NIGERIA

REMOTE SENSING ANALYSIS OF BORNO STATE

Exploring proxy measures of vulnerability in hard-to-reach areas

22 October 2020

REACH Informing more effective humanitarian action

United Nations Institute for Training and Research

UNOSAT

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LIST OF ACRONYMS

BAY	Borno, Adamawa, & Yobe States
IDP	Internally displaced person
MSNA	Multi-sector needs assessment
AoK	Area of knowledge
LGA	Local government area
KI	Key informant
HNO	Humanitarian needs overview
HRP	Humanitarian response plan
OCHA	United Nations Office for the Coordination of Humanitarian Affairs
FSL	Food security and livelihoods
IPC	International Phase Classification
NDVI	Normalized difference vegetation index
FEWSNET	Famine Early Warning Systems Network
SRTM	Shuttle Radar Topography Mission
SWIR	Shortwave infrared
VV	Vertical-vertical polarization (radar)
VH	Vertical-horizontal polarization (radar)


Fields outside of Maiduguri, Nigeria (January, 2017)   © Maxar / Digital Globe

INTRODUCTION

Almost eight million people are affected by the humanitarian crisis in north-east Nigeria, and since the start of the conflict in 2010, more than 50,000 people have been killed and 1.6 million displaced. In spite of the turmoil and the critical humanitarian conditions faced by the conflict-affected populations, significant proportions of the displaced have begun to return to their areas of origin.

As the protracted crisis in north-east Nigeria progresses into its tenth year, and despite a sustained number of humanitarian actors responding to the crisis, humanitarian needs in Borno, Adamawa and Yobe (BAY) States remain dire and multi-faceted. The conflict has resulted in an estimated 7.1 million individuals in need of humanitarian assistance in 2019 – more than 50% of the entire estimated population of the three affected States.[1]

Moreover, over 80% of internally displaced persons (IDPs) were located in Borno State only, the epicentre of the protracted crisis, with a majority living in urban host communities, making it difficult for actors to reach them and to plan responses appropriate to urban contexts. In addition, in 2020, an estimated 1 million people are located in hard-to-reach areas, with limited to no access to humanitarian assistance.[2]

The humanitarian crisis has been exacerbated by mass population movements, a breakdown in basic infrastructure, multi-faceted poverty, and chronic long-term underdevelopment in the north-east. The fluid situation makes comprehensive, up-to-date data necessary to efficiently and effectively respond to humanitarian needs of affected populations. Yet, humanitarian actors working in Nigeria continue to face significant information gaps lacking required granular and comprehensive evidence to efficiently inform their response planning

To address information gaps facing the humanitarian response, including a lack of consistent response-wide information on the needs, and vulnerabilities of crisis-affected populations in north-east Nigeria, REACH has been conducting the following two recurring multi-sectoral data collection exercises since 2018:

- **annual multi-sector needs assessments** (MSNAs) in the BAY states, and;
- **monthly assessments of hard-to-reach areas** in north-east Nigeria.

Multi-Sector Needs Assessment

The MSNA is a crisis-wide assessment to identify inter-sectoral humanitarian needs, which aims to provide a strong evidence base for the Humanitarian Needs Overview (HNO) and Humanitarian Response Plan (HRP). Co-led by OCHA and facilitated by REACH; the MSNA in particular is not meant to be sector-specific and strives to gain a better understanding of cross-sectoral needs, dynamics and response. Following a robust methodology, household level data is representative at the LGA level with 90% confidence interval and 10% margin of error of all accessible areas in the BAY States. The overall, inter-sectoral research question guiding this assessment is: *What are the priority multi-sectoral humanitarian needs of the crisis-affected population, and how do these vary between geographical locations, population groups and household profiles?*

Assessment of Hard-to-Reach Areas

Using its Area of Knowledge (AoK) methodology, REACH remotely monitors the situation in hard-to reach areas through monthly multi-sector interviews in accessible Local Government Area (LGA) capitals with the following typology of Key Informants (KIs):

- KIs who are newly arrived internally displaced persons (IDPs) who have left a hard-to-reach settlement in the last 3 months
- KIs who have had contact with someone living or having been in a hard-to-reach settlement in the last month (traders, migrants, family members, etc.)

Selected KIs are purposively sampled and are interviewed on settlement-wide circumstances in hard-to-reach areas, rather than their individual experiences. Responses from KIs reporting on the same settlement are then aggregated to the settlement level. The most common response provided by the greatest number of KIs is reported for each settlement. When no most common response could be identified, the response is considered as 'no consensus'.

1 OCHA, Humanitarian Needs Overview 2019 Nigeria
2 OCHA, Global Humanitarian Overview 2020, Nigeria chapter

Limitations of Existing Assessments

Despite the considerable scale of these two exercises, significant limitations remain, largely due to consistent patterns of insecurity and the resulting access barriers.

The MSNA covers accessible areas of Adamawa, Borno and Yobe States only, the representative data drawn from the sample therefore does not inform needs in areas that could not be assessed, due to security constraints or lack of partners to conduct data collection. Due to severe access constraints in Borno State, the sampling is generally limited to urban centres (with the exception of South Borno), which affects data results compared to other areas in Adamawa and Yobe.

The findings from assessments in hard to reach areas are only indicative of broader trends in assessed settlements, and are not statistically generalisable. Findings are only reported on LGAs where at least 5% of populated settlements and at least 5 settlements in the respective LGA have been assessed.

Problem Statement / Research Question

With the above limitations in mind, this pilot exercise aims at evaluating whether remote sensing analysis can help to fill gaps in current primary data collection methodologies employed in Nigeria.

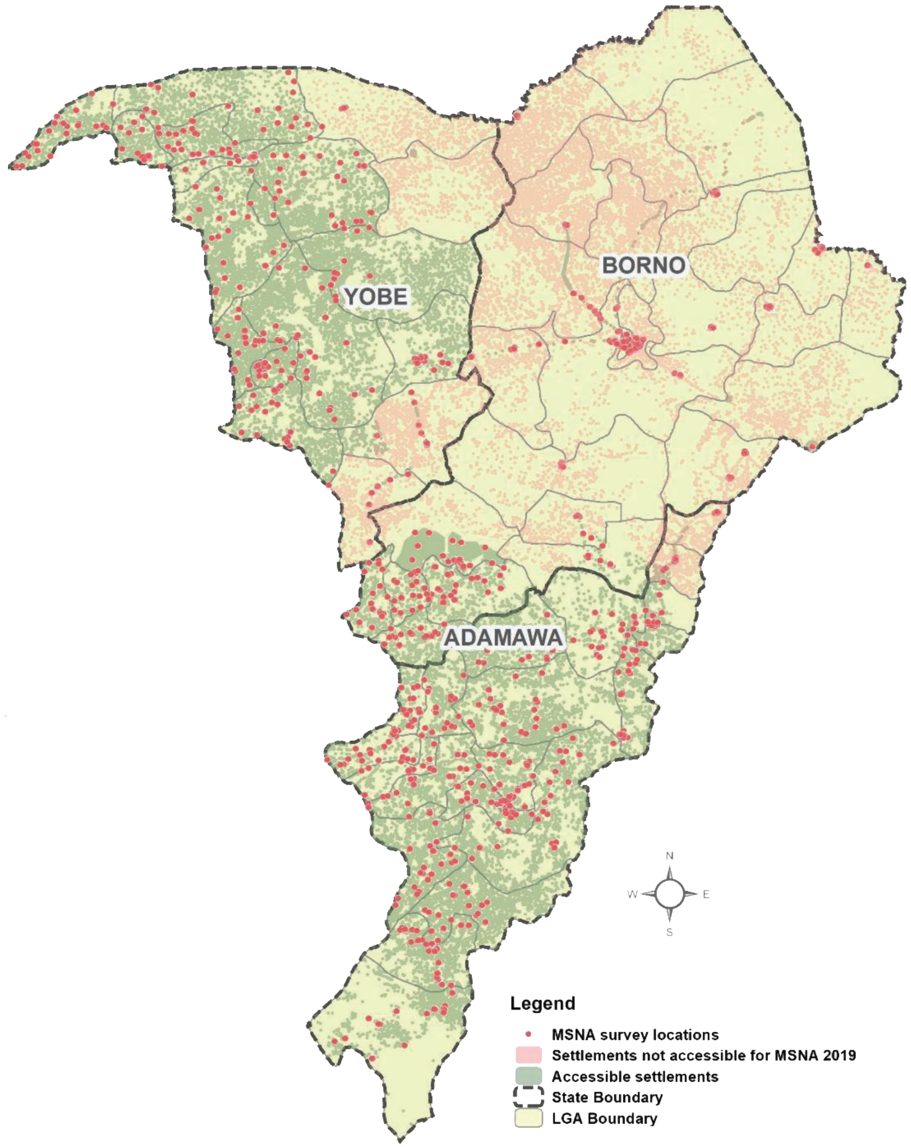
More specifically, can remote sensing analysis:

