USING REMOTE SENSING IN ENVIRONMENTAL IMPACT ASSESSMENT OF AGRICULTURAL AREAS

A Case of Kikonge Dam and Irrigation Project in Tanzania

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Abstract

This thesis looks at the capabilities of satellite remote sensing for use in environmental impact assessment (EIA), using an agricultural project area in Southwestern Tanzania as a case study.

The “cloud” based GIS software Google Earth Engine is utilized for the analysis, which consists of four parts: land use mapping, a normalized differentiated vegetation index (NDVI) time series chart, the extent of dry season crops, and differences in NDVI for various part of the agricultural areas.

The results show that 50% of the study area consists of fields and have a very high accuracy for all land cover classes, except for built up areas. The NDVI time series chart illustrates that better cloud filtering should be investigated in order to have a clearer view of the annual phenology. Furthermore, the extent of fields with dry season crops have been measured to be 20%, which is only 1/3 of what other sources state. This indicates that further research is needed to look into this gap. However, the areas found to have dry season crops correspond well with areas that have been mapped to have a high yearly NDVI, which could suggest that these areas might have better growing conditions and/or better farming practices being applied to them.

No field studies have been conducted in the case study area because of logistical and financial constraints, and it is therefore recommended that the findings from this thesis are validated through fields surveys in the area. This approach should always be strived for when conducting remote sensing analysis, including EIA projects.

This thesis also recognizes that remote sensing cannot aid in all issues regarding EIAs in developing countries, as not all are related to a lack of data but instead societal structures such as poverty, lack of well-functioning government institutions, corruption etc. Hence, remote sensing is deemed to be one of many approaches needed for improving EIAs and environmental protection.

Frontpage photo: Thea Caroline Wang

Synopsis

Befolkningstallet er stigende globalt og denne faktor, kombineret med en voksende middelklasse, ligger pres på verdens lande for at øge produktionen af afgrøder. Dette er især tilfældet i Afrika. En måde at øge produktionen på er ved hjælp af kunstvanding, og det kan bl.a. ske ved at opføre dæmninger. Disse har dog uheldigvis ofte negative påvirkninger på både miljø og mennesker. Derfor er denne type projekter oftest underlagt miljøvurderinger, der har til formål at finde og afhjælpe disse negative konsekvenser. Desværre mangler der tit fyldestgørende data i især udviklingslande, og her kan et værktøj som telemåling med satellitter være behjælpeligt.

Dette speciale udforsker derfor mulighederne for at anvende satellitbilleder til miljøvurderinger i landbrugsområder. Studiet anvender et case område i det sydvestlige Tanzania, og fire forskellige telemålingsanalyser udføres: undersøgelse af arealanvendelse, vegetations indeks' (NDVI) tidsserie over plantevæksten, kortlægning af tørtidsafgrøder samt undersøgelse af forskelle i produktiviteten af marker i projektområdet.

Analysen udføres ved hjælp af det "cloud" baserede Google Earth Engine, som er en geografisk informationssoftware, der anvender Googles enorme computerkapacitet fra deres datacentre. Dette gør det muligt at arbejde med et stort antal satellitbilleder, hvilket er med til at forbedre analysernes præcision. Det gør det samtidigt lettere og hurtigere at bearbejde dataene.

Resultaterne viser, at halvdelen af projektområdet er udgjort af marker, og præcisionen af disse landtype klassificeringer er alle nær 100% med undtagelse af bebyggede områder, hvilket indikerer at yderligere målinger kunne være nødvendige for præcist at beskrive denne overfladetype. Der er samtidig et sammenfald mellem områder, der er identificeret som havende tørtidsafgrøder og områder, der er målt til at have en høj produktivitet, hvilket kan indikere at disse jorder muligvis har bedre vækstbetingelser og/eller at andre og bedre landbrugsmetoder anvendes her. Imidlertid er mængden af identificerede tørtidsafgrøder kun 1/3 af hvad andre kilder angiver, hvilket kan antyde at dette område har brug for nye målinger og mere dybdegående undersøgelser. Ydermere viser resultaterne, at det kan være fordelagtigt at undersøge bedre metoder til at filtrere skyer væk fra billederne. Endeligt anbefales det også at telemålings analyserne bliver valideret med feltundersøgelser i det givne projektområde.

Det anerkendes også at adskillige problemer eksisterer i forhold til miljøvurderinger i udviklingslande og brug af telemåling i denne forbindelse. Nogle af disse problemer kan afhjælpes ved hjælp af telemåling, men adskillige kræver anderledes og komplekse løsninger, da det er omfattende problemer som f.eks. fattigdom, mangel på offentlige institutioner, korruption m.m., der ligger til grund for det. Men brugen af telemåling vurderes stadig til at have en vigtig rolle at spille for at opnå bedre miljøvurderinger og i beskyttelsen af mennesker, natur og miljø.

Acknowledgements

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Problem Analysis

The world's human population is estimated to reach around ten billion people in 2050 and this factor, combined with a growing middle class, will put more pressure on the global agricultural sector as a significant increase in food production have to take place (FAO 2018). The biggest increase in populations is happening in Africa and this trend is believed to continue in the future (UN 2019a). The requirements for higher agricultural productions are therefore great in Africa. However, the pressure on natural land areas along with soil and water resources from agricultural and urban development are also increasing on the continent, e.g. with the clearing of forests, degradation of fertile soils, draining of wetlands and increasing use of freshwater (USAID 2012; The World Bank 2017).

Future increases in agricultural production should therefore take steps to reduce, mitigate and reverse these impacts on the natural environment and its resources. This involves optimizing the use of land and water resources, and it is important because natural land areas such as wetlands and forests provide many valuable ecosystems services that are beneficial to humans. These include water purification, flood regulation, air quality improvements, recreation etc., and they are also vital habitats to many plant and animal species (RAMSAR 2018; Masiero et al. 2019). Furthermore, freshwater scarcity, water pollution and soil salinization are on the rise globally and in Africa, primarily because of human activity, and insuring a sustainable use of soils and water is essential (FAO 2011).

These issues are also present in the East African country of Tanzania (Figure 1), which currently have a population of about 60 million people. This number is expected to reach almost 140 million people in 2050 (Worldometers 2019). This means that more food has to be imported and/or the domestic agricultural sectors need to be strengthened. The agricultural sector in Tanzania is a large and important part of the country's economy and employs nearly 70% of the population and contributes with 30% of the GDP (Tanzania Invest 2019).

As of 2014, agricultural areas with crop production were estimated to take up 100.000 km^2 of the land mass of Tanzania, or around 11%, but only an estimated 440.000 km^2 is deemed suitable for crop production (Kimaro and Hieronimo 2014). Lack of financial resources, week institutions and inadequate farming technologies are some of the factors that are limiting the expansion of arable land in the country (Leyaro and Morrissey 2013). The primary food crops in Tanzania include maize, rice, bananas, cassava etc., and cash crops such as coffee, tea, tobacco, cotton etc. (Global Yield Gap Atlas 2019).

Figure 1: Map of Tanzania.

Developing the agricultural sector has been a priority in Tanzania, both to increase food security but also to alleviate poverty (URT, UNDP, and UNEP 2014). Poverty in Tanzania is still a major issue with about 70% of the population living for less than $2 a day (The World Bank 2019). The majority of the population live in rural areas with agriculture being the primary source of income (Faura 2016). Most of the farms are small in size, and they generally need improved farming practices that increase yields and limits soil erosion etc. (USAID 2012). In addition to this, floods and droughts are also challenging efforts to create a secure food production and protecting people's livelihoods (CIMA and UNISDR 2018).

One way to achieve higher agricultural yields and more food security is through the use of irrigated agriculture (Kruashvili et al. 2016). Higher yields could minimize the need to change more natural areas to agriculture as well as give a higher income to farmers (FAO 2019). Currently most agriculture is rainfed in Tanzania (GACSA 2016) but the country has a great potential for irrigation because of its many lakes, rivers and underground sources of water (Global Yield Gap Atlas 2019).

On a global scale, irrigated agriculture is the largest user of freshwater, consuming 70% of all freshwater, and this is estimated to continue to increase in future (Global Agriculture 2019). Water is relatively scarce in Tanzania, and the renewable per capita freshwater resources are currently just below the 1.700 cubic-meter per person threshold, which makes it a water stressed country (The World Bank 2017). This is expected to continue to decrease in the future so proper water management is crucial, especially in the agricultural sector which uses almost 90% of all freshwater in Tanzania (The World Bank 2017).

Irrigation is often accomplished by the construction of dams, which allows for reservoirs to be created that are used for the process of water storage for the irrigation schemes (ICOLD 2019). Furthermore, these dams can also be utilized for energy production through hydropower (ICOLD 2019). In 2016, only 33% of households in Tanzania were connected to the electrical grid but the need for electricity is growing almost 15% per year, making it vital for the country's continued development and economic growth to increase the installed generation capacity, which is currently only around 1500 MW (Export.gov 2019).

However, the construction of a dam has consequences for the natural environment and the human population both upstream and downstream of the chosen site (ICID 2000). This can involve the resettlement of people, changes in sedimentation, river hydrology, fish migration etc. (Tilt, Braun, and He 2008; Ritchie et al. 2018; FAO 2002). In order to find, minimize and mitigate these impacts, as well as enhance the positive outcomes (Dougherty and Hall 1995), large dam projects are subject to environmental impact assessments (EIA) in most countries in the world (UN United Nations 1991; IAIA 2009). This is also the case in Tanzania. Therefore, the reasoning behind these assessments and their goals are further explored in this project.

Impact assessments

An impact assessment is a study of the future consequences for a given project, policy, program or plan, e.g. the construction of a new dam (IAIA 2009). This includes a variety of different types of assessments that look upon various issues such as health, gender issues, economic impacts, ecologic assessment etc. (Morrison-Saunders et al. 2014). The assessments aim to provide information to the decision makers, promote public participation and transparency, find procedures that can mitigate and monitor possible impacts, and create a sustainable development (IAIA 2009).

The first and most widely used type of impact assessment is the environmental impact assessment (EIA), which was first adopted in the United States in 1970 after decades of concern about the impacts that human actions were having on not only the natural environment but also human wellbeing (Burdge 1991). This later spread internationally with the European Union approving a directive on EIA in 1985, and the United Nations' declaration on EIA in 1992 (IAIA 2009). The kind of subjects that an EIA cover vary around the world. For instance, the African Development Bank uses the term environmental and social impact assessment (ESIA) to include the social aspects and highlight their importance (IAIA 2009). Because of the need to use EIA on a more strategic level (policy, plan, program etc.), the concept of Strategic Environmental Assessment (SEA) was also developed to be used as a tool early in the decision-making at the regional or sectoral scale (IAIA 2009).

Generally, an EIA process have the following steps (Verma 2016):

- Screening
- Scoping
- Impact analysis
- Impact prediction
- Mitigation and impact management
- Implementation and follow-up

The first step covers the initial investigation on whether an EIA have to be made or not. This generally depends on the size of the project and whether it is likely to have significant impacts on the environment (Dougherty and Hall 1995). If it is deemed necessary to conduct an EIA, the scoping phase begins, and it is decided what key environmental concerns are to be included in the assessment, and how they are to be measured (Dougherty and Hall 1995). Afterward, an analysis of the impacts of various project alternatives is performed, and at this stage a baseline study is also conducted to investigate the conditions at the current moment as this is needed to predict the future impacts (FAO 1996).

When the potential impacts have been identified, the focus shifts to mitigation and impact management, which includes avoiding and/or limiting the severity of the impacts and creating compensation mechanisms for unavoidable ones (IISD 2019). Finally, when the EIA has been approved by the decision-makers, the project is implemented and a follow up process is initiated to monitor the potential changes and impacts (Marshall 2005). During these steps, depending on the country, public participation can take place under various stages of the process with the option to make complaints and suggestions (Hasan, Nahiduzzaman, and Aldosary 2018).

However, one concern with EIA in many countries is the poor quality of data for assessments and the fact that governments push to spur economic growth by speeding up projects, both of which can possibly weaken the environmental and social protection (Morgan 2012). Hence, among other improvements, there is a need for applying methods that are cost-effective, fast and give comprehensive information. One such tool, which gives managers the ability to collect data and monitor a given area of interest, is remote sensing.

Remote sensing

The science of remote sensing involves the collection of data about an area without being in physical contact with it (ESA 2010). This includes a variety of platforms but the most common are satellites, aircrafts and drones (Chang and Clay 2016). These platforms can carry different sensors that gather information and are generally divided into two main categories: passive (optical) and active instruments (NASA 2018b), the former being the focus of this study.

Optical sensors work by measuring the solar energy that is either reflected or emitted (as is the case with thermal radiation) from surfaces (Government of Canada 2015). This energy is captured in so-called bands that represent a part of the electromagnetic spectrum such as the red, green and blue bands. These are part of the spectrum, and thereby the colors that the human eye can see (Wasser 2018). However, there are also wavelengths that humans cannot perceive such as ultraviolet and infrared radiation but these can be detected by the sensors and used for data analysis (Bhatia 2008). As various materials reflect this electromagnetic radiation differently, it is possible to use the information to differentiate between surfaces like water, bare soil, vegetation etc. (Wegmann, Leutner, and Dech 2016).

An important factor to take into consideration is the sensors' resolutions, which can generally be divided into three main categories: spatial, temporal and spectral (Kadhim, Mourshed, and Bray 2016). The spatial resolution describes the size of each pixel in the imagery; e.g. a 10-meter spatial resolution means that each pixel is 10x10 meters. The temporal resolution is the frequency of which the sensor passes over a given spot on the planet, and this is most often described for the equator (for satellites) where the resolution will be lowest. Finally, the spectral resolution is associated with the number of bands in the sensor's electromagnetic spectrum.

