The accuracy of classification for the class meadows or fallowed croplands was 86 %. The overall accuracy achieved for the three major LULC classes was 92 % with a Kappa coefficient of 0.84 (see Table 2 for details). In general, the cross-validation and validation results presented in Tables 1 and 2 showed that the RF classification was performed with an acceptable accuracy.

3.3 Relative importance of factors influencing undercover cropland area

The Boosted Regression Trees fitted model for each of the influential factors of undercover cropland area calculated from field estimated percent cover is presented in Figure 3. The area of undercover cropland rises with increasing elevation, slope, and distance to major settlements while it decreases with distance from the national park. However, after certain limit the graph remains constant with a value of 0 showing that there is no undercover cropland above such limits. Similar patterns of the relationships between aspect and undercover cropland area were observed (Figure 3).

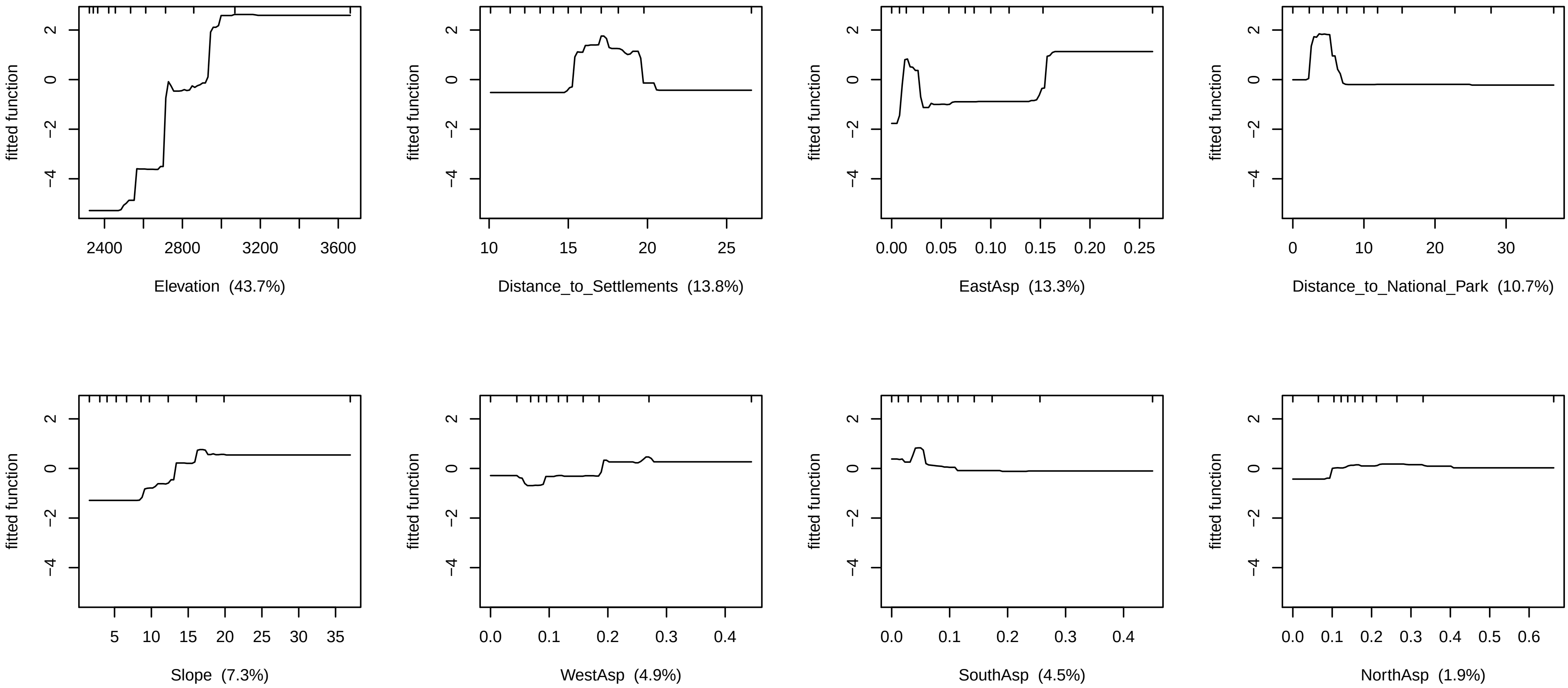

Figure 3 Boosted Regression Trees fitted model showing the relative importance of influential factors of undercover cropland area calculated from field estimated percent cover.

The results of the BRTs model of undercover cropland area showing the relative influence of the variables considered and predictive performance of the model are summarized in Table 3a and b respectively. The Boosted Regression Trees model for area of undercover cropland calculated from field estimated percent cover can explain 70.35 % of the total deviance. The deviance was determined using Gaussian family distribution function and is a measure equivalent to R^2.

Table 3a) Influential factors of undercover cropland area (ha) calculated from field estimated percent cover derived using BRTs model with tree complexity, *tc* of 2, learning rate, *lr* of 0.008 and bag fraction, *bf* of

Explanatory variables	**Relative influence (%)**	**Rank**
Elevation	43.7	1
Distance to Settlements	13.80	2
East aspect	13.30	3
Distance to National Park	10.70	4
Slope	7.30	5
West aspect	4.90	6
South aspect	4.50	7
North aspect	1.90	8

Table 3b) Predictive performance of the BRTs model

Mean total deviance	**Mean residual deviance**	**Estimated CV Deviance**	**CV correlation**
41.25	12.23	26.94 (SE ± 4.5)	0.59 (SE ± 0.05)

Elevation is the most influential factor accounting for more than 43 % of the variance explained. Distance to settlements and east aspect consist of about 27 % while distance to national park and slope consist of about 12 % of the total deviance explained. West aspect, south aspect and north aspect were found to account for about 11 % of the deviance.

Besides the undercover cropland, for comparison, the BRTs results of cropland area and its influential factors is provided in the electronic supplementary information. Cropland area here refers to the area of land in sample plots where crops are grown i.e. including the area of cropland estimated as an undercover and the area of cropland in open areas. Figure S2 in File S1 shows BRTs fitted model for influential factors of cropland area calculated from plot-level field estimated percent cover. The proportion of total deviance explained by slope, elevation and distance to national park are 34.7, 30 and 19.7 % respectively while aspect appears less influential for cropland area estimated at sample points (Figure S2 in File S1). The BRTs fitted models for plot-level cropland area calculated from RapidEye images (Figure S3 in File S1) show that elevation is most influential factor accounting for 57.7 % of the total deviance explained. Due to difficulty in calculating undercover cropland from RapidEye images, the calculated cropland area here refers to what can be captured with the images without including the undercover cropland. Distance to national park and distance to settlements each account for 8.7 % of the deviance. Aspect appears less influential compared with the aforementioned parameters (Figure S3 in File S1). For details on the relationship between the holdout deviance and the number of trees in BRTs model for undercover cropland area calculated from field estimated percent cover, cropland area calculated from field estimated percent cover and RapidEye images, refer to Figure S4 in File S1.

3.4 Predicted undercover cropland

The land use in the study site includes cropland inside the remnants of forests. Though the classification of RapidEye images shows forest as dominant LULC type in the upstream areas, there is cropland under the tree canopies. The undercover cropland area predicted using only the most influential variables slope, elevation and east aspect ranges from 0 to 32 m^2 per pixel (Figure S5a in File S1). Undercover cropland predicted from all the topographic variables elevation, slope, east aspect, west aspect, north aspect and south aspect using BRTs is presented in (Figure S5b in File S1). Probability of undercover cropland in the area ranges from 0 to 25 m^2 per pixel when all topographic factors are included in the prediction. Figure S6 in File S1 compares undercover cropland area predicted using all variables (Figure S5b in File S1) with selected variables slope, elevation and east aspect (Figure S5a in File S1). The scatter plot showed that there is no much difference between undercover cropland area predicted using only most influential variables and all the variables. Figure S7 in File S1 presents the comparison of cropland area calculated from RapidEye images and area estimated in the field. In this study, we assumed that remote sensing underestimates area of cropland since undercover cropland cannot be detected. However, results at some of the sample plots showed that classification of RapidEye images overestimated cropland area which might be due to error in classification of LULC classes such as meadows as croplands (Figure S7 in File S1). Although classification of remote sensing images provides useful information, it is usually subjected to unavoidable uncertainties that are calling for more research in this discipline. The undercover cropland map produced by overlaying the probability map with the forest layer from RapidEye image classification is shown in Figure 4.