(a) complement ongoing assessments;

(b) corroborate assessment findings; and/or

(c) shed new insights on currently inaccessible areas?

Figure 1: 2019 REACH MSNA Coverage



STUDY FOCUS

Considering the number of multi-sector indicators assessed and the overall geographic area of the BAY states, it was necesssary to narrow the focus of this exercise both thematically and spatially.

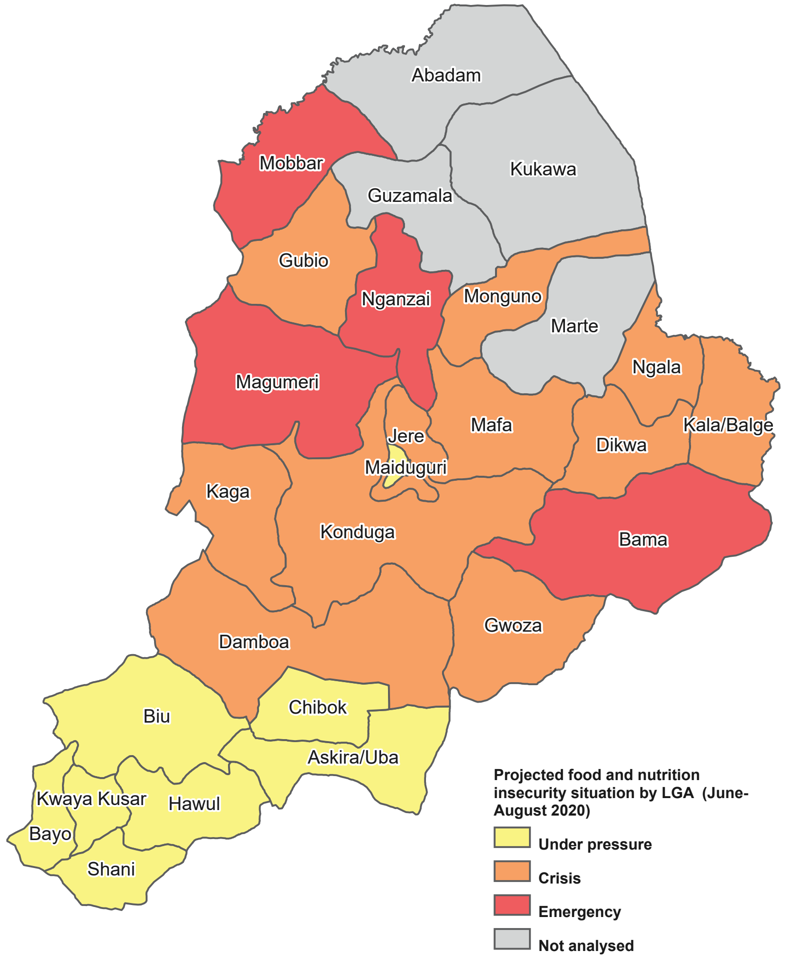
Borno state serves as the primary geographic area of interest for this study since it has been the epicentre of the protraced crisis and hosts the majority of northeast Nigeria's IDPs.

After reviewing REACH assessment findings (see Figures 3 and 4 on the opposite page), it was determined that Food Security and Livelihoods (FSL) should be the primary thematic focus for evaluating alignment with remote sensing analysis approaches. As there are consistent reports of people having less land for cultivation as compared to previous years and high proportions of settlements reporting subsistence farming and cultivation as both the main source of livelihood and food (Hard to Reach Assessment) as well as considerable proportions of households with unmet needs in FSL (MSNA), the priority aim of this study is to look at the status of agricultural activity in Borno state using available satellite data.

Secondary sources further support the thematic area selection, particularly the Cadre Harmonisé analysis of the food and nutrition insecurity situation for the BAY states, which classifies the food security situation in nearly all of Borno in crisis or emergency (see Figure 2). Notably, the Cadre Harmonisé indicates 4 LGAs were not analysed due to inadequate evidence in the north-east of Borno State along the Lake Chad shore, further highlighting the difficulty of reporting on the situation in hard-to-reach areas.

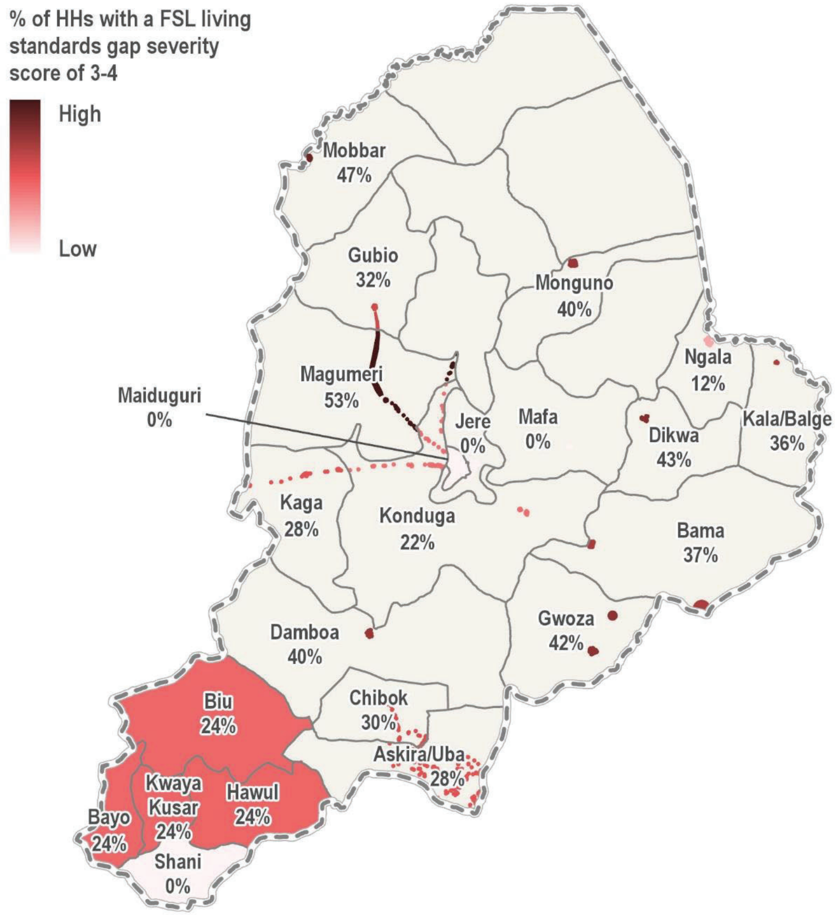
As this is an initial investigation, the decision was made to look for trends over recent years as opposed to the entire duration of the crisis. Further, two smaller study areas, in Bama and Monguno LGAs, were selected based on reports of declining agricultural activity.

