Multi-scale assessment of land changes in Ethiopia – understanding the impact of human activities on ecosystem services

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Academic dissertation

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This thesis is dedicated to my family: My wife ABEBA MULUGETA, and my two precious children NAAMAN and MARIAMAWIT

Abstract

Remote sensing provides land-cover information on a variety of temporal and spatial scales. The increasing availability of remote sensing data is now a major factor in land-change analysis and in understanding its impact on ecosystem services and biodiversity. This wider accessibility is also leading to improvements in the methods used to integrate these data into land-cover modelling and change analysis. Despite these developments in current technology and data availability however, there are still questions to be addressed regarding the dynamics of land cover and its impact, particularly in areas such as Ethiopia where the human population is expanding and there is a need for improvement in the management of natural resources.

Multi-scale approaches (from the national to the local) were used in this thesis to assess change in land cover and ecosystem services in Ethiopia, specifically in terms of provisioning (the production of food, i.e. cash crops) and regulating (climate control for vegetation cover). These assessments were based on multi-scale remote sensing (very high spatial resolution remote aerial sensing, high-resolution SPOT 5 satellite imaging and products of medium-resolution satellite remote sensing) and climate data (e.g., precipitation, temperature).

The main focus in this thesis is on mapping and modelling the spatial distribution of vegetation. This includes: (i) forest mapping (indigenous and exotic forests), (ii) modelling the probabilistic presence of understory coffee, (iii) *Coffea arabica* species distribution modelling and mapping and (iv) simulating pre-agricultural-expansion vegetation cover in Ethiopia.

The results of the applied predictive modelling were robust in terms of: (i) identifying and mapping past vegetation cover and (ii) mapping understory shrubs such as coffee plants that grow as understory. I present a reconstruction of earlier vegetation cover that mainly comprised broadleaved evergreen and deciduous forest but was replaced in the course of agricultural expansion. Given the spatial scale of the latter, the environmental modelling was complemented with high spatial resolution satellite (2.5m) and aerial images (0.5m). The results of the Object Based Image Analysis show that indigenous forests were separated from exotic forests. Current and future suitable locations that are environmentally favourable for the growth of understory coffee were identified and mapped in the coffee-growing areas of Ethiopia.

In conclusion, the information presented in this thesis, based on the multi-scale assessment of land changes, should lead to the better-informed management of natural resources and conservation, and the restoration of major areas affected by human population growth.

Keywords: remote sensing, multi-scale, predictive modelling, human population, vegetation, *Coffea arabica*, Ethiopia.

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First of all, thank you, GOD, for making this PhD possible! Without Your help nothing I have achieved during this period would have been possible.

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Helsinki, December 2015 **Binyam Tesfaw Hailu**





List of original articles

I. **Binyam Tesfaw Hailu**, Eduardo Eiji Maeda, Pekka Hurskainen & Petri K. E. Pellikka (2014). Object-based image analysis for distinguishing indigenous and exotic forests in coffee production areas of Ethiopia *Applied Geomatics* 6, pp. 207–214. DOI: 10.1007/s12518-014-0136-x

II. **Binyam Tesfaw Hailu**, Eduardo Eiji Maeda, Petri Pellikka & Marion Pfeifer (2015). Identifying potential areas of understorey coffee in Ethiopia's highlands using predictive modelling. *International Journal of Remote Sensing* 36:11, 2898–2919. DOI: 10.1080/01431161.2015.1051631

III. **Binyam Tesfaw Hailu**, Eduardo Eiji Maeda, Janne Heiskanen & Petri Pellikka (2015). Reconstructing pre-agricultural expansion vegetation cover of Ethiopia. *Applied Geography* 62: 357–365. DOI:10.1016/j.apgeog.2015.05.013

IV. **Binyam Tesfaw Hailu**, Mika Siljander, Eduardo Eiji Maeda & Petri Pellikka. Assessing spatial distribution of *Coffea arabica* L. in Ethiopia's highlands using species distribution models and geospatial analysis methods. (Submitted).

PUBLICATION CONTRIBUTION

	Original Ideas	Conceptualising methodology	Remote Sensing & geospatial data	Field data collection	Data Analysis &Modelling	Manuscript Preparation
B.T.H.	P (I,II,III, IV)	P (I,II,III, IV)	P (I,II,III, IV)	P (I,II,III, IV)	P (I,II,III, IV)	P (I,II,III, IV)
E.E.M.	P (III)	P (I,II,III, IV)				P (I,II,III, IV)
P.P.	P (II)					P (I,II)
P.H.		P (I)	P (I)			P (I)
J.H.		P (III)				P (III)
M.S.	P (IV)	P (IV)				P (IV)
M.P.			P (II)			P (II)

P: Paper, B.T.H: Binyam Tesfaw Hailu, E.E.M.: Eduardo Eiji Maeda, P.P.: Petri Pellikka, P.H.: Pekka Hurskainen, J.H.: Janne Heiskanen, M.S.: Mika Siljander, and M.P.: Marion Pfeifer

List of abbreviations

ANN	Artificial Neural Network
CEPF	Critical Ecosystem Partnership Fund
CIMP5	Coupled Model Intercomparison Project Phase5
CSR-UFMG	Centro de Sensoriamento Remoto of the Federal University of Minas Gerais
CRGE	Climate Resilient Green Economy
CSS	Contrast Splitting Segmentation
DEM	Digital Elevation Model
DN	Digital Number
DOS	Dark Object Subtraction
EABH	Eastern Afromontane Biodiversity Hotspot
EMR	Electromagnetic Radiation
EPACC	Ethiopian Program of Adaptation on Climate Change
ERDAS	Earth Resources Data Analysis System
ET	Evapotranspiration
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agricultural Organization Statistics
GCM	Global Climate Model
GLM	Generalized Linear Model
GPM	Geospatial Predictive modelling
GSD	Ground Sampling Distance
HPF	High Pass Filtering
HRG	High Resolution Geometric
HRVIR	High Resolution Visible Infrared
ICO	International Coffee Organizations
IMF	International Monetary Fund
IR	Infrared
LCCS	Land Cover Classification System
LULC	Land Use/Land Cover
MER	Main Ethiopian Rift
MFG/MVIRI	Meteosat First Generation/METEOSAT Visible and Infrared Imager
MODIS	Moderate Resolution Imaging Spectroradiometer
MRS	Multi Resolution Segmentation
NAP	National Action Program
NDVI	Normalized Difference Vegetation Index
NIES	National Institute for Environmental Studies
NN	Nearest Neighbour
NPP	Net Primary Productivity
OBIA	Object Based Image Analysis
PET	Potential Evapotranspiration
PSNP	Productive Safety Net Program
PT	Precipitation
RCP	Representative Concentration Pathways
RMSE	Root Mean Square Error
SDM	Species Distribution Models

SDS	Spectral Difference Segmentation
SF	Shadow Fraction
SID	Surface Incoming Direct
SLMP	Sustainable Land Management Program
SMACC	Sequential Maximum Angle Convex Cone
SPOT	Système Pour l'Observation de la Terre
SR	Simple Ratio
SRad	Solar Radiation
SVM	Super Vector Model
SWIR	Shortwave Infrared
Tmax	Maximum Temperature
Tmin	Minimum Temperature
TWI	Topographic Wetness Index
UTM	Universal Transverse Mercator

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Contents

1. Introduction

1.1. Background

Land-use and land-cover mapping and analysis determine the structure, functions and dynamics of most landscapes throughout the world (Wu and Hobbs, 2002). On the general level, land use land cover (LULC) change, also called land change, refers to the modification of the Earth's terrestrial surface by humans. Although humans have been modifying land for thousands of years to obtain food and other essentials, the rate, extent and intensity are far greater now than ever before, driving extraordinary modifications in ecosystems and environmental processes on global, regional and local scales. These changes encompass the greatest environmental concerns of human populations today, including climate variability, biodiversity loss and the pollution of water, soils and the air. It is essential to understand the distribution and dynamics of land cover to be better able to conceptualise the earth's fundamental characteristics and processes, including the productivity of land and the diversity of plant species. For example, assessing and monitoring the distribution and dynamics of vegetation cover are top priorities in studies on different scales of environmental change as well as in planning and management. Thus, information on land cover and its change is needed in order to manage natural resources and monitor all scales of environmental change and its consequences (Loveland and Belward, 1997b).

Remote-sensing data play an increasingly important role in LULC modelling. Remote sensing provides the information needed for the effective and sustainable future management of the Earth, and it has become essential. One reason for this is the rapid and continuing increase in the global population and the depletion of natural resources, as the world is experiencing the possible consequences of human-induced climate change (Liang et al., 2012). For instance, satellite remote sensing provides ideal data for monitoring changes in land-surface characteristics on a range of scales, with sufficient spatial and temporal resolution. Therefore, LULC models need remote-sensing data such as (i) current/historical remote-sensing images and ii) environmental and scenario data derived from them (Heistermann et al., 2006).

Africa's mainland constitutes 20 per cent of the earth's surface with its unique eco-regions and biologically rich landscapes including tropical forests, montane forests, woodland, and grass savannas. According to FAOSTAT (2014), 16 per cent of the world's population, increasing by 2.5 per cent annually on average since the year 2000, which is the highest known rate of increase, live in this continent. Of those, 60 per cent live in rural areas, and 52 per cent of the economically active population depend on agriculture. The economy of the continent is based mainly on natural resources, which are primary products. The utilisation of these resources tends to relate to the degradation and loss of forests and woodlands, the loss of animal and plant species, the degradation of land, an increase in water shortage and a decline in water quality (Geri, 2012). The effects of land change on natural vegetation and biodiversity may also have a long-term impact on natural resources such as forests and sustainable food production (Foley et al., 2005). As a result, given the rapidly increasing population in Africa, a number of countries in the continent may face a potentially challenging food-security scenario. Hence, assessing and modelling the land cover and its dynamics to enhance understanding of the underlying causes is acknowledged as a key area of research on regional and global environmental change.

The Eastern Afromontane Biodiversity Hotspot (EABH) in East Africa needs special attention in terms of the management of natural resources for ecosystem services: it is one of 35 biodiversity hotspots, the most biologically rich yet threatened areas around the globe (CEPF, 2012). It encompasses scattered but bio-geographically similar mountain ranges in eastern Africa, stretching from Ethiopia to Zimbabwe. The region is unique in its biological attributes, being of major economic and cultural importance. Moreover, it has strong ecosystem service value: food production from major crops such as maize, cabbages, and cash crops such as coffee. The high human population density has resulted in resource competition in areas such as agriculture, forestry, biodiversity conservation, water provision and carbon sequestration. Given the changes in climate and land use, aggravated by the high population increase, the EABH is at risk of extreme climatic change, and the goods and services its ecosystems provide are under significant threat. The area is therefore considered worthy of special scientific attention, specifically in this thesis on the southwest highlands of Ethiopia. The fact that it is the most prolific coffee-producing region in Ethiopia makes it an ideal research object.

Coffee is a very important cash crop for the country's economy, accounting for 41 per cent of the total exports, and is the main contributor to community livelihood (IMF, 2006). There is also an urgent need for scientific geospatial tools and information to facilitate the sustainable management of natural resources and food production from major cash crops. I address these issues in Papers I, II and IV, which discuss the importance of remote-sensing technology with its integrated climate data for mapping and modelling the distribution and geospatial extent of coffee plantations, which is the understory in the indigenous forest (Figure 1).

The other side of the rapid-population-growth problem observed in the East African highlands during the past century concerns the implications for land use and the subsequent impact on natural vegetation cover and biodiversity (Brink & Eva, 2009). Africa currently has the highest rate of deforestation in the world on account of overdependence on primary resources (Ademiluyi et al., 2008; Johnson & Chenje, 2008). Forest cover in the tropics continues to decrease, mainly because of conversion to agricultural land (Ahrends et al., 2010; DeFries et al., 2010; Hundera et al., 2013). These changes in the natural landscape were established long before the advent of remote-sensing technologies. As a consequence, the exact extent and spatial patterns of Ethiopia’s vegetation cover before agricultural expansion is uncertain. Uncertainties concerning the original land-cover patterns in Ethiopia also hinder the identification of the biophysical and socio-economic factors that contributed to defining current landscape patterns. Effective conservation actions are critically compromised in the absence of general knowledge of historical landscape patterns in that the identification of areas at risk of land degradation would be largely subjective. Furthermore, the full biodiversity loss caused by the expansion of agricultural lands is unknown, causing logistical and implementation problems for projects aimed at rehabilitating degraded areas of natural vegetation. Therefore, in Paper III I present a simulation of natural vegetation cover in Ethiopia during the past century, and estimate the extent to which it has been affected by agricultural expansion.

