Title

Trend Mapping in Nigeria:
A Case Study for Conflict Analysis

Abstract

Current means of monitoring areas in a state of crisis, especially in regards to satellite imagery, are more reactive than proactive in their approach to analysis and management. The use of satellite imagery has evolved in recent years to play a significant role in disaster and crisis management and mitigation. This case study on Nigeria examines a proactive approach to imagery analysis by means of trend mapping using linear regression. By examining multiple image collections from various sensors, processing data in Google Earth Engine, and performing additional analysis using ArcGIS, it was found that trending Areas of Interest (AOI's) accurately align with locations where violent events have occurred historically. This work suggests that rapid satellite imagery processing has the ability to play a more contributive role in crisis prediction and mitigation techniques used by government and aid workers in acquiring meaningful, situational intelligence.

Introduction

Governments and humanitarian groups have long demonstrated a need for accurate and timely situational intelligence. Following village attacks by Boko Haram in January 2015, *The Guardian* published satellite images of the town of Baga showing widespread destruction indicative of a high death toll. Nigeria has been marred by years of conflict and surges in violence linked to Boko Haram. While satellite imagery and traditional GIS analysis of events and environments have proven to be essential in assisting with the analysis of such events, new and innovative techniques in satellite image processing may be even more effective.

The proliferation of satellite imagery platforms and related analytical tools provides a unique opportunity for people to reliably monitor remote and otherwise inaccessible areas of interest (AOI's). While simple imagery analysis itself is capable of providing such insights, it does not allow us to monitor events and occurrences over periods of time, or in broad detail. Rather than comparing the outputs of various image collections and processing techniques to one another, this project aims to use Google Earth Engine to identify trending AOI's as they relate to conflict evolution, using Nigeria as a case study.

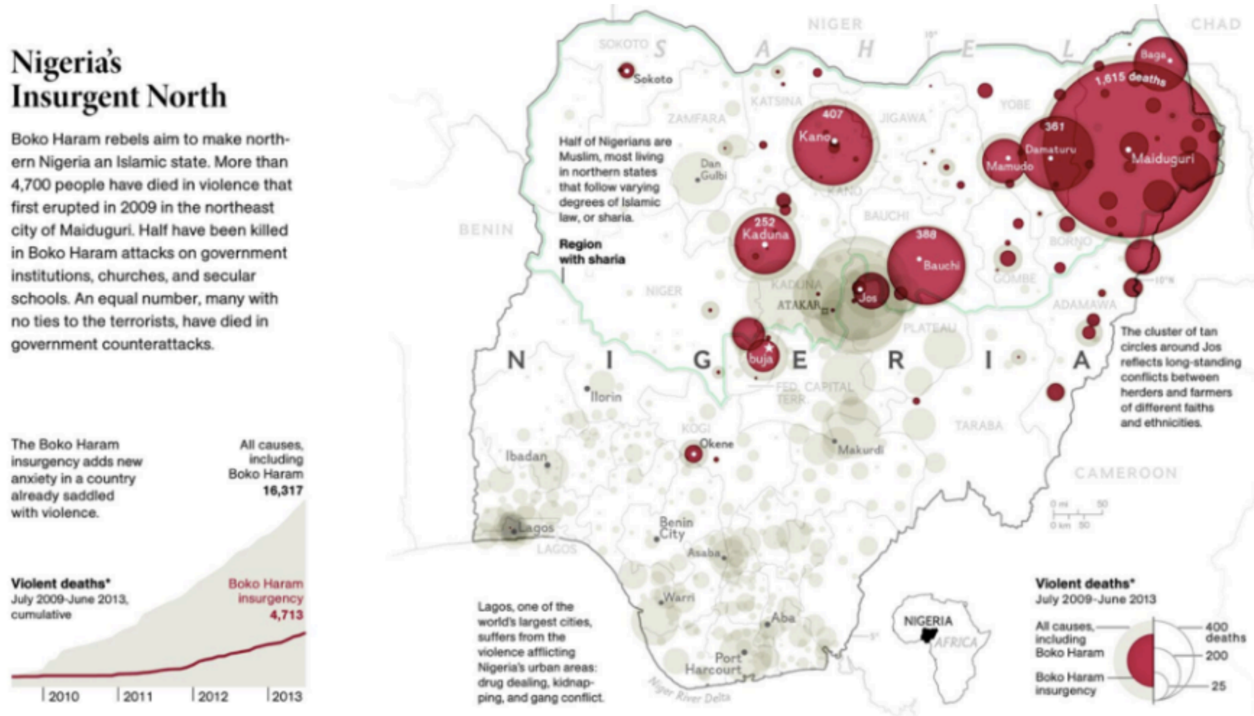

Figure 1. Image depicting "Nigeria's Insurgent North", courtesy of National Geographic.[1]

Linear trend analysis is already a popular tool in desertification monitoring and various other environmental pursuits. Trend analysis as it relates to conflict is less common. A 2015 study on Syria analyzed nighttime satellite images and found that 83% of lights in the country had gone out.[2] Such studies are important to the international community, though they often serve mainly to provide a post-conflict analysis of events. By mapping trending AOI's, it becomes easier to keep track of evolving circumstances in real time. Looking at these trending areas as they relate to one another, as well as to event data points, allows us to make new discoveries and observations as they pertain to the nature of an area in a state of crisis or conflict.