Figure 2: Cadre Harmonisé food insecurity situation in Borno State



Data source: FAO

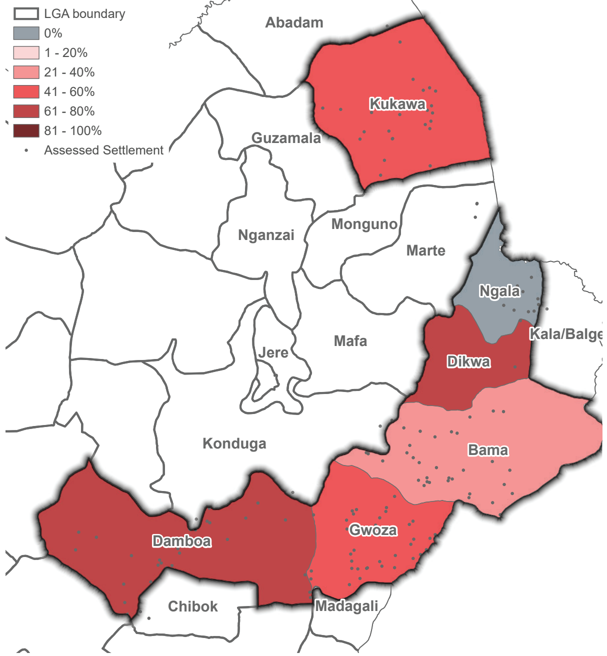
Figure 3: Food Security & Livelihoods Living Standards Gap (2019 MSNA)



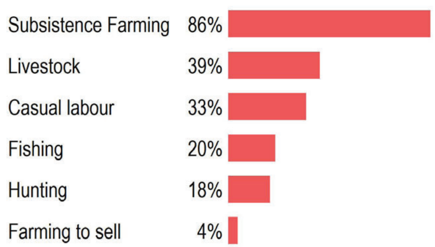
Note: Within the MSNA analysis, the "Living Standard Gap" corresponds to the sectoral analysis (excluding nutrition which is a "well being" pillar component). For each sector, a composite indicator was designed and agreed upon with the sectors. After adding up scores for each indicators, HHs are then classified following a sectoral needs severity scale from "No/minimal" severity of needs, to "Extreme" severity of needs.

Figure 4: Key Findings from Hard to Reach Assessment (April 2020)

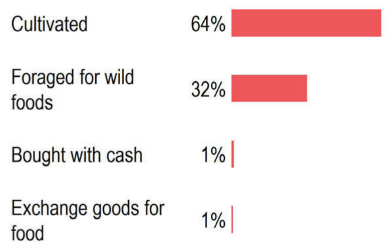
Proportion of assessed settlements reporting most people having less land for cultivation available as compared to the same time in the year before:



Main livelihood sources reported by assessed settlements (multiple answers per settlement possible):



Main sources of food reported by assessed settlements:

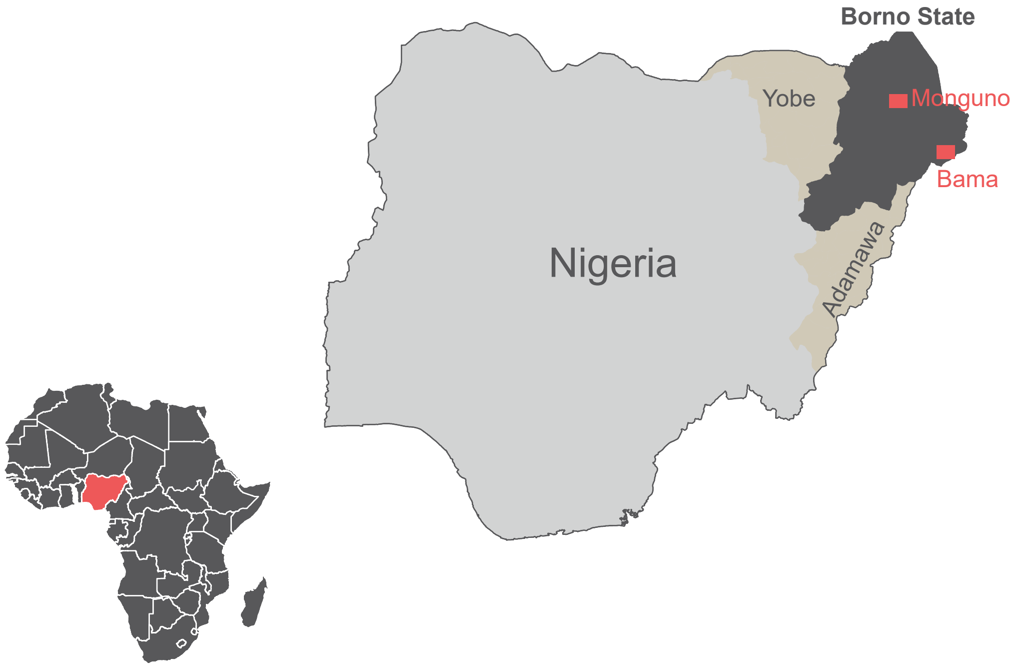


METHODOLOGY

In order to analyze how the crisis has affected agriculture in Borno State, a multi-tiered approach was developed based on available data sources. First, smaller areas of interest in Bama and Monguno LGAs were evaluated for agricultural activity and changes between 2013 and 2019. Then, a complete state-wide analysis of Borno was conducted, identifying agricultural areas and vegetation changes comparing yearly normalized difference vegetation index (NDVI) values between 2016 and 2019. Note: NDVI is a routine measure in remote sensing used to monitor agriculture, capturing how much more near infrared light is reflected compared to visible red, which helps differentiate bare soil from grass or forest, detect plants under stress, and differentiate between crops and crop stages. Lastly, more detailed analysis was conducted to identify regional variations among Borno's 27 LGAs.

For locations of Monguno and Bama study areas see Figure 5, which also displays the extent of the Borno State.

Figure 5: Location of Monguno and Bama study areas in Borno State



Bama and Monguno NDVI Analysis

As the Bama and Monguno areas are quite small (100 km2 and 75 km2 respectively), the main idea was to compare the difference of NDVI values during the highest NDVI activity period from 2013 to 2019. Following a literature review, it was concluded that the highest NDVI value should be between 1 September and 15 October.

In order to provide an analysis as precise as possible, Landsat-8 was chosen for the years 2013 to 2015 and Sentinel-2 for 2016 to 2019, sensors which have a spatial resolution of 30/15 meters and 10 meters respectively. For the analysis of agricultural areas, an unsupervised classification was performed. This classification was based on pansharpend Landsat-8 and Sentinel-2 imagery. The Landsat-8 imagery was pansharpend in order to obtain a similar spatial resolution as the Sentinel-2 imagery.

To obtain yearly NDVI data, the most suitable imagery from the period suggested by the literature was used. This resulted in 7 annual NDVI layers, which were later compared to one another to get 6 yearly change layers.

Borno State NDVI Analysis

For the state-wide NDVI analysis, Sentinel-2 imagery was filtered by date and area of interest. This subset of imagery had a cloud mask applied to reduce the influence of clouds on the NDVI results. NDVI was then calculated for each image in the filtered collection. The NDVI data was then split into two parts; one to represent the season with high NDVI values and the other for the season with low NDVI values. The period for the high NDVI is between 19 June and 7 October, and the low 20 January to 31 March. The season when agriculture and NDVI values are at its peak varies across the state, it tends to be earlier in the north than in the south.

To capture the peak for all parts of the state, a wider timeframe was chosen compared to the timeframe capturing the lower season. Each seasonal subset was later split by year, to get the NDVI data for each year. The seasons were later reduced to a single layer by choosing the maximum value in the subset for the high NDVI seasons, and the mean for the lower NDVI season.

