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Identifying large-scale land acquisitions and their agro-ecological consequences

- a remote sensing based study in Ghana

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Abstract

Large-scale land acquisition (LSLA) can be considered as necessary investments or land grabbing and it is important to study their consequences. Few studies investigate agro-ecological consequences and water use of LSLAs. Hence, this study aims to (1) identify LSLAs and their previous land use in Ghana, and (2) investigate the suitability of the current crops choice of LSLAs and compare with the previous crop choice of residents. The identification of LSLAs and previous land use is based on interpretation of satellite images and additional literature and statistics on land use and land covers of Ghana, whereas the results of agro-ecological suitability are generated from a global agro-ecological zoning (GAEZ) model.

Eventually 20 LSLAs was identified, however their locations were confirmed with different levels of certainty. The previous land use was then determined and four different land use classes were found: small-scale farming, multifunctional land use, commercial forestry and large-scale cultivation. A crop suitability index (CSI) was generated for previous and current crops and the results showed that the CSI had increased significantly ($p < 0.05$) due to the LSLAs.

The identification of LSLAs and the determination of previous land use using remote sensing were time consuming and field observations is needed to fully assess the certainty and the significance of the method. The increasing CSI indicate that either current crop choice or management are more suitable for the areas than previous crop choice or management. However, a combination of agro-ecological suitability and socio-economic suitability is required to obtain a holistic view of the consequences of LSLAs. Nevertheless, this study managed to identify LSLAs with open access data and remote sensing as well as assessing the agro-ecological suitability of the crops of the LSLAs.

Keywords: Physical Geography and Ecosystem analysis, Ghana, Land acquisition, Remote sensing, Agro-ecology

Sammanfattning

Storskaliga markförvärv kan ses som nödvändiga investeringar eller som fråntagandet av mark från fattiga och det är viktigt att studera dess konsekvenser. Denna studie utgår från Ghana, där få studier har genomförts som undersöker agroekologiska konsekvenser och vattenanvändning av storskaliga markförvärv. Syftet med studien är därför att (1) identifiera storskaliga markförvärv och tidigare markanvändning, och (2) undersöka lämpligheten av grödval i de förvärvda områdena och jämföra med grödval hos lokalbefolkningen. Identifieringen av storskaliga markförvärv och tidigare markanvändning bygger på tolkning av satellitbilder samt litteratur och statistik om markanvändning i Ghana. Grödornas agroekologiska lämplighet är genererad av en modell som är baserad på globala agroekologiska zoner (GAEZ).

Totalt 20 storskaliga markförvärv kunde, med olika säkerhetsnivåer, identifieras och bekräftas av oberoende källor. Därefter bestämdes den tidigare markanvändningen i områdena och fyra olika markanvändningsklasser hittades: småskaligt jordbruk, nyttjad mark, skogsbruk och storskalig odling. Slutligen modellerades ett lämplighetsindex för de traditionella grödorna och för de nuvarande grödorna. Resultaten visade att lämpligheten hade ökat avsevärt i områdena som ett resultat av förändringen av grödor och förvaltningsmetoder.

Identifieringen av de storskaliga markförvärven och bestämningen av den tidigare markanvändningen med hjälp av fjärranalys var tidskrävande och fältobservationer behövs för att fullt ut kunna bedöma säkerheten och signifikansen av metoden. Den ökande lämpligheten indikerar att antingen de nuvarande grödorna eller brukningsmetoderna är mer lämpliga för områdena än de tidigare grödorna eller brukningsmetoder. En kombination av agroekologisk lämplighet och socioekonomisk lämplighet krävs emellertid för att få en helhetssyn av konsekvenserna av storskaligt markförvärv. Icke desto mindre lyckades den här studien med att identifiera storskaliga markförvärv med hjälp av öppna data och fjärranalys samt att utvärdera grödornas agroekonomiska lämplighet i de storskaliga markförvärv.

Nyckelord: Naturgeografi och ekosystemanalys, Ghana, markförvärv, satellitbilder, agroekologi

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1. Introduction

Today there are more than 45 million hectares (ha) of concluded large-scale land acquisitions (LSLAs) in the low- and middle- income countries around the globe (The Land Matrix Global Observatory 2017a), which affect the ecological and social systems of those areas. The investors are either individuals, companies, investment funds or state agencies and the top three investor countries are the USA, Malaysia and the United Kingdom (Nolte et al. 2016).

The global food and energy crises in the 2007-2008 led to worldwide price hikes for important food crops such as corn (*Zea mays*), rice (*Oryza sativa*) and wheat (*Triticum*) (Demeke et al. 2008), and it is thought to be a major contributor to the on-going LSLAs (Zoomers 2010; Borras Jr and Franco 2012; Arezki et al. 2015; Schoneveld and German 2014). Another factor thought to have intensified the process of LSLA is the goal set by the European Union and the USA to increase the use of liquid biofuels in the transport sector to partly replace fossil fuels (Oxfam International 2008). As a consequence of the increased demand for biofuels, LSLAs with fields of jatropha (*Jatropha curcas*), an oil plant originating from Mexico (Pecina-Quintero et al. 2014), can be traced throughout the African continent south of Sahara (Hall 2011).

LSLA is a controversial topic and is often referred as land grabbing by those who address the negative effects of LSLA (Borras Jr and Franco 2012), whilst other prefer to address it as land investments (Zoomers and Otsuki 2017; U.S. Department of the Interior and U.S. Geological Survey 2006a). While the latter term emphasises investment and job opportunities for the residents, the term land gabbing emphasises how land is being grabbed from the poor (Boamah 2014a). Whether it is referred to as large-scale land acquisition, land grabbing or land investment, the phenomena originate from large land deals where the right to utilise the land is moved from the local people to the investors (The Land Matrix Global Observatory 2017c).

To fully understand ecological and social impacts of LSLAs, it is important to investigate current and previous land use, ownership as well as conflicts over lands in affected areas (Bottazzi et al. 2016; Johansson et al. 2016). Studies in Africa have observed that LSLA created new and intensified conflicts over lands between residents (Bottazzi et al. 2016; Campion and Acheampong 2014). The area of interest in this study is Ghana, in western Africa, where approximately 235,000 ha of land have been acquired by mainly foreign investors (The Land Matrix Global Observatory 2017b).

Ghanaian authorities such as the Water Resource Commission, Ghana Irrigation Development Agency, and the Ministry of Food and Agriculture are normally not consulted when deals are concluded between land owners and the investors during a land acquisition (Williams et al. 2012a). Hence the suitability and sustainability of the investors' crop choices and water demands are often left uninspected. A recent study investigated changes in water use from LSLAs in Africa, by using a dynamic global vegetation model (Lund-Potsdam-Jena managed Land) to estimate the amount of freshwater and rainwater that crops on acquired land require (Johansson et al. 2016). The authors noted that there is a knowledge gap in the literature concerning previous land use and water demands in areas where land is acquired. This information is needed in order to understand how pressures on local ecosystems and freshwater sources change, before and after the LSLA (Johansson et al. 2016).

1.1 Aim and research questions

On account of the sparse information regarding previous land use, this study aims to determine previous and current land use with remote sensing, in areas that are subject to LSLA in Ghana. Whereas several studies have been conducted on social and economic consequences of LSLA in Ghana, few address ecological consequences of LSLA (Williams et al. 2012b). Therefore, this study also aims to investigate the ecologically suitability of the previous and current crop choice and land management, based on a global agro-ecological zoning (GAEZ) model. The research questions that will be addressed in this study are the following:

i. How can the locations of LSLAs be identified using remote sensing tools?
ii. What were the land use prior to the land acquisitions and how can they be determined using remote sensing?
iii. Is the previous crop choice of local residents or the current crop choice of LSLAs most agro-ecologically suitable for the area?

2. Background

With approximately the same size as the United Kingdom, Ghana has attracted 41 investors since 2000, of which 20 is included in this study (The Land Matrix Global Observatory 2017c). The purpose of this background section is to unravel the why, how and what of LSLAs in Ghana: why are investors attracted to Ghana? How is the land acquired? And, what are the consequences of LSLAs in Ghana? However, first a brief introduction to the climate of Ghana is required and a definition of LSLA needs to be established.

2.1 Ghana

The Republic of Ghana is situated along the northern shore of the Gulf of Guinea, on the west coast of the African continent. The country shares its western borders with Côte d'Ivoire, its eastern borders with Togo and adjoins Burkina Faso in the north (figure 1).

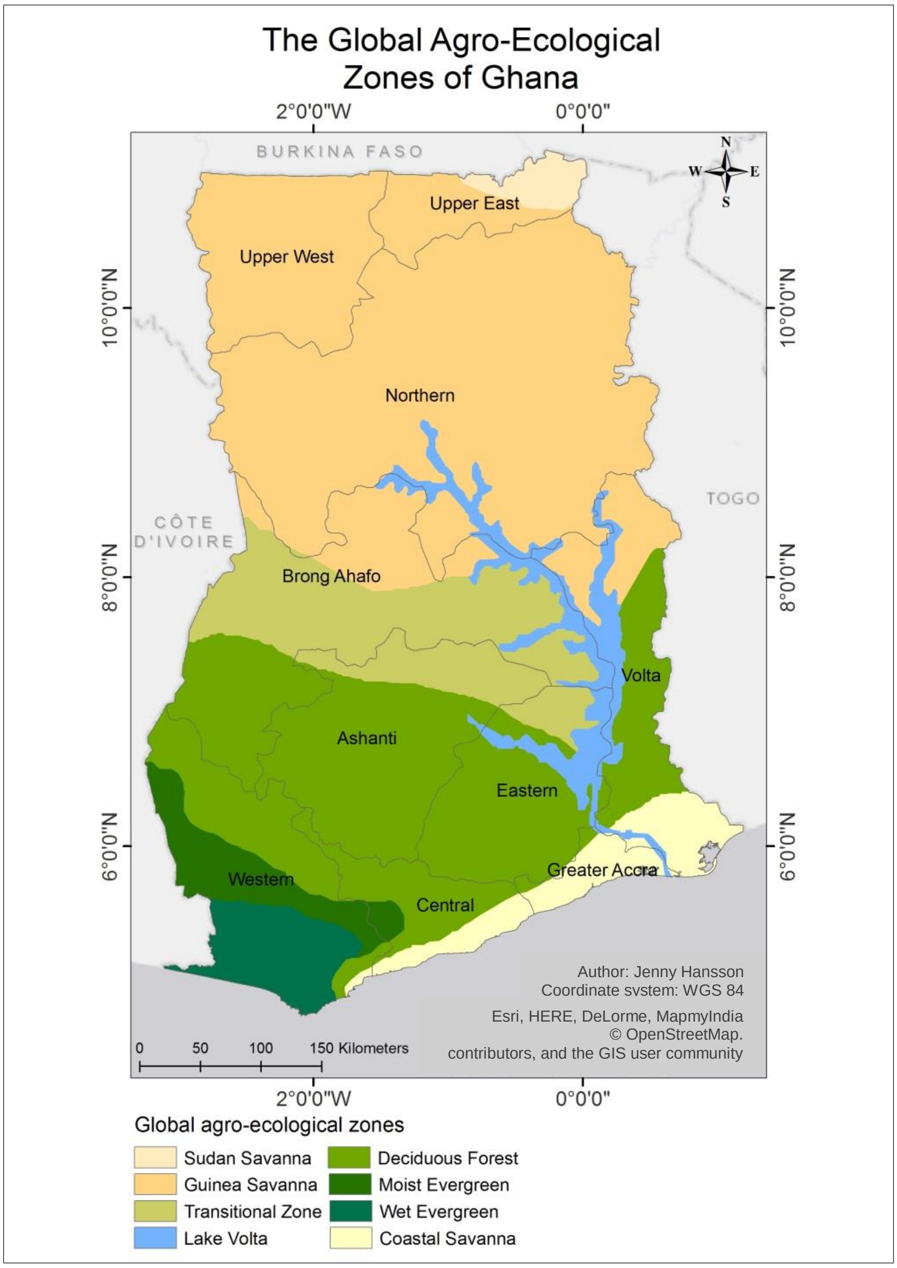

Figure 1 The agro-ecological zones in Ghana. Adapted from FAO (Food and Agriculture Organization of the United Nation (FAO) 2004).

2.1.1 Climate and agro-ecological zones

Ghana can be divided into seven different agro-ecological zones (AEZ): rainforest, deciduous forest, transitional zone, guinea savannah, sudan savannah and coastal savannah (figure 1). The AEZs are utilised for mapping potential land resources based on the climate, soil profile, landform, land cover and specific restrictions for land (Food and Agriculture Organization of the United Nation (FAO) and the Land and Water Division 1996).

The mean annual precipitation is continuously decreasing along a transect running from the Rainforest in the southwest (2,200 mm/year) to the Sudan savannah in the far northeast corner of the country (1,000 mm/year). The coastal savannah is an exception and receives the least annual precipitation (800 mm/year) (Food and Agriculture Organization of the United Nation (FAO) and Aquastat 2005). The annual precipitation pattern can be divided into four different areas based on their rainy seasons. North of the transitional zone there are two different precipitation schemes consisting of one rainy season. The two southern precipitation schemes on the other hand experiences two rainy seasons annually (Ghana Meteorological Agency 2016b). Whilst the southern area of Ghana has two rainy seasons the national mean precipitation falls between May and September, with the highest amount of rainfall occurring in June and September (figure 2).

The average annual temperature is approximately 27.5 °C and the monthly average never falls beneath 25 °C (figure 2). The highest temperatures can be found in the northern parts of Ghana where the monthly maximum temperatures are above 30 °C throughout the year, and the lowest maximum temperature around 26 °C (Ghana Meteorological Agency 2016a).

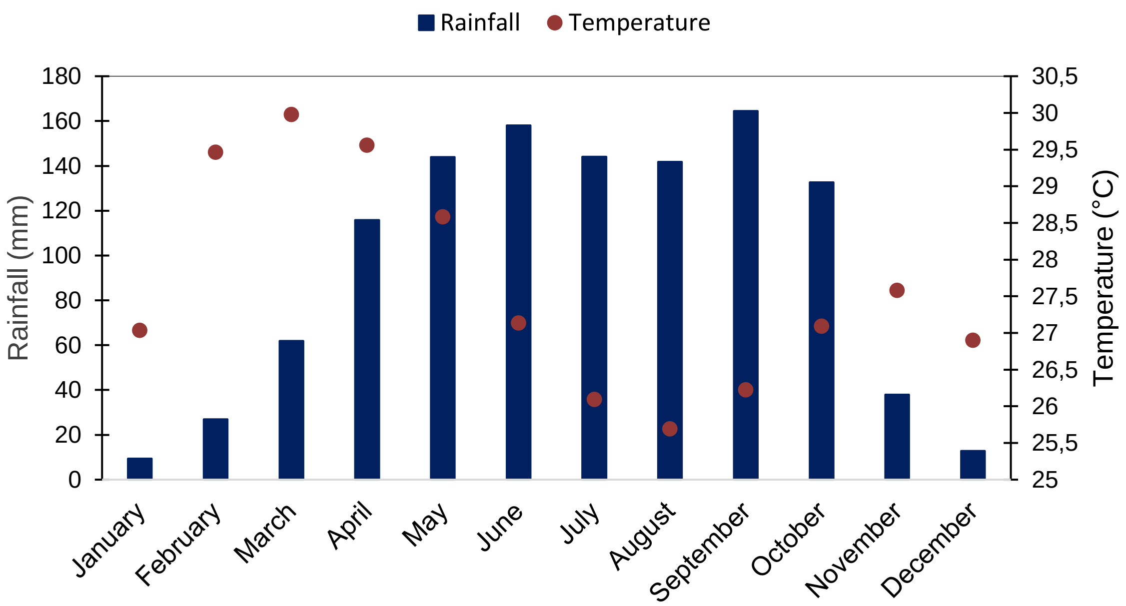

Figure 2 Monthly mean rainfall and temperature in Ghana, based on the years 1991-2015 (Jones and Harris 2013).

2.1.2 Land cover and land use

Approximately 50% of Ghana's population lives in cities and the urban areas around the capital of Accra are advancing due to a fast urbanisation (Shih et al. 2016; Ghana Statistical Service 2013). Yet a recent land cover classification estimated that as much as 50.2% of Ghana's surface is under some kind of agricultural use (Hackman et al. 2017). Additionally, 36.5% of the land cover is shrublands, whereas 8.1% of the total land cover is forest (Hackman et al. 2017). The forested areas are sparsely scattered throughout the wet evergreen and moist evergreen AEZs (figure 1) and are almost entirely forest reserves (Hackman et al. 2017). In northern Ghana, agricultural land has expanded at the expense of grasslands and areas of mixed vegetation with tree cover, mainly due to population growth and increased rainfall variability (Kleemann et al. 2017). Another study explains the decrease in savannah grasslands as a result of increasing mining activities (Basommi et al. 2015). In central Ghana, closed canopy forests have decreased continuously since 1990, whereof two forest reserves lost 50% of their closed canopy forest cover between 1990-2010, mainly due to logging (Addo-Fordjour and Ankomah 2017). Local fuelwood collection is estimated to be responsible for 35 % of the total deforestation in Ghana (Amlalo and Oppong-Boadi 2015). Whether it is due to population growth, urbanisation, more effective forestry or mining, the land use and land cover in Ghana are constantly changing.

Apart from the large proportion of land used for agriculture, Ghanaians utilise land in multiple other ways, and approximately 20 % of rural household income is gathered form natural resources (Pouliot et al. 2012). Important resources are fuelwood (38 % of the energy supply in Ghana), bush meat, wild foods, and construction material (Energy Commission of Ghana 2016; Pouliot et al. 2012; Appiah et al. 2009).

2.2 Definition of large-scale land acquisition

The Land Matrix database, an independent initiative that gathers and stores information on LSLAs around the world, has defined several characteristics that define a LSLA (The Land Matrix Global Observatory 2017c). Firstly, the purpose of the deal should be either to gain agricultural yield or timber, carbon trading, industry, renewable energy production, conservation or tourism. Secondly, the land deal should cover an area of at least 200 hectares, and the investor has the right to use, control or own the land. Lastly, the land deal results in a transition from small-scale agriculture, local community use, or important ecosystem services, into an area of commercial use (The Land Matrix Global Observatory 2017c).

2.3 Large-scale land acquisition in Ghana

The LSLAs in Ghana are mainly intended for agriculture, and only 4 out of 41 listed LSLAs have another primary intention. Besides from agriculture, forestry is also a main purpose of LSLAs in Ghana (The Land Matrix Global Observatory 2017b). The most common crops grown are corn, oil palm (*Elaeis guineensis*), jatropha, soybeans (*Glycine max*) and rice. Rice is the only crop solely grown for food, unlike the other crops that are grown partly for biofuel production (Landis et al. 2008; Kusin et al. 2017; Li et al. 2014; Zhou et al. 2016). Jatropha, corn, oil palm and soybeans are so called flexible crops, which mean that they can be grown for multiple purposes (Borras et al. 2016). Unlike corn, oil palm and soybean, jatropha is not edible, however, it can be used for medical purposes or animal feed after processing (Ye et al. 2009). Jatropha is mainly produced for the purpose of biofuel production (Acheampong and Campion 2014; Aha and Ayitey 2017; Ahmed et al. 2017; Campion and Acheampong 2014; Hesselberg 2008; Kolnes n.d.), and is classified as biofuel in this study whereas corn, oil palm and soybeans are classified as flexible crops.

2.3.1 Why are investors attracted to Ghana?

The favourable climate and the political stability of Ghana are the foremost reasons why companies are attracted to Ghana. Other benefits are abundant water resources and the relatively good infrastructure (Smart Oil 2 Srl. n.d.; Kolnes n.d.; Levi n.d.; Africa Atlantic 2013a; Formako Farms n.d.; Mim Cashew and Agricultural Products Ltd. n.d.-b; Compagnie Fruitière n.d.; Gold Coast Fruits Ltd. n.d.). Also the Ghana Investment Promotion Centre (GIPC) emphasises the political stability, the good workforce and the infrastructure of Ghana as reasons why foreign companies should invest in Ghana (Ghana Investment Promotion Centre (GIPC) 2017).

