Mapping of farmer-led irrigated agriculture with remote sensing

A case study in Central Mozambique

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by

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Resilience
Resilience

An electronic version of this thesis is available at http://repository.tudelft.nl/.
This thesis represents the completion of my degree in Civil Engineering at the TU Delft. My years as an engineering student are not easily described in a few lines, so all I will say here is that it was quite an experience. I am very grateful for all the chances and opportunities that I got during my student time, one of them being my thesis! About 9 months ago, I was ready for a new adventure: three months of fieldwork in Mozambique for my thesis. I was really excited and looking forward to collect my own data. I kind of expected to go in to the field, collect data, start processing my data as soon as possible and to be able to produce perfect land use maps with irrigated fields organized by crop type, all within my time in Mozambique. In this way, I figured I could start working on all kinds of cool applications to support Mozambican farmers and to direct policies on agriculture when I was back in The Netherlands. However, once I arrived in Mozambique, one of the first Portuguese phrases that I learned was ‘espere um pouco’, which means so much as ‘wait a bit’. This perfectly illustrated that I needed to step down a little and adjust my typical ‘muzungu’ attitude to the Mozambican rhythm. This also applied to my fieldwork plans. Luckily, it resulted in amazing experiences, not always easy ones but interesting and challenging without a doubt. I got to deal with various kinds of snakes - from huge pythons to tiny poisonous ones -, numerous break downs of chapas and motorbikes and a couple of terrifying storms. More important, I learned that the Mozambican farmers that I visited for my fieldwork are very friendly people who work incredibly hard and have very little, yet were always prepared to offer me a plate of ncima, a local dish of maize porridge. As a bonus, I got the chance to gain valuable information regarding my thesis.

Once I came back to The Netherlands, I had a ton of data (at least, that was how I saw it) but no clue on how to proceed working on this. Luckily, my supervisor Susan Steele-Dunne turned out to have a solution to basically every problem that I encountered and somehow managed to guide me into the right direction, every week again. I am very thankful that Susan took the time to supervise me and to be really involved in my research. In addition, I would like to thank my other supervisors from the TU Delft: Nick van de Giesen for his extensive knowledge on African agriculture that helped me to finetune my research, Ramses Molijn for updating my knowledge on remote sensing and Lorenzo Iannini, who was so kind to join my committee just last month and provided valuable feedback.

I also own a huge thanks to Resilience. I am very happy that I got to work with a company that shares the same passion and values that I have. Thanks to Wouter, who introduced me to this topic and who was always available for questions, even though I might have asked him a hundred times about how fieldwork actually works before I went to Mozambique. Thanks to Janwillem, who kept me sharp regarding my language and took the time to provide useful feedback. A big thanks to Nicky, who opened her house in Chimoio to me and took me on different trips to explore Central Mozambique. Thanks to Piloto, one the friendliest persons I have ever met, for making me feel very welcome and for always meeting my coffee needs in the Chimoio office, not just with Ricoffy but with Nescafe. Thanks to Helio. Unfortunately, we were not able to work together for longer than a couple of weeks, but I got to know him as an enthusiastic and open person. Also, a huge thanks to David Muchena, my guide and translator. Without him, this whole research would not have been possible.

In addition, I want to thank my roomies in room 4.93 for providing a motivating and lively study atmosphere in which there was always room for coffee, cookie breaks or ice cream. A special thanks to the Rinny Huizinga Stichting, who supported my stay in Mozambique and therefore made my dream of performing part of my thesis abroad possible. Last but not least, I want to take the opportunity to thank my sisters, who mean the world to me, for being there for me, and my parents, who always have been very supportive and who never cease to believe in me.

Vera Hollander
Delft, June 2018
Abstract

In the fertile hills of Manica Province in Central Mozambique, agricultural activities consist for a significant part of farmer-led irrigated agriculture. In this type of agriculture, irrigation is initiated by local farmers. These farmers construct and maintain their own irrigation systems with local inputs and have a commercial intent. Organization is often individual and farmers receive zero to minimal external support from donors, government or non-governmental organizations. This type of agriculture seems to work quite well. It is increasing quite fast and has a high production rate per hectare. In addition, it can boost agricultural production and contributes to higher food security, poverty alleviation and economic growth.

Despite the considerable role of farmer-led irrigation within Central Mozambique, its presence and significance are often not fully recognized, due to the fact that there is little documentation or data on farmer-led irrigated agriculture among other things. Therefore it is unclear what the actual extent of irrigated agriculture is. In Central Mozambique there is a certain perception that a lot of land in this area is unused, so that there is a large potential for new agricultural development. Nevertheless, much of this land is already used by farmer-led irrigated agriculture. Hence, it is important to have information reliable information on the extent of this. A way to obtain this might be making use of satellite imagery and remote sensing. However, the feasibility of this depends on various factors and is not proved yet. Therefore, this study aims to provide insight in the possibilities and limitations of remote sensing regarding the identification and mapping of farmer-led irrigated agriculture in Central Mozambique, by using optical satellite imagery combined with ground data.

This study consists of three parts: ground data collection, classification and additional analysis. Ground data is collected during fieldwork in Central Mozambique in three catchments, to serve as training and validation for land use classification and for gaining insight in local farmers’ practices. Fieldwork consisted of interviews with local farmers and mapping land uses with GPS, with a focus on the mapping of irrigated fields. Classification is performed with a Maximum Likelihood classifier and uses optical satellite imagery acquired by Sentinel 2. Different combinations of images and bands are used. Additional analysis consists of terrain analysis with a Height Above Nearest Drainage raster, examination of distances to streams for land uses throughout the research area, determination of the reach of irrigation canals and looking into the possibilities of thermal remote sensing.

The classification results are mixed and inconsistent, especially regarding irrigated fields and light seasonal vegetation. A more detailed analysis of spectral signatures and scatterplots shows spectral overlap between these land uses. Analysis on field level shows that spectral responses reflect agricultural practices in some cases, but in general results are unreliable. Results of the additional analysis show similarities between irrigated fields and light vegetation as well for Height Above Nearest Drainage and thermal remote sensing. Also, distance to streams is not suitable as an indicator for irrigation, because irrigation canals increase the reach of the streams.

It can be concluded that optical remote sensing as applied by this study does not give accurate results regarding the identification and mapping of farmer-led irrigated agriculture in the study area, because of similarities in the spectral responses of irrigated fields and light vegetation. This low inter-class separability is mainly a result of the heterogeneity of the area and the flexibility of agricultural practices. Due to these diverse practices, the agricultural plots show different and unique patterns both over time and over space, which makes it hard to generalize and classify them. However, even though an accurate substantiation of the extent of farmer-led irrigated agriculture is not feasible, valuable information obtained by this study contributes to better grasping the presence of irrigated agriculture in Ruaca, Chirodzo and Godi catchments.
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>F-IR-IS1</td>
<td>Follow-up classification for first irrigation season with IR combination of S2 bands</td>
</tr>
<tr>
<td>F-IR-IS2</td>
<td>Follow-up classification for second irrigation season with IR combination of S2 bands</td>
</tr>
<tr>
<td>F-RE-IS1</td>
<td>Follow-up classification for first irrigation season with RE combination of S2 bands</td>
</tr>
<tr>
<td>F-RE-IS2</td>
<td>Follow-up classification for second irrigation season with RE combination of S2 bands</td>
</tr>
<tr>
<td>F-VIS-IS1</td>
<td>Follow-up classification for first irrigation season with VIS combination of S2 bands</td>
</tr>
<tr>
<td>F-VIS-IS2</td>
<td>Follow-up classification for second irrigation season with VIS combination of S2 bands</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GRASS</td>
<td>Geographic Resources Analysis Support System</td>
</tr>
<tr>
<td>HAND</td>
<td>Height above nearest drainage</td>
</tr>
<tr>
<td>IM-VIS</td>
<td>Intermediate classifications with VIS combination of bands</td>
</tr>
<tr>
<td>IR</td>
<td>Combination of Sentinel bands in the red, near infrared and shortwave infrared spectrum</td>
</tr>
<tr>
<td>IS1</td>
<td>First irrigation season, approximately from April till July</td>
</tr>
<tr>
<td>IS2</td>
<td>Second irrigation season, approximately from August till November</td>
</tr>
<tr>
<td>KS</td>
<td>Kolmogorov-Smirnov test</td>
</tr>
<tr>
<td>L8</td>
<td>Landsat 8</td>
</tr>
<tr>
<td>LST</td>
<td>Land Surface Temperature</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NIR</td>
<td>Near infrared spectrum</td>
</tr>
<tr>
<td>QGIS</td>
<td>Quantum Geospatial Information System</td>
</tr>
<tr>
<td>RED</td>
<td>Red spectrum</td>
</tr>
<tr>
<td>S2</td>
<td>Sentinel 2</td>
</tr>
<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
</tr>
<tr>
<td>VIS</td>
<td>Combination of Sentinel bands in the visible and near infrared spectrum</td>
</tr>
<tr>
<td>WS</td>
<td>Wet season, also referred to as rain season, approximately from November till April</td>
</tr>
</tbody>
</table>
## Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preface</td>
<td>iii</td>
</tr>
<tr>
<td>Abstract</td>
<td>v</td>
</tr>
<tr>
<td>List of acronyms</td>
<td>vii</td>
</tr>
<tr>
<td>1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Background</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Problem statement</td>
<td>2</td>
</tr>
<tr>
<td>1.3 Research objective</td>
<td>2</td>
</tr>
<tr>
<td>1.4 Outline</td>
<td>3</td>
</tr>
<tr>
<td>2 Study site</td>
<td>5</td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>5</td>
</tr>
<tr>
<td>2.2 Characteristics of the research area</td>
<td>6</td>
</tr>
<tr>
<td>2.3 Agricultural practices</td>
<td>8</td>
</tr>
<tr>
<td>3 Data and Methods</td>
<td>11</td>
</tr>
<tr>
<td>3.1 Data</td>
<td>11</td>
</tr>
<tr>
<td>3.1.1 Ground data</td>
<td>11</td>
</tr>
<tr>
<td>3.1.2 Remote sensing data</td>
<td>11</td>
</tr>
<tr>
<td>3.2 Methods</td>
<td>13</td>
</tr>
<tr>
<td>3.2.1 Fieldwork</td>
<td>13</td>
</tr>
<tr>
<td>3.2.2 Classification</td>
<td>15</td>
</tr>
<tr>
<td>3.2.3 Images and bands</td>
<td>17</td>
</tr>
<tr>
<td>3.2.4 Training maps</td>
<td>19</td>
</tr>
<tr>
<td>3.2.5 Verification visits</td>
<td>20</td>
</tr>
<tr>
<td>3.2.6 Additional analysis</td>
<td>21</td>
</tr>
<tr>
<td>4 Results</td>
<td>25</td>
</tr>
<tr>
<td>4.1 Ground data</td>
<td>25</td>
</tr>
<tr>
<td>4.2 Classification</td>
<td>29</td>
</tr>
<tr>
<td>4.2.1 Overview</td>
<td>29</td>
</tr>
<tr>
<td>4.2.2 Area calculation</td>
<td>32</td>
</tr>
<tr>
<td>4.2.3 Accuracy assessment</td>
<td>33</td>
</tr>
<tr>
<td>4.2.4 Verification visits</td>
<td>33</td>
</tr>
<tr>
<td>4.3 Spectral signatures</td>
<td>34</td>
</tr>
<tr>
<td>4.4 Spectral response single fields</td>
<td>36</td>
</tr>
<tr>
<td>4.4.1 Scatter plots</td>
<td>36</td>
</tr>
<tr>
<td>4.4.2 NDVI analysis</td>
<td>38</td>
</tr>
<tr>
<td>4.5 Additional analysis</td>
<td>42</td>
</tr>
<tr>
<td>4.5.1 Terrain analysis</td>
<td>42</td>
</tr>
<tr>
<td>4.5.2 Distances to streams and canals</td>
<td>43</td>
</tr>
<tr>
<td>4.5.3 Thermal remote sensing</td>
<td>44</td>
</tr>
<tr>
<td>4.5.4 Rainfall analysis</td>
<td>46</td>
</tr>
<tr>
<td>5 Conclusion and recommendations</td>
<td>49</td>
</tr>
<tr>
<td>5.1 Conclusion</td>
<td>49</td>
</tr>
<tr>
<td>5.2 Recommendations</td>
<td>50</td>
</tr>
<tr>
<td>5.2.1 Improvements fieldwork</td>
<td>50</td>
</tr>
<tr>
<td>5.2.2 Single field analysis</td>
<td>50</td>
</tr>
<tr>
<td>5.2.3 Higher spatial resolution</td>
<td>51</td>
</tr>
</tbody>
</table>
Introduction

1.1. Background

Society is dealing with numerous complex challenges. Many of them are a result of the vast increase of the world's population, which is expected to reach 9.6 billion by 2050 and 11.2 billion by 2100 (United Nations, 2017). This affects food security and puts large pressure on natural resources and ecosystems (McIntyre, 2009). To satisfy future food demands, it is estimated that food production has to increase with 70 to 100 percent (Food and Agriculture Organization, 2009). However, the availability of fresh water sources is limited, which constrains the food production (Molden, 2013). The agricultural sector plays a key role in this challenge. About 70 percent of the global withdrawal of water is used for irrigated agriculture, while in low income countries this can be as high as 90 percent (Food and Agriculture Organization, 2016; Johansson, 2005; Shiklomanov, 2000). Little water is left for other uses, such as industrial or domestic use. This competition for fresh water calls for sustainable and effective management of water resources.

Also in food security, the importance of irrigation is undeniable. Irrigated areas take up approximately 18 percent of cultivable land and are responsible for about a third of the total agricultural production (Johansson, 2005). In general, irrigated fields have higher yields than rainfed agriculture and help mitigating the effects of droughts (Bruinsma, 2017; Lobell et al., 2009; Siebert et al., 2005). Furthermore, the agricultural sector is crucial in terms of poverty reduction, since it is the biggest employment sector in the world and fulfills people's primary needs. In Sub Saharan Africa, where poverty rates are very high, agriculture is the most important source of income and agricultural development is the key to decreasing poverty (Cervantes-Godoy and Dewbre, 2010; Xie et al., 2014; You et al., 2011).

Already, various development policies and investments are aimed at irrigated agriculture (Cai et al., 2017). However, many large-scale irrigation projects throughout Africa have disappointing results when it comes to performance and productivity or are considered as failures (Rosegrant et al., 1997; Tafesse, 2003; Woodhouse, 2012). Policy directions regarding irrigated agriculture in Sub Saharan Africa have been subject to debates and discussions for the last couple of decades. As a result, donors shied away from funding or got meager performance gains for their investments (Lankford, 2009). Luckily, there are also cases of irrigated agriculture in Africa that present a more positive image, such as smallholder irrigated agriculture (Abric et al., 2011; Tschirley et al., 2011). This type of irrigation seems to account for about 80 percent of food production in developing countries (den Besten, 2016). The terminology for this type of irrigated agriculture is not very consistent. Sometimes it is referred to as 'informal irrigation' (Drechsel et al., 2006) or 'small private irrigation' (de Fraiture and Giordano, 2014) to accent the fact that public entities officials are not involved. In this study, the term 'farmer-led irrigated agriculture' is used, based on research by Nkoka et al. (2014) to emphasize the farmers' active role and initiative. In this type of agriculture, irrigation systems are initiated and sustained by local farmers. These farmers construct and maintain their own irrigation systems with local inputs and have a commercial intent. Organization is often individual and farmers receive zero to minimal external support from donors, government or NGOs (Beekman et al., 2014).
Farmer-led irrigated agriculture seems to work quite well. It grows with a rate of 4 percent in some areas in Africa, which is quite high when compared to the growing rate of 0.5 to 0.7 percent in overall irrigation expansion, and it has a high production rate per hectare (Lankford, 2005). In addition, it can increase agricultural production and contributes to higher food security, poverty alleviation and economic growth (de Fraiture and Giordano, 2014; Veldwisch et al., 2009).