The use of satellite imagery and other remote sensing platforms is widely used throughout the world for various applications, both commercial and scientific. These include agriculture, construction, drought monitoring, forest loss etc. (Wickramasinghe, Vu, and Maul 2018; Kussul et al. 2018; Walters and Scholes 2017; AghaKouchak et al. 2015). Compared to ground measurements, remote sensing has the advantage that large areas can be monitored continuously throughout the year and data can be compared between different years (Atzberger 2013).

In order to work with imagery obtained from remote sensing platforms, a geographic information system (GIS) is needed. This is software that enables the user to process, analyze and visualize different kinds of spatial information that can be obtained through fields studies, census data, remotely sensed images etc. (Dalgleish et al. 2010). In the past, this has primarily referred to software installed on a personal computer but this has been changing in recent years with the introduction of cloud based programs such as Google's Earth Engine. The engine utilizes Google's large network of data centers, which in turn allows multiple computers (up to thousands) to work at the same time to process and visualize the data the user needs (Gorelick et al. 2017). This makes it possible to execute analysis of remotely sensed data much faster and in some cases perform analysis that was not previously possible with only a single computer.

Remote sensing in environmental impact assessment

To examine the use of remote sensing in EIA for projects in Africa, a review of the available literature is made using the African Development Banks's database for environmental and social impact assessments (ESIAs) (African Development Bank 2019). The 30 most recent ESIA reports are studied for their use of remote sensing and GIS (reports in French are not reviewed), and include projects on road construction, urban development, agricultural expansion and irrigation projects etc. (Appendix 1). Only one report have utilized remote sensing for the EIA (African Development Bank 2018), in this case for land cover mapping of a farm block development project. However, the use of GIS is more common with applications related to illustrating project boundaries, showing areas in most risk, specifying protected areas etc.

To further study the use and application of remote sensing in EIA (and SEA), scientific literature from the Web of Science database is investigated (Clarivate Analytics 2019). There exist nearly 200.000 publications on the topic of remote sensing and more than 6.000 for EIA/SEA. However, only 93 studies from the database were found to mention both remote sensing and EIA/SEA. This could indicate that it is an interdisciplinary field that requires more attention and research.

Khanna and Kondawar (1991) argue for the implementation of remote sensing in EIA since there often is a need for extensive data collection over vast areas but only limited time, manpower and financial resources. The authors make the case that accurate baseline information on land use, e.g. water, vegetation, settlements etc. , is the backbone of an EIA in order to predict and evaluate the impacts on both the physio-ecological and socio-economic environment. Two decades later, Vorovemcii (2011) makes the same case but also specifies that satellite remote sensing can be particular useful in EIA in areas where there is a lack of spatial data, which is often the case in many developing countries. This can cover a very broad spectrum of areas such as urban development, mining, agriculture etc. Furthermore, he stresses the importance of using a time-series of images, which is especially beneficial for monitoring land cover changes as well as the use of vegetation indices to monitor changes in the ecosystems.

Vegetation indices are based on the fact that green vegetation reflects little light in the red spectrum and more in the near infrared (NIR) compared to less green vegetation where the opposite is true (Pettorelli et al. 2005). The most commonly used index is the normalized difference vegetation index (NDVI) defined as: (NIR – red)/(NIR + red). This gives each pixel on the remotely sensed image a value between -1 and +1 with higher values indicating a greater content of chlorophyll and therefore greener vegetation (Yengoh et al. 2014). Among other, NDVI has shown a correlation between plant productivity and biomass, and it has also been used to differentiate between different ecosystems, detect droughts, floods and vegetation phenology, e.g. the length of the growing season (Yengoh et al. 2014; Pettorelli et al. 2005).

Shanwad et al. (2012)**,** who also utilized remote sensing in EIA for land cover mapping and to investigate changes in vegetation vigor before and after watershed development using NDVI, emphasized that the cost-benefit analysis performed indicated that using remotely sensed data was half as expensive and required 1/6 of the man-hours compared to the conventional method of surveyors doing field work. Of course, this would depend on the size of the project area as well as the salary levels in the country but it does indicate that if remote sensing is applied there could be opportunities for saving time and money in EIAs.

At the start of the millennium, Makin, Bastiaanssen, and Molden (2000) wrote: "Presently, remote sensing is essentially a research tool…" and argued that many managers and policy makers were simply not aware of the possibilities of remote sensing. Based on the literature presented, this seems to still be the case for EIA professionals today.

This thesis will therefore look at the capabilities of remote sensing in EIA for an agricultural project area, using the 'Kikonge dam and irrigation project' in Tanzania as a case study. This includes land cover mapping as well as the use of NDVI for assessing the land cover. This information is important for various reasons, including food security and general land management (Thenkabail et al. 2012), e.g. how much of the total land area agriculture occupy compared to natural areas. Finally, it functions as important baseline information that can later be compared to follow-up data after the given project has been implemented.

Research question

How can remote sensing benefit an environmental impact assessment (EIA) of an agricultural project area?

Sub questions

- How are the different land covers distributed in the study area?
- Which parts of the agricultural areas have the lowest and highest NDVI values?
- What are the limiting factors for using remote sensing in EIA of agricultural areas?

Thesis workflow

In answering these questions, the purpose is to give the reader a clear idea of how remote sensing can improve an EIA for a project area that is similar to the one in this thesis while also showcasing the tool's limitations, both technical and non-technical. The workflow of the thesis is visualized in Figure 2.

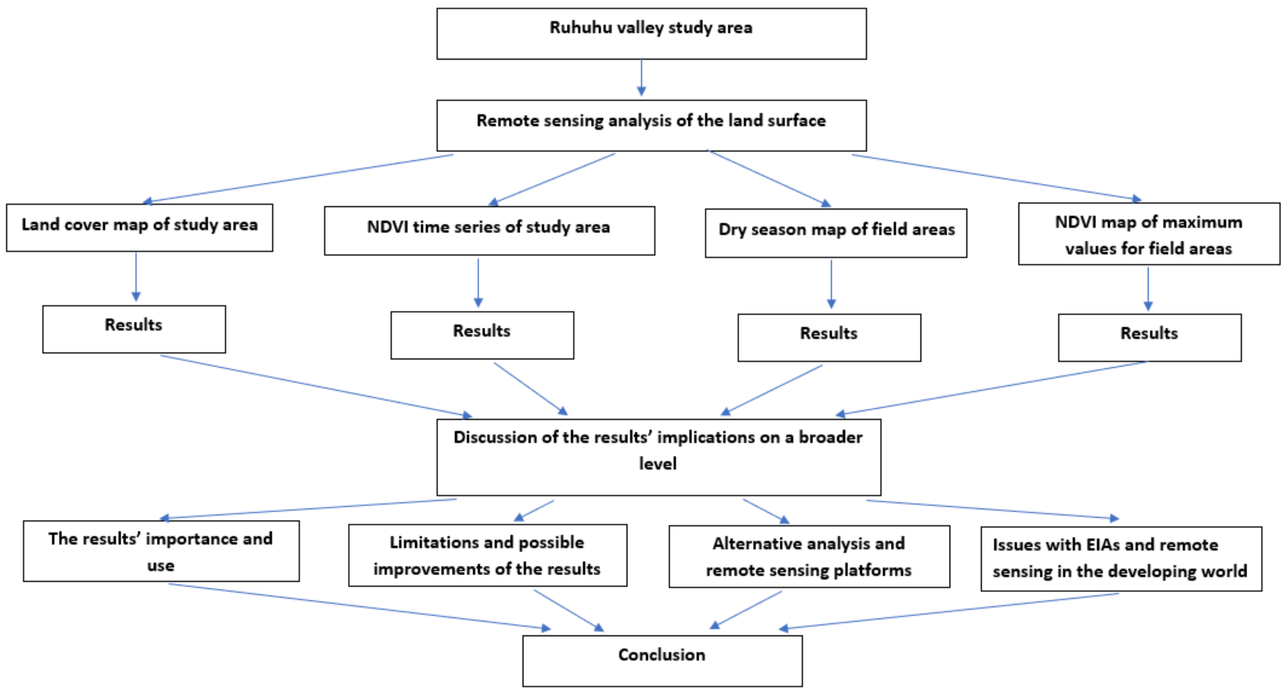

Figure 2: The workflow of the thesis.

Four different remote sensing analyses are performed on the study area. Afterward, the results are discussed in order to deliberate the possibilities and limitations of using remote sensing for other similar EIA projects.

Theory & Methods

The following chapter describes the theory and methods used in the thesis and functions as the foundation for the analysis and discussion.

Applied geography

Applied geography involves the utilization of geographical knowledge to resolve environmental, social and economic problems in the real world (Bailly and Gibson 2004). This involves both human and physical geography as well as the combination of both where a variety of tools can be applied, including GIS and remote sensing (Bailly and Gibson 2004). Geography does not have fundamental theories that are unique to the discipline because it is an integrative science with a holistic view (Lee and Sui 2015).

Applied geography can mean different things to professionals in various sub-fields like economic geographers, climatologists, and remote sensing experts. However, these have common traits such as how people interact with their environments, and the spatial changes that takes place etc. (Lee and Sui 2015). Like geography itself, applied geography is very diverse and can include elements from humanities, social sciences, engineering, and physical sciences (Lee and Sui 2015).

In contrast to pure research geography where new theories and methods are developed, applied geography uses current methods and theories to solve issues in society (Michael Pacione 1999). A fundamental value in applied geography is the use of a problem-orientated approach (Michael Pacione 1999), although it is not only concerned with solving practical problems but also discovering why there is a problem in the first place and who will benefit from the work (Lee and Sui 2015).

The different kinds of principal sciences - positivism, hermeneutics, and realism - have various goals and can hold relevance for applied geography. An empirical-analytical approach based on positivism is especially used in physical geography to understand and solve environmental issues (Michael Pacione 1999), and the use of remote sensing in this thesis also falls under this category because it is highly quantitative. However, when working with environmental problems, management practices are of great importance and involves social constructions such as values and power structures. Also, remote sensing might be able to measure changes and spatial patterns but it will not always be able to explain the reason behind these. A pluralist approach is therefore needed in order to understand how remote sensing can benefit environmental impact assessments (EIAs) and create overall positive impacts on the three pillars of sustainability: social, economic, and environmental.

Case studies

A case study is a comprehensive investigation of a single example (Flyvbjerg 2006). Several types of case studies exist (Flyvbjerg 2006), however for this thesis a critical random sampled case is applied. The choice of study area is randomly selected as it is chosen based on the data availability with the third-party cooperation partner, Multiconsult. Still, it is critical because it is deemed likely that if remote sensing cannot be used in an agricultural area like this, then it probably cannot be used for similar agricultural areas where the same farming practices exist. An inductive approach is therefore used in the research design, which is common in case studies as one goes from a specific observation to a general conclusion.

The study area

The 'Kikonge Dam and Irrigation Project' involves the construction of a 300 MW hydroelectric dam in Southwestern Tanzania and an irrigation project in the Ruhuhu valley, downstream of the dam location, where the overall goals of the project are economic development and alleviation of poverty (Multiconsult 2019). This thesis will focus on the area where the irrigation scheme is to be implemented. The exact study area boundaries are approximated (Figure 3) from the 'Ruhuhu Valley Multi-Purpose Scheme' area that are included in the strategic environmental & social assessment (SESA) report from Multiconsult (2019) and in CRIDF (2014). The SESA study is funded by the African Development Bank and executed by the consulting firm Multiconsult with assistance from NORPLAN Tanzania and G. Karavokyris & Partners Consulting Engineers (Multiconsult 2019).

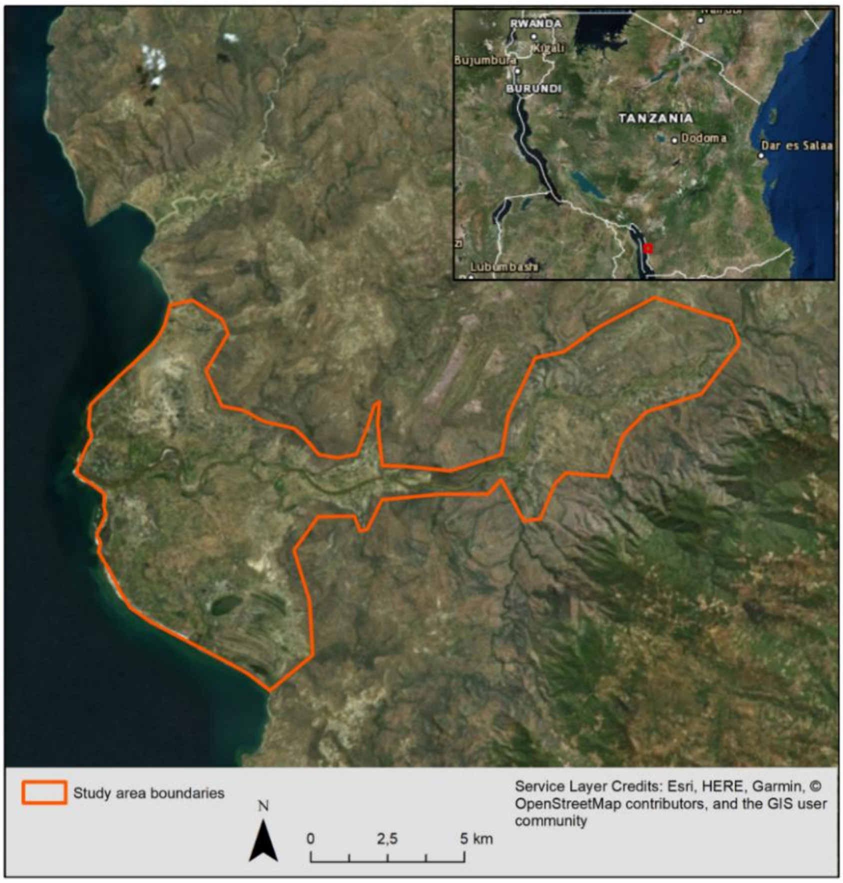

Figure 3: The study area. The boundaries are approximated from the 'Ruhuhu Valley Multi-Purpose Scheme' area (Multiconsult 2019).