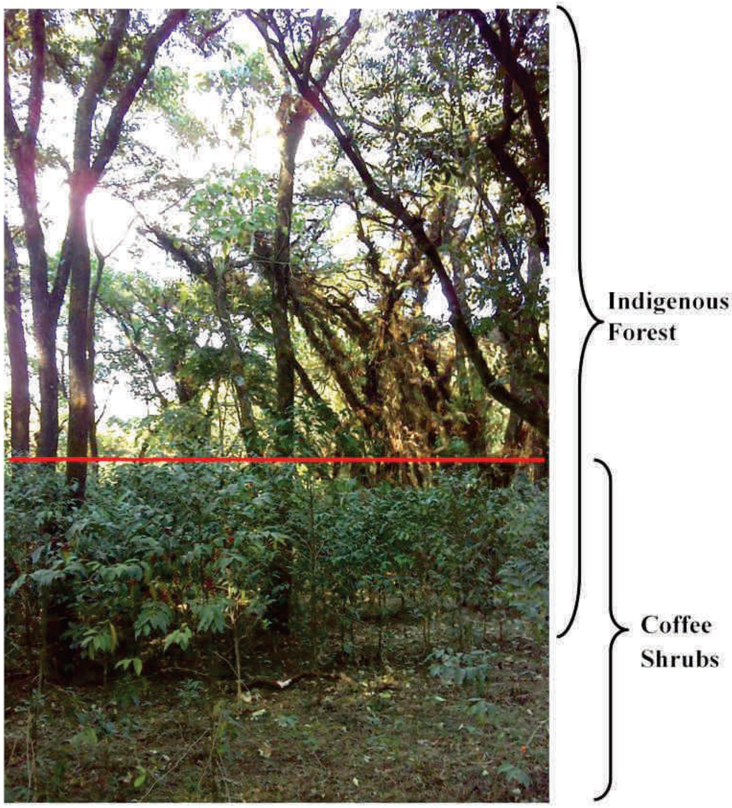

Figure 1. Understory coffee plants in the indigenous forest, southwest highlands of Ethiopia (Papers I, II, and IV and Photo: Binyam T. Hailu, May 5, 2012).

1.2. The objectives of the thesis

The main objective is to enhance understanding of the impact of human activities on ecosystem services in Ethiopia through the assessment of land changes from the local to the national level, by means of remote sensing and modelling.

This research objective is addressed in the four individual papers.

The aim in **Paper I** is to discriminate between indigenous and exotic forests in a coffee-growing area of Ethiopia given that these coffee shrubs only grow in indigenous forests. A multi-scale approach is adopted, based on satellite imagery: field data and aerial imagery are analysed using advanced image-processing techniques. First, pre-processing served the purpose of satellite image correction and fusion. Next, the pre-processed satellite image was subjected to Object Based Image Analysis (OBIA). Finally, the results were validated using field data and aerial imagery.

Paper II presents an approach to mapping potential areas of understory coffee in Ethiopia's southwest highlands using predictive modelling. Indigenous forests typically associated with understory coffee shrubs were mapped using remote sensing analysis, which is described in detail in Paper I (PI). A probabilistic predictive model was then built to link the understory coffee to forest and environmental variables. Finally, potential changes in coffee suitability maps were evaluated against projections of climate change for the year 2050.

Paper III simulates the 20th-century natural vegetation cover of Ethiopia with a view to estimating the extent to which it was affected by agricultural expansion. First, the natural vegetation was separated from the agricultural areas and its net primary productivity (NPP) was assessed based on climatic productivity constraints. Second, multivariate regression was used to assess the relationship between NPP and the climatic variables (water availability, solar radiation and minimum temperature), which were the main productivity constraints. The model was then used to simulate NPP over the agricultural lands of Ethiopia, the aim being to provide a proxy for identifying the original natural vegetation in this area.

Paper IV determines the distribution and extent of the *Coffea arabica* L. species in the southwest highlands of Ethiopia by means of Species Distribution Models (SDMs) such as the Super Vector Model (SVM), Artificial Neural Networks (ANN), MaxEnt and the Generalized Linear Model (GLM). Building on Paper II (PII), it also assesses the predictive capacity of SDMs (SVM, ANN, MaxEnt and GLM) for estimating the presence/absence of the *Coffea arabica* species. The analysis is based on climatic variables (Precipitation, Minimum Temperature, Maximum Temperature, Evapotranspiration), remote-sensing variables (Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Shadow Fraction (SF)), and landscape variables (distance to roads, distance to rivers, Digital Elevation Model (DEM) and slope).

2. Conceptual framework

This chapter introduces the main topics that are covered in this thesis, which comprises a multi-disciplinary study with Remote Sensing as the focal discipline, and Geography (PI, PII, PIII, PIV), Forestry (PI), Ecology (PII, PIV), and Environmental (PII, PIII, PIV) and Climate (PII, PIII, PIV) studies as umbrella disciplines (Figure 2): remote sensing in earth resource analysis can be applied in the physical, natural and social sciences (Jensen, 2000). The aim is to show how remote sensing is applied in different disciplines, especially those concentrating on the management of natural resources and ecosystem services and using multi-stage and multispectral sensing systems. In other words, data about a site are collected from multiple altitudes in *multistage sensing,* and are obtained simultaneously in several spectral bands via *multispectral sensing* (Lillesand et al., 2007).

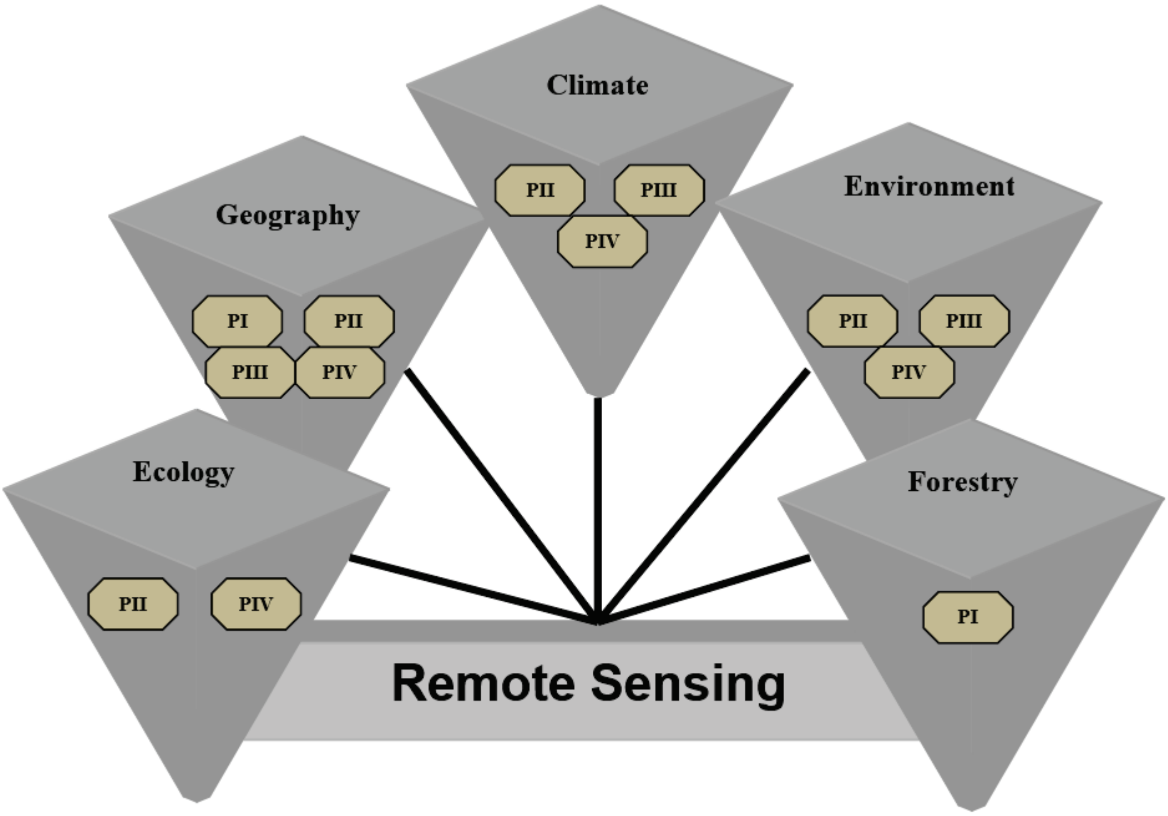

Figure 2. Multidisciplinary applications of remote sensing.

2.1. Characteristics of remote sensing data

There are two types of remote sensors, analogue and digital. Remote sensing could be defined as the science and art of obtaining information about an object, area or phenomenon, which is the earth's surface in this dissertation, through the analysis of data acquired by a device or sensor that is mounted on an aircraft or satellite and is not physically in contact with the phenomenon under investigation (Lintz & Simonett, 1976; Lillesand et al., 2007). Aerial photographs, as an example of analogue images although some are digital, have the clear advantage of recording extremely fine spatial details. Satellite images, which are digital, tend to be of a higher quality in terms of spectral, radiometric and temporal resolution (Lillesand et al., 2007; Wang and Weng, 2013). According to Wang and Weng (2013), the trend over the past 40 years has been towards improving the resolution of both image types. Resolution in remote sensing falls into four categories: spatial, spectral, radiometric and temporal.

Spatial resolution refers to the area covered on the ground by a single pixel, often expressed as ground sampling distance (GSD) (Navulur, 2007; Lillesand et al., 2007; Wang and Weng, 2013). The resolution could be low if a pixel refers to a large area of ground and high when it refers to a small area. Spectral resolution depicts the number of spectral bands (Electromagnetic Radiation (EMR) wavelength ranges) on a given sensor that could be mounted on the satellite or aircraft. Most aerial and satellite sensors capture images in the visible and infrared regions of the EMR spectrum (Navulur, 2007; Lillesand et al., 2007; Wang and Weng, 2013). High (e.g., 0.5m in aerial photographs and 2.5m in processed satellite images) and low (e.g., 1 km in Moderate Resolution Imaging Spectroradiometer (MODIS) products) spatial-resolution data were used in all the papers included in this thesis (PI, PII, PIII and PIV). The spectral resolution also differed. For example, the SPOT 5 satellite image is a multi-spectral image that covers visible and infrared regions of EMR (PI, PII, PIV). Radiometric resolution is defined as the number of grey levels that can be recorded for a given pixel. In other words, the reflected signal is captured as an analogue signal and then converted to a digital number (DN) or a grey-level value, which is expressed as radiometric resolution for a given image. For example, SPOT 5 imagery (PI, PII, PIV) has a radiometric resolution of eight bits that results in pixel values ranging from 0–255.

2.2. Remote sensing for mapping land cover

Remote sensing data have long been used for deriving land cover maps, even before the launch of the first Landsat platform in 1972. Aerial photography served as a primary source of information on land cover when satellite imagery was not available. It is still an important source of information (Akbari et al., 2003; Cots-Folch et al., 2007), and is used for analysing historical LULC change (Thomson et al., 2007; Gerard et al., 2010). Aerial photographs were acquired and processed for mapping land cover in relation to this thesis (PI), for example. With the advent of remote-sensing satellites, land-cover has been assessed from the local (PI) to the regional (PIII) scale.