2.3.2 How is land acquired?

It is stated in the Constitution of the Republic of Ghana that that a non-Ghanaian citizen does not have the right to possess any land in Ghana (Government of Ghana 1992), yet transnational companies manage to acquire land in Ghana. These LSLAs are enabled by the structure of the customary land tenure system in Ghana, where the chief of a local community and the company sign long term leases (Campion and Acheampong 2014; Kuusaana and Gerber 2015; Aha and Ayitey 2017). Approximately 80-90 % of the undeveloped land in rural Ghana is under customary land tenure, meaning that the right to use land is approved by the local communities, families, first settlers or clans rather than the government (Ministry of Lands and Forestry 1999; Kasanga and Kotey 2001). Customary land tenure is normally gained through inheritance from ancestors and can follow either a matrilineal or a patrilineal path (Gyasi 1994; Kasanga and Kotey 2001; Ollennu 1962).

Even though inheritance still is the main way of gaining land, the land tenure system has been shown to adapt to land requests, with more frequently occurring land sales and land leases as a result (Gyasi 1994; Kasanga and Kotey 2001). The land leases resulting in LSLAs are often signed without any consultancy of the members of the community and with little governance form the government (Campion and Acheampong 2014; Kuusaana and Gerber 2015; Aha and Ayitey 2017). A recent study from the regions of Yeji and Ejura showed that 93 % of the relocated farmers participating in the survey were not asked about their land being leased to foreign companies before the deal was signed. The farmers claimed that it was the chief and his council that made the decision on their own (Aha and Ayitey 2017). As a consequence of the land tenure insecurity and the exclusions of the community members in the land leases, it is suggested that the role of the chief in land deals is better controlled or changed in order to make the land deals proper fair and transparent (Ahmed et al. 2017).

2.3.3 What are the consequences of large-scale land acquisition in Ghana?

LSLAs might intensify already existing problems such as local food insecurity, land tenure insecurity and landless farmers, increased emigration of young people towards the south, and displacement of people from culturally and socially important places (Kidido and Kuusaana 2014). Other consequences of LSLAs in Ghana are the displacement of farmers without proper compensation, and failure to bring benefits to the local people due to failures of many projects (Anseeuw 2013; Kuusaana and Gerber 2015; Aha and Ayitey 2017; Ahmed et al. 2017).

Local food insecurity is often associated with land tenure insecurity where landless households more frequently experience food insecurity (Nyantakyi-Frimpong and Bezner Kerr 2017). The displacement of farmers due to LSLA sometimes leave farmers with less fertile land, hence increasing food insecurity (Timko et al. 2014). It has also been shown that land holders in areas where LSLA has occurred show less willingness to invest in their lands, which leads to food insecurity even among land holders (Aha and Ayitey 2017). This is seen as a consequence of other farmers being displaced due to LSLA which has led to land tenure insecurity amongst the land holders (Aha and Ayitey 2017). Land holders can also be constrained in how long they can leave their land in fallow when large amounts of land are acquired in the area (Timko et al. 2014; Kidido and Kuusaana 2014). With less land available the ration between cultivated land and fallow land increases, which in turn can decrease the crop yield (Gaiser et al. 2011), thus affecting food security. There are also concerns among displaced farmers that the fertile land they once used for growing food crops now is used for growing jatropha intended for biofuel production (Timko et al. 2014). Planting crops for biofuel production instead of food crops is commonly discussed when relating LSLA to local food insecurity (Tomei and Helliwell 2016). However, food insecurity as a result of LSLA can also be related to people being denied the access to natural resources and wild food (Laura et al. 2011; Pouliot et al. 2012).

Even though LSLA can lead to food insecurity, it can also generate employment and benefits such as new water wells, schools, medical clinics and road maintenance (Laura et al. 2011; Timko et al. 2014). As an example, one LSLA that was initiated in 2003 has employed more than 2,000 employees and has recently established a health care centre (Golden Exotics Limited (GEL) 2015). At the same time, many of the LSLA that focused on jatropha failed on an early basis, leaving few employments and empty promises behind (Ahmed et al. 2017; Boamah 2014a). Unfulfilled promise of employment and increased social infrastructure has been suggested to be a larger problem than the LSLA itself (Kidido and Kuusaana 2014). A recent review of failed jatropha projects in Ghana shows that there is not one simple reason behind the failures, but rather a combination of different circumstances that contribute to the failures of the jatropha projects. The Ghanaian state, the Land Commission, local communities, community chiefs, community based organisations (CBOs) and non-governmental organisations (NGOs), and the foreign agribusinesses all contributed to their part in the failures (Ahmed et al. 2017). Boamah (2014a) observed that jatropha projects that are described as land grabbing by CBOs and NGOs are more likely to fail and are less likely to benefit the local people and contribute to local development (Boamah 2014a). In Ethiopia, it has been suggested that a major reason behind the failure of jatropha projects is the misbelief that jatropha can be cultivated in large scale on marginal lands and yet produce sufficiently for the extraction of biofuel (Wendimu 2016).

3. Data and methods

The methodology can be separated into three different substudies based on the structure of the research questions: (i) identifying and observing LSLAs, (ii) determining the previous land use and (iii) investigating the crop suitability index (CSI) of the previous and current crops (figure 3). First a brief description of the data will be presented, followed by a section describing the three steps of the methodology.

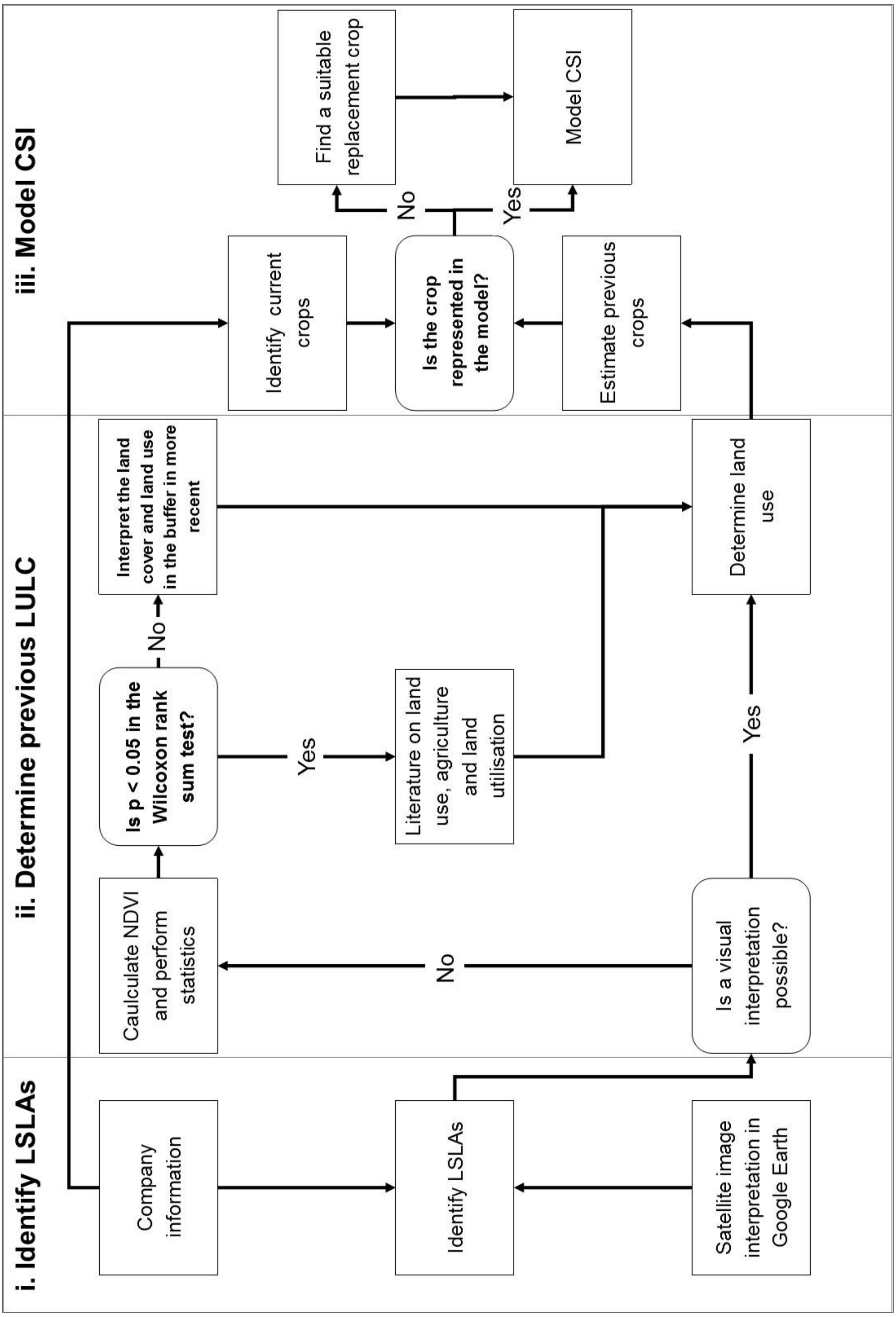

Figure 3 The flowchart describes the main methods, divided into three substudies, of this study.

3.1 Data and data management

The data used in this study was derived from the Land Matric Observatory, Google Earth Pro and Earth Explorer and will be briefly presented in this section (The Land Matrix Global Observatory 2017b; Google Inc. 2017b; U.S. Department of the Interior and U.S. Geological Survey 2017). A comprehensive documentation of the data can be found in Appendix A.

3.1.1 The Land Matrix Observatory

The spatial data on LSLAs in Ghana were obtained from the Land matrix database, which covers LSLAs in the low- and middle-income countries worldwide (The Land Matrix Global Observatory 2017b). The Land Matrix collects data of land deals, from year 2000 and onwards, and the database is constantly updating the areas that have been identified as LSLAs. The LSLAs within the database are mainly derived from six different types of sources: (1) research papers and policy reports, (2) personal information, (3) field-based research projects, (4) official government records, (5) company sources and (6) media (The Land Matrix Global Observatory 2017c).

The LSLAs documented in the Land Matrix database are in different stages of the land acquisition process: not started, start-up phase, in production, project abandoned or of unknown status (The Land Matrix Global Observatory 2017c). Only LSLAs in production or with unknown status were examined since LSLAs that has not yet be initialised will be impossible to identify through remote sensing. In Ghana, there are currently 20 LSLAs in production and 7 with unknown status, which initially were observed and analysed in this study, although some were removed at an early stage due to inadequate information.

It is important to accurately identify the spatial distribution of the land acquisitions in order to understand the social and ecological effect in those areas (Eckert et al. 2016), however the spatial accuracy of the Land Matrix data is widely varied and imprecise (Messerli et al. 2014). As a consequence, a comprehensive examination of the areas in Google Earth Pro was required in order to find the exact position of the LSLAs. Since the LSLAs are changing in extent and activity it is important to note when the data was obtained from the Land Matrix database. The data for this study was downloaded on the 18 January 2017 and is displayed in Appendix B.

3.1.2 Google Earth Pro

Google Earth provides the user with an opportunity to investigate a larger area without having to download large data sets. It further provides the user with layers and labels that together with the ability to search for locations and land features facilitate when searching for unknown locations in populated areas (Google Inc. 2017b). The built-in Street View application was also utilised to identify areas and to understand characteristics of the surrounding landscape. If an approximate location of a LSLA was known the Street View could be used to explore the area from a street level point of view, that is to say if street view images had been collected by Google. Consequently, LSLAs situated along major roads could possibly be identified from road signs or street level observations. Additionally, Google Earth is a software that is easy to access and the basic version is free of charge (Google Inc. 2017a). A free trial version of Google Earth Pro version 7.1.8.30.36 was utilised in this study, mainly because it enables the user to perform measurements and create polygons directly in the program (Google Inc. 2017b).

3.1.3 Landsat 7 and Landsat 8 satellite data

Initially the methodology of observing LSLAs and determining the corresponding previous land use was based on the utilisation of Google Earth Pro and its functions. However, it was realised early on that the quality of the satellite data as well as the ability to investigate historical images were highly limited, therefore additional satellite data was acquired. Both more recent and historical satellite data, recorded before the land acquisitions, were acquired from the Earth

Explorer, which is operated by the U.S. Department of the Interior and the U.S. Geological Survey (U.S. Department of the Interior and U.S. Geological Survey 2017). The Earth Explorer offers a variety of dataset that covers the earth and the service is free of charge (U.S. Department of the Interior and U.S. Geological Survey 2017).

Satellite data from Landsat 7 and 8 were acquired from the Landsat Collection Tier 1, which means that the satellite data are cross-calibrated over the Landsat instruments and has been pre-processed to the same level (U.S. Department of the Interior and U.S. Geological Survey 2016b). The data is also geometrically corrected with ground control points (GCPs) and digital elevation models (DEMs) and the geometric accuracy of Tier 1 products have a root mean square error (RMSE) of < 12 meters (U.S. Department of the Interior and U.S. Geological Survey 2016b; Young et al. 2017). Landsat 7 satellite data is recorded over 8 bands whereas Landsat 8 records data over 11 different bands (table 1; U.S. Department of the Interior and U.S. Geological Survey 2016a). Besides from bands that cover the visible spectra the satellite sensors records data in the near infrared (NIR), short-waved infrared (SWIR), thermal infrared (TIR) and panchromatic spectra.

Table 1 The spectral bands and the spatial resolution of the satellite data for Landsat 7 and Landsat 8 (U.S. Department of the Interior and U.S. Geological Survey 2016a).

Band	**Landsat 7 ETM+ Sensor**			**Landsat 8 OLI Sensor and TIRS Bands**		
		Spatial Resolution (m)	Spectral Range (µm)		Spatial Resolution (m)	Spectral Range (µm)
1	Blue	30 × 30	0.44 - 0.51	Ultra blue	30 × 30	0.44 - 0.45
2	Green	30 × 30	0.52 - 0.60	Blue	30 × 30	0.45 - 0.51
3	Red	30 × 30	0.63 - 0.69	Green	30 × 30	0.53 - 0.59
4	NIR	30 × 30	0.77 - 0.90	Red	30 × 30	0.64 - 0.67
5	SWIR 1	30 × 30	1.55 - 1.75	NIR	30 × 30	0.85 - 0.88
6	TIR	60 × 60	10.31-12.36	SWIR 1	30 × 30	1.57 - 1.65
7	SWIR 2	30 × 30	2.06 - 2.35	SWIR 2	30 × 30	2.11 - 2.29
8	Panchromatic	15 × 15	0.52 - 0.90	Panchromatic	15 × 15	0.50 - 0.68
9				Cirrus	30 × 30	1.36 - 1.38
10				TIR 1	100 × 100	10.60-11.19
11				TIR 2	100 × 100	11.50-12.51

3.2 Methods

The purpose of the first substudy was to find a remote sensing based method to identify LSLAs. The second substudy involved determine the previous land use of the LSLAs identified in the first substudy. The third substudy then utilised the results of the first two substudies to investigate the change in crop suitability before and after the land acquisitions.

3.2.1 Identifying large-scale land acquisitions with remote sensing

The locations of LSLAs were identified in three different steps: (1) the approximate locations, obtained from the Land Matrix database, were positioned in Google Earth Pro and the LSLAs were colour coded based on their land use. (2) Company sources were then used together with peer-reviewed articles, NGO documents, and newspaper articles to find a more precise location of the land acquisition. Additional company information from different social media such as YouTube and Facebook greatly facilitated the identification of the location of some of the LSLAs. In some cases, recently released Street view imageries in Google Earth helped to determine the location of a company farm or factory. (3) Once the approximate locations of the LSLAs were modified and confirmed with independent sources, established image interpretation techniques were used to identify the exact locations from satellite images.

When an unknown object is to be identified in satellite data there are several techniques that facilitate the interpretation process (Paine and Kiser 2012). The interpretation techniques used in this study are the: (i) relative size of the object related to surrounding object with a known size, (ii) shape of the object, (iii) shadow of the object, (iv) colour and the hue of the object, (v) texture of the object, (vi) visible patterns in the area, (vii) location of the object, and (viii) how the object is associated with other features (Paine and Kiser 2012). Some examples of how theses image interpretation techniques were used are displayed in figure 4 and figure 5a and 5b. Once the LSLAs were identified they were named following the order they appeared in the Land Matrix: L1, L2, Lx …L20.

Figure 4 is a good example of the different interpretation techniques, and displays some features that were characteristics for oil palm plantations. Firstly, the oil palm plantations that were identified had a distinct pattern of paths running through the plantation. They were either straight paths, as displayed in figure 4, or paths that had the appearance of contour lines. Secondly, the shape and colour of the oil palms themselves were easy to distinguish, on account of their fanlike appearance and the green colour of the crown that has a blue shade to it. These characteristics also facilitated the distinguishing of oil palms even when they were mixed with other types of vegetation. Thirdly, even though the crowns are fanlike the texture of oil palm fields is smooth and continuous.

Figure 4 Part of the oil palm plantation of L14a. The crowns of the oil palm are easily distinguished as well as the paths, dividing the area into smaller patches (Google Earth Pro 2016j).

Figure 5a displays a rice field that was identified as L10 on the account of a nearby factory that previously had be identified as the factory of L10. When the approximate location was identified, from the Land Matrix and additional sources, the factory could be identified from a picture on the company webpage. The picture displayed two large silos in association with the farm and these could be identified in satellite images. The silos are evident next to the factory building in the satellite image of figure 5b. Furthermore, the small road at the top of the satellite image in figure 5b connects the farm with the large rice field in figure 5a. The two examples of figure 4 and figure 5a and 5b demonstrate how the land use and the LSLAs could be identified using image interpretations techniques. As for Figure 5a and 5b, where more than one possible site could be the LSLA, finding a connection between one of the sites and additional information in the satellite image helped to identify the LSLA with a higher level of certainty.

Once all the LSLAs were observed in Google Earth Pro and a polygon had been created for each LSLA, a certainty level was set to each LSLAs. The certainty levels were based on whether the location could be confirmed by another source than the Google Earth scenery, the Landsat satellite data and, on whether the initial location could be obtained from the Land Matrix database or not. The certainty levels ranged from high certainty to low certainty on a five-step scale. Some of the LSLAs could have multiple small fields in different locations or adjacent fields that could be observed with different levels of certainty and for that reason those

Figure 5a A satellite image of the rice field of L10 (Google Earth Pro 2013e).
Figure 5b A satellite image of the factory buildings of L10 (Google Earth Pro 2013d)

LSLAs were divided into subareas in the analysis.

3.2.2 Determining previous land use

While land cover, which is the physical characteristics of the surface, often can be distinguished using remote sensing only, interpretation of land use requires knowledge of land utilisation in the area to complement the visual interpretation (Giri 2012). Since this study aims the determine previous land use of LSLAs, this was mainly done through visualisation of historical satellite images combined with information on land utilisation, however identification of previous land use was not always possible due to insufficient quality of the satellite images. Consequently, areas where previous land use could not be determined by satellite visualisation were supplemented with two additional methods: (1) comparison of histogram statistics of the NDVI from within and outside the LSLAs, and (2) literature review on land use, natural vegetation and LSLAs in Ghana.

Visualisation of historical satellite images

Historical satellite images were obtained with the Google Earth historical imagery function and from the Landsat 7 satellite. The initial interpretation was performed using Google Earth's historical imagery, which provides an opportunity to observe changes in an area during different years without having to download a satellite image for each year (Google Inc. 2017b). However, too coarse resolution made it difficult to determine previous land use from Google Earth and additional Landsat 7 satellite data were acquired and analysed in ArcMap 10.3.1 (ESRI Inc. 2014). The interpretation of the historical satellite images then followed the same interpretations techniques as those mentioned in section 3.2.1, although the quality of the historical satellite images often was limited. Frequent cloud contamination, coarse resolution, insufficient quality of the satellite data or error strips caused by a failure in the Landsat 7 scan line corrector (SLC) contributed to difficulties in determine the previous land use (Hayes et al. 2007). Problems with frequent cloud contamination and the failure of the SLC when working with Landsat 7 data covering Ghana are also recognised by Shih et al. (2016).

Using NDVI to detect similarities in land use and land covers

Since many of the historical satellite images in Google earth and from the Landsat Collection were of insufficient quality for visually determining previous land use, a quantitative approach was tested in order to determine the previous land use of the LSLAs. The areas bordering the LSLAs appeared unchanged when they were observed in a time sequence using the historical imageries function in Google Earth Pro (Google Inc. 2017b). This insight led to the idea to utilise NDVI histograms in order to detect similarities or differences, which were not fully visible in the satellite images. NDVI has previously been used as input in land cover classifications, where the spatial or temporal histogram profile of the NDVI is used to divide a satellite image into different land cover classes (Loyarte 2002; Shao et al. 2016; Loveland et al. 2000). NDVI is a combination of the red and the NIR bands of a satellite data scene. Even though green reflectance is associated with vegetation, the combination of the red and NIR reflection highly outperforms the reflectance of the green band when it comes to monitoring the density and variation in vegetation cover (Tucker 1979). The reflectance from green vegetation is considerably higher in the NIR wavelength compared to the reflectance in the visible wavelengths and increases with increasing vegetation density whereas the reflection in the visible red wavelength normally decreases with increase vegetation cover (Delegido et al. 2015; Ding et al. 2014). These reflectance characteristics of the visible red and NIR in vegetation makes the NDVI a good option for observing changes in vegetation density and condition.

