

Detecting crop residues burning using Sentinel-2 imagery: conservation agriculture promotion in Central Malawi

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List of abbreviations and acronyms

AVHRR: Advanced Very High-Resolution Radiometer
 CA: Conservation Agriculture
 CIMMYT: Centro Internacional de Mejoramiento de Maíz y Trigo (International Centre for Improvement of Maize and Wheat)
 CSI: Char Soil Index
 dNBR: Differenced Normalized Burn Ratio
 ESA: European Space Agency
 FAO: Food and Agriculture Organization of the United Nations
 Landsat TM: Landsat Thematic Mapper sensor
 Landsat ETM+: Landsat Enhanced Thematic Mapper Plus sensor
 MIRBI: Mid Infrared Bispectral Index
 MODIS: Moderate resolution Imaging Spectrometer
 NDVI: Normalized Difference Vegetation Index
 NDWI: Normalized Difference Water Index
 NGO: Non-Governmental Organisation
 NIR: Near Infrared
 NOAA: National Oceanic and Atmospheric Administration
 Sen-2 Agri: Sentinel-2 for Agriculture System
 SPOT: Satellite Pour l'Observation de la Terre (Satellite for Earth's Observation)
 SWIR: Shortwave Infrared
 UTM: Universal Transverse Mercator
 WGS: World Geodetic System

Introduction

Smallholder farmers from all regions of the world face increasing and numerous challenges, all the more in the Southern Hemisphere. As the population is quickly rising and a majority of it practices farming, an improvement of agricultural yields and productivity would be incredibly beneficial. To this end, conservation agriculture endeavours have been implemented by numerous NGO's, agencies, as well as governments. These aim to change farming practices in order to attain better yields, optimize the use of inputs and reduce harmful environmental impacts. These programmes and their efficiency need to be monitored. However, on-ground monitoring can be expensive, time-consuming notwithstanding potential physical obstacles.

Remote sensing is the detection of phenomenon and collecting of information from a distance. This seems like a more convenient and quicker way of assessing new technique's adoption rate. Remote sensing has been used for agricultural purposes successfully for a long time now. It has also been applied extensively to development projects in developing countries (Hilbert, 2016) as well as in the prevention of hazards and so on.

The democratization of platforms such as Unmanned Aerial Vehicle and the existence of free satellite imagery make this feasible in any country. Remote sensing has developed so much in the past few years, its spectral and spatial resolution have improved greatly. This has paved the way for a better detection of practices on individual fields.

Malawi, in South-Eastern Africa, is a small country where agriculture plays an overwhelmingly important role in the economy. Half of the country's area (57.000 km²) is indeed agricultural land. It constitutes the majority of its Gross Domestic Product as well as vital sustenance and livelihood for rural communities. The country has had recurrent issues with food security and is ranked 105 out of 113 countries in terms of food security (The Economist Intelligence Unit, 2017). Particularly, the 2016 season has seen a 12% production decline compared to 2014/2015 as a result of dry spells linked to El Niño phenomenon. This explains that 46% (6.7 millions) of the population analysed by the FAO in October 2016 were food insecure (Food Security Information Network, 2017).

This is why conservation agriculture has been advocated in the country for several decades now by a multitude of programmes including one from the European Union. CIMMYT and the local NGO Total Land Care have been partners since the mid 2000's, promoting those practices to rural communities through input packages and demonstration plots. As part of monitoring this project, UAV flights were conducted in core promotion areas of the Central Region. This can help evaluate the impact of this promotion on the landscape. The availability of those high-quality images and their context were what launched the idea for this thesis and the ensued collaboration with CIMMYT.

Thus, the core question of this thesis links conservation agriculture and remote sensing in the Central Region of Malawi through satellite and Unmanned Aerial Vehicle imagery. The

focus is put on a specific practice part of Conservation Agriculture: crop residues retention and its traditional alternative of residue burning.

This master thesis will be structured in the following manner. To begin with, a brief review of current relevant literature linked to the subject is necessary. It will address conservation agriculture's definition and application, its promotion conditions especially in Southern Africa; as well as burned area monitoring and mapping. This will lead us to set more precise objectives and working hypothesis to guide us. The next section will explicit in detail our data sources and the successive steps to achieve mapping accurately crop residues burning. Finally, the maps and other results will be visually displayed and interpreted. We can then analyse if the set objectives were met and explore possibilities for future research.

Chapter 1

Literature review

This literature review will discuss the practices gathered under the term conservation agriculture, the agricultural context in Malawi as well as the conservation agriculture application and promotion in this country. Thereafter, we will examine technical aspects, linked to methods of detecting crop residues on fields and methods for the detection of burned areas in landscapes.

1.1. Conservation agriculture

Conservation agriculture (CA) is a vision of agriculture with integrated management of the soil and water resources. That denomination was first used by the Food and Agriculture Organization at the first Conservation Agriculture Congress in 2001 (Kassam *et al.*, 2009). It encompasses a number of soil conserving practices, the three main ones being minimum or no tillage, diversified crop rotations and permanent organic matter cover of soil (via mulching or cover crops) (Giller *et al.*, 2009; Kassam *et al.*, 2009; Knowler and Bradshaw, 2007).

In traditional farming systems, fire is a quick way to remove residues left after harvesting, could improve short-term soil fertility and also serves as a good weed and pest control (McCarty *et al.*, 2009). However, burning of field residues reduces soil organic matter and nutrients contributing to a loss of long-term soil fertility, impedes water infiltration and can impact human and animal health by deteriorating air quality (Lohan *et al.*, 2018).

Retention of crop residues on fields can have a very positive impact on productivity especially in warm climates. Indeed, it helps maintain soil moisture; ensuring that crops can still grow during dry periods, prevents runoff and with his shading effect reduces soil temperature (Kassam *et al.*, 2009; Lohan *et al.*, 2018). Erosion of the soil by wind and water is also lessened (Giller *et al.*, 2009). Conservation agriculture might become increasingly adapted as climate change becomes more prevalent because of the erosion, flooding and drought prevention effect it has on fields. Cover crops or mulching also allow for a better fixation of CO₂ in the soil and less release to the atmosphere which eventually contributes less to global warming (Giller *et al.*, 2009; Marongwe *et al.*, 2011), but the importance of this phenomenon is being debated. Furthermore, residues form a good terrain for nutrient recycling and microbial activity and increase organic matter content which will consequently save some costs on fertilisers (Lohan *et al.*, 2018). Legume residue retention, in particular, will permit a higher fertility (Snapp *et al.*, 2002). Soil covering has also been linked with less crop failure thanks to a better water utilization especially in arid zones. This is important for farmers in developing countries who do not have a lot of insurance or savings to cope in case of a bad harvest (Giller *et al.*, 2009; Wall, 2007). Finally, conservation agriculture might have decreasing effect on diseases and pest infestation, namely because the rotation breaks the pests life cycle (Kassam *et al.*, 2009). Yet, residues on fields can easily become a reservoir for termites and some other pests (Giller *et al.*, 2009).

The possible positive impacts of this type of agriculture are varied but many of them might be societal benefits instead of benefits reaped solely by the farmholder (Knowler and Bradshaw, 2007). There are no universal variables conditioning the success of conservation

agriculture in every location and situation. So, a specific effect of conservation agriculture may be more favourable in certain regions of the world. For example, the insulation linked to crop residue cover lowers temperature closer to the optimum in tropics, but it might provide a too high insulation under temperate climate (Brouder and Gomez-Macpherson, 2014). Conservation agriculture cannot be applied as is, it requires an adaption in the context, even more so if the inputs are hard to access, and environmental conditions are not favourable. If access to inputs is limited and agro-environmental conditions are difficult, the technology options should be adapted accordingly (*ibid.*).

In most CA reviews, the no-tillage practice caused a yield reduction in the first years, which could then vary with time (Brouder and Gomez-Macpherson, 2014). However, many papers reporting CA impacts on yields do not show consistent results or a clear methodology. Many factors (socio-economic as well as environmental) in those reviews are not properly accounted for, so minimum data regarding the study needs to be made more available (*ibid.*). It is also difficult to assess the true outcomes of that type of agriculture insofar as various complementary practices are implemented; fertilisation regime and crop rotation for instance, might make a higher difference than true CA practices (Andersson, personal communication, 2018).

1.2. Agricultural situation in Malawi

Malawi's population suffers regularly from food crises. In particular, 2015 and 2016 have been bad years for agricultural production due to droughts linked to the El Niño phenomenon which have worsened the food security situation (Food Security Information Network, 2017). The availability and affordability of food are especially problematic. 46% (6.7 millions) of the population analysed by the Food and Agriculture Organization in October 2016 were food insecure. Historically, until 2004, interventions such as Targeted Input Programmes and Starter Pack, supplying free inputs to farmers were decided by the government with the intention of improving food security and reducing the need for food aid (Andersson and D'Souza, 2014). Agriculture in Malawi employs over 85 % of the rural population and represents more or less 35% of Gross Domestic Product (Ngwira *et al.*, 2013). The main cash crops are identified as burley tobacco, sugar cane and tea (Sahn and Arulpragasam, 1991). In terms of food crops, a majority of households all over Malawi (over 90%) are cultivating maize and cassava, but in Central Malawi, our region of interest, a lower percentage of households produce cassava (Haggblade and Nielson, 2007). Cotton, rice, groundnuts and soybeans constitute some other important crops. Pigeon pea and cowpea are sometimes cultivated in intercrop systems with maize (Thierfelder *et al.*, 2016).

The agricultural sector is predominantly made out of smallholder farmers (Tchale, 2009) which cultivate from 0.2 to 3 hectares (Ngwira *et al.*, 2013; Snapp *et al.*, 2002). Population is growing at 2.8% per annum and land holding sizes are decreasing more and more. The efficiency is quite low amongst Malawi's farmers, but it is comparable to those of other developing countries (Chirwa *et al.*, 2006). Efficiency could grow massively if some factors such as input prices, land holding sizes and so on were properly targeted (Tchale, 2009). There needs to be improvement in agricultural wages and consumer products prices in order to improve household's food security. A wider access to credit would also enable farmers to buy inputs in period of food shortages (Sahn and Arulpragasam, 1991). The removal

of government support to small farmers has caused rising issues of poverty in rural communities. In addition, worry over land degradation and decline in agricultural productivity has resulted in NGOs' and private companies' initiatives to support conservation agriculture practices in Malawi (Andersson and D'Souza, 2014).

Ridge and furrow is the main agricultural system in Malawian fields as promoted by colonial government from the 1930's to allegedly reduce soil erosion. This cultivation system usually performed similarly or better than minimum tillage systems and has had good weed control, even if herbicides were not available. In terms of residues, the tradition is to burn them and there was still, in 2012, a lot of residue burning especially for groundnut as well as maize in some parts of the country (Snapp *et al.*, 2002). This practice is still common in regions with few livestock (Giller *et al.*, 2009).

Livestock farming is not a prominent activity in many parts of Malawi, especially not on the lakeside. Indeed the country's National Census of Agricultural and Livestock from 2006-2007 puts an average of 0.07 cattle per household and 2.7 heads of pig/goat/sheep per household (National Statistical Office, 2010).

1.3. Conservation agriculture promotion in Africa

Multiple challenges and constraints can slow down the implementation of conservation agriculture in Africa. In zones where livestock herding is an important activity, a conflict might appear between the utilization of crop residues for mulch and for feed (Wall, 2007). This competition might intensify in arid zones, where the productivity is low and less crop residues are produced thus the residues might not be able to offer the field cover recommended in principle (Andersson and D'Souza, 2014). If that is the case the benefits of mulching might not outweigh its costs (Giller *et al.*, 2009). In Malawi, crop residues disappear mostly due to burning to clear the land, termites attack as well as livestock feeding (Bouwman, 2017). This means zones with few livestock are certainly more adapted to the application of conservation agriculture principles, such as is the case in Malawi (Andersson and D'Souza, 2014). It is hard to assess the yield benefits of mulching, these tend to be variable (constant, positive or negative) depending on the region, type of soil, and the climatic conditions. The benefits may not manifest in short term but might in a longer term and conservation agriculture might have to be applied for a long period such as 10-20 years in order to see the full effect of the practices (Giller *et al.*, 2009; Kassam *et al.*, 2009). Indeed, several studies in Malawi have reported a yield reduction with mulching as opposed to burning residues or removing it, especially in the initial years (Bouwman, 2017). And a long history of research has recognized ridge and furrow system yields equal or superior to minimum tillage ones (*ibid.*). However, as shown by another experiment in the central region of the country, significant yield gains were obtained from the application of conservation agriculture practices (no tillage, mulch cover and some fields with intercropping) in a shorter period of approximately 5 years (Thierfelder *et al.*, 2016).

Despite competition in intercropped fields, the yields of the main crop were maintained (*ibid.*). The same study found higher net financial benefits for the farmers applying these practices. Without tillage, weed infestation becomes more significant and the weeding may require more labour in households where it is often a limiting factor (Giller *et al.*, 2009;

Kassam *et al.*, 2009) especially for hand weeding (Wall, 2007). However, in conservation agriculture systems, less labour will be needed to prepare the land (namely tilling) than in conventional systems (Thierfelder *et al.*, 2016). A reduction from 45 to 60% of labour has been linked with the transition to a conservation agriculture (*ibid.*) Another study in Ghana has shown a reduced labour burden in no tillage systems and farmers found that it required less work at critical times of the agricultural season (Wall, 2007). Ridging was found to be more labour-intensive than no-tillage systems in the eyes of Malawian farmers, even when it required more work objectively (Bouwman, 2017). Still, the weed issue makes the use of herbicides necessary at least in short term (Giller *et al.*, 2009; Wall, 2007). It was recognized that the ridge-and-furrow system offered better control of weed if no herbicide is used, because of the manual destroying (Bouwman, 2017). For that reason, the matter of weed infestation is undoubtedly the most critical surrounding conservation agriculture (*ibid.*). This will result in higher input costs linked to CA systems (Thierfelder *et al.*, 2016), however costs linked to machinery and fuel are inferior (Knowler and Bradshaw, 2007). If there is a cover crop or mulching, farmers should fence their fields to impede grazing from animals. This can cause conflict between villagers as common free grazing constitutes a traditional right in some communities (Giller *et al.*, 2009; Wall, 2007).

Conservation agriculture is mostly promoted in the context of development projects which originate among others from the FAO, the French Agricultural Research Centre for International Development (CIRAD) and the International Centre for Improvement of Maize and Wheat (CIMMYT). New Partnership for Africa's Development (NEPAD) and the African Conservation Tillage Network as well as other more local institutions are supporting those projects (Kassam *et al.*, 2009) but this type of agriculture has also been a big focus point for national policies (Andersson and D'Souza, 2014). Amongst all African countries, Malawi seemed to have a good potential for implementation of CA. As said earlier, plot areas are relatively small and as such intensification is a good way to increase productivity, there are very few livestock which could be in concurrence for the use of residues and markets for herbicides are already present (Bouwman, 2017). Conservation agriculture was first promoted in Malawi by the European Union under a minimum tillage programme in 1996. Many demonstration plots have been put into place even without proper testing under the local conditions and proof of its efficiency. Another NGO called Saskawa Global 2000 has promoted conservation agriculture from 1998 in collaboration with the government and input sellers. This was able to increase yields in particular via the supply of a package containing herbicides (Mloza-Banda, 2005).

CA is not necessarily suitable in every situation and might be more easily and quickly adopted by farmers with enough cash and labour (Giller *et al.*, 2009; Kassam *et al.*, 2009). Indeed, it has been mostly implemented across large farms even though a substantial amount of smallholders have adopted no tillage farming for instance in Brazil, India, Zimbabwe, Ghana (Thierfelder *et al.*, 2016; Wall, 2007). This can be explained partially by the fact that conservation agriculture is knowledge intensive and requires an access to information systems, which is easier for richer farmers. Small farmers get the biggest part of their information on new technologies from within their communities through extension workers or neighbours and not from the outside (Wall, 2007). On large farms, CA cuts down costs in fuel and machines, but such is not the case on small farms, which are generally not mechanized (Andersson, personal communication, 2018). In 2011, it was reported that out of 1500 rural wards in Zimbabwe, 1060 had had some farmers applying conservation agriculture

practices (Marongwe *et al.*, 2011). However, those are generally applied on smaller plots so the contribution to household food security remains limited (*ibid.*). It is hard to give exact adoption figures as reports from CA promotion agencies might be biased and it is not clear what the term “adoption” really involves. The FAO Aquastat database from 2011 mentions 16,000 adopters in Malawi but some numbers are higher (Andersson and D’Souza, 2014). Nonetheless, all the principles of CA are very rarely adopted all simultaneously: sufficient ground cover, multiple rotations and zero soil tillage; for example in Malawi 15% of the land that is not tilled can be said to be truly under CA conditions (Bouwman, 2017). Furthermore, adoption in Malawi was found to be mainly linked to participation in projects. In total, a recent study reports an adoption rate of 2.6% of minimum tillage, but the total percentage of land under CA remains unclear, although it might be close to 0% (Brown *et al.*, 2017).

The promotion is done in part with participatory learning initiatives such as experiencing and field schools for farmers (Kassam *et al.*, 2009). In southern Africa, it also includes focus groups for interested farmers. Demonstration plots have been installed in some villages as well as research trials (Wall, 2007). Input packages containing fertilizers and seeds have been offered to farmers (Marongwe *et al.*, 2011). In Malawi specifically, the promotion of conservation agriculture has been and is still undertaken by CIMMYT as well as the extension and research department of the national government with the collaboration of some local NGO such as Total Land Care (Thierfelder *et al.*, 2016). The biggest feature of it in Malawi, was the promotion of minimal tillage and the abandonment of the hoe. It has also been focused on mulching and keeping a sufficient layer of crop residues, use of herbicides, agroforestry as well as legume-maize intercropping (with groundnuts usually) and less about rotating crops (Andersson and D’Souza, 2014). In practice, the farmers had to stop tilling and applying the ridge and furrow system. Furthermore, it was often advised for CA plots to be closer to roads to give them a higher visibility and facilitate the monitoring from promoters (*ibid.*). In terms of residues practices, farmers will either bring some residues from outside the parcels (ex situ mulching) or just keep them directly on the field (in-situ mulching) (Bouwman, 2017). Maize seems to be the most adapted crop in this context on which to apply CA. Indeed, tobacco or cotton respectively require a big amount of residues retention or burning of residues and harvesting of root vegetables usually is disturbing to the soil (*ibid.*). Crops that require removal of residues (such as groundnuts) during harvest can also make it complicated to implement CA practices (*ibid.*).

Lack of adoption of practices is often linked to low resources: labour, feed for livestock, manure, money to purchase inputs... (Giller *et al.*, 2009). Between these, since yields are generally low in Africa, level of available crop residues is certainly the biggest constraint. Farmers in Malawi have to bring residues from outside the fields to achieve a sufficient ground cover to suffocate weeds (Bouwman, 2017). An expansion of CA would then increase the demand on crop residues, which is not likely to be met (*ibid.*). In addition, conservation agriculture is often promoted as a whole package whose practices have to all be implemented but in reality, farmers do not always have the inputs or possibility to apply all of them together (Giller *et al.*, 2009). Sometimes it is an apparent adoption due to the promotion of a package which also include fertilizers and herbicides and if those are discontinued farmers go back to non-CA practices, when the project stops (Giller *et al.*, 2009; Thierfelder *et al.*, 2016). Adoption will certainly be incremental and not immediate, and there are many different manners of adopting, as many as there are different contexts and farmers. The promotion campaigns need to be specific and adapted to the local situation and personal farmer’s situation namely

his resources and current cropping system (Thierfelder *et al.*, 2016). In order to achieve this, large levels of farmer participation and involvement through dialogue are necessary (Marongwe *et al.*, 2011; Wall, 2007). Moreover, it is a very complex set of practices which requires a lot of knowledge to be put into place as well as institutional and policy support to be implemented (Kassam *et al.*, 2009). The need for experienced extension workers which can assist the farmers on the field is evident (Thierfelder *et al.*, 2016), but it might not be enough to ensure adoption for such an intricate technology (Wall 2007). Innovation networks is a means to diffuse a change of agricultural practices which has been proven successful in Latin America and South Asia. Innovation network or system consists in a diffusion of information about a technology and its benefits in multiple directions to stakeholders such as: farmers, extension agents, input suppliers, scientists... (Thierfelder *et al.*, 2016; Wall, 2007). Indeed, all successful promotion campaigns involved networks with participatory research approaches (Wall, 2007). At a personal level, the farmer's awareness of soil problems and the presence of some information and communication channels were factors that favoured adoption of conservation agriculture according to a study over 130 farms, other factors showed not to be determinant (Knowler and Bradshaw, 2007). Finally, a wide array of conservation agriculture options and solutions should be offered to farmers so that they can choose themselves the technologies that most interest them (Wall, 2007).

1.4. Crop residues monitoring

Some of the methods for mapping residues cover and their amount or composition on cultivated soils will be reviewed here. There are multiple methods on the field such as photographic techniques, visual estimation or line transect but they are long and tedious to realize (Bannari *et al.*, 2006). Thus, remote sensing constitutes a more effective way of estimating crop residue cover.

For crop residue cover to be mapped accurately via remote sensing, a high temporal and spatial resolution of images is very important (Zheng *et al.*, 2014). It can be done by using multispectral data obtained by sensors. This takes advantage of crop residues particular absorption and reflection features namely those in the short wave infrared and near infrared (Jacques *et al.*, 2014), which allows to calculate a percentage of soil cover.

1.4.1. Indices

Some techniques include the calculation of different types of residues and dry vegetation indices, based on the available imagery. The Normalized Difference Index uses a ratio of the differences of reflectance between Landsat TM band 4 (0.76-0.90 μm) and band 5 (1.55-1.75 μm), which presents a good correlation with fields crop residue cover (Arsenault and Bonn, 2005; McNairn and Protz, 1993). Derived from the same principle as the precedent, the Soil Adjusted Corn Residue Index was developed but it takes into account the soil line equation which considers the reflectance of bare soil in those two spectral bands (Arsenault and Bonn, 2005). The Crop Residue Index Multiband works with any combination of several wavebands and estimates the residue cover percentage through the calculation of a residue line (Biard and Baret, 1997). According to several studies, this index showed a higher accuracy in estimating the residue cover than the above mentioned (Arsenault and Bonn, 2005; Bannari

et al., 2006). The Normalized Difference Tillage Index (Jacques *et al.*, 2014; Zheng *et al.*, 2014) has also been used quite frequently. It represents the ratio in the difference between two Landsat TM wavebands, namely the 5th and 7th (2.08-2.35 μm). Its efficiency of estimation is quite good, superior to that of the Normalized Difference Index, which might be because band 7 corresponds to the absorption of cellulose (Thoma *et al.*, 2004). The Cellulose Absorption Index exploits the characteristic high reflectance at 2.1 μm of a compound very present in residues, cellulose. It calculates the mean intensity of reflectance at that wavelength and increases linearly with the residue cover fraction (Nagler *et al.*, 2003; Thoma *et al.*, 2004). Since bare soil has a low reflection for that specific wavelength, this index was found to be very efficient to discriminate bare soil from residues (Thoma *et al.*, 2004). Most of these indices were created using spectral bands from Landsat satellites but can also be adapted to other sensors.

1.4.2. Statistical models

Without using an index, it is possible to create regression models on the base of pixel values at different wavebands and field measured residue covers (Thoma *et al.*, 2004). This method has found that a combination of Landsat TM band 3 (0.63-0.69 μm), 5 and 7 gave the best results, but the technique can be quite time consuming and will be accurate only for that particular scene (*ibid.*).

Linear spectral mixture analysis can also be used for crop residues mapping purposes. This method considers that a pixel's spectrum constitutes a mixture of the spectrum of different elements that composes it. So, its reflectance is a combination of the reflectance of each element multiplied by its abundance on the surface. Some categories such as residues and soil are chosen and for each of these, examples of endmembers are identified. Their spectrum is then extracted and can be used to identify the frequency of each endmember on one pixel. This allows to find out the percent of crop residue cover and distribution of residues in the study area (Bannari *et al.*, 2006).

1.4.3. Alternative data sources

Hyperspectral remote sensing data is also useful in assessing crop residues cover on fields. It can allow the calculation of some dry vegetation indices such as the Cellulose Absorption Index (Daughtry *et al.*, 2006). With these hyperspectral images, the linear spectral mixture analysis can also be used (Bannari *et al.*, 2006). The efficiency of these methods was good, they outperformed multispectral data methods, because they have several narrow bands in the shortwave infrared which are very representative of residues (Bannari *et al.*, 2006).

Passive reflectance approaches make it difficult to differentiate residues from bare soil and even more in case of weathering (Thoma *et al.*, 2004), indeed the reflectance spectrum is similar for both and just varies in amplitude at some wavelengths (Daughtry *et al.*, 2006). The composition and state of residues, namely their age and water content can also impair their detection (Jacques *et al.*, 2014). It has however been proven that dark soils, due to the bigger contrast they form with the residues, are more accurately classified (Thoma *et al.*, 2004).

It is also possible to use fluorescence properties of crop residue in comparison with that of soils in order to detect their distribution. Crop residue and soil have fluorescence emission maxima at different wavelengths. Fluorescence was reported by some studies to provide

better identification of crop residue than reflectance techniques (Daughtry *et al.*, 1996; McMurtrey *et al.*, 1993).

1.5. Burned area monitoring

Biomass burning happens often and in large areas of southern Africa in the dry season from May to November (Roy *et al.*, 2001).

Field surveys, aerial photography and remote sensing through multispectral satellite data are means to obtain information over burned areas (Koutsias *et al.*, 2013). However, only remote sensing imagery in multiple spatial, spectral and temporal resolutions allows to delineate and monitor large burned areas quickly and efficiently (Kontoes *et al.*, 2009; Roy *et al.*, 2001).

Burned area's particular spectral properties are an effect of the vegetation's elimination and the deposition of charcoal and ash (Pereira *et al.*, 1997; Roy *et al.*, 2001). Those two consequences together are unique to burning, as vegetation removal can be linked to other causes (Pereira *et al.*, 1997). Reflectance in wavebands situated in the infrared allowed for a better differentiation of burned areas from other land use types. Healthy vegetation shows a high reflectance in the near infrared which decreases for burnt vegetation (Kontoes *et al.*, 2009; Koutsias *et al.*, 2000). The reflectance after a fire in the shortwave infrared and mid infrared is also higher (García and Caselles, 1991; Kontoes *et al.*, 2009). Indeed, reflectance in MODIS band 5 (1.230-1.250 μm) was reported as lower after a burn especially in an African context (Giglio *et al.*, 2009).