Land cover refers to the physical and biological cover above the earth's surface, including vegetation, bare soil, water and/or artificial structures (Comber et al., 2005; Ellis and Pontius 2006). Land use, on the other hand, reflects the arrangements, activities and inputs instituted by people in a certain land-cover type to produce, change or maintain it (Comber et al., 2005; Liang et. al., 2012). Information on land cover is required to facilitate understanding of the environment and its management on a variety of spatial and temporal scales, and decision makers are increasingly demanding detailed spatial coverage with high temporal frequency in order to evaluate changes in the extent and condition of species habitats, forests and vegetation, for example.

For the purposes of this thesis, land cover was mapped to identify indigenous forests (PI, PII, PIV) based on satellite images to facilitate the management of natural resources and ecosystem services, specifically provisional ecosystem services. In fact, indigenous forest management and conservation are of major importance in the provision of ecosystem services in the EABH. Wild coffee (*Coffea arabica* L.) shrubs constitute the understory in the indigenous forest in this region, specifically Ethiopia's southwest highlands (Gole et al., 2008; Hernandez-Martinez et al., 2009).

Coffee is the world's most prolific commercial crop plant and the second most valuable commodity (Davis et al., 2012). Globally, about 20 million farming families depend on coffee for their livelihood. *Coffea arabica* L. originated in the highlands of Ethiopia (Teketay, 1999; Labouisse et al., 2008; Davis et al., 2012). It is one of the 100 species of the *Coffea* genus, which together with *Coffea canephora* (robusta coffee) dominates the world coffee trade with a 99-per-cent share, and accounts for 70 per cent of coffee consumed (Damatta & Ramalho, 2006). In 2014, coffee accounted for exports worth an estimated US$ 13.9 billion, some five billion kg being shipped, and the total number of people employed in the coffee sector was estimated to be about 26 million in 52 producing countries (ICO, 2015). Specifically, the most diverse varieties *Coffea arabica* L. grow in the southwest highlands of Ethiopia (Gole et al., 2008). Coffee is the backbone of the country's economy, contributing 41 per cent of its total foreign exchange earnings in 2005 (IMF, 2006). The coffee plants contribute to the ecosystem processes of these forests, which include habitat provisioning for a diverse wildlife community, soil conservation, and the regulation of climate and atmospheric fluxes in carbon dioxide. PI, PII, and PIV focus mainly on land-cover mapping, the modelling of potential *Coffea arabica* L. growing areas, and the estimation of its geographical extent by means of remote-sensing and climate data.

2.3. Geospatial predictive modelling

A predictive model is a mathematical algorithm that predicts a target variable from a number of factor variables. Predictive modelling leverages statistics to predict outcomes. Most events to be predicted are in the future (PII), but predictive modelling can also be applied to any type of unknown event, regardless of when it occurred (e.g., predicting what was present in the past (PIII)). According to Beauvais et al. (2006), Geospatial Predictive Modelling **(**GPM) is theoretically embedded in the principle that the incidence of events being modelled is limited in distribution: incidences are neither consistent nor arbitrary. There are spatial environmental aspects such as sociocultural, infrastructure-related and topographical factors, for example, that restrict and influence the locations at which these events take place. The aim of GPM is to explain these influences and constraints by correlating occurrences of historical geospatial locations with environmental factors that characterise the constraints and influences in spatial terms. GPM is a process of analysing events through a geographic filter to produce statements of likelihood for event emergence.

GPM falls into two categories, deductive and inductive modelling. The former depends on qualitative data (subjective information) to explain the relationship between event occurrences and factors that describe the environment. In other words, the modeller could impose limitations by specifying a number of factors. For example, highly suitable locations for a particular group of events are constrained and influenced by non-empirically calculated spatial ranges, and other locations would appear less suitable. The depth of the qualitative data included in a deductive model limit it in terms of accuracy and detail. Inductive modelling (PII, PIV), on the other hand, is based on the empirically calculated spatial relationship between known (historic) event-occurrence locations and factors that frame the environment (e.g., topography and infrastructure). Each event occurrence is plotted in geo-space and a quantitative relationship is defined between the occurrence and the environmental factors. Then, the values obtained from these quantitative relationships are processed statistically to establish spatial patterns of high and low suitability for event occurrence.

3. The study areas

This thesis comprises four case studies conducted in Ethiopia, in the Horn of Africa. The country is situated at 34°30'–45°30' E and 3°30'–15° N and covers an area of 1.1 million km^2 in the northeast part of Africa (Figure 3). Even though the study was conducted in Ethiopia, three of the case studies were local in scale (PI, PII, PIV), and one covered the whole country (PIII).

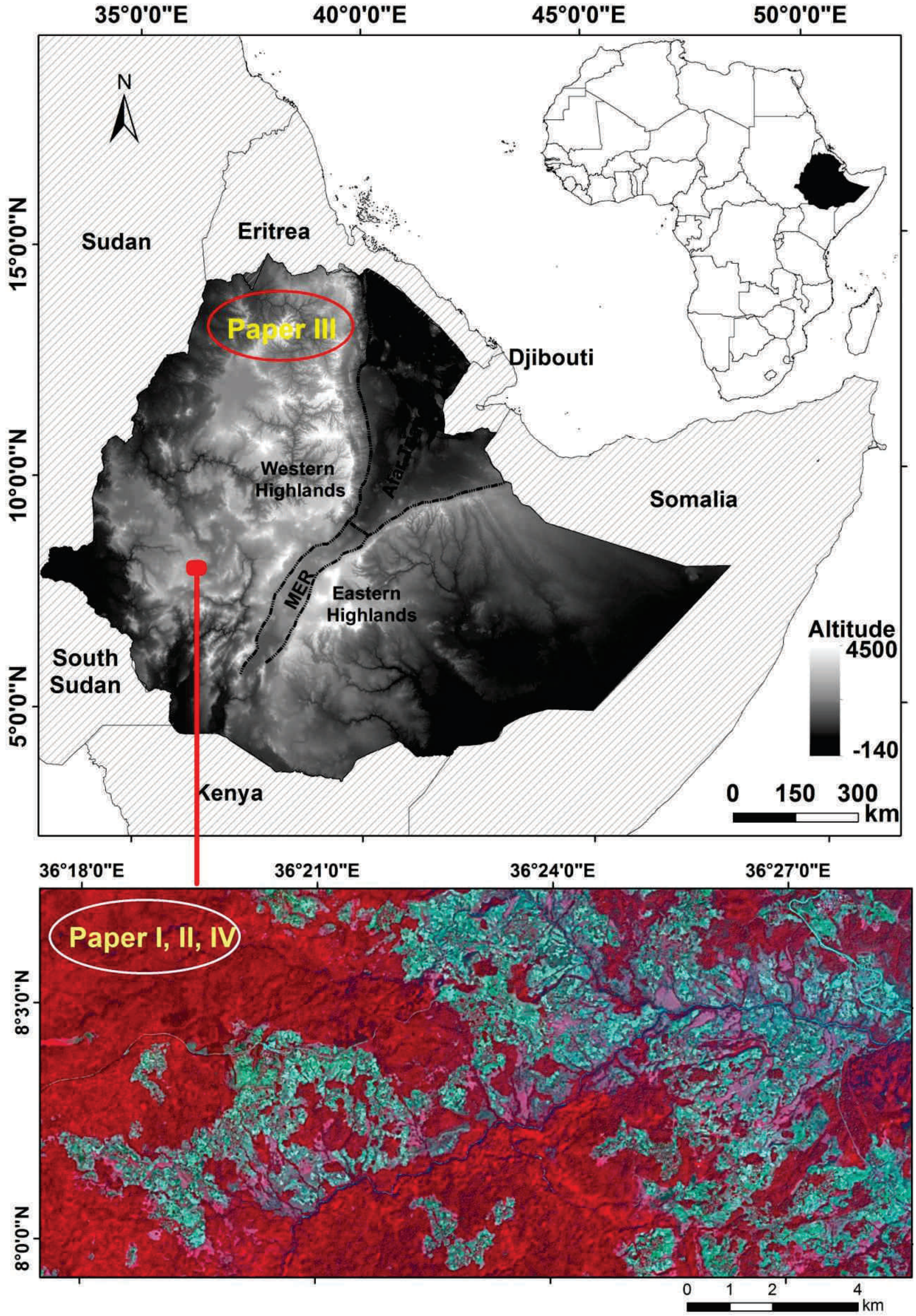

Figure 3. The geographical locations of the study areas: the whole of Ethiopia (Paper III) and the coffee-growing area in the southwest highlands in SPOT 5 false colour (R,G,B: NIR, R,G; Papers I, II and IV).

Morphologically, Ethiopia is divided into three major regions (PIII: Figure 1), the Main Ethiopian Rift (MER), the Afar Triangle and the Ethiopian Highlands (Skovitina et al., 2012). This altitude varies from about 110 m below sea level in the Afar depression to 4620 m above sea level on Mt. Ras Dashen in the northern part of the Ethiopian highlands. The country possesses 50 per cent of the land above 2000 m in Africa, which makes it one of the largest highland areas in the tropics. The area that covers 73 per cent of the region over 2000 m asl receives 1185 mm mean annual rainfall during the main rainy season, which is from June to September (Seleshi and Demaree, 1995). The mean monthly rainfall is between 9 mm in the Afar rift and 185 mm in the highlands, and the mean annual temperature is between 3.9^{o} C in the high peak of the highlands and 31.2^{o}C at the bottom of the Afar Triangle.

According to Friis et al. (2011), the closeness of the Equator (the southern boundary of Ethiopia at approximately 3^{o}30' N) and the complexity of the relief govern the climate. The altitudinal range also strongly influences the climate, with the formation of microclimates ranging from the cool highlands to the hot desert (Seleshi and Zanke, 2004). The traditional Ethiopian climate classification is based on altitude and differentiates three zones (Conway, 2000): i) Kolla, which is below 1800 m asl. with a mean annual temperature of 20 °C –28 °C; ii) Woina Dega, 1800–2400 m asl with a mean annual temperature of 16–20°C; and iii) Dega above 2400 m asl with a mean annual temperature of 1 °C–6 °C.

The local-scale study area that was the main focus in PI, PII and PIV is located between latitudes 7.95° and 8.08° North and longitudes 36.3° and 36.5° East upstream of the Didessa river basin. The Didessa river is a tributary of the Blue Nile River located in southwest Ethiopia. The study area was 19,100 ha (PIV: Figure 1), varying in altitude between 1400 m.asl. downstream of the Didessa River to 2400 m.asl. in the upstream section. The topography is rugged with slopes between 0^{o} –50^{o}. The mean temperature ranges between 17.5 and 20.5 at the lowest and highest altitudes, respectively. Rainfall ranges from 144mm/month downstream of the Didessa River to 161mm/month in the natural forest.

4. Material and methods

4.1. Geospatial and field data

The material consists of three main geospatial datasets encompassing remote-sensing, climate and landscape data (Figure 4). Nine of the 17 datasets that were used in this thesis comprised remote-sensing data: namely, NDVI (Rouse et al., 1974), SR (Jordan, 1969), Principal Component Analysis (PCA), Reflectance's (Ref. B), Shadow Fraction (SF), Net Primary Productivity (NPP), Potential Evapotranspiration (PET), Topographic Wetness Index (TWI) and Solar Radiation (SRad). The climatic data covered Precipitation (PT), Minimum Temperature (Tmin), Maximum

Temperature (Tmax), and Evapotranspiration (ET), and the landscape data comprised the Digital Elevation Model (DEM), Slope, Distance to River, and Distance to Roads.