In this study the NDVI distribution of a LSLA and the NDVI distribution from its bordering area (defined by a one kilometre buffer zone) were derived from a historical satellite image from a time prior to the land acquisition. If the histogram profiles of the two NDVI distributions were similar, it was assumed that they had the same land cover. Since the land cover in the bordering area had not changed noticeably over the years, observations of the bordering areas in more recent satellite images would imply the previous land cover of the LSLA. Knowing the previous land cover, the previous land use could then be visually interpreted or estimated using additional information about land utilisation and land cover statistics. In other words, more recent and detailed satellite data were utilised to determine previous land use of the LSLAs by assuming (1) that the bordering areas of a LSLA have the same land cover at present as they had at the time before the land acquisition, and assuming (2) that if the NDVI histogram of a LSLA, derived from a satellite image recorded at a time before the land acquisition, and the NDVI histogram of the bordering area in the same satellite image are similar the land cover in these two areas are similar.

The preparation of the Landsat satellite data

In order to remove the influence of the sun in the pixel values and enable comparison between multiple years and images, the digital number (DN) of the Landsat satellite data had to be converted to top of the atmosphere (TOA) reflectance for each band, using the equation (1) (U.S. Department of the Interior and U.S. Geological Survey 2016a).

$$\rho_{\lambda} = \frac{M_{\rho} \times Q_{Cal} + A_{\rho}}{Sin(\theta)}$$

Equation 1

Where,
ρ_{λ} = The TOA reflectance for the specific band
M_{ρ} = The reflectance multiplicative scaling factor for the specific band
Q_{Cal} = The pixel value in DN
A_{ρ} = The reflectance additive scaling factor for the specific band
θ = The solar elevation angle

The information needed for the calculations can be derived from the meta data file, which is supplied when acquiring the satellite data, and the calculations were performed in ArcMap version 10.3.1 (ESRI Inc. 2014).

Following the conversion into reflectance values, the NDVI for each image can be derived from the red and the NIR bands using the equation (2) (Tucker 1979).

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$$

Equation 2

Where,
NDVI= normalized difference vegetation index
ρ_{NIR} = The TOA reflectance for the NIR band
ρ_{Red} = The TOA reflectance for the red band

Due to the effect of the atmospheric condition on the TOA reflectance, NDVI is preferably calculated from the surface reflectance of the NIR and red bands of a scene (Vermote et al. 2002). However, information regarding the atmospheric conditions at the time when the satellite image is recorded is required to calculate the surface reflection. Since this study utilized more than 20 different Landsat scenes and no information regarding the state of the atmosphere was easily accessible, the TOA reflectance had to be sufficient for this study.

The compilation of the NDVI histogram analysis

Once the NDVI had been calculated for a historical satellite scene, the NDVI-values of the LSLA and the NDVI-values of the one kilometre (km) buffer zone were separately extracted for a comparison analysis. Initially a ten kilometre buffer zones was used, however the number of cells in the buffer zone highly exceeded the number of cells within the LSLAs. Ideally, the area of the LSLA and the area of the buffer zone should be equal in size for an adequate comparison. For that reason a one kilometre buffer zone appeared more suitable and similar to the LSLAs in size. If the cloud cover was excessive in the satellite scene, the clouds were removed by assigning ‘No Data’ to those NDVI-values that were overrepresented by clouds. The same procedure was also performed if error stripes, caused by the failure of the Landsat 7 SLC, were present (Hayes et al. 2007).

The NDVI distributions of the LSLAs and their respective buffer zones were analysed in MATLAB R2015a (The MathWorks Inc. 2017), where the NDVI histogram from each LSLA area was plotted in the same graph as the histogram from the corresponding buffer zone for a visual interpretation. If the two histograms are similar this indicates that the land use of the LSLA area and the buffer zones are similar.

A statistical test was then performed to see if the NDVI of the LSLA and the buffer zone had the same median, and hence originated from the same distribution. The NDVI-values were not normally distributed nor were the area and buffer zone of the same sample size, thus the Wilcoxon rank-sum test was chosen since it is a nonparametric test which can perform with different sample sizes (Sprent and Smeeton 2007). The Wilcoxon rank-sum test ranks the values from the two sets to test whether the medians are equivalent or not. A rejection of the null hypothesis means that the samples have different medians, hence do not originate from the same distribution (Sprent and Smeeton 2007). The statistical testing of the NDVI values was performed to test if previous land use of LSLAs could be determined using this method. If it was stated that the NDVI distribution of the LSLA area and the NDVI distribution from the buffer zone were significantly different ($p < 0.05$) this would indicate that they did not have the same land use before the land acquisition, following the assumptions of this methodology.

Figure 6, 7 and 8 displays the methodology for comparing histograms, beginning with the historical satellite image of coarse resolution and continuing with the histogram of the NDVI distribution within the LSLA area and in the buffer zone. The final step displays the investigation of the land use in more recent satellite data of better quality.

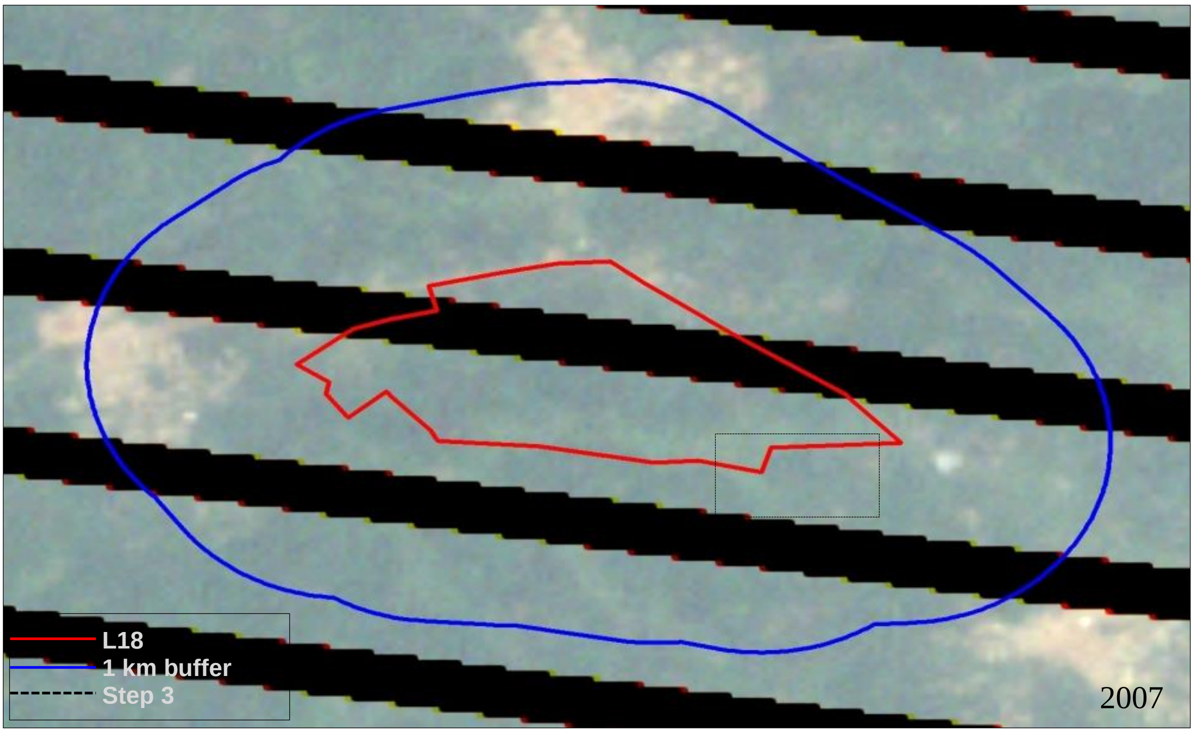

Figure 6 The quality of this historical satellite image is too insufficient in order to visually determine the previous land use of L18. For that reason, a 1 km buffer zone was created around L18 and the NDVI was calculated for the entire satellite image. The NDVI values of L18 and the NDVI values of its buffer were then extracted separately (step 1) (U.S. Department of the Interior and U.S. Geological Survey 2007b).

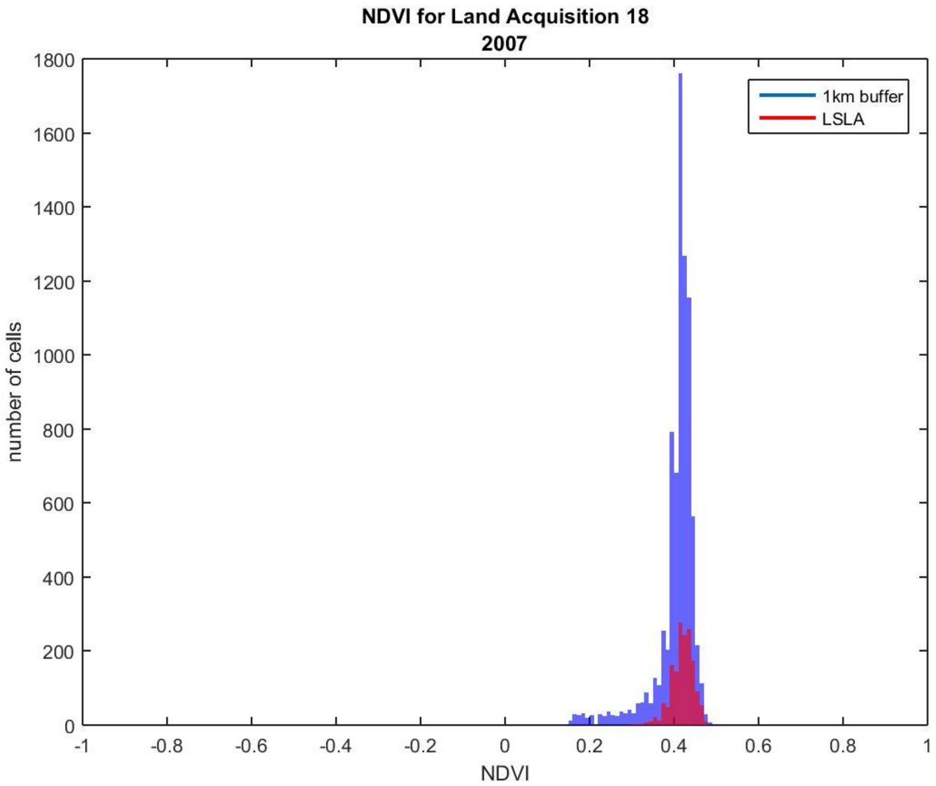

Figure 7 The NDVI profiles of L18 and its buffer is represented by the two histograms. Except for the left-sided tail of the buffer histogram they appear to be centred on the same range of NDVI values (0.4 – 0.5). The histogram analysis was then supplemented with a Wilcoxon rank-sum test in order to see if the there was a significant different between the NDVI distribution of L18 and the NDVI distribution of its buffer. Since no significant difference was proven ($p = 0.391$) it was assumed that L18 and its buffer had similar LULC at the time when the satellite image was recorded (step 2).

Figure 8 In this, more recent (2015) satellite image, oil palms, cleared areas and forest stands are evident in the buffer zones. If no significant difference was proven in step 2, it was concluded that the LULC of L18 was oil palms, cleared areas and forest stands prior to the land acquisition (Google Earth Pro 2015h).

3.2.3 Determining the crop suitability with the Global Agro-Ecological Zoning Model

The third and final research question to be addressed in this study involves investigating whether the current crop of the LSLA or the crop that previously was cultivated in the acquired area is most suitable for that specific area. Consequently, in this study the term current crop refers to the crops that grow on acquired land whereas the term previous crop refers to crops that grow in the corresponding areas prior to the land acquisitions. The GAEZ model (GAEZ v3.0), launched by FAO and the International Institute for Applied Systems Analysis (IIASA) in 2002 and updated in 2012, appeared to be a good method for studying crop suitability, hence the GAEZ model v3.0 was utilised for this crop suitability study (Fischer et al. 2012).

Model description

The GAEZ models originate from the AEZ methodology, developed by the FAO already in the 1970s to estimate the productivity of crops, based on their environmental requirement and management method. Aside from crop specific inputs, the initial AEZ methodology also includes soil and climate characteristics as well as other physical factors specific for the area (Food and Agriculture Organization of the United Nation (FAO) and the Land and Water Division 1996). The GAEZ model combines crop specific characteristics and spatial data inputs, such as soil and terrain, to generate a raster in which the crop suitability for a crop was assessed step by step for each grid cell (Fischer et al 2012). The crop suitability is calculated through five different steps where the first step assigns spatial climate characteristics to each grid cell. The second step adds information on land utilisation and other spatial data inputs (table 2) to calculate potential plant biomass and crop yield for each grid cell. In the third and fourth steps agro-climatic limitations and soil and terrain limitations, such as water stress and limited soil nutrients, are included in each grid cell to simulate possible declines in crop yield. In the final step, an algorithm combines the factor generated in previous steps in order to assign a suitability to each grid cell (Fischer et al. 2012).

The inputs for the GAEZ model are climatic data, crop statistics, land utilization types and spatial data sets, including soil type, terrain, land use and land cover, protected areas, irrigated areas, population and livestock density and the accessibility to the local markets (table 2).

Table 2 The spatial inputs of the GAEZ models are derived from multiple sources and are in different resolutions (Fischer et al. 2012; Tóth et al. 2012).

Input	Data Type	Resolution
Baseline climate	Raster created from interpolated observed data.	10 and 30 arc-minute
Climate scenarios	General circulation models (GCMs) and emission scenarios from the international panel of climate change (IPCC) were used to estimate agriculture productivity for future climate scenarios	30 arc-minute
Soil	Soil type raster derived from a harmonised soil database and updated soil information.	30 arc-second
Elevation and terrain	Digital elevation model (DEM) created from radar data.	3 arc-second
Land cover	Land cover raster compiled from six geographic data sets.	5 arc-minute
Protected areas	Protected areas raster derived from raster and polygon data over protected areas.	30 arc-seconds
Irrigated areas	Raster created from a digital map of irrigated areas.	5 arc-minute
Population	Raster created from population inventory (person/km^2).	30 arc-seconds
Livestock density	Raster (cattle equivalent/km^2).	30 arc-seconds

Given these standard inputs, the GAEZ model can generate results within five different major themes, in which the user can decide between different parameter and filter settings (Fischer et al. 2012). For this study, it is a crop suitability index (CSI) raster of approximately 10 km (5 arc-minute latitude/longitude) resolution that is the desired result and it can be produced from the theme ‘Suitability and potential yield’. The model theme and subtheme as well as the parameter and filters that were used to generate the desirable result are presented in figure 9.

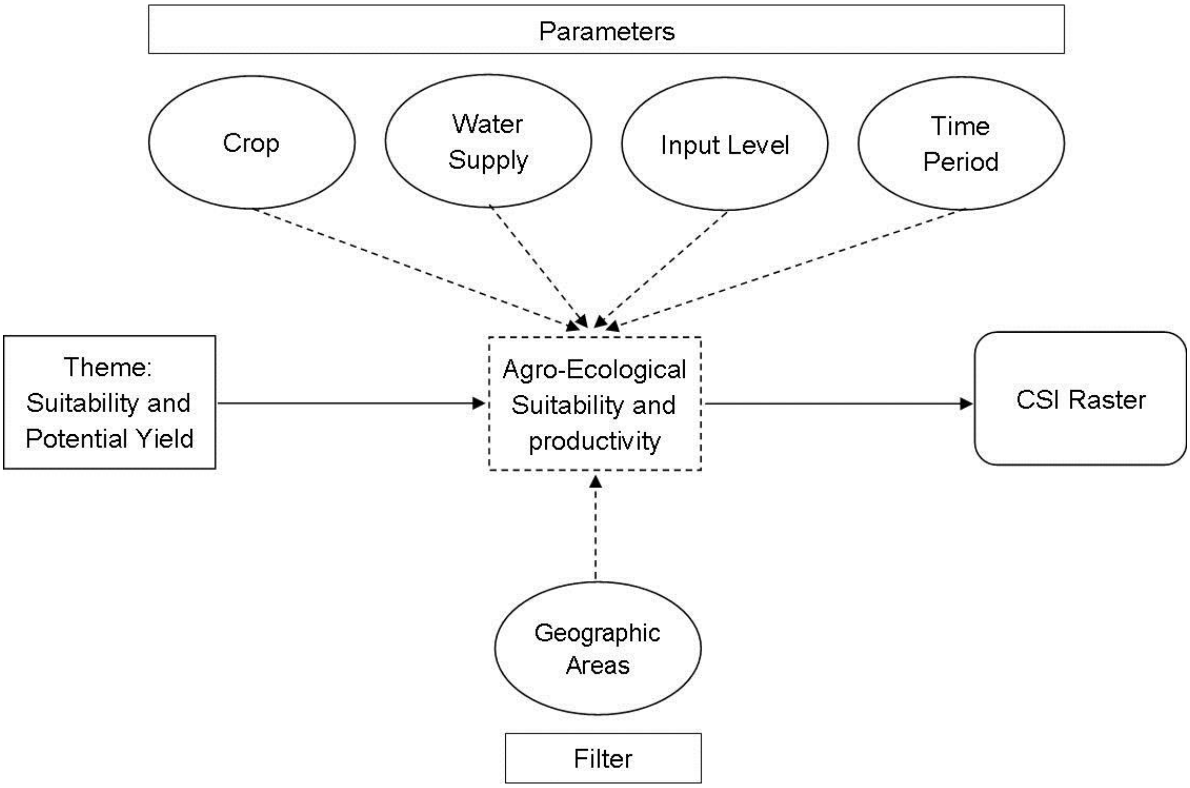

Figure 9 Flowchart for the GAEZ model as it was utilised in this study.

Parameter settings

The filter 'Geographical area' (Ghana) and the parameter 'Time period' (baseline 1961-1990) were held constant throughout the model runs whereas the parameters 'crop', 'water supply' and 'input level' varied between the model runs. When the 1961-1990 baseline is utilised in the time period setting the model generates a crop suitability index for a reference climate based on climatic data from the years 1961-1990 (Fischer et al. 2012).

The model generated results for the current crops grown on acquired land, as well as previous crops grown in the area. The previous crops were estimated from agricultural statistics, where the local crop with the highest average yield (tonnes/hectare) in a district where a LSLA is located was chosen to represent the previous crop of that LSLA in the model (Appendix C). Information on the current crop, on the other hand, was derived directly from the Land Matrix database (The Land Matrix Global Observatory. 2017b).

The model includes 48 different crops in the parameter settings, however not all current crops were represented by the model. Consequently, the crops that were not represented in the model had to be represented by a crop with similar ecological constrains (Appendix D). The crops that were not represented are teak (*Tectona grandis*), eucalyptus (*Eucalyptus*), pineapple (*Ananas comosus*), cashew (*Anacardium occidentale*), moringa (*Moringa oleifera*), mango (*Mangifera indica*) and butternut squash (*Cucurbita moschata*). Information on what type of crop that is grown on acquired land was derived from different company sources.

The parameter of water supply indicates if areas are irrigated or rainfed (Tóth et al. 2012). The model allows the user to choose between three different types of irrigation: gravity irrigation, sprinkler irrigation and drip irrigation, but if the irrigation type is unknown for the user it is possible to choose irrigation with no further details. If irrigation with no further details is chosen, the model decides on the irrigation type that is associated with the crop chosen (Tóth et al. 2012). Initially the current crops with confirmed irrigation were intended to be modelled with the water supply parameter set to irrigation, however this setting turned out to generate very restricted results and only eight LSLAs could be modelled as irrigated. Consequently, even though some LSLAs use irrigation systems for their crops, all the current crops were also modelled with the water supply parameter set to rainfed. Only 0.5% (in 2005) of the traditional agriculture in Ghana utilizes irrigation techniques (Food and Agriculture Organization of the United Nation (FAO) and Aquastat 2005), for this reason the input for the modelling of previous crop suitability assumed rainfed water supply only. The term rainfed is used in the GAEZ model for areas that are not irrigated, and the term was adapted and used throughout this study.

