Climate-smart livestock production at landscape level in Kenya

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Summary

Greenhouse gas (GHG) emissions from unsustainable land-use practices around the world contribute significantly to anthropogenic climate change. Growing population pressure and low efficiency of agricultural production systems in Sub-Saharan Africa (SSA) trigger the expansion of agricultural land into natural ecosystems, which leads to deforestation and land degradation, and causes GHG emissions. At the same time, prolonged droughts and increasingly erratic weather patterns due to climate change jeopardise food security in SSA countries such as Kenya.

The concept of 'Climate-Smart Agriculture' (CSA) as a global development goal was introduced to guide the transformation of agricultural systems towards sustainable food production systems by integrating measures of climate change adaptation, mitigation and food security. To achieve this goal in SSA, the largely smallholder-driven food production has to be intensified on existing agricultural land. The sustainable intensification of smallholder production systems is crucial to avoid compromising environmental goals such as safeguarding the carbon (C) sink capacity of forest ecosystems.

Kenya's agricultural sector is the largest contributor of the country's total GHG emissions, while 90 % of the agricultural emissions stem from livestock production alone. To curb the increase of GHG emissions, Kenya as a member state of the UN Framework Convention on Climate Change (UNFCCC) has been developing national and sectoral policies that aim to mitigate GHG emissions from agriculture, while increasing agricultural productivity. As part of its ambitious economic development plan, Kenya seeks to boost its dairy sector in order to meet the increasing demand for milk, which results from the fast growing population.

Prior to the implementation of interventions that aim to realise CSA policy objectives, candidate interventions (e.g. climate-smart livestock feeds) have to be evaluated, prioritised and targeted. Decisions must be made by policy makers and planning institutions about the specific practices that are targeted at certain locations. To do so, quantitative information is required that shows whether the interventions at hand can realise 'win-win' potentials for smallholder farmers and climate change mitigation. However, the necessary approaches to obtain this information are often missing. The objectives of this PhD thesis are i) to improve the support of decision-making processes that aim to prioritise and target

CSA practices robustly at national scale and ii) to elucidate the potential of intensified smallholder dairy production in Kenya to increase milk yields and to reduce direct and indirect GHG emissions effectively through feed improvements.

Chapter 2 - *CSA-targeting and decision-making*: "targetCSA", a spatially-explicit framework to target CSA practices was developed and applied in Kenya. The framework strengthens evidence-based decision-making by integrating i) knowledge and opinions on the prioritisation of CSA practices obtained from cross-sectoral stakeholders and ii) spatially-explicit data on climate change vulnerability and CSA suitability. Vulnerability and suitability indices were calculated and weighed by the various preferences of involved stakeholder groups. A multi-criteria optimisation model was used to find consensual preferences, which were then mapped to explore the potential effects of various decision-making outcomes based on group-specific preferences and the approached consensus among stakeholder groups. The integration of quantitative information and stakeholder views to explore and find consensus solutions enables more informed and transparent decisions on targeting CSA interventions.

Chapter 3 - *Dairy feed improvements and land availability*: The improvement of dairy cattle feeds can lead to synergies between increased farm production and climate change mitigation. However, land-use change (LUC) resulting from the cultivation of improved feeds and the shortage of arable land required to grow the additional feed alternatives can result in GHG emissions that outbalance mitigation or render the implementation of certain feed alternatives unfeasible. By applying a spatially-explicit livestock model, 'win-win' potentials to increase milk yields and to mitigate agricultural GHG emissions, including emissions from LUC, for the entire dairy production region in Kenya were assessed. Moreover, potential productivity gains and GHG emission reduction potentials were linked to related quantitative targets at national scale. The results indicate that Kenya's dairy sector can reduce GHG emission intensities by up to 31 % through feed improvements that increase the forage quality through Napier grass and increase the supplementation of dairy concentrate. In addition, these feed improvements are promising options to meet Kenya's national climate change mitigation target, while the milk yield target could be achieved partially by up to 41 %. In contrast, LUC emissions from feed conservation based on maize increase the risk to compromise Kenya's mitigation target at national level. The shortage of land that would be required to cultivate additional fodder maize renders the implementation of related feed improvement options largely unfeasible.

Chapter 4 - *Sustainable intensification and forest disturbance*: Negative spillover effects such as C leakage may result from fragmented mitigation approaches that fail to link agricultural and forest land uses. Assessing the impact of agricultural production beyond farm boundaries is therefore crucial to target CSA practices that result in effective mitigation outcomes. The effects of farm practices and characteristics such as cattle management

and fuelwood consumption on forest disturbance were quantified based on empirical farm data and a forest change detection algorithm using Landsat time-series data. The results show that the intensification of smallholder dairy farming in Kenya can alleviate the pressure on local forests. Improved dairy cattle and feeds, and more trees on farms located closely to forests lower the need to use these forests for cattle grazing and as source for fuelwood, reducing the risk of forest disturbance.

Chapter 5 – *Mitigating emissions from agriculture and forests*: The combined agricultural and forest mitigation potentials of on-farm CSA practices such as the improvement of dairy feeds, including closing the yield gaps of fodder maize was quantified for the entire dairy production region in Kenya. Forest C loss due to dairy cattle was quantified by using remote-sensing time-series data on aboveground C change. The results indicate that GHG emission intensities on agricultural land can be reduced by up to 20 % through closing the maize yield gap. The effect of reduced GHG emissions from avoided LUC was up to five times higher than the increase of GHG emissions from fertiliser application required to close the yield gap. The lowered demand for arable land to cultivate alternative dairy feeds close to forests could reduce forest C loss due to avoided grazing of dairy cattle inside forests by up to 94 %. However, improved forage quality through Napier grass and the increased supplementation of dairy concentrates showed i) the highest potential to reduce emission intensity (29 %), ii) the lowest demand for arable land and iii) the highest reduction of forest C loss (270 %). These feed improvements could reduce combined total GHG emissions by 2.5 % and, therefore, lead to a net mitigation of direct and indirect GHG emissions from dairy production. Dairy feed improvements may turn mountain forests in Kenya into C sinks.

Overall, the results of this PhD thesis show that context-specific and detailed *ex-ante* impact assessments are essential to inform integrated CSA policies that target effective climate change mitigation across land use sectors and agricultural development. This thesis provides novel approaches and information that contribute to the evidence-based prioritisation and targeting of CSA interventions. These approaches allowed to study interactions between the agricultural and forestry sectors based on empirical data and enabled to identify and quantify synergies and trade-offs that were not known before.

Zusammenfassung

Treibhausgasemissionen (THG) aus nicht nachhaltigen Landnutzungspraktiken tragen weltweit erheblich zum anthropogenen Klimawandel bei. Wachsender Bevölkerungsdruck und geringe Effizienz landwirtschaftlicher Produktionssysteme in Subsahara-Afrika (SSA) bewirken die Ausdehnung landwirtschaftlicher Flächen hinein in natürliche Ökosysteme. Derartige Expansionsprozesse führen zu Entwaldung und Landdegradation und verursachen THG-Emissionen. Gleichzeitig gefährden die aufgrund des Klimawandels zunehmenden Dürreperioden und unberechenbarer werdende Wetterlagen die Ernährungssicherheit in SSA-Ländern wie Kenia.

Das Konzept der „Climate-Smart Agriculture" (CSA, klima-intelligente Landwirtschaft) wurde als globales Entwicklungsziel eingeführt, um die Transformation landwirtschaftlicher Produktionssysteme hin zu einer nachhaltigen Nahrungsmittelproduktion durch die Integration von Maßnahmen zur Anpassung an den Klimawandel, zur Eindämmung des Klimawandels und zur Ernährungssicherheit zu steuern. Um diese Ziele in SSA zu erreichen, muss die weitgehend kleinbäuerliche Nahrungsmittelproduktion auf bereits bestehenden landwirtschaftlichen Flächen intensiviert werden. Die nachhaltige Intensivierung von kleinbäuerlichen Produktionssystemen ist von entscheidender Bedeutung, um Umweltziele wie die Sicherung der Kohlenstoff-Senkenfunktion von Waldökosystemen nicht zu gefährden.

Kenias Landwirtschaftssektor hat den größten Anteil an den THG-Emissionen des Landes. Allein 90 % der landwirtschaftlichen Emissionen stammen aus der Tierproduktion. Um den Anstieg der Treibhausgasemissionen einzudämmen, hat Kenia als Mitgliedsstaat der UN-Klimarahmenkonvention (UNFCCC) nationale und sektorale Strategien und Richtlinien entwickelt, die darauf abzielen, die THG-Emissionen aus der Landwirtschaft zu verringern und gleichzeitig die landwirtschaftliche Produktivität zu steigern. Im Rahmen des ambitionierten Plans zur ökonomischen Entwicklung des Landes will Kenia den Aufbau seines Milchsektors fördern, um der steigenden Nachfrage nach Milch, die sich aus der rasant wachsenden Bevölkerung ergibt, gerecht zu werden.

Vor der Implementierung von Interventionen, die darauf abzielen, die gesteckten CSA-Ziele zu erreichen, müssen potenzielle Optionen wie z. B. klimafreundliche Tierfuttermittel evaluiert, priorisiert und deren Umsetzung gezielt geplant werden. Politische Entschei-

dungsträger und Planungsinstitutionen müssen Entscheidungen über den Einsatz bestimmter CSA-Praktiken und deren Auswirkungen an den Orten ihrer Umsetzung treffen. Dazu sind quantitative Informationen erforderlich, die zeigen, ob die zur Verfügung stehenden Interventionen „win-win"-Potenziale für Kleinbauern und den Klimaschutz realisieren können. Die notwendigen Ansätze, um diese Informationen zu erhalten, fehlen jedoch oft. Die Ziele dieser Dissertation sind i) die Verbesserung der Unterstützung von Entscheidungsfindungsprozessen, die darauf abzielen, CSA-Praktiken auf nationaler Ebene zu priorisieren sowie deren Umsetzung zu planen, und ii) das Potenzial einer nachhaltig intensivierten, kleinbäuerlichen Milchproduktion in Kenia aufzuzeigen, die Milchleistung zu steigern sowie direkte und indirekte THG-Emissionen durch Futterverbesserungen effektiv zu reduzieren.

Kapitel 2 - *CSA-Priorisierung und Entscheidungsfindung*: „targetCSA", ein räumlich-explizites Konzept zur multi-kriteriellen Unterstützung von Entscheidungsprozessen für die Planung von CSA-Praktiken wurde entwickelt und in Kenia angewendet. Das Konzept stärkt evidenzbasierte Entscheidungsfindung durch die Integration von i) Wissen und Präferenzen der einbezogenen, sektorübergreifenden Interessengruppen im Hinblick auf die Priorisierung von CSA-Praktiken und ii) durch die Einbindung räumlich-expliziter Daten zur Anfälligkeit für den Klimawandel und der CSA-Eignung. Anfälligkeits- und Eignungsindizes wurden mit Hilfe der verschiedenen Präferenzen der involvierten Interessengruppen berechnet und gewichtet. Ein multi-kriterielles Optimierungsmodell wurde verwendet, um konsensuale Präferenzen zu finden, die dann kartiert wurden, um die möglichen Auswirkungen verschiedener Entscheidungsergebnisse auf der Grundlage von gruppenspezifischen Präferenzen und dem angenährten Konsens zwischen Interessengruppen zu untersuchen. Die Integration von sowohl quantitativen Informationen als auch qualitativer Informationen bezüglich der Ansichten von Interessengruppen, unterstützt die Suche nach Konsenslösungen und ermöglicht informierte und transparentere Entscheidungen im Hinblick auf die Planung von CSA-Interventionen.

Kapitel 3 – *Verbessertes Futter für Milchvieh und Flächenverfügbarkeit*: Die Verbesserung von Milchviehfutter kann zu Synergien zwischen der Steigerung landwirtschaftlicher Produktion und der Reduktion von Treibhausgasemissionen führen. Landnutzungsänderungen, die sich aus dem Anbau verbesserter Futtermittel ergeben, und der Mangel an Ackerland, das für den Anbau der zusätzlichen Futteralternativen erforderlich ist, können jedoch Treibhausgasemissionen zur Folge haben, die letztlich zu einer Nettoerhöhung der Treibhausgasemissionen führen oder die Potentiale zur Umsetzung bestimmter Futteralternativen gravierend einschränken. Durch die Anwendung eines räumlich-expliziten Simulationsmodells wurden „win-win"-Potenziale zur Steigerung der Milchleistung und zur Minderung der landwirtschaftlichen THG-Emissionen, einschließlich der Emissionen von Landnutzungsänderungen, für die gesamte Milchproduktionsregion in Kenia berechnet. Darüber hinaus wurden potenzielle Produktivitätszuwächse und Minderungen der Treibhausgasemissionen mit entsprechenden quantitativen Zielen auf nationaler Ebene

verknüpft. Die Ergebnisse zeigen, dass Kenias Milchsektor die Intensität der Treibhausgasemissionen um bis zu 31 % reduzieren kann, indem die Futterqualität durch Napiergras erhöht und das Viehfutter mit Konzentraten ergänzt wird. Darüber hinaus sind diese Futterverbesserungen vielversprechende Optionen die dazu beitragen können, Kenias nationales Klimaschutzziel zu erreichen, während das Milchertragsziel um bis zu 41 % erreicht werden kann. Im Gegensatz dazu erhöhen Emissionen als Folge von Landnutzungsänderungen, die nötig wären um den zusätzlichen Mais zur Futterkonservierung anzubauen das Risiko, Kenias Klimaziel auf nationaler Ebene zu gefährden. Der Mangel landwirtschaftlicher Flächen, die für den Anbau von zusätzlichem Futtermais benötigt würden, reduziert ferner die Machbarkeit der Umsetzung entsprechender Futterverbesserungsoptionen drastisch.

Kapitel 4 - *Nachhaltige Intensivierung und Degradation von Wäldern*: Negative Übertragungseffekte wie die bloße geografische Verdrängung, anstatt der effektiven Minderung, von THG-Emissionen können durch fragmentierte Maßnahmen politischer Steuerung entstehen, die die Verknüpfungen zwischen der Nutzung von Landwirtschafts- und Waldflächen nicht berücksichtigen. Die Analyse der Auswirkungen landwirtschaftlicher Produktion über die Grenzen kleinbäuerlicher Höfe hinaus ist daher von entscheidender Bedeutung für die Planung und Umsetzung von CSA-Praktiken, die zu wirksamen THG-Reduktionseffekten führen sollen. Die Auswirkungen der landwirtschaftlichen Praktiken und Charakteristiken im Hinblick auf Viehwirtschaft und Brennholznutzung auf die Degradation von Wäldern wurden auf der Grundlage von empirischen Befragungen und eines Algorithmus zur Erkennung von Waldveränderungen unter Verwendung von Landsat-Zeitreihendaten quantifiziert. Die Ergebnisse zeigen, dass die Intensivierung der kleinbäuerlichen Milchviehhaltung in Kenia den Druck auf die örtlichen Wälder verringern kann. Produktivere Milchkühe und verbessertes Futtermittel sowie mehr Bäume auf Höfen in der Nähe von Wäldern verringern die Notwendigkeit, diese Wälder als Weidegrund und als Brennholzquelle zu nutzen, wodurch das Risiko von Waldschäden verringert wird.

Kapitel 5 - *Minderung von Emissionen aus Landwirtschaft und Wäldern*: Die kombinierten Potenziale von CSA-Praktiken, wie der Verbesserung von Milchviehfutter, einschließlich der Erhöhung von Futtermaiserträgen, THG-Emissionen aus Landwirtschaft und Wäldern zu reduzieren wurden für die gesamte Milchproduktionsregion in Kenia quantifiziert. Der Verlust von Kohlenstoff aus Wäldern durch Beweidung von Milchvieh wurde mit Hilfe von Zeitreihendaten über die von Satelliten beobachtete Veränderung oberirdischer Biomasse in Wäldern ermittelt. Die Ergebnisse zeigen auf, dass die Intensität von THG-Emissionen auf landwirtschaftlichen Flächen durch Schließung der Ertragslücken für Mais um bis zu 20 % reduziert werden kann. Der Effekt reduzierter THG-Emissionen durch vermiedene Landnutzungsänderungen ist bis zu fünf Mal höher als der Anstieg von THG-Emissionen durch den erhöhten Eintrag von Düngemitteln, der erforderlich wäre um die Ertragslücken zu schließen. Der dadurch sinkende Bedarf an Ackerland für den Anbau von alternativen Milchviehfutter auf landwirtschaftlichen

Flächen in der Nähe von Wäldern könnte den Verlust von Kohlenstoff aus Wäldern um bis zu 94 % reduzieren, da die Notwendigkeit Wälder als Weidegrund zu nutzen verringert wird. Eine verbesserte Futterqualität durch Napiergras und die Ergänzung des Futters mit Konzentraten zeigten jedoch i) das höchste Potenzial zur Verringerung der Emissionsintensität (29 %), ii) den niedrigsten Bedarf an Ackerland und iii) damit die größte Verringerung des Kohlenstoffverlusts aus Wäldern (270 %). Verbessertes Milchviehfutter basierend auf den letztgenannten Optionen könnte die Gesamtemissionen von Treibhausgasen um 2,5 % verringern und somit zu einer Nettoverminderung direkter und indirekter THG-Emissionen aus der Milchproduktion führen. Klima-intelligente Milchviehhaltung kann somit die kenianischen Bergwälder in Kohlenstoffsenken verwandeln.

Insgesamt zeigen die Ergebnisse dieser Dissertation, dass kontextspezifische und detaillierte *ex-ante* Folgeabschätzungen wesentlich sind, um integrierte CSA-Maßnahmen zu planen, die auf eine wirksame Reduktion von THG-Emissionen aus Landnutzungssektoren und der landwirtschaftlichen Entwicklung abzielen. Diese Arbeit liefert neue Ansätze und Informationen, die zur evidenzbasierten Priorisierung und Planung von CSA-Interventionen beitragen. Diese Ansätze erlaubten es, Interaktionen zwischen Landwirtschaft und Wäldern basierend auf empirischen Daten zu untersuchen und Synergien sowie Zielkonflikte, die bisher nicht bekannt waren, zu identifizieren und zu quantifizieren.

Contents

Chapter 1

Introduction

1.1 Background

Negative impacts of climate change on food production are observed already and will become more evident in the near future, especially in regions that are vulnerable to climate shocks such as droughts and floods (Niles & Salerno, 2018). In the tropics, these extreme weather events are shown to detrimentally affect crop yields and to increase livestock mortality and are expected to cause large-scale failures of food production systems, including rapid increases of food prices with more frequent and widespread occurrences (IPCC, 2014). Consequently, climate change affects food security, which is defined as the sufficient access to healthy and nutritious food supplied through domestic production or imports (Wheeler & von Braun, 2013). One of the most food insecure continents is Africa, where currently about 1.3 billion people live. Africa's population is projected to increase up to 2.5 billion by 2050 (UN, 2017b). The fast growing population will further rise the continent's demand for food, which is produced predominantly by smallholder farmers (van Ittersum et al., 2016).

The global sustainable development is targeted by the United Nations (UN). With 'Sustainable Development Goal 2' (SDG 2), the UN seeks to "end hunger, achieve food security and improved nutrition, and promote sustainable agriculture" (UN, 2017a, p. 4). Particularly in Sub-Saharan Africa (SSA), where about 30 % of the undernourished people worldwide live (FAO et al., 2017), research and development efforts must be strengthened to achieve this goal. Many SSA countries are lacking food self-sufficiency, which is defined as the ratio between domestic food production and consumption (van Ittersum et al., 2016). The shortage of food produced domestically makes these countries dependent on food imports and renders them highly vulnerable to climate change, particularly given the expected, drastic population increases. Growing population pressure and low efficiency of agricultural production systems in SSA trigger the conversion of natural ecosystems into agricultural land, which leads to deforestation and land degradation, and causes greenhouse gas (GHG) emissions (Fisher, 2010; Hosonuma et al., 2012), thus, contributing to further climate change.

In Kenya, East Africa, the expansion of mostly smallholder-driven agriculture has dwindled the original extent of Afromontane forests to fragmented patches of isolated mountain forests that suffer from anthropogenic disturbance due to high intensity of forest use (Government of Kenya, 2009b; Kinyanjui, 2011). These remaining forest systems, called 'water towers', however, offer valuable ecosystem services such as the supply of water, the sequestration of carbon (C), and erosion control (Jacobs et al., 2017). The forest cover in Kenya amounts to about 7 %, while land allocated to largely rain-fed agriculture accounts for about 49 % of the country's land surface (Government of Kenya, 2015b). Nutrient-depleted agricultural soils, stagnating and even declining crop yields, scarcity of arable land and decreasing farm sizes represent significant constraints of the Kenyan food pro-

duction systems that have to feed a growing population (Tittonell et al., 2009; Vanlauwe et al., 2014; Zhou et al., 2014; van Ittersum et al., 2016). At the same time, Kenya faces increasingly prolonged drought spells and a higher frequency of erratic weather patterns, which have led to crop harvest failures and livestock loss (Molua et al., 2010; Gachathi & Eriksen, 2011).

Kenya has recently committed to the UN Framework Convention on Climate Change (UNFCCC) to combat climate change (Government of Kenya, 2015a). All member states of the framework agreed to limit the impact of climate change by halting the ongoing global temperature rise by the end of this century, known as the '2 degrees Celsius target of the Paris agreement' (UN, 2015). To curb the global temperature increase below two degrees Celsius above pre-industrial levels, Kenya as a UNFCCC member state must contribute by developing and putting in place policies and planning schemes that mitigate GHG emissions throughout economic sectors.

1.2 Agricultural and forestry land use sectors: the livestock focus

GHG emissions from 'Agriculture, Forestry and Other Land Uses' (AFOLU) account globally for roughly 24 % (10 – 12 Gt CO_2eq yr^{-1}) of the total anthropogenic GHG emissions (IPCC, 2014). GHG emissions from agriculture, including related land use changes (LUC) and forestry have with 5.0 – 5.8 Gt CO_2eq yr^{-1} and 4.3 – 5.5 Gt CO_2eq yr^{-1} respectively the largest shares of GHG emissions from the AFOLU sector (IPCC, 2014). GHG emissions from global livestock production represent the dominant part of agricultural emissions. Livestock emissions are responsible for about 10 – 14.5 % of all human-induced GHG emissions (Westhoek et al., 2011; Gerber et al., 2013). Large ruminants such as cattle used in the beef and milk production sectors contribute 66 % to the total livestock emissions (Gerber et al., 2013). Beef is responsible for 2.9 Gt CO_2eq yr^{-1} while the production of milk from cattle emits 1.4 Gt CO_2eq yr^{-1}. Disaggregating livestock-related emissions into sources shows that methane (CH_4) emissions from enteric fermentation and nitrous oxide (N_2O), carbon dioxide (CO_2), and CH_4 emissions from feed production and processing account for about 39 % and 45 % respectively, which are by far the largest proportions of the total livestock emissions (Gerber et al., 2013). The intensity of emissions, i.e. the rate of emission per unit output (e.g. kg milk or protein produced), varies across regions. The highest emission intensity of milk production is shown for SSA where on average 9.0 kg CO_2eq kg fat and protein corrected milk (FPCM)$^{-1}$ are emitted, compared to less than 1.7 kg CO_2eq kg FPCM^{-1} from intensified production systems in North America and Europe (Gerber et al., 2013). Such a high emission intensity indicates in general low efficiencies of dairy production in SSA, which

is largely smallholder-driven.

Kenya's agricultural sector is with 30 Mt CO_2eq yr^{-1} the largest contributor of the country's total GHG emissions, while 90 % of the agricultural emissions stem from livestock production alone (Government of Kenya, 2015b). At the same time, agricultural production in Kenya is of paramount economic importance. The entire sector contributes directly and indirectly about 51 % of the country's gross domestic product (GDP) and assures the livelihood of 80 % of the rural population (Government of Kenya, 2010). Livestock production contributes 12 % to the GDP in Kenya. Dairy production accounts for about 4 % of the GDP and represents the largest agricultural sub-sector (Government of Kenya, 2010). Milk is predominantly produced (roughly 70 - 80 %) by about two million smallholder farmers, which represent 35 % of the rural population in Kenya (Udo et al., 2016; Government of Kenya, 2017b). Nevertheless, low feed quality and the fluctuating availability of cattle feeds, increasing herd sizes, and overgrazed and degraded pastures are determinants for the relatively low productivity of smallholder dairy farms and the high environmental burden of dairy production in Kenya (Bosire et al., 2016).

The global loss of forests contributes about 6 – 17 % of the total anthropogenic GHG emissions (Baccini et al., 2012). Roughly 80 % of the deforestation worldwide is caused by agricultural expansion. Smallholder agriculture is with about 40 % the predominant reason for the loss of forests in SSA (Hosonuma et al., 2012). Forests are vital ecosystems, which offer a wide array of goods and services that people depend on (Foley et al., 2005). The unsustainable use of forests, however, leads to forest disturbance, which causes GHG emissions through the net removal of biomass or the suppression of vegetation regrowth. Timber harvest, fuelwood extraction and livestock grazing are named as common drivers of forest disturbance in SSA. In SSA countries that passed the peak of deforestation, such as Kenya, fuelwood extraction (58 %), timber harvest (33 %) and livestock grazing inside forests (8 %) represent the most important drivers of forest disturbance (Hosonuma et al., 2012). The role of fuelwood extraction was assessed by several studies for SSA in general and for Kenya in particular (e.g. Bailis et al., 2015; Pearson et al., 2017). However, estimates of the extent and impact of the presence of domestic livestock in forests are missing yet. Remote-sensing data such as satellite imagery over longer time periods, obtained from the Landsat archive offer promising opportunities to study the effects of livestock management on forests. This knowledge is important to improve the understanding of the interactions between agricultural production and the state of forests. Moreover, the knowledge is needed to quantify the agricultural GHG emissions that result directly from farm operations and occur indirectly beyond the farm gates.

1.3   Climate-Smart Agriculture

Feeding a growing population sufficiently while reducing the environmental footprint of food production requires the transformation of current agriculture towards sustainable food production systems. The umbrella concept of 'Climate-Smart Agriculture' (CSA) was brought forward to guide this transformation (FAO, 2013). CSA integrates the three pillars of food security, climate change adaptation and mitigation to ensure the availability of healthy food world-wide, produced from agricultural systems that are well adapted and resilient to the various effects of climate change while releasing the lowest levels of GHG emissions or even removing them, if possible (Lipper et al., 2014). To achieve this goal, especially in regions that are characterised by smallholder farming systems such as SSA, the efficiency of food production on existing agricultural land has to be increased. Higher yields per unit land must be attained through sustainable intensification (Smith et al., 2013). Closing the yield gap, i.e. the difference between the actual yield and the yield that can be potentially achieved for a certain crop or livestock product at a given location is shown to contribute to the intensification of smallholder farming without compromising environmental goals (Foley et al., 2011; Mueller et al., 2012). Yield gaps are estimated to be high across SSA, e.g. about 58 % for maize (Hillocks, 2014). There is great potential to increase actual yields in SSA, for instance, though improved resource management such as the appropriate use of organic and synthetic fertilisers for crops and through improvements in the quality of livestock feeds to increase milk yields from dairy production (Lukuyu et al., 2012; van Ittersum et al., 2016).

The climate-smartness of agricultural production has to be studied beyond the level of single farms to assess whether interventions are likely to be effective in achieving CSA objectives. Farms as units of agricultural production are embedded in landscapes, which consist of different land use types such as cropland, pastures and natural ecosystems (e.g. forests) that interact with each other (Scherr et al., 2012). The way how farms are managed has implications for other parts of the landscape. Thus, the landscape level offers a suitable scale at which the effects of CSA practices on different parts of the landscape can be studied. Landscape approaches enable inter and transdisciplinary assessments that integrate several land use sectors and stakeholders to explore the potential impact of targeted CSA practices on the landscape, including synergies and trade-offs between CSA objectives and constraints that limit the feasibility of their implementation (Reed et al., 2016). Hence, direct and indirect emissions can be analysed to assess whether intensification is sustainable throughout the broader landscape. Focusing on synergies between CSA objectives such as the increase of agricultural productivity and the reduction of GHG emissions is important (i) to increase the likelihood that farmers adopt targeted CSA practices and (ii) to concentrate the financial investment on promising interventions that realise 'win-win' potentials for farmers and climate change mitigation (FAO, 2013).

1.4 Research gaps

Following from the commitments to the UNFCCC, countries in SSA have to build capacity to achieve their national targets to reduce the impact of agricultural production on the climate system. Kenya targets to curb the increase of its total GHG emissions by 30 % during the period of 2010 – 2030, as defined in the country's 'Nationally Determined Contribution' (NDC) (Government of Kenya, 2015a). Frameworks and approaches are required urgently, which aid the data-driven and evidence-based integration of climate change mitigation into policy instruments that promote the sustainable development of the agricultural sector and aim to ensure food security. Kenya has developed a national CSA strategy to guide and foster the implementation of measures that increase agricultural productivity sustainably, improve resilience of food production and minimise its GHG emissions by 2026 (Government of Kenya, 2017a). The strategy includes (i) the mitigation of GHG emissions from livestock production through improved feeds and manure management, (ii) the reduction of emissions from deforestation and forest disturbance, and (iii) the development of 'Measurement, Reporting and Verification Systems' (MRVs) to improve the reporting of mitigation actions (Government of Kenya, 2017a). Furthermore, policies that facilitate the development of Kenya's dairy sector are put in place such as the national dairy master plan, which targets the sustainable increase of productivity in the sector by 2030 to meet higher demands for dairy products due to the growing population (Government of Kenya, 2010). Kenya's dairy 'Nationally Appropriate Mitigation Action' (NAMA) seeks to develop a low-emission and climate resilient dairy sector by focusing on synergies between the mitigation of GHG emissions, the increase of milk yields and farmers' incomes (Government of Kenya, 2017b).

Prior to the implementation of interventions that aim to realise CSA-related policy objectives, candidate sets of CSA practices have to be evaluated, prioritised and targeted. Decisions must be made by policy makers and planning institutions about the specific practices that are targeted at certain locations. These decisions should be based on evidence and require, therefore, information that shows the urgency to intervene in specific areas due to their high vulnerability to climate change and the suitability of candidate practices at hand (Notenbaert et al., 2017). However, integrated frameworks that are able to couple spatially-explicit information on climate change vulnerability and CSA suitability with the heterogeneous stakeholder knowledge and opinions to support the decision-making on targeting CSA are missing.

Spatially-explicit information that indicates the 'win-win' potentials to increase the productivity of livestock production and to mitigate GHG emissions of specific CSA options such as feed improvements is missing. The knowledge on *ex-ante* impacts of candidate interventions is crucial to target CSA effectively. The scarcity of arable land in agricultural landscapes with high population density, such as in Central and Western Kenya

(Vanlauwe et al., 2014), is often neglected in CSA assessments. In order to assess the feasibility of implementing candidate practices and to avoid negative spillovers such as C leakage, it is important to include information about constraints such as the availability of arable land into landscape-level approaches that are used to analyse livestock feed improvements. The leakage of C results from the unintended displacement of GHG emissions that may occur outside the geographical scope of mitigation interventions (Minang & van Noordwijk, 2013). Approaches that are being developed and applied in this context have to integrate various data on livestock production such as feed intake, feed quality, yields of included feed types, and cattle breeds as well as emission-related parameters such as emission factors. Livestock and spatial modelling techniques need to be coupled to estimate baseline and scenario-related livestock productivity, GHG emission levels, and to upscale this information based on agro-ecological information and production systems.

The intensification of smallholder farming is shown to increase productivity, e.g. milk yields, while mitigating GHG emissions on farms by reducing emission intensities (Campbell et al., 2014; Descheemaeker et al., 2016). Knowledge on the quantitative effects of smallholder intensification on local forests is, however, missing. Answering questions such as to what extent can GHG emissions from forests be avoided due to sustainable intensification of livestock production is crucial to inform CSA policies about the effectiveness of candidate interventions across land use sectors prior to their implementation. In addition, this information is required to evaluate targeted CSA practices regarding their achievement of sectoral and national mitigation targets. Kenya does not have a specific legal framework of 'Reducing Emissions from Deforestation and Forest Degradation' (REDD+) yet. Quantitative information on the potential reduction of GHG emissions from forests due to the improved management on farms could contribute, therefore, to the design of policy instruments that integrate CSA and REDD+.

1.5 Research objectives

The main objectives of this thesis are i) to improve the support of decision-making processes that aim to prioritise and target CSA practices robustly at national scale and ii) to elucidate the potential of intensified smallholder dairy production in Kenya to increase milk yields and to reduce direct and indirect GHG emissions effectively through feed improvements. Based on these objectives, four research questions (RQ) are addressed:

 A. How can 'multi-criteria decision-making' support national climate change adaptation and mitigation planning to target CSA practices?

 B. Which climate change mitigation options in the Kenyan dairy sector contribute to climate mitigation and food production targets defined at national level?

 C. How does the intensification of smallholder dairy farming affect forest disturbance?

D. What is the potential of livestock intensification options to reduce GHG emissions from agriculture and forests?

1.6 Thesis outline

This thesis is structured into four chapters that address the RQs outlined in Section 1.5 (Figure 1.1) and finishes with a concluding synthesis chapter.
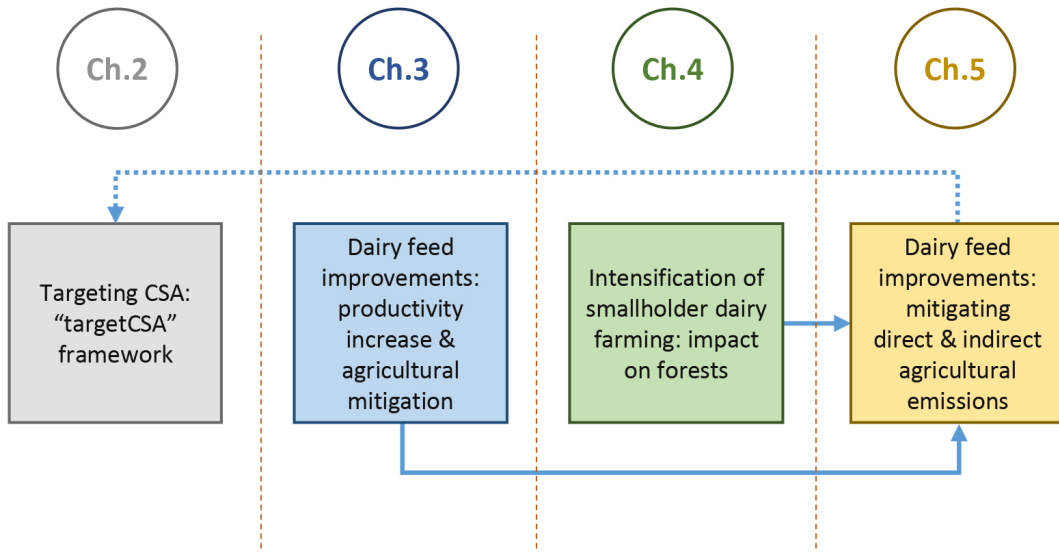
Figure 1.1: Overview of chapters that address the four research questions outlined in Section 1.5

Chapter 2 presents the decision-support framework "targetCSA", which was developed to aid the targeting of CSA practices (**RQ A**). The framework uses spatially-explicit data on climate change vulnerability and CSA suitability and integrates related stakeholder knowledge and opinions. An optimisation technique is applied to find the most consensual stakeholder preferences regarding the prioritisation of CSA practices. Stakeholder preferences, vulnerability and CSA suitability are coupled to derive an index of CSA potential, which is mapped to explore consensus-driven CSA targeting scenarios and the potential effects of differences in stakeholder opinions. The applicability of the framework is demonstrated in Kenya.

Chapter 3 assesses dairy feed improvements regarding their synergistic potentials to increase milk yields and to mitigate agricultural GHG emissions for the entire dairy production region in Kenya, including emissions from LUC (**RQ B**). Livestock and spatial

modelling techniques are used to estimate and upscale productivity and GHG emissions. The demand for land and the availability of potentially arable land are analysed to evaluate the feasibility to implement the feed improvement scenarios. In addition, the scenarios are linked to national mitigation and productivity targets to assess to what extent these targets can be achieved.

Chapter 4 quantitatively relates farm indicators and farm types to forest disturbance across an agriculture-forest landscape located in the Kenyan highlands to analyse the effects of the intensification of smallholder farms on forest disturbance (**RQ C**). Farm information is obtained from empirical ground data. Forest disturbance data is derived by applying a novel forest change detection algorithm based on time-series data from satellite imagery.

Chapter 5 capitalises on the approaches and findings from Chapters 3 and 4 to assess the potential of dairy feed improvements to reduce direct and indirect GHG emissions from the agricultural land and from forests by avoiding the forest C loss that results from the presence of dairy cattle (**RQ D**). A subset of feed improvement scenarios from Chapter 3 is complemented by scenarios that increase the yields of maize used as silage to explore the effects on the demand for arable land of feed improvement scenarios that turned out to require most land in Chapter 3. Data on forest C change were derived from satellite-based time-series products.

Chapter 6 synthesises and highlights the main findings of this thesis and reflects on the relevance and implications for the CSA policy arena. In addition, an outlook is given outlining further research. The chapter concludes by giving key recommendations inferred from this thesis to policy-makers.

Chapter 2

How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework "targetCSA"

Abstract

Planning for agricultural adaptation and mitigation has to lean on informed decision-making processes. Stakeholder involvement, consensus building and the integration of comprehensive and reliable information represent crucial, yet challenging, pillars for successful outcomes. The spatially-explicit multi-criteria decision support framework "targetCSA" presented here aims to aid the targeting of climate-smart agriculture (CSA) at the national level. This framework integrates quantitative, spatially-explicit information such as vulnerability indicators (e.g. soil organic matter, literacy rate and market access) and proxies for CSA practices (e.g. soil fertility improvement, water harvesting and agro-forestry) as well as qualitative opinions on these targeting criteria from a broad range of stakeholders. The analytic hierarchy process and a goal optimisation approach are utilised to quantify collective, consensus-oriented stakeholder preferences on vulnerability indicators and CSA practices. Spatially-explicit vulnerability and CSA data are aggregated and coupled with stakeholder preferences deriving vulnerability and CSA suitability indices. Based on these indices, relevant regions with the potential to implement CSA practices are identified. "targetCSA" was applied in Kenya exploring group-specific and overall consensus-based solutions of stakeholder opinions on vulnerability and CSA under different consensus scenarios. In this example, 32 experts from four stakeholder groups who participated in two surveys were included. The subsequent analyses revealed consistently regions with high CSA potential but also highlighted different high potential areas depending on the applied consensus scenario. Thus, this framework allows stakeholders to explore the consequences of scenarios that reflect opinions of the majority, minority or are based on a balance between them. "targetCSA" and the application example contribute valuable insights to the development of policy and planning tools to consensually target and implement CSA.

2.1 Introduction

Addressing climate change is crucial to safeguard food provisioning from agricultural systems. Hence, planning efforts are urgently needed to target and implement agricultural adaptation and mitigation options in line with governmental strategies, such as national climate change action plans (Preston et al., 2011; Conway & Mustelin, 2014). Climate-smart agriculture (CSA) as a global development goal was introduced to guide the transformation of agricultural systems integrating adaptation, mitigation and food security (FAO, 2013). Alleviating vulnerability and fostering resilience of agricultural systems to climate change to secure the sustainable provisioning of food while reducing greenhouse gas (GHG) emissions are the major objectives of CSA (Harvey et al., 2014a).

The targeting of CSA at the national level is fraught with several challenges that, if not properly dealt with, potentially hamper the legitimacy and outcome quality of made decisions. First, relevant stakeholder groups have to be involved in the decision-making process that contribute their valuable expert knowledge but also might disagree due to conflicting interests and views (Nordström et al., 2010). Second, high complexity and uncertainty may arise from the multitude of criteria that need to be considered for the selection and prioritisation of CSA practices at specific locations (Greene et al., 2011). Third, reliable quantitative and spatially-explicit data are required to identify regions suitable for targeting certain CSA practices. Such a database should include biophysical, social and economic determinants on agricultural vulnerability to climate change, consequently, offering a demand-based perspective on CSA (Fellmann, 2012; FAO, 2013). A framework that integrates knowledge and opinions from a broad range of expert stakeholders, weighs those opinions based upon consensus and couples them with spatially-explicit datasets on vulnerability and CSA practices is of paramount interest to support robustly the decision-making on targeting CSA. To the authors' knowledge, such a framework has not been published so far.

The aim of this study was to develop a decision support framework for the spatially-explicit targeting of CSA, named "targetCSA", which includes multiple stakeholders, vulnerability indicators and suitable CSA practices. The applicability of this framework is demonstrated through an example from Kenya. Large parts of the country are characterised by arid or semi-arid climate with agricultural production dominated by smallholder farming. Erratic weather patterns, frequent droughts and reduced growing seasons are threats that will increase the vulnerability of the agricultural sector in Kenya (Molua et al., 2010; Gachathi & Eriksen, 2011). The national climate change action plan recently passed by the Kenyan government calls for urgent implementation of CSA practices, thus, rendering "targetCSA" highly relevant for the development of policy and planning instruments (Government of Kenya, 2012).

2.2   Material and methods

2.2.1   Conception of the decision support framework "targetCSA"

Background

Supporting decision makers in their assessment of options based on several criteria can be achieved through multi-criteria decision-making (MCDM) analyses (Romero & Rehman, 2003). MCDM aims to elicit transparently individual and subjective stakeholder judgements, aggregate them to collective preferences and help to explore their implications for decision-making processes (Greene et al., 2011). Spatial information has to be integrated into MCDM since implementing CSA involves landscape planning. Geographic information systems (GIS) can be applied to link the spatial attributes of criteria to stakeholder preferences (Boroushaki & Malczewski, 2008). MCDM is based on a well-established set of methods that have been frequently applied to different planning contexts such as the targeting of projects on the mitigation of GHG-emissions or the design of ecological reserves and corridors (cf. Ferretti & Pomarico, 2013; Lin et al., 2014; Tammi & Kalliola, 2014).

Adaptation and mitigation planning is the centrepiece of coping strategies for climate change such as action plans passed by national governments (Preston et al., 2011). The decision support framework proposed here is designed to aid planners and decision makers that aim to implement CSA at the regional or national level. Such a planning process involves several sectors such as governmental institutions, civil society, science and the private sector making it mandatory to involve respective stakeholder organisations (FAO, 2013). Therefore, the framework integrates multi-sectoral stakeholder groups to contribute expert knowledge on the selection and importance of vulnerability indicators as well as CSA practices that fit into a country's or regional profile due to prevailing environmental and socio-economic conditions. However, stakeholder perceptions on what is important might differ and result in conflicting judgements and trade-offs among decision options (Nordström et al., 2012). Hence, an adequate decision support framework should allow the exploration of trade-offs and minimise dissent. Integrating expert knowledge and spatial information into MCDM is crucial for informed and robust decisions based on evidence and acceptance (Preston et al., 2011). "targetCSA" uses an optimisation-based approach developed by González-Pachón & Romero (2007) that applies distance minimisation algorithms to reduce disagreement among the stakeholders' opinions and to facilitate the exploration of different consensus scenarios. Moreover, consensus-oriented opinions from stakeholders are coupled with quantitative and spatially-explicit vulnerability and CSA data building the factual foundation for decisions on where to target CSA. "targetCSA" is structured into three main stages (Figure 2.1).
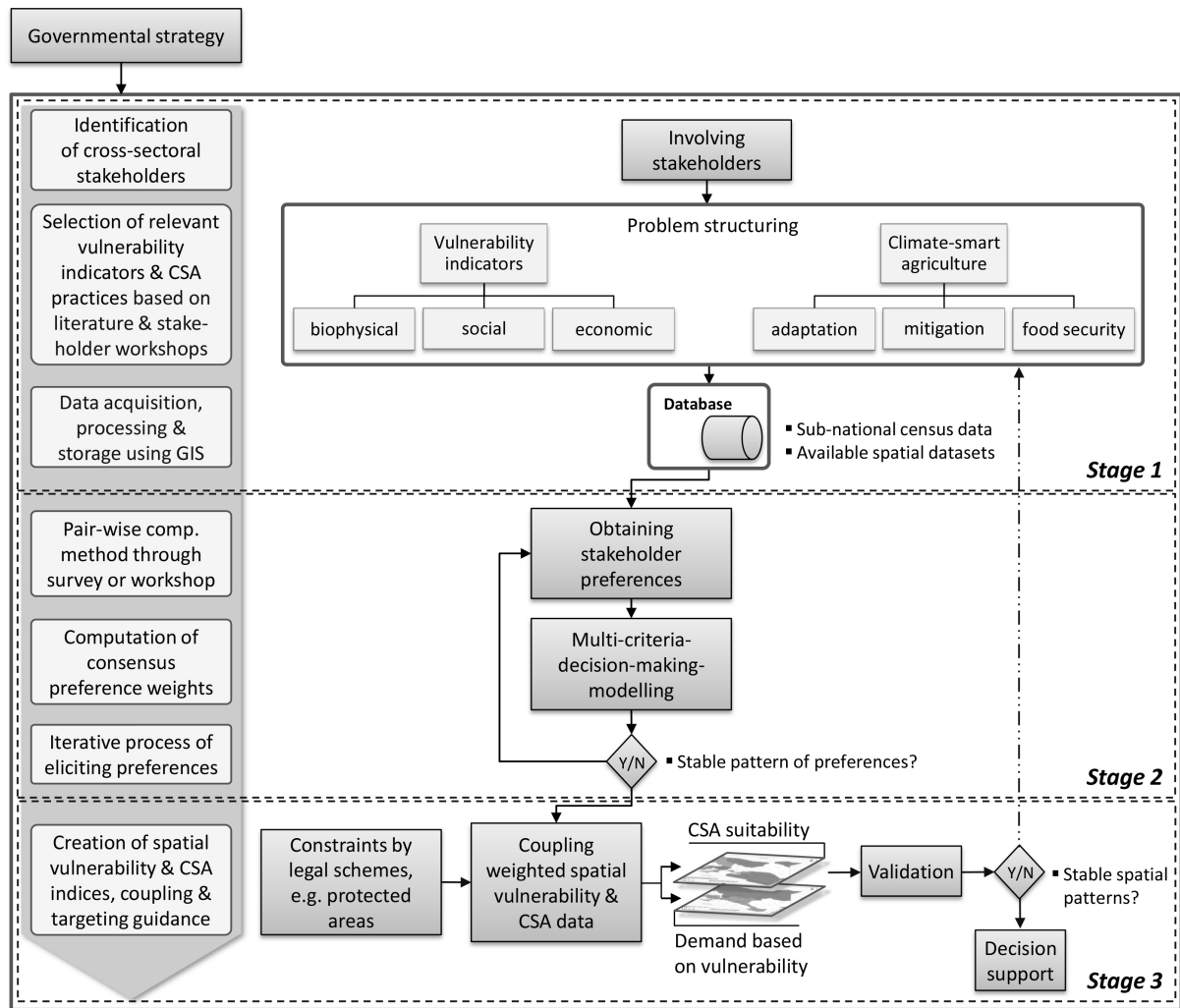
Figure 2.1: Conceptual overview of the decision support framework "targetCSA".

Climate change vulnerability and climate-smart agriculture

The vulnerability of a system to stressors such as droughts or floods depends on its sensitivity to perturbations, the degree of exposure, and its capacity to adapt on the impact (Challinor et al., 2007; Abson et al., 2012). Climate change is expected to increase the vulnerability of farmers by threatening their livelihood strategies as well as entire food productions systems (Challinor et al., 2007; Harvey et al., 2014b; Thornton et al., 2014). The concept of CSA couples climate change and food security through the integration of adaptation and mitigation measures. It aims to reduce vulnerability by improving the adaptive capacity of agricultural systems to climate stress and, hence, secures the provision of food while reducing GHG-emissions from agricultural practices and land uses contributing to climate change (Scherr et al., 2012; Campbell et al., 2014; Harvey et al., 2014a). Thus, a short (adaptation) and long term (mitigation) perspective are

integrated into the CSA concept which should be considered in proper targeting and planning processes.

By explicitly including the vulnerability concept into CSA-targeting, a demand-based perspective is taken, meaning that regions with higher climate change vulnerability require more urgently interventions that strengthen their adaptive capacity. The vulnerability of the agricultural sector to climate change is influenced by environmental and socio-economic factors (Abson et al., 2012; Fellmann, 2012). Thus, information about relevant biophysical (e.g. climate), social (e.g. education) and economic (e.g. market access) dimensions should be taken into account to inform an assessment of where specific CSA practices are suitable.

Stage 1: Structuring the decision-making problem

Stakeholder involvement and data collection. Relevant stakeholders should be identified at the beginning of the planning process (Nordström et al., 2010). During the first stage (Figure 2.1), meetings with cross-sectoral stakeholders are conducted, e.g. from governments, civil societies, science and private sectors to develop a structured catalogue of context-specific vulnerability indicators and CSA practices (cf. Patt et al., 2010; Fellmann, 2012; Scherr et al., 2012). Related datasets can be obtained from publicly available geo-databases such as the FAO GeoNetwork, HarvestChoice and GEO-Wiki branches or compiled and made spatially-explicit based on sub-national census data using GIS.