[1] http://ngm.nationalgeographic.com/2013/11/northern-nigeria/insurgent-north-map
[2] http://www.theguardian.com/world/2015/mar/12/satellites-capture-how-the-lights-have-gone-out-in-syria

Context & Intent

This case study on Nigeria features applications of image-processing techniques and linear functions to various image collections. The linear regression analysis on our processed imagery is what gives us our "trending" AOI's. This type of analysis can be particularly useful in providing a quick overview of a place to gain fast, accurate, overall situational intelligence. The AOI's will also consider areas of overlap and relationships to Armed Conflict Location & Event Data Project (ACLED) points of interest.[3] Pairing the resulting information with additional vector and point datasets could allow someone to perform a more fine-tuned analysis.

The use of satellite imagery in human rights has been of particular interest in recent years. There are multiple examples of the added value of satellite imagery for human rights investigations, as imagery analysis gives us (remote) access to an area that is largely inaccessible to independent observers such as investigators and journalists. This imagery allows us to establish damage counts and a timeline of events, thus providing visual evidence for crisis situations. One of the most stunning examples of a use cases of satellite imagery in human rights and crisis awareness is seen in Nigeria itself (*figure 2,* on the following page).

[3] http://www.acleddata.com/

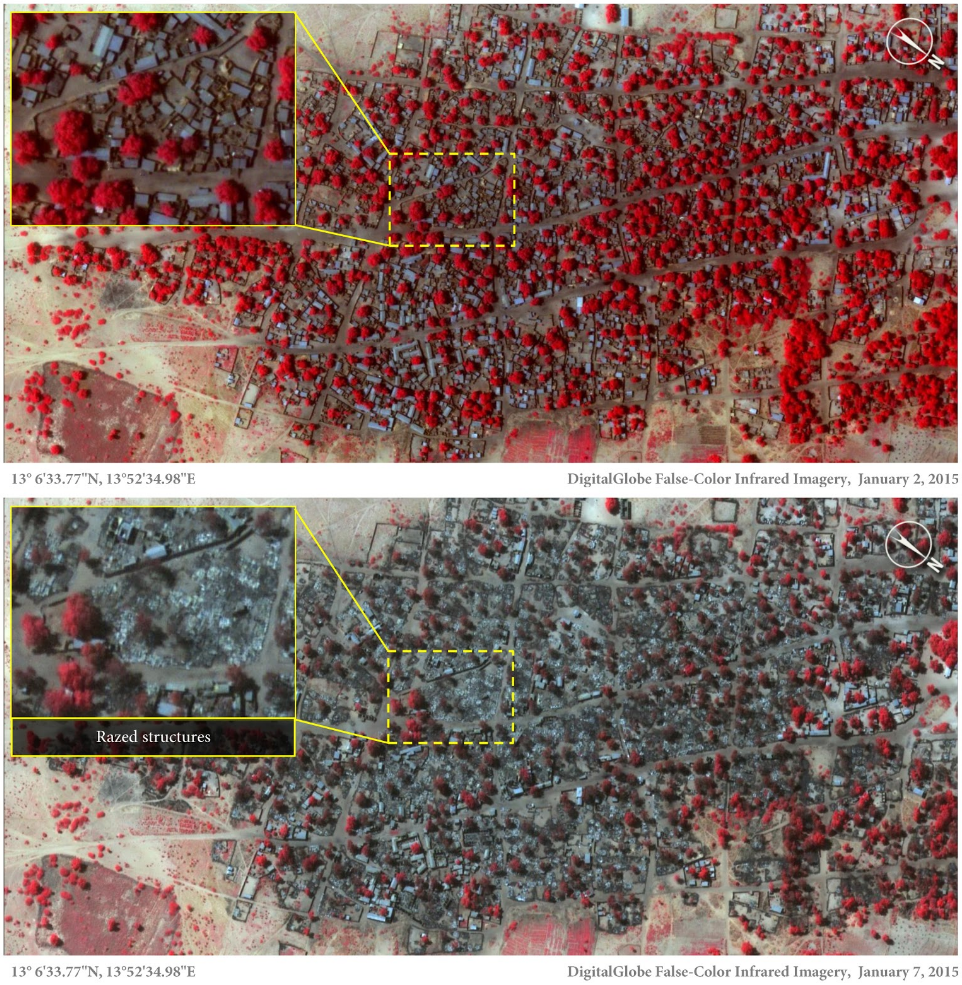

Figure 2. These DigitalGlobe false-color infrared images taken in early January 2015 highlight the damage caused by Boko Haram, an Islamic terrorist group based in Northeast Nigeria.[4]

Before-and-after images reveal more than 3,100 structures damaged or destroyed by fire, 620 of those structures in the 2 square kilometer city of Baga alone. This analysis, though vastly helpful for policymakers and humanitarian aid workers, does not hold much measurable "predictive" power. As such, this case study features the application of Google Earth Engine (GEE) to extrapolative trend and crisis analysis in Nigeria. This work is useful in circumstances where traditional GIS and remote sensing methods may not be as advantageous. We aim to design this study and application of GEE by identifying trending areas of interest in order to support government and aid workers in gaining higher levels of situational awareness surrounding a specific event or region.