Burned zones are easy to see visually, but harder to identify automatically since they have such spectral variability across space and time linked to the burn age, the vegetation burned and the conditions of the region (Koutsias *et al.*, 2000). Water bodies, urban areas and cloud shadows have been often confused in classification with burned areas (Koutsias *et al.*, 2000; Pereira *et al.*, 1997). In some regions, ploughed field can cause errors in mapping of burned area since their colour is darker and their reflectance signal can be confused with that of burning (Roy *et al.*, 2005).

Among the remote sensing methods, a main distinction can be made between active fire methods and methods exploiting change in spectral properties following a fire (Smith, Adams, *et al.*, 2007).

We can use active fire products which detect the thermal energy of the fire via the use of a mid-infrared spectral band and thermal infrared band, which are namely found on the NOAA satellite's sensor. There are then several possible algorithms, which use threshold values over the spectral bands to detect fires (Fraser *et al.*, 2000). The thresholds can be fixed, being specific, adapted to the study region (Li *et al.*, 2000) or dynamic ones extracted automatically from some background pixels information (Justice *et al.*, 1996; Smith, Adams, *et al.*, 2007). Fixed threshold methods are more time consuming and less adaptable to other region and conditions. An example of a dynamic threshold algorithm is that from Justice *et al.* (1996). Reflectance from both bands are changed into temperature brightness, the temperature brightness threshold to detect fire pixels will depend on the thermal characteristics of some background pixels of that image (Justice *et al.*, 1996). This makes the

method adaptable to many different regions. Another study has used a dynamic threshold algorithm as well as day- and night-time images to calculate burned fields area (Smith, Adams, *et al.*, 2007). This estimation was done by using the proportion of fire hotspots and parameters such as the average area of burned fields derived from a survey conducted amongst farmers. But that study showed very little stubble burning detection from satellite imagery, even though field size was not correlated with the accuracy of detection (*ibid.*).

Active fire products techniques only show fires burning at the time of the satellite overpass, thus it is likely that some fires will not be identified. Detection can be further impeded by clouds covering the region (Giglio *et al.* 2009; Roy *et al.* 2001). Some small fires might not emit enough energy to be detected by the sensor (Li *et al.* , 2000; R. Smith *et al.*, 2007). These active fires methods then tend to underestimate total burned area but can also overestimate it if the thresholds used are not adapted to the region (Fraser *et al.*, 2000; Li *et al.*, 2000). So, the estimation of burned areas via active fires might not supply very accurate results.

The other group of methods uses the change in images spectral properties following a fire (Fraser *et al.*, 2000), this change is more persistent over a period of time (Roy *et al.* 2001) whose duration depends on vegetation's recovery speed and climatic conditions (Pereira *et al.*, 1997). These methods allow to detect many fires, namely smaller ones, that would be missed by hotspots detection (Fraser *et al.*, 2000; Giglio *et al.*, 2009).

This type of methods can be gathered in several groups from the processes they use to identify burned areas: spectral properties and indices extracted from a single post-fire image, study of change in indices or spectral values between multitemporal images or image classification techniques which can be done either with uni- or multi-temporal images (Kontoes *et al.*, 2009; Koutsias *et al.*, 2013).

Based on these processes, various techniques have been applied to differentiate and map burned regions. They can be simple such as basic visual interpretation as well as more complex ones such as principal component analysis (Pereira, 1992; Siljestrom and Moreno, 1995), multi-temporal thresholding of vegetation indices (Kontoes *et al.*, 2009), supervised and unsupervised classification (Chang *et al.*, 2013; Gitas *et al.*, 2004; Kontoes *et al.*, 2009; Mitri and Gitas, 2002), machine learning (Brewer *et al.*, 2005), spectral mixture analysis (Sá *et al.*, 2003) or regression analysis (Bastarrika *et al.*, 2011; Koutsias *et al.*, 2000).

1.5.1. Single date approaches to burned area mapping

Some indices can be used which facilitate the detection of vegetation or lack thereof. The Normalized Difference Vegetation Index (NDVI) has been used countless times in order to detect green vegetation. It is given by the following equation:

$$NDVI = \frac{\rho_{\text{red}} - \rho_{\text{near infrared}}}{\rho_{\text{red}} + \rho_{\text{near infrared}}}$$

With ρ the reflectance, the red corresponding to the spectral region of 0.58–0.68 μm , and near infrared the region between 0.73–1.1 μm . We subtract the NDVI between a post and pre-fire image composite. After examining change in the index over the study region, we extract a threshold which permits the classification of burned pixels (Fraser *et al.*, 2000). Using the

difference in NDVI in composite imagery works for the detection of very large fires, indeed 88% of forest fires superior to 40,000ha in area were detected when only 72% of fires under 1000ha were identified (Kasischke and French, 1995). However, NDVI decrease can also be due to droughts or cloud contamination; another issue is that the use of a fixed threshold might cause errors, since the suitable threshold can be variable across space and time. Therefore, using a dynamic NDVI threshold depending on the magnitude of NDVI change observed in the wider region can be a solution (Fernández *et al.*, 1997). Other indices derived from a single post-fire image include the Normalized Burn Ratio (NBR) which is very widely used. It is presented as a declination of the NDVI, and they are calculated in a similar way except the reflectance in the red is replaced by that in the mid infrared, which is more impacted by a fire. The NBR equation is the following:

$$NBR = \frac{\rho_{\text{near infrared}} - \rho_{\text{mid infrared}}}{\rho_{\text{near infrared}} + \rho_{\text{mid infrared}}}$$

With ρ the reflectance, the near infrared corresponding to the region between 0.73-1.1 μm and the mid infrared to that between 3-5 μm (Key and Benson, 2006; Kontoes *et al.*, 2009). This index has shown able to effectively map burned areas in many different landscapes across the world (Kontoes *et al.*, 2009). Furthermore, an index combination approach has performed better than a decision tree classification in this case, notably by presenting a lower omission error (Figure 1).

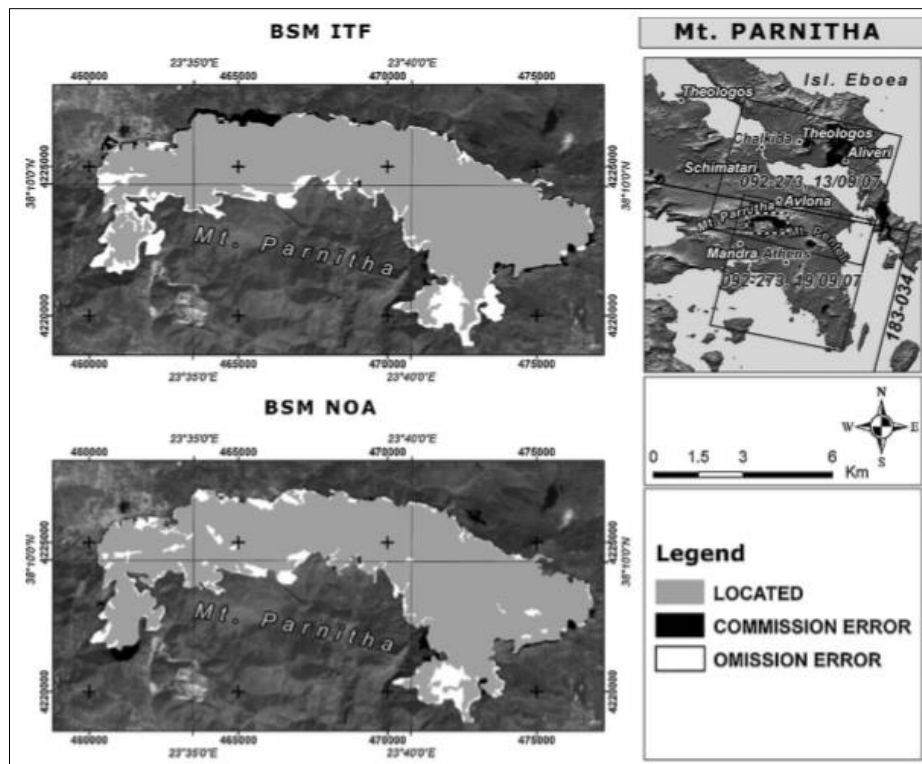


Figure 1: Results of burn mapping in Greece with a decision tree classification (top) and a fixed thresholding of several indices (bottom), (Kontoes, 2009).

Moreover, a differenced burn ratio requiring pre-fire information can be used. The albedo index representing a surface's brightness can also present an advantage in detecting burned pixels (*ibid.*). This index averages reflectance values in the red and near infrared wavebands. Minimum albedo information in combination with a fixed threshold algorithm allowed to identify burn scars in a savannah context (Barbosa *et al.*, 1997).

A fixed empirical threshold of the Mid-Infrared Bispectral Index (MIRBI) applied on post-fire images can also serve the same purpose:

$$MIRBI = 10 * \rho_{\text{shortwave infrared}} - 9.8 * \rho_{\text{longer near infrared}} + 2$$

With ρ the reflectance, the longer near infrared corresponding to the region between 1.5-1.75 μm and the shortwave infrared to that between 2.08-2.35 μm . It has been used successfully for burns in Botswana's savannah (Smith, Drake, *et al.*, 2007). Char Soil Index (CSI) detects a spectral signature typical of char from burned vegetation. This index is defined as the ratio of reflectance in the near infrared with the one in the longer shortwave infrared. Amongst several indices, it showed the lowest commission errors and most consistent accuracies: between 96 and 98% to map fires in steppes environments (Sparks *et al.*, 2015) (Figure 2). Furthermore, CSI was reported to be a very good predictor of burned surfaces in savannah (Smith, Drake, *et al.*, 2007; Sparks *et al.*, 2015). In an heathland environment, a comparison of indices showed higher accuracies for the classic NBR as compared to other burn indices such as CSI and MIRBI (Schepers *et al.*, 2014).

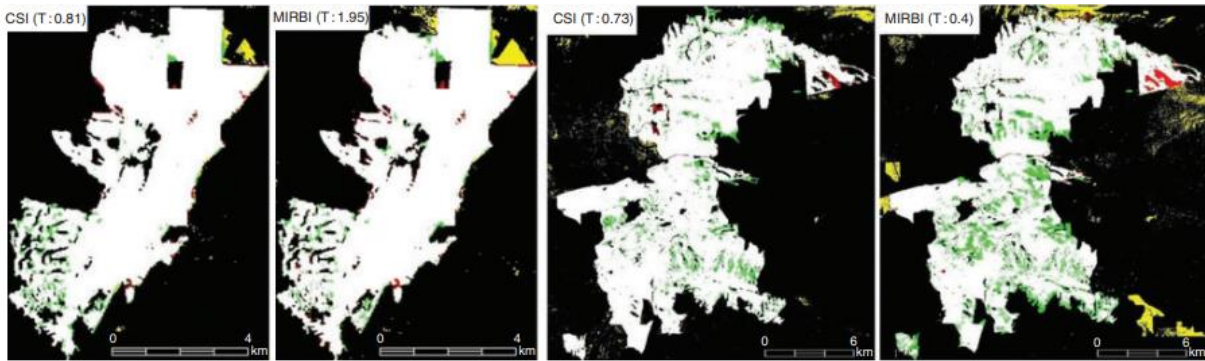


Figure 2: Detection of burned areas in two shrub-steppes of western USA with the CSI and MIRBI. Correctly classified burn areas are shown in white, commission errors in red and omission errors in green (Sparks *et al.*, 2015).

A thresholding approach of the NDVI, NBR and albedo index can be used conjointly in order to more efficiently map burned regions (Kontoes *et al.*, 2009). This method was reported to be slightly more accurate than a supervised classification method in identifying burned areas in the same landscape (*ibid.*).

Furthermore, Sentinel 2's MultiSpectral sensor is very sensitive in the red-edge domain compared to other current satellite's instruments (Fernández-Manso *et al.*, 2016). It has been proven that indices computing reflectance in Sentinel 2's band 5 (705 nm) with band 7 (783 nm) or 8 (842 nm) are the most suitable to map burned zones and assess their severity (*ibid.*). In particular, the Chlorophyll Index Red-Edge (CI_{re}) created originally to track chlorophyll content, showed the highest accuracy (*ibid.*). This index is calculated with:

$$\text{Chlorophyll Index red - edge} = \frac{\rho_{B7}}{\rho_{B5}} - 1$$

With ρ the reflectance, B7 the Sentinel-2 band corresponding to 783 nm and B5 the band corresponding to 705 nm.

Some of the indices usually used for dry vegetation can also detect burned soil. For example, the Soil Tillage Index is the ratio between the reflectance in MODIS bands 6 (1.628-

1.652 μm) and 7 (2.105-2.155 μm) and recently burned zones present a high index value (Jacques *et al.*, 2014). After the fire, the pixel's index value decreases to fall to bare ground value. Indeed, the reflectance of the burned area forms a combination of bare soil and char reflectance's which both have flat signatures in MODIS band 6 and band 7 (*ibid.*). This index shows good accuracy in herbaceous landscapes; however, it was not tested for agricultural residue mass. These indices can also be used with multitemporal data, which should increase their accuracy.

Burned vegetation being spectrally and visually very different from green vegetation, the Intensity Hue Saturation (IHS) model exploits that particularity (Koutsias *et al.*, 2000). For this transformation, an algorithm changes the values of an RGB colour model into an IHS one. Each component from this model has different coordinates: intensity and saturation vary between 0 and 1 and the hue element ranges from 0 to 360 degrees. A remote sensing multispectral image taken after a fire is used. The reflectance values at three different channels of an RGB model are replaced by their IHS value equivalents. This method does not require the use of training areas or any radiometric correction, which makes it easy to implement. The spectral values from Landsat bands 4 (0.76-0.90 μm), 7 (2.08-2.35 μm) and 1 (0.45-0.52 μm) were the most useful in mapping burned areas (*ibid.*). The study has found that the hue component showed lower value for burned zones than for unburned ones, so hue is a suitable component in identifying burned pixels. Bare soils had hue values quite close to burned vegetation, but a study of saturation values then permits to differentiate the two (*ibid.*). A drawback of this method is the need to determine an empirical threshold value (*ibid.*).

Machine learning approaches such as artificial neural networks can be implemented on single post-fire images (Brewer *et al.*, 2005). The algorithm is trained on burned pixels using a back-propagation method and the weights will adjust to each node in the network to produce an output, which is a map of burned areas (*ibid.*). The mapping accuracy with machine learning will improve upon using multi-temporal images (*ibid.*).

1.5.2. Classification methods for burned area mapping

Methods of classification have been used extensively in remote sensing, namely in the context of burned areas. Classification is the sorting and organizing of objects into groups based on the relationships between them (Sokal, 1974). We can separate hierarchical and non-hierarchical systems. The hierarchical one is a structure containing a basis level and a superior level (*ibid.*). Many different spectral image classification techniques exist such as pixel wise, sub-pixel wise or object-based and their accuracy varies (Li *et al.*, 2017). Pixel classification supposes that a pixel is pure and corresponds to one land cover type, sub-pixel classification considers that each pixel is mixed, and the percentage of each land cover or land use is estimated (*ibid.*). Finally, geographical objects generated from an image segmentation are the base units for object-based classification (*ibid.*). Object-based classification generally shows higher accuracy than the other classification types (*ibid.*).

Pixel-wise classification can provide correct burned areas maps. Here are two examples of supervised pixel-wise classification. The first one uses the maximum likelihood function (Chang *et al.*, 2013). Using training areas of representative burned and other types of fields identified on the ground, the spectral response of the training pixels were extracted and averaged within a class. Then using a maximum likelihood function, the pixel is assigned to the most likely class. After verification with ground data, the study reported an accuracy of 98%

in detecting burned fields (*ibid.*). However, this method requires some time-consuming groundwork in order to identify burned fields. A classification by decision tree approach is also feasible (Kontoes et al., 2009). Some model processes the images and creates layers describing each pixel in terms of vegetation type, soil type, water and cloud information. A decision tree forms a set of hierarchical decision rules (node) applied successively to the input information layers. At each step, thresholds separate the data into two groups. This classification allows to identify burnt pixels at the last step. Those classified burnt pixels are labelled as fire seeds, probable burnt pixels are added to those fire seeds. A region-growing algorithm is then used to grow fire areas at their maximum extent that does not include green vegetation (*ibid.*). Another classification method, which is less common in burned area mapping, is Random Forest (RF). RF constitutes a collection of decision trees aggregated to one result. Holden *et al.* (2009) used pre- and post-fire Landsat images of a forest and calculated a Relative differenced NBR (RdNBR) for each pixel. The severity of the fires was then measured on the field, which showed a high correlation with the RdNBR from satellite imagery (Holden *et al.*, 2009). A dozen of independent variables linked to topography and vegetation were drawn from a digital elevation model of the same forest. RF algorithms were used to evaluate the link between those variables and burn severity (*ibid.*). The RdNBR data: separated into burned and unburned as well as different burn severity classes were put into the algorithm which was then applied to the different variables. Random Forest showed moderate accuracy (76 and 64%) in detecting burned areas of several severity classes based on the vegetation type variables (*ibid.*). A predictive model was then conceived to map the probability of certain burn severities (Figure 3).

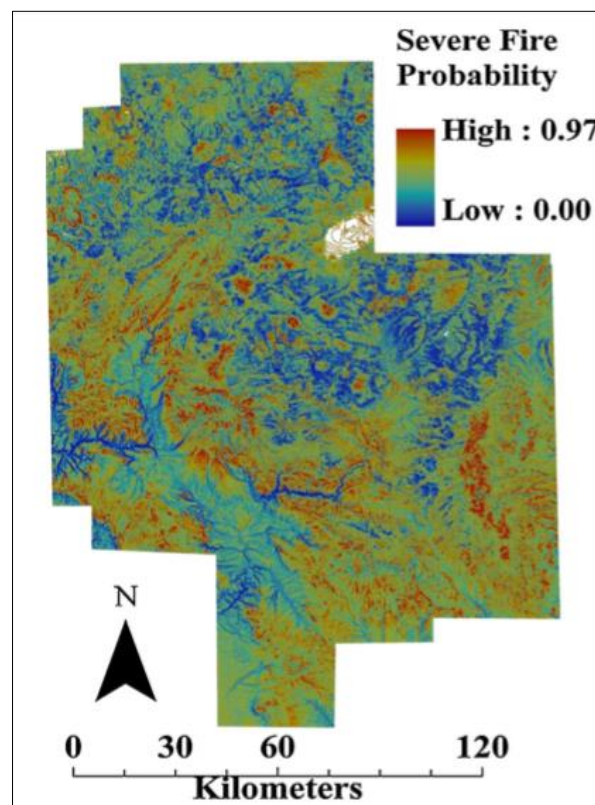


Figure 3: Map of burn severity probability in USA forest using a random forest algorithm with data from 1984 to 2004 (Holden *et al.*, 2009).

Object-based classification can also be applied for that same purpose (Gitas *et al.*, 2004; Mitri and Gitas, 2002). The first step is an image segmentation which subdivides image into distinct regions. First, there are one-pixel objects that grow by adding other pixels with similar visual characteristics such as smoothness, scale, colour. Band 4 (10.3-11.3 μm) of NOAA's sensor was seen as the most useful (Gitas *et al.*, 2004). Then these objects from the segmentation step were put into 3 categories: unburned, small area fires and large area fires. The categories descriptions are defined by fuzzy expressions (rules for being assigned in a category), defined by membership functions which give the values of a feature that are typical or non-typical of a class. At a second classification level, the two burned classes were then joined into one. This classification overestimated (by 900ha) the burned area and the delineations of the areas were less precise as compared with official fire perimeters (*ibid.*). The finer the spatial resolution (Landsat TM compared to NOAA AVHRR) of the satellite image, the better the classification was found to be (Gitas *et al.*, 2004; Mitri and Gitas, 2002).

1.5.3. Multitemporal approaches to burned area mapping

Most of the methods used multitemporal data which is more accurate since they allow less confusion with other land cover types (Kontoes *et al.*, 2009; Koutsias *et al.*, 2000, 2013). An issue that has been noted with this approach is the ability to match the pre-and post-fire images on a radiometric and geometric level, which is an important source of error in detecting burned areas (Koutsias *et al.*, 2000).

Ashes on burned surfaces give a low reflectance in the shortwave infrared domain. Moreover, the surface brightness temperature obtained via thermal infrared band values increases just after a fire (Eva and Lambin, 1998). Surface brightness temperature is typically higher for forest and vegetated areas than for other types of land cover. This mapping algorithm uses rules based on analysis of the temporal behaviours of those two properties calculated for each of the image pixels (*ibid.*). Thus, a pixel showing an increase in brightness temperature matching a decline in shortwave infrared band reflectance was labelled as burned. This technique, however, requires empirical thresholds to be set which can be time demanding (*ibid.*).

Sentinel-2 imagery with its relatively high resolution (10/20m) and 10 days revisit time, can be a good material in detecting burned areas, although it has not yet been used extensively (Verhegghen *et al.*, 2016). Another vegetation index, called Normalized Difference Water Index (NDWI) is given by:

$$NDWI = \frac{\rho_{\text{near infrared}} - \rho_{\text{shortwave infrared}}}{\rho_{\text{near infrared}} + \rho_{\text{shortwave infrared}}}$$

With ρ the reflectance, the near infrared corresponding to the spectral region between 0.73-1.1 μm and shortwave infrared to the region between 0.7-2.5 μm . A difference in this NDWI as well as in NDVI was calculated from a pre-fire image as well as time series over the fire period. Setting an empirical threshold for those indices then allowed to map burned areas in Congo (*ibid.*). Sentinel-1 radar data was also used, the combination allowing to compensate the limits of both sensors to burning detection (*ibid.*). However, variation in soil moisture content has caused certain confusion with fire scars (*ibid.*).

In the Mediterranean and North American area, a two phases algorithm has been applied (Bastarrika *et al.*, 2011). The first phase detects with stricter rules seed burned pixels

and the second looks at proximity from those seed pixels and add the ones spectrally similar to a burn. This aims in reducing errors of commission and omission, respectively prevent false detection of burned pixels and detect all the burned pixels. To achieve this, the combination of burned area indices rules that present the lower commission errors is chosen. Then a region-growing algorithm is implemented to add pixels to the burned region. Logistic regression approach is chosen to run the growing process of the burned areas (*ibid.*). This method proved more accurate in mapping large rather than small fires, yet still attained a kappa score of 0.85 for one of the regions (Figure 4). Furthermore, results showed that reflectance in the visible near infrared, and two wavebands in the shortwave infrared were ideal to map burned areas (*ibid.*). This spectral resolution is characteristic of the MODIS and the Landsat TM/ETM+ sensors. A similar method was used in Koutsias *et al.* (2013). Spectral signatures of burned regions are examined in comparison with these pre-fire regions and their land type signatures (Koutsias *et al.*, 2013). The series of different rules is created flexible enough in order to minimize omission errors but strict enough to differentiate burned from other land covers so as to remove commission errors. Some of these rules were for example a higher reflectance in Landsat band 5 compared to Landsat band 4 on the post fire image, which differentiates it from a vegetated area. Or a higher reflectance in Landsat band 3 compared to the 1st, which is characteristic of all land cover except water bodies, thus limiting the confusion observed between that class and burned areas (*ibid.*). Rules linked to the variation of reflectance in the before and after fire images were also implemented (*ibid.*)(Koutsias *et al.*, 2013)(Koutsias *et al.*, 2013)(Koutsias *et al.*, 2013). This method provided high accuracy in identifying most of the fires. The fires not detected were very small ones, which is usually due to the limited spatial resolution of the sensor, here of 30m. Such automatic methods reduce processing time needed, do not require training data and provide better objectivity (*ibid.*).

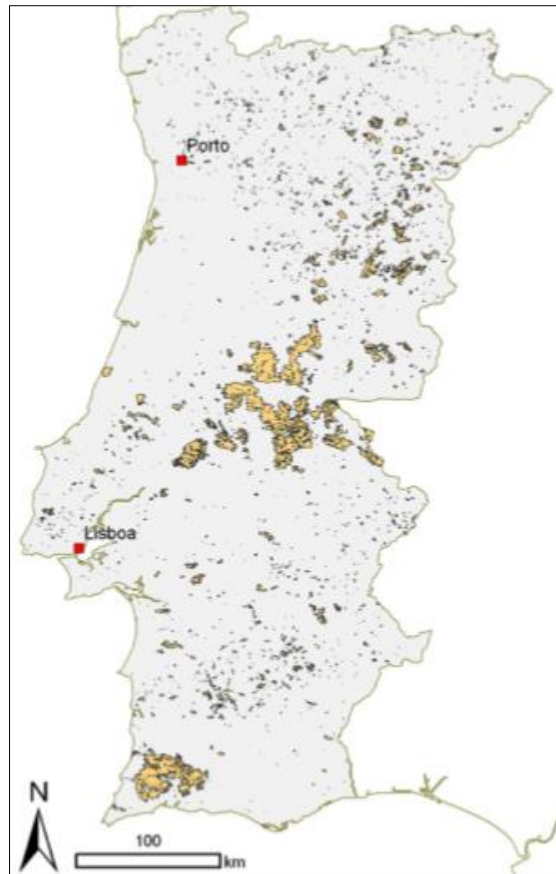


Figure 4: Map of burned areas in Portugal using a fixed and borders algorithm for the 2003 fire season (Bastarrika *et al.*, 2011).

An algorithm identifying changes in surface reflectance was also used (Roy *et al.*, 2001). Bidirectional Reflectance Distribution Function (BRDF) represents the probability for an incident photon to be reflected at a certain angle, that is to say; it gives reflectance as a function of the sun target sensor geometry. These directional effects of land surfaces cause changes in the values of vegetation and other indices. The BRDF change algorithm is used with multitemporal satellite data to detect change in reflectance of MODIS band 5 (1.230–1.250 μm), which allows for the best distinction between burned and unburned. Variations in observed reflectance is due to directional effects. The BRDF model used can replicate those variations by taking satellite reflectance data. This model's parameters can then be taken up to predict other satellite observations in other locations. Differences between expected and observed values will show changes in surface reflectance, if those changes are constant over a large period of time that will identify persistent changes in spectral properties due to burning. This model seemed to be effective in mapping large burned areas over an extensive region of southern Africa (*ibid.*). But the change algorithm has also detected modifications of reflectance due to persistent cloud shadows. From the verification using an active fire product, the algorithm was useful in detecting the location but also the date of burning (*ibid.*).

