

Faculty of Bioscience Engineering

Assessing cropland abandonment in rural conflict areas using satellite imagery in humanitarian contexts.

**The case of Baga and Dikwa
Borno province, Nigeria.**

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List of acronyms

ACLED	Armed Conflict Location and Event Data Project
ASAP	Anomaly Hotspots of Agricultural Production
BH	Boko Haram
DTM	Displacement Tracking Matrix
EOS	End of Season
ESA	European Space Agency
EU	European Union
FCC	False color composite
GED UCDP	Georeferenced Event Dataset Uppsala Conflict Data Program
GEE	Google Earth Engine
GIS	Geographical Information Systems
IDP	Internally Displaced Person
INGO	International Non-Governmental Organizations
IOM	International Organization for Migration
ISWAP	Islamic State's West Africa Province
JRC	EU Commission's Joint Research Center
LGA	Local Government Area
MNJTF	Multinational Joint Task Force
MODIS	Moderate-Resolution Imaging Spectroradiometer
MOS	Middle of Season
MVC	Maximum Value Composite
NAF	Nigerian Armed Forces
NDMI	Normalized difference moisture index
NDVI	Normalized difference vegetation index
NGO	Non-Governmental Organizations
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
PS	Planetscope
RF	Random Forests
S2	Sentinel-2
SAR	Synthetic Aperture Radar
SOS	Start of Season
UNHCR	United Nations High Commissioner for Refugees
VAM	Vulnerability Analysis and Mapping
VHR	Very High (spatial) Resolution
WFP	World Food Programme

Chapter 1. Introduction

Agriculture remains a vital component of the economy in many developing countries, particularly in rural areas where most of the population relies on farming for their livelihood. Cropland abandonment, especially in conflict-affected regions, has significant implications for food security, health, and socio-economic stability. In this context, endeavors to assess land abandonment of croplands in rural conflict areas have been implemented by numerous organizations and governments.

Understanding the dynamics of cropland abandonment in these conflict-affected regions can help inform policy-making and resource allocation for rehabilitation and recovery efforts. Estimating the dynamics of the conflict, the population displacement and the agricultural changes is crucial to assist affected populations.

Remote sensing is widely defined as the detection of phenomenon and collecting data from a distance. Satellite imagery offers a powerful tool to monitor land-use changes, including cropland abandonment, in regions where ground-based assessments are difficult, expensive, or dangerous. In recent years, advancements in remote sensing technology and the increased availability of high-resolution satellite imagery have significantly improved our ability to detect and quantify land abandonment. Combining this data with internally displaced people (IDP) data and conflict data allows for a more comprehensive understanding of the factors contributing to land abandonment in conflict areas and the subsequent impacts on rural communities.

Organizations such as the World Food Programme (WFP) have been monitoring cropland abandonment in hard to reach conflict areas for the past few years, especially in the north-eastern state of Borno and north-western states of Zamfara (WFP, 2022). In these areas conflict and insecurity have led to population displacement and significant loss in cropland thus diminishing food production and increasing population vulnerability.

While studies have mostly shown cropland abandonment at a provincial level without considering other factors such as the population displacement or the conflict data. This master thesis's endeavor will be to identify patterns between conflict, affected population displacement and their monitoring through high resolution satellite imagery. Moreover, on-ground monitoring can be dangerous in areas of conflict, time-consuming, and expensive, remote sensing can bring an answer to some of these challenges while establishing a strict, 'simple but not simplistic' methodology that can assist the humanitarian response.

Chapter 2. Literature review

This literature review synthesizes the current knowledge on the use of satellite imagery to assess cropland abandonment in conflict-ridden rural areas. This will allow to define the master thesis's scientific contribution, to develop an experimental protocol inspired by current research and justify the choices regarding the methodology and hypothesis.

2.1. Detection and change detection for cropland abandonment.

Detecting croplands and performing their change detection can be a challenge for several reasons. Data can be heterogeneous over years and may not be collected regularly due to the nature of modern conflicts. This makes it difficult to track and map cropland abandonment on larger temporal and spatial scales (Eklund et al., 2017). Most studies on cropland abandonment rely on medium resolution satellite images which may not provide sufficient detail for crop reflectance (Chen et al., 2022; Hazaymeh et al., 2022; Jaafar & Woertz, 2016). Although very high-resolution data is available, it is often expensive and not widely used (Olsen et al., 2021; Witmer, 2009). Challenges can also be methodological as detecting cropland abandonment can vary on the environment and datasets used (Witmer, 2009). WFP has been using the *Sen2Agri* system (Defourny et al., RSE2019) which facilitates the Sentinel-2 time series to provide code, algorithms and best practices to detect and monitor croplands.

2.1.1. Detecting croplands with satellites

To classify the croplands correctly, we first need to identify the patterns of the crops. Most commonly in literature, this can be done by identifying the crops using their growing season.

This method is called “Temporal NDVI Change Detection”. It involves analyzing the differences in Normalized Difference Vegetation Index (NDVI) values between the start, mid and end of the growing season to identify croplands. By comparing these differences to defined thresholds, you can create binary images that differentiate croplands from other types of vegetation. The final step combines the binary images to produce a map highlighting the cropland areas.

Other methods are also used to detect croplands, such as identifying the maximum value composite (MVC) of the NDVI (max green) or the maximum value composite of the RED band (max red). Finally, a visual inspection using very high resolution (VHR) imagery can be used to identify croplands. These methods are rarely combined in literature to identify cropland abandonment; thus this study will attempt to combine the aforementioned methods.

Chen et al. (2022) focuses on the Yangtze River Economic Belt in China to assess the risk of farmland abandonment using multiple aspects, including topographic conditions, climate, soil context, and utilization conditions. The assessment reveals that farmland abandonment risk has

strong spatial heterogeneity, and the NDVI time series change detection validates the risk assessment system.

Hazaymeh et al. (2022) used a time series analysis of the NDVI from Landsat-5 and Landsat-8 images between 1986 and 2021 to monitor abandoned cropland in the Yarmouk River Basin. They analyzed agricultural phenological profiles and investigated the impact of the Syrian crisis on cropland abandonment.

Valero et al. (2016) discusses through the report of a benchmarking study, the construction of a dynamic cropland mask for agricultural monitoring using Sentinel-2 data and temporal NDVI timeseries. The mask is a binary map of annual-cropland/no-annual-cropland, produced several times during the growing season. The authors used feature extraction and classification techniques, comparing one pixel-based and two object-based strategies.

Dara et al. (2018) developed a trajectory-based NDVI change detection approach to identify cropland abandonment between 1988 and 2013 and recultivation between 1991 and 2013. They used an annual time series of cropland probabilities derived from Landsat imagery, which resulted in reliable maps.

Eklund et al. (2017) distinguished cropland from other land uses by analyzing the distinct phenology of different vegetation types with NDVI and identifying the seasonal profile using 250 m MODIS satellite-based time-series data.

Wei et al. (2021) focused on analyzing the spatial and temporal pattern of changes in abandoned farmland in Hebei, China using multispectral images from Sentinel-2A, Landsat-7. The researchers developed rules for the identification of abandoned farmland and carried out remote sensing monitoring of the abandonment status of the cultivated land in the study area.

2.1.2. Change detection method : post-classification comparison.

Change detection methods in remote sensing involve the analysis and comparison of satellite images captured at different time intervals to identify and quantify changes occurring in each area. These methods play a crucial role in detecting various land use types including cropland abandonment (Jin et al., 2016). According to the literature the most performant method is to use the post-classification comparison (Olsen et al., 2021). However, methodologies are context sensitive as change detection methods can vary depending on the environment and various datasets to detect cropland abandonment in conflict. Vegetation especially can have an impact on how some sensors like Landsat would be efficient in dense vegetation areas such as in Europe but may need recalibration when used in the Sahel region (Witmer, 2009).

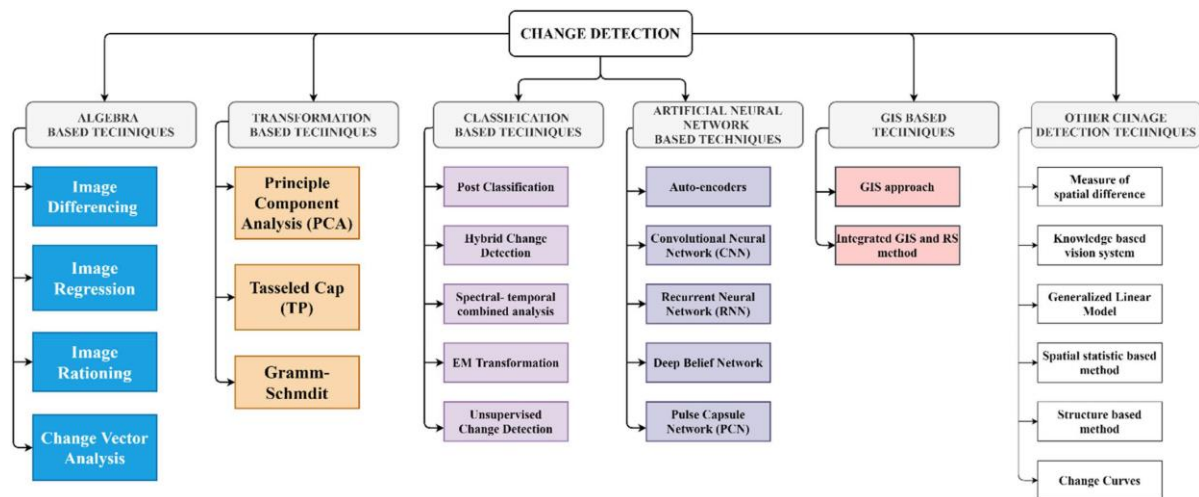


Figure 1: Variety of change detection methods in remote sensing (Afaq & Manocha, 2021)

This method involves classifying images independently and then comparing the resulting thematic maps to identify changes. The classification can be done using various algorithms where each image is classified into a set of land cover classes based on the spectral, spatial, or temporal properties of the pixels. The classification outputs are then compared pixel-by-pixel and changes are quantified. The output is a change map that highlights areas with the land cover transitions. In the endeavor to make the methodology simple but not simplistic, less time consuming and to be applicable anywhere on the globe especially in humanitarian contexts, this was the chosen technique. This technique seems the most appropriate as it is less prone to radiometric differences and can thus account for changes in the calibration or atmospheric conditions between images. It can also be blended with other sources of remote sensing data such as synthetic aperture radar (SAR), multispectral and hyperspectral. However, this method has a strong dependence on the classification accuracy, and we may encounter error propagation. This method is also intensive computationally when dealing with complex classification algorithms such deep learning. The expertise of the analyst is also taken in count as the expert defines the classes. If the pixels are mislabeled, then the detected change will be falsified.

Goswami et al. (2022) discussed ideas on improving the classification accuracy of machine learning techniques by reviewing training samples and comparing post-classification comparison with image differencing in the algebraic technique. The experimental results showed that the post-classification comparison method produced better results compared to the image algebra change detection technique.

Asokan and Anitha (2019) looked at the literature by the unit of analysis and the comparison method used to identify change, providing a clearer view of the field. It identifies seven units of analysis and six comparison methods, describing their advantages and limitations within a change detection workflow. The pixel and post-classification comparison are the most popular

choices, and their review provided guidance for applied change detection research and future benchmarking experiments.

Tewkesbury et al. (2015) addresses the increasing complexity and disparity of remote sensing change detection techniques due to the constant development of new methods and algorithms. The authors provide an overview of current change detection approaches, identifying seven units of analysis and six comparison methods, while highlighting the advantages and limitations of each within a change detection workflow. Among these approaches, pixel and post-classification change methods remain the most popular choices. Their review supports future research by clearly separating the analysis unit and the post-classification comparison method, offering guidance for applied change detection research.

Hu et al. (2018) used the post-classification comparison in a multi-year setting as the study aims to describe the urban wetland resources and their changes over time. The study demonstrated the advantages of using multi-year high resolution satellite imagery to provide an accurate analysis in land cover over time. Their multi-temporal and high-resolution satellite imagery proved the efficiency of the post-classification comparison method and argued by providing the “from-to” change information, the landscape transformations can be calculated and mapped easily.

2.1.3. Multi-sensor and multi-year approaches

In the context of change detection for croplands, multi-sensor, multi-year methods have emerged as an effective approach to monitor and analyze agricultural land use dynamics over time. By integrating data from multiple remote sensing sensors and spanning several years in the form of time series, these methods provide comprehensive and accurate information on cropland changes. By fusing data from these complementary sensors, researchers can achieve more reliable and accurate change detection results. Additionally, multi-year methods allow for the assessment of long-term trends, seasonal variations, and inter-annual variability in cropland changes, which are crucial for understanding agricultural land use dynamics and their impact on food security, water resources, and ecosystems.

Olsen et al. (2021) employed a multi-sensor, multi-year approach to assess the relationship between cropland abandonment and armed conflicts. The research used ~7,500 multisource satellite images from Sentinel-1, Sentinel-2, Landsat-8, and MODIS. By processing and combining these datasets, they ensured high-quality land cover classification in Google Earth Engine (GEE). The study leveraged the strengths of each sensor by integrating optical and synthetic-aperture radar (SAR) data to overcome individual limitations allowing for a comprehensive analysis of cropland changes in South Sudan from 2016 to 2018. Optical sensors provided high spatial and spectral resolution, while SAR sensors offered consistent data coverage unaffected by weather conditions. The study showcased the effectiveness of this approach in detecting cropland changes and informing timely aid provision in conflict-affected, food-insecure regions like South Sudan.

Wei et al. (2021) also used a similar approach to analyze spatial and temporal patterns of abandoned farmland in China. They utilized multispectral images from Sentinel-2A, Landsat-7, and Landsat-8 satellites, combined with random forest (RF) classification and vegetation index change detection methods. The study focused on the period from 2010 to 2020 and achieved an overall accuracy of the land-use time-series map ranging from 90.20% to 96.92%.

Hu et al. (2018) monitored changes in land use/cover in an urban wetland area (Hangzhou Xixi Wetland) using multitemporal high spatial resolution imagery with QuickBird, WorldView2 and IKONOS from 2000, 2005, 2007, 2009, and 2013. The eight-class classification accuracies averaged 84.47% for the five years, demonstrating the advantages of using multi-temporal and multi-sensor high spatial resolution satellite imagery for accurate and cost-effective monitoring of land cover changes over time.

Alcantara et al. (2012) estimated crop production of wheat and barley in ISIS-controlled areas in both Syria and Iraq for the years 2014–2015 and irrigated summer crops production in Northeast Syria. The researchers used evidence from MODIS Aqua and Terra Satellites as well as Landsat imagery to find that agricultural production in ISIS-controlled Syrian and Iraqi zones has been sustained in 2014 and 2015, despite the detrimental impact of conflict. The multi-year, multi-sensor approach allowed the researchers to analyze the impact of water flows along the Euphrates on production and estimate the revenue that ISIS can derive from wheat and barley production. The study demonstrated that this remote sensing approach could provide a credible estimation of agricultural production in the absence of statistics.

2.1.4. Classifiers for cropland detection: random forest

Numerous machine-learning classifiers have been employed to map land cover using remotely sensed data, with RF being a popular choice. RF is a supervised machine-learning classifier that constructs a collection of independent tree-structured classifiers, allowing them to vote for the most popular class (Breiman, 2001). This classifier has been utilized in many studies, proving its relevance and effectiveness in remote sensing projects and image analysis (Immitzer et al., 2016). To achieve optimal results, a RF model must be trained to recognize and classify data into distinct classes. In the context of land cover type mapping, satellite images need to have designated training zones for each defined class. These training zones are categorized as samples to train the model, enabling it to associate data from these zones with the corresponding categories. Once the classifier is trained and a specific model is generated, it can be applied to classify larger areas and evaluate its accuracy. The RF classifier derives its name from the ensemble of decision trees created and the random selection of training samples during the training process. Multiple RF models can be trained for the same purpose using different features to evaluate the most relevant input bands making it a versatile classifier. By comparing the performance of various RF models, researchers can determine the most effective configuration for their specific remote sensing applications.

In the case of classifying croplands in conflict areas, RF can be a specifically good option as shown in recent literature. Olsen et al. (2021) strikes as the best example of RF use in the case of detection of cropland abandonment in conflict areas. The classifiers were applied to the satellite data to classify the imagery into seven land-cover classes, which were later combined into fewer categories. Their study utilizes the *SciKit* feature selection package in Python to conduct sensitivity tests for RF parameters and feature selection based on training data. The RF classifier plays a crucial role in this study, enabling the assessment of cropland abandonment in conflict-affected regions, such as South Sudan.

Dara et al. (2018) used RF classification to map cropland probabilities for each year using the annual Landsat spectral variability metrics as predictor variables. They then used the temporal segmentation and change detection algorithm *LandTrendr* on the annual time series of cropland probabilities to map the timing of cropland abandonment.

Du et al. (2022) uses RF classifier to generate annual land-cover maps in the northern China crop-pasture band, an area experiencing widespread agricultural land abandonment and retirement. The researchers leveraged spectral features obtained from Landsat images and employed sample migration and the RF classifier within GEE to create land-cover maps for the period of 1998 to 2019. The overall accuracy of the classification was 0.87. To further improve the classification performance, a temporal consistency check method was proposed, raising the overall accuracy to 0.92. This study demonstrates the effective application of the RF classifier in monitoring agricultural land abandonment and retirement, potentially extending its use to other land-cover change studies.

2.2. Triangulation between conflict, displaced population, and cropland abandonment

Understanding the complex relationship between these factors and their impact on each other can be difficult. Academic research tends to focus on the effects of armed conflicts on land systems, however we know little about the outcome of such events that could include cropland abandonment (Eklund et al., 2017). When we include the affected people in the scope of the other two parameters, the correlation between the three seems evident, however the methodological challenges are limiting research on it. The complex relationship in this context where food insecurity, armed conflict and displacement of the population drive each other and causes a cession of farming activities such as in South Sudan (Olsen et al., 2021; WFP, 2023). Cropland abandonment is thus a potential outcome of this relationship (Prishchepov, 2020; Tong et al., 2017). A recent study did showcase this relationship in the province of Borno where our area of interest is located where there was a clear link between security incidents and population displacement (WFP, 2023).

2.2.1. Cropland abandonment and the impact of conflict

The abandonment of farmland is characterized as a system of process of cessation of activities (Ustaoglu & Collier, 2018). Farmland abandonment increases food insecurity and the risk of multiplied crisis (Olsen et al., 2021). Armed conflicts have impacts on local and regional food security through disruption of agricultural food and trade (Eklund et al., 2017). Some conflict-related papers confirm that the conflict had an impact on cropland abandonment, but some argue that the croplands remain sustained, as some armed groups derive their revenue and influence from agriculture (Jaafar & Woertz, 2016).

Yin et al. (2019) treated the Chechen Wars (1994 – 2009) and its impact on land abandonment and how factors such as distance to conflict and conflict intensity affected agricultural abandonment. Abandonment rates were measured as the proportion of pixels relative to all agricultural land at each distance interval and used the Uppsala Conflict Data Program (GED UCDP) for conflict data. It showed a positive correlation between conflict intensity and agricultural land abandonment, highlighting the significant impact of armed conflicts on agriculture.

Hazaymeh et al. (2022) study confirmed the impact of the Syrian crisis on agricultural land use. Comparison of NDVI and Normalized Difference Moisture Index (NDMI) profiles during the crisis (2013-2021) with those before the crisis (1986-2010) revealed that the crisis led to smoother, bell-shaped, single-peak NDVI and NDMI values, indicating the growth of natural vegetation and fallow land, as opposed to the irregular profiles before the crisis or during the de-escalation/reconciliation period, which indicated regular agricultural and cultivation practices.

Olsen et al. (2021) developed a “propensity score”, establishing a statistical relationship between cropland abandonment and armed conflicts, leading to significant decreases in food supply. The study highlights that the abandoned croplands could have supported at least a quarter of the population in southern South Sudan.

Jaafar & Woertz (2016) however, found that agricultural production in ISIS’s Syria and Iraq was sustained and the harvest cropland was significantly above the pre-conflict mean. It also adds that this “war economy” is not sustainable in the long run and could be affected by military collapse.

Large-scale conflict data collection projects such as the Armed Conflict Location Events Dataset (ACLED) and the Uppsala Conflict Data Program (UCDP GED) play a crucial role in understanding the relationship between conflict and cropland abandonment. These datasets provide researchers with valuable information on the dynamics of conflicts, including spatial and temporal dimensions, enabling a deeper analysis of how conflict influences agricultural land-use patterns (Eck, 2012). By correlating disaggregated conflict event dates with cropland abandonment data, researchers can identify patterns and trends in how agricultural land is

affected during and after conflicts (Olsen et al., 2021; Yin et al., 2019). Researchers are thus able to demonstrate a statistical relationship between cropland abandonment and armed conflicts.

2.2.2. Displaced population impact on agricultural land cover.

When cropland abandonment occurs during conflict, farmers leave the cultivated area and become either IDPs or refugees. These population displacements can impact the cropland abandonment dynamics. Their return as ‘returnees’ will impact the cropland re-cultivation. While finding direct correlation data between the displaced population dynamics and the impacts on the agricultural land cover is difficult, we can find related literature around the evaluation of human activity on agricultural land cover.

IDPs are defined according to the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) as people who are forced to flee their homes due to armed conflict, generalized violence, violations of human rights, or natural or human-made disasters, but who remain within their own country (OCHA, 2021). The term is often used interchangeably with internally displaced peoples, it may also refer to a broader group of people who have been forced to leave their homes, including refugees and asylum-seekers. According to the United Nations High Commissioner for Refugees (UNHCR), “A refugee is someone who has been forced to flee their country and have crossed an international border to find safety in another country”. The causes can vary, from violence, conflict or persecution, these affected populations are defined and protected in international law by the Convention and Protocol Relating to the Status of Refugees (UNHCR, 1951). There are no concrete definitions of a returnee in UNHCR or OCHA. But according to the European Commission, a returnee is a person going back to his habitual residence after spending a significant period of time in the host country, voluntary or forced, assisted or spontaneous (EU Commission, 2011). However, this definition does not take into consideration the notion of IDPs. A returnee can very well be someone who never left their country or their province but got displaced due to a conflict or situations of violence and came back to their area of origin. In the case of this study, this second definition will apply as most of the displaced population in our areas of interest never left their country.

Joireman et al. (2012) used remote sensing and GIS to analyze the placement of homes before, during, and after the conflict in Northern Uganda. Two study sites were examined, one that experienced extensive violence and another with more limited violence. The findings showed that during the post-conflict period, there was a clustering of home placement, as well as increased location of homes near roads in the site with high levels of violence. These observations provide insights into the dynamics of displaced population and resettlement patterns visible through remote sensing.

Agidew & Singh (2017) showed population pressure can drive land use and land cover change, these can be monitored with geographical information systems (GIS) and their impact can be analyzed from remote sensing methods. Researchers analyzed spatial and temporal changes and

found that forest lands declined significantly, while crop lands and rural settlements increased during the studied period.

Mohamed et al. (2019) showed that land use changes can be detected through remote sensing. They established the relationship between soil organic carbon and human activity under arid conditions in the east area of the Nile Delta, Egypt. They used satellite imagery from Landsat 5 TM and OLI to model the soil organic carbon pool. They found significant variations in the SOCP among different soil textures and land uses. Human activity, specifically the conversion of agricultural land to fishponds, was found to have a significant impact on the variation of soil organic carbon values.

Friedrich & Van Den Doek (2020) used Landsat and Sentinel satellite image time series to analyze the establishment and growth of the Pagirinya Refugee Settlement in Northern Uganda. The study achieved 85.7% accuracy in detecting settlement disturbances and provided a more effective functional boundary than UNHCR settlement boundary data. The research moves towards a near real-time approach for refugee settlement monitoring, evaluation, and planning, which could aid in refugee response efforts. It showcases that data from international agencies such as the UNHCR, OCHA and the International Organization for Migration (IOM) can provide data in help of monitoring the displaced population, whether they are refugees or returnees.

2.3. Synthesis of the literature review

The literature review of this master thesis explores the detection and monitoring of cropland abandonment in conflict areas, as well as the complex relationships between phenology, conflict, displaced population and cropland abandonment. The review highlights the challenges in detecting and assessing cropland abandonment due to data heterogeneity, irregular collection, and methodological challenges. The use of satellite imagery, particularly medium resolution images is a common practice, suggesting the need for a higher resolution analysis to detect changes, with temporal NDVI change detection and post-classification comparison being popular methods. Multi-sensor, multi-year approaches and the RF classifier have emerged as effective tools for analyzing cropland abandonment over time.