The irrigation scheme is planned to consist of an area of about 4,000 hectares, which would benefit around 8000 households with an average land possession of 0.5 hectares (CRIDF 2014). The crops grown in the area are similar to those grown in the rest of the country with paddy rice amounting to around 50% of the crops in the wet season, cassava amounting to more than 60% in the dry season and fallow lands amounting to approximately 30% for both seasons (CRIDF 2014). The project area is remote with no paved roads and it has a lower income than average in Tanzania but there is a stable food supply with especially cassava as a staple, and livestock and fishing provide additional protein while cash crops includes vegetables, fruits, coffee, tea etc. (Multiconsult 2019). Water is a main constraint to agricultural development and improving livelihoods, in addition to poor farming methods, inadequate skills for adding value to the products, diseases in rice, lack of market access and shortage of storage facilities (Multiconsult 2019).

The weather in the project area is characterized by a long, wet season from October/November until April/May with almost no rain during the other parts of the year, resulting in dry condition and frequent droughts (Multiconsult 2019). Similar to other tropical areas, dense cloud cover is also an issue through much of the year (Ndayisaba et al. 2017). This affects the amount of usable remote sensing data that is available with optical sensors as they cannot "see through" clouds, and therefore only cloud free image pixels can be utilized for the land cover assessments.

Satellite imagery

The remote sensing platforms chosen for the land cover analysis are the Sentinel-2 satellites. The Sentinel-2A and Sentinel-2B satellites were launched in 2015 and 2017 respectively by the European Space Agency (ESA) and are part of the larger Copernicus Earth Observation Program (ESA 2018). Each satellite carries an optical sensor with 13 different bands in the visible, near infrared and short wave infrared part of the electromagnetic spectrum with spatial resolutions ranging between 10 and 60 meters depending on the band (ESA 2019d). The sensors have a swath width of 290 km and the temporal resolution is five days when both satellites are utilized (ESA 2019d). Aside from their relative high temporal, spatial and spectral resolution, the advantage of using data from the Sentinel-2 satellites is first of all that the imagery is free and can easily be obtained through various channels, including Google Earth Engine.

The Sentinel-2 image products chosen for the land cover analysis in this thesis are the Level-1C scenes, which consist of "raw" Sentinel-2 imagery preprocessed by ESA, and these are then obtained through Google Earth Engine. Each scene is 100x100 km^2 in size, and they are calibrated to top of atmosphere (TOA) reflectance (ESA 2019a), which helps to limit the variability between various images that can be caused by different solar zenith angles, varying distances from the sun to the earth at the time of acquisition etc. (Chander, Markham, and Helder 2009). Furthermore, the Level-1C products are orthorectified using a 90 meter digital elevation model (DEM) (ESA 2019e), which limits distortions in the imagery caused by various elevations on the ground (Satellite Imaging Corporation 2019).

Image classification

When classifying remotely sensed images, two fundamental approaches exist: unsupervised and supervised classification (Mohammady et al. 2015). For this report, supervised classification will be used and is therefore the focus of this section.

When performing a supervised classification, the user selects training data samples (Figure 4) from the imagery to be classified for each land cover class that is to be mapped. This can either be done from visual inspection of remote sensed imagery or by field data collection with the former method being applied in this thesis. The GIS program then applies this information to classify the rest of the image's pixels (Tiner, Lang, and Klemas 2015). This operation can be performed by a variety of training algorithms, and it is an iterative process that can be performed several times with new training data until a final output is produced (Wegmann, Leutner, and Dech 2016).

Figure 4: Example of some of the training data sample polygons used to classify the study area. Blue (water), yellow (fields), orange (sparse vegetation), green (dense vegetation), purple (bare soil), red (built up land).

One of the most popular and accurate algorithms is Random forest (Belgiu and Dragut 2016), and this will also be utilized for this thesis. It is an extension of the Classification and regression tree algorithm, and it creates multiple so-called decision trees for each pixel on the image that is to be classified (Tiner, Lang, and Klemas 2015). In the land cover mapping for this study, 600 decisions trees are created for each pixel. Each of these decision trees is constructed by a randomly selected subset of the training data (with replacement), and this data is used to perform a number of splits of this information by "asking" a number of binary (yes or no) questions (Figure 5) (Breiman 2001). Each tree has its own subset of binary rules that classifies the data, and the class that has the most trees "voting" for it is the land cover class assigned to that specific pixel (Tiner, Lang, and Klemas 2015). The training data for optical remote sensing images consists of the different spectral bands and their individual reflectance that are present for the pixels in training samples of the known land cover.

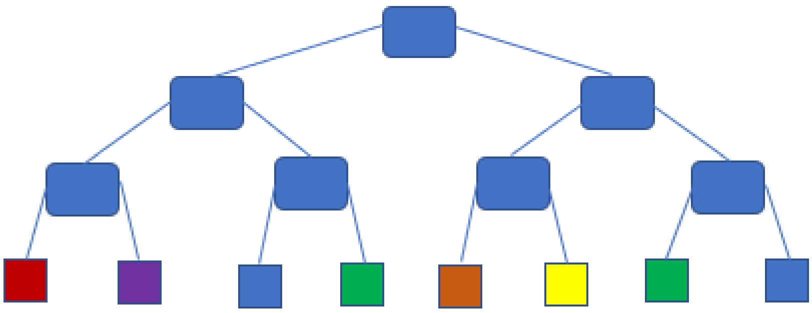

Figure 5: Example of a simple decision tree. A number of binary splits are performed until a final land cover class is selected (<u>one</u> of the colored squares). This procedure is executed a number of times based on the amount of trees specified in the training algorithm. From all of these trees' results, the final classification class is determined by the class with the most "votes". This operation is completed for every single pixel in the study area.

The training data for the study area is identified using high resolution imagery from Google Earth. However, the newest images date back to 2013 so possible changes could have occurred in the meantime. Therefore, several Sentinel-2 images from the 2016, 2017 and 2018 are also examined to verify the high resolution data from 2013. For this study, six land cover classes are created: water, fields, bare soils, dense vegetation, sparse vegetation, and built up areas.

For the water class, training data pixels are all "collected" from the Ruhuhu river that runs through the study area. The field data is from places where a clear, annual abrupt change in the surface cover can be identified, which should be associated with harvest, and further examined using the high-resolution imagery. Bare soils are the areas that show no or very little sign of vegetation at any point during the year, whereas sparse vegetation are areas with some vegetation during parts of the year and are also further verified with high-resolution imagery. Dense vegetation are the areas that remain vegetated all year and have a high degree of greenness compared to the other areas and are most likely forested areas. Finally, the built up areas are identified using both high resolution imagery and Sentinel-2 images but because of the limited amount of buildings in the area, substantially less training data is available for this class.

Land cover classification of study area

Initial classification of the land cover shows that it is difficult to distinguish the different classes using just one image since the various land covers are quite similar in their spectral reflectance to each other. Furthermore, as mentioned earlier, many of the images are obstructed by clouds and are thus not useable. Therefore, the Sentinel-2 imagery that covers the study area is first filtered to access all the cloud free images. This is done for the years 2016, 2017, and 2018 to obtain more data than what would have been possible if only a single year was used.

A total of 17 images are obtained (Table 1) and from these image composites are created of the minimum, maximum, mean and median values of the spectral reflectance for the different bands (Appendix 3). This is done in order to create a more accurate land cover map by taking the temporal changes on surface into account. One example of such is the the fact that fields and forests might have the same spectral reflectance during the wet season but not during the dry season, and fields could have a similar spectral reflectance as bare soils during the dry season but not during the wet season etc.

Table 1: The 17 cloud free Sentinel-2 images used for the land cover mapping of the study area.

Scene ID	**Acquisition Date**
COPERNICUS/S2/20160514T075819_20160514T113022_T36LXP	14-05-2016
COPERNICUS/S2/20160723T075726_20160723T112728_T36LXP	23-07-2016
COPERNICUS/S2/20160802T075556_20160802T112941_T36LXP	02-08-2016
COPERNICUS/S2/20160822T075212_20160822T075818_T36LXP	22-08-2016
COPERNICUS/S2/20160901T073612_20160901T075722_T36LXP	01-09-2016
COPERNICUS/S2/20170608T075211_20170608T075753_T36LXP	08-06-2017
COPERNICUS/S2/20170723T073609_20170723T075425_T36LXP	23-07-2017

COPERNICUS/S2/20170817T073611_20170817T075545_T36LXP	17-08-2017
COPERNICUS/S2/20170906T073611_20170906T075203_T36LXP	06-09-2017
COPERNICUS/S2/20170916T075211_20170916T075748_T36LXP	16-09-2017
OPERNICUS/S2/20180109T074259_20180109T074852_T36LXP	09-01-2018
COPERNICUS/S2/20180218T073949_20180218T075508_T36LXP	18-02-2018
COPERNICUS/S2/20180330T073609_20180330T080207_T36LXP	30-03-2018
COPERNICUS/S2/20180728T073609_20180728T075940_T36LXP	28-07-2018
COPERNICUS/S2/20180802T073611_20180802T075248_T36LXP	02-08-2018
COPERNICUS/S2/20180807T073609_20180807T075246_T36LXP	07-08-2018
COPERNICUS/S2/20180827T073719_20180827T080007_T36LXP	27-08-2018

Because the second Sentinel-2 satellite was first launched in March 2017, there are less total yearly images available for 2016 and 2017 for the analysis compared to 2018, and therefore also less usable cloud free images. It becomes apparent that most images are from July, August, and September, which could indicate that these are the driest months of the year with the least amount of cloud cover to obscure the study area.

Temporal NDVI assessment

In order to investigate the phenology of the study area, the annual and inter-annual changes In NDVI values are investigated by utilizing a NDVI time series. In order to do so, all 167 Sentinel-2 images from 2016, 2017, and 2018 are filtered for clouds and these are masked out. This leaves 124 images from the period where at least parts of the area should be cloud free. From these, a time series chart is created for the mean NDVI value over the entire area for each given date (Appendix 3).

Classification of dry season fields

Since one of the main benefits of irrigation is that double or even triple annual crops become possible (Schoengold and Zilberman 2014), the current extent of dry season crops is explored in the study area. An image from September 16, 2017, is used as this is the latest cloud free image in the dry season before the harvest of the dry season crops that happens in October (Multiconsult 2019). This is done to determine how large a percentage of the total field areas are still vegetated in the dry season. It is assumed that areas that are green in September, which should generally be the driest month, are all dry season crops (almost exclusively cassava) but it could potentially also be fallow land (CRIDF 2014). Wet season crops, which are primarily rice but also maize and vegetables, are first planted in November after the wet season have begun (Multiconsult 2019). The wet season crops are not mapped seeing as it is not possible to make distinctions between the different land covers in the fields during this time of year with Sentinel-2 imagery due to the fact that they all have similar spectral reflectance (Figure 6).

Figure 6: Example of rice fields and other vegetation types from the study area, April 2019. Photo: Thea Caroline Wang.

Spatial differences in NDVI

The spatial distribution of NDVI is examined in order to study whether there are significant differences in the NDVI for various fields in the study area. Firstly, clouds are masked out for all images from the study area from 2016, 2017, and 2018. Next, non-field areas are also removed. A map is then created using the max NDVI value for each pixel in the field areas. This is divided into four classes of NDVI values in ArcMap using Natural Breaks (Jenks). These are reclassified to obtain an attribute table with the number of pixels in each class. Natural Breaks is chosen because it is a data clustering method that is built on finding the best group value breaks in order to maximize the characteristics of each giving class, and the classes are therefore divided where the largest changes in the data values occur (ESRI 2019).

Accuracy assessments and error matrices

In order to verify the accuracy of the classification of remotely sensed data, an accuracy assessment is executed, which is a measurement of the compliance between the pixels classified by the algorithm and the confirmed physical land cover (PennState 2018). This assessment can be executed in various ways, for example by using field validation of the classified areas. However, this is occasionally not possible so alternatively one can use some of the training samples' data for validation. This can often be accomplished by splitting it up between approximately 2/3 for classification and 1/3 for validation (Wegmann, Leutner, and Dech 2016). The latter approach will be utilized in this thesis.

The accuracy assessment is created using an error matrix where the land cover assigned by the classification algorithm is compared to the actual land cover in the validation pixels at the given location (Wegmann, Leutner, and Dech 2016). The accuracy can then be described in several ways: producer's, user's, and overall accuracy (Congalton and Green 2009). The producer's accuracy (the point of view of the maker of the map) is the accuracy of the classification of each land cover class, based on how often the actual features on the ground are classified correctly as that specified class. The user accuracy (the point of view of the user of the map) is the reliability of the map or how often a land cover class from the map will be present on the ground. Lastly, the overall accuracy is the total count of correctly classified sample pixels divided by the entire amount of validation pixels.

Results

This chapter contains the results of the remote sensing analysis of the study area as well as the accuracy assessments of the land cover classifications.

Study area land cover

The classification of the whole study area into the six different surface classes clearly indicates that agricultural fields are the dominant land covers in the area (Figure 7).