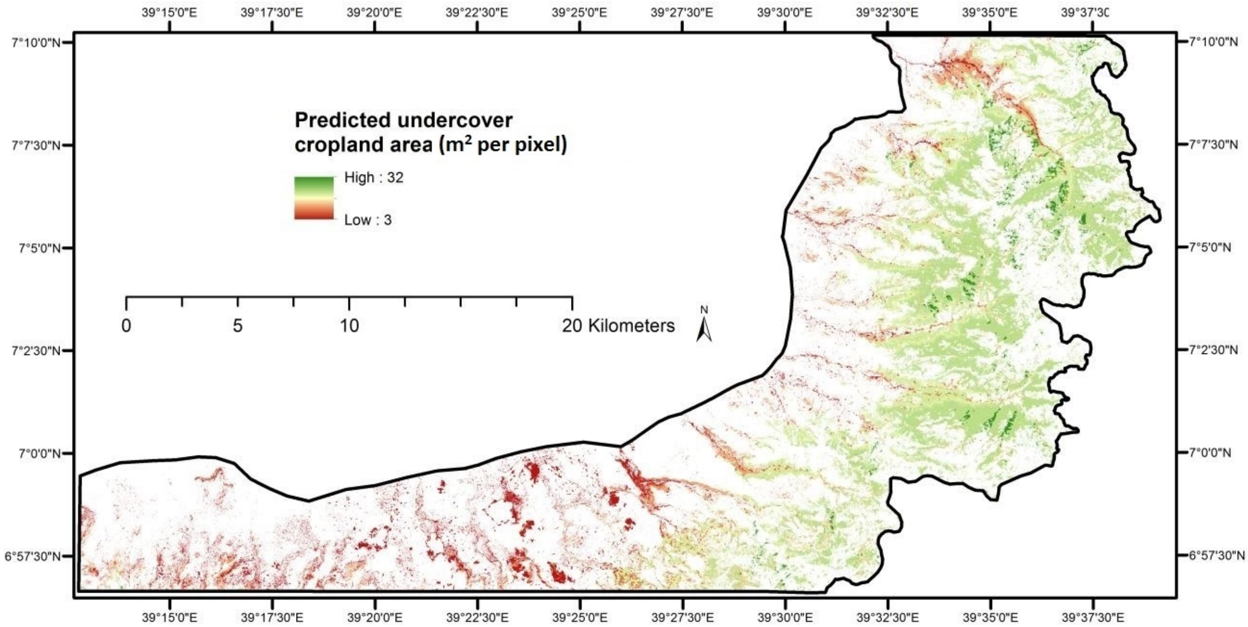

Figure 4 Undercover cropland area predicted from most influential topographic factors identified using Boosted Regression Trees (Pixel size of 100 m^2).

Undercover cropland is located in the upper escarpments though there is no undercover cropland in the upper most extremes of the site (Figure 4). The upper most extremes are dominated with dense *Erica arborea* shrubs and are not suitable to grow crops due to the extremely cold climatic condition and also the dense shrubs that require complete clearing for growing crops. Thus, the larger portion of undercover cropland forms a belt in the upper escarpments of the study site (Figure 4). Field observations confirmed that this belt is dominated with *Juniperus procera* trees. The undercover cropland forms a vertical strata with cropland as undergrowth and trees being the upper canopy (Figure 5). As it was observed in the field, the major crop cultivated inside the forest is wheat. Reasons for this preference of farmers are most likely the high market demand for wheat and provision of improved seeds and fertilizer by the government due to its recent plan to improve crop production.

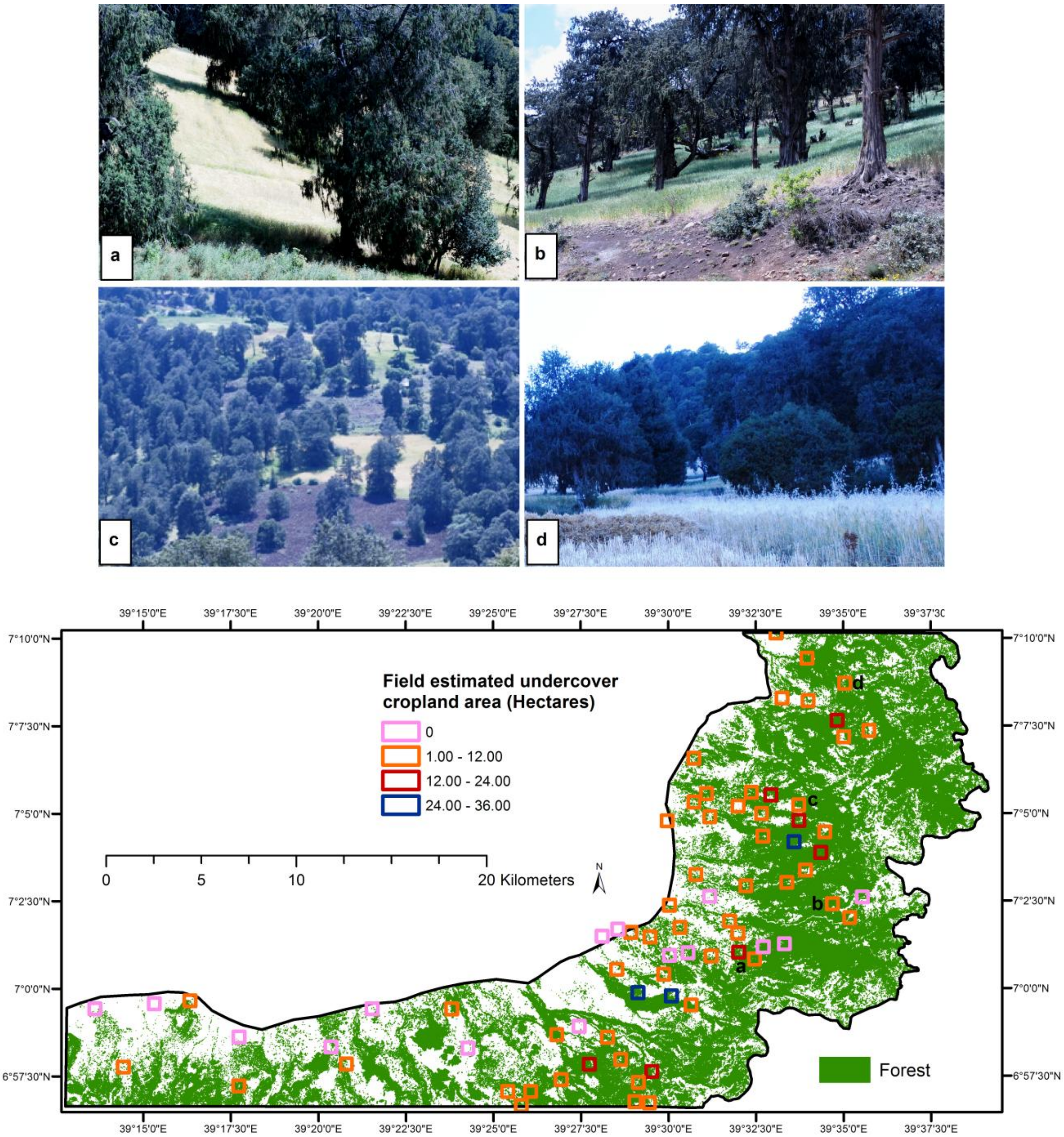

Figure 5 Undercover cropland area calculated from field estimated percent cover for selected sample plots with an area of 36 hectares. Photos labeled ***a*** to ***d*** show close range view of the undercover cropland taken at the location on the map labeled with the same letters.

The photos in Figure 5 show a close-range view of undercover cropland inside forests from sample plots. They reveal hidden cropland inside the areas that was classified as forest using the RapidEye images which mainly capture view of forest canopy from top. Cropland was observed inside forests including very steep terrains that were entirely covered with forest and/or with semi-open woody pasturelands that were previously used for livestock grazing.

4. Discussion

4.1 Influential factors of undercover cropland

Growing of food crops in the Bale Mountains involves not only cultivation of open lands with moderate slope but also cultivation inside forests in the upper escarpments. The findings of this study confirmed that topographic parameters such as elevation, slope and aspect are important factors that influence cropland area in mountainous regions. These parameters were found also important determinants of soil properties and vegetation types in the Bale Mountains (Yimer et al. 2006a, 2006b). Similar studies in mountainous areas also demonstrated that elevation, slope and aspect are among the influential factors that need to be considered in mountain ecosystem conservation and habitat management (Grêt-Regamey et al. 2012, Hole et al. 2011, Littell et al. 2012, Pollock et al. 2012).

