

Mapping cropland in smallholder farmer systems in South-Africa using Sentinel-2 imagery

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List of abbreviations

ANNs	Artificial Neural Network Ensembles
ARC	Agricultural Research Council
DEM	Digital Elevation Model
ESA	European Spatial Agency
UCL	Univeristé Catholique de Louvain
MSI	Multispectral Imager
NIR	Near-infrared
SWIR	Short Wave Infrared
LAI	Leaf Area Index
MLC	Maximum Likelihood Classifier
ML	Machine learning
MTPA	Mpumalanga Tourism and Parks Authority
NDVI	Normalized Vegetation Difference Index
OA	Overall Accuracy
PICES	Producer Independant Crop Estimate System
L1C	Level-1C
RF	Random Forest
RBF	Radial Basis Function
SA	South Africa
SVM	Support Vector Machines
SiQ	Spatial intelligence
SHF	Smallholder farming
TOA	Top-Of-Atmosphere
TWDTW	Time-Weighted Dynamic Time Warping algorithm
VHSR	Very High Spatial resolution

1 Introduction

With a growing world population, issues such as increasing food demand and the need for global food security are major challenges which researchers, policy makers and institutions will have to face in this century. These concerns are especially relevant in developing countries, where food supply is already an issue in many areas and where climate variability, characterised by less frequent and more intense rain events, is increasing small farmers' vulnerability to food insecurity (FAO, 2008). Understanding smallholder farmers' mode of operation, locating these farms and characterising their spatial distribution, and monitoring growth on their parcels is a first step to help increase productivity on smallholder farms and ensure food security in parts of the world where smallholder farms provide the bulk of food supply (Dioula et al., 2013).

Accurate mapping of smallholder fields is challenging for several reasons, beginning with the fact that the term 'smallholder' isn't rigorously defined. The vast diversity of smallholder systems across the world makes it difficult to come to a universal definition, leading to confusion regarding the extent of the term 'smallholder' when attempting to map these systems and comparing results obtained between different studies. Furthermore, the small size of the fields, the high degree of heterogeneity within these fields, and the lack of clarity in field boundaries make it challenging to differentiate between cultivated areas, abandoned fields, and natural vegetation, as opposed to easily distinguishable commercial fields (Debats et al. 2016). This task is especially difficult in savannas, where smallholder systems predominate, and the characteristics of savanna vegetation make it particularly hard to distinguish from cultivated areas. The difficulty in distinguishing cropland from savanna is evidenced by disagreements between global estimates of cropland, derived from statistical inventories, and previous national products derived from remote sensing that can differ up to 40% in some areas. Yet, this difference remains largely attributable to the difficulty of mapping cropland in smallholder systems (Sweeney et al., 2015). Previous available satellite missions have often lacked the spatial resolution and temporal consistency to map these systems.

With the launch of Sentinel-2A in 2015, new opportunities emerged for monitoring agricultural applications across varied landscapes. The Sentinel-2 mission is characterised by a higher revisit frequency than previous missions (5 to 10 days), high spatial resolution (10 m), and a larger amount of spectral bands (13 in total); especially in the red-edge part of the spectrum.

In parallel, the Sen2Agri processing system was developed during a three-year project, which ended in May 2017. The Sen2Agri system is a fully automated production system, aimed to facilitate the use of Sentinel-2 imagery for producing agricultural information, with a focus on food security applications (ESA, 2015). The development of the system was funded by the European Space Agency (ESA, 2015) and carried out by a consortium including the Université Catholique de Louvain (UCL). The Sen2Agri system provides the international user community with an open source processing system, including validated algorithms, to derive products relevant for agricultural monitoring from Sentinel-2 imagery in a facilitated and operational way.

The Sen2Agri processing system was designed to be as automated as possible, providing the international user community with easy access to state-of-the-art technology, thus creating valuable new opportunities for agricultural applications¹.

The use of Sentinel-2 imagery and the Sen2Agri system has already proven highly effective in commercial farming areas across the world, representing a variety of agricultural landscapes. However, the Sen2Agri processing system has not yet been used to map small scale farming, and the potential and limits of Sen2Agri must still be benchmarked in small scale farming systems.

In the framework of the Sen2Agri project, this thesis evaluates the performance of the open source processing system of Sen2Agri when classifying a cropland mask in a highly heterogeneous landscape, characterised by small scale farming. The test site is located in the north-east of the Mpumalanga province in South Africa. The use of various sampling procedures and manipulations of the time series in the Sen2Agri system is also studied, for its impact on the accuracy of the cropland mask. In parallel, two separate classifications are carried out based on other methods, using the Support Vector Machine classifier in Orfeo Toolbox and classifying by Normalized Difference Vegetation Index (NDVI) thresholds. Finally, the thesis assesses the adequation of Sentinel-2-derived imagery, with a 10 m spatial resolution, for monitoring smallholder systems.

This thesis was completed in collaboration between the UCL and the Agricultural Research Council (ARC) in Pretoria, South Africa. Joint fieldwork and research between the ARC and UCL was held during a 3 month internship in Pretoria. The ARC is a science institute that conducts research, develops human capital and fosters innovation to support and develop the agricultural sector in South Africa. Their main objectives are to promote sustainable and equitable agricultural development and growth in related industries, to facilitate and ensure nature conservation and to focus on promoting national food security².

¹ Retrieved from: www.esa-sen2agri.org/objectives/

² Retrieved from: www.arc.agric.za/Pages/Home.aspx

2 Literature Review

The main objective of the literature review is to give an extended yet concise understanding of the problematic and its context, to explain how state-of-the-art tools and research related to the subject of interest can help provide a response and understand where we are situated today in answering the problematic.

The first section of this chapter assesses small scale farming trends around the world and in South Africa. It goes into further detail on the characteristics of small scale agriculture in South Africa, and addresses general agricultural trends in country. Finally, this section explains the specific data collection method for crop estimates in country is explained.

The second section of the literature review addresses the specificities of the Sentinel-2 satellite mission.

The third section is an introduction to image classification methods and the types of algorithms that can be used: unsupervised and supervised classification methods, parametric/non-parametric and machine learning/non-machine learning classification algorithms, object-based or pixel-based approach classification.

The fourth section details the different classifiers that have previously been used by several researchers for mapping smallholder systems, or at least savanna characterised landscapes. These classifiers are: Maximum Likelihood Classifier, Support Vector Machine, Artificial Neural Network, Random Forest and Time-Weighted Dynamic Time Warping. Some concluding lines are drawn based on the performances achieved using these classifiers in smallholder systems in various studies.

The final section of the literature review details the Sen2Agri processing system and classification method, which yield four different products relevant for agricultural monitoring.

2.1 Smallholder farming and South African agriculture

2.1.1 Smallholder farming: from global diversity to local assessment

Smallholder farming is the most prevalent form of agriculture in the world, supporting many of the planet's most vulnerable populations, and often located in some of the most diverse and threatened landscapes (Samberg et al., 2016). It is estimated that more than 470 million farms world-wide are defined as small (< 2 ha) and family-run (Lowder et al., 2015), of which two-thirds are part of the rural population (IFPRI, 2007). Combined, they control between 40% and over 50% of global farmland and it is estimated that they produce over 50% of global agricultural output (Macmillan, 2016).

Of the regions where smallholder agriculture dominates, Sub-Saharan Africa is the most important, because of its geographic size and because it is a potential center of major agricultural growth in the coming decades. Increasing agricultural productivity is especially crucial in Sub-Saharan Africa, since its population is expected to double by 2050 (Haub et al., 2013). 80% of all

farms in this region, commercial and smallholder combined, are smaller than 2 ha (IFAD and UNEP, 2013; Lowder et al. 2014).

These numbers remain approximate, since there is little information about the exact location of small farms and research on this, especially in the remote sensing community, is still scarce. This makes it difficult both to estimate their numbers correctly and to implement effective agricultural development and land use policies (Samberg et al., 2016). Research and interest in small scale agriculture has only developed recently, with countries reinforcing their rural development policies and addressing food security issues:

“In recent years, the attention of global agriculture and development communities has turned toward the world’s smallest farms. Evidence is mounting that smallholder and family farms are crucial to feeding the planet, and that successful policies aimed at poverty alleviation, food security, and protection of biodiversity and natural resources depend on the inclusion and participation of small farmers.” (Birner et al., 2010; FAO, 2014).

In South Africa as well, food security has been prioritised by the government in 2010 (AMIS, 2015).

“Smallholder agriculture in South Africa has been identified as the vehicle through which the goals of poverty reduction and rural development can be achieved. To fulfill such potential, the need arise to understand diversity amongst these households to formulate effective policy interventions” (Pienaar, 2015).

A lot seems to be expected from these smallholder systems, whose productivity is still marginal and who, with increasing climate variability, are more vulnerable then ever before. Smallholders are disproportionately affected by climate change, as they depend heavily on rain-fed agriculture, and therefore are highly vulnerable to any changes in precipitation patterns (Holland et al., 2017).

A first step into mapping the spatial distribution of smallholder systems is to understand and define these systems, yet a universal definition of the term ‘smallholder’ is lacking because of the diversity of such systems across the world. Even in South Africa, there is confusion regarding what exactly is meant by a smallholder or small-scale farmer (Kirsten et al., 1998; Pienaar, 2015). Using the term “smallholder” generically suggests that these farmers are relatively homogenous, which tends to blur differences between them, and causes misleading assumptions about common interests in development planning (Cousins, 2010; Pienaar, 2015). Characteristics such as agricultural practices, average field sizes and income, exposure to risk and access to markets, and technical equipment vary tremendously according to the country, social-economic context and even region or province.

Nevertheless, some general trends can be outlined for South Africa.

Smallholder farmers typically cultivate small areas with few available resources to maintain or increase productivity, and use traditional production techniques that are labour intensive. They often live in environmentally fragile and remote locations, which translates into a general lack of access to technical assistance, credit, or governmental support (Vorley et al. 2012; Louw, 2013).

These smallholder households develop different livelihood strategies said to be conducive to the given opportunities and constraints in their specific environment (Titttonell et al., 2010).

Smallholder agriculture usually features rain-fed production mainly for household consumption, use of family labor and minimal technology (Gollin, 2014). Field wise, these systems often present small, heterogeneous, and often indistinct field patterns (Eastwood et al. 2010) which grow crops using low soil intensity practices (Jain, 2013). Smallholders in South Africa typically grow maize as their main staple food with mixed crop-livestock systems (Vink & Kirsten, 2003).

2.1.2 Agriculture, land cover and small scale farming in South Africa

The agricultural sector in South Africa is dualistic (Vink & Kirsten, 2003), divided between a large diversity of large scale and smallholder agriculture. The large scale, conventional farming system consists of a well integrated, highly capitalised commercial sector representing an approximate 35 000 farmers, producing around 95% of the country's agricultural output on 87% of total agricultural land (Aliber & Hart, 2009). In contrast, the smallholder sector consists of a vast community of 4 million farmers farming in the former homeland³ areas, on 13% of agricultural land of South Africa (Aliber & Hart, 2009). The former homelands were relatively more disadvantaged and less fertile areas located in the savanna range landscapes of the country, they are home to most of the smallholders in South Africa (Lovo, 2010).

South Africa's main agricultural activity is organised as following (Figure 1): sheep farming and fruit production are dominant in the western, arid regions of the country. In the center of the country, commercial intensive crop production is dominant and spreads over the three provinces of Free State, Northwest and and the eastern part of Mpumalanga, also called the summer grain region. The summer grain region produces the vast majority of final grain production, the rest being produced by small scale farmers. The average field size in the country is approximately 40 ha, with the major crops being maize, followed by wheat, sunflower and soybean (FAO, 2015).

³ The homelands were established under the Apartheid Government, and consist of designated areas for the different ethnic groups of South Africa. Retrieved from: www.sahistory.org.za.

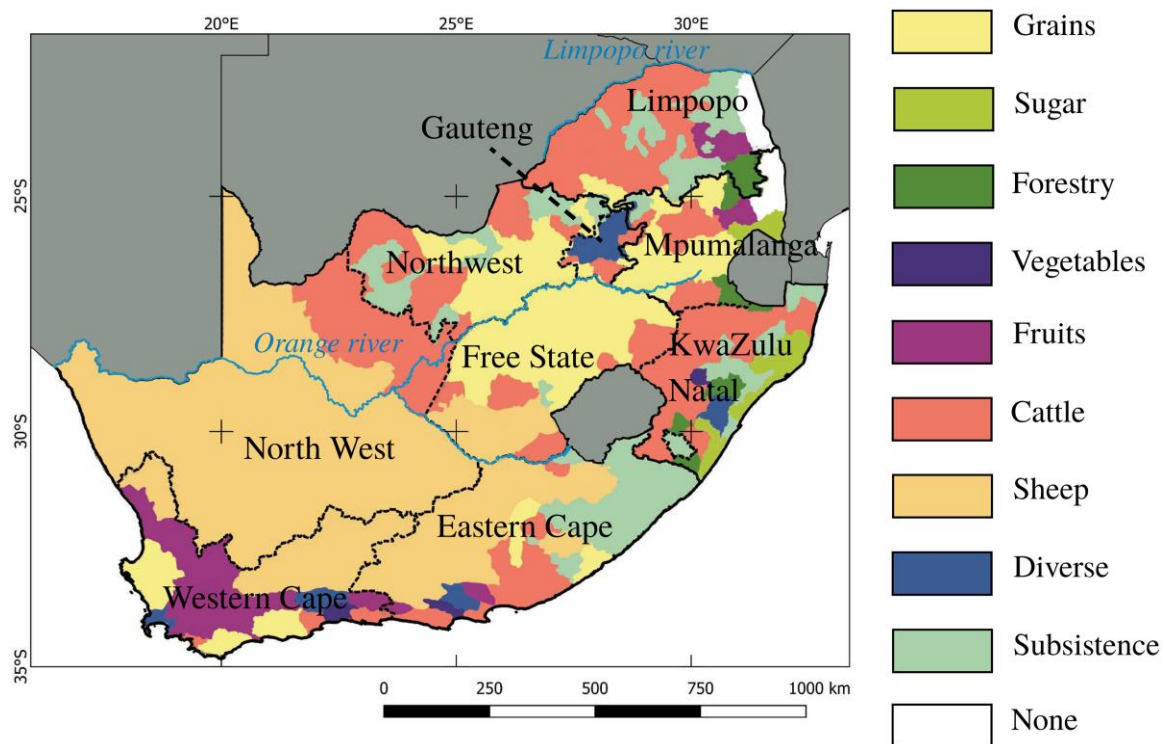


Figure 1: Agricultural activity in South Africa (Waldner et al., 2017)

In recent years, growing conditions in South Africa have become increasingly dry. Over the last 5 years, annual rainfall has decreased throughout the country (Figure 2), with some areas experiencing severe droughts. Increasingly dry growing conditions has resulted in a decrease of 18% of households involved in agriculture between 2013 and 2015 (Figure 2) (AMIS, 2016)

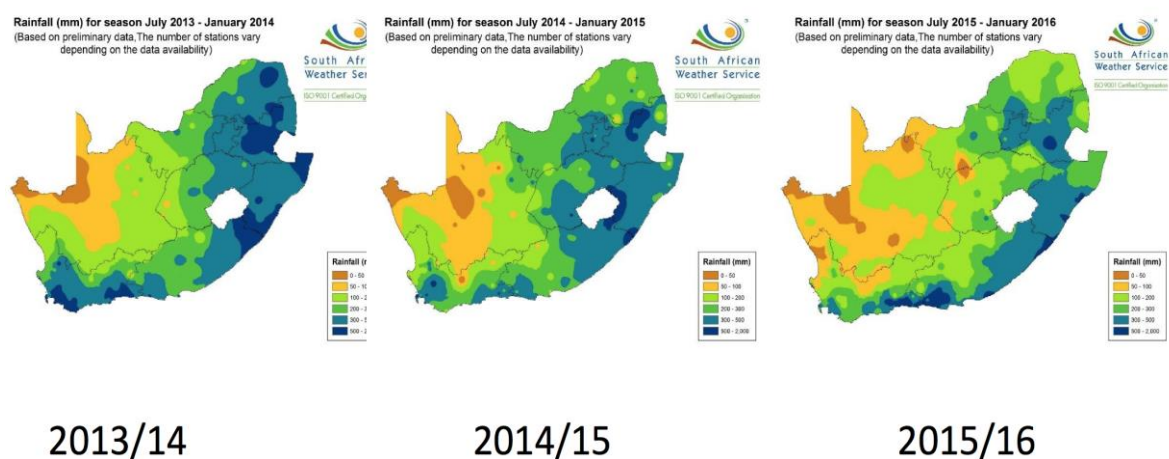


Figure 2: Decrease of rainfall trend from 2013-2016 (AMIS, 2016)

2.1.3 The Producer Independent Crop Estimates System in South Africa

Crop estimates relying on field-based gathering of information and farmers' participation has proven to be extremely costly and has failed to provide complete and accurate information. The necessity to accurately and efficiently estimate areas planted with grain crops in South Africa has thus led to the development of the Producer Independent Crop Estimates System (PICES), which is now being used in 8 provinces of the country (Fourie, 2009). The PICES was developed by the Spatial Intelligence company (SiQ) and has been used for crop estimation surveys since 2002.

PICES uses crop field boundaries digitised from SPOT5 satellite imagery (2.5 m resolution), together with a point frame sampling methodology and aerial field surveys to objectively estimate the area planted for each grain crop (Fourie, 2009). The aerial survey is conducted by a small aircraft, flying at low altitudes over a trajectory traced over the sample points. These sample points are located in agricultural regions, and distributed randomly according to a 2 x 2 km grid over the region. The survey team consists of a pilot and an observer, who is a member of the agricultural community and thus is experienced at distinguishing different crops and differentiating dry land from irrigated cultivations. For each sample point, representing a field, the field observer identifies the crop that is planted in the field and captures it on a Tablet PC connected to a GPS. The Tablet PC has a running user-friendly ArcPad interface and a field boundary map of the agricultural fields as basemap, to select the field corresponding to the sampling point. Additional information about whether the field is rain-fed or irrigated is also collected. The fields surveyed for national crop estimates in the context of PICES are conventional commercial farms (Fourie, 2009).

PICES has proven to increase the accuracy of crop estimates by 40% compared to previous crop estimate systems, and shows a Coefficient of Variance (CV) of less than 2% at national level⁴. Surveys performed by the PICES are able to cover an area of approximately 12 million hectares in a two-month period, using just three aerial field observation teams.

SiQ claims to have succeeded, for the first time in South Africa, in providing information at commercial farming level as well as small scale farming level (Fourie, 2009), but little information about their accuracy at small scale level seems to be available. The survey conducted on small scale farms in the framework of this thesis is detailed in Chapter 4, Section 4.2.2.

⁴ Retrieved from: siq.com.za

2.2 Sentinel-2 mission and exploitation of a new high revisit frequency

Satellite platforms are better disposed than any other platform at providing users with regular imagery because of their fixed orbit, resulting in easily retrievable time series with a fixed revisit frequency. UAV's and airplanes, on the other hand, are not able to capture imagery automatically and consistently over the same area, since every flight must be programmed in advance. When mapping agricultural thematics, the seasonality of landcovers and phenological cycles of crops are of major importance to discriminate between cropland and non-cropland and between crop types. Crops' phenological cycles give different spectral responses along the season and each crop is characterised by its distinguishable spectral profile along the season (Lillesand, 2007). Often, crops that appear very similar at one date will look quite different at another date, and several dates of image acquisition may be necessary to obtain unique spectral response patterns from each crop type (Lillesand, 2007).

For these reasons, time series analysis have been increasingly popular in the remote sensing community. However, imagery with a high temporal resolution isn't always available at the desired high spectral resolution. Sentinel-2 fills that gap by providing both high temporal and spatial resolution. With its high revisit frequency, the chances of getting cloud-free images are maximised, allowing to track the growing cycle of vegetation on a continental or even global scale, which was not considered feasible with previous missions (ESA, 2015).

The Sentinel-2 mission undoubtably offers new opportunities to assess the various growth stages and temporal changes of crops and other landcovers, providing a new level of information to the monitoring of agriculture.

2.2.1 Product description of Sentinel-2

The Sentinel-2 mission comprises twin polar-orbiting satellites; Sentinel 2A and 2B, and the mission is part of the European Copernicus program and funded by the ESA. It provides systematic global coverage of land surfaces between latitudes 56° South and 83° North (ESA, 2015). Numerous applications include: Agriculture, land-cover change, mapping of biophysical variables such as leaf chlorophyll content, leaf water content and leaf area index (ESA, 2015).

Launched in June 2015, Sentinel-2A offers a global coverage of the Earth's land surface every 10 days and, combined with Sentinel-2B (launched in March 2017), the coverage has decreased to every 5 days. The two satellites are identical and carry a unique combination of global coverage: systematic acquisition of images, high revisit frequency of 5 days, wide field of view of 290 km, high spatial resolution of 10 m and by reason of a state-of-the-art Multispectral Imager (MSI); a total number of 13 spectral bands (Gascon, 2014; ESA bulletin 2015), of which three are in the 'red edge' part of the spectrum.

The 'red edge' provides key information on the state of vegetation and Sentinel-2 is the first civil optical Earth observation mission of its kind to include those three bands (ESA 2017).

The spatial resolution of Sentinel-2 varies depending on the spectral band. These bands and their corresponding spatial resolution, central wavelength and bandwidth are illustrated in Table 1.

Table 1: Sentinel-2 spectral bands characteristics

Sentinel-2 Bands	Central Wavelength (nm)	Spatial Resolution (m)	Bandwidth (nm)
Band 1 – Coastal aerosol	443	60	20
Band 2 – Blue	490	10	65
Band 3 – Green	560	10	35
Band 4 – Red	665	10	30
Band 5 – Vegetation Red Edge	705	20	15
Band 6 – Vegetation Red Edge	740	20	15
Band 7 – Vegetation Red Edge	783	20	20
Band 8 – NIR	842	10	115
Band 8A – Narrow NIR	865	20	20
Band 9 – Water vapour	945	60	20
Band 10 – SWIR – Cirrus	1375	60	20
Band 11 – SWIR	1610	20	90
Band 12 – SWIR	2190	20	180

The different band specifications can be described as follows (ESA, 2017; Addabbo et al., 2017):

1. The five bands at 10 m resolution (four in the visible, one in the near-infrared (NIR)) satisfy user requirements for basic land cover classification.
2. The four bands at 20 m resolution (three in the 'red edge', one in narrow NIR) address requirements for enhanced land cover classification and for the retrieval of biophysical parameters. The 'red edge' is located between the red band (Band 4) and the NIR band (Band 8), as can be seen on Figure 3 below. The red portion of the electromagnetic spectrum is one of the areas where chlorophyll strongly absorbs light, whereas, in the NIR, the leaf cell structure strongly reflects light (Weichelt et al. 2013). The transition between the red absorption and the NIR reflection in plants provides valuable additional information about vegetation and its characteristics (Weichelt et al. 2013). Thus, the bands in the 'red edge' are very useful for crop monitoring.