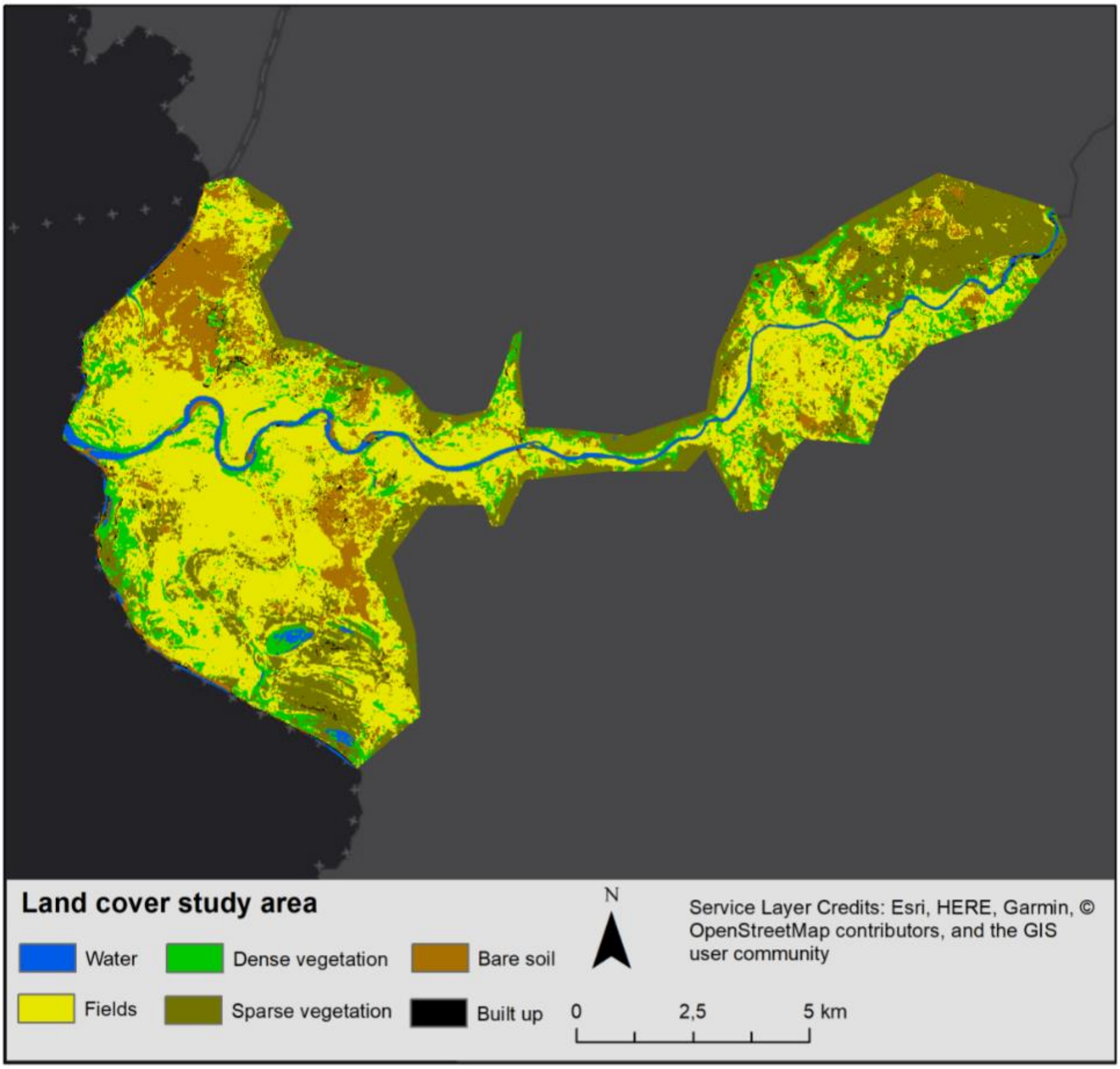

Figure 7: Land cover map of the study area, using Sentinel-2 imagery from 2016, 2017 and 2018. See Appendix 3 for online map.

Fields make up 50% of the study area's 98 km^2, followed by sparse vegetation which occupy 25% (Table 2) predominantly in the outskirts of the area, which tend to have a higher slope and/or elevation identified using high resolution imagery and the SRTM digital elevation model (Farr et al. 2007). Both dense vegetation and bare soils occupy 10% of the area with the former being scattered throughout the area, especially close to the river and lake, and the latter primarily being focused in two large patches north and south of the river.

Table 2: The distribution of different land cover types in the study area.

Land cover	**Area size in km^2**	**Area size in percentage**
Water	3	3
Fields	49	50
Bare soil	10	10
Dense vegetation	10	10
Sparse vegetation	25	26
Built up	1	1
Total	98	100

Built-up areas take up only 1% of the study area. However, when investigating the accuracy of the land cover classification (Table 3), it becomes clear that the built-up class has the lowest user accuracy of all the classes. This is caused by confusion between built-up areas and bare soil with bare soils being wrongly classified as built-up land (Appendix 2). The other land cover classes all have high accuracies, both user's and producer's, ranging from 97.47-100%.

Table 3: Accuracy assessment for land cover classification of the whole study area.

Accuracy in %	Producer's	User's	Overall
Water	100,00	100,00	
Fields	99,77	100,00	
Bare soil	99,26	100,00	
Dense veg	97,47	97,47	
Sparse veg	98,86	98,31	
Built up	100,00	81,82	
			99,34

NDVI time series chart of study area

The changes in NDVI during the time period 2016, 2017, and 2018 capture the seasonal changes from wet to dry season with higher NDVI values from January-July each year (Figure 8).

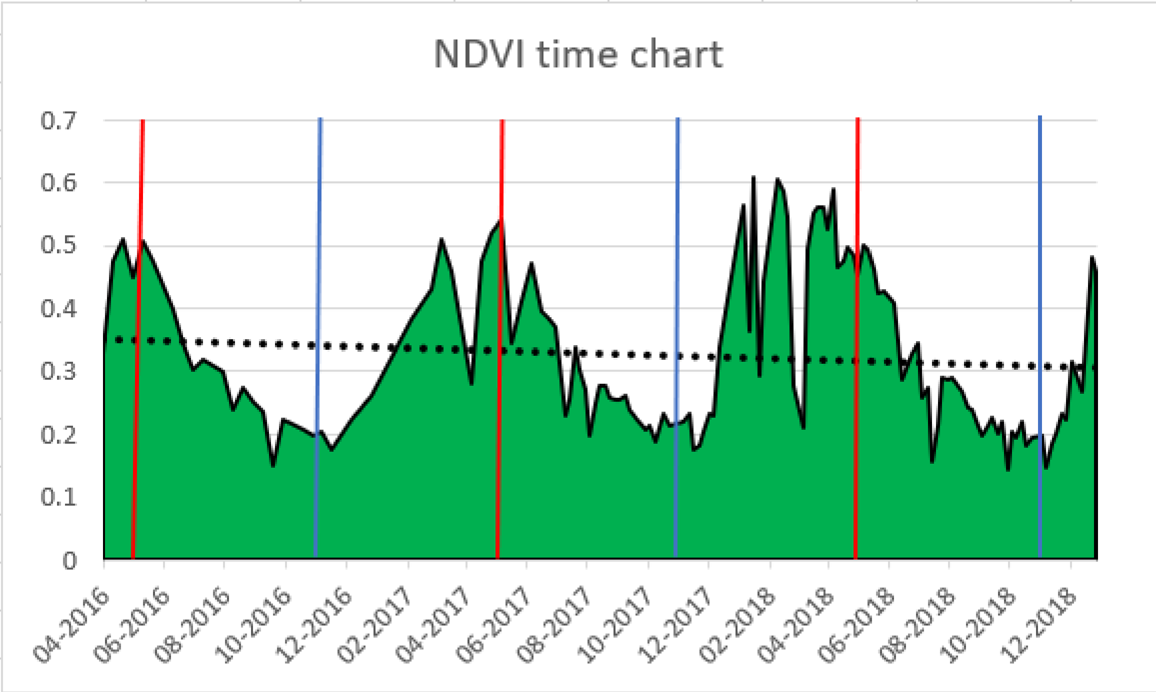

Figure 8: NDVI time series for the years 2016, 2017 and 2018. The red lines indicate the start of the dry season, while the blue the start of the wet season. The black dotted line is the trend in the data for the time period.

From the figure it can be observed that the maximum average NDVI for the whole study area is just over 0.6, and the lowest is around 0.2. The large, sharp spikes down (and possibly also some of the smaller ones) in NDVI are almost without a doubt caused by unfiltered clouds because the NDVI should not be able to fall and rise so quickly for such a large area.

Dry season land cover map of fields

The land cover classification of the dry season fields indicates that the majority of agricultural areas do not have crops on them during the dry season (Figure 9).

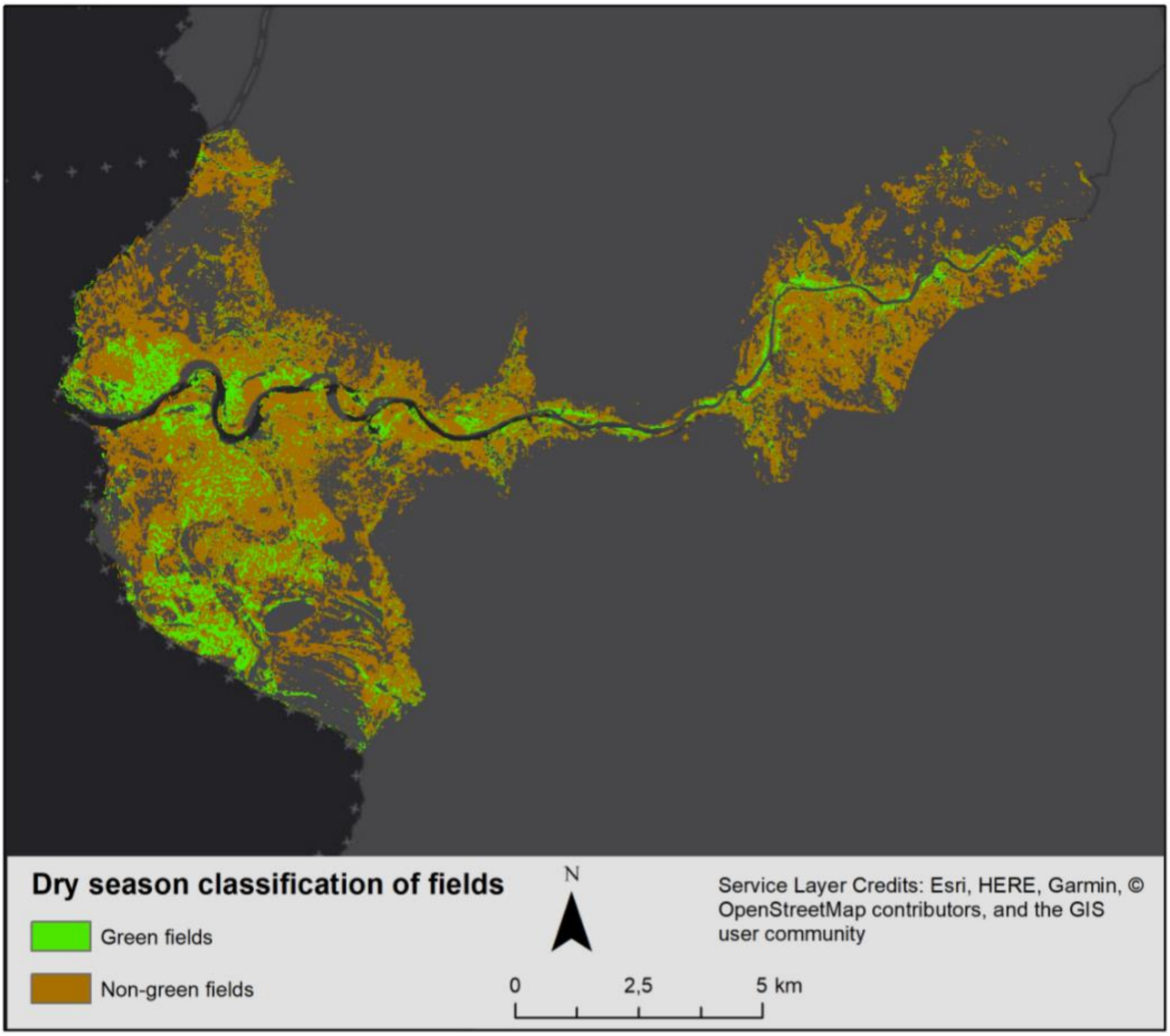

Figure 9: Land cover map of the dry season fields, using a Sentinel-2 image from September 2017. See Appendix 3 for online map.

The fields that have been classified as being green during the dry season make up 20% of the area (Table 4). However, data from CRIDF (2014) state that around 60% of the fields during the dry season should have cassava crops planted. This could indicate that the classification should be improved or that some changes from 2014 to 2017 have taken place in regard to the amount of dry season crops present in the study area.

Table 4: The distribution of dry season land cover in the field areas.

Land cover	**Area size in km^2**	**Area size in percentage**
Green fields	10	20
Non-green fields	39	80
Total	49	100

The accuracy assessment indicates high accuracy for both the user's and producer's accuracy (Table 5), however this is only based on the training/validation data provided so changes in these could alternate the results.

Table 5: Accuracy assessment for land cover classification of dry season fields.

Accuracy in %	Producer's	User's	Overall
Green fields	97,62	100,00	
Non-green	100,00	98,04	
			98,91

Spatial NDVI differences in the fields

The analysis of the study area's fields' maximum NDVI values indicates that there are some spatial differences in the NDVI (Figure 10).