[4] http://www.theguardian.com/world/2015/jan/14/satellite-images-reveal-devastation-boko-haram-massacre-nigeria

Objective

The geographic area of this project is Nigeria. This country was chosen in part because the Environmental Justice Atlas considers Nigeria to have the most cases of conflict caused by climate and environmental disputes.[5] Aside from such disputes, more specific actions, like those taken by Boko Haram, a terrorist group based in northeastern Nigeria, have specific imagery "signatures". The signatures of events like burning or razing structures, for example, may be seen using various image-processing techniques (NDVI, etc.). These events may benefit greatly from the use of satellite imagery, especially in a country where traditional vector data may be unavailable or inaccurate. In addition, much of our image processing is particularly suited for environmental monitoring on a large scale. The goal of this project is to uncover said signatures as AOI's to determine the predictive capabilities of linear regression and trend analysis in a given region.

Data

ACLED Event Data:

We began this project using data points from Google's Database of Events, Language, and Tone, however, it is believed that the ACLED data is better suited for our analysis as it specifically aims to capture the types, agents, dates and locations of violent events as they occur within developing states. ACLED data points are collected each week after individual coders have scrutinized the information from reports; they are then aggregated and revised by the first coding reviewer, investigated and cross-checked by the second reviewer and then event notes and details are inspected by the third and final reviewer.[6] The process is designed to assure (1) validity through intra- and inter-coder checks; (2) accuracy to correct mistakes in coding; and (3) relevance by determining whether each compiled event constitutes an act of political violence or protest.

[5] https://ejatlas.org/
[6] http://www.acleddata.com/

Nigerian Administrative Boundaries:

Nigerian administrative boundary data was gathered from GADM, which has been developed by Robert Hijmans, in collaboration with colleagues at the University of California, Berkeley Museum of Vertebrate Zoology (Julian Kapoor and John Wieczorek), the International Rice Research Institute (Nel Garcia, Aileen Maunahan, Arnel Rala) and the University of California, Davis (Alex Mandel), and with contributions of many others. We used the smallest level of political boundaries possible, one smaller than provinces, in order to gain the most accurate AOI's.

Nighttime Lights Imagery:

I used the VIIRS Nighttime Lights 2012 dataset maintained by NOAA, which shoes lights visible at night from space (NOAA/DMSP OLS/NIGHTTIME_LIGHTS). The Defense Meteorological Program (DMSP) Operational Line- scan System (OLS) has a unique capability to detect visible and near-infrared (VNIR) emission sources at night. Version 4 of the DMSP-OLS Nighttime Lights Time Series consists of cloud-free composites made using all the available archived DMSP-OLS smooth resolution data for calendar years. In cases where two satellites were collecting data - two composites were produced. The products are 30 arc second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude. We mapped trends using the stable_lights: band, which is the cleaned up avg_vis contains the lights from cities, towns, and other sites with persistent lighting, including gas flares. Ephemeral events, such as fires have been discarded. The background noise was identified and replaced with values of zero.

From this dataset, we will look at areas that have gained nighttime lights—because some regions of the country are quite underdeveloped, a gain in nighttime lights (especially when seemingly unrelated to urban sprawl) would be more curious than a loss. This is in comparison to the Syrian example discussed previously, where a *loss* of nighttime lights would be of more importance.

Vegetation Imagery:

I used the MODIS (MODIS/MYD13A1) imagery, and specifically made use of the enhanced vegetation index (EVI). This index characterizes bio-physical/biochemical states and processes from vegetated surfaces. This global time series record from each of the Terra and Aqua MODIS sensors comes in at varying spatial (250m, 1km, 0.05 degree) and temporal (16-day, monthly). The VI products are validated with accuracies depicted by a pixel. From this dataset, we will look at the *loss* of healthy vegetation, which, as noted by the Environmental Justice Atlas, can lead to disputes where water is scarce.

Burn Imagery:

The MCD45A1 Burned Area product is a monthly Level-3 gridded 500-meter product, which contains burned area and quality information on a per-pixel basis. Produced from both the Terra and Aqua MODIS-derived daily surface reflectance inputs, the algorithm analyzes the daily surface reflectance dynamics to locate rapid changes, uses that information to detect the approximate date of burning, and maps only the spatial extent of recent fires. It provides varied quality assessment information and a single summary quality assessment score for each pixel. The monthly MCD45A1 product is based on three months of atmospherically- and geometrically-corrected, cloud-screened daily reflectance data. From this dataset, we will look at the *gain* of burned areas, which, especially in the case of Boko Haram, constitute a type of imagery "signature" specific to a certain actor or type of conflict (i.e. burning/razing of villages).