The triangulation between conflict, displaced population, and cropland abandonment remains a challenging task due to the complex and dynamic nature of these factors. Cropland abandonment can lead to increased food insecurity and crisis, while conflict can disrupt local and regional food systems. Large-scale conflict data collection projects, such as ACLED and GED, are valuable resources for researchers studying these relationships. Displaced populations, including IDPs, refugees, and returnees, can influence cropland abandonment and re-cultivation dynamics. Remote sensing and GIS, in combination with data from international agencies like UNHCR, OCHA, and IOM, play a crucial role in monitoring displaced populations and their impacts on agricultural land cover dynamics in the context of an armed conflict.

Chapter 3. Objectives

3.1. General context

For over 14 years, armed conflicts have persisted in the Lake Chad region, affecting bordering countries such as Chad, Niger, Nigeria, and Cameroon. From large-scale provincial offensives between 2009–2014, the conflict has shifted since 2015 to a more localized nature, with targeted attacks and skirmishesⁱ. There are several actors in this conflict, the radical insurgent groups ‘Boko Haram’ and the Islamic State's West Africa Province (ISWAP) opposing the Nigerian Armed Forces (NAF) as well as the Multinational Joint Task Force (MJTF). The civilians have been caught in the crossfire since the beginning of this conflict in 2009, the armed conflict is still active to this day.

The Borno province in Nigeria, which borders Lake Chad, has experienced a significant impact from this conflict, with around 2,100,000 IDPs as of 2022, primarily due to conflict (IOM, 2022). The ongoing Lake Chad crisis presents a humanitarian challenge, with limited access to basic social services, production systems, and humanitarian support. Population displacement dynamics in the region are primarily driven by the armed conflict against Boko Haram since 2009, leading to food insecurity, social unrest, political instability, and armed conflict. This affected population suffers from food insecurity that is closely linked to social unrest, political instability, and armed conflict.

A 2023 report by the WFP indicated a positive correlation in Borno between cropland area losses and population displacement due to security-related events (WFP, 2023). Borno north, home to 40% of the state population, has been heavily impacted by cropland losses, while Borno south has experienced moderate effects. This dichotomy is an interesting point as the croplands will be affected differently in these two areas.

Remote sensing can bring clarity to this context and understand the relationships between these factors.

3.2. Problem and knowledge gap

Detecting abandoned croplands in conflict areas presents a significant challenge due to the presence of hard-to-reach areas, difficult logistics, and the potential endangerment of humanitarian personnel. Furthermore, it also faces challenges related to data scarcity and heterogeneity when factors such as population movement during conflicts and phenology come into play. These challenges necessitate context-specific research with timely and accurate information on the spatial distribution of drivers contributing to cropland abandonment. Additionally, cropland detection can be hampered by coarse resolution, particularly in global south countries where croplands cannot be detected from space as ‘stratified’ and geometrical, and smallholder farming is the majority type of farming.

Existing studies and reports on this topic primarily utilize medium-resolution satellite imagery, such as Landsat or MODIS. When some studies employ high-resolution satellite imagery, they are limited to research at the provincial level and not local conflict-specific areas. As the conflict in the Borno province, especially around Lake Chad, has shifted from large-scale provincial offensives to localized skirmishes, a more granular approach is required to understand these patterns and relate them to other parts of the province.

There is a significant knowledge gap in the current literature, as no recent studies have investigated cropland change using high-resolution remote-sensing data in local conflict contexts, particularly in the Lake Chad region of northeastern Nigeria. The reports produced by international non-governmental organizations (INGOs) focus on the provincial scale, leaving room for further investigation at the local scale. This knowledge gap is notable as no recent studies have triangulated the impact of population displacement (abandonment and return) with change detection methods of cropland abandonment.

3.3. Objectives

The overall objective of this master thesis is to address this knowledge gap by quantifying cropland abandonment in conflict areas using satellite imagery and change detection methods in the conflict-ridden Borno region. This research aims to demonstrate the importance of triangulating population displacement data, conflict data and high-resolution open access remote sensing data by developing a ‘simple but not simplistic’ methodology to better and rapidly understand the dynamics of cropland abandonment in conflict-affected areas.

The overall objective is comprised of three parts. First, we will analyze patterns, such as conflict intensity, phenology (seasonality), and displaced population movements (IDPs and returnees). Second, we will undertake a remote sensing analysis, which involves initial inputs and processing (classification, change detection, etc.). Finally, we will assess and analyze cropland area changes, comparing these results to pattern outputs to understand the relationships between conflict, displaced population, and cropland abandonment. The specific objectives that can be derived from the overall objective are:

- Assessing respective results and accuracy performances of multi-sensor, multi-year and multi-area classification and change detection methods for cropland abandonment analysis in conflict areas.
- Triangulating displaced population data and conflict data with remotely sensed data to identify potential correlations and assess their impact on cropland abandonment.
- Developing a simple but not simplistic methodology for institutions and agencies to apply in their operations to monitor and address cropland abandonment issues in conflict zones effectively.

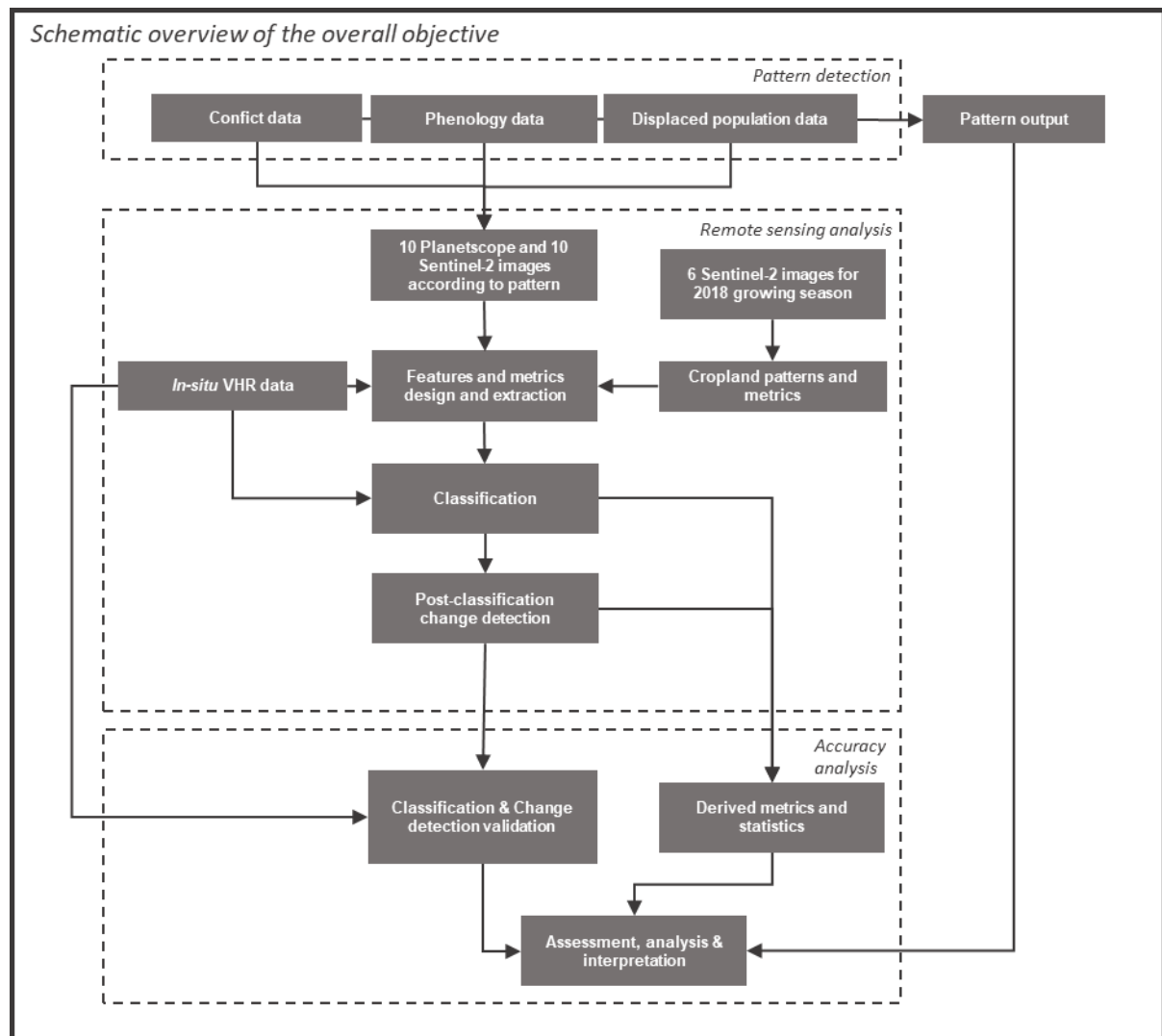


Figure 2: Schematic overview of the overall approach to achieve the objectives

Chapter 4. Materials and method

This chapter outlines the methodology and protocol followed throughout this master's thesis, including the data sources and steps taken in the analysis process.

First, we will describe the Areas of Interest (AOIs) and their local context within the Borno province framework. We have two AOIs: Baga AOI and Dikwa AOI, each of which will be discussed separately to highlight their unique characteristics and significance. Then an explanation of how the satellite images were selected for these AOIs will be explained through pattern detection of the conflict, phenology, and the displaced population.

Next, we will explain the selection process for satellite images within the AOIs, based on pattern detection of conflict, phenology, and displaced population dynamics. Following this, we will detail the initial setup, which involves inputting 10 PlanetScope and 10 Sentinel-2 satellite images for the years 2018 to 2022, assessing the composition of the spectral bands, and performing pre-processing. To aid in cropland detection, we also utilized six additional Sentinel-2 images (three per AOI) from the 2018 growing season, which helped establish a greenness seasonal profile.

Subsequently, the primary processing step was conducted, using detected croplands with the growing season profile to guide sampling for the cropland class calibration set. The other five classes were sampled normally. This expert-based sampling process led to a RF classification calibrated with 50 very high resolution VHR satellite data sampling points. The resulting post-classification change detection allowed to derive cropland abandonment metrics.

Finally, by integrating all the outputs, it is possible to interpret, evaluate and assess the relationships between conflict, population displacement, and cropland abandonment. This comprehensive analysis provides a deeper understanding of the factors influencing cropland abandonment dynamics in conflict-affected areas.

4.1. Materials

This study required the use of multiple platforms, software applications, and data sources to conduct a comprehensive and accurate analysis of land abandonment in the selected rural conflict areas.

Satellite Imagery: Sentinel-2 and Planetscope data were the primary sources of satellite imagery for this study. The Sentinel-2 data was acquired through the Sentinel Hub platform, which is accessible by creating an account. The Planetscope data was obtained from Planet Explorer, a platform owned by Planet Labs. To access this data, an Academic, Non-governmental organization, or Humanitarian organization must request a free license from Planet Labs.

Ground-Truth Data: To establish '*in-situ*' data that represented 'real croplands', Google Earth Pro was utilized. The platform's 'Historical time slider' tool provides access to historical VHR imagery, which can serve as 'ground-truth' data, particularly in conflict areas that are difficult to access.

Geospatial Software: ArcGIS Pro was employed for geospatial visualization and minor image processing tasks. This software also facilitated the organized storage of the image data.

Cloud-Based Processing: Google Earth Engine served as the primary platform for most of the image processing tasks required for this study. The platform's powerful server capabilities significantly expedite the processing of large datasets. However, due to the sensitive nature of displaced population data, such information was not processed using Google's servers.

Statistical Analysis: Microsoft Excel was used for statistical analysis and chart generation. Excel also played a crucial role in locally processing sensitive displaced population data.

Additional Data Sources: To corroborate the portability of the RF classification model, seasonality data was sourced from the EU Commission's Joint Research Center (JRC) Anomaly Hotspots of Agricultural Production (ASAP) platform. The WFP's Vulnerability Analysis and Mapping (VAM) platform provided phenology patterns, while migration data was sourced from the IOM's Displacement Tracking Matrix (DTM) platform. In addition, direct contact with IOM teams supplied valuable '*in-situ*' data. Conflict data was acquired from the ACLED dataset, a reliable source of geolocated conflict events data, accessible through a free license.

4.2. Study areas

This section introduces the two Areas of Interest (AOIs) of this master's located within the Borno province of Nigeria: Baga (Kukawa district) and Dikwa (Dikwa district). Then explores the unique characteristics of each area, with a particular focus on the aspects of conflict that make them of special interest for this study (Figure 3).

Both AOIs were created by choosing a square 100 km² shape, which simplifies the interpretation of statistics when expressed as a percentage of the area. Baga is situated on the shores of Lake Chad, at the heart of the armed conflict, while Dikwa is closer to the central region of the Borno province.

We know from the WFP reports¹ that Baga is a 'hard to reach area' while Dikwa is more accessible and is a center for IDP camps². Baga has also been the site of multiple massacres throughout the conflict. We thus anticipate more cropland abandonment and resettlement dynamics in Baga, particularly given that our study spans five years from 2018 to 2022 and the Lake Chad Basin offensive³ lasted from two years between 2018 – 2020 (Zenn, 2020).

The north-south rainfall gradient is also expected to differ between these AOIs, as Baga is located farther north than Dikwa and is situated within a 'flooded grassland and savanna' ecoregion, according to the WWF Ecoregions (Figure 4). In contrast, Dikwa lies within a 'subtropical grasslands, savannas, and shrublands' ecoregion. Baga is also subject to the Lake Chad frontier, and some of its cropland area is regularly flooded by heavy rains and lake overflow. These factors will affect the identification of croplands, as the croplands will not have the same spectral signatures in both AOIs, underscoring the significant role of environmental factors.

Selecting two AOIs for this master's thesis will address the secondary objective of 'evaluating the transferability of the methodology to other regions.' The methodology was initially applied to Baga and subsequently to Dikwa, allowing for an assessment of its adaptability across different contexts.

¹ Satellite Imagery Analysis 2022: Cropland Change Detection Analysis in Hard-to-Reach Areas (March 2023) <https://docs.wfp.org/api/documents/WFP-0000147544/download/>

² UNHCR Northeast Nigeria Operational Update 2022 : <https://data.unhcr.org/en/documents/download/91182>

³ Lake Chad Basin campaign (2018 – 2020) : [https://en.wikipedia.org/wiki/Chad_Basin_campaign_\(2018%E2%80%932020\)](https://en.wikipedia.org/wiki/Chad_Basin_campaign_(2018%E2%80%932020))

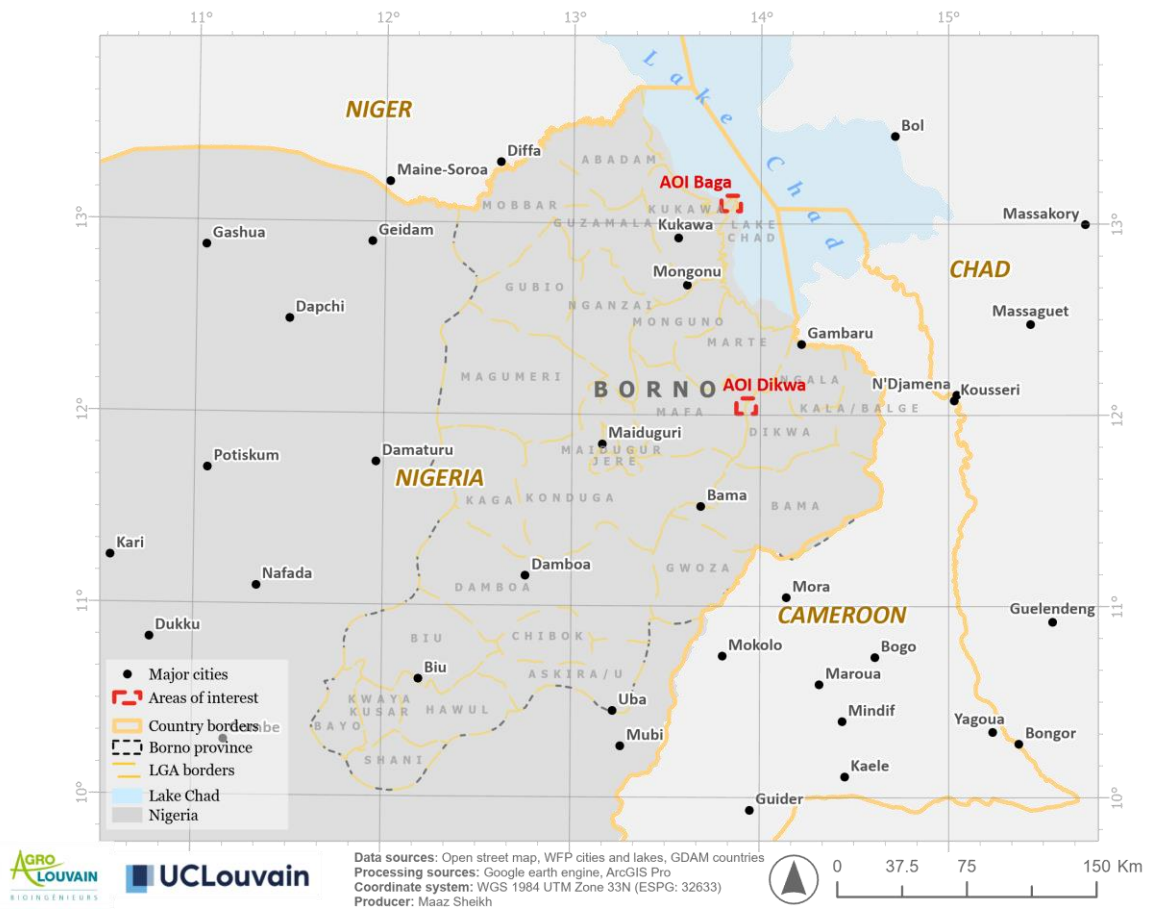


Figure 3: Areas of interest of the study at 1:35 000 000

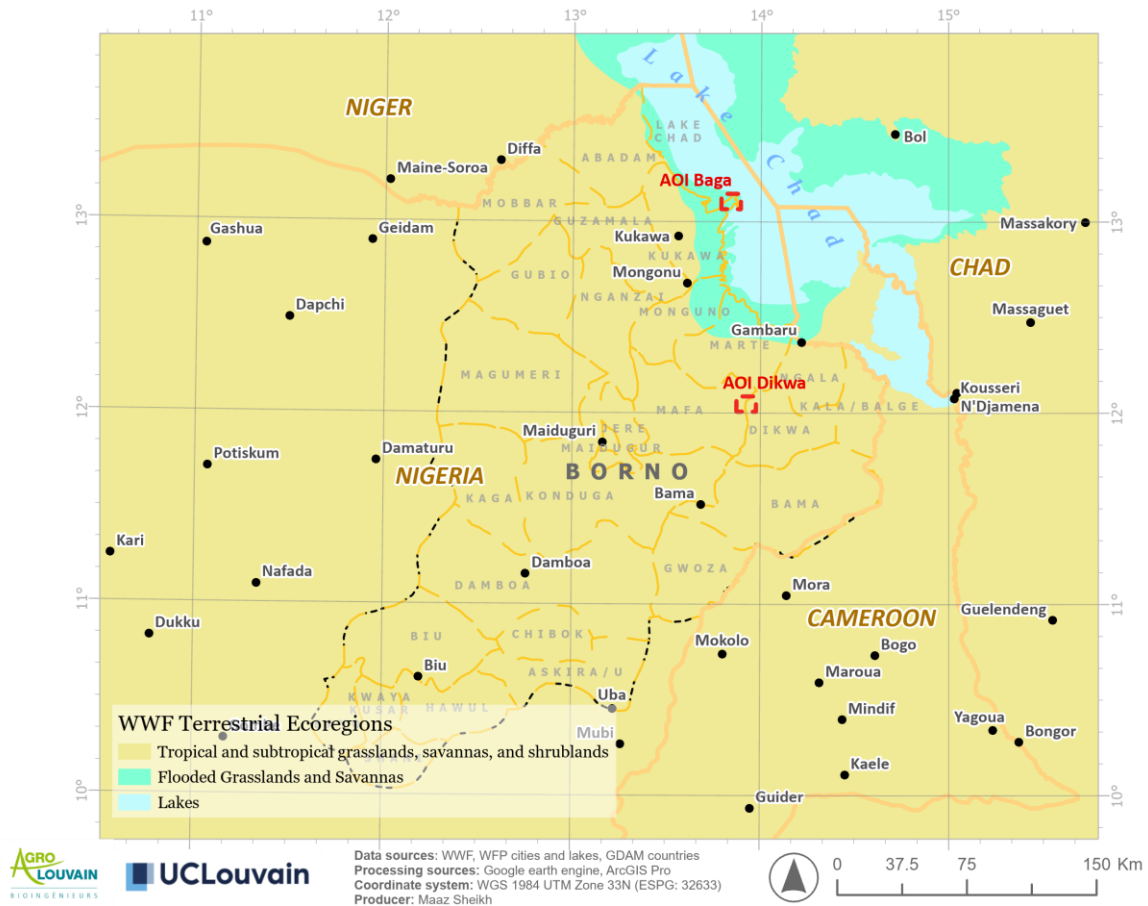


Figure 4: Areas of interest of the study with the WWF Terrestrial Ecoregions at 1:35 000 000

4.2.1. Baga AOI

Baga is a town located in the Kukawa local government area (LGA) of Borno province, situated near the shores of Lake Chad (Figure 6). The town and its surrounding areas such as Doro Gowon have been severely affected by the ongoing conflict involving Boko Haram and the Islamic State's West Africa Province (ISWAP). Baga's strategic location near Lake Chad has made it a target for these extremist groups, as the lake provides resources like water, fish, crops, and potential escape routes into the Sahara. Over the years, Baga's population of 10 000 (2015) has experienced numerous attacks that have resulted in the displacement of large portions of the population, destruction of infrastructure, and abandonment of croplands. The conflict between government forces and insurgents makes this AOI an ideal case study for examining the direct impacts of armed conflict on local communities, and thus, Baga is the primary AOI of this master's thesis for understanding the relationships between armed conflict, population displacement, and cropland abandonment.

The 2013 Baga massacre (Human rights watch, 2013) and the 2015 Baga massacre (Human rights watch, 2015) caused much of the local population to flee the area (Figure 5). However, the Lake Chad Basin campaign of 2018 (Zenn, 2020) led to even more massive departures. This

offensive, launched by government forces and the Multinational Joint Task Force (MNJTF) in 2018, aimed to push back insurgent groups into the Sahara, but the results were inconclusive, and the campaign ended in 2020. Nigerian Armed Forces (NAF) recaptured the town in 2022, but the surrounding savanna and wastelands still remain difficult to access and contested by all parties in the conflict.

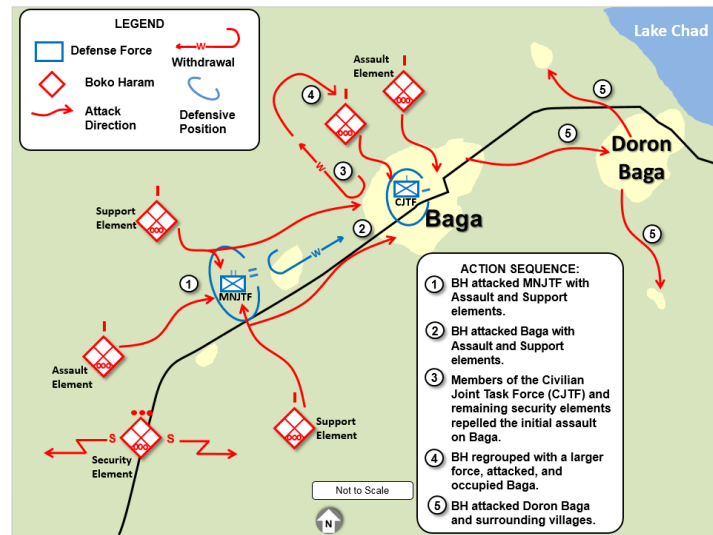


Figure 5: Battle of Baga (2015), US Army Threat and Tactics Report, 2015.