To be able to detect the change of NDVI over the years, the following year maximum layer needed to be subtracted from the previous year maximum layer. This was done for all 4 years and resulted in 3 yearly change layers. The change layers were reclassified to quantify areas of increase, decrease and no change (stable).

To estimate total agricultural area in the state, a combination of the previously-created NDVI layers was used. A new layer was created to identify areas with seasonal change by calculating for each year the change between the season with the lowest NDVI values and the season with highest NDVI values. This layer was combined with the seasonal yearly layers to extract vegetation. Finally, the yearly layers were added to create a single layer representing agricultural areas from 2016 to 2019.

LGA Comparative Analysis

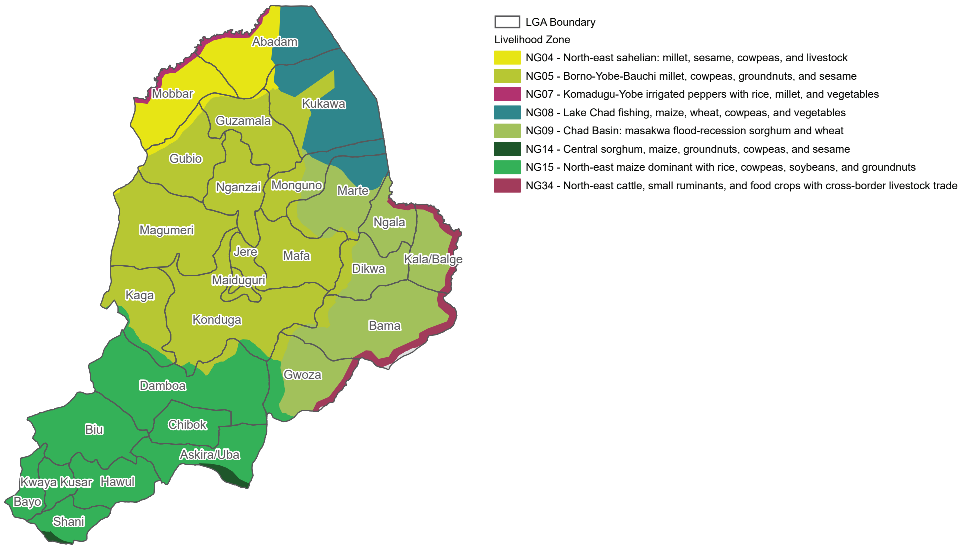
To identify regional variations in the 27 Borno LGAs, the agriculture classification was improved by using more input data. The refined approach was modelled after a crop calendar (see Figure 7) based on the crops found in Borno according to FEWSNET Livelihood Zones for Nigeria[3] (see Figure 6). To summarise and quantify the results from the agriculture classification for each LGA, cloud-masked surface reflectance imagery from Landsat-8 and

Figure 7: Crop Calendar for Borno State

Crop Type	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec	# LGAs Present	Source
Cowpeas							Sowing	Sowing	Growing	Harvesting			26	Nigeria Farmers Group
Groundnuts					Sowing	Sowing	Sowing / Growing	Growing	Growing	Harvesting	Harvesting		25	USDA
Millet						Sowing	Growing	Growing	Harvesting	Harvesting			18	FAO
Maize					Sowing	Sowing	Growing	Harvesting	Harvesting				15	FAO
Rice (Main)						Sowing	Sowing	Growing	Growing	Growing	Harvesting	Harvesting	13	USDA
Rice (Second)	Sowing	Sowing	Growing	Growing	Harvesting	Harvesting							13	USDA
Sorghum					Sowing	Sowing	Sowing	Growing	Harvesting	Harvesting	Harvesting		13	FAO, USDA
Soybeans					Sowing	Sowing	Growing	Growing	Growing	Harvesting			11	USDA
Wheat	Growing	Growing	Growing	Harvesting							Sowing	Sowing	11	Legit

Sowing
Growing
Harvesting

Figure 6: FEWSNET Livelihood Zones for Borno State



Sentinel-2, radar imagery from Sentinel-1's C-band, and SRTM elevation data were used. Due to the variation in spatial resolution of the data types, it was necessary to resample the data to the cell size of Landsat-8, which is 30 meters. Furthermore, the data was merged into intervals of 6 months from January 2015 to December 2019, on the basis of the median value each pixel in the period. The interval periods were designed based on the crop calendar for Borno in Figure 7 and by taking into account the rainy season in northern Nigeria[4]. The first interval spanned from 1 January to 30 June which aimed to capture the sowing season, and the second interval was from 1 July to 31 December which aimed to capture the growing period. Additionally, for each interval, an NDVI layer and a slope layer were calculated from the multi-spectral sensors and SRTM elevation data, respectively.

For the random forest classifications, two manually generated training sample datasets were used, one representing cropland present in all 5 years and the other representing areas with non-cropland for each year. These training samples together with the bands blue, green, red, near infrared, SWIR1, SWIR2, VV, VH, NDVI, and slope were the inputs in a random forest classifier with a limit of 10 classification trees. The classifier resulted in five raster datasets representing agricultural land for the years 2015, 2016, 2017, 2018 and 2019.

3 https://fews.net/fews-data/335
4 https://fews.net/west-africa/nigeria/seasonal-calendar/december-2013

RESULTS

NDVI Analysis of Bama and Monguno Areas

In both Bama and Monguno, an overall decrease of agricultural land could be observed. Initially for Monguno, an increase was visible between the years 2014 and 2016, but between 2016 and 2017 an 88% decrease was detected. Moreover, the 2018 and 2019 results have to be considered as merely an indication of decrease since the classification of agricultural land was not able to detect all fields within the analysis extent. For Bama, the most significant decrease was between 2013 and 2014, when a 59% decrease can be observed. The decrease continues after 2014 until 2016 but with less intensity, after that a positive trend is detected for the areal extent of agricultural land. See Figure 8 for the change of agricultural land area between 2013 and 2019.

Figure 8: Agriculture area change from 2013 to 2019 (Monguno and Bama)