A machine learning approach is relevant to mapping not only with unique fire images, but also with multi-temporal imagery (Brewer *et al.*, 2005). A particularity of machine learning is the consideration not only of the pixel's spectral information, but also its neighboring context (*ibid.*). A backpropagation method was used to calculate the gradient required for the functioning of the artificial neural network. This allows training a neural network to learn to map the given inputs into a correct known output. The backpropagation is thus a supervised

learning method. It has shown an overall accuracy of 100 % for burned and unburned areas detection, higher than that of a differenced NBR or a principal component analysis (*ibid.*). Yet, the map produced was more homogenous and chunkier than for the other two methods (*ibid.*). Adding the vegetation type (grass, shrub and tree) as an input decreased the overall accuracy of the artificial neural network and increased that of the other two methods (*ibid.*).

Some methods combine the use of active fire products with a study of change occurring after a fire. For instance, Giglio *et al.* (2009) have created an automatic hybrid algorithm using maps of active fires to generate probability density functions. This algorithm identifies training samples of burned and unburned pixels, applies a region growing approach and differences burned and unburned pixels with spectral and textural values (Giglio *et al.*, 2009). A vegetation index was calculated from satellite multispectral data and decreased post-fire. The unburned training pixels are chosen amongst the ones presenting low differences in vegetation index value. The active fire mask helps identifying burned training pixels; those are confirmed by looking at the day of maximal change in vegetation index value. Pixels situated next to core burned ones, which were not chosen as unburned training pixels can be added to the burned region if their vegetation index is close to that of burned pixels. With the help of the burned and unburned training pixels, the probability density functions with regards to a certain vegetation index variation are calculated. These density functions permit to classify the next pixel tested as burned or not. This method has found that, in most of Africa, the reflectance in MODIS band 5 (1.230–1.250 μm) decreased after a fire and that the minimum burned area detectable as such by the sensor is half a pixel (*ibid.*). It performed better in identifying burns in lower tree cover zones as opposed to higher tree ones (*ibid.*).

Hotspots and NDVI difference approaches are combined in the HANDS (Hotspot And NDVI Differencing Synergy) method which uses a vegetation mask, a detected hotspots mask as well as NDVI pre- and post-fire composites (Fraser *et al.*, 2000). NDVI difference images are used to confirm hotspot fires. These confirmed hotspots serve to determine thresholds in NDVI difference values that characterize burned pixels at regional and more local scale. The confirmed fire hotspot's mean and standard deviation of NDVI difference are calculated in each region. These statistics are used to constitute a regional threshold, which finds the pixels with a NDVI drop higher than that of hotspots. Those potential burned pixels are confirmed as burned if they exceed a second NDVI difference threshold calculated at a local scale. This algorithm adapts to the fire damage observed in a specific area and extracts the thresholds automatically from the input data so that the scientist does not have to empirically select them (*ibid.*). Accuracy of burned area estimation was superior than the one obtained from a simple NDVI difference and very close to official forest fire statistics (Figure 5). The HANDS method also performed better than hotspots detection, which tended to underestimate burned area (*ibid.*). McCarty *et al.* (2009) also employed a hybrid method in order to represent the distribution of crop residue burning. A region-specific NBR threshold was applied to differentiate burned from unburned pixels (McCarty *et al.*, 2009). Active fire products served in detecting burned fields that had not been identified with the NBR approach (that is fire area under 80% of a pixel's resolution or 20ha). Accuracy of the burned residues area estimation was approximately of 84 % with this approach though it depended on the type of crops burned and irrigation of the fields (*ibid.*).

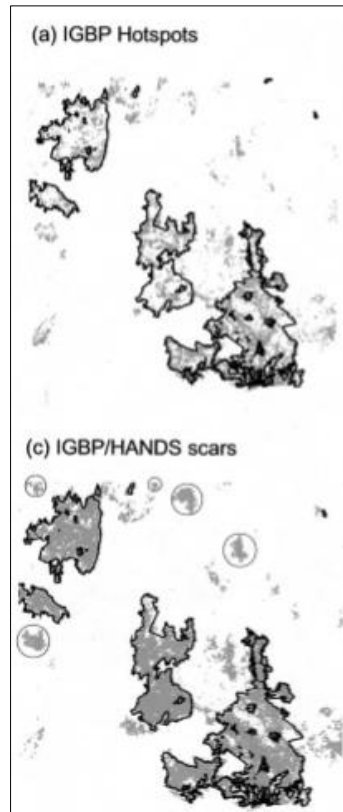


Figure 5 : Burned area mapping in Canada for 1995 and 1996 using a) hotspots extracted from the International Geosphere Biosphere Programme (IGBP); b) the HANDS algorithm. Surveyed fire areas are framed in black (Fraser *et al.*, 2000).

Most methods have used moderate resolution satellite sensors such as MODIS or AVHRR, which with their high revisit times can accurately detect large area fires. However we can assume that higher spatial resolution such as that of Sentinel 2's sensor could be more useful in detecting burning of residues on small fields (Verhegghen *et al.*, 2016).

In conclusion, we can now assess the feasibility and efficiency of those burned area-mapping methods to our situation. Multi-temporal Sentinel-2 imagery is available for the whole of the season. We can thus consider uni-temporal as well as multi-temporal methods. Combination of active fires products with variation in spectral properties of images seems like a promising method; however, we do not have access to any high-resolution fire product for the region and season of interest. Classification methods mostly require ground data, but they are easy to implement. However, object-based classification does not seem to yield convincing results for burned area detection. The index differentiation approach seems efficient to map burned scars but might be more adapted to large forest surfaces rather than small fields. Those various indices will allow tracking the general patterns of burning at landscape level, as well as different severity in burning. A two-phase algorithm as seen in Koutsias *et al.* (2013) and Bastarrika *et al.* (2011) showed high accuracy and could be interesting even though they require more complex manual operations.

Chapter 2

Objectives

In southern Africa, conservation agriculture has been particularly experimented and theorized as a means to limit labour demand, preserve resources, improve soil fertility. It has been advocated to smallholder farmers through various incentives. As it is incredibly difficult to study this phenomenon in such a large area, we chose to limit ourselves to a specific country and region. This was the Central Region of Malawi, where long-lasting CA demonstration sites and promotion activities by CIMMYT and local NGO's were in place. We also had access to recent UAV imagery over these areas as well as a detailed agricultural survey on local farmers. These provided additional welcomed sources of information. The main issue that prompted this thesis was that of conservation agriculture initiative's efficiency in the region.

Amongst the three pillars constituting CA, we chose the specific practice of crop residues retention as the focus. The core hypothesis throughout this work is that this retention promotion will have an impact on the tradition of crop residues burning. We selected this practice particularly because we assumed that residues burning or retention would be very visible through remote sensing. On the contrary, ploughing and crop rotation seemed too subtle to be distinguished with satellite imagery. Satellite imagery then constitutes a tool to explore the practice at a large landscape level. Another key point to keep in mind is that crop residues burning is extremely variable in time and space. Indeed, harvest time varies depending on the labour available, the type of crop and the number of plots owned by the household. In a similar way, farmers can burn any time after harvest, it does not occur simultaneously in all villages and plots. Some farmers do not burn at all. Consequently, it is not a linear and easy practice to investigate. This was made clear from reading the literature, in particular the master thesis examining CA practices in the region as well as discussing with Jens Andersson.

Thus, our main objective will be a quantitative assessment and spatial distribution analysis of the occurrence of burned residues in cropland using satellite imagery.

Specific objectives will be pursued in the process. They are (1) assessing cropland mapping accuracy using Sen-2 Agri with and without use of UAV in a context of smallholder farming systems; (2) evaluating the interest of UAV imagery to monitor adoption as part of a development project; (3) impact assessment of the CA promotion in the study region. The efficiency of Sentinel-2 imagery in detecting cropland and specific field management techniques will be tested. First, we can question if its spatial resolution is sufficient to differentiate fields from other small sized features. The studies of crop cover on individual fields that we mentioned in literature were carried out mostly with Landsat-5 or Terra satellites, which both have coarser spatial resolutions than Sentinel-2. Thus, it is likely that only very small plots and thin roads or rivers will not be identified. However, it is possible that if burning or retention is only applied to small parts of the field, we might not detect it clearly. The spectral resolution is another issue to consider. Are the spectral bands suitable to recognize burned ground? We should think so, since satellites with similar band numbers and wavelengths were able to accurately map burned zones. Yet, literature mainly focused on forest and savannah fires, perhaps field fires have a different spectral signature due to the

lesser amount of material burned. We might have to adapt some of the information found in literature to our agricultural context.

Finally, another aim of this work could be to compare or validate some of the results obtained in the aforementioned agricultural survey. It was carried out in July of 2016, which is precisely when the earliest agricultural fires occur. The survey records which plots had residues retention, or which were burned. However, the household samples are limited to the villages where CA promotion has historically taken place and not the rest of the landscape. Furthermore, geographic coordinates of specific plots were not available to us. This means that it will be difficult to really make use of the survey results and compare the location of the burning and retention practices with our burned area analysis, though we can still observe their frequency according to both sources.

Through this thesis, we could also look into the feasibility of using UAVs in development projects. They are relatively easy to manipulate and provide images with an extremely high spatial resolution. This makes differentiating crop types, agricultural management practices and boundaries between fields evident. It could thus be a valuable tool for NGO's or institutions to assess adoption of different initiatives and projects, namely here CA practices. Nonetheless, the enquired area has to be limited and the cost might be more important than by using free satellite imagery or just in the field investigation methods. It seems that for localised practices happening at a known time that do not appear clearly on small scale images, UAV might be a remarkable solution. In our case, crop residues burning is too spread out in the landscape to make it feasible to use only UAV. We would also have to repeat the flights often since burning can occur all along the harvest season. Furthermore, the UAV imagery is available only for the month of April and for limited areas. It will be useful in spotting specific features and points of interests that we need for further analysis as well as get an understanding of the villages and fields organisation. However, as crop harvest and residues burning is still limited in April, we cannot base our study on these images.

Now that we have presented our core and specific objectives, as well as our key working hypotheses, we can describe the general approach to address these objectives. UAV imagery will serve as a basis to identify specific villages or plots with a given management as well as to understand the organisation of fields in the landscape. We will be using all the cloud-free Sentinel-2 data available spread out along the burning season. Based on these, we will test as many different classification and analysis methods as possible. It is indeed important to look at their accuracy in recognizing individual farming practices and their respective shortcomings. The one with the most promising results can then be reused, should a study on the other CA principles be conducted. After mapping all burned areas, we will need a way to select only areas that were once cultivated. This will ensure we do not account for natural fires whilst assessing the numbers of residues fires.

Chapter 3

Study area

The study area is located in the Central Region of Malawi, specifically in the Nkhoskhota and Salima districts. It forms an area of medium altitude (300 to 900 meters) in close proximity to Lake Malawi and close to the Nkhoskhota game reserve (Figure 6). Lake Malawi constitutes one of the largest and deepest lake in the world. Amongst those districts, the Salima district is more populated and has more economical activity.

The three main study sites were selected because they had hosted long-lasting CA promotion activity and demonstration plots. They were in Salima, Mwansambo and Zidyana as well as neighbouring villages. UAV flights were conducted there and are marked in orange on the map (Figure 6). An in-depth description of those flights can be found in the Material and Method section. The physical and biological features linked to the sites are characterized down below.

3.1. Topography

Topography varies according to the study sites. Zidyana has flat to undulating topography with around 400 m of elevation; it is part of the Nkhoskhota lakeshore lowlands. Mwansambo has an undulating to hilly topography with approximately 650 m high; it constitutes the foothills areas of the Rift Valley scarp. And the Salima region is on the flat lakeshore plain with very low undulation and approximately 500 m of altitude.

3.2. Climate

The general climate in Malawi is continental tropical and divided into two seasons: the dry and cold season from May to September and the humid season from November to April, with equatorial rains and warm temperature.

The climate is variable from zones to zones. The Salima area has a mean temperature of 24°C with total rainfall of 762-1143 mm per year. The Nkhoskhota area has a hot, wettish climate with an average temperature during the year of 23-24°C and 1143 to 1524 mm of rainfall. The Mwansambo climate is warm to hot and wettish with a mean temperature of 18-24°C and rainfall of 1016-1524 mm per year.

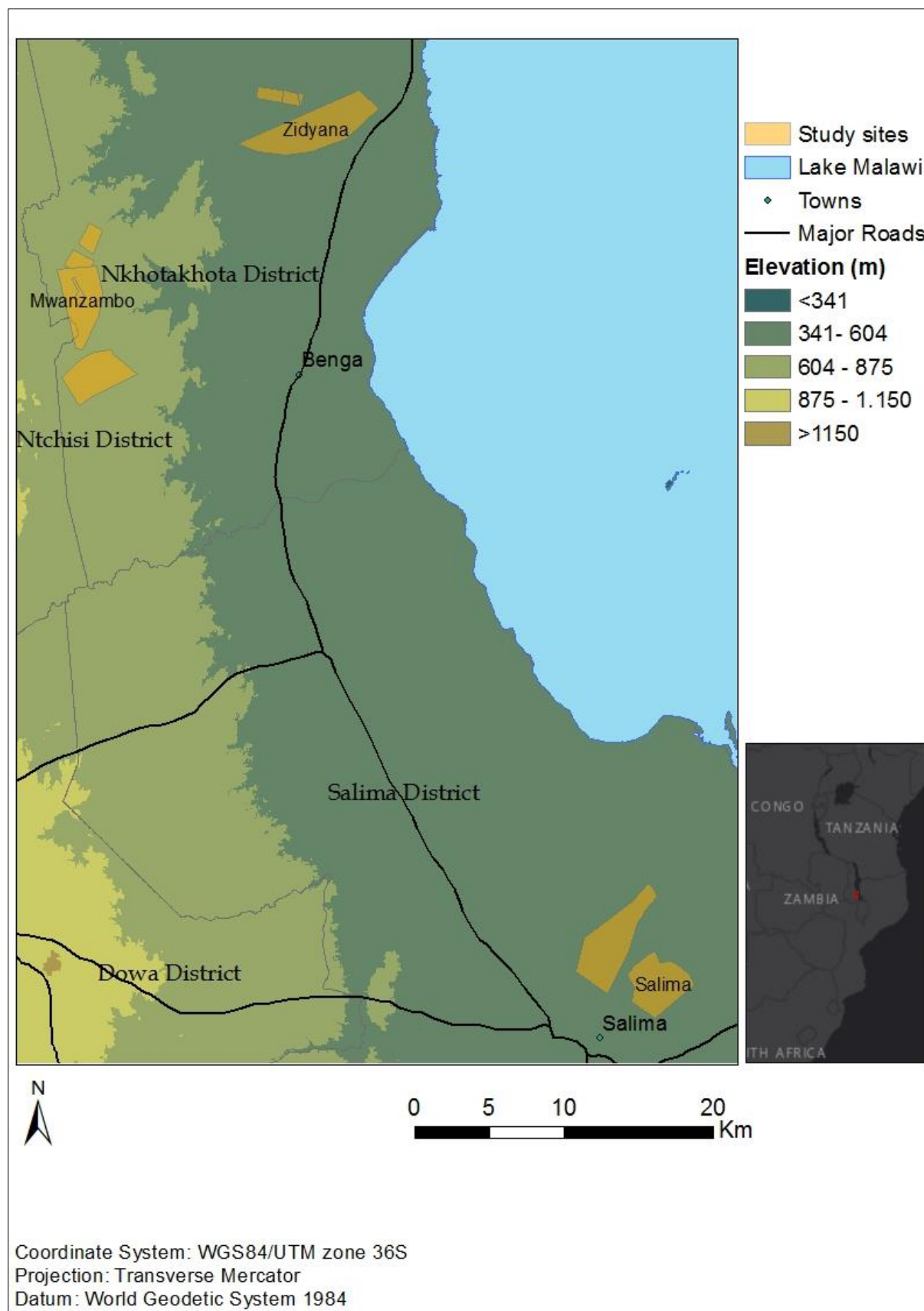


Figure 6: General map of the study region (GIS data from Malawi Spatial Data Platform).

3.3. Vegetation

Vegetation type across the country in general depends on the climate as well as elevation. There are savannahs with short trees and shrubs close to Salima. In Zidyana, the main vegetation type is defined as plateau woodland and marsh grasslands as well as lake shore savannah. The Mwansambo area is constituted of mixed woodland of the Rift Valley scarp foothills.

3.4. Crops cultivated and cropping calendar

In the Central Region, maize constitutes 67.9% of plots and their area is usually one hectare, 14.4% of plots grow groundnuts, which are on average 0.8 ha. The next most common crops are beans with 12.1%, soybeans with 12%, as well as tobacco with 7.1% (National Statistical Office, 2007). It is reported that on average Salima district has more maize and less groundnut and rice cultivation than the Nkhotakhota one. Furthermore, neither of these areas is a very important cash crop (tobacco, sugar, tea...) producer.

The UAV image below highlights the organisation of cropping system (Figure 7). We can recognize groundnuts with the smaller, green plots with visible ridges. Bigger, yellowish fields are maize ones. Framed in red, there is a stack of crop residues from a recently harvested field, that will soon undergo burning.



Figure 7: UAV image from Zidyana showing the typical cropping organisation. A harvested field with stack of residues is framed in red (CIMMYT).

The staple crop of maize can have growth cycles in the rainy and dry seasons with different planting and harvesting periods as is visible here (Figure 8). Groundnuts are planted at the very start of the rainy season and harvested around February to April. Cassava and sweet potatoes can be harvested any time of year.

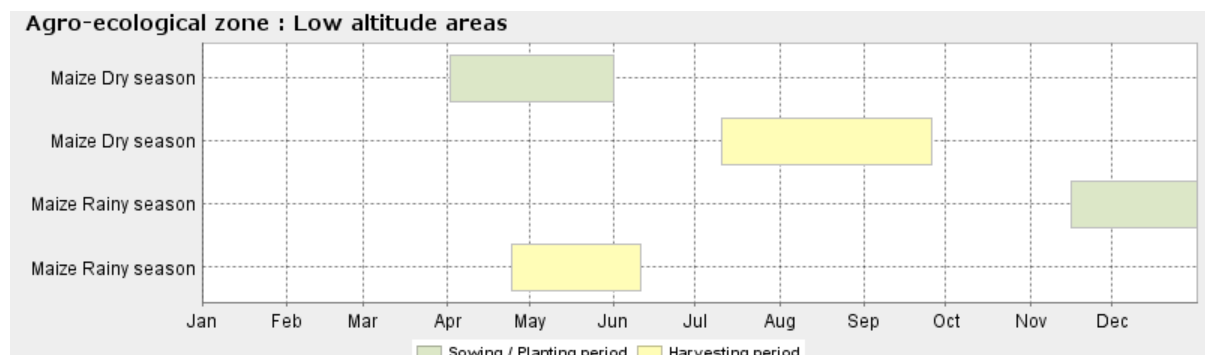


Figure 8: Cultivation cycles of maize in dry and rainy season in Malawi (FAO).

Crop residue burning, otherwise known as stubble burning, is a traditional and prevalent practice in all the Central Region of Malawi. This is especially the case on maize fields (Figure 9).



Figure 9: Crop residues burning in a maize field in Malawi (Ripple Africa NGO).

Chapter 4

Material and methods

This chapter will introduce the methods that allowed uncovering our results. We will first explore the data sources, namely the UAV and Sentinel-2 satellites, specifically the Sentinel-2 for Agriculture system. A workflow is there to summarize the rest of the operations. We will then move on to the methodology used to validate the cropland mask product, which will play a vital role later on. Thereafter, we will detail the application of the three classification methods. Finally, it is important to explain how we extracted numbers and densities of burned fields based on those classified maps.

4.1. Data sources

4.1.1. *Unmanned Aerial Vehicle*

An Unmanned Aerial system is very variable but made out of several components: a ground control station, a navigation system, an orientation system as well as a sensing instrument such as a camera or laser scanner (Colomina & Molina, 2014). All these parts can be combined differently depending on the situation studied.

The UAV imagery was made available by the CIMMYT team who had captured them as part of monitoring operations in Malawi. The UAV used was a fixed wings eBEE RTK from Sensefly®. The ground control station was an AG-542 Global Navigation Satellite System Receiver with a Zephyr Geodetic 2 antenna. The UAV itself has a 3 cm horizontal and 5 cm vertical accuracy. Real Time Kinematic (RTK) is a technique to correct positioning based on carrier wave's characteristics between the satellite and the rover station (here the UAV), using a reference station; this ensures higher accuracies than if RTK is not used. The sensing instrument to acquire the images was a Canon ELPH RGB camera. This UAV has a battery lifetime of approximately 25 minutes, and a cruise speed of 40 to 90 km/h.

The flights were all performed under supervision of Francelino Rodrigues Jr., between 9:30 a.m. and 4:30 p.m., across variably cloudy conditions, specifics on the flights such as dates and resolutions can be found below (Table 1).

In this case, no ground control points for correction were needed because of the differential GPS. The individual images were geotagged and stitched as a mosaic on PIX4D® mapper.

Location	Date	Area (km ²)	Spatial resolution (cm)	Number of flights	Height of the flight (m)	RTK correction
Zidyana South	12/04/2016	19	10	11	510	No
Zidyana	15/04/2016	1	2	3	520	Yes
		3	4	4		
		1	10	1		
Mwansambo	13/04/2016	14.5	10	12	658	Yes
	13/04/2016	0.7	4	2		
Mwansambo South	19/04/2016	10	4	8	680	Yes
Salima	14/04/2016	15.5	10	9	510	Yes
Salima South	20/04/2016	12	4	9	500	Yes

Table 1: Specifications linked to the UAV flights (CIMMYT).

4.1.2. Sentinel-2 satellites

The Sentinel 2 mission is composed of two satellites sent by the European Space Agency in June 2015 and March 2017. They operate both at a 180° angle of each other and 186 km of altitude. They have a width swath of 290 km and a five days revisit time. The world imagery data is divided into a number of tiles of 100 by 100 km in UTM/WGS84 projection. The tiles 36LXK and 36LXL cover our study area (Figure 10).

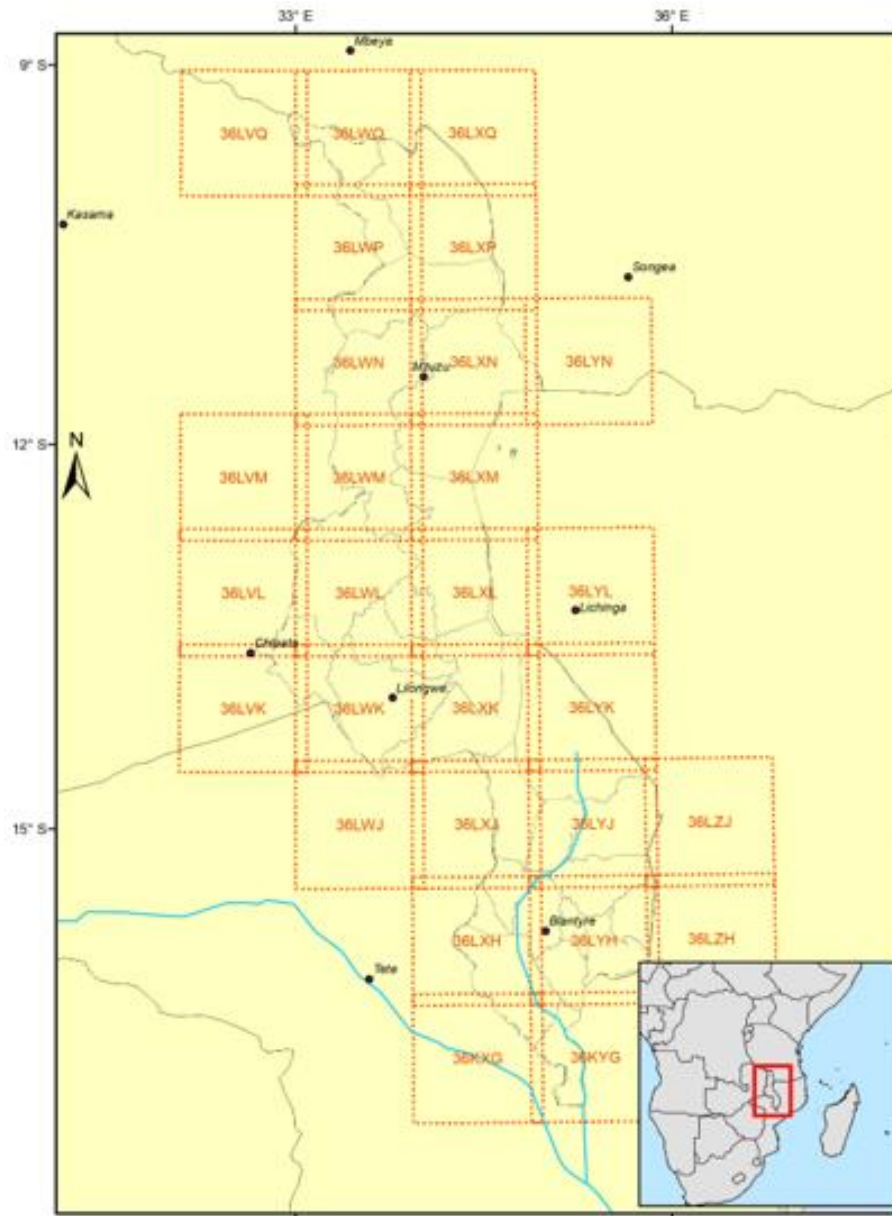
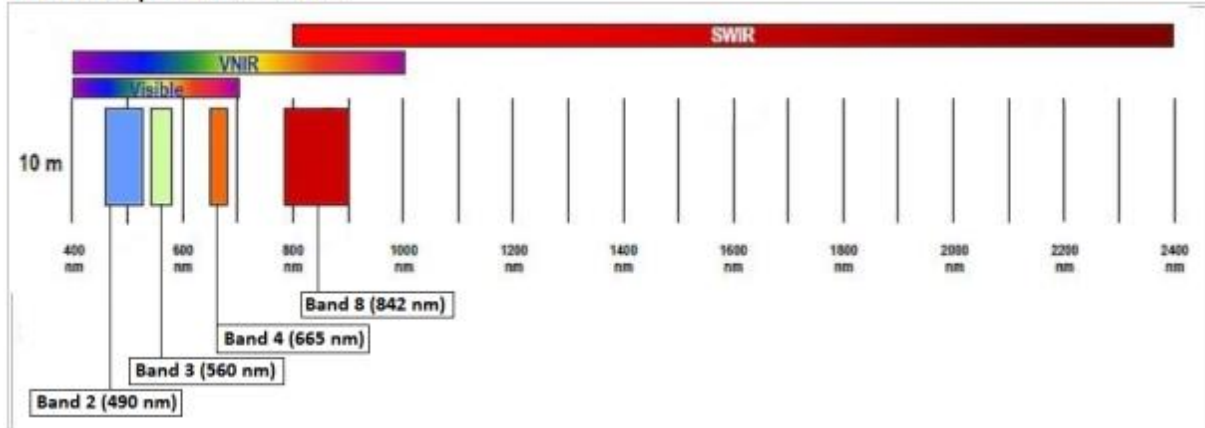


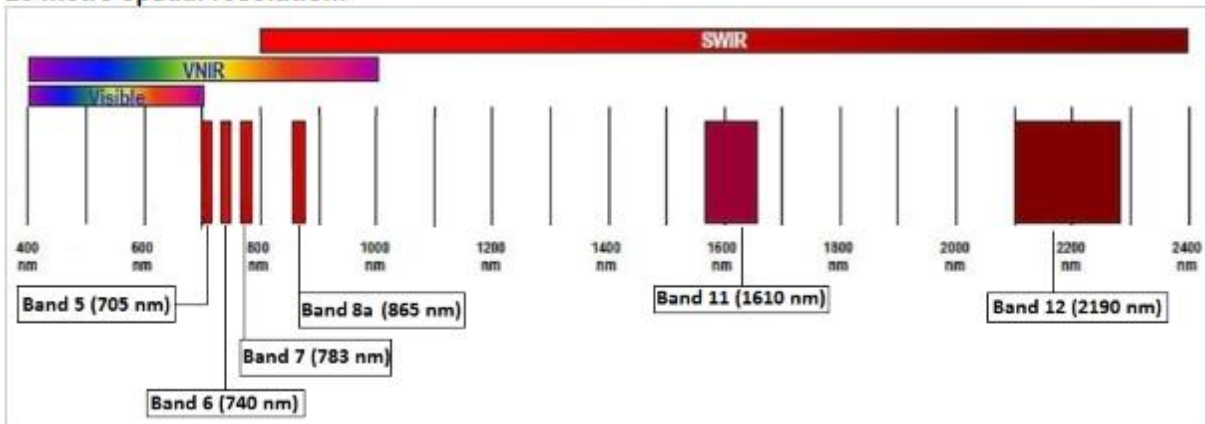
Figure 10: Sentinel-2 tiles division for Malawi (ESA).