Baga is subject to multiple environmental factors that make it a particularly interesting AOI. The Lake Chad waterfront is dynamic and varies annually depending on rainfall. Heavy rains can cause flooding and abandonment of hundreds of hectares of previously used landmass. The Baga canal, located northwest of the town, serves as the entry point to Lake Chad and a strategic choke point for the Nigerian navy. Croplands are mostly situated around the town of Baga and

the village of Doro Gowon, while market gardens are directly north of the town. The southern and eastern parts are dominated by drylands and rocky areas with savanna shrubs.

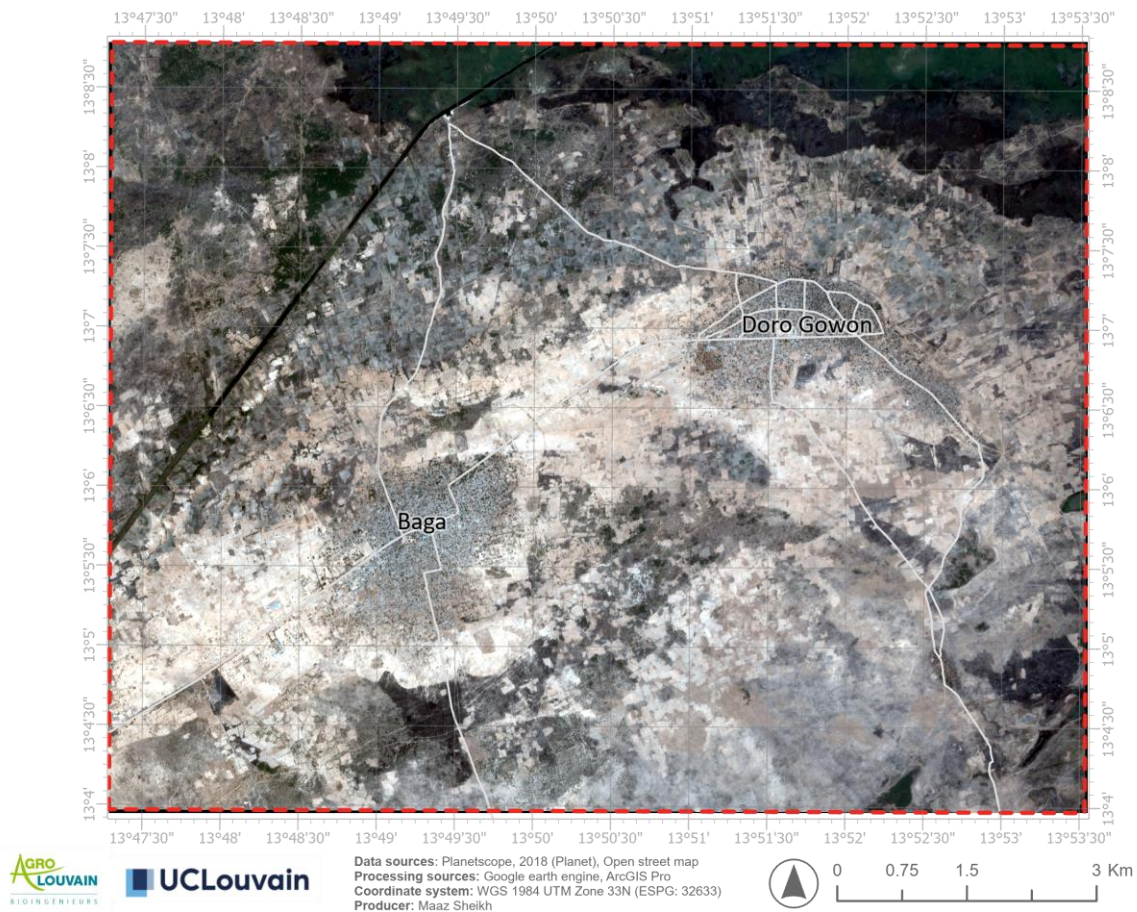


Figure 6: AOI Baga at 1:70 000m, Planetscope RGB 'true color' composite, October 2018

4.2.2. Dikwa AOI

Dikwa is a town located in the Dikwa LGA of Borno province, further south from Baga and more centrally positioned within the province (Figure 7). With its population of around 25 000 inhabitants (2010), Dikwa has also been affected by the conflict involving Boko Haram and the Islamic State's West Africa Province (ISWAP), though to a lesser extent compared to Baga. Dikwa's relative accessibility and more central location have made it an important hub for IDP camps and a center for humanitarian operations in the region. Despite the ongoing conflict, Dikwa has managed to maintain some semblance of stability, although sporadic attacks and security threats persist. This makes Dikwa a crucial AOI for this master's thesis, as it allows for the examination of the relationships between armed conflict, population displacement, and cropland abandonment in a less severely affected area compared to Baga.

Dikwa has experienced fluctuations in population movements during the peak years of the conflict in that region (2015 – 2016), with some residents fleeing violence while others have returned or settled in IDP camps nearby. The town has several IDP camps that host displaced

persons from other conflict-affected areas within the Borno province. As a result, the area has seen an increased demand for agricultural production and food resources to support the growing population. Contrary to Baga, the croplands are expected to increase, and abandonment is expected to be less significant than Baga. In this AOI, the role of IDPs will be very important.

The environmental characteristics of the Dikwa AOI differ from those of Baga. Located east of the capital of the Borno province 'Maiduguri', Dikwa is well connected with the rest of Borno. The landscape primarily consists of grasslands, savannas, and shrublands, with agricultural activities focused around the town and its surrounding villages of Bulonguwa and Ajiri. Croplands in this area are generally more stable compared to those near Lake Chad, as they are not subject to the same flooding, conflict intensity and dynamic waterfront issues as Baga. However, Dikwa is in a more arid region than Baga as the latter is located in a humid area near Lake Chad, making Dikwa more prone to droughts and dry years.

Including Dikwa as a secondary AOI in this master's thesis allows for a comparison of the proposed methodology in two different contexts, helping to evaluate its transferability to other regions affected by conflict and population displacement.

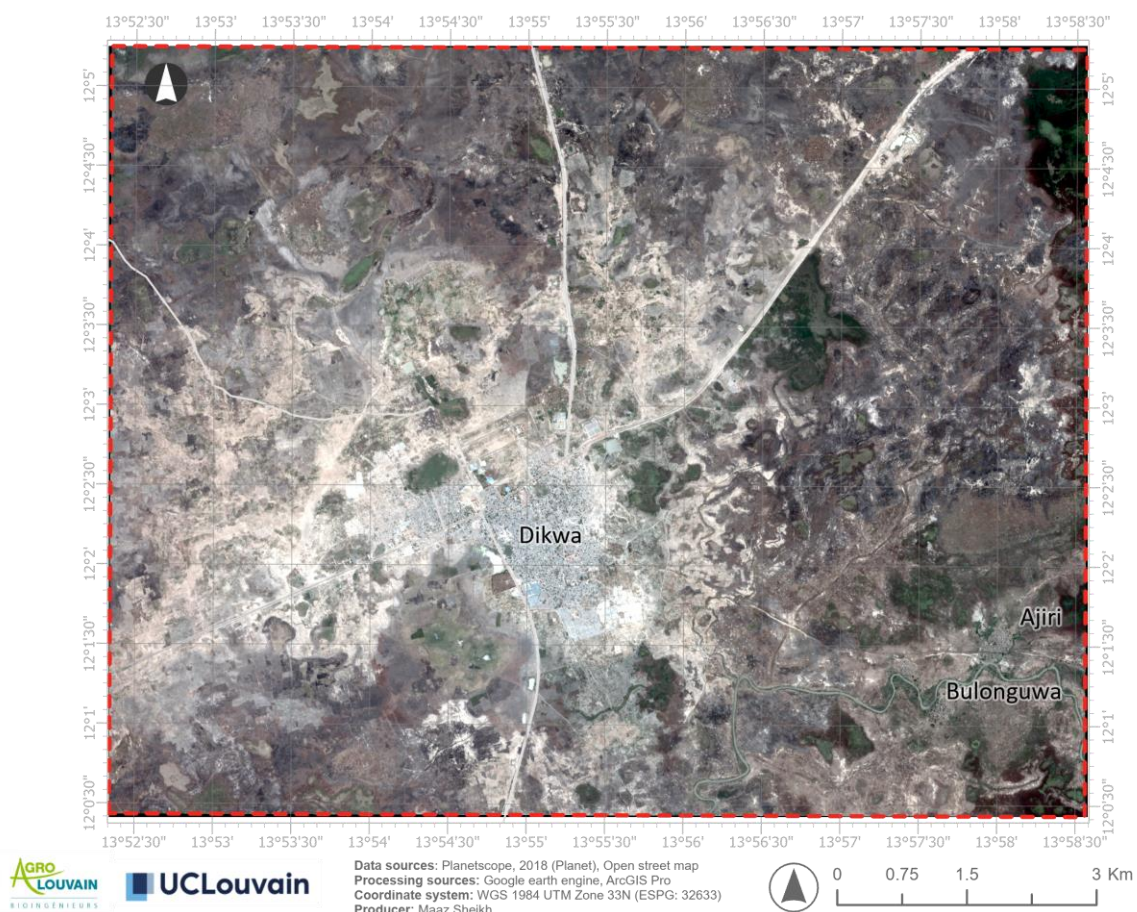


Figure 7: AOI Dikwa at 1:70 000m, PlanetScope RGB 'true color' composite, October 2018

4.3. Pattern detection

The pattern detection section of the methodology chapter comprises three sub-sections: conflict patterns (4.3.1), phenology patterns (4.3.2), and displaced population patterns (4.3.3). These patterns provide essential insights into understanding the dynamics and relationships between conflict, population displacement, and cropland abandonment. They will help us identify the correct moment and timespan to select the satellite imagery to assess cropland abandonment.

4.3.1. Conflict intensity patterns

To assess the conflict patterns within the Borno province from 2018 to 2022, this study utilized data through ACLED data. ACLED is a widely recognized and reliable source of information on political violence and protests, covering various conflict-related events, including battles, attacks, riots, and strategic developments, as well as actors involved and locations affected (Raleigh et al., 2010).

The ACLED data for Borno province was downloaded in an .xls format containing the data for the entirety of Nigeria. The data then had to be cleaned and filtered to obtain the relevant conflict events in the Borno province. The subsequent actions involved importing the table into ArcGIS Pro and displaying the coordinates for each event point. The conflict events were then extracted first by the relevant main event type then subtypes (Table 1) to understand the particularities of the event.

Table 1: ACLED selected type and sub-type of event

ACLED main event types selected
Battles
Explosions / Remote violence
Violence against civilians
ACLED sub event types selected
Air/drone strike
Armed clash
Attack
Non-state actor overtakes territory
Remote explosive/landmine/IED
Shelling/artillery/missile attack
Suicide bomb

The events were spatially analyzed to identify trends and hotspots of conflict within the region, specifically focusing on the two AOIs, Baga and Dikwa. This data provided valuable insights into the intensity and spatial distribution of the conflict, including the activities of armed groups such as Boko Haram and ISWAP, as well as the actions of the Nigerian government forces and other regional actors.

4.3.2. Phenology pattern

This study utilized the Vulnerability Analysis and Mapping (VAM) platform⁴ provided by the WFP. The VAM platform's DataViz tool and its 'Seasonal Explorer' module were employed to assess the Normalized Difference Vegetation Index (NDVI) and rainfall patterns in the region.

The VAM platform's 'Seasonal Explorer' allows users to access time series datasets of rainfall and vegetation for nearly global administrative divisions. The primary data sources include the CHIRPS gridded rainfall dataset produced by the Climate Hazards Group at the University of California, Santa Barbara, and the MODIS NDVI CMG data made available by NOAA-NASA. Data coverage is limited to countries within 50°N to 50°S.

The data can be downloaded down to the LGA level and came in a .csv format with cumulated rainfall rates per month (mm) and the NDVI values (between -1 and 1). The data had to be thoroughly cleaned, and queries were made to select the relevant data. By analyzing the NDVI and rainfall patterns in charts on Excel, it was possible to identify the rainy season, dry season, and periods of vegetation growth in the Borno province. As crops growth starts slightly later than natural vegetation (due to the seeds taking time to sprout) the information that could be derived from the module was essential for selecting the optimal time to download satellite images, ensuring that rainfall and cloud cover were minimal and that crops were either just sowed or just harvested, thus emitting a distinct spectral signal with regards to the surrounding fallows and natural vegetation. Finally, the post-harvest season which begins at the end of September was selected rather than the much more variable sowing season. The appropriate time window for croplands discrimination was determined to be the end of October.

Understanding the phenology patterns in the study areas helps to account for the seasonal variability in crop growth and agricultural practices, which may impact cropland abandonment. Moreover, it provides a solid foundation for interpreting the relationships between conflict, population displacement, and cropland abandonment in the context of the Borno province's seasonal dynamics.

4.3.3. Displaced population patterns

For the analysis of displacement population patterns, this study utilized the DTM⁵ platform provided by the IOM as well as data that IOM provided directly for this study. DTM collects data through assessment rounds done at the country level with key informants and other INGOs. The DTM enabled the identification of patterns related to IDPs and returnees within the Borno province. The DTM data is available in CSV format as 'master tables' from 2014 to 2022.

⁴ WFP VAM DataViz platform: https://dataviz.vam.wfp.org/seasonal_explorer/rainfall_vegetation/visualizations

⁵ IOM Displacement tracking matrix: <https://dtm.iom.int/about-dtm>

However, due to inconsistencies in the data, it required thorough cleaning and reorganization before being suitable for use in this master's thesis.

IDP and returnee data are collected by IOM through 'Assessment rounds' each quarter of the year, starting from 2014. The IDP data was analyzed at the LGA or district level for both Dikwa AOI (Dikwa LGA) and Baga AOI (Kukawa LGA).

A request was made to the IOM and data was received for both AOIs. The data for Kukawa (Baga) is only limited to areas with accessibility to DTM field enumerators. For IDPs, data before 2021 is condensed for both AOIs, meaning that the years 2018, 2019, 2020 output only one number. For returnees, data is missing from the Baga AOI in 2018 and 2019 while for Dikwa AOI it is missing in 2021 and 2022. IOM communicated that DTM has not been able to collect data in Kukawa LGA (Baga AOI) between 2018-2020 as their access was limited due to the high conflict intensity until 2022 when DTM gained access to some accessible locations in Baga. According to the IOM team it is important to note that in 2022, some IDPs were relocated to Dikwa and Kukawa (Baga) as their places of origin/initial displacement, but majority are regarded as internally displaced persons because they are still hosted in camps or informal settlements.

Both the IDPzZ and returnee data were processed using Excel and then plotted on graphs. The integration of this data within the study helps to establish relevant relationships to understand the patterns and dynamics in cropland abandonment of both AOIs.

4.4. Initialization and set-up

This section of the methodology involves initializing the research process by cleaning the pattern data, defining the areas of interest, and applying the pattern data to the two AOIs. The initialization also includes downloading of the remotely sensed data (satellite imagery) for the end of October of each year between 2018 – 2022. Then extracting the spectral information from each band and pre-processing the satellite imagery. This section also includes the identification of the growing season profile with specific techniques.

4.4.1. Pre-processing and cleaning of the pattern data

The initial step of the study was the pre-processing and cleaning of the pattern data obtained from the various sources, such as ACLED, the WFP VAM platform, and IOM's DTM platform. This involved organizing the data, eliminating inconsistencies, and preparing it for further analysis in the context of the AOIs.

4.4.2. Defining the area of interest

Using ArcGIS Pro, the AOIs were defined by creating a 100 km² square for both Baga and Dikwa. This ensured that the selected areas were comparable in size and facilitated the calculation of statistics as a percentage of the total area.

4.4.3. Application of pattern data to the areas of interest

The cleaned pattern data was then applied to the AOIs of Baga and Dikwa. This process enabled the study to focus on the specific characteristics and dynamics of these regions, enhancing the accuracy and relevance of the results.

4.4.4. Detecting croplands

This section will address the challenging preliminary task of detecting croplands in our AOIs where the farms are diverse and field heterogenous in the form of small holder farm patches seen from space. The goal will be to understand the cropland signature and the appropriate time period for cropland mapping.

To understand the growth and seasonal patterns of croplands, this study utilized six Sentinel-2 images (Table 2) representing the start (SOS), middle (MOS), and end (EOS) of the growing season for 2018. These images were used to experiment with four primary detection methods.

There are various methods to identify croplands, however as this study is proposing a ‘simple but not simplistic’ solution, three main methods are proposed and can be used interchangeably and combined for better results.

Table 2: Baga AOI & Dikwa AOI satellite imagery for the temporal NDVI change detection

File name (AOI_Sensor_DD_MM_YYYY_MN_SC)	Sensor	Resolution in meters	Date of capture (DD/MM/YYYY)	Time of capture	Cloud cover on AOI (in %)	Comment
Baga_S2_10_08_2018_0941.tif	Sentinel-2	10/20	10/08/2018	09 :41	10	Mid of season (peak vegetation)
Baga_S2_29_09_2018_0945.tif	Sentinel-2	10/20	29/09/2018	09 :45	0	End of season (smoke visible due to slash and burn agriculture)
Dikwa_S2_13_07_2018_0936.tif	Sentinel-2	10/20	13/07/2018	09:36	0	Start of season
Dikwa_S2_12_08_2018_0933.tif	Sentinel-2	10/20	12/08/2018	09:33	5	Mid of season
Dikwa_S2_26_09_2018_0931.tif	Sentinel-2	10/20	26/09/2018	09:31	0	End of season
Baga_S2_10_08_2018_0941.tif	Sentinel-2	10/20	10/08/2018	09 :41	10	Mid of season (peak vegetation)

Baga_S2_29_09_2018_0945.tif	Sentinel-2	10/20	29/09/2018	09 :45	0	End of season (smoke visible due to slash and burn agriculture)
Dikwa_S2_13_07_2018_0936.tif	Sentinel-2	10/20	13/07/2018	09:36	0	Start of season

Method 1: Temporal NDVI Change Detection

This method involves analyzing the differences in NDVI values between the SOS, MOS, and EOS of the growing season to identify croplands. By setting specific thresholds, binary images distinguishing croplands from other vegetation types were created and combined to form a comprehensive cropland map. The final step combines the binary images to produce a map highlighting the cropland areas. This method was done with our three images for each AOI. This performed well on the Dikwa AOI (Figure 9), but not on Baga AOI (Figure 8) where it confused dryland (grassland/shrubs/savanna) with cropland, as dryland can also follow the same greenness pattern as crops in some areas such as Baga AOI.

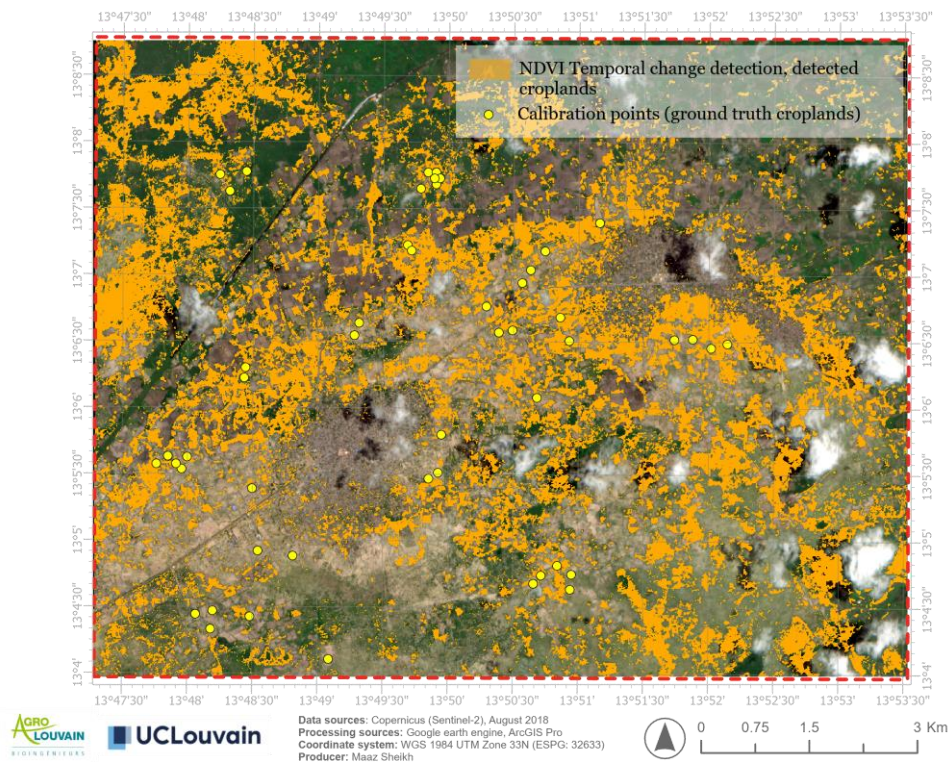


Figure 8: Baga AOI Cropland detection with method 1: NDVI Temporal change detection

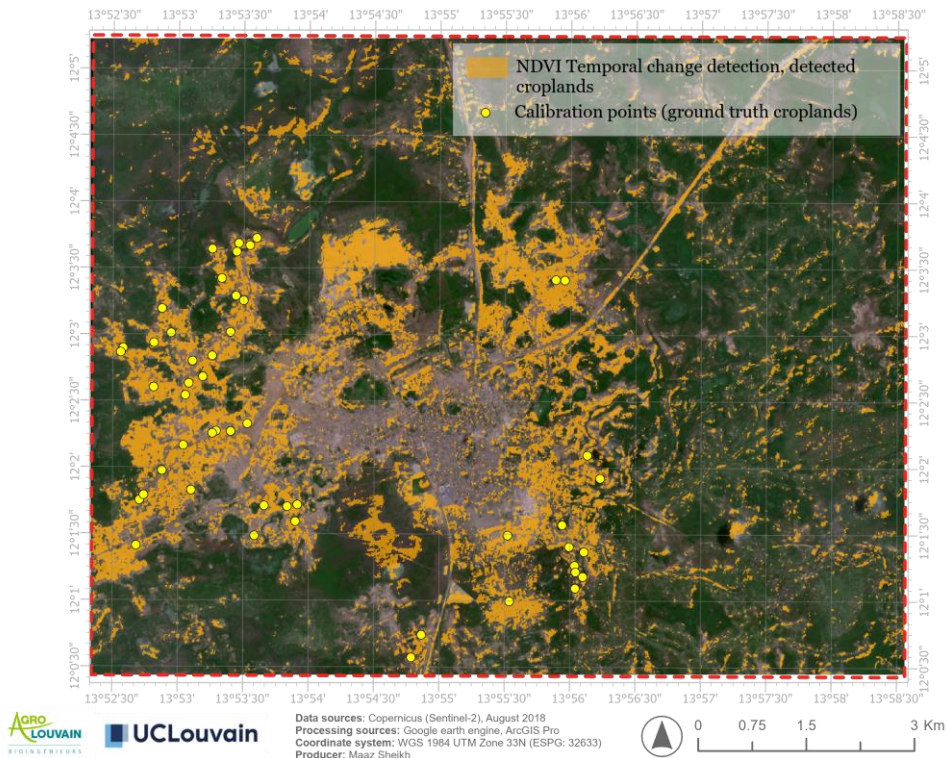


Figure 9: Dikwa AOI Cropland detection with method 1: NDVI Temporal change detection

Method 2: NDVI Maximum Value Composite

The MVC ‘max green’ method can also be used to detect croplands. This method involves combining the NDVI values from the start, mid, and end of the season images by selecting the maximum NDVI value for each pixel. The resulting composite image represents the maximum greenness or peak vegetation growth during the entire growing season. Croplands generally have higher NDVI values compared to other land covers, thus the peak can be classified by a threshold value to identify cropland areas.

However, this method was sensitive to other highly vegetated areas, such as forests or grasslands, which could also present high NDVI values. Consequently, MVC did not perform optimally for our AOIs.