1.2. Problem statement
Although farmer-led irrigation accounts for a considerable part of total agriculture in Africa, its presence and significance is often not fully recognized, due to a couple of challenges. One of them is the fact that there is a critical attitude against farmer-led irrigated agriculture, some sort of engineering bias. This prejudice considers farmer-led irrigated agriculture as inefficient and backwards. It claims that it does not contribute to poverty alleviation and proposes that large-scale investments are necessary in order to increase irrigated agricultural areas (Beekman et al., 2014; Bolding, 2007; Tschirley and Benfica, 2000; Woodhouse et al., 2017). This critical attitude is strengthened by the fact that there is little documentation or data on farmer-led irrigated agriculture. Information derived from case studies is often rejected as unrepresentative for bigger areas. Therefore it is unclear what the actual extent of irrigated agriculture is and farmer-led irrigation is not clearly on the radar of relevant actors such as policy makers (Cai et al., 2017; Ozdogan and Gutman, 2008; Woodhouse, 2012). However, sufficient knowledge of the extent of irrigated areas is necessary for efficient irrigation management and water productivity (Droogers et al., 2010; Van Dam et al., 2006). In addition, accurate information about agricultural water demands, irrigation and food production is significant to address current and future problems regarding the food and water balances (Salmon et al., 2015; Senay et al., 2007).

1.3. Research objective
As long as there is no proper recognition of farmer-led irrigated agriculture, various kinds of support will most likely still be on trying to create more irrigation potential instead of focusing on what already exists. It is important to have reliable information on the actual extent of farmer-led irrigation, so that it is clear what already has been achieved, hence support can build on this. A way to obtain this might be making use of satellite imagery and remote sensing. Various studies have shown that it is possible to use remote sensing for monitoring and mapping irrigated agriculture on different scales (Peña and Brenning, 2015; Salmon et al., 2015). With remote sensing, accurate and objective information about land surface processes, water management, cultivated areas and vegetation can be obtained in a cost-effective way, on a large scale and on regular basis (Bastiaanassen et al., 2000; Schmugge et al., 2002; Tatsumi et al., 2015). Therefore, remote sensing data might be very valuable regarding the unclarity of the extent of farmer-led irrigation. However, the feasibility depends on various factors and is not proved yet.

With this study, it is aimed to get more insight in this feasibility. The focus of this research is on an area in Central Mozambique, where many examples of farmer-led irrigation are found. However, there is a prevalent perception - among government officials for example - that a lot of land in this area is unused, so that there is a large potential for new agricultural development. In some extreme cases, this has led to constructing irrigation systems in areas where there already were functioning systems, resulting in damaging the existing infrastructure. If remote sensing can be used to identify and map the irrigated areas, objective information on the extent of farmer-led irrigation could be obtained. This information could then be used to show that there is something to build on rather than that there is a clean sheet, hence support existing agricultural practices and policy decisions. Furthermore, if there is technical feasibility, additional applications could be investigated, such as information on best planting periods or the health of certain crops. This leads to the following objective of this study:

*Provide insight in the possibilities and limitations of remote sensing regarding the identification and mapping of farmer-led irrigated agriculture in Central Mozambique, by using satellite imagery combined with ground data.*
To obtain this objective, research is split in two parts: ground data collection in Central Mozambique and analysis with remote sensing data. There are numerous types of remote sensing. This research focuses on optical satellite imagery. The study is part of a larger research project concerning farmer-led irrigated agricultural development performed by Resilience BV, a Dutch consultancy in water and agribusiness solutions, that aims to identify drivers that caused the development of small-scale irrigation canals in Mozambique and to map the missing numbers on farmer-led irrigated agriculture.

1.4. Outline
This report starts with an introduction of the study site in Chapter 2. In this chapter, the location of the research area is presented and some characteristics of both the area and of farmer-led irrigated agriculture are considered. Chapter 3 covers the data and methodologies used for this study. The fieldwork activities performed to obtain ground data are explained. In addition, the various analyses that were performed with a combination of satellite data and ground data are presented. In Chapter 4, the results of this study are discussed. Chapter 5 closes the research with a conclusion regarding the objective of this study. In addition, various suggestions for improvements and further research are proposed. For clarity, a list of key acronyms is included at page vii.
2.1. Introduction

Mozambique has a dynamic past with many challenges, due to colonial repression, a civil war and resulting political unrest. Although economic growth rates are impressive, it is still one of the poorest countries in the world, with severe poverty especially in rural areas (Durang and Tanner, 2004; G4AW, 2014; IFAD, 2016). Throughout the whole country, the agricultural sector is very important. It provides work to about 80 percent of the population and contributes a quarter to the Gross Domestic Product of Mozambique (Jansen et al., 2008). In Manica Province, the economy consists largely of agricultural activities as well. In the hilly central west of Manica Province, an active and thriving movement of farmer-led irrigated agriculture has emerged over the past century, which has led to an irrigated agriculture extent of more than 10,000 hectares in the whole province (Beekman et al., 2014; Bolding, 2007). This region is the focus of this study. The research area is presented in figure 2.1. In the small figure in the top left of the map, the location of Mozambique, Manica Province and the research area are presented. The main figure shows the research area up close. It is located in the central west of Manica Province, nearby the border with Zimbabwe. Three small catchments are examined: Ruaca, Godi and Chirodzo.
2.2. Characteristics of the research area

The research area consists of gentle slopes, covered with evergreen sub-tropic forests at higher elevations and deciduous crop- and grasslands at lower elevations. In figure 2.2a an elevation map with shaded relief of the research area is showed, together with the mains streams in the catchments, that are delineated based on the elevation model. This model uses elevation data from the Shuttle Radar Topography Mission (USGS, 2000). The catchments are bordered by a steep ridge on the east side. The streams originate on this ridge and flow down in western direction, where the slopes are more moderate. In figure 2.2b, a photograph shows how gentle slopes get steeper towards the ridge.

The landscape is very heterogeneous and there are no large areas with a single land use. In the upstream parts of the catchments, especially for Godi and Chirodzo, the hills are pretty steep and covered with dense evergreen trees. The middle part has gentle slopes and is a mix of shrubs, grasses, agricultural fields and groups of small houses. The downstream part is more flat, with lighter vegetation and wetlands, and houses and agricultural fields as well. For more insight in land use in the research area, the Sentinel 2 prototype Land Cover 20 meter map of Africa of the European Space Agency (ESA) is consulted (European Space Agency, 2017). This map is created by the ESA Climate Change Initiative and makes use of Sentinel 2 satellite images acquired in 2016. It describes land uses at a spatial resolution of 20 meter. A map is presented in figure 2.3a. Four different land uses can be distinguished for the research area: trees cover, shrubs cover, grassland and cropland. Trees are mainly found on the steep ridge in the east and a mix of the other three land uses is found midstream and downstream, on the more moderate slopes. In figure 2.3b, a photograph with information about land use in the area is presented. A mix of land covers is visible, such as trees, grasses, bare ground and agricultural plots.
2.2. Characteristics of the research area

(a) Elevation map with shaded relief for the research catchments, presented with the stream network that flows in western direction. The research area is quite hilly, with a steep ridge in the east and moderate slopes towards the west.

(b) This photograph shows the differences in elevation in the research area. On the foreground, the hills have moderate slopes. They get more steep towards the ridge, visible in the background.

Figure 2.2: Information about topography and elevation in the research area.

(a) Land cover in the research area as determined by the European Space Agency CCI land cover project in 2017. Land cover in the area consists of trees, shrubs, grassland and crop land.

(b) This photograph shows different land covers in the research area, such as trees, small houses, agricultural fields, bare ground and small bushes and grasses.

Figure 2.3: Examples of land cover and land use in the research area.
2.3. Agricultural practices

Conditions in Manica Province are generally favorable for agriculture. The hilly areas have fertile soils, a warm and moderately tropical climate and an average rainfall of 1100 millimeter per year (Food and Agriculture Organization, 2001). However, this is very unequally distributed in time, with wet summers and dry winters. In figure 2.4, the mean monthly rain values for the years 2012, 2013, 2014, 2015, 2016 and 2017 are showed. Rain data is provided by Resilience BV and is measured by a local farmer on daily basis in Godi catchment with a rain gage.

Most crops have a growing cycle of about three to four months, which means that there are three agricultural seasons possible per year. The unequal temporal distribution of rain influences the planting and cultivation periods. Based on both the rain and on the growing cycles of the crops, there are approximately three different agricultural seasons distinguishable:

1. The wet season, in which rainfed crops such as maize and sorghum are cultivated. This period is approximately from November/December till April and is here referred to as WS, wet season. This is the season with the most agricultural activities.

2. The dry season with enough water, in which most of the farmers have enough water to irrigate their crops. This period is approximately from May till July and is here referred to as IS1, the first irrigation season. Agricultural activities are present to a lesser extent than in the wet season, but still a big part of the research area is being used for the cultivation of various crops.

3. The dry season with water scarcity, in which there sometimes is not enough water downstream to irrigate the crops. Generally, irrigation is possible in the mid- and upstream parts of the catchments. This period is approximately from August till November and is here referred to as IS2, the second irrigation season. Agricultural activities are constrained by water availability and are present to a lesser extent than in IS1.

In general, the seasons are not strictly distinguishable into three separate periods. There are no fixed planting, harvesting or irrigation periods, so there is some overlap. Timing differs per farmer, per season and per plot. Agricultural activities are very dynamic and flexible, so situations may change rapidly. Therefore, the three cultivation seasons give more a general idea of agricultural practices and may differ per case. An approximate time line of agricultural seasons is presented in figure 2.5.

![Mean monthly rainfall for 2012-2017 measured with a rain gage in Godi catchment. The graph shows that there is an unequal temporal distribution in rainfall, with wet summers and dry winters.](image)

![Time line of the three agricultural seasons. WS (wet season) indicates the rain season, IS1 indicates the first irrigation season and IS2 indicates the second irrigation season. The seasons are not strictly separable and overlap is possible.](image)
2.3. Agricultural practices

The most common form of irrigation in this area is furrow irrigation with small canals, although a small part of the farmers make use of pumps and wells, retention basins or sprinkler systems. Fresh water comes from sources on the steep ridge, where small streams emerge and flow in western direction. Water for irrigation is diverted from these streams and is distributed by gravity through small canals to the fields. These canals are manually constructed with locally available materials. Smallholders are somewhat organized concerning irrigation. The exact form of organization differs per canal, but the general pattern is similar: the original constructor of the canal is the owner and other farmers are obliged to ask permission to use water from his canal. This requires joining maintenance activities and acting conform a certain irrigation schedule. This schedule prevents that farmers all irrigate simultaneously, leading to conflicts concerning water abstractions. There is no continuous supply of water to most of the fields. In general, farmers use natural materials such as stones or mud to create obstacles to control the water. When it is their turn to irrigate, the obstacles are temporarily removed so that water can flow to their fields. Irrigation is a labor intensive activity. Figure 2.6 shows two examples of irrigation: on the left a farmer who is irrigating his tomatoes that he just planted and on the right a dry irrigation canal for which at the moment water is hindered to flow through.

Figure 2.6: Irrigation canals in study area. The photograph on the left shows a farmer in a downstream part of Godi catchment, who is irrigating his field on which he just planted tomatoes. The photograph on the right shows an example of a dry irrigation canal in an upstream part of Chirodzo catchment.
3

Data and Methods

3.1. Data

3.1.1. Ground data

For mapping and land use classification, it is important that there is enough good quality training data and understanding of local farming practices (Shao et al., 2010; Zheng et al., 2015). Therefore, a significant part of this study consisted of fieldwork for ground data collection. The ground data were collected in Godi, Chirodzo and Ruaca catchments from 03 October 2017 till 08 December 2017. This period falls within the second irrigation season, IS2, which provided the chance to get a clear insight in local irrigation practices and locations of irrigated plots. Data was collected for various objectives:

- To serve as training data as input for classification
- To serve as validation for accuracy assessment
- To gain understanding of the agricultural practices of local farmers

The ground data consist of two parts: interviews and GPS measurements. The methodology that is used to collect ground data is described in section 3.2.1.

3.1.2. Remote sensing data

A way to automatically map irrigated areas and therefore provide information on the extent and locations is through land use classification. To examine the feasibility of land use classification regarding farmer-led irrigated agriculture, the ground data collected in the three research catchments is combined with optical remote sensing, with imagery in the visible and near infrared spectrum. Optical remote sensing is suitable for land use classification, due to its spectral features in bands with various wavelengths, which can contribute to accurate mapping (Tabak, 2015). Farmer-led irrigated agriculture often takes place on fields that are quite small. Therefore, the satellite imagery used for this study has to have a high spatial resolution, to be able to identify small scale details and to perform analysis on field level. It is also important that there is a high temporal resolution, because the research area is quite dynamic. A last requirement is that the data is freely available, so everyone is able to make use of the information provided.

Optical remote sensing – Sentinel 2

A satellite that meets all requirements mentioned above is Sentinel 2. It exists of two twin polar-orbiting satellites and is part of the Global Monitoring for Environment and Security mission, a cooperation between the European Commission and the European Space Agency (ESA). One of the key objectives of Sentinel 2 is to provide high-resolution, multi-spectral imagery for land-cover maps (Drusch et al., 2012). Sentinel 2 has a high spatial resolution: 10 meter for bands in the blue, green, red and near-infrared spectrum and 20 meter for bands in the red-edge and shortwave infrared bands. It has a revisit time of 5 days at the equator. All these characteristics support the objective of this study and therefore, Sentinel 2 imagery will be the main type of remote sensing in this study. All Sentinel 2 images used in this report are produced from ESA remote sensing data and retrieved from the Copernicus Open Access Hub (2017). In table 3.1, the bands of Sentinel 2 that are relevant to this study are presented.
Several preparation steps have to be performed in order to use the Sentinel 2 imagery for classification. Satellite imagery is subject to various errors, uncertainties or inconsistencies, due to misalignment, cloud cover, geolocation errors, sensor noise and more (Salmon et al., 2015; Storey et al., 2016). To minimize these negative effects, the images were atmospherically corrected with Sen2Cor, a processor for Sentinel 2 images. Sen2Cor applies atmospheric, terrain and cirrus correction to the Top-of-Atmosphere input data and converts it to Bottom-of-Atmosphere reflectance images (Müller-Wilm, 2016; SNAP, 2018). After atmospheric correction, the data is resampled, so all the bands have the same spatial resolution of 10 meter, and clipped to the research area.

**Thermal remote sensing – Landsat 8**
Landsat 8 is a cooperation between the United States Geological Survey and the National Aeronautics and Space Administration. This satellite measures both in the optical and the thermal spectrum. For this study only Landsat’s thermal bands are used, to complement the optical bands of Sentinel 2. The images are obtained from the Earth Explorer by the United States Geological Survey (USGS, 2017). In table 3.2, the bands of Landsat 8 that are relevant to this study are presented. The images are pre-processed with the Semi-Automatic Classification Plug-in, which applies an image-based atmospheric correction (Congedo, 2016), after which they are clipped to the study area.