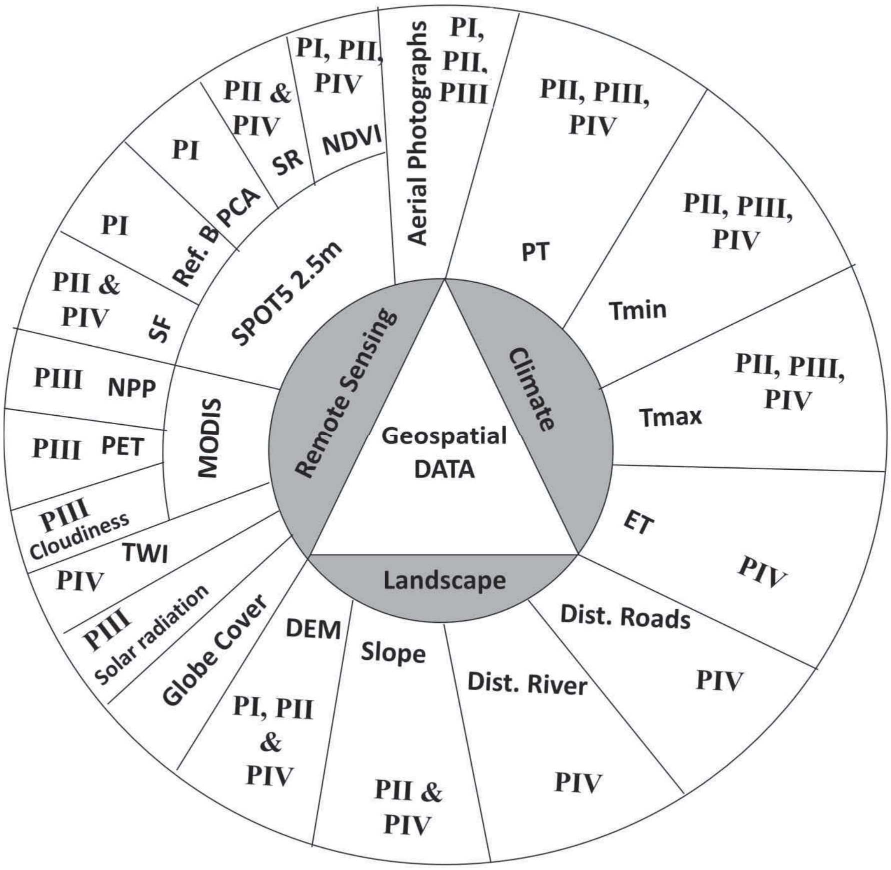

Figure 4. The geospatial data used in this thesis.

4.1.1. Remote sensing data

Remote sensing data basically comprises digital images captured remotely. According to Panigrahy and Ray (2006), the components of such data include: (i) the energy source / illumination (EMR provision); (ii) interaction with the target (atmosphere or object); (iii) the recording of energy; (iv) transmission, reception and processing (storage in digital format or as images); and (v) interpretation and analysis (PI, PII, PIII, PIV). These digital images are produced from airborne or space-borne platforms that transmit a wide variety of valuable data about the earth's surface for global and detailed analysis such as mapping (e.g., land cover), environmental monitoring and natural resource management (Benz et al., 2003).

(i) Satellite images and products

The land use and land cover of the study areas on the local (detail mapping described in PI) and regional (GlobeCover 2009 product) scale were the major products of the remote-sensing data used in this thesis. The local-scale LULC map was based on SPOT 5 satellite imaging. SPOT 5 is one of the ‘Satellites Pour l’Observation de la Terre’ (SPOT) series that have been providing high-quality, consistent optical imaging of the Earth since 1986. Seven satellites have been launched to date, of which SPOT 5, SPOT 6 and SPOT 7 are currently in orbit and fully operational.

SPOT 5 was launched on 4 May 2002 and carries two High Resolution Geometric (HRG) instruments. These sensors are a further development of the High Resolution Visible Infrared (HRVIR) sensors on SPOT 4, which was launched on 24 March 1998 and stopped functioning in July 2013. The spatial resolution of the bands in the multispectral mode is 10 m, except for the Shortwave Infrared (SWIR) that is actually imaged at 20 m and is distributed after resampling to 10 m to match the spatial resolution with others. The panchromatic band was a green-red bandwidth (0.48-0.71 µm) with a spatial resolution of 5 m. Furthermore, each HRG sensor operates with two panchromatic images, which are super mode and are acquired simultaneously by two dedicated arrays of Charge Coupled Device (CCD) detectors. These CCDs are vertically and horizontally offset by half a pixel (2.5m) in the focal plane. In an original three-phase process, a 2.5-metre resolution black and white image can then be generated from these 5m images. Moreover, 5m and 2.5m resolution colour imagery can be derived operationally by combining the panchromatic information with simultaneously acquired 10m multispectral data.

The two satellite images captured simultaneously by SPOT 5’s HRG2 sensor (path 134 / row 334) on 17 December 2008 were utilised in this thesis (PI, PII, PIV): (i) in panchromatic mode at 2.5m spatial resolution with 0.48–0.71 µm wavelengths, and (ii) in multispectral mode at 10m spatial resolution with four bands: 0.50–0.59 µm (green), 0.61–0.68 µm (red), 0.78–0.89 µm (near infrared) and 1.58–1.75 µm (short-wave infrared). ERDAS Imagine®2011 software was used in the pre-processing of the satellite images (e.g., orthorectification, atmospheric correction and topographic normalization). Atmospheric correction was achieved in accordance with the empirical and image-based Dark Object Subtraction (DOS3) method (Chavez, 1996), and topographically normalized by means of c-correction methodology (Teillet et al., 1982). The corrected image was then fused with the panchromatic band to obtain a 2.5m multi-spectral image using the pan-sharpening, high-pass-filtering (HPF) resolution-merging method (Gangkofner, 2008).

The processed SPOT 5 satellite image discussed in Paper I was further enhanced (Band ratio) to identify the variables (e.g., NDVI, SR) that were used in Papers II and IV. The satellite-image products that were used included spectral vegetation indices and land cover data such as NDVI (PI, PII, PIV), SR (PII, PV), TWI (PIV), SF (PII, PIV) and GlobCover land cover (PIII), as shown in Figure 4. The NDVI is a standardised spectral vegetation index that allows the generation of an image displaying the greenness of vegetation that takes advantage of the contrasting characteristics of two bands from a multispectral raster dataset: chlorophyll pigment absorptions in the red band (R) and the high reflectivity of plants in the near infrared band (NIR). This is given as:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R})/(\mathrm{NIR} + \mathrm{R}) \qquad (1)$$

SR (equation 2) is among the simplest measures of the general quantity, dynamism and characteristics of green vegetation (McDonald et al., 1998; Xavier et al., 2004), and is calculated from the ratio of near infrared reflectance and red reflectance.

$$\mathrm{SR} = \mathrm{NIR}/\mathrm{R} \qquad (2)$$

Gruninger et al. (2004) developed a method for creating a shadow fraction they called the Sequential Maximum Angle Convex Cone (SMACC) method using ENVI software. This method was applied in Paper II as one of the remote-sensing variables in the model. *Coffea arabica* L. grows in the shade of indigenous forest in the southwest highlands of Ethiopia, preventing drought stress and facilitating higher yields (Van Der Vossen, 1985). A shadow fraction was calculated to show the degree of shade within the study area (Paper II), and further used in the model after obtaining endmember abundances.

The Topographic Wetness Index 'equation (3)', developed by Beven and Kirkby (1979) within the runoff model TOP-MODEL, was used in Paper IV to determine the distribution of *Coffea arabica* L.

$$\mathrm{TWI} = \ln(\mathrm{a}/\tan\beta) \qquad (3),$$

where $\boldsymbol{a}$ is the local upslope area draining through a certain point per unit contour length and tan β is the local slope.

MODIS NPP (PIII), the Meteosat First Generation/METEOSAT Visible and Infrared Imager (MFG/MVIRI) solar radiation (PIII), MODIS cloudiness (PIII) and GlobCover 2009 (PIII), all of which yield low-resolution data, were used in addition to the remote-sensing products obtained from the SPOT 5 image in gathering the national-scale data for this thesis. NPP was the main remote-sensing data used in the predictive modelling reported in Paper III. This is a measure of vegetation growth, representing the carbon flux from the atmosphere to the biosphere (Churikina and Running, 1998). Annual NPP was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) NPP (kg C day-1) product (Zhao et al., 2005), which is a global product of 1km spatial resolution (Running et al., 2004) and provides a reliable measure of terrestrial vegetation growth and productivity (Turner et al., 2006). Meteosat First Generation/METEOSAT Visible and Infrared Imager (MFG/MVIRI) data were used in Paper III to measure solar radiation in terms of Surface Incoming Direct (SID) radiation (Wm-2). MODIS cloudiness (MOD06) was also taken into consideration in estimating the solar radiation for the unavailable years: cloudiness is the most important factor determining the amount of solar radiation reaching the Earth's surface, and the intensity of direct radiation decreases as the sun is covered partially or fully by cloud (Matuszko, 2012).

The FAO Land Cover of Ethiopia map (post-processed vector version of the GlobCover product) was used to obtain data on land cover (PIII). This data was obtained from the original raster-based GlobCover regional (Africa) archive (FAO, 2009) and was first produced in 2009 from the Medium Resolution Imaging Spectrometer Instrument Fine Resolution (MERIS FR) surface reflectance mosaics (Rast et al., 1999). It has been post-processed to generate a national-level vector version of the Land Cover Classification System (LCCS) regional legend that has 46 classes for the whole of Africa. There are 14 classes for Ethiopia (PIII: Figure 2). The classes of natural vegetation are open broadleaved deciduous forest, broadleaved evergreen or semi-deciduous forest, closed to open shrubland, mosaic forest shrubland/grassland, mosaic grassland/forest-shrubland and closed to open grassland (PIII: Figure 2). According to the GlobCover map, the area covered by forest (broadleaved evergreen or semi-deciduous forest and open broadleaved deciduous forest) accounts for 6.6 per cent of the country's land, whereas agricultural land cover accounts for 33.4 per cent.

(ii) Aerial photographs

Aerial photographs, like satellite images, are digital images or analogue (film) photographs taken from a plane using a camera, and provide a bird's-eye view of the earth's surface. For the purpose of this thesis, true-colour aerial photographs were taken on a series of flights in October 2012 using a NIKON D3X camera and the EnsoMOSAIC aerial imaging system (MosaicMill, 2013). The flight altitude was 1000 m with 50% and 60% overlap between lines and image overlap lines, respectively. During the flight campaign, 705 aerial images were photographed for Didessa block and 888 images for Kofele blocks. Didessa block images were used for this research and the final spatial resolution of the aerial image mosaic was 0.5m after pre-processing and aerial triangulation.

4.1.2. Climate data

Climate refers to long-term weather patterns in particular areas (Thornthwaite, 1948). It is measured in accordance with patterns of variation in meteorological variables such as temperature and precipitation in a given region over a period of time. Climate data comprises long-term patterns of weather information captured and stored in a system for the purpose of solving complex problems affecting the earth and the atmosphere. Given the long-term implications and complexity of the decision-making concerning the climate and how it is changing, it is very important that the decisions are based on the best available data (i.e., an understanding of the quality and provenance of the evidence, and of any assumptions made in generating it).

The climate data included in this thesis, specifically for modelling purposes, are precipitation (PII, PIII, PIV), minimum temperature (PII, PIII, PIV) and maximum temperature (PII, PIII, PIV).

These data were obtained from WorldClim data (Hijmans et al., 2005) and a subset covering the specific area of interest on the national (PIII) and local (PII, PIV) scale. The coordinate system was projected onto the Adindan / UTM zone 37N and the data were resampled to 20 m (PII: Figure 4, PIV: Figure 2). The objective of the resampling procedure is not to add to the spatial information in the climate datasets, but simply to match the spatial resolution of the climate variable raster with the other input dataset for the model.

Future climate scenarios were also used in Paper II to evaluate how changes in precipitation and temperature are likely to affect the presence of understory coffee by the year 2050. These data comprise a downscaled global climate model (GCM) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). The models used in PII were the Community Climate System Model version 4 (CCSM4) (Gent et al., 2011), the Geophysical Fluid Dynamics Laboratory Earth System Model 2 (GFDL ESM2) (Dunne et al., 2012) and the Hadley Centre Global Environmental Model, Version 2 (HadGEM2-AO) (Baek et al., 2013). According to Jury (2014), the above climate models have the best performance over the Ethiopian highlands. Next, the average of the three models was used for analysing the effect of climate change. Following the selection of the climate models, two representative concentration pathways (RCPs) (VanVuuren et al., 2011) were used for the analysis: (i) RCP2.6, which was developed by the Integrated Model to Assess the Global Environment (IMAGE) modelling team of the PBL, Netherlands Environment Assessment Agency (Van Vuuren et al., 2007a) and (ii) RCP6, which was developed by the AIM modelling team at the National Institute for environmental studies (NIES) in Japan (Fujino et al., 2006, Hijioka et al., 2008).