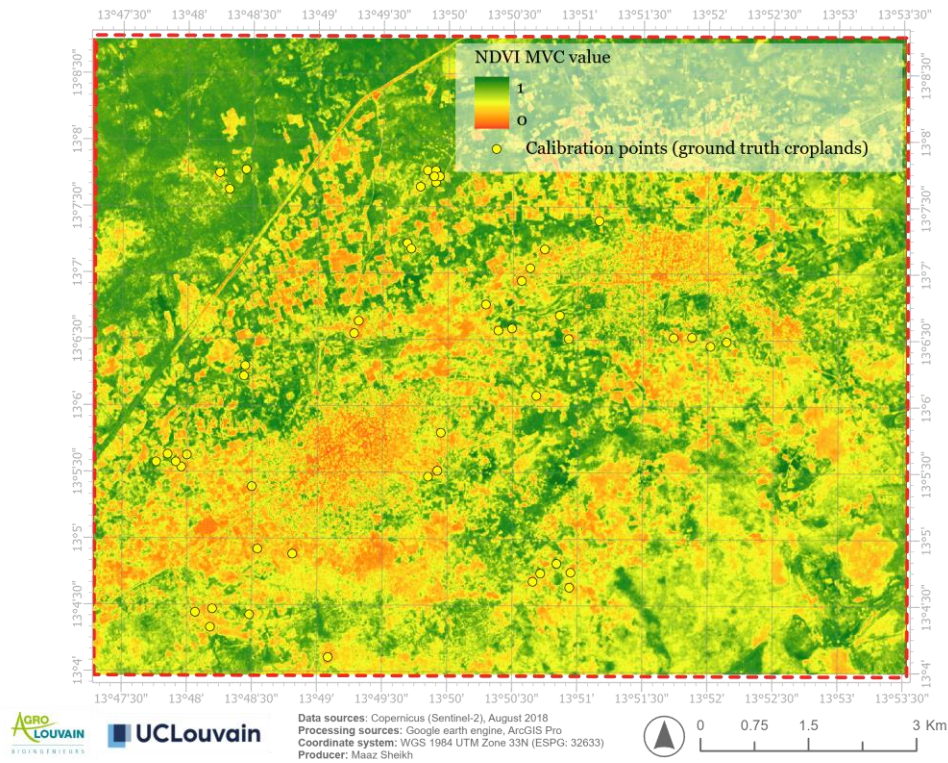


Figure 10: Baga AOI Cropland detection with method 2: NDVI Maximum value composite

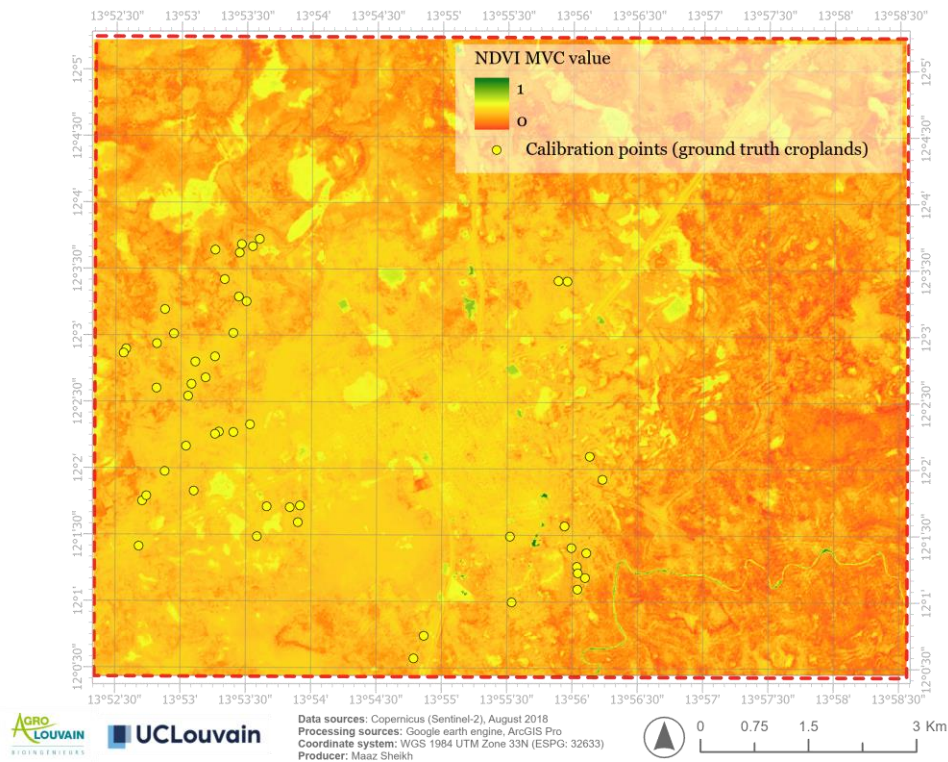


Figure 11: Dikwa AOI Cropland detection with method 2: NDVI Maximum value composite

Method 3: RED Maximum value composite

The red band MVC ‘max red’ is a technique used to detect croplands using multi-temporal satellite imagery. After having acquired three sets of Sentinel-2 captured at different times for each AOI in the growing season - the SOS, the MOS, and the EOS. We can extract the red band, as it's known that clean bare soil prepared before sowing and harvested fields show the highest red reflectance of the season as healthy, growing crops strongly absorb light in the red part of the electromagnetic spectrum. For each corresponding pixel across the SOS, MOS, and EOS red band images, it selects the maximum value to create a new composite image. The underlying assumption is that the maximum red reflectance observed during the growing season is indicative of cropland. The ground truth data taken with method 4 (VHR visual check) corresponds very well to the detected croplands. It is thus noted that this method is performing well compared to the other ones. However, it does pick up some savanna and shrubs as being croplands in the southeast of the Baga AOI, thus requiring the assistance of the other methods to understand the cropland pattern better in the Baga AOI.

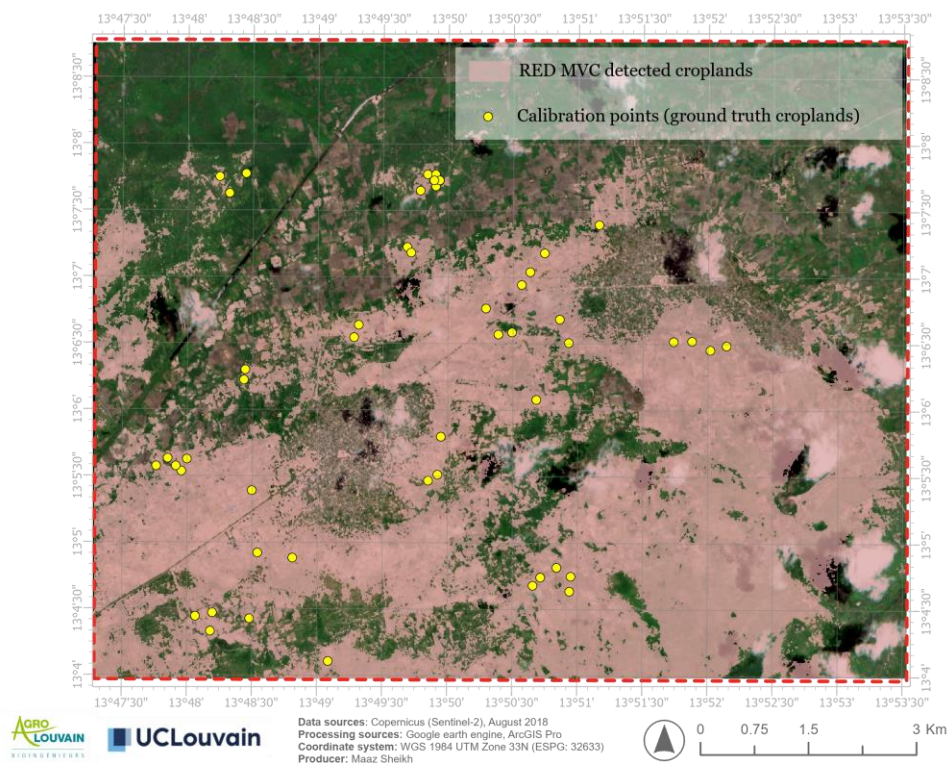


Figure 12: Baga AOI Cropland detection with method 3: RED Maximum value composite

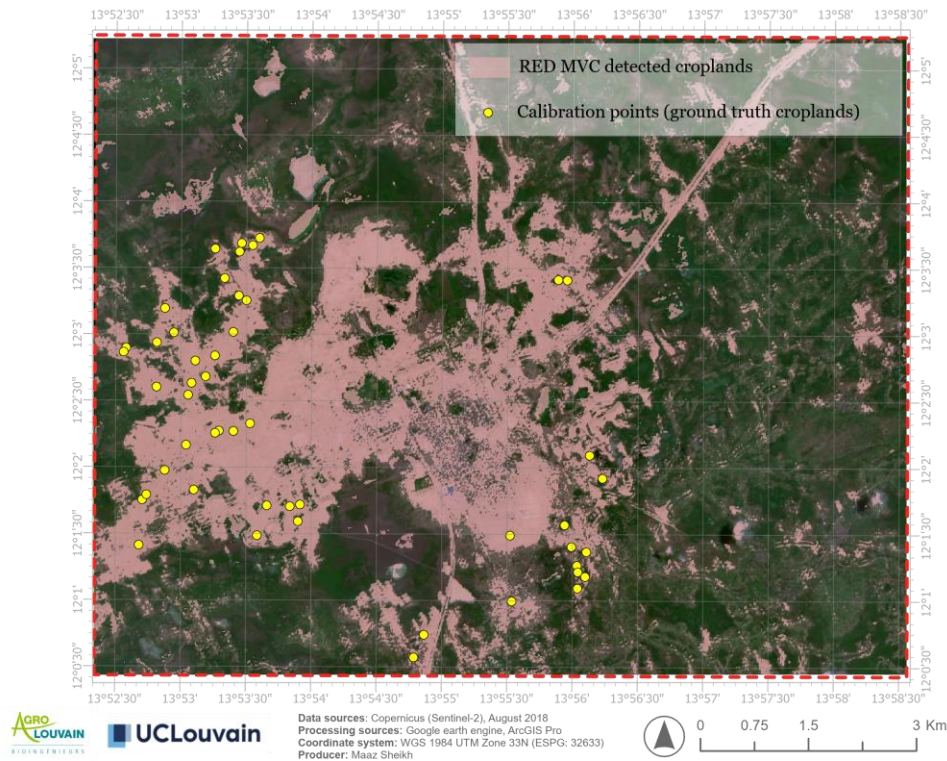


Figure 13: Dikwa AOI Cropland detection with method 3: RED Maximum value composite

Method 4: The Very High Resolution (VHR) image visual interpretation

This method involves a visual manual interpretation on Google Earth Pro, using the ‘time tool’ to go back in time and visualize Very High Resolution (VHR) satellite imagery from Maxar for the year 2018 as it was the chosen year for classification as well as the first among five years during which this study takes place. The interpretation took place during the growing season for both AOIs. By doing this, we can visually identify croplands, and collect enough ground truth calibration samples to understand what a cropland is and what is not a cropland for both AOIs.

However, this is where issues were encountered, where market gardens (Figure 15) were emitting a very different spectral signature (similar to bare soil or built up) than actual croplands. Thus, these could confuse the model by having drastically different spectral signatures and were identified as drylands and not considered as croplands (Figure 14).



Figure 14: Baga AOI, visual identification of cropland patches, Maxar WorldView 28/09/2018



Figure 15: Baga AOI, market gardens (grey/purple stratified patches), Maxar WorldView 28/09/2018

How this master thesis detected croplands:

For the Baga AOI, methods 3 and 4 performed the best, albeit with some limitations. Method 3, despite occasional confusion, covered most calibration points and helped understand the cropland pattern. For Dikwa AOI, methods 1, 3, and 4 were the most effective, as the cropland pattern was more discernible. The preliminary analysis corresponds to the cropland signature that this study understood using various methods' combined use facilitated an accurate understanding and built confidence in our visual interpretation identifying 'what constitutes a cropland' in both AOIs. This analysis also confirms that the VHR image visual interpretation is appropriate to select calibration and validation samples and the end of the season is the appropriate time period for cropland mapping.

4.4.5. Setup of the satellite images

Satellite images were acquired for each year between 2018 and 2022, focusing on the end of October for each year thanks to the pattern detection done earlier, which is crucial for capturing the appropriate phenological stages of croplands. Two sensors were used for this master's thesis, they are both easy to access and their licenses can be obtained for research, non-governmental and academic use for free, making these sensors very accessible.

Sentinel-2 was created as part of the Copernicus program developed by the European Space Agency (ESA). Sentinel missions provide high-resolution, ready to use operational and open-source data on a long-term basis as the Sentinel-2 sensor has been running since 2016. Sentinel-2 provides a high temporal resolution on a geostationary orbit, making it very interesting for accurately monitoring changes.

The Sentinel-2 images were manually downloaded on the Sentinel-hub platform⁶. They came pre-processed as radiometrically calibrated surface reflectance including atmospheric correction and georectification. As the images were mostly cloud-free (Table 3), no cloud mask was applied as it could lead to error propagation. Added to this, eight bands were downloaded per image but only higher resolutions bands of either 10m or 20m were retained for processing.

The PlanetScope sensor was developed by Planet Labs, a private American company specializing in earth observation. The sensor is mounted on a fleet of 'shoe box sized' satellites called "Doves" which provide high-resolution imagery with global coverage. The PlanetScope constellation proposes a resolution between 3 to 5 meters depending on the version of the sensor. PlanetScope came in different versions as the data from 2018 and 2019 is captured on the PlanetScope Dove Classic while the 2020, 2021 and 2022 data is captured on the PlanetScope Super Dove version which can be harmonized with Sentinel-2 data. This factor is

⁶ Sentinel Hub platform to download Sentinel-2 imagery: <https://www.sentinel-hub.com/>

important as the absence of radiometric calibration and atmospheric correction on Planet images induces reflectance changes which can alter the results in some areas.

Planetscope images were also manually downloaded on the Planet Explorer platform⁷. They came also pre-processed with surface reflectance and geometric correction. However, unlike the Sentinel-2 images, they were not mosaicked and were divided into separate images. This required additional processing to combine and integrate them into the analysis effectively.

A total of 20 images were downloaded and processed, with 10 images designated for the Baga AOI (Table 3), including five Planetscope images and five Sentinel-2 images, and 10 images for the Dikwa AOI (Table 4), also comprising five Planetscope images and five Sentinel-2 images. The images for both sensors were usually taken at the local time (GMT+1) in the morning between 8 am and 10 am. The image selection was done on the criteria of the low presence of clouds, artefacts, a coherent reflectance with a matching date with the other years, as well as the presence of an image in the given AOI for all five years.

Table 3: Baga AOI Satellite images

File name (AOI_Sensor_DD_MM_YYYY_MN_SC)	Sensor	Resolution in meters	Date of capture (DD/MM/YYYY)	Time of capture	Cloud cover on AOI (in %)	Comment
Baga_PS_24_10_2018_0907.tif	Planetscope Dove classic	3	24/10/2018	09 :07	0	OK
Baga_PS_30_10_2019_0819.tif	Planetscope Dove classic	3	30/10/2019	08 :19	0	OK
Baga_PS_29_10_2020_0940.tif	Planetscope Super dove	3	29/10/2020	09 :40	0	Southeast of AOI: plots burning smoke visible
Baga_PS_26_10_2021_0845.tif	Planetscope Super dove	3	26/10/2021	08 :45	0	OK
Baga_PS_26_10_2022_0858.tif	Planetscope Super Dove	3	26/10/2022	08 :58	0	West of AOI: Burnt plotlands
Baga_S2_24_10_2018_0946.tif	Sentinel-2	10/20	24/10/2018	09 :46	0	East of AOI : Burnt plotlands, smoke visible
Baga_S2_29_10_2019_0947.tif	Sentinel-2	10/20	29/10/2019	09 :47	0	OK
Baga_S2_28_10_2020_0947.tif	Sentinel-2	10/20	28/10/2020	09 :47	0	OK
Baga_S2_28_10_2021_0947.tif	Sentinel-2	10/20	28/10/2021	09 :47	0	Northeast of AOI: burning plotlands, smoke visible
Baga_S2_28_10_2022_0947.tif	Sentinel-2	10/20	28/10/2022	09 :47	0	Northeast of AOI: burning plotlands, smoke visible

⁷ Planet Explorer platform to download Planetscope imagery: <https://www.planet.com/explorer/>

Table 4: Dikwa AOI Satellite images

File name (AOI_Sensor_DD_MM_YYYY_MN_SC)	Sensor	Resolution in meters	Date of capture (DD/MM/YYYY)	Time of capture	Cloud cover on AOI (in %)	Comment
Dikwa_PS_28_10_2018_0916.tif	Planetscope	3	28/10/2018	09 :16	0	Dry period
	Dove classic					
Dikwa_PS_30_10_2019_0911.tif	Planetscope	3	30/10/2019	09 :11	0	Slash and burn visible
	Dove classic					
Dikwa_PS_27_10_2020_0840.tif	Planetscope	3	27/10/2020	08 :40	1	OK
	Super dove					
Dikwa_PS_29_10_2021_0855.tif	Planetscope	3	29/10/2021	08 :55	0	Dry period
	Super dove					
Dikwa_PS_31_10_2022_0911.tif	Planetscope	3	31/10/2022	09 :11	0	Slash and burn visible
	Super dove					
Dikwa_S2_31_10_2018_0934.tif	Sentinel-2	10/20	31/10/2018	09 :34	0	Dry period
Dikwa_S2_31_10_2019_0937.tif	Sentinel-2	10/20	31/10/2019	09 :37	0	Slash and burn visible
Dikwa_S2_30_10_2020_0937.tif	Sentinel-2	10/20	30/10/2020	09 :37	0	Burning farms and smoke visible
Dikwa_S2_25_10_2021_0937.tif	Sentinel-2	10/20	25/10/2021	09 :37	0	Dry period
Dikwa_S2_25_10_2022_0937.tif	Sentinel-2	10/20	25/10/2022	09 :37	0	Slash and burn visible

4.4.6. Pre-processing of the satellite imagery

Additional pre-processing was performed on ArcGIS Pro, including operations such as clipping the images to each AOI, mosaicking the Planetscope images, applying band combinations (Infrared B8, B4, B2 for Sentinel and Infrared B4, B3, B2 for Planetscope) to improve visual differentiation of vegetation, croplands, dry soil, and other features, calculating indices such as NDVI. This further prepared the images for detailed analysis in GEE within the context of the study.

4.5. Classification

Now that croplands have been visually identified, we can start sampling them and start the RF classification to classify and create a cropland mask. The methodology relied on the application of the RF classification algorithm. The initial step involved arbitrary sampling of data points with a wide distribution over both AOIs and with both sensors using the end of October image for the year 2018. For the cropland class, a total of 50 training samples were selected, informed by the cropland patterns previously detected. The remaining classes - water, vegetation, built, bare, and dryland - were sampled using 20 points each, identified visually with false color composite images. Training and validation samples were delineated using a stratified random sampling strategy, where approximately 80% of the samples were used for model training and the remaining approximately 20% for validation. The model was calibrated using an additional

50 'in-situ' cropland data points representing ground truth, sampled on the Maxar WorldView sensor for both AOIs for the same period. This resulted in a total of 100 points for cropland (50 for training and 50 with calibration) and 100 points for non-cropland classes (20 per each non-cropland class). RF classification was applied to each sensor data separately due to the variation in bands or indices used for classification. The model was developed on the 2018 images and subsequently applied to the succeeding years and ran simultaneously thereby testing the model's portability across different time periods.

4.5.1. Sampling

The sampling was initially done in an arbitrary manner on the Google earth engine interface on both AOIs and both sensors on the year 2018 image of the end of October image.

The cropland patterns detected in earlier steps helped to guide sampling for the 50 training sample points for the cropland class. The other five classes were sampled by visually identifying with Infrared false color composite images for both sensors with 20 points.

Out of all these sample points, approximately 20% were randomly selected within the sample sets for validation of this classification and verify it's accuracy, the rest of the 80% were used to train the RF model. In GEE when using the sampleRegions() function the algorithm applies a stratified random sampling strategy. The sample size might not exactly match the expected proportions due to the complexity of spatial structures and the inherent randomness in the sampling process.

Table 5: Table of classification samples and classes

Class ID	Class	Number of training samples	Final class after reclassification
1	Water	20	Non-cropland
2	Vegetation	20	Non-cropland
3	Built	20	Non-cropland
4	Bare	20	Non-cropland
5	Dryland	20	Non-cropland
6	Cropland	50	Cropland

4.5.2. Random forest classification

The RF classifier was trained separately for each sensor due to the difference in bands or indices used for classification (Table 6). This approach allowed for a comprehensive analysis and comparison of the classification performance of the two sensors using the RF algorithm.

Table 6: Bands input for RF classification

Sensor	Bands or index used for classification	Wavelengths of the chosen bands
Sentinel-2	'b2', 'b3', 'b4', 'b5', 'b6', 'b7', 'b8', 'b11', 'ndvi'	490nm to 1610nm

The training samples proportion (80% of total samples) were inputted in a RF classification (Breiman, 2001). The RF algorithm was used to classify the images for each year and each AOI by using the samples of the 6 previously mentioned classes into binary reclassified classes: cropland and non-cropland. The RF algorithm used these samples from the classes to create a multitude of decision trees, each trained on a random subset of the training data. Each tree in the forest then made a vote for the class of the sample, and the class receiving the most votes determined the final classification. This approach leveraged the strength of the ensemble to ensure a robust and accurate classification of the land into cropland and non-cropland areas.

Table 7: RF Classification parameters

RF Parameter	Parameter value
Number of trees	100
variablesPerSplit	2
minLeafPopulation	1
bagFraction	0.5

The model was created in the year 2018 using the 2018 images to sample but was also applied to the following years of study (2019, 2020, 2021, 2022) and ran at the same time, thus assuming the portability of the model from one year to another.

4.5.3. Calibration of the model

The RF classification model was calibrated with 50 assumed '*in-situ*' data representing 'ground truth' that were sampled on Google Earth Engine on the VHR sensor Maxar WorldView for both AOIs for the same period. This provided an additional 50 points that the model used to refine the classification, resulting in a total of 100 sampling points each for the cropland and non-cropland classes.

These same calibration points were then used for validating the change detection, as each of these points represent a 'real cropland area', this study was able to see the value of the point change over time. By doing this we can draw the relationship between ground truth, the performance of the classification model and the change detection.

This means that for the change detection assessment the calibration and validation were not completely independent in this study, meaning that the consistency of the model's predictions over time is evaluated against the known data points (50 *in-situ* points representing croplands in 2018), in this case the goal is to see how well the model can accurately track changes in cropland over time. However, the classification accuracy assessment for the year 2018 is independent in both calibration and validation datasets.