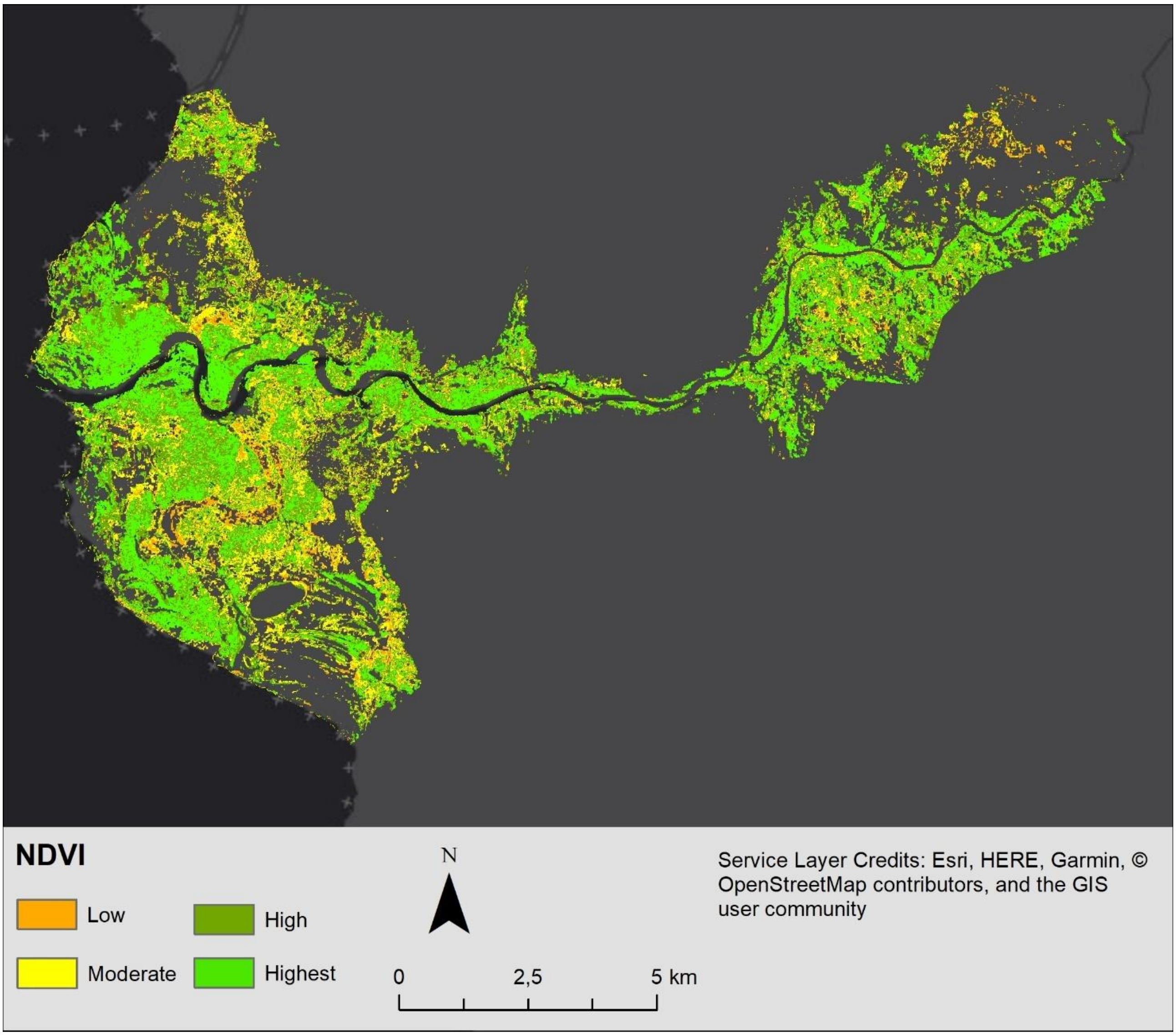

Figure 10: The spatial distribution of the maximum NDVI values for the agricultural fields, using Sentinel-2 data from 2016, 2017 and 2018. The NDVI value ranges are: Low (0.270-0.613), Moderate (0.613-0.692), High (0.692-0.753), Highest (0.753-0.864). See Appendix 3 for online map.

36% of the field areas are classified as having the highest NDVI value, 38% high, 21% medium and 6% low (Table 6), while the average NDVI value across the study area is 0.721. The areas with the highest NDVI values are generally the same areas as the ones that have been identified to have dry season crops, and this could indicate that there is some connection between the maximum yearly NDVI and the present dry season crops.

Table 6: The distribution of NDVI values across the agricultural field areas. Note that the total area size is one km^2 larger than previously. This is most likely caused by how Google Earth Engine processes edges differently depending on the functions applied, e.g. whether a mask or clip function is applied to an image or image collection.

NDVI values	**Area size in km^2**	**Area size in percentage**
Low	3	6
Medium	10	21
High	19	38
Highest	18	36
Total	50	100

Discussion

This chapter discusses the project's results and considers the implications and limitations. Furthermore, it looks at the social and structural obstacles that are in the way for using remote sensing in environmental impact assessment (EIA) in a constructive way.

The results' importance and use

The results from the land cover analysis show that the study area is predominantly made up of agricultural fields; this corresponds well with the coarser land cover map that can be found in CRIDF (2014). The agricultural fields are spread throughout the area but with some differences in mapped occurrence of dry season crops as well as the maximum NDVI values. Since there is an overlap between the areas with measured dry season crops and highest maximum NDVI, this could suggest that these areas have more favorable growing conditions such as higher soil moisture content throughout the year and/or indicate better farming practices. Hence, it provides managers and decision makers with an overview of the areas that would be most relevant to investigate further to establish if changes to practices can be made or if they have a higher water requirement for irrigation.

Furthermore, investigating the NDVI using a tool like a time series chart makes is possible for managers to investigate the changes in plant productivity during the current and coming years, e.g. to identify potential abnormal occurrences in phenology that could reveal an upcoming drought. The NDVI time series helps to give a clear indication of the potential benefits of irrigation as, when these schemes are implemented, the maximum annual NDVI over the area should be higher and the values throughout the whole year would generally also tend be higher since more dry season crops are implemented with the use of the irrigation systems. All of this information functions as baseline data, i.e. the state of the area before the implementation of the 'Kikonge Dam and Irrigation Project'. Therefore, with this information at hand, it is possible to make continuous measurements and comparisons of the land cover both during and after the project construction, which includes not only the cropland but also the extent and distribution of other land cover types, e.g. sparse and dense vegetation.

Google Earth Engine and GIS

This thesis also highlights the advantages of using a cloud based program like Google Earth Engine because the tool allows the user to easily access all cloud free images for a given project area and use these to create various composites such as the minimum, maximum, mean, and median that can be used for classification. The program therefore makes it much simpler and faster to use several satellite images for a land cover analysis, which generally have been found to increase the accuracy of classifications (Waldner, Canto, and Defourny 2015; Maus et al. 2016; Song et al. 2017). Without the program, an approach like this would require a lot more time using a "conventional method" of just a single personal computer where the user has to manually go through all the satellite data, find the cloud free images and download these before an analysis can be carried out.

Remote sensing and GIS in general can also function as a strong communication tool to both decision makers and the public. The old saying that a picture is worth a 1000 words can readily be applied here seeing as spatial data, such as land cover extent and change, is best understood through the use of maps. This can further be enhanced in its communication impact potential by creating interactive maps, videos of land cover time series etc.

Improved decision making

A common dilemma when assessing the impacts of a project is whether to make important decisions regarding the environmental issues early in the process, since this is where there is the most room for changes to the construction plan, or later in the process when the knowledge about these consequences is bigger, since said knowledge usually increases as time progresses (Private communication, Ivar Lyhne 2018). Remote sensing can be of help in this situation by being applied both as an early tool to assess the initial situation as well as a tool toto monitor an area during and after the project period.

The remotely sensed data could also become even more valuable for political decision making, in the case of EIAs, if this kind of quantitative collection on land cover changes becomes common practice for similar projects - and EIAs in general. It would thereby make it easier to understand the dynamics and changes of the implementation of irrigation to previously rainfed agricultural areas. This comprehensive information could be important for better decision making in relation to EIA policies, laws regarding land use etc.

Limitations and possible improvement of the results

The accuracy of the land cover maps is very high for this study and, as mentioned earlier, some of this can probably be contributed to the use of multiple images from various times throughout the year. However, an issue with using the same dataset for accuracy assessments as well as for the training data, as is the case in this thesis, is that it solely relies on this single set. Hence, if the user has wrongly "drawn" a training/validation polygon on an area believed to be dense vegetation but in reality it is fields or sparse vegetation, then this is not necessarily identified and demonstrated through lower accuracies in the accuracy assessment.

Therefore, it would be optimal to validate the accuracy of the maps by conducting field work in the study area. Unfortunately, this was not possible for this project due to financial and logistic constraints. Generally, s good approach would be to first collect training data in the field in conjunction with remotely sensed imagery and next conduct field work after the land cover classification to validate the results. By also collection training data in the field, it would be easier to "calibrate" the classifications and make the best possible distinctions between land cover classes, the number of classes to choose etc. The downside of this approach however is that it is more time-consuming and financially expensive so a balance must be struck between accuracy and cost.

The only land cover class that shows a relatively low accuracy in this thesis is the built up areas. The user's accuracy for this class is 81.82%, and this is caused by confusion with the bare soils class (Figure 11).

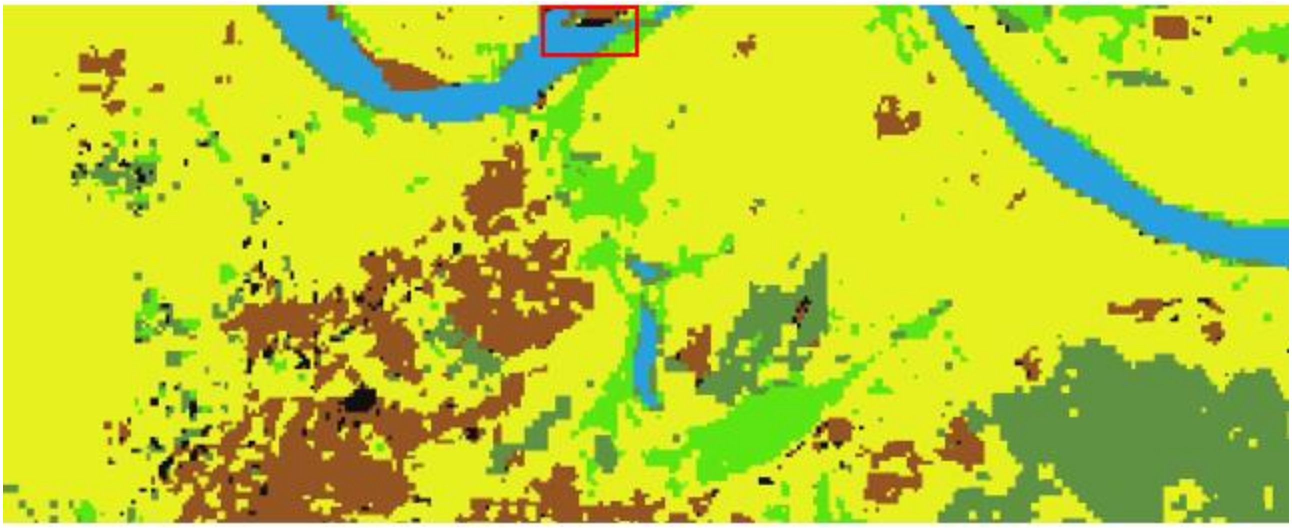

Figure 11: Comparison between an RGB mean composite of Sentinel-2 imagery from 2016, 2017, and 2018 (top), and the classified image (bottom). Note that some of what appears to be a sandbank in the river (red square) is classified as being built up (black).

When inspecting the imagery, it is noticeable that there are some areas where there is, or at least could be, confusion between primarily built-up areas and bare soils. However, it should also be noted that the road going through the lower right part of the image is incorrectly classified as being fields. This could be caused by the occurrence of mixed pixels throughout parts of the year, e.g. the “road pixels” being partly vegetated for certain periods. Mixed pixels are a general issue in remote sensing, for example when the land cover in the individual pixels is not homogenous (Choodarathnakara, Kumar, and Koliwad 2012). The information would then be fed into the Random Forest algorithm, and the land cover is consequently wrongly classified as being fields. Another feasible explanation is that changes have occurred during the years 2016, 2017, and 2018 in terms of the extent of the road and since data from all three years have been applied in the classification, this could also impact the results.

High resolution imagery

In order to better identify built-up areas, higher spatial resolution imagery is required, possibly utilizing object-based image analysis (OBIA) classification as the spectral reflectance from some buildings are like other land covers. In OBIA, spectral reflectance as well as the size and shapes of the objects/surfaces on the ground is used as a classification parameter (Hossain and Chen 2019). Furthermore, for improved validation of the land cover classifications in general, newer high spatial resolution imagery would also be beneficial since the current imagery in the study area is from 2013 and many changes could have occurred since then. Alternatively, drones could be utilized when conducting field research in the area as a way of collection images with a higher spatial resolution. These platforms also have the advantage that they can fly below the cloud cover and be applied whenever remotely sensed data is most relevant for land cover mapping, for instance just before and after harvest etc.

High resolution imagery, with assistance from ground surveys, could also make it possible to accurately create more and narrower land cover classes such as wetlands, different types of forests and crop types etc., by allowing for better visual distinctions between surfaces when creating training data examples (Figure 12). However, whether this is feasible would also depend on the similarity in spectral reflectance for these various land covers as well as their phenology etc.

Figure 12: Example of vegetation in the study area close to Lake Malawi. Different types of trees can be identified, as well as areas that appears to be natural wetlands (1) and possibly some rice fields (2). Photo: Thea Caroline Wang.

Another important factor to take into consideration when applying remote sensing on an agricultural area, is the spatial arrangement and size of the fields because this determines how well the sensors can be used for land cover mapping. In many parts of Sub-Saharan Africa, small fields with mixed-cropping are dominating the landscape, which makes crop classification difficult with remote sensing, even for high spatial resolution platforms (McKenzie, Sparrow, and Guerschman 2016). Therefore, it might not be possible to make very accurate crop type maps for study areas similarly to the one in this thesis like it is done in Europe and North America where large homogenous fields are the norm (McKenzie, Sparrow, and Guerschman 2016).

Issues with dry season classification

When investigating the extent of dry season crops, it is discovered that it is significantly lower than what is recorded by CRIDF (2014). 20% of the fields in 2017 are determined to have dry season crops but according to CRIDF (2014) up to 60% should have cassava, 5% maize and vegetables, and the rest should be fallow land. This variation could be caused by differences in the amount of dry season crops per year but it could also indicate that the classification is not accurately describing the land surface (Figure 13).