The analytic hierarchy process. The analytic hierarchy process (AHP) is widely used in MCDM with numerous applications (Wind & Saaty, 1980; Saaty, 1994; Nordström et al., 2012). A complex problem is decomposed into pairs of criteria (decision options) through pair-wise comparisons (PC), where two criteria are compared with each other at a time (Wind & Saaty, 1980). Stakeholders assign numerical preference weights as expression of their opinion to one of the paired criteria that are compared on a measurable scale known as the Saaty scale (Saaty, 1977). It orders the importance of potential judgements from 1 = equal preference to 9 = extreme preference towards one of the paired criteria. Finally, the individual stakeholder preferences are aggregated deriving a normalised vector of overall preferences for considered criteria (Saaty, 1977).

Stage 2: Eliciting stakeholder preferences and consensus building

Multi-criteria decision-making model. The second stage integrates and aggregates formalised stakeholder opinions (Figure 2.1). Individual preference weights are queried through PC questionnaires that are administered through workshops, expert surveys or interviews (cf. Diaz-Balteiro et al., 2009; Sae-Lim et al., 2012). A commonly used

technique to aggregate individual stakeholder preferences in group decision-making processes is to calculate overall priority vectors (Eigenvectors) through geometric or arithmetic mean methods (Ishizaka & Labib, 2011; Nordström et al., 2012). "targetCSA", however, utilises a goal programming (GP) approach by implementing a set of MCDM models that are based on linear optimisation. These models were developed by González-Pachón & Romero (2007) and applied by Diaz-Balteiro et al. (2009) as well as Gebrezgabher et al. (2014). The GP approach has two advantages compared to the conventional Eigenvector-based aggregation methods: i) stakeholder preferences do not have to be consistent throughout the PC questionnaire (González-Pachón et al., 2003; González-Pachón & Romero, 2007) and ii) the MCDM models are designed to minimise distances among obtained PC questionnaires enabling the search for a collective consensus. Hence, this approach offers integrated support for participatory management and planning processes that rely on consensus (Sae-Lim et al., 2012; Gebrezgabher et al., 2014).

The GP approach computes a consensus matrix, which shows minimised differences to the input PC matrices derived from the questionnaires and infers the consensus preferences from this matrix by using a distance minimisation algorithm (González-Pachón & Romero, 2007). In this context, consensus is specifically defined as a mathematical optimisation goal achieved by minimising matrix distances using certain boundary constraints to find a solution that represents the minimum disagreement between individual preferences. The meaning of consensus from an optimisation point of view does not coincide with the general meaning of the term consensus used in group decision-making processes, where consensus refers to reaching decisions that all stakeholders willingly agree on (Bressen, 2007).

The optimisation process can be controlled by following different consensus scenarios moving along a trade-off curve between majority and minority consensus (González-Pachón & Romero, 2011). The majority consensus represents the closest solution to all stakeholder preferences whereas the solution based on the minority consensus seeks to satisfy preferences of the stakeholder far apart from the majority. The MCDM models were numerically programmed in R (v. 3.1.1) using the linear programming library 'lpsolve' (v. 5.6.10). A detailed description of the models can be found in Appendix (S1).

Eliciting stakeholder preferences. Stakeholder preferences represent a source of uncertainty in the decision making process (Mosadeghi et al., 2013). Therefore, it is recommended to elicit preferences iteratively (Nordström et al., 2010). The iterations allow to capture, assess and to reduce the variability of preferences which result from adjusted stakeholder opinions that might affect the targeting outcome (Mosadeghi et al., 2013). Evaluating the robustness of preferences is important to obtain a transparent measure of how reliable the included expert knowledge is for final decision-making (Xu & Zhang, 2013).

Stage 3: Spatial aggregation and coupling of vulnerability and CSA indices

Deriving vulnerability and CSA suitability indices. The third stage combines elicited preferences with spatial data representing quantitative vulnerability indicators and data reflecting CSA practices (Figure 2.1). Weighed linear combination (WLC) is a widely applied aggregation rule where high values of one criterion can be offset by low values of another criterion (Eastman et al., 1995; Greene et al., 2011; Lin et al., 2014). In "targetCSA", values of standardised spatially-explicit criteria are multiplied with related stakeholder preferences and finally summed up deriving combined vulnerability and CSA suitability scores using WLC. Spatial information of constraints, such as regions with legal restrictions or a lacking relevance are masked and excluded from the decision-making process.

Finally, two standardised and spatially-explicit indices depicting climate change vulnerability and CSA suitability are generated. Subsequently, a re-scaling of both indices into low, mid and high vulnerability as well as CSA suitability allows to superimpose them and to assess overlaying classes for the identification of areas with high potential for selected CSA practices. Maps showing these indices can be used to explore the consequences of different consensus scenarios on the CSA targeting and guide decision-making.

Validation. If stakeholder preferences are elicited at several occasions they can be used to validate the robustness of the calculated spatial indices (Figure 2.1). This is crucial to assess how reliable and, hence, how useful the vulnerability and CSA suitability indices are as source of information in a decision-making process (Delgado & Sendra, 2004). Several sets of aggregated and coupled indices can be spatially compared. Large differences in areas of CSA potential could point to high uncertainties associated to blurred stakeholder opinions and knowledge gaps which have to be addressed (Nordström et al., 2010; Mosadeghi et al., 2013).

2.2.2 Application example from Kenya

Study area

Kenya covers a total area of 581,881 km^2 and has a population of about 38 million people (Figure 2.2) (Wiesmann et al., 2014). While the most productive land is situated in the Central and Western, sub-humid parts of Kenya, about 80 % of Kenya is characterised as semi-arid or arid lands with erratic rainfall, droughts and sporadic floods (Molua et al., 2010; Gachathi & Eriksen, 2011). The agricultural sector plays a pivotal role for food provisioning and the country's economy. However, it suffers from recurring crop failure, livestock mortality and food insecurity (Grace et al., 2014). A large part of Kenya's labour force works in the agricultural sector, which makes about 75 % of the national gross domestic product (Odera et al., 2013). The vulnerability of the mainly rainfed

agricultural sector to climate change is marked by its exposure and sensitivity to harsh biophysical factors relating to climate and soil as well as low adaptive capacity determined by the socio-economic context, e.g. poverty, poor access to education and health facilities as well as to markets (Eriksen & O'Brien, 2007).

Selection of stakeholders, vulnerability indicators and CSA practices

The CSA targeting process started in 2013 through discussions between the Kenyan Ministry of Environment, Water & Natural Resources and the Research Program on Climate Change, Agriculture and Food Security (CCAFS). Stakeholders were selected from four groups representing governmental organisations (GOs), civil society (NGOs), scientific institutions and the private sector (Appendix S2, Table S2.1). A stakeholder workshop was held in early 2014 to select vulnerability indicators and CSA practices. Subsequently, related quantitative data were collected, compiled and processed in ArcGIS (v. 10.1). All datasets were derived from publicly accessible databases or censuses conducted by governmental institutions in Kenya. Resulting grid data were resampled to match a consistent resolution of approximately 10 x 10 km. A subset of six vulnerability indicators and CSA practices was selected, suitable to test the applicability of "targetCSA" (Table 2.1).

Table 2.1: Overview of the stakeholder-based selection of climate change vulnerability indicators and CSA practices for the application example in Kenya, including descriptions as well as linkages between indicators and practices.

Indicators of climate change vulnerability	Data description and sources	Linkages climate change vulnerability - CSA
Biophysical		
Annual precipitation:	Annual precipitation based on the period: 1950-2000 (Hijmans et al., 2005).	'Annual precipitation' was selected as indicator for water availability and ecosystem productivity. The availability of water largely determines agricultural productivity. The improvement of water harvesting and management and the introduction of drought tolerant crop varieties represent viable CSA practices to deal with vulnerability to water shortages (Harvey et al., 2014a).

Table 2.1: continued

| Soil organic matter: | Organic carbon content in the top soil layer, up to 30 cm depth, contained in (decomposed) plant and animal residues, tissues and cells (Nachtergaele et al., 2012). | 'Soil organic matter' is an indicator of soil fertility and, thus, ecosystem productivity. Regions with low soil organic carbon need CSA practices that alleviate nutrient depletion such as measures to stop erosion to build up soil carbon through organic fertilisers and integrated practices such as agroforestry (Lal et al., 2011). |

Social

| Percentage of households with access to safe water sources: | Proportion of households per county with access to safe water sources such as: boreholes, protected wells and springs, piped water and collected rainwater (Government of Kenya, 2009a; Wiesmann et al., 2014). | 'Percentage of households with access to safe water sources' was selected as an indicator of household well-being. Required CSA practices should, thus, improve the management of water that is used for agricultural purposes as well as drinking water and thereby safeguard its availability (Wiesmann et al., 2014). |

Table 2.1: continued

Literacy rate:	Proportion of the population (aged 15+) per county that is able to read and write (Government of Kenya, 2013).	'Literacy rate' is an education indicator. High illiteracy reflects reduced capabilities (adaptive capacity) of making informed decisions regarding viable coping strategies under climate change (Atela et al., 2014). Thus, it reflects obstacles for implementing CSA due to lack of knowledge and information. CSA practices in turn have to contribute necessary knowledge, thus, help to reduce information gaps as well as facilitate relevant practical skills.

Economic

Female participation in economic activities:	Active female labour force divided by the total female labour force per county (Government of Kenya, 2009a; Wiesmann et al., 2014).	'Female participation in economic activities' is understood as an indicator for women empowerment and economic development. Gender inequality increases the susceptibility to sudden changes and threats as such climate change. Integrated CSA practices such as conservation agriculture and agroforestry have the potential to promote gender equality and improve livelihoods for women and men while supporting mitigation and adaptation (Beuchelt & Badstue, 2013).

Table 2.1: continued

Connectivity through transport infrastructure:	Degree of connection between places across Kenya, based on time needed for travelling to the next city > 50000 inhabitants (Uchida & Nelson, 2009).	'Connectivity through transport infrastructure' indicates farmers' accessibility to markets for selling farm produces and buying inputs as well as accessing extension services such as vaccination. A reduced access adds additional risks for farmers under climate change (Abson et al., 2012). CSA practices are supposed to support farmers to deal with the impacts of climate shocks such as losses of livestock or crop failures. CSA examples are insurance schemes and drought tolerant varieties/breeds, improved soil and water management (Harvey et al., 2014a; Vrieling et al., 2014).

CSA practices	Examples, proxy datasets and assumption of use	Link to indicators of climate change vulnerability
Improvement of soil fertility and soil management:	Example: low-cost soil fertility enhancement options, such as green manures, legumes, composting, animal manure management, improved fallows and conservation agriculture; Proxy dataset: low nutrient capital reserves (Sanchez et al., 2003); Assumption: Depleted nutrient stocks in soils call for improved soil fertility management through CSA.	Biophysical: 'Soil organic matter'; Social: 'Literacy rate'

Table 2.1: continued

Identification and distribution of drought tolerant cereal crops:	Example: sorghum, millet and maize; Proxy dataset: suitability of rainfed cereal crops assuming an improved management scenario in terms of labour, fertiliser use, pest control and conservation measures (van Velthuizen et al., 2007); Assumption: The biophysical suitability for cereals under region-specific farm management reflects the potential to grow drought tolerant cereal varieties.	Biophysical: 'Annual precipitation'; Social: 'Literacy rate'
Reduction of greenhouse gas emissions from the livestock sector:	Example: manure management, more efficient breeds, species, feeds and biogas technologies; Proxy dataset: Methane and nitrous oxide emissions from livestock per kg protein, including cattle, sheep, goats, pigs and poultry (Herrero et al., 2013); Assumption: High livestock-based emission intensities show high demand for GHG mitigation practices.	This is a mitigation practice that, in a long-term perspective, reduces the vulnerability to climate change in general. Therefore, it links to all vulnerability indicators included here.

Table 2.1: continued

Improvement of water harvesting and water management:	Example: community water pans, micro-catchments and dams constructed to harvest, store and distribute water for crop irrigation and livestock; Proxy dataset: aridity index (Zomer et al., 2008); Assumption: Agricultural practices in drylands, such as pastoralism, are prone to water deficits. Hence, these regions reflect high demands to improve the harvesting and management of water.	Biophysical: 'Annual precipitation'; Social: 'Percentage of households with access to safe water sources', 'Literacy rate'; Economic: 'Connectivity through transport infrastructure'
Identification and establishment of agroforestry practices:	Agroforestry integrates trees into croplands and pastures. Example: identifying agroforestry practices (based on surveys etc.), establishing community agroforestry, tree nurseries; Proxy dataset: percentage of cropland area (Fritz et al., 2015) restricted to regions with a tree cover < 10 % (Hansen et al., 2013). Assumption: Regions with higher proportions of cropland show potential for integrating trees into agricultural landscapes that lack a minimum tree cover aligning this CSA practice with the national policy target in Kenya to achieve a tree cover of at least 10 % (Government of Kenya, 2007).	Biophysical: 'Soil organic matter'; Economic: 'Female participation in economic activities'

Table 2.1: continued

| Implementation of livestock insurances: | Example: monetary subsidies for farmers in cases of severe climate mediated livestock mortality; Proxy dataset: Insurance premium rates for livestock mortality based on remote-sensing time-series data (normalised difference vegetation index, NDVI) from 1981 - 2012 (Vrieling et al., 2014). Assumption: Regions with increased drought risks and water shortages have a higher demand for livestock insurance schemes. | Biophysical: 'Annual precipitation'; Social: 'Percentage of households with access to safe water sources', 'Literacy rate'; Economic: 'Connectivity through transport infrastructure' |

This choice was based on three criteria. First, the selection of vulnerability indicators was based on the scientific vulnerability literature dealing with climate change in Africa (cf. Challinor et al., 2007; Abson et al., 2012; Atela et al., 2014). Selected CSA practices are also listed in a catalogue that is part of the Kenyan National Climate Change Action Plan (Government of Kenya, 2012). Second, the data quality was ensured through peer-reviewed published datasets and consultation of experts. Third, there was no high collinearity among vulnerability and CSA datasets (Spearman's rho < 0.75).

There was no information about the effectiveness of selected CSA practices on alleviating vulnerability of the agricultural sector in Kenya. Therefore, this application example represents a spatially-explicit *ex-ante* assessment that explores the potential to target CSA practices consensually by focusing on regions that are shown to be vulnerable and suitable.

2.2.3 Expert survey

The designed questionnaire comprised two parts. The first part dealt with the pairwise comparison of six selected vulnerability indicators, while the second part focused on comparing the six selected CSA practices. The number of PC items was restricted to six avoiding potential reductions in consistency and quality of the answers (Saaty, 1977). The leading questions in both parts were formulated to elicit preference weights according to the relative importance of the items compared to each other. For this application example, a slightly reduced rating scale was used compared to the original Saaty scale,

ranging from 1 to 7, based on results from a pre-test. In order to separate the different intensities of possible preferences more clearly, they were defined as: 1 = equal preference, 3 = slight preference, 5 = moderate preference and 7 = strong preference. Five different versions of the questionnaire were created differing in their sequence of comparisons based on randomisation to prevent a possible bias resulting from a fixed order of comparisons (Podsakoff et al., 2003).

The survey took place between September and November 2014 interviewing eight experts from each of the four stakeholder groups (n = 32). Each interview took approximately 20 minutes. Before an interview started, the questionnaire was explained and put into the CSA targeting context to avoid misguided judgements due to potential misconception of queried items (Keeney, 2002). During a stakeholder workshop conducted in November of 2014, the survey results were presented, discussed and preferences were re-elicited using the identical PC questionnaire for the validation of spatial indices. Furthermore, the questionnaire was sent to stakeholders that could not attend, including supplementary information about the workshop results. Finally, 16 validation questionnaires were filled covering 50 % of each originally sampled stakeholder group.

2.2.4   Multi-criteria decision-making model

Applying the GP optimisation approach developed by González-Pachón & Romero (2007) allowed us to explore both conflicting group interests and consensus solutions regarding stakeholder preferences for vulnerability indicators and CSA practices. The MCDM models were fitted i) to aggregate group specific preferences separately keeping the experts in each group as individuals and ii) to search a consensus based on the entire set of included expert opinions, referred to as the overall consensus, assuming a collective interest in striving for consensus in a decision-making process. The ability of the MCDM models to move towards mutually exclusive majority or minority oriented consensus scenarios was tested by González-Pachón & Romero (2007). In this example, three scenarios were applied to explore results that reflect the preferences of the i) majority, ii) minority, and iii) the optimal trade-off indicating the consensus solution that is most balanced in representing the stakeholder opinions (González-Pachón & Romero, 2011). The latter scenario characterises a compromise, which is especially interesting in a decision-making context where no information is available about the socially desired outcome of the negotiation process. A detailed description of the applied optimisation model used to find the consensus with the most balanced trade-off (i.e. compromise scenario) can be found in Appendix (S1). The modelling procedure was applied on stakeholder preferences obtained from both expert surveys enabling the assessment of changes in opinions among stakeholders.

2.2.5 Spatial aggregation and coupling of weighted vulnerability and CSA suitability indices

The WLC rule was used to combine linearly each of the two sets of spatial data (Table 2.1), excluding constraints such as protected areas, forests, lakes and settlements, with preferences inferred from the overall consensus, deriving combined vulnerability and CSA suitability indices (Eastman et al., 1995). Spatial datasets reflecting these constraints were obtained during the initial data collection process. A detailed description of the WLC rule can be found in the Appendix (S1).

By overlaying the indices of vulnerability and CSA suitability, it was possible to assess the targeting potential of selected CSA practices based on their suitability in regions that bear high vulnerability. The indices were computed for three different consensus scenarios (majority, minority, and the most balanced trade-off) to explore differences in regions with high CSA potential. For validation, the CSA potential was computed based on stakeholder preferences derived from both surveys applying the consensus scenario with the most balanced trade-off. Through comparison of CSA potentials, areas where the survey results (dis)agree were investigated.

2.3 Results

2.3.1 Vulnerability indicators and CSA practices

Both biophysical indicators, 'annual precipitation' and 'soil organic matter' show relatively high vulnerability in Northern and Eastern parts of Kenya (Figure 2.2A). The social indicator 'households with access to safe water sources' reveals a more heterogeneous pattern of vulnerability than the indicator 'literacy rate' which shows higher illiteracy in the North and, thus, elevated vulnerability compared to the rest of the country. The two economic indicators depict a contrasting pattern. Whereas 'female participation in economic activities' highlights the South-Eastern regions as more vulnerable, the indicator 'connectivity through transport infrastructure' emphasises the North and partially the East as more remote and, hence, potentially more vulnerable.
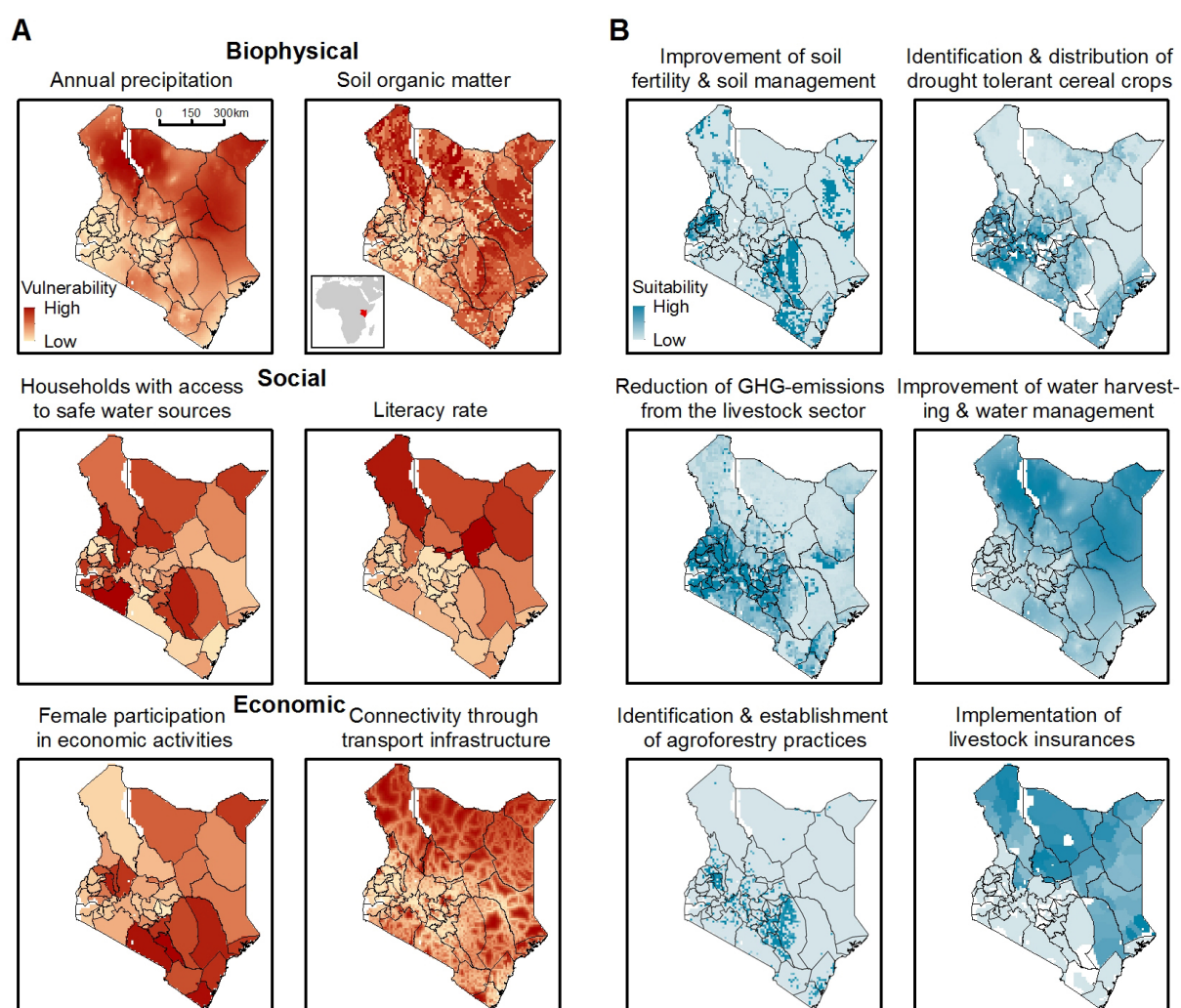
Figure 2.2: Maps show the spatial distribution of consistently re-scaled datasets used to represent (A) vulnerability indicators and (B) CSA practices ranging from 0 - 1. For the vulnerability maps, dark red colour means highly vulnerable, for the CSA suitability, dark blue colour means highly suitable for the selected CSA practice. Included CSA practices are reflected by proxy datasets explained in Table 2.1.

Focusing on CSA practices, the dataset on soil nutrients shows a scattered pattern of areas in the North-East, West and South of Kenya where CSA practices relating to the 'improvement of soil fertility and soil management' are potentially suitable (Figure 2.2B). For the 'identification and distribution of drought tolerant cereal crops' regions in Western, Central and coastal Kenya indicate favourable conditions using the dataset on suitability for cereal crops. The arid areas in the North and East are shown as not or marginally suitable for cereals due to prevailing biophysical conditions rendering crop-based agriculture impossible in general, except for the narrow belts along rivers that are not captured by this dataset due to its grid cell resolution of 10 x 10 km. Relatively high methane and nitrous oxide emissions due to livestock production identify Western, Central and

partially Eastern as well as Southern regions as suitable for mitigation interventions focusing on the 'reduction of GHG-emissions from the livestock sector'. Increased aridity in the entire North and North-East of Kenya compared to its Western and Central regions reveal areas for the 'improvement of water harvesting and water management'. The percentage of croplands, constrained by low tree cover, used as proxy for the 'identification and establishment of agroforestry practices' delineates Western and Central regions from the rest of the country emphasising them as suitable for related interventions. Insurance premium rates for livestock mortality as proxy for the 'implementation of livestock insurances' reveals Northern and Eastern areas as prone to higher risks offering eligible conditions for implementing this practice.

2.3.2 Aggregated group-specific and overall consensus-based preferences

The distribution of preference weights inferred from each stakeholder group separately and based on the overall consensus, including all experts, are shown for vulnerability indicators (Figure 2.3A) and CSA practices (Figure 2.3B). Illustrated preferences result from the consensus scenario that shows the most balanced trade-off between majority and minority. The results for majority and minority scenarios can be found in the Appendix (S2, Figure S2.1 and S2.2). Stakeholder groups differed in their preferences for each of the vulnerability indicators and CSA-practices indicated by across group standard deviation (SD) ranging from 0.02 - 0.09 for vulnerability indicators and from 0.00 - 0.12 for CSA practices. However, the vulnerability indicator and CSA practice that were weighed low across all groups, namely 'connectivity through transport infrastructure' and 'implementation of livestock insurances', show a relatively homogenous pattern of preferences with the lowest across group SD. Highly preferred vulnerability indicators across stakeholder groups are 'annual precipitation' and 'households with access to safe water sources'. These indicators relate to the biophysical and social dimensions of vulnerability to climate change. The economic vulnerability indicator 'connectivity through transport infrastructure' and the social indicator 'literacy rate' were weighed low throughout the stakeholder groups except for the science group, which assigned slightly lower preferences to 'female participation in economic activities'. For CSA-practices, high preferences were assigned to 'improvement of water harvesting and water management' and 'identification and distribution of drought tolerant cereal crops'. Yet, NGOs deviated from this pattern giving higher importance to 'identification and establishment of agroforestry practices'. Low weighed CSA practices across stakeholder groups are 'implementation of livestock insurances' and 'reduction of GHG-emissions from the livestock sector'.
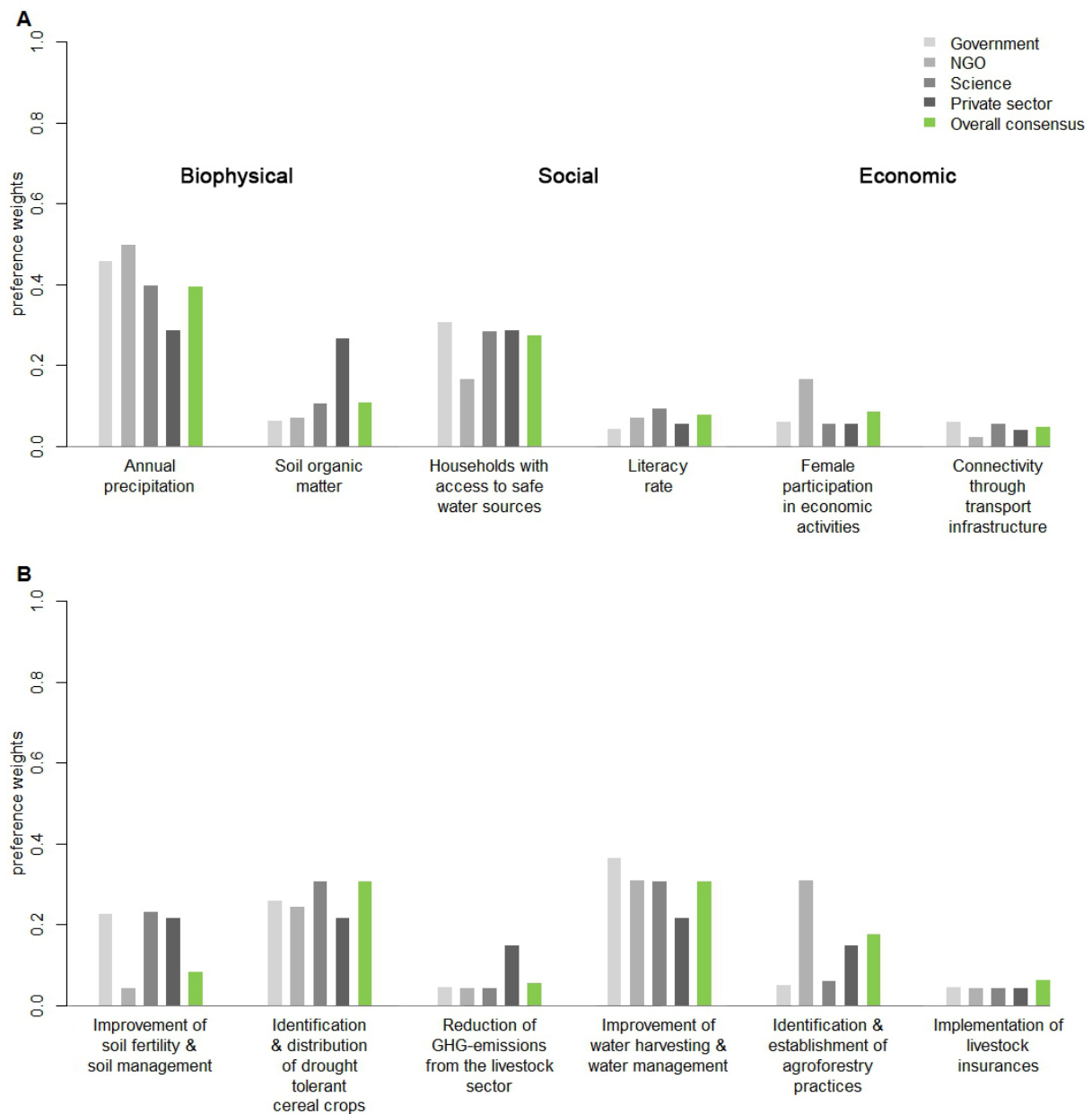
Figure 2.3: Preference weights for each stakeholder group and the overall consensus, including all experts, resulting from the consensus scenario showing the most balanced trade-off between majority and minority for (A) vulnerability indicators and (B) CSA practices.

The preferences based on the overall consensus largely resemble the distribution of group-specific preferences. However, they rank within the ranges of group preferences for each of the indicators and CSA practices except for 'implementation of livestock insurances' indicating minimised distances among stakeholder opinions by using consensus matrices to infer the overall consensus.

2.3.3 CSA potential: coupling spatial indices of vulnerability and CSA suitability under different consensus scenarios

The combined indices for vulnerability and CSA suitability derived from the overall consensus preferences, including all experts, as well as CSA potential maps that resulted from coupling the indices are shown for the majority (Figure 2.4A), minority (Figure 2.4B) and the most balanced trade-off (Figure 2.4C) consensus scenarios. In general, high vulnerability to climate change based on the included indicators is shown for the North and to some degree in Eastern parts of Kenya whereas high CSA suitability is indicated for Western, Central, coastal and partly in Northern parts throughout applied consensus scenarios. However, there are differences in vulnerability among the consensus scenarios at county level. The majority consensus led to higher vulnerability for Turkana and Kitui counties than the minority consensus, which identified the same counties as medium or marginally vulnerable. In contrast, the minority consensus indicated higher vulnerability for Wajir and Tana River counties. The consensus scenario with the most-balanced trade-off shows a pattern of vulnerability intensities that lays between those indicated by majority and minority for these counties. Differences in CSA suitability between the consensus scenarios are less pronounced, yet obvious in several parts of Kenya.

Overlaying CSA suitability on top of high vulnerability regions reveals areas with high CSA potential in Baringo, Mandera and Wajir counties in agreement with all three consensus scenarios. The consensus scenarios disagree on areas of high CSA potential in Turkana, Kitui and Marsabit counties. Comparing majority and minority consensus scenarios, these differences become most obvious for Turkana and Kitui counties. The most-balanced trade-off consensus reflects areas with high CSA potential whose extents rank between those indicated in the majority and minority consensus scenarios.
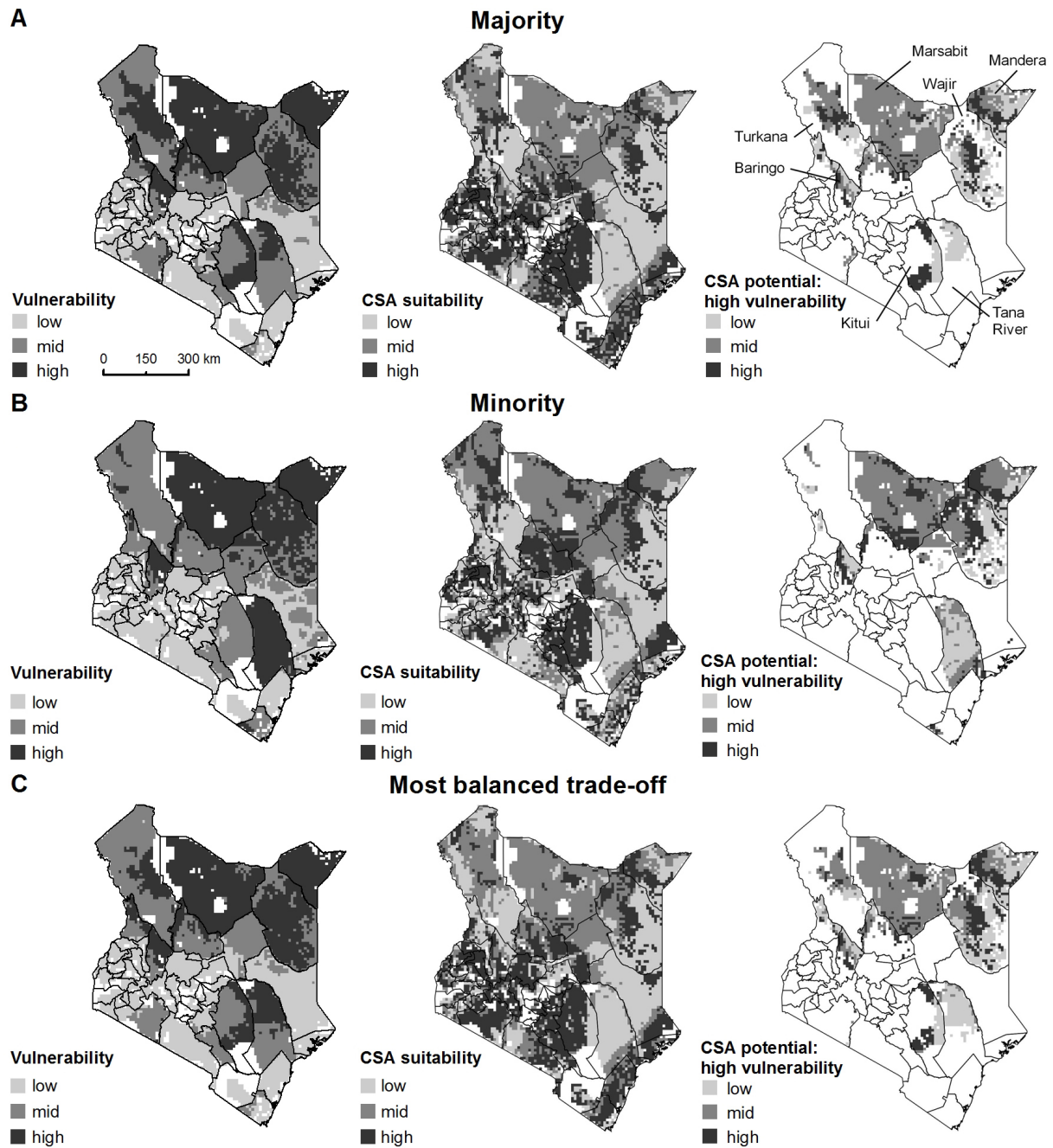
Figure 2.4: Maps show the spatially-explicit indices of vulnerability and CSA suitability as well as the CSA potential for high vulnerability regions based on consensus scenarios of the (A) majority, (B) minority and (C) most-balanced trade-off. Underlying stakeholder preferences were inferred from the overall consensus, including all experts. Classes of vulnerability and CSA suitability indices (low, mid and high) resulted from quantile splits to preserve equal n sizes per class.

2.3.4 Validation

The preferences inferred from the overall consensus based on two expert surveys differed as shown for vulnerability indicators (Figure 2.5A) and CSA practices (Figure 2.5B) under the consensus scenario with the most-balanced trade-off between majority and minority. These differences are less pronounced for vulnerability indicators than for CSA practices indicated by mean differences between the preferences from the two surveys of 0.08 and 0.13 respectively. However, Wilcoxon signed-rank tests did not reveal significant median difference among the two sets of vulnerability indicators and CSA practices ($p > 0.05$).
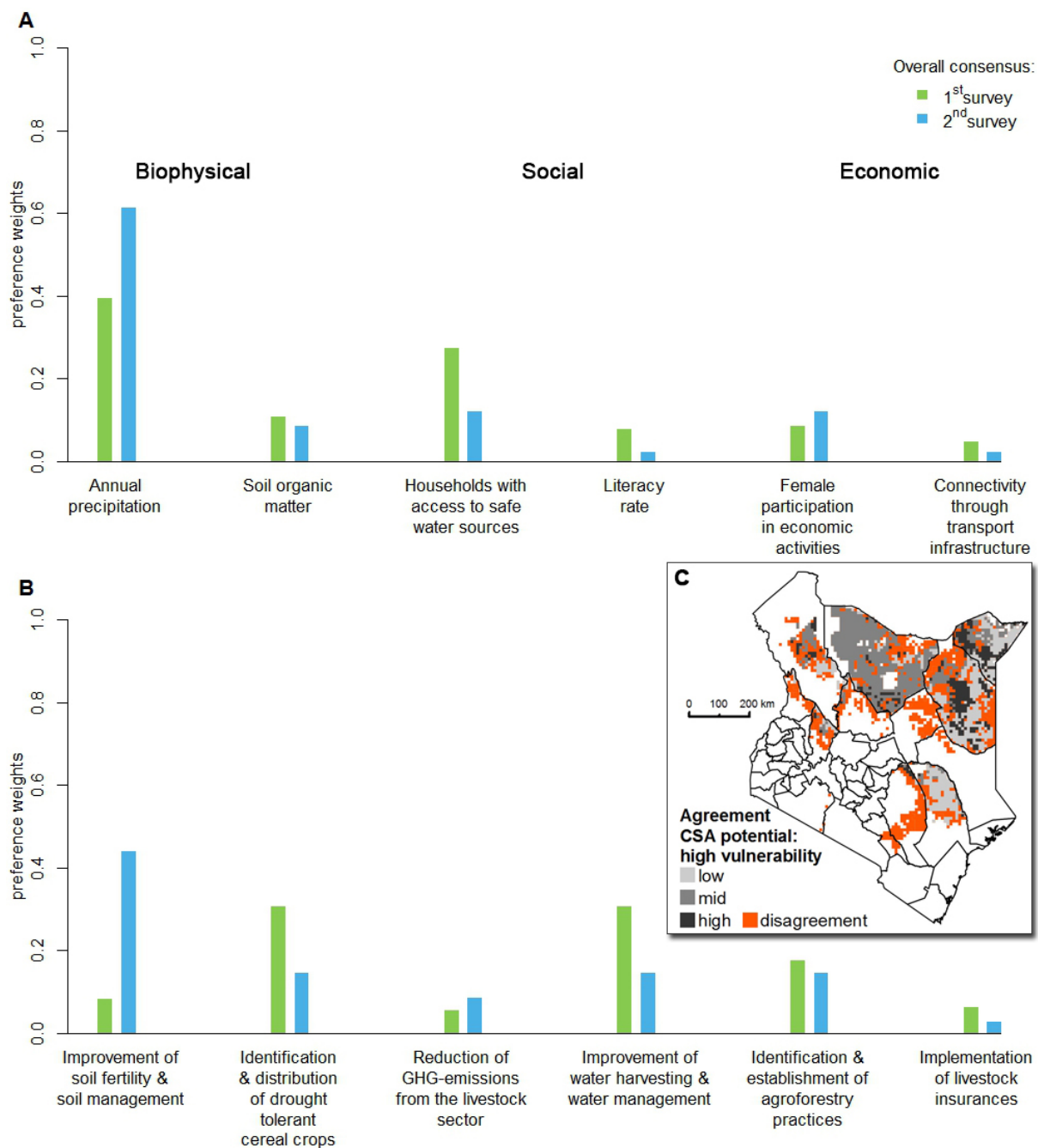
Figure 2.5: Comparison of preferences inferred from the overall consensus (including all experts) based on two expert surveys for (A) vulnerability indicators and (B) CSA practices under the consensus scenario with the most-balanced trade-off. Inset map (C) illustrates agreement on low, mid and high CSA potential in areas with high vulnerability among the two expert surveys under the same consensus scenario. Regions where the surveys disagreed on CSA potential are coloured in orange.

Mapping the CSA potential based on the two sets of vulnerability and CSA suitability indices under the consensus scenario with the most-balanced trade-off depicts agreement

among surveys on areas with high CSA potential in the North and North-East of Kenya mainly located in Wajir and Mandera counties (Figure 2.5C). Areas of disagreement due to differing stakeholder preferences derived from the two surveys are distributed across the North and Central-East of Kenya.

2.4 Discussion

2.4.1 Informing decisions with "targetCSA" using spatially-explicit vulnerability and CSA suitability indices

The combined and spatially-explicit indices reveal a picture of where to target stakeholder selected CSA practices to reduce agricultural vulnerability to climate change at the national level. For Kenya, areas of high vulnerability contrast with areas potentially suitable for implementing CSA practices based on the empirical information included here. This study showed that regions of high vulnerability in Kenya mainly coincide with semi-arid and arid climate resulting in harsh biophysical conditions, confounded by low availability of education and health infrastructure as well as reduced access to markets (Odera et al., 2013; Wiesmann et al., 2014). High vulnerability to climate change for arid and semi-arid areas was also reported at the global scale (Allen et al., 2007). In contrast, high suitability for selected CSA practices concentrated around sub-humid, to some degree semi-arid areas, and is discontinuously spread across arid climate (Grace et al., 2014). Nevertheless, areas of high CSA potential were identified and could be targeted for CSA pilot projects. The Western and Southern parts of Mandera county in the North-West of Kenya represent an example of high CSA potential consistently shown for specific areas across different consensus scenarios as well as expert surveys. The introduction of drought tolerant cereals on moderately suitable lands, the improvement of water management in areas of high aridity, or the implementation of livestock insurances addressing high mortality risk may represent promising CSA measures (Figure 2.4). By coupling the computed spatial indices, the originally unrestricted space could be narrowed to specific regions of high CSA potential enabling a targeted exploration of areas of interest, potentially leading to decisions that are informed by quantitative data and expert opinions.

2.4.2 CSA-targeting as a consensus-driven approach

Climate change adaptation planning calls for stakeholder participation integrating perceptions and opinions from a broad range of stakeholders to strive for legitimate decisions and sustainable planning solutions (Conway & Mustelin, 2014; Krellenberg & Barth, 2014). However, stakeholder integration may lead to dissent about the importance of planning objectives reflected by measurable preferences on multiple AHP-criteria as shown in this

example (Figure 2.3). This has also been reported for group decision processes in forest planning (Linares & Romero, 2002; Kangas et al., 2010). Different interests, highly complex problems and resulting uncertainties are common causes of dissent in multi-criteria decision-making applications (Nordström et al., 2010). Approaching consensus solutions by finding a PC matrix that shares the highest degree of similarity with the stakeholder-derived PC matrices reduces discrepancy and hence dissent inherent to group-specific preferences.

The question of what is the appropriate consensus scenario should be asked in a certain decision-making context though. Following different consensus scenarios, changes the patterns of inferred preferences, which determine the location of regions with high potential for targeting selected CSA practices (Figure 2.4). Other studies have shown similar effects on the distribution of stakeholder preferences (Diaz-Balteiro et al., 2009; Nordström et al., 2012). The ability to choose between consensus scenarios and to explore their potential impact on decisions grants higher flexibility and legitimacy to the democratic modes that shape group decision-making processes. Relying on the majority could be a proper principle when all stakeholders possess similar influence on decisions. Instead, giving more weight to the minority might be suitable when marginalised stakeholders such as indigenous people are involved who usually have low influence on decision-making. If no agreement on opting for the majority or minority principle is achievable, a compromise solution, such as the one adopted here, is to select the most balanced trade-off between these two mutually exclusive alternatives (González-Pachón & Romero, 2011). Hence, the explicit role of "targetCSA" is to structure decision-making problems and to facilitate the exploration as well as the discussion of discrepancies among stakeholder opinions to eventually achieve consensual solutions that aid decision-making processes where a broad range of stakeholders are involved.

2.4.3 Sticking points of a decision support framework for targeting CSA

Capturing and reducing uncertainty from stakeholder preferences

Stakeholder opinions may vary over time, as shown here (Figure 2.5) and represent a source of uncertainty for decision-making processes (Xu & Zhang, 2013). The detected discrepancies regarding the preferences for some of the CSA practices are most likely an effect of shifts in stakeholder opinions due to changes of knowledge or interests. A reduction of this uncertainty is attainable through an iterative mode of preference elicitation, e.g. by following the Delphi method (Chung et al., 2014). Yet, this might be unfeasible in very conflict prone decision-making situations that are not consensually manageable or due to time and budget constraints (Nordström et al., 2010). Alternatively, additional experts may be involved in case of controversial situations to integrate specific knowledge that was missing but has the potential to mitigate such situations. An approach to analyse and un-

derstand social dynamics behind preference changes and their effects on decision-making systems is the use of agent-based models (Bousquet & Le Page, 2004).

Applicability of "targetCSA"

This example demonstrated the applicability of the presented decision support framework for targeting selected CSA practices. For instance, "targetCSA" could be used in different CSA related planning initiatives at national level such as Kenya's national CSA framework or the Nationally Appropriate Mitigation Action (NAMA) that is currently developed for the dairy production sector in Kenya to support the decision-making on the prioritisation of adaptation and mitigation options. The framework is applicable on a stratified, regional scale, capturing the heterogeneous characteristics within a given country by involving region-specific stakeholders, vulnerability indicators and CSA practices. Furthermore, the restricted sets of vulnerability indicators and CSA practices that were chosen for this application example are easily extendable and adoptable to other countries differing in their biophysical, social and economic conditions. This includes vulnerability indicators that reflect projected changes of temperature and precipitation, e.g. trends of decreasing precipitation and increasing temperature would translate into higher vulnerability and vice versa.

The main objective of "targetCSA" is to support decisions for adaptation and mitigation planning at the national and regional level by structuring decision-making problems as well as exploring and building consensus among different stakeholder groups. However, several scales have to be integrated eventually into a comprehensive planning for adaptation and mitigation (FAO, 2013; Conway & Mustelin, 2014). Hence, this framework could be coupled with bottom-up approaches to properly deal with local realities and to allow for fine-scale planning (Chaudhury et al., 2014; Rosenstock et al., 2014).

2.4.4   Further research

Research efforts should be invested into elucidating the impact of CSA practices on vulnerability alleviation and analyses of synergies and trade-offs among adaptation and mitigation options in specific areas, including assessments of implementation costs and benefits for farmers (Harvey et al., 2014a). Information that links the implementation of CSA practices to their local effects could be derived from household surveys and exhaustive meta-analyses of CSA case studies relating costs and profitability to biophysical and social conditions prevailing in regions of interest. The resulting spatially upscaled indices of CSA costs and benefits would represent further layers of information supporting the decision-making on CSA prioritisation together with the aggregated vulnerability and CSA suitability indices. Moreover, vulnerability indicators need to be further elaborated

to meet the needs of the planning process and to allow for quantitative analyses of interactions and feedback mechanisms between biophysical indicators mostly pointing to exposure and sensitivity as well as social and economic indicators mainly determining the adaptive capacity of agricultural systems (Fellmann, 2012). Shedding light on how to couple the national top-down approach of CSA-targeting with bottom-up initiatives is necessary to synchronise local and broad scale adaptation planning (Conway & Mustelin, 2014).

2.5   Conclusions

Climate change adaptation and mitigation efforts need to be coordinated through national planning processes that implement properly climate change action plans. Related decisions should be made in accordance with relevant stakeholders and guided by quantitative information including biophysical, social and economic conditions. Especially the latter point might be challenging in data-deficient regions, yet, the exemplary application of "targetCSA" in Kenya showed that it is potentially feasible.

The main benefits of "targetCSA" for decision-makers are:

1. Problem structuring and complexity reduction by using AHP and pair wise comparison methods.

2. Spatially-explicit indices are built upon consensual preferences from cross-sectoral stakeholders on multiple criteria reflected by included vulnerability indicators and CSA practices.

3. The ability to choose between different consensus scenarios and to explore their potential effects on decisions may lead to more sustainable planning outcomes due to higher acceptance.

4. By using a three-dimensional concept of vulnerability, including biophysical, social and economic factors a demand-based assessment of CSA potential becomes possible.