3. The two Short Wave Infrared (SWIR) bands at 20 m and remaining bands at 60 m, show a high contrast between moisture and dry content. They are dedicated mainly to atmospheric corrections (water vapour and aerosols detection) and cirrus-cloud screening.

The exact location of these spectral bands in the electromagnetic spectrum is illustrated on Figure 3.

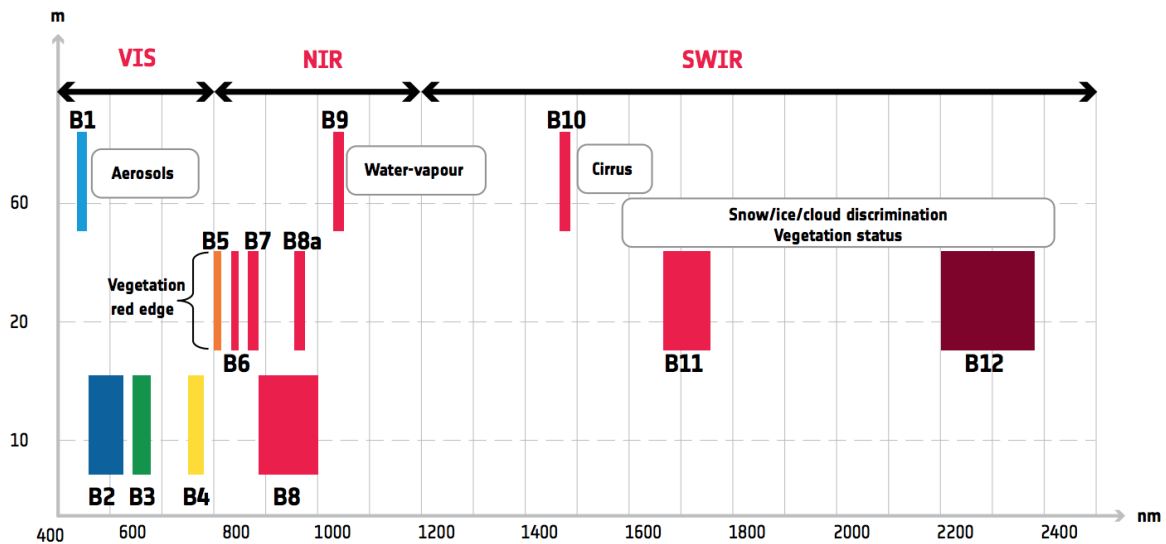


Figure 3: Spatial resolution plotted as a function of wavelength for the different Sentinel-2 spectral bands (ESA, 2017)

Due to the improved features compared to previous missions, Sentinel-2 is able to detect very early changes in plant health, to distinguish between different crop types, and deliver timely data on different biophysical variables. These elements can help end users and policy makers to detect early signs of food shortages in developing countries (ESA, 2015).

2.2.2 Sentinel-2 Data Distribution

The Copernicus Open Access Data Hub is the official website of the ESA and provides free and open access to all of the Sentinel-2 imagery. Satellite images are available to download at: <https://scihub.copernicus.eu/>. From the raw captured Sentinel-2 data, to the data made available to users, a series of pre-processing steps are performed on the images including reprojecting and orthorectifying using a Digital Elevation Model (DEM). The raw captured image is called a Level-0 product, and the products distributed online are called Level-1C products.

Level-1C (L1C) images are Top-Of-Atmosphere (TOA) products, meaning that each pixel contains the values of reflectance (and the parameters to convert into radiance) measured on top of the atmosphere; including clouds, water vapour and shadows. Each tile of L1C is a 100 x 100 km² orthoimage in UTM/WGS84 projection (ESA, 2017).

2.3 Image classification

This section details all the necessary information to understand the successive steps of image classification and the different classification methods available.

2.3.1 Introduction to image classification

Image classification is used to produce thematic maps from imagery, by the process of assigning pixels to different type of classes in order to extract land information. It is one of the most often used methods of information extraction in remote sensing (Choodarathnakara et al. 2012). Cropland mapping through image classification provides statistical and spatial information, such as crop area estimation, offering important decision support in agriculture (Torres-Sánchez et al., 2013).

Classifications may be based on two different types of variables: *categorical variables* and *continuous variables*. Classification of *categorical variables*, or thematic classes assign a pixel to a particular class or category (Yates et al., 2003). For example, a cropland map is a binary map and a crop type map has a fixed amount of classes to which pixels are assigned. On the other hand, *continuous variables* can technically take an infinite number of values, but practically they often take any value between two thresholds in order to be physically relevant. *Continuous variables* are relevant for the quantification of biophysical variables such as Leaf Area Index (LAI) and Normalized Vegetation Difference Index (NDVI).

The process of image classification typically involves five steps (ITC, 2013):

1. Selection and preparation of the imagery considering the type of sensor, spatial resolution, spectral bands, and acquisition date(s).
2. Selection of a *supervised* or *unsupervised* classification approach depending on available data and knowledge about the study area.
3. Algorithm selection whether *parametric* or *non-parametric*; *machine learning* or *non-machine learning*.
4. Classification at *pixel* or *object* level.
5. *Validation* of the classification and quality assessment of the product

Image classification can broadly be divided between supervised and unsupervised classification techniques.

Unsupervised classification method

In remote sensing, unsupervised classification has the particularity of assigning pixels to spectral classes without the user having foreknowledge of the existence or names of those classes (Richards et al., 2006). In a remotely sensed image, unsupervised algorithms will identify, clusters or natural groups sharing similar features based on spectral information. Typical unsupervised procedures of image classification use clustering algorithms, the resulting clusters form the premises of classes, as they often need to be reorganised by the user to make physical sense (Ulmann et al. 2014). In a second step, the clusters can be identified to their corresponding class

by associating a sample of pixels in each class with available reference data, which can include maps or information from in situ fieldwork (Richards et al., 2006).

Common drawbacks associated with unsupervised classification is the determination of the 'correct' or 'optimum' number of clusters (Milligan et al., 1985), and the computational cost of the classification. Another potential issue is that the resulting classification rarely shows a 1-to-1 relationship with classes derived from ground-truth data (Lathrop et al. 2006; Brown et al. 2012). On the other hand, they are useful for analysing the spectral class composition of the data, which is not always known by the user otherwise, and can thus be used prior to a detailed analysis by supervised classification with ground truth data (Richards et al., 2006).

Supervised classification method

In supervised classification, the image analyst 'supervises' the pixel categorisation by specifying beforehand the amount and the name of classes that are present on the image. These classes are fixed, as opposed to unsupervised classification where it is the spectral information that determines the clusters, which are then named (Richards et al., 2006).

Supervised classification algorithms have in common that the algorithm extracts information only about the training samples selected by the user. The training samples can for example be collected through a field survey or by selecting polygons through visual interpretation. The training samples should be representative of each of the known classes and represent most of the spectral variations of the class in the area.

The algorithm trains on the input data for each class of interest, characterises it, and then applies those characteristics to classify unclassified pixels over the whole image. Each pixel is thus classified according to what it resembles the most in the training data.

All classification algorithms discussed further in this thesis are supervised classification methods, since they are better qualified for mapping smallholder systems, where the diversity of spectral signatures is high, and ground truth representativeness is important.

2.3.2 Parametric or non-parametric classification algorithms

The terms parametric and non-parametric refer to the way in which the classification algorithm characterises the input data. These terms can be misleading, as they appear to imply that one method uses parameters to characterise the input data, while the other one does not. The difference lies in the fact that a parametric algorithm has a finite or fixed number of parameters to characterise the data, while non-parametric algorithms have a potentially infinite amount of parameters (Cai, 2014), meaning that in non-parametric models the complexity of the model grows with the size of the training set. Supervised and unsupervised classification methods can both use parametric or non-parametric algorithms (Roberts, 1996).

The term parametric is, in the field of statistics, also referring to a probability distribution that the data is assumed to follow, and this distribution can be described by a finite number of parameters (eg. mean, standard deviation and normal distribution). So that each class can be modelled by a

probability distribution in multispectral, space and completely described by a few parameters. Other techniques also exist, in which neither distribution models nor parameters are relevant, these are referred to as being *non-parametric* (Raschka, 2016). Intuitively, a non-parametric algorithm does not make any assumption on the data distribution, it uses a flexible number of parameters, and the number of parameters grows with the size of the training set (Raschka, 2016).

Parametric algorithms may perform well if the strong assumptions made on the distribution of the data turn out to be correct. If not, however, the accuracy of the classification can be strongly affected (Cai, 2014), especially since remotely sensed data rarely have normal distributions (Belgiu & Drăgu, 2016). *Non-parametric* methods can overcome these limitations since they are not constrained by assumptions regarding frequency distribution (Lów et al., 2013).

In the classifiers discussed in Section 2.4., the Maximum Likelihood Classifier (MLC) and linear Support Vector Machine (SVM) are both qualified as parametric algorithms. The MLC uses a popular statistical distribution, which is the normal or Gaussian distribution.

Non-parametric algorithms discussed in Section 2.4, are the Artificial Neural Network ensemble (ANN), Radial Based Function (RBF) kernel Support Vector Machines (SVM) and Random Forest (RF).

Machine learning or non-machine learning classification algorithms

Classification algorithms, which are very popular within the remote sensing community, are machine learning or ensemble algorithms such as ANN, SVM and RF.

Defined in 1959 by Samuel A., machine learning is a "*Field of study that gives computers the ability to learn without being explicitly programmed*", meaning that the algorithm is able to learn from past experience and improve itself without being explicitly programmed to. Machine learning (ML) is a subdivision of artificial intelligence that is based on the biological learning process (Lary et al. 2016). In classification, such algorithms have a great advantage over non-machine learning algorithms because of their ability to detect subtle and complex patterns in data using robust statistical techniques with a high degree automation (Blaschke, 2010; Rodriguez-Galiano et al., 2012), and optimise their classification accuracies using example data or past experience (Alpaydin, 2010). In ML, example-training data sets are constructed based on the input training data, and cover as much of the system parameter space as possible. ML classifiers also facilitate the assimilation of vast quantities of data (Debats et al., 2016). Ensemble algorithms or ensemble learning is a machine learning method that creates multiple models and combines them to improve results (Lary et al. 2016). The ANN and RF are both ensemble-learning algorithms.

Algorithms that do not make strong assumptions about the form of the mapping function are called non-parametric machine learning algorithms. By not making assumptions, they are free to learn any functional form from the training data.

Even though most machine learning techniques are supervised, there are some unsupervised machine learners as well (Roberts, 1996). Machine learning algorithms can be parametric or non-parametric. The non-parametric machine learning algorithms (ANN, RBF kernel SVM and RF) are

free to learn any functional form of the training data, as opposed to parametric machine learners (linear SVM) which are restricted to the assumptions of the model.

2.3.3 Pixel-based or object-based classification approach

Pixel-based or object-based approaches refer to how the spectral information is extracted from the remote sensed imagery and how the classification is applied to the image; at the individual pixel level, or at the object level. The choice between pixel or object based classification does not exclude one or other classifiers mentioned in the above section.

Pixel-based procedures only extract the information provided by each individual pixel as if it were isolated from neighbouring pixels (Figure 8), thus neglecting spatial or contextual information related to the pixel of interest. This creates a so-called ‘salt and pepper’ noisy effect in classification, which may wrongly classify pixels that are actually part of the same class. This effect can be reduced by using existing post-filtering methods, such as the one used in the Sen2Agri system and explained in Section 2.7. To avoid these limitations of local decision taking in pixel-based classification, the object-based approach offers an alternative (Duro et al. 2012).

Object-based procedures extract the information of an image at the object level instead of the pixel level. The remote sensed imagery is analysed through its different objects, which can be defined as homogeneous groups according to certain homogeneity criteria. Objects are groups of pixels that are similar to each other, sharing the same defined properties. Dividing the image according to a homogeneity criteria, defined by users, is called segmentation and is acknowledged to be a time consuming step, as the parameters of the segmentation need to be optimised (Valero et al. 2016). The resulting objects are then classified using supervised or unsupervised classifiers (Blaschke, 2010, Veljanovski et al. 2011). Object-based analyses use both individual pixel information (called low-level features) and object level information conjunctively to extract what is called high-level features (Crommelinck et al. 2016).

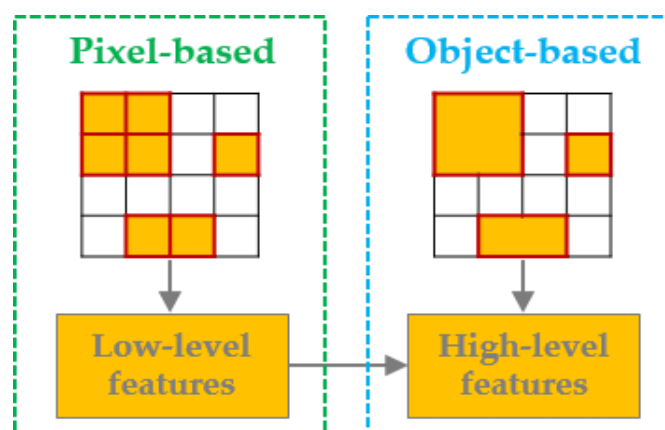


Figure 4: Pixel-based versus Object based feature extraction (Crommelinck et al. 2016).

The object-based classification approach works well for structured landscapes with high geometric and contextual properties and low heterogeneity inside the objects (O’Connell et al. 2015), such as urban areas or non-cropped features: trees, hedgerows and grassy margins for example (O’Connell et al. 2015).

Validation and quality assessment

To evaluate the accuracy of a classification product, a number of measures can be adopted to assess the performance of the classifier, by computing a confusion matrix and derived accuracy measurements. They are detailed in Section 5.3.

2.4 Review on classification methods used for mapping cropland in smallholder systems

The goal of the work presented in the following section is to assess to what extent state-of-the-art supervised classification methods have been applied on smallholder systems. In these systems, a combination of small field size, residual trees, crop diversity, and agricultural practices (low intensity and few intrants) magnify the within-class variability of cropland while blurring the spectral distinction between cropland and non-cropland on one side, and between different types of crops.

Though the described classifiers are most commonly used by the remote sensing community, their application to mapping small scale farming systems is more recent, with high spatial resolution imagery becoming increasingly available. Few studies have been conducted so far in these types of diverse landscapes and none of them compare different type of classifiers' performance over the same study area. The classifiers used in the censed papers are Maximum Likelihood Classifier, Support Vector Machines, Artificial Neural Networks and Random Forest, as well as a more recently developed classifier: the Time Weighted Dynamic Time Warping method, which will also be addressed.

2.4.1 Supervised non-machine learning classifiers

Maximum Likelihood classifier

The MLC is a parametric classifier, was the first rigorous algorithm to be employed widely for remote sensing applications, and has been the most common classifier for many years (Richard, 2013). It is simple in its conception as it makes use of a very well known statistical concept: the normal Gaussian distribution. The MLC relies on the Gaussian probability density function to classify each pixel: by assuming that the statistics for each class in each spectral band are normally distributed, it calculates the probability that a given pixel belongs to a specific class (Kumar et al. 2002). It considers variability by taking into account the variance-covariance within the class distribution (Erdas, 1999). Each pixel is assigned to the class to which it has the highest probability of belonging, or, in other words, the maximum likelihood (Kumar et al., 2002). For visual understanding, the example below (Figure 5) shows two classes, A and B with their respective probability density function for the spectral band 1. An unlabelled pixel 'X' shows that for band 1, it is more likely, with a certain probability, to belong to class B than A. When looking at a different band, the class distributions of A and B will be different, and so will the position of the pixel 'X' in the scatter diagram. In each spectral band, the MLC calculates the probability of 'X' belonging to each class, and the pixel is then assigned to the class towards which it shows the highest overall probability, all bands combined.

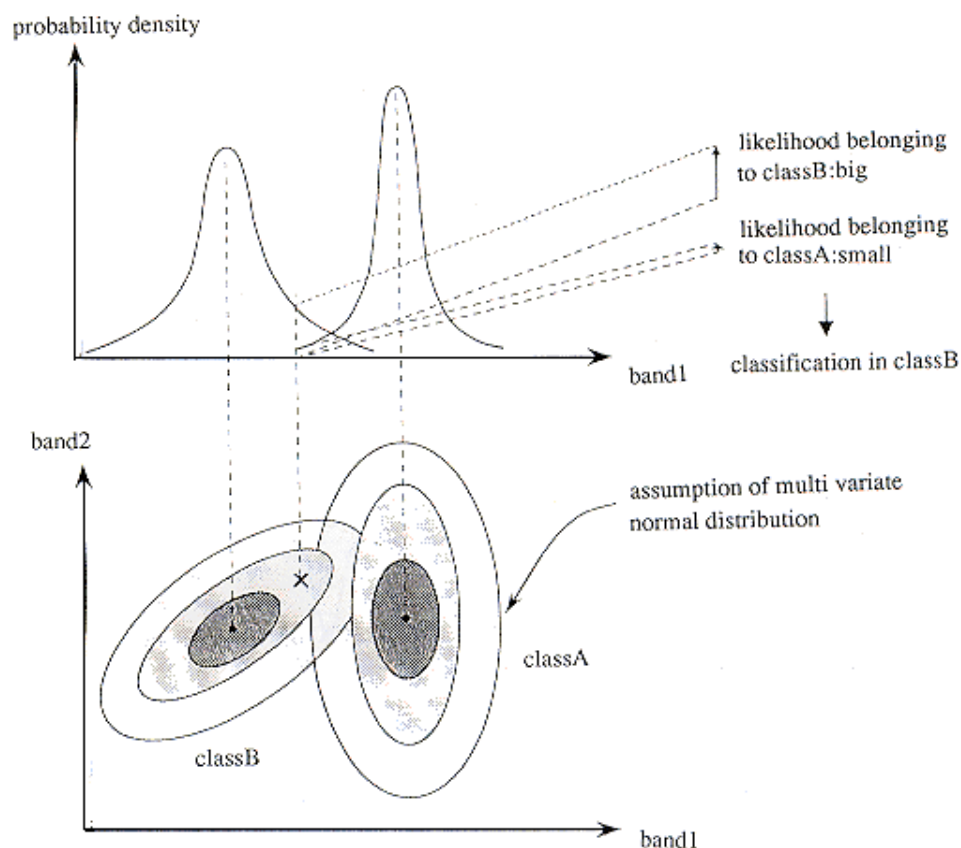


Figure 5: Concept of maximum likelihood method (Murai, 1999)

The successful application of the MLC is dependent on a correct delineation of the spectral classes in the image data of interest (Kumar et al. 2002), since each class is to be modelled by a normal probability distribution. If a class happens to be multimodal and this is not resolved, or if the data is non-normally distributed, then the results may not be satisfactory (Richards, 2006, Otukey & Blaschke, 2010). This is where an unsupervised clustering analysis of the data becomes particularly relevant. Each class also needs to be well represented with sufficient training data, which must cover the spectral diversity of each class, in order to reliably derive class-specific covariance matrices. Even though the MLC makes strong assumptions about a dataset's distribution, it is often used as a reference for classifier comparison because if the class probability density function are indeed Gaussian, it is the optimal classifier (Paola et al., 1995)

Other drawbacks of the MLC, apart from its normal distribution assumption, is the computational cost required to classify each pixel, particularly when either a large number of spectral bands are involved or a large number of spectral classes must be differentiated (Lillesand et al., 2002).

The MLC has been applied, after an unsupervised clustering analysis, by Sweeney et al. (2015) to map cropland in smallholder-dominated savannas over Zambia's Southern Province with Landsat 5 Thematic Mapper (30 m resolution). Using two acquisition dates, one in pre-season and one during harvest season, five primary land cover categories were mapped including cropland (forest, savanna, water, settlement and cropland). The classification produced an overall accuracy of 88.18%, and the F-score of the cropland class was 89.1%. However, the F-score for the savanna class was low (79.25%) and was mainly confused with cropland and natural forest.

Although the study highlights the importance of mapping cropland in these smallholder systems, they do not once mention the average field-size of the study area, nor do we know if fields smaller than the pixel size were also surveyed and are included in the final dataset. Even though the F-score of the cropland class seems low, we cannot conclude anything about this accuracy measure since it is not clear if it represents the study area's smallholder cropland diversity.

2.4.2 Supervised machine learning classifiers

Support Vector Machines

Gualtieri et al. (1998) first introduced the support vector concept to remote sensing image classification. Support vector machines (SVM) aim to define a boundary that separates most optimally the training classes in a feature space, that is, the optimal separation hyperplane. The classification of new data is then based upon the side of the decision boundary in which the data point falls, thus, linearly separating classes (Huang et al., 2002). As can be seen on Figure 6, the 'optimal' hyperplane is drawn by choosing the boundary, which maximises the distance (also called the margin), between the classes' closest points. The points lying on the boundary are called *support vectors*. The *support vectors* are pixel vectors that are closest located to the optimal separating hyperplane, and upon which the marginal hyperplane are drawn (Huang et al., 2002).

In the case of non-linearly separable points, which is most often the case with ground truth data and remote sensing applications, finding the optimal boundary requires data points to be projected in a higher-dimensional space, where the data points effectively become linearly separable (Meyer, 2017). The projection is performed by a Radial Basis Function (RBF) kernel. The RBF kernel SVM is the most common choice for classification tasks. When classes still overlap, data points on the “wrong” side of the discriminant margin are weighted down to reduce their influence (Meyer, 2017).

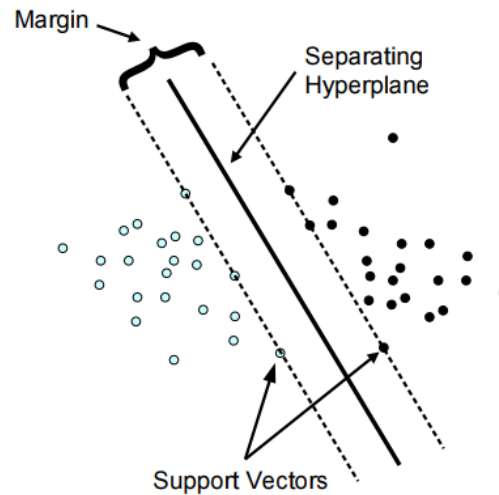


Figure 6: Schematic representation of an optimal separating hyperplane using SVM (Huang et al., 2002)

RBF kernel SVM are non-parametric classifiers capable of handling complex, non-linear class boundaries, as opposed to the MLC. They are considered to frequently outperform the latter as well as other parametric classifiers, and are used for landcover change detection (Estes et al., 2012). Although linear SVM is a non-machine learning classifier, the SVM with RBF kernel uses machine learning concepts, and it is also more widely used for remote sensing applications.

SVMs have been used in various studies regarding landcover and crop type mapping and have often performed well (Estes et al., 2012; Zafari et al. 2017). Parameter tuning has a great influence on the performance of the classifier and lack of time dedicated to the tuning of the parameters might explain why this method does not always perform as well as it should (Li et al. 2011; Stephens et al., 2014).