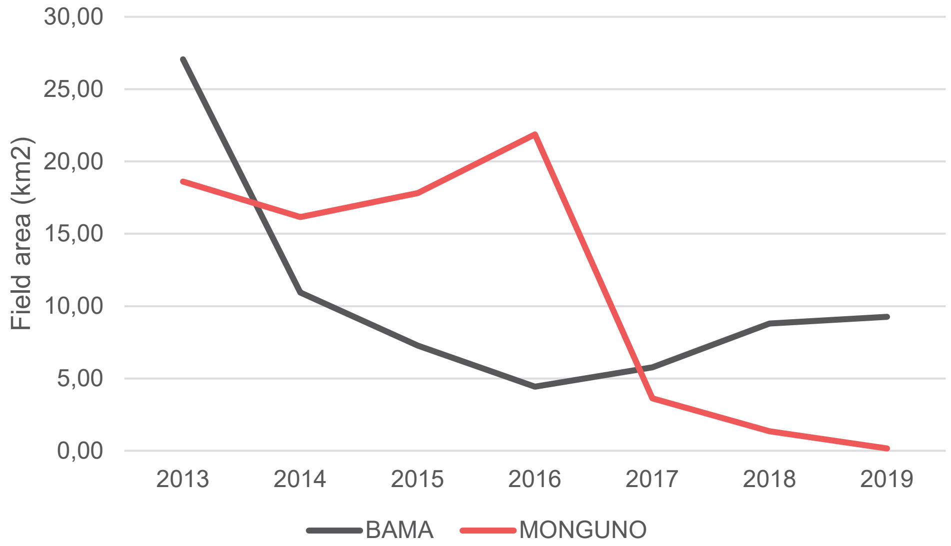
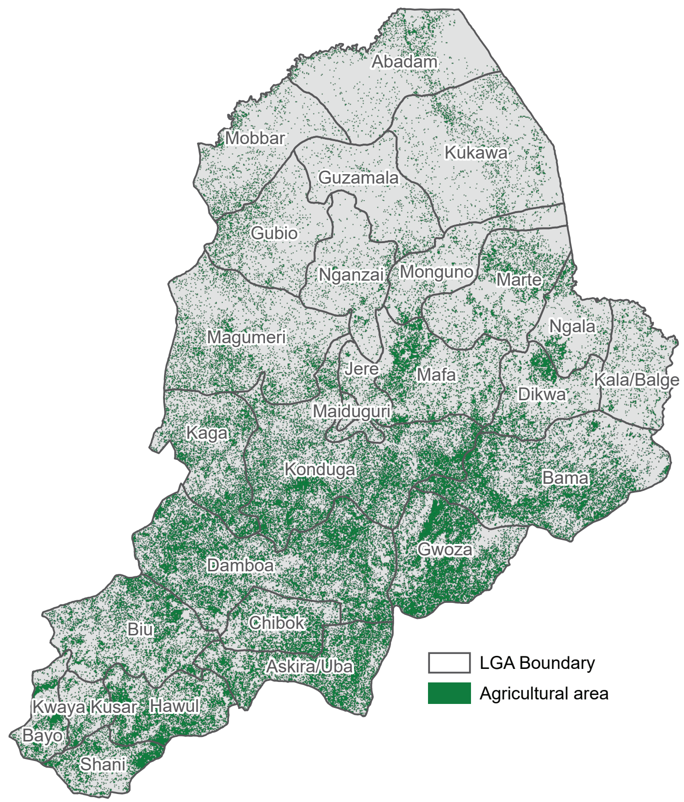
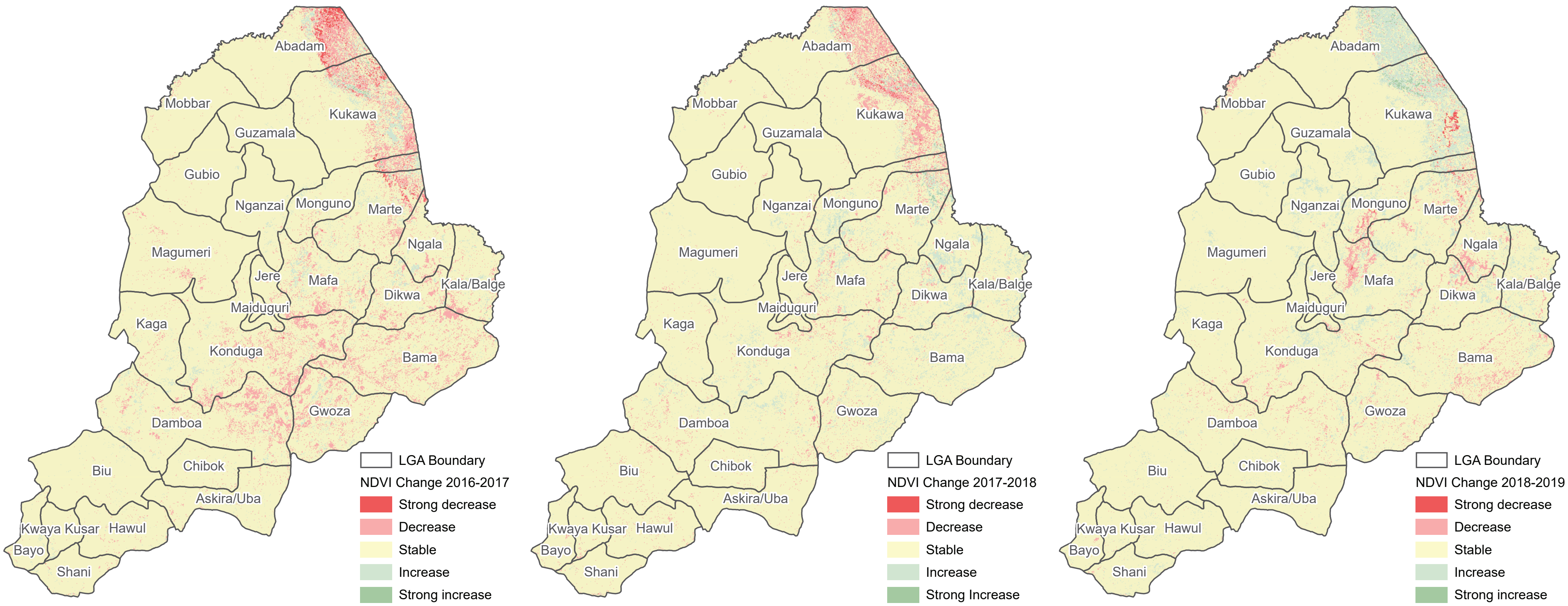


Figure 9: Borno State agricultural area 2016 - 2019



It is important to note that these results only consider the field area detected using the unsupervised classification, which extracts clearly visible, defined crop areas. Therefore, the classification is probably underestimated due to the fact that subtle area is not detected by the classification, yet remains visible on the NDVI difference layer. It should also be noted that NDVI provides a measure of all vegetation, and not just agricultural land, which should be kept in mind when interpreting state-wide NDVI results. In some instances, there is a clear over-estimation of cropland, notably around the Sambisa Forest area, south-east of Maiduguri.

Figure 10: Borno State Annual NDVI change between 2016 and 2019



Borno State NDVI Analysis

The analysis estimates that 28% of Borno comprises agricultural land, equaling 22,762 square kilometers, most of which is located in the southern parts of the state (see Figure 9 for the extent of agricultural land).

The highest NDVI values are found in the Lake Chad area and in the southern parts of the state. Around 90% of the state the NDVI values remain stable throughout the years 2016 to 2019. Even though, in general there is a notable positive increase of NDVI each year. However, these areas are only around 5% of the total area of the state. The decrease observed between 2016 and 2017 is mainly notable in the Lake Chad area in the north-eastern part of Borno. The same north-eastern part also has the strongest increase between 2017 and 2018, whereas the Lake Chad area has a decrease of NDVI for the same period. Between 2018 and 2019, the most notable increase can be seen in the eastern parts of Borno state. Maps showing the areas with the strongest change in NDVI can be seen in Figure 10.

RESULTS

LGA Comparative Analysis

Borno State has an area of 72,181 square kilometres and between 2015 and 2019, the state's cropland extent varied between 22,529.4 km2 and 27066.9 km2, which is between 31% and 37% of the state's total area. The LGA in Borno with the greatest cropland extent recorded for all the studied years was Magumeri, where the maximum extent was observed in 2016 with a 51% coverage. Furthermore, the LGA with the relative highest agricultural extent is Jere in the Senatorial Districts of Borno Central, with an annual average of 64% and 539 km2. For the agricultural extent of all LGAs in Borno see Figure 11.