The GAEZ model also allows the user to choose between three levels of input concerning the management of the crop: *low-level input*, *intermediate-level input* and *high-level input*. When the *low-level* input is chosen, the model assumes that a crop is local and cultivated under traditional management with labour intense techniques. Additionally, no or low levels of nutrient or pesticides are assumed to be added under *low-level input* management (Tóth et al. 2012). The *low-level input* was assumed to be suitable for the previous crops in this study. For the current crops, on the other hand, a *high-level input* with machineries and fertilizers were assumed since this appears to be the standard in many LSLAs (Golden Exotics Limited (GEL) 2015; AgDevCo n.d.; Formako Farms n.d.; Africa Atlantic 2013b; Solar Harvest AS (Norway) and Solar Harvest Ltd. (Ghana) 2013).

ArcMap 10.3.1 (ESRI Inc. 2014) was used to combine each CSI raster, representing a specific crop and adapted parameter settings, with each LSLA that grows the corresponding crop with the corresponding parameter setting. The same procedure was then done for the previous crops, thus resulting in the CSI of each current and previous crop, with adapted parameter settings (figure 10). The resulting CSI for each crop ranges from 1-8, where 8 is the highest possible suitability (table 3).

When each LSLA was assigned a CSI for previous and current crop production, a Wilcoxon signed rank statistical test was performed in MATLAB (The MathWorks Inc. 2017), in order to conclude if there were any statistically change in CSI after the LSLAs. Both a left sided and a right sided one-tailed Wilcoxon signed rank test was performed, in order to detect if there were any significant ($p < 0.05$) change in any direction (Chapman McGrew Jr et al. 2014).

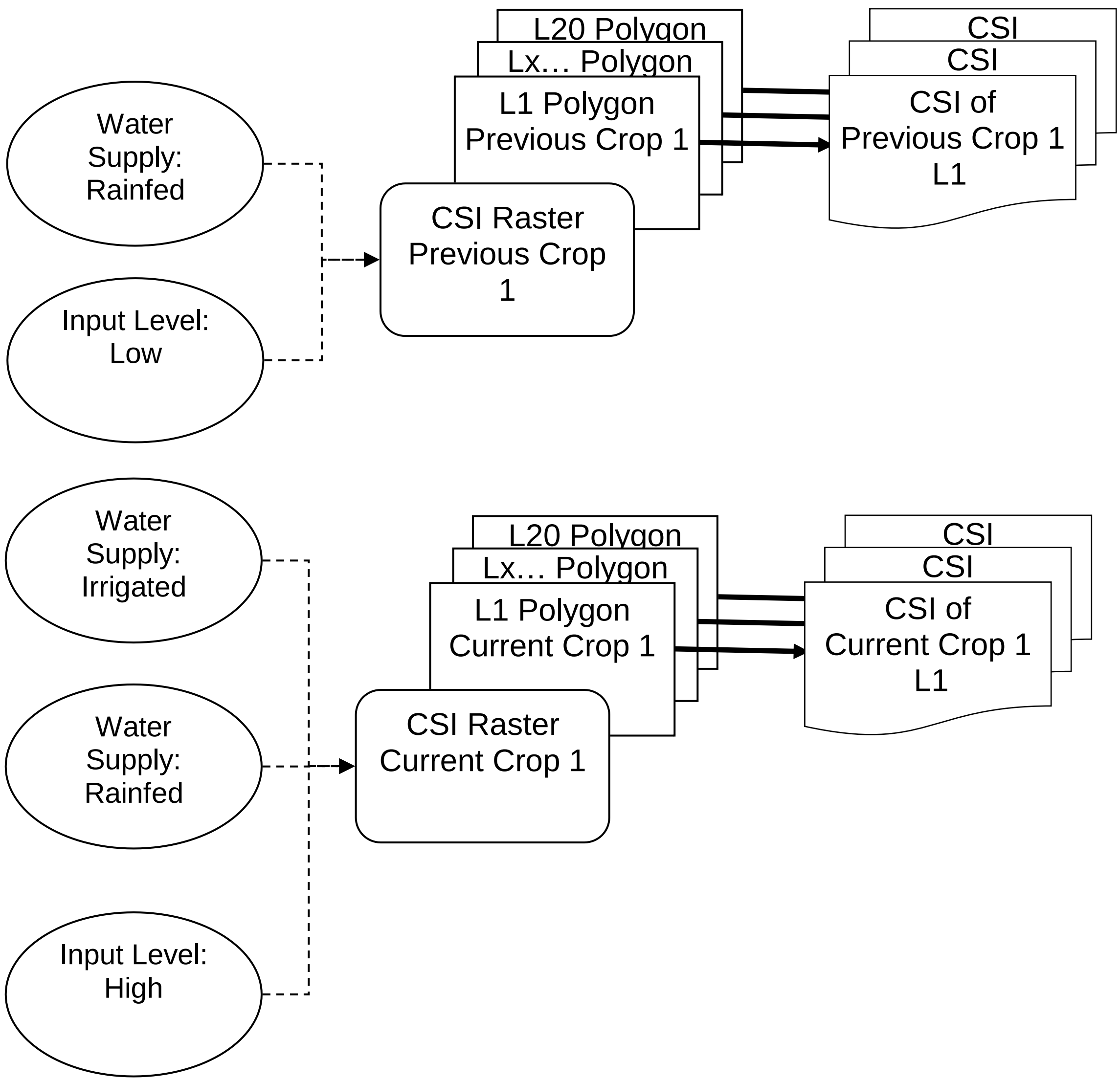

Figure 10 The flowchart describes the process of combining the CSI, generated by the GAEZ model, of the previous and current crops with the corresponding LSLAs. This was performed in ArcMap (ESRI Inc. 2014).

Table 3 The definition of each grade in the CSI.

Crop suitability index (CSI)	1	2	3	4	5	6	7	8
Definition	Not suitable	Very marginal	Marginal	Moderate	Medium	Good	High	Very high

4. Results

The first section presents the location of each LSLA and the certainty level associated with their observed locations. The second section presents the identified previous land use for each location and lastly, the third section presents the crop suitability of the previous and current crops.

4.1 Identifying large-scale land acquisitions with remote sensing

The location of the 20 LSLAs in this study could be approximated with different levels of certainty (figure 11). The certainty level of LSLAs is determined by whether the location of the LSLA was confirmed by other sources, independent of the satellite data (table 4). Such sources could be passing a sign addressing the LSLA farm while using Google Earth Street view (Google Inc. 2017b), a company video on YouTube or a picture posted on the company webpage showing large features that could be identified in satellite images. Other, more sophisticated sources could be drawings over the area on the company web page or a map in a research paper. High level of certainty means that the location of a LSLA was confirmed by multiple sources or that the location was distinct in satellite images.

Table 4 The locations of the LSLAs could be observed and identified with different levels of certainty, which is explained in the table. The colour code of the certainty levels coheres to the colour code in figure 11.

Certainty Level	Explanation of the Certainty Levels	Example
High	The exact location can be confirmed with an independent source and is evident in satellite data.	L4 was confirmed by the study of Boamah and Overå (2016), and the location was clear in satellite images.
	The exact location can be confirmed with an independent source, but the area is not easily distinguished in satellite images.	The acquired area of L8 was displayed in a company presentation (Osei-Peprah 2015), however, only scattered fractions of their operation within that area are evident in satellite images.
	The approximate area can be confirmed with an independent source but the exact location of the LSLA within that area is not certain in satellite images.	The pineapple farm of L11b was confirmed to be situated in the village of Obom (Golden Exotics Limited (GEL) 2014), however there are several adjacent pineapple farms outside Obom.
	Independent sources give an indication of approximately where the LSLA could be located and a possible area was found in satellite images.	The name of the village that owns the land leased by L2 is mentioned in a study, however no other information is available (Campion and Acheampong 2014).
Low	Only a larger approximated area could be confirmed by independent sources and the location suggested in this study is not confirmed.	The village mentioned in the Land Matrix data was the only information found on L18.

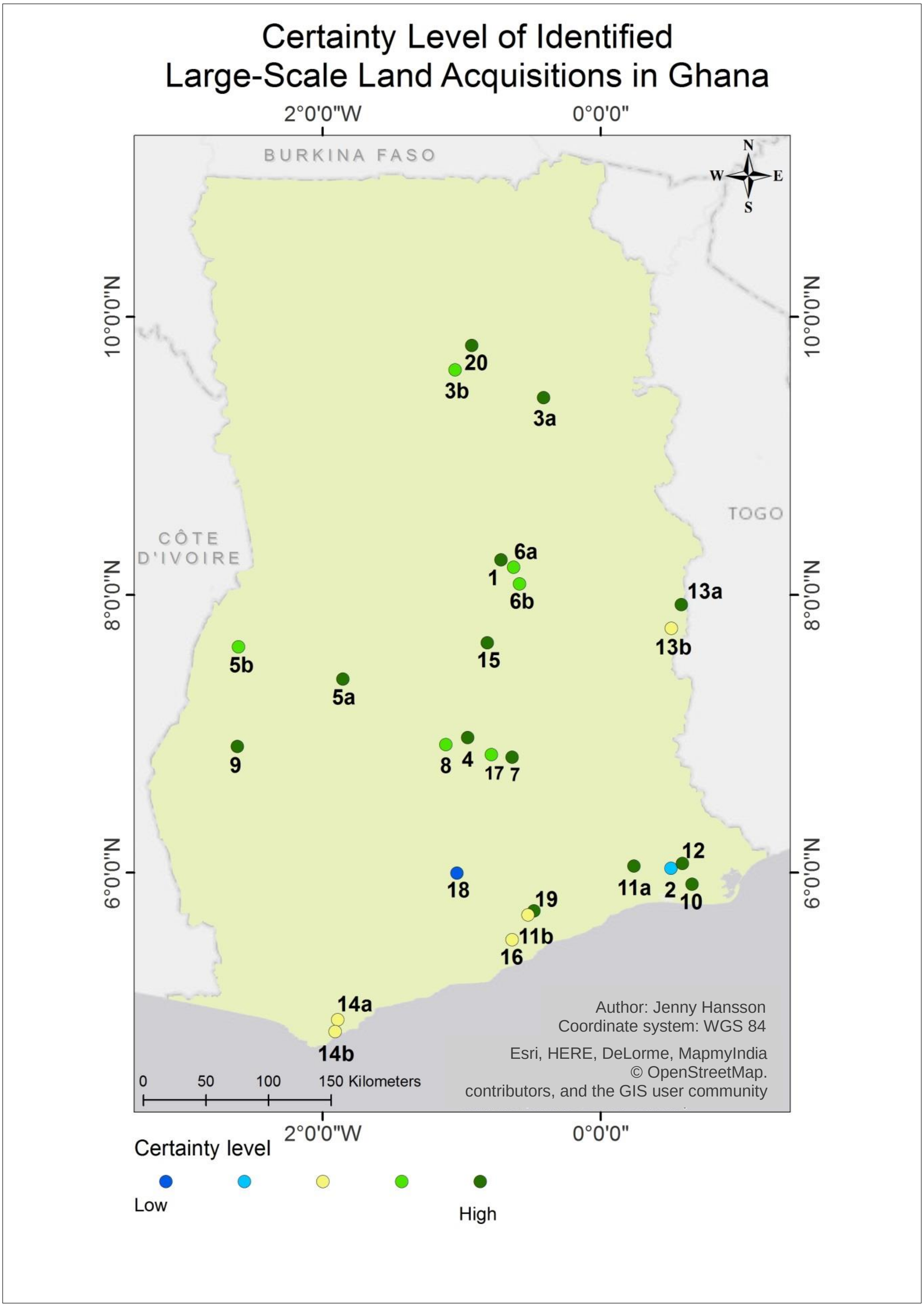

Figure 11 The certainty levels of the identified LSLAs, where the dark shade of green represents the highest level of certainty and the darker blue indicates low level of certainty.

4.2 Determining previous land use

The previous land use of LSLAs and their subareas could be determined with remote sensing and additional literature and statistics about land use and land utilisation. Information about the natural vegetation cover and the GAEZ highly facilitated the interpretation of the different features in the satellite images, thus helping to determine previous land use. Four different land use classes were identified, where ‘small-scale farming’ and ‘multifunctional land use’ appeared to have dominated the land use prior to the land acquisitions. ‘Commercial forestry’ and ‘large-scale cultivation’ could also be identified (table 5). In the event that a LSLA fell within different GAEZs or appeared to have different land use the LSLA was divided into subareas, which are presented individually in table 5.

A satellite image representing each previous land use class is displayed in figure 12 (L1), figure 13 (L11b), figure 14 (L9) and figure 15 (L14a) together with a more recent satellite image recorded after the land acquisition. A brief description of the reasoning behind the categorising of the L1, L11b, L9 and L14a into the different previous land use classes will be presented in this section, whereas a complete collection of the satellite images displaying the previous and current land use for each LSLA is accessible in Appendix E together with a description of the reasoning and method behind the determination of each previous land use.

Table 5 The numbers represent the different LSLAs and the GAEZ at which each LSLA falls within, along with the previous land use of the LSLAs are evident from the position of each LSLA in the table.

		Global Agro-Ecological Zones				
		Guinean savannah	**Transition zone**	**Deciduous forest**	**Wet evergreen forest**	**Coastal savannah**
Previous Land Use Class	**Small-scale farming**	L1, L3a, L3b, L6a, L20	L6b, L15	L19, L13a		L12
	Multifunctional land use		L5a, L5b	L4, L7, L11b, L17		L2, L10, 11a, L16
	Commercial Forestry			L9		
	Large-scale cultivation			L8, L13b, L18	L14a, L14b	

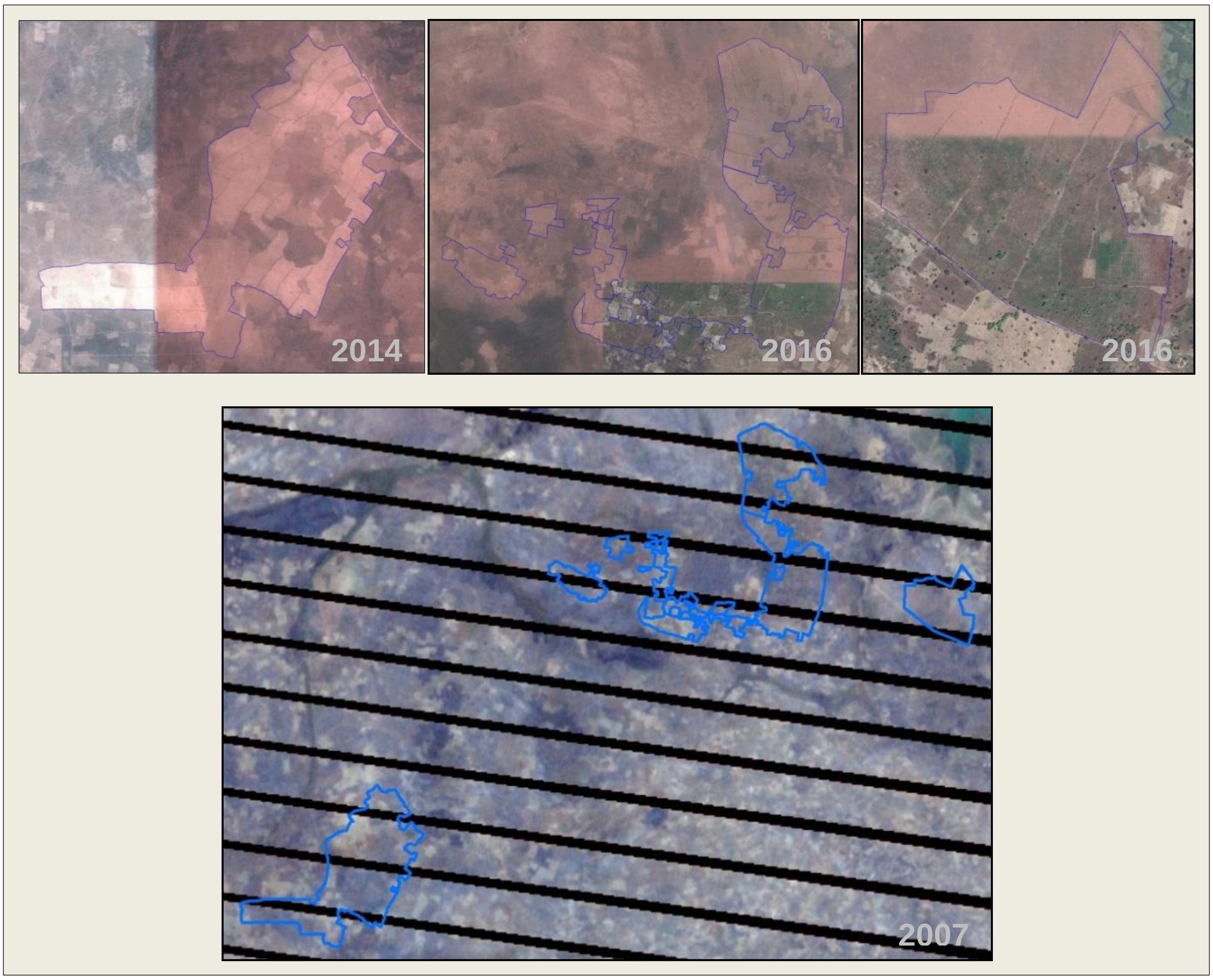

Figure 12 The current LULC of L1 is displayed in the three upper images and the previous LULC is displayed in the lower image (U.S. Department of the Interior and U.S. Geological Survey 2007a; Google Earth Pro 2014a, 2016a, b). The previous land cover was interpreted as predominately small-scale farming on behalf of the rectangular features in the scene, which were interpreted as agriculture fields.

Figure 13 L11b was classified as multifunctional land use on the behalf of the high abundance of roads and the vicinity to built-up areas. Moreover, the vegetation in the area appear less dense than other parts of the deciduous zone (Google Earth Pro 2015d; U.S. Department of the Interior and U.S. Geological Survey 2002a).

Figure 14 The abrupt end of the forest in the satellite image from 2002 indicates that a large-scale clearance has occurred. Information from the company behind L9 could further confirm that the area had been industrial forestry prior to the LSLA (U.S. Department of the Interior and U.S. Geological Survey 2001c; Google Earth Pro 2015c; U.S. Department of the Interior and U.S. Geological Survey 2002b; Mim Cashew and Agricultural Products Ltd. n.d.-a).

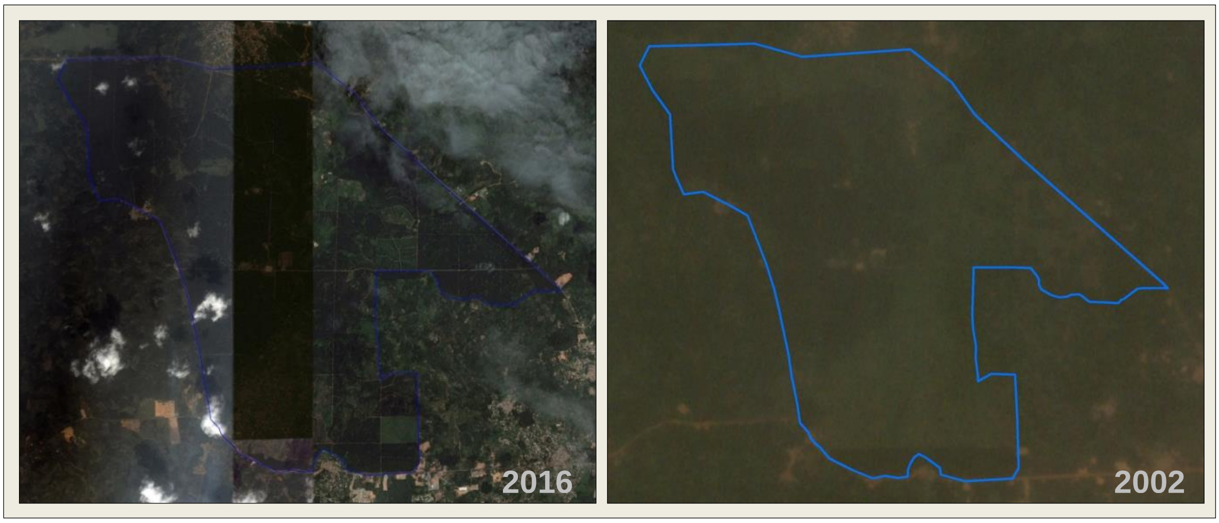

Figure 15 Cloud disturbance was frequent in the satellite data covering L14a, yet evidence of large-scale cultivation or management can be distinguished in the satellite data. Large dark features with straight boarders and corridors running through them are evident in the centre of L14a in the satellite image from 2002 (U.S. Department of the Interior and U.S. Geological Survey 2002b; Google Earth Pro 2016f)

The use of NDVI to detect similarities in land cover was supposed to help determine previous land cover in areas with poor satellite data, such as L14a. However, even though the NDVI histogram for the LSLA areas and their buffer zones appeared similar in several LSLAs, the results from the Wilcoxon rank-sum tests showed that the NDVI of the previous land cover in the LSLA was significantly different ($p = 0.391$) from the NDVI in the buffer zone in all LSLAs except for one, L18. Consequently, an analysis of the land use of the buffer zone in more recent satellite images could only be utilised for determine the previous land cover of L18.