In the Bale Mountains, there is difference in the impacts of topographic parameters on cropland area as a whole and the area of cropland which is cultivated as an undercover. For instance, inverse relationship was observed between cropland area and topographic parameters such as elevation above sea level and slope (in degrees) which conforms to the findings in other mountainous areas (Yuejiao 2013). However, area of cropland cultivated as an undercover showed increment with increasing elevation and slope inside semi-protected forests. The extremely steep terrains correspond to high elevation areas that were not suitable for growing cereal crops. Nevertheless, recently farmers started growing crops in these areas which is an indication of impacts of climate change in the region. Undercover cropland is influenced also by topographic aspects that modify microclimate conditions. East lying aspect was found more determinant compared with other topographic aspects. The main reason for this may be the exposure of land under forest canopies to morning sunlight which provides favorable condition for vegetation growth inside forests (Wondie et al. 2012).

Besides the topographic parameters, the extent of undercover cropland was found to be influenced by location parameters such as distance to national park and settlement areas. There is a positive relationship between cropland area and distance to the national park whereas the area of cropland cultivated as an undercover showed inverse relationship with distance to national park. An inverse relationship might result from the fact that areas close to national parks are relatively protected and hence, farmers' only option has become growing crops as an undercover. Cropland area in general increases close to settlement areas but area of cropland cultivated as an undercover inside forests decreases near major settlement areas.

Generally, the study indicated the major topographic and location parameters that limit human activities regarding growing of food crops in the mountainous region. The pattern of growing crops as an undercover inside forests in the mountain escarpments could have series consequences on ecosystem services demanding for prompt solutions to address the ongoing challenge in the region. The potential consequences on ecosystem services and the challenges of growing crops as undercover are discussed in sections 4.2 and 4.3 below.

4.2 Consequences on ecosystem services

The study site we investigated supplies diverse ecosystem services that are essential for livelihood of the local people. The undercover cropland in this mountainous region thus has multifaceted impacts on supplies of these ecosystem services. For instance, the forest in the area is the major source of timber and fuelwood for the local people and to markets in the surroundings. However, the recent undercover growing of crops inside the forest in the upper steep slope areas gradually degrades the forest thereby declining supplies of timber and fuelwood. Moreover, most of the forested areas where undercover cropland is going on was previously mixed with pasture. Hence, cultivation of cropland as an undercover may decrease the supply of fodder for livestock, indirectly reducing the livestock production (Baptist et al. 2001, Stephens 2001).

Cropland under forest canopies often exposes soil to erosion especially in the extremely steep terrains (Blanco and Lal 2010; García-Ruiz 2010). In addition, land degradation is likely to happen as more fertile soil is washed away. This may in turn damage the agricultural prospects as well as the supplies of other ecosystem services in the area (Clark 2012). As it was observed during the field surveying, soil that is eroded from the upstream area of the Bale Mountains has already been a threat to the supply of electricity by the local hydropower, Melka Wakena, due to the deposition of sediments in the reservoir. During rainy seasons the hydropower reservoir is usually filled with sediments coming from the upstream area. Sediment deposition in the reservoir increases the cost for cleaning and maintenance of the reservoir if undercover cropland continues without considering preservation of forests in the upstream areas. Increased runoff from the upstream areas and sediment deposition in the rivers and reservoir affects also the supplies of clean water to nearby beneficiaries (Nelson et al. 2009; Ayanu et al. 2011; Nguyen et al. 2013).

4.3 Challenges in transforming an undercover cropland into a sustainable agroforestry system

Conversion of open forests with herbaceous layer to undercover cropland inside forests in the Bale Mountains cannot be regarded as a sustainable agroforestry system. The undercover cropland lacks the following major features of an agroforestry system that need to be addressed.

Selection of tree-crop combination: An agro-forestry system involves multistory land use and is widely acknowledged for its capacity to ensure sustainable land use and resource management (George et al. 2012, Smith et al. 2012). Traditional agroforestry is usually a multistory composition of selected multipurpose trees, crops like maize, fruit trees, and vegetables (Alebachew 2012, Plath et al. 2011). Agroforestry systems can be used as a remedy for severe environmental problems in highland areas but require selection of proper species of trees and crops (Mahboubi et al. 1997; Khybri et al. 1992, Cao et al. 2010; Zhang et al. 2013). Unlike traditional agroforestry systems involving planned selection and growing of tree-crop combinations, the undercover cropland is intended mainly for expanding cropland area without proper selection of tree-crop combination.

Management of trees and crops: In a well-managed agroforestry system, growing crops like wheat under tree canopies (e.g. Eucalyptus) provides favorable microclimate conditions for the crops (Kohli and Saini 2003; Singh and Sharma 2007; Smits et al. 2012). Tree canopy structure and distance from crops affects crop performance (Sharma 1992; Singh et al. 1993; Li et al. 2008). In some cases, toxic effects from trees could reduce the crop yield (Singh et al. 1998; Gill et al. 2009). Management practices in an agroforestry system depend on the crops growing under the canopies (Anthofer et al. 1998). Considering the aforementioned typical features of tree-crop combinations, the undercover cropland lacks proper management of trees and crops as a multistory land use since the main goal of the farmers is to find a land for growing food crops.

***Farmers' lack of experience in agroforestry*:** In the Bale Mountains, traditional knowledge of agroforestry is limited because the people in the area are mainly used to monocropping and livestock production. Thus, the undercover cropland introduced in the area brings forth dilemmas as to whether the farmers are adopting the knowledge of agroforestry from other parts of the country or creating a room for clearing forests and expanding cropland in unoccupied forest land restricted by the government. It was introduced by the local farmers as a strategy for acquiring more land for growing crops inside remnants of the forest in the uplands where clearing of forest is restricted by the government. The system emerged as a result of desperate needs for food crop production and resembles a traditional agroforestry system because it involves growing of crops under tree canopies.

In general, given its current status, the undercover cropland would not eventually develop to an agroforestry system and it will only aggravate forest degradation. Thus, it can only be considered as an initial stage of deforestation which will later end up in complete clearing of the forests by gradually decreasing the forest density (Peres and Schneider 2012). The use of open forests for livestock production instead of undercover cropland might be a more sustainable land use. At least it was a very well established traditional land use, e.g., in the European Alps known as wood pasture (Grimmi et al. 2008).

5. Conclusions

Although satellite image classification can be used for LULC mapping, assessment of undercover cropland inside forests requires detailed field surveying. The study confirmed that analysis of field observed percent cover and topographic parameters such as elevation, slope and aspect using Boosted Regression Trees enables assessment of undercover croplands in forested areas which otherwise are not detectable with remote sensing data. The findings showed that extent of undercover cropland is determined by elevation, slope, aspect, distance to national park and distance to settlements. Among the topographic parameters elevation, slope and east aspect were found the most influential factors for growing of crops inside forests having a positive relationship between undercover cropland area. Similarly, distance to settlements showed positive relationship with undercover cropland area while an inverse relationship was observed with distance to national park. Therefore, while planning land use and ecosystem management in mountainous regions, decision-makers should take into account the relative importance of these parameters.

Further research is essential to find methods for designing and implementing policies that ensure sustainable supplies of ecosystem services and nature conservation such as Payments for Ecosystem Services (PES) schemes. Stakeholders such as farmers, government officials, environmental authorities, Hydropower Company, and the Bale Mountains National Parks (BMNP) should be incorporated in decision making. Further research is needed also to create awareness and find alternative solutions for the livelihood of the local people to reduce the expansion of cropland in extremely steep areas of this mountainous region. Since the undercover cropland resembles a traditional agroforestry system, there is potential to transform it in to a more sustainable agroforestry system. The following points should be considered to develop an undercover cropland into a sustainable agroforestry system. Firstly, proper selection of tree-crop combinations that are suitable for mountainous areas needs to be identified and used by the farmers in the area. Secondly, management practices for trees and crops in the undercover cropland areas should aim at ensuring sustainable supplies of ecosystem services. Lastly, knowledge transfer from well-established agroforestry areas to the mountainous undercover cropland areas is essential.