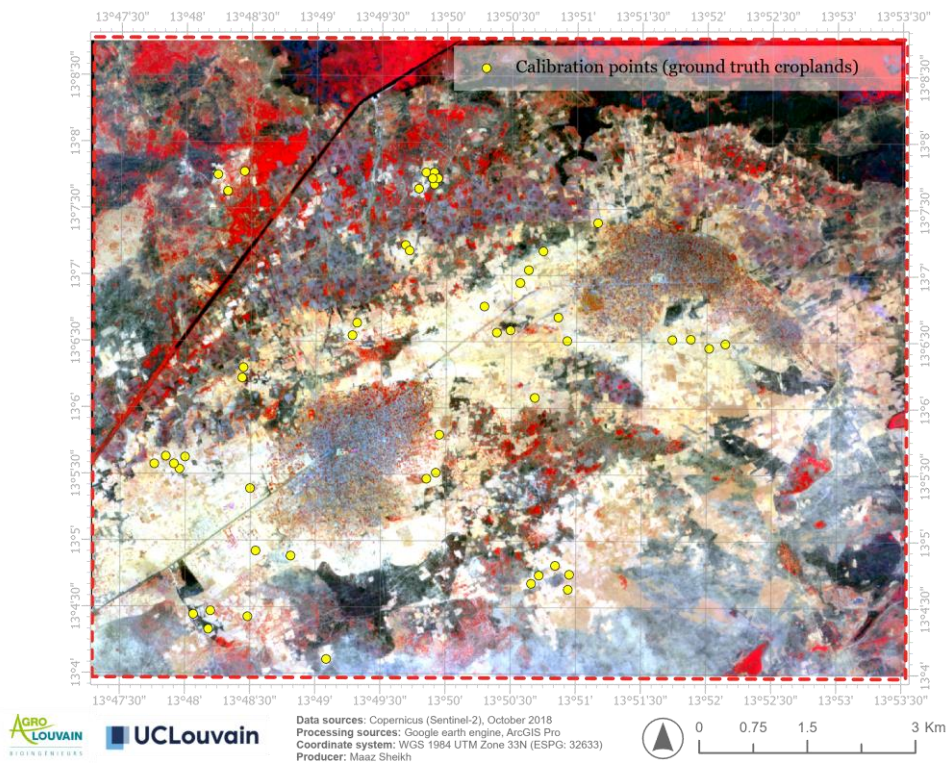


Figure 16: AOI Baga calibration points seen with a S2 false color composite (8,4,2)

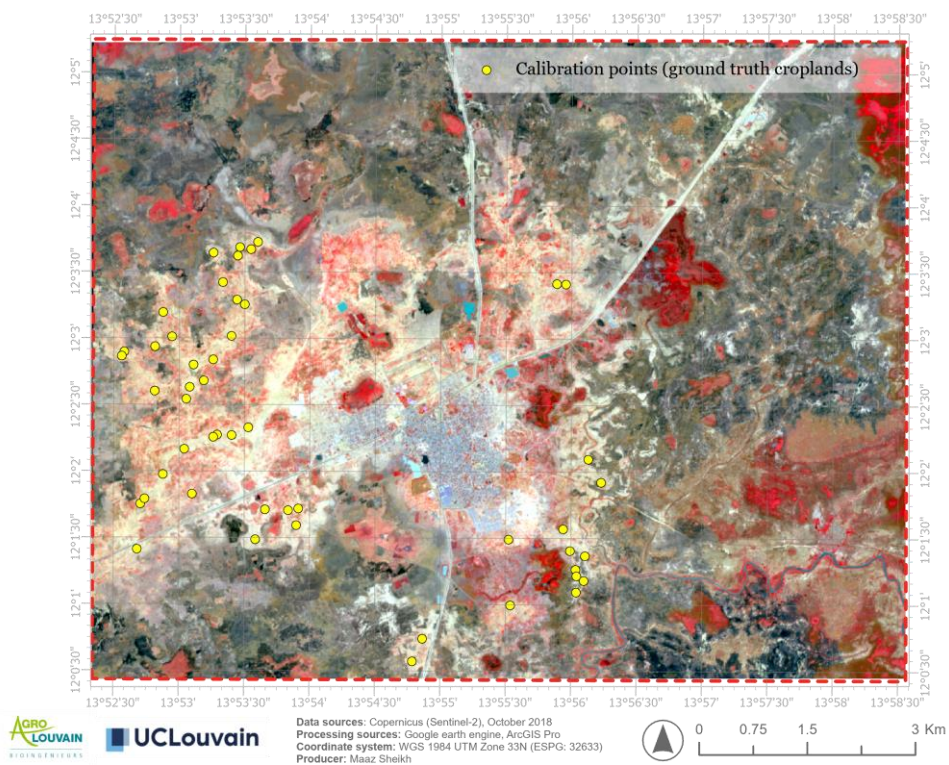


Figure 17: AOI Dikwa calibration points seen with a S2 false color composite (8,4,2)

4.5.4. Portability of the RF model

The RF model was trained on the 2018 image and applied to the images from 2018 to 2022 simultaneously. This approach assumes the model's portability from one year to another, which is contingent on the assumption that the seasonal timing and observation conditions don't drastically change the spectral signature of the different classes from one year to another. This assumption could be challenged when using different versions of the PlanetScope sensor (Dove classic and Super dove).

The European Commission's Joint Research Center (JRC) has developed the Anomaly Hotspots of Agricultural Production (ASAP)⁸ tool. By utilizing their *High-Resolution Viewer* module and designating a point at our selected cropland, we can establish a seasonal profile of the chosen plot across the years 2018 – 2022 with the aid of three sensors including Sentinel-2, thereby facilitating a discussion on the portability of our RF classification model. To establish portability, we selected a plot of land that remained 'cropland' for most of the years.

A plot in Baga AOI was chosen, which remained as 'cropland' when viewed through VHR imagery on Google Earth Pro across the years, except in 2019, during the Lake Chad campaign when the population vacated the area, which wasn't related to reflectance issues. The ASAP profile of the plot also confirms no significant anomalies in the seasonal profile, apart from high NDVI values in 2019, which aligns with our understanding of cropland abandonment and subsequent vegetation growth. Thus, we can reasonably assume the portability of our model (Appendix A). In short, the portability was assessed by comparing a selected cropland that was consistent over the years 2018 – 2022, using both VHR imagery and the JRC's ASAP tool to confirm no large anomalies in the seasonal profile.

Another plot in Dikwa AOI was chosen and the same exercise was done there as well. The profile confirmed no major anomalies in the seasonal profile. We can thus confirm our model portability.

4.6. Change detection.

Having developed reliable annual cropland masks for both the Baga and Dikwa AOIs using both sensors, it is now relevant to identify the dynamics of land abandonment by detecting changes over the years. This processing step will allow to compare the area (in hectares) of cropland lost or gained, thereby providing insights into the complex relationship between population displacement and resumption of cultivation activities.

⁸ ASAP European Commission : <https://mars.jrc.ec.europa.eu/asap/about.php>

4.6.1. Binary reclassification

The RF classification process resulted in binary maps for both AOIs, where '0' represents non-croplands (an amalgamation of five classes) and '1' signifies croplands (the single cropland class). This binary reclassification is a pivotal step for accurate change detection, as it simplifies the comparison between different time points.

4.6.2. Post classification change detection

The post-classification change detection method, a technique widely used in remote sensing studies, was employed to identify shifts in cropland areas. This technique involves an initial classification of each image, followed by a thematic overlay of these classifications and the generation of a comprehensive “from-to” change matrix, detailing the transitions between each class over the studied period.

One of the main advantages of this method is its simplicity and resilience against radiometric changes. However, it is important to note that the accuracy of this method is directly tied to the classification accuracy, potentially leading to error propagation from one processing stage to another. This method could be considered as appropriate as the expected order of magnitude of land use change is significantly larger than the annual map errors.

The post-classification change detection was carried out on the binary maps. The identified changes were assessed on a yearly basis, focusing on the transitions between cropland (1) and non-cropland (0) areas.

This approach facilitated analyzing the transitions between cropland and non-cropland areas on an annual basis, enabling a comparison of differences between consecutive years in the dataset. By doing so, this study was able to pinpoint and visually represent the areas where these changes have taken place. This provides a valuable tool for understanding the temporal dynamics of cropland abandonment and recovery in our selected conflict regions.

4.7. Accuracy assessment and validation

The subsequent sections are focused on the evaluation of the mapping output accuracy and the reliability of our methodology, specifically, the classification and change detection processes. Accuracy assessment is a critical component of any remote sensing study to ensure the validity of the derived results. For the classification assessment, this study employed a suite of statistical metrics, including the overall accuracy, producer's and user's accuracy, F1 score and the Kappa coefficient, which were derived from a confusion matrix. On the other hand, the change detection assessment utilized calibration points collected in 2018 as ground truth data to evaluate the temporal consistency of our classification results. The main goal of this assessment was to track potential shifts in croplands by analyzing the yearly classification of these points.

4.7.1. Classification assessment

The classification process in this study was subjected to a randomized process to ensure its accuracy and reliability. Earlier, the dataset was divided into a training set, comprising 80% of the samples, and a validation set consisting of the remaining 20%. This division was performed randomly to avoid any potential bias that could impact the assessment results. It's worth noting, however, that despite our stringent division of the dataset, the number of validation points for different sensors and AOIs may not align perfectly with the expected proportions due to the complexities of spatial structures and the inherent randomness in the stratified sampling process.

The performance of our classification model was evaluated using several statistical metrics derived from the confusion matrix, assessing the performance of the classification model as it provides a detailed breakdown of how the predicted classes correspond to the actual classes.

The first metric we calculated was the overall accuracy, which provides a general measure of how often the model correctly classified the samples. It is calculated as the sum of correctly predicted samples over the total number of samples.

The second metric was the producer's accuracy which measures the likelihood that a given class on the ground is correctly classified in the model. It was calculated as the total number of correct predictions for a class, divided by the total actual number of that class.

Conversely, user's (or consumer's) accuracy measures the probability that a pixel classified on the image actually represents that class in reality. It is calculated as the total number of correct predictions for a class, divided by the total predicted number of that class. These two metrics provide a more nuanced understanding of the model's performance by highlighting its strengths and weaknesses in classifying specific classes.

F1 score is the harmonic mean of precision (user's accuracy) and recall (producer's accuracy). It ranges from 0 to 1, with 1 being the best possible F1 score. In essence, the F1 score can help understand the balance between how well the model is correctly identifying a class (precision) and how well it is at not missing any instances of that class (recall). This is particularly useful when the costs of false positives and false negatives are roughly equivalent, which might be the case when classifying land as either cropland or non-cropland.

Lastly, the Kappa coefficient was calculated to provide a measure of the agreement between the predicted and actual classes, corrected for chance agreement. The Kappa coefficient is a complementary measure of the overall accuracy metric as it considers the possibility of the agreement occurring by chance.

4.7.2. Change detection assessment.

The accuracy of the change detection methodology in this study is assessed with the use of the 50 calibration points collected in 2018, which served as the ground truth data for validating the classification results from 2018 to 2022.

The primary aim of this assessment is to evaluate the temporal consistency of our annual cropland masks. This is achieved by examining whether the calibration points, which were identified as croplands in 2018, have retained their cropland classification in subsequent years, or if they have been reclassified as non-cropland areas. By tracking the classification of these points over time, we can investigate potential shifts in land use.

This assessment essentially presents a longitudinal study of these calibration points, providing insights into how consistently our classification model identifies and maintains these specific locations as croplands. A high degree of consistency with the classification would indicate that the model is robust and reliable in its ability to detect changes in land use over time. Conversely, significant shifts in classification could signal changes in land use patterns, potentially due to factors such as displacement, conflict, or other socio-environmental dynamics. This method provides a nuanced understanding of the model's performance and its sensitivity to real-world changes, enabling a rigorous assessment of the model's portability in detecting land use change over time.

4.8. Overall approach

The schematic flowchart below underlines the methodology followed during this master's thesis.

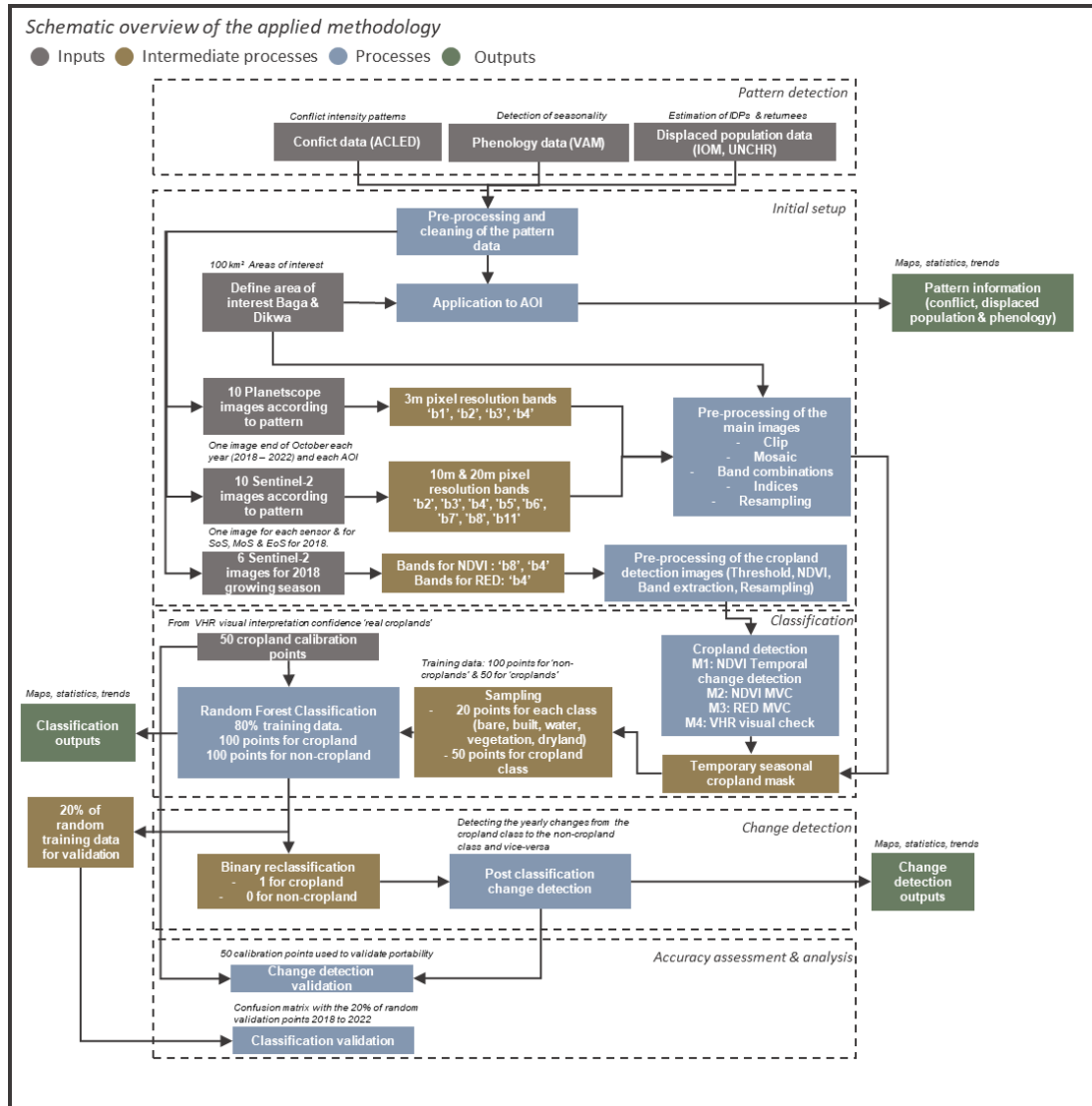


Figure 18: Schematic overview of the applied methodology

Chapter 5. Results and discussion

The ensuing chapter delivers an interpretation and discussion of the results derived from the application of the study's methodology. We commence by analyzing the overarching patterns encompassing conflict, phenology, and displacement. Following this, we will scrutinize the results from our classification and change detection processes, complete with their accuracy assessments. Additionally, we shall discuss the results, address the challenges and proposed perspectives according to this master thesis's experience.

5.1. Pattern detection quantitative analysis

Employing the adopted approach, this study succeeds in elucidating the prevailing patterns. It's essential to recall that the analysis of phenology and displacement patterns were conducted at the LGA level (admin 03), whereas the conflict patterns were scrutinized at the level of Borno province (admin 02).

5.1.1. Phenology pattern analysis

Figures 19 and 20 exhibit a concordant rainfall pattern. Notably, Baga, being proximate to the Sahara frontier, records lower overall rainfall than Dikwa, as illustrated by a difference of approximately 50mm cumulative rainfall during the peak season in August. A well-established north-south rainfall gradient in this province also allows for the inference of the dry (November – March) and wet (June – September) seasons. Consequently, the optimal moment for classifying croplands without substantial remotely sensed reflectance disparities from wet soil year on year appears to be October, post-harvest in September and prior to the croplands drying out completely.

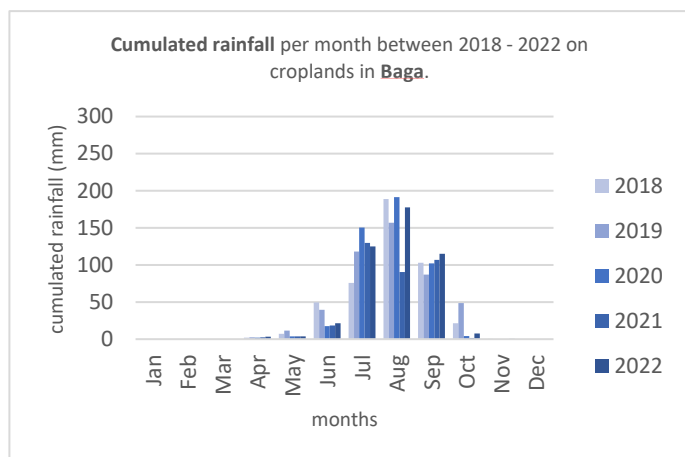


Figure 19: Baga AOI cumulated rainfall on croplands per month between 2018 - 2022

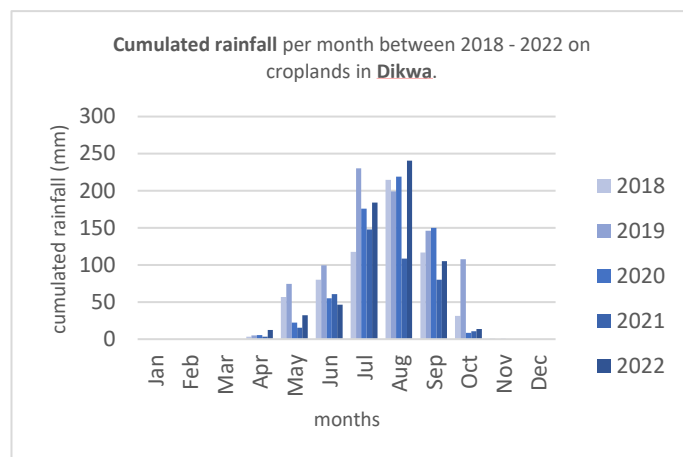


Figure 20: Dikwa AOI cumulated rainfall on croplands per month between 2018 - 2022

Figures 21 and 22 affirm the positive correlation between NDVI values and the rainfall pattern presented in Figures 19 and 20. They also delineate seasonality by indicating that in October, there remains enough vegetation to facilitate the detection of croplands. For the Dikwa AOI, Figure 22 shows overall higher NDVI values, reflecting a greater proportion of vegetation in the area. Vegetation information is important as it influences the period selected for applying the classification and subsequently get results for cropland abandonment. With the incorporation of both rainfall data and vegetation greenness (NDVI) data, our choice of October as the base month for analysis is validated.

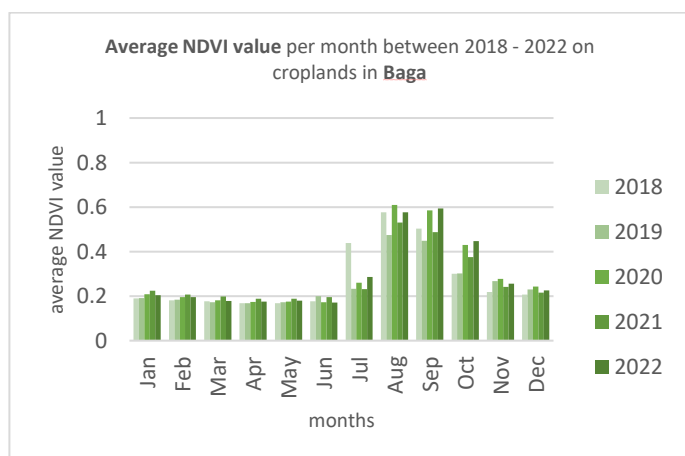


Figure 21: Baga AOI average NDVI value on croplands per month between 2018 - 2022

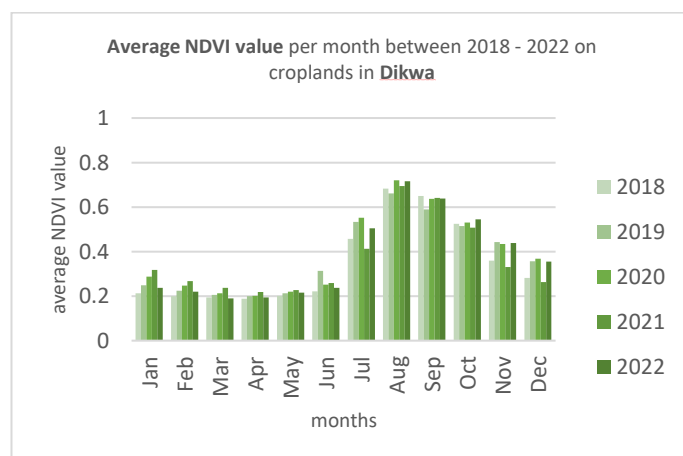


Figure 22: Dikwa AOI average NDVI value on croplands per month between 2018 - 2022

5.1.2. Conflict pattern analysis

Figure 23 illustrates a pattern of conflict intensification followed by a gradual but moderate decrease in conflict events, particularly battles. This pattern corroborates our initial assertion that the Lake Chad basin campaign (2018-2020), led by the Nigerian Armed Forces, impacted the number of battles documented in this graph. There remains a correlation with our displaced population numbers that increased during the same period. The post-campaign period of 2020 – 2022 still exhibits high numbers of conflict events, with Baga AOI continuing to be a hard-to-reach area. However, the numbers of conflict events have declined, indicating a potential return to the situation prevalent in 2018.

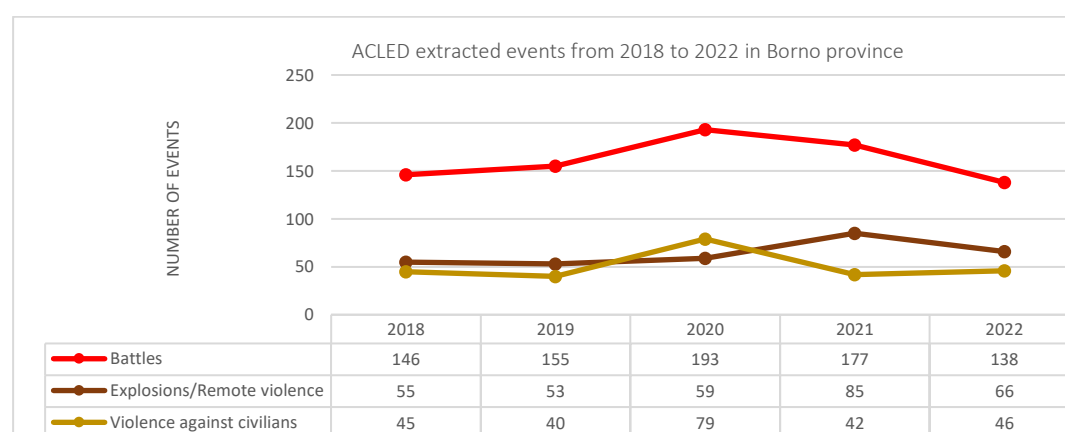


Figure 23: Borno, ACLED extracted events between 2018 - 2022

5.1.3. Displaced population analysis

The data regarding displacement patterns was inconsistent across the years as per the IOM team's notes. There was a distinction between the data collected between 2014 and 2020, and from 2021, the surveys became annual. Data on returnee numbers is missing for some years due to hard-to-reach areas such as Baga or the recommencement of surveys after the Chad basin campaign in 2020. Through this analysis, we can comprehend the magnitude of IDPs from each LGA at a particular year, thereby discerning the dynamics of population displacement. Figures 24 and 25 demonstrate a decline in IDPs from the Kukawa LGA (Baga AOI) and Dikwa LGA (Dikwa AOI) post-2020, potentially indicating a return of IDPs to their original residences. As the intensity of the conflict diminishes, the number of IDPs desiring to return home seems to be on the rise, as demonstrated by the multiple return intention surveys⁹ carried out by the UNHCR in 2021.

⁹ Borno State Government Led Return Dashboard October 2021 <https://data.unhcr.org/en/documents/details/89476/>

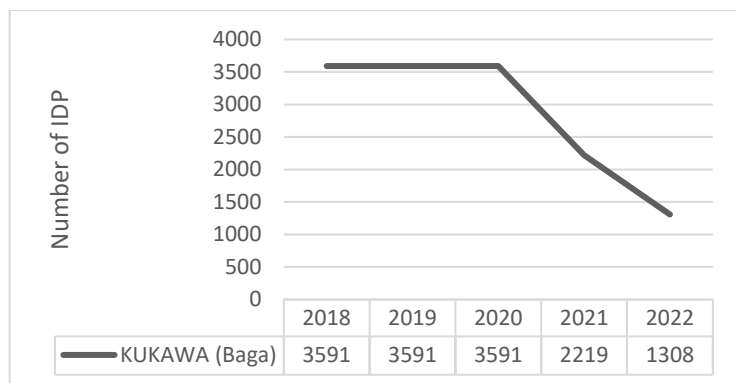


Figure 24: Number of reported IDP from Kukawa LGA (Baga AOI) per year – IOM

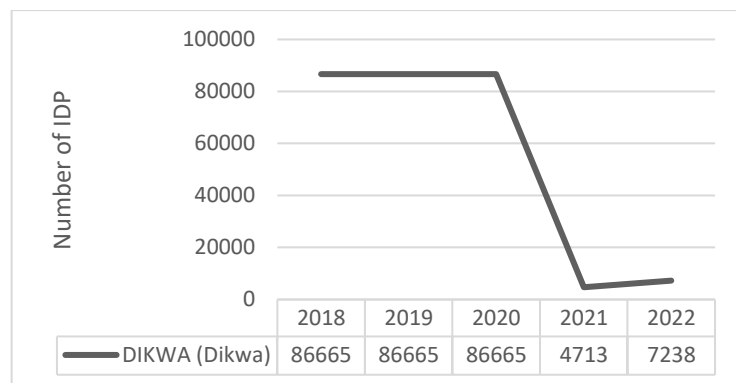


Figure 25: Number of reported IDP from Dikwa LGA (Dikwa AOI) per year – IOM

Figure 26 showcases the lack of data prior to 2020, a testimony to the hard-to-reach status of the Kukawa LGA. However, the surge in returnee numbers in 2020, 2021 and 2022 is a noteworthy indicator. For the Dikwa AOI, the data is missing after 2020. At this point, we cannot rely on such sparse data to discern and establish a definitive returnee pattern due to insufficient data for our chosen study areas and selected time period. Hence, we resort to the interpretation of existing reports from UNHCR¹⁰ which indicate a general trend of increased returnees post-2020 (UNHCR, 2021, 2022). The current assessment underlines the need for further research into this dynamic, possibly leveraging additional datasets and refined methodologies to gain deeper insights.