SVMs are often used in comparison with the ensemble learning RF classifier, and both usually show similar results. Zafari et al. (2017) performed a comparison between RBF kernel SVM and RF, in a study aiming to map crop types over Mali for five crop classes (cotton, maize, millet, peanut, and sorghum), using a time-series of WorldView-2 images (<50 cm resolution and 1.1 day revisit time). The RBF kernel SVM and the RF achieving very similar Overall Accuracies for both methods, 83% and 82% respectively (Zafari et al. 2017).

The RBF kernel SVM was also tested in the framework of the Sen2Agri project for the construction of an automated crop type map over 12 national test sites, using a time-series of Spot 4 (Take 5), with a 20 m spatial resolution, and Landsat 8, with a 30 m spatial resolution (Inglada et al. 2015). SVM and RF were applied on all test sites for the main types of crops. The RF outperformed SVM

for all test sites. The outperformance was not significant for most the test sites and both methods yielded highly accurate results, except for two sites featuring small scale farming (Burkina Faso and Madagascar). On these two test sites, both methods obtained a low Overall Accuracy: approximately 50% using RF and 30% using SVM. Considering that the study did not focus on small scale farming and that the data was collected on commercial fields mainly, the RF shows some potential using ground thruth data collected on smallholder farms and imagery with higher spatial resolution.

Artificial Neural Networks

Artificial Neural Networks (ANNs) attempt to simulate human learning processes through the establishment of linkages between input and output data (Murmu et al., 2015). These linkages are like pathways, forming the analogy with the human learning process as they are reinforced by repeated associations between input and output in the training process. Those same pathways are then used to link input and output in the absence of training data (Murmu et al., 2015).

The construction of this type of model is referred to as a network since it can be viewed as three layers of connected nodes, as seen on Figure 7.

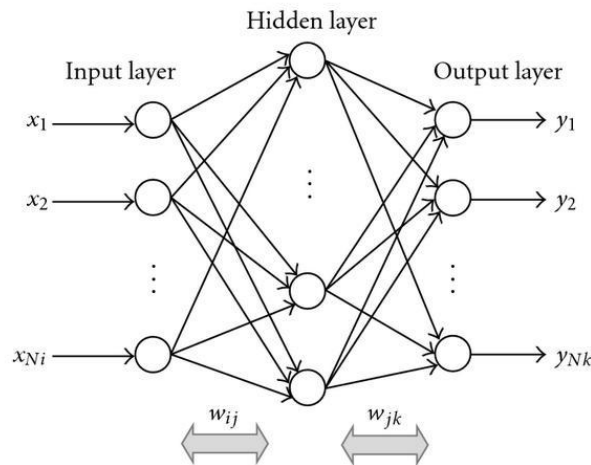


Figure 7: Schematic diagram of a general neural network (Chen et al., 2009)

The input layer nodes represent each input feature, whereas the output layer contains a node for each class to be predicted. In between input and output layers is a 'hidden' layer of nodes, and all the layers are interconnected as seen on the Figure 7. The number of nodes in the hidden layer is decided by the user during the tuning phase (Stephens et al., 2014). The association between input data and output data is established during the training phase, by determining the weights (w_{ij}) of the hidden layers (Murmu et al, 2015). Each connection is then assigned the weight that was 'learnt' during the training phase. The input to each node of the hidden layer is the sum of weighted values (w_{ij}) from the input layer. These value are further used into a logistic or sigmoid function with the output being class probabilities that sum up to 1 (Stephens et al. 2014).

In the context of remote sensing, the repeated associations between classes and digital values, as expressed in the training data, strengthen weights within hidden layers that permit the ANN to

assign correct labels when given unlabelled spectral values. Neural networks are fast to process new data but the training phase has been evaluated as being resource- and time-consuming (Waldner et al., 2016). ANNs have been used for crop mapping in general, with satisfying accuracies. Descriptions of these studies can be found in Murmu et al. (2015).

The potential of ANN for discriminating between crops in West Shewa, an area with small scale farming in central Ethiopia, was tested using high resolution (30 m) and very high resolution (4 m) images. The high resolution images yielded good results for commercial farming, yet displayed difficulties dealing with mixed pixels due to the small size of the parcels. Using very high resolution images (4m), their results were not satisfactory either, because the high resolution imagery only covered a subset of the region (Delrue et al., 2013).

Random Forests

The Random Forest (RF) classifier, originally developed by Breiman in 2001, is a collection of numerous decision trees. The trees are created by drawing a random subset of training samples through replacement, following a bagging approach, to produce multiple decision trees. Each decision tree is trained on a random selection of the training data with replacement. This random selection can be seen as a random vector sampled independently and with the same distribution for all trees in the forest (Breiman, 2001). A simplified version of the RF is illustrated on the following Figure 8.

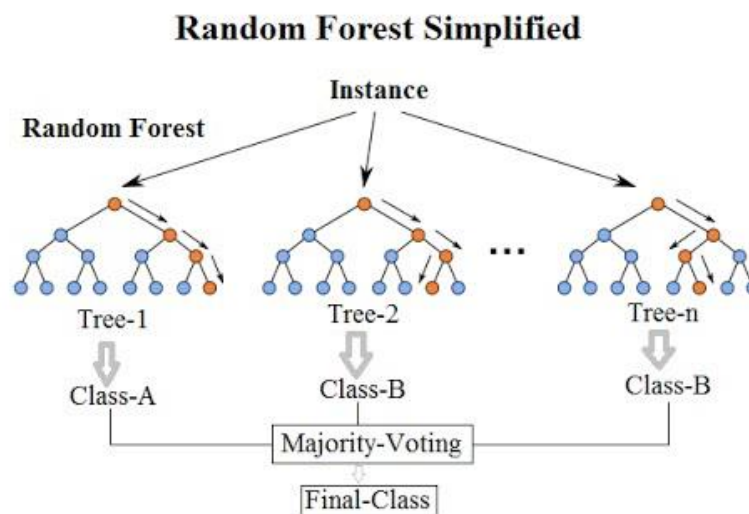


Figure 8: Simplified representation of a random forest (Kumar et al., 2002).

In bagging, successive trees do not depend on earlier trees, they are each independently constructed using a bootstrap sample of the data set (Liaw et al., 2002). This “bagging” (stands for Bootstrap Aggregating) is a way to decrease the variance of the final prediction by generating additional data for training from the original dataset, using combinations with repetitions to produce multisets of the same cardinality and size as the original data. The samples are divided into two groups: one is used for training the model, the second one is for validation of the result. Each tree is composed of multiple nodes and as the training data passes through the decision tree,

it is split at each node based on the threshold value of a set of variables that is randomly selected. The training data is then further, passed on to the next level of nodes. Eventually, from this randomisation over multiple iterations emerges discernible patterns, then used to classify unlabelled pixels.

The final classification occurs at the terminal node of each tree. The class assignment probabilities are then calculated and averaged across the different trees to obtain a class probability for each pixel. Then, each tree votes for a class membership, and finally the membership class with the maximum votes will be the one that is finally selected (Belgiu & Drăgu, 2016). In other words, since a tree can make a prediction mistake, combining multiple decision trees, mistakes are made at different places; when taking the majority of vote between trees in the 'forest', the final attributed class to the observation is the most accurate.

The two main sources of random behaviour, random subsets of data for training individual trees and random subsets of features for node selection, increase generalisation performance by creating independent decision trees that do not overfit to the training dataset (Liaw & Wiener, 2002). The generalisation error for the forest (ensemble of trees) converges to a limit, as the number of trees in the forest becomes large, and depends on the strength of the individual trees in the forest and the correlation between them. By increasing the size of the training dataset, the model's predictive force cannot be improved, but it decreases the variance, narrowly tuning the prediction to expected outcome. This approach makes the algorithm less sensitive to noise in the data (Rodriguez-Galiano et al., 2012). Because the RF can handle big quantities of data, users can combine multi-source and multi-temporal data to improve classification accuracy without overfitting the algorithm. However, only relevant datasets should be included to reduce the computational burden (Belgiu & Drăgu, 2016). The RF classifier is also sensitive to the sampling procedure, to the size and representativeness of the training sample.

The RF is particularly attractive because it requires little guidance for parametrisation. Growing an ensemble of decision trees and allowing them to vote for the most popular class also produces a significant increase in classification accuracy for land cover classification (Rodriguez-Galiano et al., 2012; Belgiu & Drăgu, 2016).

Results of the RF for cropland mapping

The RF algorithm has proven to be an efficient crop classifier, due to its classification accuracy and speed of processing, in several studies (Löw et al. 2013, Belgiu & Drăgu, 2016, Stephanian, 2017) as well as in the Sen2-Agri testing phase. Inglada et al. (2016) highlighted the adequacy of the classifier for land cover mapping and justified the choice of this approach by noting that the classifier can yield high-quality mapping for a variety of crop types. For these reasons, the RF was selected for classifying the crop mask and crop type map in the in the Sen2Agri system. Li et al. (2016) also suggested that RF should be considered in most cases for agricultural mapping.

RF appears in two studies that have aimed at mapping small scale farming landscapes (Debats et al., 2016; Lebourjois et al. 2017).

In the study carried out by Debats et al. (2016), the RF classifier was applied using an object-based. The authors were able to achieve high performances for their cropland map, in the Southeast region of South Africa, using satellite imagery from DigitalGlobe Worldview-2 imagery (<2 m spatial resolution). They focused on mapping the diversity within the study area, and not only on smallholders, sampling three types of dominant forms of agriculture: smallholder rain-fed subsistence, rain-fed commercial, and centre pivot irrigated commercial fields, achieving Overall Accuracies of 90%, 93% and 94% respectively. The approach of Debats et al. (2016) is based on the extraction of five complex feature types using computer vision, which enables to automatically detect, recognise and track complex objects in images, followed by a RF classifier. They determined that multi-temporal information increased performance more than the addition of multi-spectral bands available in DigitalGlobe Worldview-2 imagery. This suggests that seasonal changes in texture and patterns are more descriptive than the spectral signatures themselves, which can be highly variable within the dominant smallholder class. The study lacks information about the field sizes and an accurate definition of the three forms of agriculture considered, as well as the proportion of each form of agriculture in the training set.

Lebourjois et al. (2017) used an object-based RF classifier to map smallholder agricultural crop types in Madagascar. The study is based on a simulated Sentinel-2 time series, obtained by combining imagery from SPOT 5 (20 m) and Landsat 8 (30 m), associated with a very high spatial resolution (VHSR), at 0.5 m spatial resolution coverage and a digital elevation model (DEM). The authors obtained an Overall Accuracy of 91% for cropland, and 61% for the crop type classes. While the mean size of an agricultural field in the study area is very small (about 0.05 ha), contiguous fields of the same crop type were common, giving rise to larger crop patches. The also sought to analyse the importance of the different data sources and of different spectral variables. They found that spectral variables derived from high resolution time series, such as Sentinel-2, were shown to be the most discriminating, with a better score for spectral indices (NDVI) over the reflectances. VHSR data were only found to be essential when implementing the segmentation of the area into objects and not for the spectral or textural features they can provide during classification.

2.5 Other methods

Time-Weighted Dynamic Time Warping

First introduced in remote sensing by Maus et al. in 2015, the Time-Weighted Dynamic Time Warping algorithm (TWDTW) was developed in the context of increased availability of time series. It uses temporal patterns of the training samples computed from different indices and/or spectral features, realigns them in a way that the signals no longer seem out of phase and then classifies the agricultural fields of interest. The algorithm compares two time series and finds their optimal alignment, providing a dissimilarity measure as a result (Maus et al. 2015).

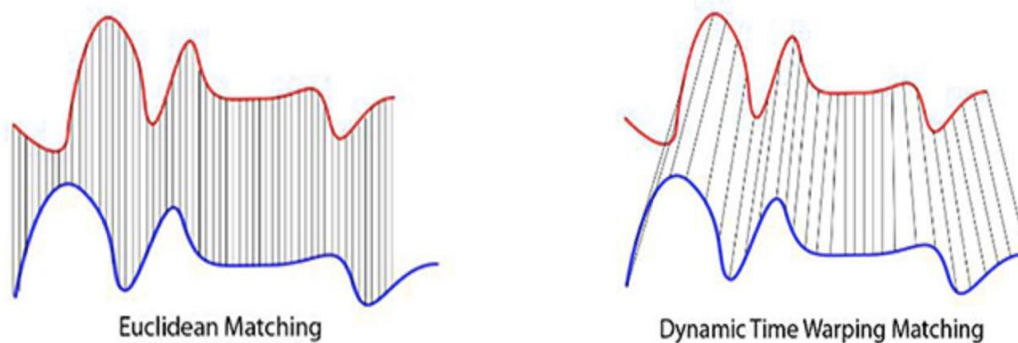


Figure 9: Classic euclidian alignment versus Dynamic Time Warping matching (Martin et al., 2016)

The method is based on the Dynamic Time Warping (DTW), which was used, amongst others, for speech recognition, to cope with different speaking speeds (Sakoe et al., 1978), and more recently widely used for data mining in time series. Maus et al. modified this method to account for the seasonality of land cover types with interannual variability. The resulting algorithm is flexible to account for different cropland systems, tropical forests, and pasture using few training samples.

Applying TWDTW method requires three main steps: first, generating the temporal patterns of the training samples based on the NDVI raster time-series, second, applying the TWDTW analysis, and finally classifying the time-series. The R package called dtwSat (Maus et al., 2016) can be used to execute the workflow in order to obtain a TWDTW classification based on objects (Csillik et al., 2017).

Maus et al. (2016) originally tested the algorithm on a MODIS time-series of 13 years in Brazil for three landcover classes: forest, pastureland and cropland with a pixel-based approach, obtained high Overall Accuracies of respectively 94%, 88.41% and 92%. They highlighted the potential of the TWDTW to improve land use, land cover products, and contribute to agricultural statistics, and the advantage of the method performing well with a small amount of patterns training samples.

Using Sentinel-2 time series, a very recent study by Csillik et al. (2017) applied an object-based TWDT algorithm to 13 Sentinel-2 images from 2016. The study area, in Romania, comprises both commercial farming and small scale farming.. It is the only study on smallholders so far to have made use of Sentinel-2 imagery. The image objects, which were delineated by applying multi-

resolution segmentation algorithm, were classified using the TWDTW method to map the following 5 classes: wheat, maize, rice, sunflower and forest. The resulting cropland map achieved an Overall Accuracy of 93.43%. The lowest user's accuracy was yielded for the rice class (78.8%) because of the confusion with the maize class, whereas the highest user's accuracy was achieved by the wheat class (99.72%), followed by the forest, maize and sunflower classes. The high misclassification rate of the maize class was caused by the confusion with rice and sunflower. The study only focused on the visible bands of the Sentinel-2 sensor (band 2, band 3 and band 4) and near-infrared band (band 8) for the segmentation process, while the phenological cycles of the land use/land cover classes of interest were computed using the NDVI. The mean NDVI values for each object were then classified by the TWDT. Unfortunately, the authors used raw Sentinel-2 images (level 1C) which correspond to Top Of Atmosphere reflectance, instead of Level 2C (Bottom Of Atmosphere), which is habitually used for classification. Furthermore, the authors did not use the three bands in the 'red edge', which could have increased accuracies. Another drawback of this study is that it did not compare accuracies on both agricultural systems separately. Moreover, it applied the same segmentation process to both areas, resulting in an under-segmentation for the smallholder's fields. Under-segmentation causes several fields to be merged together in the process, which poses a problem if the fields have different crop types. Finally, the authors do not mention how many smallholder fields are included in the training data, as well as the average field size.

Although the TWDT method promises a new interesting workflow, rigorous research must still be pursued to understand the limits and benefits of the method compared to other classification methods.

2.6 Comparison of studies

2.6.1 Pixel- versus object-based smallholder mapping

Working at very high resolution (<5 m), Castillejo-González et al., (2009) concluded that object-based procedures outperformed pixel-based procedures for all the classifiers, whereas Valero et al., (2015) concluded that with lower spatial resolution (20 m), results obtained by pixel-based and object-based procedures were quite similar. Yet, the pixel-based approach yielded better numerical results, especially for datasets comprising a small number of images, significant cloud cover and a small number of in situ data samples. Duro et al. (2012) also concluded that there was no advantage in using one method over the other, in a study using 10 m resolution imagery.

The study of Valero et al. focuses on comparing the two classification approaches for the choice of a crop mask classification algorithm within Sen2Agri. Some test sites in this study (using Spot Take 5 image series) included small scale dominated areas (Madagascar, Burkina Fasso and Morocco). In these test sites, pixel-based approaches performed better, although not very significantly, then object-based ones, achieving 92% of accuracy over Burkina Fasso, 78% over Madagascar and 34% for Morocco for their cropland map. Morocco's low accuracies were due to a large amount of mixed crop fields, which were classified as non-crop. Results over the remaining seven sites, which feature commercial agriculture, always achieved accuracies higher than 90%. Poorer results over the three smallholder-dominated sites could be attributed to the complexity of the landscape, poor training samples and cloudy images.

The consideration of additional information brought by neighbouring pixels, in the object-based approach, can be seen as a significant improvement. However, Gao et al. (2008) and Cleve et al. (2008) found that the spatial resolution of the images is an important factor determining the advantage of object-based over pixel-based approaches. They claim that, in general, object-based approaches are more suitable for very high resolution images (<5 m). Using an object-based approach with Sentinel-2 imagery alone (10 m) does not provide any statistically-significant advantage over a pixel based one. Duro et al. (2012) and Inglada et al. (2016) also support this statement.

The high degree of heterogeneity in small scale farming landscapes make the segmentation process more difficult, as defining homogeneous objects becomes more difficult, resulting in less performing classification results. This is also confirmed by Li et al. (2016), who showed that classification accuracies were related to the homogeneity/heterogeneity of the segmented objects for all classifiers (Manchun et al., 2016).

2.6.2 Vegetation indices for mapping small scale farming in savanna landscapes

Otukei et al. (2010) stated that the two most pertinent features for crop classification in general were the surface (TOC) reflectance and the NDVI. Other pertinent features include the NDWI (Normalised Difference Water Index) and the soil brightness. Yet, using NDVI in savanna landscapes can be problematic as the index is affected by soil colour and spatial scale (Jiang et al., 2006). Another recent study (Zafari et al., 2017) compared three classifiers (SVM with a RF kernel

function, RF, and RBF kernel SVM) for crop mapping over Mali using a Worldview-2 time-series. They noticed that adding vegetation indices to the analysis did not result in a significant difference, even with a decrease of 1% for the first two classifiers. When using phenological indices, accuracy is largely dependant on having images available throughout the season (Jiang et al., 2006). Even with high temporal availability, cloud contamination can still be a problem.

2.6.3 Concluding remarks on the different of classifiers

Based on the previous sections, what immediately comes to mind is that there seems to be a gap between the various maps realised at a 20-30 m resolution and the crop type maps at very high resolution (0.50-2.5 m). Sentinel-2 fills that gap with its 10 m spatial resolution.

Selection of the classification algorithm alone does not explain accuracies measured in the previously cited studies. Rather, the classifier is part of an entire workflow, which was designed and thought through to specifically address the problematic. Other elements, such as the representativeness of the training data, setting of the parameters, specificities of the study area, the use (or not) of multi-temporal imagery, and other characteristics of the sensor (spatial resolution and number of spectral bands), all have an influence on the final product accuracy. All these variables also make it difficult to objectively compare results between studies; classifiers' accuracies should be measured on a case-to-case basis.

Since there is no study on smallholders that uses different classification methods in the same study, apart from that of except Zafari et al., (2017), the studies on which the classification comparisons are based are more specifically oriented toward commercial farming. Yet, two general trends appeared from those studies :

- 1) Machine learning usually performs better than statistical methods (Murthy et al., 2003)
- 2) SVM and RF are both popular classifiers for mapping agricultural subjects and both achieve similarly high results.

Some studies came to the conclusion that the difference in accuracy between SVM and RF is not significant (Duro et al., 2012; Pal, 2005; Zafari et al., 2017). While some studies concluded that RF yields better results (Inglada et al., Otukey, 2010; Belgiu & Drăgu, 2016), others claim the SVM gave better results (Huang et al., 2002, Hansen et al., 2017). Rodríguez-Galiano et al. (2012), showed that RF is easier to set up and does not suffer from over-learning, compared to SVM (Driessen, 2016).

What most of the studies lack (except Debats et al., 2016, Lebourjeous et al., 2017) is a qualitative description of the type of smallholders censused in their study area and their representative weight in the ground truth dataset. Information regarding average field-size and agricultural practices (eg. use of fertilisers, rain fed or irrigation, intercropping) is often neglected. This makes it difficult to both interpretate their results and draw conclusion on their performances.

2.7 System Overview of the Sen2Agri system

The Sen2Agri system delivers, in a highly automated way, products that are relevant for agricultural monitoring, such as cropland and crop type maps over the surfaces covered by Sentinel-2. The system appears as a valuable classification tool as it handles all the pre-processing steps necessary to prepare the imagery and make it ready to use for the classification algorithm. The cropland and crop type products are obtained through Sen2Agri's RF classifier, which was designed to make optimal use of the available data.

Behind the Sen2Agri processing system is the open-source Orfeo toolbox (OTB) image processing library. OTB was funded and developed by CNES (French Space Agency). It provides the functions that are essential for image classification, including pre-processing of images, feature extraction, image segmentation, and classification. The integration of OTB in the Sen2Agri system has been successful both in terms of quality and performance (Grissonet et al., 2017).

The Sen2Agri system can be run in command line interface or through a platform which provides a user-friendly interface called SNAP (Sentinel Application Platform). SNAP is a free software for all the processing of Sentinel-2 satellite data and is distributed by the ESA. It provides users with a rich set of visualisation, analysis and processing tools for the exploitation of all Sentinel-2 data (ESA, 2015).

2.7.1 General overview of the Sen2Agri system and processors

The processing chain of the Sen2Agri system is a standalone process including several independent processing modules that are designed to be interactive and user-friendly. Users can generate any product in an operational way, and tailor products to their needs. In total, four products at 10 m resolution can be generated for agriculture monitoring (Figure 11) (Popescu et al. 2016):

- *Cloud free composites* of surface reflectance values;
- *Dynamic cropland masks*, delivered on a monthly basis during agricultural seasons;
- *Cultivated crop type maps* and area extent for main crop groups, delivered twice along agricultural seasons;
- *Biophysical vegetation status indicators*: NDVI and Leaf Area Index (LAI), describing the vegetative development of crops on a 7 to 10 days basis.