**Digital Elevation Model – Shuttle Radar Topography Mission**
A Digital Elevation Model with land elevation data with a spatial resolution of 30 meter from the Shuttle Radar Topography Mission is used. This mission was a cooperation between the NASA and the National Geospatial Intelligence Agency (USGS, 2000). The images are obtained from the Earth Explorer by the United States Geological Survey.
3.2. Methods

The main methodology applied in this study is land use classification. A schematic overview of this methodology is presented in figure 3.1. This overview is divided in four different types:

- Data that is used as input. This concerns data that is obtained from external sources, so data that is not a result of actions performed in the course of this study. This is indicated with a black box.
- Activities/methods that were performed to obtain data and results, such as fieldwork or preprocessing Sentinel 2 images. These activities are presented in the orange boxes. If there was a specific type of software used, then this is indicated between brackets. Most of the processing is performed in Quantum GIS, an open source Geographic Information System, and in GRASS, an open source Geographic Resources Analysis Support System.
- Intermediate results used as input for the various activities. These are presented in the blue boxes.
- Final results of the various activities. These are presented in the green boxes.

The arrows indicate what the next step will be. Some steps require combining two steps or two inputs. This is indicated by the joining of arrows. Splitting of arrows indicate that input is used for more than one sequential step.

3.2.1. Fieldwork

Data collection consisted of two components: interviews with local farmers and mapping different land uses with GPS. The fieldwork was executed in cooperation with a local farmer, David Muchena, who acted as a guide and translator. Fieldwork days were alternated with office days, to make sure that the information collected was documented properly.

Interviews

Interviews were conducted in a casual way and took place at the homes of the farmers or at their agricultural fields. No appointments were made beforehand. The farmers were visited by foot or on motorbike, dependent on how accessible the houses or fields were. Site selection was based on David's knowledge of the area.
and on the availability of the farmers. It was tried to visit as many farmers as possible to provide a complete representation of the research area. The interviews made use of open questions and focused on three aspects:

1. Crop type - which types of crops is the farmer currently cultivating?
2. Timing of planting and harvesting for the currently cultivated crops - when did the farmer plant the crops and when is harvest scheduled?
3. Irrigation type - does the farmer irrigate the crops? If so, what type of irrigation is used?

**Mapping irrigated fields and other land uses**

After interviewing the farmer, his or her fields were visited and mapped with a Garmin eTrex 10 GPS in collaboration with the farmer. For most of the mapping, the function 'Area Calculation' was used. This function measures the size of an area and maps it as a polygon, which is a good way to represent the exact outline of an agricultural plot. In a couple of cases, mapping used the function 'Mark Waypoint'. In this case, a point measurement is taken. A way point is a less accurate representation of a field, because it only displays one point instead of the whole field. Therefore, most measurements used 'Area Calculation' instead of 'Mark Waypoint'. The last option was only chosen when there were problems with the batteries or the memory of the GPS, or when the direct surroundings of the field were too densely vegetated to walk around.

It was tried to measure different crops types and different fields separately, to obtain homogeneous sites. However, this was not always possible because mixing of different crop types happens quite often. For every field, mapping started with activating the Area Calculation function. Then there was walked around the perimeter of the field. Once the beginning point of mapping was reached, the Area Calculation was turned off and the track was saved. After the mapping, pictures of the field were taken and the farmer was asked about more information, which partly overlapped with the interview questions. This approach was chosen to be able to collect as much information as possible and to make sure that the information obtained during the interviews was understood correctly. Also, various field characteristics were noted, such as crop height or greenness, so that the combination of all the collected information provided a good impression of how the field looked like. An example of the collected information for three fields is provided in table 3.3. The following characteristics of the mapped field were noted:

- Crop type(s)
- Size of the field
- Planting date
- Expected harvest date
- Type of irrigation
- Approximate crop height
- Impression of overall greenness and vegetation density of the field (for example: bare, quite bare, quite green, very green)
- Information on past and future activities on the specific field
- Additional comments if applicable
- Date and time of measurement

<table>
<thead>
<tr>
<th>Information</th>
<th>Example field 1</th>
<th>Example field 2</th>
<th>Example field 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time GPS</td>
<td>10:25</td>
<td>10:38</td>
<td>11:51</td>
</tr>
<tr>
<td>Crop type</td>
<td>Chilies</td>
<td>Tomatoes</td>
<td>Onion</td>
</tr>
<tr>
<td>Planting date</td>
<td>July</td>
<td>August</td>
<td>October</td>
</tr>
<tr>
<td>Estimated harvest</td>
<td>Mid November</td>
<td>Start begin November</td>
<td>December</td>
</tr>
<tr>
<td>Type of irrigation</td>
<td>Furrow</td>
<td>Furrow</td>
<td>Furrow</td>
</tr>
<tr>
<td>Crop height estimation</td>
<td>50 cm</td>
<td>40 cm</td>
<td>1199</td>
</tr>
<tr>
<td>Size (m²)</td>
<td>400</td>
<td>1199</td>
<td>1939</td>
</tr>
<tr>
<td>Comments</td>
<td>Very green</td>
<td>Very green, mixed with maize</td>
<td>Quite bare</td>
</tr>
<tr>
<td>Past</td>
<td>Beans March till May</td>
<td>Rainfed maize, Nov 2016 till May</td>
<td>Rainfed maize, rain season 2016</td>
</tr>
<tr>
<td>Future</td>
<td>Nothing</td>
<td>Rainfed maize, rain season</td>
<td>Rainfed maize, rain season</td>
</tr>
</tbody>
</table>

Table 3.3: Example of information about three agricultural plots, collected during the mapping of irrigated fields.
3.2. Methods

The focus of mapping was on irrigated fields, but to complement the field measurements and to have additional data for training and validation, other land uses were mapped with GPS as well. Mapping took place in the same way as mapping the fields, so by walking around the outline of the areas of interest while using the Area Calculation function or by taking a waypoint. After the mapping, the type of land use, the time of the measurement and the size of the area were noted down. In addition, a picture was taken.

3.2.2. Classification

Classification is a technique that can be used to (semi-)automatically identify different land uses on a satellite image, thus to create land use maps. For this study, classification is a good way to investigate whether it is possible to map irrigated fields. A satellite image is composed of a collection of pixels. Classification categorizes all pixels in an image into land uses (Jones and Vaughan, 2010). This study uses classification based on spectral signatures. Spectral signatures are the radiation values that are reflected for a certain surface over a range of wavelengths measured by a satellite. When radiation values for a specific wavelength are considered, the measured reflected radiation is referred to as a spectral response. When spectral responses are considered over time, the measured reflected radiation is referred to as a spectral response pattern. Theoretically, different land uses have different spectral signatures and different spectral responses. Spectral classification makes use of these differences to categorize pixels into the right land uses.

**Expectations spectral response**

Regarding this study, it is expected that the spectral response of irrigated fields differs from the spectral response of other types of land uses, especially during the dry season, because the irrigated areas will consist of healthy vegetation whereas the surroundings will mostly consist of drier, less healthy vegetation or bare ground. Sentinel 2 has a lot of different bands in different wavelengths in the optical spectrum. Wavelengths that are expected to have the most useful information for this study are the red spectrum and the near infrared (NIR) spectrum, because the red spectrum absorbs chlorophyll, which is present in healthy plants, and the near infrared spectrum scatters the mesophyll leaf structure, which makes that vegetation has a high reflectance in the near infrared spectrum (Pettorelli et al., 2005). Hence, these wavelengths are sensitive to vegetation and suitable for land cover mapping (Elvidge and Chen, 1995; Hansen et al., 2003; Tucker, 1979), thus useful to map agricultural activities. Therefore, this study makes extensive use of these bands. In the dry season, irrigated crops are expected to have high values in the near infrared spectrum and low values in the red spectrum, which is an indication of healthy vegetation. Natural vegetation in the dry season is expected to have higher values in the red spectrum, which is an indication of drier, less healthy vegetation (Lillesand et al., 2014). The spectral response of irrigation will vary over the duration of an agricultural season, because the irrigated crops will go through different growing phases, whereas spectral responses for other land uses probably remain the same or steadily increase or decrease. Hence, different land uses will show different spectral response patterns during the dry season. Vegetation will get drier towards the end of the dry season, which might result in a steady increase in the reflected radiation in the red spectrum for the last months of the dry season, where irrigated fields do not get drier and stay covered with green and healthy vegetation, thus show a different spectral response pattern.

**Normalized Difference Vegetation Index**

Examination of the Normalized Difference Vegetation Index (NDVI) might be suitable for this study. This is a widely used vegetation index for quantifying green vegetation and has been proved to be a useful indicator to obtain crop information (Consoli et al., 2006; Inman et al., 2008). The NDVI uses the red and near infrared bands:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

NDVI values range from -1 to +1. Negative values correspond to water. Values around 0 correspond to bare ground, rocks and sand. For vegetation, the values increase in proportion to the density of the vegetation and the greeness. For example, forests have a higher NDVI than grasslands. The NDVI might be useful to analyze irrigated fields, because for an irrigated field it is expected that the NDVI during planting has a low value, because the plot is bare, and that it will gradually increase during the growing cycle, because crops will start to grow and the plot will get greener.
Maximum Likelihood Classification

The spectral responses of land uses in the research areas are examined with classification. This is performed by a supervised maximum likelihood classification algorithm. Supervised means that there is already a part of the satellite image defined with training samples of which the land use is known. For this study, the GPS measurements that were collected during fieldwork serve as training samples. The training samples are divided into different classes, training sets, that each represent a certain kind of land use. Maximum Likelihood Classification determines the spectral signatures of different land uses based on the spectral values of the different training sets. It consists of two main parts:

1. Determine the spectral signatures of the training sets
2. Classify each pixel by comparing its value in different bands of the satellite imagery to the spectral signatures

Maximum Likelihood classifications assumes that the statistics for each land use class are normally distributed and assigns pixels to a land use class that is most likely, based on equiprobability contours around the statistical means of land use classes (Lavender and Lavender, 2015). Figure 3.2 provides an example of how these equiprobability contours for different land use classes look like.

The Maximum Likelihood classification algorithm considers the statistical mean, variance and covariance of these spectral signatures. Due to this statistical basis, it is regarded as an accurate classifier (Shalaby and Tateishi, 2007). In addition, it is simple and straightforward in use and has short calculation times (Nitze et al., 2012). It is therefore an efficient way to discover which possibilities there are for land use classification regarding farmer-led irrigated agriculture.

Accuracy assessment

The accuracy is examined by means of calculating the kappa index \( \kappa \). This is an assessment of how well the classification agrees to a given set of reference data that represents reality. The \( \kappa \) index compares the observed accuracy against the probability that classification is correct by chance:

\[
\kappa = \frac{\text{observed agreement} - \text{expected agreement}}{1 - \text{expected agreement}}
\]
Values generally range from 0 to 1, where 0 means that classification is not better than a random assignment of pixels and 1 means that classification is perfect, thus a \( \kappa \) closer to 1 means a better classification performance. Negative values mean that classification is very poor (Congalton and Green, 2008; Lillesand et al., 2014). For this study, 20 percent of the ground data collected for fieldwork is used as reference data for accuracy assessment. This 20 percent is excluded from the training data for classification, so that the accuracy assessment is unbiased.

**Spectral response analysis**

Analysis of spectral responses can provide more insight in the usability of optical satellite imagery to identify irrigated fields. For example, the spectral signatures created in the first step of Maximum Likelihood Classification can be used to construct spectral response patterns per training sample, in which the spectral pattern of land uses over time is presented. Another possibility for examining the spectral responses of land uses is to derive spectral responses for each training sample by combining S2 images with the training map. This can be used to analyze spectral responses on field level by creating scatter plots, in which the spectral response of each training sample is plotted for different wavelengths. Scatter plots can give insight in the spectral variability of training sets. Theoretically, training samples that belong to the same land use will cluster together. In addition, spectral response patterns for individual fields can be analyzed, to see if these patterns match the information about agricultural practices.

### 3.2.3. Images and bands

Various classifications were undertaken, with different band combinations and different images. Only optical satellite imagery from Sentinel 2 is used in this stage, because of the high spatial resolution. The classifications can be divided in two categories: intermediate classifications (IM) and follow-up classifications (F). Intermediate classifications were performed during the period of fieldwork in Mozambique. In this way, it gave some insight in possible problems that might arise with classification and provided the possibility to check the outcomes. Follow-up classifications were performed after the fieldwork period in Mozambique. In table 3.4, an overview of the different classifications and inputs is presented.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Images</th>
<th>Bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>IM-VIS-A</td>
<td>26-9-2017</td>
<td>2, 3, 4, 8</td>
</tr>
<tr>
<td>IM-VIS-B</td>
<td>1-10-2016 8-6-2017 17-8-2017 26-9-2017</td>
<td>2, 3, 4, 8</td>
</tr>
<tr>
<td>IM-VIS-C</td>
<td>1-10-2016 8-6-2017 17-8-2017 26-9-2017</td>
<td>2, 3, 4, 8</td>
</tr>
<tr>
<td>F-VIS-IS1</td>
<td>8-6-2017 28-6-2017 13-7-2017 23-7-2017</td>
<td>2, 3, 4, 8</td>
</tr>
<tr>
<td>F-IR-IS1</td>
<td>8-6-2017 28-6-2017 13-7-2017 23-7-2017</td>
<td>4, 8, 11, 12</td>
</tr>
<tr>
<td>F-RE-IS1</td>
<td>8-6-2017 28-6-2017 13-7-2017 23-7-2017</td>
<td>4, 5, 6, 7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>8, 8A, 11, 12</td>
</tr>
</tbody>
</table>

Table 3.4: This table shows the different stages of classifications and the Sentinel 2 images and bands that are used as input. There are two stages of classifications: IM and F. IM-classifications are intermediate classifications that were performed in Mozambique and F-classifications are follow-up classifications that were performed after Mozambique. VIS, IR and RE indicate different band combinations. VIS consists of bands in the visible and near infrared spectrum. IR consists of bands in the red, near infrared and shortwave infrared spectrum. RE consists of bands in the red, near infrared, shortwave infrared and red edge spectrum. A, B and C are meant to distinguish the different intermediate classifications based on input and training data. IS1 indicates the first irrigation season, IS2 indicates the second irrigation season.

The S2 images that are used are selected based on timing and on cloud cover. To minimize errors, it is aimed to use only images that were mostly free of clouds. Concerning timing, only imagery that is acquired during the irrigation seasons IS1 and IS2 is used as input. This is chosen for multiple reasons. Logically, irrigation is mostly present during these seasons, so these images are the best change of providing information regarding irrigation practices. In the wet season, irrigation can take place, but this is mostly not on regular basis. Furthermore, there is less chance on cloud cover in the irrigation seasons because the weather is generally more
3. Data and Methods

clear, so there are more high quality images available. Lastly, the biggest difference between irrigated fields and other land uses will be during the irrigation season, as natural vegetation will be drier whereas irrigated fields are still green and healthy, as explained before. In the wet season, the whole area will be green and healthy vegetation is able to grow everywhere, so it will probably be hard to distinguish agricultural plots.