Methodology

Exploratory Analysis:

Although we hypothesized that events involving armed conflict would likely be concentrated around cities and especially in the northeast, where Boko Haram operates, we wanted to take a look at the visualization of the events gathered from January 2015 to May 2016.

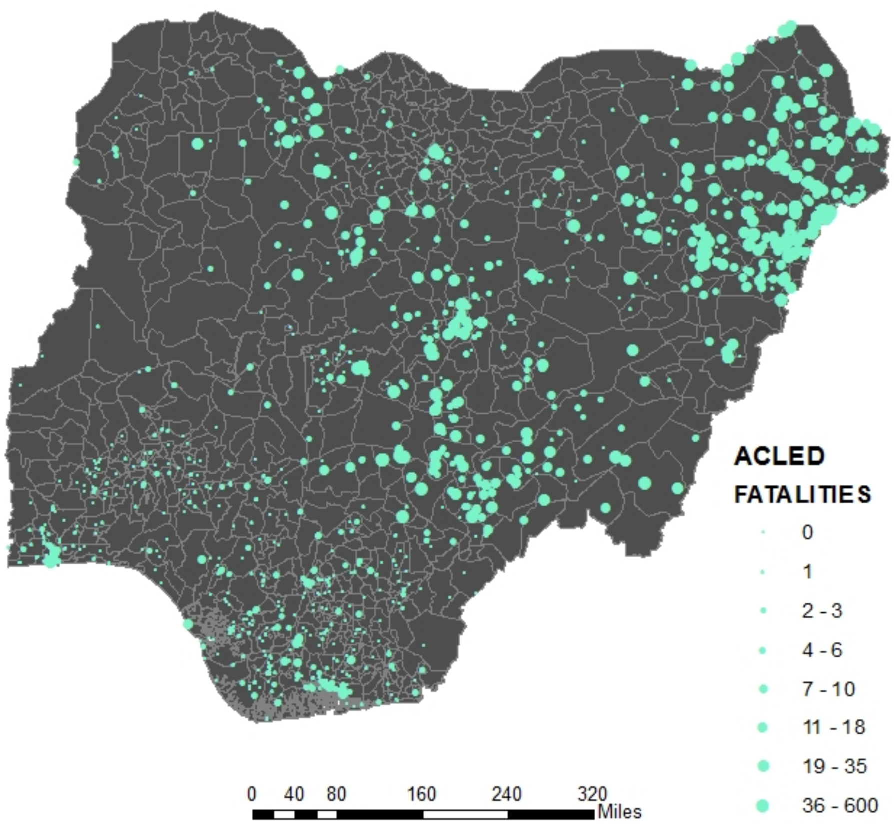

Figure 3. Visualization of the distribution of ACLED points throughout Nigeria.

The distribution of points in *figure 3* above (visualized by gradual symbols) does, in fact, highlight the differences between the Northeastern/Eastern parts of the country and the southern parts of the country in terms of fatalities. A majority of these events are classified as "Battle-No change of territory" or "Battle-Government regains territory", which differentiates them from some of the territorial disputes and riots/protests focused in the Southern and Western regions of the country. In order to get the most accurate representation of violent events throughout the country in terms of what might be "predicted" through imagery signatures,Wechose to mainly consider those events with greater than five fatalities each, as depicted below in *figure 4*.