The MultiSpectral Instrument onboard the satellites gathers light reflected from the earth, which is then filtered either on a focal plane in the visible and near infra-red or one in the shortwave infrared. It provides views in 13 spectral bands of different spatial resolutions: a green, red, blue and near infra-red band at 10 m resolution; three vegetation red-edge, one narrow infra-red and two short wave infra-red bands at 20 m resolution and finally three bands for atmospheric correction at 60 m resolution (cirrus, aerosols detection, water vapour correction) (Immitzer *et al.*, 2016). The spatial and spectral resolutions of each bands of the sensor is specified below (Figure 11).

10 metre spatial resolution:



20 metre spatial resolution:



60 metre spatial resolution:

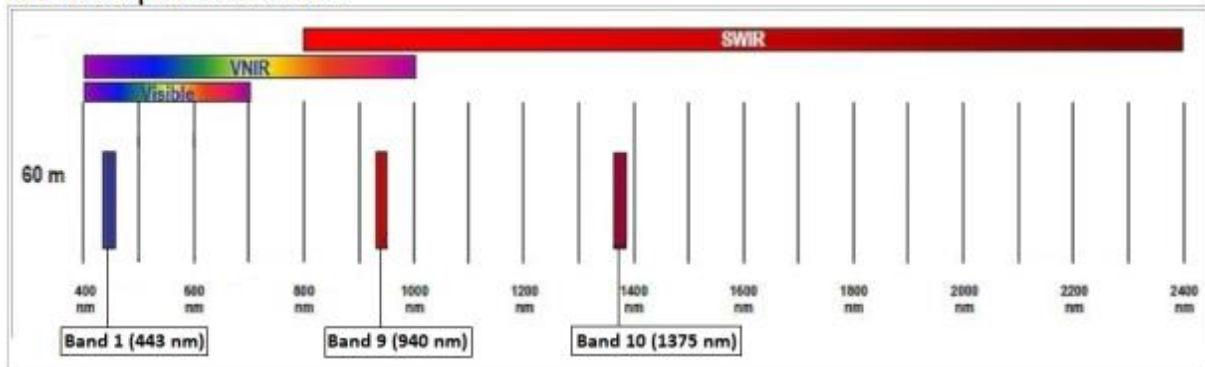


Figure 11: Spatial and spectral resolution of Sentinel-2's MultiSpectral Instrument (ESA).

This allows for high-quality satellite images, which can be compared with other satellites' images because of the high spatial and spectral similarity between them (*ibid*). Furthermore, Sentinel 2's overpass time is the same as SPOT and close to Landsat which means we can create long time series (Drusch *et al.*, 2012). Furthermore, it has been suggested even before their launches that Sentinel 2 data would be helpful to remotely detect burned areas (Malenovský *et al.*, 2012).

4.1.3. The Sentinel-2 for Agriculture system as data processing environment

The Sentinel-2 for Agriculture project is an open source system released by UCLouvain in 2017 with a focus on applications in the agricultural realm. It forms a processing system providing products based mainly on Sentinel-2 (as well as Landsat-8) satellites time series. The products are:

- cloud free composites of reflectance at 10 and 20 m spatial resolution on a monthly basis;
- cropland masks at 10 m spatial resolution on a monthly basis;
- crop type maps at a 10 m spatial resolution twice per agricultural season;
- vegetation status maps: normalized difference vegetation index (NDVI) and leaf area index (LAI) at each of the satellite's acquisition.

The system requires the definition of a season, which we defined as the whole year 2016. For these products, time series of Sentinel-2 as well as Landsat-8 satellites, occasionally, are used. They are first turned into bottom of atmosphere reflectance images complemented with snow, water, cloud as well as cloud shadow masks (L2A products). For this thesis, the products of interest are mostly the cloud-free composite (L3A product), the cropland mask (L4A product) as well as the crop type map (L4B product).

For the composite product, corrections to compensate for different angles of observation are applied on the Sentinel-2 images, a weighted average method is then used to create the composite (Matton *et al.*, 2015).

The L4A product presents a binary map of annual cropland and non-cropland areas. Cropland is here defined as a zone of minimum 0.25 ha, which is able to be harvested at least once during the year following its sowing (Matton *et al.*, 2015). There are two levels of L4A products.

The first level uses a reference land cover map as a basis to create training data of cropland and non-cropland. The map used is the European Space Agency Climate Change Initiative Land Cover 2010 map produced by UCLouvain. The second method uses reference polygons of cropland and non-cropland supplied by the user (in-situ data) to create the cropland mask product. A certain number of these will serve as training data for the cropland map and a number as validation polygons. These polygons should have an attribute table following a certain formalism, for instance the land cover code is given by the Joint Experiment for Crop Assessment and Monitoring (JECAM) guidelines.

The L4B product presents a map of the main crop types, it is generated on the cropland identified with the cropland mask product (Matton *et al.*, 2015). The map can be generated once in the middle of the season and once at the end of it. This product requires the input of reference on-ground data of different crop types. The accuracy is expected to improve along the season as crops are growing.

4.1.4. Data visualization environment

The software ArcMap 10.4. from Esri © and the open-source equivalent QGIS 2.18.22 were both used to visualize and process the Sentinel-2 and UAV imagery. An in-depth observation of the composite images allowed understanding of the patterns of crop residues burning. The 10 m resolution version of the product was converted into an infrared false colour composition. This showed burned fields in dark green while vegetation appeared in red and pink. On the composite example here, there is a river originating from Lake Malawi. A village is visible west of it, and a few dark green burn patches are around it (Figure 12). The colour of burned vegetation in this band combination was confirmed by using UAV as well as Google Earth images of the same period.



Figure 12: Example of False Infrared Sentinel-2 composite on the 21st of September.

4.2. Overall approach description

Throughout this work, we used the Sentinel-2 for Agriculture products as a basis. We have visualized and identified visually the burned areas on our composite images. Two distinct classifications methods were applied on the products to identify burned areas. These were realized mainly on the ArcMap 10.4 software. A cropland mask obtained through the same system was used to extract burned cropland zones, to select only burned areas in fields. Another classification method was tested using the Sen-2 Agri algorithm that produces crop type map (see section 4.1.3. of Material and methods) and diverting it to map burned areas.

A validation step was implemented to assess the accuracy of those burned area maps. This was done through a confusion matrix for each date and classification method. These

matrices allowed to calculate user and producer's accuracy for burned and unburned class, as well as the global accuracy. The f1 score representing the method's performance in classifying both classes was also evaluated. It is actually the harmonic mean between the recall and precision metrics. After validation of the three methods, the results were displayed in maps. The burned cropland classification products were turned into quantitative data: numbers and densities of burned fields in the landscape.

A workflow provides a more visual approach of the methods employed to calculate burned fields numbers, those methods are explained more in-depth in the following sections (Figure 13).

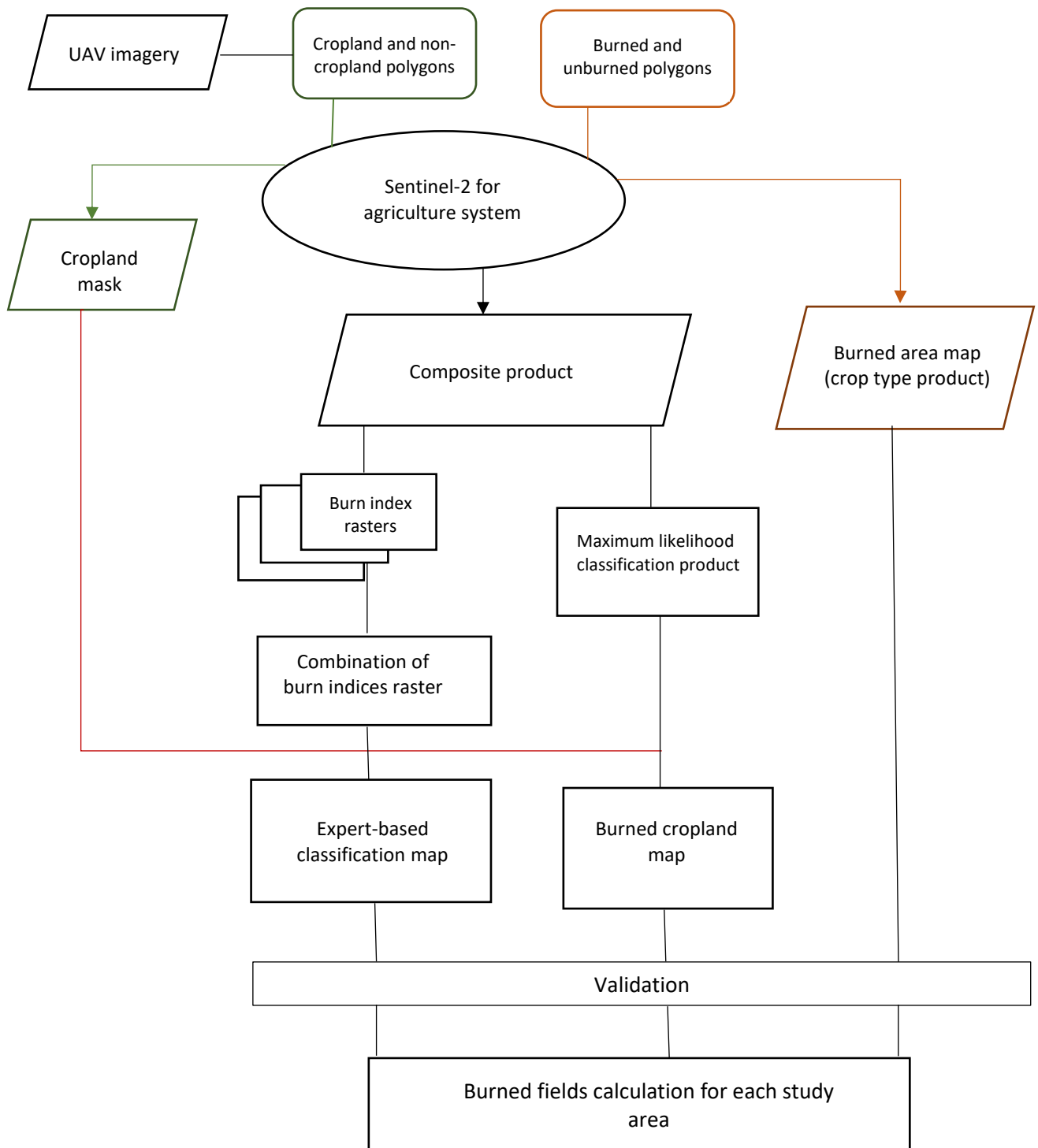


Figure 13: Workflow of the different methods used.

4.3. Main methodological steps

4.3.1. *Cropland mask*

4.3.1.1. Cropland mask production

The Sen-2 Agri cropland mask product will be necessary in further steps to filter burned areas in fields from other ones. Thus, it needs to be validated, to ensure it can correctly distinguish between the two. We have produced a quantity of cropland masks, which we have tested against a set of non-random validation samples. This led to the creation of a confusion matrix, designed to assess the performance of the algorithm. A confusion matrix is a table confronting the instances in the predicted class with those in the actual class. It compares the number of cropland and non-cropland predicted pixels with the actual numbers in the validation samples. We were then able to calculate global, user's and producer's accuracy. We also evaluated the recall and precision for the cropland and non-cropland categories, which allowed to calculate their harmonic mean, the f1 score.

As explained, in Section 1.3. of this chapter, there are two levels of cropland masks. For the level without-in situ, we expected a lower accuracy. We have tested 9 different time periods during which data is collected by the system, the assumption being the longer the period the better it should identify cropland.

For the cropland mask produced with in-situ, a ratio of training to validation polygons has to be set inside the system; we have tested a ratio of 0.66, 0.75 and 0.80. This in-situ method also allows the use of Sentinel-2 only imagery or a combination of Sentinel-2 with Landsat-8 images, which were both tested. To supply the system, polygons were created for each of the seven UAV mosaic by visual interpretation in order to reflect the diversity of cropland and non-cropland situations. In total, approximately 75 polygons were drawn for each mosaic, which constitutes 452 polygons in total, from which 262 of cropland (coloured in orange) and 190 of non-cropland (coloured in grey) (Figure 14). Their land use was verified against composite images of a similar period.



Figure 14: Creation of cropland (in orange) and non-cropland (in grey) polygons from the UAV image at 12th of April (CIMMYT).

4.3.1.2. Cropland mask validation

The input data used for the in-situ cropland mask, consisting of 262 cropland and 190 non-cropland polygons, will also serve as the validation data for the cropland masks obtained with both methods. The validation samples were converted into raster data. We then could count pixels falling into four situations, depending on the class: cropland or non-cropland according to the Sen-2 Agri product and to our validation raster. This allowed filling a confusion matrix confronting validation data with the cropland mask. We were finally able to calculate quality metrics such as global accuracy, user's and producer's accuracy as well as f1 score.

4.3.2. Burned area detection

4.3.2.1. Burned area indices

An index is a combination of spectral bands in order to make certain properties more apparent. Burn indices have been designed to bring out burned areas on remote sensing imagery. However, thresholds still need to be determined to differentiate burned fields from other land covers in our specific context. Those threshold raster images will help visualize the burning distribution and also become the foundation for the expert-based classification, detailed later.

Three burn indices drawn from the literature were selected. They are the differenced Normalized Burn Ratio, the Char Soil Index and the Mid-Infrared Bispectral Index.

The L3A cloud-free composites downloaded from Sen-2 Agri serve as the basis material for this step. This product is separated in two raster images: one with the four spectral bands at 10 m spatial resolution and one with the six bands at 20 m resolution. Indices are calculated from the spectral reflectance of the pixel in the considered band. The resulting output for the CSI and dNBR index had a 20 m resolution since they required the use of 10 and 20 m resolution bands. The resolution was also 20 m for the MIRBI index output image, which only used near-infra red bands. The dates corresponding to cloud-free satellite images were studied and are the: 8th of August, 23rd of August, 12th of September, 21st of September, 2nd of October, 26th of October as well as 5th of November. The next step was to deduce thresholds of the indices to differentiate burned areas from unburned areas.

dNBR values can be classified into several burn severity classes. A value superior to 0.35 shows moderately severe burns, one superior to 0.50 is typical of a severe burn and a dNBR superior to 0.65 signifies a high severity burn (Humboldt State University, 2015). Meanwhile, unburned pixels correspond to a value between -0.1 and 0.1 (Escuin *et al.*, 2008). A comparison with the composite images allowed us to choose a suitable threshold. A 0.35 threshold seemed to show too many burned pixels, perhaps some very lightly burned patches that do not constitute an entire field. Thus, in this case, a threshold of 0.45 was chosen.

For MIRBI, other studies in savannah in Southern Africa have determined a threshold of 1.7 is optimal to detect burns (Smith, Drake, *et al.*, 2007; Trigg and Flasse, 2001). We have tested this with Sentinel-2 images and found it to be an adequate threshold.

Finally, it was more difficult to find a threshold that worked with the CSI, since it seemed that burn pixels could take on a variety of index values. A threshold of 0.9 was combined with the threshold for the dNBR in order to select burned areas more accurately.

The presence of Lake Malawi and other water bodies seemed to cause interferences by having the same index value as burned pixels. To address this issue, the Normalized Differenced Water Index looked like an efficient solution (McFeeters, 1996; Verhegghen *et al.*, 2016). It was calculated and subtracted to the other index values. The threshold was chosen dependently on the image date and tile in question. This provides “water-masked” images for each of the three indices with the burn areas well highlighted.

4.3.2.2. Preliminary exploration of burning patterns

Before applying the proper classification process, it was important to get a rough understanding of the burning patterns across space and throughout time. The principle was to estimate the numbers of burned areas within certain distances of the promotion sites as the season progresses. This step makes use of the burn index layers complete with watermarks and the suitable threshold allowing to detect burns.

Three dates were evaluated: one in August, in September and November. Continuous buffers enclosing the study sites (UAV flight zones) were created for different distances: 5, 10, 15, 20, 25 and 30 km. We just had to select and count the number of burned polygons intersecting the different buffers, for the dates considered. However, we are aware that the burns tallied here could be of any origins and not only crop residues, since we did not use a

cropland mask. Down below is a visual example of the method, for calculated CSI in September (Figure 15).

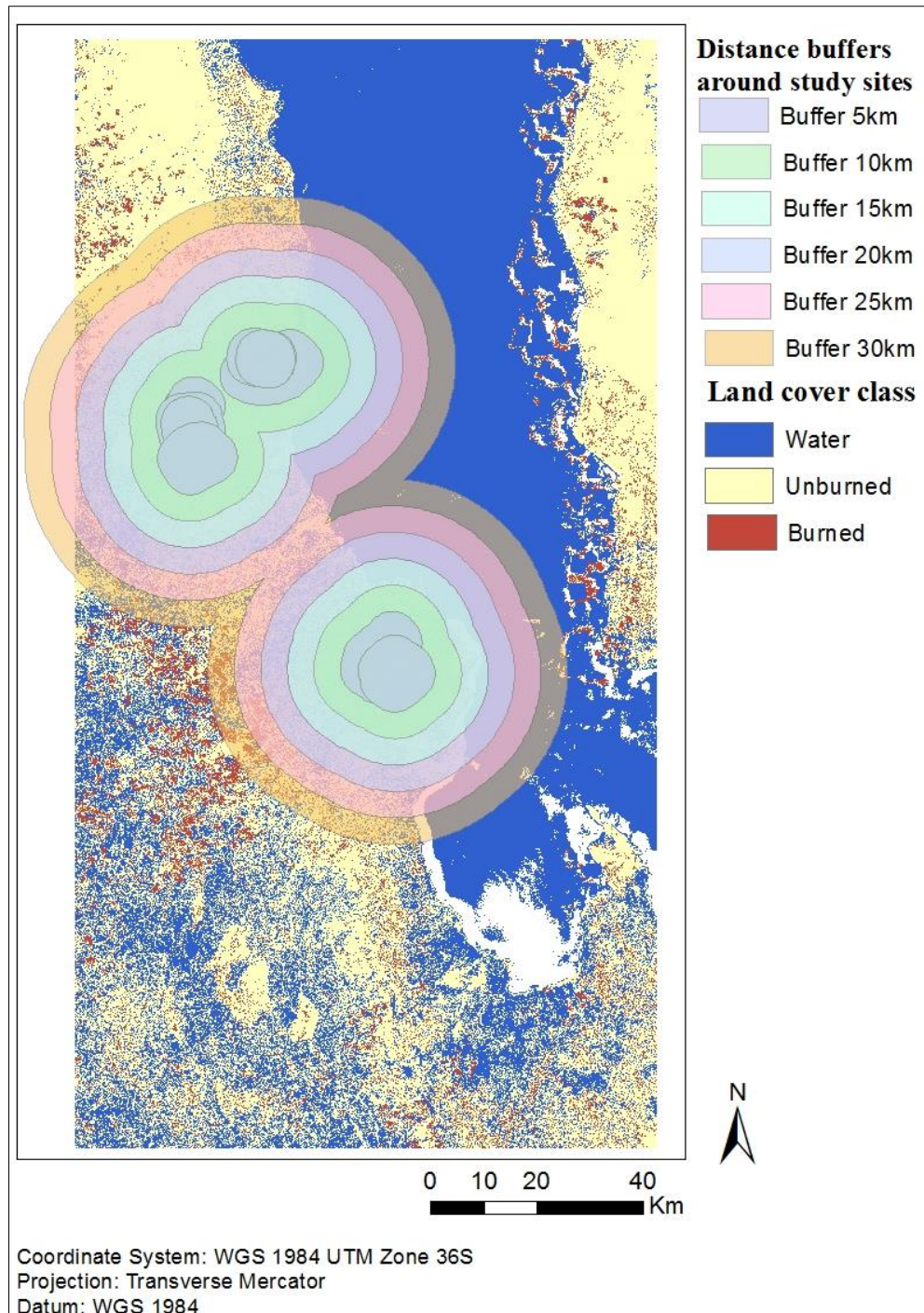


Figure 15: Map showing method for exploring burned areas with CSI at 21st of September.

4.3.2.3. Expert-based classification

The logic for this so-called expert-based classification is combining values of the different burn indices in order to map burned areas for several dates. The thresholds

determined in the previous section will indicate if the area is burned or not according to a certain index. We will give a new value to the pixel depending on the combination of the indices' values. Those new values can be interpreted as a specific probability for the pixel to be burned. To first assess accuracy of the index in detecting burned areas, we will use a set of random points. For each point, we will carefully examine if it corresponds to a burned or unburned zone according to each index and compare it with a reference composite image. We will finally stack the raster corresponding to each new value into a complete map evaluating burn certainty. A cropland mask needs to be added as the final step to extract exclusively burned areas that had been a field in the last year. To judge the quality of the classification, we carried out a validation using a set of burned and unburned samples. The corresponding confusion matrix was constructed, and we calculated accuracies, recall, precision and f1 score metrics.

Two hundred and fifty random points were cast on the studied two tiles for one date. This study allowed us to establish which index was closest to satellite reality in terms of burned areas. Out of 250 random points, 113 were burned according to at least one index. The number of burned points for the indices and composite is presented in below graph (Figure 16).

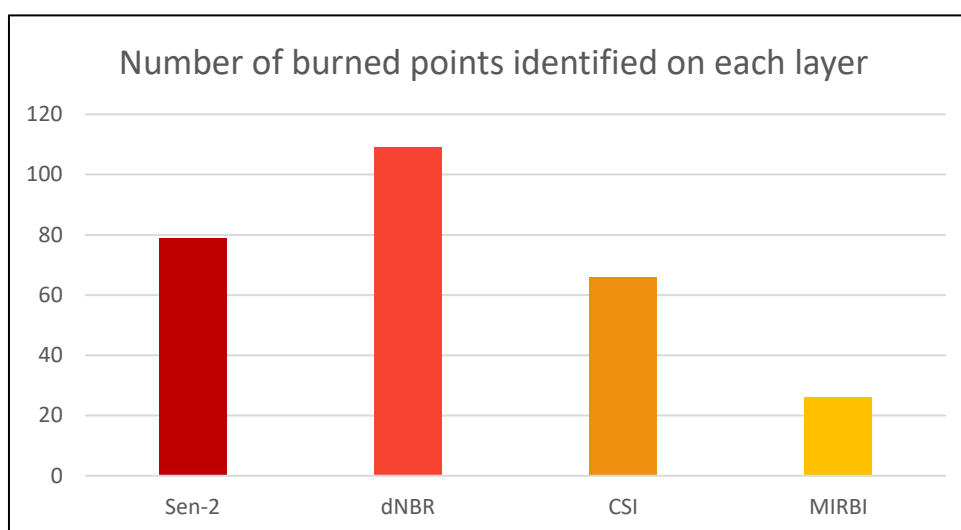


Figure 16: Graph counting the number of points inside a burned area according to several indices.