To give an idea of how the area looks on satellite data, an overview of bands in the red and near infrared spectrum is presented in figure 3.3. This figure shows images acquired on three dates: 13 July 2017, 26 September 2017 and 26 October 2017. The figure shows the Bottom-of-Atmosphere reflectance values. For the pictures measured in the red spectrum, the ridge in the east is clearly visible as a dark area with low reflectance. This indicates that vegetation on the ridge is healthy. A couple of small clouds can be detected for the image of 13 July. There are also visible differences between the three images in the red spectrum. The longer into the dry season, the higher the overall reflectance in the red spectrum gets. This increase in reflectance in the red spectrum indicates that the vegetation in the area gets drier and less healthy in September and October, towards the end of the dry season. The pictures in the near infrared spectrum show a similar tendency, although it is a bit harder to see. In addition, the bands in the near infrared spectrum show higher reflectances for the ridge and around the streams, which indicates healthy vegetation.

Figure 3.3: Example of Sentinel 2 images acquired on 13 July 2017, 26 September 2017 and 26 October 2017. Bands in the red and near infrared spectrum are showed for the study area to give an overview of how the area looks on satellite imagery.
3.2. Methods

Bands for intermediate classifications (IM)
There are three intermediate classifications performed: IM-VIS-A, IM-VIS-B and IM-VIS-C. A combination of four Sentinel 2 bands is used. This combination is referred to as VIS because it uses bands in the visible spectrum: band 2 (blue spectrum), band 3 (green spectrum) and band 4 (red spectrum). In addition, band 8 (near infrared spectrum) is used. These bands are selected because they all have a high spatial resolution of 10 meter. The three classifications use different combinations of Sentinel 2 images acquired on 1 October 2016, 8 June 2017, 18 August 2017 and 26 September 2017, as presented in table 3.4. The images that are used as input comprise a year and were all taken within the irrigation season.

Bands for follow-up classifications (F)
There are six follow-up classifications performed: F-VIS-IS1, F-VIS-IS2, F-IR-IS1, F-IR-IS2, F-RE-IS1 and F-RE-IS2. In order to perform these classifications, three different combinations of bands are created:

1. Visible (VIS): visible and near-infrared bands
2. Infrared (IR): red, near-infrared and shortwave infrared bands
3. Red edge (RE): red, near-infrared, shortwave infrared and red-edge bands

In addition, there is a distinction made based on agricultural seasons, so irrigation season 1 (IS1) and irrigation season 2 (IS2) are classified separately. The shorter time windows are chosen to better grasp the fast-changing dynamics of the agricultural activities and to reflect the growing cycles of irrigated crops more accurate. These cycles mostly comprise about three months. By looking at time windows of a couple of months, the different growing stages of irrigated crops will possibly be better captured by classification. The classifications for IS1 have been performed with less Sentinel 2 images than the classifications for IS2 and the images used do not cover the whole irrigation season, but only the second half. This was due to heavy cloud cover during the first half of IS1, so there was no suitable satellite imagery.

3.2.4. Training maps
Three different training maps were created for the different classifications. In figure 3.4 the different training maps are visualized. In table 3.5 an overview of the training data in terms of amount and different classes is provided.

Figure 3.4: Overview of the three training maps that were used for the different classifications. IM-VIS-classifications indicate intermediate classifications, performed in Mozambique. F-classifications indicate follow-up classifications, performed after Mozambique. Training data differ because new training samples were added during and after the intermediate classifications.
Table 3.5: Overview of the amount of training samples that were used for the different classifications. IM-VIS-classifications indicate intermediate classifications, performed in Mozambique. F-classifications indicate follow-up classifications, performed after Mozambique. The amount of training data differs because new training samples were added during and after the intermediate classifications. Also, there is a difference in land use classes between IM and F classifications.

<table>
<thead>
<tr>
<th>Land use class</th>
<th>IM-VIS-A and IM-VIS-B</th>
<th>IM-VIS-C</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irrigated fields</td>
<td>12</td>
<td>30</td>
<td>142</td>
</tr>
<tr>
<td>Non-irrigated fields</td>
<td>6</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Light seasonal vegetation</td>
<td>10</td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td>Dense evergreen vegetation</td>
<td>10</td>
<td>12</td>
<td>25</td>
</tr>
<tr>
<td>Houses</td>
<td>10</td>
<td>16</td>
<td>32</td>
</tr>
<tr>
<td>Bare ground and rocks</td>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>58</td>
<td>88</td>
<td>219</td>
</tr>
</tbody>
</table>

3. Data and Methods

**Training data for intermediate classifications (IM)**
The training data for intermediate classifications were collected in Godi and Chirodzo catchments. Training samples in six classes are created: irrigated fields, non-irrigated agricultural fields, dense evergreen vegetation, light seasonal vegetation, houses and rocks/bare ground. These classes are based on the land uses and measurements as determined during the fieldwork.

**Training data for follow-up classifications (F)**
There are a couple of differences between the intermediate and follow-up classifications. Firstly, the follow-up classifications comprise a bigger area, to include additional ground data that were collected in Ruaca catchment during the last weeks in Mozambique. Also, the follow-up classifications use training sets in four different classes instead of six: irrigated fields, light seasonal vegetation, dense evergreen vegetation and bare ground/houses/rocks, to narrow the classification a bit more to the interest of this study. Non-irrigated fields are taken out because the follow-up classifications focuses on irrigation seasons, in which non-irrigated agriculture is not of a large significance. The land use class 'rocks and bare ground' is merged with the land use class 'houses' because these land uses are quite similar in spectral response. In addition, there is more training data used for the follow-up classifications and the ground data collected during fieldwork is randomly divided in a group with 80 percent of the data and a group with 20 percent of the data, to ensure input for both training the classification algorithm and evaluating its accuracy.

3.2.5. Verification visits
A preliminary form of verification was performed during fieldwork, to check the results of intermediate classifications and to obtain more insight in the performance of the classifications. Various sites within Godi and Chirodzo catchments were selected. In figure 3.5 the locations of these sites are presented.

Selection was based on the results of the classifications IM-VIS-B and IM-VIS-C. These visits focused on sites that were classified as irrigated areas, that displayed notable differences between the two classification attempts, that were very mixed with lots of individual pixels or that gave wrong or odd results. The sites were visited with GPS. For each site visited, it was noted down which land uses were encountered and how the area looked like. In addition, a picture was taken.
3.2. Methods

3.2.6. Additional analysis

To complement optical remote sensing land use classification and to improve its results, additional features are analyzed. Ancillary data can help to increase classification accuracy (Dorren et al., 2003; Eiumnoh and Shrestha, 2000), for example by serving as additional criteria applied to the maximum likelihood classifier. Also, the analysis of additional features gives more insight in dynamics and processes in the study area.

Terrain analysis

Terrain analysis is performed for the research area. This analysis uses a Height Above Nearest Drainage (HAND) raster. This raster indicates the vertical distance of each point in the research area to the closest drainage. To compute HAND, the methodology of Liu et al. (2016) is applied in combination with TauDEM (Tarboton, 2005), a set of tools that can be used to perform hydrological analyses based on topography. Input for the terrain analysis is a digital elevation model acquired with the Shuttle Radar Topography Mission. The methodology is presented in figure 3.6.

First, the digital elevation model is clipped to the research area. Then stream delineation is performed. The elevation model is corrected by removing pits, which are generally artifacts in the model that may faulty influence the watershed delineation. Then the flow direction and contributing area are determined by TauDEM. This is used as input to delineate the stream network. Together with the pit-filled elevation model and the flow direction, this stream network serves as input for determination of HAND, which is calculated with a vertical distance measure as a function of TauDEM. This HAND raster is then combined with a training map with ground data for statistical analysis. First the HAND values for the training samples are determined. Then these values are compared to each other to see what information HAND can give regarding irrigated fields.
Comparison of these values is performed with looking at basic statistics such as the mean and the standard deviation. Also, the Kolmogorov-Smirnov test is applied. This is a statistical test that examines whether two data sets are drawn from the same distribution by testing the null hypothesis, that assumes that data sets belong to the same distribution (Razali et al., 2011). If the null hypothesis cannot be rejected, then the sets are drawn from the same distribution and it is not possible to differentiate between the sets. First, the cumulative distribution function of the HAND values for each training set is constructed. Then, the Kolmogorov-Smirnov test is applied on these distributions. This test is based on three parameters:

- $D =$ the maximum vertical distance between two different cumulative distribution functions. The smaller $D$ is, the more likely that two training sets were drawn from the same distribution.
- $p-value =$ quantification of evidence against the null hypothesis. The higher the $p-value$, the less significantly different the two data sets are.
- $\alpha =$ level of significance, that indicates the probability of falsely rejecting the null hypothesis. This is set at 0.05, a common significance value (Craparo, 2007)

These parameters are calculated for the different training sets. To determine whether the null hypothesis can be rejected, the $p-value$ is compared to $\alpha$. If $p-value > \alpha$ it is not possible to reject the null hypothesis. In this case, the two data sets that were tested are drawn from the same distribution and it is not possible to differentiate between the sets.

**Distances to streams and canals**

Water for irrigation is diverted from small streams that originate at the ridge in the east of the research area. The closer the irrigated plots are to the streams, the easier irrigation can take place, because the water does not have to be transported over long distances and there is less chance that leakages or other water abstractions occur. Therefore, distances to streams might be an indicator for irrigation. To examine this, the horizontal distances of irrigated fields to the nearest drainage are analyzed. The methodology that is used for this analysis is presented in figure 3.7.
3.2. Methods

Figure 3.7: Methodology that is used to examine whether distances to streams can be useful to obtain extra information about irrigated fields.

The start of the methodology is similar to the methodology applied for HAND. Stream delineation is performed for the research area, after which the horizontal distance to the nearest stream is determined. This is combined with ground data to determine distances to streams for the training data. However, the presence of numerous irrigation canals increases the reach of the streams. Therefore, the locations of irrigation canals have to be taken into account as well. In figure 3.8, an overview of irrigation canals for the research area is presented. Canal data for Ruaca, Godi and Chirodzo catchment was measured by Resilience BV. Canals in Chirodzo and Ruaca were mapped in 2011 and canals in Godi in 2016, so this information is not completely accurate and up to date, but it provides a good impression. The reach of the canals is determined and compared to the distances to streams, to give more insight in whether distances to streams can provide useful information about irrigated fields and other land uses.

Figure 3.8: Map of the research area with the locations of different irrigation canals.
Thermal remote sensing

In theory, the presence of irrigated areas can also be examined with thermal remote sensing. Thermal remote sensing measures land surface temperature, which depends on actual evapotranspiration, and is suited for agricultural studies (Bastiaanssen et al., 2000). Irrigation leads to cooler soil, higher evapotranspiration values and a lower sensible heat flux, so technically land surface temperatures should be lower for irrigated plots in the research area. To examine whether this holds, land surface temperature (LST) values for the ground data obtained with fieldwork are analyzed. The methodology for this analysis is showed in figure 3.9.

Three images of Landsat 8 are used in this analysis. The images are acquired on 3 June 2017, 22 August 2017 and 23 September 2017, all during irrigation seasons. Only thermal band 10 of Landsat is used, according to recommendations of Gerace and Montanaro (2017). Atmospheric correction with the Semi-Automatic Classification Plug-in is applied to obtain the at-satellite brightness temperature $T_B$ and the images are clipped to the research areas. $T_B$ is then used to calculate the land surface temperature according to the method of Weng et al. (2004) with the following equation:

\[
\text{Land surface temperature} = \frac{T_B}{[1 + (\frac{\lambda}{T_B} \cdot \frac{h}{c}) \cdot \ln(\epsilon)]}
\]

- $T_B$: the at-satellite brightness temperature
- $\lambda$: the central wavelength of Landsat 8 band 10, which is 10.8 $\mu$m as presented in table 3.2
- $h$: Planck’s constant = $6.626 \times 10^{-34}$ J s
- $c$: velocity of light = $2.998 \times 10^8$ m/s
- $s$: Boltzmann constant = $1.38 \times 10^{-23}$ J/K
- $\epsilon$: emissivity of land surface = 0.96, based on research by Mallick et al. (2012)

Land surface temperature values for the three Landsat images are combined with ground data to obtain the land surface temperature values for training samples. Those values are then statistically analyzed, again with basic statistics and the KS-test, to see if thermal remote sensing can provide useful information about irrigated fields.
4.1. Ground data
In total, 58 farmers in Godi, Ruaca and Chirodzo catchment were interviewed and over 300 sites were visited and mapped. A map with an overview of the measurements is presented in figure 4.1.

Figure 4.1: Overview of the sites mapped during fieldwork. 58 farmers were visited and over 300 sites were mapped. The sites are divided in the following land uses: irrigated fields, light seasonal vegetation, non-irrigated fields, dense evergreen vegetation, rocks/bare ground and houses. The streams and outlines of the three research catchments are displayed as well.
The main land uses that were encountered are irrigated agricultural fields, non-irrigated agricultural fields, light seasonal vegetation, dense evergreen vegetation, rocks/bare ground and houses/roads, of which agricultural land cover types and light vegetation are dominant in the research area.

**Irrigated fields**
Irrigated agricultural fields are generally small, about 0.2 hectare on average. They are unevenly distributed over the area, dependent on the location of small streams, ownership of the ground and natural characteristics. In most cases, the plots are found together in small groups throughout the region, clustered around an irrigation canal. By far the largest part of irrigation is performed with furrow canals. During the first irrigation season, IS1, there are more irrigated plots than for the second irrigation season, IS2. In the wet rain season, WS, irrigation may take place in case of long periods without rain, but this does not happen regularly. A variety of crops is cultivated. Irrigated crops consists mostly of tomatoes, beans, onions, cabbage and chilies. The largest part of the crops is sold at local markets or to traders, who distribute the crops throughout the country. In some cases the farmers separate the crops they are cultivating per fields, so they have individual fields with for example only tomatoes or only beans. However, subsistence crops such as maize or pumpkin are often mixed on these fields as well. Also, different crops are located very close to each other due to the small scale of the fields, so mixing of the crops happens often. In figures 4.2a and 4.2b, examples of irrigated crops and mixing of different crops are showed.

![Irrigated field with tomatoes](image1.png) ![Irrigated field with cabbage and maize](image2.png)

Figure 4.2: Examples of irrigated fields with various crops. The left picture shows a field with tomatoes as the only crop on the field. The right picture presents an irrigated field on which a mix of cabbage and maize is cultivated.

**Non-irrigated fields**
Non-irrigated fields mostly consist of maize and in a smaller quantity sorghum, although in dry times maize is sometimes irrigated as well. Many fields for non-irrigated crops emerge in the rain season. During these months, a large part of the areas is covered with maize. The location of these fields is not restricted by the presence of rivers or irrigation canals. In the dry season, these areas often become overgrown with natural vegetation, although there is still a number of plots on which non-irrigated crops are cultivated. In figures 4.3a and 4.3b, a future maize field and a maize field that is currently used are showed.

**Light seasonal vegetation**
Light seasonal vegetation mostly consists of shrubs, grasses and small bushes. An example of light seasonal vegetation is presented in figure 4.4a. Light seasonal vegetation is abundantly present right after the rain season, when the whole area is green and vegetation is thriving. Over the dry months, light vegetation gets drier and less green, but it is still present and it is quite a dominant land cover type in the research area. Sometimes sites with light seasonal vegetation get partly cleared for cultivation, so a mix of natural vegetation and crops is possible, as is showed in figure 4.4b.
4.1. Ground data

(a) Future maize field

(b) Current maize field

Figure 4.3: The picture on the left shows a site that will be used for the cultivation of non-irrigated maize during the rain season. The picture on the right shows a non-irrigated plot where maize is already cultivated.