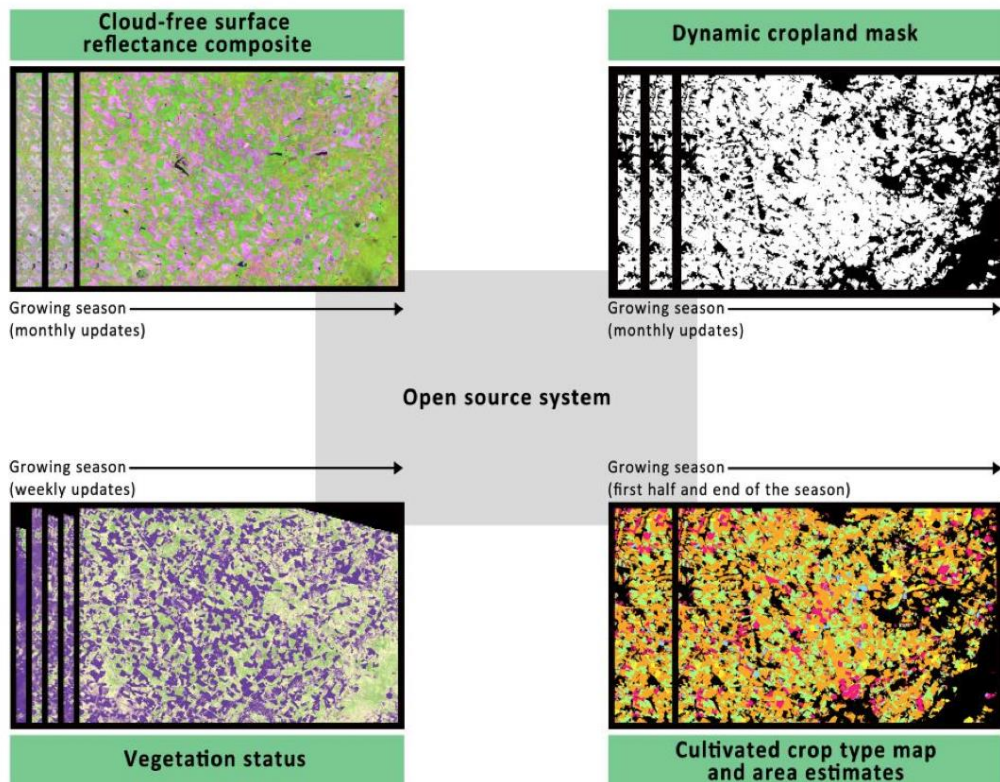


Figure 10: The four Sentinel-2 derived products.

These different products are delivered through a set of four processors (referred to as generators on the Figure 11). The data flow between processors is organised as follows (Figure 11):

The Sen2Agri Orchestrator is the main component of the system, used to manage the algorithm or sets of algorithms that serve through the different processors. Its main functions are to determine the processing chain to be launched and monitor its execution (Popescu, 2016).

The following inputs are necessary to run the operational system: a time series of Level-1C products, a defined area of interest and a duration of the monitoring period. In situ data can be taken into account for supervised classification and product validation. The system is run in an automatic mode: the Orchestrator implements the system to automatically download the data, process it until the end of the season and deliver the output products.

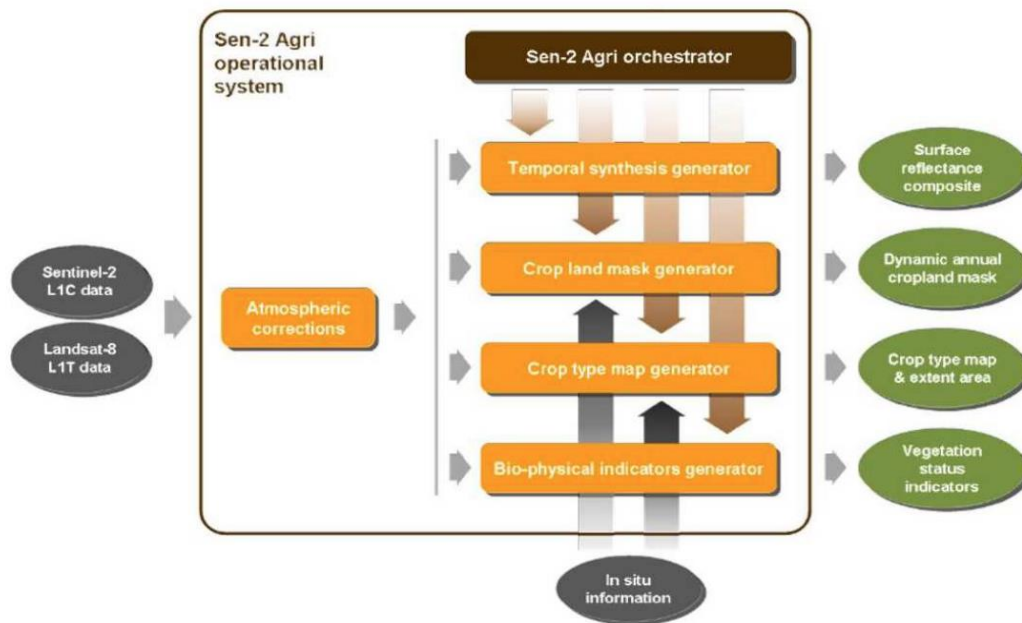


Figure 11: Logical data flow of the Sen2-Agri system (Popescu, 2016)

The processors are the modules dedicated to delivering the different Sen2Agri products. They are the following:

2.7.1.1 L2A processor

On the user side, the Level-2A (L2A) processor performs atmospheric corrections on the L1C (TOA reflectance) products, resulting in a L2A product with Bottom-Of-Atmosphere (BOA) reflectance values, which are the values used for classification. The L2A image is also delivered with its own snow, water, cloud and cloud shadow masks.

To obtain the L2A BOA products and the various masks, the Level-2A processor operates on a Multi-sensor Atmospheric Correction and Cloud Screening (MACCS) algorithm (Hagolle et al., 2016). The MACCS is a software tool made out of a chain of algorithms designed to characterise the atmosphere and detect clouds in the L1C images. Based on a multi-temporal algorithm, it makes optimal use of image time series by improving the detection of clouds along the season (Lonjou et al., 2016).

L2A-processing is split into two parts. The MACCS realises those two parts (Hagolle 2015):

- First, it detects the clouds and their shadows, snow and water vapour based on the reflectance values of the pixels in the L1C image. The result of this step is a separate mask with different classes and values for clouds, cloud shadows, snow and water vapour etc.
- Second, the MACCS transforms TOA reflectance into BOA reflectance. This is the L2A product.

As seen on Figure 11, the atmospherically corrected L2A products are used as input for the processing chain delivering different types of products within the Sen2Agri operational system. Before being able to further process a L2A time-series, the Sen2Agri system must superimpose the mask produced at the first point with the L2A image produced at the second point so as to literally 'mask' the clouds, cloud shadows, etc., on the images, whose aberrant reflectance values

would otherwise be classified as well. This is done automatically when launching one of the following processors.

2.7.1.2 Cloud-free temporal syntheses (L3A) processor

The L3A processor delivers a monthly cloud-free composite of surface reflectance values by compiling all the masked L2A images obtained throughout the month. Temporal resolution is of 1 month, with a 30 to 50 days moving window (Popescu, 2016). The Sen2-Agri system recognises the classified values of the cloud mask and considers them as being NoData; they are filled with information of the precedent and following images. This process is also called gap filling, and is done by the L3A processor using a *weighted average composite approach* (Popescu, 2016; Vancutsem et al. 2007). The purpose is to create a single map merging all the information from that month and with the fewest possible NoData pixels.

Although the other processors do not further use it, the cloud-free composite allows users to track crops on a monthly basis (Popescu, 2016).

As seen on the figure below, the L3A processor operates as following (Popescu, 2016):

- First, when dealing with several tiles, the directional effects must be corrected. These effects occur when the observation angle of the satellite varies.
- Second, the input for the *weighted average approach* is each L2A tile product available at time t, but also the temporary product generated at the previous date t-1. This t-1 product is updated iteratively with the new data until the compositing period is completed.

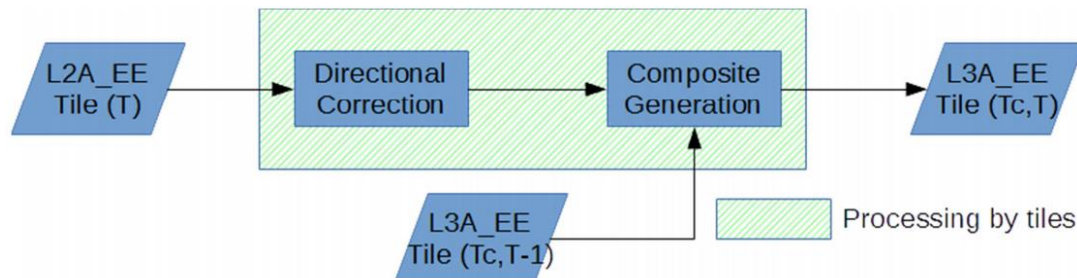


Figure 12: Logical data flow of the L3A processor

The following discussed processors use actual image classification in order to deliver the consecutive products. They are:

2.7.1.3 Biophysical vegetation (L3B) processor

The L3B processor delivers maps classified according to three different biophysical indicators that can inform on the evolution of the vegetation. The input for this processor is a L2A time series and can be turned into three different types of L3B products:

- The *Normalized Difference Vegetation Indice* (NDVI), is a vegetation index, commonly used as an indicator for vegetation monitoring. The NDVI may be used to quantify the density of plant growth. By monitoring the evolution of the NDVI, anomalies in vegetation can be tracked in early stages. The NDVI is computed using a standard formulation applied to the red (band 4) and the narrow NIR (band 8a) bands (Weier et al., 2010): $NDVI = (NIR - Visible\ red) / (NIR + Visible\ red)$.

- The *Leaf Area Index* (LAI) determines the size of leaf interface for exchange of energy and mass between the canopy and the atmosphere. The size of the leaf interface imposes important controls on photosynthesis and respiration, as well as other processes that link vegetation to climate (GCOS, 2004).

The LAI retrieval is performed using machine learning to build a non-linear regression model. The regression model is estimated using reflectance values simulated with the ProSail model (Popescu, 2016).

- Phenology indices, also referred to as *NDVI metrics*, inform the users about specific key parameters of the growing season, for example: the starting date, season length and date of maximum growth rate (Popescu et al., 2016). The NDVI metrics are extracted from NDVI time profiles through a double logistic function fitted to each pixel (ref).

2.7.1.4 Cropland mask (L4A) processor

The cropland mask represents a binary map legend of crop/non-crop that highlights the separation between annual cropland and non-cropland areas. It is produced on a monthly basis throughout the agricultural season, to serve for instance as a mask to monitor crop growing conditions, as basis for sampling stratification and to follow agricultural dynamics (for instance extension or abandoning). Its accuracy is expected to increase along the season as new images are integrated⁵.

Two alternative approaches are available for producing the cropland mask: the first one uses actual in situ data to distinguish between crop and non-crop classes, whereas the second one builds its own sample collection from a “reference map”, which is the CCI land cover map developed by the ESA. In both cases, the product is generated using a RF classifier. The data set is split for algorithm calibration and products validation. The resulting map is complemented by a posteriori filtering, based on a per-object approach, to smooth out the resulting mask (Popescu, 2016). The purpose of applying a post-filtering on the cropland mask is to reduce pixel-wise classification noise of the classification map, also known as salt-and-pepper effect, in order for the resulting cropland mask to feature more homogeneous crop areas (Matton et al., 2016).

2.7.1.5 Crop type map (L4B) processor

The L4B processor generates, over the crop area identified in the crop mask, crop type maps twice during the growing season, by the intermediary of the generated cropland mask. A first delivery is available in the middle of the season; the second one at the end. The crop type product is classified according to the main different crop types. They are defined as those covering a minimum area of 5 % of the annual cropland in the region, representing a cumulated area higher than 75 % of the latter. Four or five main crop types are usually considered. The processor requires in situ data for each expected crop type, as well as the crop masks generated by the system for the same dates (Popescu, 2016).

The processing chain is based on a supervised RF classification built on in situ data to be collected during the growing season of the crops of interest (Inglada, 2015). In situ information is split for algorithm calibration and products validation.

3 Objectives

Smallholder farms feed a significant portion of the global population, are located in some of the world's most diverse and fragile landscapes, and are home to many of the planet's most vulnerable people (Samberg et al., 2016). Despite recent spotlight on small farms and increasing consensus on their importance, detailed information on location and size of smallholder farms remains scarce. Yet, successful policies aimed at alleviating poverty, boosting food security and protecting biodiversity and natural resources with sustainable land use, depend on the inclusion and participation of small farmers (Birner et al., 2010; FAO, 2014). Information about the location and distribution of small farms can be retrieved through the bias of global tools like cropland and crop type maps. Global tools must be adapted for local issues; they must represent a local reality and diversity, so that the information they provide isn't biased by national interests. Only then can they effectively help to better guide investments, target policies for sustainable agricultural development and other broad strategies.

With continuous advancements in remote sensing technologies, high resolution imagery has become increasingly available. Each new satellite that is launched marks a new opportunity to analyse more complex subjects and landscapes, and becomes a benchmark in answering today's global challenges we face. Programs such as the Sentinel-2 mission establish a new pillar for the remote sensing community. However, as with every new available technology, the limits and scope of possible applications must be tested and defined. Sentinel-2 offers new ways of analysing small scale complex landscapes, but its actual potential and limitations for small scale farming still needs to be framed.

The main objective of this thesis is to benchmark the potentialities and limits linked to the Sen2Agri classification system, and the ability of the Sentinel-2 mission to map smallholder systems in the Northeast of South Africa. In parallel, two other classification methods will be used. With Sen2Agri's RF classifier serving as a baseline, the sensitivity of the classifier to different sampling procedures and temporal availability will be tested, in order to understand how they affect accuracies of the cropland map. The second classification method evaluated is the SVM classifier implemented in the OTB platform. The SVM classifier and the RF are both machine learning methods that are often used in agricultural monitoring studies; both methods are often compared as they both usually yield high accuracies. The third and final classification method performed is through the selection of NDVI thresholds in *Arcmap*. Although it is a more simplistic method compared to the two other classification methods, it provides valuable information about the pattern changes in NDVI along the agricultural season in small scale farming savanna landscapes.

Rigorous research on small scale farming in general is still poor, and previous studies lacked crucial information such as organisation and diversity of smallholders in the landscape, average field size, agricultural practices, and whether the classes actually represent the diversity of the landscape. With this information lacking, evaluating performances of classification methods between different studies remains difficult.

This thesis also aims at providing qualitative information about the smallholders surveyed and how they can be characterised. Understanding patterns and dynamics of smallholders, and

defining the main groups of smallholders found during the fieldwork, will also help to interpret the results of the different classification methods and to understand how they affect accuracies.

In the context of the region's growing climate variability, vulnerability to drought poses a significant and increasing risk to agriculturally based livelihoods (Holland et al., 2017). Understanding how climate variability and other elements have affected local crop production over the last 2 years could offer a valuable tool to the region.

4 Description of the study area and data

The following chapter aims to locate the study area in the province of Mpumalanga in South Africa, to describe its main relevant characteristics for this study, including climate, geology and land use, and to describe the various activities that take place on and nearby the study area. Each of the different sources of collected data are also explained, including a more precise description regarding the ground truth data collected during a two-week field campaign and a PICES helicopter flight.

4.1 Study area

4.1.1 Location and characteristics of the study area

The study area is located in the Northeast of the province of Mpumalanga and stretches over a 45 x 88 km area, located between latitude S 21°1 51" and longitude E 31°10'5". Mpumalanga has more than 4 million inhabitants on its 79.490 km² territory. The province is divided into three district municipalities, which are in turn divided into seventeen local municipalities. The study area covers part of two local municipalities: Bushbuckridge and Mbombela.

Location of the study area

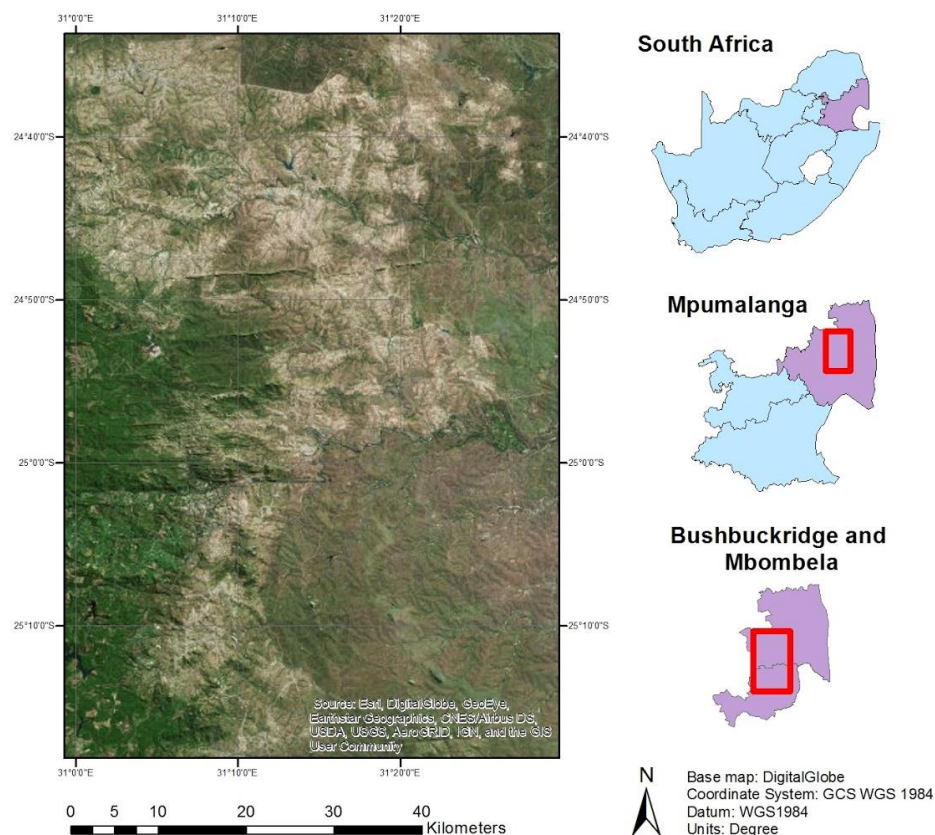


Figure 13: Location of the study area (natural colour composite).

On its 45 x 88 km area, the study area features the biggest concentration of small scale farms in the whole province, stretching over a savanna type of landscape. According to a hand digitised cropland map of PICES in early 2015, shown on Figure 14, a total area of approximately 29.255 ha was farmed by smallholders. The study area is bordered in the Northwest by the Blyde River Canyon Nature Reserve (zone A on Figure 14) and in the East by the Kruger National Park, which are both touristic hotspots in South Africa, with the Kruger National Park receiving about 1.5 million visitors annually (environment.gov.za). Hazyview is the biggest city in the study area and is located in its centre. Since it is situated between both touristic destinations, Hazyview developed accordingly to its location and offers a variety of high-standing accommodation and various touristic activities. Despite the touristic developments in the region, the study area remains predominantly rural, but benefits from a relatively well-developed road infrastructure (tar roads) between the main different parts of the area, with gravel type secondary roads.

Smallholder farming fields were mainly located in more remote areas, and were accessible through gravel roads then on foot. The contrast observed between the more rural areas, around the cities of Alexandria A, Rolandsey, Lillydale, Chochocho, Belfast, Thulamahashe, Acornhoek etc., and the area surrounding Hazyview was also evidenced by the way agriculture is organised. Around Hazyview, small scale agriculture takes place in more commercial forms, benefitting from a well-developed road infrastructure, while a more substantial part of the small scale farming community is located in the less developed surroundings and in other areas.

General overview of the study area and surroundings

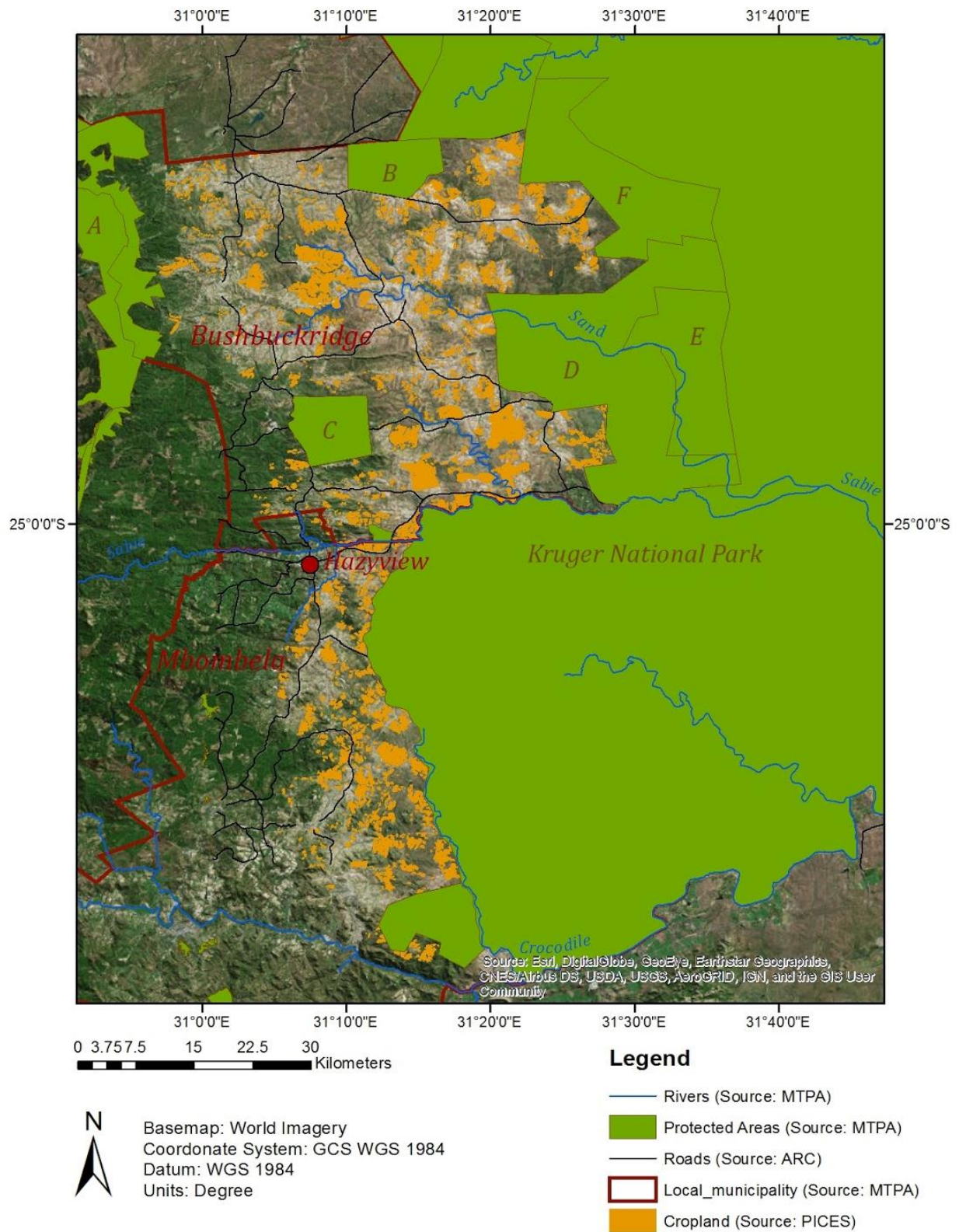


Figure 14: General overview of the study area and surrounding (Mpumalanga Tourism and Parks Authority (MTPA))

4.1.2 Geological and climatic context

The Drakensberg Escarpment forms a mountainous chain that divides the province of Mpumalanga into the so-called Highveld and Lowveld (Figure 15). On the western side, the Highveld consists of mainly high-altitude plateau grasslands (1250-1800 m). The South African Highveld also covers the three provinces of the summer grain region. In the eastern part, the Lowveld designates lower altitude plains (<500 m) that are part of a vast subtropical savanna landscape (Hachigonta, 2013).