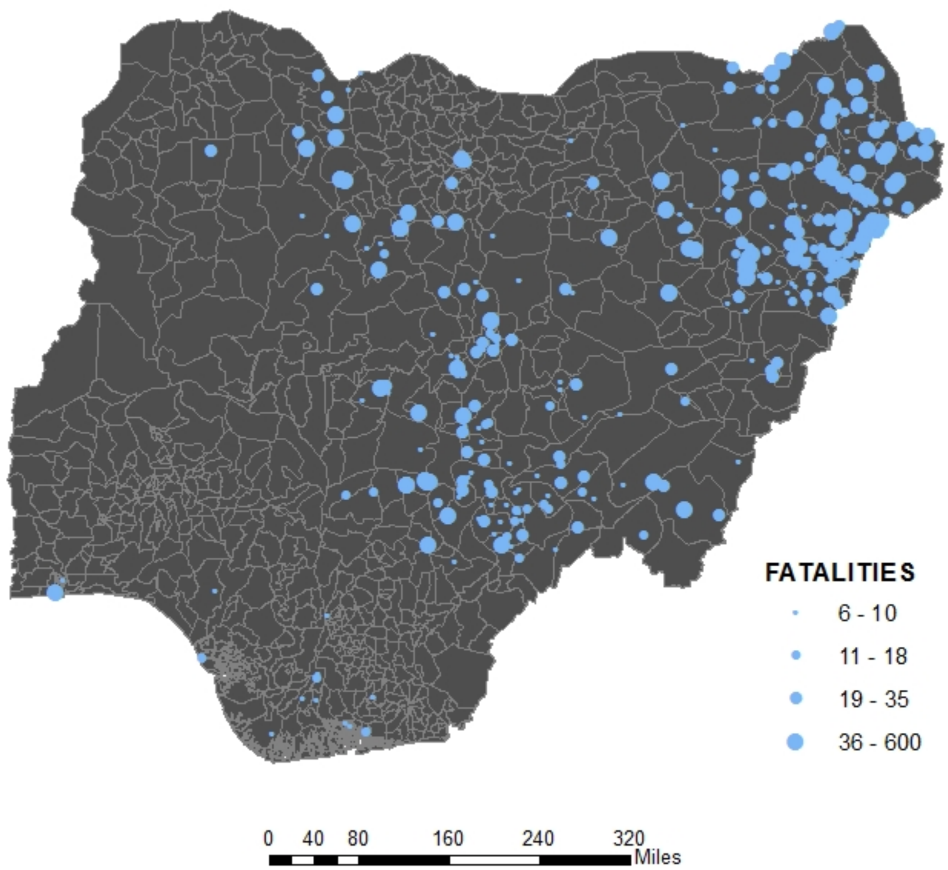

Figure 4. Visualization of the distribution of ACLED points with 6+ fatalities throughout Nigeria.

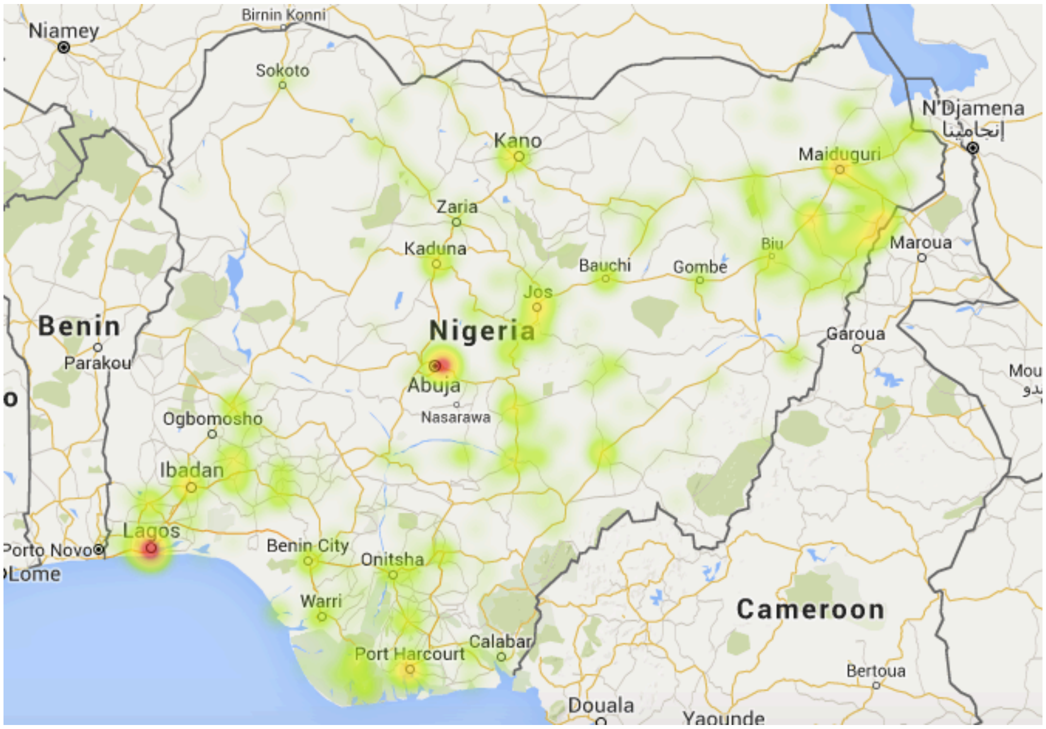

Figure 5. Heat map of the ACLED points throughout the country. Here, we see a high concentration of events relating to armed conflict surrounding Nigeria's two biggest cities, Abuja and Lagos.