(a) Light seasonal vegetation

(b) Mix between light vegetation and tomatoes

Figure 4.4: The picture on the left shows an example of light seasonal vegetation. Often this consists of grasses, small bushes and shrubs. The picture on the right shows a site where mixing of light vegetation with irrigated crops happened. Tomato plants are mixed with small shrubs.

Dense evergreen vegetation

Dense evergreen vegetation in the research area is mostly present at the ridge in the east of the catchments, where the streams originate. This ridge is covered with large trees and bushes. Other sites with dense evergreen vegetation are found along the stream network and in small groups distributed over the whole research area. In figures 4.5a and 4.5b examples of dense evergreen vegetation are presented.

Houses and roads

In the three research catchments, there are no large villages, but most houses are clustered together in small groups. An example is showed in figure 4.6a. Those groups are distributed over the whole research area and vary in size from about 100 m² to 1000 m². In total, they do not make up a big part of the area. There are no paved roads in the area, so transportation takes place on dirt roads, of which many are not accessible by car. In figure 4.6b an example of dirt roads is presented.

Rocks and bare ground

This land use does not comprise a big part of the research area; there are just a couple of sites that are permanently bare or covered with rocks. Most of them are not very big and they are found on and nearby the ridge and in the north of the study area. An example of rocks is presented in figure 4.7.
4. Results

(a) Dense evergreen vegetation

Figure 4.5: Examples of dense evergreen vegetation. The picture on the left shows a group of large trees. The picture on the right shows dense vegetation on the ridge in the background.

(b) Dense vegetation on the ridge

(a) Small houses in Ruaca

Figure 4.6: Examples of houses and roads in the research area. The picture on the left shows a couple of houses grouped together in Ruaca catchment. The picture on the right shows two dirt roads in Godi catchment.

(b) Roads

(a) Rocks in Godi

Figure 4.7: Example of rocks in the research area

(b) Rocks in Chirodzo

Heterogeneity of the study area

The area is very mixed and heterogeneous. It is a dynamic region, where land use changes happen frequently and agricultural practices are quite flexible. There is not always a clear distinction between irrigated and non-irrigated fields. Most fields with irrigated crops become fields for non-irrigated crops in the rain season. In
addition, many fields for non-irrigated crops emerge during the rain season. Furthermore, there is a kind of rotation system for field use. Almost all the land in the three catchments belongs to someone, but not everything is used for cultivation at the same time. Most farmers do not grow crops on all the land they own, but they use a part of their land and rotate their cultivated plots between agricultural seasons. This makes the spatial occupation of the land quite flexible. In addition, the timing of agricultural practices differs a lot, thus the division in different agricultural seasons is not a strict separation. Not all the crops that are cultivated will be in the same growing phase at the same time, even if they are planted at the same field. Mixing of crops on the same field happens quite often. Lastly, farmers change the type of crop they are growing on a certain field between agricultural seasons. If the same field is used for two seasons in a row, a different crop will be cultivated.

The main aim of fieldwork was to collect ground data for irrigated fields, so data collection was centered around this land use. Therefore, the largest part of the data consists of irrigated field measurements and most of the other ground data was collected nearby irrigated fields instead of randomly selected over the study area. To mitigate this, part of the samples for other land uses were collected during walks in the study area, where they were not located particularly close to irrigated areas. Unfortunately, it was not always possible to visit desired or selected areas, due to constraints concerning weather, transport or topography. Another side note concerning the ground data is the fact that these data largely reflect the situation in the second irrigation season, because this was when the fieldwork took place. However, it is possible that a couple of months later or earlier the situation is quite different, since it is a dynamic region, so the irrigated fields mapped for this study are not necessarily always irrigated fields. Some kind of both historical and future mapping was tried to integrate in the fieldwork, to obtain information for a longer period than just October till December, but mostly, this information was vague or contradicting. For example, it was not always clear what the exact location was of former irrigated plots, which crops were cultivated and when exactly agricultural practices took place. Therefore, it was decided to not incorporate it in this study. Information about the current situation was sometimes unclear as well, due to language and interpretation problems. In addition, the use of GPS also introduced some uncertainties, especially when the mapping of land uses was performed by taking waypoints instead of polygons. This appeared to introduce displacements in location in some minor cases, which resulted in erroneous coordinates of waypoints. When the reliability of information or the accuracy of the measurements was doubted, the data were excluded from the research.

4.2. Classification

4.2.1. Overview

In figure 4.8, the classification results are displayed for the intermediate classifications. In figure 4.9 the follow-up classifications are presented. A more clear visual overview of each classification is provided in appendix A.

**IM-VIS-A**

In this classification result, the dominant land use is a mix between light seasonal vegetation and non-irrigated agricultural land. Considering the satellite image that is used as input, acquired at 26 September 2017, this is odd, because this is during the dry season, in which non-irrigated agriculture is not present in such large quantities. In reality, part of this will probably be light seasonal vegetation. Irrigated areas are primarily located at the slopes of the ridge in the east, where the sources of the natural streams are. This is partly corresponding to the real situation. Upstream in the catchments is often enough water available for irrigation, so this a favorable position for irrigated plots. More downstream, there is hardly irrigation classified. This does not correspond to the real situation; although mid- and downstream irrigation can be constrained by water availability, there are still several irrigated plots. Dense evergreen vegetation is primarily classified on the ridge, which matches the real situation. There are also some larger rocky areas classified throughout the area. This does not correspond to the real situation. There are some small rocks in the area, but not this many big rocks.

**IM-VIS-B**

In this classification result, there is hardly any non-irrigated agriculture and way more light vegetation. Although the time series of satellite images comprises a year and non-irrigated area is quite dominant at certain times, the images that were used for classification are all acquired during the first or second irrigation sea-
son, when there is little cultivation of non-irrigated crops, so this might explain the absence of non-irrigated fields. The dominance of light seasonal vegetation is quite realistic, although it seems a bit overclassified downstream at the expense of agricultural land use. Classified irrigation is mostly found at the steeper slopes of the ridge, but also a bit more downstream. These classified locations both match with the real situation. However, it seems that there is too much irrigation nearby the ridge, and too little more downstream. In addition, it seems that dense vegetation along the stream is misclassified as irrigation. There are also a lot of rocks and houses classified throughout the area, which both add up to too big areas to correspond to reality. Dense vegetation is classified on the ridge, but also in some spots distributed over the area. This matches the real situation.

**IM-VIS-C**

This classification result is notably different from IM-VIS-B, while the input imagery is the same. This shows that the applied classifications do not provide consistent information. In this classification result, it stands out that a lot of the area is classified as houses. Since there are no large areas with only houses, because houses in the study catchments are small and distributed throughout the region, this is not correct. Also, a lot of non-irrigated fields are present, which seems quite odd due to the fact that only images acquired during irrigation seasons are used as input for classification, so there will be not a lot of non-irrigated agriculture in reality. Irrigated areas are classified throughout the whole area, which is quite realistic, although it seems there is too much irrigation classified upstream and too little downstream. The classification of dense evergreen vegetation, mainly on the ridge and some small spots throughout the area, seems quite reasonable. The light vegetation classification corresponds to reality as well. Lastly, there are not much rocks classified, which also matches the real situation.
4.2. Classification

Figure 4.9: Follow-up classifications. The VIS combinations use S2 bands in the visible and near infrared spectrum. The IR combinations use S2 bands in the red, near infrared and shortwave infrared spectrum. The RE combinations use S2 bands in the red, near infrared, shortwave infrared and red edge spectrum. IS1 indicates the first irrigation season and uses S2 images acquired in June and July. IS2 indicates the second irrigation season and uses S2 images acquired in August, September, October and November.

**F-VIS-IS1**
In this classification result, light seasonal vegetation is very dominant throughout the whole area. This seems realistic, although the amount is perhaps a bit overestimated by the classification at the expense of agricultural land use. The classified dense vegetation, mostly present at the ridge in the east but also in some smaller quantities throughout the area, corresponds to reality as well, both in terms of location and in quantity. Irrigated areas seem to match the locations of the measured irrigated fields in a couple of cases, but are also sometimes misclassified. The area that is covered by irrigated fields seems realistic. Concerning the classification of rocks, bare ground and houses, it seems that this classified area is too big in some cases, taking into account the fact that this land use is very dispersed over the whole area and appears in small sizes, so this is not very realistic.

**F-VIS-IS2**
This classification result shows a large amount of classified irrigated areas, which is too big to reflect reality, and an increase in irrigation with respect to F-VIS-IS1. This increase is odd, because F-VIS-IS2 is constructed with satellite images acquired during IS2, the second irrigation season. This is longer after the rain season and the area is drier than for IS1, the first irrigation season. Therefore, in reality there is less irrigation in IS2 than in IS1. This overestimation of irrigated areas is at the expense of the classification of light seasonal vegetation, which seems to be too low in this case. Dense vegetation is classified at the eastern ridge, which is realistic, and in small groups throughout the catchment, corresponding to the real situation quite well. Concerning the classification of rocks, bare ground and houses, it seems that the total classified area is too large, just like with F-VIS-IS1.

**F-IR-IS1**
For this classification, light seasonal vegetation is dominant. The locations and the size of the areas covered by this land use seem to reflect reality quite well. Also, the irrigation areas seem to be in the right direction and amount, but the location is not always correct and there are some misclassifications. The classified dense vegetation, mostly present at the ridge but also in some smaller quantities throughout the area, matches the real situation quite good. Rocks, bare ground and houses show the same tendency as with F-VIS-IS1.
This classification also shows too much irrigated fields, especially for Ruaca catchment in the north. Again, it is striking that there is a big increase in irrigated areas with respect to the F-IR-IS1 classification, which does not correspond to the real situation. In addition, it seems that dense vegetation is a bit overestimated by the classification. Light seasonal vegetation appears to reflect the real situation, although it suffers from the overestimation of irrigation and is therefore underestimated. Rocks, bare ground and houses seem to reflect the real situation in a more realistic way, although there are some misclassifications.

F-RE-IS1
This classification result shows largely the same tendency as the other band combinations for IS1, the first irrigation season. Dense vegetation seems to be classified corresponding to the real situation. The size of the areas that are classified as rocks, bare ground and houses seem in most cases a bit too big and to appear too often. Irrigated areas seem to be a bit overestimated and misclassified in some cases, but also matches reality in other cases. Light seasonal vegetation appears to reflect the real situation.

F-RE-IS2
This classification result shows a large amount of classified areas again, which appears way too big to reflect the real situation, and an increase of irrigated areas with respect to F-RE-IS1, which is not correct. This large overestimation of irrigated areas results in a too small amount of classified light seasonal vegetation. In some spots there is a bit overestimation of dense vegetation, but in most cases the classified dense evergreen vegetation reflects reality quite well. The same accounts to the classified rocks, bare ground and houses.

The results of the three intermediate classifications show considerable differences. Even when the same satellite imagery is used, which is the case for IM-VIS-B and IM-VIS-C, the classifications vary notably. In addition, the location of some irrigated areas changes per classification. The results of the follow-up classifications are not very consistent as well. When the two agricultural seasons, IS1 and IS2, are compared for the same combinations of bands, the locations of the classified irrigated areas show inconsistency. This is also the case for different band combinations in the same season. Especially the distinction between light seasonal vegetation and irrigated fields seems to cause problems. Furthermore, the classification results do not always match the fieldwork observations. Striking is that the total area of classified irrigation is way bigger for IS2 than for IS1. Clearly, the classification methodology that is applied here does not provide consistent and reliable information.

### 4.2.2. Area calculation

To analyze the results quantitatively, the area of total classified irrigation is calculated. The results are showed in table 4.1. As explained in chapter 3, the research area for the follow-up classifications is larger than the research area than for the intermediate classifications, because the follow-up classifications include extra ground data that were collected during the last weeks of fieldwork, after the intermediate classifications.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Classified irrigated area (ha)</th>
<th>Whole area (ha)</th>
<th>Irrigated (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IM-VIS-A</td>
<td>334</td>
<td>3105</td>
<td>11</td>
</tr>
<tr>
<td>IM-VIS-B</td>
<td>337</td>
<td>3105</td>
<td>11</td>
</tr>
<tr>
<td>IM-VIS-C</td>
<td>3995</td>
<td>3105</td>
<td>13</td>
</tr>
<tr>
<td>F-VIS-IS1</td>
<td>382</td>
<td>4800</td>
<td>8</td>
</tr>
<tr>
<td>F-VIS-IS2</td>
<td>1297</td>
<td>4800</td>
<td>27</td>
</tr>
<tr>
<td>F-IR-IS1</td>
<td>448</td>
<td>4800</td>
<td>9</td>
</tr>
<tr>
<td>F-IR-IS2</td>
<td>1233</td>
<td>4800</td>
<td>26</td>
</tr>
<tr>
<td>F-RE-IS1</td>
<td>712</td>
<td>4800</td>
<td>15</td>
</tr>
<tr>
<td>F-RE-IS2</td>
<td>1577</td>
<td>4800</td>
<td>33</td>
</tr>
</tbody>
</table>

Table 4.1: Absolute and relative area size of the classified irrigated fields for each classification

For every intermediate classification, the total area of irrigation is around 11 to 13 percent of the whole area, which seems reasonable. For the follow-up classifications, the total area of irrigation differs per type of classification. There is a difference between band combinations and between seasons. Regarding band combi-
nations, it is found that the RE-combination results in the largest values. IR and VIS are in the same range and give values that seem more realistic than the RE combination. Regarding seasons, it is found that in IS1 the irrigated fields comprise about 8 to 15 percent of the total area. This seems quite reasonable. For IS2 however, the irrigated areas comprise a quarter to even a third of the total research area, which is too high to be realistic.

4.2.3. Accuracy assessment

To give an objective estimate of the performance of classification, an accuracy assessment is performed for each classification by calculating the kappa index $\kappa$, to examine how well the classification agrees to the ground data that were split from the training samples for validation. In table 4.2 the results of the accuracy assessment are presented. $\kappa$ is calculated for the classification accuracy of irrigated fields with respect to the classification of the other land uses and for the overall accuracy of the whole classification.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Kappa irrigated fields</th>
<th>Kappa overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>IM-VIS-A</td>
<td>0.25</td>
<td>0.33</td>
</tr>
<tr>
<td>IM-VIS-B</td>
<td>0.38</td>
<td>0.42</td>
</tr>
<tr>
<td>IM-VIS-C</td>
<td>0.59</td>
<td>0.56</td>
</tr>
<tr>
<td>F-VIS-IS1</td>
<td>0.75</td>
<td>0.62</td>
</tr>
<tr>
<td>F-VIS-IS2</td>
<td>0.89</td>
<td>0.85</td>
</tr>
<tr>
<td>F-IR-IS1</td>
<td>0.60</td>
<td>0.59</td>
</tr>
<tr>
<td>F-IR-IS2</td>
<td>0.78</td>
<td>0.80</td>
</tr>
<tr>
<td>F-RE-IS1</td>
<td>0.56</td>
<td>0.60</td>
</tr>
<tr>
<td>F-RE-IS2</td>
<td>0.65</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Table 4.2: Accuracy assessment with $\kappa$ values for irrigated fields and total classification

Section 3.2.2 explains that a higher $\kappa$ means a better performance of the classification, since the value 1 indicates a flawless classification. As is showed in table 4.2, the intermediate classifications have low $\kappa$ values and thus perform not very well. Especially IM-VIS-A has low values for both performance on irrigated fields and overall performance. The addition of extra Sentinel 2 images for IM-VIS-B and IM-VIS-C increases the accuracy, just like the use of extra training data for IM-VIS-C compared to IM-VIS-B. However, values are still quite low. For most follow-up classifications, the $\kappa$ values are higher than for the intermediate classifications, which indicates a better performance of the series of follow-up classifications. Particularly the VIS-combinations perform very well, especially for the irrigated areas. The RE-combinations have the lowest accuracy. Also, the classifications of IS2 results in higher $\kappa$ values than those of IS1.