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Unveiling undercover cropland inside forests using landscape variables: a supplement to remote sensing image classification

Supporting Information

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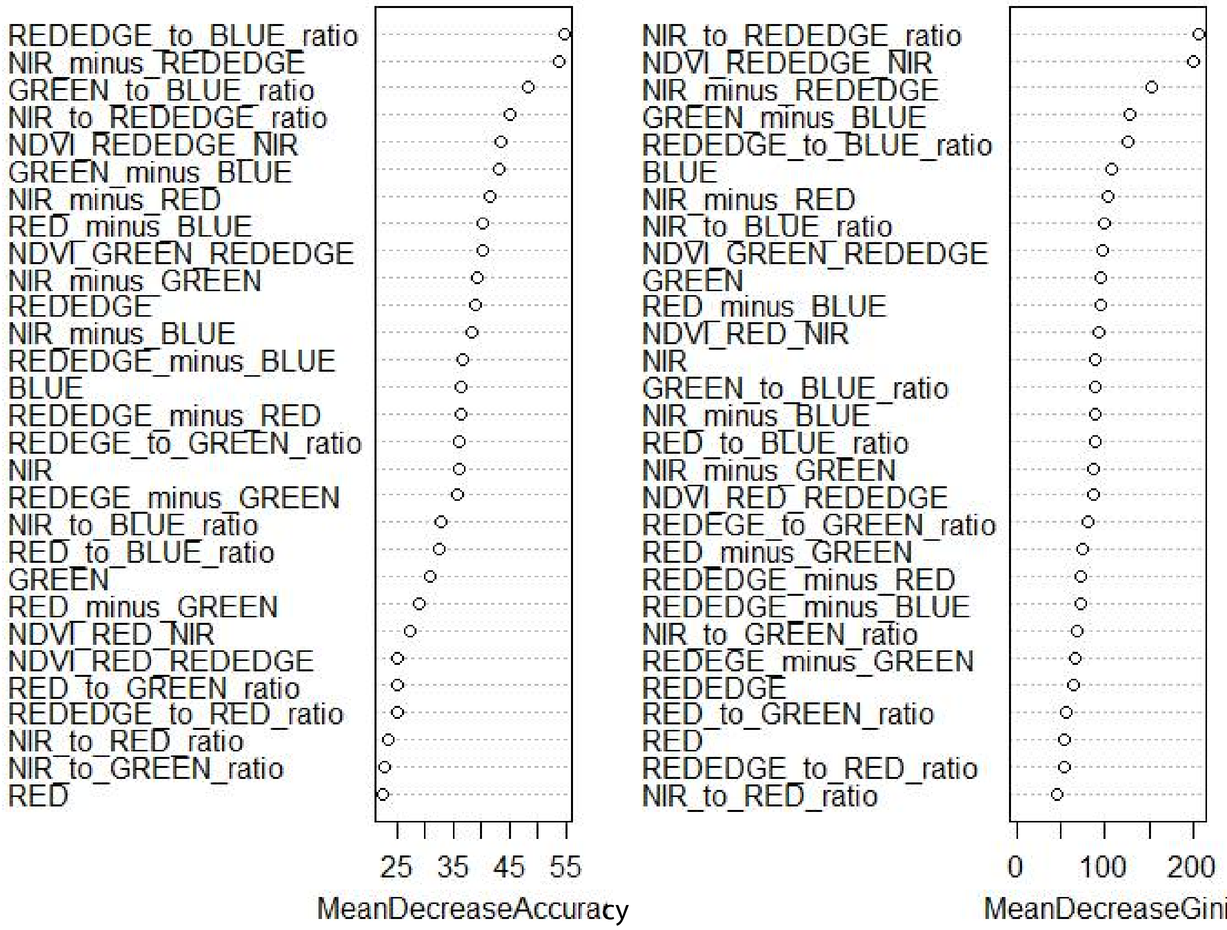


Figure S1 Relative importance of features used for classification of RapidEye images using RF classification.

Mean Decrease in Accuracy (MDA) indicates the extent of decrease in accuracy in the Out-Of-Bag (OOB) samples when a variable is excluded from the predictive model. Variables with higher values of MDA are more important for classification. Mean Decrease Gini (MDG) defines the total decrease in Gini impurity (measure of datasets impurity) when a given variable is used for spliting at a node of all trees. Variables with higher MDA values are more important for classification (cf. Golino and Gomes 2014).

Reference

Golino, H. F., & Gomes, C. M. A. (2014). Visualizing Random Forest's Prediction Results. Psychology, 5(19), 2084.

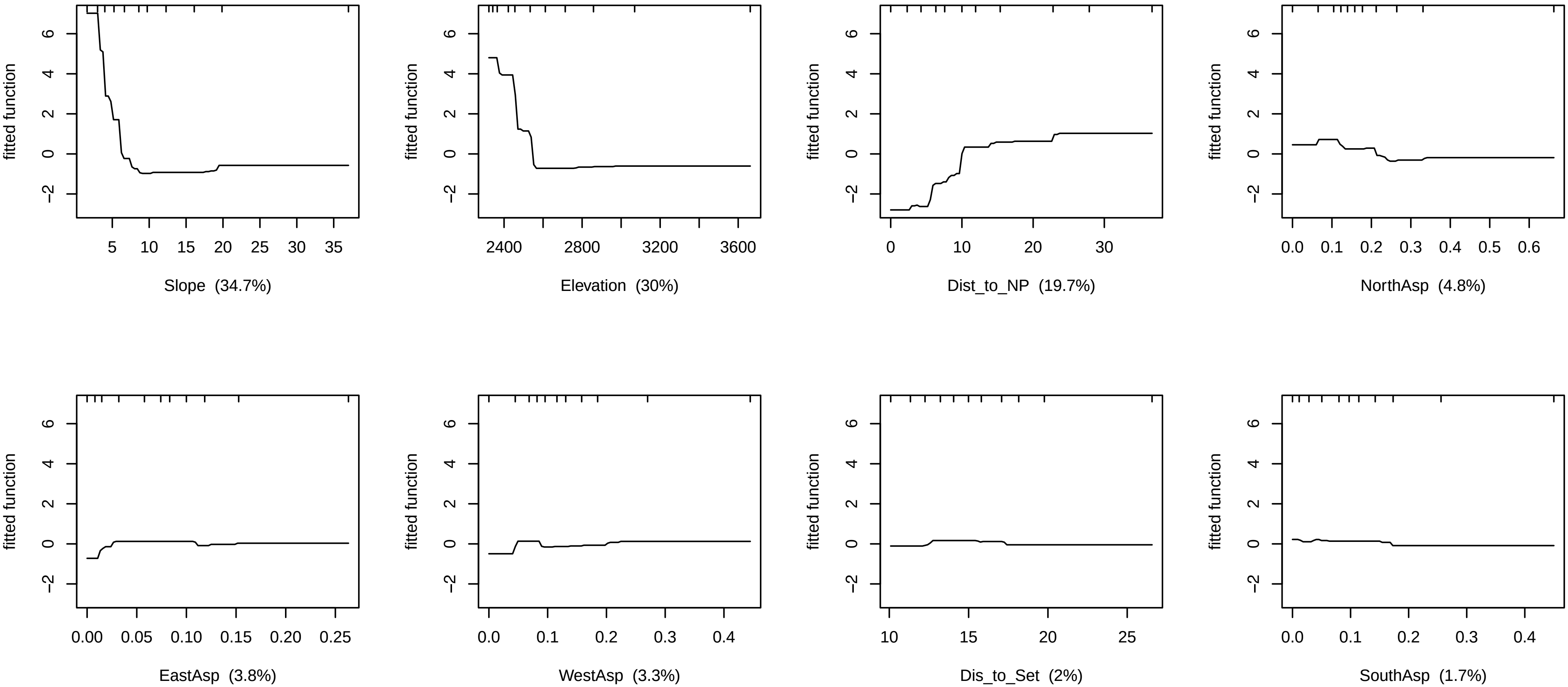


Figure S2 Boosted Regression Trees (BRTs) fitted model showing relative importance of influential factors of cropland area calculated from field estimated percent cover

Variables with higher values are more influential. For instance, Slope and Elevation are more important than distance to settlements and South Aspect. Field estimated cropland area showed inverse relationship with Slope and Elevation while it increases with increase in distance from the national park.