4.3 Determining the crop suitability with the Global Agro-Ecological Zoning Model

The study aimed to determine whether the previous or current crop choice is the most ecologically suitable for that area. This is best demonstrated by figure 16, where the direction of change in CSI, from previous crop to current crop, is displayed for each LSLA. The results from the GAEZ model showed that the CSI for the current crops were significantly higher ($p = 0.0203$) than the CSI for the previous crops, when no irrigation was assumed for the current crops. The CSI was also significantly higher ($p = 0.0098$) among the current crops compared to the previous crops when the current crops were assumed to be irrigated, although it is important to note that the current crops modelled as irrigated were considerably fewer.

The LSLAs in Ghana are well distributed throughout the country with a higher density in the central parts (figure 16), yet the previous crops were represented by only two food crops, based on local agriculture statistics (appendix C). Besides from the two food crops, one type of flexible crop and one type of commercial forestry crop was also evaluated as previous crops (table 6). The LSLAs, on the other hand, grow both biofuel, food crops, flexible crops and commercial forestry crops (table 6), where the different crop types were almost equally common (table 7). The CSI for each previous and current crop in the LSLAs are displayed in table 7.

Table 6 The crop types that were evaluated in the GAEZ model.

Crop Type	Previous Crop	Current Crop
Biofuel		Jatropha
Flexible crop	Oil palm	Oil palm, corn, soybean
Food crop	Cassava, yam	Butternut squash, cashew, rice, banan (*Musa*), pineapple, cacao (*Theobroma cacao*), mango
Commercial forestry	Teak	Teak, eucalyptus

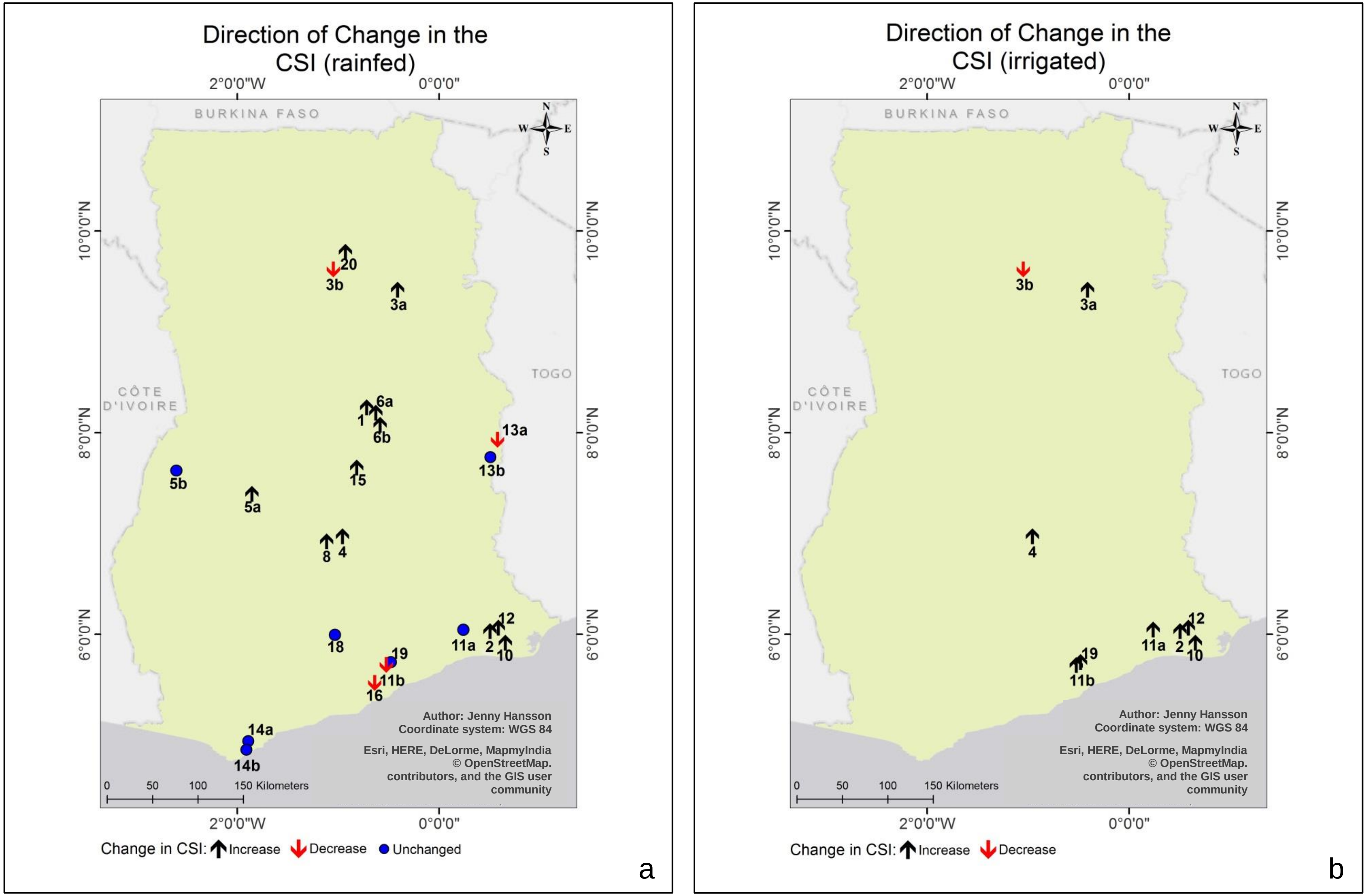

Figure 16 The change in CSI prior to and after the land acquisition. There was a significant ($p < 0.05$) increase in CSI with both the rainfed (a) and the irrigated (b) parameter settings.

Table 7 The CSI, generated by the GAEZ model, for each previous and current crop of the LSLAs (the direction of change in CSI for each LSLA is displayed in figure 16).

LSLA	**Previous Crop (*CSI*)**	**Current Crop Rainfed (*CSI*)**	**Current Crop Irrigated (*CSI*)**
1	Cassava (***4.0***)	Jatropha (***5.5***)	
2	Cassava (***4.5***)	Jatropha (***7.5***)	Jatropha (***7.0***)
3a	Yam (***3.0***)	Corn (***6.5***) Jatropha (***5.0***)	Corn (***7.0***) Jatropha (***7.0***)
3b	Cassava (***3.0***)	Butternut squash (***1.0***)	Butternut squash (***1.0***)
4	Cassava (***5.0***)	Jatropha (***6.5***) Corn (***7.0***) Soybean (***7.0***)	Jatropha (-) Corn (-) Soybean (***6.0***)
5a	Yam (***4.5***)	Teak (***5.0***)	
5b	Cassava (***5.0***)	Teak (***5.0***)	
6a	Cassava (***4.0***) Yam (***3.0***)	Jatropha (***5.0***) Moringa (***5.0***)	
6b	Yam (***3.5***)	Jatropha (***6.0***) Moringa (***6.0***)	
8	Teak (***5.5***)	Teak (***5.5***) Eucalyptus (***6.0***)	
10	Cassava (***2.5***)	Rice (***3.5***)	Rice (***7.0***)
11a	Cassava (***3.0***)	Banana (***3.0***)	Banana (***5.5***)
11b	Cassava (***5.5***) Yam (***5.0***)	Pineapple (***5.0***)	Pineapple (***7.0***)
12	Cassava (***3.5***)	Rice (***4.0***)	Rice (***7.0***)
13a	Cassava (***4.0***)	Oil palm (***1.5***)	
13b	Oil palm (***2.0***)	Oil palm (***2.0***)	
14a	Oil palm (***6.0***)	Oil palm (***6.0***)	
14b	Oil palm (***6.0***)	Oil palm (***6.0***)	
15	Yam (***4.5***) Cassava (***5.5***)	Eucalyptus (***8.0***)	
16	Cassava (***5.5***)	Corn (***6.0***) Cacao (***5.0***) Pineapple (***5.0***)	
18	Oil palm (***7.0***)	Oil palm (***7.0***)	
19	Cassava (***5.0***)	Pineapple (***5.0***)	Pineapple (***7.0***)
20	Yam (***2.5***)	Mango (***5.5***)	

5. Discussion

This study showed that the current crops of LSLAs are more suitable than the previous crops that were assumed to have been cultivated in the areas prior to the land acquisition. Moreover, this study demonstrated that Google Earth can be utilised as a remote sensing tool to identify LSLAs, and the identified locations could be confirmed with different levels of certainty by independent sources. However, when historical satellite images were used to determine the previous land use, Google Earth proved to be limited by the poor quality of the historical satellite images. Thus additional Landsat 7 satellite images were obtained for each LSLA. Despite individual Landsat 7 images for each LSLA the ability to visually interpret the previous land use was still limited, the previous land use could be determined for each LSLA by supplementing information on local land use and land utilisation. An attempt was made to quantitatively compare the NDVI values of the previous land use in a LSLA and the NDVI values of a 1 km buffer zone around the LSLA, in order to conclude if they belonged to the LSLA belonged to the same land use class as its surrounding before the land acquisition. However, this method was not very useful. Despites this, four different previous land use classes could be determined through remote sensing and additional information.

5.1 Identifying large-scale land acquisitions with remote sensing

Even though remote sensing using Google Earth was the primary tool for the identifying the locations of the LSLAs, the identification would not have been possible using exclusively remote sensing. Complemented with street view imageries, company sources, research papers and local media, remote sensing enabled the identification of 20 LSLAs in Ghana. Notwithstanding these supporting sources of information, there were many factors that influenced the ability to accurately observe and identify the locations of the LSLAs. This was demonstrated by the different levels of certainties that were assigned to the LSLAs. Factors that contributed to uncertainties were lack of company sources, inconsistent quality and origin of satellite data, misspelling of villages and places, vague information concerning the land use and the permanency of the LSLAs, and the appearance of similar projects in the same area.

The certainty levels were based on how accurately the LSLAs could be identified and to what degree the exact location could be confirmed. All areas except for two were assigned a medium to high level of certainty due to independent sources confirming their location. Whether these sources were a published photography, a road sign in Google Street view or a map in a research paper they were treated similarly. Another way to categorise the certainty could be by the academic relevance of the independent sources, however this would highly neglect important sources that were used in the identification process. The LSLAs with low level of certainty obviously contribute to uncertainties also in the results of the determined previous land use and the crop suitability. It can be argued that these LSLAs should have been excluded from further analyses. The LSLAs determined with high levels of certainty, on the other hand, can contribute to increase the accuracy of the spatial information, which often is associated with uncertainties, on these LSLAs in the Land Matrix datasets (The Land Matrix Global Observatory 2017c).

Many LSLA projects fail early in the process and the information gathered from company sources were not always straight forward about the permanency of the project (Ahmed et al. 2017). Even though most of the LSLAs were identified with high certainty, it would be of interest to study whether they are still in operation or not, thus bringing yet another dimension to the suitability of LSLAs in Ghana.

5.2 Determining previous land use

The most common land use as a consequence of LSLA in Ghana were from small-scale farming or multifunctional land use to the cultivation of either flexible crops, food crops, biofuels or commercial forestry. The multifunctional land use contained traces of human utilisation, e.g. villages, but no obvious agricultural fields were present. Also five large-scale cultivations and one commercial forestry operation were found. Small-scale farming could often be decided from remote sensing only, whereas the other land use classes had to be supplemented with literature in order to estimate the previous land use.

5.2.1 Small-scale farming

The principal method for inferring farming activity was based on the presence or absence of rectangular features in the satellite images since straight and rectangular features most likely are human constructions (Paine and Kiser 2012), hence rectangular features of vegetation or bares soil were interpreted as agriculture fields. With 69.5 % of the economically active people in rural Ghana working with agriculture, forestry or fishery, it is likely that agriculture is a pronounced land use in rural Ghana (Ghana Statistical Service 2013). The high amount of interpreted small-scale agriculture is further supported by a recent study that classified 50.2 % of the land area in Ghana as either agriculture fields or orchards (Hackman et al. 2017). Even though small-scale farming was most frequent in this study the presence of agriculture in the satellite images could have been underestimated due to the fallow system, which is widely practice in agriculture in Ghana (Ewel 1986; Adiku et al. 2009; Norgrove and Hauser 2016). The fallow period if sometimes longer than the active period (Temudo and Santos 2017), thus leading to an increased risk that the fallow fields might be interpreted as grasslands instead of agriculture if the borders are not clear. Also, only 17% of the agricultural land is estimated to be covered by permanent crops and besides from fallows the other agricultural lands are utilised as meadows and pasture land, which further contributes to the risk of underestimating the extent of small-scale farming (Food and Agriculture Organization of the United Nation (FAO) 2017). Although the fallow system, meadows and pasture lands might contribute to difficulties in detecting the fields in satellite images, the LSLAs were classified as small-scale farming even if only a small part of the areas was covered with fields. This might have counteracted the possible underestimation of agriculture due to the presence of fallow fields.

The transition from small-scale farming to LSLA could directly affect the food security of the residents of the affected areas through the loss of agricultural fields and lack of proper compensation for the loss of crop yields (Kidido and Kuusaana 2014). If the LSLA fails to provide secure employments and other benefits for displaced farmers this could further decrease food security for the residents (Kidido and Kuusaana 2014; Anseeuw 2013; Ahmed et al. 2017). On the contrary, the transition to LSLA could also generate employment and benefits such as new water wells, schools, medical clinics and road maintenance if it is driven properly (Laura et al. 2011; Timko et al. 2014).

5.2.2 Multifunctional land use

The land use class multifunctional land use was used to cover areas that appeared to have traces of human disturbance or utilisation, but showed no clear signs of agricultural activity. Signs of human disturbances could be less dense or more scattered vegetation than the surrounding, the presence of clear borders and straight lines, and human settlements in the vicinity (Paine and Kiser 2012). The reason why multifunctional land use was common as previous land use of the LSLAs could be the Ghanaians' frequent utilisation of the commons land (Pouliot et al. 2012). For example, collection of fuelwood is a common utilisation of the common lands and it is normally collected within 3 - 4 km from the place of consumption (Amoah et al. 2015), resulting in a higher probability that wood is collected from the utilised lands if human settlements are present. Yet fuelwood is not the only environmental resource originating from the forest and savannah lands of Ghana and approximately 20% of rural household income originates from these common lands (Pouliot et al. 2012). In other words, it is unlikely that common lands close to human settlement are left pristine and unutilised. This reasoning partly explains why many previous land use were classified as multifunctional land use. The land use class multifunctional land use covered a broad spectrum of land utilisations, hence this land use class varied more in appearance than the other land use classes.

Literature on the natural vegetation and land utilisation of the specific area was often utilised to understand features in the satellite images. L10, for example, is situated in a well-documented wetland sites (figure x, Appendix D; Anthony 2015; Tufour 1999), and this information could be used to understand the marshy features of the previous land cover. Despite this, L10 was classified as multifunctional land use and not wetlands due to straight features in the area and roads and villages in the vicinity.

When multifunctional land uses are turned into LSLAs they become inaccessible for the residents and the natural resources that used to be provided by the land is no longer available (Pouliot et al. 2012), thus could contribute to increasing food insecurity and loss of income. It could also affect how farmers can extend their fields when other fields are left in fallow, also contributing to decreasing crop yield and consequently increasing food insecurity (Timko et al. 2014; Kidido and Kuusaana 2014; Gaiser et al. 2011).

The reasoning behind the classification of areas into multifunctional land use was primarily based on assumptions of intense human utilisation of common lands. Following the high fire wood consumption, high degradation rate and the utilisation of environmental product it was assumed that traces of human settlement equalled utilisation of land (Pouliot et al. 2012; Energy Commission of Ghana 2016; Peprah 2015). It was then further assumed, based on the fallow system and the intense utilisation of lands, that these utilised lands previously could have been cultivated, hence they were included in the crop suitability analysis (section 4.3).

5.2.3 Large-scale cultivation

In four of the LSLAs that were large-scale cultivations, even prior to the land acquisitions, oil palm was cultivated. The land use of one of these LSLAs was determined from company sources (Volta Red Limited 2016), whereas the land use of two LSLAs were interpreted in historical satellite images and the land use of one LSLA was determined through the comparison of NDVI histograms. Palm oil is traditionally important in Ghana and evidence of the use of palm oil, dated to 3,600-3,200 BP, was found in an archaeological site in Ghana (Logan and D'Andrea 2012). It has continued to be an important product and the government of Ghana expressed the need for more oil palm cultivations already in the 1970s, which resulted in the growth of 4,000 hectares of oil palm (World Bank 1975). With the long tradition of oil palm cultivation in mind it is likely that some of the LSLAs growing oil palm has acquired already established oil palm cultivations, thus probably not changing the land use substantially.

5.3 Determining the crop suitability with the Global Agro-Ecological Zoning Model

The result of the GAEZ model showed that there was a significant increase in CSI when the previous and the current crops were compared. However, this increase could be a result of the modern crop management and input practice rather than the LSLA and change in crop type. Under the high-level input the model assumes that an ideal amount of nutrients, pesticides and herbicides are applied, whereas no nutrient or chemicals are assumed to be applied in low-level input (Fischer et al. 2012). If the model could generate the parameter with the highest influence on the resulting CSI, it would have added an interesting aspect to the analysis these results. An idea could be to model the previous crops with high input level or irrigation in order to see whether the previous crops were still less suitable or not. This could indicate if it is the crop per se or the management method that affect the CSI the most.

The highest CSIs, when water supply was set to rainfed, were found in association with the growth of jatropha (***7.5***), corn (***7***), soybean (***7***), eucalyptus (***8***) and oil palm (***7*** and ***7***), whereof all except for one of the oil palm indices were modelled as a current crop. The eucalyptus, however, was modelled as jatropha, due to their similar physiological traits (well drained soils, tropical climate and do not require excessive rainfall), consequently eucalyptus followed the CSI of jatropha (Janick and Paull 2006). Both corn and soybean are considered drought tolerant in the model (Fischer et al. 2012), which could explain their high CSI. Jatropha is sensitive to waterlogged soils in the model (Fischer et al. 2012), hence it is probably most affected by the rainfall pattern and the soil type. Even though there was a significant increase in CSI after the land acquisitions, the lowest crop suitability indices were found among two current crops: butternut squash (***1***) and oil palm (***1.5***). This implies that the area chosen by these LSLAs were not suitable for the crop choice. The LSLA growing butternut squash was located in the northern part of Ghana, which experiences less rainfall than the southern areas (Food and Agriculture Organization of the United Nation (FAO) and Aquastat 2005). Butternut squash need irrigation if it grows in sparse regions (Janick and Paull 2006), thus this area might not be suitable for growing butternut squash. On the other hand, butternut squash was modelled as cacao, which prefers the same well drained soils, temperature range and relatively high amount of rainfall (1,500-2,800 mm) (Janick and Paull 2006), and this might have affected the resulting CSI of the butternuts squash. The oil palm plantation with low CSI was located on a dividing line, above which, no area in Ghana is suitable for growing oil palm. This clear dividing line, separating suitable south from unsuitable north, probably depends on a model input that highly affect the suitability of oil palms. The model documentation mentions that oil palm is restricted by its water requirement and is sensitive to high ground water tables, associated with the soil type (Fischer et al. 2012). Studying the rainfall and soil maps of Ghana, the rainfall pattern appears more similar to the oil palm suitability map than the soil distribution, hence it is likely that the limiting factor for oil palm cultivation is the rainfall scarcity of northern Ghana (Food and Agriculture Organization of the United Nation (FAO) 2004).