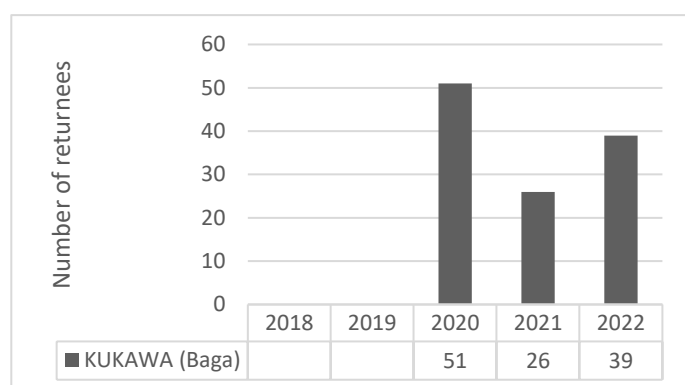


Figure 26: Number of reported returnees in Kukawa LGA (Baga AOI) per year – IOM

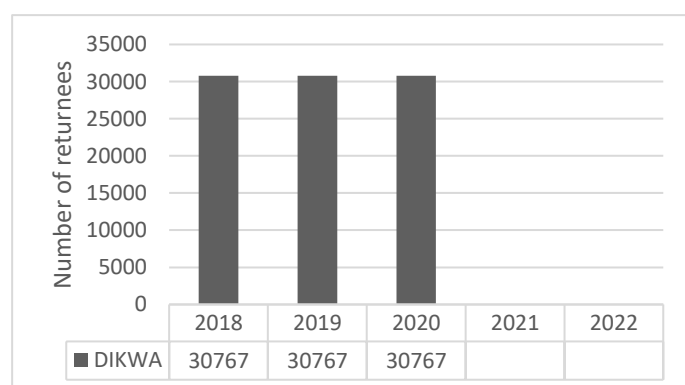


Figure 27: Number of reported returnees in Dikwa LGA (Dikwa AOI) per year - IOM

¹⁰ Quarterly Factsheet April - June 2022: <https://data.unhcr.org/en/documents/details/94492>

5.2. Classification results

The RF algorithm was used to classify the two classes from the output – ‘cropland’ and ‘non-cropland.’ Both AOIs were scrutinized from the perspective of each sensor used in the study over the study period between 2018-2022.

Cropland mask

5.2.1. Baga AOI classification

Table 8 presents the detected cropland within the Baga AOI based on Sentinel-2 sensor data. Visual inspection and Figure 33 illustrate a decline in the initial cropland area in 2019 and 2020, with subsequent recovery in 2021 and 2022. This pattern coincides with the height of the Lake Chad campaign (2018-2020) when the population largely vacated the conflict-ridden areas. Sentinel-2 data confirmed this hypothesis.

Table 9 offers the Planetscope sensor’s representation of the Baga AOI. This American sensor portrays a similar trend to its European counterpart, as shown in Figure 39, indicating cropland reduction during the same period and subsequent growth upon the return of the IDPs in 2021.

Comparison of both sensors unveils variations in reflectance values in the RGB background image. The 'percent clip' stretch used to display the images reveals that Sentinel-2 images are darker while Planetscope images are brighter highlighting the poorer calibration. As expected, the Planetscope sensor with its higher resolution of 3m captures is more detailed in the quantification of the cropland area than Sentinel-2. In fact, in 2019 at the lowest value of cropland areas it displays 137 hectares of cropland compared to Sentinel-2 who displays 310 hectares of cropland in the AOI, showing either a more precise detection or an underestimation.

Despite these differences, both sensors confirm a general trend: cropland decreases during peak conflict (2018-2020) and increases as the conflict intensity subsides (2020-2022), thereby showcasing the dynamics of cropland abandonment and restoration in line with population displacement and subsequent return.

Table 8: Baga AOI Sentinel-2 cropland classification at 1:60 000

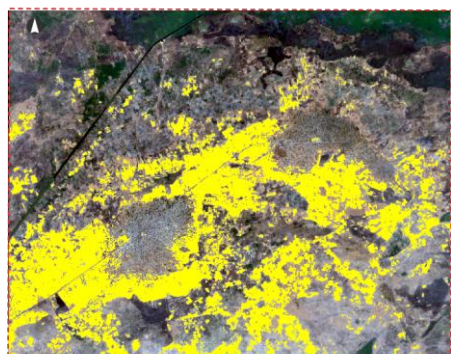


Figure 28: Baga S2 24.10.2018 class

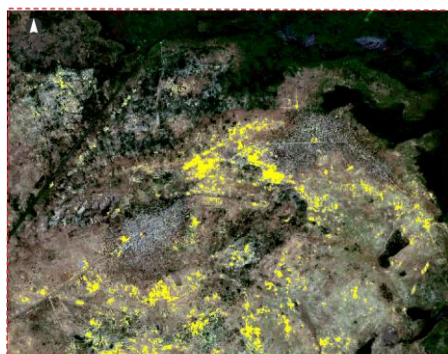


Figure 29: Baga S2 29.10.2019 class

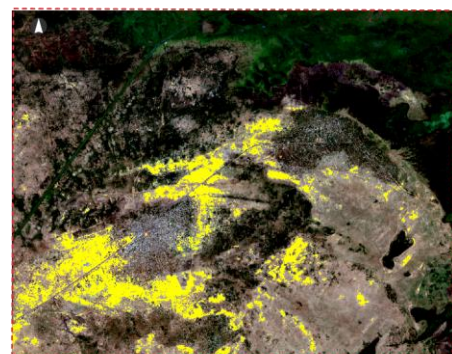


Figure 30: Baga S2 28.10.2020 class

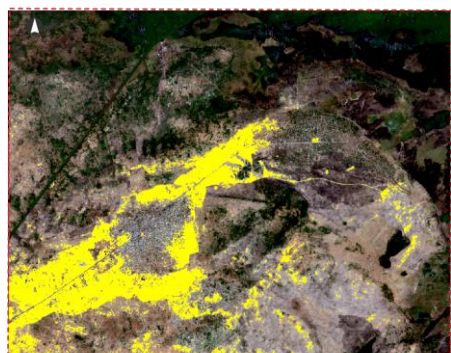


Figure 31: Baga S2 28.10.2021 class

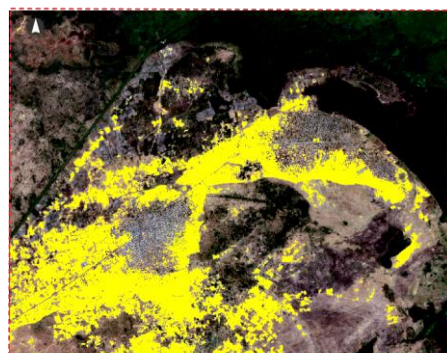


Figure 32: Baga S2 28.10.2022 class

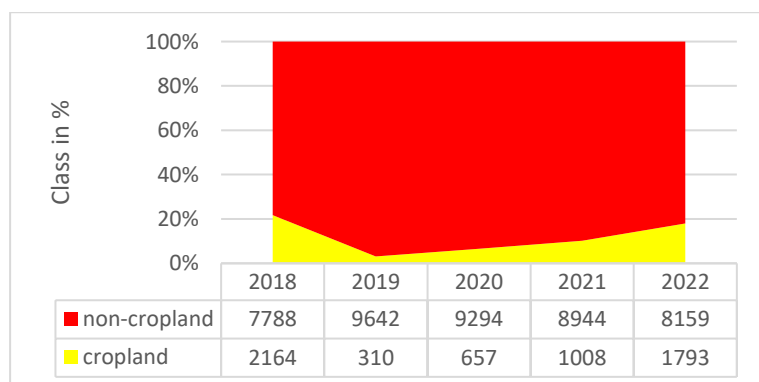


Figure 33: Baga Sentinel-2 (10m) cropland mask in ha

Table 9: Baga AOI PlanetScope cropland classification at 1:60 000

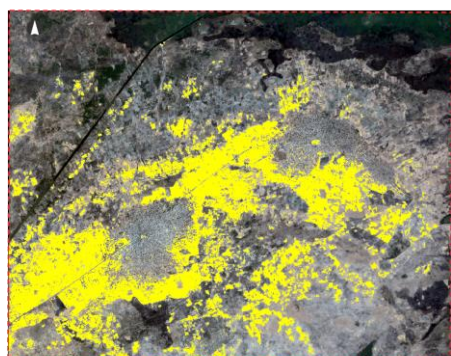


Figure 34: Baga PS 24.10.2018 class

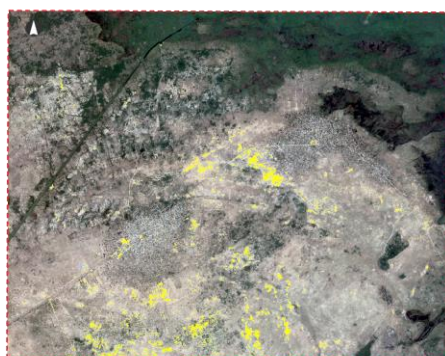


Figure 35: Baga PS 30.10.2019 class

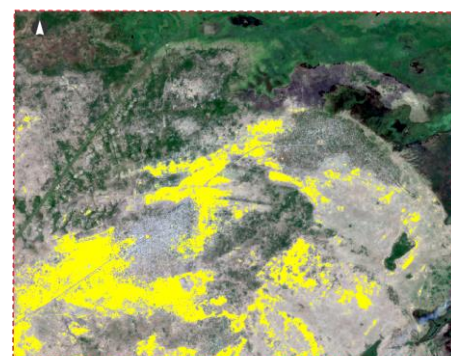


Figure 36: Baga PS 29.10.2020 class

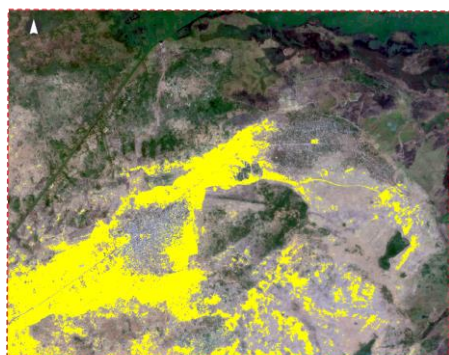


Figure 37: Baga PS 26.10.2021 class

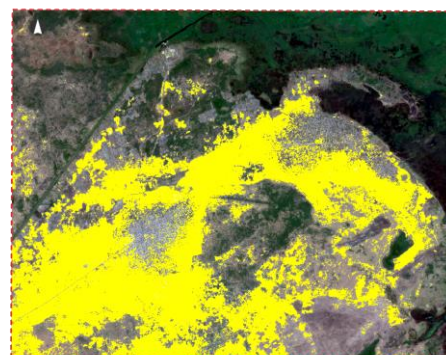


Figure 38: Baga PS 26.10.2022 class

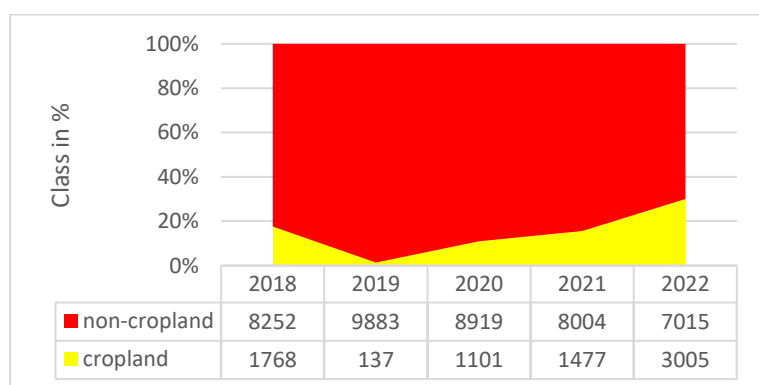


Figure 39: Baga PlanetScope (3m) cropland mask in ha

5.2.2. Dikwa AOI classification

Unlike Baga, Dikwa remained relatively stable throughout the study period, being under governmental control. As a consequence, this stability resulted in a consistent cropland pattern, with no drastic fluctuations. Dikwa serves as an important center for IDPs, currently hosting thousands to this day, primarily from other LGAs in Borno such as the conflict-affected Kukawa LGA.

The Planetscope sensor displayed a peak cropland of 2025 hectares in 2021 (Figure 45), which could be attributed to the exceptionally dry year as shown previously in the Phenology pattern analysis, causing bare soil areas such as roads (Figure 43) to be erroneously identified as croplands. However, both sensors agree on a consistent cropland pattern in Dikwa AOI, which attests to the region's stability during the studied period while Baga located near the frontlines has a more fluctuating and dynamic cropland mask related to its population displacement.

Table 10: Dikwa AOI Sentinel-2 cropland classification at 1:60 000

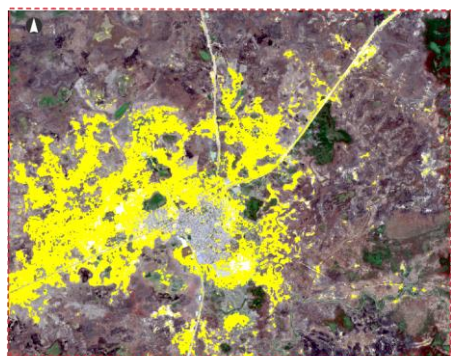


Figure 40: Dikwa S2 31.10.2018 class

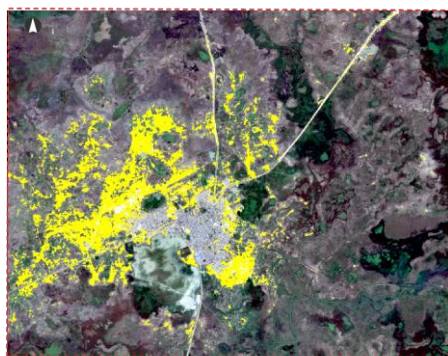


Figure 41: Dikwa S2 31.10.2019 class

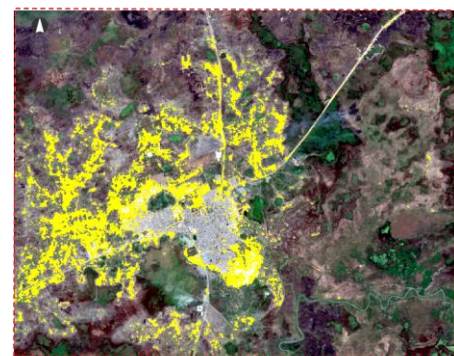


Figure 42: Dikwa S2 30.10.2020 class

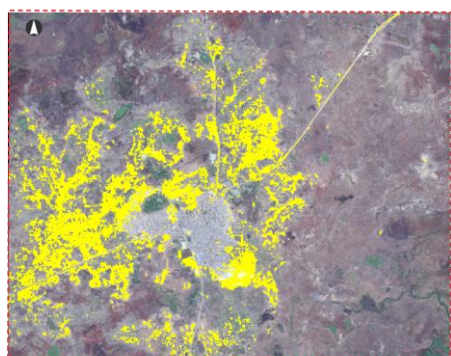


Figure 43: Dikwa S2 25.10.2021 class

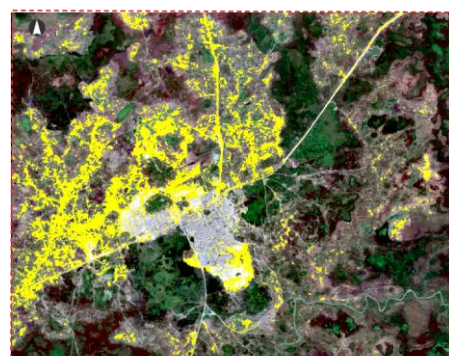


Figure 44: Dikwa S2 25.10.2022 class

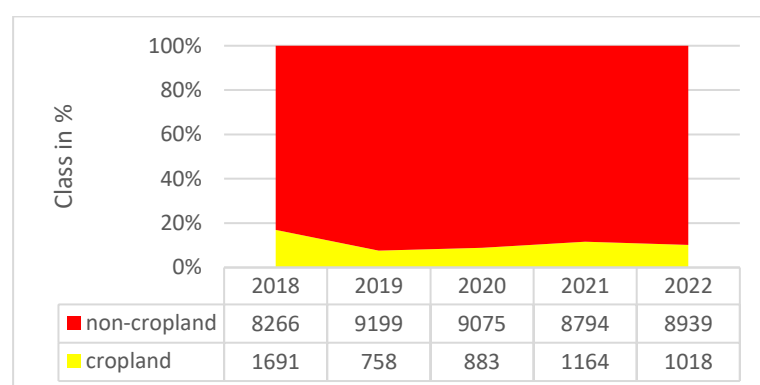


Figure 45: Dikwa Sentinel-2 (10m) cropland mask in ha

Table 11: Dikwa AOI Planetscope cropland classification at 1:60 000



Figure 46: Dikwa PS 28.10.2018 class

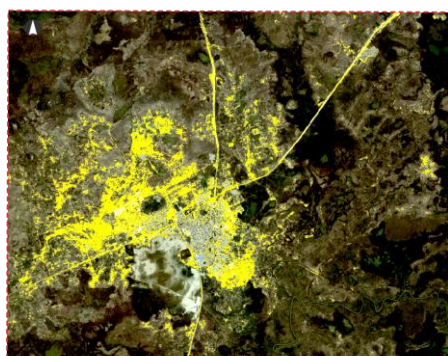


Figure 47: Dikwa PS 30.10.2019 class

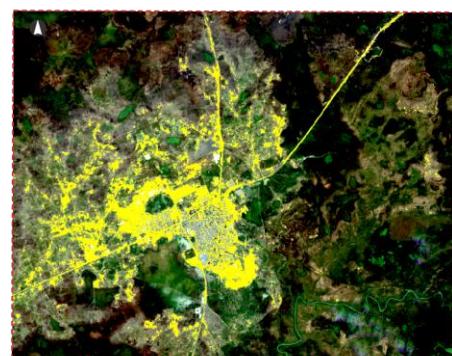


Figure 48: Dikwa PS 27.10.2020 class

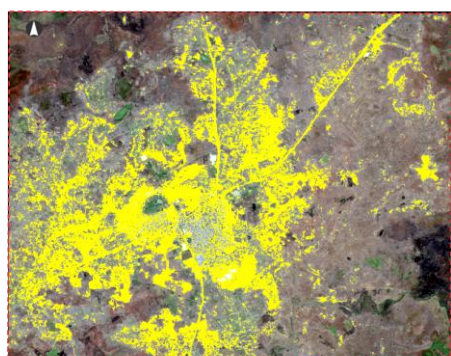


Figure 49: Dikwa PS 29.10.2021 class

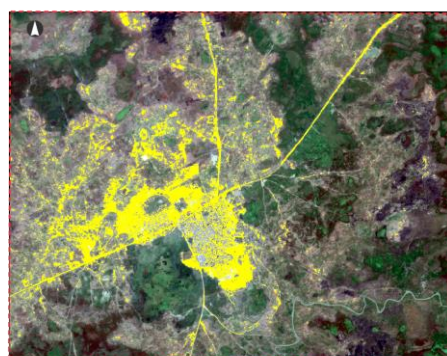


Figure 50: Dikwa PS 31.10.2022 class

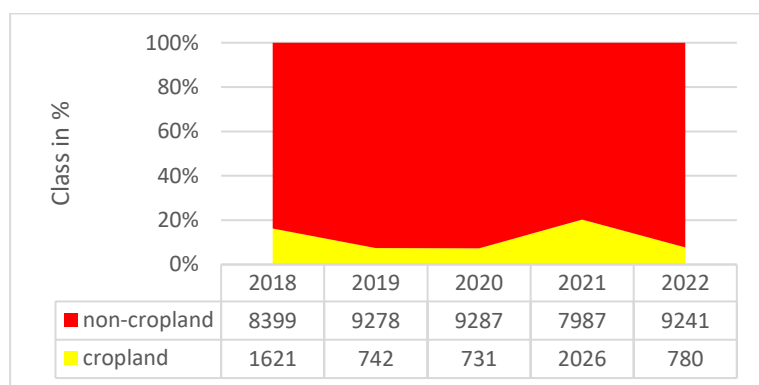


Figure 51: Dikwa Planetscope (3m) cropland mask in ha

5.2.3. Multiyear cropland mask

For both AOIs, multiyear overlap maps were produced, this process entailed the synthesis of annual masks, which allowed to visualize enduring croplands over the examined period, effectively highlighting the constancy and change of these agrarian landscapes. These resultant multi-year maps underscore the intensity and stability of cropland detection over time. Specifically, areas exhibiting a brighter yellow hue denote zones of consistent crop cultivation, indicating that these areas have remained agricultural over the years. Thus, through the gradation of color, this presents a vivid portrait of the continuity of croplands, serving as a testament to the various shifts occurring in croplands over time. Upon visual analysis, it was observed that both AOIs and sensors consistently identified the same locations as cropland year after year. This illustrates a spatial consistency in cropland distribution, indicating that, despite changes in the overall cropland mask over time, the geographical extent of these croplands remains largely unaltered. This persistence, despite the ongoing conflict and environmental changes, provides strong evidence to validate the identification of these areas as croplands.

Table 12: Multiyear overlap masks for both AOIs and both sensors at 1:70 000

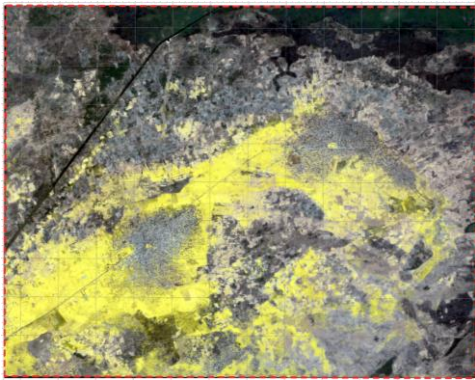


Figure 52: Baga PS multiyear cropland mask overlap

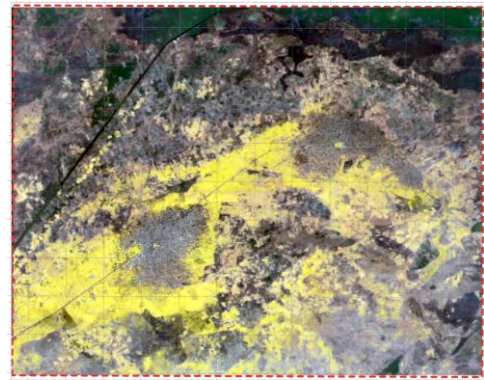


Figure 53: Baga S2 multiyear cropland mask overlap

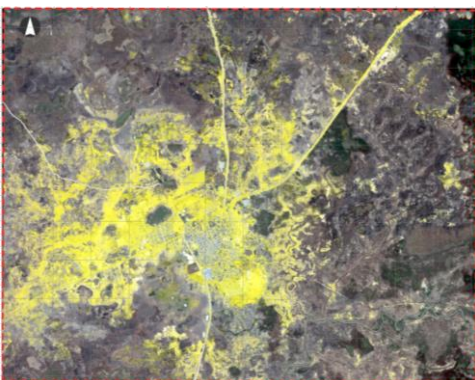


Figure 54: Dikwa PS multiyear cropland mask overlap

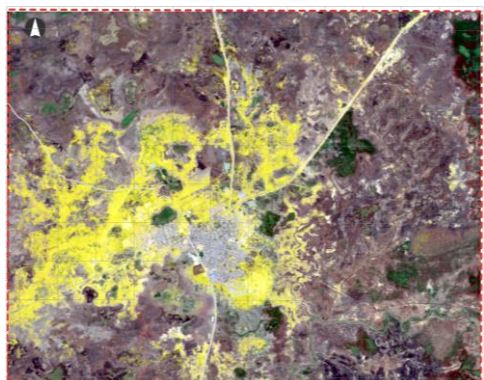


Figure 55: Dikwa S2 multiyear cropland mask overlap

5.2.4. Classification accuracy assessment

A confusion matrix was utilized to evaluate the classification accuracy (Table 13 & Table 14) for the year 2018, as it is the year that our classification is based on. The overall accuracy was high for both AOIs and sensors, with the exception of Sentinel-2 in the Baga AOI. The accuracy issues in this case may be partly attributed to the sensor's coarser resolution and the dynamic environment of the AOI.