Figure 11: Average cropland extent by LGA

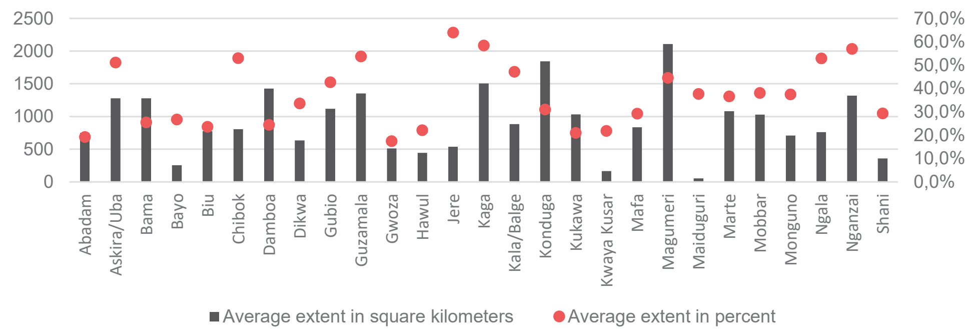
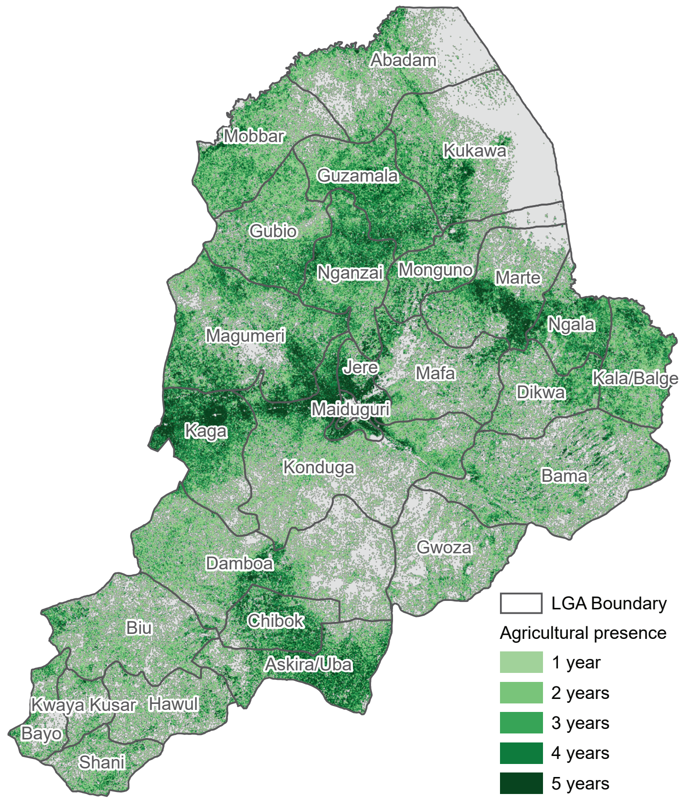


Figure 12: Total agriculture area over study years (in km2)

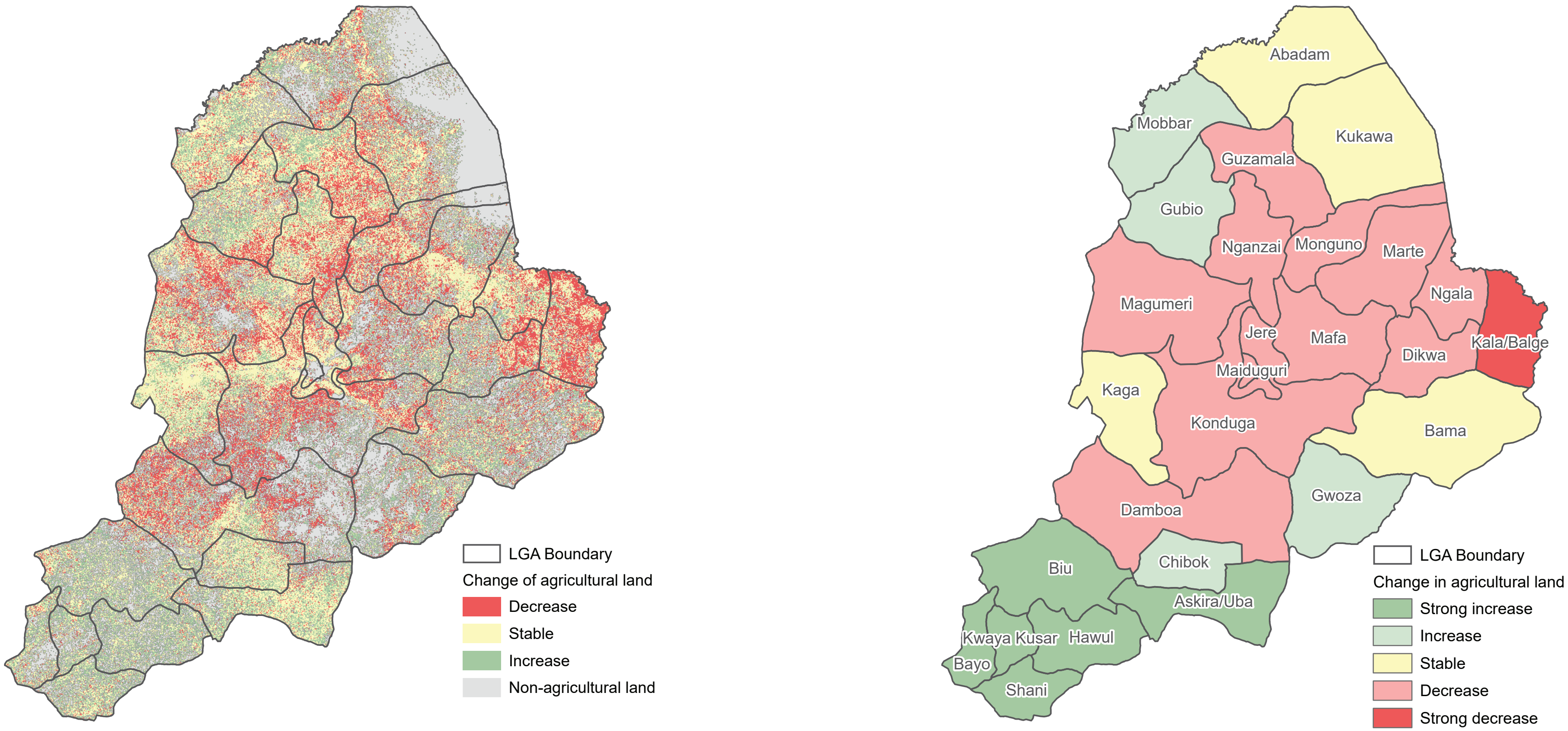
Figure 13: Presence of agricultural land 2015 - 2019



Between 2015 and 2019, Borno state has seen a 5% decrease in total agricultural land. The most remarkable change in agricultural land took place between 2016 and 2017, where there was a 17 % decrease in agricultural land. However, from 2017 to 2019 there was an overall increase 11%. For the variation in cropland extent see Figure 12.

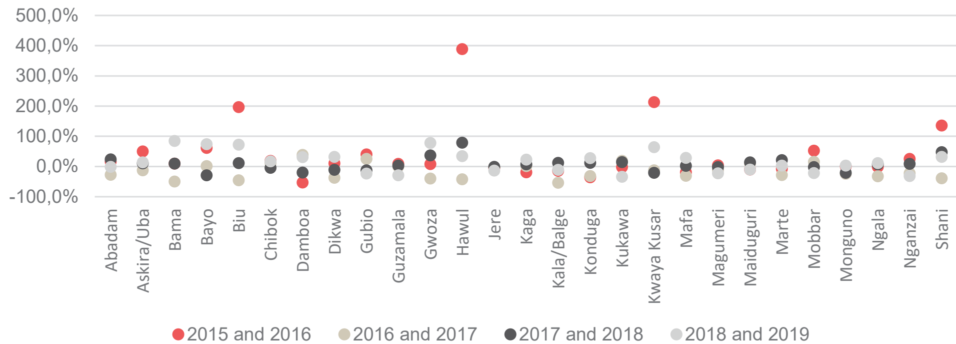
The permanent presence of agricultural land in Borno is concentrated mainly to the central and northwestern parts of the state and particularly around the state's capital Maiduguri. Additionally, the LGA of Askira/Uba in the southern part shows a strong permanent presence of agriculture. For the distribution of cropland in Borno see Figure 13.

Figure 14: Changes in agricultural land by LGA 2015 - 2019, at the pixel level (left) and generalised to LGA (right)



The most significant increase of agriculture land in percent occurred in the LGAs Biu, Hawul, Kwaya Kusar, and Shani, all located in southern Borno. For these LGAs most of the increase took place between 2015 and 2016. Decrease in agricultural land, on the other hand, is mostly detected in central parts of Borno, where 11 LGAs have seen a decrease. Moreover, a remarkable decrease is observed in the east in the LGA of Kala/Balge, where the most dramatic decrease took place between 2016 and 2017. See Figures 14 and 15 for change in agriculture land per LGA.