According to the accuracy assessments, the follow-up classifications perform quite good, especially F-VIS-IS2. However, these good results do not correspond to the findings of the visual analysis and the area calculation. This inconsistency might be partly caused by the training data. There is an imbalance in training data, because fieldwork was focused on irrigated areas, hence there is a large number of training samples for irrigated fields and less training samples for other land uses. Furthermore, the chosen time frames influence the results as well. For the intermediate classifications, a possibility that might cause the inconsistency and the bad performance is the time frame of a year. Because agricultural seasons are generally just a couple of months and situations change rapidly, this large time frame is probably too broad to catch significant characteristics. For the follow-up classifications, the chosen time frame is shorter and comprises just one agricultural season. However, the cultivation of most of the irrigated fields does not exactly follow the timing of these seasons, but instead is more flexible, so for some irrigated fields the chosen time frame will not cover a whole growing cycle and most crops will not be in the same growing phase at the same time.

4.2.4. Verification visits

Results of the intermediate classifications were checked during verification visits in the area. These visits focused on sites that were classified as irrigated areas, that displayed notable differences between the two classification attempts, that were very mixed with lots of individual pixels or that gave wrong or odd results. With GPS, the selected sites were visited. Not all the sites were accessible due to absence of owners, topographical characteristics or weather constraints. The verification visits showed that the classification results do not correspond to the real situation in several cases. The intermediate classifications display often a mix
in land use and lots of single pixels. When these areas were visited, it turned out in most cases that the areas were indeed very mixed, but the land uses were not necessarily correctly classified. The classified irrigated areas display inconsistency; in some cases classified irrigation was indeed irrigation in reality, in other cases there was no sign of irrigation. Also, some selected areas turned out to be irrigated fields, while classification showed other land uses, such as light vegetation. To give an idea of how this verification visits were performed and what kind of findings it led to, an example of a verification visit for a selected site in Godi catchment is presented in figure 4.10.

Figure 4.10: The pictures on the top show the results of two intermediate classifications, IM-VIS-B and IM-VIS-C, for the same site. The site outlined in blue was selected for a verification visit on 5 December 2017, to see if the land uses in the selected site match the classification results. The photographs show examples of what land uses were encountered. This was mostly light vegetation, but also a bit agriculture and signs of old irrigation canals.

Example verification visit
This site was visited on 5 December 2017. It was selected because the results of both the IM-VIS-B and the IM-VIS-C classifications showed that a big part of this site consists of irrigated fields. When the area was visited, there were several land uses encountered. The photographs show light vegetation with grasses, bushes, weeds and shrubs. Also some agricultural activity in the form of maize cultivation was found and an old irrigation canal. This shows that classification sometimes gives quite reasonable results, but it is not very accurate nor reliable and there is chance on misclassification between light vegetation and irrigated fields. This also turned out to be the general result of other verification visits.

4.3. Spectral signatures
Because the classifications give mixed and inconsistent results, the spectral signatures of the training sets use for follow-up classification are examined. This analysis is limited to irrigated fields and light seasonal vegetation, because of the interest of this study and the problematic mixing of these two classes as encountered during the verification visits and follow-up classifications. Spectral signatures of training sets are created by Maximum Likelihood Classification. They can give insight in the spectral variability of the landscape and the ground data, thus provide additional information on the usability of Sentinel 2 images. With the spectral signatures, the mean and standard deviation of each band of the Sentinel 2 images are determined for the training data of irrigated fields and light seasonal vegetation. They are used to create a spectral response pattern over time for each wavelength in which S2 measures. The images that are examined are cloud free Sentinel 2 images used for the follow-up classifications, acquired during IS1 and IS2. The red band (RED, B4) and the near infrared band (NIR, B8) are discussed here, because these wavelengths are most sensitive to the presence of vegetation, as explained in chapter 3.
In figure 4.11, the spectral response pattern in the red spectrum, band 4 of Sentinel 2, is presented. The mean values of the training samples for light seasonal vegetation and for irrigated fields are shown, together with the standard deviation of the values, to give an idea about how the values of the training samples vary. The means of the two land uses show the same pattern and are in the same range. Also, the standard deviations show a lot of overlap. The same accounts to the spectral response pattern in the near infrared spectrum, as showed in figure 4.12. There is a bit more difference in the mean values for certain dates, but there is also similarity concerning the values of the standard deviations, which means that the training data for light seasonal vegetation and irrigated fields fall largely in the same range of spectral signatures. The other Sentinel 2 bands display the same overlap in mean and standard deviations. Their timeseries can be found in appendix B.
4.4. Spectral response single fields

The spectral response patterns present the mean of all irrigated fields and light seasonal vegetation, so the training samples are averaged out. This might not be entirely representative for irrigated fields, because not all the fields will be in the same growth phase at the same time, since agricultural practices are so flexible in terms of timing. Since classification is based on the spectral signatures, this might affect classification results as well. Therefore, it is chosen to examine single fields in addition to the average spectral response for all irrigated fields.

4.4.1. Scatter plots

To get more insight in the spectral response pattern of single fields, scatter plots are analyzed. Scatter plots are a representation of spectral responses for separate training samples. Theoretically, different land uses will cluster together in scatter plots. The scatterplots in figure 4.13a and 4.13b show the spectral response patterns of the training samples for band in the red and near infrared channel again. Sentinel 2 images of 13 July and 26 September are picked because they fall within IS1 and IS2, the first and the second irrigation season, thus provide valuable and relevant information on land use.

![Figure 4.13: Scatter plot of the spectral responses of light vegetation and irrigated fields in the red and near infrared spectrum](image)

Figure 4.13: Scatter plot of the spectral responses of light vegetation and irrigated fields in the red and near infrared spectrum

A probability contour for the training data for irrigated fields and light seasonal vegetation is included, which covers 95 percent of the training data. It can be seen that both land uses are quite spread out and that the largest part of the contours for the different land uses overlap for both images. This indicates again that irrigated fields and light seasonal vegetation have the same spectral response pattern, thus classifiers will most likely confuse these two classes with each other.

Because all the samples for irrigated fields and light seasonal vegetation are lumped together, it is hard to analyze the scatter plot more detailed. It could be that the fields in the top left are all covered with dense vegetation and therefore have a high reflection in the near infrared spectrum and a low reflection in the red spectrum, or that the fields in the upper right are all dry, bare fields that are not used at the moment that the Sentinel 2 images were acquired, thus have high values in both the near infrared and red spectrum. To have better insight in this, the training samples can be divided into smaller groups to see if they form clusters within the scatter plot. In general, using more classes to train the classifier can provide more accuracy. The use of more classes leads to spectrally more compact classes, clusters of data grouped together, instead of the large spread displayed by the irrigated fields and light vegetation, and decreases misclassification (Liebe, 2002). To examine whether this is feasible, the training data for irrigated fields are divided into subclasses based on crop type. Crop type is chosen because the variety of crops results in different types of land cover, which might be reflected by the spectral response. An example of how different crops lead to variations in
land cover can be found in figures 4.14a and 4.14b, where a field with chilies is compared to a field with onions. Onions are quite thin and small, whereas chilies are large crops with big leaves that cover fields more densely.

![Irrigated field with chilies](image1) ![Irrigated field with onions](image2)

Figure 4.14: Examples of how land covers of irrigated crops look different, thus may result in different spectral responses

To see whether dividing the training samples leads to clusters of spectrally more compact classes, a scatter plot for the Sentinel 2 image of 26 September 2017 is created with bands in the red and near infrared spectrum. Because the fields were visited in October, November and December, information concerning crop types for each irrigated field around the end of September is not always available. This is accounted for by leaving out the samples where this is the case. The remaining training samples for irrigated fields are split in different crop types, resulting in categories of beans, cabbage, chilies, maize, onions, tomatoes and a group with mixed crops. Also the samples for light seasonal vegetation are added. The scatter plot is presented in figure 4.15.

![Scatter plot of the spectral responses of light vegetation and irrigated fields](image3)

Figure 4.15: Scatter plot of the spectral responses of light vegetation and irrigated fields in the red and near infrared spectrum for a Sentinel 2 image acquired on 26 September. The irrigated field samples are divided based on crop type.

The scatter plot shows that even when the training samples are divided into subgroups, the spread is still large and it is not possible to construct spectrally more compact classes, because the different subgroups are overlapping. Therefore, separating the data based on crop type is not a way to obtain spectrally more com-
pact classes and to avoid confusion in classification.

A similar kind of analysis is done with a division of the training samples based on growing phase, in which the growing cycles of the crops are split in months. To create a scatter plot, once again the red and near infrared spectrum of the Sentinel 2 image acquired at 26 September 2017 are used, so the division of the training samples in different growing phases is performed with respect to the situation around the end of September. The training samples for irrigated fields are grouped in four categories:

- Phase 1: this phase consists of crops that are in the first month of their growing cycle at the end of September.
- Phase 2: this phase consists of crops that are in the second month of their growing cycle at the end of September.
- Phase 3: this phase consists of crops that are in the third month of their growing cycle at the end of September.
- Phase 4: the crops on the field are in the fourth month or more of their growing cycle at the end of September.

The scatter plot in figure 4.16 shows the division of the training samples in different growing phases. It can be seen that the samples for different growing phases again show overlap in spectral response and that it is not possible to identify subgroups or clusters. Therefore, separating the data based on growing phases is not a way to obtain spectrally more compact classes and to avoid confusion in classification.

![Scatter plot showing the division of training samples in different growing phases.](image)

Figure 4.16: Scatter plot of the spectral responses of light vegetation and irrigated fields in the red and near infrared spectrum for a Sentinel 2 image acquired on 26 September. The irrigated field samples are divided based on growing phase.

### 4.4.2. NDVI analysis

To further examine the single fields, four fields are randomly selected for a more detailed examination. The locations of the fields are presented in figure 4.17. This examination takes place by means of the Normalized Difference Vegetation Index (NDVI). First, a time series of average NDVI during IS1 and IS2 is constructed for light vegetation and irrigated fields, to get insight in the general NDVI pattern. Then, the NDVI pattern for the selected fields is compared to the information on those fields that was obtained during the fieldwork, to see whether the NDVI pattern matches the timing of agricultural practices. In addition, the classification results for the selected areas area are checked. It is expected that for a full growing cycle of an irrigated crop the NDVI will be low in the beginning, high in the middle and low at the end. The low NDVI in the beginning is because the field is cleared before the crops are planted, so the field will be quite bare and bare ground has a low NDVI. When the crops start to grow, the NDVI will increase. Harvesting the crops will make the field bare again and therefore the NDVI will drop after harvest.
4.4. Spectral response single fields

Figure 4.17: Map of the locations of the four irrigated fields that were randomly selected for a more detailed examination.

**NDVI for averaged training samples**

The general averaged NDVI pattern for the training samples of irrigated fields and light seasonal vegetation is presented in figure 4.18. It can be seen that for both irrigated fields and light seasonal vegetation the NDVI decreases during the dry season till October. After this, the NDVI increases as a result of the start of the rain season.

Figure 4.18: Graph of the average Normalized Difference Vegetation Index in IS1 and IS2 for training samples of irrigated fields and light seasonal vegetation. The NDVI is calculated with the red and near infrared bands of Sentinel 2 images.

In addition to the general NDVI pattern over time, the average NDVI for the research area is presented in figure 4.19. This map is created with Sentinel 2 images acquired during the first and second irrigation season, IS1 and IS2. It uses the same images as the follow-up classifications as introduced in table 3.4. This picture shows that on average, the NDVI is the highest for the forest on the ridge in the east, that is covered with dense evergreen trees. There are some spots with a low NDVI, but in general, the whole area is quite green throughout the irrigation season.

Figure 4.19: Map of the averaged NDVI pattern for the research area.
Figure 4.19: Average Normalized Difference Vegetation Index map for the research area. The NDVI is calculated with Sentinel 2 images acquired in IS1 and IS2, that are also used for the follow-up classifications.

**NDVI for tomato field 12 October 11.04**

This field is mapped at 12 October 2017 at 11.04. A picture of the field is presented in figure 4.20a. The field has a size of 6397 m$^2$. At the time of the measurement, the field was bare. It was cleared and prepared for planting tomatoes, which were planted around the beginning of November. The NDVI pattern is presented in figure 4.20b. The NDVI gets quite low around the middle of October, which could reflect the clearing of the field, and increases after the end of October, which could reflect the growing of the tomatoes. The field is correctly classified as an irrigated field for all the types of classifications. However, this pattern also matches the averaged NDVI pattern for all the training data of the irrigated fields, so it is not certain that the spectral response of this single field reflects the timing of the agricultural practices or just the general NDVI pattern.

![Tomato field](image1)

![NDVI pattern](image2)

**Figure 4.20:** Photograph and NDVI pattern for tomato field mapped on 12 October 2017 at 11.04, to check whether the NDVI pattern corresponds to the timing of the agricultural practices

**NDVI for tomato field 16 October 13.17**

This field is mapped at 16 October 2017 at 13.17 and has a size of 5604 m$^2$. A picture of the field is presented in figure 4.21a. Tomatoes were planted on the field around the end of July and the start of the harvest was expected to begin around the end of October. In figure 4.21b the NDVI pattern is presented. This pattern matches perfectly the information on timing of agricultural practices for this field. Planting is started around the end of July, so before this, the field is bare and has a low NDVI. After the tomato crops are planted, they start growing and the NDVI increases. Around the end of October, the tomato plants are harvested, so the...
NDVI decreases again. This is an example of an irrigated sample for which the timing of the agricultural practices and spectral response pattern correspond to each other. Also, the field is correctly classified as an irrigated field for all the types of classifications.

Figure 4.21: Photograph and NDVI pattern for tomato field mapped on 16 October 2017 at 13.17, to check whether the NDVI pattern corresponds to the timing of the agricultural practices

**NDVI for mixed crop field 16 October 13.03**

This field is mapped at 16 October 2017 at 13.03 and has a size of 3370 m$^2$. A variety of crops is mixed: onions, beans, pumpkin, maize and madumbe, some kind of root. A picture of the field is presented in figure 4.22a. Planting started around mid-August and harvest is expected to begin in November. In figure 4.22b the NDVI pattern is presented. This pattern does not match with the information on timing of agricultural practices for this field. Based on that information, it is expected that after planting in mid-August the NDVI will increase. However, the NDVI for this field decreases. After the end of September, the NDVI increases, which corresponds to the growing of the crops, but then there is an odd decrease in NDVI around half October. After this, the NDVI increases again, but this is probably a result of the rain. The classification results for this field show inconsistent results. For most classifications, a mix of irrigated fields and light seasonal vegetation is classified. Therefore, for this field the spectral response is not representative in relation to the agricultural practices.