Due to the irrigation parameter being restricted to areas that already have a known irrigation system, substantially fewer results were produced when irrigation was chosen as water supply (Fischer et al. 2012). Of the current crops that could be modelled with irrigation, rice increased the most in CSI compared to when it was modelled as rainfed. This is probably due to the fact that rice paddies without irrigation often generate a low yield (Fischer et al. 2012). Also banana, pineapple and corn increased in CSI when irrigation was assumed compared to rainfed conditions, while jatropha increased in one area and decreased in another area compared to when it was rainfed. Butternut squash was left unchanged compared to rainfed conditions, while soybean decreased after applied irrigation. The decrease in CSI as a result of the crop being modelled as irrigated compared to rainfed could be a consequence of the soil or terrain of the areas not being suitable for irrigation systems (Fischer et al. 2012). Additionally, soybean is sensitive to waterlogging in the model (Fischer et al. 2012), and might be restricted by irrigation if a rainfed water supply already is sufficient. Although some crops decreased in CSI when they were modelled as irrigated compared to when they were rainfed, all of these current crops except for butternut squash had a higher CSI than their corresponding previous crop.

5.4 Strengths and limitations of the methods

The locations of the LSLAs identified with remote sensing relied solely on secondary sources to confirm the identified location and ground control points (GCPs) from the field would lower the uncertainties associated with the identified locations. Even though no situations arose that questioned the credibility of the secondary sources, poor quality of the secondary sources could contribute to an incorrectly assessed certainty of the identified location, in the same way that poor GCPs can contribute to wrongly assessed accuracy of a land use or land cover classification (Foody 2009). On the other hand, the use of secondary sources contributed to making this study more cost efficient and time efficient than if GCPs were to be collected.

There are several possible reasons why the method of comparing NDVI distributions to detect similarities in land cover was ineffective and only could be utilised for one LSLA. Firstly, the LSLA areas and the buffer zones contained different amount of cells, which might have influenced the statistical test. Secondly, NDVI is sensitive to atmospheric conditions, gets saturated in dense vegetation and biased by soil in sparse vegetation, which all could affect the results (Birky 2001; Huete 1988; Gutman 1991). Thirdly, while NDVI histogram could work to roughly classify larger areas (Loyarte 2002), it might not be suitable for this small scale (Pettorelli 2013). An attempt was made to remove the clouds from the satellite images, however this might not have been performed accurately enough. Additionally, thin clouds present in the satellite image can be difficult to detect, thus influencing the NDVI without the user's awareness (Gao and Li 2000)

The primary benefits of the GAEZ model are that it allows a variety of parameters settings and inputs, and that it can produce multiple outputs. This has also been recognised in other studies (Liu et al. 2015; Królczyk et al. 2014). Besides from some socioeconomic criteria used in the model settings, the model does not consider socioeconomic suitability when it generates the results (Fischer et al. 2012). Additionally, the resulting CSI is not affected by what crop type that is produced. Whether it is a food crop, biofuel crop, forestry crop or a flexible crop the CSI is generated solely based on agro-ecological parameters. Consequently, food insecurity as a possible effect of acquired lands and crops being produced for biofuels or export, instead of targeting the local food market, is not considered (Hall 2011; Oxfam International 2008). Considering the many socioeconomic consequences of LSLAs presented in the introduction, it is important to include these also when analysing the agro-ecological suitability. As for Ghana, it appears as if the socioeconomically consequences are many (Anseeuw 2013; Kuusaana and Gerber 2015; Aha and Ayitey 2017; Ahmed et al. 2017; Kidido and Kuusaana 2014), and it can be discussed whether the agro-ecological benefits found in this study, possibly due to LSLAs, can be considered as benefits if they fail to benefit the residents of the area. Even though the productivity of an area increases due to LSLA, it is not always for the benefit the people living in the area (Anseeuw 2013).

6. Conclusions

This study demonstrates how different open access tools can be utilised to observe the extent and the agro-ecological consequences of large-scale land acquisitions in Ghana. The results of this study can be separated into three different substudies, where the first substudy laid the foundation for the following two substudies.

First and foremost, this study demonstrates that it is possible to utilise remote sensing for identifying areas of large-scale land acquisitions and even though the method is time consuming it has the strength of being cost effective and easy to revise. Additional field work and ground control points from the areas are desirable to further evaluate the significance of this study.

Secondly, a visual interpretation of the previous land cover and land use of the large-scale land acquisitions was highly limited in this study due to poor quality historical satellite images. Instead a combination of historical satellite images, supplemental information on common land cover and land use, agricultural statistics and information on land utilisations were used in order to determine the previous land cover and land use of the large-scale land acquisitions.

Lastly, it was found that agro-ecological crop suitability increased when the previous crops were compared with the current crops, however it could not be concluded what factor that mostly contributed to the increase in crop suitability index. Furthermore, the socio-economic suitability was not considered in this model. A combination of agro-ecological and socio-economic suitability is essential to obtain a more holistic approach, and should be considered for further studies in this subject.

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Appendices

Appendix A

Data and data sources

Table i The Landsat scenes and the position in Google Earth that were utilised for each LSLAs in this study are displayed in this table together with their sources.

LSLA	Landsat 7 and Landsat 8	Position in Google Earth
1	LE07_L1TP_194054_20070113_20170105_01_T1 LC08_L1TP_194054_20170305_20170306_01_RT	8°13'51.11"N, 0°44'51.32"W
2	LE07_L1TP_193056_20061205_20170107_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	6°1'4.06"N, 0°30'38.26"E
3a	LE07_L1TP_194053_20061126_20170106_01_T1 LC08_L1TP_194053_20170305_20170316_01_T1	9°27'5.89"N, 0°19'4.61"W
3b	LE07_L1TP_194053_20061126_20170106_01_T1 LC08_L1TP_194053_20170305_20170316_01_T1	9°36'50.86"N, 1°2'4.46"W
4	LE07_L1TP_194055_20080201_20161231_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	6°58'3.69"N, 0°57'37.09"W
5a	LE07_L1TP_194055_20060211_20170110_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	7°23'10.93"N, 1°51'27.56"W
5b	LE07_L1TP_195055_20081208_20161223_01_T1 LC08_L1TP_195055_20161120_20170318_01_T1	7°36'54.91"N, 2°36'26.36"W
6a	LE07_L1TP_194054_20070113_20170105_01_T1 LC08_L1TP_194054_20170305_20170306_01_RT	8°10'4.41"N, 0°37'39.98"W
6b	LE07_L1TP_194054_20070113_20170105_01_T1 LC08_L1TP_194054_20170305_20170306_01_RT	7°59'31.45"N, 0°32'48.44"W
7	LE07_L1TP_194055_20100206_20161217_01_T1 LE07_L1TP_194055_20110329_20161209_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	6°49'48.09"N, 0°38'5.53"W
8	LE07_L1TP_194055_20100206_20161217_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	6°55'45.87"N, 1°1'19.21"W
9	LE07_L1TP_195055_20010409_20170206_01_T1 LC08_L1TP_195055_20161120_20170318_01_T1	6°54'18.81"N, 2°36'33.77"W
10	LE07_L1TP_193056_20061205_20170107_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	5°55'34.17"N, 0°40'0.52"E
11a	LE07_L1TP_193056_20011207_20170202_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	6°2'59.09"N, 0°14'41.12"E
11b	LE07_L1TP_193056_20021226_20170127_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	5°42'12.39"N, 0°27'20.44"W
12	LE07_L1TP_193056_20061205_20170107_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	6°3'29.83"N, 0°34'58.09"E
13a	LE07_L1TP_193055_20091229_20161216_01_T1 LC08_L1TP_193055_20170210_20170217_01_T1	7°55'40.28"N, 0°34'17.55"E
13b	LE07_L1TP_193055_20091229_20161216_01_T1 LC08_L1TP_193055_20170210_20170217_01_T1	7°45'16.52"N, 0°30'30.17"E
14a	LE07_L1TP_194057_20020115_20170201_01_T1 LC08_L1TP_194057_20161231_20170314_01_T1	4°56'29.15"N, 1°53'24.95"W
14b	LE07_L1TP_194057_20020115_20170201_01_T1 LE07_L1TP_194057_20000517_20170211_01_T1	4°51'11.07"N, 1°54'43.13"W

	LC08_L1TP_194057_20161231_20170314_01_T1	
15	LE07_L1TP_194055_20080201_20161231_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	7°40'36.63"N, 0°46'47.62"W
16	LE07_L1TP_193056_20030212_20170126_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	5°31'5.05"N, 0°38'11.80"W
17	LE07_L1TP_194055_20110329_20161209_01_T1 LC08_L1TP_194055_20170305_20170316_01_T1	6°50'49.65"N, 0°46'33.73"W
18	LE07_L1TP_194056_20070113_20170105_01_T1 LC08_L1TP_194056_20161231_20170314_01_T1	5°59'52.43"N, 1° 2'6.29"W
19	LE07_L1TP_193056_20061205_20170107_01_T1 LC08_L1TP_193056_20170125_20170311_01_T1	5°43'18.14"N, 0°28'46.52"W
20	LE07_L1TP_194053_20011011_20170203_01_T1 LC08_L1TP_194053_20170305_20170316_01_T1	9°47'35.56"N, 0°55'36.26"W
(The Land Matrix Global Observatory 2017b)	(U.S. Department of the Interior and U.S. Geological Survey 2017)	(Google Inc. 2017b)

Table ii The Boundary files that were used for the analysis and are displayed below.

Ghana Country Division	**File Name**
Country	GHA_adm0
Region	GHA_adm1
District	GHA_adm2
Source: (GADM database of Global Administrative Areas 2015)	

Appendix B

The original data from Land Matrix

Table iii Part of the original data obtained from Land Matrix, where the LSLA in this study is highlighted in bold (The Land Matrix Global Observatory 2017b).

deal_id	location	investor_name	investor_country	intention
1322	**Yeji, Ghana**	**Agroils**	**Italy**	**Biofuels**
1323	**Volta Region, Ghana**	**Galten Global Alternative Energy**	**Israel**	**Biofuels**
1324	Nsuta,Sekyere, Ghana	Hazel Mercantile Ltd.	India	Biofuels
1330	Prang, Ghana	Constran S/A, Sekab	Brazil, Sweden	Biofuels, Food crops, Renewable Energy
1334	Brong Ahafo, Ghana	Kimminic Corp.	Canada	Biofuels
1337	Sege, Ghana, Gomoa, Ghana	Bionic Group	United States of America	Agriunspecified, Biofuels, Food crops, Livestock
1338	Brong Ahafo, Ghana	Jatropha Africa, Unnamed investor 193	United Kingdom of Great Britain and Northern Ireland, Ghana	Biofuels
1348	Volta, Ghana	Prairie Texas, Government of Ghana, Ghana Commercial Bank	United States of America, Ghana	Food crops
2237	**Yendi, Ghana, Hohoe, Ghana, Tamale, Ghana**	**Solar Harvest AS**	**Norway**	**Food crops**
2241	**Agogo, Ghana**	**Scanfuel Ltd**	**Norway**	**Food crops, For wood and fibre**
2242	Ghana	J. García-Carrión	Spain	Food crops
3389	**Asubima Forest Reserve, Ghana**	**Form International Ltd**	**Netherlands**	**For carbon sequestration/REDD, For wood and fibre**
3393	Ashanti, Ghana	Viram Plantation Ltd., Unknown Ghanaian Investor	India, Ghana	Biofuels, Food crops, Non-food agricultural commodities, Renewable Energy
3398	**Yeji, Ghana**	**Natural African Diesel Ghana Limited**	**South Africa**	**Biofuels**
3399	**Lake Volta, Ghana**	**Africa Atlantic Holdings Ltd**	**United States of America**	**Food crops**
3404	**Agogo, Ghana**	**Miro Forestry Company**	**United Arab Emirates**	**For wood and fibre**
3761	**Asunafo South, Ghana**	**Mim cashew & Agricultural Products Ltd.**	**Singapore**	**Biofuels, Food crops**
3764	**Volta, Ghana**	**Brazil Agro-Business Group**	**Brazil**	**Food crops**
3765	**Akuse, Ghana, Nsawam, Ghana**	**Compagnie fruitière**	**France**	**Food crops**
3766	Winneba, Ghana	Symboil AG	Germany	Biofuels, Food crops, Livestock
3767	Agona, Ghana, Mpohor, Ghana	DOS Palm Oil Production Limited (UK)	United Kingdom of Great Britain and Northern Ireland	Agriunspecified

3768	**Volta, Ghana**	**Gadco Enterprise PLC**	**United States of America**	**Food crops**
3770	**Brewaniase, Ghana**	**Volta Red**	**United Kingdom of Great Britain and Northern Ireland**	**Agriunspecified**
3772	Shai Hills, Shai Hills Production Reserve, Ghana	Agricon Global Corporation	United States of America	Food crops
3773	**Prestea, Ghana, Ahanta, Takoradi, Ghana**	**Norpalm AS, PZ Cussons Ghana Ltd.**	**Norway, Ghana**	**Agriunspecified**
3778	Volta River, Ghana	VP Group	Kenya	Food crops
3781	Ashanti, Ghana	Global Environment Fund	United States of America	Food crops, For wood and fibre, Renewable Energy
3798	**Sene, Ghana**	**African Plantation for Sustainable Development Ghana Ltd.**	**South Africa**	**For carbon sequestration/REDD, For wood and fibre**
3915	**Agona, Ghana**	**Formako Farms**	**United Kingdom of Great Britain and Northern Ireland**	**Food crops**
4341	**Ashanti, Ghana**	**Hulstein Warren Co Ltd**	**United States of America**	**Food crops**
4354	Afram Plains, Ghana	Unknown Investor, Unknown investor	Denmark, Ghana	Food crops, Livestock
4359	Atebubu, Ghana	Ghana Farms		Food crops
4362	Atebubu, Ghana	African Plantation for Sustainable Development Ghana Ltd.	South Africa	For carbon sequestration/REDD, For wood and fibre
4582	**Abenase, Ghana**	**YONEC GmbH & Co. Naturenergie KG, Unknown Ghanian Company**	**Germany, Ghana**	**Agriunspecified, Food crops, Non-food agricultural commodities**
4583	**Adeiso, Ghana**	**Unknown (German), Unknown (British), Unknown (Ghanaian)**	**Germany, United Kingdom of Great Britain and Northern Ireland, Ghana**	**Food crops**
4730	**Volta, Ghana**	**Volta Red**	**United Kingdom of Great Britain and Northern Ireland**	**Agriunspecified**
4795	Ampabame, Kumasi, Ghana	Juaboso Agro Processing Company (JAPC), Unknown Investor	Ghana, United States of America	Food crops
4940	Kintampo, Ghana	AgDevCo	United Kingdom of Great Britain and Northern Ireland	Food crops
5055	Daboase, Ghana	SOCFIN	Luxembourg	Agriunspecified, Non-food agricultural commodities

5131	Ghana	Jiangxi Yu Sheng Food	China	Food crops
5316	**Tamale, Ghana**	**Wienco, Nanton Chief , African Tiger Mutual Fund, Tamale Investments, Komma BV**	**Ghana, Netherlands**	**Conservation, Food crops**

Appendix C

The previous crops of the large-scale land acquisitions

Table iv The previous crop which were derived from the average yield (tonnes/hectare) for each district for the years 2006 and 2007.

LSLA	Previous Crop	Region	District
1	Cassava	Brong Ahafo	Pru
2	Cassava	Volta[2]	-
3a	Yam	Northern	Yandi
3b	Cassava	Northern	Tolon-Kumbungu
4	Cassava	Ashanti	Asante Akim North
5a	Yam	Ashanti	Offinso
5b	Cassava	Brong Ahafo	Berekum
6a	Cassava Yam	Brong Ahafo	Pru
6b	Yam	Brong Ahafo	Sene
7	Yam	Eastern	Afram Plains
8	Teak[1]	Ashanti	Asante Akim North Sekyere East
9	Commercial forestry[1]	Brong Ahafo	Asunafo North
10	Cassava	Volta[2]	-
11a	Cassava	Greater Accra	Dangbe East
11b	Yam Cassava Cassava	Eastern Greater Accra Central	West Akim Ga West Awutu Efutu Senya
12	Cassava	Volta[2]	-
13a	Cassava	Volta[2]	-
13b	Oil palm[1]	Volta[2]	-
14a	Oil palm[1]	Western	Mpohor Wassa East
14b	Oil palm[1]	Western	Ahanta West
15	Yam Cassava	Brong Ahafo	Sene
16	Cassava	Central	Gomoa
17	Cassava	Ashanti	Asante Akim North
19	Oil palm[1]	Eastern	Birim North
20	Cassava	Greater Accra	Ga West
21	Yam	Northern	Savelugu Nanton

Source: (Ministry of Food and Agriculture 2016)
1. Analysis of previous land cover.
2. Regional statistics were used due to no statistics over the districts being available.

Appendix D

Replacement crops for the GAEZ model

Table v The crops that were not represented in the GAEZ model had to be replaced by another crop with ecological requirements.

Current Crop	**Replacement Crop**
Teak	Cacao
Eucalyptus	Jatropha
Pineapple	Cacao
Cashew	Cacao
Mango	Jatropha
Moringa	Jatropha
Butternut squash	Cacao

Appendix E

Satellite images after and prior to the large-scale land acquisitions

Table vi The figure number and the corresponding LSLA.

Figure	LSLA
i	2
ii	3a
iii	3b
iv	4
v	5a
vi	5b
vii	6
viii	7
ix	8
x	10
xi	11a
xii	12
xiii	13a
xiv	13b
xv	14b
xvi	15
xvii	16
xviii	17
xix	18
xx	19
xi	20

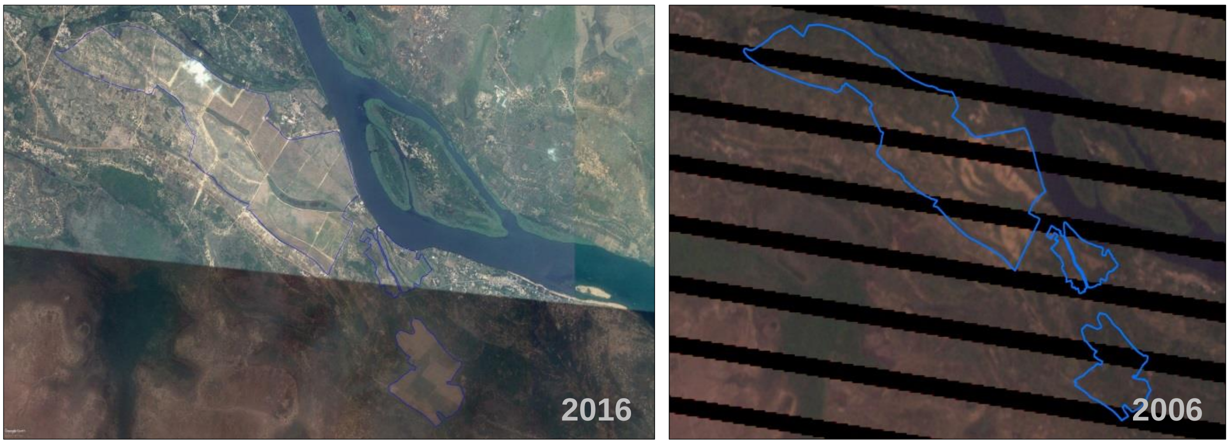

Figure i The previous land cover class of L2 is difficult to distinguish from old satellite data, with the most pronounced features being larger irregular patches of bare soil or sand. L2 is situated on the opposite side of the Volta River form L12, thus also bordering the coastal wetlands (Anthony 2015). Hence, the large patches that apparent as bare soil could be the result of sediment deposition from the river Volta or its tributaries (Omengo et al. 2016; Day et al. 2008). Although no traces of agriculture are evident from the old satellite data, there are several communities dispersed around L2, indicating that the area might have been utilised for different purposes. Besides from communities being present in the more recent satellite images, agricultural fields intertwined with savannah tree stands are evident in surrounding area in the new images. This leads to the conclusion that the previous land cover class of L2 probably was of multifunctional land use.
Satellite data: (Google Earth Pro 2016c; U.S. Department of the Interior and U.S. Geological Survey 2006a).