In conclusion, dNBR tended to slightly overestimate burned areas whereas CSI underestimated them and MIRBI highlighted only very severely burned pixels. We could then decide on a hierarchy of the reliability of our indices. We found that dNBR was the most reliable index based on its frequent and successful use in literature. The smaller number of burned points on the composite was perhaps due to a bad visual interpretation that made us overlook some burned areas. Since CSI is in combination with dNBR, it received the second priority. Finally, MIRBI missed a high amount of burns, so it was given the lowest significance. Using conditional statements, new values were assigned according to each burn index's value, with the rules detailed in the table below (Table 2).

dNBR	CSI	MIRBI	New pixel value
Burned	Burned	Burned	10
Burned	Burned	Unburned	8
Burned	Unburned	Burned	8
Unburned	Burned	Burned	5
Burned	Unburned	Unburned	6
Unburned	Burned	Unburned	4
Unburned	Unburned	Burned	2

Table 2: New value assigned to a pixel based on the value of the different indices.

Those new assigned pixel values were equalled to a certain burn likelihood class, the higher the value the most likely it was to be burned. This was done for the seven dates in the crop residues burning season for which we calculated burn indices, described in Section 8 of this chapter. We used the most accurate cropland mask obtained in Sen-2 Agri to select burned areas in cropland. This allows a differentiation between big savannah or forest fires and crop residues fires.

4.3.2.4. Maximum likelihood algorithm classification

The maximum likelihood algorithm uses a stochastic approach based on Bayes theorem and the hypothesis of a normal distribution of each pixel inside a sample class. The sample area's distribution of spectral statistics is computed and allows to create equal probability zones around those samples. Then a probability of each non-sampled pixel to belong to a given class is calculated and the pixel is assigned to the class for which its probability is the highest.

To put this logic into practice, a maximum likelihood algorithm was readily available with the ArcMap 10.4 software. The principle here was to pick equal numbers of representative burned and unburned samples from the composite to create a signature file. This is part of the training phase of the algorithm which will then produce a binary burned/unburned map. A cropland mask allows to extract only burned areas contained in cropland, and not wildfires, which are of no interest to us. For this stage, we will be using the best available cropland mask obtained through this research.

4.3.2.5. Random forest classification of burned areas using Sentinel-2 for Agriculture

The principle is to make use of the supervised random forest algorithm embedded in the Sen-2 Agri system. The training of this type of algorithm combines a multitude of decision trees together. A series of training inputs is fed to the decision tree which creates from them a set of rules. These rules can be used to predict a value for other pixels. The rest of the samples will serve as validation. Particularly the L4B Sen-2 Agri product uses in-situ data provided by the user, split between training samples and validation samples. We know it can provide crop type maps, but we assumed it could also produce high quality burned area maps.

To this end, we have created a set of non-random polygons containing burned area, several crop types as well as non-cropland area. As the algorithm uses a cropland mask already generated as a basis, we did not need to filter the product manually to get only agricultural burns. In terms of validation, the algorithm performs its own with a portion of the input samples. However, to make sure the validation focused on burned and unburned areas, and not specifically on the crop types, we realised a second validation, detailed in section 4.3.2.6.

The input polygons for the crop type map consisted of 150 polygons corresponding to burned areas, 150 of unburned cropland and 50 of other land uses (bare soils, build-up surfaces, water bodies). The different types of cropland; groundnuts, maize... were hard to differentiate with a 10 m spatial resolution. We had to assume the crop type, looking at the frequency of that pixel's colour or its position in relation to some specific feature. For example, we know that maize is the most common crop, that rice is cultivated near rivers and cassava closer to villages. As the JECAM land cover typology does not include a burned area class, we assigned the burned polygons to the class "Other crops" since we wanted the algorithm to consider the burns that appeared inside cropland zones. We verified land use identified on the composite via Google Earth, burned areas are easily visible there from their dark brown colour (Figure 17).



Figure 17: Google Earth image for the 25th of September and verification of the burned polygons (in blue and yellow here).

We used the best available cropland mask obtained with this research as the input for this algorithm. We have tested different ratio of training to validation polygons: 0.66, 0.75 and

0.80. The classification can use solely Sentinel-2 satellite imagery or also Landsat-8 one, both options were assessed. This was repeated for the seven dates across the season which had cloud-free Sentinel-2 imagery (08/08, 23/08, 12/09, 21/09, 02/10, 26/10 and 05/11).

4.3.2.6. Validation of the classification methods

We performed the validation of the products of each classification method, to assess their quality. A set of validation data was created methodologically from composite imagery for each date. It consisted of 200 burned and 200 unburned polygons, which were selected to reflect the diversity of the landscape. For the unburned class, samples were of varied land covers, including water, roads, villages, cultivated fields, forests... We were able to fill the confusion matrix, which compares the pixels assigned to either of the classes and those who are actually part of this class. The global, producer's and user's accuracies as well as f1-scores were calculated based on this confusion matrix. These metrics allow to compare the performance of the various classification methods. The same validation data and method were used for each of the classification techniques presented through sections 4.3.2.3. to 4.3.2.5.

4.3.2.7. Burned area segmentation investigation

Thus far, we have only tested pixel-based classification methods to map burned areas and it was interesting to compare the results with an object-based method. To this end, we have tested a segmentation of the Sentinel-2 composite imagery into objects, which are image primitives, that carry information and can serve as building blocks for a future classification (Gitas *et al.*, 2004).

The software ECognition Developer from Trimble © allows the creation of objects of similar characteristics based on remote sensing imagery. The features used for segmentation are shape, scale as well as compactness. The shape parameter is set quite low because here colour is more important than shape to segment. We tested a lot of different scale values but did not obtain satisfying objects. All the objects had very unnatural shapes, roads were constantly not detected, and fields were cut into very small areas. Literature provided proof that object-based classification does not perform incredibly well and is not very common method in burned area mapping, indeed we could only find two references to it (Gitas *et al.*, 2004; Mitri and Gitas, 2002). Furthermore, segmentation is generally used and more efficient with very high spatial resolution imagery. For instance, a 10 m resolution image had 6 times more unrecognized objects from a reference set of objects than a 50 cm one (Mesner and Ostir, 2014). Thus, we chose not to test the object-based classification, knowing that the resolution was too low and objects not realistic enough and it would result in very low accuracy

4.3.3. Spatial and temporal distribution analysis of burned areas

After these classification steps, we were able to map more or less accurately the burned areas in space and time and visualize burning patterns. However, to conclude on the issue at hand, a more quantitative approach was required, namely converting the number of burned polygons into fields based on field's average area. We had to evaluate specifically

burned residues field's distribution around promotion centres. The logic was to identify core CA demonstration villages in the Zidyana, Mwansambo and Salima area from the UAV imagery and count the number of burned fields within certain distances of them. We also used distance buffers to calculate burned field density in each region.

This stage was pursued for all products of any classification method showing a global accuracy over 85%. Main promotion villages were identified on UAV images by the presence of demonstration plots and storage hangars (Figure 18). The distance buffers created around each promotion site to study numbers and density of burned fields had the following radiuses: 3, 5, 10, 15 and 20 km. The first buffer represented the limits of the promotion village and its immediate surroundings. The other ones allowed to reach burned plots in nearby villages in all directions. The 20 km mark seemed like an appropriate limit of influence for each promotion area. Indeed, we made the assumption that villages that are more distant than this would not get frequent contact with one another. And if we looked further than 20 km from a promotion village, we either reached another promotion area or Lake Malawi.



Figure 18: Examples of two promotions centres in Salima (left) and Zidyana (right) (CIMMYT).

We had the number of burned polygons obtained from the classification and we wanted to turn them into a number of actual burned fields. For this, we used the area of an average field in this region, which we found from the agricultural survey was 0.4 ha and the average area of the polygons for this classification product. The polygon's area varied a lot through space, and it was impossible to adapt the field numbers to each of the polygon's area. This is why we used an average area. Through a simple cross multiplication calculation, we deduced the number of burned fields. To calculate density, we just divided the number of burned fields by each buffer's area. When it comes to Mwansambo and Zidyana, quite close to each other, their buffers started intersecting from 10 km outwards. Yet, we wanted to take into account the density only in one given region's buffer and not in the intersection of those two regions' buffers. So we subtracted from the total buffer area, for the 10, 15 and 20 km buffers, the area of the overlap before calculating the density. We also calculated the density in these overlapping areas between the Mwansambo and Zidyana buffers.

This method, however, of using an average polygon area has one major flaw; it will over- and underestimate the surface of the smallest and biggest polygons. We do not take into account that the size of them can vary, considering our position in the landscape. Thus, we should not consider these burned field numbers and densities as definitive and compelling facts, but rather consider their relative abundance in time and space.

Chapter 5

Results and discussion

5.1. Validation of cropland mask

We have tested the accuracy of Sentinel-2's cropland masks for both without and with in-situ reference data.

In the first case, the product with no in-situ was tested for periods of variable lengths. The global accuracy ranged from 35.8 to 63.6% depending on the length of the season used. The maximal global accuracy for this method was achieved with a season lasting from June to October, confusion matrix in this situation was the following (

Table 3). In the confusion matrix table, the class 0 corresponds to non-cropland whereas the 1 class corresponds to cropland. Producer, user, global accuracy as well as misclassification, true positive and false positive rates are all given in percent.

	Cropland Mask Sentinel-2 Agri (06/06 to 29/10)					Producer Accuracy
UAV validation polygons		0	1	Total pixels		
	0	1241	3042	4283		29.0
	1	361	4705	5066		92.9
	Total pixels	1602	7747	9349		
User Accuracy		77.5	60.7			

Global accuracy	63.6
Misclassification rate	36.4
True Positive rate	0.9
False Positive rate	0.7

F1 score for cropland class	
Precision	0.6
Recall	0.9
F1 score	0.8

F1 score for non-cropland class	
Precision	0.8
Recall	0.3
F1 score	0.4

Table 3: Confusion matrix for highest accuracy cropland mask obtained without in-situ data (6th of June to 29th of October).

This gives us a global accuracy of 63.6%. Furthermore, the confusion matrix seems to show that there is a high probability of confusion between crop and non-crop. Indeed, the producer's accuracy for the non-cropland class is the lowest, which means that more often than not a non-cropland pixel is classified as cropland when it should not. The f1 score for non-cropland is very low, which shows a lack of both recall and precision. It is a bit higher for cropland, this indicates that the recognition of cropland is better than non-cropland. Recall for cropland class was a lot lower than precision, thus there were not many correctly predicted pixels.

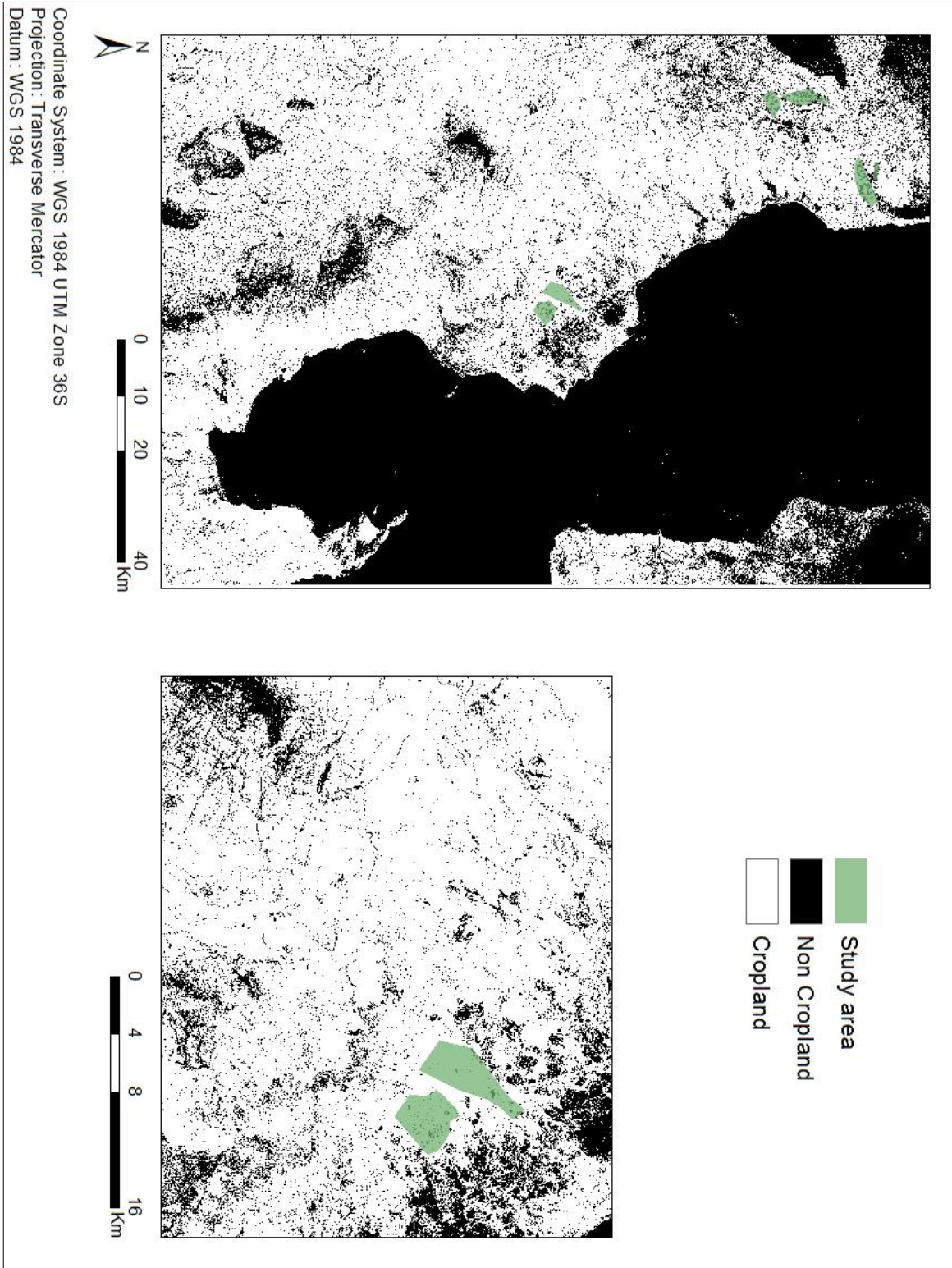


Figure 19: Map of highest accuracy cropland mask obtained without in-situ data.

We can observe from the zoom on the right that the distinction between crop and non-cropland is very poor (Figure 19). The outline of fields is not sharp; there is a mass of cropland in the landscape. This type of product is not suitable to differentiate with sufficient certainty between a burned field and another type of burned surface.

However, the use of in-situ polygons has shown some interesting results. We had tried several ratios of training to validation polygons. The one that showed highest accuracies was the cropland mask using a ratio of 0.66. The addition of Landsat 8 images caused in all cases a decline in accuracy. This might be due to the lower spatial resolution of Landsat-8 satellite sensor: 30 m compared with that of Sentinel-2. Down below is a comparison of the global, producer's, user's accuracy as well as f1 scores for the three ratios tested (Table 4).

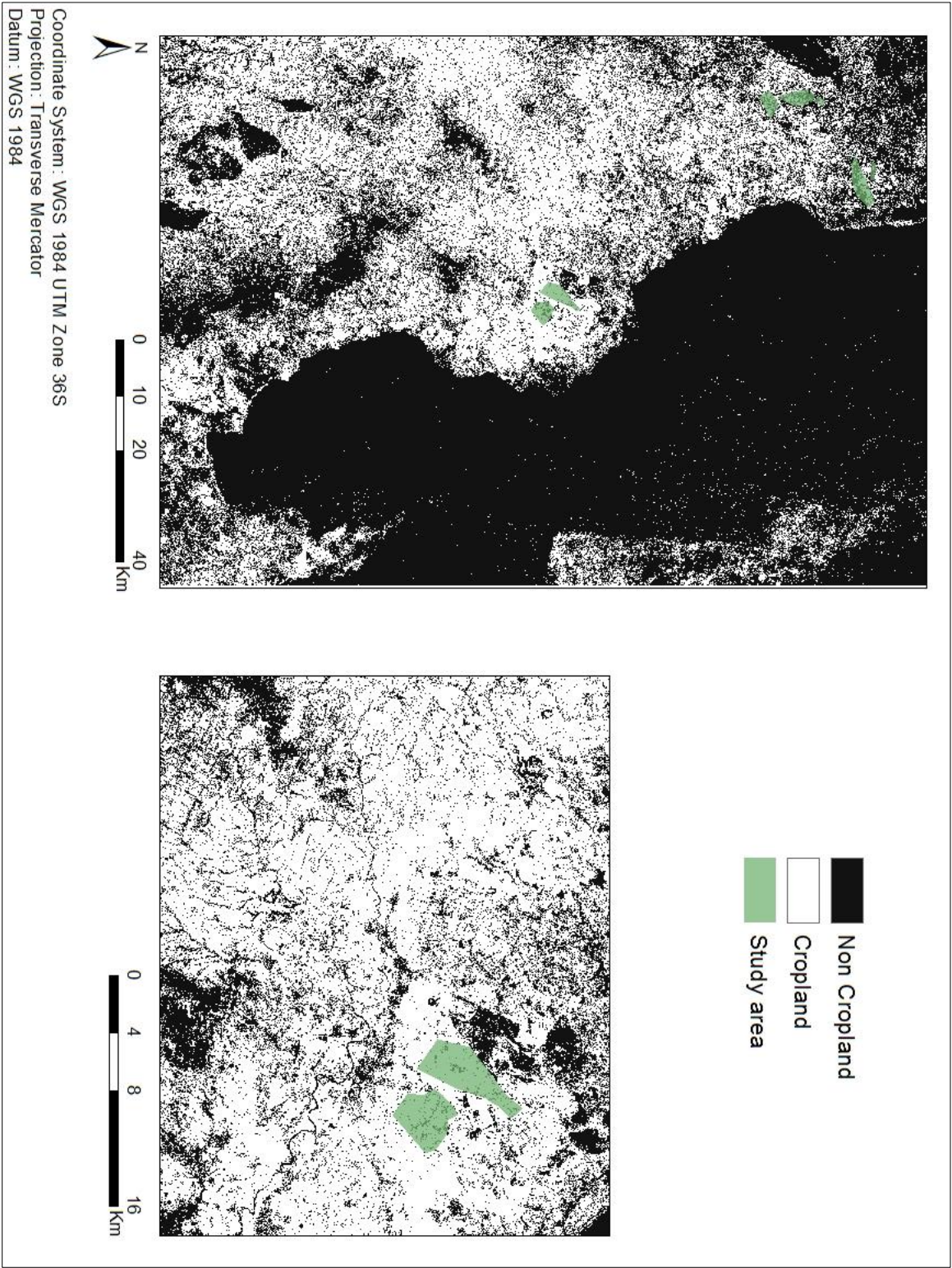


Figure 20: Map of highest accuracy cropland mask obtained with in-situ polygons.

The result is clearly more accurate and closer to reality with the in-situ method, individual fields can be discerned easily, as well as rivers and roads (Figure 20). A comparison with Sentinel-2 imagery (from mid-April) underlines how similar the two representations are, for instance the river in the South belongs to non-cropland (Figure 21). The forest in the North along the study area looks correctly classified as well; however, roads are not always entirely detected as non-cropland (Figure 21).

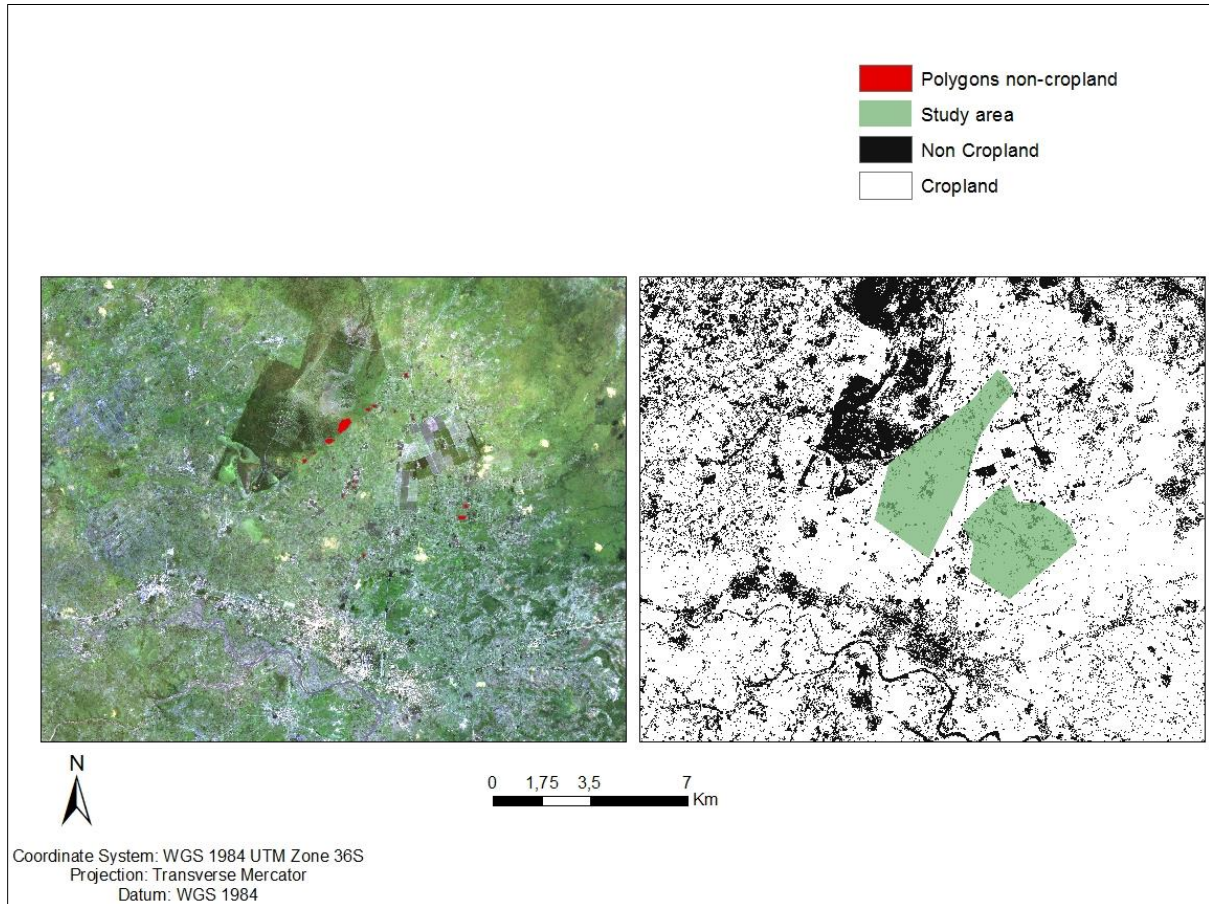


Figure 21: Comparison between Sentinel-2 image (14th of April) and cropland mask with in-situ data for the same location.

The accuracies, f1 scores and other statistics were calculated for cropland masks with several ratios of training to validation polygons and the use or not of additional Landsat-8 imagery (Table 4).

Ratio of training to validation polygons	0.66		0.75		0.80	
Presence of additional L-8 images	No	Yes	No	Yes	No	Yes
Global accuracy	90.8	83.2	89.2	87.8	89.4	88.4
F1 score cropland	0.2	0.2	0.2	0.2	0.2	0.2
F1 score non-cropland	0.9	0.4	0.9	0.8	0.9	0.8

Table 4: General statistics for the different cropland masks obtained with in-situ polygons.

It seems that for all of these masks, the greatest difficulty is to classify cropland as such. Indeed; their f1 score is constantly lower than the non-cropland class one. This can be explained by a few different reasons. A plausible reason is that the fields not detected are the ones smaller than 0.25 ha, not considered within Sen-2 Agri (see section 4.1.3 of Material and methods), indeed fields in Malawi can have a very small size, up to 0.2 ha. We can also hypothesize that spectral signature could be similar between fields and natural vegetation such as shrub land and humid areas.

The most accurate of those cropland masks uses a ratio of 0.66 training to validation polygons and no Landsat-8 images. It will be used in further steps to filter burned areas in fields from them elsewhere. Down below is the detailed confusion matrix for the cropland and non-cropland classes (Table 5).

	Cropmask Sentinel-2 Agri					Producer Accuracy
UAV validation polygons		0	1	Total pixels		
	0	4366	189	4555		95.9
	1	1286	10113	11399		88.7
	Total pixels	5652	10302	15954		
User Accuracy		77.2	98.2			

Global accuracy	90.8
Misclassification rate	9.2
True Positive rate	0.9
False Positive rate	0.04

F1 score for cropland class	
Precision	0.9
Recall	0.9
F1 score	0.9

F1 score for non-cropland class	
Precision	0.8
Recall	0.9
F1 score	0.9

Table 5: Confusion matrix and statistics for the highest accuracy cropland mask obtained with in-situ polygons.

The global accuracy is a lot higher than for the cropland mask with no in-situ data. We can observe that the cropland pixels are in 98% of cases classified as cropland and almost never in another class. However, the user's accuracy for non-cropland class is a bit lower than the others meaning that some of the pixels were incorrectly classified in that category.

Similarly, as seen for the method without in-situ, f1 score is highest for the cropland class; it shows also an extremely high precision. Of all the cropland areas present, we identified a great part of them. For the non-cropland class, the precision was the lowest of the two. Out of all the pixels labeled as non-cropland, approximately a quarter were actually cropland in reality. The algorithm probably has troubles differentiating between small fields and grassland or shrubland.

5.2. Burned area detection and distribution analysis

5.2.1. Preliminary investigation of burned patterns

This step is just a rough estimate of the number of burned polygons linked to different indices at different distances from the study sites. We can already draw some first hypotheses from these results.

23th of August			
Number of burned polygons for each burn index			
Buffer distance (km)	dNBR	CSI	MIRBI
5	81,240	28,881	1,478
10	127,648	57,507	3,249
15	134,297	70,351	3,484
20	114,969	60,083	3,094
25	96,997	47,619	2,790
30	94,592	35,523	1,817

21st of September			
Number of burned polygons for each burn index			
Buffer distance (km)	dNBR	CSI	MIRBI
5	103,231	81,201	10,493
10	162,317	152,103	26,459
15	165,508	164,146	27,615
20	132,275	141,174	17,011
25	108,449	99,929	11,179
30	95,521	69,754	8,461

5th of November			
Number of burned polygons for each burn index			
Buffer distance (km)	dNBR	CSI	MIRBI
5	47,176	31,523	5,442
10	66,330	51,381	9,342
15	69,178	60,322	11,256
20	56,791	62,228	13,205
25	40,737	45,057	8,721
30	38,303	32,179	7,047

Table 6: Number of burned polygons according to different burn indices for 3 dates in the residues burning season.