The whole study area is located in the South African Lowveld, which tends to be relatively flat, with some interspersed rocky outcrops, with the exception of areas close to the Drakensberg Escarpment. The Lowveld also reaches further up north, through Zimbabwe and Zambia as far as Central Africa.

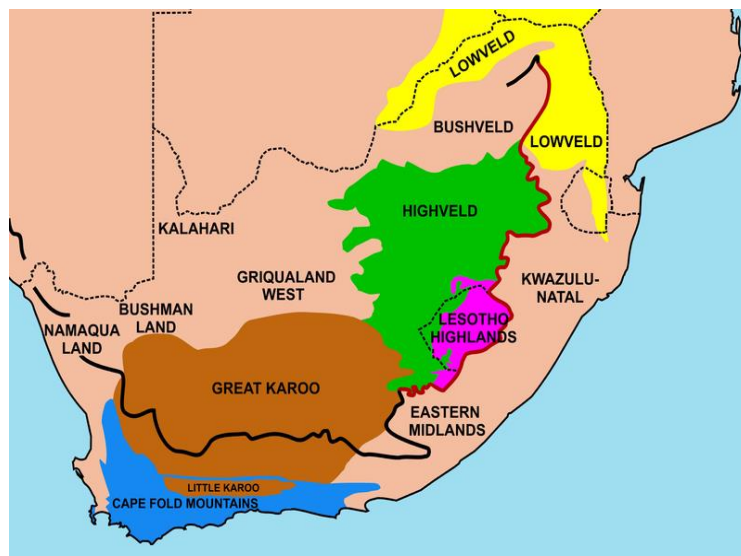


Figure 15: Geological formations in South Africa.

The Drakensberg Escarpment that cuts through Mpumalanga exceeds heights of 2000 m in most places, making Mpumalanga's central region very mountainous. The Blyde River Canyon Nature Reserve, on the border of the study area, is located in the Drakensberg Escarpment. The Lebombo Mountains, at the eastern end of the province and located 50 km from the study area, form a narrow, low-altitude (400-800 m) mountain chain on the border between the Kruger national park and Mozambique.

Mpumalanga's topography dictates the climate, with the subtropical Lowveld being comparatively warmer (up to 6-8 degrees difference) and drier (up to 100 mm difference on annual precipitation) than the western Highveld. This is mainly due to its lower altitude, proximity to the Indian Ocean and position in relation to the Drakensberg Escarpment (MCCVA, 2015). The province depends mostly on summer rainfall (September-March), whereas winter rainfall (April-August) is very scarce. Throughout the year, the Drakensberg Escarpment, including Blyde River Canyon Nature Reserve, receives most of the precipitations.

The western part of the study area and beyond, which is closer to Blyde River Canyon Nature Reserve, features a dry sub-humid climate, while the central and eastern portions of the study area are part of the semi-arid zoning (ARC-ISCW, 2004).

Rainfall over the last 10 years in the study area has varied between 600 and 800 mm a year (worldweatheronline.com), with a general tendency towards drier conditions (Figure 16) and higher average temperatures (Figure 17). The rainfall patterns have shifted as well, with the wettest months (rainfall peaks on Figure 16) shifting from mid-December until January, to February until mid-March. The year of 2015-2016 (July 2015 - July 2016) was recorded as being particularly dry, with an annual average of only 376.38 mm.

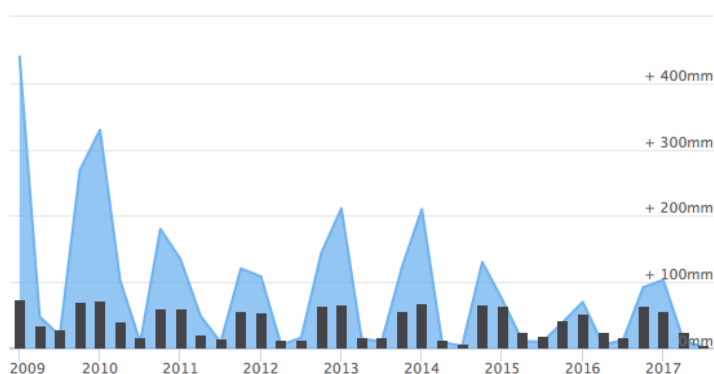


Figure 16: Total and average monthly rainfall, in blue and black respectively (worldweatheronline.com)

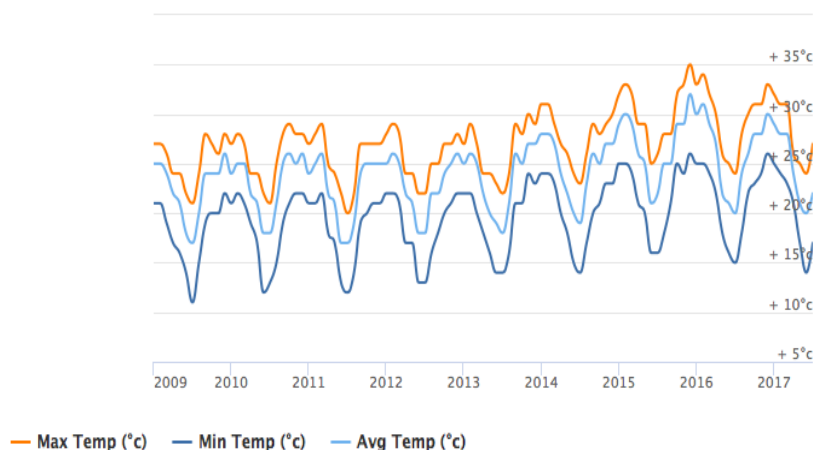


Figure 17: Maximum, minimum and average annual temperature (Source: worldweatheronline.com)

In the period between July 2016 and July 2017, which covers the agricultural season of interest, the average rainfall was 665,9 mm. Monthly rainfall during the wettest month (February) and driest month (June) was 154.5 mm and 0.2 mm, respectively (worldweatheronline.com).

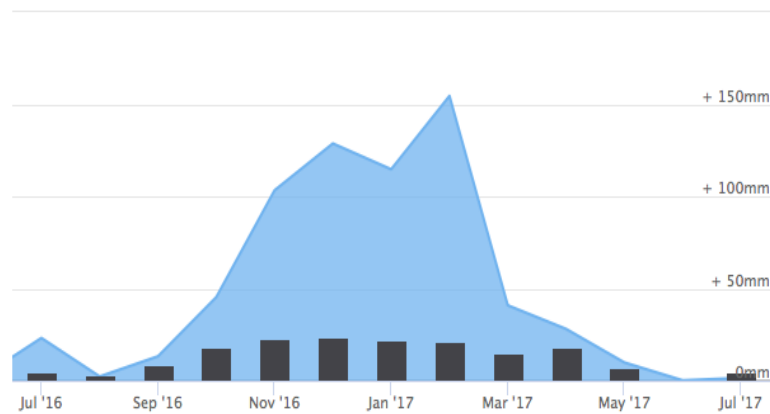


Figure 18: Average monthly rainfall for July 2016 - July 2017
(Source: worldweatheronline.com)

The mean temperature in the area is also higher than in the rest of the province: between 20-30° on a monthly average. In the period between July 2016 and July 2017, a maximum temperature of 33°C was recorded in December, whereas the lowest temperature (14°C) was recorded in June (worldweatheronline.com).

The study area benefits from the Sabi-Sand River system and the Injaka dam, the latter storing water mainly for domestic purposes. The Sabi-Sand River system has 11 tributaries (Klein Sabie River, Mac Mac River, Marite River, Motitse River, Ngwaritsana River, Sabane River, Sand River, flowing into the Sabie River (Figure 14). The Sabi-Sand River system rises in the Drakensberg, flows eastwards through the Lowveld and further across the Kruger National Park, and from there flows on to Mozambique (RHP, 2015).

4.1.3 Ecology

Mpumalanga comprises areas with a very rich biodiversity, with 18.1% of the province being under formal biodiversity protection within national parks, provincial parks or private reserves (Morris et al. 2009). The majority of the province's diverse flora and fauna borders the study area in protected nature reserves, including the notorious Kruger national park, Blyde River Canyon nature reserve (A), Andover (B) and Bosbokrand (C) nature reserve, Sabi-Sand private game reserve (D), Mala-Mala nature reserve (F) (Figure 14).

The study area and surrounding Lowveld are part of the savanna biome. Savanna biomes are home to many of the mega fauna species found on the African continent, and they hold a large range of highly specialised plants and animals that depend on each other to balance the ecosystem (Baillie, 1987). This justifies the conservation efforts in the areas surrounding the study area. There are several types of savanna, which, in general, are characterised by a successive dominant grass layer and an upper layer composed of shrubs and trees in varying densities (Figure 19).



Figure 19: Savanna typed landscapes found in the study area.

Savanna biomes are fragile ecosystems that are often mismanaged. When overgrazed or overfarmed, the soil quickly becomes infertile. However, these biomes also require a certain level of disturbance in order to keep their hierarchical structure: the lack of sufficient rainfall, coupled with grazing and fires, prevents the upper shrub and tree layer from dominating (Giller, 2014).

Figure 20 shows a savanna which lost its hierarchical structure, with the shrub layer becoming dominant. In these situations, which occurred frequently throughout the study area, savannas can easily be confused with natural forests. In the back of the figure, savanna-type grasses become dominant again.



Figure 20: Unbalanced savanna dominated by shrubs

Savanna biomes feature different types of soil which, in general, are often characterised by sandy porous soils, with rapid water drainage and only a thin layer of humus to provide the vegetation with nutrients. For these reasons, these biomes are usually not regarded as suitable for farming. In South Africa, most of the savanna vegetation types are used for grazing purposes, mainly by cattle or game (Rutherford et al., 2016)

The Sabi-Sand River system is in a good general ecological state. However, in several localized spots are more severely impacted, mainly due to forestry industries on the western side of the study area, to urban development, and to the presence of invasive species (RHP, 2015). A very noticeable invasive species in the study area's rivers is Spanish reed (*Arundo donax*). Spreading effectively by vegetative reproduction, it is listed amongst the five worst invaders in provinces surrounding Mpumalanga (Milton, 2004). Spanish reed influences rivers' hydrological processes such as sedimentation, and alters stream hydrology. It also takes up a considerable amount of water through leaf transpiration, thus reducing the amount of readily available water in the area. For those reasons, Spanish reed was recognised as a threat to water security for South Africa's growing human population (Milton, 2004). At present day, mechanical and chemical removal are the only available methods to reduce the densities of Spanish reed.

Conservation of biodiversity and parsimonious agricultural management are important to maintain and ensure the fertility of the savanna biomes, but they exert a certain pressure on local populations. Wessel et al. (2003) identified potential conflict areas between land transformation and biodiversity conservation in the north-eastern parts of South Africa. This concern is especially valid in the study area, as the population density is higher than anywhere else in Mpumalanga, as can be seen on Figure 21.

4.1.4 Main agricultural activity

In Mpumalanga's grassland Highveld, intensive crop farming is practiced under irrigation, with the main crops being maize, wheat, barley and soybean. This area, on the western side of the province, is part of South Africa's summer grain region, along with the Free State and North West provinces (FAO, 2015). Large cattle herds and mining centres may also be found in the area.

Towards the East, in the drier, savanna-type Lowveld, commercially cropped fields make place to vast forestry plantations, subtropical fruit and vegetable orchards (MCCVA, 2015). Low-productivity small scale farming, together with free range (small scale) cattle farming, is mainly concentrated in the delimited study area. Small scale farmers grow maize as their main staple food, together with groundnuts, soybeans, and sweet potato as other main crops. Other, less frequent crops are cassava, chilli and butternut.

Population density in Mpumalanga is particularly high in the study area, as shown on Figure 21. In the province, an estimated population of 50% is living in conditions of poverty, and over 60% of the population resides in rural areas. Of all of South Africa's provinces, Mpumalanga also has the fifth lowest per annual average household income (MCCVA, 2015). The high vulnerability of rural livelihoods, which are mainly based on agriculture and livestock, is a major matter of concern of the province, with several development and economic growth plans aimed to alleviate it.

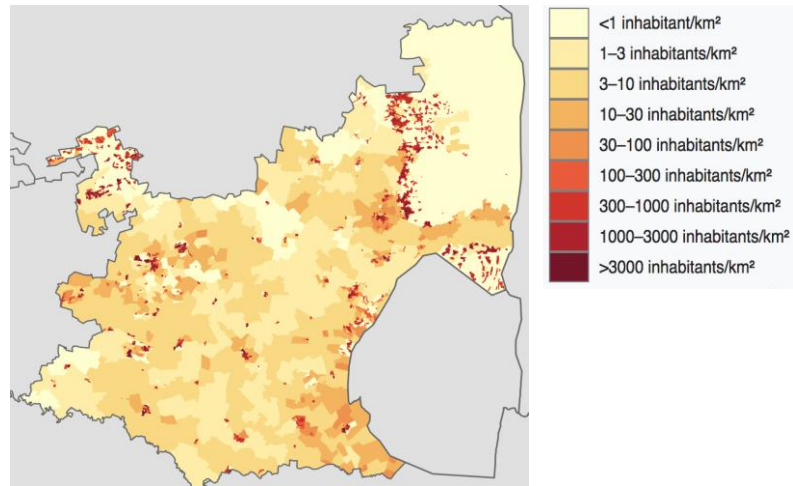


Figure 21: Population density of Mpumalanga (citypopulation.de)

In locations near the study area, just outside the small scale farming cropland mask shown in Figure 14, the two main agricultural activities are forestry plantations and fruit orchards, which are both farmed commercially. Vast forestry plantations of eucalyptus and pine can be found southwest of Hazyview, with very little small scale farming activity in the area. To the northwest of Hazyview, the area mainly features subtropical and citrus fruit orchards. Mbombela Local Municipality, including Hazyview, is responsible for one third of the country's export in oranges (MCCVA, 2015), making it the second largest citrus producing area in South Africa.

The PICES cropland mask of early 2015 (Figure 14) shows where the main small scale farming activity can be found. The crop season in the study area usually begins in mid-November and ends in mid-May. However, in the 2016-2017 growing season, farmers only began planting end of December 2016 due to delayed rainfall. In small scale farming systems, the exact times at which the agricultural season begins and ends are approximate, as smallholders are conditioned by rainfall patterns, and the first substantial rains usually mark the beginning of the season. Because the 2016-2017 growing period started later than usual, it was expected to finish by the end of May or beginning of June.

4.2 Available data

4.2.1 Satellite imagery

A Sentinel-2A L2A (BOA) time series of tile 36JUT, with a 10 and 20 m spatial resolution and a 10-day revisit frequency, was downloaded over the period spanning from 21 July 2016 till 18 July 2017. Because the images throughout the season were often cloudy, the time series was selected in order to span a period that is longer than the agricultural season. Images corresponding to dates outside of the growing season allowed to obtain additional information to discriminate between cropland and non-cropland. A total of 22 images of the time-series were kept of the original 23. The first image of the time series (3 July 2016) was set aside, as its corresponding cloud mask did not cover all the clouds. This isn't unexpected, since the MACCS algorithm used in Sen2Agri for detecting clouds and water vapour gets more precise as additional cloud free images are integrated into the algorithm. For this image, the MACCS wasn't able to detect the thin cloud formations like cirrus, but thicker cloud formations were accurately masked. It is therefore advisable to quality check the first images' corresponding cloud masks.

The dates of all the images, and their relative cloud coverage, are summarized in Table 2. The percentage of cloud cover is relative to the whole 36JUT tile (100 x 100 km). Thus, they are not proportional to the size of the study area.

Table 2: Timeline of the different collected data sources and relative cloud coverage of the image

	Cloud coverage	Agricultural Season (Approximate span)
23 July 2016	<0,5%	
02 August 2016	19,6%	
12 August 2016	<0.5	
22 August 2016	0%	
01 September 2016	0%	
21 September 2016	38,16%	
11 October 2016	<0,5%	
31 October 2016	35,6%	
10 November 2016	42,95%	
22 November 2016	52,72%	
30 November 2016	64,72%	
20 December 2016	70%	Beginning of the season of 2016-2017
19 January 2017	0%	
08 February 2017	20%	
7-11 March: Fieldwork 1		
23-24 March: PICES airborne survey		
30 March 2017	38,8%	
09 April 2017	15,4%	
18-21 April: Fieldwork 2		
09 May 2017	3.6%	
19 May 2017	1.5%	
29 May 2017	<0,5%	End of the Agricultural season
08 June 2017	0%	
28 June 2017	0%	
18 July 2017	0%	

4.2.2 PICES Airborne survey

As explained in section 2.1.3, national crop estimation surveys in South Africa are conducted with the Producer Independent Crop Estimate System (PICES), developed by the private company SiQ. Their specialised methodology allows them to accurately estimate areas planted under grain crops in the country. This methodology is more specifically aimed toward commercial farms but they can collect crop information on small scale farming as well, with a slightly different sampling methodology explained further in the text. PICES also operates on a regular basis to update field boundary maps of the country. The field boundary map is available for agricultural-related research and is updated regularly. In smallholder systems, the PICES field boundary map corresponds to a cropland mask, delineating areas of small scale farming activity instead of individual field parcels.

The PICES flight performed over the study area was the fruit of a collaboration held between the ARC and the private company SiQ. The survey was performed by Eddie Viljoen and Hennie Jacobs, and provided a unique opportunity to collect data at a higher scale and bigger scope, than if the survey were limited to ground fieldwork.

PICES performed an airborne survey over the study area in two days' time, the 23 and 24th of March 2017, using a ZS-ROE helicopter (Figure 22). The helicopter had an average flying speed of 60-70 nods and average altitude of 500 feet above ground. The altitude during the flight was conditioned by some mountainous landscape, which didn't always make it possible to keep that altitude.



Figure 22: ZS-ROE helicopter and flight track over a part of the study area (Source: SiQ)

Because this survey was specifically addressed toward small scale farming, PICES did not follow the same sampling procedure as they generally use for national crop surveys. For national crop surveys, as is explained in section 2.1.3, the trajectory of the helicopter is traced over sample points which are located in the field boundary map of the considered agricultural region, and the samples are distributed randomly according to a grid representative for the region. The observer captures crop information only for those randomly distributed crop samples. For the small scale region, the field boundary map of PICES does not represent single field boundaries. Rather, it

delineates plots of lands where small scale farming activity is present (in orange on Figure 23), which makes pre-locating crop samples difficult.

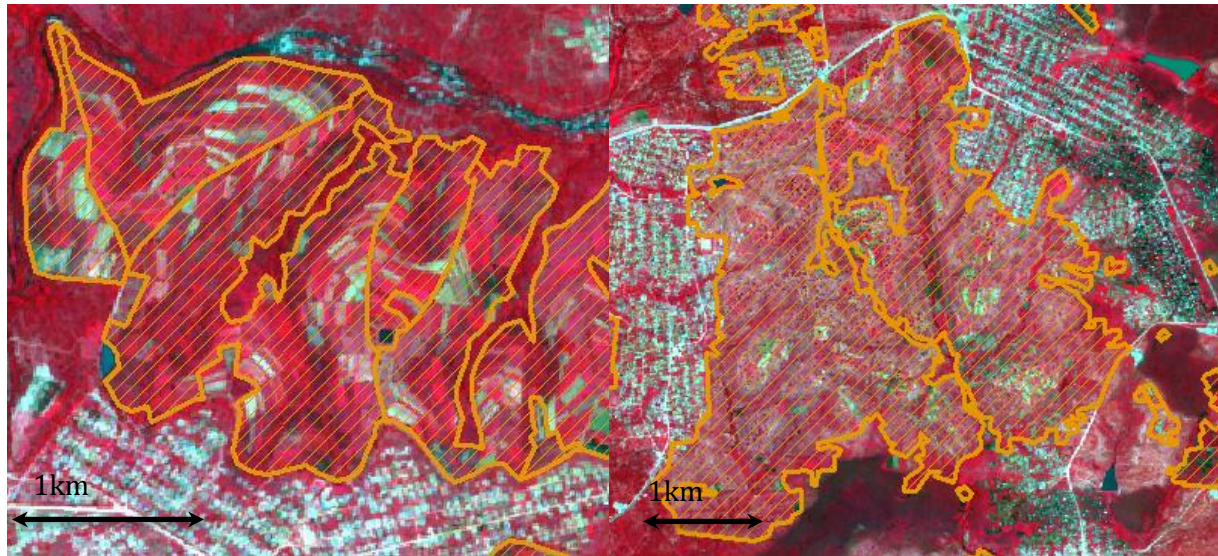


Figure 23: Illustration of the PICES field boundary or cropland map in the small scale farming study area (Sentinel-2 false colour composite).

Land cover and crop type information in the study area was collected following a 2 x 2 km grid, with the cropland map of the study area as basemap (Figure 24). The observer follows the track and the cropland map on his interactive ArcPad, and focuses on distinguishing fields inside the cropland boundary map in each square of the grid. At least 1 land cover point per square is selected; with priority to cropland, if not possible to non-cropland.

By selecting a point on the ArcPad interface, the point is automatically captured with its corresponding GPS reference, and the observer must then specify the crop type class or landcover class.

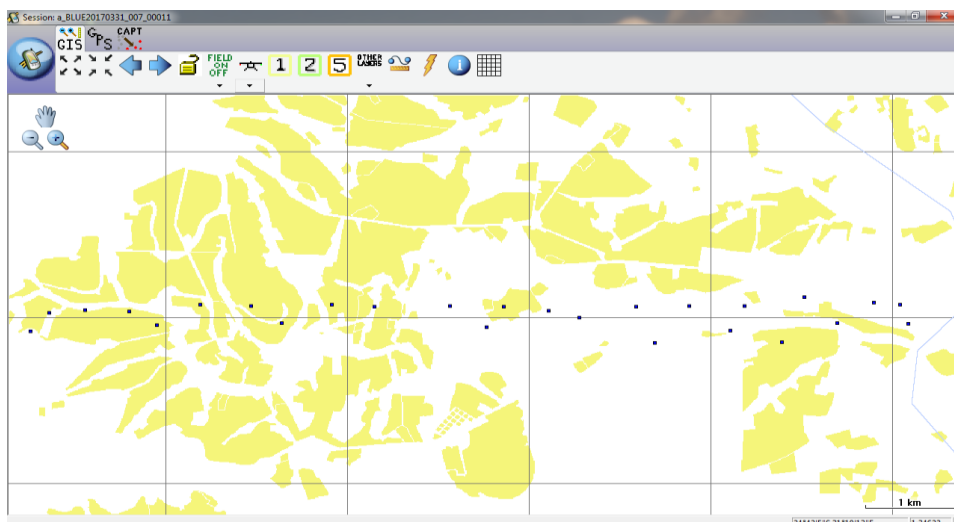


Figure 24: ArcPad interface with grid over the cropland mask and selected points

4.2.3 Ground truth collected data

Information regarding crop types and land cover, for the calibration and validation of the cropland mask, was collected during two field campaigns held from the 7th to the 11th of March and from the 18th to the 21st of April, along roads and gravel tracks accessible by car. The samples were collected using a Garmin Montana 650 GPS.