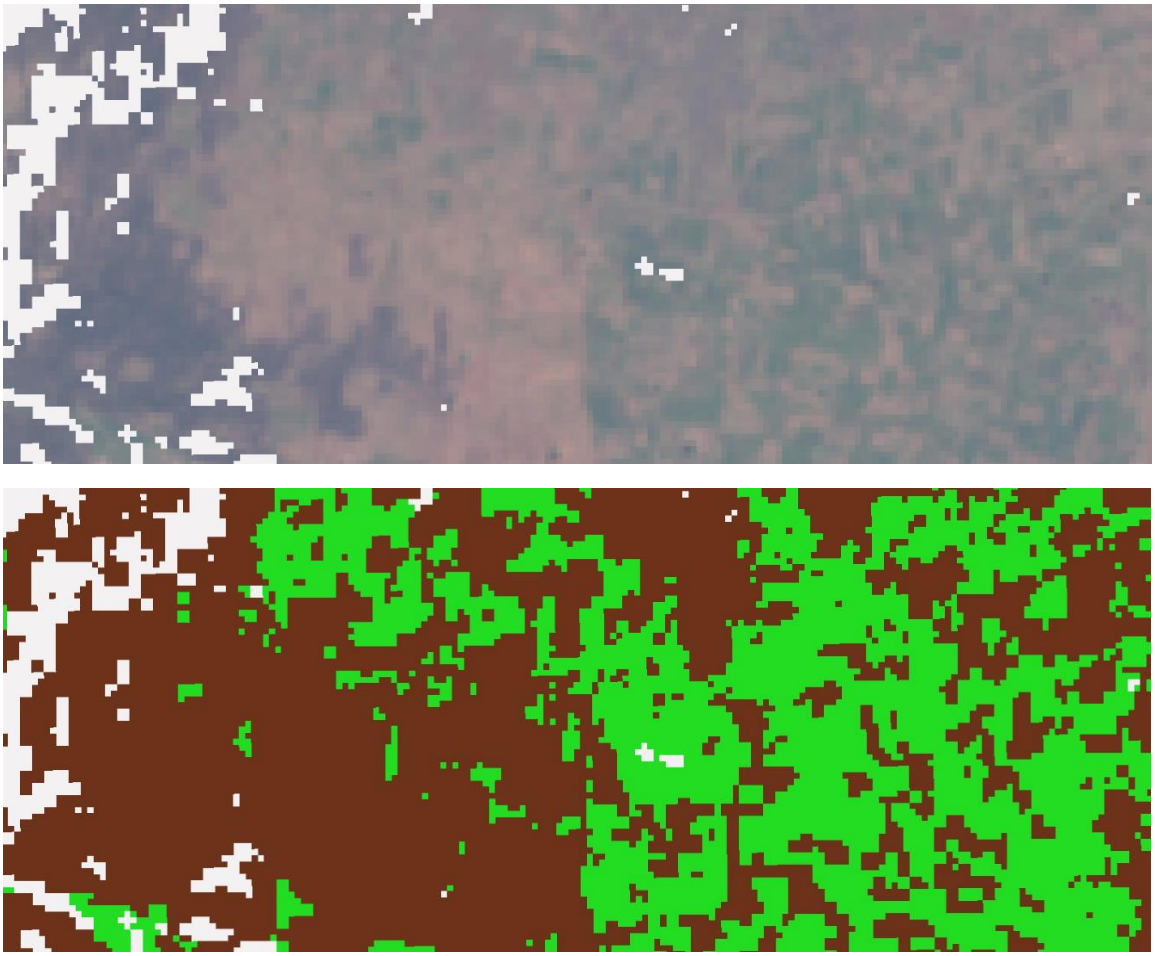

Figure 13: Comparison between the Sentinel-2 RGB image from September 2017 (top) that is used for the classification of green fields and non-green fields (bottom). The white areas are then non-field areas that are masked out.

This difference could, among other reasons, be caused by a sparse vegetation cover of cassava crops, which is not uncommon as the rows of crops are often planted wide apart to allow for intercropping with other crop types (Howeler 1983). During the dry season however, the soils between the cassava rows will often be bare because few other crops are grown during this time of year. This could make some pixels dominantly bare even though they might still have plants on them (Figure 14). A possible solution could again be to use high spatial resolution imagery from either satellites, aircrafts or drones to collect training data in the area and create a land cover map directly from these images. Alternatively, this data could also be combined with Sentinel-2 or other medium spatial resolution satellite imagery as an up-to-data ground validation input to the land cover classifications with these coarser sensors. It must be noted however that high resolution satellite imagery as well as the usage of drones will be costlier than utilizing Sentinel 2 imagery alone but probably cheaper than extensive field work without these technological tools.

Figure 14: Example of sparsely covered cropland that could be difficult to classify as being vegetated for dry season classification. Note that the crop type is not known. Photo: Thea Caroline Wang.

Cloud cover

When exploring the graph of the NDVI time series for the study area through the years, it is clear that there are some outliers with very low values. This is most likely Sentinel-2 images that still have some cloud cover, even though there has been applied a cloud filter (Figure 15). When applying the NDVI time series chart to even smaller areas (polygons) than the whole study area, this becomes an even greater issue. Therefore, when utilizing the current cloud filter, it is difficult to make much out of this information in terms of harvest date and highest and lowest NDVI because it is challenging to interpret the time series for these smaller areas because of the outliers.

Such time series of NDVI data for different fields or other locations could however be valuable in order to compare the various parts of the study area and their changes though time. This could include comparing the efficiency and need for water in an irrigation scheme's different irrigation blocks. Hence, it would make sense to explore the possibilities to optimize the cloud cover filter so even more usable imagery data is obtained for each given time period, which would also allow for better NDVI time series to be created.

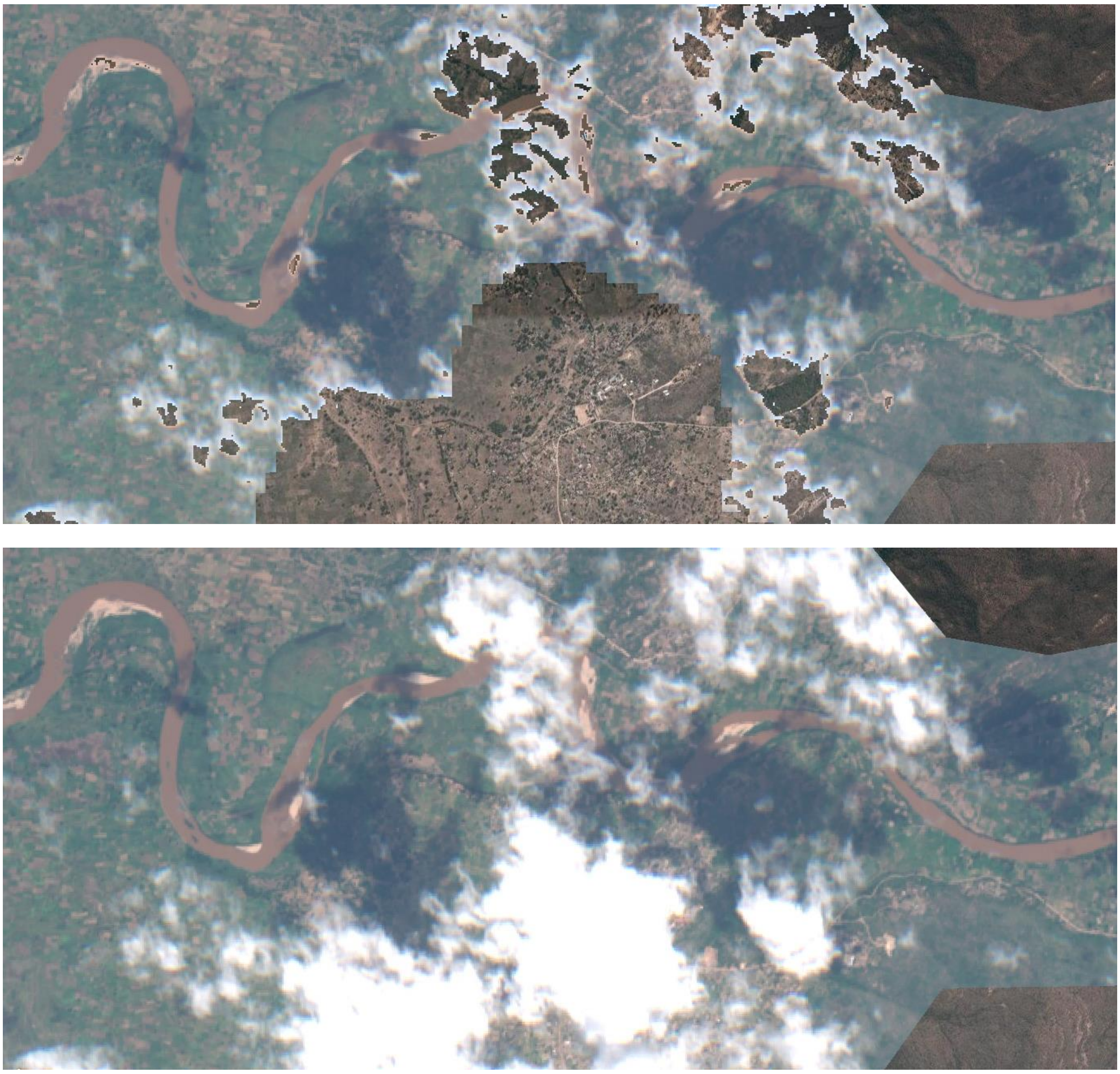

Figure 15: Example of a Sentinel-2 image from the study area with a cloud filter applied (top), and the same image without a cloud filter (bottom). It is noticeable that not all clouds are filtered out and that areas shaded by clouds are not filtered out either.

Future Sentinel-2 products for monitoring

For future monitoring of project areas using Sentinel-2 satellite imagery, it might be beneficial to utilize the Level-2A products instead of the Level-1C, which has been used in this thesis. This data consists of "raw" Sentinel scenes that have been processed by ESA to bottom of the atmosphere (BOA) reflectance instead of top of atmosphere (TOA) as is the case with the Level-1C products (Figure 16).

Figure 16: Comparison between a Level-1C (top) and Level-2A (bottom) Sentinel-2 image from the same date and location in the study area.

Because the Level-2A images show the reflectance at the surface rather than at the top of the atmosphere, which makes the images foggier and more blurred, the imagery appears clearer and with greater contrast. This could make it easier to identify different features and land cover types on the ground for classification and also simply make cleaner pictures for visualization purposes. However, the Level-2A products have only had global coverage from December 2018 (ESA 2019b) so less total imagery is therefore available for analysis compared to the Level-1C which spans back to June 2015.

Alternative analysis and remote sensing platforms

The remote sensing analysis included in this thesis obviously does not cover the wide range of capabilities of the tools, both for EIA in general and for the assessment of agricultural areas. Firstly, for a project like the ‘Kikonge Dam and Irrigation Project’, it could also be relevant to investigate the land cover near the dam site. Many changes could potentially occur, both intentional and unintentional, such as clearing of land for buildings and roads, the flooding of areas for reservoirs, degradation of habitats etc. All these factors could be quantified using remote sensing land cover analysis similar to the ones used in this thesis for the agricultural areas downstream of the site.

Landsat

Other satellite platforms that must be mentioned when discussing remote sensing are the Landsat satellites. The Landsat satellite program run by the United States is the longest ongoing monitoring of the surface of the earth by satellites and has been in commission since 1972 until present day (NASA 2018a). During the years, several platforms have been sent into orbit, each with a temporal resolution of 16 days and 30 meter spatial resolution for most bands (from Landsat 4 and forward) but only Landsat 8 is still active (USGS 2019). The long temporal record available with the Landsat imagery makes it ideal for analyzing land cover changes during the last 40+ years and for some EIA applications this knowledge might be useful.

Furthermore, as the newer Landsat platforms also carry a thermal sensor this could also be applied for assessing the surface. This is especially useful in agricultural areas for mapping evapotranspiration, which is associated with plants’ water requirements. The use of thermal imagery obtained with Landsat satellites have achieved good results for this application (Ma et al. 2018; Elnmer et al. 2019).

Sentinel-1

Platforms carrying completely different types of sensors could also be utilized to expand the range of information acquired for the area of interest. An example could be using active sensors, such as synthetic aperture radar (SAR), which are found onboard the Sentinel-2’s sister satellites the Sentinel-1’s (ESA 2019c). Contrary to the optical sensors, these emit microwaves to illuminate the surfaces which are then reflected back to the sensors differently, depending on the surface cover (Figure 17) (Bhatia 2008). The main advantage of SAR sensors is that they can penetrate cloud cover, which is a great advantage in areas similar to the one in this thesis where persistent cloud cover is present for much of the year.