These tables can already give us some information. It seems that burning is at its maximum in September time, based on the number of burned polygons for all indices. It seems that closest to the study site (5 km buffer) the number of burned areas is halved between September and November. Furthermore, this allows us to recognize the number of burned areas with regards to distance from the study sites. The number rises with distance as far as 15 km buffer for August and September where it is maximum. In November, the number increases up to 20 km. After this, the number of burns decreases with distance for all dates.

We can attribute this observation to different causes. First of all, promotion of residues retention in the villages sites (5 km) has led to less burning which is visible for each of the dates. The furthest we go from the village, the lower the influence of this promotion is. We can speculate that promotion from CIMMYT is limited to the village and does not extend that far. Information might not be transmitted because the distance is too important to be walked easily, or perhaps the social connections are not very developed amongst those villagers.

Anyhow, farmers start burning their residues again. This distribution could also be linked to cultural and historical factors outside of the promotion. Indeed, there has been many contradictions in agricultural practices promotion in Malawi (Bouwman, 2017). Crop residues retention and ploughing have been on and off promoted throughout history, which can explain why some zones have quite different practices from nearby others.

But why is burning reduced again after a 15 km distance? This could be due to two factors. We are either too far from any villages for any fields to exist, never mind any residues burning. The second option is that at this distance we reach the buffer linked to another study site close by where residue retention promotion has been under way. We can see an example of this with the 10, 15, 20, 25 and 30 km buffers merged together for different study sites (Figure 22). Our observation shows that the latter might be the most frequent cause to explain this phenomenon.

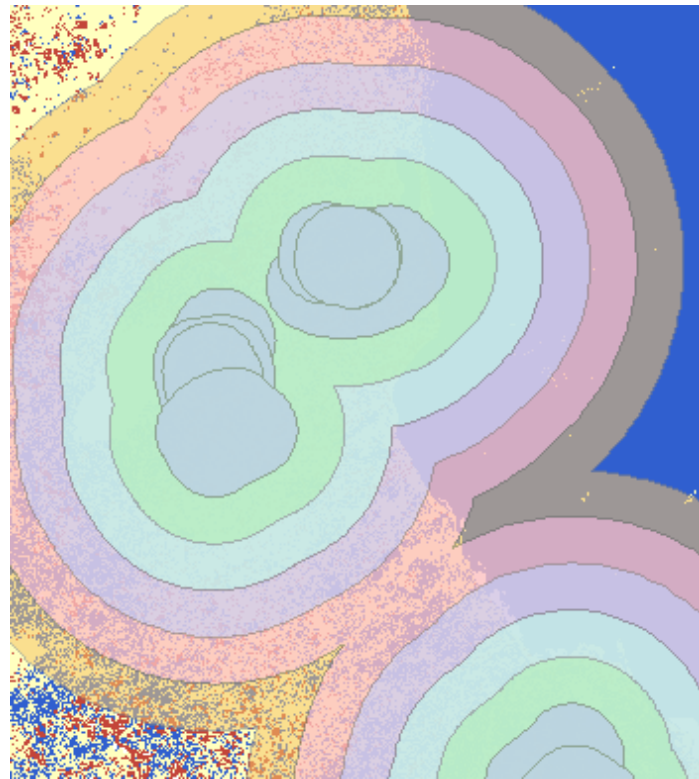


Figure 22: Intersection of buffers for different study sites (zoom on Figure 15 map).

5.2.2. Expert-based classification of burned areas

We gave new pixel values to the combinations of index values described in Table 2 of Material and Method section. In some cases, the combination of indices with a score of five did not exist. This means there was no occurrence where CSI and MIRBI detected a burned area that dNBR failed to detect. This makes sense because CSI is combined with dNBR and MIRBI is the lowest performing index of the three. For some dates, the score four was not assigned to any pixel. This is not surprising knowing that CSI is combined with dNBR so there should in principle be few instances of CSI indicating a burn that dNBR would not detect. The

results of this classification method for each date were depicted in maps (Figure 23). These show the distribution of an array of burn certainty classes in cropland area on the two tiles.

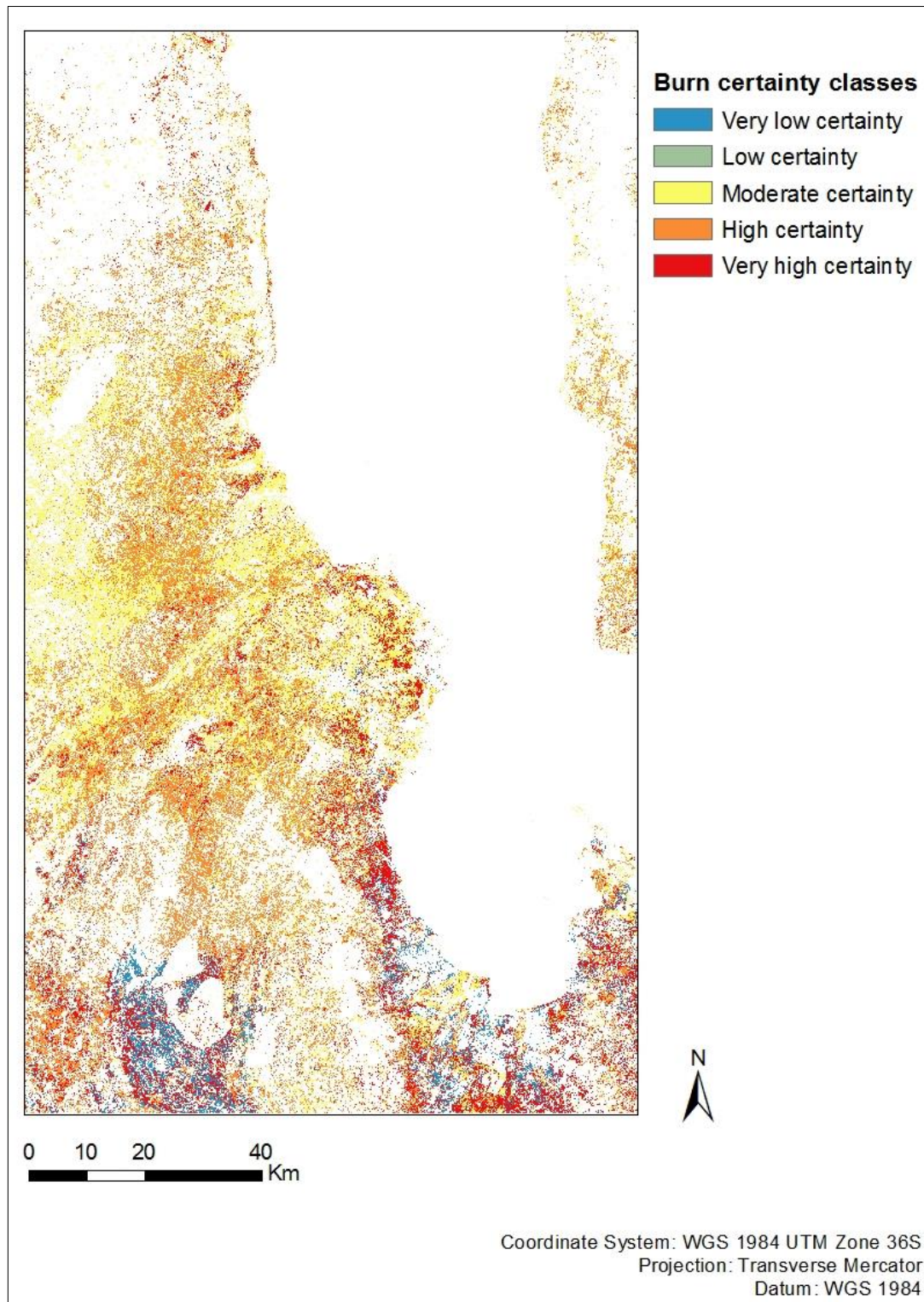


Figure 23: Expert-based classification of burned areas for 5th of November.

Tables 7 to 14 present the confusion matrices for the seven burn season dates available as well as other statistics. In the confusion matrix table, the class 0 corresponds to non-burned

whereas 1 is the burn class. Producer, user, global accuracy as well as misclassification, true positive and false positive rates are all given in percent.

	Expert-based classification 08/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	1762	740	2502		70.4
	1	383	640	1023		62.6
	Total pixels	2145	1380	3525		
User Accuracy		82.1	46.4			

Global accuracy	68.1
Misclassification rate	31.9
True Positive rate	0.6
False Positive rate	0.3

F1 score for burned class	
Precision	0.5
Recall	0.6
F1 score	0.5

F1 score for unburned class	
Precision	0.8
Recall	0.7
F1 score	0.8

Table 7: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 8th of August.

	Expert-based classification 23/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	2300	110	2410		95.4
	1	820	68	888		7.7
	Total pixels	3120	178	3298		
User Accuracy		73.7	38.2			

Global accuracy	71.8
Misclassification rate	28.2
True Positive rate	0.08
False Positive rate	0.05

F1 score for burned class	
Precision	0.4
Recall	0.08
F1 score	0.1

F1 score for unburned class	
Precision	0.7
Recall	1.0
F1 score	0.8

Table 8: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 23rd of August.

	Expert-based classification 12/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	2234	323	2557		87.4
	1	266	690	956		72.2
	Total pixels	2500	1013	3513		
User Accuracy		89.4	68.1			

Global accuracy	83.2
Misclassification rate	16.8
True Positive rate	0.7
False Positive rate	0.1

F1 score for burned class	
Precision	0.7
Recall	0.7
F1 score	0.7

F1 score for unburned class	
Precision	0.9
Recall	0.9
F1 score	0.9

Table 9: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 12th of September.

	Expert-based classification 21/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	212708	349	213057		99.8
	1	862	1385	2247		61.6
	Total pixels	213570	1734	215304		
User Accuracy		99.6	79.9			

Global accuracy	99.4
Misclassification rate	0.6
True Positive rate	0.6
False Positive rate	0.002

F1 score for burned class	
Precision	0.8
Recall	0.6
F1 score	0.7

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 10: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 21st of September.

	Expert-based classification 02/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	2715	327	3042		89.3
	1	255	687	942		72.9
	Total pixels	2970	1014	3984		
User Accuracy		91.4	67.8			

Global accuracy	85.4
Misclassification rate	14.6
True Positive rate	0.7
False Positive rate	0.1

F1 score for burned class	
Precision	0.7
Recall	0.7
F1 score	0.7

F1 score for unburned class	
Precision	0.9
Recall	0.9
F1 score	0.9

Table 11: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 2nd of October.

	Expert-based classification 26/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	766	19	785		97.6
	1	243	202	445		45.4
	Total pixels	1009	221	1230		
User Accuracy		75.9	91.4			

Global accuracy	78.7
Misclassification rate	21.3
True Positive rate	0.5
False Positive rate	0.02

F1 score for burned class	
Precision	0.9
Recall	0.5
F1 score	0.6

F1 score for unburned class	
Precision	0.8
Recall	1.0
F1 score	0.9

Table 12: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 26th of October.

	Expert-based classification 05/11					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	7141611	72398	7214009		99.0
	1	41844	33307	75151		44.3
	Total pixels	7183455	105705	7289160		
User Accuracy		99.4	31.5			

Global accuracy	98.4	F1 score for burned class		F1 score for unburned class	
Misclassification rate	1.6	Precision	0.3	Precision	1.0
True Positive rate	0.4	Recall	0.4	Recall	1.0
False Positive rate	0.01	F1 score	0.4	F1 score	1.0

Table 13: Confusion matrix and statistics for burned and unburned classes with expert-based classification at 5th of November.

The highest global accuracy for the expert-based classification (99.4%) was attained for the 21st of September and the lowest (68.1 %) for the 8th of August. Two dates have a global accuracy superior to 90%.

For almost all dates, confusion matrices show a low user accuracy for the burned class, ranging between 31% for the 5th of November and 91% for the 26th of October. This conveys that a high number of polygons classified as burned were actually not burned in reality. For the November date for instance, 31 out of 100 polygons were incorrectly assigned to the burn class.

The producer accuracy of the burned class sinks even lower for some dates though it is higher for other ones. The lowest one: 7% is found on the 23rd of August. This reflects that burned pixels were often recognized as non-burned. The user and producer's accuracies linked to non-burned pixels all exceed 70%.

F1 score of the unburned class is significantly superior to the burned one for all dates. Once again, this is due to a higher difficulty in the recognition of burned pixels compared to unburned ones. For five out of seven dates, precision of burn class is lower than recall, meaning that among all pixels labelled as burned a small majority is actually unburned. The unburned class presents a lesser difference between recall and precision, and f1 score never falls under 0.8.

In conclusion, non-burned pixels were accurately classified as such in all maps, as shows the f1 scores and high user and producer's accuracies. However, there has been some issue in detection of burned areas and indeed its f1 score is very low. It also appears that on average burned pixels user's accuracy is lower than producer's one. So this means there is a high number of actual unburned pixels in the burned class. But a smaller number of burned pixels were labelled as unburned. Unburned pixels are mistakenly considered as burned. It is

probably due to a threshold setting of the indices that was not optimal, perhaps too low, since too many pixels are included that should not be.

Besides, the two dates in August show the poorest global accuracies and non-burned f1 scores. The beginning of the harvest season should have a lot less field burning than later in the season, the burn indices thresholds should be adapted accordingly compared to later dates. For the 8th of August, burn user's accuracy is particularly low, meaning the threshold was too accepting and many unburned pixels were incorporated as burned. But later in August, an exceptionally low burned producer's accuracy was calculated, the thresholding was too strict, keeping burned pixels outside of the burn class. A lack of adaptation of indices thresholds to the environment explains the poor performance of classification in August. An error could have also been made during the creation step of the validation polygons, for example a confusion between burned and unburned class. As there was less burned ground on the image, it was more difficult to differentiate between it and other land use such as urban zones.

In contrast, September was the period with the highest number of crop residues fires (see section 5.2.1 of this chapter). It is also the most accurate of all classification. The setting of burn indices thresholds seems optimal for a date with a lot of field burning.

Expert-based classification appears very efficient in mapping burned areas when the number of fires in the landscape is high. However, mapping for dates at the early or late season requires more adaption of the indices thresholds, perhaps even the use of several other burn indices. This could be facilitated if there was more literature available, using burn indices in Malawi or in similar conditions area. Some on-ground data listing the number of fires at different dates would be another means of tuning the thresholds more finely.

For the classification products with a sufficient global accuracy (superior to 85%), the number of burned polygons within certain distance ranges of promotions area were counted. We also noted the number of villages in each study area, that is Zidyana, Mwansambo and Salima and the average area of burned polygons on the product. We then were able to calculate numbers of burned agricultural plots, as well as densities of burned plots which are catalogued in Tables 14 to 17.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	977			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2,173	3,204	12,796	16,879	18,220
Density of burned fields within certain distance (number/km ²)				
0.038	0.029	0.021	0.021	0.018
Density in overlapping areas (number/km ²)				
		0.53	0.060	0.027

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	977			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2,222	2,626	13,526	28,168	32,787
Density of burned fields within certain distance (number/km ²)				
0.031	0.024	0.019	0.030	0.025

Salima				
Number of villages	Mean polygon area (m ²)			
20	977			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2,080	3,294	22,656	34,914	26,856
Density of burned fields within certain distance (number/km ²)				
0.028	0.026	0.026	0.023	0.010

Table 14: Number of burned fields in each area identified with expert-based approach for the 21st of September.

In the three areas, number of burned fields increases with distance to the promotion village. The biggest leap occurs between the 3-5 km and 5-10 km ranges. There must be a close by village with a high amount of burned areas in both cases. But in Salima, over 15 km the number decreases strangely. It appears there is a burning epicentre just around the promotion village that appears from 5 km outwards. The density of burned fields declines with distance in Zidyana and Salima. In Mwansambo, density of burning decreases until the 10-15 km range, where it goes back to the value of the 3 km buffer. When we look at the overlap regions between Zidyana's and Mwansambo's buffers, the density is indeed superior when the concerned area is smaller.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	2			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2.7	5.7	11.4	18.0	20.0
Density of burned fields within certain distance (number/km ²)				
0.097	0.11	0.045	0.058	0.044
Density in overlapping areas (number/km ²)				
		1.4	0.17	0.079

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	2			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2.3	3.0	14.8	26.8	36.2
Density of burned fields within certain distance (number/km ²)				
0.083	0.061	0.058	0.086	0.079

Salima				
Number of villages	Mean polygon area (m ²)			
20	2			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2.3	4.1	18.2	28.4	26.3
Density of burned fields within certain distance (number/km ²)				
0.081	0.082	0.069	0.064	0.032

Table 15: Number of burned fields in each area identified with expert-based approach for the 2nd of October.

For the 2nd of October, all areas seem to have comparable number of burned plots for each distance range. In Salima and Mwansambo the number increases with distance as we assumed. However, in Zidyana there is a higher number of burned fields within the promotion village than 20 km away from it, this might be an error in the calculation or one coming from earlier in the classification step. In Salima, the density declines with the distance to the promotion centre, as the area gets bigger. In both Mwansambo and Zidyana, density drops with the buffer's distance, rises in the 15 km buffer and then decreases again.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	0.34			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1.1	1.5	5.3	6.6	8.3
Density of burned fields within certain distance (number/km ²)				
76.8	63.8	50.3	54.3	40.0
Density in overlapping areas (number/km ²)				
		1372	171	71.3

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	0.34			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
0.9	1.2	4.8	9.3	11.3
Density of burned fields within certain distance (number/km ²)				
78.5	52.3	53.2	90.5	71.9

Salima				
Number of villages	Mean polygon area (m ²)			
20	0.34			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
0.8	1.3	6.8	10.1	8.1
Density of burned fields within certain distance (number/km ²)				
73.5	65.6	0.2	0.2	0.07

Table 16: Number of burned fields in each area identified with expert-based approach for the 5th of November.

At 5th of November, there are a lot less burned field overall. The number 0.9 and 0.8 are probably due to an approximation of decimals in the calculation and we can suppose they equal to one burned field. The burned areas number increases very slowly with distance from the promotion area to attain a maximal of between 8 and 11. Once again, for Salima burning decreases with increasing distance to promotion centre. But density gets smaller with the distance until 10 km, where it slightly increases and then decreases again, in the Zidyana and Mwansambo region.

In total, there seems to be ten times or more burned fields in September, than in October and November. This confirms the findings from Section **Erreur ! Source du renvoi introuvable.** of the Results and Discussion as well as the visual assumption we made. Furthermore, 21st of September had the most accurate classification so we can give more credit to those burned field numbers than the ones for the two other dates.

Overall, burned field density decreases with an increase in the distance buffers in Salima. This makes sense, since the area becomes bigger for each buffer, so the density gets smaller. For the two other locations, the density of burned fields is highest in the 3 km buffer,

then it gets smaller with distance until the 15 km buffer, where it rises. It is hard to say what this is due to, but there seems to be a lot of burned fields closer to each other inside the 15km buffer. Looking at the map, this dense field burning mostly seem to be just between the two sites, South and South-West of Zidyana and East of Mwansambo (Figure 24). Overlapping areas between Zidyana and Mwansambo show high density because of the small area concerned. According to this method, burned field density in the whole landscape appears to be at its maximum in November, and drops to extremely low values for the August date. This proves the interest of analysing also the density and not only the numbers of burned fields, as we can draw different conclusions from both.

Finally, in September time Mwansambo was subject to more burning than the two others. In October, we can observe the least amount of burns in Zidyana area. And in November, all areas have a very similar number of burns. Overall, in terms of the number of burned polygons surrounding the sites Mwansambo was first, followed by Zidyana and Salima.

Down below are two maps showing the distribution and quantity of burned polygons around the study areas for the 2nd of October (Figure 24). According to the map, a region completely void of burned fields is visible west of the Mwansambo area as well as southeast to a lesser degree. In the West lies mountains, which include no fields whatsoever, and southeast of Mwansambo is a river surrounded by shrub-land and a few fields. Around Zidyana, there is a very dense network of burned fields, mostly a flat agricultural region. This stops at the shore of Lake Malawi. Salima is surrounded by a high number of burned fields as well. The gap directly in the North of the villages in black corresponds to a river and grasslands and all along the East is the shore of the lake again.

We can confirm visually the results from Table 15, indeed there is a higher number of burned polygons very close to the Zidyana villages, than further away. Moreover, Salima and Zidyana have a very similar number of burned polygons in each distance range around them.

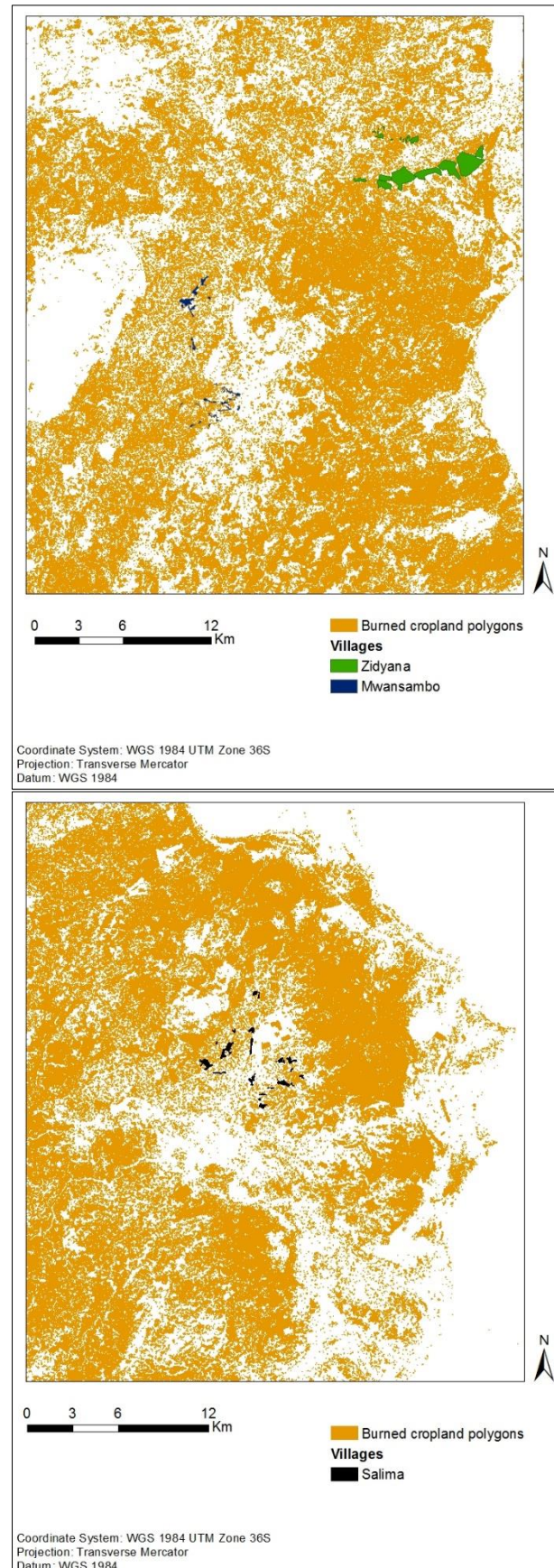


Figure 24: Map of burned polygons identified by expert-based classification around the study areas for the 2nd of October.

5.2.3. Maximum Likelihood algorithm for burned area mapping

A maximum likelihood algorithm was applied to seven dates from August to November on both tiles (Figure 25) As a cropland mask was applied, the maps show only burned and unburned zones situated inside cropland area.

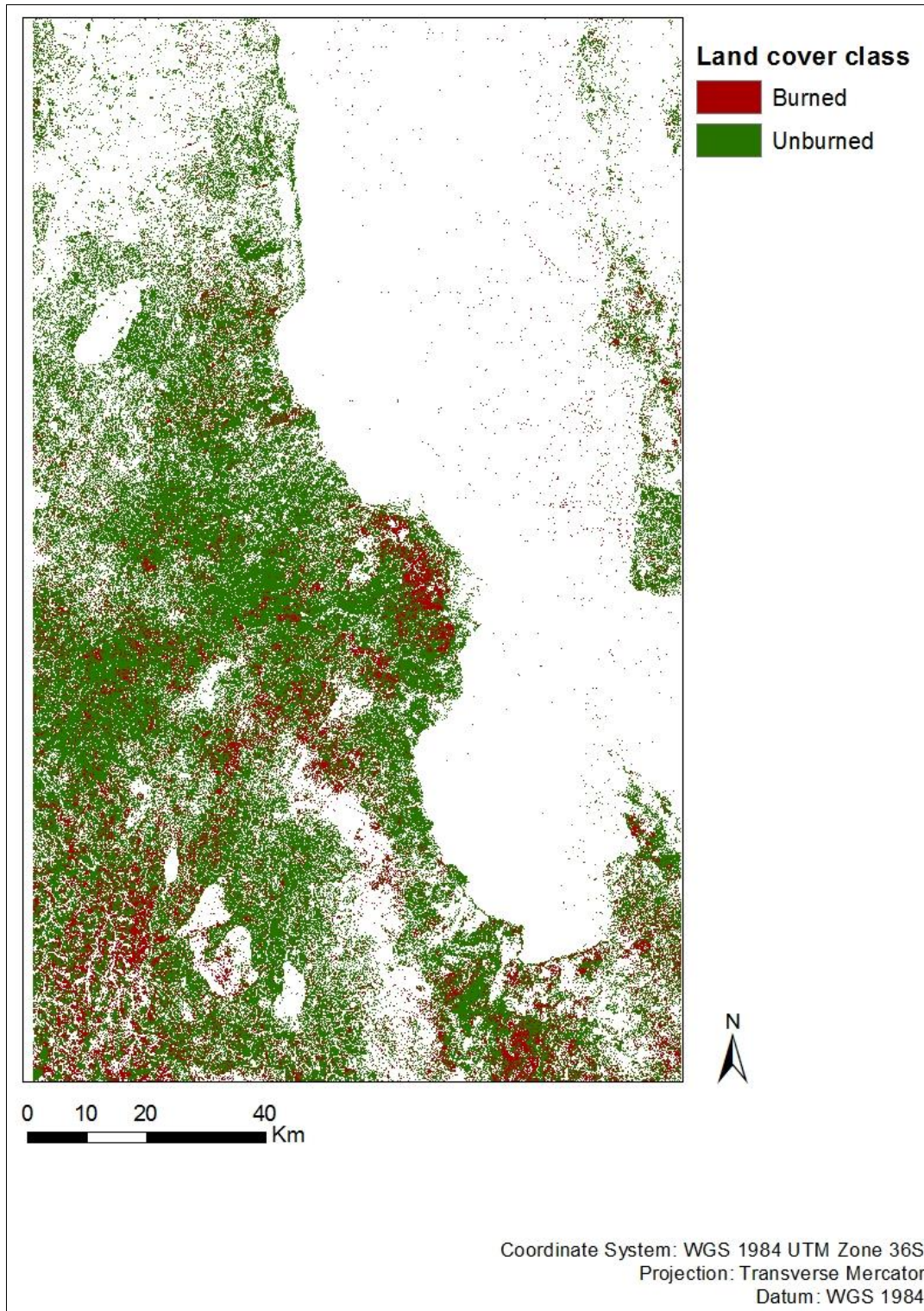


Figure 25: Maximum likelihood classification of burned and unburned cropland for the 21st of September.