5. Its transferability to other countries makes the applicability of the framework highly flexible.

Acknowledgments

Chapter 3

The contribution of sectoral climate change mitigation options to national targets: a quantitative assessment of dairy production in Kenya

Abstract

Reducing greenhouse gas (GHG) emissions from agriculture has become a critical target in national climate change policies. More than 80 % of the countries in Sub-Saharan Africa (SSA) refer to the reduction of agricultural emissions, including livestock, in their 'Nationally Determined Contributions' (NDC) to mitigate climate change. The livestock sector in Kenya contributes largely to the gross domestic product and to GHG emissions from the land use sector. The government has recently pledged in its NDC to curb total GHG emissions by 30 % by 2030. Quantifying and linking the mitigation potential of farm practices to national targets is required to support realistically the implementation of NDCs. Improvements in feed and manure management represent promising mitigation options for dairy production. This study aimed (i) to assess mitigation and food production benefits of feed and manure management scenarios, including land use changes covering Kenya's entire dairy production region and (ii) to analyse the contribution of these practices to national targets on milk production and mitigation, and their biophysical feasibility given the availability of arable land. The results indicate that improving forage quality by increasing the use of Napier grass and supplementing dairy concentrates supports Kenya's NDC target, reduces emission intensities by 26 - 31 %, partially achieves the national milk productivity target for 2030 by 38 - 41 %, and shows high feasibility given the availability of arable land. Covering manure heaps may reduce emissions from manure management by 68 %. In contrast, including maize silage in cattle diets would not reduce emission intensities due to the risk of 10-fold higher emissions from the conversion of land required to grow additional maize. The shortage of arable land may render the implementation of these improved feed practices largely infeasible. This assessment provides the first quantitative estimates of the potential of feed intensification and manure management to mitigate GHG emissions and to increase milk yields at sectoral-level and at a high spatial resolution for an SSA country. The scientific evidence is tailored to support actual policy and decision-making processes at the national level, such as 'Nationally Appropriate Mitigation Actions' (NAMAs). Linking feed intensification and manure management strategies with spatially-explicit estimates of mitigation and food production to national targets may help the sector to access climate financing while contributing to food security.

3.1 Introduction

Greenhouse gas (GHG) emissions from 'Agriculture, Forestry and Other Land Uses' (AFOLU) are estimated to contribute 24 % to the total anthropogenic GHG emissions (Smith et al., 2014). The global livestock production as a sub-sector of AFOLU emits between 10 - 14.5 % of total GHG emissions, of which 4 % are due to dairy production (Gerber et al., 2010; Westhoek et al., 2011). Total GHG emissions from dairy production are projected to increase by 82 % under 'business as usual' (BAU) trajectories until 2050 compared to 2000, as production expands to keep up with the milk demand of a growing human population (O'Mara, 2011).

Current food insecurity in many low-income countries, especially in Sub-Saharan Africa (SSA), and sustained population growth call for assessments that contribute to both the mitigation of AFOLU emissions and the improvement of food provisioning from agricultural systems (Smith et al., 2013). The development of schemes that mitigate AFOLU emissions such as 'Nationally Appropriate Mitigation Actions' (NAMAs) have recently gained attention from governments that ratified the Paris climate agreement under the 'United Nations Framework Convention on Climate Change' (UNFCCC, 2011; Grassi et al., 2017). Countries express their mitigation targets in the 'Nationally Determined Contributions' (NDCs). Kenya's NDC targets to limit the increase in total GHG emissions projected in the national BAU scenario by 30 % between the base year of 2010 and 2030 (Government of Kenya, 2015b). Reliable estimates of sectoral baseline emissions and effective mitigation options are still missing and required urgently to develop NAMAs that help achieve the NDC targets. Focussing on livestock production in Kenya is highly relevant since it is responsible for about 30 % of its total GHG emissions and contributes about 45 % to the agricultural gross domestic product (McDermott et al., 2010; Government of Kenya, 2015a).

The dairy sector in Kenya sustains the livelihood of about two million smallholder households, who contribute approximately 80 % to the 3.4 M t of milk produced in the country (Udo et al., 2016). In addition, dairy products supply a range of valuable nutrients and therefore contribute to the human population health. Culturally, milk is a vital component of agro-pastoralists diets in East Africa (Rufino et al., 2013). The population of dairy cattle has increased by about 31 % to 4.3 M heads from 1998 to 2014 (Muriuki, 2011; Government of Kenya, 2014), whereas feed inputs for dairy cattle have increased by about 32 % from 1998 to 2006 (Muriuki, 2011). Increased animal numbers and the additional demand for feeds contribute largely to emissions of non-carbon dioxide GHGs, namely methane (CH_4) and nitrous oxide (N_2O) through enteric fermentation, manure and soil management. In addition, the trend of increasing livestock numbers leads to emissions from degraded rangelands and forests (Kumar et al., 2009; O'Mara, 2011; Bosire et al., 2016).

The dairy sector has to increase production sustainably by 2030 to be able to meet the projected milk demand estimated in the national policy framework for the development of the dairy sector, called Kenya's national dairy master plan (Government of Kenya, 2010). Several initiatives such as the 'East Africa Dairy Development' (EADD) program, the 'Smallholder Dairy Commercialization Programme' (SDCP) supported by the 'International Fund for Agricultural Development' (IFAD) and the 'Kenya Dairy Sector Competitiveness Program' (KDSCP) supported by the 'United States Agency for International Development' (USAID) are actively engaged in the development of the dairy sector in East Africa. These initiatives are increasingly looking for development outcomes that realise climate change mitigation benefits at the same time. A challenge to realise the projected growth of the dairy sector is that to date, a large share of cattle diets consists of low quality roughage from overstocked grazing land and crop residues (McDermott et al., 2010). Improving feed quality is needed to increase milk yields (Lukuyu et al., 2012). However, the conversion of land to grow higher quality fodder and the GHG emissions resulting from land use change (LUC) may compromise expected reductions from changes in feeding practices advocated in national policies (Valin et al., 2013). In addition, the shortage of arable land may constrain the implementation of feeding practices that increase the demand for cropland.

This study aimed to answer the question: to what extent the improvement of feed quality and manure management may contribute to the milk productivity target of Kenya's national dairy master plan and to the national mitigation target (NDC) given the availability of arable land. The objectives were: i) to quantify total GHG emissions and GHG emission intensities under current feed and manure management conditions, and alternative feed intensification scenarios, including manure management, ii) to assess the potential of these scenarios to meet the national targets and the biophysical feasibility to implement the practices, and iii) to map total baseline GHG emissions, milk production, and the potential changes for the dairy sector. Such analyses are relevant to inform the development of climate mitigation policies.

3.2 Material and methods

3.2.1 Study area

The main dairy region of Kenya is characterised by rainfed (71 %) and irrigated (29 %) mixed crop-livestock production systems covering the Central and Western highlands as well as humid areas in the West of Kenya with an area of approximately 65,000 km^2 and 24 counties (Appendix S3, Figure S3.1). The delineation of the study area was based on (Herrero et al., 2014) who assessed smallholder development trajectories in mixed crop-dairy production systems. Dairy production takes place in a region with high

agricultural potential, where about 68 % of the total human population lives (Herrero et al., 2014). Typical smallholder farms are small with an average size of 0.47 ha (Lowder et al., 2014).

3.2.2 Calculating GHG emissions and milk production

The emission source categories (IPCC, 2006) included in this analysis are: CH_4 emissions from enteric fermentation, CH_4 emissions from manure management, direct and indirect N_2O emissions from manure management, direct and indirect N_2O emissions from managed soils, and N_2O and carbon dioxide (CO_2) emissions from LUC converting grazing land to cropland using data from Don et al. (2011) and Hengl et al. (2015). This study followed the IPCC tier 2 approach for most categories. For a detailed description of emission parameters see (Appendix S3, Table S3.1). All emission source categories were quantified separately for dairy cattle using a classification of livestock production systems (LPS) (Appendix S3, Figure S3.2): mixed rainfed system in arid areas (MRA), mixed rainfed system in humid areas (MRH), mixed rainfed system in tropical highlands (MRH), mixed irrigated system in arid areas (MIA), mixed irrigated system in humid areas (MIH) and the mixed irrigated system in tropical highlands (MIT). This LPS classification, developed by Robinson et al. (2011), has been used to analyse different environmental and economic aspects of livestock production (Thornton & Herrero, 2010; Herrero et al., 2013; Rufino et al., 2014). GHG emissions that result from dairy concentrate supplementation, including the cultivation of feed ingredients were calculated using an emission factor from Weiler et al. (2014). This factor was used in a dairy life cycle assessment at farm level in the Kenyan highlands, assuming that the concentrate ingredients originate from Kenya and Uganda (Appendix S3, Table S3.1).

Conversion factors (expressed as CO_2 equivalents) for CH_4 and N_2O were applied according to the most recent global warming potentials (GWP) from the fifth assessment report of the 'Intergovernmental panel on climate change' (IPCC, 2014). GHG emissions are reported as total GHG emissions and emission intensities. The later notion is expressed on product basis and converted into kg CO_2eq per kg fat and protein corrected milk (FPCM). Both notions were selected to relate the mitigation potential of the scenarios to the NDC target (total emissions) and to communicate efficiency gains for each scenario, relevant for a NAMA (emission intensity).

3.2.3 The Livestock Simulator: LivSim

The dynamic production model 'LivSim' was used to simulate milk yields, and faecal and urine excretion for individual dairy cattle on a monthly basis (Rufino et al., 2009). The 'HeapSim' model, coupled with LivSim, was used to integrate the dynamics of manure decomposition during storage, including the nutrient losses, and manure application

(Rufino et al., 2007). LivSim was extended with a GHG emission module to compute GHG emissions from the different source categories (Appendix S3, Table S3.1) following (IPCC, 2006). The models were run using the open source language for numerical computations GNU Octave (v.4.0) (Eaton et al., 2015). Each run simulated a dairy cow over the maximum lifetime of 13 years and was replicated 100 times for each LPS to account for stochasticity in calving and mortality.

LivSim was calibrated with information derived from literature and feed datasets (Anindo et al., 1994; Rufino et al., 2009; Katiku et al., 2011; Herrero et al., 2013; Weiler et al., 2014; Castellanos-Navarrete et al., 2015), cattle breeds and emission parameters (Kategile et al., 1987; Stares et al., 1991; IPCC, 2006; Monfreda et al., 2008; Rufino et al., 2009; Potter et al., 2010; Herrero et al., 2013) representing the baseline conditions for each LPS in Central and Western Kenya (Appendix S3, Table S3.1). Emission uncertainties were estimated using a twofold approach. First, Latin hypercube sampling (LHS) (Xu et al., 2005) was applied to the baseline simulations sampling the ranges of 23 emission parameters. One parameter at a time was sampled through LHS while keeping all others constant at the mean of their ranges (ten Broeke et al., 2016) (Appendix S3, Table S3.1). Second, the emission uncertainties of the modelled scenarios were calculated one parameter at a time sampling at the minimum and the maximum of the parameter ranges.

3.2.4   Spatial upscaling of GHG emissions and milk production

Spatially-explicit datasets on LPS and cattle density, at a spatial resolution of 1 x 1 km per grid cell (Robinson et al., 2011, 2014), were used to upscale and to map output tables of GHG emissions and milk production derived from LivSim (Figure 3.1). Since this study focused on GHG emissions from dairy production, the density of dairy cattle was calculated using sub-national county level data on cattle types excluding cattle used for beef production (Government of Kenya, 2014). Moreover, herd composition data were applied to reflect the proportion of productive and non-productive animals in dairy herds according to Bebe et al. (2002). The spatial upscaling procedure was implemented using the statistical computing language R (v. 3.2.3), including the R library 'raster' (v. 2.5) (Hijmans, 2016; R Core Team, 2016). Feeds were assumed to be grown locally within one grid cell. Therefore, no transport emissions were included.
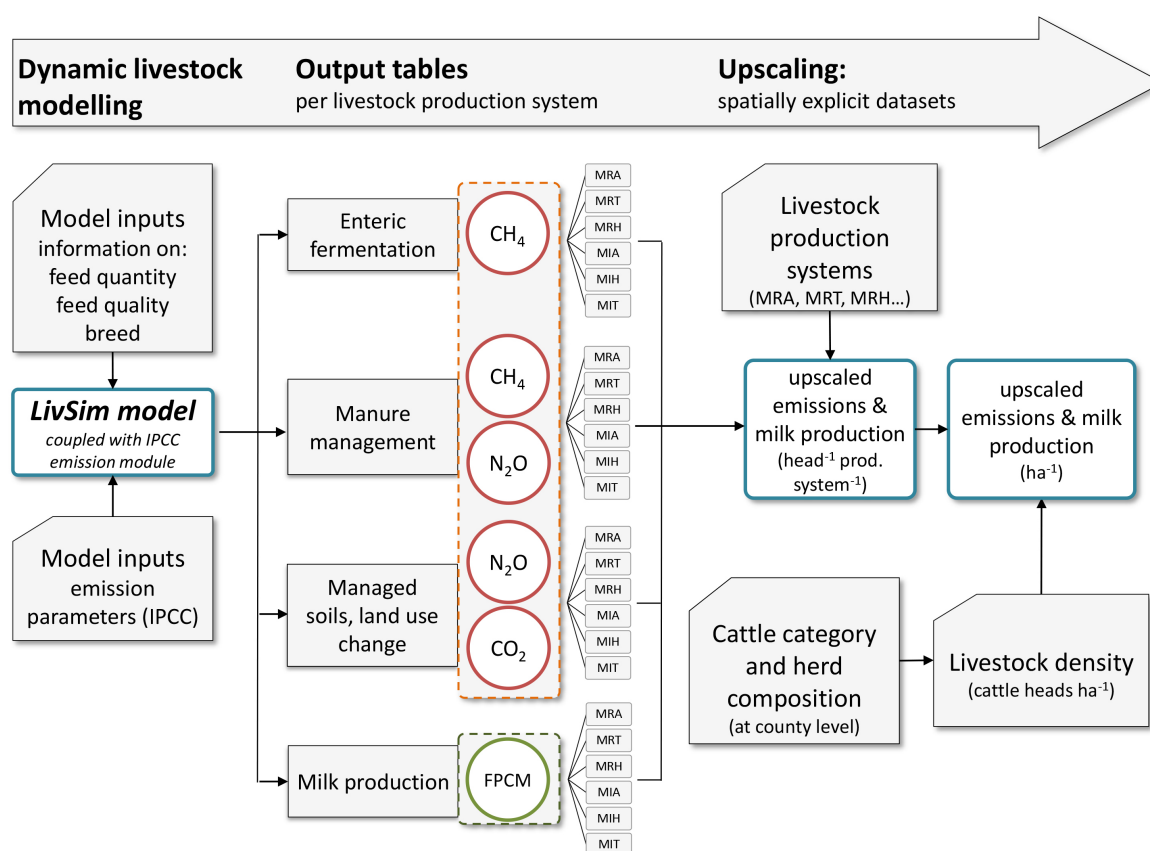
Figure 3.1: Flowchart shows the model framework applied in this study consisting of a dynamic livestock modelling approach to compute output tables of GHG emissions and milk production. Subsequently, these tables were upscaled based on livestock production systems and mapped using data on herd composition, cattle category and density.

3.2.5   Feed and manure management

Baseline feeds

Feed composition and quantity data used to model the baseline reflected typical diets for dairy cattle kept by smallholders across the Kenyan highlands. Feed data were obtained from Rufino et al. (2009), Katiku et al. (2011), Herrero et al. (2013), Weiler et al. (2014), and Castellanos-Navarrete et al. (2015). Agro-climatic conditions present in the various LPS used were taken into account leading to differences in dry matter intake (DMI). Annual DMI ranged between 2,414 – 2,475 kg per tropical livestock unit (TLU). The baseline diet was composed of native grass from grazing land (36 – 52 %), Napier grass (*Pennisetum purpureum*) (24 - 42 %), maize stover (21 – 27 %), and dairy concentrate (1 %) (Appendix S3, Table S3.2). Feed quality data, including quality differences due

to seasonal variation were derived from Rufino et al. (2009) and from the 'Sub-Saharan Africa feed composition database' (Anindo et al., 1994).
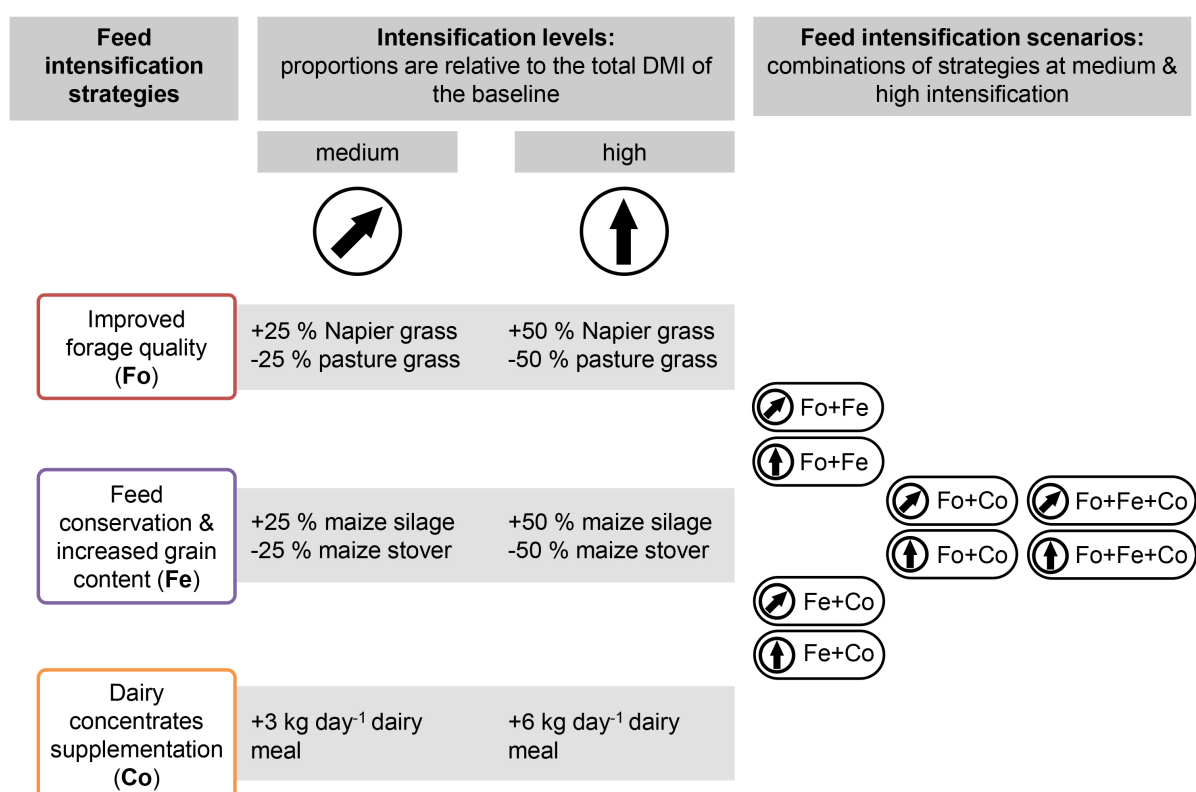
Feed intensification scenarios

Feeds with high energy and protein density increase feed digestibility and milk yields (Hristov et al., 2013a). Thus, using these feeds would reduce the demand for feeds from the low productivity and low quality natural pastures. Dairy farming in Kenya relies primarily on these natural pastures as main source of feed. Different regional estimates show that 41 - 90 % of the dairy farmers use native grass as main feed resource (Katiku et al., 2011; Lukuyu et al., 2011; Njarui et al., 2011). Feeds of high quality pass the rumen faster, which reduces anaerobic fermentation and methanogenesis due to post ruminal digestion and, thus, results in lower production of CH_4 (Eckard et al., 2010; Knapp et al., 2014). Highly degradable feedstuffs with high protein and starch contents reduce ruminal pH and shift the fermentation process from acetate to propionate formation increasing the consumption of H_2, which is consequently unavailable for CH_4 production (Dijkstra et al., 2011; Soren et al., 2015). However, increased protein content in diets may cause higher N excretion leading to potential trade-offs between CH_4 and N_2O emissions (Dijkstra et al., 2011). Feed intensification scenarios developed in this study were based on plausible strategies that can improve milk yields and reduce GHG emission intensities:

Improved forage quality (Fo): Increasing forage digestibility improves the efficiency of milk production and can reduce CH_4 emissions per unit FPCM ranging from 2.5 - 21 % (Boadi et al., 2004; Knapp et al., 2014; Trupa et al., 2015). Napier grass is a perennial fodder crop with higher quality than native grass and is widely grown as fodder crop by dairy farmers in Kenya (Kariuki et al., 1999; Muia et al., 2001). It is estimated, that 21 - 93 % of the farmers plant Napier grass in the region (Katiku et al., 2011; Lukuyu et al., 2011; Njarui et al., 2011). Hence, there is potential to increase the proportion of Napier grass in the dairy diet (Lukuyu et al., 2012; Owen et al., 2012).

Feed conservation and increased grain content (Fe): Ensiling fresh fodder such as whole maize plants is proposed as feed conservation strategy for dairy farmers to reduce feed scarcity during the dry season (Lukuyu et al., 2012). CH_4 emissions can be reduced by up to 33 % per unit FPCM replacing grasses with maize silage (Boadi et al., 2004; Chagunda et al., 2010; Brask et al., 2013). Increasing the proportion of grain in the diet leads to higher starch concentration, lower fibre content and decreased ruminal pH, which reduces methanogenesis and CH_4 emissions per unit feed (Beauchemin et al., 2008; Dijkstra et al., 2011). Crop residues such as maize stover are also commonly fed to dairy cattle by 33 - 100 % of the Kenyan dairy farmers (Katiku et al., 2011; Njarui et al., 2011). Since maize is an important food crop, additional maize and arable land are required to produce silage and to avoid compromising food security. The conversion of grazing land to cropland

causes N_2O and CO_2 emissions, which are henceforth defined as emissions from LUC (de Boer et al., 2011; Don et al., 2011).

Dairy concentrates supplementation (Co): Higher proportion of concentrates in the diet especially during the first half of the lactation can increase milk productivity by 8 - 37 % (Agle et al., 2010; Richards et al., 2016). Higher concentrate proportion in the diet, replacing roughage can decrease CH_4 emissions by 15 - 39 % (Chagunda et al., 2010; Hristov et al., 2013b; Knapp et al., 2014). About 10 - 88 % of dairy farmers in Kenya supplement dairy concentrates, although at very low rates (Katiku et al., 2011; Lukuyu et al., 2011; Njarui et al., 2011).

Figure 3.2: Feed intensification scenarios based on combinations of three feed intensification strategies at medium and high level of intensification (DMI = dry matter intake). Dairy concentrates supplementation was increased during the first 150 days of lactation. For details on the baseline diet, see Appendix (S3, Table S3.2)

The scenarios were derived through combinations of the three feed intensification strategies (Figure 3.2) and are henceforth called: 'forage quality and concentrate supplementation' (FoCo), 'feed conservation and concentrate supplementation' (FeCo), 'forage quality and feed conservation' (FoFe), and 'forage quality, feed conservation and concentrate supplementation' (FoFeCo). Each scenario was developed at medium and high level of intensification (Figure 3.2). For the Fo and Fe strategies, baseline feeds were replaced by

25 % and 50 % with higher quality alternatives. The supplementation of dairy concentrates was increased for the Co strategy by 3 kg day^{-1} and 6 kg day-1 during the first 150 days of lactation.

Manure management

Direct and indirect N_2O emissions result from nitrification and denitrification of ammonium and nitrate contained in manure, the leaching of nitrate, and the volatilisation of ammonia (NH_3) (IPCC, 2006). Manure management can prevent the loss of N during the storage. Manure that is rich in nutrients can be used to improve soil fertility and farm productivity (Tittonell et al., 2009, 2010). Covering manure heaps can reduce leaching and volatilisation and, thus, N_2O and NH_3 emissions by about 30 % and 90 % respectively compared to uncovered heaps (Chadwick, 2005; Hou et al., 2015). However, CH_4 emissions can be increased due to anaerobic conditions (Montes et al., 2014). Covering heaps is considered a feasible practice for smallholders in SSA compared to other options such as the separation and cooling of slurry or anaerobic digestion (de Boer et al., 2011). It is uncommon for smallholders to cover manure heaps (Tittonell et al., 2010), thus uncovered heaps were assumed for the baseline (Appendix S3, Table S3.1). For all scenarios, the covering of heaps reduced the baseline factor for direct N_2O emissions by about 1 % for arid LPS and by about 0.25 % in the humid and highland LPS. The volatilisation and leaching fractions were lowered by 5 % and 10 % respectively, across LPS in relation to the baseline (IPCC, 2006).

3.2.6 Scenarios, national targets and their biophysical feasibility

Feed intensification and manure management scenarios were analysed in terms of: i) milk yield increases in relation to the dairy master plan target, ii) total GHG emission increases and the NDC target, and iii) the demand for arable land. Scenario increases in milk yield (X_i) were re-scaled (0 – 100 %) to the baseline milk yields (X_{min}) and the projected relative increase in milk yield per dairy cow between 2010 - 2030 (X_{max} = dairy master plan target) using equation (3.1). Scenario increases in total GHG emissions (X_i) were re-scaled (0 – 100 %) to the baseline total GHG emissions (X_{min}) and the projected relative increase in total GHG emissions between 2010 - 2030 (X_{max} = national BAU scenario). The relative GHG emission increase of the BAU scenario and the tolerable increase according to the NDC target, which reduces the increase in total GHG emissions by 30 % in relation to the BAU scenario, were calculated by following steps (1 – 5) in Appendix (S3).

$$V_{\text{res}} = \frac{(X_{\text{i}} - X_{\text{min}})}{(X_{\text{max}} - X_{\text{min}})} \times 100 \tag{3.1}$$

V_{res} = re-scaled scenario values of increases in milk yield (%) and total GHG emissions (%)

X_i = original scenario values of increases in milk yield (%) and total GHG emissions (%)

X_{min} = minimum values derived from the baseline model for milk yield and total GHG emissions representing 0 %

X_{max} = maximum values derived from the dairy master plan and Kenya's national BAU scenario representing 124.1 % of milk yield increase and 95.9 % of total emission increase between 2010 – 2030.

The biophysical feasibility of the scenarios was assessed comparing their demand for arable land and its availability. Only current grazing land was considered suitable for the conversion to grow Napier grass and maize, as the remaining forests in Kenya are protected and the expected GHG emissions from deforestation would be high (Don et al., 2011; Carter et al., 2015). A spatially-explicit dataset on current grazing land was used to analyse the availability of arable land for dairy cattle (van Velthuizen et al., 2007). The demand for cropland was calculated for each scenario based on the crop-specific feed intake per cow, density of dairy cattle, and expected yields per feed type (Appendix S3, Table S3.3, equations S3.1 & S3.2). The shortage of arable land was calculated for each scenario based on the proportion of grid cells, throughout the study area, where the demand for land exceeds the amount of grazing land available (minimum = 0 %, maximum = 100 %). The multivariate measure of Euclidean distances was calculated (Crawley, 2007) to quantify how close each scenario approaches the theoretical optimum for the three dimensions included. The optimum is hereby defined as 100 % milk yield increase, 0 % total emission increase and 0 % shortage of arable land.

3.3 Results

3.3.1 Effects of feed intensification and manure management on total GHG emissions and emission intensities

Across all scenarios, the simulations showed an average increase in total GHG emissions of 39.5 ±23.0 % (standard deviation, SD) per TLU compared to the baseline. The lowest increase was shown for the FoCo scenario at medium level of intensification and the highest increase was indicated for the FoFeCo scenario at high level of intensification. The increase in total emissions throughout the scenarios was largely caused by higher emissions from manure management (35.6 ±32.9 %), emissions from soils due to the cultivation of feeds including concentrates (206.1 ±163.4 %), and LUC emissions resulting from the conversion of grazing land to cropland (Figure 3.3A). The increase in emissions

from these sources outweighed the reduction of CH_4 emissions from enteric fermentation (9.5 ±6.7 %) achieved through substituting low quality feed ingredients by higher quality alternatives. This effect was most pronounced for scenarios that included maize silage at high level of intensification. The reduction of CH_4 emissions from enteric fermentation achieved in these scenarios was 11.2 ±8.6 %, whereas the increase of N_2O emissions from feed cultivation (mainly dairy concentrates) was on average four times higher compared to the baseline. Feed conservation caused on average three times higher CO_2 emissions from LUC compared to scenarios that did not include this strategy at high intensification level. Throughout the scenarios, the covering of manure heaps reduced the increase of related direct N_2O emissions due to elevated N excretion on average by 77.0 ±1.0 % when compared scenarios without this management option. Indirect N_2O emissions from N leaching and volatilisation (NH_3) were on average reduced by 15.3 ±3.0 %.

Variability in emissions (shown by SD) among LPS for the baseline and scenarios ranges between 1.6 - 5.1 % for CH_4 emissions from enteric fermentation, 6.5 - 20.3 % for CH_4 and N_2O emissions from manure management, 2.1 – 23.8 % for soil emissions from feed cultivation, and 6.2 - 13.7 % for LUC emissions. This variability resulted from differences in feed quality across LPS (1 - 2 %) leading to variation in N excretion rates (2.3 - 28.3 %). Differences between the yields for Napier and maize (6.6 - 12.9 %) also influenced the demand for additional cropland among the LPS.

Four scenarios showed a decrease in emission intensities in relation to the baseline, namely FoCo at medium (27.2 %) and high intensification (20.4 %), FoFeCo at medium intensification (11.2 %), and FeCo at medium intensification (9.1 %) (Figure 3.3B). Scenarios that included the use of silage, especially at high intensification level, did not reduce emission intensities, largely due to high LUC emissions. Higher milk yields were achieved, yet LUC emissions increased largely due to the conversion of cropland needed to grow additional maize. These emissions were on average ten times higher than those of the high intensification scenario using Napier instead of silage, outweighing the reductions in CH_4 emissions from enteric fermentation by 8.4 % ±6.2.
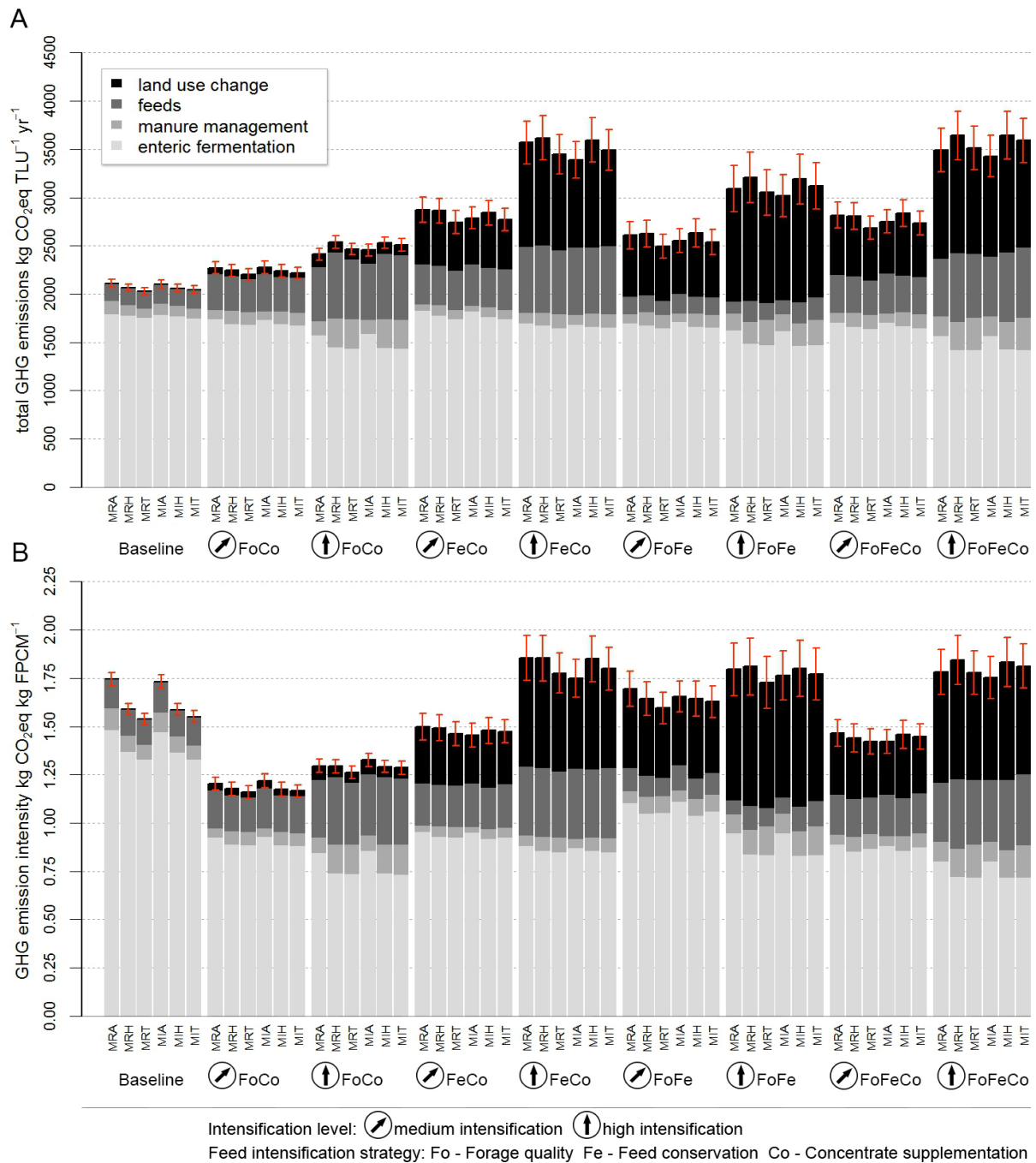
Figure 3.3: For the baseline and scenarios (A) shows total GHG emissions per TLU (tropical livestock unit) for different LPS (livestock production systems, Appendix S3, Figure S3.2) and (B) indicates GHG emission intensities per kg FPCM (fat and protein corrected milk). CH$_4$ and N$_2$O emissions were converted to kg CO$_2$eq. Barplots represent i) CH$_4$ emissions from enteric fermentation, ii) CH$_4$ and N$_2$O emissions from manure management, iii) N$_2$O emissions from soils, including manure deposition on pasture, manure application to fodder crops, crop residues from fodder crops and fertiliser application to fodder crops and emissions from concentrate supplementation, and iv) N$_2$O and CO$_2$ emissions from land use change (LUC), including N mineralisation and loss of soil organic carbon. Error bars indicate standard deviations of calculated total GHG emissions derived from Latin Hypercube Sampling (baseline) and sampling the minimum and maximum of the parameter ranges (scenarios).

3.3.2 National targets and biophysical feasibility of scenarios

Two scenarios met Kenya's NDC target, increased milk yields considerably associated with a marginal shortage of arable land throughout the study region (Figure 3.4). The FoCo scenarios at medium and high level of intensification increased total GHG emissions by 3.6 and 12.6 % respectively. Taking into account the emission uncertainties, total emissions increased by 13.7 and 24.3 % respectively at the upper 95 % confidence limit. For the NDC, an increase of total emissions by 67.1 % by 2030 relative to the base year 2010 would be tolerable. Only 0.5 % (medium intensification) and 2.8 % (high intensification) of the study region would not have enough arable land to implement these two scenarios. Through productivity increases in the same scenarios, the projected annual milk yield by 2030, as targeted in Kenya's dairy master plan was on average achieved by 38.3 – 40.5 %. Euclidean distances to the theoretical optimum were also shortest for the FoCo scenarios at medium and high level of intensification (Figure 3.4).
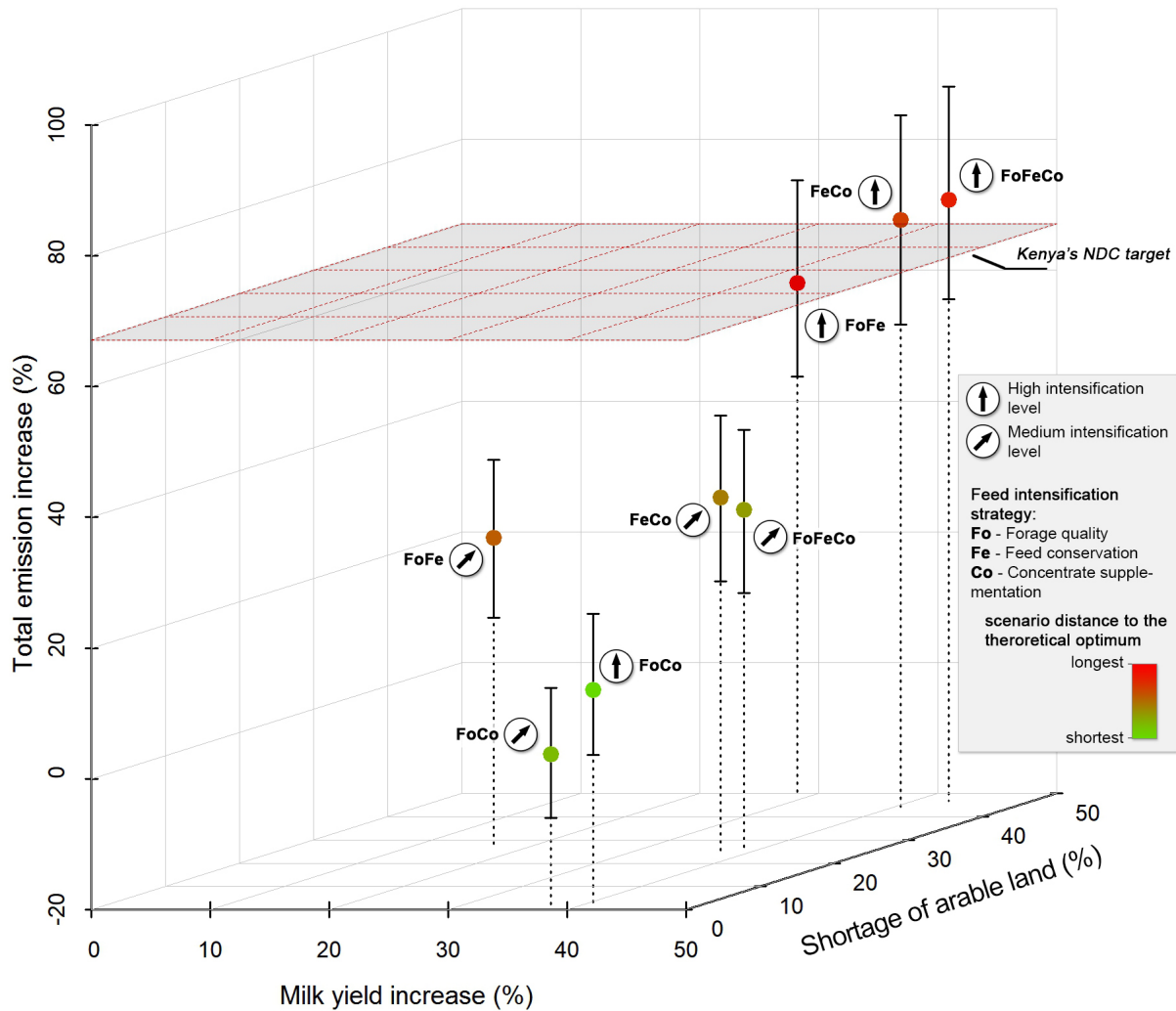
Figure 3.4: Scenarios (filled circles) are shown in 3-dimensional space marked by the increase in milk yield relative to the baseline and the milk yield target of Kenya's dairy master plan (x-axis), the increase of total GHG emissions in relation to the national BAU scenario of the NDC (y-axis), and the shortage of arable land (z-axis). Colours show the Euclidean distance of each scenario to the theoretical optimum (defined as 100 % milk yield increase, 0 % total emission increase and 0 % shortage of arable land). The dark grey plane indicates the threshold of tolerable total emission increases according to the NDC target. X and z-axes are cut at 50 % to improve visualisation. Error bars reflect the range of relative emission increases due to the overall uncertainty in emission parameters at 95 % confidence levels.
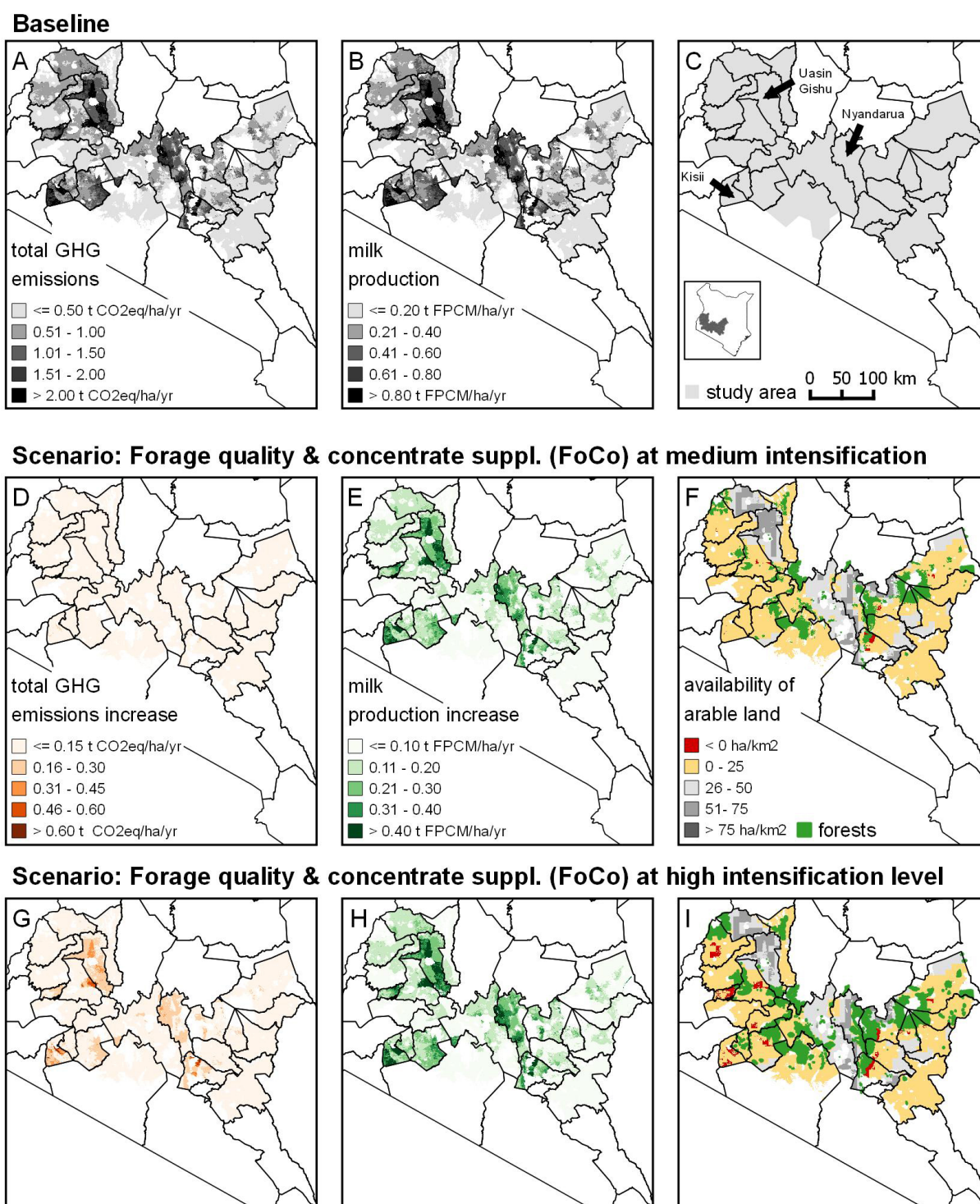
3.3.3   Baseline and mitigation scenarios at landscape level

Three Kenyan counties (Nyandarua, Uasin Gishu, and Kisii) within the dairy production region show the highest total GHG emissions and milk production ranging between 1.3

$\pm 0.5 - 1.6 \pm 1.2$ t CO_2eq ha^{-1} yr^{-1} and $0.6 \pm 0.2 - 0.7 \pm 0.5$ t FPCM ha^{-1} yr^{-1} respectively (Figure 3.5A - C). These counties have the highest densities of dairy cattle ranging from $0.7 \pm 0.5 - 0.9 \pm 0.6$ TLU ha^{-1}. Increases in total GHG emissions, milk production, and the availability of grazing land were mapped for the two scenarios that complied with Kenya's NDC target and showed a marginal shortage of arable land (Figure 3.4), namely FoCo at medium (Figure 3.5D - F) and high level of intensification (Figure 3.5G - I). The total emission increases ranged between 3.4 ± 3.3 - 12.1 ± 4.5 %. Milk production increases ranged between 47.6 ± 7.2 - 50.2 ± 5.6 %.

Baseline

Scenario: Forage quality & concentrate suppl. (FoCo) at medium intensification

Scenario: Forage quality & concentrate suppl. (FoCo) at high intensification level

Figure 3.5: Baseline results were mapped for (A) total GHG emissions from dairy production and (B) milk production. Scenario changes relative to the baseline were mapped for increases in (D, G) total emissions and (E, H) milk production. Maps (F, I) illustrate the availability of arable land that could be converted to cropland required to grow additional maize and Napier grass (red = shortage of arable land). Only the two scenarios that complied with Kenya's NDC target and showed the smallest shortage of arable land are indicated.

The mean baseline emission intensity across LPS was 2.4 $\pm$0.13 kg CO_2eq kg FPCM^{-1}. Mean emission intensities decreased in relation to the baseline across LPS for the FoCo scenarios at medium (30.6 $\pm$1.7 %) and high level of intensification (25.7 $\pm$1.6 %) ranging from 1.7 $\pm$0.03 to 1.8 $\pm$ 0.03 kg CO_2eq kg FPCM^{-1} respectively (Figure 3.6).
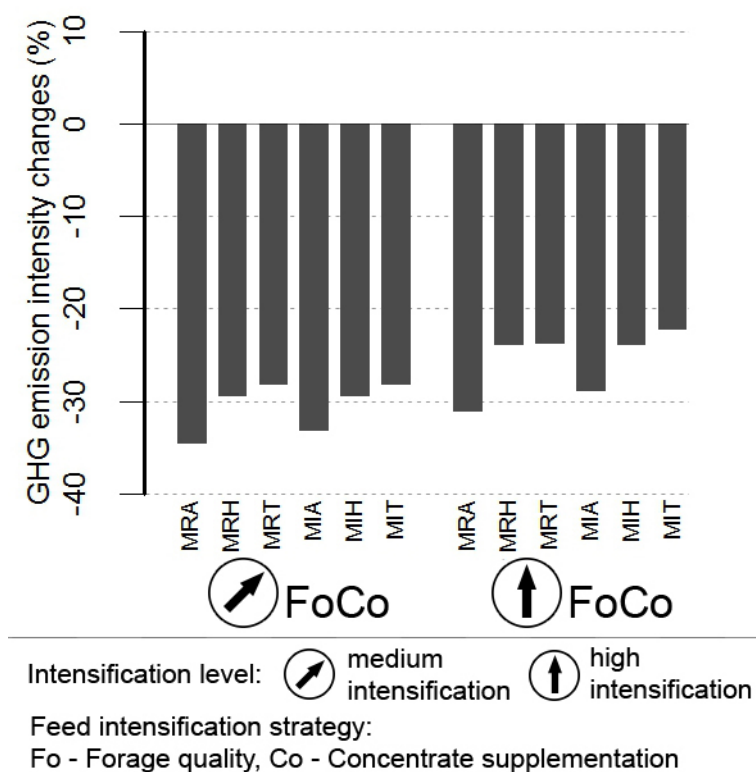
Figure 3.6: Mean GHG emission intensity changes, relative to baseline model, of the two scenarios that complied with Kenya's NDC target. Bars represent the different LPS (Appendix S3, Figure S3.2).

3.3.4 Uncertainties

Overall variability in total GHG emissions and emission intensities (pixel-based SD across LPS) due to uncertainties in emission parameters was smallest for the baseline ($\pm$1.9 %) and highest for the FoFe scenario at high level of intensification ($\pm$7.8 %) (Figure 3.3A & B). The emission parameters used to quantify the baseline GHG emissions following the IPCC methodology had different impact on the variability of emissions. The methane conversion factor (Y_m), with a range of 5.5 – 7.5 % was the parameter that showed the strongest influence on the variation in baseline total GHG emissions with $\pm$7.2 % relative to the mean total GHG emissions across LPS (Appendix S3, Figure S3.3). The SOC emission factor applied to calculate LUC emissions caused the largest uncertainty in total GHG emissions of the FoFe scenario at high intensification level. Total GHG emissions

varied by ± 47.5 % across LPS (Appendix S3, Figure S3.4). Uncertainty in livestock densities (expressed as mean SD across LPS) had the largest effect on CH_4 emissions from enteric fermentation (Figure 3.5). The smallest effect was indicated for the baseline (± 1.8 %), whereas the largest was shown for the FoFe scenario at high intensification level (± 4.4 %). The mean SD of milk production was lowest for the baseline (± 1.8 %) and was highest for the FoFeCo scenario at high intensification level (± 4.2 %).

3.4 Discussion

3.4.1 Baseline emission intensities and mitigation potential of scenarios

In this study, the mean baseline emission intensity was 2.4 ± 0.13 kg CO_2eq kg FPCM^{-1} per grid cell. Most recent estimates for smallholder dairy production in Kenya report similar emission intensities ranging from 2.4 - 3.1 kg CO_2eq kg milk^{-1} for semi-intensive and extensive production (Government of Kenya, 2017b). Emission intensities derived from life cycle assessments calculated for smallholder farms across the Kenyan highlands range from 1.8 - 2.0 kg CO_2eq kg milk^{-1} for free grazing farms (Weiler et al., 2014; Udo et al., 2016). Baseline emission intensities calculated in this study were within the range estimated in other studies for Kenya. Emission intensities can vary due to different feed quality values used to calculate CH_4 emissions from enteric fermentation and manure management based on the IPCC tier 2 methodology (IPCC, 2006). For this study, these values were obtained from the East-African feed database and literature (Anindo et al., 1994; Rufino et al., 2009).