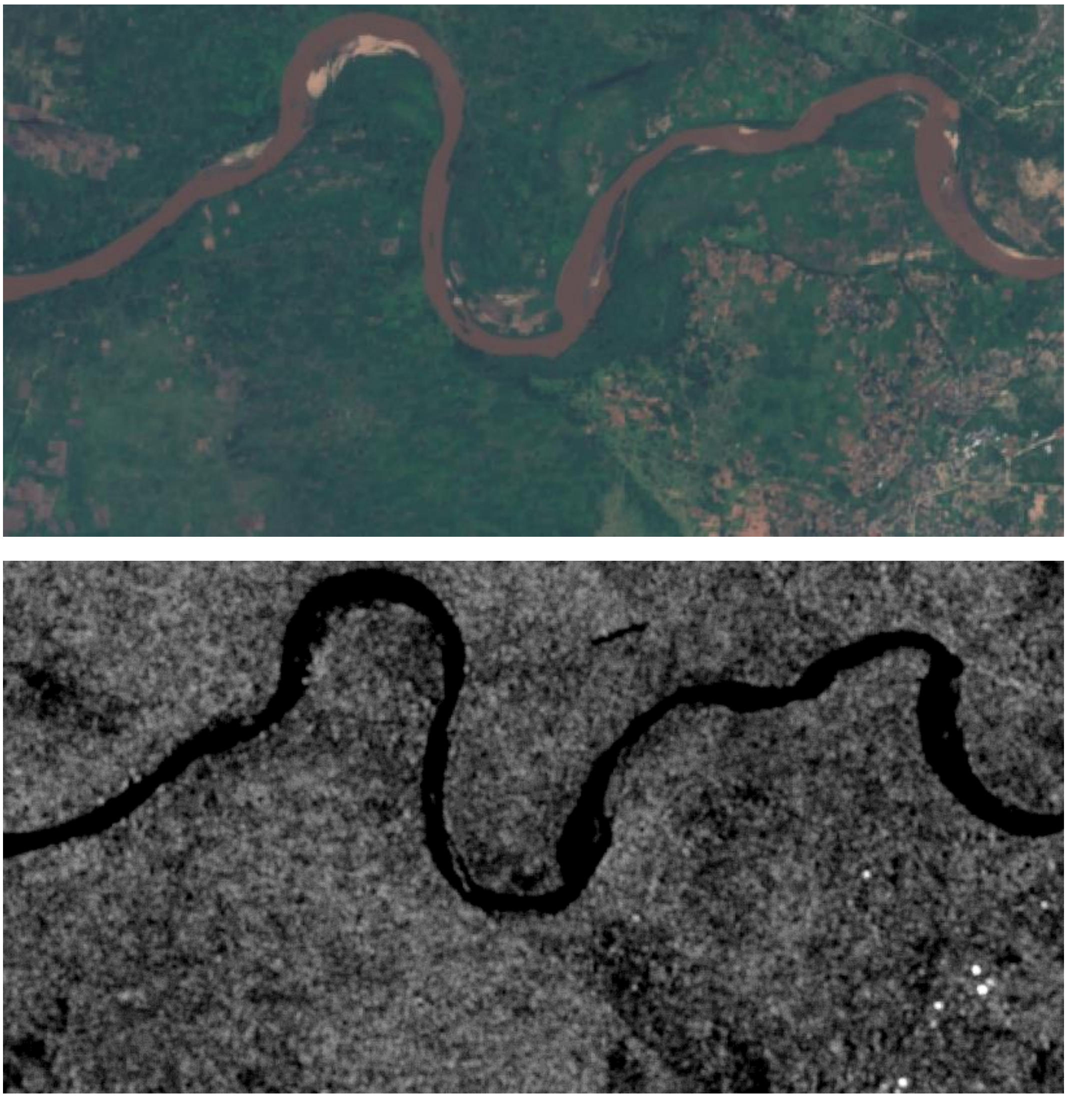

Figure 17: Comparison between a Sentinel-2 (top) and Sentinel-1 (bottom) image from the study area.

From the above images it is clear that the optical Sentinel-2 imagery is easier to interpret seeing as the electromagnetic radiation is in the red, green and blue colors, the way humans normally see the world. The SAR image on the other hand shows the surfaces differently depending on the so-called backscatter of the microwaves, which is determined by the roughness of the surface (Bhatia 2008); here it can be noted that water is black and (some) buildings are white. However, aside from buildings and water it is difficult to make much sense out of the image without further knowledge of the area, either though optical imagery or ground data. Furthermore, topography can greatly affect the SAR image since the sensors illuminate the surface at an angle and this, among other factors, can create more processing steps for the user when working with this kind of imagery.

Nonetheless, good results for land cover classifications have been achieved using SAR, especially when combined with optical imagery (Kaplan and Avdan 2018; Gómez 2017), and this is a technology that should be considered especially in cloud prone areas. SAR imagery would also be easier to interpret and use in areas where the land cover is more homogenous and/or contains larger features, e.g. bigger fields that contains the same crops, larger towns etc.

Issues with EIAs and remote sensing in the developing world

An EIA is created with the intended goal of providing information to decision makers so they can make better choices that should result in more sustainable project outcomes; not only taking economics into consideration but also environmental and social aspects and acting upon them. However, some critics point out that the assessments have generally had less positive effects than what was hoped for (Morgan 2012). This especially seems to be a problem for low- and middle income countries, and it is caused by factors such as unclear legislation, weak organizations, including enforcement and monitoring capabilities, the socio-economic situation in the country etc. (Khosravi, Jha-Thakur, and Fischer 2019). In many developing countries, such as Rwanda, Kenya, and Tanzania, there is also a lack of follow-up on implemented projects because developers tend to create the EIA solely in order to have the given project approved. This, combined with lack of resources for the authorities responsible for enforcement, can make the EIA less effective (Marara et al. 2011).

The setting of the EIA

Another cause of problems with EIAs in the developing world could be that the reasoning behind these assessments have been pushed forward by the international donor organizations and not by the politicians and the public of the countries themselves as Marara et al. (2011) also argues. Therefore, there might not be the same political pressure from the inhabitants to deal with the issues regarding EIAs. This also makes sense when many of these countries battle with issues such as lack of jobs and education, diseases, corruption etc. that generally holds a higher importance for this group of people (MYWorld 2019). Hence, additional data inputs to EIAs from remote sensing will do little good if this information is not acted sincerely upon.

Furthermore, the EIA practices and procedures have more or less been directly adopted from Europe and North America where they function in a very different societal context (Appiah-Opoku 2001). The cultural and economic situation in the country of which the EIA is conducted should therefore always be considered, also when it comes to the use of remote sensing and whether this information can effectively be responded to in the given setting; otherwise it simply becomes redundant. Also, a lack of public participation in developing countries (Marara et al. 2011) can create a lack of ownership among the inhabitants for the afflicted areas (Sosovele 2011)**,** which might further decrease the success of the given project in terms of its environmental impacts.

Therefore, it would be important to have more bottom-up initiatives that involves pressure from the public and national NGO’s to incorporate better environmental practices into legislation. However, such efforts could take a long time as people generally only start to make environmental concerns a priority after they reach a certain wealth and prosperity themselves, e.g. as seen in the Scandinavian countries (MYWorld 2019)**.** Because the living conditions in the developed countries are higher, they can “afford” to focus more on the problems of tomorrow, including environmental degradation, climate change etc., whereas people in developing countries have more pressing needs in the present that have to be fulfilled first.

Lack of tenure data

In the developing world, the opportunity to improve the environment and social protection is also being held back by a lack of data, such as ownership rights of land. An example of this regarding the study area of the thesis, is that in order to compare the effectiveness of the irrigation scheme for the Ruhuhu valley, spatial tenure data would be of great benefit. With this data, different NDVI values can be compared between the various fields and farms, so farmers who do better than average can be identified and their practices can be spread to others. Nevertheless, such information is not available for the study area and this is also a global issue because there is a general lack of this sort of data in many developing countries, including Tanzania (Pott 2018). Furthermore, in the Ruhuhu valley area, 88% of the households have customary land tenure ownership while the remaining do not have any formal rights but have occupied unused land (Multiconsult 2019), which can also cause issues.

The laws regarding customary land ownership are often unclear (Komu 2003), and the people and their rights can therefore be vulnerable when various development projects are initiated. This is even more so the case for people living informally on lands. Furthermore, when property claims are uncertain, people might not risk to invest in new practices, technologies, and crop types because of fear of losing their land (McKenzie, Sparrow, and Guerschman 2016). So formal tenure information serves as important auxiliary data for remote sensing for improving the agricultural production, securing the rights of people living in the developing countries, protecting their livelihoods when new projects are proposed, and creating better overall conservation of the environment.

Precision agriculture

McKenzie, Sparrow, and Guerschman (2016) argue that remote sensing can only contribute positively if the information helps to minimize the uncertainties of the decision makers choices on all scales from the farmers to the government politicians, thereby making it easier to pick the best management options. However, since the farms in many developing countries, including Tanzania, are much smaller than farms in Europe or North America, the farmers in the developing countries have a better knowledge of their land, and they do not have the same need for remote sensing as the latter (McKenzie, Sparrow, and Guerschman 2016).

That is not to say that remote sensing is useless in these countries but it will most likely be of more importance on a higher decision-making level, such as municipal or national. Seeing as there often is a lack of spatial data in these countries, and remote sensing is a relatively cheap tool for gathering data, this also makes it valuable. Inspiration for methods can be drawn from precision agriculture as practiced in the developed world, although in the developing countries the data analysis would probably not be carried out by the individual farmers but by a governmental office. Precision agriculture is defined as "Management of farm practices that uses computers, satellite positioning systems and remote sensing devices to provide information in which enhanced decisions can be made" (Finch, Samuel, and Lane 2014). The impacts on the environment in a study area similar to the one in this thesis is highly defined by the agricultural practices of the smallholder farmers, and it is thus important that these are optimized as much as possible.

Precision agriculture was once deemed irrelevant for small farmers in the developing world but some research now points to the fact that it may be beneficial as there can be variability in the yield output on even small hectares of land (Cao et al. 2012). Therefore, measurement of NDVI differences in the fields, as performed in this thesis, can be of great value to these countries, especially if executed on a national or regional level. Furthermore, precision agriculture is not only about technology, it is also about better use of fertilizers, such as applying it directly to the roots at a specific time (ICRISAT 2019), which can help to minimize the pollution of water while at the same time being more cost-effective.

Small scale irrigation and high value crops

Aside from precision agriculture, increasing the use of irrigation in the developing countries can also give significant economic gains to the farmers. Examples from Zambia show that small farm holders that used irrigation in the dry season could earn 35% more than those who did not use irrigation for their crops (You et al. 2010). This is not large scale irrigation from dams but instead small scale irrigation where small pumps and ponds on the farms are utilized, and these have actually been shown to have a greater return of investment by a factor of four (You et al. 2010). Hence, a focus could also be placed on creating more small-scale irrigation. Although EIAs are probably not relevant here, the use of remote sensing certainly could be. It is probably also unlikely that dams, like the ones that are planned in Kikonge, are going to provide enough opportunities for irrigated agriculture on a global scale. So supplementing large scale irrigation with small scales seems to be the best solution, and the latter ones also tend to have fewer impacts on the environment (FAO 1997). But politicians and donors tend to favor larger project because they are more visible and easier to monitor and evaluate (You et al. 2010).

By applying irrigation, either from small or large scale sources, farmers can not only grow crops all year but also have the ability to grow crops with a higher value that requires more water. If farmers simply increase the yield of common crops such as cassava and maize that might not create a large economic benefit for them. These have lower prices in the first place, and the farmers might not be able to compete with large scale industrial agriculture and, compared to the European and North American farmers, they generally do not receive as many subsidies from their governments (Jayati Ghosh 2013). Therefore, it tends to be more profitable for farmers in the developing countries to produce more high value crops, especially ones that have a local advantage for growth (McKenzie, Sparrow, and Guerschman 2016).

Considerations for using Google Earth Engine

As mentioned in the beginning of this chapter, the analysis performed in this thesis would be very time consuming to perform in the traditional way by using a GIS software on a personal computer with a standard graphical user interface (point and click). However, a point to consider with Google Earth Engine is that the user instead interacts with the program using scripts of code (JavaScript or Python) and a basic level of coding skill is therefore required. This could potentially discourage some users and it does at the very least require some degree of training for EIA professionals interested in this tool. Also, although Google Earth Engine is free for scientific research, education, and non-profit work, it is not free for commercial use. The price is not known, as it not publicly available and is only given on a contact basis, but this could of course hinder its use for some, depending on the price. Finally, the use of Earth Engine requires a strong internet connection, which could pose a problem for some developing countries.

Public monitoring

When the above mentioned criteria have been dealt with, remote sensing, utilizing a free program like Google Earth Engine with imagery such as Sentinel-2, has the advantage that it can be used effectively by the public to hold developers and decision makers accountable by investigating the actual impacts compared to the predicted impacts of a project. Hence, national environmental NGOs or simply individuals with the resources to use such a tool, can create their own quantitative information regarding changes in the environment if they do not find the official data to be enough. Because the historic satellite imagery is freely available online, the data cannot be hidden away by decision makers that do not want the information to be publicly known, as could be the case with other environmental measurements.

Furthermore, the development and launches of more so-called micro-satellites (Cappelletti, Battistini, and Graziani 2018) enables cheaper access to high spatial and temporal resolution imagery that can be applied on the demand where and when it is most needed. The same applies for the decrease in cost of drones and their consequently increased use for environmental monitoring and protection (Wich and Koh 2018). There is a global increase in cheaper remotely sensed data, however many people in developing countries still do not have access to this or might not have the necessary skill to process it (McKenzie, Sparrow, and Guerschman 2016).

But given the access and skillset to work with remotely sensed information, anyone can become an applied geographer who can assist in creating survey systems for the environment that in turn can apply pressure on governments to limit the degradation and improve the natural environment. The development of geospatial technologies in general in the recent years have also allowed citizens to utilize geographic data to a much larger degree for data collection, monitoring etc. (Lee and Sui 2015). An example is the use of volunteered geographic information (VGI) where users collect data and create free content (Senaratne et al. 2016), examples being OpenStreetMap and WikiMapia.

Moreover, books, seminars, and courses that teach open-source coding, GIS, and remote sensing are spreading around the world (Remote-Sensing-Biodiversity.org 2019; CodeforAfrica 2019) and helps to educate and empower individuals to work with all the geospatial data that is available in today's world. In the future, citizens could become an ever increasing and important factor for environmental monitoring.

Climate change

When dealing with remote sensing for environmental monitoring, an important factor to consider is climate change, which is also currently a top political priority globally; including many developing countries who are also beginning to experience changes in weather patterns. In Tanzania, for example, there have been less rainfall, about 3.3% per decade, and higher temperatures, approximately 1 degrees Celsius increase since 1960, and these changes are predicted to continue in the future (Irish Aid 2015).