The cropland mask was able to filter out with a great deal of detail Lake Malawi, other water bodies as well as some mountainous areas that do not bear any fields.

Tables 17 to 23 present the confusion matrices, f1score calculations and other statistics for the seven dates studied. In the confusion matrix table, the number 0 represents the non-burned class while the class 1 corresponds to burned. Producer, user, global accuracy as well as misclassification, true positive and false positive rates are all given in percent.

	Maximum likelihood classification 08/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	1071	22	1093		98.0
	1	20	722	742		97.3
	Total pixels	1091	744	1835		
User Accuracy		98.2	97.0			

Global accuracy	97.7
Misclassification rate	2.3
True Positive rate	1.0
False Positive rate	0.02

F1 score for burned class	
Precision	1.0
Recall	1.0
F1 score	1.0

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 17: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 8th of August.

	Maximum likelihood classification 23/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	782	10	792		98.7
	1	17	623	640		97.3
	Total pixels	799	633	1432		
User Accuracy		97.9	98.4			

Global accuracy	98.1
Misclassification rate	1.9
True Positive rate	1.0
False Positive rate	0.01

F1 score for burned class	
Precision	1.0
Recall	1.0
F1 score	1.0

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 18: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 23rd of August.

	Maximum likelihood classification 12/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	874	14	888		98.4
	1	4	699	703		99.4
	Total pixels	878	713	1591		
User Accuracy		99.5	98.0			

Global accuracy	98.9
Misclassification rate	1.1
True Positive rate	1.0
False Positive rate	0.02

F1 score for burned class	
Precision	1.0
Recall	1.0
F1 score	1.0

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 19: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 12th of September.

	Maximum likelihood classification 21/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	212724	333	213057		99.8
	1	1248	999	2247		44.5
	Total pixels	213972	1332	215304		
User Accuracy		99.4	75.0			

Global accuracy	99.3
Misclassification rate	0.7
True Positive rate	0.4
False Positive rate	0.002

F1 score for burned class	
Precision	0.8
Recall	0.4
F1 score	0.6

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 20: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 21st of September.

	Maximum likelihood classification 02/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	3006	36	3042		98.8
	1	17	925	942		98.2
	Total pixels	3023	961	3984		
User Accuracy		99.4	96.3			

Global accuracy	98.7
Misclassification rate	1.3
True Positive rate	1.0
False Positive rate	0.01

F1 score for burned class	
Precision	1.0
Recall	1.0
F1 score	1.0

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 21: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 2th of October.

	Maximum likelihood classification 26/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	149	3	152		98.0
	1	10	316	326		96.9
	Total pixels	159	319	478		
User Accuracy		93.7	99.1			

Global accuracy	97.3
Misclassification rate	2.7
True Positive rate	1.0
False Positive rate	0.02

F1 score for burned class	
Precision	1.0
Recall	1.0
F1 score	1.0

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 22: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 26th of October.

	Maximum likelihood classification 05/11					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	35701	101897	137598		25.9
	1	43066	4073	47139		8.6
	Total pixels	78767	105970	184737		
User Accuracy		45.3	3.8			

Global accuracy	21.5
Misclassification rate	78.5
True Positive rate	0.09
False Positive rate	0.7

F1 score for burned class	
Precision	0.04
Recall	0.09
F1 score	0.05

F1 score for unburned class	
Precision	0.4
Recall	0.3
F1 score	0.3

Table 23: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 5th of November.

For all dates in the season, global accuracy reaches between 97.3 and 99.3%, except for the 5th of November, which shows a surprisingly low global accuracy of 21.5%. The maximum likelihood classification overall was more accurate in mapping burned areas than the expert-based one. This is rather unexpected since the expert-based method is constructed with indices specifically designed to detect burned areas. However, it requires manual setting of indices thresholds, which can be complex whereas maximum likelihood uses only spectral signatures of both categories to assign classes.

The f1 score once again reveals a better performance in classifying unburned pixels than burned ones. It is indeed very slightly lower for every date, except the 21st of September. In three dates out of seven, recall of the burn class is below the precision. This signifies that the classification did assign incorrectly quite a bit of real burned pixels. For the rest of dates, when precision is lower, it reflects that some of the identified burned pixels were not burned in reality.

The user and producer accuracy for both classes are usually superior to 90%. The exception are the user and producer's accuracy of the burn class for 21st of September and all the accuracies for 5th of November. For September, apparently some unburned pixels were assigned to the burn class. But the main issue is with the producer accuracy meaning a lot of burned pixels were classified as unburned. This could be linked with a confusion of the spectral signature of burned field being too close to that of some other land use for example build-up surfaces of a similar colour shade.

For the 5th of November, the classification performance appears very poor in all aspects. The burn class user accuracy of 4% shows an important confusion of true unburned and burned pixels, the recognition of burns is not optimal. The reason for this is definitely a bad definition of the burn class by using samples that are not representative enough, for

instance non-homogenous burned areas that accidentally include unburned pixels. This could be critical in the performance of the classification. Errors during the creation of validation polygons could be another possibility.

Tables 24 to 28 present the number and density of burned fields for six dates around each study area. The November date was not taken into account, since its global accuracy was too low. Indeed, the calculation was realized for each classification product with a global accuracy superior to 85%.

Zidyana				
Number of villages	Mean polygon area (m ²)			
17	1,783			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,569	1,956	7,803	8,947	9,450
Density of burned fields within certain distance (number/km ²)				
55.4	39.0	30.7	28.6	20.7
Density in overlapping areas (number/km ²)				
		662	79.7	35.8

Mwansambo				
Number of villages	Mean polygon area (m ²)			
20	1,783			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
682	729	4,905	12,024	16,175
Density of burned fields within certain distance (number/km ²)				
24.1	14.5	19.3	38.7	35.5

Salima				
Number of villages	Mean polygon area (m ²)			
20	1,783			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
902	2,028	12,108	23,028	31,068
Density of burned fields within certain distance (number/km ²)				
31.9	40.4	45.9	52.0	38.2

Table 24: Burned plots identified in each study area with maximum likelihood for the 8th of August.

In early August, the number of burned plots was increasing with distance. Salima region had the highest number of burned plots. However, there was an unusually high number of burned fields around the Zidyana villages compared to the other ones.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	320			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
0.3	0.6	0.9	0.1	0.8
Density of burned fields within certain distance (number/km ²)				
0.011	0.011	0.0035	0.0003	0.002
Density in overlapping areas (number/km ²)				
		0.05	0.004	0.001

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	320			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
0	0	0	0.9	0.2
Density of burned fields within certain distance (number/km ²)				
0	0	0	0.003	0.0005

Salima				
Number of villages	Mean polygon area (m ²)			
20	320			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
162	423	2,301	4,917	7,025
Density of burned fields within certain distance (number/km ²)				
5.7	8.4	8.7	11.1	8.6

Table 25: Burned plots identified in each study area with maximum likelihood for the 23rd of August.

Mwansambo presented no burned areas until the 10 to 15 km range. It seems like the promotion was very efficient in that region. In Zidyana and Salima, the number raised in accordance with distance. There was an exception with a decline in field number for Zidyana between 10 and 15 km.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	809			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
191	233	1,195	1,516	1,428
Density of burned fields within certain distance (number/km ²)				
17.1	11.8	11.9	12.3	7.9
Density in overlapping areas (number/km ²)				
		272	36.0	14.5

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	809			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
699	1,493	10,881	2,236	2,662
Density of burned fields within certain distance (number/km ²)				
5.0	6.0	8.7	18.2	14.8

Salima				
Number of villages	Mean polygon area (m ²)			
20	809			
Number of burned plots within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
162	423	2,301	4,917	6,034
Density of burned fields within certain distance (number/km ²)				
14.5	20.3	21.6	26.5	17.1

Table 26: Burned plots identified in each study area with maximum likelihood for the 12th of September.

As seen in the table, a higher number of burned fields was found in Mwansambo close to the promotion site comparatively to the other areas. But the number decreased over the 10-15 km range. There was less residues burning in Zidyana overall and a lot more going further away than 10 km from the Salima area.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	1,079			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
422	519	3,561	5,622	5,637
Density of burned fields within certain distance (number/km ²)				
14.9	10.3	14.0	18.1	12.4
Density in overlapping areas (number/km ²)				
		410	57.3	23.2

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	1,079			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
275	584	4,300	9,457	10,960
Density of burned fields within certain distance (number/km ²)				
9.7	11.6	16.9	30.4	24.1

Salima				
Number of villages	Mean polygon area (m ²)			
20	1079			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
162	511	2,054	4,698	6,384
Density of burned fields within certain distance (number/km ²)				
5.7	10.2	7.8	10.6	7.8

Table 27: Burned plots identified in each study area with maximum likelihood for the 21st of September.

Around the 21st of September, the furthest away from the promotion village, the more burned fields were detected, and this occurred for all the study sites. However, the numbers overall were superior in Mwansambo compared to Salima.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	1,941			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
2,510	3,283	11,225	13,569	15,671
Density of burned fields within certain distance (number/km ²)				
88.7	65.4	44.2	43.6	34.4
Density in overlapping areas (number/km ²)				
		968	110	49.8

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	1,941			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
462	1,228	7,344	15,308	19,951
Density of burned fields within certain distance (number/km ²)				
16.3	24.4	28.9	49.2	43.8

Salima				
Number of villages	Mean polygon area (m ²)			
20	1,941			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
982	283	5,691	12,030	14,475
Density of burned fields within certain distance (number/km ²)				
34.7	5.64	21.6	27.2	17.8

Table 28: Burned plots identified in each study area with maximum likelihood for the 2nd of October.

Similarly, for this date, more field burning occurred furthest away from the village centre. The exception was a diminution of burned field numbers in Salima around 3 to 5 km.

Zidyana				
Number of villages	Mean polygon area (m ²)			
20	1,413			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,145	1,487	6,534	8,077	8,685
Density of burned fields within certain distance (number/km ²)				
40.5	29.6	25.7	26.0	19.1
Density in overlapping areas (number/km ²)				
		547	64.1	28.8

Mwansambo				
Number of villages	Mean polygon area (m ²)			
17	1,413			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
336	642	3,950	8,803	11,892
Density of burned fields within certain distance (number/km ²)				
11.9	12.8	15.5	28.3	26.1

Salima				
Number of villages	Mean polygon area (m ²)			
20	1,413			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,366	1,598	6,445	10,744	7,682
Density of burned fields within certain distance (number/km ²)				
48.3	31.8	24.4	24.3	9.44

Table 29: Burned plots identified in each study area with maximum likelihood for the 26th of October.

Salima showed the highest number of burned fields close to the promotion centre but a diminution around the 15 to 20 km range. For the two other sites, increase in number followed the distance. Mwansambo had lower numbers than Zidyana close to the village but the tendency inverted after the 10-15 km mark.

Looking across the whole residues burning season, 2nd of October seemed to have the highest number of it and 23rd of August had very low numbers or even no burning in some sites. The tendency overall for each date is for the number to rise with the distance to a promotion village. With some dates and sites, this observation is not verified and the number declines for some distance ranges. Between all sites, Salima had the highest presence of burned fields in its surroundings, followed closely by Mwansambo and then Zidyana, which showed a lower number. Observation of maps can help us understand why this is. Salima has a very dense zone of burned fields in the South and Northeast. Mwansambo has quite an even

amount all around it, except eastward. Finally, Zidyana is very close to Lake Malawi and another lake, which must play a part in reducing this number.

Concerning the density of burned fields in comparison with the distance to the promotion centre, it is quite variable between dates and regions. The Zidyana region shows, at four dates out of the six, a constant decrease in burned fields density with the distance. This is probably linked to the increase in area when we go further from the promotion village. For the other dates, the density decreases until we reach the 10 km buffer where it starts increasing again up to the 20 km buffer, where density gets smaller. The case is similar for almost all dates and region, where the maximum density occurs at either the 10 or 15 km buffer. There must be a high occurrence of burning at 10 to 15 km from the promotion centres. This is visible east and southeast of Mwansambo, as well as north of Zidyana and south of Salima (Figure 26). However, for all dates, obviously burning density is higher in the smallest and lower in the biggest of overlapping regions between Zidyana and Mwansambo. Finally, burned fields density reaches the highest values on average for the 26th of October and 23rd of August and are abnormally low for the late August date. The results are quite different for the numbers and density calculation, which proves the importance of exploring both.

All those complex considerations make it that much harder to conclude over which promotion site has been the most efficient. At first glance, it appears that Zidyana has been effective in its action and less farmers burn fields around it. It also seems that farmers continue to burn crop residues quite a lot around the Salima area.

As we saw in Figure 24, Zidyana is surrounded by dense burned polygons with the exception of the shore of Lake Malawi to the East; the number of burned fields is quite high for all distance ranges. There is a front of burned fields to the East of Mwansambo but not to the West and Southwest, which are more mountainous areas. The close proximity of Salima villages is void of burned fields, but the number increases if we look further to the Southeast and South (Figure 26). This is in accordance with the numbers from Table 38.

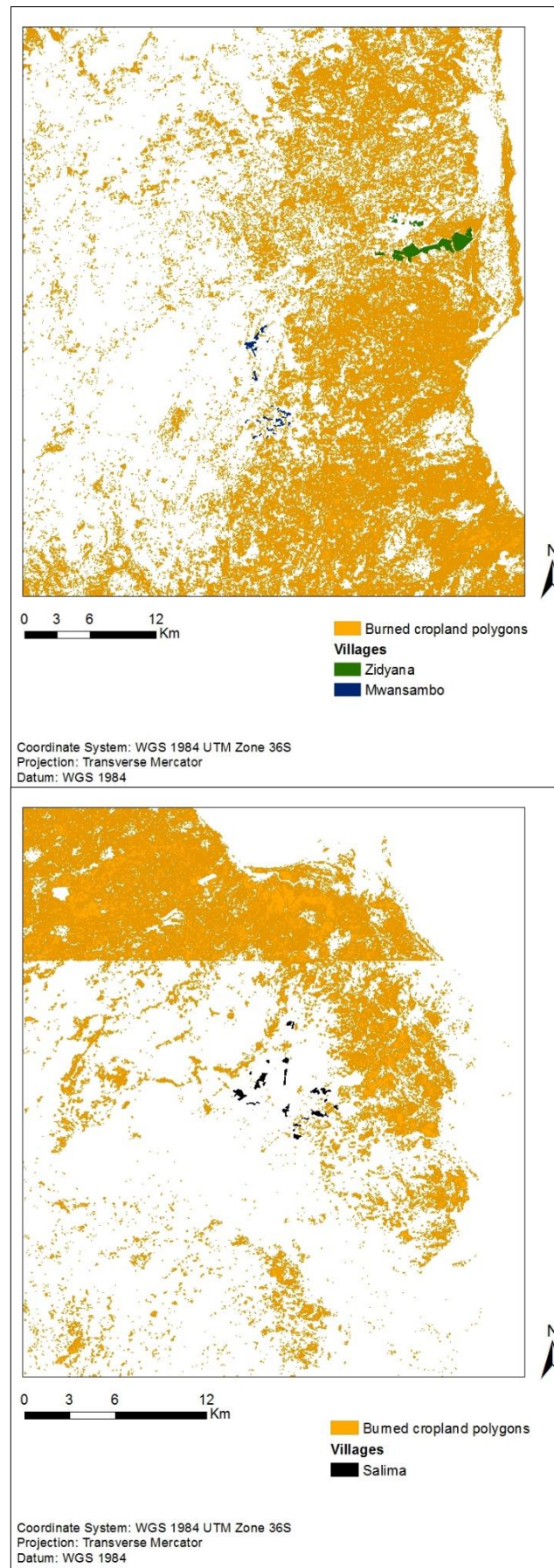


Figure 26: Map of burned plots identified by maximum likelihood classification for the 21st of September.

5.2.4. Random forest classification of burned areas using Sentinel-2 for Agriculture

As explained in the Material and Method section, we have loaded a set of polygons into the Sentinel-2 for Agriculture system in order to obtain a L4B Crop Type Map. This was realized for the dates specified in the aforementioned section. An example map is presented below as well as statistics for all dates.

First, we tested the efficiency of the system with polygons created on the 21st of September. We could then choose the parameters that allowed the best accuracy in order to classify for all the other dates.

Ratio of training to validation polygons	0.50	0.66		0.75		0.80	
Presence of additional L-8 images	No	No	Yes	No	Yes	No	Yes
Global accuracy	99.5	99.4	99.5	99.5	99.3	99.4	99.4
F1-score burned	0.6	0.7	0.6	0.6	0.5	0.5	0.5
F1-score unburned	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 30: General statistics of crop type maps for various parameters at 21st of September.

In general, a ratio of 0.75 training to validation polygons shows a slightly higher accuracy than for the other ratios. The use of Landsat-8 satellite images increases accuracy for the 0.66 ratio, which might be linked to a more suitable spectral resolution of this satellite, though the spatial resolution is lower. The unburned class's f1 score is equal for all those parameters. It appears that it is the maximum possible value, there is always a small remainder of unburned land that is not classified. The f1 score for the burn class varies between 0.5 and 0.7; recall is responsible in keeping this number low. The number of true burned pixels correctly and incorrectly classified are very similar. Thus, some spectral characteristics of burned areas cause confusion with other land covers or the samples of burned areas were not very representative of this class. The most accurate crop type map is visible down here (Figure 27), Lake Malawi and mountain ranges are classified correctly in the 'Other' class. However, roads and rivers are confused as cropland, probably because they are narrow and enclosed in fields. The different crop classes: rice, groundnuts and maize are not necessarily well differentiated, as explained in section 4.3.2.5 of the Material and methods chapter.

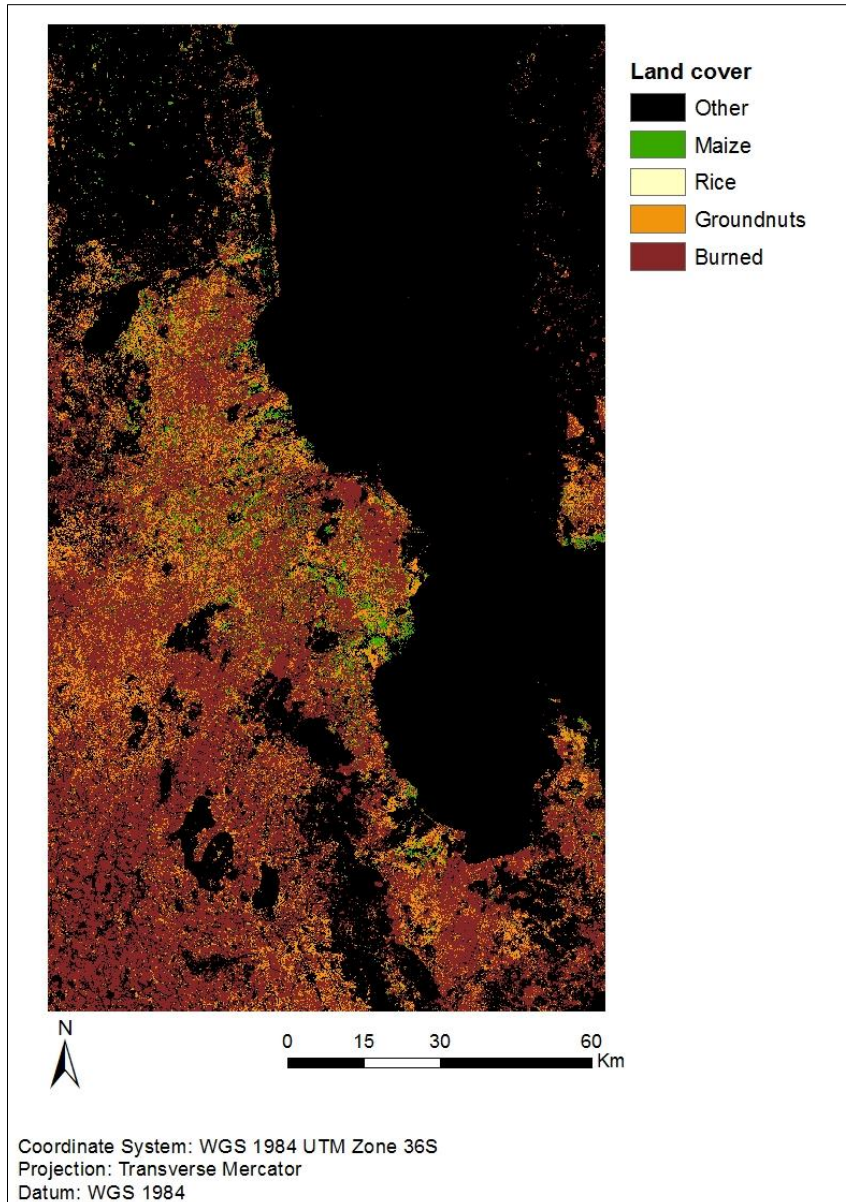


Figure 27: Highest accuracy Sentinel-2 for Agriculture map at 21st of September

For all remaining dates, we used the parameters that presented the highest accuracy, namely a 0.75 ratio with no Landsat-8 image. The confusion matrices and statistics are available down below. In the confusion matrix table, the class 0 is linked to unburned and the class 1 corresponds to burned. Producer, user, global accuracy as well as misclassification, true positive and false positive rates are all given in percent.

	Random forest classification 08/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	3245	209	3454		93.9
	1	327	798	1125		70.9
	Total pixels	3572	1007	4579		
User Accuracy		90.8	79.2			

Global accuracy	88.3
Misclassification rate	11.7
True Positive rate	0.7
False Positive rate	0.06

F1 score for burned class	
Precision	0.8
Recall	0.7
F1 score	0.7

F1 score for unburned class	
Precision	0.9
Recall	0.9
F1 score	0.9

Table 31: Confusion matrix and statistics for burned and unburned classes with random forest classification at 8th of August.

	Random forest classification 23/08					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	2642	71	2713		97.4
	1	155	1403	1558		90.1
	Total pixels	2797	1474	4271		
User Accuracy		94.5	95.2			

Global accuracy	94.7
Misclassification rate	5.9
True Positive rate	0.9
False Positive rate	0.03

F1 score for burned class	
Precision	1.0
Recall	0.9
F1 score	0.9

F1 score for unburned class	
Precision	0.9
Recall	1.0
F1 score	1.0

Table 32: Confusion matrix and statistics for burned and unburned classes with random forest classification at 23rd of August.

	Random forest classification 12/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	2928	440	3368		86.9
	1	369	766	1135		67.5
	Total pixels	3297	1206	4503		
User Accuracy		88.8	63.5			

Global accuracy	82.0
Misclassification rate	18.0
True Positive rate	0.7
False Positive rate	0.1

F1 score for burned class	
Precision	0.6
Recall	0.7
F1 score	0.7

F1 score for unburned class	
Precision	0.9
Recall	0.9
F1 score	0.9

Table 33: Confusion matrix and statistics for burned and unburned classes with random forest classification at 12th of September.

	Random forest classification 21/09					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	212909	148	213057		99.9
	1	968	1279	2247		56.9
	Total pixels	213877	1427	215304		
User Accuracy		99.5	89.6			

Global accuracy	99.5
Misclassification rate	0.5
True Positive rate	0.6
False Positive rate	0.001

F1 score for burned class	
Precision	0.9
Recall	0.4
F1 score	0.6

F1 score for unburned class	
Precision	1.0
Recall	1.0
F1 score	1.0

Table 34: Confusion matrix and statistics for burned and unburned classes with random forest classification at 21st of September.

	Random forest classification 02/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	3929	58	3987		98.5
	1	298	969	1267		76.5
	Total pixels	4227	1027	5254		
User Accuracy		93.0	94.4			

Global accuracy	93.2
Misclassification rate	6.8
True Positive rate	0.8
False Positive rate	0.02

F1 score for burned class	
Precision	0.9
Recall	0.8
F1 score	0.8

F1 score for unburned class	
Precision	0.9
Recall	1.0
F1 score	1.0

Table 35: Confusion matrix and statistics for burned and unburned classes with random forest classification at 2nd of October.

	Random forest classification 26/10					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	4209	56	4265		98.7
	1	485	1281	1766		72.5
	Total pixels	4694	1337	6031		
User Accuracy		89.7	95.8			

Global accuracy	91.0
Misclassification rate	9.0
True Positive rate	0.7
False Positive rate	0.01

F1 score for burned class	
Precision	0.9
Recall	0.7
F1 score	0.8

F1 score for unburned class	
Precision	0.9
Recall	1.0
F1 score	0.9

Table 36: Confusion matrix and statistics for burned and unburned classes with maximum likelihood classification at 26th of October.

	Random forest classification 05/11					Producer Accuracy
Sentinel-2 polygons		0	1	Total pixels		
	0	4322	12	4334		99.7
	1	418	1200	1618		74.2
	Total pixels	4740	1212	5952		
User Accuracy		91.2	99.0			

Global accuracy	92.8	F1 score for burned class		F1 score for unburned class	
Misclassification rate	7.2	Precision	1.0	Precision	0.9
True Positive rate	0.7	Recall	0.7	Recall	1.0
False Positive rate	0.003	F1 score	0.8	F1 score	1.0

Table 37: Confusion matrix and statistics for burned and unburned classes with random forest classification at 5th of November.