Precipitation, minimum temperature and potential evapotranspiration (PET) data for the whole of Ethiopia were used in the modelling in Paper III, given that they are limiting factors for plant growth (Nemani et al., 2003; Mu et al., 2007b). PET refers to the evapotranspiration that occurs when the ground is completely covered by actively growing vegetation and there is no limitation in the soil moisture (PIII). PET data was obtained from the MODIS evapotranspiration product (MOD16) (Mu et al., 2011). The annual MODIS PET for 2001 to 2010 was used to compute the mean PET in mm/yr. Although precipitation is traditionally considered a major climatic driver of vegetation productivity, evapotranspiration primarily determines plant growth (Churkina and Running, 1998). Water from precipitation is never completely available to vegetation, but represents the maximum possible amount of accessible water. PET was used in Paper III to normalise the precipitation to get the maximum possible amount that is eventually used for plant growth because this ratio indicates the water-limiting condition (Nemani et al., 2003).

4.1.3. Landscape data

The landscape variables were distance to roads (DTRo), distance to river (DTRi), Digital Elevation Model (DEM) and slope (Figure 4). The roads and rivers were digitised from the SPOT 5 satellite image acquired in 2011, and the Euclidian distance from these features was calculated in the GIS environment. A digital elevation model (DEM) was built as follows: 1:50,000 scale topographic paper map sheets provided by the Ethiopian Mapping Agency (EMA) were digitally scanned and utilised in the generation of DEM and its derivate (PI, PII, PIV). The scanned map sheets were then geo-referenced and the 20m interval contour lines digitised on-screen from the respective areas in ArcGIS software. The TOPOGRID function in ArcGIS was used to interpolate a 20-m planimetric resolution raster DEM for the study area. The outcome of this process was a raster DEM in a UTM Zone 37 projection with Adindan / UTM zone 37N Spheroid. The digital elevation model (DEM) was also used for the topographic correction and orthorectification of the SPOT 5 satellite imagery used in this thesis (PI). A slope calculated from 20m DEM describes the steepest downhill slope for a location on a surface (PIV), in other words the maximum rate of change in elevation over each cell and its eight neighbours. Therefore, the lower the slope value the flatter the terrain, and the higher the slope value the steeper the terrain.

4.1.4. Field data

The field work was conducted in May 2012 and December 2013 for 9 and 7 days, respectively. These two time periods are dry seasons in Ethiopia which are in the same season of the flight campaign. It was mainly to collect ground control points (GCPs) for the purpose of preprocessing the SPOT satellite image, training areas for land use land cover classification and validation points for modelling. Training samples, which were randomly collected from field data using GPS and aerial photographs, were overlayed with the segmented objects in ArcGIS. These samples (segmented objects) were used only for LULC mapping of the area. However, for the modelling, I used the sample points that was collected using GPS device. This device was handheld GPS Oregon 550 with ±3 m accuracy. The points were collected from indigenous forest cover that have coffee trees as understory, which covers more than 100 m^2.

4.2. Methods

Three main methods were used to achieve the objectives set for this thesis: remote-sensing data processing (PI, PII), land-cover mapping (PI) and modelling (PII, PIII, PIV).

4.2.1. Remote sensing data processing (Paper I, II, and III)

The imageries were pre-processed and processed for land-cover mapping. ERDAS Imagine® 2011 software was used in the pre-processing of the satellite images (e.g., orthorectification, atmospheric correction and topographic normalisation). The SPOT 5 Orbital Push broom sensor model with a Root Mean Square Error (RMSE) of 0.678 and 0.261 for the panchromatic and multispectral bands, respectively, was used for the purpose of orthorectification. Atmospheric correction followed the empirical and image-based Dark Object Subtraction (DOS3) method (Chavez 1996), topographically normalised by means of c-correction (Teillet et al., 1982). The corrected image was then fused with the panchromatic band to obtain a 2.5m multi-spectral image using the pan-sharpening, high pass filtering (HPF) resolution-merging method (Gangkofner, 2008).

4.2.2. Object-based land cover mapping (Paper I)

The land-cover mapping was based on Object Based Image Analysis (OBIA) as applied in eCognition 8.7 software using the SPOT5 fusion image with image segmentation and classification (PI). The former includes multi-resolution segmentation (MRS), spectral-difference segmentation (SDS) and contrast-splitting segmentation (CSS). The classification was applied on two levels: (i) major classification for distinguishing forest cover from other targets (e.g., urban and agricultural areas) and (ii) the separation of indigenous and exotic forests from the forest cover. The Nearest Neighbor (NN) supervised classification (Land Cover Classification System (LCCS)) method was used to categorise the segmented image objects. Training samples were collected based on field data and aerial photographs. ArcGIS software was used for the sampling was done in by overlaying the two with the segmented vector file. K fold cross-validation (Efron and Tibshirani, 1993) was used for assessing the classification accuracy. Thus, two-fold and four-fold cross-validations were applied for the first- and second-level classifications, respectively.

4.2.3. Modelling (Paper II, III, and IV)

The modelling methods used in this research included predictive modelling of the potential presence of understory coffee (PII), predictive modelling of past natural vegetation converted to agricultural land (PIII), and *Coffea arabica* L. species-distribution and spatial-extent modelling (PIV).

Predictive modelling of understory coffee occurrence

The probability of understory coffee-plantation occurrence was modelled combining GIS, remote-sensing data and statistical methods (Figure 5). The modelling platform was the DinamicaEGO (Soares-Filho et al., 2007), which was developed at the Centre for Remote Sensing of the Federal University of Minas Gerais, Brazil (CSR-UFMG) and has been widely applied in a large range of studies on land change. It has been used, for instance, to explore agriculture-expansion scenarios in Kenya (Maeda et al., 2010), and to delineate deforestation scenarios in the Amazon (Soares-Filho et al., 2002, Maeda et al., 2011).

Input data for the model included landscape maps and additional explanatory variables. Two Land Use Land Cover (LULC) maps with LCCS (PI) were used to represent the landscape patterns in the study area and to identify indigenous forests that are currently used for coffee production. The location of understory coffee is unknown on the first map (LULC-NC), whereas its presence was identified on the second by means of field observation and aerial imagery (LULC-C). The maps comprise nine classes: Closed Herbaceous Vegetation, Indigenous Forest-NC (No-Coffee), Small Sized Field of Graminoid Crop(s), Closed to Open Woody Vegetation, Rivers, Roads, Extraction Sites, Urban Areas and Exotic Forest. Initially, some objects from the Indigenous Forest-NC class with the presence of understory coffee were identified from field observation and aerial photographs, and then converted to Indigenous Forest-C (with coffee) as an additional class in the final landscape within the model.

The Dinamica-EGO platform and the Weights of Evidence (WoE) method were used to calculate the probability of the presence of understory coffee in each cell. The WoE is a Bayesian method developed to facilitate the combining of evidence to support a hypothesis: in this case the effect of each landscape variable on a transition was calculated independently of any combined solution (Soares-Filho et al., 2002). In other words, the WoE was used to combine a set of geospatial attributes in order to identify the factors responsible for defining the landscape patterns (PII: equations 8-9). The understory coffee shrubs identified from field surveys and aerial imagery were divided in two groups: training and validation. The training group was used to create the LULC-C map, and subsequently used in the WoE method. The validation group was used to test the reliability of the model output. Namely, the resulting understory coffee-probability map was validated by creating a histogram showing the proportion of known sites falling into which portion of the map that was predicted as being a probable area for the presence of understory coffee. The model was calibrated and validated in accordance with current climate conditions, then future climate scenarios were used to evaluate how changes in precipitation and temperature were likely to affect the presence of understory coffee by the year 2050.

Coffea arabica L., species distribution and spatial extent modelling

The modelling comprised four processing and analytical steps.

1) Collecting presence/absence data for *Coffea arabica* L.: two methods were used to collect data on 112 *Coffea arabica* L. presence points. First, coffee presence places were identified by means of field surveys. Second, to avoid sampling bias aerial photographs were used to collect *Coffea arabica* presence data covering the whole study area.
2) Land cover mapping (PI)
3) Factor importance analysis: this was used in selecting the variables that determined the presence or absence of the species in a given pixel. In other words, the input explanatory variables were tested for spatial independence. Pearson's correlation coefficients were used to test for spatial dependence between pairs of variables (PIV: Table 1). Factors with coefficients greater than |±0.50| were considered to be auto-correlated and were thus excluded from the explanatory variables.

4) Species distribution modelling: Four predictive models (GLM, ANN, MaxEnt and SVM) were evaluated. ModEco (Guo and Liu, 2010) was used as a model environment for pseudo-absence-based and background-based models. MaxEnt, SVM, GLM and ANN were implemented as background-based models and pseudo-absence-based models. The difference between the two is that the former sample the "pseudo-absence data" from the whole study area, which results in certain types of conditional probability depending on the models used (Phillips and Dudík, 2008). Of the 112 random presence points identified during the field survey and from 0.5m-resolution aerial photographs, 84 were used for the training model and 28 for validation. In order to apply all the models, 168 absence points, which was twice the number of training-data points, were created randomly from background-based and pseudo-absence data.
5) Geospatial analysis: the modelling results were used to analyse and map the areal extent of *Coffea arabica* L. distribution.

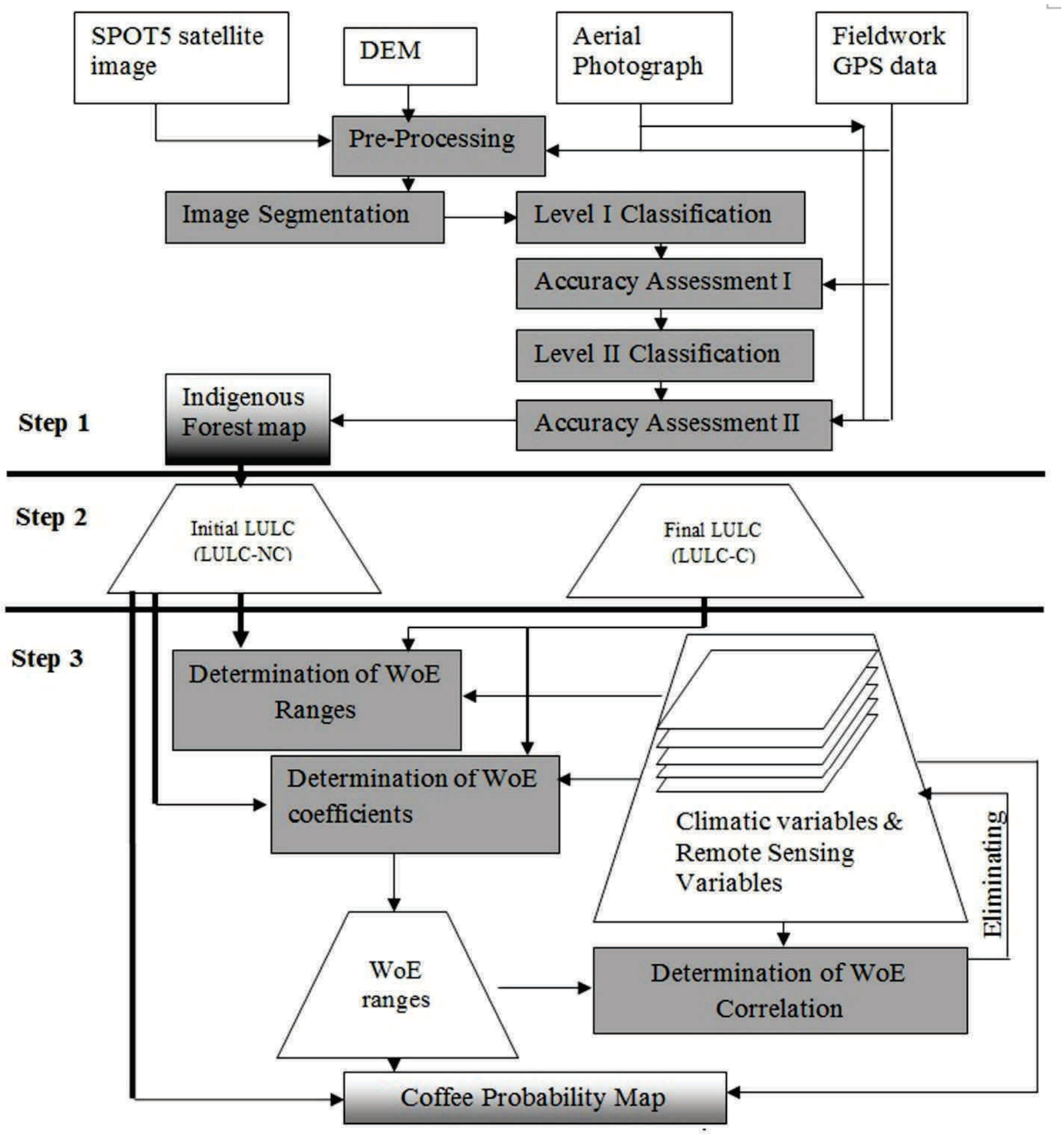

Figure 5. Methods used to identify potential areas suitable for understory coffee (Paper II).