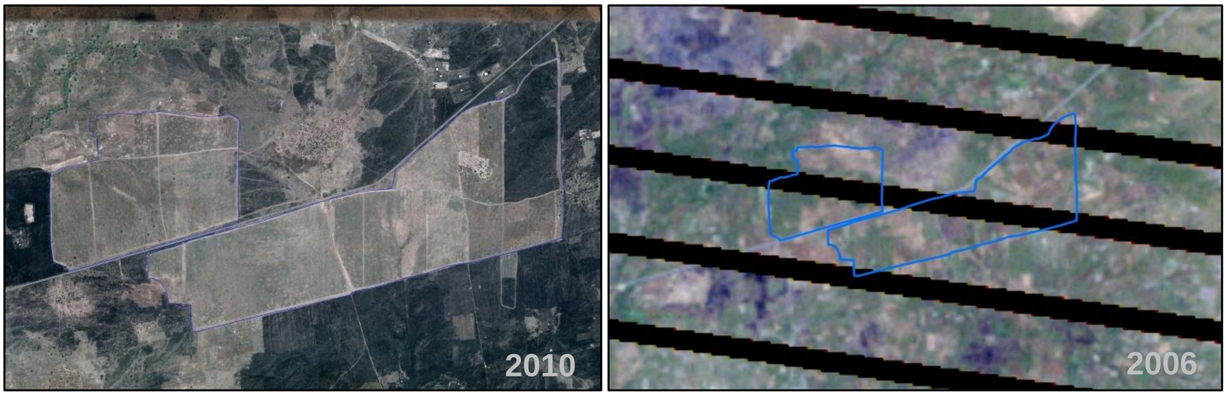

Figure ii The small rectangular patches in the image from 2006 indicate that the previous LULC of L3a was small-scale farming.
Satellite data: (Google Earth Pro 2010a; U.S. Department of the Interior and U.S. Geological Survey 2006b).

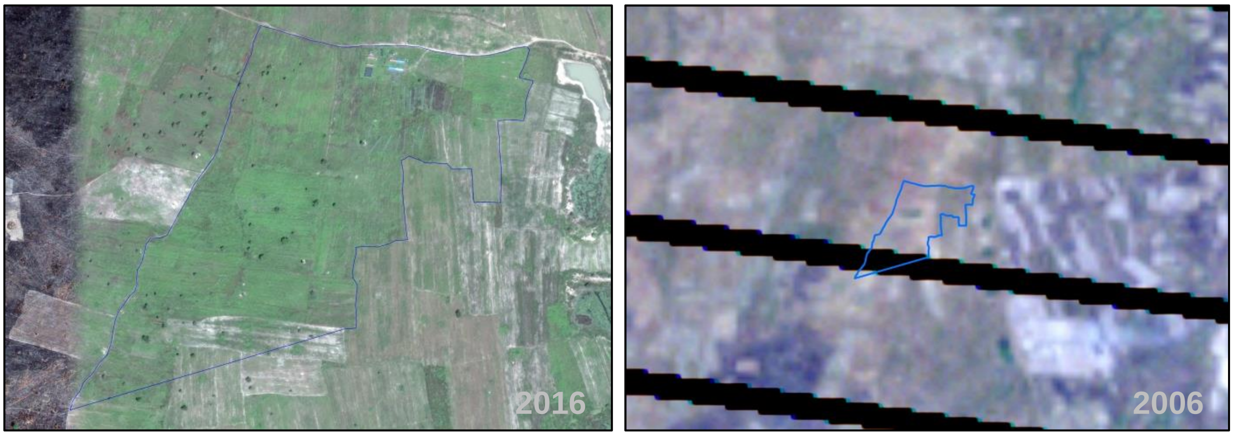

Figure iii Even though the resolution is course in the image from 2006 it appears as if there are some fields present which indicate that the previous LULC of L3b was small-scale farming.
Satellite data: (Google Earth Pro 2016d; U.S. Department of the Interior and U.S. Geological Survey 2006b).

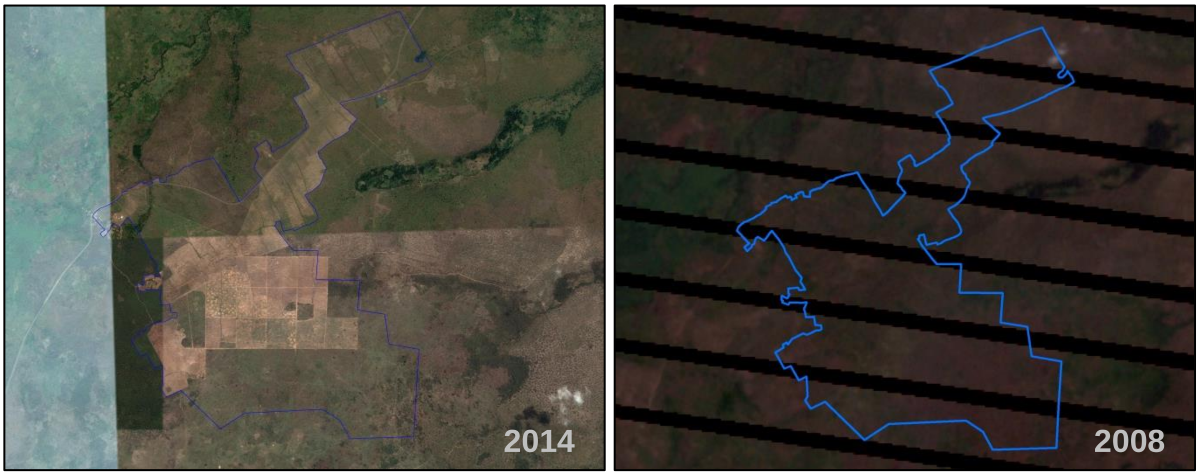

Figure iv The L4 is situated close to a major road and at least two villages are situated less than two kilometres from L4, which suggests that the area was utilised prior to the LSLA. Except for the road, no straight features can be traced in the area it appears irregularly patchy with lighter and darker features, possibly evidence of the area's location close to the transit zone between deciduous forest and Guinean savannah.
Satellite data: (Google Earth Pro 2014b; U.S. Department of the Interior and U.S. Geological Survey 2008a).

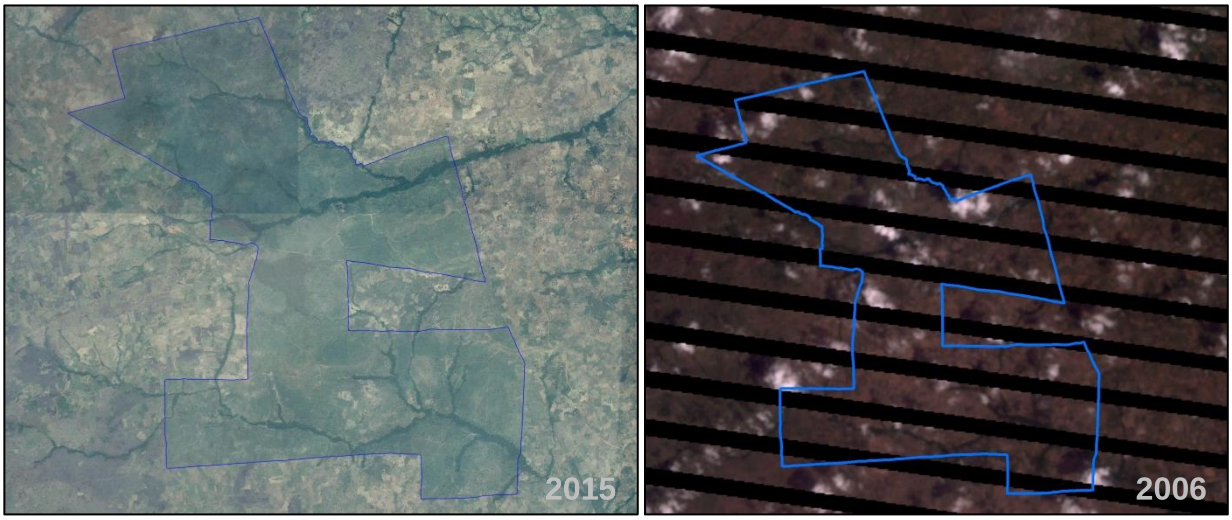

Figure v Both subareas of L5 are situated in two different forest reserves, Asubima Forest Reserve and Tain Tributaries Block II Forest Reserve (Wanders and Tollenaar 2016; Westerlaan and Tollenaar 2013), and the satellite images prior to the teak plantations of L5 display highly degraded forests in both locations. There are no evident signs of agriculture, however the area surrounding L5a is today dominated by agriculture and consequently some human disturbances could be expected to have caused the degradation. Additionally, a study conducted in the area of the forest reserve in L5a in the years 2007-2008 concluded that human disturbances were common in the Asubima reserve, mainly through collection of fuel wood and bushmeat (Pouliot et al. 2012).
Satellite data: (Google Earth Pro 2015a; U.S. Department of the Interior and U.S. Geological Survey 2006c).

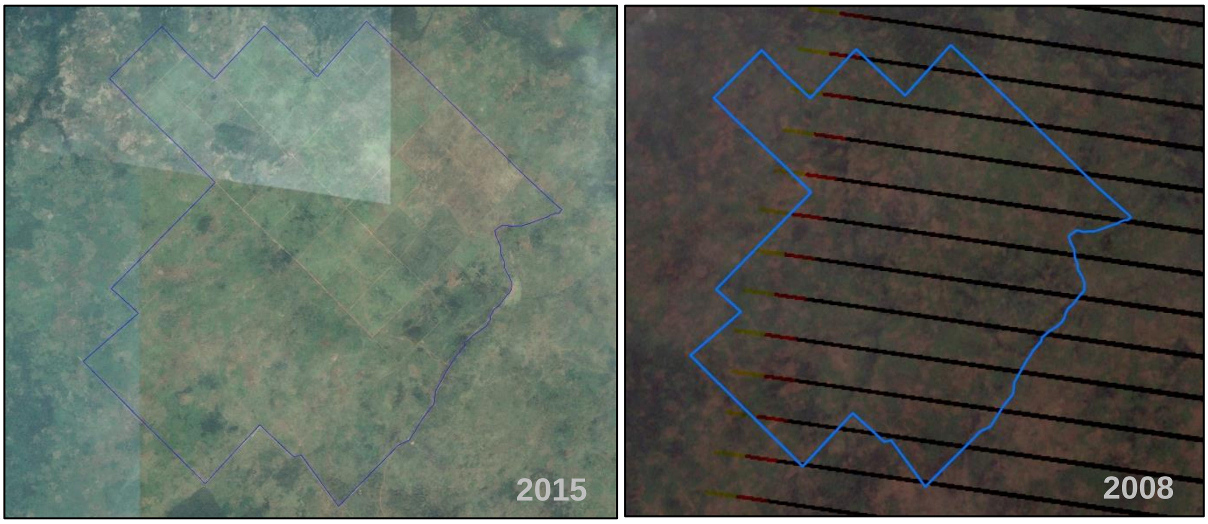

Figure vi L5b: see above figure v.
Satellite data: (Google Earth Pro 2015b; U.S. Department of the Interior and U.S. Geological Survey 2008b).

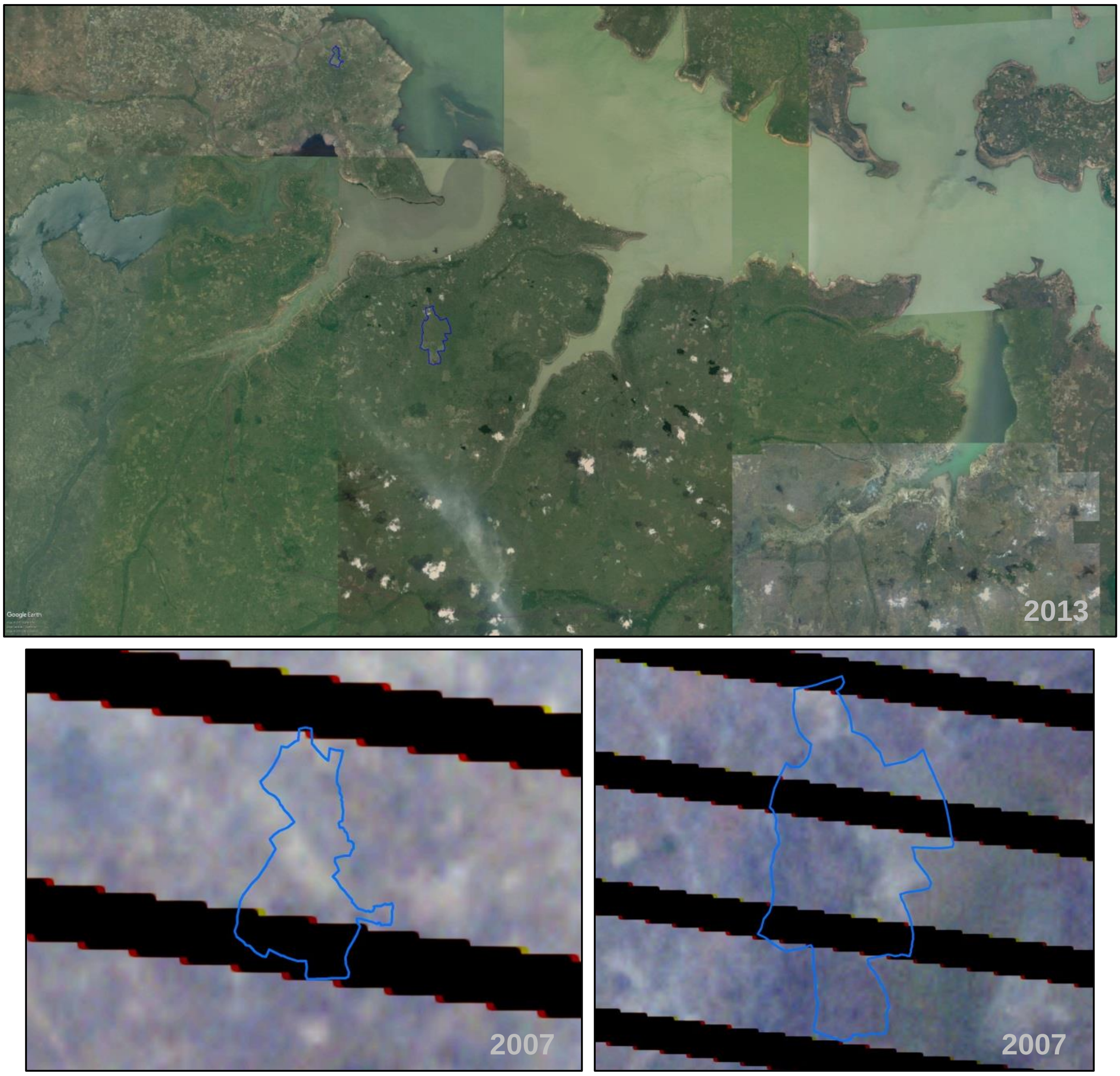

Figure vii The adjacent subareas of L6 are situated on different sides of the border between the Transition zone and the Guinean savannah zone. Yet the features of the previous land cover are very similar with a mosaic of agricultural fields and savannah forest and grass land, which often characterises the Guinean savannah zone (Liu et al. 2017).

Satellite data: (Google Earth Pro 2013a; U.S. Department of the Interior and U.S. Geological Survey 2007a).

Figure viii L7 is situated close to a village which indicated that it used to be utilised by humans before the land acquisition.
Satellite data: (Google Earth Pro 2013b; U.S. Department of the Interior and U.S. Geological Survey 2011).

Figure ix The site for the L8 that could be identified in this report appears to have been used for large-scale tree cultivation prior to the land acquisition in 2011. A part of the acquired area used to be a teak plantation (Osei-Peprah 2015), which could explain why the area appeared to be cultivated with trees prior to the land acquisition.
Satellite data: (Google Earth Pro 2014c; U.S. Department of the Interior and U.S. Geological Survey 2010).

Figure x The L10 is situated within the Keta Lagoon Complex Ramsar Site in the Volta River Delta (Anthony 2015; Tufour 1999). Ramsar is an international agreement to protect important wetlands of the world and agreement originated from a convention in Ramsar, Iran, arranged by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (1994; Google Earth Pro 2002b). The previous land cover appears to be a mosaic of bare soil, trees and marshes. This correspond well with the ecological characteristics of the area, which is grass thicket and shrubs in the elevated grounds and marshes in the lower grounds (Tufour 1999). However, there are also features within the area that are rectangular and appear to be purposely made by humans. The appearance of roads and villages in the vicinity of the area further contribute to the conclusion that the land probably is utilised by humans. Satellite data: (Google Earth Pro 2013c, 2002a).

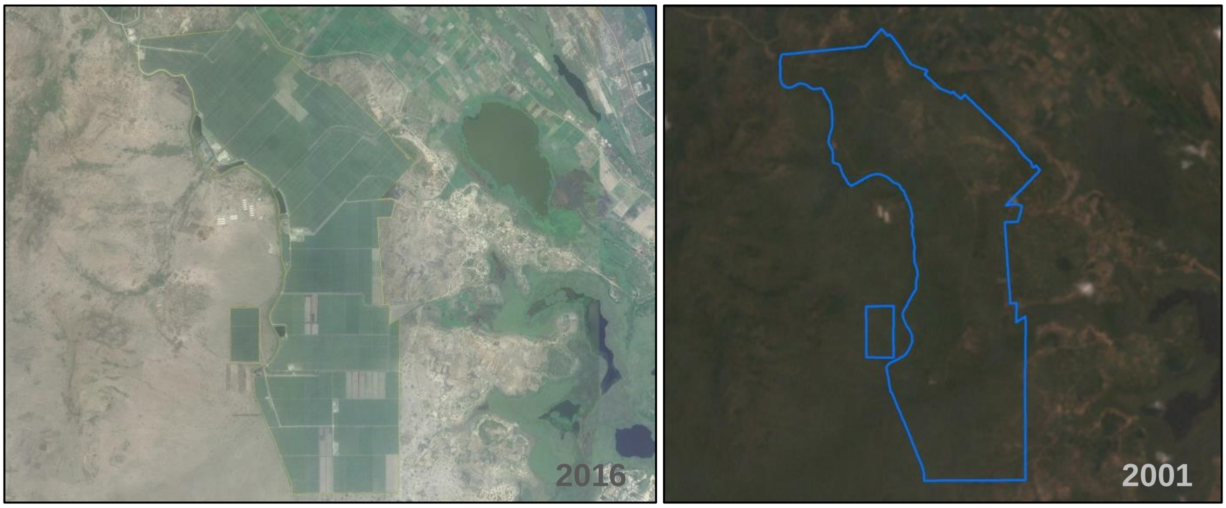

Figure xi The old satellite images covering the L11a are of insufficient quality and as a result is was difficult to visually distinguish the previous LULC class. Because of the inability to visually determine the previous land cover class, the behaviour of the NDVI-histograms of the old satellite image, within the area and in the buffer zone, was investigated. The two histograms showed a similar shape and variance, which indicated that the vegetation cover within and outside of the area is similar, however the NDVI distributions were statistically different hence more recent satellite data of the surrounding could not be used to estimate the previous LULC of L11a. Due to the area being densely populated the LSLA was probably utilized before the land acquisition.
Satellite data: (Google Earth Pro 2016e; U.S. Department of the Interior and U.S. Geological Survey 2001a).

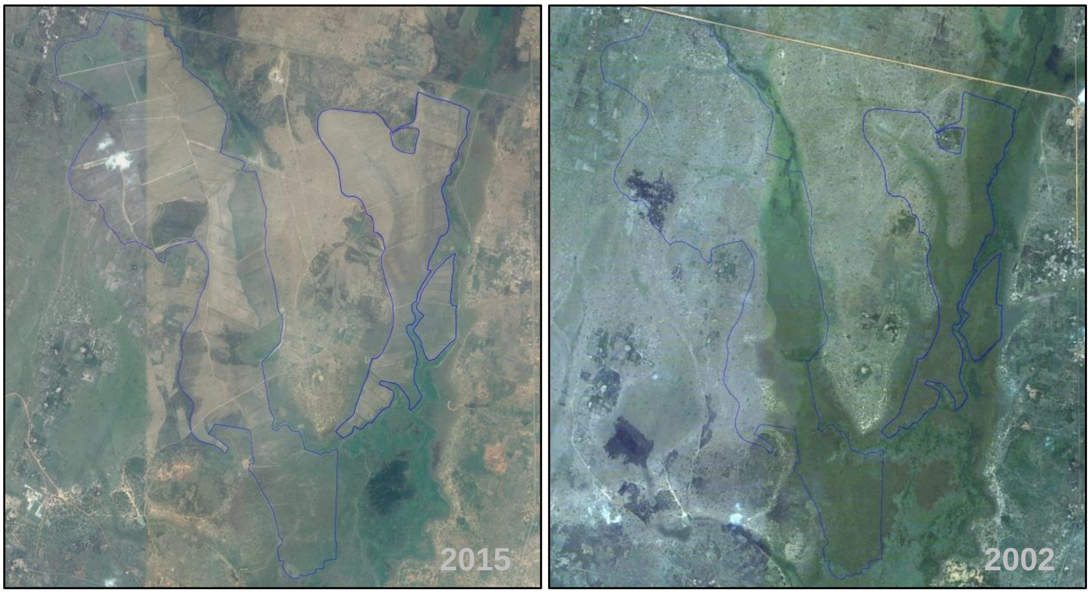

Figure xii The rice farm of L12 is situated on the eastern side of Volta River, just north of the Volta River Delta and on the border to the coastal wetlands (Anthony 2015). The southern part of the area appears as marshes whereas the northern parts sparse savannah and agriculture.
Satellite data: (Google Earth Pro 2015e, 2002b).