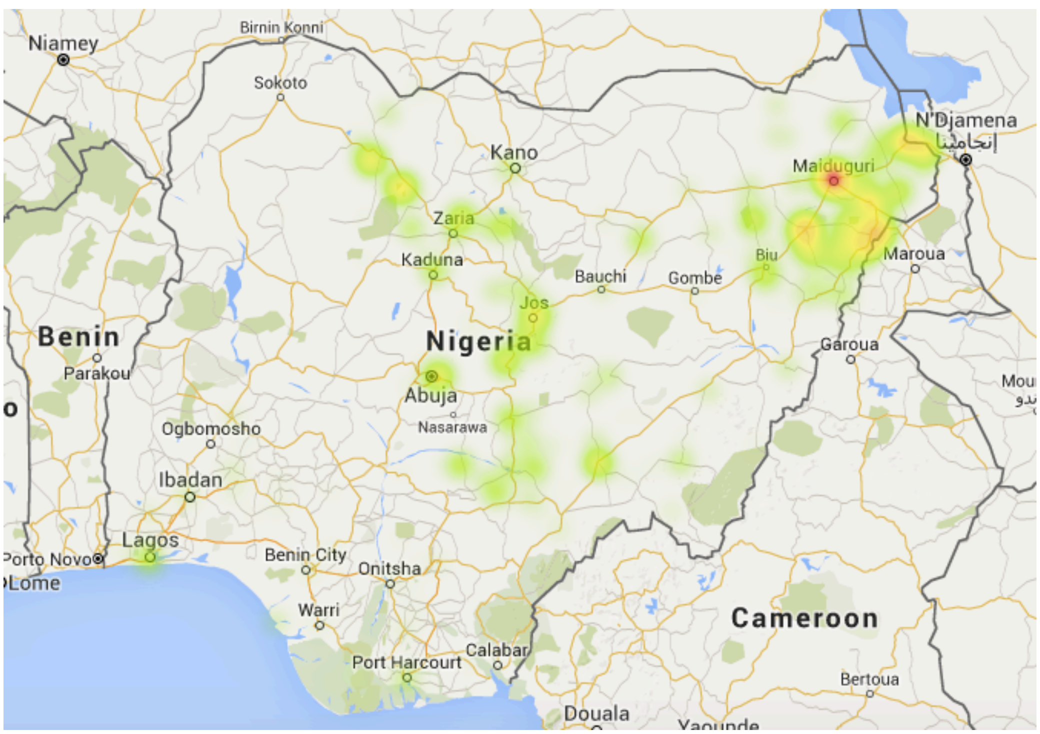

Figure 6. Here, event points are displayed again as a head map and weighted by fatalities. As expected, we do see a higher concentration of these events in the northeastern region of the country, where Boko Haram operates.

It is useful to take a look at these heat maps to gain overall awareness about the distribution of points and the factors that might relate to those areas of conflict in terms of satellite imagery signatures and image collections. Our hope is that the trending and overlapping AOI's extracted from the various satellite imagery collections will fall similarly in space to these points and hot spots of interest.

Image Processing:

After loading this data to take an initial look at the spread of events in the area, we then loaded the nighttime lights collection and the two MODIS sets (EVI and burn). The goal of this project was to compute linear trends in vegetation, burning, and light loss throughout the country, so as to see how these factors relate to crisis events as mapped by ACLED. As such, we will be performing linear regression using reducers for both of these data sources.

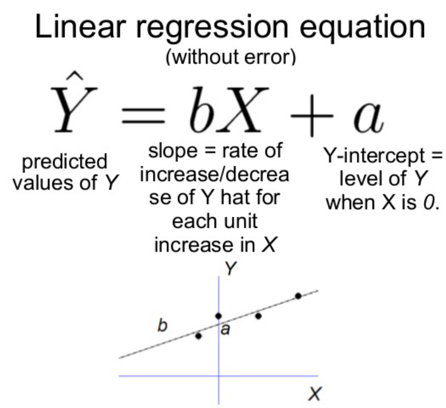

Figure 7. Linear regression equation.

After loading our image collections and again mapping a time band over it to assist with looking at the long term linear trend over the collection, we selected the bands to model with the independent variable first and computed the linear trend over time, clipping the resulting image to our area of study. Recall, that in simple linear regression, we predict scores on one variable from the scores on a second variable (equation shown in *figure 7*, above). The variable we are predicting is called the criterion variable and is referred to as Y. The variable we are basing our predictions on is called the predictor variable and is referred to as X. Earth Engine contains a variety of methods for performing linear regression using reducers. The simplest linear regression reducer is ee.Reducer.linearFit() which computes the least squares estimate of a linear function of one variable with a constant term.[7] As noted, the data should be set up as a two-band input image, where the first band is the independent variable and the second band is the dependent variable.

The output of the reduction in this case is a two banded image with one band for the slope of a linear regression ('scale') and one band for the intercept ('offset'), and a resulting image depicting the trend with increasing slopes in a palette of our choice. After initial processing, we created binary thresholds from incides to the areas of particular interest in the case of each collection based on cell value, and classified then extracted cells with our values of interest, creating rasters with values of 0 and 1 (no data/no interest, and trending AOI, respectively). Once the appropriate image collections were processed, including the appropriate trend functions and manipulations of those results, we combined our trending areas to gain insights on where violent events are most likely to occur.

Determining our Areas of Interest:

Once the factors had been determined as they related to an area of conflict, we overlaid the resulting trend areas of the processed imagery to establish areas of particular concern throughout the country using raster calculator. To further aid in analysis, we then related these AOI's to our points of interest by distance from individual events with over 5 fatalities. This was accomplished by determining which cells were located in what administrative boundary, and then by counting the number of event points located within those areas. This also gives us the opportunity to determine what trending areas are linked to what *type* of violence or crisis data (i.e. can we relate loss of vegetation to areas where razing villages can be attributed to extremists etc.?) This type of analysis would be particularly helpful in terms of situational intelligence.

[7] https://developers.google.com/earth-engine/reducers_regression

Results

Image Collection Processing:

Results of the linear regression reducer ee.Reducer.linearFit() on the nighttime lights dataset gave the output in *figure 8* on the following page. In this image, areas with increasing trends are shown in blue, areas of decreasing trends are shown in red, and brightness is depicted as the color pink. Much of the increasing trends in stable nighttime lights near the bottom of the map can likely be attributed to urban sprawl from the densely populated southern regions. Because the northeast, where Boko Haram operates, is less developed and less densely populated, we would be interested in increasing trends in lights here as opposed to decreasing. As such, the blue spots are our AOI's; we are particularly interested in those spots that are not accompanied by large areas of brightness (i.e. those near cities, which would likely be related to population growth rather than some external factor).