Figure 15: Percent change in area of agricultural land by LGA (2015 - 2019)



Correlation with conflict

Data from ACLED[5] shows there has been a continuous series of violent events in Borno between the years 2015 and 2019, with 1,731 conflict events recorded. The years with most conflict events are 2017 and 2018, with 376 and 378 events respectively. However, the months with the greatest number of conflict incidents are March 2015 with 58 events and December 2019 with 61 events. The distribution of conflict events between the years 2015 and 2019 can be seen in Figure18.

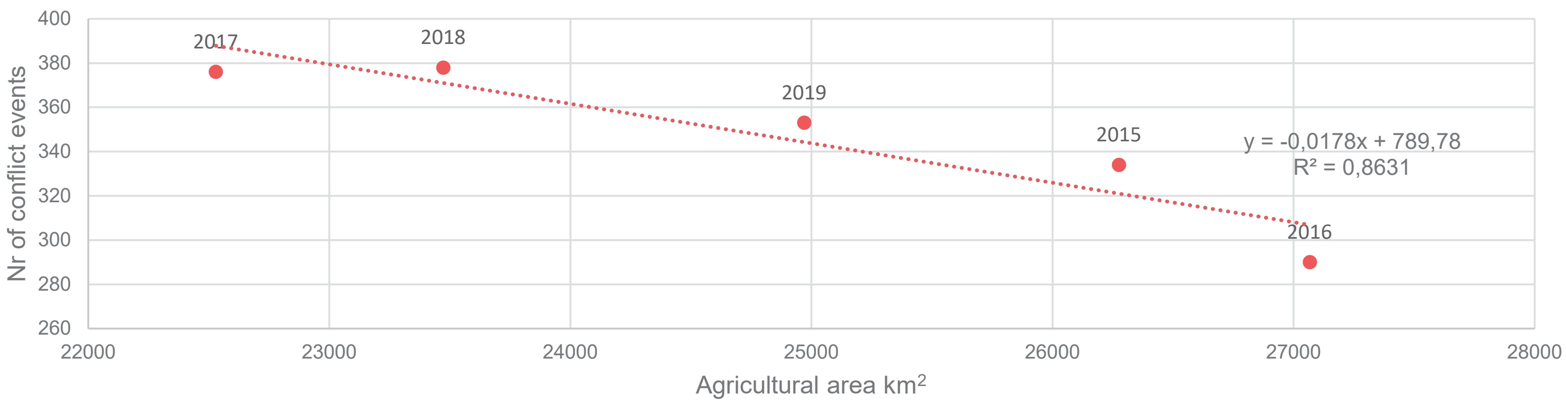
Between 2015 and 2019 conflict events occurred in all LGAs except in Bayo. There are three LGAs where significantly more conflict events have been recorded than the others, these are Maiduguri, Guzamala, and Bama, with all over 150 events. On the contrary, the LGAs Kwaya Kusar and Shani both only have three events recorded in the same period

By correlating overall agricultural extent and number of events for each year, a strong relation is detected with the coefficient value of 0.86, see Figure 16. This indicates that a year with a higher number of conflict events has less agricultural extent, and years with fewer events have a larger extent of agriculture land.

When looking at the correlation between conflict events and agriculture land at the LGA level, however, the relationship is not as evident as on the state level, with a coefficient value of 0.07. Nevertheless, the tendency is the same as for the whole state where a low number of conflict events correlates with a higher coverage of agricultural land. The same pattern is observed when entering more data points in the correlation with both year and agricultural extent per LGA, then the R2 value is 0.06.

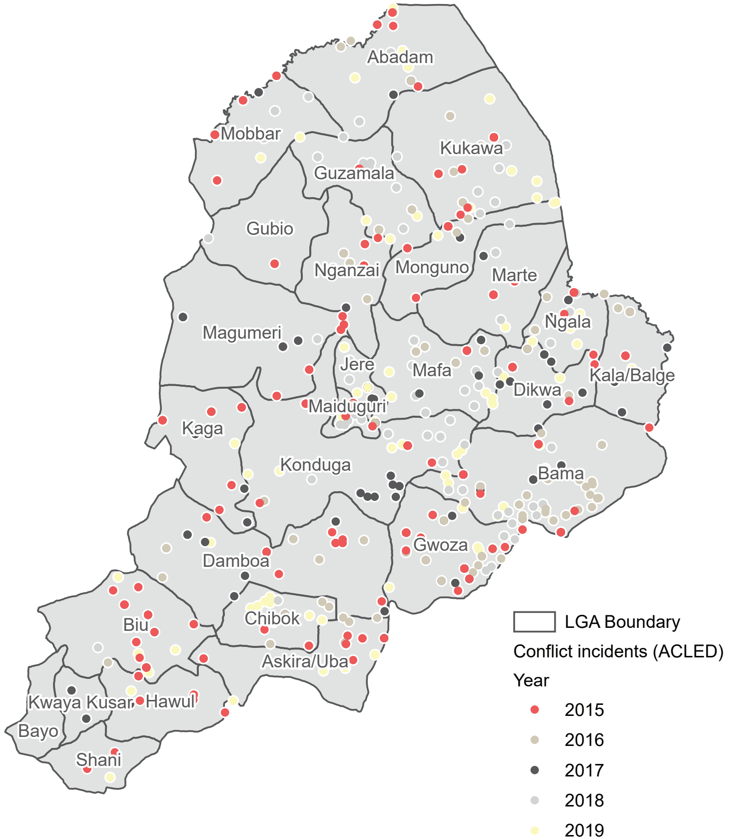
By spatially correlating the conflict events and the change in agricultural land, no strong relation can be observed, see Figure 17.

Figure 16: Correlation between total agriculture area and number of conflict events in Borno State



[5] ACLED. (2019). "Armed Conflict Location & Event Data Project (ACLED) Codebook, 2019"

Figure 17: Location of conflict events by year (left) and decrease in agricultural area during study period (right)



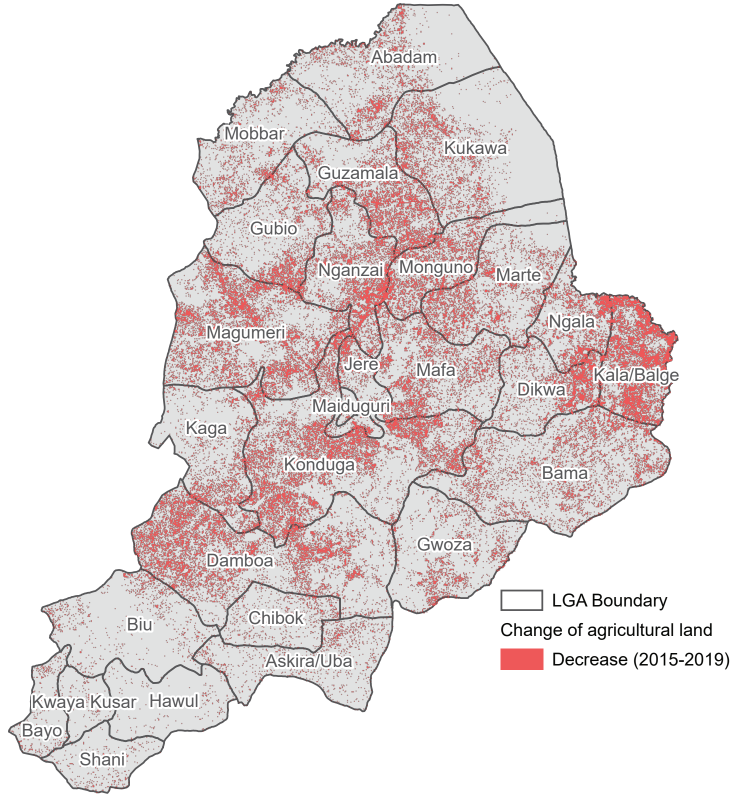
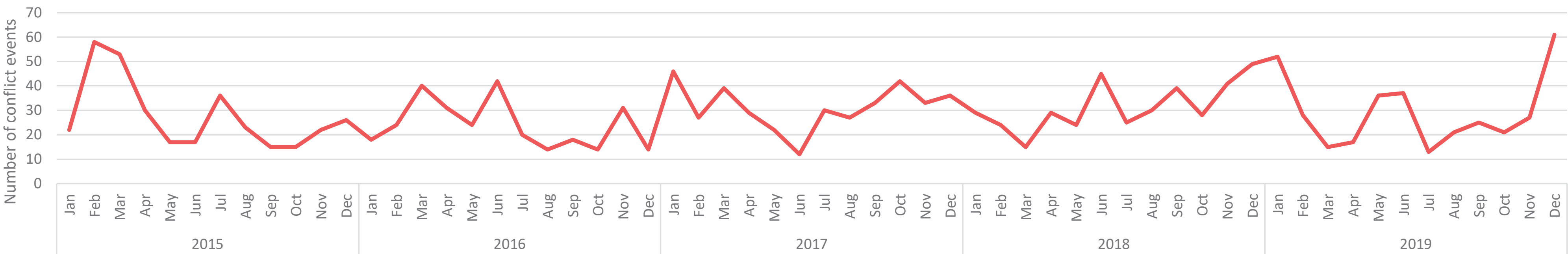