Global accuracy for the random forest-based classification ranges from 82 to 99.5%. 5 dates out of the 7 show a high accuracy, superior to 90%. The dates in early August and early September are the ones with the lowest accuracies. Global accuracies are slightly inferior than for the maximum likelihood method. However, they are more consistent here because maximum likelihood showed one outlier date with an extremely low accuracy.

The burned class producer accuracy is always the lowest in the confusion matrix (between 56.9 and 90.0%). This signifies that a high number of burned pixels are classified as unburned. The shapefile must not contain enough representative homogenous burned samples to have a really clear signature. Otherwise, the signature of burned area could be quite similar to another land use, which could cause error.

For every date, f1 score of the burned class is lower than the one for the unburned category. The recall is the one keeping the f1 score to a low value. Some of the actual burned areas are incorrectly put in the unburned class. This is probably an issue of a poor definition of the burn field signature. The f1 score for unburned class is superior to 0.9 in all situations; the varied unburned areas are very well recognized.

The main source of error in this classification could be due to the use of a cropland mask as basis for the crop type map. Indeed, this implies that fields smaller than 0.25 ha are not recorded as cropland and thus will not appear in the burned class. Furthermore, perhaps some more samples of burned areas were required, or we maybe were not careful enough in choosing homogenous uniformly burned areas. Including even a tiny bit of unburned pixels inside one of the samples could slightly false the results. However, the Sentinel-2 for Agriculture random forest algorithm looks perfectly performant in detecting practices on fields and not only the type of crops cultivated.

We have chosen every date for which the classification product showed a global accuracy over 85% (all but the 12th of September). The burned polygons classified were converted into a likely number and density of burned fields, following the same procedure as previously. Tables 38 to 43 presents the numbers for several distance ranges from a promotion centre.

Zidyana				
Number of villages	Average polygon area (m²)			
20	1,336			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
750	9,28	2,313	3,250	4,494
Density of burned fields within certain distance (number/km²)				
26.5	18.5	9.10	10.4	9.86
Density in overlapping areas (number/km²)				
		373	37.2	16.4

Mwansambo				
Number of villages	Average polygon area (m²)			
17	1,336			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,263	1,301	4,832	6,545	7,230
Density of burned fields within certain distance (number/km²)				
44.6	25.9	19.0	21.0	15.9

Salima				
Number of villages	Average polygon area (m ²)			
20	1,336			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,007	1,291	4,743	6,092	7,972
Density of burned fields within certain distance (number/km ²)				
35.6	25.7	18.0	13.8	9.8

Table 38: Burned plots identified in each study area with random forest for the 8th of August.

Similar to the other methods, burned fields numbers increase constantly in relation to the distance from the villages. The burning overall is more widespread in Mwansambo and a lot rarer in Zidyana. In Salima, densities show a constant decrease, as the buffer got larger, but in the two other areas, there is an exception to this trend with a higher density in the 15 km buffer.

Zidyana				
Number of villages	Average polygon area (m ²)			
20	1,288			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
236	347	1,433	1,946	1,925
Density of burned fields within certain distance (number/km ²)				
8.33	6.90	5.64	6.25	4.22
Density in overlapping areas (number/km ²)				
		178	22.6	9.47

Mwansambo				
Number of villages	Average polygon area (m ²)			
17	1,288			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
218	273	1,974	4,009	4,852
Density of burned fields within certain distance (number/km ²)				
7.70	5.44	7.76	12.9	10.6

Salima				
Number of villages	Average polygon area (m ²)			
20	1,288			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
464	550	2,033	4,055	4,403
Density of burned fields within certain distance (number/km ²)				
16.4	10.9	7.70	9.16	5.41

Table 39: Burned plots identified in each study area with random forest for the 23rd of August.

The number of burned fields decreases for the largest buffer in Zidyana. But for all other sites, numbers increase with the distance to the promotion village. For all buffers, except the last one, Salima shows the most burning, just a bit over Mwansambo and a lot higher than in Zidyana. Density in relation to the distance follows the same pattern in all areas. It actually decreases up until 15 km, where density rises, then gets smaller again at 20 km.

Zidyana				
Number of villages	Average polygon area (m ²)			
20	888			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
619	768	2,176	2,347	3,115
Density of burned fields within certain distance (number/km ²)				
21.9	15.3	8.56	7.54	6.84
Density in overlapping areas (number/km ²)				
		295	28.0	12.5

Mwansambo				
Number of villages	Average polygon area (m ²)			
17	888			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,234	1,038	3,476	5,030	5,807
Density of burned fields within certain distance (number/km ²)				
43.6	20.7	13.7	16.2	12.7

Salima				
Number of villages	Average polygon area (m ²)			
20	888			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
883	1,359	4,883	7,291	8,858
Density of burned fields within certain distance (number/km ²)				
31.2	27.1	18.5	16.5	10.9

Table 40: Burned plots identified in each study area with random forest for the 21st of September.

As pointed out before, when the distance to a promotion site increases, the burned field numbers do too. This is the case everywhere, except in Mwansambo the number was lower for the 5 km buffer than for the 3 km one. This could be linked to an error during the process, or perhaps an effect of the promotion that would decrease burning at this distance. In Salima and Zidyana, burned fields density follows the natural trend of decreasing, as the area of the buffer rises. This is not the case in Mwansambo, where there is a peak in density in the 15 km buffer.

Zidyana				
Number of villages	Average polygon area (m²)			
20	2,570			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
625	744	2,948	3,802	3,908
Density of burned fields within certain distance (number/km²)				
22.1	14.8	11.6	12.2	8.58
Density in overlapping areas (number/km²)				
		391	45.1	17.8

Mwansambo				
Number of villages	Average polygon area (m ²)			
17	2,570			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
879	1,061	4,551	8,070	8,838
Density of burned fields within certain distance (number/km ²)				
31.1	21.1	17.9	25.9	19.4

Salima				
Number of villages	Average polygon area (m²)			
20	2,570			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
932	1,259	4,099	7,026	8,486
Density of burned fields within certain distance (number/km²)				
32.9	25.1	15.5	15.9	10.4

Table 41: Burned plots identified in each study area with random forest for the 2nd of October.

On the early October date, numbers increase constantly in relation with the distance to the promotion centre. Residues burning appears more commonplace in Salima for the closest buffers. But from 10 km onwards, it is Mwansambo that shows more burning than Salima. Densities display the same behaviour for all regions, they get smaller as the buffer gets larger, with the exception of the 15 km one where they increasing slightly.

Zidyana				
Number of villages	Average polygon area (m ²)			
20	2,802			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
942	1,168	3,507	3,676	4,591
Density of burned fields within certain distance (number/km ²)				
33.3	23.3	13.8	11.8	10.1
Density in overlapping areas (number/km ²)				
		425	42.0	17.4

Mwansambo				
Number of villages	Average polygon area (m²)			
17	2,802			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
1,335	1,376	4,645	7,391	7,844
Density of burned fields within certain distance (number/km²)				
47.2	27.4	18.3	23.8	17.2

Salima				
Number of villages	Average polygon area (m ²)			
20	2,802			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
577	1,145	4,636	6,750	8,743
Density of burned fields within certain distance (number/km ²)				
20.4	22.8	17.6	15.2	10.7

Table 42: Burned plots identified in each study area with random forest for the 26th of October.

On this date, for all sites, the number of burned fields is increasing with the distance to the promotion area. Amongst all areas, the numbers are highest in Mwansambo up to the 15 km buffer, and then Salima takes the lead. Zidyana, again, shows a lot less burning. In Mwansambo, density of burned fields decreases with the distance buffers, except 20 km away, when it gets higher. However, there was a constant decrease of the density once we move away from the centres, in both Salima and Zidyana.

Zidyana				
Number of villages	Average polygon area (m ²)			
20	2,839			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
508	632	2,527	2,999	2,794
Density of burned fields within certain distance (number/km ²)				
18.0	12.6	9.94	9.64	6.13
Density in overlapping areas (number/km ²)				

Mwansambo				
Number of villages	Average polygon area (m ²)			
17	2,839			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
413	617	2,893	5,980	6,965
Density of burned fields within certain distance (number/km ²)				
14.6	12.3	11.4	19.2	15.3

Salima				
Number of villages	Average polygon area (m ²)			
20	2,839			
Number of burned fields within certain distance (km)				
0-3	3-5	5-10	10-15	15-20
824	1,016	3,330	6,755	6,953
Density of burned fields within certain distance (number/km ²)				
29.1	36.6	19.6	26.9	23.2

Table 43: Burned plots identified in each study area with random forest for the 5th of November.

Each site for the six dates shows an increase in burned field numbers linked with distance to the promotion centre. The only exception is a slight decline in burning between the 0-3 and 3-5 km ranges in Mwansambo for the 21st of September. Following the same logic as before, the burning practice seems more common in Salima and the number of burned fields are a lot higher, especially from 10 km outwards. However, this is not the case for the 2nd and 26th of October where Mwansambo actually presents more burning. For several dates, Mwansambo also has a higher number of burns close to the promotion site than Salima but this situation reverses when we move away from it.

A constant trend is for Zidyana to have a low number of burned fields compared to the other sites. This could be linked to a better efficiency of CA promotion. But we should not reject that the position of Zidyana and its proximity to water bodies is another possible cause.

We can also observe the density of burned fields depending on the distance to promotion sites in the landscape. For most dates and regions, including all the Mwansambo area, the density gets lower with distance, but rises in the 15 km buffer, before decreasing

again in the 20 km buffer. As pointed out for the maximum likelihood method, there is a very important density under 3 km but also at 15 km from the promotion centres. We can see a very dense cloud of burned polygons on a small surface northeast of Salima, as well as just in the middle of the other sites (southwest of Zidyana and east of Mwansambo) (Figure 28). For half of the dates in the Salima and Zidyana region, burning density decreases with the distance, which is logical since the buffer area gets greater and greater. Density was more important overall for the 8th of August and 26th of October, and the lowest density appeared for the late August date.

Regarding time dynamics, August shows a significantly lesser number of burned fields. Crop residues burning is more widespread in October and late September. The number declines in November. This was similar to the results found with the maximum likelihood product. Still, the density and number of burned fields across time does not seem to correspond, the maximum and minimum for both occur at a different date.

The results from Table 38 to 43 are confirmed if we look at a map of burned polygons in the different areas (Figure 28). We can easily observe that more burning occurs around Salima, it is denser along the coast from 15 km. There is a gap in burned polygons in the Northwest, corresponding to a high elevation shrub area and one in the South, where the river is. As we discovered in the tables, Zidyana has few burned areas around it, especially not in the mountainous zones in the South and lakes in the vicinity. There are a high number of burned fields close to the Mwansambo centre, a number that decreases in the South and East. Those zones without burned fields match with mountainous forests seen on the composites.

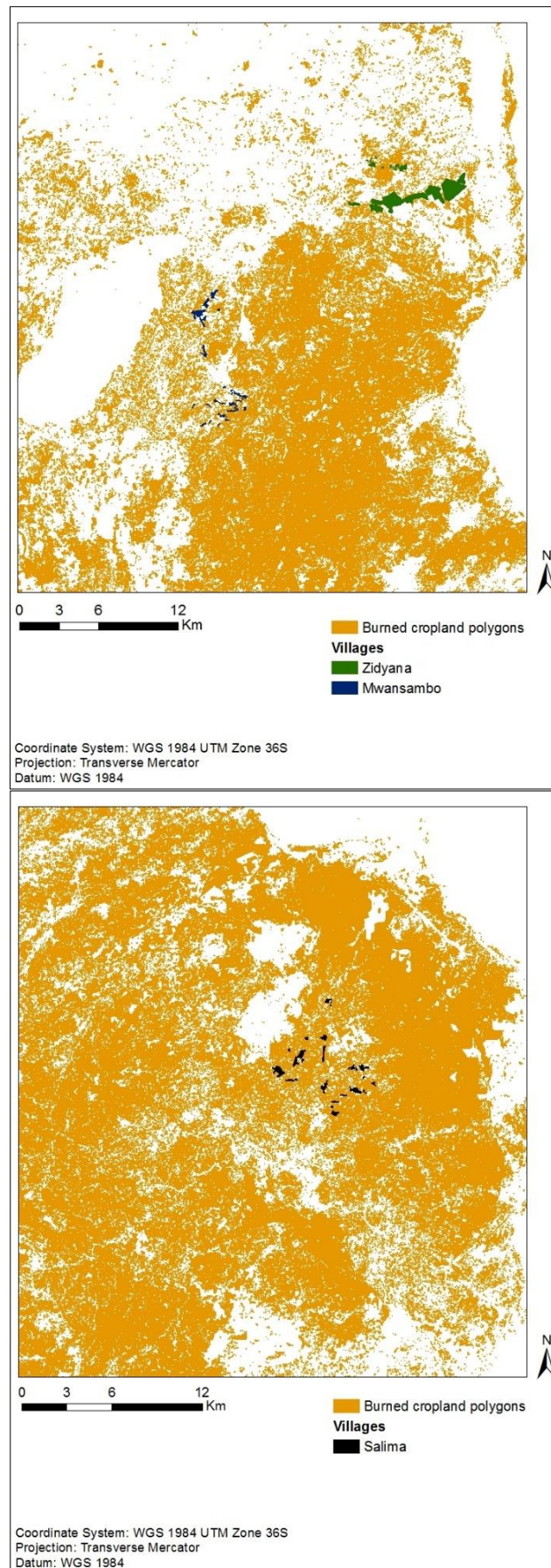


Figure 28: Map of burned plots identified by random forest classification for the 21st of September.

5.3. Interpretation of results from the agricultural survey

A master student from Wageningen University, Tristin Bouwman, realized a survey on Malawian farmers' agricultural practices in July of 2016. 275 households were included in the survey. They were situated in the Zidyana and Mwansambo in Nkhosachota district and Tembwe in Salima district. Those regions were chosen because they seemed very susceptible to be adopting CA practices. Indeed, livestock herding is not a prevalent activity (which means crop residues are generally more available to farmers) and CA has been actively and long-lastingly promoted there, namely with CIMMYT on-farm trials. The questions covered general characteristics of plots, adoption of various CA practices and the reasons behind the adoption or lack thereof. Specifically, it also asked questions about crop residues burning and retention.

Burning in fields is a very common practice in rural Malawi, it does not happen only to empty the field from the previous harvest residues. Amongst all 367 plots, 80 had residues disappearing because of burning for land clearing, 61 burned for mice hunting and 4 for disease control reasons. This means that in total, 145 plots had had burning at some point in the season, that is 39.5% of all plots surveyed. This is only the number in promotion villages, we do not have information on the rest of the region. Furthermore, 52% of tilled plots had burning of residues for diverse reasons, 31 % of fields with in-situ crop residues retention and 18 % of fields with residues brought from the outside were burned. This proves that even when residue retention is planned, burning can still occur.

77 out of 184 randomly selected households practiced some kind of crop residues retention, either with residues brought from outside the field or not. However, these results seem to show that even among non-burned fields, there is not necessarily any residues retention, some residues can be used for other purposes such as feeding livestock for a minority of them or being brought to other plots. Nonetheless, there is still incorporation of residues on tilled land even if less common than on untilled land. "Putting the differences in the amount of losses and the causes of losses together, it is evident that NT (untilled) systems have reduced residue losses and that this is primarily caused by a reduction burning at land clearing" (Bouwman, 2017). It seems according to the survey's results and this affirmation that untilled fields undergo less burning of residues and so retention promotion is efficient in some ways.

Still, burning is the most convenient means to get rid of weeds when herbicides are not available, so it will probably continue to be practiced.

However, this survey does not allow us to compare with villages outside of the promotion centre. But it provides some leads in how to interpret our results. For instance, it is not unlikely to see burned fields just next to a promotion centre, as we have found for each study area and date. Besides, burning of crop residues can still happen on plot that will later undergo crop retention.

The promotion of conservation agriculture was pushed in Salima, Zidyana and Mwansambo since 1996 (Bouwman, 2017). Salima, especially, had a very high number of demonstration plots in the 1990's. Later, the NGO Total Land Care has promoted CA application and research more intensely in Zidyana and Mwansambo for at least 10 years (Thierfelder *et al.*, 2016). Those two sites and the CIMMYT/TLC collaboration have registered a high number of adopters comparatively to other countries and sites (Bouwman, 2017). There

is no recent research about the Salima promotion area, but a fair assumption is that there is a less intense promotion there nowadays. We can hypothesize that, in Zidyana and Mwansambo, the residue-burning practice should be less commonplace than in Salima. Is this effectively the case?

As we already explained in section 4.3.3 of Material and methods, our method to deduce burned fields number is not optimal. Indeed, we will overestimate smaller burned area and underestimate bigger ones. For this reason, the number of burned plots obtained are just estimation of the number of fields and their distribution in the landscape, but not exact figures.

We will not give as much credit to the expert-based classification since its global accuracy was on average lower. Thus, we only calculated burned fields number for three dates out of the seven. But for these, burning occurred more often in Mwansambo and Zidyana than Salima. For the other two methods, we can compare the distribution of burned fields in the landscape around the promotion sites better. According to the random forest method, in Salima, the burning practice seems more widespread in the distance and a bit less near the promotion centre. Mwansambo overall has a high number of burned fields but mostly close to the village and Zidyana has the lowest amount. This is verified in the maximum likelihood classification.

Concerning the density of burned areas, methods showed similar results. It generally became smaller with distance to the promotion site, then rose to quite a high value in the 10 or 15 km buffer, then decreased again in the 20 km one. There seems to be a tendency to have higher numbers of burned fields per square kilometres at 10 to 15 km from the promotion villages. Of course, density is mostly higher in the 3 km buffer, because even if there are few burned fields they are scattered around a limited area. So, this could indicate a highest concentration of burning at 10 and 15 km, considering the surface. It might be a sign of a distance effect in discouragement of residues burning. That is to say, retention promotion appears efficient up until 10 km from the site, then its influence is less noticeable and burning density is more important. For some dates, in Salima and Zidyana, the density just followed a natural trend of decreasing with the distance to the site. This just expresses that the buffer area increases with distance, making density number decrease. Burned fields density did not follow the same trend as the actual numbers of fields, similarly to what we discovered for the maximum likelihood method.

The month of October was the densest in residues burning according to the maximum likelihood method. August and November had a lesser number of burned fields all over the landscape. This is validated by the results of the random forest classification. Finally, according to the expert-based approach, September displayed most of the burning, which declined more and more as we approached the end of the year.

If we cross these information, Salima in October presents the highest number of burned areas. And as we move to the North, the practice seems less and less widespread, and similarly as time passes to the humid season. The assumption that there might be less impact of the retention promotion in Salima seems correct. However, the multitude of other factors, such as the physical characteristics of the area could also explain why that is.

Conclusion and perspectives

We will first dive into the core question of this thesis: the efficiency of CA initiatives in Malawi. Were we able to provide an acceptable answer for this?

Regarding the intermediate steps of this work, a reliable cropland mask was necessary in order to filter burns of agricultural origins from other burns. The Sentinel-2 for Agriculture system managed to produce a cropland mask with an accuracy of 90.6%, though only if we used a set of input polygons. Without input polygons, the accuracy dropped to 36 up to 64%. UAV imagery available proved really valuable in the creation of detailed cropland and non-cropland training and validation polygons.

The expert-based classification using burn indices has shown rather unconvincing results with a global accuracy very variable between the dates. A higher accuracy was found in recognizing burned areas with the random forest algorithm included in the Sentinel-2 for Agriculture system. Finally, the maximum likelihood algorithm reported an extremely high performance overall, over 97%, albeit one outlier low accuracy date. Contrary to some of the results found in literature, a thresholding approach of burn indices was not optimal to map burn areas. This can be attributed to a wrong choice of the indices or their thresholds or a lack of basis empirical data. Random forest is not commonly used in burn areas mapping and the performance is moderate in literature (Holden *et al.*, 2009), comparatively to the very high accuracy obtained in our context. More research needs to be conducted about random forest algorithm for the detection of burned areas, to have more reference points. Maximum likelihood supervised classification methods were as accurate as in literature (Chang *et al.*, 2013), even without the on-ground burned field samples.

On the topic of the efficiency of CA promotion, it is hard to give a proper conclusion. We have been looking at CA adoption as being opposed to the practice of crop residues burning. But we know now that they are not in direct link with each other as burning and residues retention can happen on the same plot. And sometimes neither of those practices are applied. With this in mind, we can still study the distribution of burned fields in the landscape and in relation to promotion areas. Overall, burned field numbers tended to increase consistently with the distance to the three promotion centres considered. We have found the highest numbers of burned fields in proximity to the Mwansambo site or in the south of the Salima site. This spatial distribution was not modified by the time dynamics. Regarding the season, analysis of the most accurate results shows there is not yet a high number of burned fields in August. The majority of overall burning occurs around October. When the rainy season starts, in November, the practice tends to become rarer.

In general, there was a high density of burned fields in a 3 km circle around the promotion village, due to the limited area considered. There was also a peak in density at a 15 km distance for a lot of the dates. This could signify that residues retention promotion loses its influence when we go further away from the village, since burning looks more concentrated for this buffer. In that sense, burning density calculation brought new insights that we did not get from the field numbers analysis.

As we reach the end of this thesis, it is time to reflect upon the complementary objectives we chose to set ourselves. Remote sensing, and especially UAV, can be considered as effective in detecting farming practices. UAV with its very high spatial resolution was a valuable tool to recognize the types of crop and the features of the landscape. Differentiating diverse practices such as plowing, crop residues burning, or crop residues retention was also very straightforward. Sentinel-2 imagery has a 10 to 20 m spatial resolution, which is not sufficient to distinguish which crops are cultivated, or which practices are applied. This issue might be exacerbated due to the small size of plots in Malawi. The resolution could also explain some of the shortcomings of the chosen burn indices to accurately map burned areas.

We also planned on comparing the household survey data with our results in number of burned fields. However, this was not possible because the coordinates of the plots treated with a certain practice were not available to us. Furthermore, the survey was realized only in the promotion focus villages of Mwansambo, Zidyana and Tembwe (in the Salima district) and not further away from it. Therefore, we could not see how the practices shifted outside of those and compare with our burned fields numbers through distance ranges.

A pursuit of this survey in other villages would have been very useful to confirm the results from the three different classification methods. Besides, coordinates and details about actual burned fields could have been taken on-ground in the Central Region of Malawi. This would have added a lot of perspective and information to this work and confirm some of the results we obtained. Unfortunately, the visit that was first planned had to be cancelled due to time concerns. The broadness of the question raised in this thesis caused some issues. First, it made it difficult not to get overwhelmed and engage in too many paths at once. There were a lot of techniques and tools available that could have been tested or delved into. For instance, we could have made a greater use of the high-quality UAV imagery. But it was necessary to narrow the question and methods used, which took a long time. However, this leaves a lot of possibilities for people wanting to go further into this subject. A study of the two other conservation agriculture principles and their adoption in this region would have been relevant and extremely interesting. It is a great perspective for the future research. More studies exploring conservation agriculture adoption in other regions of Malawi or neighbouring countries could really provide information to clarify our results.

This master thesis constituted a real learning experience. We obviously gained knowledge on conservation agriculture and its promotion in a development context but also on remote sensing and analysis methods. Beyond this, an array of other competences was solicited. It was our first occasion to really investigate a theme intensely for a whole year, in this sense it taught us time management and how to keep motivation. We also had to find workarounds and creative solutions to avoid getting stuck in some issues. This thesis was a way to get familiarized with scientific literature as well as to learn to summarize and draw information from it. We also discovered the vastness of remote sensing literature and that burned area mapping has been studied extensively, though not through an agricultural practice angle.

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Detecting crop residues burning using Sentinel-2 imagery: conservation agriculture promotion in Central Malawi

Présenté par Lisa Hammarström

Résumé

Malawi is a country which struggles with food security and where a performant agriculture is particularly important. NGO's and the government have a history of developing projects and initiatives to try to improve agriculture's productivity. The most widely promoted technique in Malawi historically has been conservation agriculture (CA). The question we scrutinized through this study was that of one particular practice under this umbrella, namely crop residues retention. This practice conflicts with the residues burning tradition, which we chose to observe via remote sensing. The study area was the Central Region of Malawi and specifically the three conservation agriculture promotion sites of Zidyana, Mwansambo and Salima. We focused on the residues burning season of 2016: from early August to November.

We have tested three pixel-wise classification methods based on Sentinel-2 satellite imagery. The first one was an expert-based classification combining three different burn indices. The second was a maximum likelihood classification and the last one was a random forest algorithm set out through the Sentinel-2 for Agriculture system. We then calculated statistics of the performance of those methods. The maximum likelihood method showed the highest accuracies, all over 97% (except for an outlier dates). Random forest showed a good performance as well, whereas the expert-based classification was rather inconsistent with values ranging from 68 to 99%. The distribution of burned fields across space and time was explored, which allowed calculating numbers and densities of burned fields. Seasonally, burning occurs more rarely in August and reaches a peak mostly in September and October and is less practiced in November. Spatially, our analysis has shown a higher prevalence of the burning practice in the Salima region. For all sites, the trend is for the number to increase with distance to the promotion site. We could infer that promotion of CA has been effective in Central Malawi, more so in the more established promotion sites of Zidyana and Mwansambo. Time dynamics have shown that burning occurs mainly at the end of the dry season. It is less common the more we approach the humid season's beginning, where harvest does not take place anymore. Nonetheless, our method to obtain field numbers and densities is flawed and possibly overestimate the number which makes it hard to draw any conclusions. We can in any case rely on the visual interpretation of burned areas maps obtained with the three methods.

This master thesis is a proof that remote sensing can be a valuable tool in assessing CA practices adoption. UAV is without a doubt even more accurate and useful in this context than satellite imagery. However, contrary to our hypothesis, residues burning is not necessarily a suitable proxy to grasp adoption of crop residue retention in the landscape.

Keywords: Remote sensing, Conservation agriculture, Crop residues burning, Sentinel-2, Residues retention, Malawi