Predictive modelling of past natural vegetation that was lost due to agricultural expansion

Net primary productivity (NPP) was modelled based on the climatic constraints of natural vegetation growth derived from the remote-sensing and climate data. This model was used to simulate the productivity of the agricultural area and thus to identify the original extent of natural vegetation cover. The modelling proceeded in four main stages.

1) Areas of natural vegetation were separated from agricultural areas and their net primary productivity (NPP) was calculated based on climatic productivity constraints. These constraints include minimum temperature, solar radiation based on cloudiness, and water availability (Nemani et al., 2003). Water availability was computed as the ratio of precipitation to potential evapotranspiration (P/PET), indicating water-limiting conditions for plant growth. The range of minimum temperatures, water availability and solar radiation variables (-5–5 ^{o}C, 0–0.75 and 0.1–1, respectively) were rescaled to 0–1 to show the degree of productivity limits (Nemani et al., 2003).
2) Three thousand random points of natural vegetation cover were created to tabulate the three constraints and NPP in PIII. The points were separated at a minimum distance of five kilometres to avoid spatial autocorrelation. Of these samples, 75 per cent were used for the NPP training model and 25 per cent were used for validation.
3) Multivariate regression was used to assess the relationship between NPP and the climatic variables (water availability, solar radiation and minimum temperature). The regression model was also used to identify the environmental variables that have more influence on natural vegetation NPP. The relative impact of these variables on the NPP of each type of vegetation cover was determined by means of standardised coefficients (beta). These coefficients are measured as standard deviations, unlike the regression coefficients that are expressed in the units of the variables.
4) The model was used for simulating NPP over the agricultural lands of Ethiopia, the aim being to provide a proxy for identifying the original natural vegetation in this area. The simulated productivity map classified based on threshold function in order to show how agricultural expansion affected the natural vegetation.

5. Results

5.1. Assessment of local-scale patterns of land use and land cover

Distinguishing between indigenous and exotic forests and mapping their extent (Paper I)

The 2.5m SPOT 5 image of the study area was split into four major categories by means of NN classification to obtain a second-level classification of forest cover (Figure 6). The first-level categories were: (i) Small Sized Field(s) Of Graminoid Crop(s) (**C**); (ii) Closed Herbaceous Vegetation (**H**); (iii) Closed Trees and Scattered Trees (**T**); and (iv) Closed to Open Woody Vegetation (**W**) (Figure 6). The land-cover map shows that most of the area (67.6%) is covered with Closed Trees and Scattered Trees, and generally encompasses a mixture of indigenous and scattered exotic forests. The overall accuracy of this first-level classification was 87.8 per cent, with a kappa coefficient of 0.78 based on two-fold cross-validation (Table 1a.). User and producer accuracy for the class were 96.9 and 93.3 per cent, respectively, with a kappa coefficient of 0.92.

On the second level the Closed Trees and Scattered Trees (**T**) category was reclassified as indigenous (**I**) and exotic (**E**) forest to capture data on indigenous forest for the modelling in PII and PIV. The resulting image shows how the indigenous and exotic forests were classified (Figure 6c). A total of 234 samples (160 and 74 for indigenous and exotic forests, respectively) were used for the NN classification and integrated into the knowledge-based threshold-function classification ('see PI'). A four-fold cross-validation showed that indigenous and exotic forests were classified at an overall accuracy of 84.3 per cent with a kappa coefficient 0.605 (Table 1b).

Table 1. Cross-validation of the Object Based Classification: (a) first-level classification (b) second-level classification.

(a)		Accuracy %		Kappa	overall	Overall
		Producer	User	per class	Acc. %	Kappa
1	**C**	78.5	78.3	0.757	88.9	0.790
	H	89.8	79.0	0.874		
	T	97.9	94.3	0.939		
	W	26.4	86.8	0.246		
2	**C**	63.4	95.6	0.568	86.7	0.769
	H	87.4	75.2	0.840		
	T	95.9	92.2	0.895		
	W	80.0	57.1	0.798		
Avg.	**C**	71.0	87.0	0.663	87.8	0.780
	H	88.6	77.1	0.857		
	T	96.9	93.3	0.917		
	W	53.2	72.0	0.522		

(b)		Accuracy %		Kappa	Overall	Overall
		Producer	User	per class	Acc. %	Kappa
1	**I**	96.1	77.8	0.863	81.7	0.613
	E	62.6	98.5	0.480		
2	**I**	94.7	84.9	0.768	84.2	0.610
	E	60.8	93.4	0.509		
3	**I**	95.1	90.0	0.701	87.2	0.586
	E	57.6	80.0	0.501		
4	**I**	91.8	85.9	0.693	83.9	0.612
	E	66.6	79.7	0.548		
Avg.	**I**	94.4	84.7	0.756	84.3	0.605
	E	61.9	87.9	0.510		

Identifying the spatial distribution of understory coffee plantations in Ethiopia's highlands (Paper II and IV)

The association between the understory coffee probability transition (UCPT) and a certain remote sensing or climatic attribute that was obtained during the model calibration (Figure 7) shows the most relevant W+ values in determining the probabilistic presence of understory coffee in the area. In other words, the transition is from indigenous forests without understory coffee (IFWOUC) to indigenous forests with understory coffee (IFWUC). The significant attributes with regard to UCPT probability were PT, Tmax, SR, NDVI and the shadow fraction.

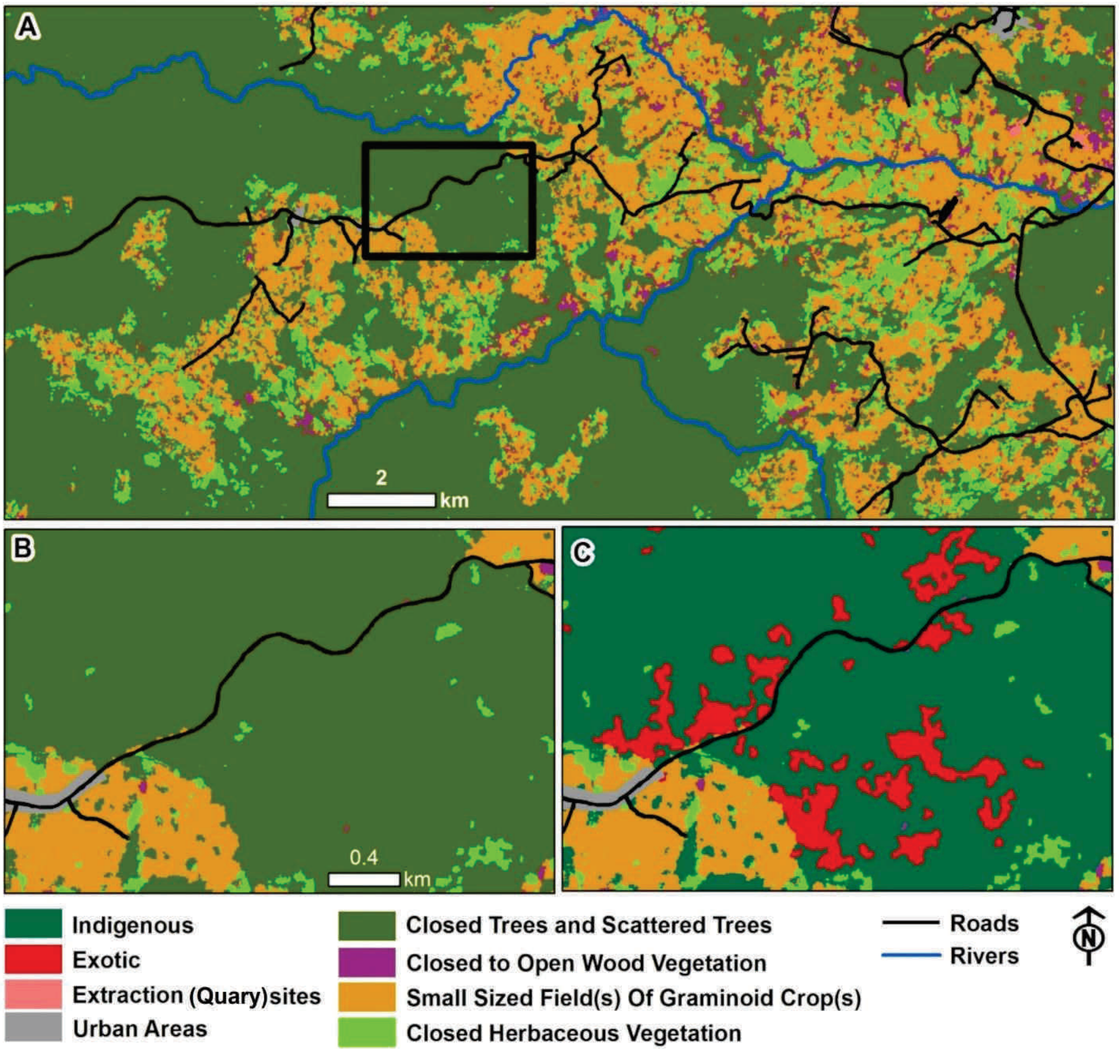

Figure 6. Land use/Land cover map of the coffee-production area (OBIA).

The map showing the probabilistic presence of understory coffee (Figure 8) was produced following application of the W+ values derived in Paper II, equation 8. It indicates that the presence of understory coffee is higher in indigenous forests close to rivers and the darkest (dark blue) area in the map shows the highest presence probability, for example. Conversely, lowest in the dense indigenous forests, which is light yellow colour in the map. This result was validated based on the known understory coffee areas. The probability of the presence of understory coffee ranges from 0.1 to 1 for the known forest area, as described in Paper II, Figure 8. The validation result shows a probability of between 0.50 and 1 in 72 per cent of the known understory coffee pixels, and a probability of between 0.75 and 1 in 55 per cent of the same area. This implies that 72 per cent of the known understory coffee pixels fall in the darkest (dark blue) areas of the probability map. Analyses of the descriptive statistics of the probability values also confirmed the goodness of fit.

For example, the mean probability value of the known understory coffee areas was 0.67 within 20 square metres of indigenous forest, which is the pixel size.