Total GHG emissions were higher for all scenarios in relation to the baseline, with the lowest increases of 3.4 - 12.1 % for the FoCo scenarios at medium and high level of intensification respectively. However, the reduction of emission intensities by 30.6 % (1.7 ± 0.03 kg CO_2eq kg FPCM^{-1}) and 25.7 % (1.8 ± 0.03 kg CO_2eq kg FPCM^{-1}) was achieved through improvements in forage quality by increasing the proportion of Napier grass in the diet and through supplementing dairy concentrates during early lactation. In addition, emission intensities were reduced by covering manure heaps. The overall reduction of N_2O emissions from manure management by 68 % is in line with the reduction potential reported in the literature on management of cattle manure (Chadwick, 2005; Hou et al., 2015). Mottet et al. (2016) estimated the potential to reduce emission intensities by up to 14 % through the improvement of feed quality alone in East Africa at a regional scale. Bryan et al. (2013) reported a potential to reduce emission intensities (CH_4 emissions only) by up to 60 % through the increase of feed quality in a modelling study covering highland areas in Kenya, yet omitting likely emissions from LUC. With reductions of 26 – 31 %, this study ranks moderately compared to these findings, yet is more robust as detailed feed data and LUC emissions were included.

The FoCo scenarios at medium and high intensification level led to relatively high achievement rates of the national dairy master plan target (Government of Kenya, 2010), increasing milk yields by 38.3 and 40.5 % respectively. These scenarios led to the lowest increase in total GHG emissions by 3.4 and 12.1 % respectively, complying with the NDC target (Government of Kenya, 2015a), while facing the smallest shortage of arable land across the dairy region (0.5 and 2.8 % respectively) (Figure 3.4). Thus, these two scenarios present the lowest trade-offs between national level targets.

3.4.2 Synergies from implementing the most beneficial mitigation scenario

Average milk yield increases of the two FoCo scenarios were 47.6 – 50.2 % higher than the baseline, which are modest increases compared to estimates by (Rufino et al., 2009) of 63 - 79 % for single dairy cows fed with similar diets. Experimental studies conducted in Kenya estimated gains in milk yield of 37 % and 63 % supplementing 3 kg day^{-1} and 7.8 kg day^{-1} of dairy concentrates during lactation (Moran, 2005; Richards et al., 2016). Growing Napier grass can have further positive effects on farm productivity for instance as effective vegetative barriers preventing soil erosion and nutrient losses (Owino et al., 2006; Guto et al., 2011). In addition, Napier grass can be a lucrative feed alternative. Compared to diets of lower quality, Napier increased the net revenue for milk production in Central and Western Kenya most at medium intensification level (by 0.08 – 0.12 USD l milk^{-1}) (Bryan et al., 2013). A medium level of intensification was also the most profitable choice (573 USD yr^{-1}) for smallholder dairy farmers when compared to low and high intensification levels (473 and 360 USD yr^{-1} respectively) (Bebe et al., 2002). Dairy concentrates are relatively expensive for smallholders, which seems to be the reason for low adoption rates associated with fluctuations in milk prices (Lukuyu et al., 2011; Owen et al., 2012). Therefore, the FoCo scenario at medium intensification would be the most viable, with lower adoption barriers due to relatively high gains in milk yield, and lower financial risks for smallholders compared to the high intensification scenario.

3.4.3 Supporting the development of sectoral and national mitigation plans

As quantified in this study, the total land use based GHG emissions from dairy production in Kenya represent 12.9 % of the total emissions from the agricultural sector. Agriculture is the largest contributor to GHG emissions in Kenya, totalling 30 Mt CO$_2$eq in 2010 (Government of Kenya, 2015b), which emphasises the significance of sectoral mitigation actions. Kenya's national mitigation target defined in the NDC sets the scene for mitigation actions such as a dairy NAMA (Government of Kenya, 2017b). The findings of this study fill several knowledge gaps. First, it provides for the first time transparent quantifi-

cations of baseline emissions and milk yields and changes in emissions and productivity resulting from intensification scenarios at a sectoral scale. Increases in productivity of smallholder dairy farms through feeding practices is one of the main objectives of Kenya's dairy NAMA (Government of Kenya, 2017b). This study identified promising mitigation practices such as the improvement of forage quality and supplementation of dairy concentrates at medium intensification level. Second, the mitigation potential of specific practices was assessed against the NDC, enabling an evaluation of their performances to contribute to national mitigation targets. Demonstrating the technical potential of certain practices to fulfil mitigation and productivity targets opens the door for climate financing schemes that require reliable estimates to monitor the achievement of targets (Government of Kenya, 2010, 2015a). Building a business case to finance climate mitigation, e.g. through NAMAs, requires quantitative information about the mitigation potential and productivity gains of specific practices in regions where these practices are feasible and an evaluation of inherent uncertainties (Grassi et al., 2017) as provided by this study. Third, considering changes in land availability and demand for land resulting from mitigation actions before their actual implementation is crucial to achieve effective mitigation. That is minimising the risk of negative spillover effects such as GHG emissions from indirect LUC. GHG emissions from the conversion of arable land required to grow additional high quality feeds can be substantial (Figure 3.3). Increasing the grain content in cattle diets, e.g. through ensiling maize can compromise the effective mitigation potential of feed intensification due to the relatively high demand for additional cropland.

Information provided by this study is required for 'Measurement, Reporting and Verification' (MRV) of agricultural mitigation actions and could guide the targeting of specific practices at the sub-national level (Lipper et al., 2011). For instance, the baseline emissions mapped in this study could aid in prioritising pilot projects in areas (e.g. counties) that show the highest total emissions (Figure 3.5).

3.4.4 Climate-smart options that increase the mitigation potential for Kenya's dairy sector

At herd level, emission intensities can be reduced through improved reproduction such as lowering the proportion of unproductive animals by artificial insemination (Hristov et al., 2013a; Knapp et al., 2014). Vaccination programmes ameliorate animal health, lower mortality rates and increase lifetime productivity of cattle (Mottet et al., 2016). De-stocking of animals with low productivity and replacement by breeds showing higher productivity would, in conjunction with improved feed management, decrease emissions and maintain or increase production (Herrero et al., 2016). Low productivity due to nutrient depleted soils is common in Kenya (Tittonell et al., 2009). Improving the retention and recycling of available nutrients through the management of manure and application to soils as organic fertiliser is important to sustain soil fertility and to increase crop yields

(Rufino et al., 2007; Tittonell et al., 2010; Castellanos-Navarrete et al., 2015). Covering manure heaps, included in this study, is one option to minimise the loss of N during the manure storage phase (de Boer et al., 2011). In addition, the combination of organic and mineral fertiliser is proposed to compensate relatively small amounts of available animal manure in smallholder dominated production systems (Tittonell et al., 2010). A modelling exercise at global scale demonstrated that closing yield gaps could reduce LUC emissions, including deforestation, in Africa effectively outweighing potential increases in N_2O emissions associated to fertiliser application (Valin et al., 2013).

3.4.5 Uncertainty implication and data limitations

In this study, the methane conversion factor (Y_m) was the largest source of uncertainty for CH_4 emissions from enteric fermentation in the baseline. Data from laboratory measurements on cattle breeds and feeds managed under conditions that represent tropical production systems, especially from SSA, are required to derive improved estimates. Feeding trials on native cattle breeds from Kenya, currently conducted by the International Livestock Research Institute (ILRI) to estimate CH_4 emissions from enteric fermentation are promising efforts (Pelster et al., 2016). The loss of SOC due to the conversion of grazing land to cropland for additional feed crops influenced the uncertainty of scenario emissions most. High impact of LUC on total emissions due to the production of feeds by up to 877 % were shown by van Middelaar et al. (2013). Dynamic land use models simulating soil-vegetation dynamics in response to LUC could reduce the uncertainty. However, a comprehensive parameterisation based on empirical data is required, which might prove difficult in data deficient regions such as SSA (Kim et al., 2016). Cattle density data were an additional source of uncertainty for upscaled emissions and milk production since the spatially-explicit dataset was derived from predictive modelling to match a very high resolution at sub-county level (Robinson et al., 2014). More detailed census data at sub-location level could reduce the related uncertainty in cattle densities. Feed intensification scenarios can be further improved by more comprehensive feed quality information, including empirical data on pastures and fodder trees. This would allow exploring alternative feed strategies and scenarios such as improved pasture and silvopastural management options.

3.5 Conclusions

This study demonstrated that specific farm-level practices focusing on feed intensification and manure management can improve the efficiency in smallholder dairy production by improving productivity significantly while increasing total GHG emissions only marginally. At the same time, these practices can contribute to national targets reducing the impact

of the agricultural sector on the climate system and safeguarding food security through sustainable intensification in dairy production. Quantitative spatially-explicit estimates showing 'win-win' situations resulting from gains in agricultural productivity and climate change mitigation at sub-national level are crucial to implement climate change policies successfully. Assessing demand for land due to the intensification of feed production is essential to obtain realistic estimates of how effective certain mitigation practices are at landscape scale and to support tailor-made, location-specific mitigation planning at sub-national level. Otherwise, mitigation planning could neglect the risk of GHG emissions from LUC triggered by feed intensification, outweighing potential gains from promising practices. Governments and the private sector could design financing instruments for farmers that seek to increase milk yields in compliance with mitigation targets through feed intensification and manure management using the findings of this study.

Acknowledgments

Chapter 4

Sustainable intensification of dairy production can reduce forest disturbance in Kenyan montane forests

Abstract

Increasing demand for food and the shortage of arable land call for sustainable intensification of farming, especially in Sub-Saharan Africa where food insecurity is still a major concern. Kenya needs to intensify its dairy production to meet the increasing demand for milk. At the same time, the country has set national climate mitigation targets and has to implement land use practices that reduce greenhouse gas (GHG) emissions from both agriculture and forests. This study analysed for the first time the drivers of forest disturbance and their relationship with dairy intensification across the largest montane forest of Kenya. To achieve this, a forest disturbance detection approach was applied by using Landsat time series and empirical data from forest disturbance surveys. Farm indicators and farm types derived from a household survey were used to test the effects of dairy intensification on forest disturbance for different farm neighbourhood sizes ($r = 2 - 5$ km). About 18 % of the forest area was disturbed over the period 2010 – 2016. Livestock grazing and firewood extraction were the dominant drivers of forest disturbance at 75 % of the forest disturbance spots sampled. Higher on-farm cattle stocking rates and firewood collection were associated with 1 – 10 % increased risk of forest disturbance across farm neighbourhood sizes. In contrast, higher milk yields, increased supplementation with concentrated feeds and more farm area allocated to fodder production were associated with 1 – 7 % reduced risk of forest disturbance across farm neighbourhood sizes. More intensified farms had a significantly lower impact on forest disturbance than small and resource-poor farms, and large and inefficient farms. The results show that intensification of smallholder dairy farming leads to both farm efficiency gains and reduced forest disturbance. These results can inform agriculture and forest mitigation policies which target options to reduce GHG emission intensities and the risk of carbon leakage.

4.1   Introduction

Poor management of agricultural land and forests leads to deforestation and land degradation worldwide. The expansion of smallholder agriculture is one of the main drivers of deforestation in Sub-Saharan Africa (SSA) (Hosonuma et al., 2012). Such unsustainable land uses cause greenhouse gas (GHG) emissions and affect adversely ecosystem services such as soil carbon (C) sequestration and biodiversity (Barlow et al., 2016; Herrero et al., 2016; Grassi et al., 2017). Rising human population in many SSA countries has increased the demand for food and reduced the availability of arable land (Carter et al., 2018b). Thus, climate-smart practices are required to intensify production on smallholder farms sustainably, which improve food security and contribute to climate change mitigation.

Recently, an intensification trend of smallholder farming has been documented for the East African highland regions, particularly in Kenya (Herrero et al., 2014). However, in the past large parts of the Kenyan montane forests have been converted to agricultural land. Remaining forests are threatened by ongoing anthropogenic disturbance causing GHG emissions from forests. The 'land use, land use change and forestry' (LULUCF) sector contributes about 38 % to total GHG emissions in Kenya (Government of Kenya, 2015b). Three quarters of forest-related GHG emissions result from small-scale forest disturbances such as fuelwood extraction, selective logging and wildfires (Pearson et al., 2017). Thus, mitigation efforts to effectively reduce these emissions are required. Kenya has committed to the United Nations framework convention on climate change (UNFCCC) defining mitigation targets in its nationally determined contribution (NDC) (Government of Kenya, 2015a). However, mitigation planning at national level is separated in land use sectors, i.e. agriculture and forests, which is likely to render the reduction of GHG emissions ineffective. Quantifying the relationship between agricultural land use practices and forest disturbance could be used to develop integrated mitigation approaches that minimise the risk of spillover effects such as C leakage (Minang & van Noordwijk, 2013).

The Mau Forest located in the Kenyan highlands is the largest remaining montane forest complex in East Africa. The forest plays an important role as water tower for the whole region as it is the headwater area for 12 major rivers supplying freshwater to about five million people (Jacobs et al., 2017). The unsustainable use of the forest leads to disturbances that impair ecosystem services such as C storage, freshwater supply and biodiversity (Kinyanjui, 2011). To date, forest disturbance and its main drivers have not yet been quantified or characterised, neither for Kenya's forests nor for the Mau Forest, in particular.

The Mau region is dominated by smallholder crop-livestock production (Robinson et al., 2011). Smallholders throughout the highlands commonly engage in dairy farming contributing about 80 % to Kenya's total milk production (Udo et al., 2016). Increasing the

productivity of smallholder dairy farming throughout East Africa is promoted by several agricultural development programs to meet the demand for dairy products (Government of Kenya, 2010). Sustainable intensification of agricultural production is urgently required to improve the livelihood of smallholder farmers and is often reported as a promising measure to achieve climate mitigation targets (Campbell et al., 2014; Vanlauwe et al., 2014; Ortiz-Gonzalo et al., 2017). Human presence in landscapes that were formerly dominated by forests has been linked to changes in forest cover in SSA (Sassen et al., 2013; Ryan et al., 2017). However, an assessment of local human activities and their effects on adjacent forests is missing. A quantitative analysis of the relationship between specific practises of smallholder dairy farming and forest disturbance is needed to assess whether intensification is sustainable beyond individual farms. This analysis is also needed and highly relevant for other montane regions in East Africa that share comparable farming and forests systems and are exposed to similar pressures due to the increasing demand for food.

Intensification of smallholder dairy farming includes changes in cattle management e.g. feeds and breeds which have the potential to increase milk production (Rufino et al., 2009) and to reduce GHG emissions per unit of product (Herrero et al., 2016; Udo et al., 2016). To date, there are no comprehensive studies on the effects of intensification in smallholder dairy farming on adjacent forests, which can undermine the climate change mitigation effect of the farming practices promoted (Brandt et al., 2018b). This study aims to answer two questions. First, what are the dominant anthropogenic drivers of forest disturbance across the Mau Forest? Second, what is the intensification effect of smallholder dairy farming on forest disturbance? The approach applied to answer these questions involved i) the quantification of forest disturbance and the characterisation of the dominant drivers using a spatially-explicit framework to detect forest disturbance based on a Landsat time series and forest disturbance surveys and ii) the estimation of intensification effects of smallholder farms on forest disturbance based on empirically-derived farm indicators and farm types.

4.2   Material and methods

4.2.1   Study area

The Mau Forest is located in the Western highlands of Kenya (Figure 4.1) and represents the largest remaining Afromontane forest in the country covering about 400,000 ha (Kinyanjui, 2011). It primarily consists of broadleaf tree species and bamboo forests, the latter in regions above 2400 m (Ng'Eno, 1996). Large parts of forest have been converted to agricultural land due to favourable biophysical conditions such as high annual precipitation and well drained soils. The region is characterised by high densities of human

and livestock populations (Herrero et al., 2014; Robinson et al., 2014). Apart from small-holder crop-livestock production systems there are large-scale tea plantations (Baldyga et al., 2008; Jacobs et al., 2017). The Mau Forest is used for fuelwood, for livestock grazing and for timber production, which is mainly harvested from tree plantations (Government of Kenya, 2009b; Olang et al., 2011).
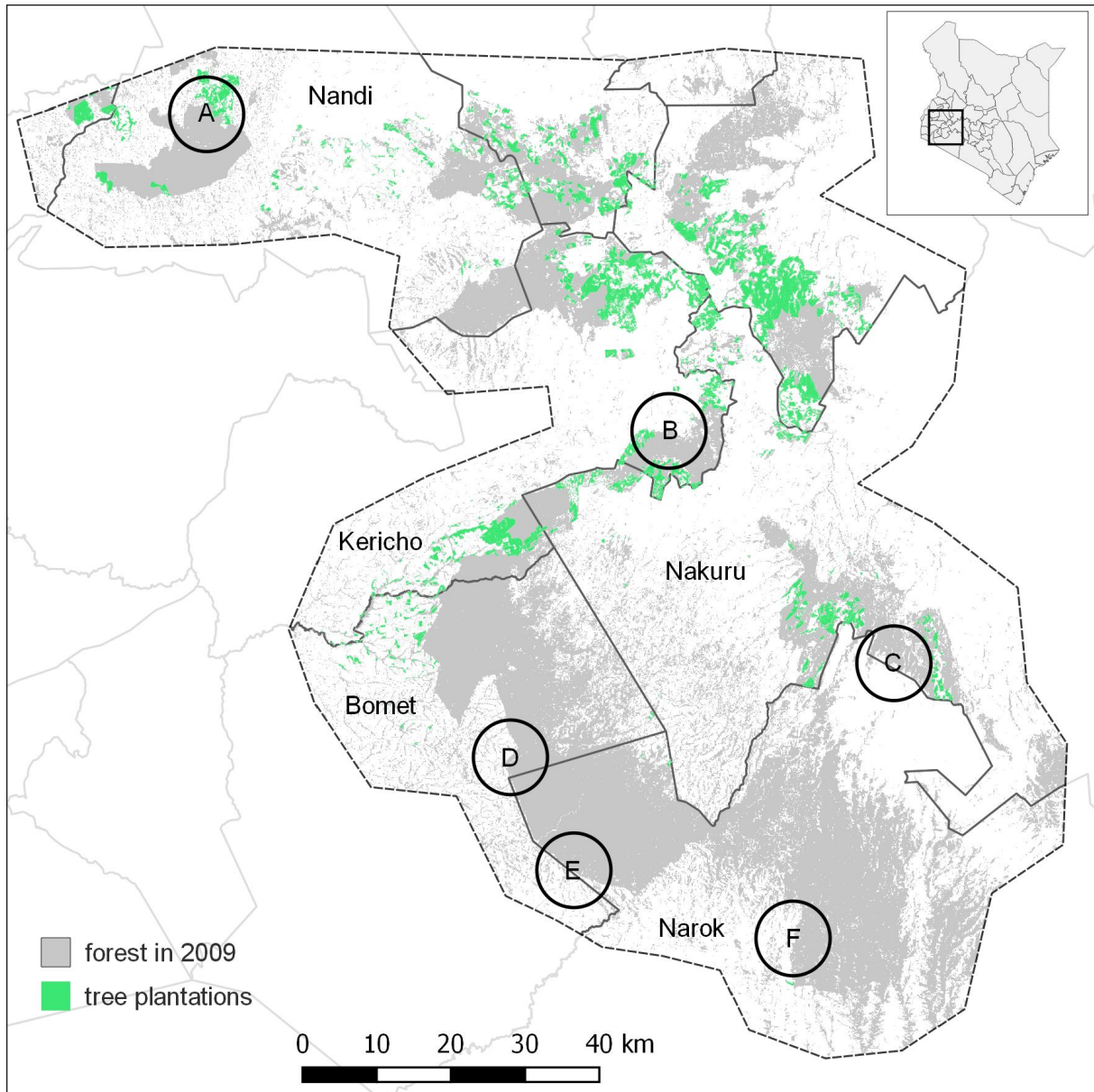

Figure 4.1: The study area of the Mau Forest complex in Kenya. Circles and letters indicate sampling sites selected to conduct farm and forest disturbance surveys: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, and F) Maasai Mau Forest.

4.2.2   Analysis approach

The approach followed in this study is shown in (Figure 4.2). First, remote sensing data were acquired and pre-processed. Data on farm practices and forest disturbance were obtained through field surveys (Section 4.2.3). Second, forest disturbance was detected from remote sensing data using the 'Space Time Extremes and Features' (STEF) algorithm (Hamunyela et al., 2017) (Section 4.2.4). Third, farm indicators and farm types were derived from farm survey data (Section 4.2.5). Fourth, the effects of farm indicators and farm types on forest disturbance intensity were modelled by using generalised linear mixed effect models (GLMMs) (Section 4.2.6).
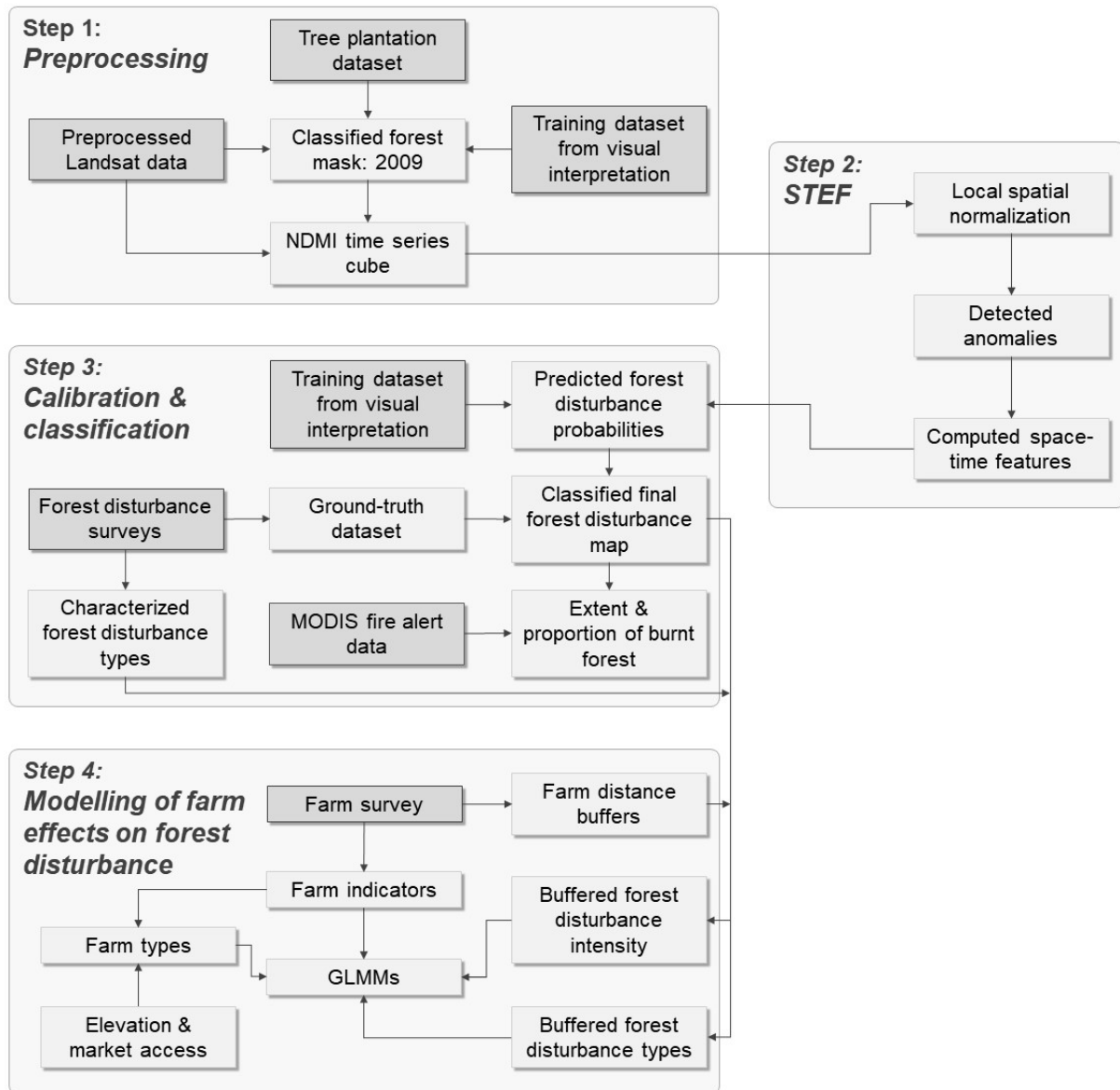
Figure 4.2: Flowchart of analysis steps followed in this study. Dark boxes represent data inputs from remote sensing and field observations. NDMI = Normalised Difference Moisture Index, STEF = Space Time Extremes and Features approach, GLMMs = Generalised Linear Mixed Effect Models.

4.2.3 Acquisition and pre-processing of data

Remote sensing data

All available terrain-corrected (L1T) multi-spectral satellite images (n = 639) acquired by Landsat 5-TM, Landsat 7-ETM+, and Landsat 8-OLI sensors (Figure 4.2, step 1) from

January 2005 to December 2016 were downloaded from the United State of America's Geological Survey (USGS) Earth Explorer platform. The 'Normalised Difference Moisture Index' (NDMI) (Jin & Sader, 2005) was computed from each image. NDMI is sensitive to changes in canopy moisture. It was chosen as it is known to discriminate well changes in tropical wet forests (DeVries et al., 2015a). NDMI was used to study small-scale disturbance in another Afromontane forest (DeVries et al., 2016). Clouds and cloud shadows were masked using the 'cmask' algorithm (Zhu et al., 2015).

A benchmark forest mask was created (Figure 4.2, step 1) to constrain the forest disturbance detection algorithm to forested areas. Clouds and cloud shadows were masked in the available Landsat spectral band images from 2009. Gaps were filled by mosaicking the images. A random forest model (Breiman, 2001) was trained to classify the study area into forest and non-forest regions using all Landsat spectral bands as predictors. The model was trained on randomly sampled polygons maintaining equal sample sizes (n = 40) for both classes each containing at least 10000 Landsat pixels. This training dataset was obtained by visual interpretation of very high resolution Google Earth imagery. Forest patches smaller than 0.5 ha were excluded from the forest mask to satisfy the minimum forest area criterion of the 'Food and Agriculture Organisation' (FAO) of the UN forest definition (FRA, 2000).

A time series dataset of all pre-processed NDMI images was created. In addition, tree plantation data (Government of Kenya, 2015c; Jacobs et al., 2017) were used to exclude forest plantation areas from the forest disturbance analysis. Monthly fire alert data (Giglio, 2015) from the 'Moderate Resolution Imaging Spectroradiometer' (MODIS, MCD14ML) were used to determine the extent and proportion of burnt forests over the monitoring period.

Seasonal variability influences vegetation dynamics across the study area leading to fluctuating spectral signals which impair the accuracy of forest disturbance detection algorithms (Hamunyela et al., 2016b). A local spatial normalisation approach (Hamunyela et al., 2016a, 2017) was used to reduce the effect of seasonality in the NDMI time series (Figure 4.2, step 2). The normalisation procedure was applied on each NDMI image in the time series prior forest disturbance detection. The local neighbourhood was defined using a spatially-moving window with a size of 15 x 15 Landsat pixels. Each centre pixel within the window was divided by the 95th percentile computed from pixel values within the window (Hamunyela et al., 2016b). A 15 x 15 pixel window was deemed sufficient because forest disturbances in the study area occur at small-scale.

Field data

Two field surveys were conducted between November and December 2016 to collect information about smallholder farms (farm survey) and forest disturbance (forest disturbance

survey) in adjacent forests by using 'Open Data Kit' (ODK) questionnaires (Figure 4.2, step 3 & 4). Sampling sites for each survey were selected based on a stratified sampling design using spatially-explicit datasets on cattle density (Robinson et al., 2014) and forest loss (Hansen et al., 2013). Forest loss data were converted to forest disturbance density by using the kernel density tool in ArcGIS 10.3. Cattle and forest disturbance densities were reclassified based on quantile splits to derive six combinations of sampling strata ranging from low cattle and forest disturbance density to high cattle and disturbance density (Appendix S4, Figure S4.1). Circular sampling sites (radius = 5 km) were placed into the sampling strata derived. Furthermore, by ensuring a forest cover of 50 % in each site and by excluding tree plantations (Figure 4.1), the number of sampling sites was constrained, which led to the selection of the following areas: A) South Nandi Forest (n = 37 farms and m = 36 disturbance spots sampled), B) Western Mau Forest (n = 39, m = 30), C) Eastern Mau Forest (n = 34, m = 32), D) South West Mau Forest (n = 35, m = 44), E) Transmara Mau Forest (n = 39, m = 45), and F) Maasai Mau Forest (n = 32, m = 34). A minimum sample size of 30 farms and 30 forest disturbance sports per site was targeted. Often, additional farm and forest disturbance data could be obtained.

The farm survey was conducted to gather information on cattle numbers, milk yields, feed types, farm area allocated to fodder production, farm size, and amount of firewood collected from the forest. Farms were sampled based on locations randomly selected within each sampling site (n = 216). The forest disturbance survey characterised disturbance spots sampling randomly forest loss pixels derived from Hansen et al. (2013) that were still forest according to the forest mask created (n = 221) to avoid the sampling of deforested land. During this survey, information on disturbance types such as cattle grazing, firewood extraction, wildfires, and charcoal burning was collected. In this analysis, forest disturbance is defined as negative change in canopy cover over time directly or indirectly induced by anthropogenic activities. A detailed list of variables collected during the surveys is available in the supplementary information (Appendix S4, Table S4.1 & S4.2). The field data gathered from this forest disturbance survey were used, in combination with additional forest disturbance data collected during a previous forest disturbance survey (n = 127). The later survey was conducted in the Mau Forest between March and April 2016 (Bewernick, 2016), to validate an earlier forest disturbance detection in a sub-region of the study area.

4.2.4 Forest disturbance detection, calibration and classification

Forest disturbances were detected by using the STEF algorithm (Hamunyela et al., 2017). STEF detects forest disturbances as extreme events in local data cubes of satellite-derived time series (Figure 4.2, step 2). A local data cube was defined around each pixel containing both spatial and temporal extents which are user-defined (Hamunyela et al., 2017). The temporal extent corresponded to the full length of the NDMI time series. A moving

spatial window of 9 x 9 Landsat pixels was used as the spatial extent of the local data cube. STEF takes the spatio-temporal context of an observation into account to reduce the sensitivity to data noise, e.g. introduced by cloud remnants increasing the algorithm's accuracy (Hamunyela et al., 2016b, 2017). Extreme events are identified as abnormally low observations in the monitoring period, by using an extreme value approach (Zscheischler et al., 2013). A pixel was considered abnormally low if its value was below the threshold computed from spatio-temporal observations in the history period of the local data cube. The history period of the time-series analysis was defined from 2005 - 2009 and the monitoring period was set to 2010 - 2016. Following an application of STEF on Afromontane forests in Ethiopia (Hamunyela et al., 2017), the 5th percentile was chosen as the anomaly threshold. A pixel was flagged as potentially disturbed if the algorithm detected two consecutive anomalies in the monitoring period. Once consecutive anomalies are detected, STEF extracts 17 space-time features from the local data cube (Hamunyela et al., 2017). The features include information on the proximity of the extreme event to forest edges, existence and number of anomalies in the neighbourhood of the pixel where the extreme event is detected, and the spatial variability across the local data cube at the time step where a potential forest disturbance is detected (Hamunyela et al., 2017). These space-time features were subsequently used to confirm forest disturbances.

Forest disturbance was confirmed by first calculating the probability for forest disturbance by using the extracted space-time features as predictors of forest disturbances (Hamunyela et al., 2017). The probability of disturbance was calculated by using a trained random forest model. Random forest classifiers have the advantage to be of non-parametric nature and can handle many predictors without overfitting (Breiman, 2001). The random forest model was trained by using a calibration dataset (n = 204) acquired through visual interpretation of multispectral Landsat images (Figure 4.2, step 3), complemented by very high resolution imagery available in the Google Earth, based on methodology proposed by Cohen et al. (2010). A stratified random sampling design was used to derive the calibration data. The magnitude of change, which is one of the features extracted by STEF indicating the deviation between detected anomaly and the 95th percentile of the history distribution, was used to stratify the map of potential disturbances, produced from STEF. The magnitude of change was sampled randomly along the quantiles to derive four strata ranging from high to low magnitude.

Moreover, ground-truth data (n = 348) from forest disturbance surveys (Section 4.2.3) were used to determine the optimal probability threshold (P) (Figure 4.2, step 3). A series of probability thresholds, ranging from 0 to 1 at an interval of 0.01 was created. Each probability threshold was used to classify the probability values derived for the ground-truth data into disturbed and undisturbed forest while calculating user's accuracy (UA = inverse of commission error) and producer's accuracy (PA = inverse of omission error). The probability threshold that indicated the lowest area bias, which is the minimum trade-off between commission and omission error was used to generate the final forest

disturbance map (DeVries et al., 2015b; Hamunyela et al., 2017).

4.2.5   Defining farm types

Field data derived from the farm survey were used to cluster farms (Figure 4.2, step 4) into distinct types based on indicators that reflected differences in the degree of intensification and which were expected to influence the effect of dairy farming on the forest. Indicators chosen to cluster the farms were: number of cattle, milk yields, proportion of grass from on-farm pastures in the diet, farm area allocated to fodder production, quantity of feed concentrates supplemented, farm size, and amount of firewood collected. A correlation analysis was conducted prior to the clustering to exclude highly correlated variables (Spearman's rho >= 0.7). The k-means partitioning algorithm was applied in R to cluster the farms, after farm indicators were standardised, by using the Euclidean distance measure (R Core Team, 2016). The number of farm types was determined visually based on the drop in intra-cluster variation as a function of increasing numbers of clusters (Kassambara, 2017). In addition, farm types were tested regarding differences in elevation and market access by using an elevation dataset ('Shuttle Radar Topography Mission', SRTM) and a proxy dataset indicating travel time to cities with more than 50.000 inhabitants (Jarvis et al., 2008; Uchida & Nelson, 2009). This analysis enabled an interpretation of how the remoteness of farms affects intensification of smallholder dairy production.

4.2.6   Modelling the effects of farms on forest disturbances

Using the 'raster' package in R (Hijmans, 2016), circular distance buffers with radiuses of 2, 3, 4, and 5 km were created around recorded farm centroids, henceforth called farm neighbourhoods (Figure 4.2, step 4). The neighbourhood sizes were deemed to be appropriate to study the effects of local farm practices and characteristics on forest disturbance in forests adjacent to smallholder farms based on field observations and interviews with local forest rangers from the Kenyan Forest Service. The different neighbourhood sizes were chosen to assess the sensitivity of farm-related effects on forest disturbance over discrete changes of neighbourhood sizes through a sensitivity analysis. Two different response variables were generated. First, the proportion of forest disturbance pixels within each farm neighbourhood was calculated by dividing the number of these forest pixels by the total number of forest pixels. The proportion of forest disturbance pixels were used as a measure of 'disturbance intensity'. Second, forest disturbance sampled and characterised during the forest disturbance survey were counted within farm neighbourhoods to model farm effects on specific forest disturbance types.

GLMMs were used by applying the 'lme4' package in R (Bates et al., 2015) to model the association between farm characteristics and forest disturbance intensities. The as-

sociations were interpreted as driver-response relations, that is, farm characteristics were assumed to influence disturbance intensities. Farm indicators, farm types, and farm distances to the closest forest edge were included as fixed effects (explanatory variables). A categorical variable, which represented the sampling sites was included as a random effect. Binomial and Poisson GLMMs were run for the proportional disturbance intensity and the counted forest disturbance types derived from forest disturbance detection and survey data, respectively. Different GLMMs were run for each farm neighbourhood size separately (Figure 4.2, step 4). Model evaluation and selection was based on the Akaike information criterion (AIC) by applying likelihood ratio tests (Zuur et al., 2009). The model candidates that showed the lowest AICs were chosen.

To understand the effects of farm indicators on forest disturbance intensity derived from the binomial GLMMs, a relative risk measure was used. The relative risk quantifies the likelihood of an outcome (forest disturbance intensity), as a result of exposure to specific treatments such as farm practices and farm characteristic represented by chosen indicators (Akobeng, 2005). The effects of interactions between farm types and farm distances to the closest forest edges were explored to show potential differences of farm type effects along a farm distance to forest gradient on forest disturbance intensity. To characterise the influence of farm types on certain types of forest disturbance, modelled farm type effects on forest disturbance types observed during the survey are shown.

4.3   Results

4.3.1   Forest disturbance across the Mau Forest

A lowest area bias of 0.7 % was achieved at P = 0.39 where the UA was 77.9 % and the PA was 78.6 % (Appendix S4, Figure S4.2). Hence, the threshold of 0.39 was chosen as the probability threshold to classify each forest pixel into disturbed and non-disturbed forest.

In total, 17.7 % of the forested land was found to be disturbed between 2010 and 2016. The intensity of forest disturbance varied across the Mau Forest complex with the largest impacts in central and southern forest regions (Figure 4.3). Forest disturbance also strongly differed between sampling sites. The proportions of disturbed forest detected at the Western Mau Forest (42.4 %) and the Maasai Mau Forest (17.0 %) were the largest (inset Figure 4.3). With 3.9 %, the South Nandi Forest had the smallest proportion of disturbed forest.
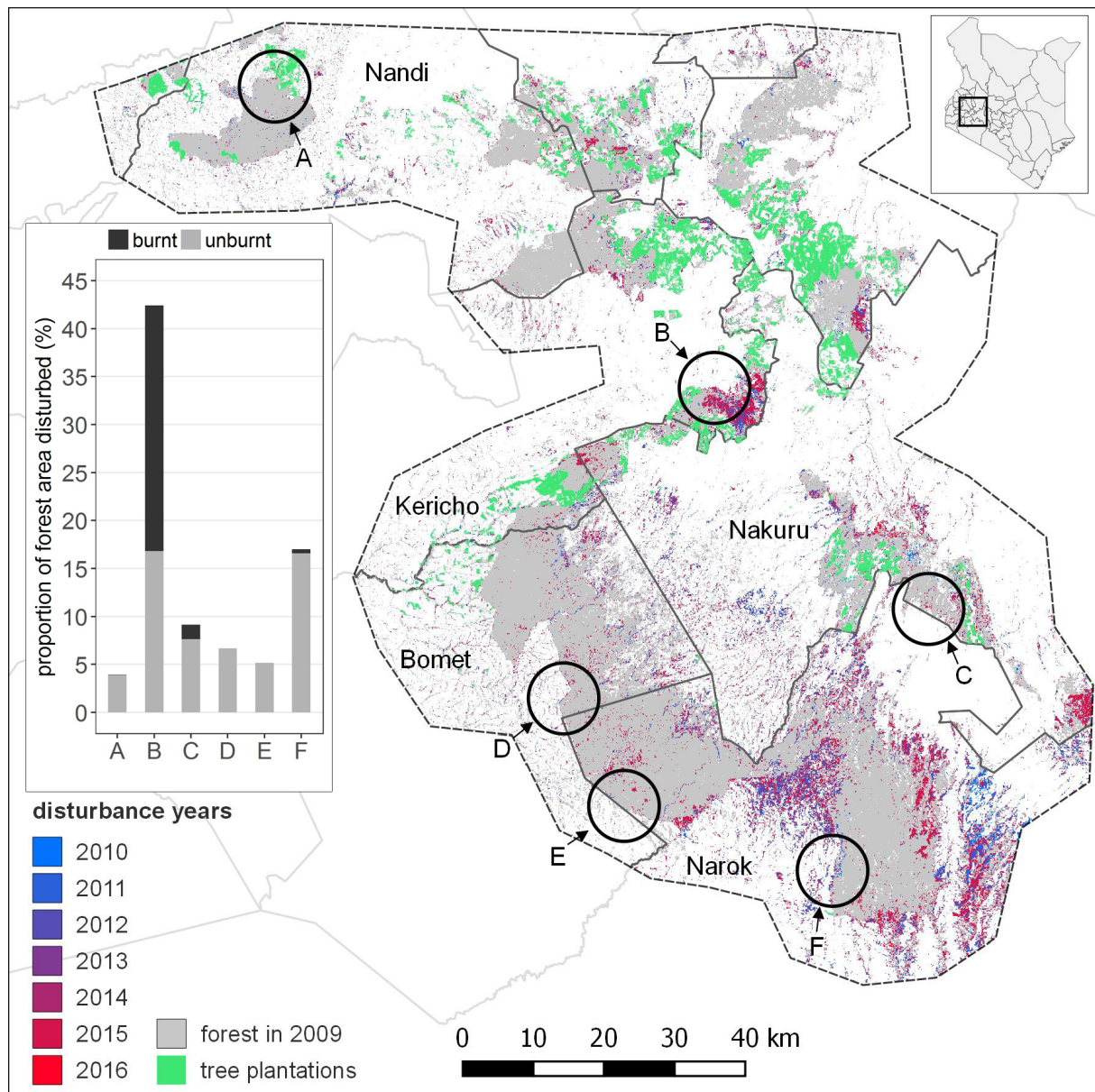
Figure 4.3: Forest disturbance mapped for 2010 to 2016 across the Mau forest. Circles indicate sampling sites for the field surveys: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, and F) Maasai Mau Forest. Inset bar plot shows proportions of disturbed forest area that was burnt and unburnt for each sampling site.

4.3.2 Dominant drivers of forest disturbance across sampling sites

Firewood extraction and cattle grazing inside the forest were the most dominant drivers of forest disturbance at all six sampling sites. Firewood extraction was observed at 76 % and cattle grazing at 75 % of all disturbance spots visited. Burnt tree stems were observed

on 31 % of all spots sampled at four sampling sites, suggesting wildfires are an important driver of disturbance. Wildfire events observed on the ground were confirmed by MODIS fire alert data for three of the six sampling sites, detecting wildfires at the Western Mau Forest, Eastern Mau Forest, and Maasai Mau Forest at 25.6 %, 1.5 %, and 0.4 % of the forested land respectively (inset Figure 4.3). The most common combination of drivers observed on 48 % of all visited spots was firewood extraction and cattle grazing inside the forest (Figure 4.4). This co-occurrence of drivers was predominant across the sampling sites except for the Maasai Mau Forest site where forest grazing and wildfire were found to co-occur more often (Figure 4.4).
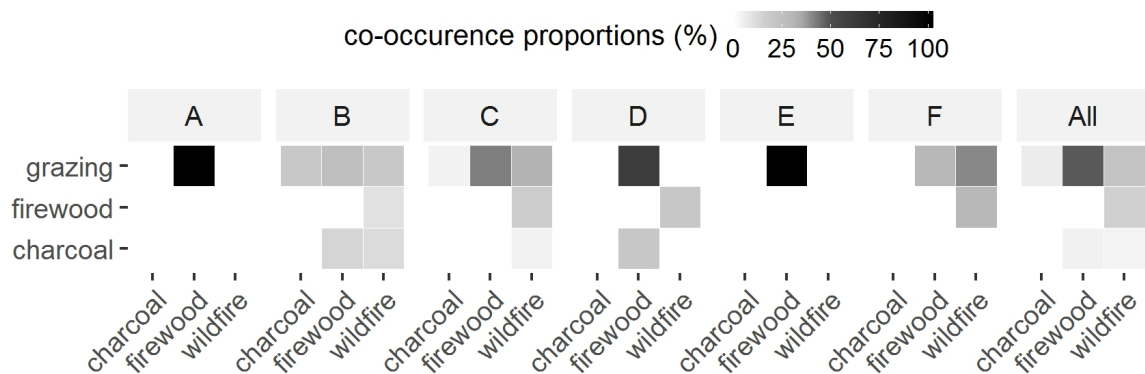

Figure 4.4: Co-occurrence proportions of forest disturbance drivers (%). Forest disturbance spots were characterised during a forest survey at each sampling site: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, F) Maasai Mau Forest, and All) all sampling sites.