Figure 18: Number of conflict events in Borno State from 2015 to 2019 (ACLED)



LIMITATIONS

The primary limitation of the method is of course the complete lack of locally collected field data points for agricultural areas. Similarly, locally collected field data on crop types is also lacking.

All estimates of agricultural areas are based on general models developed for this project, based on an assumed size and shape of agricultural fields. The high-resolution analysis did provide a good training set, yet, considering the lack of field data, findings should be viewed with caution. In particular, given the spatial resolution of the Landsat and Sentinal data, many smaller agricultural fields were excluded from this analysis, while they may comprise a significant extent of agricultural land that would have impacted the results.

Although NDVI is very commonly used for agriculture detection, it is not without limitations, notably a lack of differentiation between vegetation types.

It should also be noted that a number of potential drivers for agricultural change were not evaluated in this study, from more regular variation in rainfall patterns to climatic shocks, such as flooding or drought. It is very likely that there is a complex combination of factors involved, and isolating one or even a few potential contributing factors, out of possibly very many, makes for a rather significant limitation.

Finally, while ACLED data is laudable, it is likewise limited due to it being based on media and open source information, so events not reported on in some manner are unlikely to be featured in ACLED data. Notably, incidents in the hardest-to-reach areas are least likely to be reported. Therefore, ACLED is exposed to the same risk of data gaps and bias resulting from inaccessibility as other actors.

CONCLUSIONS

Returning to the research question highlighted in the introduction:

Can remote sensing analysis (a) complement ongoing assessments; (b) corroborate assessment findings; and/or (c) shed new insights on currently inaccessible areas?

It becomes clear that the answer to all three components is at least a qualified yes.

The changes observed and measured in agricultural area can clearly compliment ongoing assessments and monitoring efforts. The general trends witnessed appear to match reports from survey respondents, indicating potential or partial corroboration of assessment findings. This analysis also highlights how information can be extracted from areas with insufficient access or inadequate evidence from other sources. And new insights, particularly the correlation with conflict data, may prove useful.

However, it is also clear that much is still missing. At first glance, the results look less severe than the situation reported from the people assessed through REACH assessments. Therefore, generalizing findings to the LGA level may run the risk of hiding underlying vulnerabilities within, at the community level. However, large parts of the population did not have a great deal of agricultural land even before the crisis. So it is possible that when even a small proportion of that land is lost, it can have dramatic impacts on their livelihoods.

Current indicators assessed also do not fully align with what is being measured through remotes sensing analysis, making direct 'apples to apples' comparison difficult if not impossible.

And while the observed correlation between total agricultural area and number of conflict incidents in Borno State is indeed an interesting finding, it should be treated with caution as the correlation was not observed at the LGA level, and of course, correlation does not imply causation.

As this was an initial pilot study, some limitations were expected. As highlighted in the limitations section, there remains room to further refine the analysis approach. In the end, this study offered a cursory glance that shed light on an interesting pathway for future analysis. Hence, the current analysis might serve as a stepping stone; more work remains to be done to better pair remote sensing analysis with field assessment data, and to triangulate this with secondary information, to in turn support deeper understanding of the humanitarian situation in hard-to-reach areas.

NEXT STEPS

Develop better linkages between remote sensing and assessment data

Through this process it has become clear that current FSL indicators and survey questions do not align directly with remote sensing analysis. A key question going forward will be centered on how this connection can be improved, whether within ongoing MSNA or hard to reach assessments or in a more tailored assessment. It does appear that some existing survey questions could be modified to capture corresponding time periods assessed in remote sensing analysis. But this will require a dialogue between FSL sector specialists and remote sensing experts.

Expand agricultural analysis

There are a number of ways to expand upon this agriculture analysis that will be explored, including:

- Establishing a pre-crisis agricultural baseline - this would entail analysis of decades of pre-crisis archive imagery to identify the average extent;
- Evaluating agricultural change for the entire crisis period to date - different trends may be revealed going back to the start of the crisis;
- Exploring more localized analysis - whether at the level of individual livelihood zones, hardest to reach LGAs and below the LGA level, at the community level, more detailed analysis is needed;
- Investigate opportunities for collecting data locally on agricultural areas as well as crop types (ground truthing);
- Combing more localized analysis with ground truthed data to map crop types and degree of crop land loss;
- Looking more in depth at the seasonal calendar, evaluating sowing, growing and harvest periods individually to the extent possible.

Incorporate other potential drivers of change

There are a number of factors that this study overlooked that should be included in any further analysis. Of particular importance are:

- Environmental factors (e.g. precipitation);
- Displacement and settlement dynamics, conflict-related and otherwise;
- Shocks or events (e.g. flooding, drought, climate change).

All of which can be interrelated and can be linked to agriculture and insecurity, highlighting the complex interplay of potential factors leading to increased vulnerability.

Develop a more complete and nuanced picture of insecurity

Given the limitations of existing conflict datasets, it will be worthwhile to establish links to other forms of conflicict analysis, including remote detection of shelter damage or loss, triangulation with key informants, participatory mapping exercises, and/or self-reported protection concerns, to establish a more complete picture of insecurity.

Existing conflict data can be leveraged futher and evaluated in different ways, particulary looking at types and magnitude of events. It may be possible that key findings are missed by only using frequency and not including a proxy for severity. Both frequency and mortality based estimates of severity could be linked to disruption in planting for instance. In future, it may be worthwhile to develop corresponding categorizations based on deeper exploration of existing data.

Further, it will be important to evaluate the timing of conflict events to the extent possible, both on an annual basis and seasonally. It is unclear currently if conflict events have a greater effect in the current year or in years following. And with more robust seasonal remote sensing analysis it may be possible to look at conflict and any related disruptions to sowing, growing and harvest periods.

ABOUT REACH

The REACH Initiative facilitates the development of information tools and products that enhance the capacity of aid actors to make evidence-based decisions in emergency, recovery and development contexts. The methodologies used by REACH include primary data collection and in-depth analysis, and all activities are conducted through inter-agency aid coordination mechanisms. REACH is a joint initiative of IMPACT Initiatives, ACTED and the United Nations Institute for Training and Research - Operational Satellite Applications Programme (UNITAR-UNOSAT).

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