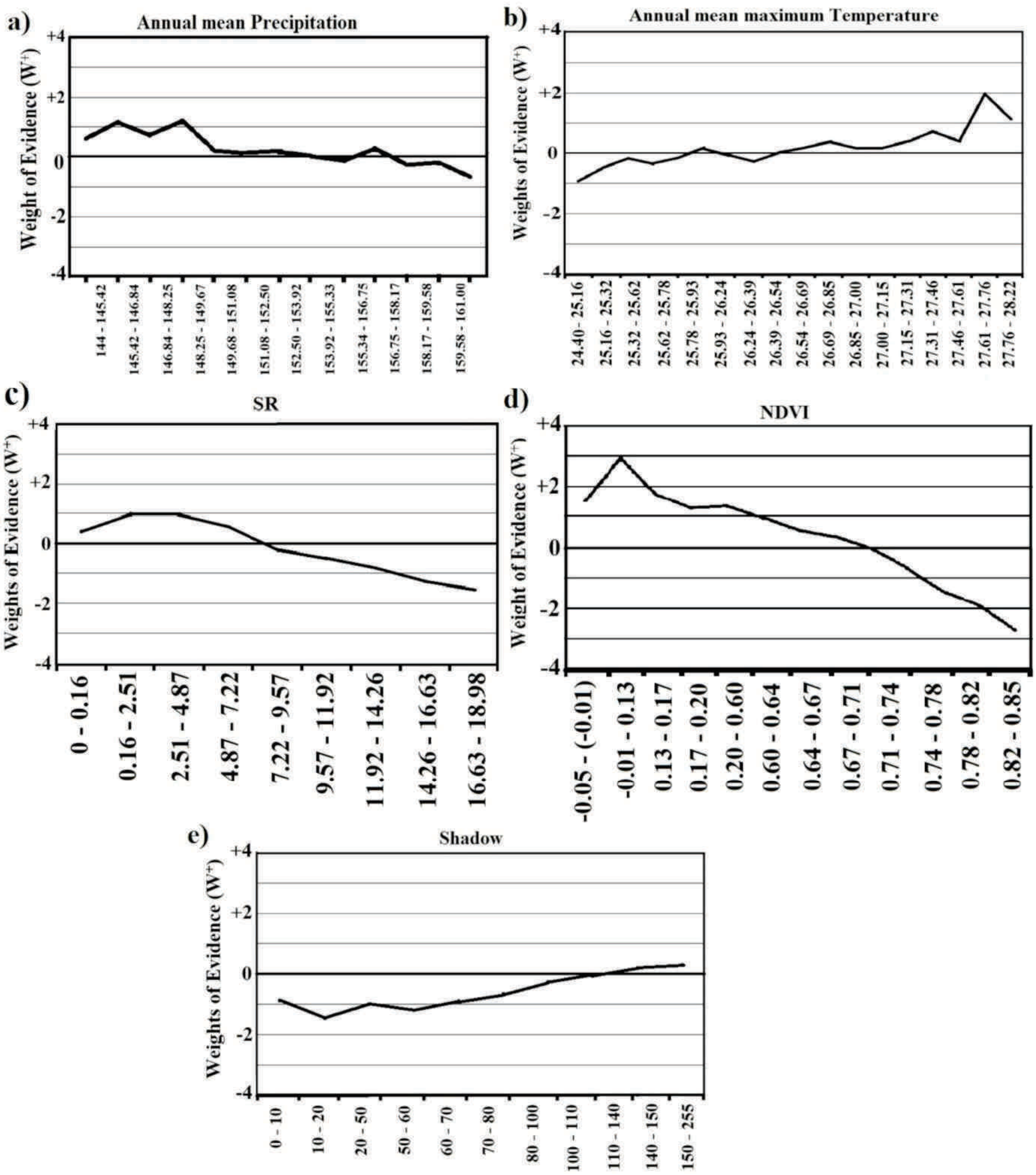

Figure 7. Weights of Evidence (W+) values for the variables: a) annual mean precipitation, b) annual mean maximum temperature, c) Simple Ratio, d) Normalised Difference Vegetation Index and e) Shadow fraction.

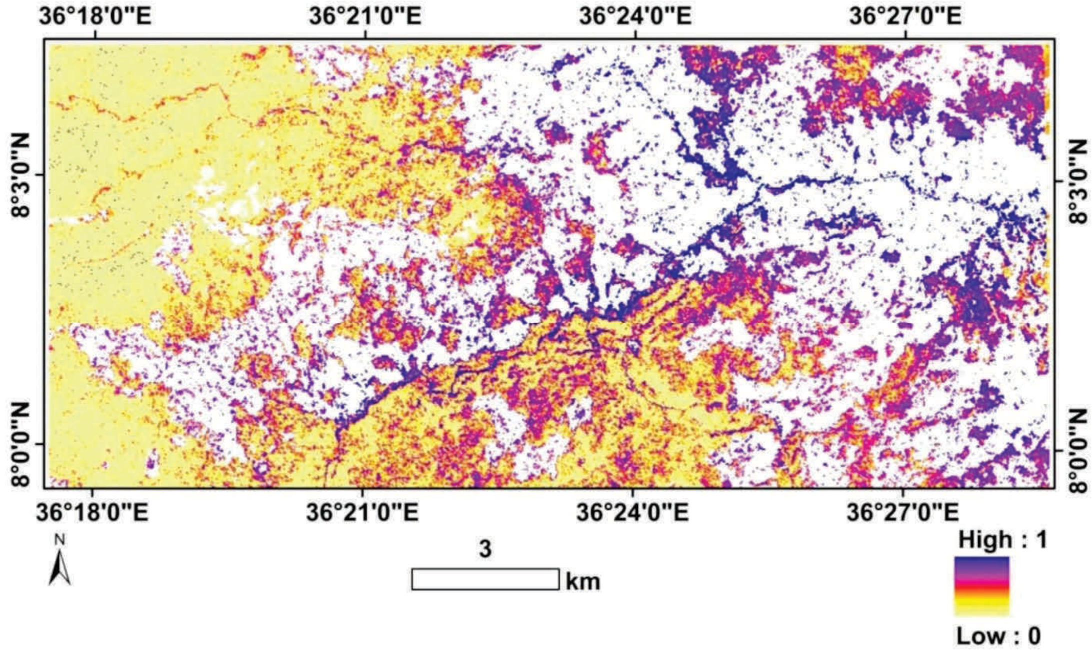

Figure 8. The probabilistic presence of understory coffee.

As a result of climate change (precipitation and temperature) there is an increasing probability of understory coffee at higher altitudes (PII: Figure 11), and a shifting of optimal growing zones of *Coffea arabica* L. in the area.

Determination of the geospatial extent of *Coffea arabica* L. in the coffee-growing area in Paper IV was based on four species-distribution-modelling methods. Figure 9 depicts the results of the four methods with pseudo absence and background absence. The grey and red colours represent indigenous forest and the predicted presence of understory coffee, respectively. MaxEnt with pseudo absence data and SVM with background absence revealed the highest levels of understory coffee presence prediction with 12.2 and 23.1 per-cent of indigenous-forest coverage, respectively (PIV: Table 3), whereas the lowest levels of eight and 6.4 per cent were based on ANN with pseudo absence and background absence data, respectively.

The model's performance was tested using the confusion matrices' of GLM, ANN, MaxEnt and SVM (PIV: Table 4). According to the results, the true positive rates of GLM, ANN, MaxEnt and SVM were 0.821, 0.548, 0.810 and 0.821, respectively. In other words, both the GLM and the SVM models performed better (TPR=0.821) whereas the ANN model showed the lowest performance (TPR=0.548). On the other hand, the TPRs of GLM, ANN, MaxEnt and SVM based on background absence were 0.821, 0.679, 0.964 and 0.964, respectively. This indicates that MaxEnt and SVM were the most robust modelling methods (TPR=0.964) and ANN was the least robust (TPR=0.679).

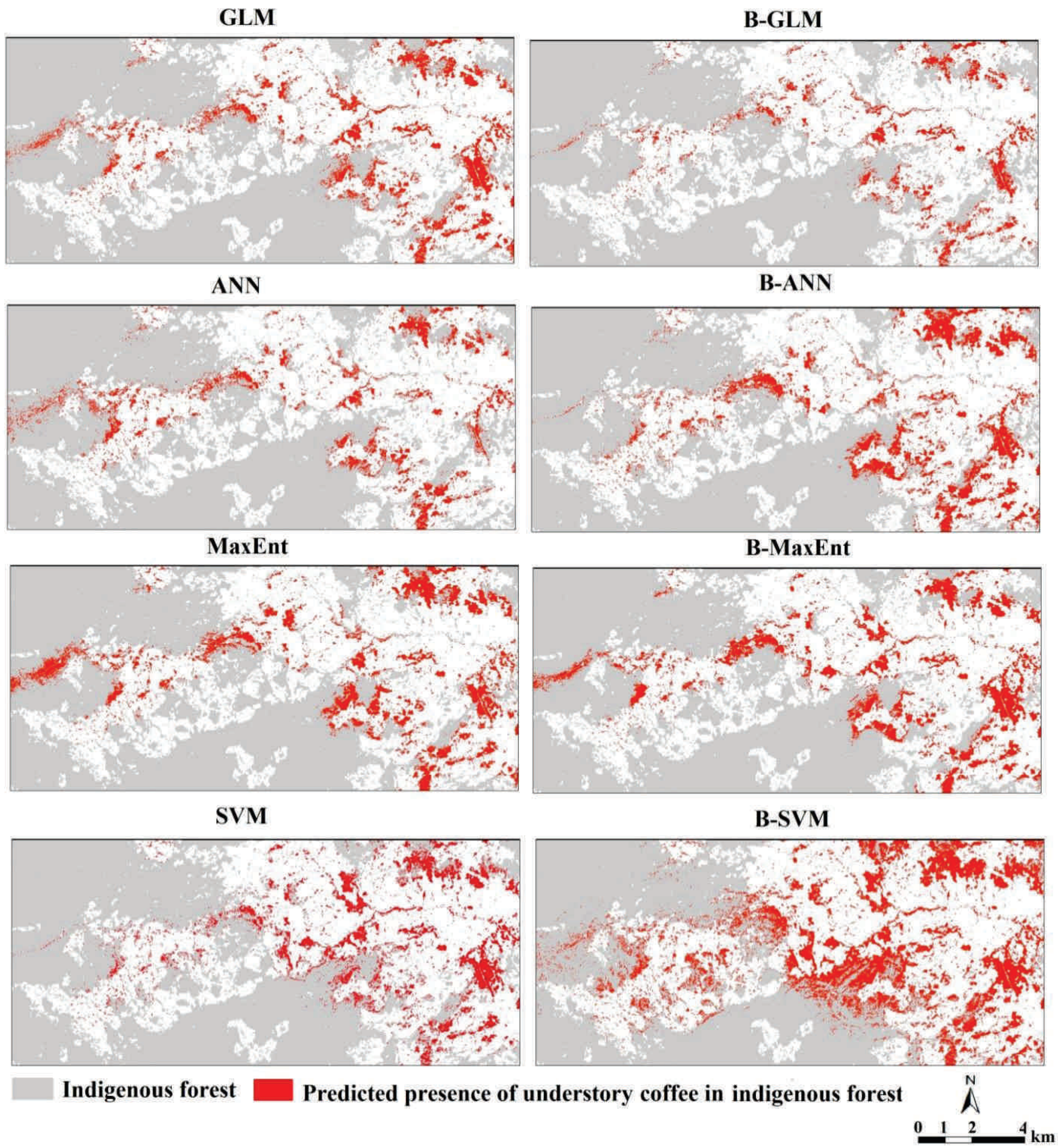

Figure 9. Model results based on the pseudo absence of GLM, ANN, MaxEnt, SVM and a background absence of GLM (B-GLM), ANN (B-ANN), MaxEnt (B-MaxEnt), SVM (B-SVM).