4.3.3 Effects of farm indicators on forest disturbance intensity

Firewood collection rates, farm sizes, and cattle numbers were associated with a significantly increased risk of forest disturbance across farm neighbourhood sizes by 3 – 10 %, 1 – 5 %, and 1 – 5 % respectively (p < 0.001, Figure 4.5). In contrast, higher milk yields were related to a significantly lower risk of forest disturbance by 3 – 7 % across farm neighbourhood sizes (p < 0.001, Figure 4.5). Larger farm area allocated to fodder production, increased supplementation of dairy concentrates and higher proportion of grass from on-farm pastures in the diet were associated with a significantly lower risk of forest disturbance by 2 - 5 %, 1 – 2 %, and 1 – 2 % in 3 (Figure 4.5B, C, D), 2 (Figure 4.5A, D), and 2 (Figure 4.5C, D) of the farm neighbourhoods respectively (p < 0.001). The risk of forest disturbance intensities decreased significantly by 8 – 15 % across all farm neighbourhood sizes (p < 0.001), when farms were located further away from the forest. In general, the effects of farm indicators to increase or reduce disturbance risks remained relatively constant over the different neighbourhood sizes. However, effects sizes of farm

indicators became smaller with increasing size of farm neighbourhoods except for cattle numbers, which slightly increased the risk of forest disturbance in larger neighbourhoods (Figure 4.5). The variability around the effects shown by their 95 % confidence intervals was low across farm neighbourhoods. For details on model selection see Appendix (S4, Table S4.3).
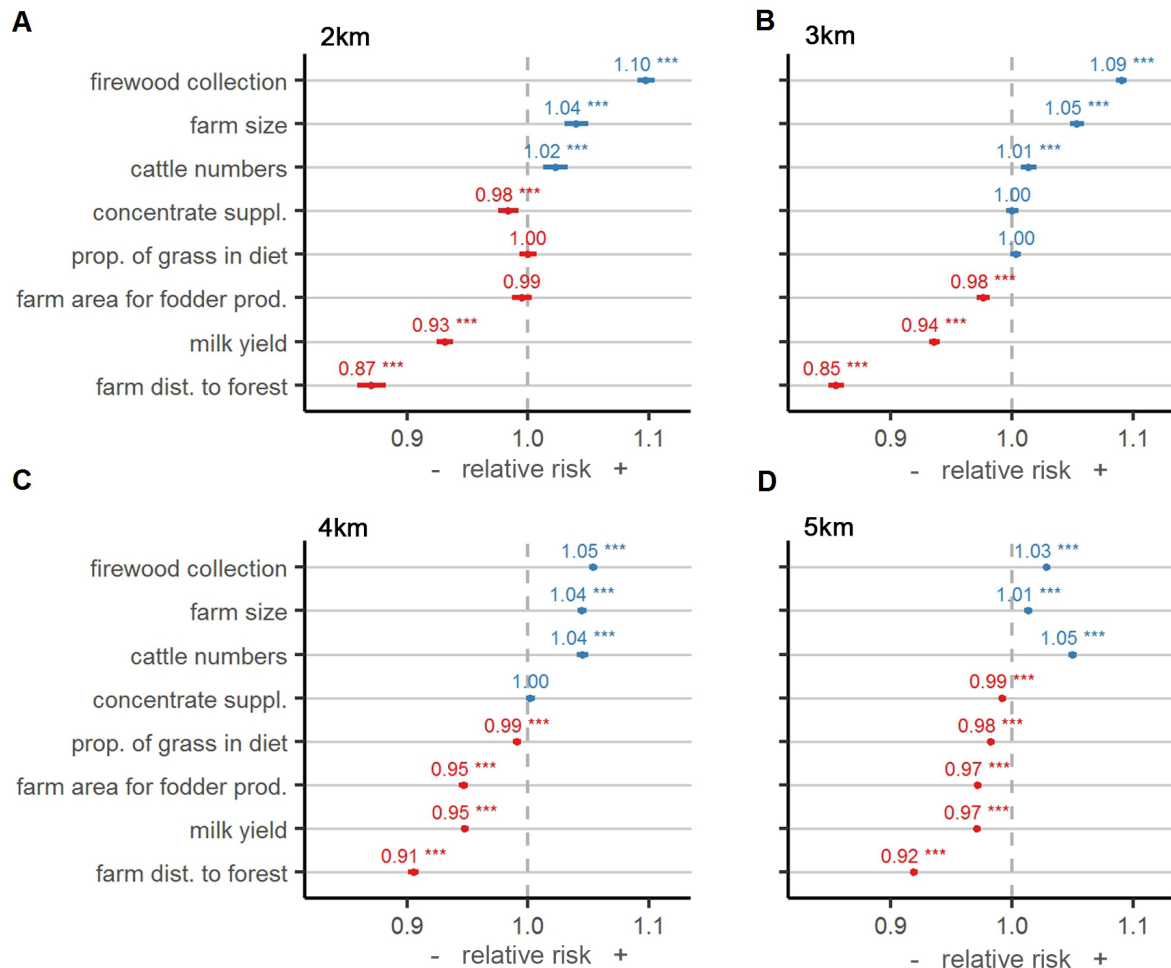
Figure 4.5: Relative risks of forest disturbance as response to farm indicators. Relative risks were derived from GLMMs for different farm neighbourhood sizes (buffer radiuses): A) 2 km, B) 3 km, C) 4 km, and D) 5 km. Horizontal bars show mean effect and 95 % confidence intervals for each indicator. Stars show significance levels. Vertical dashed lines indicate no effect.
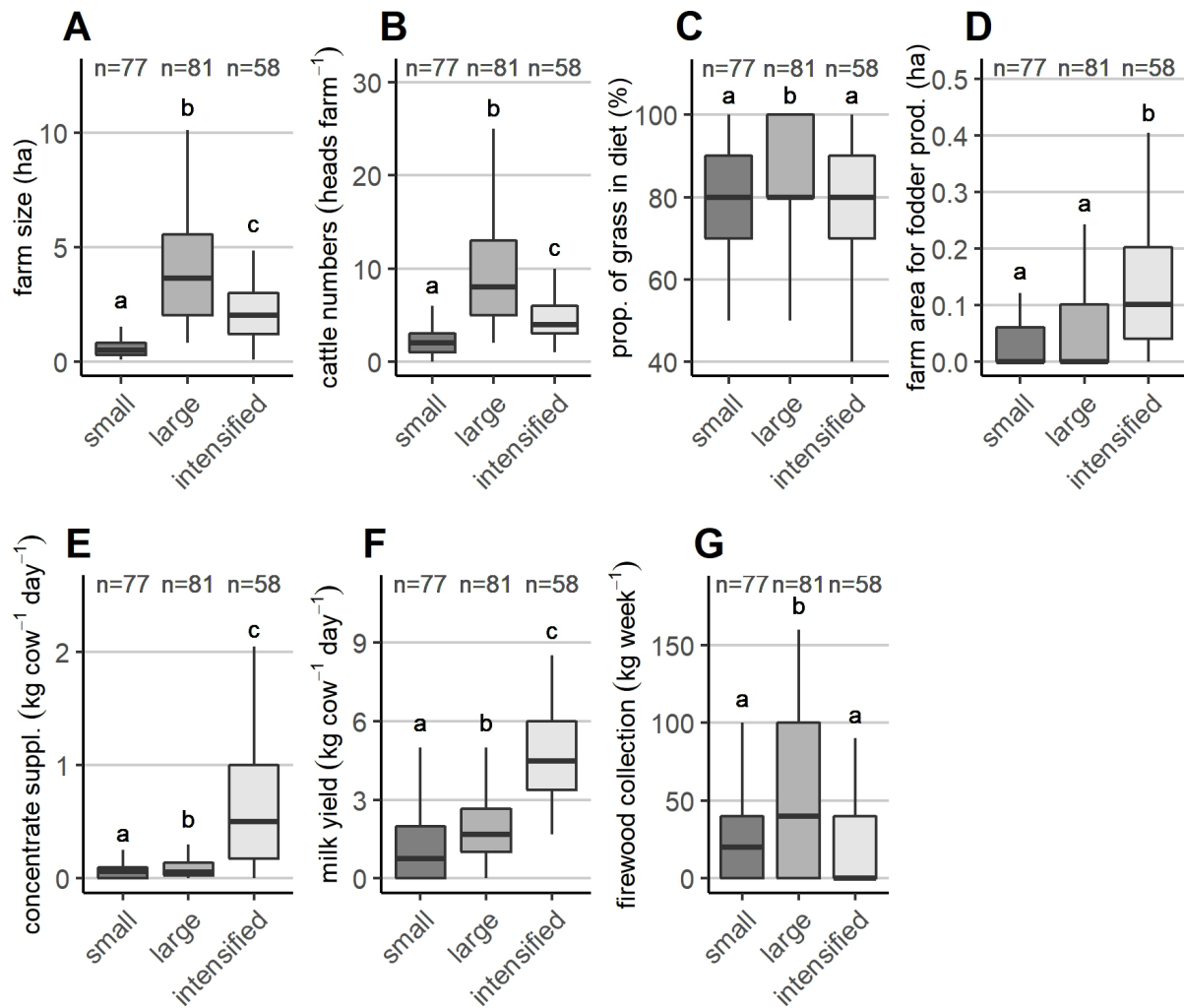
4.3.4 Farm types

Three farm types were inferred from the cluster analysis: 'small and resource-poor farms', 'large and inefficient farms' and 'intensified farms'. Small and resource-poor farms had the smallest mean sizes (0.7 ±0.6 ha, Figure 4.6A), the lowest total number of cattle herds

(2.3 ±1.8 heads, Figure 4.6B) and the lowest number of dairy cattle (0.5 ±1.0 heads). The quality of cattle feed was low indicated by a relatively low proportion of native grass from pastures in the diet (72.7 ±30.4 %, Figure 4.6C), little farmland allocated to grow higher quality fodder (0.03 ±0.04 ha, Figure 4.6D) and the smallest supplementation rate of concentrated feed (0.08 ±0.11 kg cow^{-1} day^{-1}, Figure 4.6E). Milk yields were the lowest (1.2 ±1.4 kg cow^{-1} day^{-1}, Figure 4.6F). Firewood collection rates were intermediate (36.5 ±79.3 kg week^{-1}, Figure 4.6G). In addition, the farm survey data show for this farm type comparatively low proportions of farms with planted trees on on-farm pastures (13 %), cropland (5 %), farm boundaries (84 %), and in woodlots (26 %).
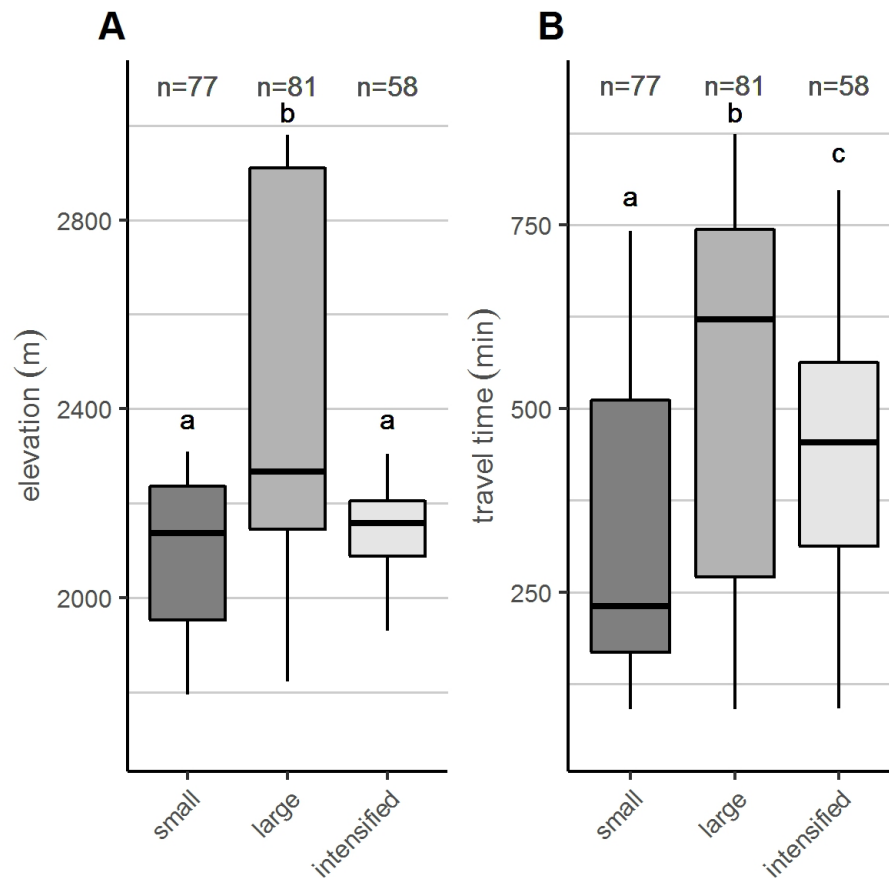
Large and inefficient farms had the largest mean sizes (4.9 ±5.5 ha) and cattle herds (14.0 ±16.7 heads) combined with a moderate number of dairy cattle (2.5 ±11.4 heads). Feed quality was low shown by the highest proportion of native grass from pasture in the diet (86.5 ±11.7 %), little farmland allocated to grow high quality fodder (0.10 ±0.45 ha), and low supplementation rates of feed concentrates (0.11 ±0.14 kg cow^{-1} day^{-1}). Milk yields were only slightly higher than those of the small and resource-poor farms (1.8 ±1.2 kg cow^{-1} day^{-1}). Firewood collection rates for this farm type were the highest (84.5 ±160.6 kg week^{-1}). The farm survey data indicate that the proportions of farms with planted trees on on-farm pastures (16 %) and cropland (6 %), farm boundaries (78 %), and in woodlots (25 %) were similar to those of the small and resource-poor farms.

Relatively more intensified farms had medium sizes (2.5 ±2.1 ha), moderate cattle head sizes (5.0 ±2.9 heads) but the highest numbers of dairy cattle (3.0 ±3.5 heads). These farms had the best feed quality indicated by a moderate proportion of native grass from on-farm pastures in the diet (78.3 ±16.4 %), the largest farm area allocated to fodder production (0.23 ±0.55 ha), and high rates of concentrated feed supplementation (0.9 ±1.0 kg cow^{-1} day^{-1}). Milk yields were the highest (5.1 ±2.2 kg cow^{-1} day^{-1}). Firewood collection rates were the lowest (31.2 ±81.6 kg week^{-1}). This farm type had the highest proportions of farms with planted trees on on-farm pastures (26 %), cropland (14 %), farm boundaries (90 %), and in woodlots (40 %).

Figure 4.6: Farm indicators used to cluster farm types. Farm types were (x-axes): small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms. Included indicators were: A) cattle numbers, B) milk yields, C) proportion of grass from on-farm pastures in the diet, D) farm area allocated to fodder production, E) concentrate supplementation, F) farm size, and G) firewood collection. Different letters above whiskers indicate significant differences between farm types by using pairwise Wilcoxon rank sum tests (p-values were corrected for multiple testing).

Large and inefficient farms were located at higher elevation and show longer travel time to cities compared to small and resource-poor farms and intensified farms (p < 0.001, Figure 4.7A & B). Therefore, large and inefficient farms were located more remotely and had less market access.

Figure 4.7: Elevation and remoteness of farm types. Boxplots show A) elevation and B) travel time to cities by farm type: small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms). Different letters above whiskers indicate significant differences between clusters farm types by using pairwise Wilcoxon rank sum tests (p-values were corrected for multiple testing).

4.3.5   Farm types and forest disturbance intensity

Farm types had a significant effect on forest disturbance intensity ($p < 0.05$) for all farm neighbourhood sizes. Interactions between farm types and farm distance to forest edges show that more intensified farms had significantly smaller effects on the intensity of forest disturbance than the small and resource-poor farms and the large and inefficient farms for the different neighbourhood sizes ($p < 0.001$, Figure 4.8). However, differences in effects between large and small farms were not significant for the 4 km farm neighbourhood size (Figure 4.8C). In general, the effect of farm types on forest disturbance intensity became smaller with increasing farm distance to the forest edges. For the 5 km neighbourhood size, effects of farm types were less distinguishable and their slopes decreased (Figure 4.8D), indicating that the influence of farm types on forest disturbance intensity are more

difficult to disentangle from external effects. The 95 % confidence intervals around the effects indicate an increased variability of the interaction effects of farm types along farm distance to forests across farm neighbourhoods. The lowest variability of effects was shown for intensified farms in all farm neighbourhood sizes. For details on model selection see Appendix (S4, Table S4.4).
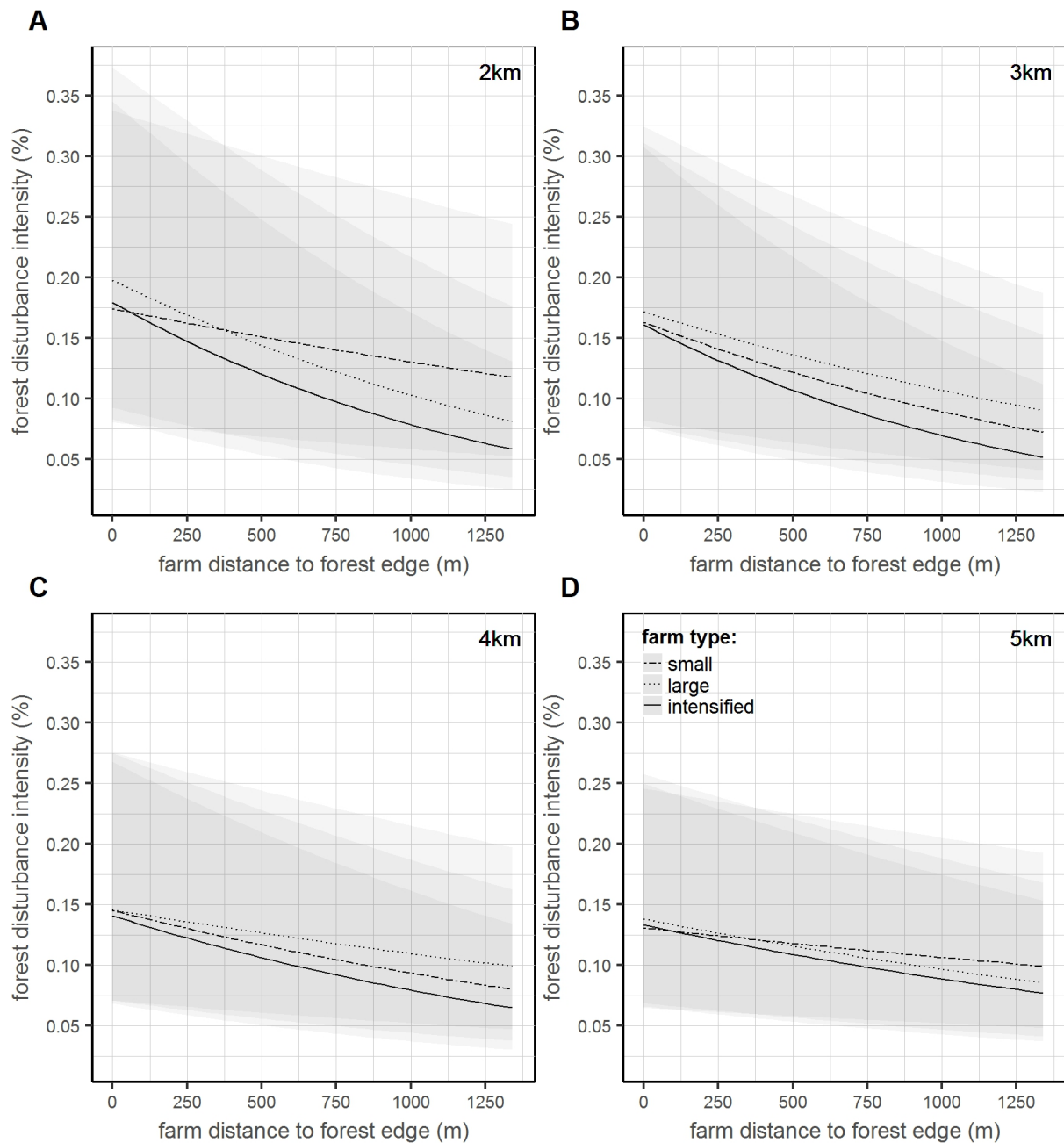
Figure 4.8: Effects of farm types on forest disturbance intensity. Effects of farm types interacting with farm distance to forest edges were derived from GLMMs for different farm neighbourhood sizes (buffer radiuses): A) 2 km, B) 3 km, C) 4 km, and D) 5 km. Shaded areas indicate 95 % confidence intervals for each farm type (small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms).

Effects of farm types on the two most important forest disturbance types (i.e. disturbance drivers) observed during the survey (Figure 4.4) also differ (Figure 4.9). Intensified farms were associated with significantly lower intensities of forest disturbance ($p < 0.05$) where firewood collection (Figure 4.9A, C) and cattle grazing (Figure 4.9D) were recorded,

compared to small and resource-poor farms as well as large and inefficient farms. An exception is shown for forest grazing within the 2 km farm neighbourhood where large farms were associated with a significantly higher disturbance intensity ($p < 0.05$) than small and resource-poor farms and intensified farms (Figure 4.9B). Results are only shown for the 2 and 3 km farm neighbourhoods due to few disturbance samples from the forest survey within the 4 and 5 km farm neighbourhoods (Figure 4.9D). The variability around the farm type effects was smallest for intensified farms shown by 95 % confidence intervals. For details on model selection see Appendix (S4, Table S4.5).
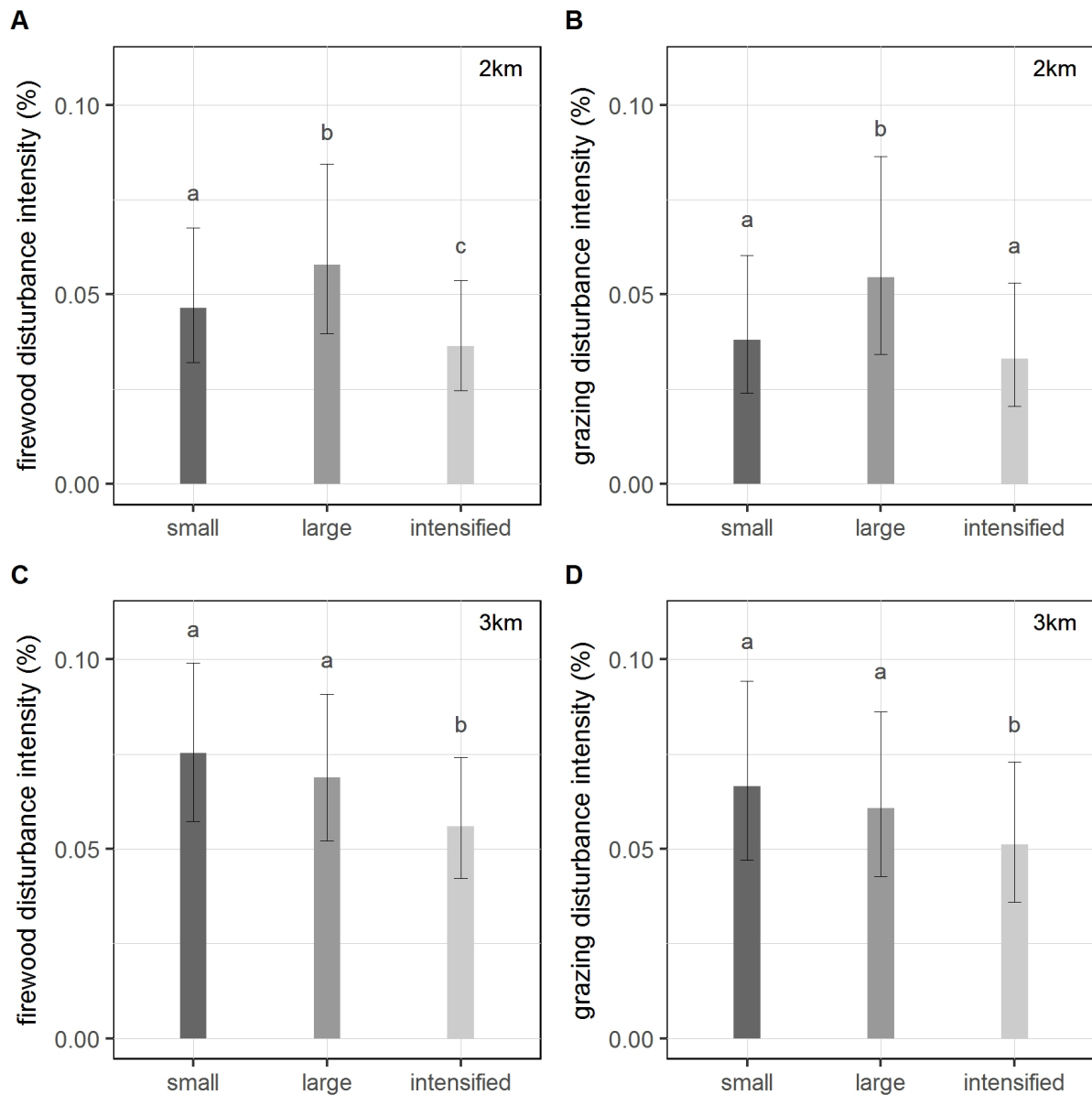
Figure 4.9: Farm types effects on forest disturbance types. Effects of farm types are shown for firewood collection (A, C) and cattle grazing in the forest (B, D) modelled for the 2 and 3 km farm neighbourhood sizes. Different letters above bars indicate significant differences between farm types (small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms). Vertical bars indicate 95 % confidence intervals.

4.4   Discussion

4.4.1   Drivers of forest disturbance in context

Forest disturbance across SSA is responsible for large parts of the land-based GHG emissions (Bailis et al., 2015; Pearson et al., 2017). In this study, the dominant drivers of forest disturbance were the extraction of firewood primarily used by local smallholder farmers living adjacent to the Mau Forest and cattle grazing inside the forest as opportunistic feed resource for cattle owned by local smallholders (Figure 4.4). Grazing happens mostly on forest land opened through fuelwood extraction or wildfires. Although grazing is not a primary driver of forest disturbance in the montane forests studied, it prevents the regrowth of woody vegetation, affects negatively C sequestration and, thus, reduces the C sink capacity of forests (Samojlik et al., 2016). Wildfires occur across the Mau Forest, often caused by human activities such as charcoal production or attempts to clear forested land, which increase the risk to spread fire during dry seasons.

Firewood extraction from forests partly covers the demand for fuelwood, which is the main driver of small-scale forest disturbance in SSA (Hosonuma et al., 2012). The high demand for fuelwood in East African countries such as Kenya exceeds the supply capacity of forest ecosystems (Mutoko et al., 2015). Therefore, Kenya is among the countries that show the most unsustainable fuelwood production across the tropics (Bailis et al., 2015). GHG emissions from fuelwood extraction and utilisation in tropical forests account with 0.62 Gt CO_2eq year^{-1} for about one third of the forest emissions, compared to timber production (1.09 Gt CO_2eq year^{-1}) and wildfires (0.35 Gt CO_2eq year^{-1}) as estimated by Pearson et al. (2017). Livestock grazing in forests is with 8 % ranked as the third most important driver of disturbance as estimated by Hosonuma et al. (2012) after fuelwood extraction (58 %) and timber production (33 %) for SSA countries that are in their late forest transition phase such as Kenya. In this study, forest livestock grazing showed a more prominent role on forest disturbance, as it occurred at all six sampling sites at 75 % of all spots visited (Section 4.3.2). Forest disturbance spots located deep inside the forest were not visited. It is likely that the intensity of forest grazing decreases further inside the forest with limited access. In addition to negative effects of C storage in forests, livestock grazing was shown to modify nutrient cycles and to reduce species richness in forests (Close et al., 2008; Denmead et al., 2015).

4.4.2   Mitigation potential on forested and agricultural land

Intensification may reduce the impact of smallholder farms on forests

The increase in agricultural production in SSA has been mostly achieved through expansion of agriculture into natural ecosystems, including forests (Fisher, 2010). Increasing productivity without compromising environmental goals is required to meet future food demand and to contribute to climate change mitigation (Smith et al., 2013). This study shows that larger farms and higher cattle numbers increased the risk of forest disturbance by 1 – 5 % (Figure 4.5). Higher firewood collection rates had an even stronger impact on the forest increasing the risk of disturbance by 3 – 10 % (Figure 4.5). On the contrary, higher milk yields decreased these risks by 3 – 7 % (Figure 4.5). The effects of indicators related to feed intensification such as larger farm area allocated to fodder production, supplementation of dairy concentrate and increased proportion of grass in the diet were less pronounced. These indicators reduced the risk of forest disturbance by 1 – 5 % (Figure 4.5). The results indicate that farms which own more cattle and collect more firewood are likely to cause more disturbance in the nearby forest than more intensified farms with high milk productivity and improved feed quality. The analysis of farm type effects on forest disturbance confirmed this pattern. More intensified farms had a lower impact on forests in general but also on disturbance caused by firewood extraction and livestock grazing in particular (Figure 4.8 & 4.9). Compared to small and resource poor farms and large but inefficient farms, intensified farms planted more trees on farmland (Section 4.3.4) e.g. in woodlots or on farm boundaries. These trees represent fuelwood sources available on-farm (Mbow et al., 2014), potentially translating into lower firewood extraction from the forest (Figure 4.6G). Small farms that lack resources such as land and access to higher quality feeds, and large but inefficient farms with many low productivity cattle (Figure 4.6A - F) increase the risk to remove biomass from local forests unsustainably by exceeding the regrowth rates. Yet, effect sizes of farm indicators and differences among the effects of farm type on forest disturbance were, despite significant, relatively small. The inefficiency of large farms is likely related to their location at higher elevation (Figure 4.7). Remoteness and lack of infrastructure result in reduced market access for these farms, rendering it more difficult for smallholders to buy higher quality feeds and feed supplements, and to sell the milk produced (Makoni et al., 2014).

The effects of dairy production and intensification on local forests can be quantified by relating farm practices and characteristics to forest disturbance patterns. Including farm-related activities outside the farm boundaries that affect the broader landscape is relevant to assess the effectiveness and sustainability of policies that target climate change mitigation and food security (DeFries & Rosenzweig, 2010). Potential spill over effects can be revealed, causes be identified and the risk of C leakage be minimised.

4.4.3 Increase of farm efficiency and on-farm tree cover

Dairy production in SSA shows the highest GHG emission intensities compared to dairy production in other continents which points to low efficiency of smallholder dairy production (Gerssen-Gondelach et al., 2017). Mitigation and development policies seek for 'win-win' situations where increased farm production goes hand in hand with the avoidance of additional GHG emissions (Brandt et al., 2018b). Low quality feed from natural pastures and from opportunistic cattle grazing inside the forest result in low milk yields and high GHG emission intensities (Lukuyu et al., 2012). Increasing milk yields on smallholder farms can be achieved through feed intensification by improving the protein and energy density in feeds (Agle et al., 2010; Trupa et al., 2015). The intensified farm type showed the highest milk yields (Figure 4.6F). The quality of feed that is either grown on-farm such as fodder grasses or supplemented as concentrated feed such as dairy meals was also highest for intensified farms compared to the other two farm types (Figure 4.6D & E). Perennial fodder grasses such as Napier grass show high potential for feed intensification as it has a higher quality than native grass from pastures and is widely accepted by smallholders across the Kenyan highlands (Katiku et al., 2011). Higher supplementation of concentrates during lactation periods was related to the increase in milk yields in this study (Figure 4.6E) and was also reported to improve milk yields in Kenya (Rufino et al., 2009; Richards et al., 2016).

However, C leakage emerging from intensification processes have to be considered. Feed imports from other regions or countries may raise due to feed intensification if the increased demand of higher quality feeds cannot be covered locally (Meyfroidt et al., 2014). GHG emissions from indirect land use changes due to agricultural expansion could be the consequence. Styles et al. (2018) conducted a life cycle assessment (LCA) of dairy intensification in the United Kingdom showing possible cascade effects of pasture-crop displacement and expansion of pastures that lead to deforestation in Brazil. Therefore, appropriate mitigation policies and funding schemes need to integrate measures (e.g. protocols on land use legacies, certification) that enable feed production which does not undermine effective climate change mitigation.

Depleted soils due to nutrient mining is a common reason for stagnating or falling crop yields in Kenya (Tittonell et al., 2010). Increasing the efficiency of nutrient cycling through improved manure management can increase soil fertility and crop yields as shown by Castellanos-Navarrete et al. (2015) for smallholder crop-livestock production systems in Kenya. Closing the yield gap is especially important for small farms that lack land to grow fodder. Furthermore, intensified farms had less cattle than large and inefficient farms (Figure 4.6B, F), and instead owned more improved breeds (Section 4.3.4). Reduced stocking rates with higher herd efficiency and the replacement of local cattle with improved breeds that produce more milk accompanied by better access to animal health services are additional factors to increase the efficiency of milk production and to reduce

GHG emission intensities on smallholder dairy farms in Kenya (Bryan et al., 2013; Mottet et al., 2016). Adopting the dairy hub model, developed by the 'East African Dairy Development' (EADD) program, could facilitate the improvement of market access. This can be achieved by infrastructure funds and by linking the different actors throughout the dairy value chain such as dairy farmers, feed producers and dairy companies (EADD, 2014).

Agroforestry could increase the C sequestration potential of smallholder farms in the tropics and offset GHG emissions resulting from agricultural production (Mutuo et al., 2005; Abbas et al., 2017; Ortiz-Gonzalo et al., 2017). Kenya's target to increase the tree cover from about 6 % in 2000 to 10 % by 2030 is the policy frame to improve the tree cover on farm land (Government of Kenya, 2015b). However, between 2000 and 2010, the tree cover on farm land in Kenya on average increased by about 1 % (Zomer et al., 2016). Thus, incentives such as climate financing schemes are required to encourage smallholder farmers to plant trees on their farms which could be used as fodder trees or as fuelwood source. Moreover, more efficient cooking stoves would reduce the demand of fuelwood and indoor air pollution translating into health improvements (Malla et al., 2011). Improved forest management that actively involves local communities could enable the sustainable use of forest resources e.g. by establishing regulated wood pastures located at the forest edges or tree plantations used for a certified fuelwood production (Börner & Wunder, 2012; Chidumayo & Gumbo, 2013; Mutoko et al., 2015).

4.4.4   Limitation and benefits of the approach

This is the first study that combines a remote sensing approach with an analysis of farm production to investigate the connection between dairy production and forest disturbance in Africa. It is also one of the first studies that applied a forest disturbance detection approach utilising the spatio-temporal information from Landsat time-series (Hamunyela et al., 2017). The approach was shown to outperform change detection based on temporal information only in terms of accuracy especially in environments where forest disturbances occur mainly at small-scale (Hamunyela et al., 2016b, 2017). The spatial accuracy achieved here (UA = 77.9 %, PA = 78.6 %) is comparable to Hamunyela et al. (2017) who studied small-scale disturbances in the Ethiopian highlands (UA = 76.8 %, PA = 78.3 %). By reducing false detections of small-scale disturbances, STEF could improve national forest monitoring capabilities especially in regions where these disturbance patterns are dominant such as in many SSA countries (DeVries et al., 2015b). The spatial resolution of Landsat sensors limits the detection of small-scale disturbances. However, new satellite systems such as the Sentinal platform bears high potential for forest monitoring applications due to increased spatial and temporal resolution (Mitchell et al., 2017).

Training and validation data obtained from the ground are necessary to improve the detectability of forest disturbances even more so if they occur at small-scale and visual interpretation methods based on high resolution satellite imagery become unsuitable. Involving local experts into the monitoring can enhance the validity of detected changes and enable the characterisation of their drivers e.g. through community-based forest monitoring integrating remote-sensing and smart phone technologies (DeVries et al., 2016). Higher variability in the effects of farm type on forest disturbance reflected uncertainties that were introduced through the clustering of farm types by using farm survey data. Such uncertainties have to be reduced to improve the quantification of agricultural drivers and GHG emissions resulting from forest disturbance – e.g. through comprehensive measuring and reporting efforts.

4.5 Conclusions

This study revealed that the main anthropogenic drivers of forest disturbance across the Mau Forest are extraction of firewood and cattle grazing inside the forest. Both drivers are related to farm practices and characteristics of local smallholder farms. Intensification of smallholder dairy farming was associated to a lower risk of forest disturbance. Less forest disturbance translates eventually into reduced GHG emissions from forests. Thus, these results are informative for policy formulation and decision-making targeting mitigation options that increase farm efficiency and minimise negative effects on forests at the same time.

Incentive-based climate financing instruments are required for stakeholders such as farmers, cooperatives and the private sector involved in dairy production. These funds could be accessed once certain criteria are fulfilled such as the implementation of on-farm practices such as feed intensification that mitigate direct and indirect GHG emissions and increase farm productivity. A nationally appropriate mitigation action (NAMA) currently in development for the dairy sector in Kenya offers a promising policy framework to develop low emission dairy production, including capacity development and investment support targeting about two million smallholder households. However, assessments and criteria that minimise the risk for carbon leakage through indirect land use changes have to be integrated into policy development to achieve effective mitigation in the land use sector.

Based on the key results, policy recommendations are: i) reducing the emission source potential of agriculture through the increase of production efficiencies on dairy smallholder farms and through the improvement of their offsetting potential (i.e. the increase of tree cover on farmland) and ii) enhancing the C sink potential of forest systems by minimising forest disturbances through sustainable intensification of farming and improved forest management.

Acknowledgments

Chapter 5

Intensification of dairy feeds increases GHG mitigation potential across the land use sectors of agriculture and forestry in Kenya

Abstract

Countries in Sub-Saharan Africa (SSA) need to produce more food to feed their fast growing populations. Agriculture drives forest disturbance in SSA through forest livestock grazing by preventing vegetation regrowth, which reduces the carbon (C) sink capacity of forests and causes greenhouse gas (GHG) emissions. Smallholder farming hast to be intensified sustainably by producing more food on agricultural land and by releasing the pressure on forests, which contributes to climate mitigation. Kenya aims for the low-emission development of its dairy sector to meet the growing demand for milk. This study assessed the potential of dairy feed improvements, including closing the yield gap of fodder maize, to mitigate agricultural GHG emissions and forest C loss linked to dairy cattle. The livestock production model LivSim was applied to estimate and upscale GHG emissions and milk yields for different feed improvement scenarios. Forest C loss due to dairy cattle was quantified by using remote-sensing data on aboveground C change. The shortage of grazing land potentially available to cultivate improved dairy feeds was analysed around forests to relate the scenarios and forest C loss due to dairy cattle. Scenarios that closed the maize yield gap could increase milk yields by up to 51 % and lower GHG emission intensities by up to 19 % due to reduced land requirements. The reduction of GHG emissions from land use change was up to 5 times higher than the increase of GHG emissions from additional fertilizer application. Forest C loss due to dairy cattle could be reduced by up 225 %, which turns forests into C sinks. However, only the scenario that improved forage quality based on Napier grass and increased concentrate supplementation would achieve a net reduction of combined total agricultural GHG emissions and forest C loss due to dairy cattle. The combined total emissions would be 2.5 % lower than in the baseline, while the milk yield could be increased by 45 %. Thus, dairy feeds can realise productivity and effective mitigation benefits across land use sectors. The approach followed can aid the targeting and planning of interventions that improve the climate-smartness of smallholder livestock production.

5.1   Introduction

Low agricultural productivity and rising human population in Sub-Saharan Africa (SSA) jeopardize food security and degrade natural ecosystems through unsustainable land-use practices (Herrero et al., 2016; Grassi et al., 2017). Agriculture is shown to drive forest disturbance in SSA, which causes the loss of forest carbon (C) and greenhouse gas (GHG) emissions (Carter et al., 2015). In addition to the conversion of forests into farm land, timber logging, and fuelwood extraction, cattle grazing causes forest disturbance by preventing the regrowth of vegetation (Hosonuma et al., 2012; Pearson et al., 2017; Brandt et al., 2018a). Forest disturbance reduces the sequestration of C and, thereby, decreases the C sink capacity of forests, and affects water and nutrient cycling, and biodiversity, which feedback negatively on agricultural production (Barlow et al., 2016; Arias-Navarro et al., 2017; Jacobs et al., 2017; Wanyama et al., 2018). Safeguarding and improving the supply of nutritious food is one of the 'Sustainable Development Goals' (SDG 2) of the 'United Nations' (UN) to achieve food security globally but especially in SSA (UN, 2017a). The majority of food in SSA is produced by smallholder farmers that are often affected by low livestock productivity, low and stagnating crop yields due to nutrient-depleted soils, and small farm sizes (Tittonell et al., 2009; Zhou et al., 2014; Brandt et al., 2018b). Food production on smallholder farms in SSA has to be intensified sustainably to reduce malnutrition and to reach SDG2. The concept of 'Climate-Smart Agriculture' (CSA) was brought forward to adapt agricultural systems to climate change, to mitigate anthropogenic impacts on the climate system and to safeguard food security (FAO, 2013).

Agriculture in East Africa is increasingly prone to erratic weather patterns and prolonged drought spells. To address these challenges, Kenya set up a national CSA strategy to transform the country's agricultural sector towards climate-smart food production systems. Agriculture is not only the country's economic backbone but also contributes with about 40 % to its GHG emissions budget. About 90 % of the agricultural emissions stem from livestock production (Government of Kenya, 2015b). As part of its ambitious economic development plan, Kenya seeks to develop its dairy sector to be able to meet the increasing demand for milk, which results from the fast growing human population (Government of Kenya, 2010). Dairy production engages approximately two million small-holder farmers, who contribute about 80 % to the total milk production in Kenya (Udo et al., 2016). However, higher cattle numbers and the increasing demand for feeds will lead to higher GHG emissions from enteric fermentation, animal manure, the additional arable land allocated to feed production and pastures. Low yields of feed crops, small farm sizes and the shortage of agricultural land in Kenya increase the pressure on remaining natural forests and the risk of forest C loss due to forest cattle grazing (Kumar et al., 2009; O'Mara, 2011; Bosire et al., 2016; Brandt et al., 2018a). Therefore, sustainable intensification of the dairy sector is required, which increases milk yields by producing

higher quality feeds more efficiently on available agricultural land without the need to expand into natural ecosystems.

Kenya defined targets in various national and sectoral mitigation and development policies such as the 'Nationally Determined Contribution' (NDC) and the national dairy master plan. The increase of total GHG emissions in Kenya has to be lowered by 30 % relative to projected business as usual emissions between 2010 - 2030 (Government of Kenya, 2015a). Within the same time frame, milk yields of dairy cattle have to be increased by 150 % (Government of Kenya, 2010). The 'Nationally Appropriate Mitigation Action' (NAMA) for the dairy sector in Kenya focuses on the low-emission development of smallholder dairy farming by increasing on-farm productivity through the improvement of dairy feeds (Government of Kenya, 2017b). To analyse weather these targets can be met effectively, the impact of feed improvements on dairy-related GHG emissions from the entire 'Agriculture, Forestry and Other Land Use' (AFOLU) sector have to be included into the assessments.

Brandt et al. (2018b) reported synergies between improving dairy feeds, milk yield increases, and GHG mitigation benefits on agricultural land. In addition, intensified smallholder dairy farms located close to forests are shown to reduce the risk of local forest disturbance (Brandt et al., 2018a). However, changes in cattle diet may require the conversion of potentially arable land such as grazing land to cultivate more nutritious feeds, which can cause GHG emissions from land use change (LUC) (van Middelaar et al., 2013), and ultimately render certain feed improvement options unfeasible (Brandt et al., 2018b). Promoting dairy production in a region with shortages of agricultural land for feed cultivation could, therefore, increase the risk of negative spillover effects such as C leakage as farmers may use close-by forests for grazing. Closing the yield gap of feed crops could reduce the demand for additional land and, thus, alleviate the disturbance pressure on forests. To date, there are no assessments that integrate the effects of agricultural intensification and GHG mitigation measures on forests in SSA, which are crucial for effective CSA targeting and planning, and to avoid negative spillover effects of mitigation interventions.

This study aimed to answer the questions: What is the potential of dairy feed improvements, including closing the yield gap of fodder maize, i) to reduce the direct total GHG emissions and emission intensities related to dairy production and ii) to decrease the C loss from forests due to the presence of dairy cattle? The livestock production model LivSim (Rufino et al., 2009) was used to calculate milk yields and GHG emissions for different feed improvement and intensification scenarios throughout the dairy production area in Kenya. Remote-sensing data were used to quantify forest C change and to approximate, for the first time, an estimation of forest C loss related to the presence of dairy cattle. The scenarios considered in this study are plausible and spatially-explicit 'what if' scenarios of dairy intensification and their potential effects on milk production, agricultural GHG

emissions, and forest C loss.

5.2 Material and methods

5.2.1 Study area

The study area is located in the Central and Western highlands of Kenya. The area has a size of about 65 000 km^2 and is characterized by smallholder crop-livestock production systems. The region was defined previously in the analyses of Herrero et al. (2014) on smallholder dairy development pathways for the Kenyan highlands. The area shows the highest densities of human and livestock populations throughout Kenya (Imo, 2012). The majority of milk that is marketed in Kenya originates from this region and is mainly produced by dairy smallholders (Brandt et al., 2018b). Apart from agricultural land, the remaining Afromontane forests called 'water towers' are located in the area, namely the Aberdare range Forest, the Cherangani Hills Forest, the Mau Forest, the Mount Elgon Forest, and the Mount Kenya Forest. All of these forests experience ongoing forest degradation due to the unsustainable use of forest resources such as cattle grazing on forested land and fuelwood extraction (Imo, 2012; Drigo et al., 2015).

5.2.2 Analytical framework

The framework included a number of steps (Figure 5.1): First, spatially-explicit data on net forest C loss and gain were pre-processed and a dataset on forest C loss due to the presence of dairy cattle was created. Second, farm indicators and farm types derived from a farm survey were related to net forest C loss, gain and change to quantify the relationship between smallholder farming practices and forest C change. Third, a livestock simulation model was used to compute spatially-explicit data on dairy-related agricultural GHG emissions, milk production and the requirement of arable land to meet the demand of improved feeds. This analysis was conducted by applying a typical dairy diet and scenarios of feed improvements, including closing the yield gap of maize to quantify mitigation potentials for the agricultural land. Subsequently, the shortage of land was estimated, which is required land minus available land. Land shortage was related to forest C change associated to the presence of dairy cattle, which is C gain minus C loss due to dairy cattle for each feed improvement scenario to quantify the mitigation potentials for forests.
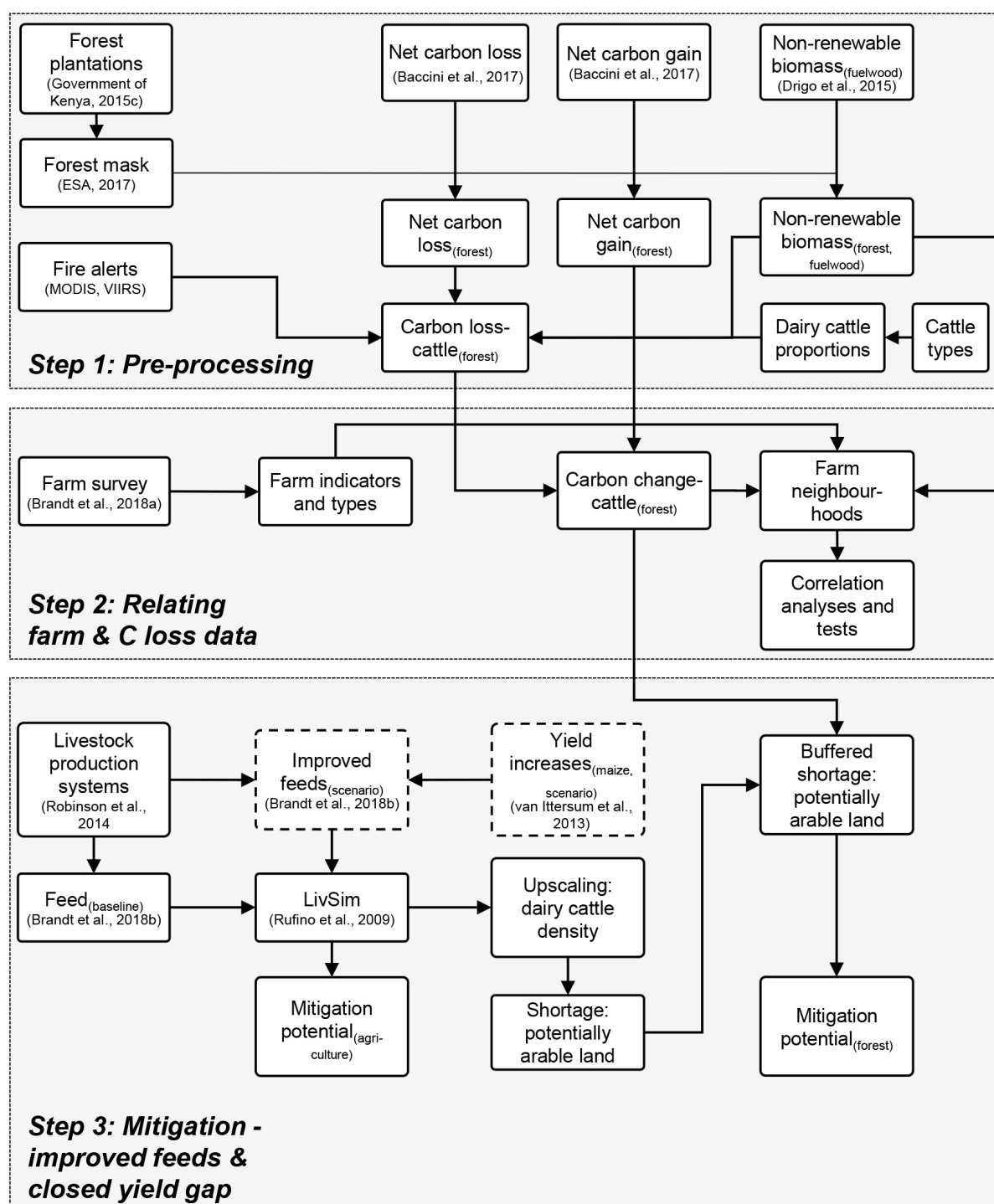
Figure 5.1: Flowchart of steps conducted to calculate mitigation potentials of feed improvement scenarios, including closing the yield gap of maize, on agricultural land and in forests. Carbon (C) loss-cattle$_{\text{(forest)}}$ = C loss related to the presence of dairy cattle in forests, Carbon change-cattle$_{\text{(forest)}}$ = Forest C change, which includes the C loss fraction related to the presence of dairy cattle, LivSim = livestock simulation model. Dashed boxes represent scenarios of feed improvement and closing the yield gap of maize used to produce maize silage by realising water-limited yield potentials.

5.2.3 Pre-processing

Spatially-explicit datasets, which indicate the changes in C density of aboveground biomass between 2003 - 2014 were obtained to quantify annual forest C changes (Baccini et al., 2017). These datasets include net gains (C gain) and losses of C (C loss) at a pixel resolution of 463 x 463 m (Figure 5.1, step 1). A forest mask was applied to restrict the C change data to land that was forested in 2016 within the study area deriving net C loss$_{(forest)}$ and net C gain$_{(forest)}$. The forest mask was based on a land cover dataset of Africa at a pixel resolution of 20 x 20 m (ESA, 2017). Moreover, a dataset of tree plantations was used to limit the forest mask to natural forests (Government of Kenya, 2015c). The various spatial resolutions of input datasets applied in this study were resampled to a pixel resolution of 1 x 1 km used consistently throughout the analyses.

Wildfires release substantial amounts of C from forests (Hurteau et al., 2008). Open forests in the aftermath of fire events represent land that is accessible for livestock and is frequently used as opportunistic grazing land. However, the C loss due to forest fires can neither be attributed to the presence of cattle in forests nor can this C loss be mitigated through improvements of cattle feeds. Therefore, pixels that indicate burnt forest between 2003 - 2014 were excluded from C loss$_{(forest)}$ (Figure 5.1, step 1) by using daily fire alert data from the 'Moderate Resolution Imaging Spectroradiometer' (MODIS, MCD14ML) (Giglio, 2015) and the 'Visible Infrared Imaging Radiometer Suite' (VIIRS) (Schroeder et al., 2014).

Fuelwood harvest from forests causes about one third of the total forest emissions in Kenya (Pearson et al., 2017). Kenya is one of the countries that show highly unsustainable patterns of fuelwood consumption exceeding the capacity of natural ecosystems such as forests to regrow the biomass that is extracted as fuelwood (Bailis et al., 2015). Thus, this source of forest C loss was accounted to approximate the aboveground C loss related to cattle presence in forests (C loss-cattle$_{(forest)}$). A spatially-explicit dataset of non-renewable biomass (NRB) harvested annually as fuelwood was obtained at a pixel resolution of 100 x 100 m (Drigo et al., 2015). The NRB dataset was subtracted from the net C loss$_{(forest)}$ data after restricting it to forests (NRB$_{(forest)}$) by using the same forest mask applied previously to derive C loss-cattle$_{(forest)}$ (Figure 5.1, step 1). County-level data on cattle types was used to calculate the proportion of dairy cattle by excluding cattle used for beef production (Government of Kenya, 2014). The C loss-cattle$_{(forest)}$ data was multiplied by proportions of dairy cattle to calculate forest C loss that could be attributed to the presence of dairy cattle. The estimate of C loss-cattle$_{(forest)}$ is a first approximation of C loss related to dairy cattle in forests and is based on previous empirical work with observations of cattle grazing in the forest (Brandt et al., 2018a). So far, there are no spatially-explicit data available that quantify the effects of livestock on carbon dynamics in Kenyan mountain forests.