Upon applying the reducer to our other image collections (MODIS EVI and Burn data), we were able to obtain additional AOI's from those outputs, as shown below. Following the application of the linear regression reducer ee.Reducer.linearFit(), we obtained our results from creating binary images from thresholds on indices—after taking our clipped trends we chose thresholds based on the visualizations the original images provided that are described in detail below.

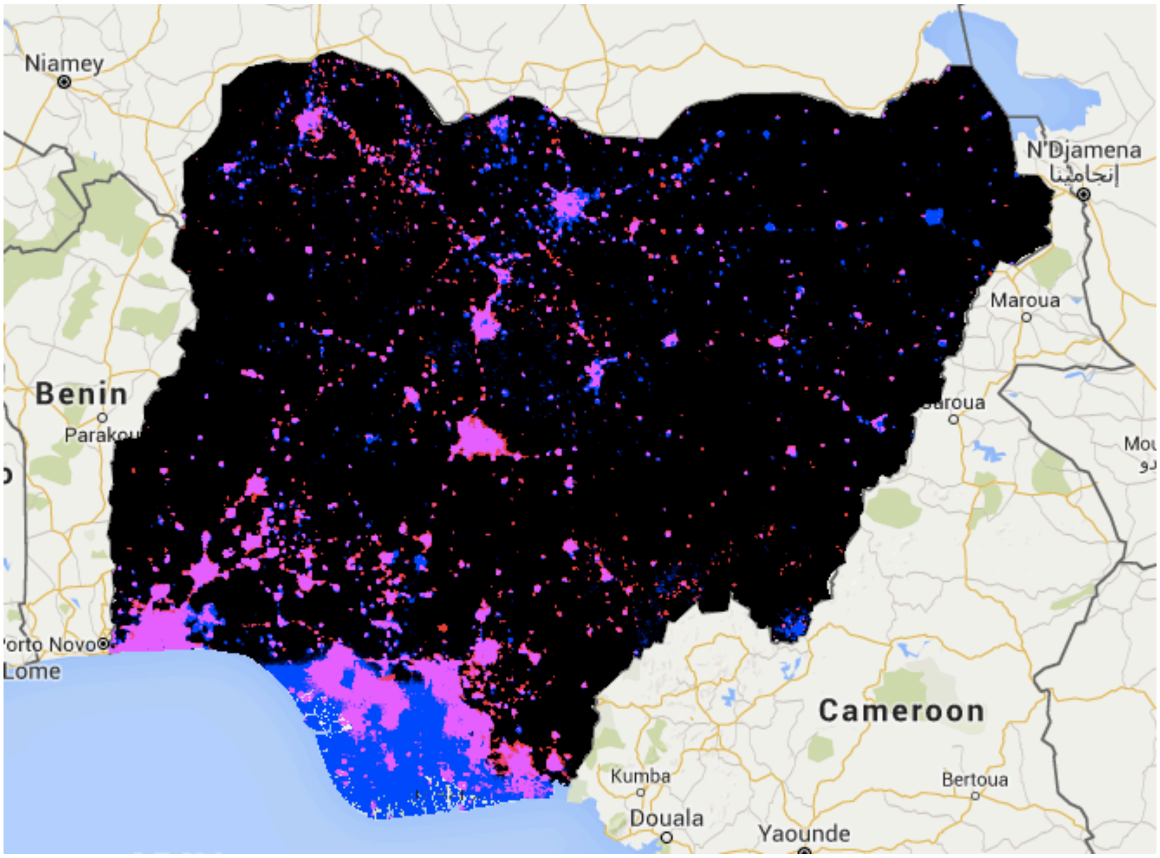

Figure 8. This image illustrates the output of the linear trend analysis for the nighttime lights collection. Here, we are most interested in the areas where lights are *increasing*, which is characterized by the blue spots (decreasing in red, brightness in pink).