5.2. Assessment of regional-scale patterns of land use and land cover

The natural vegetation cover across Ethiopia before the agricultural expansion (Paper III)

The three main results reported in Paper III are referred to in this thesis as small-scale findings.

i) Mapping the constraints of vegetation growth for Ethiopia: The main constraint on productivity on the lowlands of Ethiopia is water availability, whereas the minimum temperature is a limitation on the highest mountain peaks such as the northern part of the Ethiopian highlands and the southeast part of the country. Given that these peaks are very small in area, the main constraint on productivity in the highlands is solar radiation.

ii) The results of the multivariate regression concerning the productivity of existing natural vegetation (Globcover) and the climatic constraints: The productivity of natural vegetation cover was significantly related ($p<0.001$, $R2=0.77$) to water availability, which is one of the climatic constraints on productivity (PIII: Figure 3). However, it was not significantly limited by solar radiation or minimum temperature. Moreover, class-level analysis of vegetation productivity showed a significant association with water availability (PIII: Figure 4): for example, there was a significant relationship with closed to open grassland, closed to open shrubland, open broadleaved deciduous forest, and broadleaved evergreen or semi-deciduous forest ($p<0.001$).

iii) Modelling previous vegetation cover on the current agricultural land based on the above model: The relative coefficients and intercepts were identified from the model in order to formulate the NPP model and simulate previous natural-vegetation productivity in the area covered by agriculture (PIII: Figure 5b). Model validation showed that the simulated and the original NPP were significantly related ($p < 0.001$ and $R2 = 0.76$). The simulated NPP map of agricultural land in Ethiopia was then classified based on threshold values, as shown in Paper III, Figure 6, in order to reconstruct the original extent of the classes of natural vegetation cover (PIII, Figure 7a).

In other words, the current agricultural landscape in Ethiopia was previously covered to a significant extent (38.9%) by broadleaved evergreen and deciduous forest, the two classes of forest (open broadleaved deciduous and broadleaved evergreen or semi-deciduous) covering 27.7 and 11.2 per cent of the area, respectively. Sparse vegetation and grassland (5.7% of the area) were the least affected by the agricultural expansion. The rest of the agricultural areas were covered by closed to open shrubland and mosaic forest-shrubland/grassland (36.1% and 19.3%, respectively (PIII, Figure 7a). Construction of the map of potential natural vegetation cover in Ethiopia also entailed merging the classes of simulated NPP natural vegetation cover for the agricultural areas and the current natural vegetation cover from Globcover (PIII, Figure 7b). The respective percentages of broadleaved evergreen or semi-deciduous forest, open broadleaved deciduous forest, closed to open shrubland, mosaic forest-shrubland/grassland, sparse vegetation and grassland were 18.8, 12.4, 20.6, 31.5, and 16.8.

6. Discussion

6.1. Modelling and mapping land cover and the presence of understory coffee

- *OBIA has been applied in a large variety of remote-sensing studies and the usage of this method has become particularly popular in recent years (Blaschke, 2010).* In this thesis, Paper I in particular concerns the applicability of OBIA in separating land covers using high-resolution images, and Paper II shows the probabilistic presence of understory coffee, integrating the land cover data with SVI. The combination of these approaches has so far been insufficiently explored in terms of improving spatial analysis in studies of coffee: most of the spatial research focuses on coffee that grows in an open canopy. For example, Fabio et al. (2012) report the recognition of coffee crops using SPOT imaging with the automatic fusion of region-based classifiers. OBIA classification is a robust method for ecological applications. Zanella et al. (2012), for instance, show the importance of choosing the right classification method in the context of landscape ecology based on SPOT 2.5-m-resolution satellite images, especially OBIA.
- *Although SPOT 5 satellite images are high in spatial resolution, they are limited in spectral resolution,* which hinders the identification of both indigenous and exotic tree species. However, the tree species could be identified in the field. The major indigenous species are *Albizia gummifera*, *Croton macrostachyus*, *Cordia africana*, and *Acasia abyssinica*, and the main exotic species are *Grevillea robusta*, *Eucalyptus globulus*, *Pinus patula*, and *Cupressus lustitanica*. Therefore, this thesis does not show in detail the tree species that are characteristic of coffee forests and further research is necessary, based on high-resolution hyperspectral imageries, for example.
- *High-resolution satellite images provide the kind of habitat information that helps in distinguishing suitable sites more efficiently.* Remote-sensing variables such as SVIs and specifically NDVI showed good correlation with the presence of understory coffee plantations, with W+ values up to three, as shown in Paper II, Figure 6(d). The shadow fraction also proved to be a useful explanatory variable for identifying indigenous trees, given that coffee trees grow under the indigenous forest as understory. Other studies such as Roura-Pascual et al. (2006), Bino et al. (2008) and Shirly et al. (2013), rely on NDVI for species distribution modelling, as in Paper IV in this thesis. Specifically, Shirly et al. (2013) show the usefulness of unclassified spectral reflectance in Landsat TM satellite images (bands 1, 2, 3, 4, 5 and 7) for species-distribution modelling, in addition to the NDVI. Apart from their predictive performance, these high-resolution satellite images could give detailed information on individual canopy gaps, for example, which could be missed on the broad spatial scale that merely identifies the presence and distribution of species (Betts et al., 2006). Moreover, large-scale geospatial data is effective in predicting the accurate location of a

species and its association. For instance, the ‘Fine-Filter’ strategy for biodiversity conservation developed by Scott et al. (1993) calls for fine-scale site identification rather than the coarser remotely sensed MODIS data.

- *The probability of transition from forest without understory coffee (FWOUC) to forest with understory coffee (FWUC) is time independent,* which is not reflected in the work of Maeda et al. (2010 and 2011), for example. That is, they applied change in land use and land cover based on temporal maps and simulation to agricultural expansion and forest conversion in their respective studies. However, such temporal variables were not utilized in the study area rather favourability change for specific plant species, for example, *Coffea arabica* L. (Paper II).
- *Less attention is given to the spatial distribution of production and suitable areas for coffee growing in Ethiopia* even though *Coffee arabica* L. originated in the southwest highlands (Davis et al., 2012), and the country's economy is highly dependent on coffee (IMF, 2006). Paper II identifies the environmental and landscape conditions that favour *Coffea arabica* L. in the production area, and Paper IV shows, on the evidence of four SDMs (GLM, ANN, MaxEnt and SVM), the spatial distribution, specifically the area coverage, of the *Coffea arabica* L. species in one of the major coffee-growing area in the southwest highlands of Ethiopia. Geographic-information-based multi-criteria analysis has been used in other developing countries such as Rwanda to produce maps showing the actual spatial distribution and potential production zones of *Coffea arabica* L., and to predict the productivity level and potential yield (Nzeyimana et al., 2014). However, the geospatial data were restricted to climatic and landscape data (weighted overlay analysis) on the national scale, unlike the study discussed in Papers II and IV, which was based on remote-sensing data and focused on a large-scale coffee-growing area.
- *Although a niche-based model describes suitability in ecological space, it is typically projected into geographic space, yielding a geographic area of the predicted presence of the species (PIV: Table 3*). As Figure 8 implies, the outputs of each model are spatially different in the same survey of the species and the associated explanatory variables. Different methods have different strengths and weaknesses. Further, the choice of method depends on the data, the assumptions and the goals of the exercise (Segurado & Araújo, 2004). However, different methods with the same data and goals are taken into consideration in Paper IV. As a consequence, GLM and SVM show the highest performance when background-absence data is used, and SVM and MaxEnt models perform well in the case of pseudo-absence data. In both cases, SVM was the most robust method in terms of predicting the presence of understory coffee in the area.
- *The combining of dynamic and static variables in SDM prediction remains poorly understood and controversial* (Brook et al., 2009). Most studies only use bioclimatic data as

explanatory variables to predict species distribution (e.g., Hole et al., 2009; Carvalho et al., 2010). Non-climatic variables such as elevation, slope and aspect are also incorporated in some studies, alongside precipitation and temperature (e.g., Peterson et al., 2002). It is shown in Paper IV that local-scale studies incorporating landscape variables (distance to roads, distance to river, elevation, slope) and remote-sensing variables (NDVI, SR, TWI and Shadow Fraction) other than bioclimatic explanatory variables define species presence simply in terms of climate, excluding other important variables.

6.2. Reconstructing the natural vegetation cover of agricultural areas in Ethiopia

- *Natural vegetation cover over the past century as reconstructed in Paper III gives valuable information regarding the extent of original land cover in Ethiopia*, which thus far has not been available (Dessie and Christiansson, 2008). Although there are some studies on change in forest and land cover in the northern (Kebrom and Hedlund, 2000; Gete and Hurni, 2001; Belay, 2002; Woldeamlak, 2002) and south-central parts of Ethiopia (Dessie and Kleman 2007), there is insufficient information on a national scale. The reconstructed map of natural vegetation cover in Ethiopia could therefore be useful to policy makers and those responsible for making decisions regarding the management of natural resources that are beneficial to the country.
- *The reconstruction of the natural vegetation cover of agricultural areas presented in Paper III is potentially beneficial in many respects,* such as in the design of national and landscape rehabilitation policies. Forest rehabilitation in Ethiopia incorporates different types of policies, strategies and actors: the Forestry Conservation, Development and Utilization Proclamation No. 94/1994, the National Action Program to Combat Desertification (NAP 1997), Rural and Agricultural Development Policy Strategies (2002), the Productive Safety Net Program (PSNP) (2003), the Ethiopian Program of Adaptation on Climate Change (EPACC), the Sustainable Land Management Program (SLMP) (2008–2015), Climate-Resilient Green Economy, Phase 1 (CRGE) (2011–2030). Teketay et al., (2010) describe the common restoration strategies observed today such as reforestation/afforestation, agroforestry, exclosure and woodlot development. According to Lemenih & Bongers (2010), the management approach has shifted in recent decades, from the cultivation of large industrial plantations in the 1960s and 1970s to the current small-scale forest plantations in the form of woodlots integrated into agricultural landscapes to restore the forest that agricultural expansion destroyed.
- *The finding reported in Paper III that 38.9 per cent of current agricultural land was covered by forest implies that there was extensive deforestation in Ethiopia,* specifically related to agricultural activities. This happened because agriculture is the major source of livelihood and is being used by smallholders for subsistence. According to Hamza.and Iyela (2012),

almost 85 per cent of the population depend directly on the agricultural economy. Due to the rapid population growth and the absence of agricultural intensification, smallholders required more land to grow crops and thus to earn a living, which further resulted in deforestation and land-use conversion from other types of cover (e.g., forest) to cropland.

- There have been many studies on deforestation as a result of agricultural activities. According to Reusing (1998) and Limenih et al., (2007), agricultural expansion was the most direct driver of deforestation and forest degradation in Ethiopia given the increase in population. However, although agricultural expansion is the main driver of change in land cover, specifically in the destruction of natural forest areas, factors such as logging, urbanisation, desertification, mining and fires also have an impact (Belachew, 1996; Reusing, 1998; Darbyshire et al., 2003; Nyssen et al., 2004; Limenih et al., 2007; Tadesse et al., 2014). As the population increases so does the need for farmland and wood for fuel and construction, which relates directly to logging and urbanisation. As Belachew (1996) showed, wood products are prominent materials used for house construction in Ethiopia.

7. Conclusion

The mapping of resources on the national and the local scale contributes to a country's economic development and the management of its natural assets. In the case of Ethiopia, for example, decision makers engaged in the management of coffee production and the conservation of natural resources, specifically indigenous forest (Papers I, II, and IV), could benefit from knowing the geographical extent of suitable land supporting *Coffea arabica* L. Furthermore, the map of reconstructed natural vegetation will be of use to those responsible for restoring and rehabilitating the major areas affected by agriculture (Paper III). As a new tool it should enhance understanding of the spatial patterns of the original vegetation and the identification of socio-economic factors that contributed to defining the current agricultural landscape in Ethiopia.

Despite the importance of *Coffea arabica* L. to the country's economy and the community's livelihood, little is known about the extent and exact location of understory coffee plants in the Ethiopian highlands, which inhibits the proper management of coffee production and ecosystem services. This thesis demonstrates novel and robust modelling approaches for mapping potential areas of understory coffee using climatic and remote-sensing variables. The impact of climate change was assessed for the existence of *Coffea arabica* L. in the area by means of probabilistic presence modelling (Paper II): the various scenarios indicate that precipitation and maximum temperatures are likely to increase by 2050, affecting the dynamics of landscape patterns. There also seems to be a shifting of optimal growing areas for understory coffee to higher altitudes. Likewise, the mapping based on four different models of species distribution and geospatial analysis gives a description of the geographical distribution and extent of this species in an area of coffee growing and production (Paper IV).

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