Key

* Dist_to_NP: Distance to National Parks; NorthAsp: North Aspect; EastAsp: East Aspect; WestAsp: West Aspect; Dis_to_Set: Distance to Settlements; SouthAsp: South Aspect

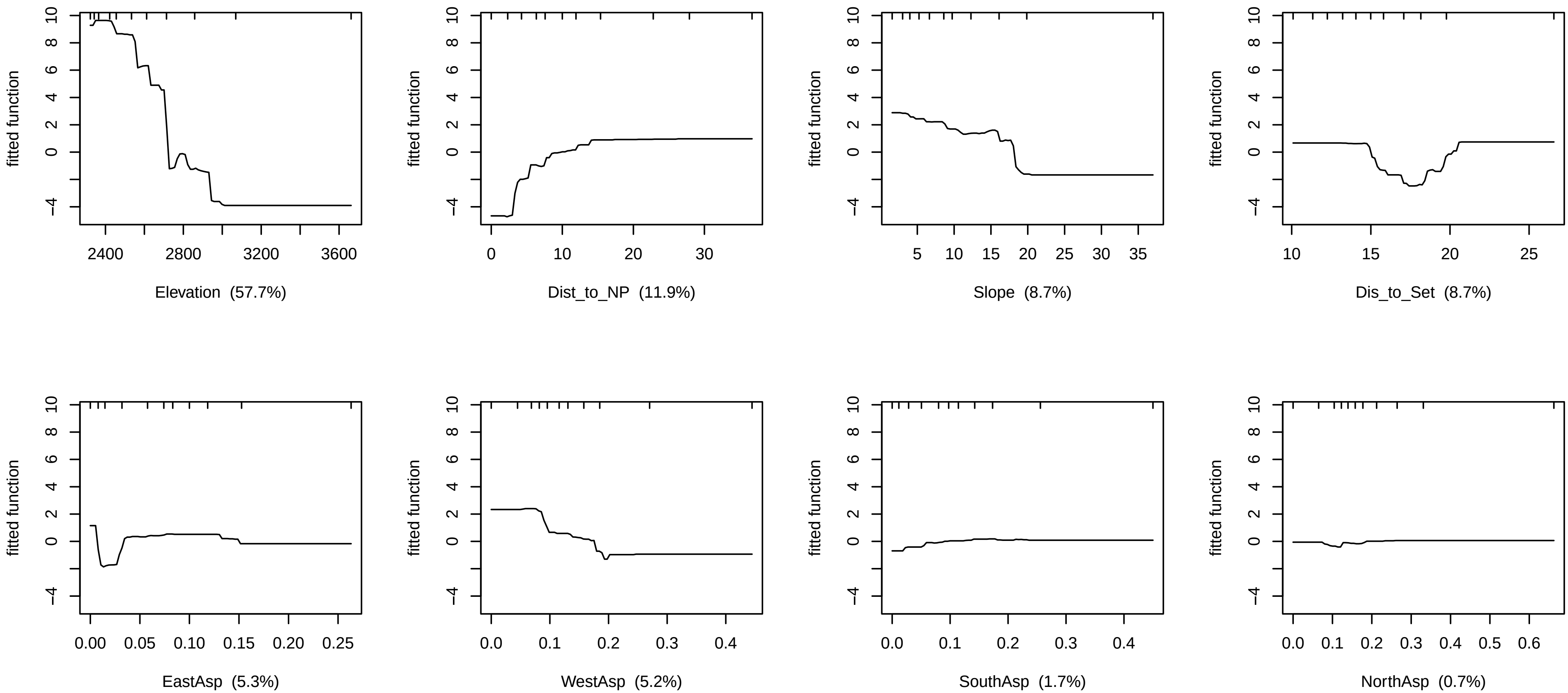
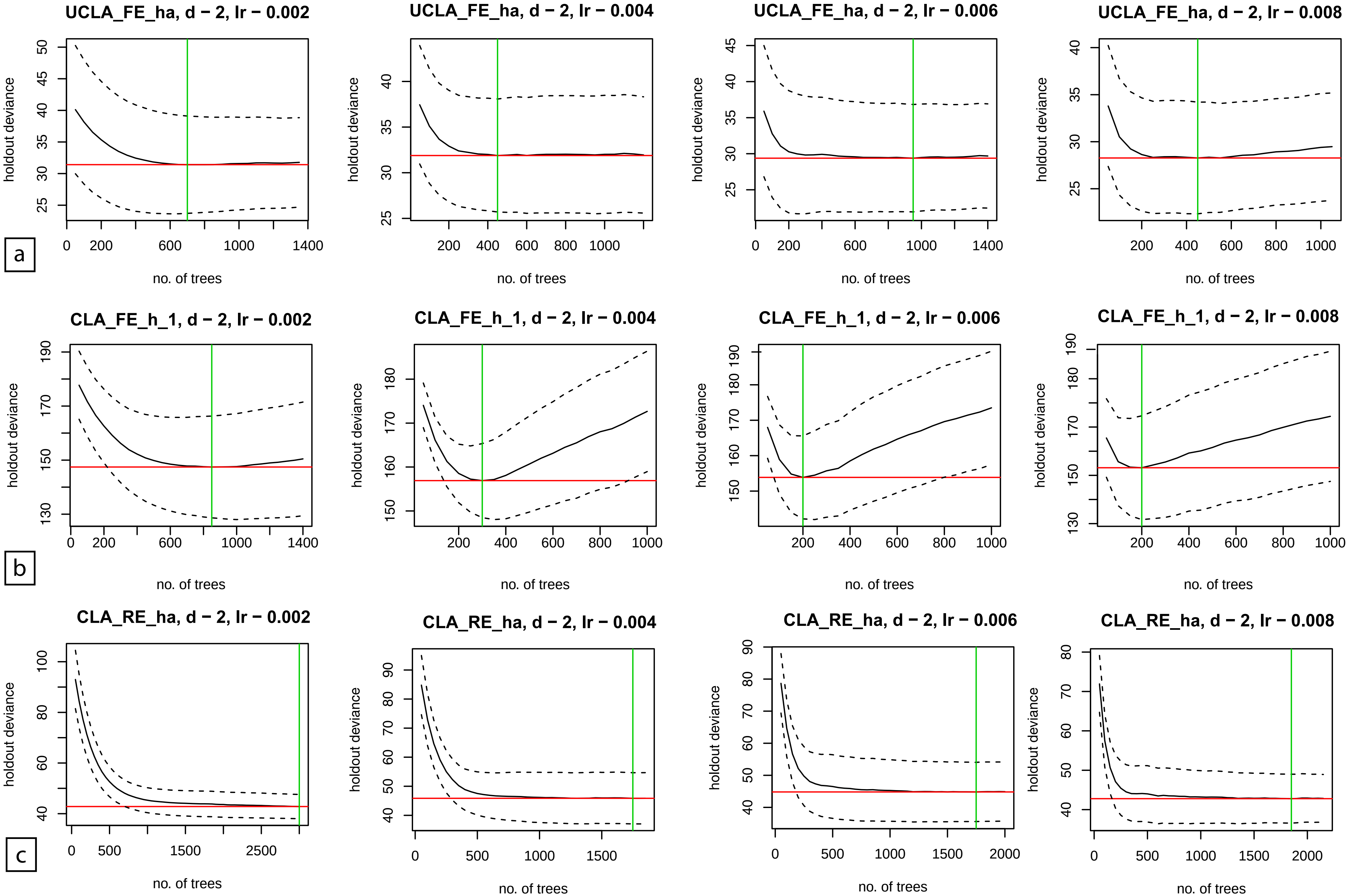


Figure S3 Boosted Regression Trees (BRTs) fitted model showing relative importance of influential factors of cropland area calculated from RapidEye images

Variables with higher values are more influential. For instance, Elevation is more important than North Aspect. Cropland area calculated from RapidEye image classification showed inverse relationship with Elevation while it increases with increase in distance from the national park.



Key: UCLA_FE: Field Estimated Undercover Cropland; CLA_FE: Field Estimated Cropland Area; CLA_RE: Cropland Area calculated from RapidEye Images

Figure S4 Number of trees vs total holdout deviance for a) undercover cropland area calculated from field estimated percent cover b) cropland area calculated from RapidEye images c) cropland area calculated from field estimated percent cover.