Table 13: Classification error matrix and accuracy metrics for Baga AOI (2018)

Predicted value	Reference value			
	Sentinel-2 Baga AOI	Cropland	Non-cropland	Total
	Cropland	9	0	9
	Non-cropland	3	12	15
	Total	12	12	24
	Planetscope Baga AOI	Cropland	Non-cropland	Total
	Cropland	13	1	14
	Non-cropland	0	18	18
	Total	13	19	32

Accuracy metrics	Sentinel-2 Baga AOI	Cropland	Non-cropland
	Producer's accuracy (Recall)	75%	100%
	User's accuracy (Precision)	100%	80%
	F1 score	85.7%	88.9%
	Overall accuracy	87.5%	
	Kappa index	87.5%	
	Planetscope Baga AOI	Cropland	Non-cropland
	Producer's accuracy (Recall)	100%	94.7%
	User's accuracy (Precision)	92.9%	100%
	F1 score	96.3%	97.3%
	Overall accuracy	96.9%	
	Kappa index	88.5%	

Table 14: Classification error matrix and accuracy metrics for Dikwa AOI (2018)

	Reference value			
Predicted value	Sentinel-2 Dikwa AOI			
	Cropland	Non-cropland	Total	
	Cropland	16	0	16
	Non-cropland	1	18	19
	Total	17	18	35
	Planetscope Dikwa AOI			
	Cropland	Non-cropland	Total	
	Cropland	13	0	13
	Non-cropland	1	18	19
	Total	14	18	32

Accuracy metrics	Sentinel-2 Dikwa AOI		
	Cropland	Non-cropland	
	Producer's accuracy (Recall)	94.1%	100%
	User's accuracy (Precision)	100%	94.7%
	F1 score	97%	94.7%
	Overall accuracy	97.1%	
	Kappa index	94.2%	
	Planetscope Dikwa AOI		
	Cropland	Non-cropland	
	Producer's accuracy (Recall)	92.9%	100%
	User's accuracy (Precision)	100%	94.7%
	F1 score	96.3%	94.7%
	Overall accuracy	96.8%	
	Kappa index	93.8%	

5.3. Change detection results.

The post-classification change detection method resulted in binary values defining the class transitions. First, the cropland to non-cropland value (1) and then the non-cropland to cropland value (2). This aided in understanding the cropland area's changes over the study period.

 **Cropland to non-cropland**

 **Non-cropland to cropland**

5.3.1. Baga AOI change detection

Table 15 illustrates the post-classification change detection performed with Sentinel-2 in Baga AOI. The shift from croplands to non-croplands is pronounced between 2018-2019 with 1948 hectares transitioning (Figure 56). The following years mark a progressive re-cultivation pattern of croplands (Figure 60) correlated with the return of the IDPs to Baga. The Planetscope sensor reflects the same pattern (Table 16) but with higher intensities (Figure 65), likely due to its superior spatial resolution.

Table 15: Baga AOI Sentinel-2 cropland change at 1:60 000

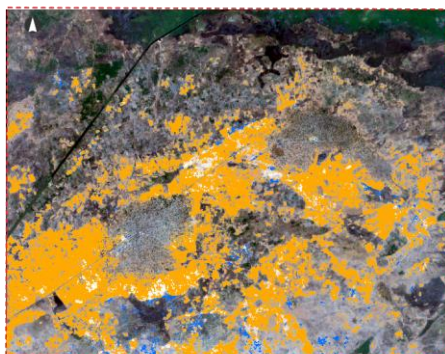


Figure 56: Baga S2 2018-2019 change

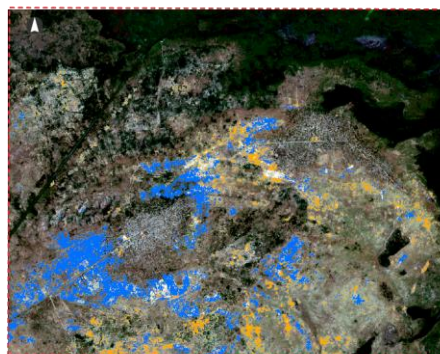


Figure 57: Baga S2 2019-2020 change

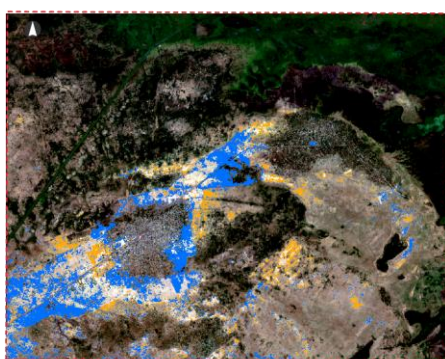


Figure 58: Baga S2 2020-2021 change

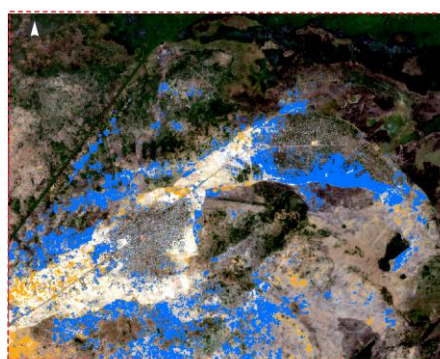


Figure 59: Baga S2 2021-2022 change

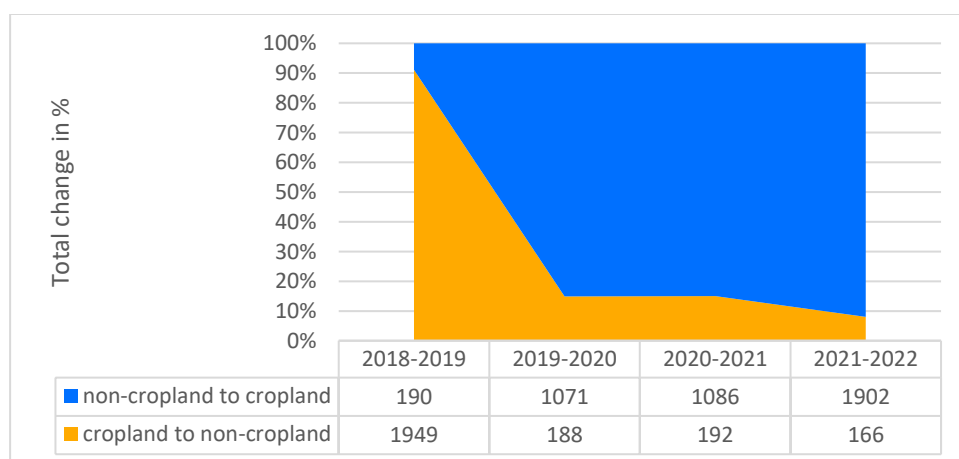


Figure 60: Baga Sentinel-2 (10m) change detection

Table 16: Baga AOI Planetscope cropland change at 1:60 000



Figure 61: Baga PS 2018-2019 change

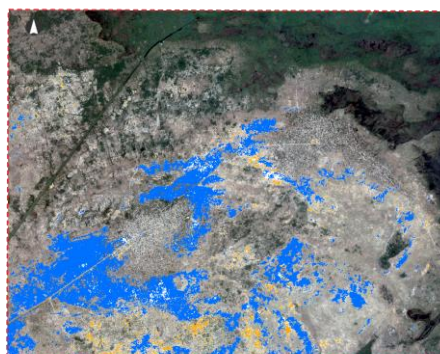


Figure 62: Baga PS 2019-2020 change

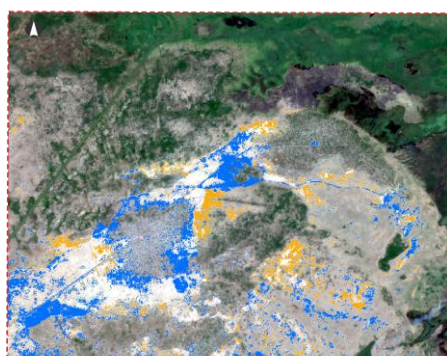


Figure 63: Baga PS 2020-2021 change

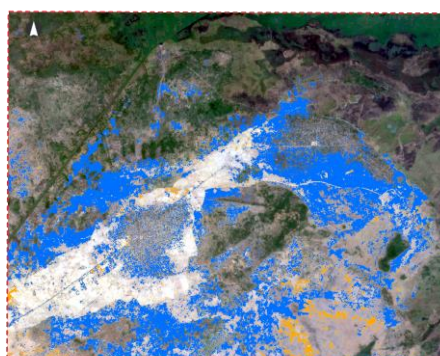


Figure 64: Baga PS 2021-2022 change

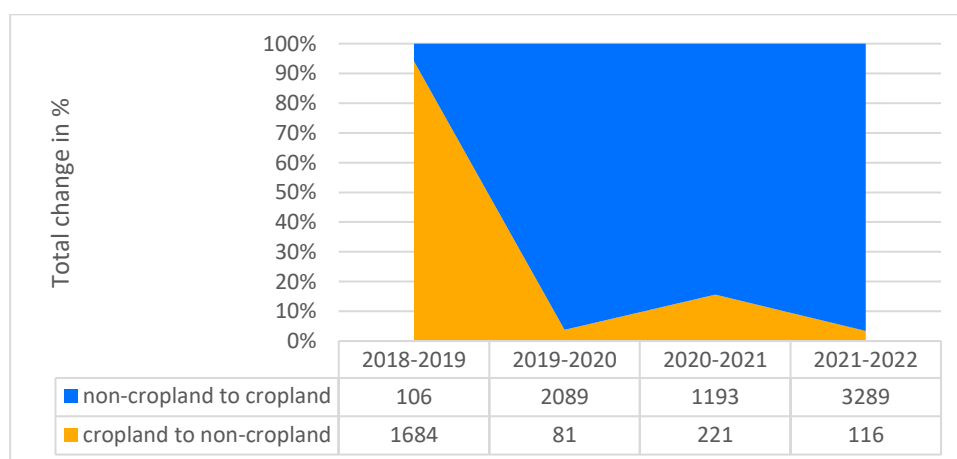


Figure 65: Baga Planetscope (3m) change detection

5.3.2. Dikwa AOI change detection

In Dikwa AOI, both sensors agree on the trend that croplands turned into non-croplands during 2018-2019 (Figure 66, Figure 71). Subsequently, non-croplands converted back to croplands between 2019-2021. However, these changes were minimal, and most areas remained stable. Thus, these changes must be minor, and the original cropland mask shown previously is the principal indicator for the Dikwa AOI. We can also deduce that Sentinel-2 overestimates the change (Figure 70) and Planetscope underestimates the change, in particular between 2021 – 2022.

However, we can deduct from this analysis that both sensors agree on the general trend and that change is occurring on a minimal scale as the cropland mask stays stable over time.

Table 17: Dikwa AOI Sentinel-2 cropland change at 1:60 000

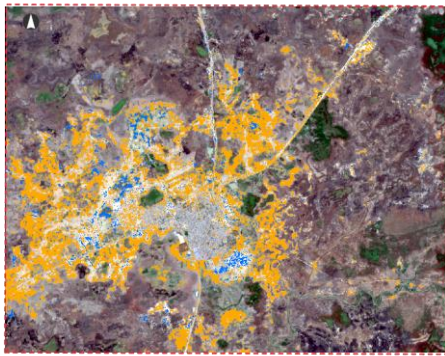


Figure 66: Dikwa S2 2018-2019 change

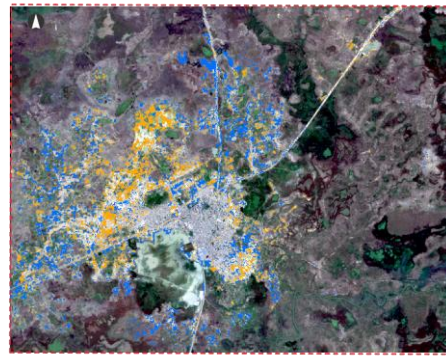


Figure 67: Dikwa S2 2019-2020 change

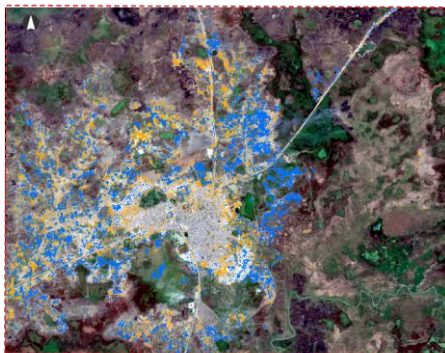


Figure 68: Dikwa S2 2020-2021 change

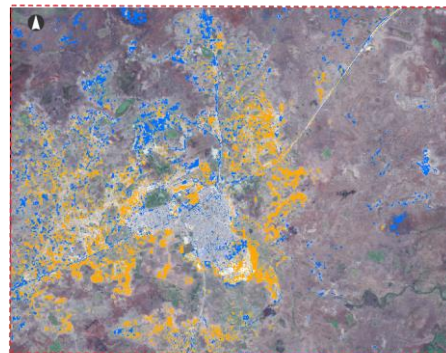


Figure 69: Dikwa S2 2021-2022 change

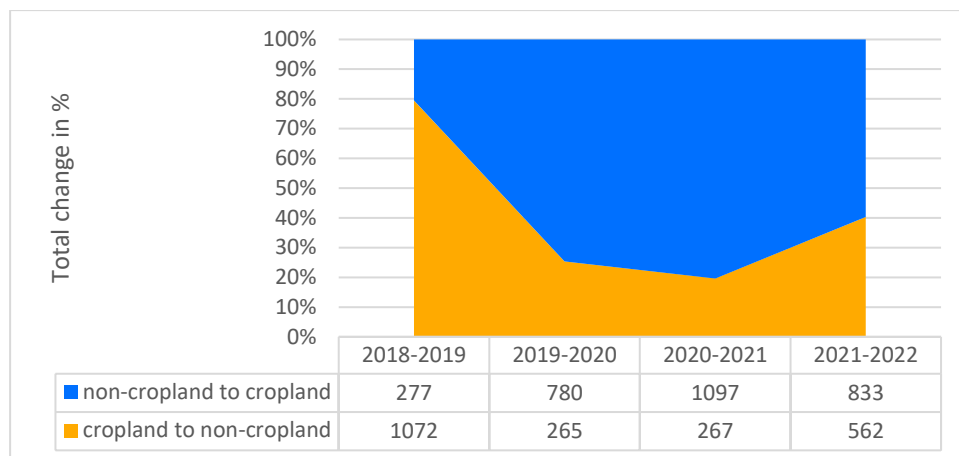


Figure 70: Dikwa Sentinel-2 (10m) change detection

Table 18: Dikwa AOI Planetscope cropland change at 1:60 000

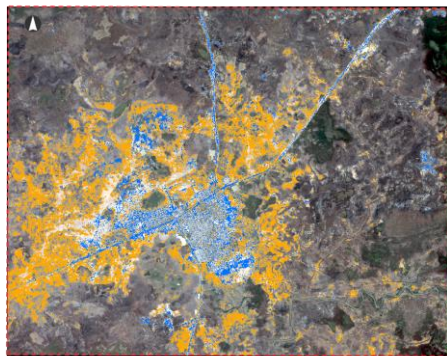


Figure 71: Dikwa PS 2018-2019 change

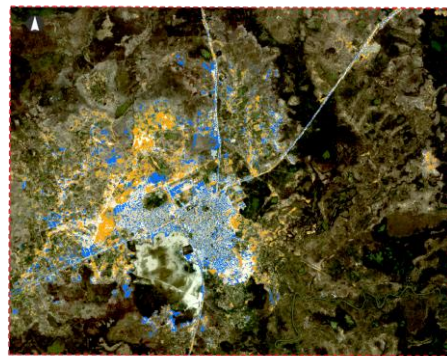


Figure 72: Dikwa PS 2019-2020 change

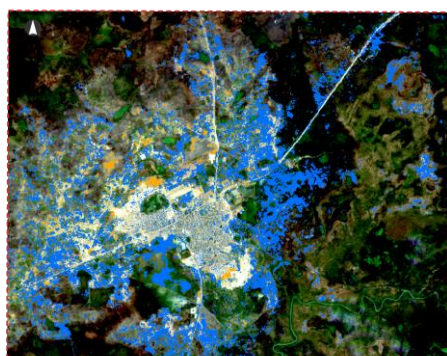


Figure 73: Dikwa PS 2020-2021 change



Figure 74: Dikwa PS 2021-2022 change

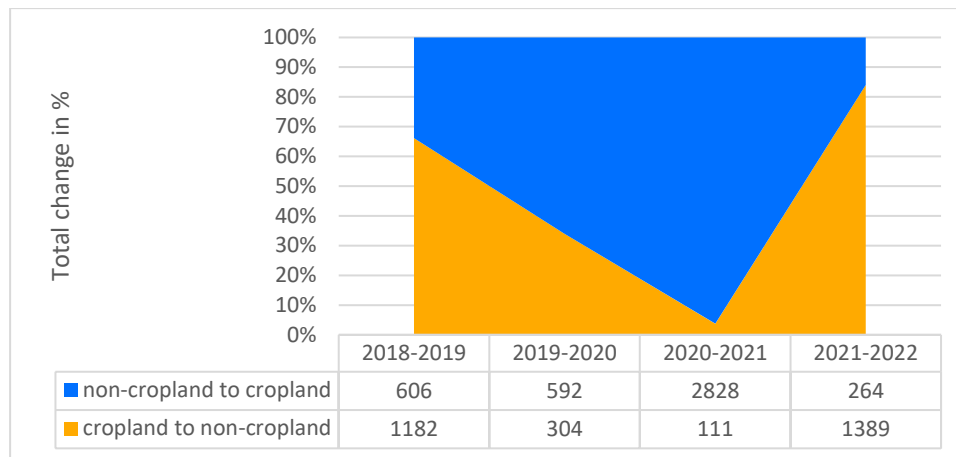


Figure 75: Dikwa Planetscope (3m) change detection

5.3.3. Change detection portability accuracy

The temporal consistency of the cropland mask classification was assessed by examining the 50 'in-situ' calibration points determining whether each calibration point that was identified as croplands in 2018 has retained or not their cropland classification in the subsequent years.

For the Baga AOI, both sensors classify 48 points as croplands at the start of the conflict intensity rising in 2018 and then 46 points at the return of the displaced population in 2022 (Figure 76, Figure 77). This trend inverses during the displacement period between 2019 – 2021 when the conflict reached its peak intensity, demonstrating the correlation between conflict intensity, population displacement, and cropland abandonment.

For the Dikwa AOI, the classification and change detection accuracy are more challenging. Both sensors agree on the general trend for 2018, 2019 and 2021 where the majority of the 50 calibration points are croplands in 2018 and 2021 and that they become non-cropland in 2019.

However, for 2020 and 2022, Sentinel-2 (Figure 78) and Planetscope (Figure 79) show conflicting results. Sentinel-2 detects the majority of the points as croplands while Planetscope detects the majority of the points as non-croplands. This discrepancy could be due to differences in the classification process or the spectral properties of the sensors.

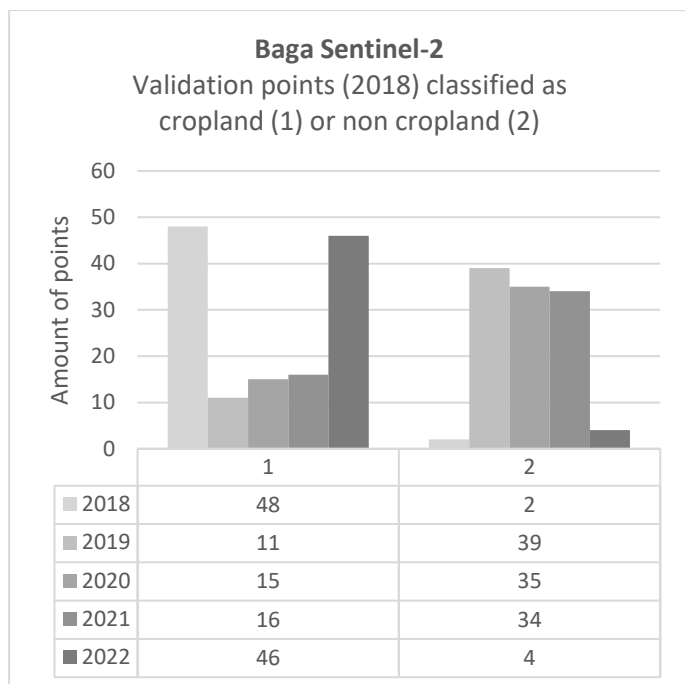


Figure 76: Baga AOI S2 change detection consistency assessment

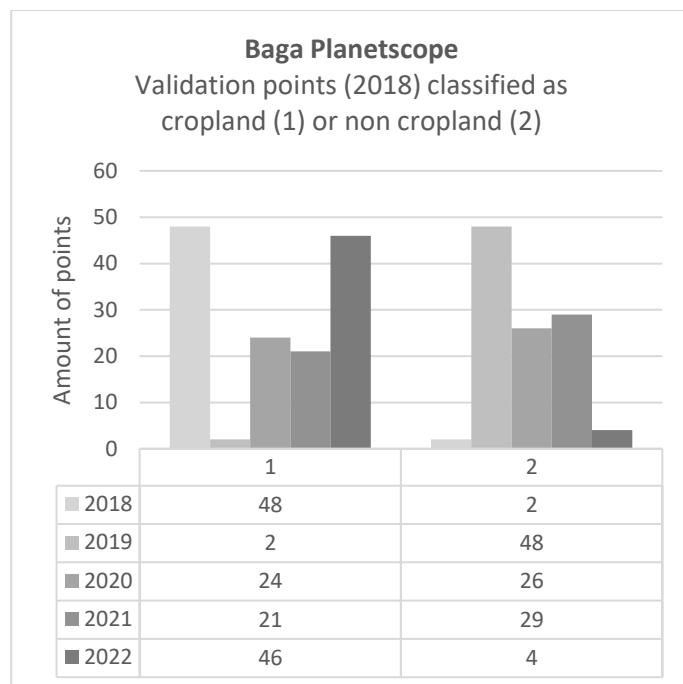


Figure 77: Baga AOI PS change detection consistency assessment

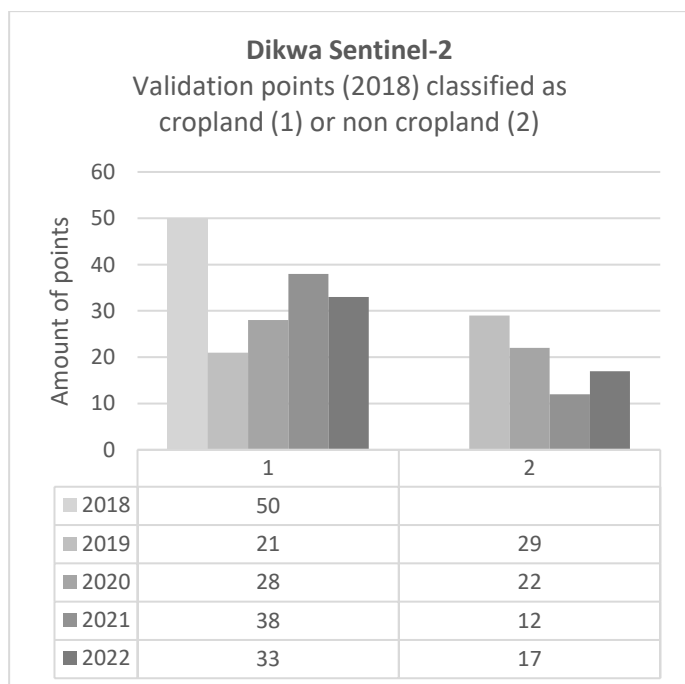


Figure 78: Dikwa AOI S2 change detection consistency assessment

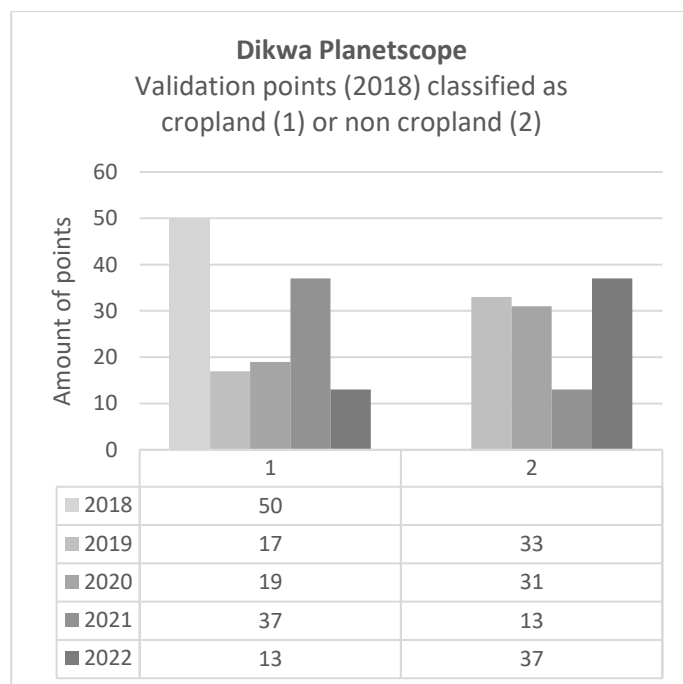


Figure 79: Dikwa AOI PS change detection consistency assessment

5.4. Discussion and perspectives

This chapter embarks upon a comprehensive discussion of the study findings and addresses the challenges encountered during the research process. Furthermore, it explores potential future research perspectives sparked by the insights and limitations of the present investigation.