Cropland samples had to represent the range of possible spectral signatures for the main crop types or crop associations over the whole study area. At the same time, they had to be representative enough of each of the classes' spectral variability. The field campaign also aimed at understanding the main features that define smallholder farming in the study area in terms of general agricultural practices, farm organisation and average field size.

Field campaign

The first field campaign's itinerary was traced using the PICES cropland map of early 2015. Visual assessment of the cropland map, together with Google Earth, allowed to detect large areas regrouping smallholder fields. In total, four major areas were identified, as illustrated in Figure 25. The first field campaign corresponded to mid-season, and, for this reason, it was traced such as to maximise the chances of observing cropped fields by following the PICES cropland map.

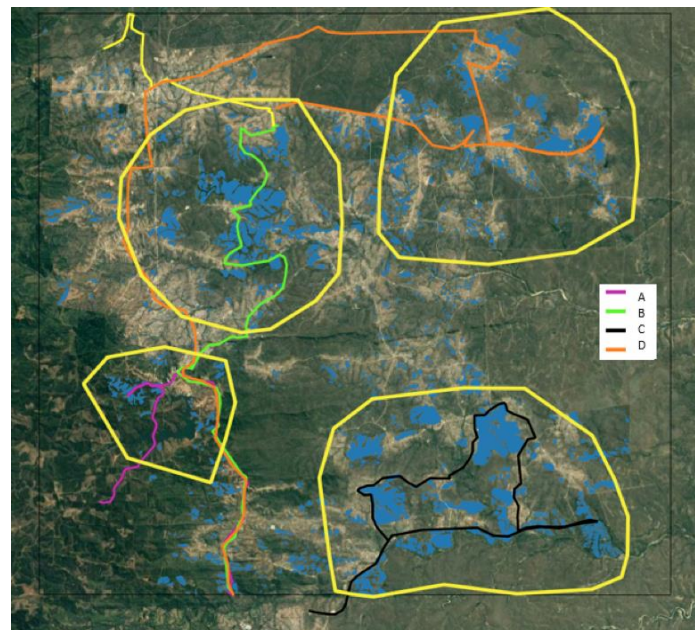


Figure 25: Traced itinerary of the first field campaign

Zone A was characterised predominantly by tree plantations, and few small scale fields were found there. Zone D was in part inside and at the border of a game reserve with restricted access to the area. Zone B and C were the only interesting areas in terms of farming activity, but the number of cropped fields was still very poor compared to expectations based on the PICES cropland map.

The amount of remaining cultivated fields inside the cropland map of early 2015 evidenced a decline in farming activity, and some delineated areas didn't have any agricultural activity at all. Figure 26 illustrates an area, which has been completely abandoned. The boundaries of the fields can still be seen on the false colour composite (Figure 26, left) but the area has evolved to a savannah (Figure 26, right).

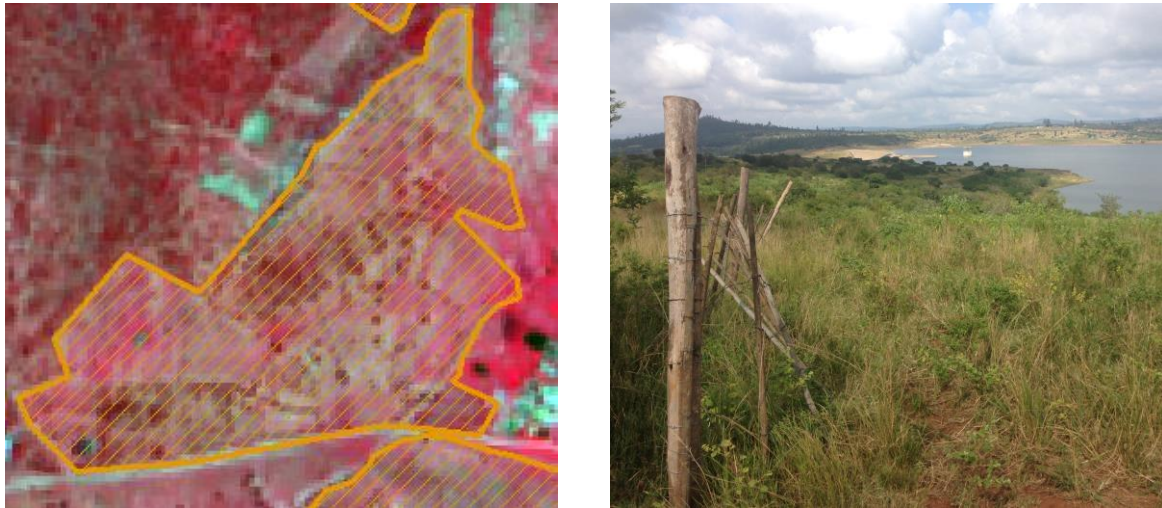


Figure 26: Abandoned fields on a false colour composite (left) and on a field picture (right).

The fields that were actually cropped represented varying states of health, growth stage and on-field densities. Diversity in the area was present in three ways:

- On-field crop diversity or heterogeneity: due to varying growth stages of crops, varying crop densities and varying crop health conditions on the same field, as well as the use of intercropping with different crop-associations. Most of these associations consisted of mixing maize with another crop, mainly peanuts, sweet potato or soybeans.
- Between-field diversity: different agricultural practices (minimum tillage or no tillage, use of fertilization/manure or nothing, on field residues, exclusively rainfed or not etc.), shape and size of the fields.
- Heterogeneity of non-cropped features: varying presence of shrubs trees and weeds between different fields.

The field pictures presented at Figure 27 show some of this diversity found for the maize crop type:



Figure 27: Varying diversities censed for the maize crop type class. Top left: maize at varying growth stages. Top right: crop association with maize and soybean. Bottom left: quite homogeneous maize field. Bottom right: low density maize with groundnuts.

The second field campaign was held later in the season (18th to 21st April), and offered the opportunity to quality check the PICES airborne data, an important step in order to be able to interpret and clean up their land cover data.

Table 3 summarises the collected land cover points for the cropland class of both field campaigns. The most abundant classes are highlighted in green.

Table 3: Crop type samples collected and their total representativeness in percentage (%).

	Fieldwork 1 7-11/03	Fieldwork 2 18-21/04	Total frequency
Agricultural bare soil	6	3	2.5%
Soybeans	5	/	1.4%
Butternut	4	3	1.9%
Cassava	4	2	1.7%
Chilli	6	1	1.9%
Maize	116	72	52%
Mixed	54	22	21.2%
Peanuts	37	7	12.3%
Pumpkin	4	/	1.1%
Sweet potato	8	5	3.6%
Total cropland points	244	115	100%

When looking at the total crop frequency, 85% of the study area's cropland is planted with: Maize (52%), crop associations (21.2%), and peanuts (12.3%).

5 Methods

The first section of this chapter covers the cleaning of the in situ land cover data, which was acquired through the two field campaigns and with the PICES airborne survey. It explains the preparation of the different samples for the calibration and validation of the classifiers.

The second part of the chapter explains in detail how the three different classification methods were applied to the combined data-sources.

5.1 In situ data cleaning

Cleaning the data collected in situ was an important step to better understand the way in which small scale farming affects the landscape's spectral signature. This step was carried out in *Arcmap*. It allowed to make the link between the visually assessed on-field diversity and the spectral diversity of both cropland and non-cropland on a false colour composite satellite image from January 19th 2017. The false colour composite highlights vegetation that is active and growing, as opposed to non-active vegetation. On false colour composites, the NIR band (Band 8) is coloured in red, the Red band (Band 4) is coloured in green and the Green band (Band 3) is coloured in blue.

On the 19th of January, vegetation in non-cropland areas had a strong response in the NIR band, reflecting the photosynthetic activity. Non-cropland thus appears in vivid red on the satellite image. Cropland had normally just been planted, between end of December and beginning of January, meaning the spectral response of the cropland fields was similar to the spectral response of bare soil. With crops having just emerged, fields appeared coloured in green on the false colour composite image.

5.1.1 Cleaning of the field campaign data

In this step, the labelled GPS points, which were collected during the field campaigns, were manually moved to the correct location. Most of the GPS points were taken (and labelled for crop type) at the corner of the fields or from the road, in order to save time. Thus, they had to be dragged to the centre of the field. For this step, the 10 m resolution Sentinel-2 image from January 19th was used as base map. The task was rendered difficult due to some characteristics of small scale farming: the smaller fields of the dataset were affected by mixed pixels, on-field heterogeneity and indistinct field boundaries, which sometimes made them indiscernible from surrounding savanna vegetation.

The difficulty in identifying the small-sized fields corresponding to the GPS points appeared to be mainly linked to the 10 m spatial resolution of Sentinel-2, which was relatively large compared to the smallest fields. Another source of difficulty may be the fact that some fields were planted after January 19th.

Ambiguities in the data cleaning could have been avoided by using the Geographical Open Data Kit (GeoODK) application for smartphones or tablets. The concept is similar to the PC tablet with the ArcPad interface used by PICES to collect information. The GeoODK allows users to directly select, by tapping on their smartphone or tablet screen, the target location of an observed feature

on an interactive map (satellite imagery or Google base map) (geoodk.com). This would have allowed to directly place the sampling point on the field, rather than on the corner or on the road. Technical constraints didn't allow the use of this application for the field campaigns, but it would be highly recommended to avoid the ambiguity of the data cleaning step.

5.1.2 Data cleaning of the PICES samples

The scale of observation of the PICES dataset was

In the PICES dataset, because the fields were surveyed by helicopter, the size of the fields was generally larger than those surveyed from the ground in the field campaigns. Thus, the fields in the PICES dataset were more easily distinguishable on the Sentinel-2 image, with a 10 m spatial resolution.

The points are selected by the observer on the fly, and captured on the PC Tablet with ArcPad interface. The Tablet PC is connected to the helicopter's GPS system. Because the helicopter is moving, its GPS system has already slightly shifted by the time the observer spots a field and captures a point. This shift can be corrected according to the Tablet PC moving interface, as it is a systematic error. The observer makes the link between the field he saw and its position on the cropland mask of the Tablet PC. This link is subject to human error, which cannot be estimated. Thus, the overall error of the survey isn't a systematic error, and land cover points had to be dragged to their corresponding feature in the landscape, based on spectral interpretation of the landscape. This led to some confusion when several fields were located relatively close to each other. In highly ambiguous cases, the corresponding data points were simply deleted.

The PICES airborne survey provided an exceptional opportunity to enrich the collected in situ data. The PICES airborne survey also enriched the non-cropland class of the data set tremendously. For the cropland class, a few elements of the PICES must be taken into consideration. PICES has more difficulties in:

- 1) Recognising intercropping, because the observations are made at high altitude, which adds some confusion to the determination of the crop type.
- 2) Recognising less commercial crops, such as peanuts, sweet potato and soybeans, which resulted in a dataset almost exclusively containing maize fields.

Table 4 summarises all the collected land cover points for the cropland class. The most abundant classes are highlighted in green.

Table 4: Crop type points collected and their total representativeness in percentage (%) in both field campaigns.

Crop type	Fieldwork 1 7-11/03	Fieldwork 2 18-21/04	Crop type frequency	PICES airborne survey
Agricultural bare soil	6	4	2.5%	/
Soybeans	6	/	1.4%	/
Butternut	5	4	1.9%	/
Cassava	5	3	1.7%	/
Chilli	7	2	1.9%	/
Maize	118	74	52%	222
Mixed	55	23	21.2%	3
Peanuts	37	8	12.3%	5
Pumpkin	5	/	1.1%	/
Sweet potato	9	6	3.6%	4
Total cropland	253	124	100%	234

The total amount of cropland points collected during both field campaigns represents 377 samples, and, combined with the PICES cropland, a total of 611 cropland points, each corresponding to an individual field.

The crop type frequency in Table 5 was evaluated using just the data of the two field campaigns, as they are more representative of the ground truth diversity found in the study area. Maize is the most farmed crop type, representing 52% of the cropland points collected during both field campaigns.

Regarding non-cropland points, the different land cover classes and their total amounts are summarised in Table 5, all surveys combined.

Table 5: Non-cropland classes and total amount of points collected with all three surveys.

Non-cropland classes	Amount
Build-up	516
Natural forest	431
Fallow (Mid and Old)	247
Savannah	236
Orchard	43
Water body	35
Pine Plantation	6
Eucalyptus plantation	7
Total	1.521

All datasets combined, the combination of observations made at different scales gave a rich, quality-controlled data set, with 611 cropland and 1521 non-cropland data points. Of these 611 fields, 487 fall inside the PICES boundary map.

Regarding non-cropland sample points, an astonishing 247 fallow areas inside the PICES cropland mask were recorded. These areas usually cover extensive surfaces, meaning that an important amount of land has been completely abandoned, not showing any signs of recent farming activity, and resembles the surrounding savanna vegetation.

5.1.3 Buffer size attributions

Pixel-based classification algorithms extract spectral information contained inside labelled polygons. The algorithm is trained on those spectral features, in order to classify unlabelled pixels. The collected cropland and non-cropland points, 2132 in total, thus had to be converted into polygons.

A field boundary map delineating individual smallholder fields isn't available for the region, and smallholder field boundaries are difficult to see on an image with 10 m spatial resolution. An alternative to hand digitising individual field boundaries was to calculate buffers around the collected cropland points, which were dragged to the estimated centre of each field. Five approximate size categories (Table 6) were labelled in the process of cleaning the ground truth data. Varying buffer sizes were then easily applied to the different size categories. In total, 5 major categories were drawn with varying diameters for the buffers: Very big (60 m), Big (34 m), Average (26 m), Small (14 m), Very small (10 m). An estimate of the average field size in these categories can be found in Table 6.

Table 6: Buffer size categories, their diameter and total amount

Size categories	Buffer size (diameter)	Total amount of fields	Approximate field size
Very big	60 m	8	0.9 ha
Big	34 m	78	0.4 ha
Average	26 m	202	0.32 ha
Small	14 m	275	0.07 ha
Very small	10 m	48	0.02 ha

For the non-cropland data points, buffers of 7 and 14 m in diameter were applied. Because the outcome of the classification is sensitive to the amount of representative pixels in each class of the training data, the buffers in the non-cropland class were chosen to be relatively small. This allowed to avoid an overrepresentation of the non-cropland class, for which there were many more data points than in the cropland class.

5.2 Image classification

The different classification methods used will be explained in the following section.

The first classification method used is Sen2Agri's RF classifier, with some variants: different sampling strategies were tested and different manipulations of the time-series, such as to understand how they affect accuracies of the classification. The different sampling strategies refer to different calibration and validation data sets.

First, a reference cropland mask of the country which was obtained with the Sen2Agri system, will be validated with the collected data on smallholder farms in the study area. The reference map was calibrated with cropland information about commercial farms.

The second sampling set used in the Sen2Agri system, combines all the collected ground truth samples. This sample set is characterised by an important amount of non-cropland samples, and the classification is applied on the whole study area.

The third sampling set applied on Sen2Agri's RF features a more balanced ratio of cropland versus non-cropland and is also applied on the whole study area.

Finally, the fourth sampling set used in the Sen2Agri system uses only a smaller area of 44 x 50 km of the study area.

Temporal availability will also be evaluated on the croplands mask accuracy using the Sen2Agri system. The Sen2Agri RF will be both run on the extended time-series (July 2016-July 2017), the agricultural season only, two well chosen dates, and finally only one well chosen image. Time-series analysis was done in Sen2Agri alone.

Both the sampling set and the selected images which performed best in Sen2Agri were further used for the two remaining classification methods.

The second classification method evaluated is the SVM classifier implemented in the OTB platform using only two well selected images.

Finally, the third and final classification method performed is through the selection of NDVI thresholds in *Arcmap*.

5.2.1 Sen2Agri's RF

Sen2Agri's RF classifier was executed in command line, through a terminal connected to the Sen2Agri system. The images are automatically pre-processed by the Sen2Agri system when launching in a command line interface one of the various products.

The cropland mask script, found at p. 65 of the Sen2Agri User Manual, only needs two inputs to be provided: the Sentinel-2 time series and ground-truth data. Ground-truth data needs to be in a very specific format for it to be recognised by the system. This format is explained at p. 81 of the Sen2Agri User Manual.

The different parameters for running the Sen2Agri cropland mask and their default values are given at p.65 of the Sentinel-2 Agriculture Software User Manual. The three parameters of Sen2Agri's RF classifier are the following:

- 1) `rfnbtrees`: The number of trees in the forest used for training the classifier (by default: 100).
- 2) `rfmax`: The maximum depth of the trees used for the classifier (by default: 25).
- 3) `rfmin`: The minimum number of samples in each node used by the classifier (by default: 5).

When referring to literature, based on a review on the RF in remote sensing, Belgiu & Drăgu (2016) suggested a value of 500 for `rfnbtrees` and a small value for the `rfmin`. Both the Sen2Agri default values and values suggested by the literature were tested.

5.2.1.1 Sampling strategies and evaluation of the time series

To understand how sample representativeness affects the cropland mask in Sen2Agri, four different sampling sets were used. In all four cases 75% of the data was used to train the algorithm and 25 % to validate the resulting map. All the collected in situ data sources were used, which includes the two field surveys and the PICES airborne survey.

The first sampling strategy (1) is related to the data collected on the summer grain region, cropping maize and wheat mainly (Free State, North West, and west of Mpumalanga) and featuring conventional commercial farming.

- (1) Calibration sample set with data on conventional commercial farming in South Africa, validation with collected data on smallholders.

The calibration data was collected in the framework of the Sen2Agri project, in the perspective of generating and validating a cropland mask and crop type map of the 5 main crop types over the three provinces of the summer grain region in South Africa. The classification algorithm was trained on this commercial agricultural data, and validated specifically with the in situ data collected on smallholders. The resulting accuracies are expected to be low but will provide a measure of comparison between the spectrally more homogeneous fields of conventional farming

in South Africa; featuring irrigation and a high demand in inputs (fertilisers), and the country's smallholder spectrally more heterogeneous fields.

The data collected on the commercial farms followed the JECAM guidelines which are restricted to minimum field sizes 30 x 30 m and homogeneous fields only (no crop-associations). The training data set included 10.113 polygons of which 6.888 cropland stretched over the summer grain region. Of these samples, only 106 covered the Sentinel-2 tile of interest (36JUT), with only one cropland polygon of maize, and the remaining polygons being labelled as forest mainly.

The second sample set (2) for training the algorithm was composed of 2132 observations over the whole study area, of which 611 cropland and 1521 non cropland. Combining all the data meant the cropland-non-cropland ratio is representative of their occurrence rate in the study area.

(2) Calibration and validation using the total amount of the samples collected over the study area

The third sample set (3) uses a more balanced ratio of cropland-non-cropland over the whole study area, with a total of 1521 samples, of which 611 cropland and 910 non-cropland.

(3) Calibration and validation using a more balanced ratio of cropland to non-cropland

Finally, a smaller area of 44 x 50 km was selected, where most of the farming activity is concentrated. A total of 1270 samples was used, of which 497 cropland and 773 non-cropland.

(4) Calibration and validation on a smaller selected area of 44 x 50 km.

5.2.1.2 Evaluation of the time series

In parallel of running Sen2Agri on the whole-time series (July 2016 - July 2017), it was also run on the agricultural season only, as well as on two well selected dates, and finally one well selected date. The two dates were selected according to two criteria: they had to be as cloud-free as possible and show a high contrast between the cropland and non-cropland class. The combined criteria left only two possible choices: the 19th January and 6th May 2017.

5.2.1.3 Post Filtering

In the Sen2Agri system, a post-filtering step is applied on the produced cropland mask, this step removes the small isolated pixels that are considered to not belonging to the cropland mask (Valero et al. 2016). Both the raw cropland product and post-filtered product were evaluated on all the performed classifications in Sen2Agri.

5.2.2 Support Vector Machine classifier

The second classifier evaluated was the SVM classifier in OTB. The classifier was run on two dates: the 19 January and 6 May 2017 using sample set (4).

OTB allows implementing a range of different classifiers, whereas Sen2Agri is restricted to the RF classifier. The drawback of using OTB is that the user must perform certain pre-processing steps before they can use one of the classifiers. Typically this includes masking the on the images with their corresponding cloud mask, the resulting 'gaps' must be interpolated between the images of the time-series to 'fill' the gaps, since OTB doesn't handle NoData values. Finally bands at 20 m must be resampled at 10 m before using a classifier.

When handling a time series, these steps can be time consuming. Since the two dates selected are cloud-free and used here only for classification purpose, only the bands at 20 m bands needed to be resampled at 10 m. The four bands at 20 m resolution (band 5, 6, 7 and 8A) were resampled at 10 m using nearest neighbor method to obtain a layer stack of 8 spectral bands. The nearest neighbor method assigns the value of the nearest cell center on the input grid to the output cell. The values that come inside the grid stay unchanged. The advantage of nearest neighbor is that it is simple to use and the input pixel values stay exactly the same after treatment, on the contrary of other resampling methods such as bilinear interpolation and cubic convolution that take a weighted average of neighboring pixels. The latter are more recommended for mapping continuous variables. The resampling is performed in R using the *gdal* package. A popularly used way to resample a grid is by using the *gdalwarp* function but a commonly encountered problem with this function is that the resulting raster is slightly shifted, in our case half a pixel, compared to the original image, it is a consequence of resampling the values to a higher resolution. This can be avoided, by using the *resample2grid* function⁶ in R. This function uses *gdalwarp* but is framed to a reference raster specified by the user, to which the resampling will be made.

OTB also doesn't handle multiple input images when implementing a classifier, it can only threat one input image. When dealing with several images the function *ConcatenateImages*⁷ has to be used, this function performs image channels concatenation and generates a single multi-channel image.

Finally, the SVM classifier, under the name of libsvm in Orfeo Toolbox, was used and the following parameters had to be specified⁶:

- SVM Kernel Type (Linear, RBF, Polynomial or Sigmoid). Usually the gaussian Radial Basis Function (RBF) is a good choice in most cases, and was used for the classification as well. It is an exponential function of the euclidian distance between the vectors.
- SVM Model Type (C, Nu or One Class): C support vector classification allows imperfect separation of classes through the cost parameter C. The cost parameter C, which is set as 1 by default, controls the trade-off between training errors and forcing rigid margins. The Nu Model Types does the same but uses the cost parameter Nu, which is harder to optimize and computationally slower. The last option (One Class) is when dealing with

⁶ <http://www.guru-gis.net/assign-the-grid-of-a-raster-to-another-on/>

⁷ https://www.orfeo-toolbox.org/CookBook/Applications/app_ConcatenateImages.html

training data from the same class and is used to build the boundary that separates the class from the rest of the feature space.