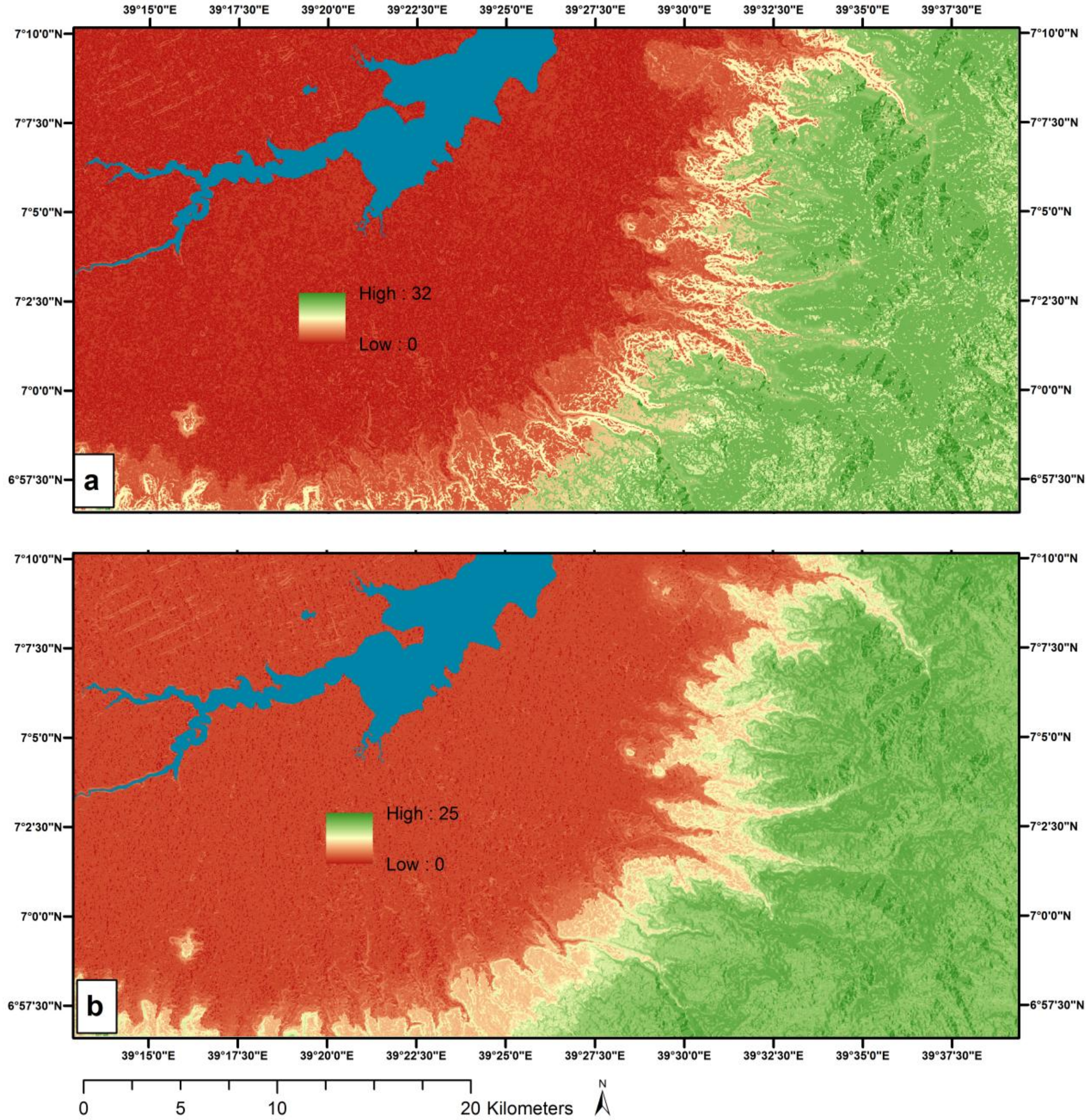


Figure S5 Predicted undercover cropland in m^2 per pixel using a) only most influential factors slope, elevation and east aspect b) all topographic factors slope, elevation, east aspect, west aspect, south aspect and north aspect. Pixel size is 100 m^2.

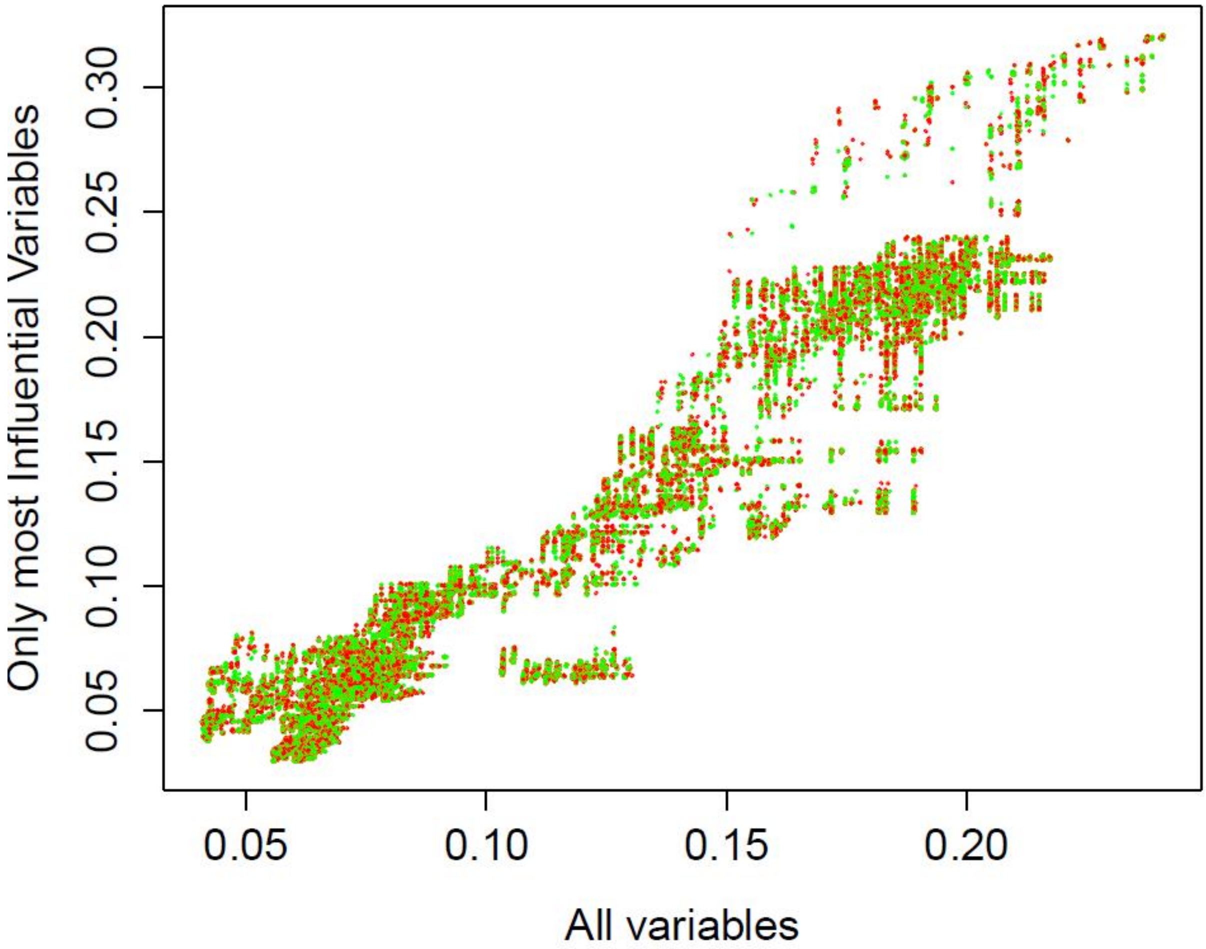


Figure S6 Comparison of undercover cropland area (hectares) predicted from X, all variables slope, elevation, and aspects (east, west, south and north) with Y, only most influential variables (slope, elevation and east aspect).