5.4.1. Discussion and challenges

Correlation between conflict intensity and cropland abandonment (Appendix C): A distinct correlation between conflict intensity and cropland abandonment was elucidated during the peak conflict period in the Baga AOI leading to significant population displacement and a consequent decrease in cropland. The direct impact of the 2018 Lake Chad campaign lends credence to this observation. However, understanding the stability of the cropland mask in the Dikwa AOI proved challenging, particularly given the non-corresponding increase in IDPs and cropland area as it was expected. The divergent dynamics observed between the Baga (conflict-ridden) and Dikwa (largely stable) AOIs underscore the need for a more nuanced understanding of how armed conflicts affect cropland abandonment.

Importance of identifying the patterns: Discerning the patterns intrinsic to the regional phenology, conflict dynamics and displacement population was crucial. This study affirmed the value of rainfall data and the correlation with NDVI values in understanding the north-south gradient of Borno province. Conflict pattern analysis through datasets played an instrumental role in decoding the conflict dynamics in both AOIs. Yet, challenges were encountered in gathering data on displaced population patterns, chiefly due to inaccessible areas and survey inconsistencies from year to year. Despite these hurdles, primary IDP patterns could still be discerned from available reports.

Environmental reliability and local practices (Appendix B): The study was confronted with specific challenges related to the local environment in both AOIs. Over the study's five-year duration, tree cover saw significant growth, complicating cropland reclamation for the affected population. Furthermore, the advancing frontline of Lake Chad replaced swathes of cropland with wetlands, posing additional hurdles for land reclamation after population return. These observations emphasize the need to incorporate the local context in future studies, as the agricultural practices seen in Borno may not be universally applicable to other countries in the Global South. Both AOIs practice slash and burn agriculture with different dates of crop burning as the seasonality differs from Baga to Dikwa, this can affect the cropland mask highly due to differences in spectral signatures of croplands and burnt-croplands.

Identifying croplands: The identification of croplands proved particularly challenging, with four different methods being deployed in both AOIs. Firstly, the temporal NDVI change detection method found limited success, followed by the NDVI maximum value composite. Then the RED Maximum value composite was indeed successful in both AOIs and finally, a visual validation using the WorldView-3 sensor on Google Earth validated or not the previous

methods. While market-gardens in the Baga AOI were initially categorized as croplands due to similar vegetative cover during the abandonment period, their spectral signature closely resembled the bare-soil or built-up class, affecting the classification output. Therefore, as this study focuses on 'croplands' these market-garden plots were ultimately classified as 'drylands' for the study's purpose (Appendix B).

The remote sensing potential for detecting cropland abandonment (Appendix D): The potential of remote sensing technology in detecting cropland abandonment was further highlighted through a multi-sensor approach. The PlanetScope constellation offered valuable detail but posed challenges in its calibration and reflectance values due to changes in sensor type (Dove Classic before 2020 to Super Dove after 2020). Another issue with the PlanetScope sensor was related to the initial images with high noise values, area coverage problems and sometimes with finding no suitable images at all. The Sentinel-2 sensor performed well overall, regardless of its coarser resolution that did not prevent an accurate detection of croplands. Despite these issues, the methodology remained robust with both sensors, affirming the value of remote sensing in assessing hard-to-reach areas such as Baga, affected by armed conflict and known for its significant population displacement.

5.4.2. Perspectives

The results of this study open several avenues for future research and provide insights that may have implications for humanitarian aid planning. The relationship between phenology, conflict intensity, population displacement and cropland abandonment, as demonstrated in this thesis, calls for more detailed investigations.

First, one of the findings of this study is the discrepancy between the Baga and Dikwa AOIs in terms of their response to conflict and population displacement. This raises questions about the nuances in how conflict impacts different areas in the same province (such as Borno here), and further investigations could unpack the complex dynamics of cropland abandonment in areas experiencing varied conflict intensities and population displacement patterns. The return and restoration of IDPs could be examined in the context of recovery and reconstruction efforts in conflict-ridden regions. It might be interesting to explore the challenges and opportunities associated with this phenomenon.

Second, the challenges encountered in gathering data on displaced population patterns, particularly in hard-to-reach areas, highlight the need for more reliable, consistent data collection methodologies in such regions. Future research could focus on looking for more robust methods to track population displacement patterns.

Third, the local practices and environmental challenges, like tree cover growth, the expanding Lake Chad frontline and the slash and burn agriculture practices, underscore the necessity of considering local environmental dynamics and practices when studying cropland abandonment.

This calls for more context-specific research to understand how environmental factors and local agricultural practices interact with conflict and displacement.

Fourth, the identification of croplands poses a challenge that invites further exploration. The deployment of multiple methods in this study highlights the complex and labor-intensive nature of this task and calls for more refined and automated techniques for cropland identification for areas such as Baga at the frontier of the Sahara and wetlands of the Lake Chad. Investigations could focus on developing and testing new remote sensing methodologies and algorithms to improve the accuracy and reliability of cropland identification with *in-situ* data.

Fifth, the portability of the model from one year to another proved successful with accurate confirmation of the hypotheses on Baga AOI, further studies could investigate the error propagation for this kind of portability application with the development of more comprehensive accuracy assessment and validation methods.

Lastly, the promise of remote sensing technology in detecting cropland abandonment, despite certain limitations, invites further exploration into the capabilities and applications of various remote sensing tools. Continued advancement in remote sensing technology and its integration with other research methods could improve the accuracy and granularity of data, especially in hard-to-reach or conflict-ridden areas. This could include evaluating the performance of newer very high-resolution sensors, developing more advanced algorithms for image processing, and integrating multi-sensor data for more comprehensive analyses.

While the study faced several challenges, these have opened avenues for future research, underscoring the value of a nuanced, context-specific approach to understanding conflict-induced shifts cropland abandonment. This study also reaffirms the potential of remote sensing technologies as indispensable tools in such investigations. Continued investigation along these lines will not only advance our academic understanding of the complex interplay between local phenology, conflict, displacement, and cropland abandonment but also provide critical insights for policymakers, planners, and humanitarian organizations working to address these challenges on the ground.

Chapter 6. Conclusion

The study attempts to elucidate cropland abandonment in rural areas affected by conflict, by identifying patterns related to phenology, conflict and population displacement while presenting their relationships with a remotely sensed analysis with both Sentinel-2 and Planetscope sensors for the two AOIs of Baga and Dikwa across the study period (2018-2022).

Rainfall patterns revealed a well-established north-south gradient, with Baga recording less overall rainfall than Dikwa. October was determined as the most suitable month for cropland classification as it is post-harvest and before the croplands dry out completely. The positive correlation between NDVI and rainfall patterns endorsed this choice, especially as NDVI values reflected significant vegetation values during this period. Conflict pattern analysis exposed an intensification of conflict events, particularly battles, during the Chad basin campaign (2018-2020), with a subsequent decline. The conflict events remained correlated with the displaced population numbers, indicating a direct impact of armed conflict on population displacement. Displaced population analysis was inconsistent due to data availability issues, notably in the hard-to-reach Baga area. However, a decline in IDPs post-2020 was noted, potentially signaling a return of the affected populations to their original residences as conflict intensity diminished. Yet, due to data sparsity, a returnee pattern couldn't be established.

Classification results, derived from the application of the successfully portable RF algorithm, identified two binary classes: 'cropland' and 'non-cropland.' In the Baga Area of Interest (AOI), both sensors recorded a decrease in cropland during peak conflict years (2018-2020), followed by an increase post-2020 as the conflict intensity subsided. This confirmed the hypothesized correlation between conflict intensity, population displacement, and cropland abandonment. On the other hand, the Dikwa AOI, under government control, displayed consistent cropland patterns, highlighting the region's stability throughout the study period.

Change detection results were produced using the post-classification change detection method, resulting in binary values defining the class transitions. In the Baga AOI, there was a noticeable shift from croplands to non-croplands during the peak conflict period (2018-2019) followed by a progressive recovery. In contrast, Dikwa AOI demonstrated minor changes with the majority of the area remaining stable, indicating that the classified cropland mask is the key indicator.

In general, both sensors demonstrated high overall accuracy even with the portability from one year to another thanks to the handpicked images discerning the spectral signatures, with a few discrepancies noted. Furthermore, accuracy in detecting change was more challenging in Dikwa AOI due to differences in classification process or spectral properties of the sensors. Overall, this thesis utilized remote sensing data to unravel the interplay between conflict, displacement, and cropland abandonment. Despite data limitations and methodological challenges, these results provide valuable insights and propose a 'simple but not simplistic' methodology into the spatial-temporal dynamics in hard-to-reach conflict-ridden areas.

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Webography

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[https://en.wikipedia.org/wiki/Chad_Basin_campaign_\(2018%E2%80%932020\)](https://en.wikipedia.org/wiki/Chad_Basin_campaign_(2018%E2%80%932020))

Planet Explorer platform to download Planetscope imagery: <https://www.planet.com/explorer/>

Quarterly Factsheet April - June 2022: <https://data.unhcr.org/en/documents/details/94492>

Satellite Imagery Analysis 2022: Cropland Change Detection Analysis in Hard-to-Reach Areas (March 2023) <https://docs.wfp.org/api/documents/WFP-0000147544/download/>

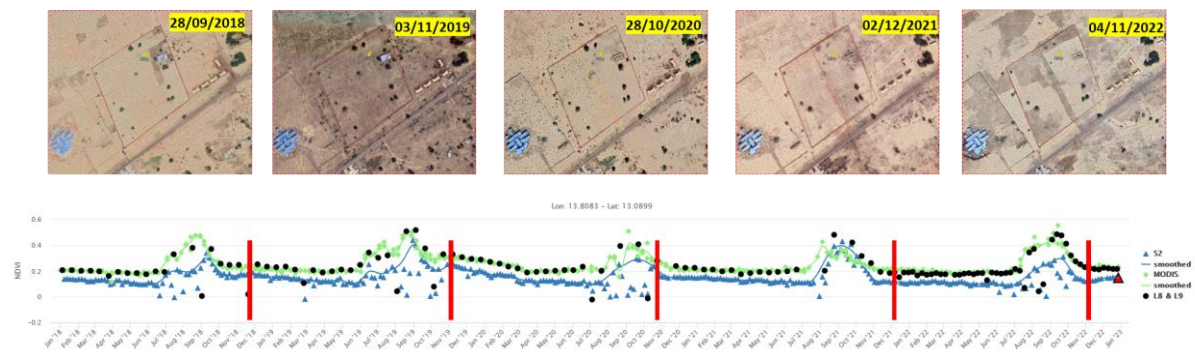
Sentinel Hub platform to download Sentinel-2 imagery: <https://www.sentinel-hub.com/>

UNHCR Northeast Nigeria Operational Update 2022:
<https://data.unhcr.org/en/documents/download/91182>

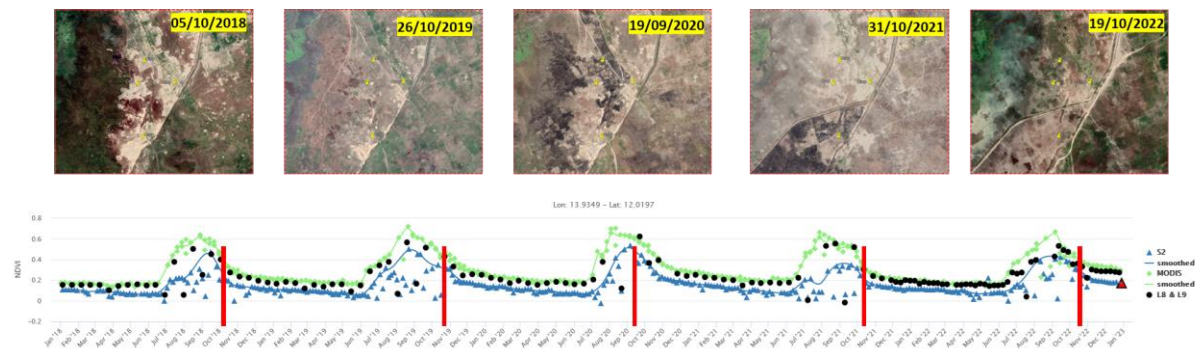
WFP VAM DataViz platform:
https://dataviz.vam.wfp.org/seasonal_explorer/rainfall_vegetation/visualizations

Appendix A. Portability of the model

Baga AOI model portability seasonal profile with VHR images



Dikwa AOI model portability seasonal profile with VHR images

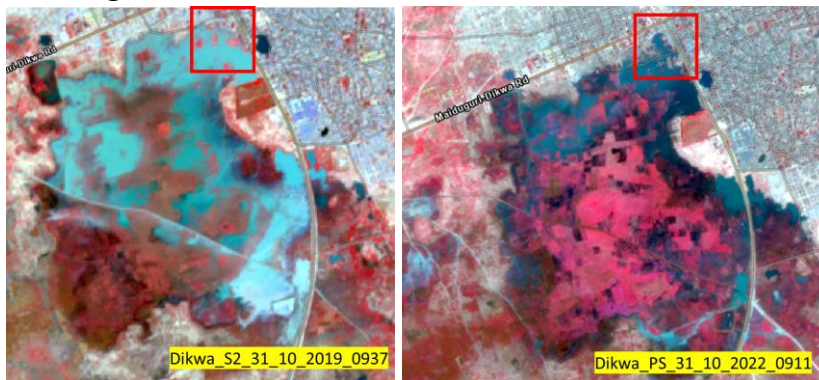


Appendix B. Challenges

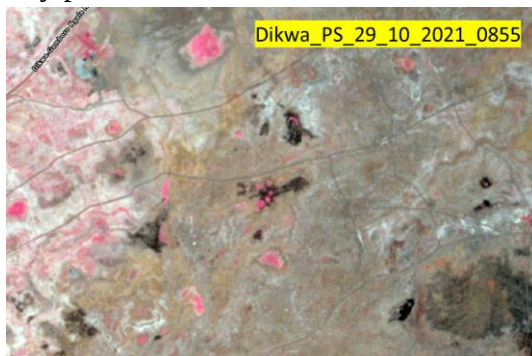
Slash and burn agriculture (seen in infrared false color composite)



Floodings



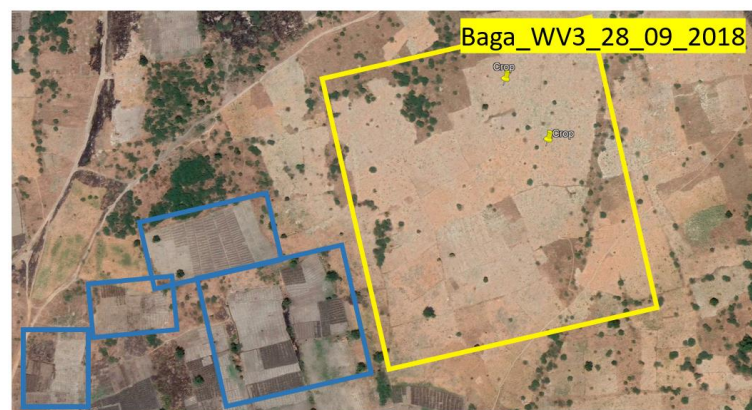
Dry periods



Lake Chad's waterfront progression and replacement of croplands by wetlands

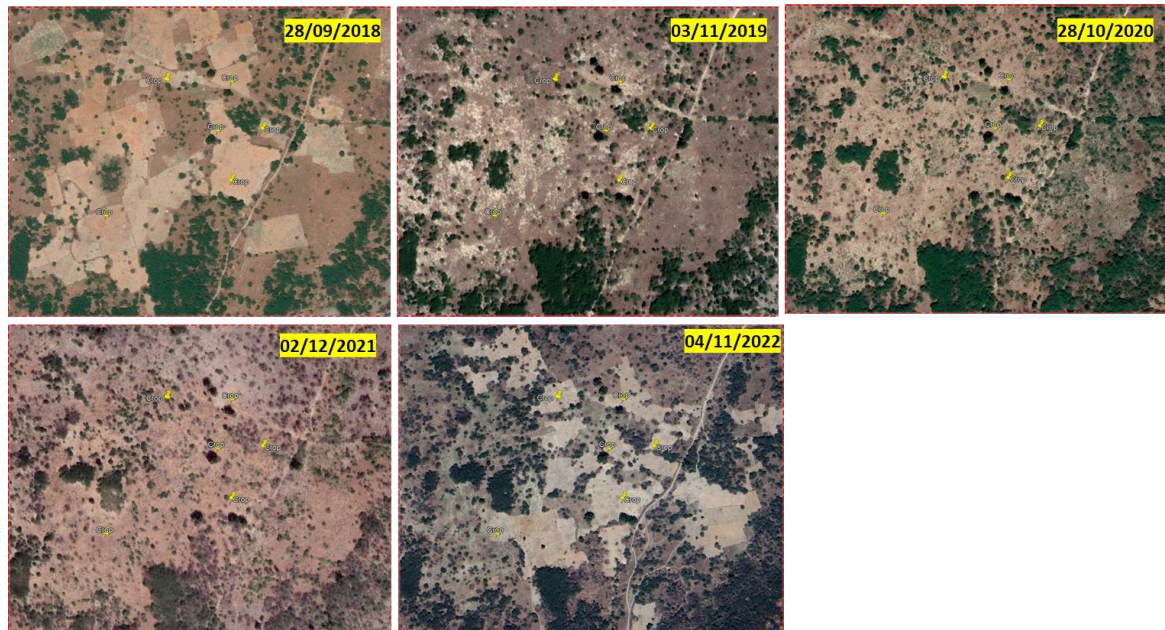


Identifying market gardens (blue) and croplands (yellow)

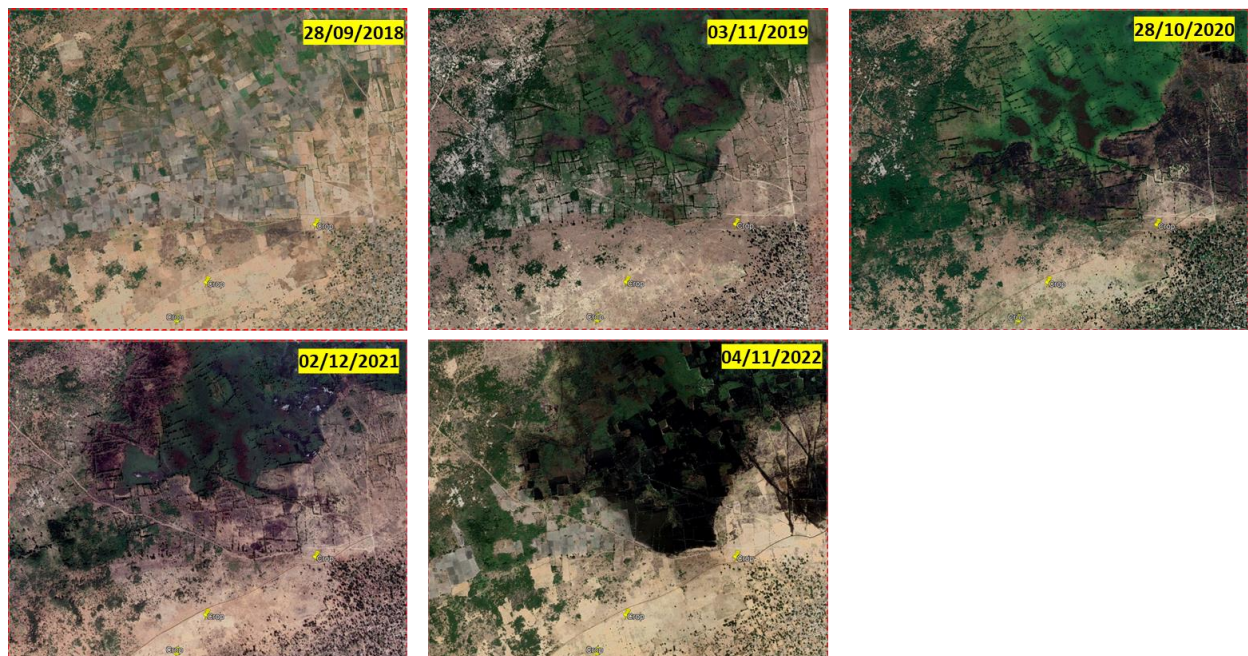


Appendix C. Cropland abandonment visualized in VHR

Baga AOI, patterns of cropland abandonment and re-cultivation seen from Maxar WV3



Baga AOI, cropland and market-gardens abandonment and gradual replacement with vegetation and wetlands seen form Maxar WV3



Appendix D. Sentinel-2 and Planetscope visual comparisons at 1:7000



Baga S2 2018: Canal view in true color



Baga PS 2018: Canal view in true color



Dikwa S2 2018 : Croplands view in FCC



Dikwa PS 2018 : Croplands view in FCC

Abstract

In the struggles of armed conflict, challenges often inhibit food related humanitarian assessments to embattled regions. One viable solution to this hurdle is the application of satellite imagery. This Master's thesis investigates the interplay of conflict and population displacement on cropland abandonment in two areas of interest of the Borno province, Nigeria through a remotely sensed analysis.

The study leverages advancements in remote sensing technology, utilizing high-resolution satellite imagery from Sentinel-2 and PlanetScope sensors to monitor cropland abandonment from 2018 to 2022, during and after the Chad Basin campaign. The research identifies temporal patterns related to phenology, conflict, and population displacement and relates these patterns to remote sensing data. A discernible north-south rainfall gradient is noted, determining October as the optimal month for cropland classification. A conflict pattern is established with the intensification of the conflict following the Chad basin campaign (2018 – 2020) correlated with population displacement and return.

The random forest algorithm for classification of 'cropland' and 'non-cropland' areas reveals variable patterns across areas of interest. The algorithm, initially based on the year 2018, has been effectively ported to subsequent years, thus validating a 'portable classification model'. Baga, subjected to intense conflict, demonstrated cropland decrease during the high intensity conflict period, followed by recovery as conflict subsided, confirming the hypothesized correlation. In contrast, Dikwa, under government control and a center of displaced population camps, displayed consistent cropland patterns, demonstrating relative stability.

Change detection results elucidate shifts from croplands to non-croplands during conflict intensification and subsequent recovery. Overall, despite the few discrepancies, the sensors demonstrated high accuracy in data portability and classification, underscoring the utility of remote sensing in monitoring spatio-temporal cropland abandonment dynamics in hard-to-reach conflict areas.

In summary, this research provides valuable insights into cropland abandonment in conflict zones and proposes a rapid, yet nuanced, remote sensing methodology to assist humanitarian response.