- Parameter optimization (true, false): When true, the optimization will find the best combination of hyper-parameters, the algorithm will iterate, generating more models, until it converges to a good combination of hyper-parameters. This doesn't mean it finds the best value of hyper-parameters since it does not test all the possible combinations.

The classifier was run only once, with the C Model type and the by default C value of 1 with the parameter optimisation option.

Finally, the third classification method explored uses two computed NDVI raster images at two different dates and is described at the following point.

5.2.3 NDVI threshold classification

The classification method through NDVI threshold consisted of selecting the two most contrasting dates in the time series, in terms of differentiating between cropland and non cropland, with NDVI indices to highlight this difference between the normal growing vegetation and the cropped fields.

Typically this would be images at the beginning of the agricultural season and at the end of the season. At the beginning of the season cropland is prepared to be planted and bare soils show contrasting spectral values with surrounding natural vegetation which will already have benefitted from the first rains of the season. As the season progresses, crops will catch up with surrounding vegetation and NDVI response of both cropland and non-cropland will be more similar. Towards the end of the season, surrounding vegetation will gradually have a decreasing response while crops will be at the peak of their NDVI response.

Using bands 8 (NIR) and 4 (visible red) of the Sentinel-2 imagery, NDVI values were calculated in *Qgis* for the most cloud-free images of the season (19th January, 19th April, 6th May, 26th May, 6th June and 14th July 2017), such as to find the most discriminating dates. The NDVI values were calculated by applying a simple band-to-band operation using the following formula: $(\text{NIR} - \text{Visible red}) / (\text{NIR} + \text{Visible red})$.

The NDVI responses of the cropland and non-cropland samples were retrieved on all considered dates using the command *Extract values to table* in *ArcMap*. In the non-cropland category, only vegetation classes were kept, urban settlements and water bodies were put aside so as to not add noise the vegetation non-cropland class. By calculating the NDVI values corresponding field statistics the following windows appeared as illustrated by Figure 28 & 19 for the 19th January.

Of all the five dates examined only one showed a distinguishable difference between the cropland and non-cropland (Figure 28 & 29). All other dates showed major overlaps between the cropland and non-cropland class.

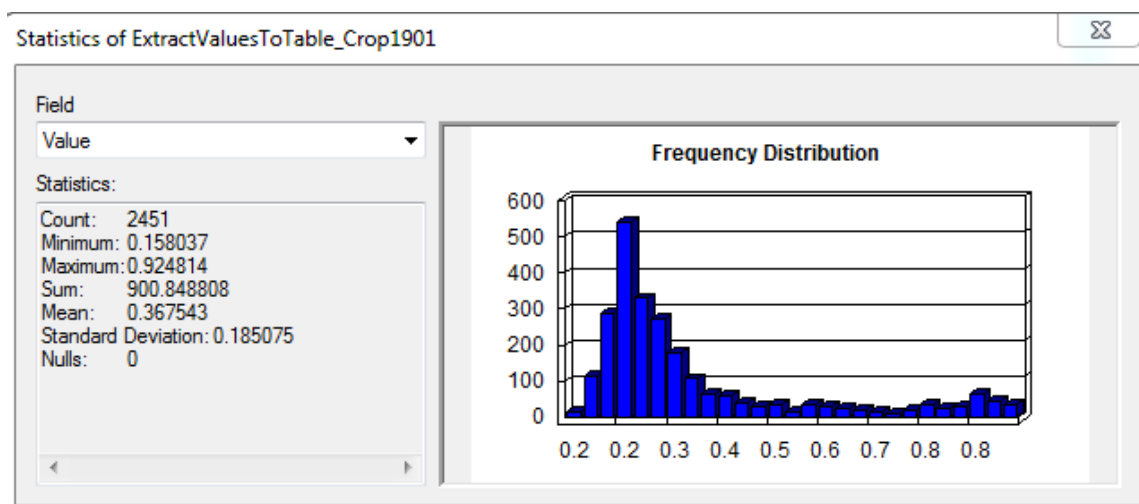


Figure 28: Cropland NDVI distribution on the 19th January

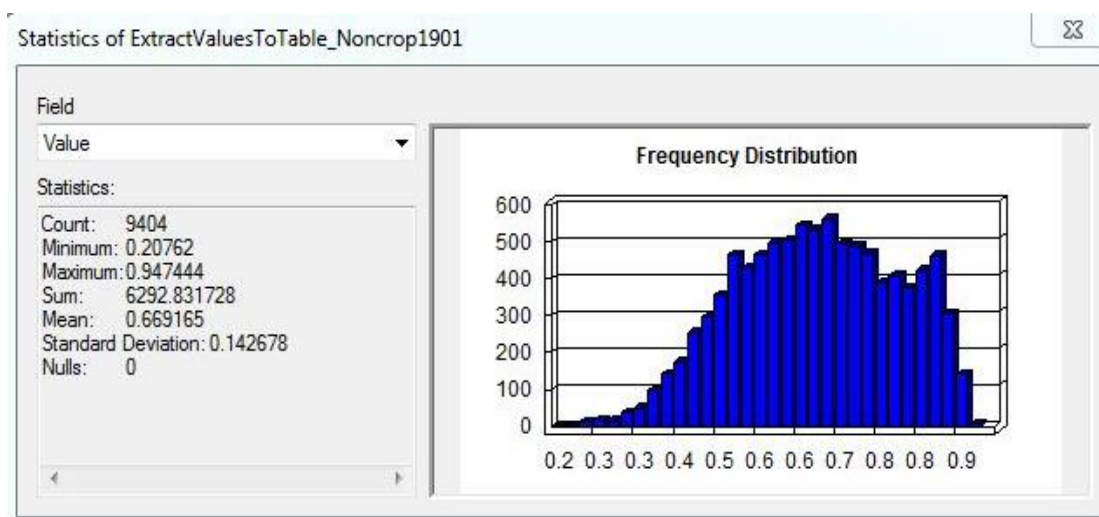


Figure 29: Non-cropland NDVI distribution on the 19th January

The NDVI threshold classification was pursued on only one image, being the 19th January. Based on the frequency distribution graph on Figure 28 & 29, and their corresponding statistics (minimum and maximum mainly), two thresholds were selected, the cropland class corresponding NDVI threshold values ranged from about 0.158 to 0.35. For the non-cropland, NDVI threshold values approximately ranged from 0.35 - 0.94. Using the function *reclassify* in *Arcmap*, the NDVI raster image was then classified into a cropland binary map, the resulting map was then validated in OTB with the validation samples of sample set (4).

5.3 Performance Assessment through validation procedure

To evaluate the accuracy and performance of the different classification products obtained, a number of measures can be adopted, by computing a confusion matrix through validation procedure, and derived accuracy measurements. The different performance measurements will be explained with regard to a cropland map.

5.3.1 Confusion matrix

The different accuracy measured are obtained through the establishment of a confusion or error matrix. The confusion matrix evaluates the map's accuracy for both classes on a pixel-to-pixel basis and gives an overview of the number of pixels that are correctly identified (Strahler et al. 2006). It is obtained through a cross-tabulation of the classes in the classification result against the reference data derived from field observations through the validation procedure.

Table 7: General confusion matrix for a cropland mask

		Reference labels	
		Cropland class (w_1)	Non-cropland class (w_2)
Produced labels	Cropland class (w_1)	n_{11}	n_{12}
	Non-cropland class (w_2)	n_{21}	n_{22}

The confusion matrix in itself just shows the amount of pixels that are correctly classified (green diagonal) and wrongly classified (red diagonal) on Table 7. The different accuracy measures that can be retrieved from the matrix, to help interpretate the map's accuracy, are defined below.

5.3.2 Global accuracy measures

Global accuracy measures evaluate the accuracy of the classified map in its whole, and gives one output accuracy for the map, all classes confused. Thematic accuracy on the other hand provides an accuracy measure for each class separately by confronting one class to the other, it provides performance information that characterises each class separately.

Overall Accuracy

The OA evaluates the overall effectiveness of the algorithm, is it calculated as the total number of correctly-classified pixels (green diagonal in Table 7) divided by the total number of validation pixels (1):

$$OA = \frac{n_{11} + n_{22}}{\sum_j^i n_{ij}} \quad (1)$$

5.3.3 Thematic accuracy measures

When thematic accuracy is more important than overall accuracy, several types of errors are more useful for interpreting the map's accuracy.

Precision

The precision of class i , also called user's accuracy, is the fraction of correctly classified pixels with regard to all pixels categorised as this class in the classification results. Concretely this means that the precision evaluates the fraction of correctly classified cropland pixels compared to all the pixels that were classified (produced label) as cropland (accurate and false). Meaning the precision takes into account the number of non-cropland pixels that were misclassified as cropland. For the cropland class (w_1) this is:

$$\text{Precision}_1 = \frac{n_{11}}{n_{11} + n_{12}} \quad (2)$$

Recall

The recall, also called producer's accuracy, for class i is defined as the correctly classified pixels of class i related to all the pixels of the considered ground truth class (reference label). For class i , the recall looks at the amount of pixels that are classified as i , and confronts them to the reference ground truth data-set. Meaning the recall takes into consideration the amount of cropland pixels that were misclassified as non-cropland: For the cropland class (w_1) this is:

$$\text{Recall}_1 = \frac{n_{11}}{n_{11} + n_{21}} \quad (3)$$

F-score

The F-score is a valuable error measure as it combines both the Precision and the Recall of a class. It can be interpreted as the harmonic mean of both error measures, with a maximum value of 1 and minimum score of 0 (Matton et al. 2016):

$$\text{F-score}_i = 2 \times \frac{\text{Precision}_i \times \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i} \quad (4)$$

6 Results and discussion

6.1 Findings from the field campaign: Defining small scale farming in the context of the study area

6.1.1 Smallholder farm typology

Three main different groups of small scale farmers were evidenced during the two field campaigns and they can generally be characterised according to three attributes explained in Table 8. They are: the small scale subsistence farmers, small scale collective farmers and small scale commercial farmers. These names were given according to each group's specificity, and is not a general term which should be referred to outside of the framework of this thesis. Readers must also keep in mind that this subdivision is characteristics of the study area and can't be generalised outside of the defined boundaries, since it is non-exhaustive and very qualitative, being based on visual understanding of the study area and discussions enhanced with several farmers. An important element to consider is the way these three different smallholders are spatially distribution inside the study area, this will be discussed further as well.

The main attribute that characterises every group quite distinctively is the way in which their farms are organised (line 1 of Table 8). The small scale commercial farmer (3) are the most distinctive from the other two groups and there exists a true gap in terms of productivity between this group and the other two. Between group (1) and (2), average field size is quite variable and agricultural practices are difficult to generalise, with every farmer seizing different opportunities according to their local constraints.

From all the small scale farms visited most of them had some sort of water supply system in place and didn't depend on rainfed water exclusively, by using trenches, dwells or buckets for the more subsistence farmers, to small sprayers or pipelines, for the more commercial ones.

Table 8: Smallholder farm typology and their main characteristics.

	Small scale subsistence farmers	Small scale collective farmers	Small scale commercial farmers
Farm organisation	• Extension of backyard mostly and on proximate communal land • Individual household level No surplus for sale purposes	• Remote areas, near river beds • Communal land mainly • Collective Some surplus for sale purposes	• Near road infrastructure • 1 land owner • Farmers are either employed, either they rent the land on which they cultivate Mainly sale purposes
Field size	1 field =<10 x 20m	Several plots of fields with varying sizes ranging from 10 x 20m to 20-30 x 40-50m	Multiple smaller fields, but that combined stretch over =< 100-200 x 200- 300m
Agricultural practice	• Little or no fertilisers and no visible water supply • No machinery • Crop associations mainly	• Little fertilisers and basic water supply with bucket and trenches. • Often machinery for preparing the fields but seeds are handplanted • Mainly maize and several other crop types, some crop associations	• Fertilisers and irrigation system • Machinery for preparing and planting • One crop type/ field, no crop-associations • 1 or 2 crop types, no crop associations

6.1.2 Small scale subsistence farmers

The main characteristics of this group is that they mostly work on an individual level, every household separately and functioning independently, they also use their harvest for their own based livelihoods and not for cash purposes. Most of the field labor is typically done by women. The fields are often spatially isolated from one another and appear randomly in the landscape, usually in proximity to villages, as is illustrated by Figure 30 (left).

The small scale subsistence farmers are found dispersed across the area, farming close to their house on the communal lands, or in extension of their backyard.



Figure 30: Small scale subsistence farming fields

Their fields are very heterogeneous, commonly featuring crop-associations with maize and groundnuts or beans as main associations (Figure 30, right). Crop health is very variable, as well as on field crop density and growth stages.

Most of them use very little or no fertilisers for their crops and they don't have any disposable machinery, except if being shared with other smallholders, fields are being prepared, planted and harvested by hand. There also isn't any noticeable water supply water to their fields.

Although the line is very thin between this group and 'backyard' or garden farmers, they differ from them in the sense that they do crop at least one field that is minimum 10 x 20 m and which is usually not attached to the house. Backyard or gardens are usually smaller and confined to the house property, surrounded by the property's fence.

The small scale subsistence farmers can be accounted for more than 40% of the total farmers in the study area.

6.1.3 Small scale collective farmers

When several small scale subsistence farmers join together to form a small community they usually farm on the communal designated lands, sharing tools and knowledge. These designated areas are remotely located from surrounding villages but cover vast spaces of which most is not used. Several fields are cropped adjacent to each other inside a fenced area (Figure 31, bottom), and feature different crop types or crop-associations (Figure 31, top). In some areas these collective farmers remain predominantly subsistence, but in most cases they are able to create a surplus that they sell in surrounding villages. The type of tools that they share are fertilisers and a small tractor mainly. The fields are typically worked on and maintained by women mainly.



Figure 31: Small scale collective farming fields

Depending on their surplus produced, a few minority was able to afford and divide the costs of a small water reservoir. In some cases the water reservoir was provided by local NGO's. Sharing tools, knowledge and labour allows them to crop on bigger fields, farm more types of crops; even more complex vegetables such as tomatoes, then the small scale subsistence farmers.

In some areas of this designated lands (mainly loop D on Figure 25), free range cattle farming pressurises the smallholder fields ; which hence need to be fenced to protect the crops from being damaged.

In all cases, most of the communal land surface wasn't farmed at all, with obvious signs of abandonment: more recently abandoned fields were covered in weeds and crop residues, while older abandoned fields were already dominated by surrounding savannah vegetation, with sometimes on field lines of the tractors still perceptible.

The majority of these collective small scale farmers can be found in loop B and C of Figure 26, they represent approximately 50% of the total farmers in the study area.

6.1.4 Small scale commercial farming

Areas surrounding Hazyview feature more commercial small scale farming, benefitting from a well developed road infrastructure and proximity to more developed town market of Hazyview. These farms have a dedicated infrastructure to clean and store their goods before shipping them of for sales (Figure 32, left). Land typically belongs to a landowner on which farmers are either employed, either they rent the land on which they cultivate. The farmers, in this case mainly men, are employed to work on the plots for commercial purposes and not for their own based livelihoods.



Figure 32: Small scale commercial farming infrastructure and sweet potato fields.

Small scale commercial farms are considerably more productive compared to the two previous categories. Their fields are far bigger and more homogeneous (Figure 32, right) compared to the two previous categories. These farms will usually feature fruit orchards of banana and mangoes, complementary to their maize and/or sweet potato production. Small scale commercial farms on the study area represent a mere 10% of the total farmers in the study area.

6.2 Accuracy assessment of the Cropland mask

The accuracy measures relevant for analysing the different obtained cropland masks at Table 9 to 11 are the thematic accuracy measures, since they provide information about the accuracy of detection of both the cropland and non-cropland class. With the F-score being the most interesting measure of comparison between the different classification methods, as it provides a combined accuracy measure of both the Precision and Recall.

Additionally, the OA doesn't seem to be sensitive to the different methods used, showing accuracies of over 90% most of the time. When we have a look at the confusion matrix of Table 7, the Overall Accuracy is strongly impacted by the higher number of cropland pixels found inside the training polygons ($\sum w_2 \gg \sum w_1$) and by the high number of correctly classified pixels in this class ($n_{22} \gg n_{12}$), explaining the high OA values obtained.

The cropland mask post-filtered products, obtained through Sen2Agri; has resulted in our case in a decrease in accuracies of more than 10% compared to the unfiltered map. Small isolated fields that were actually part of the cropland were lost during this process. The different cropland products obtained were systematically revalidated based on their unfiltered corresponding map, and with their corresponding validation sample sets, the results can be visualised in Table 9 to 11.

The results of the different cropland masks obtained through the different classification methods are figured and discussed in the three following sections, and their chronological order to reflect the logical mind flow that followed these consecutive classification approaches. These different approaches were explained in Section 5.2.

6.2.1 Evaluation of Sen2Agri's RF classifier applied on the whole study area using the time series

The first classifications performed consisted of applying Sen2Agri's RF classifier on different sampling procedures and that shared in common the same study area and time series.

As a reminder, the different sample sets applied on the whole study area in Sen2Agri are:

- (1) Calibration sample set with data on conventional commercial farming in South Africa, validation with collected data on smallholders.
- (2) Calibration and validation using the total amount of the samples collected over the study area, of which 611 cropland and 1521 non-cropland.
- (3) Calibration and validation using a more balanced ratio of cropland to non-cropland, of which 611 cropland and 910 non-cropland.

The results of these classifications are summarised in Table 9.

Table 9: Results of Sen2Agri's RF classifier applied on the whole study area using the time series.

						Cropland			Non-Cropland		
	Scope	Input images	Classifier	Sampling strategy	Overall Accuracy (%)	Precision	Recall	F-score (%)	Precision	Recall	F-score
A	SA Default study area	By default cropland mask	Sen2Agri-RF	(1)	98.4	0.243	0.658	35.5	0.997	0.986	0.992
B	SHF-study area	Sentinel-2 time series	Sen2Agri-RF	(2)	94.9	0.789	0.672	72.6	0.964	0.980	0.971
C	SHF-study area	Sentinel-2 time series	Sen2Agri-RF	(3)	93.5	0.854	0.695	76.6	0.946	0.978	0.962

On Table 9 above, we can see that as expected, the Sen2Agri by default cropland map of South Africa (SA), which was trained on the data collected from conventional commercial farms in the summer grain region, gives a very low F-score accuracy for the cropland category (35.5%) when validated with the collected in situ data on smallholder farming (SHF). This is half of the F-score obtained for cropland using in situ collected data for calibration and validation that specifically targets smallholder farming (B).

The accuracy difference shows how contrasted both agricultural systems are, and the gap that exists between the high profitable, productive, homogeneous and easily discernible commercial fields; and the low profitable, low productive, heterogeneous and indistinct smallholders fields. This highlights the need of data collection surveys being specifically aimed towards smallholder systems.

The low accuracy obtained when validating the national reference cropland mask with in situ data collected in smallholders (A), sets light on the importance of field surveys being exclusively turned towards smallholder systems and not as being part of a broader survey. Especially since the confusion matrix and accuracy measures rely on the collected ground truth data to evaluate to maps accuracy, and not on actual ground truth information, errors in the ground truth training and validation samples will propagate through the validation. If field surveys selectively collect ground truth information by not taking into account the local diversity, the landscape represented by the collected samples is simplified. This simplification propagates through the validation procedure, since the cropland mask is constructed and evaluated on the samples of the field survey.

Neglecting certain aspects of the small scale farmer's diversity, by selectively collecting in situ data will erase the ground truth diversity and result in artificially high accuracies. Researchers may take advantage of this to guide their results towards higher accuracies.

The different cropland maps obtained at (B) and (C) used the collected in situ data only. The first map (B) obtained an F-score result of 72.6 % for the cropland category; the sample set used combined all the collected in situ data, with an unbalanced cropland-non-cropland ratio of 2.5 in favour of the non-cropland. The more balanced ratio of cropland to non-cropland of sample set (3) over the region increased F-score cropland accuracies of the map by 4% compared to (B). Sen2Agri's RF thus seems sensitive to the size of the classes. This is also the case of the RF algorithm outside of Sen2Agri; according to Belgiu & Drăgu, (2016) the RF classifier is sensitive to the sampling procedure and to the size of the training samples, which is the case as well in our study.

6.2.2 Evaluation of the Sen2Agri's RF classifier applied on a 44 x 50 km area using the time series (July 2016-July 2017)

A smaller area of 44 x 50 km was selected, where most of the farming activity is concentrated. The sample set (4) consists of a total of 1270 samples, of which 497 cropland and 773 non-cropland.

(4) Calibration and validation performed on a smaller selected area of 44 x 50 km.

The resampled area features a naturally balanced cropland to non-cropland ratio, since it was in this region that most of the agricultural activity was present. The cropland samples in this data set are believed to cover the main diversity of that resampled area as it was in these areas that most of the field campaigns were held. Sample representativeness of the classes is thus believed to be higher according to the resampled area. The result of this sampling procedure is illustrated in Table 10.

Table 10: Results of Sen2Agri's RF classifier applied on a 44 x 50 km area using the time series.

						Cropland			Non-Cropland		
	Scope	Input images	Classifier	Sampling strategy	Overall Accuracy (%)	Precision	Recall	F-score (%)	Precision	Recall	F-score
D	SHF-resampled area	Time-series	Sen2Agri-RF	(4)	94.3	0.923	0.661	77.1	0.945	0.990	0.967

When comparing Table 10 to the previous Table 9, there isn't a significant difference between the cropland F-score obtained for the (C) and (D) cropland mask. Resampling the data set to a smaller area didn't have a significant impact on the maps accuracy, although the resampled area was believed to be more representative of the areas diversity in terms of spectral signature. Belgiu & Drăgu, (2016) also stated that RF is affected by sample representativeness.

The difference in accuracy was expected to be more significant with sample set (4), as it combined both a naturally more balanced crop to non-cropland ratio and samples representativeness is also higher. The remaining cropland samples that were left out when resampling the area, were believed to be more affected by error as they were mainly collected by the PICES and their random distribution made it difficult to verify these areas by car.

When resampling the data to the 40 x 50 km area, only 114 fields were left out of the total 611 in the total data set. Since the cropland samples of the whole study area is mostly concentrated in the resampled area, the possible gain in accuracy, by selecting a smaller and more representative area, was masked by the fact that this area has the most weight on the final accuracy of the cropland class.

Although the F-score and Recall class accuracy difference of the cropland class between (C) and (D) isn't significant, the Precision of the cropland class is significantly higher in (D), and exceeds 90%. It was thus decided to test the remaining classification methods with the sampling set that performed the best using Sen2Agri's RF, meaning the sampling set (4) was also applied on all further classification methods.

The different sampling procedures having been tested on Sen2Agri's RF, the impact of different manipulations of the time series on the croplands map accuracy would then be evaluated using the best performing sampling set (4). The further discussed results will thus mainly compare the F-score cropland accuracy obtained in (D) to the other remaining methods, as they use the same sampling set.