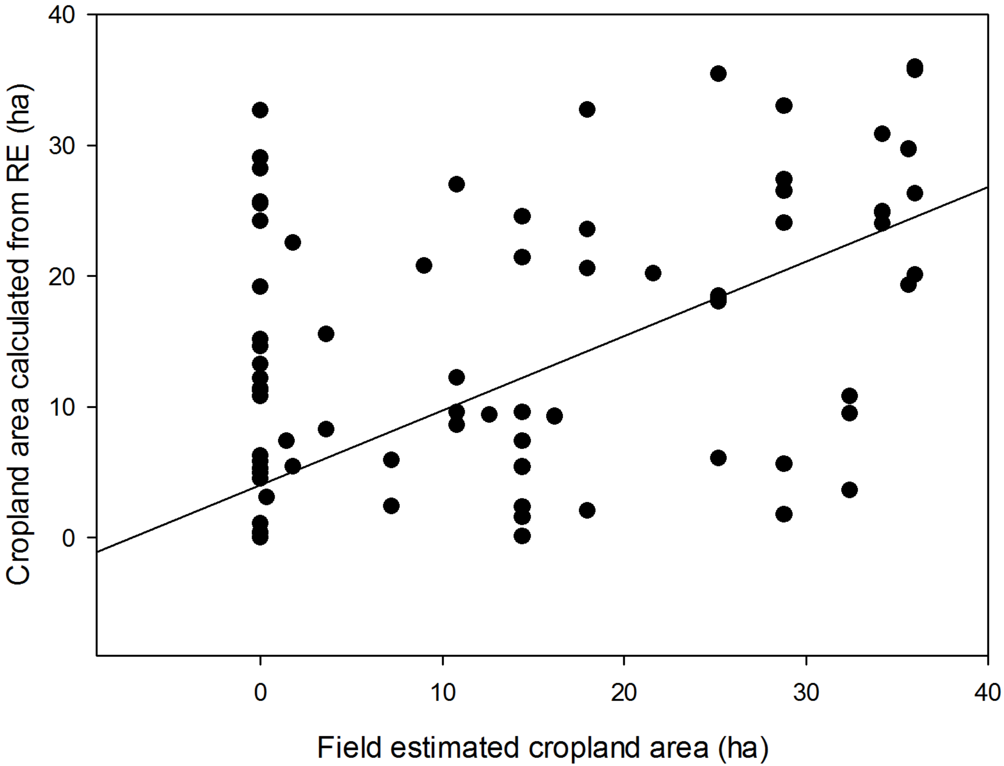


Figure S7 Comparison of cropland area (hectares) X, estimated in the field and Y, cropland area calculated from RapidEye images.

Chapter 5

Synthesis and outlook

Chapter 5 Synthesis and outlook

In this thesis, application of remote sensing in assessing land cover in fragile lands and ecosystem services was explored. The synopsis (Chapter 1) provided general background about fragile lands, land use/land cover (LULC), ecosystem services, and the major research questions of the dissertation. The case studies in this dissertation highlighted the pressing problems in land cover that are detrimental for ecosystem services in two distinct fragile lands i.e. semi-desert drylands and mountainous areas in Ethiopia.

Firstly, the threatening effects of introducing a species as an ecosystem engineering was assessed (Chapter 3) based on invasive species, *Prosopis juliflora*, in the fragile semi-desert area of the Afar regional state of Ethiopia. The findings of this study indicated that, although *P. juliflora* was introduced as an ecosystem engineer mainly for regulating soil erosion, it became highly invasive which confirms Hypothesis 1 which states that *Prosopis juliflora* invasion of the Awash basin increased over the past decade. The invasion mainly of the wetlands has had negative impacts on the supply of ecosystem services such as provisioning and cultural services. The impacts vary according to the land-use/land-cover types affected and among social groups depending on the impact of the species on their livelihoods. The trends in invasion of *P. juliflora* also showed change in the spatial distribution due to efforts in the past that only involved the clearing of invaded irrigated croplands and grasslands. The species continued to spread to new areas that were not previously invaded which made complete eradication impossible. Besides the Awash basin, *P. juliflora* has spread throughout Ethiopia and become invasive in areas such as Arba Minch, Raya Azebo, Diredawa, Borena and South Omo. Therefore, spreading of this invasive species raises high environmental concern that requires an immediate action.

Further research is needed to understand the *P. juliflora* invasion and its impacts on ecosystem services, as well as to identify appropriate approaches for controlling the spread of *P. juliflora*. Modeling, for example with the InVEST tool (e.g. Nelson et al 2009), or LUCIA (e.g. Ayanu et al. 2011), with the explicit inclusion of longer time scales and broader spatial scales is required in order to assess the impact of *P. juliflora* on ecosystem services at the landscape scale. In this context, it will be essential to distinguish between beneficiaries (nomads, agro-pastoralists, large scale farmers, and downstream residents) in order to specify in which way their well-being is affected by *P. juliflora*. Furthermore, emphasis should be given to management of *P. juliflora* before it drastically invades large areas throughout Ethiopia. The management practices for *P. juliflora* invasion control should be planned and implemented based on the invasive characteristics of the species and its perception by social groups in the affected regions.

Secondly, undercover cropland inside forests and its influential factors were investigated (Chapter 4) based on a case study site in the Bale Mountains of Ethiopia. The findings showed that with increasing demand for food crops, cropland cultivation could take place inside forests as an undercover where clearing the forest is restricted by the local government which eventually end up in deforestation (McWilliam et al. 2012). The influential factors for undercover cropland are elevation, distance to settlements, slope, east aspect and distance to national park with elevation being the most important factor. This conforms with Hypothesis 2 which states that topographic parameters such as elevation, slope and aspect as well as location factors such as distance to settlements and the national park influence undercover cropland inside forests in the Bale Mountains of Ethiopia. Therefore, ecosystem management efforts in such mountainous areas should be based on the relative importance of these influential parameters. For instance, elevation, slope and aspect are among the influential factors considered in mountain ecosystem conservation and habitat management (Grêt-Regamey et al. 2012, Hole et al. 2011, Littell et al. 2012, Pollock et al. 2012). The study also confirmed that application of Boosted Regression Trees on combinations of field observed land cover, topographic and location parameters enables assessment of undercover croplands inside forested areas.

Further research is essential to find methods for designing and implementing policies that ensure sustainable supplies of ecosystem services and nature conservation. Investigations are needed to create awareness and find alternative solutions for the livelihood of people to reduce the expansion of cropland to the extremely steep areas. For instance, modelling of ecosystem services and analysis of tradeoffs and synergies for land use scenarios using the InVEST modeling tool can be very useful.

5.1 Monitoring fragile lands and ecosystem services

The case studies in the drylands and mountainous regions of Ethiopia demonstrated that there is an urgent need for monitoring of fragile lands and impacts on ecosystem services. Fragile lands are highly threatened by global changes and hence their management raises global concern. The impact of detrimental cover types such as invasive species and growing of crops in steep slope areas is often aggravated in fragile lands due to high vulnerability and low capacity of people living in those areas (Rejmánek 2000, Robbins 2004, D'Antonio et al. 2004, Thomas and Reid 2007, Rejmánek and Richardson 2013). Therefore, continuous monitoring of LULC and its impacts is essential to develop applicable management strategies (Aranda and Oyonarte 2005, Bayramin et al. 2008, Cui and Shao 2005). Despite the efforts made in the past, globally, the impacts of invasive species on the multiple values of intensively managed lands and natural ecosystems continued to grow, highlighting the necessity of further studies in invasive species management.

5.1.1 Management guidelines for invasive species

In Ethiopia, there is no strong framework for the monitoring and control of invasive species. Therefore, a framework for fighting invasive species should be developed and implemented to prevent the loss of biodiversity and ecosystem services. The continued threat posed by invasive species calls for an interdisciplinary approach where scientists from various disciplines such as ecologists, botanists, economists, environmentalists and information technologists are involved for developing a concise management framework (Molnar et al. 2008). The concepts that should be included in the framework at global scale include:

- *Methods for quantifying impacts on ecosystem services:* Developing methods for quantifying impacts of invasive species for instance, using remote sensing and modeling tools would help to rank the invasive species based on the damage they cause. This can be used as a guideline for prioritizing management of the high risk species.
- *Database:* It is necessary to build databases for the already established invasive species and for every new species identified as an invasive. This will be useful for sharing relevant data worldwide, tracing the impacts and their regulation strategies.

- *Early warning system:* With the changing climate and rapid globalization, invasive species will continue to emerge worldwide. In some cases invasive species are not easily identifiable and/or considered as invasive before they largely threaten ecosystems capacity to supply services. Hence, incorporating an early warning system for similar agro-ecological zones where the new species emerged as an invasive would help to prevent the species from spreading.
- *Capacity to respond:* Management of invasive species requires understanding the local context in terms of responding to invasive species. The capacity to respond to an invasive species such as *P. juliflora* varies among social groups; hence, analysis of impacts of invasive species should consider social differentiation. In fragile lands (e.g. drylands), invasive species are more successful in spreading due to the competitive advantages of the species and low capacity of people to respond to the invasion. Therefore, fragile lands should be given high priority in the framework for regulation of invasive species.

Generally, the detrimental effects of invasive species are not questionable and the need for their management should get more emphasis. Introduction of new plant species to degraded areas may address short-term problems but once established, the new species could become more aggressive and turn to be invasive. Therefore, reclamation of degraded lands using plants as ecosystem engineers needs to be carried out with caution.