54 Essential Climatic Variables (ECV) that help to characterize the Earth's climate have been identified and most of these are dependent on monitoring with satellite remote sensing (GCOS 2019), which again showcases the tool's usefulness. Remote sensing is often used in combination with climate models to improve their predictions, and it is also utilized for mitigating and preventing impacts of climate change (Yang et al. 2013)**.** Hence, remote sensing is also an important tool for monitoring changes in the climate, including detecting temporal variances in EIA project areas. Remote sensing can monitor alterations in the growing season using time series of imagery, e.g. warmer springs, and thereby predict earlier growing seasons (Rodriguez-Galiano et al. 2015), which could make it necessary for farmers to plant their crops earlier.

Knowledge such as this can be valuable at both a national and sub-national level in order to mitigate and adapt to potential future changes in climate by being able to measure the spatial differences, for example that some places might get drier while others get wetter, and respond accordingly to the changes. Changes in productivity of the crops, indicated by its greenness and NDVI, can also help with the estimation of crops' yields (Pinter et al. 2003), which then in turn could enable better food security. However, these models still need information collected on the ground and there is generally a lack of statistics on agricultural production in the developing countries (McKenzie, Sparrow, and Guerschman 2016). Further resources to obtain this kind of data collection would also be needed to supplement the remotely sensed data.

The SDG's, poverty and environmental degradation

Remote sensing also has a role to play in achieving the United Nations Sustainable Development Goals (SDG's) (UN 2019b). For agricultural development projects in areas like the one presented in this thesis, the most relevant SDG's have been identified to be: Goal 1: No poverty; Goal 2: Zero hunger; Goal 6: Clean water and sanitation; Goal 8: Decent work and economic growth; and Goal 15: Life on land. When comparing these to the overall objective stated for the 'Kikonge Dam and Irrigation Project', which is economic development and alleviation of poverty, it is clear that there needs to be a balance between SDG's focusing on the alleviation of poverty/economic progress and the SDG's regarding environmental concerns, e.g. water and land use etc. This will probably also be the case for other most similar projects.

In order to achieve these goals, a considerable focus could be put on the concept of sustainable agriculture, which is agricultural activities that fulfill society's need for textiles and food without jeopardizing future generations' ability to do the same (OECD 2019). This involves integrating all three aspects of sustainability - economic benefits, social fairness, and a healthy environment - and focus on the whole "food chain" (UCDAVIS 2019). This relates to matters such as increasing yields while minimizing water use and fertilizer use, stopping soil erosion, creating better working conditions etc. (FAO 2018).

There is currently a political consensus in the developing countries in Africa that the development of agriculture is key to alleviating poverty and creating economic progress and that in order to do so the agricultural productivity must be doubled in 2025, as stated in the Malabo Declaration (African Union 2014). The declaration also states that there is a lack of solid information at all levels in the food supply system, which affects the decision making process (McKenzie, Sparrow, and Guerschman 2016). This is also where remote sensing can become a valuable tool, exactly to gather the lacking information. This has already been recognized globally with the creation of The Group on Earth Observations Global Agricultural Monitoring Initiative (GEOGLAM) in 2011 whose goal it is to improve the monitoring of agriculture globally and create better estimations of crop yields as well as weather forecasts (GEOGLAM 2019).

This development of the agricultural sector is essentially involved with creating a marketplace income for farming households, which is then able to function as a catalyst for long term change, and will most likely involve more people from the households moving away from agriculture and into the urbans areas (McKenzie, Sparrow, and Guerschman 2016). This does not necessarily reduce poverty though as there needs to be proper job opportunities in the towns and cities.

The universal environmental problems cannot be fixed without addressing poverty and wise versa because poverty and environmental issues are interlinked. Poor people tend to be more affected by environmental degradation as they rely more on the natural environment for survival but at the same time poverty often leads to more pressure on the environment because of lack of education, higher birth rates, lacking enforcement of laws because of corruption and inadequate financial resources etc. (World Vision 2006; Leitao 2016). However, poverty and environmental degradation are 'wicked problems', meaning that they are difficult to solve because they have many causes, some of which can be changing and thus challenging to recognize, and no single solution exists (Peters 2017). Remote sensing, like other potential positive contributing factors, can only be a part of the solution for these global paramount issues.

Conclusion

The rising human population is increasing the need for a larger food production worldwide and this is especially the case in Africa. A development in the agricultural sector in Africa is taking place to address this and includes the construction of dams and large irrigation schemes to maximize the yields from the fields. These large projects have environmental and social consequences and are therefore subjected to environmental impact assessments (EIA) that are supposed to find and mitigate these consequences but when it comes to developing countries these can often lack the comprehensive data that is needed to make the right decisions. A tool that has been shown to be able to quickly acquire large amounts of quantitative data for vast areas is satellite remote sensing. This technology and its possibilities for EIAs is therefore investigated in this thesis in order to answer the research question: How can remote sensing benefit an environmental impact assessment (EIA) of an agricultural project area?

Using the 'Kikonge Dam and Irrigation Project' in Southwestern Tanzania as a case study, it is found that accurate land cover maps can be created with the use of multiple images in order to take the different annual variances into consideration. This can be a great benefit for creating accurate baseline information of the surface for a given project area. Furthermore, the use of the normalized difference vegetation index (NDVI) indicates that is possible to distinguish between areas with various degrees of vegetation productivity. The areas with the highest plant productivity also correspond well with the areas that are found to have crops on them during the dry season, which could be a sign of better soil conditions and/or better farming practices. However, the extent of dry season crops is much lower than what other data specifies, which could indicate that this needs further exploration. The use of cloud filtering for the creation of cloud free images and pixels also indicates that possible improvement of the filtering technique should be investigated in order to remove more cloud congested pixels.

No fields studies have been conducted in relation to this thesis because of financial and logistical constraints but it is generally recommended that remotely sensed data is validated through data collection on the ground. Nonetheless, this thesis demonstrates that remote sensing has great potential to contribute to EIAs of agricultural areas and that it's deemed likely to be valuable under many other different surface conditions and project types. Moreover, remote sensing can also contribute to environmental protection and monitoring through public participation and monitoring where the public uses the tool to hold managers and decision makers accountable. This does require skilled individuals but the expansion of free software and data makes this possible. This trend will probably continue in the future so an increasing number of people can use their geographical skills to make a positive impact on the environment.

Aside from a lack of data, there are many other problems with EIAs, especially for developing countries who also must address poverty, corruption, weak institutions, and balance environmental concerns with economic growth. So it is recognized that remote sensing cannot address all these issues, and it should instead been seen as part of the solution for improving EIAs and environmental monitoring and protection in general.

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Appendix 1: African Development Bank's ESIA Reports

The list of the Environmental and Social Impact Assessment reports that have been studied in this thesis for their use of remote sensing.

1) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Kenya_-_KENOL_%E2%80%93_SAGANA_%E2%80%93_MARUA_Road_Project_-_ESIA_Summary.pdf
2) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Somalia_-_Somalia_Regional_Corridors_Infrastructure_Programme__SRCIP__%E2%80%93_ESIA_Summary.pdf
3) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Malawi_-_Nacala_Road_Corridor_Project_Phase_IV_Project_-_ESIA_and_RAP_Summary.pdf
4) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Nigeria_Eko_Atlantic_ESIA_ESMP_Summary.pdf
5) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Kenya_-_Kopere_Solar_Park_Power_Project_in_Kisumu_District__Nandi_County_%E2%80%93_ESIA_Summary.pdf
6) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Gabon_-_GSEZ_Port_Project_-_ESIA_Summary.pdf
7) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Multinational_-_Projet_d%E2%80%99interconnexion_des_re%CC%81seaux_e%CC%81lectriques_Burundi_%E2%80%93_Rwanda_-_Summary_ESIA.pdf
8) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/ESIA_Summary_Dodoma_City_Outer_Ring_Road_Project_-_Aug_2018.pdf
9) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Ethiopia_-_4_Proposed_Iaips_and_Rtcs_Located_in_South_West_Amhara_Region__Central_Eastern_Oromia_Region__Western_Tigray_Region_and_Eastern_SNNP_Region_%E2%80%93_ESIA_Summary.pdf
10) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Nigeria_-_Ebonyi_State_Ring_Road_Project_-_ESIA_Summary.pdf
11) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Burundi_and_Tanzania_-_PROPOSED_UPGRADING_OF_RUMONGE-BUJUMBURA_SECTION__78km__-BURUNDI_%E2%80%93_ESIA_Summary.pdf
12) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Sierra_Leone_-_Freetown_Water_Supply_Rehabilitation_Project_%E2%80%93_ESIA_Summary.pdf
13) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Zimbabwe_-_North-East_Network_Rehabilitation_Project_%E2%80%93_ESIA_Summary.pdf

14) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Uganda_-_Kampala-_Jinja_Expressway_PPP_Project_%E2%80%93_Phase_1_%E2%80%93_ESIA_Summary.pdf
15) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Zambia_-_Zambia_Staple_Crops_Processing_Zone__SCPZ__Luswishi_Farm_Block__Lufwanyama_District__Copperbelt_Province__Zambia_%E2%80%93_ESIA_Summary.pdf
16) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Malawi_-_Proposed_construction_of_main_canal_from_intake_to_lengwe_national_park_under_the_shire_valley_transformation_program__Phase_1__-_ESIA_Summary.pdf
17) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Burundi_and_Tanzania_-_Proposed_upgrading_of_nyakanazi_%E2%80%93_Kasulu_%E2%80%93_Manyovu_road__Kasulu-Kabingo_%E2%80%93_Kasulu_road_section_and_Kibondo_bypass__202_km__to_bitumen_standard_in_Kasulu__Kibondo_and_Kakonko_districts__Kigoma_region_%E2%80%93_ESIA_Summary.pdf
18) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Maroc_-_Programme_de_pe%CC%81rennisation_et_de_se%CC%81curisation_de_l%E2%80%99acce%CC%80s_a%CC%80_l%E2%80%99eau_%E2%80%93_BAD_14_%E2%80%93_RESUME_EIES-EN.pdf
19) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Cameroon_-_Bamenda-Kumbo_Ring_Road_Construction_Project_%E2%80%93_ESIA_Summary.pdf
20) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Tanzania_-_Kakono_Hydroelectric_Power_Project_-_in_Karagwe_and_Misenyi_Districts__Kagera_Region_%E2%80%93_ESIA_Summary.pdf
21) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/EIES_-_CAMEROUN_-_PROJET_DE_DEVELOPPEMENT_DES_CHANES_DE_VALEURS_DE_L_ELEVAGE_ET_DE_LA_PECHE_PD-CVEP_-_CONSTRUCTION_D%E2%80%99UN_ABATTOIR_MODERNE_DE_BOVINS_A%CC%80_DOUALA_%E2%80%93_BONENDALE%CC%81.pdf
22) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/ESIA_SUMMARY-Cote_divoire-liberia-MRU_RDTFP-PHASE_II.pdf
23) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Rwanda_-_New_Bugesera_international_airport_in_Bugesera_-_ESIA_Summary.pdf
24) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Kenya_-_Quantum_Power_-_Menengai_Geothermal_Power_Development-_1x_35mw_Project_in_Nakuru_County_Kenya_-_ESIA_Summary.pdf
25) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/ESIA_Summary-Indorama_Eleme_Fertilizer_II-NIGERIA_.pdf
26) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Nigeria_-_Pan_African_Solar_Power_Project_Katsina_-_ESIA_Summary.pdf
27) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Kenya_-_Nairobi_Rivers_Basin_Rehabilitation_and_Restoration_Program-_Sewerage_Improvement_Project_Phase_II_-_ESIA_Summary.pdf

28) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Multinational_-_Mano_River_Union_Road_Development_and_Transport_Facilitation_Programme_%E2%80%93_RAP_Summary.pdf
29) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Morocco-Tekcim_Cement_plant_project_-Summary_ESIA-10_2017.pdf
30) https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-Assessments/Ghana_-_Takoradi_Port_Expansion_Project__On_Dock_Container_and_Multipurpose_Terminal_-_ESIA_Summary.pdf

Appendix 2: Error Matrices

The error matrices for the land cover classifications of the whole study area and the dry season fields.

Error matrix for land cover classification of the whole study area. With the land cover classes; Water, Fields, Bare soil, Dense vegetation, Sparse vegetation and Built up areas.

	Validation sample							Row total
		Water	Fields	Bare soil	Dense veg	Sparse veg	Built up	
Classification	Water	93	0	0	0	0	0	93
sample	Fields	0	432	0	0	0	0	432
	Bare soil	0	0	268	0	0	0	268
	Dense veg	0	0	0	77	2	0	79
	Sparse veg	0	1	0	2	174	0	177
	Built up	0	0	2	0	0	9	11
Column total		93	433	270	79	176	9	1060

Error matrix for land cover classification of dry season fields. With the land cover classes; Green fields and Non-green fields.

	Validation sample			Row total
		Green fields	Non-green	
Classification	Green fields	41	0	41
sample	Non-green	1	50	51
Column total		42	50	92

Appendix 3: Links to map gallery & Google Earth Engine Code

Links to the gallery of maps and the coding scripts used for all four remote sensing analysis in Google Earth Engine.

Earth Engine map gallery:

https://rasmusthimm.users.earthengine.app/

Land cover classification of study area:

https://code.earthengine.google.com/68c0da34076027e01a6f021b65aafc55

Temporal NDVI assessment with time series chart:

https://code.earthengine.google.com/b6f801eb557249fdf2a34ea17e2e96ce

Classification of dry season fields:

https://code.earthengine.google.com/9e43fb09aa658a9b4c87b99bf8a2deca

Spatial differences in NDVI:

https://code.earthengine.google.com/687cb4e7f372c1180abf52b760a9a6a2