The uncertainty, which propagated into C loss-cattle$_{(forest)}$ due the uncertainties inherent to the input datasets net C loss$_{(forest)}$ and NRB$_{(forest)}$ was quantified by applying equation (5.1) (Lee & Forthofer, 2006):

$$
\begin{aligned}
var(C\ loss - cattle_{(forest)}) = \ &var(C\ loss_{(forest)})\ +\ var(NRB_{(forest)}) \\
&- 2 \times cov(net\ C\ loss_{(forest)}, NRB_{(forest)})
\end{aligned}
\tag{5.1}
$$

The reported values of relative standard deviations (SD) were used to quantify the input variances (Bailis et al., 2015; Baccini et al., 2017). The uncertainty values in this study are reported as relative SD.

5.2.4   Relating smallholder farms and forest C loss, gain and change

The effects of smallholder farms on forest C change were based on previous empirical analyses in the study area (Brandt et al., 2018a). These analyses related farming practices and characteristics obtained from a farm survey to forest disturbance derived from a remote-sensing based time-series analysis, which was validated by data from forest disturbance surveys (Brandt et al., 2018a). The farm survey was conducted in 2016 sampling 216 smallholder farms, located in close vicinity to forests. Information on total numbers of cattle, number of improved dairy cattle, milk yields, proportion of feed types in the cattle diet such as grass from on-farm pastures, fodder crops, and concentrated feed supplements, farm area allocated to fodder production such as fodder crops and on-farm pastures, and total farm size was collected, henceforth called 'farm indicators'. In addition, farms were clustered into farm types, which are henceforth called: 'small and resource-poor farms', 'large and inefficient farms', and 'intensified farms'. For details on the methodology see Brandt et al. (2018a). The results indicated stronger disturbance effects of farms that have higher total numbers of cattle and low milk yields. Farms that fed dairy cattle with improved diets showed smaller effects on forest disturbance.

To test whether similar farm effects are found when the same farm data are related to forest C changes, farm indicators and farm types were linked to forest C data within circular buffers created around farm centroids (Figure 5.1, step 2). A radius (r) of 5 km was selected for these buffers, which are henceforth called 'farm neighbourhoods'. This radius was chosen following Brandt et al. (2018a), who found that r = 5 km created the maximum farm neighbourhood size in which farm indicators and farm types could be related significantly to forest disturbance. Forest C change that includes only the C loss fraction related to the presence of dairy cattle (C change-cattle$_{(forest)}$) = net C gain$_{(forest)}$ – C loss-cattle$_{(forest)}$ was calculated within each farm neighbourhood (Figure 5.1, step 2). Farm indicators were correlated with net C loss$_{(forest)}$, net C gain$_{(forest)}$, NRB$_{(forest)}$, C loss-cattle$_{(forest)}$, and C change-cattle$_{(forest)}$. Differences between farm types were tested by using non-parametric pairwise Wilcoxon rank sum tests.

5.2.5 Mitigation potential of improving dairy feeds on agricultural land and in forests

Livestock production modelling and feed intensification

The livestock production model LivSim (Rufino et al., 2009) was used following the methodology of Brandt et al. (2018b) to quantify and upscale milk production and agricultural GHG emissions from smallholder dairy production. GHG emissions were quantified based on IPCC tier 2 methodology (IPCC, 2006) and included methane (CH_4) emissions from enteric fermentation, CH_4 emissions from manure management, direct and indirect nitrous oxide (N_2O) emissions from manure management, direct and indirect N_2O emissions from managed soils, including fertiliser application, and N_2O and carbon dioxide (CO_2) emissions from LUC. The incorporation of LUC emissions is important since changes in the cattle diet require the cultivation of energy and protein-dense feeds with higher digestibility to increase milk yields (Hristov et al., 2013a; Brandt et al., 2018b). These feeds would be cultivated on potentially arable land such as grazing land that is converted to cropland. Milk yield and GHG emissions were computed by simulating dairy cows over a lifetime of 13 years. Model outputs were upscaled and mapped by using spatially-explicit data on livestock production systems (LPS), cattle density (Robinson et al., 2011, 2014), and dairy herd composition data (Bebe et al., 2002; Government of Kenya, 2014). For details on the modelling approach, input data, and scenarios see Brandt et al. (2018b).

Milk yields and GHG emissions were calculated for the baseline feed and several scenarios (Figure 5.1, step 3), which focused on three feed intensification strategies (Brandt et al., 2018b). The baseline represented a typical diet for smallholder dairy cattle in Kenya with a large proportion of low quality grass and crop residues. Scenarios included strategies such as the increase of forage quality (i.e. Napier grass, *Pennisetum purpureum*), feed conservation based on maize silage, and increased supplementation of dairy concentrates (i.e. dairy meal). The scenarios represent combinations of the three strategies and are henceforth called: 'forage quality and concentrate supplementation' (FoCo), 'feed conservation and concentrate supplementation' (FeCo), and 'forage quality, feed conservation and concentrate supplementation' (FoFeCo). Moreover, each scenario included medium and high intensification levels. The baseline feeds were replaced by 25 % and 50 % higher quality feeds representing the medium intensification and high intensification levels respectively. Rations of dairy meal were increased to 3 kg day^{-1} and 6 kg day^{-1} during early lactation. The mitigation analyses in this study focused on three scenarios reported in Brandt et al. (2018b). The following scenarios were selected according to their mitigation potentials on agricultural land: i) FoFeCo with low potential at high intensification, ii) FeCo with medium potential at medium intensification and iii) FoCo with high potential at medium intensification level.

The ranges of GHG emission parameters were sampled by using Latin hypercube sampling (LHS) (Xu et al., 2005) to estimate overall emission uncertainties of the baseline. Each parameter was sampled separately through LHS while all others were kept at their mean. Emission uncertainties of the scenarios were estimated one parameter at a time, sampling at the minimum and the maximum of the parameter ranges (Brandt et al., 2018b).

Closing the yield gap of maize

Each of the scenarios requires a certain amount of arable land to cultivate feeds such as Napier grass and maize. Brandt et al. (2018b) reported that the scenarios, which include feed conservation based on maize silage have a high demand for arable land. In addition to cropland used to cultivate maize for human consumption, cropland to grow maize exclusively as cattle feed was needed to prevent detrimental effects on food security. In Central and Western Kenya, the yield gap of maize ranges between 30 - 82 % suggesting a high potential to intensify maize production (van Ittersum et al., 2013). Closing the yield gap of maize would increase the actual yield and could, therefore, help to reduce the land demand calculated in the scenarios. CO_2 emissions from LUC would be lowered at the expense of N_2O emissions from soils due to increased application rates of synthetic fertiliser.

The potential yield of crops is defined by several abiotic and biotic factors such as solar radiation, temperature, atmospheric CO_2 concentration, and cultivar traits (van Ittersum et al., 2013). Maize cultivation in Kenya is rainfed. The water-limited yield potential (Yw) is the most relevant benchmark indicator for rainfed crops as it further includes yield-limiting factors such as water supply, soil properties (e.g. water holding capacity), and topography (e.g. runoff). In this study, actual yields of maize in the baseline were increased by two levels realising $Yw_{(maize)}$ at 50 % and 80 %. Realising Yw at 80 % is deemed to approach the maximum exploitable yield gap. Farm yields often reach a saddle point around 80 % of Yw and are not feasible for farmers to increase further (van Ittersum et al., 2013). Actual yields (Ya) of maize cultivated in the Kenyan highlands were obtained from Monfreda et al. (2008), Weiler et al. (2014), and Castellanos-Navarrete et al. (2015). Data on $Yw_{(maize)}$ and the minimum nitrogen (N) input required to realise Yw(maize) at 50 % and 80 % in Kenya were obtained from the 'Global Yield Gap Atlas' (GYGA) and are based on agro-climatic zones used to upscale location-specific yield estimates derived from crop simulation models (van Wart et al., 2013a,b). $Yw_{(maize)}$ and minimum N input were linked to the LPS classification used in this study to upscale milk yield and GHG emissions. Each scenario that included maize silage was complemented by two versions, which closed the yield gap of maize: $Yw-50_{(maize)}$ and $Yw-80_{(maize)}$ (Figure 5.1, step 3).

Analysing availability of potentially arable land and cattle grazing in forest

The availability of potentially arable land was calculated for each scenario by comparing the extent of grazing land and demand for arable land per pixel using the R library 'raster' (v. 2.5) (Hijmans, 2016; R Core Team, 2016). Only existing grazing land was assumed to be available to cultivate additional Napier grass and maize (Brandt et al., 2018b). Scenario demands for additional cropland to cultivate feeds were quantified based on the yields ($Ya_{(maize)}$, $Yw\text{-}50_{(maize)}$ and $Yw\text{-}80_{(maize)}$) per feed type, crop-specific feed intake per dairy cow (Rufino et al., 2009; Katiku et al., 2011; Herrero et al., 2013; Weiler et al., 2014; Castellanos-Navarrete et al., 2015), and the density of dairy cattle per 1 x 1 km pixel (Robinson et al., 2014). The availability of potentially arable land was quantified by using a spatially-explicit dataset on the density of grazing land, which had an original spatial resolution of 10 x 10 km (van Velthuizen et al., 2007). All pixels that showed an excess of the demand for arable land in relation to the amount of grazing land available were labelled as pixels that have a shortage of potentially arable land. Spatially-explicit land shortage polygons were created for each scenario (Figure 5.1, step 3). For calculation details see Brandt et al. (2018b) and Appendix (S3, Table S3.3, equations S3.1 & S3.2).

The pre-processed datasets on forest C change, which include the C loss fraction related to the presence of dairy cattle (C loss-cattle$_{(forest)}$) and C gain (C gain$_{(forest)}$), and the polygons of land shortage were used to link forest C change relate to the presence of dairy cattle to the management of dairy feeds on agricultural land. All C loss-cattle$_{(forest)}$ and C gain$_{(forest)}$ pixels were assumed to reflect the baseline forest C change (C change-cattle$_{(forest)}$) without any feed improvements. For the scenarios, it was assumed that the shortage of arable land and the resulting lack of available cattle feed on agricultural land, which surrounds forests forces smallholders to bring their dairy cattle into close-by forests to cover the daily feed requirements of cattle. Brandt et al. (2018a) reported significantly negative effects between indicators related to livestock management on smallholder dairy farms and forest disturbance for farm neighbourhoods that have a maximum r of 5 km. Therefore, land shortage polygons were buffered with this distance. All C loss-cattle$_{(forest)}$ pixels that intersected with a buffered land shortage polygon were assumed to represent potential forest C losses related to the presence of dairy cattle that is likely to occur, if a certain scenario is implemented. Subsequently, the sum of C change-cattle$_{(forest)}$ pixel was calculated for each scenario and compared to the sum of baseline C change-cattle$_{(forest)}$ pixel to quantify the mitigation potential in forests (Figure 5.1, step 3).

5.3   Results

### 5.3.1   Effects of smallholder farms on C change in adjacent forests

Correlation analyses of the empirical data on farm indicators and the quantified forest C change indicate that the total number of cattle on farm was positively correlated to C loss-cattle$_{(forest)}$ ($\rho = 0.15$, p < 0.05) and negatively correlated to the C change-cattle$_{(forest)}$ ($\rho = -0.17$, p < 0.05), which reflects C gain$_{(forest)}$ minus C loss-cattle$_{(forest)}$ (Figure 5.2). The number of improved dairy cattle per farm and milk yield were negatively correlated to C loss-cattle$_{(forest)}$ ($\rho = -0.37, -0.26$, p < 0.001) and positively correlated to C change-cattle$_{(forest)}$ ($\rho = 0.39, 0.27$, p < 0.001, Figure 5.2). The farm indicators, which reflect feed intensification such as the proportion of fodder crops in the cattle diet, the supplementation of concentrated feeds, and farm area allocated to the cultivation of fodder crops were negatively correlated to C loss-cattle$_{(forest)}$ ($\rho = -0.39, -0.21, -0.34$, p < 0.001) and positively correlated to C change$_{(forest)}$ ($\rho = 0.41, 0.22, 0.36$, p < 0.001, Figure 5.2). Farm level fuelwood extraction was positively correlated with non-renewable biomass due to fuelwood harvest from forests (NRB$_{(forest)}$, $\rho = 0.47$, p < 0.001, Figure 5.2).
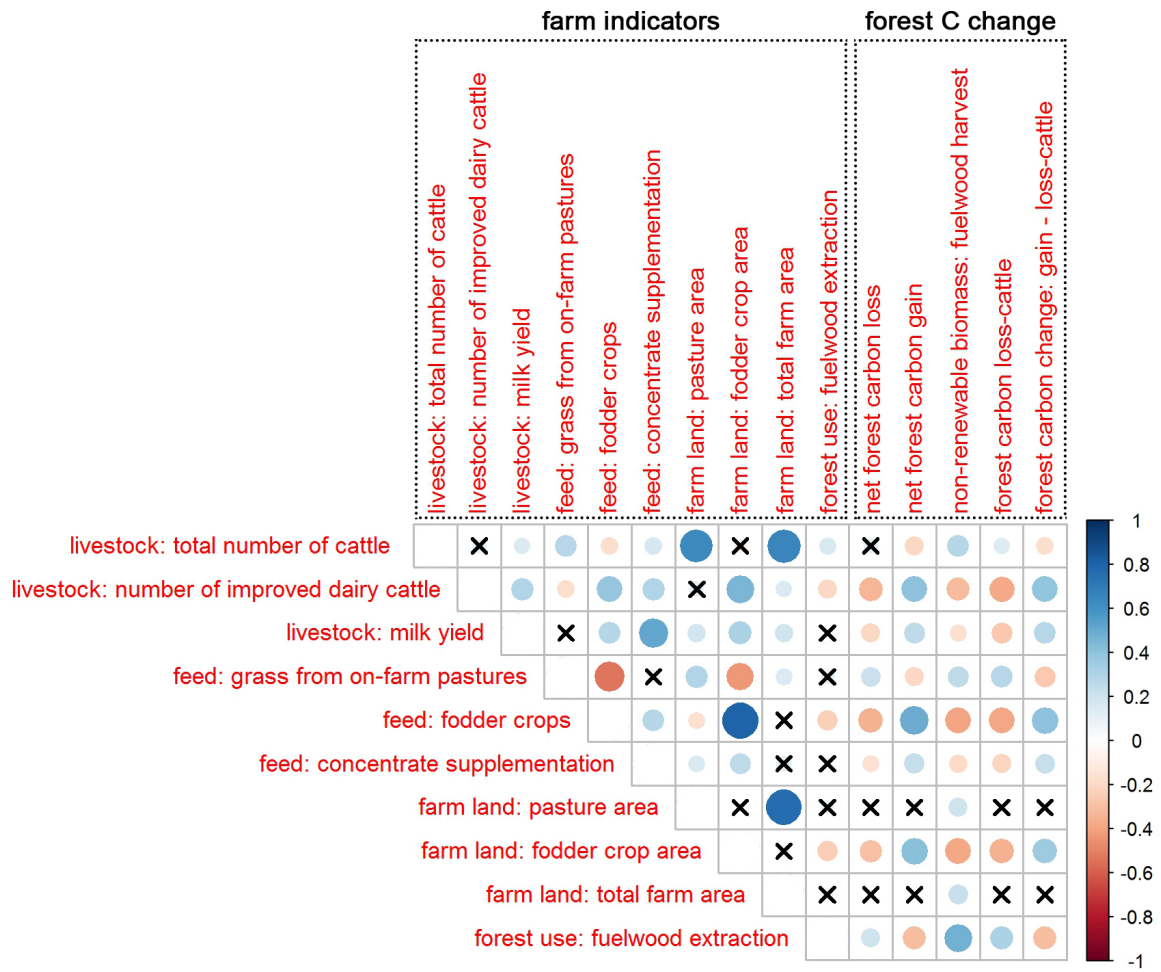
Figure 5.2: Correlation matrix of farm indicators derived from a farm survey and forest carbon (C) change variables: net forest C loss (C $loss_{(forest)}$), net forest C gain (C $gain_{(forest)}$), non-renewable biomass due to fuelwood harvest in forests ($NRB_{(forest)}$), forest C loss related to the presence of dairy cattle (C $loss$-$cattle_{(forest)}$), and forest C change (C $change$-$cattle_{(forest)}$), which includes C $gain_{(forest)}$ and the C loss fraction of dairy cattle (C $loss$-$cattle_{(forest)}$). The forest C loss data were related to farms through farm neighbourhoods, which are distance buffers around farm centroids (r = 5 km). Crosses indicate non-significant correlations.

Farm types differed in the amount of net C $loss_{(forest)}$, $NRB_{(forest)}$, C $loss$-$cattle_{(forest)}$, and forest C change (C $change$-$cattle_{(forest)}$) within their neighbourhoods (r = 5 km, Figure 5.3). Intensified farms showed significantly less mean net C $loss_{(forest)}$, C $loss$-$cattle_{(forest)}$, and C $change$-$cattle_{(forest)}$ (means = 1676.4, 512.0, and -54.6 kg C ha^{-1} yr^{-1} respectively) than small and resource-pour farms (means = 2476.5, 855.5, and -565.8 kg C ha^{-1} yr^{-1} respectively) and large and inefficient farms (means = 2564.6, 980.6, and -842.0 kg C ha^{-1} yr^{-1} respectively) (p < 0.05, Figure 5.3A, C, D). Large and inefficient farms had significantly higher mean $NRB_{(forest)}$ within their neighbourhoods (mean = 656.2 kg C ha^{-1} yr^{-1}) than small and resource-pour farms (mean = 501.0 kg C ha^{-1} yr^{-1}) and intensified

farms (mean = 463.1 kg C ha^{-1} yr^{-1}) (p < 0.05, Figure 5.3B).
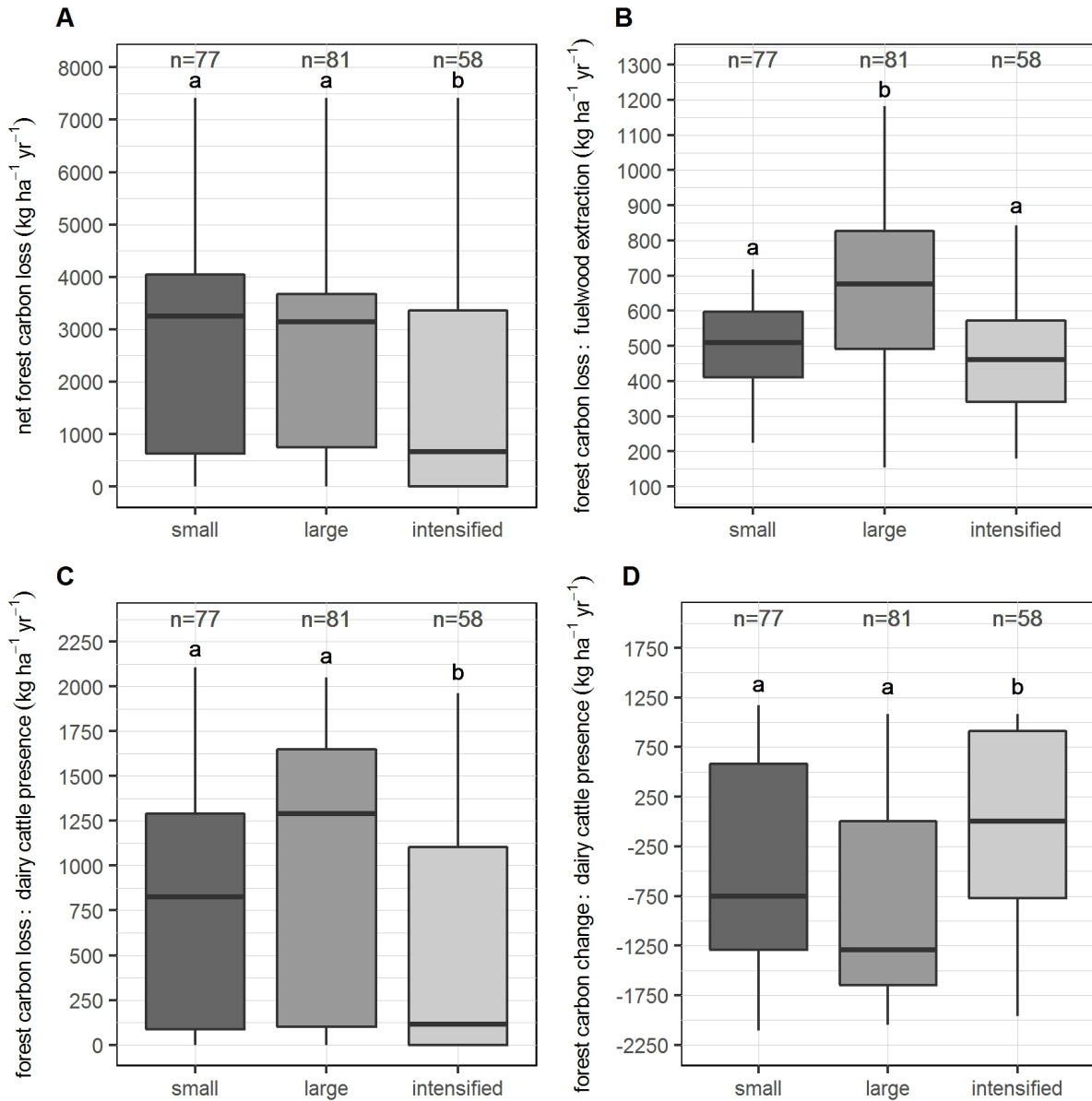
Figure 5.3: Boxplots of farm types and: A) net forest carbon (C) loss (C loss$_{(forest)}$), B) forest C loss from firewood extraction (NRB$_{(forest)}$), C) forest C loss due to the presence of dairy cattle (C loss-cattle$_{(forest)}$), and D) forest C change (C change-cattle$_{(forest)}$), which is C gain$_{(forest)}$ minus the C loss fraction of dairy cattle (C loss-cattle$_{(forest)}$). All C change variables were calculated for farm neighbourhoods with a radius of 5 km. Farm types shown (X-axes) are: small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms. Different letters above whiskers indicate significant differences between farm types computed by using pairwise Wilcoxon rank sum tests (p-values were corrected for multiple testing).

5.3.2 Agricultural and forest mitigation potentials of dairy feed improvements

Reducing forest C loss through closing the yield gap of maize: an example

The analyses show that all water tower forests were affected by C loss (C loss-cattle$_{(forest)}$) and gained C (C gain$_{(forest)}$) between 2003 - 2014. In total, forests across the study area lost 781,546.2 kg CO_2eq yr^{-1} due to dairy cattle (Figure 5.4A, B). Feed improvements on agricultural land, including closing the yield gap of maize used for silage production could potentially reduce the amount of C loss-cattle$_{(forest)}$. This effect was shown for the feed improvement scenario FeCo, which combined feed conservation based on maize silage and concentrate supplementation at medium intensification level (Figure 5.4C). However, the shortage of potentially arable land in the vicinity of forests would lead to forest C loss due to dairy cattle (C loss-cattle$_{(forest)}$) because feed deficits would be met by forest grazing. Closing the yield gap of maize may reduce the amount of arable land required to grow additional maize and, therefore, can alleviate the land shortage as shown for the Maasai Mau Forest region (Figure 5.4C - E). Higher yields of maize in areas close to forests translate into a sufficient availability of improved feeds for dairy cattle, which would result in less C loss-cattle$_{(forest)}$ as forest grazing of dairy cattle is not required.
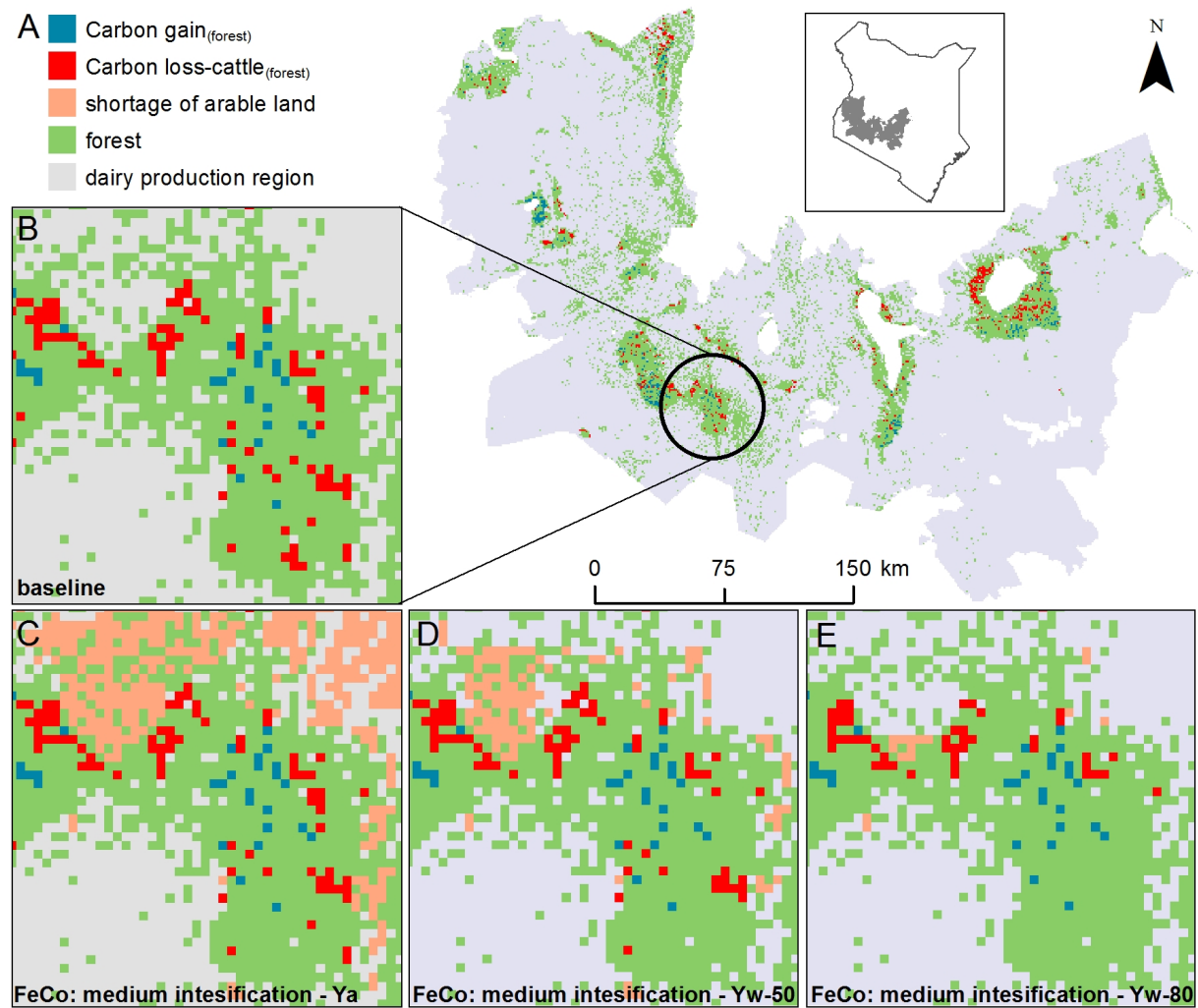
Figure 5.4: Forest carbon (C) loss due to dairy cattle and forest C gain. Map A) shows the baseline C loss-cattle$_{(forest)}$ and C gain$_{(forest)}$ for the entire dairy production region in Kenya. Inset map B) illustrates the baseline C loss-cattle$_{(forest)}$ and C gain$_{(forest)}$ for the Maasai Mau Forest region. For the same forest region, inset maps C – E) show the C loss-cattle$_{(forest)}$ due to the shortage of potentially arable land for the scenario FeCo, which combines feed conservation based on maize silage and concentrate supplementation at medium intensification level. Inset map D) indicates the shortage of potentially arable land and the potential C loss-cattle$_{(forest)}$ with actual maize yields (Ya). Realising the water-limited yield potential of maize (Yw$_{(maize)}$) at 50 % (D) and 80 % (E) may reduce the shortage of potentially arable land and C loss-cattle$_{(forest)}$ within a radius of 5 km.

Total agricultural emissions, emission intensities and forest C change

Across the study area, the feed improvement scenarios increased total agricultural GHG emissions in relation to the baseline by 3.2 – 69.4 $\pm$ 2.8 – 6.5 % (Figure 5.5A). The lowest increase of GHG emissions was indicated for the FoCo scenario at medium inten-

sification level. The highest increase in emissions was shown for the FoFeCo scenario at high intensification level and with actual maize yields (baseline $Ya_{(maize)}$), although GHG emissions from enteric fermentation were reduced by 1.9 – 21.1 %. The FoCo scenario at medium intensification level had the lowest effect on the reduction of emissions from enteric fermentation. In contrast, the FoFeCo scenarios at high intensification level, had the strongest effect on lowering enteric fermentation emissions. Emissions from manure management were increased by up to 100 % through scenarios that included the feed intensification strategy of improving forage quality such as the FoFeCo scenarios at high intensification level. More N was excreted by cattle when the proportion of Napier grass in the cattle diet increased, which led to higher N_2O emissions. GHG emissions from soils allocated to produce cattle feeds were increased by 48.3 – 266.5 %. The lowest increase of feed-related GHG emissions was shown for the FoCo scenario at medium intensification level. The highest increase was indicated for the FoFeCo scenario at high intensification level and with Yw realised at 80 % ($Yw\text{-}80_{(maize)}$). The FoFeCo scenario, which included maize to produce silage at high intensification level and a water-limited yield potential of $Yw\text{-}80_{(maize)}$ led to highest increases in feed-related emissions due to high fertiliser N application rates of 108.2 – 167.9 kg N ha^{-1} required to realise this yield potential. The scenarios that included feed conservation such as FeCo and FoFeCo showed higher emissions from LUC than the FoCo scenario, which did not include silage. Maize required more land to convert pasture into cropland than Napier grass (Figure 5.5A). However, LUC emissions from FeCo and FoFeCo scenarios were reduced by 69.0 – 75.3 % due to the increased yield of maize (from actual $Ya_{(maize)}$ to $Yw\text{-}80_{(maize)}$). There was a reduction of GHG emissions from feed production and LUC by closing the maize yield gap throughout the scenarios that included maize silage (Figure 5.5A). The reduction of emissions from LUC was 2.6 – 4.9 times higher than the increase of emissions from additional fertiliser N. Despite the reduction of emissions from enteric fermentation and LUC by closing the yield gap of maize, none of the feed improvement scenarios could achieve a net reduction of total emissions on agricultural land (Figure 5.5A).

The GHG emission intensity of the baseline was 2.36 ± 0.05 kg CO_2eq kg fat and protein corrected milk (FPCM)$^{-1}$ (Figure 5.5B). Milk production increased in all scenarios by 44.2 – 51.4 ± 1.2 – 2.6 % relative to the baseline. The feed improvement scenario FoFeCo at high intensification level, with actual maize yield did not reduce GHG emission intensity (2.64 ± 0.10 kg CO_2eq kg FPCM^{-1}). Realising $Yw_{(maize)}$ at least at 50 % reduced emission intensity compared to the baseline (Figure 5.5B). The lowest emission intensity was shown for the FoCo scenario at medium intensification level (1.68 ± 0.05 kg CO_2eq kg FPCM^{-1}).

Forest C loss due to dairy cattle (C loss-cattle$_{(forest)}$) was reduced in all scenarios by 47.9 – 270.4 ± 7.4 – 4,935.1 % relative to the baseline (Figure 5.5C). The scenarios with maize and actual maize yields $Ya_{(maize)}$ showed the lowest reduction of C loss-cattle$_{(forest)}$ (by 47.9 – 93.5 ± 121.1 – 789.3 %). Realising the yield potential $Yw_{(maize)}$ at 50 % and

80 % lowered C loss-cattle$_{(forest)}$ (by 157.4 – 225.4 $\pm$ 18.2 – 4,935.1 %) as the shortage of potentially arable land was reduced and the feed availability of maize silage on agricultural land in the vicinity of forests was increased throughout the study area. Hence, closing the yield gap of maize can turn forests into C sinks (Figure 5.5C). Nevertheless, the smallest shortage of potentially arable land, the lowest C loss-cattle$_{(forest)}$ and, therefore, the highest forest C sink potential was indicated for the FoCo scenario. This scenario showed the highest mitigation potential for the agricultural land and for forests due to the highest reduction of agricultural GHG emission intensities (by 28.8 %) and forest C loss (by 270.4 %) while increasing milk production by 45.4 %. For the FoFeCo scenario (Yw-80$_{(maize)}$), high uncertainties (relative SD = 4,935.1 %) propagated into forest C change related to the presence of dairy cattle due to high variances in input datasets of C loss$_{(forest)}$, NRB$_{(forest)}$ and C gain$_{(forest)}$ that were used to estimate C change-cattle$_{(forest)}$, which is close to zero (Figure 5.5C).
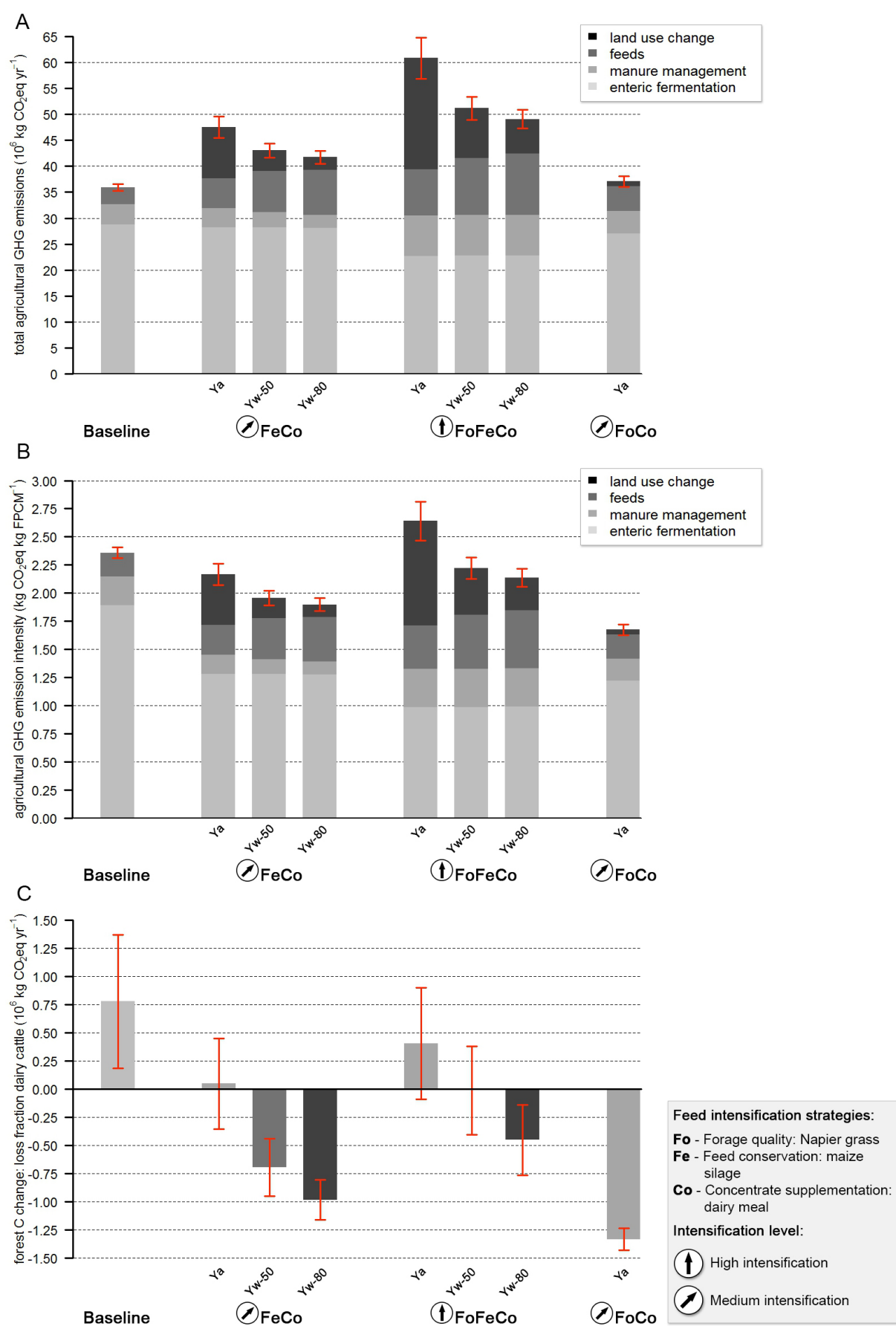
Figure 5.5: Caption follows on the next page.

Figure 5.5: Agricultural GHG emissions and forest carbon (C) change related to smallholder dairy production. Plots show: A) aggregated total agricultural GHG emissions, B) agricultural GHG emission intensity per kg fat and protein corrected milk (FPCM), and C) aggregated forest C change due to dairy cattle (C change-cattle$_{(forest)}$). Bars indicate baseline and three feed improvement scenarios, which represent combinations of three feed intensification strategies at medium or high intensification levels. The two scenarios that included maize silage use actual maize yields and two levels of water-limited yield potentials (Yw$_{(maize)}$). Ya$_{(maize)}$ = actual baseline yields, Yw-50 = Yw$_{(maize)}$ realised at 50 %, Yw-80 = Yw$_{(maize)}$ realised at 80 %. CH$_4$, N$_2$O emissions, and forest C change were converted to kg CO$_2$eq. Agricultural GHG emission sources include i) CH$_4$ emissions from enteric fermentation, ii) CH$_4$ and N$_2$O emissions from manure management, iii) N$_2$O emissions from feed production, including manure deposition on pasture, manure application to fodder crops, crop residues from fodder crops and synthetic fertilizer application to fodder crops and emissions from concentrate supplementation, and iv) N$_2$O and CO$_2$ emissions from land use change, including N mineralization and loss of soil organic carbon. Error bars indicate relative standard deviations.

5.4   Discussion

5.4.1   Intensification of smallholder dairy farms and forest C change

Total number of cattle on smallholder farms in the dairy production region was positively linked to the loss of forest C, which is related to the presence of dairy cattle in forests located within farm neighbourhoods (Figure 5.2). This is an important finding because there are no quantitative assessments of the impact of livestock production on tropical forest systems in SSA. Hosonuma et al. (2012) reported that 8 - 12 % of the forest disturbance across SSA can be attributed to livestock grazing in forests. Brandt et al. (2018a) found that cattle grazing inside tropical mountain forests in Kenya is prevalent at 75 % of the forest disturbance spots visited during a forest survey. The use of mountain forests by smallholder farmers to graze livestock is also reported for Ethiopia (Baudron et al., 2017; Duriaux Chavarría et al., 2018). Positive effects on dietary diversity and nutrient balances on farms located in the vicinity of the forests (distance = 5.5 km) that are used for grazing were found. The authors argue that the amount of herbaceous biomass removed from the forest through grazing is likely to be lower than the regrowth rates. However, these studies did not quantify the impact of forest grazing on forest disturbance and the resulting C loss. In contrast, Brandt et al. (2018a) reported an increased risk of forest disturbance by up to 5 % due to higher total numbers of cattle on smallholder farms within their farm neighbourhoods (maximum forest distance = 5 km). The results of this study show a net forest C loss due to dairy cattle within the neighbourhoods of smallholder farms ranging in average between 54.6 – 842.0 kg C ha^{-1} yr^{-1} (Figure 5.3D).

Farm indicators of improved cattle feeds and intensified milk production on smallholder farms such as the proportion of fodder crops in cattle diet, concentrated feed supplements, farm area allocated to the cultivation of fodder crops, the number of improved dairy cattle and milk yield were negatively related to forest C loss that can be attributed to the presence of dairy cattle. The same set of indicators was positively related to forest C change, which is forest C gain minus forest C loss due to dairy cattle (Figure 5.2). Intensification of smallholder agriculture is in general postulated to reduce the pressure on forest ecosystems. Higher farm productivity is likely to reduce the demand for land (Campbell et al., 2014). Valin et al. (2013) showed in a modelling exercise that intensification of livestock production can lower GHG emissions from deforestation in SSA, through improved management practices such as intensified feeds. A modelling study conducted in Brazil reported that the intensification of dairy production can reduce the pressure on forests through pasture intensification (Caviglia-Harris, 2018). Brandt et al. (2018a) reported lower risks of forest disturbance by up to 7 % within the neighbourhoods of farms that had improved dairy cattle, attained higher milk yields and fed improved cattle feeds. In addition, this study indicated that intensified farms have less C loss related to the presence of dairy cattle and gained more C in adjacent forests than non-intensified farms within their neighbourhoods of r = 5 km (Figure 5.3C, D). Brandt et al. (2018a) showed that intensified farms affected forest disturbance less within their neighbourhoods than non-intensified farms.

The intensification of smallholder dairy production in Kenya based on more nutritious cattle feeds and improved dairy cattle appears to follow the general notion that an intensification of extensive production systems reduces the negative impact on local, natural ecosystems such as forests (Wollenberg et al., 2011). Thus, apart from the agricultural mitigation potential of intensification also quantified by Ortiz-Gonzalo et al. (2017) and Brandt et al. (2018b), smallholder dairy production in Kenya shows potential to mitigate GHG emissions from forests. However, the spatial distance of the relationship between farming practices and forest C loss (5 km) was determined empirically (Brandt et al., 2018a) and should be taken with caution when extrapolating to other regions. This distance depends on the region-specific land use dynamics and has to be assessed based on farming systems and landscape configurations.

5.4.2   Mitigation of GHG emissions from smallholder dairy production across land use sectors

This study showed that dairy feed improvements and the increase in feed productivity mitigates i) GHG emission intensities on agricultural land through higher milk yields and ii) the loss of C from forests related to the presence of dairy cattle through reduced grazing inside forests (Figure 5.5). The increase of livestock productivity through higher feed digestibility has been reported to benefit agricultural mitigation mainly through

increased feed conversion efficiency and lower CH_4 emissions from enteric fermentation (Hristov et al., 2013a; Knapp et al., 2014; Herrero et al., 2016). In addition, closing the yield gaps of feed crops can play a major role in avoiding CO_2 emissions from LUC (Valin et al., 2013; Herrero et al., 2016; Weindl et al., 2017). The increased N_2O emissions due to higher fertiliser N application rates to close the yield gap of maize could be offset by reduced CO_2 emissions from LUC on agricultural land due to lower land requirements (Figure 5.5A). This finding is in line with other modelling exercises on the mitigation of livestock-related AFOLU emissions at a coarser continental scale for SSA (Valin et al., 2013; Havlík et al., 2014). The potential to close the yield gap of maize in Kenya is high (van Ittersum et al., 2013). Apart from being used as livestock feed, maize is a staple crop in Kenya and widely used for human consumption. However, the production of maize in Kenya does not meet the demand (van Ittersum et al., 2016). The country relies, therefore, on imported maize (USDA, 2017). Consequently, increasing maize yields is necessary to assure food security, especially if the livestock sector invests further into the promotion of grain-based livestock feeds. Opportunities of yield intensification increase the feasibility to implement feed improvement options, given the constraint of land availability, especially in regions that face shortages of arable land due to high densities of human and livestock populations (Gerssen-Gondelach et al., 2017; Brandt et al., 2018b). Smallholder farmers across the Kenyan highlands lack frequently the required land to grow sufficient amount of feeds with higher energy and protein density (Bebe, 2008), which leads to off-farm grazing on common land such as forests.

Throughout the study area, forest C loss related to the presence of dairy cattle could be reduced by feed improvement scenarios. For scenarios that included the strategy of feed conservation through maize silage, such as FeCo and FoFeCo, higher reductions of forest C loss were achieved by realising higher water-limited yield potentials for maize. Less shortage of potentially arable land due to the improved availability of higher quality feeds on agricultural land minimised the need to compensate the lack of feed through forest grazing (Figure 5.4 & Figure 5.5C). Realising the water-limited yield potential for maize at least at 50 %, can turn forests into C sinks as the C gain fraction overweighed the C loss due to dairy cattle (Figure 5.5C). That the increase of feed and livestock productivity can result in land sparing effects, which reduce the pressure on natural ecosystems such as forests and lower GHG emissions from LUC has been shown by several modelling studies at a coarse continental scale for SSA (Valin et al., 2013; Havlík et al., 2014; Kreidenweis et al., 2018). However, these studies did neither include empirical bottom-up information on farm practices nor spatially-explicit data on forest C loss related to the presence of cattle, which are required to identify location-specific effects of certain feed improvement options on forests and to detect land constraints that limit the feasibility of mitigation interventions.
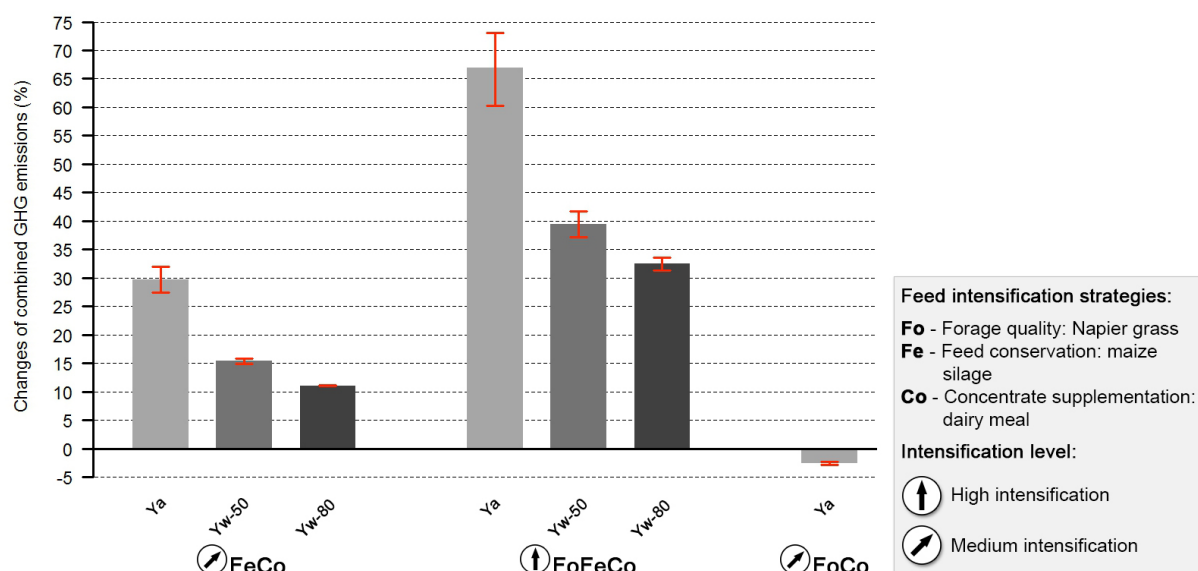
Figure 5.6: Changes of combined total agricultural GHG emissions and forest carbon (C) change, which is forest C gain minus the C loss fraction related to dairy cattle. Bars show changes of combined GHG emissions between feed improvement scenarios and the baseline. $Ya_{(maize)}$ = actual baseline yields, Yw-50 = $Yw_{(maize)}$ realised at 50 %, Yw-80 = $Yw_{(maize)}$ realised at 80 %.

Land requirements and the resulting shortage of potentially arable land were lowest for the FoCo scenario, which included the strategies of forage quality and concentrate supplementation. Almost no cattle grazing inside forests to compensate the lack of feed on agricultural land was needed for this scenario. The related forest C loss was reduced by 270 %, which led to the lowest forest C loss among all scenarios (Figure 5.5C). Consequently, the forest C sink potential was highest compared to all other scenarios. The FoCo scenario could result in a net benefit for AFOLU mitigation by reducing GHG emissions across the agricultural and forest sectors effectively, since total agricultural GHG emissions and forest C change combined were 2.5 % lower than in the baseline (Figure 5.6). The national dairy master plan and the dairy NAMA seek for feed options that realise milk yield gains and mitigation benefits (Government of Kenya, 2010, 2017b). Therefore, this feed improvement option could represent a promising candidate to be targeted by the dairy sector.

5.4.3 Policy relevance: targeting and financing the implementation of CSA practices

The added value of this study emerges from the combined mitigation potential of smallholder intensification for the entire dairy production region in Kenya by linking agricultural production and the use of forests. The mitigation estimates were quantified across

land use sectors based on empirical information from the ground (farm and forest surveys), using spatially-explicit input data on milk production, GHG emissions and forest C loss at high spatial resolution. The approach followed can shed light on the effectiveness of potential CSA practices to mitigate AFOLU emissions in the context of developing agricultural production such as dairy production in Kenya at sectoral level. Multi-objective modelling tools that aim to support decision-making processes on prioritising CSA practices based on evidence by integrating qualitative and quantitative information at various spatial and temporal scales have been developed recently (Brandt et al., 2017; Dunnett et al., 2018). This study provides input data for such tools to explore the feasibility of CSA practices in terms of land availability and their effectiveness to mitigate GHG emissions from agricultural land and forests.