5.1.2 Sustainable options for mountain ecosystems

Growing crops inside forests in mountainous areas may temporarily boost food crop production. Nevertheless, this happens at the expense of other ecosystem services such as erosion control, sediment retention, water purification and flood regulation which in turn has serious impact on the downstream users and the hydropower companies. The knowledge on topography of undercover cropland is relevant for assessing impacts on ecosystem services (e.g. slope for sediment retention). Moreover, continuous tillage for growing annual crops such as wheat and barley inside forests gradually reduces the forest cover and results in death of trees leading to the decline in supplies of services such as timber, fuelwood and carbon sequestration. Besides, since the pattern of growing crops inside forests of the Bale Mountains mainly aims at land acquisition i.e. " land grab by local people " for growing crops, the forest stands will become less stable and eventually be deforested. If the current trend continues, even the extremely steep areas of Bale Mountains that are currently covered with forests could turn to be degraded rocky terrains in the near future. Therefore, options that ensure sustainable supplies of ecosystem services and nature conservation need to be designed and implemented. The following can be alternatives for the Bale Mountains of Ethiopia:

- *Payments for Ecosystem Services (PES) schemes:* Introducing systems such as payments for ecosystem services that benefits the poor people living in extreme steep slope areas could be a useful step towards achieving the sustainable supplies of ecosystem services (Wunder 2008). Since this involves abandoning of the upstream croplands inside forests, various stakeholders such as farmers, government officials, environmental authorities, hydropower company, and the Bale Mountains National Parks (BMNP) should be incorporated in implementing PES.
- *Developing the undercover cropland into a sustainable agro-forestry system:* There is potential to transform the undercover cropland inside forests to a more sustainable agroforestry system. The points that should be considered for the transformation include:
    - proper selection of tree-crop combinations that are suitable for mountainous areas.
    - management practices for trees and crops in the undercover cropland areas should aim at ensuring sustainable supplies of ecosystem services.
    - knowledge transfer from well-established agroforestry areas such as the Gedio Zone of the Southern Ethiopia to the mountainous areas.
- *Terrain management:* The supplies of ecosystem services such as water and sediment retention in the upstream steep slope areas are essential. To ensure sustainable supplies of services from these fragile lands, terrain management techniques that consider the linkage between upland and lowland areas is essential.

Global demand for food crop production is rapidly increasing with the growing population leading to large scale acquisition of land, "land grabbing", which is mainly taking place in the developing countries where the majority of the rural poor people are entirely dependent on subsistence agriculture. This further continuous to push the local people to marginal fragile lands increasing pressure on mountainous areas. Therefore, protection of forest and other mountain resources is crucial to ensure sustainable supplies of diversified ecosystem services such as water, flood control, erosion control and sediment retention (Bales et al. 2006, Rodríguez-Rodríguez et al. 2011, Messerli 2012). Attempts to fight poverty through investment in Agriculture should not end up in the depletion and/or degradation of natural resources (Scherr 2000, Liniger et al. 2005, Foley et al. 2005). Rather, poverty alleviation should go hand-in-hand with conserving nature for the future generation to ensure sustainable supplies of ecosystem services.

In a nutshell, land use decision in fragile lands should not be made only with short-term goals but also focus on the long-term sustainable use and management of these resource base. Due to the fragility of these land forms, special emphasis should be given to land use decisions to ensure sustainable supplies of ecosystem services. Sustainable supplies of ecosystem services and biodiversity from fragile lands can only be achieved through careful management of these sensitive land forms. To reach this goal various stakeholders such as policy-makers, land owners, users (e.g. pastoralists), scientific community, development organizations, society at large and the media should be involved to ensure land use in fragile lands.

5.1.3 Future prospects in remote sensing of ecosystem services

Remote sensing enables fast and frequent data acquisition options that enable continuous monitoring of ecosystem services. There is ample potential in using remote sensing for quantifying and mapping proxies for ecosystem services besides the classical method using LULC classes. The review of remote sensing applications (Chapter 2) identified four major issues that need to be considered in selecting remote sensing data and methods for assessing ecosystem services: i) Spatial, temporal, spectral and radiometric resolution ii) Sensor types (passive vs active) iii) Uncertainty of the findings that call for validation with field data, and iv) Financial and technical capacity. Since its publication in 2012, the article has been cited by 12 authors according to the ISI Web of Knowledge showing significance of the topic in the current research in the field. The following challenging issues are key areas for research in the application of remote sensing for assessing ecosystem services:

- *Linking ecosystem services with remote sensing data:* There are no well-defined theories that directly link some ecosystem services (e.g. flood control, erosion control) with image spectra. Besides, those ecosystem services which can be quantified from image spectra (e.g. biomass) require intensive field measurement or expensive remote sensing data sources such as LiDAR. Further research is thus essential to find cost and time-efficient approaches that enable to directly extract ecosystem services from image spectra.
- *Dealing with uncertainty:* There is uncertainty involved when using remote sensing data for quantifying and mapping ecosystem services. Thus, understanding the magnitude of errors or uncertainties in the data and processing methods is necessary when interpreting the assessment of ecosystem services. Results should be validated with in situ measurements of the parameters relevant to the ecosystem services assessed.

The assessment of ecosystem services using remote sensing requires approaches where researchers from various disciplines are involved. This includes remote sensing experts who address the technical aspects and experts in the fields such as ecology, soil, forestry, agriculture, environment, economics and hydrology. This is because different ecosystem services require expert knowledge from different disciplines. For instance, sediment retention can better be explained by experts in the field of hydrology and soil sciences while foresters could better understand the concepts required for quantifying timber biomass. It should be noted that images alone cannot tell us about ecosystem services. Thus, linking an ecosystem service with remote sensing data should be based on theoretical definitions and identifying remote sensing parameters that can be used to detect indicators of the ecosystem service.

The applicability of remote sensing also varies depending on the ecosystem service to be quantified. For instance, quantifying storm regulation services can only be done through indirect method by estimating the damage in mangrove vegetation. Whereas, timber biomass can be directly mapped through regression of image spectra (e.g. NDVI) with measured biomass parameters (e.g. DBH, Height). Thus, lack of defined relationships between image parameters and ecosystem services remains a constraint in the quantification of ecosystem services using remote sensing data. Moreover, the indirect approach of deriving proxies from remote sensing data raises concern about accuracy and reliability of ecosystem services maps. The aforementioned issues confirm that quantifying and mapping ecosystem services using remote sensing image spectra is at its early stage of development calling for more research to find novel approaches and methods that produce reliable results.

5.2 Scope of the dissertation and future research interests

Three broad topics are integrated in this dissertation i.e. land cover, ecosystem services and remote sensing. As a first step leading towards the main focus of the study, potential and challenges of using remote sensing for quantifying and mapping ecosystem services was explored based on literature review. This was used to further refine the scope of the thesis based on resource availability, data and time limitations. The case studies in this dissertation were carried out solely by the individual researcher in the study areas where relevant quantitative data on ecosystem services were not possible to acquire due to lack of projects working on a similar topic. Due to limited financial budget for this dissertation, it was not possible to do intensive and repeated field work. Therefore, the study was narrowed down to assessing LULC that are detrimental to ecosystem services in two different fragile lands i.e. drylands and mountain regions in Ethiopia.

The case studies addressed the ongoing land cover related pressure on fragile lands in the world where there is immense demand for growing crops and its impacts on ecosystem services. With availability of resources and time, intensive remote sensing-based assessment of ecosystem services can be made possible. Using this dissertation as a an entry point, I would like to do further research in remote sensing applications for assessing ecosystem services. The research plans include deriving proxies by linking vegetation indices derived from remote sensing data with field data collected for indicators of ecosystem services. It includes also analysis of dynamics in ecosystem services through calibration of time series remote sensing data with field collected indicators of ecosystem services. Comparing findings of model-based and remote sensing-based analysis is also a research gap in the quantification and mapping of ecosystem services. My academic backgrounds are B.Sc. in Forestry, M.Sc. in Photogrammetry & Geoinformatics and M.Sc. in Agricultural Sciences. Past research and work experience mainly focused on remote sensing and GIS applications, spatially-explicit modeling approaches, and ecosystem services assessment shaping my expertise in these areas. My future research and career interest would thus be in relevant tasks in this direction.

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I hereby declare, to the best of my knowledge and belief, that this thesis does not contain any material previously published or written by another person, except where due reference has been made in the text. This thesis contains no material, which has been previously accepted or definitely rejected for award of any other doctoral degree at any university or equivalent institution.

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