Figure 4.22: Photograph and NDVI pattern for irrigated field with mixed crops mapped on 16 October 2017 at 13.03, to check whether the NDVI pattern corresponds to the timing of the agricultural practices
**4. Results**

*NDVI for tomato field 1 December 12.00*

This field was mapped at 1 December 2017 at 12.00 and has a size of 721 m². A picture of the field is presented in figure 4.23a. On the field, tomatoes were planted in September. Harvest is expected to start around the beginning of December. In figure 4.23b the NDVI pattern is presented. It is possible that the pattern matches the timing of the agricultural practices. Tomatoes are planted in September, so it is expected that the field is bare before September, thus has a low NDVI, and that the NDVI increases in October when the tomatoes start to grow. This corresponds to the NDVI pattern of the field. The field is correctly classified as an irrigated field for all classifications. However, the NDVI pattern also corresponds to the general NDVI pattern of all the fields, so it is uncertain whether the NDVI pattern of this field correctly reflects the timing of the agricultural practices or just reflects the general NDVI pattern.

![Tomato field](image)

![NDVI pattern](image)

**Figure 4.23:** Picture and NDVI pattern for tomato field mapped on 01 December 2017 at 12.00, to check whether the NDVI pattern corresponds to the timing of the agricultural practices

### 4.5. Additional analysis

Additional features are analyzed to complement the classification results. Because those results showed that classification only based on optical remote sensing is problematic due to spectral similarity between irrigated fields and light seasonal vegetation, this analysis focuses on the distinction between those two types of land uses. If a distinguishing feature can be identified, it may serve as an extra criterion for classification and therefore improve the classification results.

#### 4.5.1. Terrain analysis

To examine whether height above nearest drainage, HAND, can serve as a useful and unique indicator for the identification of irrigated fields, a HAND raster was constructed, for which the locations of irrigated fields and light seasonal vegetation were mapped. The HAND map is presented in figure 4.24.

Furthermore, a statistical analysis of HAND values for both irrigated fields and light vegetation is performed in which the mean, standard deviation, minimum, maximum and the 5th and 95th percentile are calculated. Also, a Kolmogorov-Smirnov test is applied, to show whether the ground data for irrigated fields and for light seasonal vegetation can be distinguished from each other. The results of the statistical analysis are presented in table 4.3 and figure 4.25.
4.5. Additional analysis

Figure 4.24: HAND map for research area with the ground data for irrigated fields and light seasonal vegetation

Figure 4.25: KS test for HAND of light vegetation and irrigated fields, with the KS-parameters included to see whether the light vegetation and irrigated field data sets are drawn from the same distribution.

<table>
<thead>
<tr>
<th>HAND (m)</th>
<th>Irr fields</th>
<th>Light veg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>21.0</td>
<td>22.8</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>21.1</td>
<td>22.6</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>101.2</td>
<td>116.2</td>
</tr>
<tr>
<td>5th percentile</td>
<td>0</td>
<td>2.2</td>
</tr>
<tr>
<td>95th percentile</td>
<td>62.0</td>
<td>39.7</td>
</tr>
</tbody>
</table>

Table 4.3: Comparison HAND statistics for light vegetation and irrigated fields

The results of the statistical analysis show that there is a considerable similarity between irrigated fields and light vegetation. The statistics of both land uses are quite alike. Furthermore, \( p \text{-value} > \alpha \) so the null hypothesis cannot be rejected and the two data sets follow the same distributions. Therefore, HAND cannot be used to distinguish between irrigated fields and light vegetation in this study.

4.5.2. Distances to streams and canals

Another characteristic that is examined to see whether it can be used to distinguish between irrigated fields and light seasonal vegetation is the distances to streams. This is mapped for the research area in figure 4.26. The map with distances to streams show that the largest part in the research area is closer than 600 meter to a stream. It also seems that most of the irrigated fields are located nearby a stream. To examine whether the distances to streams can be used to distinguish between light seasonal vegetation and irrigated fields, statistical analysis is performed. The results are presented in table 4.4.

Comparison of the statistics of the distance to streams for light vegetation and irrigated fields show that the irrigated fields in most cases are closer to streams than areas with light vegetation. However, the irrigation canals have also to be taken into account, because they can transport the water away from the streams and therefore increase the reach of the streams, hence irrigation is possible in many more areas than only locations nearby streams. The canals are mapped and their lengths are compared to the ground data and the findings from the analysis regarding distances to streams. In figure 4.27, the locations of the canals are presented, together with the reach of some canals.
4. Results

Figure 4.26: Distances to streams mapped for the research area with ground data for irrigated fields and light seasonal vegetation, to see whether distances to streams can serve as a unique indicator for irrigated fields

Figure 4.27: Map of the streams and irrigation canals in the research area. The length and reach of some irrigation canals are presented, to give an indication of how far the water can be transported by the canals

<table>
<thead>
<tr>
<th>Distance to streams (m)</th>
<th>Irr fields</th>
<th>Light veg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>139.6</td>
<td>225.3</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>94.1</td>
<td>170.1</td>
</tr>
<tr>
<td>Minimum</td>
<td>11.0</td>
<td>27.0</td>
</tr>
<tr>
<td>Maximum</td>
<td>441.3</td>
<td>650.5</td>
</tr>
<tr>
<td>5th percentile</td>
<td>24.9</td>
<td>43.2</td>
</tr>
<tr>
<td>95th percentile</td>
<td>305.6</td>
<td>586.1</td>
</tr>
</tbody>
</table>

Table 4.4: Comparison of statistics of distances to streams in the research area with ground data for irrigated fields and light seasonal vegetation

The canals can be as long as 2000 meter, so this means that irrigated plots can be located quite far from streams and that water can be transported to locations throughout the whole research area. According to the distances-to-streams raster in figure 4.26, the largest distances to streams in the research area are in the range of 600 meter and the major part of the area is closer than 600 meter to streams. The reach of the canals is much larger than 600 meter. Therefore, distances to streams cannot be used to distinguish between irrigated fields and light vegetation in this study.

4.5.3. Thermal remote sensing

For the three Landsat 8 images of 3 June 2017, 22 August 2017 and 23 September 2017, the land surface temperature is mapped for the research area. In addition, statistical analysis of these values is performed with the ground data for irrigated fields and light seasonal vegetation.

In the figure 4.28, the different Land Surface Temperature maps are presented for the three L8 images. The maps show a clear difference in land surface temperature between the images. The closer to the end of the dry season, the higher the land surface temperature. The dense vegetation on the ridge in the east is clearly visible due to its notable lower temperatures. Other features are less easy to distinguish.
The results of the statistical analysis are presented in figure 4.29 and tables 4.5 and 4.6. Figure 4.29 shows the cumulative distribution functions for the Land Surface Temperature of irrigated fields and light vegetation. They look quite similar for all three images. The same accounts for the results of the statistical analysis in table 4.5. Just like the maps, they show that the Land Surface Temperature is notably different for each L8 image and that it significantly increases towards the end of the dry season. However, when looking for differences between light seasonal vegetation and irrigated fields, it becomes clear that the expected lower temperature for irrigated fields is not reflected in the land surface temperature values. It could be that the spatial resolution of 100 meter for the thermal bands is too low in relation to the small size of the fields, but there are no notable differences between the irrigated fields and the light seasonal vegetation. The statistics for the two land classes are quite alike and the Kolmogorov-Smirnov tests show for all cases that $p - value > \alpha$, so the null hypothesis cannot be rejected and the data sets are drawn from the same distribution. Therefore, thermal remote sensing cannot be used to distinguish light vegetation and irrigated fields in this study.
4. Results

Table 4.5: Statistical analysis of Land Surface Temperatures with 3 L8 images for irrigated fields and light vegetation

<table>
<thead>
<tr>
<th>LST (°C)</th>
<th>Irr fields 03-06</th>
<th>Light veg 03-06</th>
<th>Irr fields 22-08</th>
<th>Light veg 22-08</th>
<th>Irr fields 23-09</th>
<th>Light veg 23-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>23.6</td>
<td>23.8</td>
<td>26.7</td>
<td>26.8</td>
<td>36.2</td>
<td>38.8</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.9</td>
<td>1.1</td>
<td>1.4</td>
<td>1.5</td>
<td>1.7</td>
<td>2.1</td>
</tr>
<tr>
<td>Minimum</td>
<td>20.5</td>
<td>21.4</td>
<td>22.6</td>
<td>23.4</td>
<td>33.2</td>
<td>34.2</td>
</tr>
<tr>
<td>Maximum</td>
<td>25.7</td>
<td>26.7</td>
<td>29.6</td>
<td>29.5</td>
<td>43.7</td>
<td>43.1</td>
</tr>
<tr>
<td>5th percentile</td>
<td>22.1</td>
<td>22</td>
<td>24.3</td>
<td>23.7</td>
<td>35.4</td>
<td>35.2</td>
</tr>
<tr>
<td>95th percentile</td>
<td>24.9</td>
<td>25.4</td>
<td>29</td>
<td>29.1</td>
<td>40.7</td>
<td>42.6</td>
</tr>
</tbody>
</table>

Table 4.6: Kolmogorov-Smirnov test with 3 L8 images for LST for irrigated fields and light vegetation.

<table>
<thead>
<tr>
<th>KS-test</th>
<th>D</th>
<th>p-value</th>
<th>α</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 June 2017</td>
<td>0.183</td>
<td>0.457</td>
<td>0.05</td>
</tr>
<tr>
<td>22 August 2017</td>
<td>0.173</td>
<td>0.526</td>
<td>0.05</td>
</tr>
<tr>
<td>23 September 2017</td>
<td>0.207</td>
<td>0.306</td>
<td>0.05</td>
</tr>
</tbody>
</table>

4.5.4. Rainfall analysis

This research focuses on 2017, because fieldwork took place in this year. To get more insight in how representative this year is, the rainfall of 2017 is compared to the average rainfall over the years 2012 till 2016. As explained in chapter 2, rain data is measured on a daily basis by a local farmer in Godi catchment with a rain gage. In figure 4.30, rain data for each month in 2017 is showed, as well as the average rain per month for the years 2012 to 2016.

![Figure 4.30: Rainfall per month for the year 2017 and averaged over the years 2012 till 2016](image)

The rain data show that 2017 is a wet year. In January, the amount of rain that fell is more than twice the average for January over the years 2012 to 2016. Also February and March were wet months compared to the years before. April is more dry than usual and May and June do not show large deviations. July 2017 shows again a relatively high amount of rain compared to the years before. August and September are quite standard, but it seems that the rain season started early for 2017, with larger amounts of rain than usual for October and November.
Most likely, the large amount of rain that fell in 2017 has influenced the vegetation conditions and overall greenness of the area. It might partly explain the spectral similarity between light vegetation and irrigated fields. It is possible that, due to the high rainfall in the beginning of 2017, there was a lot of moisture in the soil, thus vegetation over the whole area was able to thrive for a long period. Therefore, light seasonal vegetation in the dry season of 2017 was probably more healthy than in other years. In addition to this, the rain in July possibly gave a boost to natural vegetation again. Normally this month is quite dry, but in 2017 there fell about 80 millimeter of rain, which may have resulted in more green and healthy light vegetation. Lastly, the rain season in 2017 started quite early, with considerable amounts of rain in October and November already. Again, this might have resulted in greener and healthier vegetation. The fact that light vegetation in 2017 was probably more healthy than in other years can have resulted in a spectral pattern that is more similar to irrigated crops, since the irrigated crops are also healthy due to irrigation, and therefore the relative wetness of 2017 might have contributed to the erroneous classification results.
Conclusion and recommendations

5.1. Conclusion
This study aims to provide insight in the usability of remote sensing regarding farmer-led irrigated agriculture in Central Mozambique. Various aspects of both optical satellite remote sensing and farmer-led irrigation were examined. The results of these examinations show that optical remote sensing as applied by this study does not give accurate results regarding the identification and mapping of farmer-led irrigated agriculture in the study area, because of similarities in the spectral responses of irrigated fields and light vegetation.

There are various factors that contributed to this conclusion, which can be explained by looking at the ground data. The main reason is the heterogeneity of the study area. There are different land uses, of which light to medium vegetation and agricultural plots are dominant. These land uses are alternated with denser vegetation and small houses and everything is mixed on a quite small scale; there are no consecutive large areas with just one land use. This becomes clear when the training samples for irrigated fields are analyzed. The samples often consist of just a couple of pixels and are not homogeneous.

Another factor that complicates the use of remote sensing is the flexible timing of activities in the area. Although theoretically there are three agricultural seasons, in practice planting, irrigating and harvesting do not happen at fixed times, but depend on various aspects, thus timing may differ a lot. In addition, the area is very dynamic and land uses may change frequently. Also, the spatial organization of the area is very flexible, which appears from the mixing of different crops, the interchange between irrigated and non-irrigated agriculture and the rotation scheme between agricultural plots and unused land. Due to these diverse practices, the agricultural plots show different and unique patterns both over time and over space, which makes it hard to generalize and classify them.

The difficulties encountered become most clear when looking at the ground data for irrigated fields and light seasonal vegetation. They show the same spectral response for optical and thermal remote sensing and thrive in the same spatial conditions. A more detailed examination of scatter plots and spectral signatures present large overlap in spectral space between irrigated fields and light seasonal vegetation. Also for other classes, there is a low inter-class separability. A concise overview of aspects that complicate the possibilities of the use of remote sensing is presented in table 5.1.

It might not be possible to accurately identify and map farmer-led irrigation with the methodology as applied by this study, but still there is valuable information gained regarding the study area. First of all, there is more insight in the spectral response patterns of the land uses. The large spread of these values over different wavelengths and the absence of variability between classes provide relevant information for other remote sensing studies, both in this area as well as in other areas with farmer-led irrigated agriculture, and gives insight into heterogeneity and dynamics in the area. Analyzing the ground data taught a lot about the challenges that farmer-led irrigated agriculture poses regarding remote sensing research. Furthermore, it appears that the whole area is suited for irrigation. The presence of irrigated fields is not constrained by streams or elevations.
5. Conclusion and recommendations

<table>
<thead>
<tr>
<th>Issue</th>
<th>Challenge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale</td>
<td>Fields are generally quite small. The average size measured is 0.2 hectare for an irrigated plot. The spatial resolution of satellite images is still quite big compared to the scale of the fields.</td>
</tr>
<tr>
<td>Distribution</td>
<td>Fields are dispersed over a large area and not necessarily connected to each other, often depending on local soil characteristics, ownership of the land, the availability of rivers and irrigation canals.</td>
</tr>
<tr>
<td>Timing</td>
<td>There are no fixed planting dates or irrigation time schemes. This results in variations in planting, irrigation and harvesting periods.</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td>The study area is very heterogeneous, with no large pieces of land with a single land use. Most areas are still quite green at the end of the dry season. There is no clear distinction between different vegetation types, everything is mixed.</td>
</tr>
<tr>
<td>Flexible occupation of the land</td>
<td>There is no clear spatial distinction between irrigated fields and non-irrigated fields and between non-irrigated fields and light vegetation. Land uses are alternated. Crop types are mixed.</td>
</tr>
<tr>
<td>Similarities land uses</td>
<td>The different land uses have features that are quite similar, both for spectral and spatial characteristics.</td>
</tr>
</tbody>
</table>

Table 5.1: Short overview of aspects that complicate the possibilities of remote sensing in the study area

Canals can transport the water to basically anywhere in the area and are fairly flexible. Therefore, adjusting the systems to irrigate other areas is possible, although this also depends on other factors such as water availability, so it might not always be possible. An accurate substantiation of the extent of farmer-led irrigated agriculture is not feasible, but valuable information obtained by this study contributes to better grasping the presence of irrigated agriculture in Ruaca, Chirodzo and Godi catchments.