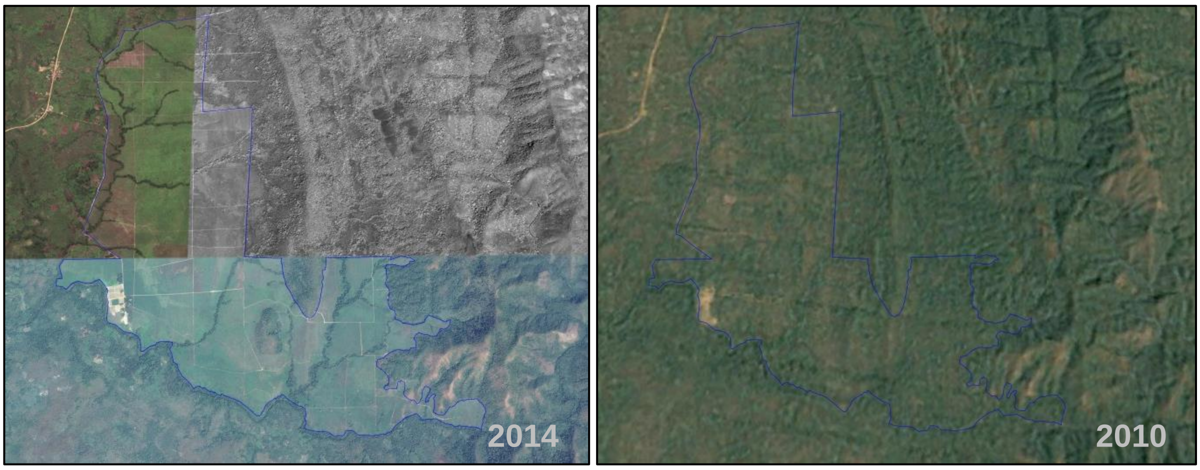

Figure xiii The L13a is situated in the deciduous forest zone and the area appears to be rather unspoilt in the eastern part, however rectangular features in the western part indicates that either agriculture or forest clearance took place there before the land acquisition.
Satellite data: (Google Earth Pro 2014d, 2010b)

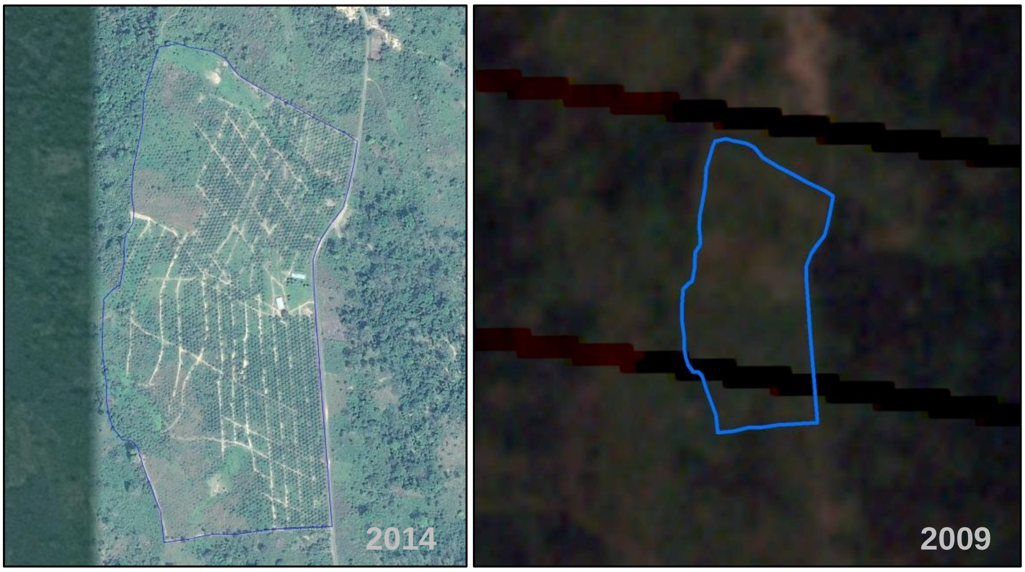

Figure xiv It was difficult to distinguish the previous land cover class of L13b from satellite data, however the company claims that the property already was an oil palm cultivation when they acquired it (Volta Red Limited 2016).
Satellite data: (Google Earth Pro 2014e; U.S. Department of the Interior and U.S. Geological Survey 2009).

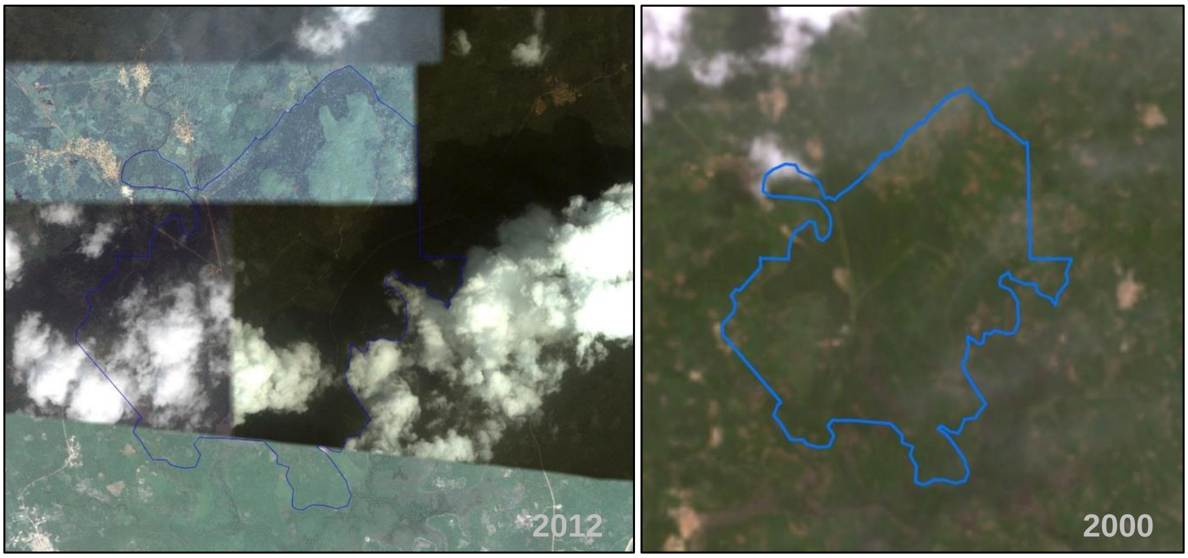

Figure xv In L14b the appearance of an oil farm is even more pronounced than in 14a due to fewer clouds.
Satellite data: (Google Earth Pro 2012; U.S. Department of the Interior and U.S. Geological Survey 2000).

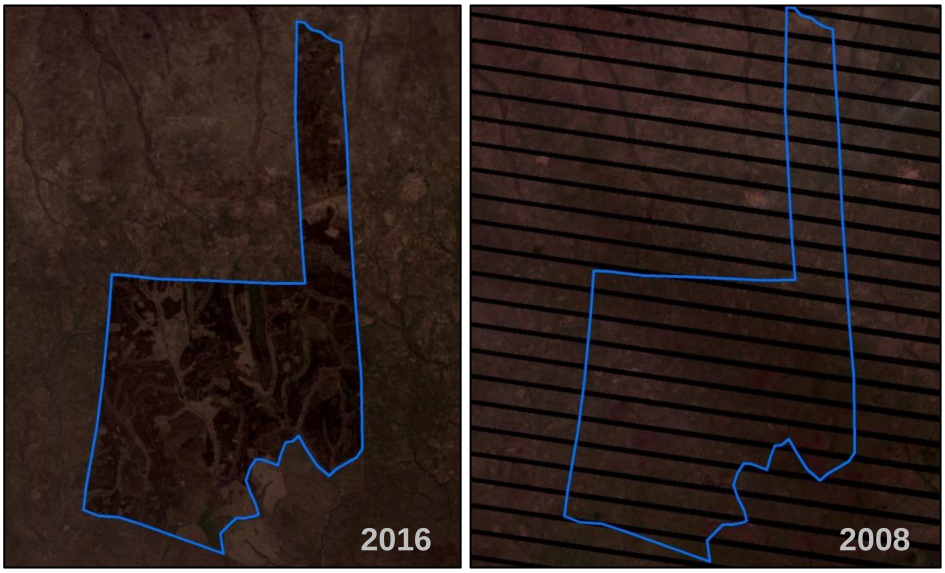

Figure xvi Even though the forested areas are sparsely scattered in the area surrounding L15, it still holds the characteristics of the Transit zone with savannah woodland being discontinued by forested areas. The previous land cover within the LSLA 15 appears in the same pattern, but with agricultural fields also being present.
Satellite data: (Google Earth Pro 2016g; U.S. Department of the Interior and U.S. Geological Survey 2008a).

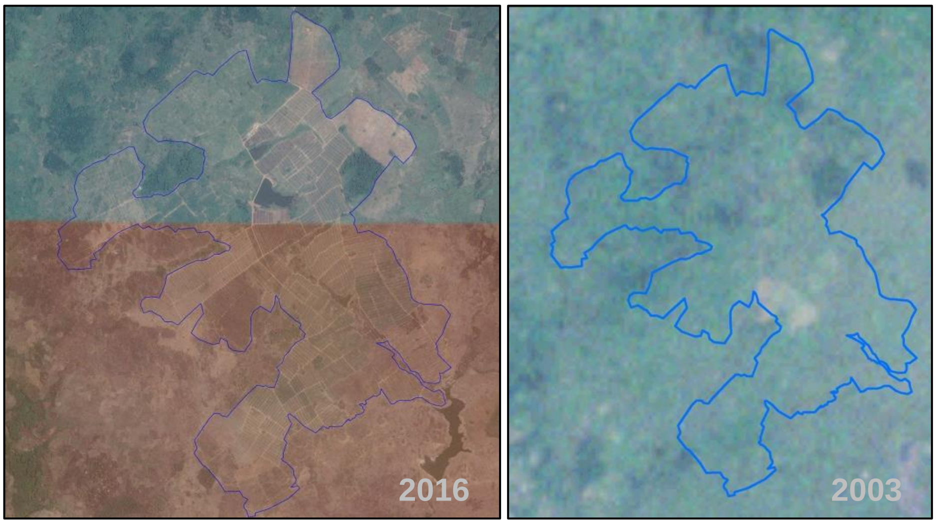

Figure xvii A mosaic of dense and sparse vegetation appears in the old satellite images of L16, but no straight borders and rectangular features indicating agriculture is evident. The adjacent areas do, however, indicate the presence of agriculture with rectangular features being scattered across the landscape along with the patches of sparse and dense vegetation. Other features indicating human disturbances in the area are the occurrence of roads and the vicinity to a larger town and smaller villages.
Satellite data: (Google Earth Pro 2016h; U.S. Department of the Interior and U.S. Geological Survey 2003).

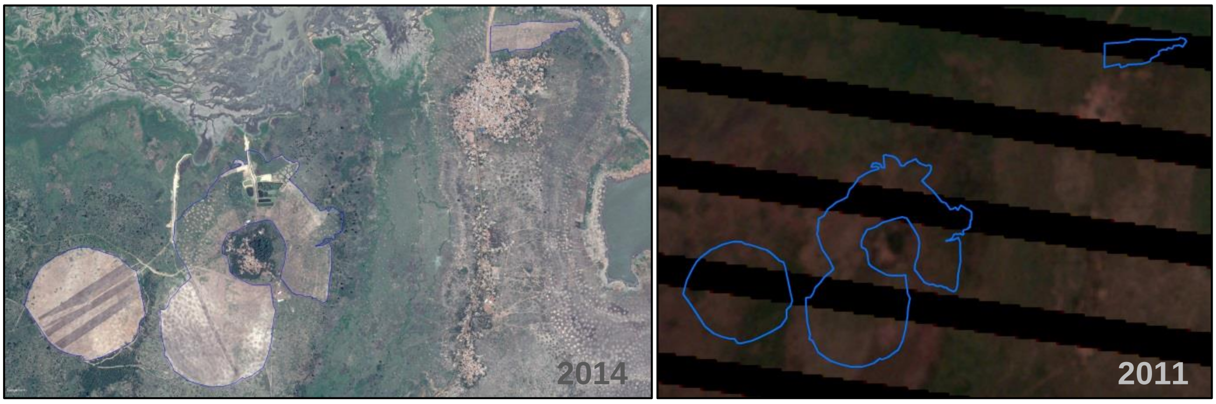

Figure xviii The old satellite images show no indications of agriculture, instead the area appears to blend in well with the surrounding, with the exception of a village located in the centre of the area of L17. Although agricultural activities might not have been present before the land acquisition, the direct vicinity of the village indicates that the area probably was utilised by humans.
Satellite data: (Google Earth Pro 2014f; U.S. Department of the Interior and U.S. Geological Survey 2011).

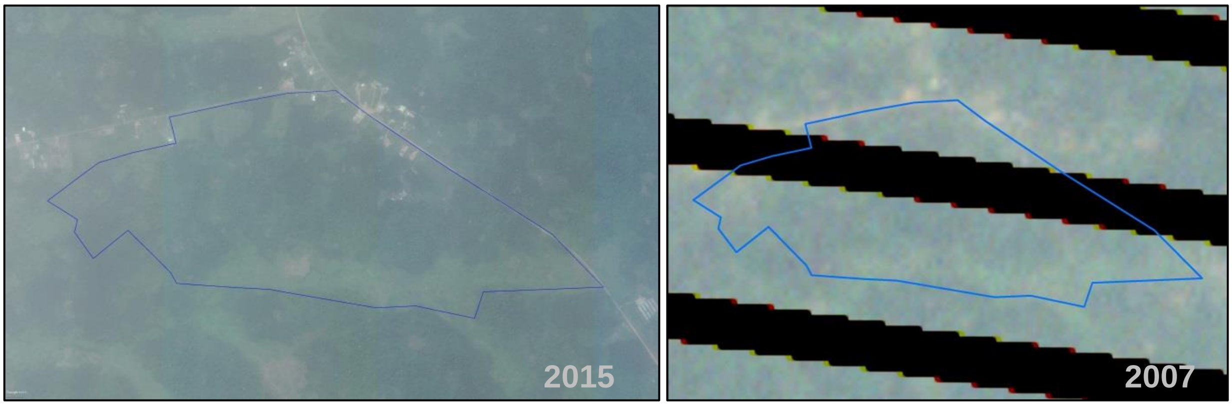

Figure xix The satellite data also contributed to difficulties in estimating the previous land cover class for Land more recent satellite data had to be utilised to understand the land covers in the area. Through the comparison of the NDVI-histograms within and outside of the area of L18, the Wilcoxon test failed to reject the null hypothesis, (p=0.391) that the NDVI-values within and outside of the LSLA had the same median at significant level of 0.05. An assumption was then made that the area surrounding L18 has not changed significantly since the L18 was initiated. The area surrounding the L18 appears to be a mosaic of forest, clear cut areas and oil palm plantation. It is then assumed that the previous land cover class of L18 is partly large-scale cultivation, more specifically oil palm cultivation.
Satellite data: (Google Earth Pro 2015f; U.S. Department of the Interior and U.S. Geological Survey 2007b).

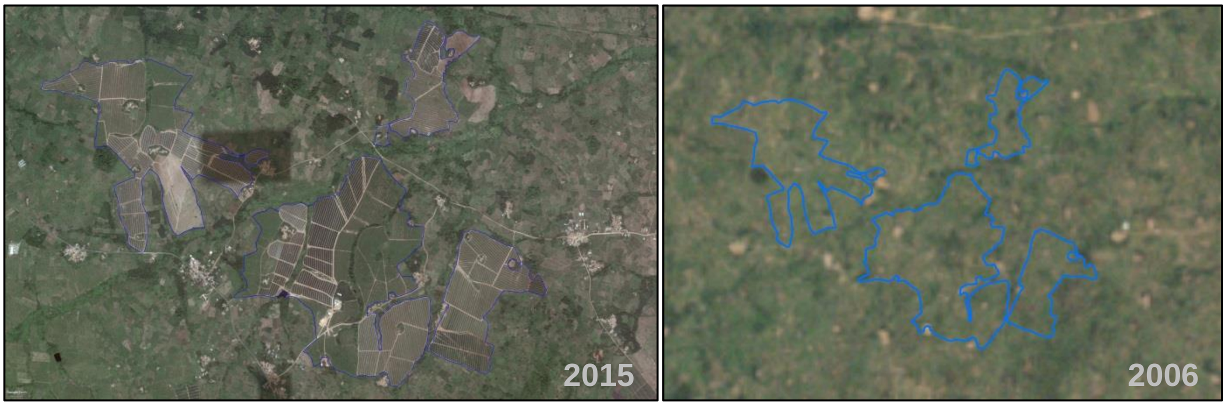

Figure xx L19 appear to have some agriculture and grasslands with forest stands.
Satellite data: (Google Earth Pro 2015g; U.S. Department of the Interior and U.S. Geological Survey 2006a).

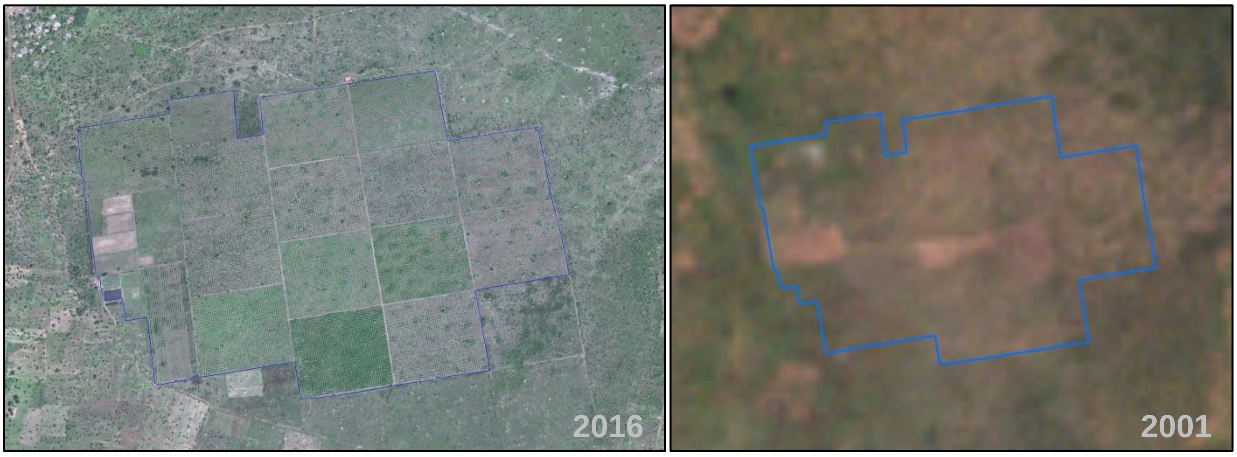

Figure xi The area surrounding L20 appear to be densely cultivated whereas the area within the L20 only show two rectangular features indicating agricultural fields. Sparsely scattered forest stands and savannah grasslands are patched between the fields (Liu et al. 2017).
Satellite data: (Google Earth Pro 2016i; U.S. Department of the Interior and U.S. Geological Survey 2001b).

Institutionen för naturgeografi och ekosystemvetenskap, Lunds Universitet.
Studentexamensarbete (seminarieuppsatser). Uppsatserna finns tillgängliga på institutionens geobibliotek, Sölvegatan 12, 223 62 LUND. Serien startade 1985. Hela listan och själva uppsatserna är även tillgängliga på LUP student papers (https://lup.lub.lu.se/student-papers/search/) och via Geobiblioteket (www.geobib.lu.se)
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