6.2.3 Evaluation of the impact of the time series on Sen2Agri's RF

Table 11: Results of the Sen2Agri's RF classifier applied on a 44 x 50 km area using the time series

						Cropland			Non-Cropland		
	Scope	Input images	Classifier	Sampling strategy	Overall Accuracy (%)	Precision	Recall	F-score (%)	Precision	Recall	F-score
E	SHF-resampled area	19 January 2017	Sen2Agri-RF	(4)	93.9	0.867	0.684	76.4	0.948	0.982	0.965
F	SHF-resampled area	19 January + 8 June 2017	Sen2Agri-RF	(4)	95.281	0.899	0.758	82.3	0.960	0.985	0.972
G	SHF-resampled area	Agricultural season	Sen2Agri-RF	(4)	94	0.864	0.699	77.3	0.950	0.981	0.965

The classification performed with (E), (F) and (G) didn't use the whole time series, spanning from July 2016- July 2017, as the previous classifications performed (A-D), as it was interesting to understand how much the contribution of the time series impacts the final cropland masks accuracy.

(E) Using only one date, cropland F-score accuracy results were comparable to the one obtained using the whole time-series in (D). Thus, evidencing that the satellite image dating from the 19th January provides most of the information for the classification and has the most impact on the final accuracy.

(F) Using only two well selected cloud free dates, it was possible to increase the cropland F-score accuracy an additional 5.1% compared to using the time-series in (D).

(G) When extending the time-series to the agricultural season only, with images from end of November till early June, F-score cropland accuracies decreased compared to the previously obtained results in (F). Between using the time series of the agricultural season only or the extended time series from July 2016 to July 2017 such as in (D), there wasn't any noticeable difference. Extending the time series outside of the season didn't provide any additional information.

Disposing of a time-series did, in our case, not improve the results, and even lowered accuracies for the cropland class when compared to using only two dates. This is due to the fact that images over the agricultural season are very cloudy, meaning the probability of a same pixel providing consistent information throughout the season is very low. In this case, the addition of images inside (extremely cloudy) and outside the agricultural season (before mid-November and after harvest⁸) only dilutes the contrasted spectral information evidenced on the 19th of January. The original idea of extending the time-series from mid-June 2016 to mid-June 2017, was to add spectral information to the classifier which would possibly help to discern the spectrally more dynamic cropland category from the less dynamic non-cropland. Yet, it later appeared that most of the images showed high similarities between cropland and non-cropland in terms of NDVI values outside of the agricultural season. When these images are included in the input image time-series, they only add unnecessary information. Valero et al. (2015) noted the importance of the quantity and quality of the images to achieve crop detection for the cropland mask. In our case, the quality highly affected classification accuracies.

Overall, even the best F-score result of 82.3% obtained for the cropland mask (F) is still quite low, considering cropland maps usually aim at least 90% accuracy for the cropland F-score.

Yet, according to Sweeney et al. (2015) satellite-derived measures of cropland in Africa, with minimum accuracies ranging between 80 and 85 percent, could already fill in statistical data gaps, provide valuable data for designing development programs and monitor dynamics of agriculture extent.

⁸ The exact date of the harvest isn't very clear, since NDVI calculated images showed major overlaps between the cropland and non-cropland as of the 19th May, which is the first almost cloud free image compared to the 19th January

6.2.4 Evaluation of the SVM classifier and NDVI threshold classification

Finally, the two remaining classification methods with the SVM classifier and NDVI threshold value classification.

Table 12: Results of the SVM classifier and NDVI threshold classification

						Cropland			Non-Cropland		
	Scope	Input images	Classifier	Sampling strategy	Overall Accuracy (%)	Precision	Recall	F-score (%)	Precision	Recall	F-score
E	SHF-smaller area	19 January + 8 June 2017	SVM	(4)	90.6	0.650	0.893	0.752	0.978	0.908	0.942
F	SHF-smaller area	19 January 2017	NDVI stratification	(4)	86.8	0.593	0.636	0.613	0.927	0.913	0.920

The results obtained with the SVM classifier were in the same range as the more average performing classifications obtained with sample set (4). The classification was performed on the same two images as the one in (F), yet the difference in F-score accuracy for the cropland class is about 7.1% in favour of the RF used in Sen2Agri.

The lower accuracy obtained with the SVM default parameters must be put in perspective with the work behind operating and optimising the Sen2Agri's RF algorithm for classification purposes, more time consecrated to optimising the parameters of the SVM classifier would have probably allowed to obtain more comparable results. The lack of optimisation time consecrated to the SVM classifier was also evidenced as being a common problem in comparative studies using the SVM classifier (Li et al. 2011; Stephens et al., 2014).

Yet, the SVM in our study is not evaluated at its true value, since we are not comparing SVM with the RF classifier, but with Sen2Agri's RF classifier. The SVM classifier was run on spectral reflectance values only, whereas Sen2Agri's RF uses temporal vegetation and spectral indices. The work and optimisation behind Sen2Agri's RF makes give this method an uncompetitive advantage compared to the SVM classifier used in OTB with the default parameters. Yet, this does underline the time efficient advantage of using Sen2Agri's RF compared to a more difficult to optimise SVM classifier.

Results obtained with the NDVI stratification method at (H) provided the worst results (61.54%) compared to other classifiers using the same sample set (4). This is in part due to the inability to find a second image showing a notable contrast in NDVI values, which would have provided complementary information to discern cropland from non-cropland. The method was pursued with the hypothesis that after harvest, bare soils would have a contrasted spectral signature compared to surrounding vegetation. Yet, the indiscernible NDVI patterns between the cropland and non-cropland throughout the season (19 April, 6 May, 26 May, 6 June and 14 July 2017) proved otherwise. Images between the 19th January and the 19 April were not cloud free enough to be analysed as well.

The fact that it wasn't possible to discern bare soils after the end of the season might be characteristic of small scale farming, due to the way smallholders operate after harvest, or the spectral behaviour of the savanna landscape throughout the season. Some characteristics of small scale farming that make it difficult to discern cropland from surrounding savanna vegetation might be that:

- 1) The harvesting is usually done by hand, but the fields don't seem to get ploughed after the harvest, even manually, although most of them did get ploughed to prepare the soils at the beginning of the agricultural season. The smallholders usually managed to get their field ploughed by a basic tractor that they would share between multiple farmers, or hand plough their fields. After harvest though, there doesn't seem to be any work done to the fields. Fields are left as fallow before the start of the next agricultural season.
- 2) On-field crop residues, mixed with remaining weeds that already covered the surveyed fields during the season, add spectral confusion compared to a bare soil and make it indiscernible from surrounding savanna vegetation, characterised by dry grasses. The difficulty of discerning savanna vegetation from cropland using NDVI was also evidenced in the literature (Jiang et al. 2006, Sweeney et al. 2015).
- 3) The diversity of crop types assessed also feature different crop cycles, which makes harvesting patterns highly unsynchronised, especially on mixed fields, making it difficult to find an estimate time range where the fields have all been harvested.

6.3 Error analysis

To understand how relative field size influences accuracies, and to what extent it is possible to detect smallholder fields with the 10 m spatial resolution of Sentinel-2, an error analysis according to field size was conducted. All 611 cropland samples were used in this analysis. This analysis consisted in validating the cropland mask that achieved the best cropland F-score accuracy results (F), with the different buffer sized categories, which were attributed in Section 5.1.3.

Results of this analysis are summarised in Table 13 below.

Table 13: Results of the size error analysis

Size categories	Buffer size (diameter)	Total amount of fields	Approximate field size	Accuracy of detection: F-score values
Very big	60 m	8	0.9 ha	92.8%
Big	34 m	78	0.4 ha	
Average	26 m	202	0.32 ha	89.2%
Small	14 m	275	0.07 ha	58.6%
Very small	10 m	48	0.02 ha	25%

The total representativeness of the fields is the amount of fields with that buffer size found in the whole data-set (611 cropland buffers).

The big and average size categories showed high accuracies with 92.8% and 89.2% for the cropland F-score. A significant accuracy drop of 30.5% was recorded between the fields labelled as small and average. It appears that fields already less than 15 m large are difficult to detect with the 10 m spectral resolution of Sentinel-2. At this size range, pixels corresponding to the field are highly affected by spectral mixing by surrounding vegetation outside the fields. Fields of this size don't feature any 'pure' pixel, representative of that field's crop spectral value. To have one pure pixel with Sentinel-2 imagery requires fields to be at least as big as 3 x 3 pixels.

Size only isn't responsible for the accuracies obtained, as size category decreases, fields tend to be more heterogeneous, are more prone to intercropping and show varying health stages and crop densities. Presence of weeds, trees and shrubs is also more important on the smaller sized fields. All these elements influence the spectral response of these fields, and makes it more difficult to discern them from surrounding vegetation.

The error analysis by size stratification can still be improved using the actual field boundaries, representative of the field's actual size and shape and would provide valuable statistical information on the real size distribution of the fields. Nevertheless, this would have biased the F-score values obtained for cropland with the different classifications performed, since the bigger sized fields would have contributed more due their more important number of pixels present in the fields, eventhough those fields are less frequent.

Furthermore, the cropland mask (F) was also validated with a sample set consisting exclusively of maize, all size confound, as it was interesting to evaluate the accuracy of detection of the main crop type of the study area. In the total data set of 611 cropland fields, maize represents 65% of the crop types (Including the PICES data). This number is different from the one given in Section 5.1.2, of 52% as it includes the PICES data, which consisted almost exclusively of maize. The results in Table 14 show that 89.77% of the maize fields was detected as cropland on the produced cropland mask. Meaning the maize category, all sizes confound, can already be evidenced quite accurately with Sentinel-2.

Table 14: Results of the size error analysis

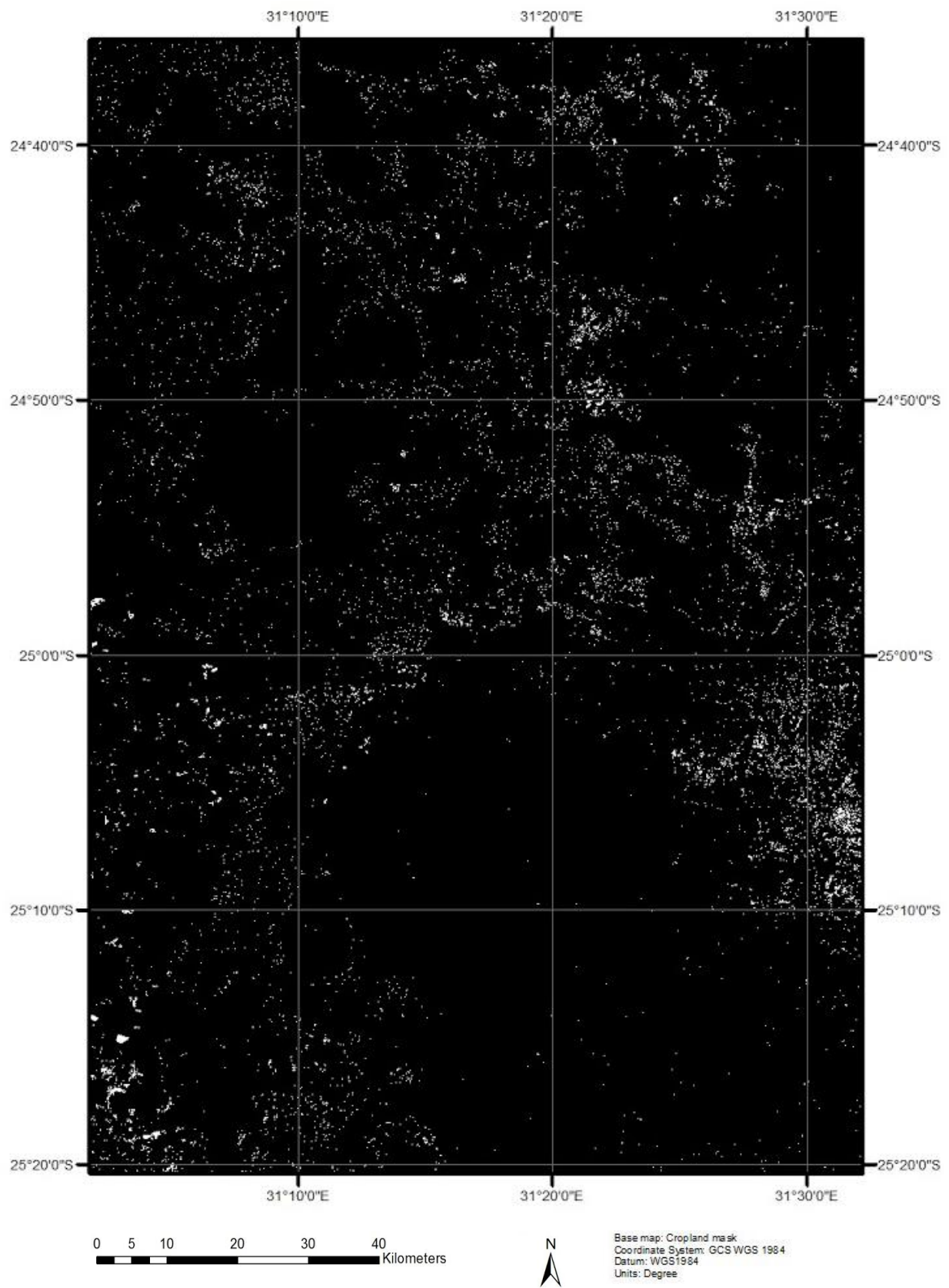
Size categories	Buffer size (diameter)	Total amount of fields	Approximate field size	Accuracy of detection: F-score values
Maize only	/ all sizes	305	76	89.77%

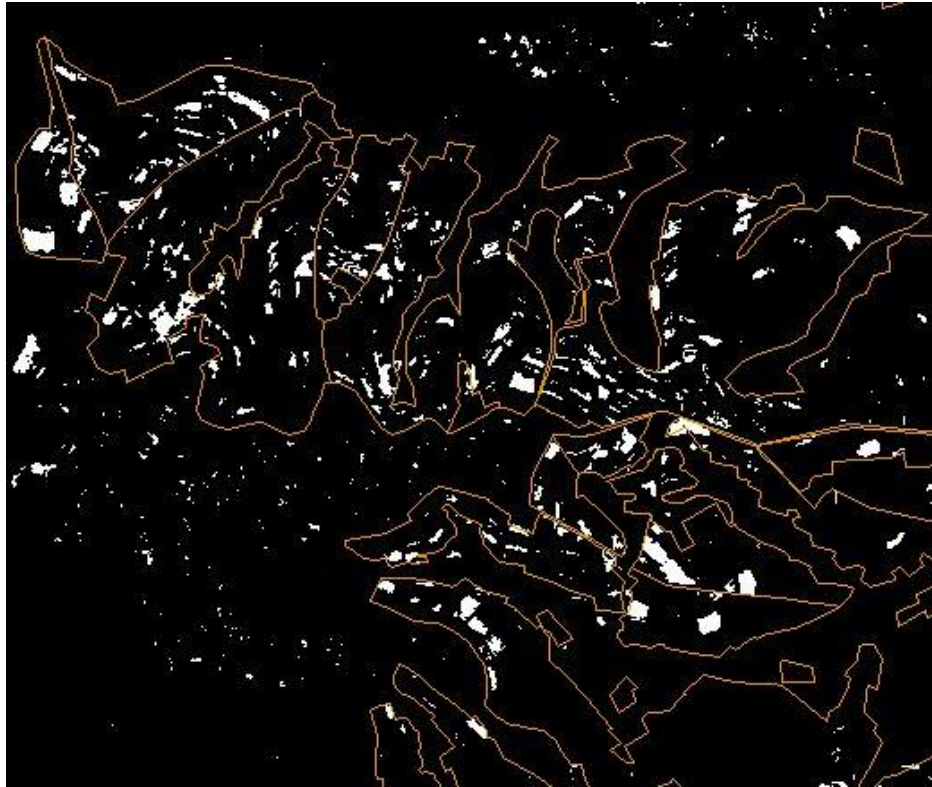
6.4 Presentation of the cropland mask

The cropland mask of the study area is presented on Figure 34. It is the product of the classification method (F) which showed the highest cropland F-score value (82.3%) compared to all other methods. Figure 35 and 36 illustrate a zoomed in area of the cropland map. On Figure 36, the cropland mask is applied on false colour composite of the 19th January 2017.

If we look at the mask on Figure 34 and compare it to Figure 14, we can see that there exists confusion between cropland and savanna vegetation on the right side of cropland mask, where misclassified cropland pixels fall inside the Kruger National Park.

Figure 33: Cropland mask over the study area





1km


Figure 34: Zoom on the cropland mask

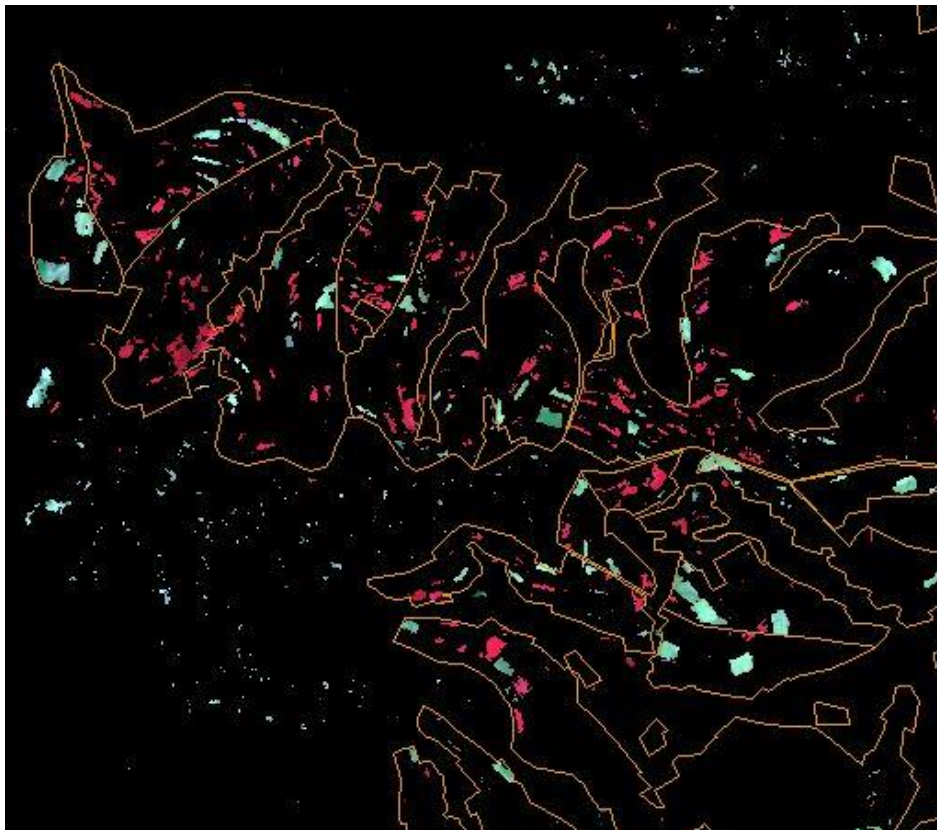


Figure 35: Zoom on the cropland mask with false colour composite of the 19th January

7 Conclusion and future perspectives for smallholders

The continuous improvement of remote sensing technologies in terms of spectral and temporal resolutions, increasing numbers of bands and improved classification methods allows to monitor cropland and crop types with always-higher levels of accuracies, even in the more difficult diverse landscapes. The launch of Sentinel-2 and the Sen2Agri processing system allows new ways to monitor agriculture closely on a big scale and across landscapes, and with that a new opportunity to map smallholders systems across the world.

This thesis investigated three different classification methods for mapping small scale farming systems in the north-west of the Mpumalanga province in South Africa. With the Sen2Agri's RF classifier being used as baseline method, different sampling strategies and availability of time series were evaluated on the classifiers performance. The adequateness of the 10 m resolution of Sentinel-2 was also evaluated through a size stratified error analysis. In parallel two other classification methods were used, one using the SVM classifier and the other one using an NDVI threshold method. While the results presented in this thesis aren't concluding for evaluating the general performance of Sen2Agri for mapping smallholders systems on a larger scale, they do set a baseline of comparison for future studies.

The importance of a balanced data set and its quality when using Sen2Agri's RF was evidenced, and the system can be used for mapping smallholder systems with a careful and dedicated approach. Advantages of Sen2Agri system are undeniable, working in a highly autonomous way and automatically pre-processing the time-series make it a very comfortable classification method to use.

The SVM classifier wasn't evaluated at its true value due to a lack of time for optimising parameters and only spectral reflectance values. Using NDVI values in savanna landscape with smallholder systems isn't recommended as there exists high confusion throughout the season between NDVI values of cropland and natural savanna vegetation.

The thesis highlighted the importance of field surveys conducted on smallholders systems, to be explicitly oriented towards smallholders, as the national cropland mask validated with smallholder in situ data resulted in very low accuracies (35%). The gap that exists between smallholder systems and conventional farming fields is big, but the gap that between the substantial smallholder farmer and the small scale commercial smallholders is as comparably as important. Assuring food security in many parts of the world will depend on the inclusion of all types of smallholders and efforts should be made towards helping collective farm associations becoming more commercial.

The quality of the images rather than the quantity affected Sen2Agri's RF classifier, although its ability to handle noise. Yet, the temporal availability of the satellite remains interesting to study smallholder landscapes and provides a major potential for using conjunctively, wisely selected Sentinel-2 image(s) with and a higher resolution sensor. The conjunct use of both sensors provide promising future results for mapping cropland in smallholder systems, since the first constraint of mapping smallholder systems is the spatial resolution.

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Mapping cropland in smallholder farmer systems in South-Africa using Sentinel-2 imagery

Summary

The continuous improvement of remote sensing technologies in terms of spectral and temporal resolutions, increasing numbers of bands and improved classification methods allows to monitor cropland and crop types with always-higher levels of accuracies, even in the more difficult diverse landscapes. The launch of Sentinel-2 and the Sen2Agri processing system allows new ways to monitor agriculture closely on a big scale and across landscapes, and with that a new opportunity to map smallholders systems across the world.

This thesis investigates three different classification methods for mapping cropland in small scale farming systems in the northwest of the Mpumalanga province in South Africa. With the Sen2Agri's Random Forest classifier being used as baseline method, two other classification methods were tested, using the Support Vector Machine classifier and one other using an NDVI threshold method but did not obtain satisfactory results.

The Sen2Agri Random Forest classifier achieved the highest accuracies compared to the two other classification methods and was able to achieve a cropland F-score accuracy of 82%, the main source of error being due to confusion between cropland and surrounding savanna vegetation.

The importance of a balanced data set and its quality, when using Sen2Agri's RF was evidenced, and the system can be used for mapping smallholder systems with a careful and dedicated approach. The quality of the images rather than the quantity affected the Sen2Agri's RF classifier's accuracy, although its ability to handle noise.