Policy instruments that aim to enable the development of climate-smart food production sectors such as NAMAs have to rely on evidence, which shows the potential to realise 'win-win' situations that benefit smallholder farmers and contribute to climate mitigation goals (e.g. NDCs) (Lipper et al., 2014; Grassi et al., 2017). In addition, mitigation policies need to support the creation of economic incentives, which are required to foster the implementation of targeted CSA practices and to reduce potential adoption barriers (Lipper et al., 2014). Climate financing schemes could use quantitative information on productivity gains and mitigation potentials of specific feed improvement options to inform decisions on the investment into candidate practices that are targeted to be implemented at farm level, yet effect largely the broader landscape. Agricultural practices affect the use of tropical forests and their C dynamics, e.g. through the removal of biomass due to grazing or fuelwood harvest (Pearson et al., 2017; Brandt et al., 2018a). This study shows that intensified feed and livestock production helps to reduce GHG emissions from forests. This finding emphasises the alignment of climate mitigation policies and financing mechanisms across the land use sectors of agriculture and forestry to achieve effective mitigation outcomes, i.e. the net reduction of AFOLU emissions. Therefore, policy frameworks are required that integrate the CSA concept and policies on 'Reducing emissions from deforestation and forest degradation' (REDD+) (Carter et al., 2018a).

5.4.4   Limitation and future research

This is the first study that quantified the impact of livestock on forest C change by using spatially-explicit, remote-sensing data. Measurements obtained from grazing experiments for different forest and cattle types are required to estimate the direct impact of cattle on above and belowground carbon stocks in forests (e.g. Schulz et al., 2016). Animal movement patterns can be traced through telemetry analyses to gain knowledge about distances that cattle walk and the time they spend inside forests (Gao et al., 2016). Aggregated spatially and temporally, this ground-truth information could be used to calibrate and validate the estimates of forest C change related to cattle grazing derived

from remote-sensing data. The approach to improve maize yields, chosen in this study, was to increase the N application from external inputs of synthetic fertiliser. Realising the water-limited yield potential of maize at 80 % required high N inputs of up to 108 - 168 kg N ha^{-1} (van Bussel et al., 2015). Fertiliser, transport and labour costs of high N application rates, however, may render the intensification of feed production economically unfeasible or simply uninteresting for smallholders, if economic returns from milk sales do not justify these investments. Consequently, moderate application rates of synthetic fertiliser of 60 – 90 Kg N ha^{-1} could be more realistic from a farmer's point of view in the Kenyan highlands (Mucheru-Muna et al., 2007, 2014). Therefore, reliable market prices for milk, improved access to markets are required for smallholders to adopt practices that close the yield gap of feed crops such as maize. To increase the adoption of dairy feed improvements, assessments of agricultural productivity and climate change mitigation have to be coupled with cost-benefit analyses that take into account seasonal variation of costs and returns and farm distances to markets to find optimal cost-benefit ratios for smallholder farmers. Moreover, apart from abiotic and biotic factors, crop management practices influence the improvement and the stability of maize yields (Kiboi et al., 2017; Rattalino Edreira et al., 2018). Hence, the dissemination of knowledge about best practices through agricultural extension is crucial.

Greater efforts to intensify smallholder agriculture have to be undertaken to improve crop and livestock yields and to achieve food security goals in SSA (van Ittersum et al., 2016). More food produced from existing agricultural land will be required to feed the continent's fast growing population. Considering the shrinking of farm sizes and the increasing shortage of arable land in SSA (Vanlauwe et al., 2014), research at landscape level has to be strengthened to explore the boundaries within which smallholder agriculture can be intensified sustainably to safeguard food security. For instance, this study did not include international C leakage effects that potentially result from the displacement of GHG emissions due to the increased demand for feed imports, which could trigger cropland expansion into natural ecosystems outside the study area (Styles et al., 2018). The market-oriented stimulation of agricultural production sectors can lead to rebound effects due to reduced prices, higher demand and, therefore, further increasing production (Valin et al., 2013). Analyses of AFOLU mitigation need to integrate various scales ranging from farm, landscape to sectoral level and have to be coupled with economic models to further improve the estimates of effective mitigation potentials by incorporating feedbacks between markets and agricultural development.

5.5   Conclusions

Dairy feed improvements may have climate change mitigation benefits for agriculture and forests and can contribute to food security by increasing milk yields in Kenya. Closing

the yield gap of maize used to produce silage could increase the feasibility to implement improved grain-based cattle feeds, and can reduce GHG emission intensities from milk production and the loss of C in local forests. However, the largest mitigation benefits across land use sectors could be achieved through the improvement of forage quality and the supplementation of concentrates. These findings emphasise the importance to assess the impact of specific CSA practices prior their targeting and prioritisation at high spatial resolution to identify mitigation potentials across land use sectors and to reveal implementation constraints such as land availability. General recommendations derived from top-down assessments conducted at coarse spatial scales risk to miss differences between candidate options identified by using bottom-up and high resolution data, which may render the implementation of targeted interventions unfeasible or may reduce the effectiveness of mitigation outcomes. Integrated mitigation and development policy frameworks and climate financing instruments could benefit from the approach followed and the information provided to prioritise the most effective CSA practices and to invest into bundles of options that show the most promising potentials for sectoral development and climate mitigation.

Acknowledgments

Chapter 6

Synthesis

6.1 Main findings

The objectives of this thesis were to i) improve the robust prioritisation and targeting of CSA practices at national level and to ii) shed light on the potential of intensified dairy feeds to reduce direct and indirect GHG emissions effectively. Four research questions were defined in Section 1.5 to address these objectives. The main findings for each question are summarised below, based on results from the previous chapters.

6.1.1 How can 'multi-criteria decision-making' support national climate change adaptation and mitigation planning to target CSA practices? (RQ A)

Adaptation and mitigation measures have to be prioritised and targeted robustly to transform agriculture into climate-smart food production systems at large scale. The multi-criteria decision-making framework "targetCSA" was developed in Chapter 2 to explore targeting options for adaptation and mitigation practices based on spatially-explicit indices of climate change vulnerability and CSA suitability. The vulnerability index shows how urgent an implementation of CSA interventions would be at certain locations. CSA suitability indicates the technical feasibility of these interventions. The indices were derived from the integration of spatially-explicit data such as biophysical, social and economic indicators of climate change vulnerability and proxy data on CSA suitability (Table 2.1). An optimisation model was used to find combinations of stakeholder preferences regarding the prioritisation of certain CSA practices that approach the potential consensus achieved through minimising the disagreement between all stakeholder preferences. Vulnerability and suitability indices were weighed by the preferences of involved stakeholder groups and the aggregated consensual preferences to map and explore the potential effects of various decision-making outcomes based on group-specific preferences and the computed preference weights that approach the consensus of all stakeholder groups. Facing decision-makers with the effects decisions based on their 'point of view' may have and contrasting these with a consensus scenario can guide further negotiations to find agreed solutions in a decision-making process. The robustness of CSA-targeting outcomes can be increased by applying "targetCSA", as it helps to explore the potential of CSA-practices based on evidence (data-driven) and the minimised disagreement among stakeholders, which could lead to more informed and transparent decisions.

The applicability of "targetCSA" was demonstrated in Kenya. Stakeholders from various sectors such as the Kenyan government, NGOs, science and the private sector involved in the development of the national CSA strategy were interviewed about the importance they assign to sets of vulnerability indicators and CSA practices. The stakeholder groups weighed the importance of vulnerability indicators and CSA practices differently accord-

ing to their agendas and interests (Figure 2.3). High dissent among stakeholders was shown for the biophysical vulnerability indicators 'annual precipitation' and 'soil organic matter' and for the CSA practices 'improvement of soil fertility and soil management' and 'identification and establishment of agroforestry practices'. Decision-making processes on complex issues such as climate change adaptation and mitigation are often characterised by disagreements among involved stakeholders. A disagreement among opinions on which CSA practices should be prioritised and targeted can slow down decision-making processes or may prevent legitimate decisions in cases that are highly conflict-prone. "targetCSA" can be used to make these differences explicit by mapping the resulting CSA-targeting scenarios and complement them with a scenario that reflects the minimised dissent among stakeholder opinions.

Furthermore, different consensus modes can be explored by minimising the dissent towards the majority of stakeholder preferences or towards the minority, which are preferences that are far apart from the majority. In this thesis, CSA potentials based on three different consensus scenarios were mapped (Figure 2.4). As a result, different regions in Northern and Eastern Kenya would be prioritised by decision-makers. Following the majority preferences, larger areas with high CSA potential concentrate in the Northwest, Northeast and Central Eastern parts of Kenya, whereas the minority would prioritise larger areas located in the North and Northeast of Kenya. A third consensus scenario that reflects the compromise between majority and minority (i.e. the most balanced trade-off) highlights larger areas with high CSA potential where both consensus modes agree, which is the Northeast of Kenya. Mapping scenarios of CSA potentials based on different consensus modes allows to explore disagreement between opinions of the majority of stakeholders and a minority group. Visualising potential effects of disagreement between stakeholder groups or the majority and minority of stakeholders could, therefore, help to find solutions in a conflict-prone decision-making process, for instance in cases where marginalised groups are involved.

Stakeholder opinions may differ over time, as shown in Figure 2.5, due to changes in knowledge, interests and organisational agendas. Relying on 'snap-shot' opinions would fail to capture, illustrate and finally reduce the uncertainty that is introduced by varying stakeholder opinions. In this thesis, a change in importance was shown most drastically for the CSA practice 'improvement of soil fertility and soil management', which was ranked as fourth important CSA practice during the first expert survey and was ranked as most important during the second survey. "targetCSA" can be used iteratively to monitor and validate the importance that stakeholders assign to vulnerability indicators and CSA practices during the process of CSA prioritisation and targeting (Figure 2.1). Decisions to target certain CSA practices at specific locations can be assumed to be more robust and legitimate once stakeholder opinions are reflected by stabilised patterns of preferences.

"targetCSA" was in general designed to structure complex decision-making processes by exploring preference scenarios derived from stakeholders based on quantitative and qualitative information to support the prioritisation and targeting of relevant CSA practices. To apply the framework in a livestock mitigation case, for instance to reduce GHG emissions from smallholder dairy production, input data should be adjusted to reflect this CSA-targeting context. Vulnerability indicators at high spatial resolution could include water and feed availability during dry seasons (e.g. mapped variability of vegetation and water indices based on remote-sensing time-series), animal health such as the occurrence of vector-borne diseases (e.g. mapped suitability of occurrence of vector species), yield gap of feed crops (e.g. mapped difference between actual yields and potentially attainable yields). Data that indicate the suitability of CSA practices could include the mapped density of local and improved dairy cattle, the mapped shortage of arable land, which shows the feasibility to implement certain livestock feed improvement practices (Chapter 3) and the mapped potential of certain feed improvement practices to reduce GHG emissions from agriculture and forests effectively (Chapter 5). The spatial extent of these input data can be constrained to the dairy production area in Kenya. Stakeholder involvement should include experts from dairy, feed and breeding companies, dairy cooperatives and farmer associations, livestock and nutritional scientists as well as agricultural and environmental ministries at county and national level.

6.1.2 Which climate change mitigation options in the Kenyan dairy sector contribute to climate mitigation and food production targets defined at national level? (RQ B)

In Chapter 3, the potential of livestock feed improvements to contribute to climate change mitigation and productivity targets at national scale was assessed. Feed alternatives that have higher protein and energy content are generally proposed to increase milk yields and to reduce GHG emission intensities in smallholder livestock production systems (Hristov et al., 2013a; Knapp et al., 2014). However, GHG emissions from LUC and the shortage of potentially arable land (e.g. grassland) required to cultivate feed crops may compromise mitigation efforts or render the implementation of promising practices unfeasible at certain locations. The analyses of feed improvement scenarios based on combinations of three feed intensification strategies (Figure 3.2) showed that feed conservation based on maize silage requires a high amount of land to be converted into cropland, which would lead to higher GHG emissions from LUC. LUC emissions from these scenarios were on average ten times higher than LUC emissions from scenarios, which included the strategy of forage quality improvement, by using Napier grass, instead of using maize to produce silage (Figure 3.3). Overall, scenarios that included the strategy of feed conservation did not reduce GHG emission intensities in regard to the baseline (Figure 3.3). In contrast, the improvement of forage quality and the supplementation of dairy concentrates reduced emission intensities

by up to 31 % (Figure 3.6). Implementing the improvement of forage quality would be more feasible in terms of available potentially arable land compared to scenarios that included maize silage used for feed conservation. Only 0.5 – 2.8 % of the agricultural land throughout the study area lacked the amount of potentially arable land that would be required to implement forage-based feed improvements. On the contrary, 26 – 50 % of the agricultural land across the study area would lack the potentially arable land required to implement scenarios that included maize silage (Figure 3.4). The shortage of potentially arable land shown for these scenarios resulted from their high demands for arable land due to additional maize that has to be cultivated in addition to existing maize, which was assumed to be grown to produce food and, therefore, was unavailable as cattle feed.

Moreover, the feed improvement scenarios were assessed to quantify their relative contribution to Kenya's climate change mitigation and milk yield targets defined in the country's NDC and in its national dairy master plan (Government of Kenya, 2010, 2015a). All scenarios increased the milk yields and contributed to the milk yield target by fulfilling it partially by 17 – 43 % (Figure 3.4). Several scenarios that included the feed conservation strategy at high intensification level exceeded the tolerable GHG emissions increase of the NDC target due to high GHG emissions from LUC (Figure 3.4). The medium intensification variants of these scenarios partially achieved the milk yield target by 17 - 39 % and increased total GHG emissions at a tolerable level according to the NDC target, yet their implementation would be unfeasible on 24 – 26 % of the agricultural land due the shortage of potentially arable land. The two scenarios that included the improvement of forage quality and the supplementation of dairy concentrates showed relatively high achievement rates in terms of the milk yield target (38 – 40 %) and increased only marginally total GHG emissions by 4 – 13 %. This increase ranged at the lower end of tolerable GHG emission increases as defined in the NDC. Based on these assessments, it can be inferred that alternative dairy feeds that are based on the improvement of forage quality and the supplementation of dairy concentrates are feasible to implement in the majority of areas across Kenya's dairy production region, are beneficial for smallholder farmers, and contribute to planning targets at national level. Increased milk yields result potentially in higher farm incomes (Bryan et al., 2013). However, the high intensification variant of these two scenarios requires farmers to invest more in dairy concentrates (6 kg day^{-1}), which could render it economically less viable for smallholders in Kenya. The medium intensification scenario, however, achieved a relatively high gain of milk yield with moderate increases of concentrate supplementation rates (3 kg day^{-1}) and, therefore, shows a lower investment risk for smallholders (Bebe et al., 2002).

Uncertainties of emission parameters used to model GHG emissions influenced total GHG emissions and emission intensities (Figure 3.3). Emission parameters were inputs to the GHG emission module of the LivSim model. The ranges of emission parameters were sampled by using the LHS approach. The methane conversion factor showed the strongest effects on the variation of modelled baseline emissions, which varied by about ±7 %. The

SOC emission factor used to estimate GHG emissions from LUC, influenced the variation of scenario emissions most. For instance, the scenario that included the strategy of feed conservation and forage quality at high intensification level varied by about ± 48 %. LUC was reported to be a significant source of uncertainty for the estimation of GHG emissions from livestock production (van Middelaar et al., 2013). Since GHG emissions from LUC play an important role in environmental impact assessments of feed production, efforts in SSA must be strengthened to reduce the related uncertainty by measuring the effects of LUC (e.g. the conversion of grassland into cropland) on SOC and by using dynamic land use models that incorporate interactions between vegetation and soils. However, these models have to be parametrised comprehensively. The empirical data required are often missing in SSA.

Chapter 3 shows that *ex-ante* impact assessments of potential feed improvements are required for a successful mitigation of GHG emissions from livestock production. Mitigation planning based on general recommendations or top-down analyses at coarse spatial scales face the risk to neglect local realities, which can be uncovered by analyses that include bottom-up information. More detailed, spatially-explicit assessments that incorporate i) the effects of converting grassland to cultivate alternative feed crops with higher digestibility and ii) the availability of land (e.g. grassland) help to decide whether certain practices result in mitigation and productivity benefits and whether their implementation is feasible at specific locations. This is especially relevant for regions such as the Kenyan highlands, which are characterised by small farm sizes and high population density (Herrero et al., 2014). Relating the effects of CSA practices on climate change mitigation and agricultural production at sectoral level to national targets enables the performance monitoring of CSA practices in regard to integrated policies such as NAMAs, which focus on low-emissions development (LED) of economies, and international commitments such as UNFCCC. These assessments could also help to define realistic sectoral targets, e.g. for the agricultural sector in Kenya. Kenya has to comply with its NDC, yet misses quantitative targets that reflect sectoral responsibilities to contribute to the achievement of the target at national scale.

6.1.3 How does the intensification of smallholder dairy farming affect forest disturbance? (RQ C)

The intensification of smallholder farming has been proposed to increase food production on existing agricultural land while releasing the pressure on natural ecosystems (Garnett et al., 2013). The effects of smallholder dairy farm practices, characteristics and types on forest disturbance were analysed in Chapter 4 to determine whether an intensification on smallholder dairy farms could reduce the impact on the Mau Forest, the largest remaining montane forest complex in East Africa, located in the Kenyan highlands. The forest plays a critical role as 'water tower' for the entire region. It is the headwater area for 12 major

rivers and provides freshwater to about five million people (Jacobs et al., 2017). Firewood extraction and cattle grazing inside forests were found to be the dominant drivers of forest disturbance present at about 75 % of forest disturbance spots sampled during a forest survey. Only sparse information exists so far on the magnitude of forest disturbance related to fuelwood extraction and cattle grazing inside forests in SSA. According to Hosonuma et al. (2012), the relative contributions of fuelwood extraction and forest cattle grazing to forest disturbance are 58 % and 8 % respectively for countries in SSA, which are in their late forest transition phase such as Kenya. Pearson et al. (2017) estimated that fuelwood extraction contributes about 30 % to the GHG emissions from tropical forests. However, none of these studies provides quantitative information about the impact of smallholder agriculture on forest disturbance based on observational data. From this thesis, the relative impact of farm-related practices such as firewood extraction and cattle grazing inside forests on forest disturbance and resulting GHG emissions can be assumed to be higher for montane forests located in the Kenyan highlands.

Farm practices and characteristics were used to calculate farm indicators for smallholder dairy farms located close to forests during a farm survey. Within farm neighbourhood sizes of r = 2 - 5 km, farm indicators such as total number of cattle, farm size and firewood collection rates were related to higher risks of forest disturbance. Risk increases ranged between 1 – 10 % (Figure 4.5). On the contrary, higher milk yields, and indicators that reflected improved cattle feeds such as larger farm area allocated to fodder production and increased supplementation of dairy concentrates were related to lower risks of forest disturbance. Risk decreases ranged between 2 – 7 % (Figure 4.5).

Moreover, different farm types were derived from the farm indicators in Chapter 4 such as small and resource-poor farms, large and inefficient farms, and intensified farms. These farm types differed in their effects on forest disturbance. Intensified farms showed in general a lower proportion of disturbed forest within their neighbourhoods (r = 2 - 5 km) than the non-intensified farm types (Figure 4.8). The effects of farm types on forest disturbance that was specifically related to firewood extraction and cattle grazing inside forests, indicated a similar pattern. Intensified farms had a lower proportion of disturbed forest related to firewood extraction and cattle grazing in their farm neighbourhoods (r = 2 – 3 km) than the two non-intensified farm types (Figure 4.9). More improved dairy cattle, higher milk yields, higher proportions of improved cattle feeds, and more frequently planted on-farm trees were found on intensified farms than on non-intensified farms (Figure 4.6). Improved cattle, cattle feeds and more trees planted on farms, which are potentially available as fuelwood supply reduce the need to use forest resources and lower the risk to disturb forests located in close proximity to smallholder farms. However, a recent study conducted in a landscape characterised by smallholder agriculture and mountain forests in Ethiopia, reported positive effects between livestock grazing in forests and livestock productivity (Duriaux Chavarría et al., 2018). Farms located closer to forests (5.5 km) showed higher milk yields and more positive nutrient balances than farms

located further away (11 km). Although quantitative estimates of forest disturbance were not included, the authors argue that the sustainable use of forest resources may increase the performance of adjacent smallholder farms.

Chapter 4 integrates empirical ground data and results from a forest change detection approach based on remote-sensing time series to relate smallholder farming and forest disturbance, which is a novel approach to assess agriculture-forest interactions. Forest disturbance and resulting GHG emissions caused by unsustainable land use practices can be alleviated by intensifying smallholder dairy farming, which is shown to realise 'win-win' potentials for smallholders through milk yield increases, and for the mitigation of agricultural GHG emissions (Chapter 3). The novel approach and the findings derived from Chapter 4 open new avenues to mitigate AFOLU emissions across the agricultural and forestry sectors (Chapter 5).

6.1.4   What is the potential of livestock intensification options to reduce GHG emissions from agriculture and forests? (RQ D)

The potential of dairy feed improvements to mitigate GHG emissions from agricultural land directly and from forests indirectly was assessed in Chapter 5 based on insights obtained from Chapter 3 and 4. Independent datasets of C change, including C gain and C loss (Baccini et al., 2017) were used to estimate the forest C loss related to the presence of dairy cattle (Figure 5.1). Farm indicators and types that were analysed in Chapter 4 were linked to forest C change variables to test whether the intensification of smallholder dairy farms can be associated with reduced forest C loss in their neighbourhoods. Farm indicators related to improved dairy cattle and cattle feeds such as the proportion of fodder crops in cattle diet, the supplementation of concentrated feeds, and farm area allocated to the cultivation of fodder crops and increased milk yields were negatively linked to forest C loss related to the presence of dairy cattle. The same set of indicators was positively linked to forest C change, which is forest C gain minus C loss related to the presence of dairy cattle (Figure 5.2). Lower forest C loss related to the presence of dairy cattle and higher forest C change (negative values closer to zero) were found in neighbourhoods of intensified farms compared to non-intensified farms (Figure 5.3). These results show that an intensification of smallholder dairy farming could reduce C loss from forests through the cultivation of improved cattle feeds on agricultural land, which lowers the need to use forests as grazing land for dairy cattle.

Using the methodology developed in Chapter 3 (Figure 3.1), three feed improvement scenarios were assessed regarding their potential to mitigate both GHG emissions from agricultural land and forest C loss. The latter one was analysed based on the scenario demand for land and the availability of potentially arable land required to cultivate additional maize (feed conservation strategy) and Napier grass (forage quality strategy). The

shortage of grazing land that could be converted into cropland close to forests was assumed to cause cattle grazing in forests to meet the demand for feeds. In addition, the three feed improvement scenarios were complemented by variants that closed the yield gap of maize by realising the water-limited yield potential at 50 % and 80 %. GHG emissions from higher application rates of synthetic fertiliser required to close the gap of maize yields increased by up to 267 %. In contrast, GHG emissions from LUC related to the conversion of grassland into cropland needed to cultivate additional feed crops was reduced by up to 75 %, which outbalanced the emission increase from soils due to higher fertiliser application rates (Figure 5.5). The effect of reduced GHG emissions from avoided LUC was up to five times higher than the increase of fertiliser-related emissions. Consequently, GHG emission intensities of scenarios that included the strategy of feed conservation by using maize silage were lowered by up to 20 % and less arable land would be required to implement them. The lowered demand for arable land to cultivate alternative dairy feeds close to forests reduced forest C loss due to avoided grazing of dairy cattle inside forests by up to 94 % (Figure 5.5). However, the scenario that included the strategies of improved forage quality and supplementation of dairy concentrates showed the highest reduction in emission intensity (29 %), the lowest demand for arable land and the highest reduction of forest C loss (270 %). This scenario was the only one modelled in this thesis that resulted in a net mitigation benefit once the effects of feed improvements on i) GHG emissions from agricultural and ii) on forest C loss were combined. Combined total GHG emissions were reduced by 2.5 % in relation to the baseline (Figure 5.6).

Chapter 5 represents the first attempt to quantify the loss of C from tropical forests that is related to the presence of dairy cattle at a larger scale by using remote sensing data. The results emphasise the importance to incorporate the impact of agricultural practices on forests into assessments that quantify and evaluate the performance and effectiveness of CSA options in the livestock sector. Integrated policy instruments that aim to mitigate AFOLU emissions (e.g. NAMAs) can make use of the approach and the results provided in Chapter 5 to target CSA practices. *Ex-ante* information of land requirements and availability and the effectiveness to reduce GHG emissions across land use sectors can help to minimise the risk of negative spillover effects such as C leakage.

6.2 Reflection and outlook

The Paris agreement has set international efforts into motion to limit the global temperature rise below two degrees Celsius. Technical and financial capacity has to be built especially in SSA countries to achieve this ambitious target. AFOLU emission baselines and reduction potentials have to be quantified to fulfil national climate change mitigation targets expressed in NDCs. Methodological frameworks to target CSA practices based on quantified mitigation benefits are required to support this process. This thesis contributes

to the development of i) frameworks that prioritise and target CSA practices and ii) approaches that assess the potential of livestock-related CSA practices to mitigate GHG emissions effectively while increasing agricultural productivity. These approaches allowed to study interactions between the agricultural and forestry sectors based on empirical data and enabled to identify trade-offs and synergies that were not known before. The following sections will reflect on the methodologies developed and applied by focusing on further research needed to increase their performance and scope through the inclusion of additional climate-smart livestock options, the integration of models and scales, as well as data improvements.

6.2.1 Further options to increase climate-smartness of livestock production

In this thesis, the potential to reduce GHG emissions from sustainably intensified livestock production was assessed by focusing on dairy feed improvements across the Kenyan highlands. The approach can be out-scaled to other regions that show comparable agricultural production systems and forest disturbance dynamics such as highland areas in Tanzania or Ethiopia (DeVries et al., 2016; Maleko et al., 2018). The need and interest to develop smallholder-driven dairy production in East Africa is marked by project activities of several international 'green' development programs such as the 'Smallholder Dairy Commercialization Programme' (SDCP) financed by the 'International Fund for Agricultural Development' (IFAD) and the 'East Africa Dairy Development' (EADD) program. These programs aim for market-oriented developments of smallholder dairy production in the region (EADD, 2014; Government of Kenya, 2017b). Apart from the feed intensification strategies considered in this thesis, other options have to be assessed concerning additional feed alternatives, animal health and herd structure as well as grazing and pasture management to increase livestock productivity and to reduce the pressure on natural ecosystems.

Further feed alternatives such as forage legumes and fodder trees should be explored to enrich the portfolio of feed improvement pathways viable for the various smallholder dairy production contexts in East Africa. Agricultural soils in SSA are often nutrient-depleted and, thus, highly N-limited, which puts legumes as protein-rich forage and their ability to fix atmospheric N_2 on the spot (Giller, 2001). Leguminous forage species such as *Desmodium*, planted as sole crop or intercropped with grasses can improve soil fertility and have a higher protein content than, for instance, Napier grass (Lukuyu et al., 2012). Fodder trees grown on farmland improve the supply of nutritious livestock feeds and offer additional services such as erosion control and on-farm fuelwood (Franzel et al., 2014). Higher number of farms with trees on-farm were shown to contribute to reduced forest disturbance at landscape level (Chapter 4). About 500 *Calliandra* trees are required to feed a dairy cow. Therefore, small farms will not be able to feed dairy cattle based on

fodder trees and have to rely on external feed inputs (Franzel et al., 2014). However, feed alternatives have to be selected carefully to avoid detrimental effects on feed and livestock productivity (e.g. through vulnerability to pest species or anti-nutritional properties). Additional work is required to improve the knowledge about nutrient quality and suitability of available legume, fodder tree and shrub species under different agro-climatic conditions in East Africa.

Apart from feeding higher quality diets, animal health has to be improved through access to vaccination services and the reduction of heat stress, which reduce mortality and increase lifetime productivity of dairy cows (Rufino et al., 2009; Mottet et al., 2016). Shorter calving intervals and an increase of the proportion of productive animals in dairy herds can improve the productivity at herd level, which further reduces GHG emission intensities per unit product (Rufino et al., 2009; Herrero et al., 2016). Based on the 'Global Livestock Environmental Assessment Model' (GLEAM), Mottet et al. (2016) estimated that the potential to mitigate GHG emissions in East Africa through an improved herd structure ranges between 4 – 10 %. The effects of animal health and herd management parameters on milk yields and resulting GHG emissions can also be explored by using models like the LivSim model, which was applied in Chapter 3 and 5.

Grass obtained from grazing on native, low-productivity pastures is one of the main feed sources in the Kenyan highlands (Chapter 3). Pastures in these areas are often overgrazed and degraded, which affects heavily the feed availability and quality especially during dry seasons (Lukuyu et al., 2012). The productivity of pastures should be improved in terms of weed control, timing and intensity of grazing, and fertility management through application of organic and inorganic fertiliser (Lukuyu et al., 2012; Mottet et al., 2016). The latter option will also contribute to the increase of GHG emissions from pasture soils, though (Wanyama et al., 2018). However, the extent of grazing land is low throughout the Kenyan highlands (Chapter 3) (Bosire et al., 2016). Therefore, improved pasture management for sustainably intensified smallholder dairy production in Kenya can be assumed to take on a supporting role.

6.2.2 Integrated AFOLU mitigation policies require integrated approaches

Policies that aim to mitigate AFOLU emissions effectively require robust information about the potential of candidate interventions to reduce GHG emissions across land use sectors, prioritisation preferences of stakeholders, adoption constraints, and the economic viability of practices that are being targeted in a certain context. Various spatial scales have to be incorporated ranging from a single farm to the national or even international level to obtain this information (Dunnett et al., 2018). Smallholders are the decision-makers at farm level on which and how agricultural goods are produced on their land.

Their decisions are determined by biophysical and socio-economic constraints such as climate, soil fertility, financial capital, and education (van Wijk et al., 2009). The decisions of policy-makers on economic development pathways and investments into climate-smart production systems are made at (inter)national and sub-national scale such as the county level in Kenya. Integrated modelling tools are needed that enable the assessment of CSA-related policy interventions at the scale where farmers make decisions (i.e. the farm level), including their implications at landscape level while incorporating feedback dynamics between changes in productivity and market responses at the scale of production sectors.

Various farm household models exist to date (e.g. van Wijk et al., 2014). The 'NUANCES-FARMSIM' model was developed specifically for smallholder systems in SSA and could be used to study the effects of changes in management practices at farm level over time (van Wijk et al., 2009). The model is able to simulate crop and livestock production on smallholder farms, including the interactions between farm components such as soils, crops and livestock. This enables the assessment of farmers' decisions on resource and nutrient flows, GHG emissions, and feed and livestock productivity in relation to constraints and changes in external systems such as climate and markets (Rusinamhodzi et al., 2015). The impacts, which would result from development pathways of farms that operate under certain biophysical and socio-economic constraints can be explored, including the opportunities and barriers to adopt certain CSA practices. Chapter 3 of this thesis used components of the FARMSIM model suite such as LivSim and HeapSim (Rufino et al., 2007, 2009). Thus, the proposed use of the FARMSIM model represents an extension of the methodology already applied and would require a broader range of input data to parameterise the model.

FARMSIM can be parametrised and run for different farm types based on a farm typology, which captures the various conditions of the landscapes and production regions that are potentially affected by climate mitigation and developmental policies. Such farm typology derived from farm censuses or farm surveys based on a stratified random sampling approach could improve the upscaling and mapping procedure applied in Chapter 3 and 5 of this thesis. So far, the simulation results from dairy cows were used for upscaling onto livestock production systems (Robinson et al., 2011). Farm type specific baseline data on agricultural production and GHG emissions as well as mitigation potentials obtained from the integrated crop-livestock production modelling based on ground data would reflect a more detailed picture on the potential benefits and trade-offs of targeted CSA practices at higher spatial scale such as the landscape or sectoral level. In addition, the effects of changes in agricultural practices and the use of forests have to be linked as demonstrated in Chapter 4. Therefore, the farm typology has to incorporate forest use variables to capture information on forest grazing and fuelwood collection.

The knowledge about temporal and spatial dynamics of forest disturbance has to be

improved to differentiate more clearly between their drivers. For instance, the analyses conducted in Chapter 4 neither revealed the initial drivers of forest disturbance nor characterised post-disturbance trajectories. This information is crucial to quantify GHG emissions from forests and to allocate these emissions to certain drivers such as livestock grazing in forests or fuelwood harvest, which are related to agricultural practices and land uses. Moreover, this information is needed to monitor implemented CSA interventions and to evaluate their effectiveness to mitigate GHG emissions from agriculture and forests. Algorithms that detect forest changes based on remote-sensing data have to be developed further to track the changes in vegetation structure, including both disturbance and regrowth dynamics. Promising approaches have been brought forward recently (e.g. DeVries et al., 2015a; Hamunyela et al., 2017), yet need to be advanced to enable the characterisation of disturbance–regrowth dynamics at larger temporal and spatial scales. Cloud computing systems such as 'SEPAL' (developed by FAO), designed explicitly to process large earth observation data and to analyse and monitor changes of the land surface provide the necessary computational power for large-scale assessments. Based on forest disturbance dynamics that are characterised more clearly and differentiated into drivers, farm types and changes in farm management could be linked more closely to their impact on forests.

Further interdisciplinary research is necessary to answer the question; to which extent is the intensification of smallholder farming sustainable? This question cannot be answered at farm level alone and includes environmental, social and economic dimensions of agricultural production. In Chapter 4, it was shown that intensified farms were related to lower levels of local forest disturbance than non-intensified farms. This relationship was used in Chapter 5 to estimate the indirect mitigation benefits that could be achieved at landscape level throughout the dairy production region in Kenya. However, it is unknown at which point the farms, analysed in Chapter 4, are exactly on their intensification trajectory. Multi-dimensional and multi-scale assessments are required to explore the boundaries of sustainable intensification. For instance, rebound effects that are triggered by policy interventions to foster the intensification of smallholder dairy farming in a certain region could lead to higher cattle numbers, which consequently increase GHG emissions in this region or may result in negative spillover effects in other regions (e.g. countries) (Meyfroidt, 2018). The increased demand for feeds, which cannot be satisfied locally or regionally due to the shortage of resources such as arable land may lead to increasing feed imports and potentially causes C leakage from indirect land use changes (Meyfroidt et al., 2014). This interaction effect between remote regions was demonstrated for intensified production systems in industrial countries by using a consequential live cycle assessment approach (Styles et al., 2018). Rebound effects were shown for the export-oriented development of commodity goods (Jadin et al., 2016) and the intensification of livestock production in Latin America (Kaimowitz & Angelsen, 2008), and were studied through modelling exercises at a coarse continental and global scale (e.g. Valin et al., 2013). Inte-

grating interactions between the intensification of livestock production, market responses and their feedback effects is, therefore, highly important to inform policies that aim to mitigate AFOLU emissions effectively. The integration of changes in agricultural production and market response is commonly done by using partial equilibrium models such as 'GLOBIOM' or 'MAgPIE' (e.g. Valin et al., 2013; Kreidenweis et al., 2018). However, these models operate on a coarse spatial scale, i.e. grid cells have a size of roughly 55 x 55 km at the equator. Future research would need to investigate opportunities to couple dynamically models of farm production (e.g. FARMSIM) with high resolution land use models and economic models at larger scale.

The outputs obtained from an integrated modelling approach to estimate *ex-ante* impacts of certain CSA practices represent potential inputs for multi-criteria decision-making frameworks such as "targetCSA" (Chapter 2). Up-scaled, bottom-up information is crucial for policy and decision-makers to prioritise and target mitigation interventions for livestock production at national and sub-national level. By using farm-level information, local conditions can be captured, which may reveal constraints and trade-offs that otherwise would have been missed. Therefore, relying on information from top-down approaches alone, could lead to low adoption rates or even negative impacts of targeted interventions. Decision-making on CSA, at large scale is likely to suffer from high complexity and is often characterised by conflicting stakeholder interests and objectives (Notenbaert et al., 2017). Thus, decision-making support frameworks would benefit from comprehensive information derived from integrated assessments to illustrate the potential effects of different stakeholder opinions on where to prioritise CSA interventions (Chapter 2). Visualising transparently various decision-making scenarios can aid eventually in building consensus among involved stakeholders and increases the legitimacy and robustness of decisions and their outcomes (Voinov & Bousquet, 2010).

6.2.3 Data improvements

Quantitative information is needed urgently to estimate GHG emission baselines, to inform CSA policies and to implement interventions robustly based on *ex-ante* impact assessments. These assessments rely on i) data regarding crop and livestock management and productivity at farm level, ii) data on forest use and its impact on C dynamics, and iii) data from measurements of GHG emissions on smallholder farms.

Efforts have been strengthened recently to measure GHG emissions from smallholder farms in East Africa, including CH_4 and N_2O emissions from croplands and pastures, enteric fermentation and animal excreta (e.g. Pelster et al., 2016, 2017; Rosenstock et al., 2016; Goopy et al., 2018; Wanyama et al., 2018). More studies are needed, conducted systematically, considering the heterogeneity of soil, agro-climatic conditions and farming systems in SSA to estimate related emission factors and to reduce the uncertainty of

GHG emissions such as quantified in Chapter 3. Especially improved estimates of GHG emissions from LUC, which result from the conversion of land used for livestock production are required to inform mitigation assessments about trade-offs of feed improvements. A promising initiative is the European-African 'SEACRIFOG' project, which aims to design a harmonised infrastructure to measure AFOLU emissions systematically based on a ground-based observation network across the African continent (López-Ballesteros et al., 2018). An improved data basis provides inputs for dynamic land use models that can be used to investigate the effects of LUC on interactions between vegetation, soils and resulting GHG emissions (e.g. Haas et al., 2013).

A standardised protocol for farm surveys that enables a consistent collection of crop and livestock production data at farm level is needed for assessments that quantify and up-scale mitigation potentials and monitor the performance of implemented CSA practices (e.g. Rufino et al., 2016; Hammond et al., 2017). This protocol should further incorporate variables on feed trade to trace changes in demand and supply of livestock feeds triggered by policy interventions. Information on the use of local forests should also be included such as the collection of fuelwood and livestock grazing inside forests to assess whether changes in farm management reduce the pressure on forests. Such a protocol could be integrated into agricultural censuses conducted regularly. However, mistrust of farmers to reveal detailed information of their farm operations may compromise efforts to collect high quality farm-level data. Trust-building measures need to be implemented such as confidentiality agreements or the dissemination of information about the benefits of CSA practices through extension services.

The effects of forest disturbance drivers on above and belowground C dynamics and GHG emissions have to be studied more closely. Measurements based on grazing experiments are potentially helpful to estimate the effects of livestock grazing inside forests on vegetation structure and the loss of aboveground and belowground C for different forest types and livestock species. Telemetry analyses of livestock can be utilised to study animal movement patterns (e.g. Zampaligré & Schlecht, 2018) such as distances covered and time spent inside forests. Based on daily nutrient and energy requirements and the resulting intake of biomass, the loss of C can be inferred and aggregated. This information is useful to calibrate and validate estimates of C change related to livestock presence in forests based on remote-sensing data (e.g. Baccini et al., 2017). Recently launched earth observation platforms such as the Sentinel-1 and Sentinel-2 satellites open new and promising avenues to improve the detection of small-scale disturbance patters (Reiche et al., 2018) and to study the effects of forest disturbance drivers on C loss due to higher spatial (5 – 10 m) and temporal resolution (revisiting time of approximately 5 days) than, for instance, the Landsat satellite platform.

6.3 Recommendations for climate mitigation policies and financing

This PhD thesis provides useful approaches and information that can assist the targeting of CSA interventions based on:

1. the quantitative integration of climate change vulnerability, CSA feasibility, and stakeholder opinions to build consensus in decision-making processes on CSA prioritisation (Chapter 2).

2. quantified potentials of dairy feed improvements to mitigate GHG emissions and to increase milk yields, including the feasibility to implement these improvements due to land constraints (Chapter 3).

3. quantified potentials of dairy feed improvements to contribute to climate change mitigation and dairy productivity targets at national level (Chapter 3).

4. knowledge, which shows quantitatively that the intensification of smallholder dairy farming reduces the negative impact on natural forests ecosystems (Chapter 4).

5. quantified potentials of dairy feed improvements to mitigate direct and indirect GHG emissions effectively across land use sectors (Chapter 5).

The following key messages for policy makers can be deduced from this thesis. Context-specific and detailed *ex-ante* impact assessments are essential to inform integrated CSA policies that target mitigation and agricultural development. Candidate interventions need to be assessed in terms of their direct and indirect mitigation benefits and productivity gains, which lead potentially to higher farm incomes. Concentrating on practices that realise these 'win-win' potentials is especially important in the context of smallholder farming in SSA, which is marked by low production efficiencies (Gerber et al., 2013; Descheemaeker et al., 2016). Analysing the demand of candidate interventions for arable land and land availability is imperative to answer the questions of how feasible and effective the implementation of the CSA practices at hand are at certain locations. Policy instruments such as the NAMA developed for the Kenyan dairy sector (Government of Kenya, 2017b) can target specific climate-smart feed practices based on *ex-ante* knowledge about their direct and indirect mitigation benefits and productivity gains that were quantified location-specific. Capacity and infrastructure development, including feed, fertiliser supply and trade, access to markets and extension services can be promoted more effectively.

Financial investment to stimulate the adoption of CSA can be channelled more closely along promoted practices that have been shown to realise mitigation and productivity benefits. The private sector has engaged recently to finance the implementation of CSA practices at farm level through micro-financing and crediting (e.g. www.f3-life.com).

Accessing these services offers promising opportunities for individual farmers to adopt certain practices. Various international climate funds exist under the umbrella of the 'African Development Bank' (AfDB), e.g. the 'Climate Investment Funds' (CIF), the 'Green Climate Fund' (GCF), and the 'Africa Climate Change Fund' (ACCF) with a current total investment volume of about USD 12 billion (AfDB, 2018). These large-scale financing schemes, which will include the reduction of GHG emissions from forests through REDD+ components, fund projects and initiatives across SSA that target and implement CSA measures on the ground. Both, small and large-scale financing schemes require evidence that indicates the effectiveness and feasibility of these practices across the agricultural and forestry land use sectors.

Kenya pledged to reduce total GHG emission increases by 30 % between 2010 – 2030, as defined in its NDC (Government of Kenya, 2015a). Linking CSA practices, implemented at farm level, to sectoral and national scales enables the assessment of the extent at which targeted practices contribute to the achievement of national mitigation targets. Up-scaling mitigation potentials, as done in this thesis (Chapter 3 & 5), could, therefore, be useful to monitor the mitigation performance and to report the status of target fulfilment (e.g. through MRVs) to the UNFCCC.

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Appendices

Appendix S1 belonging to Chapter 2 of this thesis

Computing a consensus matrix based on input PC matrices

The aim is to search a consensus matrix (c) that shows minimised differences to the input PC matrices (m) obtained from individual stakeholders (k). The distance minimisation function is translated into a linear goal programming model (S1.1) (González-Pachón & Romero, 2007).

Achievement function:

$$Min(1 - \lambda)D + \lambda \left[\sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} (n_{ij}^{k} + p_{ij}^{k}) \right]$$

i,j refer to the elements of a matrix, subjected to the following constraints:

$$m_{ij}^{c} - m_{ij}^{k} + n_{ij}^{k} - p_{ij}^{k} = 0, \quad i, j \in \{1, ..., n\}, \quad k \in \{1, ..., m\}$$

$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} (n_{ij}^{k} + p_{ij}^{k}) - D \leq 0, \quad k \in \{1, ..., m\}$$

$$1/9 \leq m_{ij}^{c} \leq 9, \quad i, j \in \{1, ..., n\}$$

$$n \geq 0, \quad p \geq 0$$

$$\lambda \in [0, 1] \, (control \, parameter) \tag{S1.1}$$

The control parameter λ is used to explore possible solutions as well as trade-offs between the consensus towards the majority ($\lambda = 1$) and the minority ($\lambda = 0$). The metric D indicates the deviation between the stakeholder matrix that is furthest from the obtained consensus matrix. The variables n_{ij}^{k} and p_{ij}^{k} measure the degree of under and over-achievement between single matrix preferences (m_{ij}^{k}) and calculated preferences of the consensus matrix (m_{ij}^{c}). They can be accumulated to the measure A, which indicates the overall deviation between the computed consensus matrix and all individual stakeholder preferences (González-Pachón & Romero, 2007). The resulting consensus matrix has the same structure as the input PC matrices.

Inferring preference weights from a single PC matrix

The preference vector (w) for i = 1,...,n criteria is calculated through the following optimisation model (S1.2) (González-Pachón & Romero, 2007).

Achievement function:

$$Min(1-\lambda)D + \lambda \left[\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} (n_{ij} + p_{ij}) \right]$$

subjected to the following constraints:

$$m_{ij}w_j - w_i + n_{ij} - p_{ij} = 0, \quad i,j \in \{1,...,n\}$$
$$n_{ij} + p_{ij} \leq D, \quad i,j \in \{1,...,n\}$$
$$\sum_{i=1}^{n} w_i = 1, w_i > 0, \quad \forall i$$
$$n \geq 0, \quad p \geq 0$$
$$\lambda \in [0,1] \, (control \ parameter) \tag{S1.2}$$

The meaning of variables λ, D, n_{ij} and p_{ij} is congruent with model (S1.1).

Inferring preference weights from several PC matrices

The following optimisation model (S1.3) is an extension of model (S1.2) applicable to (k) stakeholders. A scenario that might be interesting in a case where stakeholders are kept as individuals and do not form one consensus oriented group (González-Pachón & Romero, 2007).

Achievement function:

$$Min(1-\lambda)D + \lambda \left[\sum_{k=1}^{m} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} (n_{ij}^{k} + p_{ij}^{k}) \right]$$

subjected to the following constraints:

$$m_{ij}^{k}w_j - w_i + n_{ij}^{k} - p_{ij}^{k} = 0, \quad i,j \in \{1,...,n\}, \quad k \in \{1,...,m\}$$
$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j\neq i}}^{n} (n_{ij}^{k} + p_{ij}^{k}) - D \leq 0, \quad k \in \{1,...,m\}$$
$$\sum_{i=1}^{n} w_i = 1, w_i > 0, \quad \forall i$$
$$n \geq 0, \quad p \geq 0$$
$$\lambda \in [0,1] \, (control \ parameter) \tag{S1.3}$$

Determining the consensus matrix that shows the most balanced trade-off between majority and minority consensuses

An additive maximisation function was utilised based on standardised indices of majority (A) and minority (D) deviation by using equations (S1.4), (S1.5) and (S1.6) developed by González-Pachón & Romero (2011).

$$I_{A_\lambda} = \frac{(A_0 - A_\lambda)}{(A_0 - A_1)}, \quad \lambda \in [0, 1] \tag{S1.4}$$

I_{A_λ} = index of majority consensus, A_1 = closed point towards majority, A_0 = most distant point from majority, A_λ = A for a certain λ value

$$I_{D_\lambda} = \frac{(D_1 - D_\lambda)}{(D_1 - D_0)}, \quad \lambda \in [0, 1] \tag{S1.5}$$

I_{D_λ} = index of minority consensus, D_0 = closed point towards majority, D_1 = most distant point from majority, D_λ = D for a certain λ value

The applied utility function maximises the sum of both indices for a certain consensus matrix for $\lambda = 0$ - 1:

$$I_{A*} + I_{D*} = Max(I_{A_\lambda} + I_{D_\lambda}) \tag{S1.6}$$

The highest value is selected representing the most balanced trade-off (i.e. compromise) between majority and minority consensus (González-Pachón & Romero, 2011).

Combination and aggregation of spatial datasets and stakeholder preferences using the weighed linear combination rule (WLC)

Prior to the spatial aggregation, all single datasets have to be standardised and consistently rescaled to range from 0 - 1 (0 = low, 1 = high vulnerability and CSA suitability) by applying equation (S1.7).

$$x_i = \frac{(R_i - R_{i_{min}})}{(R_{i_{max}} - R_{i_{min}})} \tag{S1.7}$$

x_i = standardised dataset i, R_i = original dataset i, $R_{i_{min}}$ = minimum grid cell value of dataset i, $R_{i_{max}}$ = maximum grid cell value of dataset i

Subsequently, the products of standardised datasets x_i and related preference weights w_i are summed up as shown in equation (S1.8). Finally, the summed products are combined with boolean constraints c_j (e.g. areas that have to be excluded) deriving the composite index S (Eastman et al., 1995).

$$S = \sum(w_i x_i) \times \Pi c_j \tag{S1.8}$$

S = weighted composite index, w_i = preference weight relating to dataset i, x_i = standardised dataset i, c_i = boolean constraint j

Appendix S2 belonging to Chapter 2 of this thesis

Table S2.1: Overview of involved stakeholder groups and related organisations.