5.2. Recommendations

Different suggestions for both improving and expanding this study are shortly discussed. Further research can be aimed in different directions, dependent on what the objective is.

5.2.1. Improvements fieldwork

The methodology as applied during the fieldwork could be improved, for example regarding the collection of training data for different land uses. Mapping focused on irrigated fields. This resulted in a lot of collected data on irrigated fields, but also in a smaller amount of data on other land uses. Therefore, the sets of training samples are quite imbalanced and some training sets might not be perfectly representative, because there are too little training samples to fully grasp the spectral characteristics. A more elaborate data set with a randomly selected collection of other land uses could contribute to the quality of this research. Another idea that might improve this study is to select a variety of irrigated fields and observe them for a longer period, such as an entire growing cycle. This research aimed at collecting a large number of irrigated fields and each field was only visited and monitored once. If a field is being monitored during a growing cycle, this could result in more insight in the relation between growing phases and spectral responses. For example, monitor a field every three weeks. Every time the field is visited, pictures are taken and information is collected on the density of crop cover, the greenness of the area and the health of the crops. If this is compared to satellite data acquired at the approximate same moment as the monitoring, it might be easier to relate information collected in the field to spectral responses and to see what role different growing phases have in spectral responses. This study tried to examine this relation with the single field analysis in section 4.4.2, but this was difficult because there was only information collected at one moment for each field.

5.2.2. Single field analysis

This recommendation is related to the suggestion about improving fieldwork by monitoring fields for a longer period. As mentioned before, maximum likelihood classification lumps all the training data together and thereby averages out the spectral responses of single fields, thus makes it difficult to get insight in the relation
between the timing of agricultural practices and spectral responses. To find out whether a detailed examination of the spectral response pattern of single fields reflects the timing of agricultural practices, a small start was made with single field analysis in section 4.4.2. This shows that there is potential in single field analysis in some cases. Therefore, a more thorough examination on field level might contribute to the quality of this study.

5.2.3. Higher spatial resolution

The results of this study may benefit from satellite imagery with a higher spatial resolution. Sentinel 2 data has a spatial resolution of 10 meter for the visible and near infrared bands, which means that a single pixel has a size of 100 m$^2$. The bands in the red edge and shortwave infrared spectrum have a spatial resolution of 20 meter, so pixels have a size of 400 m$^2$. A considerable part of the measured irrigated fields are so small that they only consists of a couple of pixels and some fields were even smaller than a single pixel. Thermal Landsat 8 data is measured in pixels with a size of 10000 m$^2$, which is a lot bigger than the average measured irrigated field with a size of 0.2 hectare. When there is measured with a higher spatial resolution, typical characteristics of irrigated fields may be less averaged out and therefore better reflect agricultural practices. A possibility for obtaining satellite imagery with a higher spatial resolution than Sentinel 2 is to use commercial satellites, that can measure with a spatial resolution as high as a couple of meters. However, commercial satellites often charge high amounts of money in order to use their products. An exception might be Planet Labs, a company that provides satellite data with a spatial resolution of 1 meter in certain wavelengths and offers special programs for research and non-governmental organizations (Butler, 2014).

5.2.4. Microwave remote sensing

Regarding classification, it might be interesting to look at microwave remote sensing or radar, which has a couple of advantages when compared to optical remote sensing. Microwave energy is not affected by various atmospheric aspects such as clouds and haze. Also, microwave reflections are not related to reflections in the optical or thermal spectrum and can therefore provide new information (Lillesand et al., 2014), so it might give new insights in farmer-led irrigation. Various studies proved that Synthetic Aperture Radar data (SAR) can be used for crop classification, with an increasing chance of success when multiple images acquired throughout the growing seasons are used (Skriver et al., 2011). In addition, the combination of multiple frequencies generally results in higher classification accuracy for individual crops (Chen et al., 1996).

Sentinel 1 is an example of SAR that covers the study area and measures at a spatial resolution of 5 by 20 meter in its Interferometric Wide Swath mode (Hornacek et al., 2012). However, SAR data is complex to process and is subject to speckle noise. Therefore, averaging in either time or space is necessary (Jones and Vaughan, 2010). This might be problematic due to the heterogeneous and dynamic character of the study area. However, Sentinel 1 measures every 12 days, which might be a feasible period for averaging in time since it can capture different cultivation stages of crops. With SAR, the amount of coherence can be examined, which is an indication for the degree of correlation between two images acquired at different moments (Rykhus and Lu, 2011). A low coherence might indicate an intervention in the landscape. An example of such intervention can be clearing the field for irrigation. Before farmers are able to start planting their crops, they will clear their field, hence the field will be bare. Clearing the field could serve as an indicator for irrigation. However, it could also mean that rainfed crops are going to be cultivated, or that space for livestock is created. This should be taken into consideration as well.

5.2.5. Object identification

Since irrigated fields are so similar in spectral responses, it might be an idea to classify images not based on their spectral characteristics per pixel but to use other features for classification. A possibility to do this is object-based classification, in which different features such as color, shape, size and texture of objects are examined (Jones and Vaughan, 2010). Based on these features, different objects are identified. These objects can be used to create a training map as input for classification. Concerning this study, color, shapes and sizes of irrigated fields and light seasonal vegetation are still quite similar to each other, but texture might be interesting to examine. Texture is a measurement of the homogeneity of neighboring pixels or the frequency of change of relative brightness of objects on a satellite image. It is constructed by an aggregation of unit characteristics, such as tone and pattern, that may be too small to be distinguished separately, which provides the chance of distinguishing between features that are alike in terms of spectral reflectance based on their texture. The imagery will then be segmented into discrete objects. After this, classification can take place
(Lillesand et al., 2014). Object-based classification benefits from high spatial resolution imagery. A nice way to examine features would be with the use of a drone. Drones can give a very detailed overview, which supports object identification and therefore object-based classification.

5.2.6. Additional suggestions

To conclude this research, some final suggestions that might be worth to investigate are mentioned. It would be interesting to repeat this research in other areas where farmer-led irrigated agriculture is performed, to get insight in different agricultural practices and to compare different areas. In Appendix C three other areas in Central Mozambique are introduced. These areas were visited during fieldwork, to gain more general knowledge on farmer-led irrigated agriculture in Central Mozambique and to get an idea of the similarities and differences between the different sites. They were not included in the classifications or in other analyses performed for this study, but it might be interesting to use the methodologies performed for this study in these areas and examine the results.

Another aspect that is interesting to investigate is whether the same results of this study would be obtained for a different year. As explained in section 4.5.4, 2017 was quite a wet year and this might have influenced the outcomes. In dry years, there will be less moisture left in the soil for light seasonal vegetation, which can influence the spectral responses, hence give different results. This can be examined with Sentinel 2 images acquired in other years. However, the ground data collected for this study might not be completely representative for other years.

The last suggestion concerns classification. All the classifications in this research are performed with Maximum Likelihood Classification. It is already mentioned that object-based classification might be feasible for this study. In addition, there are also other possibilities regarding spectral classification, since there are numerous other classification algorithms that might be applicable. Maximum Likelihood is quite a robust classifier (Lu and Weng, 2007). More advanced classifiers can be investigated to see if they can result in a higher accuracy. A suitable classifier might be a Support Vector Machine classifier. This is a non-parametric supervised classification which can achieve high accuracy with only a limited number of training samples (Zheng et al., 2015). However, the input for classification, consisting of training data and Sentinel 2 images, stays the same for different classifiers, so the spectral responses of the land uses will not change. Therefore, the effect of using another classifier will not solve the problem of low inter-class spectral separability, but it might be worth looking into.
Classification Results
A.1. IM-VIS-A

<table>
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<th>Type</th>
<th>Sentinel 2 images</th>
<th>Bands</th>
<th>Training sites</th>
</tr>
</thead>
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<tr>
<td>IM-VIS-A</td>
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<td>26-9-2017</td>
<td>B2 = blue, B3 = green, B4 = red, B8 = near infrared</td>
<td>58</td>
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</tbody>
</table>

Table A.1: Information about classification IM-VIS-A
A.2. IM-VIS-B

<table>
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</tr>
</thead>
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<td>1-10-2016</td>
<td>B2 = blue</td>
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<tr>
<td></td>
<td></td>
<td>8-6-2017</td>
<td>B3 = green</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>17-8-2017</td>
<td>B4 = red</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>26-9-2017</td>
<td>B8 = near infrared</td>
<td></td>
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</tbody>
</table>

Table A.2: Information about classification IM-VIS-B
### A.3. IM-VIS-C

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<td>B3 = green</td>
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<td></td>
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Table A.3: Information about classification IM-VIS-C

![Map of classification results](image-url)
### A.4. F-VIS-IS1

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<th>Code</th>
<th>Type</th>
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<th>Training sites</th>
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<td>28-6-2017</td>
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<td>B3 = green</td>
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<tr>
<td></td>
<td></td>
<td>13-7-2017</td>
<td></td>
<td>B4 = red</td>
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<tr>
<td></td>
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<td></td>
<td>B8 = near infrared</td>
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Table A.4: Information about classification F-VIS-IS1
### A.5. F-VIS-IS2

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<td>B4 = red</td>
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<td>B8 = near infrared</td>
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Table A.5: Information about classification F-VIS-IS2
### A.6. F-IR-IS1

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<td>28-6-2017</td>
<td>B8 = near infrared</td>
<td></td>
</tr>
<tr>
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<td></td>
<td>13-7-2017</td>
<td>B11 = shortwave infrared</td>
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</tr>
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<td>23-7-2017</td>
<td>B12 = shortwave infrared</td>
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Table A.6: Information about classification F-IR-IS1
A.7. F-IR-IS2

<table>
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<th>Bands</th>
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<td>26-10-2017</td>
<td>B8 = near infrared</td>
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<td>20-11-2017</td>
<td>B11 = shortwave infrared</td>
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<td>11-10-2017</td>
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Table A.7: Information about classification F-IR-IS2

![Map of land use classification](image_url)
### A.8. F-RE-IS1

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<td>B11 = shortwave infrared</td>
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<td>23-7-2017</td>
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Table A.8: Information about classification F-RE-IS1
### A.9. F-RE-IS2

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<td>26-9-2017 26-10-2017</td>
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<tr>
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</table>

Table A.9: Information about classification F-RE-IS2
Spectral response patterns over time

Blue spectrum - band 2

Figure B.1: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the blue spectrum in the first and second irrigation season in 2017
Green spectrum - band 3

Figure B.2: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the green spectrum in the first and second irrigation season in 2017.

Red edge - band 5

Figure B.3: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the red edge spectrum in the first and second irrigation season in 2017.
Red edge - band 6

Figure B.4: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the red edge spectrum in the first and second irrigation season in 2017

Red edge - band 7

Figure B.5: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the red edge spectrum in the first and second irrigation season in 2017
Red edge - band 8A

Figure B.6: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the red edge spectrum in the first and second irrigation season in 2017

Shortwave infrared - band 11

Figure B.7: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the shortwave infrared spectrum in the first and second irrigation season in 2017
Shortwave infrared - band 12

Figure B.8: Spectral response pattern for irrigated field training samples and light seasonal vegetation training samples in the shortwave infrared spectrum in the first and second irrigation season in 2017
Study Visits - Background information on agriculture in Central Mozambique

Three other agricultural sites in Central Mozambique were visited to gain more general knowledge on farmer-led irrigated agriculture in Central Mozambique and to get an idea of the similarities and differences between the different sites. The location of these study visits is showed in figure C.1. This appendix shortly introduces the three areas and shows some examples of agriculture.

Figure C.1: Locations of study sites visited
C.1. Vanduzi

Vanduzi is situated at the other site of the ridge that lies east of the main research location, so it is only a short distance away, but agricultural processes are organized in a very different way. Vanduzi’s specialty is baby corn. A field with baby corn is presented in figure C.2a. Other crops that are cultivated are maize, cabbage, peppers and onion. The farmers in the area have an agreement with Vanduzi company, a large company that exports baby corn internationally. In addition, Vanduzi received financial support of the PROIRRI Sustainable Irrigation Development Project. This project is a cooperation between the World Bank and the Mozambican government amongst others and aims to increase agricultural productivity by constructing or improving irrigation systems. The project is executed in different provinces in Central Mozambique. The involvement of big companies and the government becomes evident in the organization of the fields, the good conditions of the roads, the accessibility that farmers have to various services, for example markets, and the large presence of sprinkler irrigation. Such a sprinkler system is presented in figure C.2b. Topographical characteristics are quite similar to Ruaca, Godi and Chirodzo catchments. The area is quite hilly. Water for irrigation comes mainly from streams that originate on the steep ridge that is located between the main research area of this study and Vanduzi.

![Field with baby corn in Vanduzi](image1)

![Sprinkler irrigation in Vanduzi](image2)

Figure C.2: Picture of an agricultural plot with babycorn (left) and sprinkler systems used for irrigation (right) in Vanduzi
C.2. Munedzi

Munedzi catchment is located in Manica Province, just south of Chimoio, the capital of Manica Province. Munedzi catchment is quite similar to Ruaca, Godi and Chirodzo catchments in the way that there is little external involvement and that agriculture is dispersed and fields are generally small. Agricultural activities consists of the cultivation of irrigated crops such as carrots, tomatoes, onions and cabbage and fruits trees such as oranges and bananas. The location of agriculture is dependent on the location of the Munedzi river and other characteristics of the landscape. Figure C.3a shows an irrigated field with carrots. This area is more flat than Godi and irrigation is applied in various ways. An example of pump irrigation is showed in figure C.3b. Other irrigation practices uses dams, furrows or buckets. Some farmers construct their own basins to extract water for irrigation from. Most of the water for irrigation is abstracted from surface water. There are also some wetlands in the area on which agricultural plots are constructed. It is not necessary to irrigate these areas because of the natural wet conditions of these sites.

(a) Field with irrigated carrots in Munedzi

(b) Pump for irrigation in Munedzi

Figure C.3: Picture of an agricultural plot with irrigated carrots (left) and a pump used for irrigation with an agricultural plot in the background (right) in Munedzi
C.3. Buzi

Buzi is located in a very flat part of Mozambique, nearby the sea in Sofala Province. Sofala Province is located at the east of Manica Province. Generally, it has a hotter climate than Manica Province. Buzi is an old Portuguese settlement and the administrative heart of the region. There are many wetlands and the focus of agriculture is on rice. Rice fields are often quite big and account for a large part of the total land use. An example of a rice field is presented in figure C.4a. The PROIRRI project is executed in Buzi as well, so there is government involvement. The project constructed large irrigation systems, in which water is pumped from the Buzi River and supplied to the rice fields. It is not put into operation yet, but when it does it is expected that rice will be cultivated twice a year, instead of once a year which is the situation now. There are also sites where horticulture is practiced, but not as much as for the other study sites. Sites are generally small. An example of horticulture is given in figure C.4b, where horticulture is located along the river. Irrigation for horticulture takes place with pumps, pipes of through flood irrigation. Farmers cultivate various plots to spread their risks, so that they will always have some income. Some of them cultivate both rice and irrigated horticulture crops, to increase their incomes. Horticulture crops can have up to three growing seasons per year.

![Rice field in Buzi](image1)

![Horticulture along the river](image2)

Figure C.4: Pictures of rice cultivation (left) and horticulture with maize and eggplants (right) in Buzi. Rice cultivation takes place on big scale. Horticulture is often on smaller scale present.


Food and Agriculture Organization (2016). AQUASTAT Main Database.


Bibliography