Group	Organisation
Governmental organisations (GOs)	Ministry of Agriculture Livestock and Fisheries (MoALF)
	Ministry of Environment and Mineral Resources (MEWNR)
	Ministry of Water & Irrigation
	State Department of Livestock
	Kenya Forest Service (KFS)
	National Environment Management Authority (NEMA)
	National Treasury
	National Agricultural Research Laboratories (NARL)
Non-governmental organisations (NGOs)	African Centre for Technology Studies (ACTS)
	SNV-Netherlands Development Organisation
	Kenya Community Development Foundation (KCDF)
	Consumer Unity & Trust Society Africa Resource Centre (CUTS ARC)
	Vi Agroforestry
	Kenya Climate Justice Women Champions (KCJWC)
	Wetlands International
	Kenya National Farmers' Federation (KENAFF)
Scientific institutions	South Eastern Kenya University (SEKU)
	Kenya Institute for Public Policy Research and Analysis (KIPPRA)
	IGAD Climate Prediction And Applications Center (ICPAC)
	University of Nairobi (CASELAP)
	University of Reading
	Kenya Meteorological Department (KMS)
	World Agroforestry Centre (ICRAF)

Table S2.1: continued

	International Livestock Research Institute (ILRI)
Private Sector	Kenya Private Sector Alliance (KEPSA)
	Price Water House Coopers (PwC)
	Kenya Association of Manufacturers (KAM)
	GrainPro
	African Seed Trade Association (AFSTA)
	Coffee Board Of Kenya
	Geo-EnviAgro Solutions International
	Kenya Tea Development Agency (KTDA)
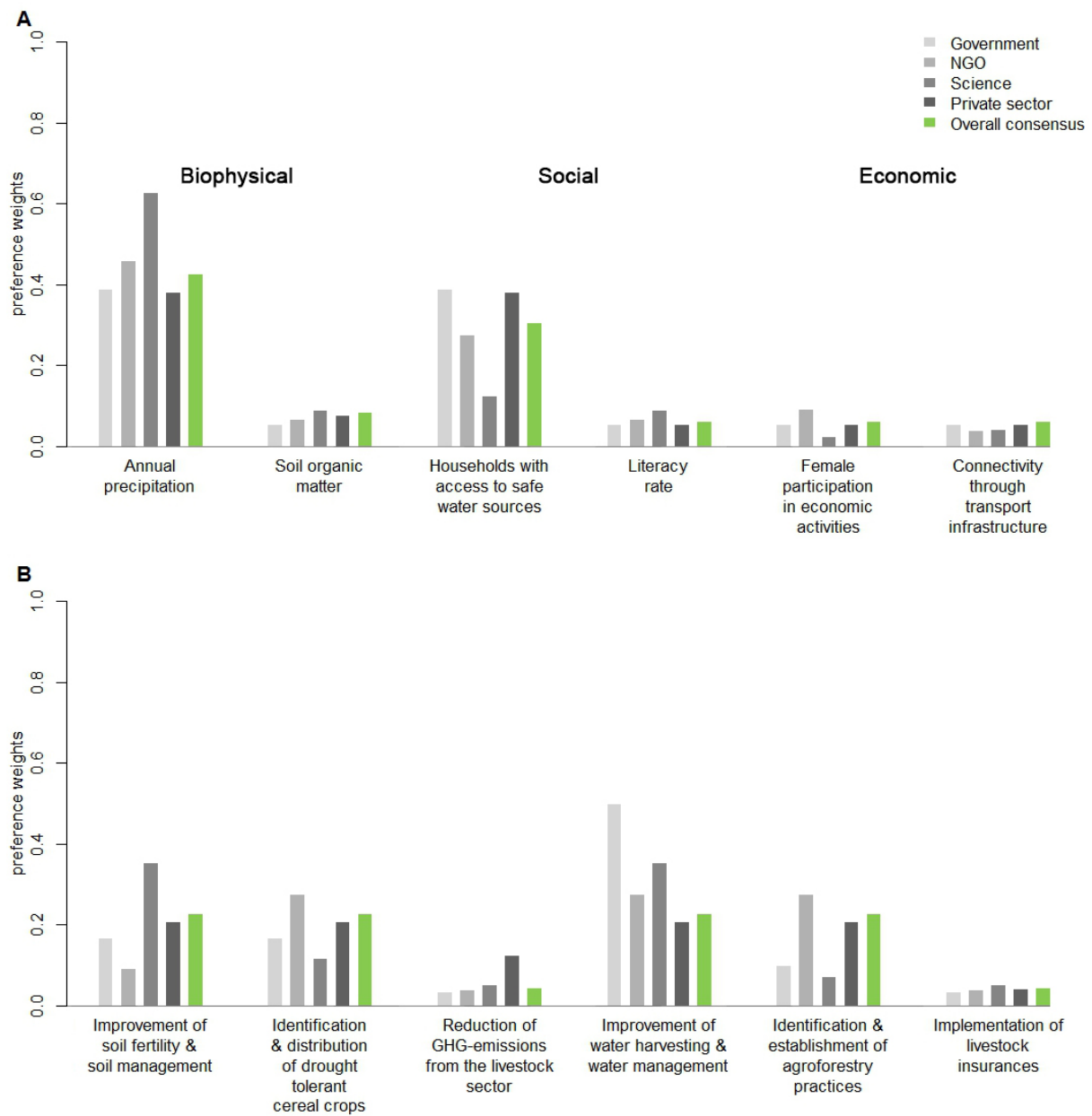
Figure S2.1: Preference weights for each stakeholder group and the overall consensus (including all experts) resulting from the majority consensus scenario for (A) vulnerability indicators and (B) CSA practices.
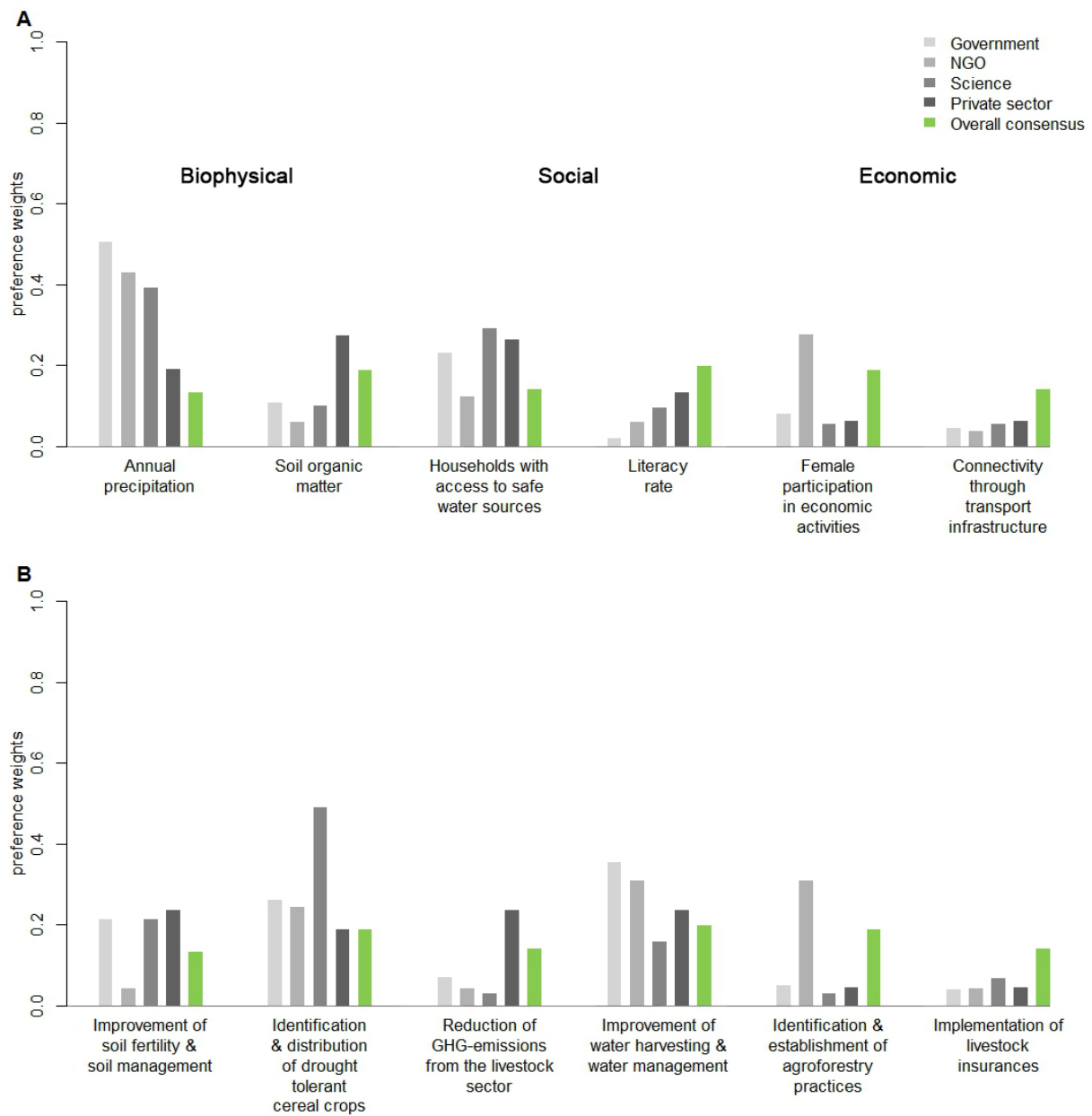
Figure S2.2: Preference weights for each stakeholder group and the overall consensus (including all experts) resulting from the minority consensus scenario for (A) vulnerability indicators and (B) CSA practices.

Appendix S3 belonging to Chapter 3 of this thesis

Study Area

Figure S3.1: Dairy production region in Kenya, adapted based on Herrero et al. (2014).
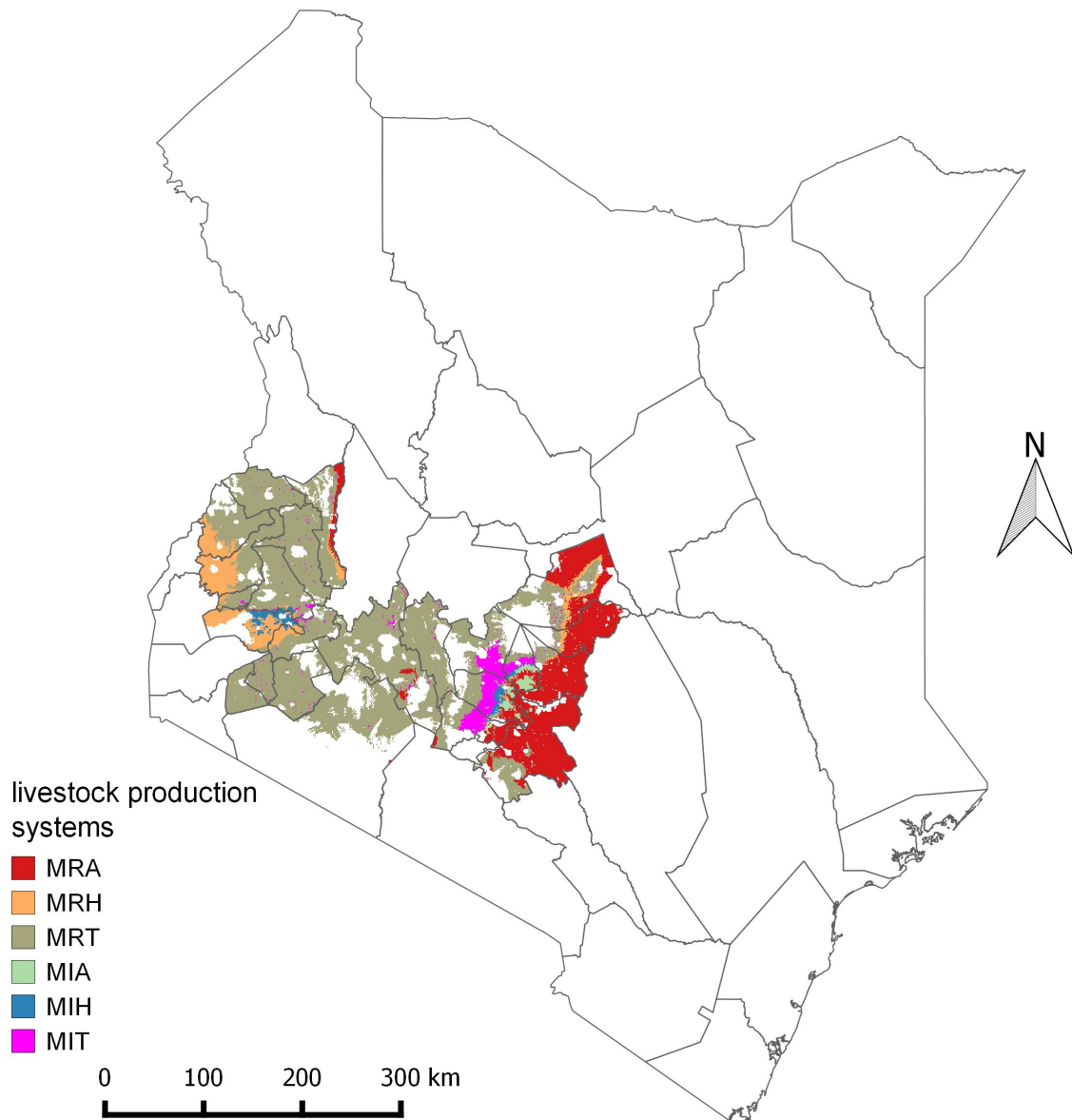
Figure S3.2: Spatial distribution of livestock production systems (LPS) within the study area: mixed rainfed system in arid areas (MRA), mixed rainfed system in humid areas (MRH), mixed rainfed system in tropical highlands (MRT), mixed irrigated system in arid areas (MIA), mixed irrigated system in humid areas (MIH) and the mixed irrigated system in tropical highlands (MIT).

The Livestock Simulator

LivSim

LivSim is an individual-based livestock production model used to simulate animal production such as milk and excreta as well as maintenance requirements (Rufino et al., 2009).

Different livestock units can be taken into account each characterised by animal species and breeds such as a specific dairy cattle breeds (e.g. Frisians). The state variables of the model are the age, weight and reproductive status of the animal. Conception, sex of the calves and mortality (involuntary disposal) are prompted stochastically. Changes in age, weight and mortality due to undernourishment are described deterministically. Intake is determined by feed quality and quantity, and animal characteristics. Each time step in a simulation represents a month. Animal production is calculated on a monthly basis.

HeapSim

The dynamics of nutrients through manure collection, storage and use as well as changes in quality due to management are simulated by HeapSim (Rufino et al., 2007). This model is able to consider the transfer efficiencies for the different processes under different livestock production systems and types of storage. HeapSim is coupled with LivSim. Manure inputs are obtained from the LivSim model dynamically during simulations on a monthly basis.

Calculation of GHG emissions from dairy production

Table S3.1: Descriptions of parameters, their values and uncertainty ranges (min - max), used to compute CH_4, N_2O and CO_2 emissions from enteric fermentation (EF), manure management (MM), managed soils (MS), including land use changes, and dairy concentrate supplementation.

Parameter	Applied IPCC-equation	Value / range	Reference
Net energy maintenance (EF)	Eq. 10.3	Cf = 0.386 for lactating cow; Cf = 0.322 for non-lactating cow	IPCC (2006, table 10.4)
Net energy activity (EF)	Eq. 10.4	Ca = 0.17 for grazing; Ca = 0 for non-grazing	IPCC (2006, table 10.5)
Net energy growth (EF)	Eq. 10.6	BW = calculated by LivSim; C = 1; WG = calculated by LivSim	IPCC (2006), Rufino et al. (2009)
Net energy lactation (EF)	Eq. 10.8	Milk yield = calculated by LivSim; Fat = calculated by LivSim (2.7 % – 4.2 %); Lactation state = calculated by LivSim	Rufino et al. (2009)

Table S3.1: continued

Net energy pregnancy (EF)	Eq. 10.13	Cpregnancy = 0.1; Pregnancy state = calculated by LivSim	IPCC (2006, table 10.7), Rufino et al. (2009)
Ratio net energy available for maintenance to digestible energy consumed (EF, MM)	Eq. 10.14	DE = feed type specific (%): • Grazing land: 45 – 55 • Napier grass: 50 - 60 • Maize stover: 45 - 55 • Maize silage: 50 – 60 • Dairy concentrate: 75 – 85	IPCC (2006), Anindo et al. (1994), Rufino et al. (2009)
Ratio net energy available for growth to digestible energy consumed (EF, MM)	Eq. 10.15	DE = see above	IPCC (2006)
Gross Energy (EF, MM)	Eq. 10.16	DE = see above	IPCC (2006)
CH_4 emissions (EF)	Eq. 10.21	Ym = 5.5 % – 7.5 %	IPCC (2006, table 10.12)
Volatile solid excretion (MM)	Eq. 10.24	DE = see above; UE*GE = 0.04; ASH = 0.08	IPCC (2006)
CH_4 emissions (MM)	Eq. 10.23	Bo(T) = 0.11 – 0.15; MCF storage (%) = 1.5 – 2 (dry lot) and 4 - 5 (solid storage); MCF grazing (%) = 1.5 - 2; MCF application (%) = 0.5 - 1; MS = proportion of manure stored based on ratio between grazing land (not managed) and cropland under feed production (managed)	IPCC (2006, table 10.17 and 10A-4)
N excretion (MM)		N content of urine and faeces = calculated by LivSim	Rufino et al. (2009)

Table S3.1: continued

Direct N$_2$O emissions (MM)	Eq. 10.25	EF3 = 0.01 – 0.02 (dry lot) and 0.0025 – 0.0075 (solid storage)	IPCC (2006, table 10.21), Herrero et al. (2013)
N volatilisation as NH$_3$ and NO$_x$ (MM)	Eq. 10.26	MS = see above; Frac-GasMS (%) = 30 – 50 (dry lot), 30 – 40 (solid storage)	IPCC (2006, table 10.22), Herrero et al. (2013)
N losses due to leaching (MM)	Eq. 10.28	MS = see above; Frac-cleachMS (%) = 0 – 20 (dry lot) and 5 – 15 (solid storage)	IPCC (2006, table 10.23), Herrero et al. (2013)
Indirect N$_2$O emissions (MM)	Eq. 10.27 and 10.29	EF4 = 0.02 – 0.01; EF5 = 0.0005 - 0.0075; N$_2$O = N * 44 / 28	IPCC (2006, table 11.3), Herrero et al. (2013)
N from animal manure applied to soils used for feed production (MS)	Eq. 11.4	FracFEED = 1 - MSO (%) (fraction of manure for other uses) 0.1 - 0.2	IPCC (2006), Herrero et al. (2013)
N in urine and dung deposited on pasture (MS)	Eq. 11.5	1 – MS = fraction of manure dropped on grazing land	IPCC (2006)
Direct N$_2$O emissions from manure deposited on pastures (MS)	Eq. 11.1	EF3PRP = 0.007 – 0.06	IPCC (2006, table 11.3), Herrero et al. (2013), Rosenstock et al. (2016)
N in synthetic fertiliser (MS)	Eq. 11.1	FSN (kg ha-1) = spatially explicit dataset	Potter et al. (2010)
N in crop residues (above and below ground) (MS)	Eq. 11.7 and 11.7A	Fcr = calculated per crop (Napier grass and maize); Yields (kg ha^{-1}): Napier grass = 12000 (MRA, MIA) – 16000 (MRH, MIH), Maize = 2335 (MRA, MIA) – 4747 (MRH, MIH) FracRemove = 0.75; Area burnt = 0; Other values taken from table 11.2, for Napier grass = perennial grasses	IPCC (2006, table 11.2), Monfreda et al. (2008), Katiku et al. (2011), Weiler et al. (2014), Castellanos-Navarrete et al. (2015)

Table S3.1: continued

Mineralised N in mineral soils due to loss of soil carbon through land use change	Eq. 11.8	R (C:N ratio) = spatially explicit dataset; Area = see equation (S3.1) below	Hengl et al. (2015)
Direct N_2O emissions (MS)	Eq. 11.1	EF1 = 0.003 – 0.005 (MRA, MIA), 0.003 – 0.02 (MRH, MIH), 0.003 – 0.01 (MRT) and 0.0004 – 0.036 (MIT)	IPCC (2006, table 11.1 and 11.2), Herrero et al. (2013), Hickmann et al. (2017)
N_2O-N from atmospheric deposition (MS)	Eq. 11.9	FracGASM = 0.05 – 0.3 (dry lot) and 0.05 – 0.2 (solid storage); FacGASF = 0.03 – 0.3; EF4 = 0.002 – 0.01	IPCC (2006, table 11.3), Herrero et al. (2013)
N_2O-N from leaching/runoff (MS)	Eq. 11.10	FracLEACH-H = 0.1 – 0.3; EF5 = 0.005 - 0.0075	IPCC (2006, table 11.3), Herrero et al. (2013)
Indirect N_2O emissions (MS)	Eq. 11.9 and 11.10	Fcr = calculated per crop (Napier grass and maize); N_2O = N_2O–N * 44 / 28	IPCC (2006, table 11.2 and 11.3), Herrero et al. (2013)
CO_2 emissions from land use change (only grazing land to cropland)		Soil carbon loss (kg C ha^{-1} yr^{-1}) = 11.1 – 688.2; Area = see formula (1) below; CO_2 = Soil carbon loss * 44 / 12	Don et al. (2011)
CO_2eq emissions from dairy concentrate		Emission factor (kg CO_2eq kg concentrate^{-1}) = 1.36	Weiler et al. (2014)
Cattle densities		Spatially explicit dataset (heads km^{-2}) used to upscale GHG emissions and milk production. Grid cell wise uncertainty ranges are calculated based on: RMSE of 0.42 = log (x + 1)	Robinson et al. (2014)

Table S3.2: Ingredients of the baseline diet and their proportions in relation to the annual dry matter intake (DMI) per tropical livestock unit (TLU) as lifetime average. Grazing refers to native grass species from natural pastures.

LPS	DMI (kg TLU^{-1} yr^{-1})	Grazing (%)	Napier grass (%)	Maize stover (%)	Dairy concentrate (%)
MRA	2470	52	24	23	1
MRH	2474	34	38	27	1
MRT	2414	36	42	21	1
MIA	2466	52	24	23	1
MIH	2475	34	38	27	1
MIT	2417	36	42	21	1

Calculation of the NDC target

Steps (1 – 5) were applied to calculate the tolerable relative GHG emission increase according to the Kenya NDC target (Government of Kenya, 2015a):

(1) National baseline 2010: 73 Mt CO_2eq

(2) National BAU scenario 2030: 143 Mt CO_2eq = 95.9 % increase relative to the baseline

(3) Expected BAU increase: 143 Mt CO_2eq – 73 Mt CO_2eq = 70 Mt CO_2eq

(4) NDC target to reduce emission increase by 30 %: 70 Mt CO_2eq * 0.3 = 21 Mt CO_2eq

(5) Tolerable emission increase (according to the NDC) relative to the national baseline: (21 Mt CO_2eq + 73 Mt CO_2eq) / 73 Mt CO_2eq = 67.1 %

Calculation of land demand and availability

Table S3.3: Data used to analyse land demand and availability.

Data	Type	Reference
Maize yields	Spatially explicit dataset with a grid cell resolution of 10 x 10 km (kg ha^{-1} yr^{-1})	Monfreda et al. (2008)
Napier yields	literature (kg ha^{-1} yr^{-1})	Katiku et al. (2011), Weiler et al. (2014), Castellanos-Navarrete et al. (2015)

<div align="center">**Table S3.3**: continued</div>

Feed intake	literature (kg TLU^{-1} yr^{-1})	Rufino et al. (2009), Katiku et al. (2011), Herrero et al. (2013), Weiler et al. (2014), Castellanos-Navarrete et al. (2015)
Dairy cattle density	tabular data at county level (%), spatially explicit dataset with a grid cell resolution of 1 x 1 km (TLU km^{-2})	Government of Kenya (2014), Robinson et al. (2014)
Grazing land	Spatially explicit dataset with a grid cell resolution of 10 x 10 km (ha km^{-2})	Velthuizen et al. (2007)

Equations (S3.1) and (S3.2) were applied to calculate land availability and the scenario-specific demand for land for each grid cell across the study area (Figure S3.1) based on data of feed intake per tropical livestock unit (TLU), fodder crop yields, and spatially explicit data on cattle density and grazing land (Table, S3.3).

$$land\ demand\ (ha\ TLU^{-1}) = \sum_{i=1}^{n} \frac{feed\ intake_{crop_i}\ (kg\ TLU^{-1})}{crop\ yield_{crop_i}\ (kg\ ha^{-1})} \tag{S3.1}$$

$$\begin{aligned} land\ availability\ (ha\ km^{-2}) &= available\ grazing\ land\ (ha\ km^{-2}) \\ &- land\ demand\ (ha\ TLU^{-1}) \times dairy\ cattle\ density\ (TLU\ km^{-2}) \end{aligned} \tag{S3.2}$$

Sources of Uncertainties
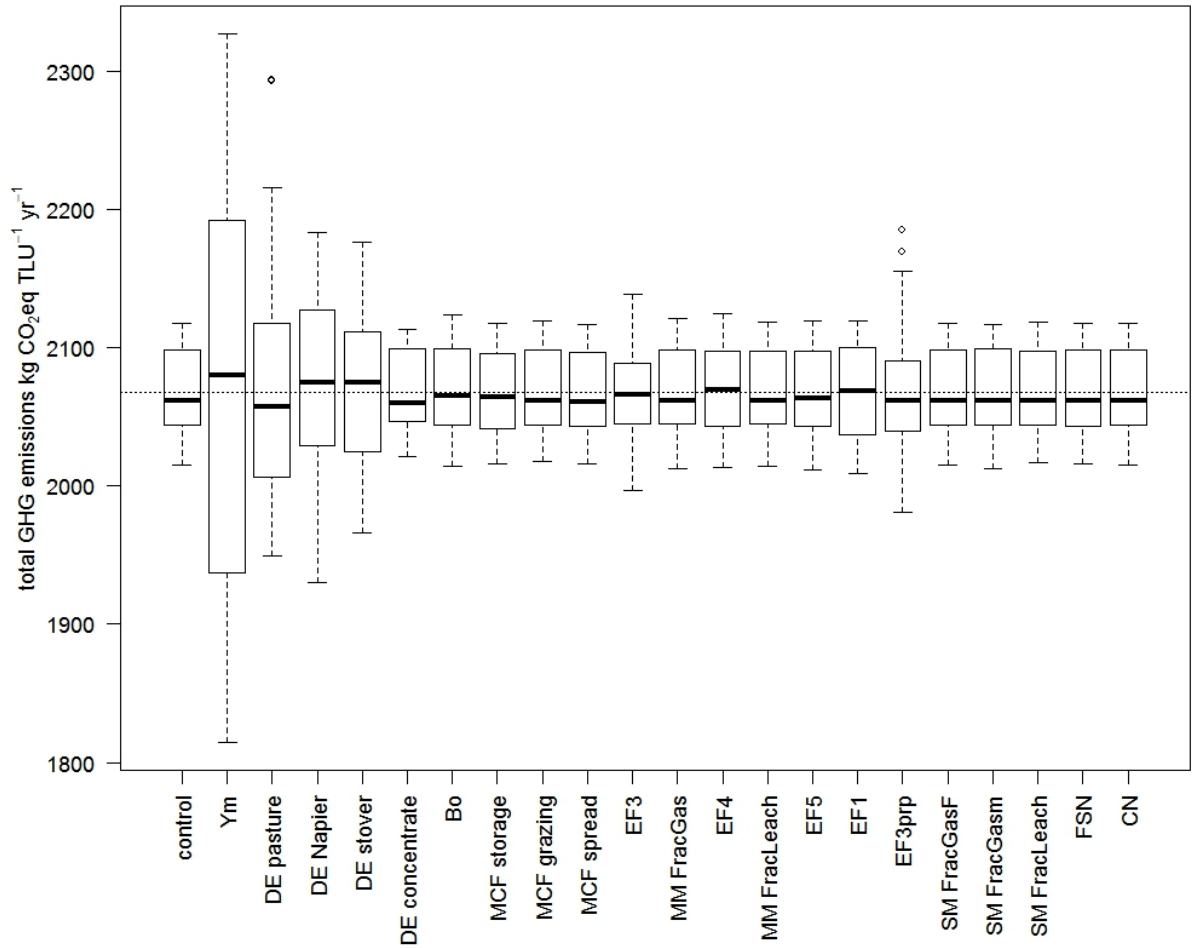
Figure S3.3: Variation in baseline total GHG emissions due to the uncertainty in applied emission parameters calculated through latin hypercube sampling derived from baseline LivSim simulations, one parameter at a time while all others were fixed at the mean of their range. Control = all parameters were fixed at the mean of their range. Dashed horizontal line represents the control mean.
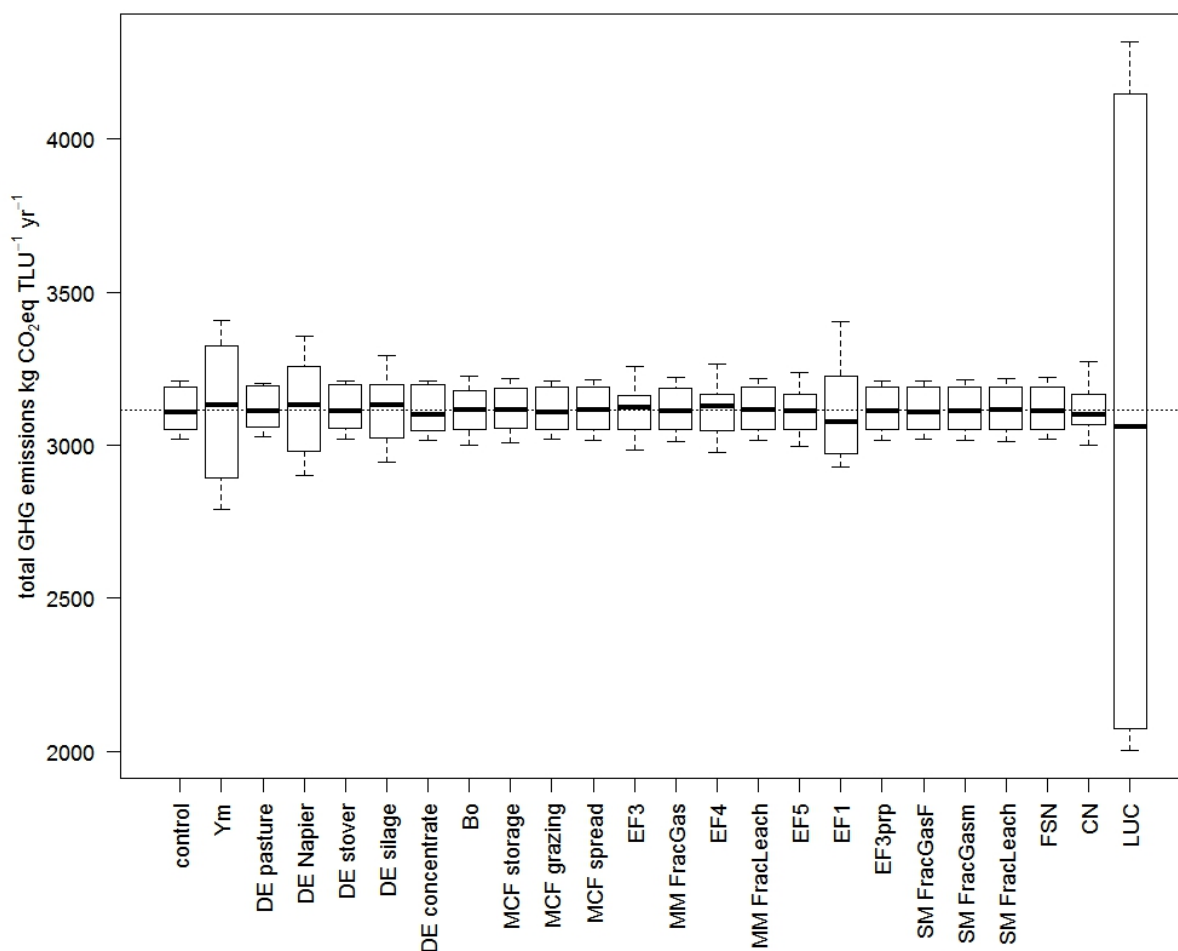
Figure S3.4: Variation of total GHG emissions shown for the scenario 'forage quality and feed conservation (FoFe)' at high level of intensification derived from LivSim simulations. The variation was caused by uncertainties in applied emission parameters calculated through sampling the minimum and maximum of each parameter range, one parameter at a time while all others were fixed at the mean of their range. Control = all parameters were fixed at the mean of their range. Dashed horizontal line represents the control mean.

Appendix S4 belonging to Chapter 4 of this thesis

Data collection

Sampling design
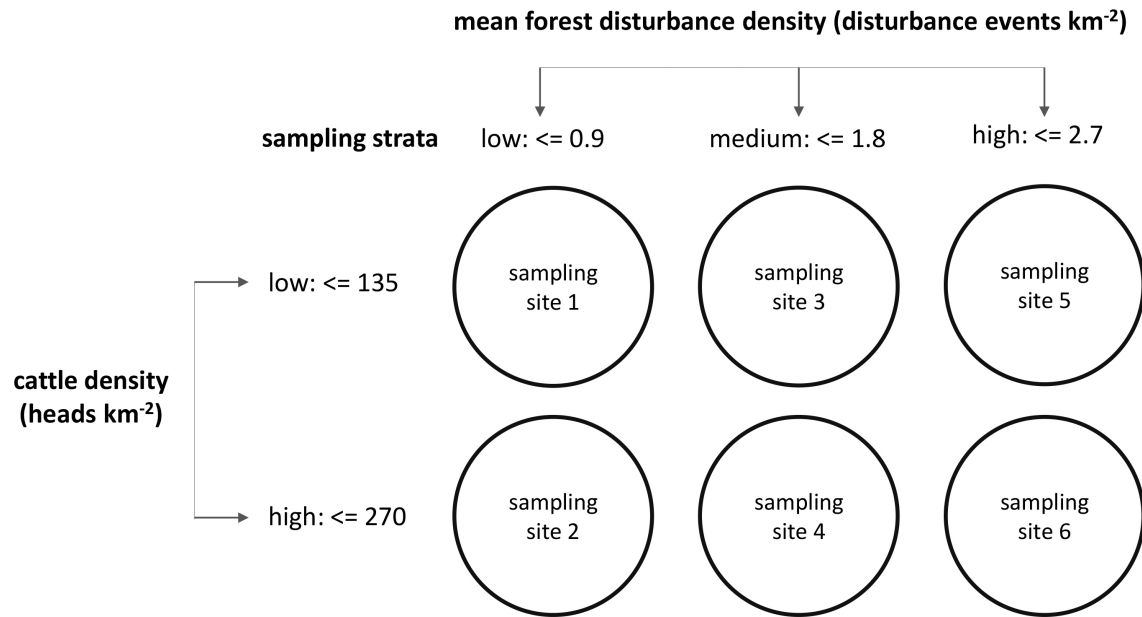
Figure S4.1: Schematic of applied stratified sampling design to collect field data through farm and forest disturbance surveys.

Collection of field data

Table S4.1: List of variables queried in the farm survey.

Category	Variables
Farm animals	cattle numbers (heads)
	breeds (categorical)
	small ruminant numbers (heads)
Dairy production	milk yield (kg cow^{-1} day^{-1})
	proportion of milk sold (%)
	milk buyer type (categorical)
	dairy herd size (heads)

Table S4.1: continued

Feeding	given feed type (categorical)
	given feed type proportions (%)
	concentrate type (categorical)
	concentrate quantity (kg cow^{-1} day^{-1})
	feed conservation (categorical)
	external feed source (categorical)
	external feed type (categorical)
Grazing	on-farm pasture area (ha)
	off-farm grazing on community land (categorical)
	on-farm pasture leased (categorical)
Fodder crops	crop type (categorical)
	farm area under fodder crops (ha)
	feed crop sold (categorical)
	fertiliser use (categorical)
Food crops	crop type (categorical)
	farm area under food crops (ha)
	feed crop sold (categorical)
	fertiliser use (categorical)
Cash crops	crop type (categorical)
	farm area under cash crops (ha)
	feed crop sold (categorical)
	fertiliser use (categorical)
Farm in general	household size (persons)
	total farm area (ha)
	tress on farm (categorical)

Table S4.2: List of variables queried in the forest disturbance survey.

Variable	Value categories
Disturbance class	logging
	charcoal
	grazing
	burned
	windfall
	other
	none
Surrounding forest type	pristine primary forest
	secondary successional forest
	heavily disturbed forest
	other
	none
Grazing signs	livestock presence
	paw prints
	dung
	other
	none
Succession type	bare soil
	herb layer only
	heterogeneous shrub and herb layers
	trees with closing canopies
	other
	none

Results

Spatial accuracy assessment
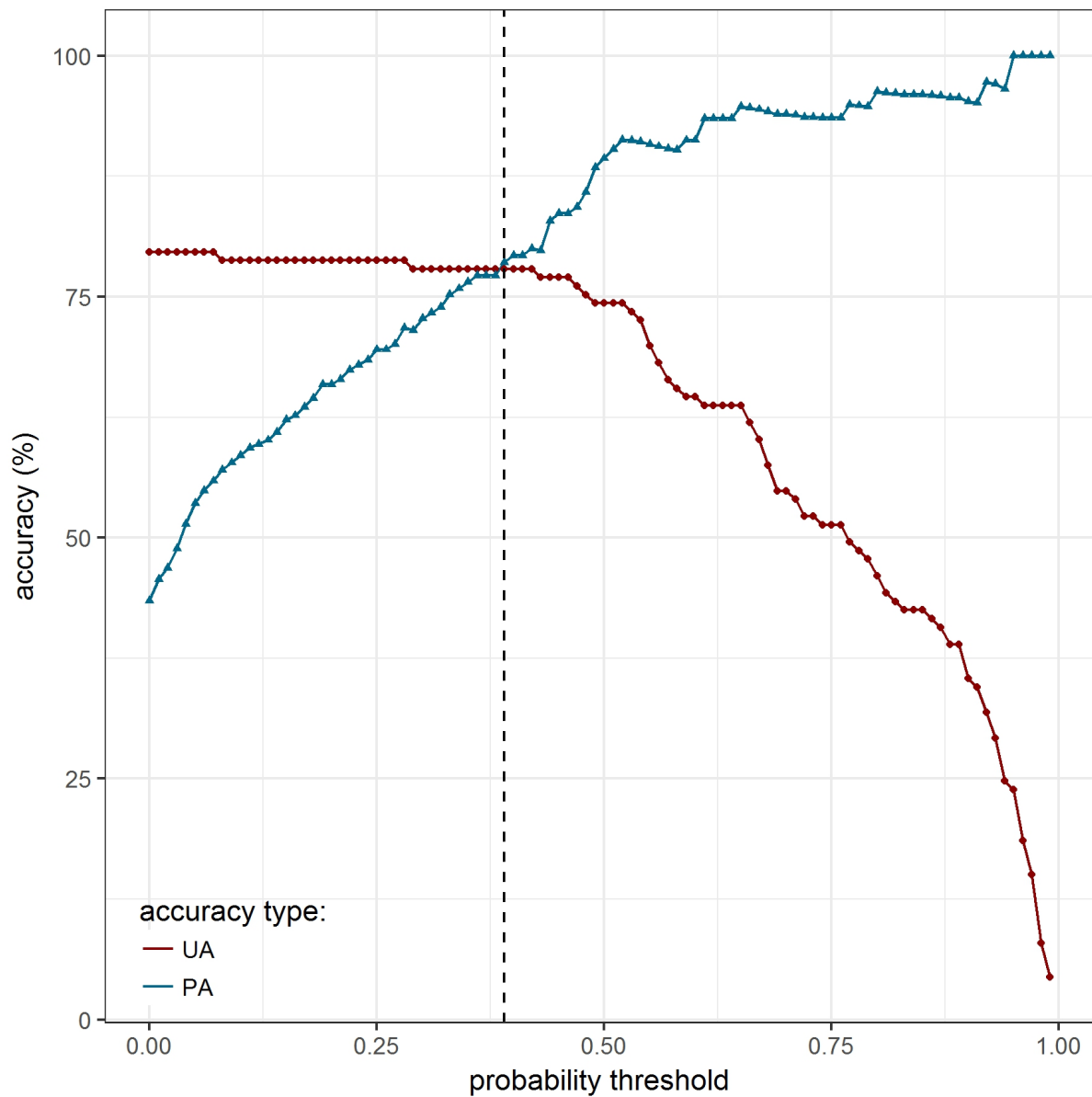
Figure S4.2: User's accuracy (UA) and producer's accuracy (PA) for disturbances detected in the Mau Forest between 2010 and 2016 across probability thresholds ranging from 0 - 1. Vertical dashed line shows optimal threshold chosen based on the crossover point between UA and PA.

Model selection

Table S4.3: Overview of GLMMs established by including farm indicators. The differences in Akaike's information criterion (ΔAIC) are shown in relation to final models. Indicated significance levels were derived from likelihood ratio tests of model candidates against Null models.

Model (fixed effects)	Neighbourhood sizes							
	2 km		3 km		4 km		5 km	
	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level
'farm distance to forest' + 'farm area for fodder production' + 'milk yield' + 'concentrate supplementation' + 'proportion of grass in the diet' + 'cattle numbers' + 'farm sizes' + 'firewood collection'	0.00	p < 0.001	0.00	p < 0.001	0.00	p < 0.001	0.00	p < 0.001
Intercept only (Null model)	1962.80		5758.05		6618.36		5929.35	

Table S4.4: Overview of GLMM selection results, including final, intermediate model candidates, and the Null models in descending order. The differences in Akaike's information criterion (ΔAIC) are shown in relation to final models. Indicated significance levels were derived from likelihood ratio tests of model candidates against Null models.

Model (fixed effects)	Neighbourhood sizes							
	2 km		**3 km**		**4 km**		**5 km**	
	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level
'farm type' + 'farm distance to forest' + 'farm type' x 'farm distance to forest'	0.00	p < 0.001	0.00	p < 0.001	0.00	p < 0.001	0.00	p < 0.001
'farm type' + 'farm distance to forest'	125.04	p < 0.001	124.22	p < 0.001	224.65	p < 0.001	280.07	p < 0.001
'farm type'	824.84	p < 0.001	2794.87	p < 0.001	2960.12	p < 0.001	3402.49	p < 0.001
Intercept only (Null model)	1200.82		3860.39		3844.11		3816.37	

Table S4.5: Overview of GLMM selection results, including final models and Null models in descending order. The differences in Akaike's information criterion (ΔAIC) are shown in relation to final models. Indicated significance levels were derived from likelihood ratio tests of model candidates against Null models.

Model (fixed effects)	Neighbourhood sizes							
	2 km		**3 km**		**4 km**		**5 km**	
	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level	ΔAIC	sign. level
'farm type'	0.00	p < 0.01	0.00	p < 0.001	0.00	p < 0.001	0.00	p < 0.001
Intercept only (Null model)	9.75		17.30		12.13		11.90	

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About the author

Patric Brandt was born in Salzwedel, Germany on September 24, 1980. Between 1997 and 2005, he worked as a land surveyor and IT specialist. Patric graduated in 2008 with a Bachelor of Science in Environmental Sciences at Leuphana University (Lüneburg, Germany). In 2010, he completed his Master of Science in Sustainability Sciences at Leuphana University (Lüneburg, Germany).

Patric worked on various research projects between 2011 and 2013 at Leuphana University (Lüneburg, Germany). His main projects dealt with ecological impacts of the Chernobyl nuclear accident and the use of transdisciplinary research approaches in sustainability science. He was engaged in the 'Rapid Assessment of the Yale framework and Adaptation Blueprint' for the North American Pacific Coastal Rainforest to integrate climate adaptation and landscape conservation planning (coordinated by the Yale School of Forestry & Environmental Studies) and assessed linkage patterns between ecosystem services and biodiversity across temperate rainforests of the Pacific Northwest region (USA). Moreover, he participated in several ecological modelling studies during this time.

In 2014, Patric started his PhD thesis entitled 'Climate-smart livestock production at landscape level in Kenya' funded by the CGIAR program on 'Climate Change, Agriculture and Food Security' (CCAFS) and the IFAD project 'Greening livestock: Incentive-based interventions for reducing the climate impact of livestock production in East Africa'. During his PhD, he has been working with various research and development organisations such as the Institute of Meteorology and Climate Research - Atmospheric Environmental Research (IMK-IFU) in Garmisch-Partenkirchen (Germany), which is part of the Karlsruhe Institute of Technology (KIT), the International Livestock Research Institute (ILRI) and the Center for International Forestry Research (CIFOR) in Nairobi (Kenya). In 2016, he came to the Netherlands to continue his PhD at the Laboratory of Geo-information Science and Remote Sensing (Wageningen University & Research).

Patric's current research interests include the impact of climate change on biodiversity and ecosystems services, climate change adaptation and mitigation, interactions between land use practices and forest ecosystems, and sustainable land use patters.

Peer-reviewed journal publications

Brandt, P., Hamunyela, E., Herold, M., de Bruin, S., Verbesselt, J., Rufino, M.C., 2018. Sustainable intensification of dairy production can reduce forest disturbance in Kenyan montane forests. *Agriculture, Ecosystems & Environment* 265, 307–319. https://doi.org/10.1016/j.agee.2018.06.011

Brandt, P., Herold, M., Rufino, M.C., 2018. The contribution of sectoral climate change mitigation options to national targets: a quantitative assessment of dairy production in Kenya. *Environmental Research Letters* 13, 034016. https://doi.org/10.1088/1748-9326/aaac84

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Rufino, M.C., **Brandt, P.**, Herrero, M., Butterbach-Bahl, K., 2014. Reducing uncertainty in nitrogen budgets for African livestock systems. *Environmental Research Letters* 9. https://doi.org/10.1088/1748-9326/9/10/105008

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Homburg, K., **Brandt, P.**, Drees, C., Assmann, T., 2014. Evolutionarily significant units in a flightless ground beetle show different climate niches and high extinction risk due to climate change. *Journal of Insect Conservation* 18, 781–790. https://doi.org/10.1007/s10841-014-9685-x

Zimmermann, H., **Brandt, P.**, Fischer, J., Welk, E., von Wehrden, H., 2014. The Human Release Hypothesis for biological invasions: Human activity as a determinant of the abundance of invasive plant species [version 2; referees: 2 approved]. *F1000Research* 3, 1–13. https://doi.org/10.12688/f1000research.3740.1

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DellaSala, D.A., **Brandt, P.**, Koopman, M., Leonard, J., Meisch, C., Herzog, P., Alaback, P., Goldstein, M.I., Jovan, S., MacKinnon, A., von Wehrden, H., 2013. Climate Change May Trigger Broad Shifts in North America's Pacific Coastal Rainforests. *Reference Module in Earth Systems and Environmental Sciences* 2, 233–244. https://doi.org/10.1016/B978-0-12-809665-9.09367-8

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PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

The C.T. De Wit Graduate School PE&RC

PRODUCTION ECOLOGY

& RESOURCE CONSERVATION
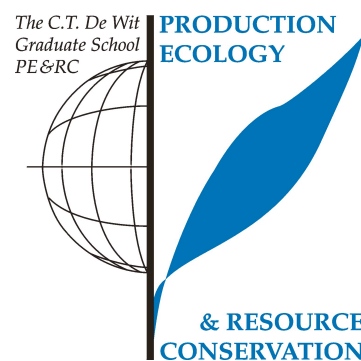
Review of literature (6 ECTS)

- Targeting climate-smart agricultural (CSA) practices

Writing of project proposal (4.5 ECTS)

- Development of targeting and planning approaches for climate-smart landscapes linking agriculture and forests in Kenya

Post-graduate courses (4.9 ECTS)

- Summer school - climate-smart agriculture: from fundamentals to application; PE&RC (2016)
- R and Big Data; PE&RC (2017)
- Multivariate analysis; Biometris (2017)
- Design of experiments; WIAS/PE&RC (2018)

Laboratory training and working visits (5 ECTS)

- Developing a decision support framework to target climate-smart agriculture; International Livestock Research Institute – ILRI, Nairobi, Kenya (2014-2015)
- Modelling of GHG emissions from smallholder dairy production in Kenya, including mitigation options; Karlsruhe Institute of Technology – KIT, Garmisch-Partenkirchen, Germany (2015-2016)

Invited review of (unpublished) journal manuscript (2 ECTS)

- Agriculture, Ecosystems & Environment: climate change mitigation in smallholder agriculture (2017)
- Agricultural systems: priority setting in research for climate-smart research (2018)

Deficiency, refresh, brush-up courses (1.5 ECTS)

- Spatial modelling and statistics; Laboratory of GIS & remote-sensing (2016)

Competence strengthening / skills courses (2.1 ECTS)

- Ethics of science course; Leuphana University Lüneburg, Germany (2010-2011)
- Scientific writing; Wageningen in'to Languages (2018)
- Research data management; Wageningen University & Research Library (2018)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.2 ECTS)

- PE&RC PhD Weekend (2016)
- PE&RC Day (2017)

Discussion groups / local seminars / other scientific meetings (4.6 ECTS)

- CSA Webinar with CGIAR scientists and other national and international research organisations; oral presentation (2015)
- CSA Workshops in Nairobi with CGIAR scientists and other national and international research organisations; oral presentations (2015-2016)
- Meetings and discussions with CGIAR scientists and other national and international research organisations; oral presentations (2015-2017)
- REDD+/CSA Discussion group at WUR; oral presentation (2016-2018)

International symposia, workshops and conferences (5 ECTS)

- International conference on global food security; oral presentation; Cape town, South Africa (2017)
- International conference on remote sensing and geoinformation of the environment; oral presentation; Paphos, Cyprus (2018)

Supervision of MSc student (1 ECTS)

- GHG emissions of smallholder dairy production in Tanzania