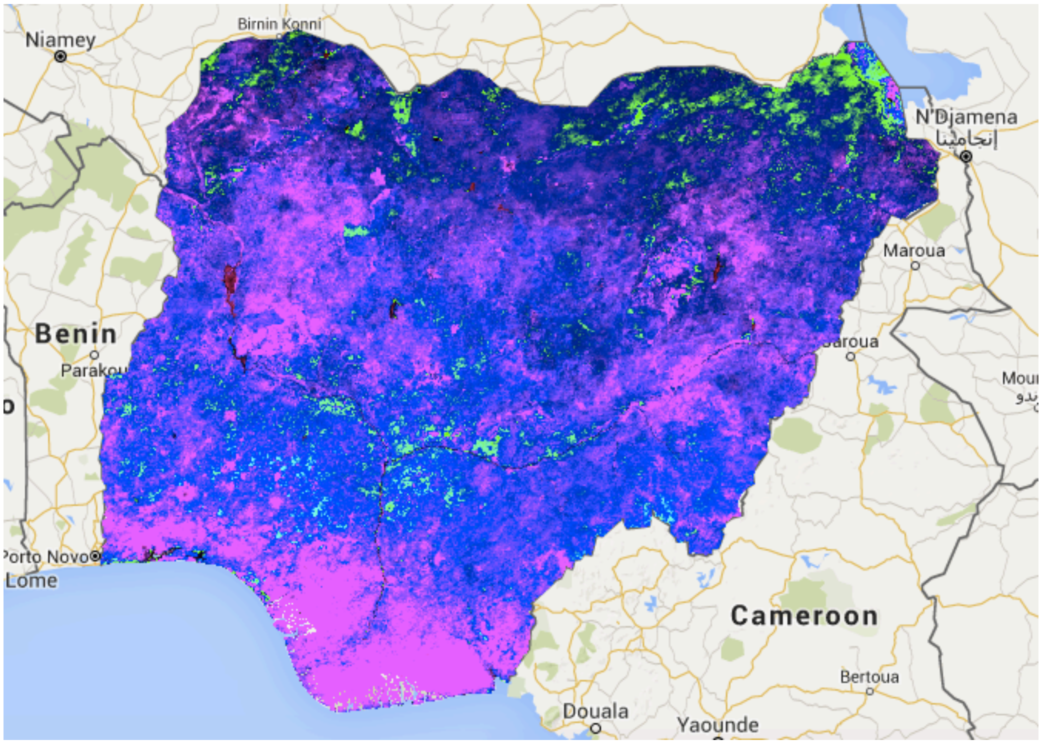

Figure 9. This image displays the output of the linear trend analysis for the MODIS EVI trend. Here, we are interested in the areas highlighted in green.

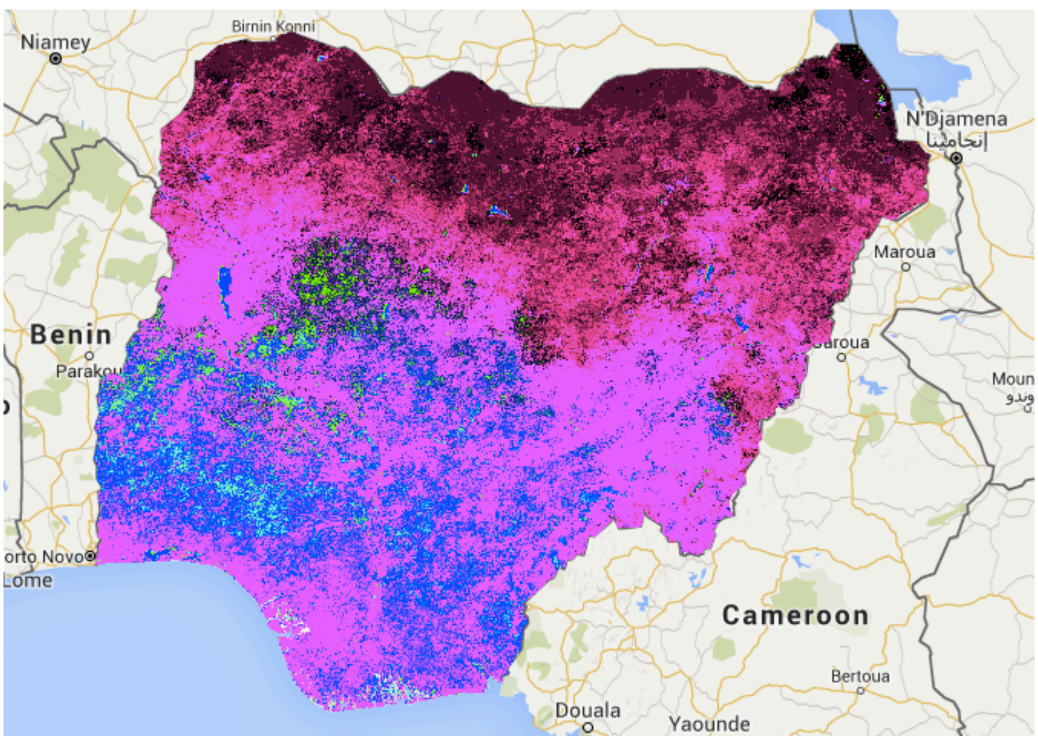

Figure 10. This image displays the output of the linear trend analysis for the MODIS Burn trend. Here, we are again interested in the areas highlighted in green.

AOI Extraction:

After applying the reducer to our other image collections and creating intermediary binary images from thresholds on indices, our images were visualized and exported to TIFF format for further analysis in ArcGIS. We were able to classify these rasters based on color of the exported regions as Google Earth Engine does not export values from visualizations (which is not problematic, as we were looking for geographic locations of interest rather than values). After reclassifying our rasters to pull only the cells of interest, we were left with three rasters representing areas that had gained nighttime lights over a period of four years, areas that had lost healthy vegetation in the last two years, and areas that had gained burned areas in the last two years. Those rasters are depicted in *figures 11, 12, and 13*.

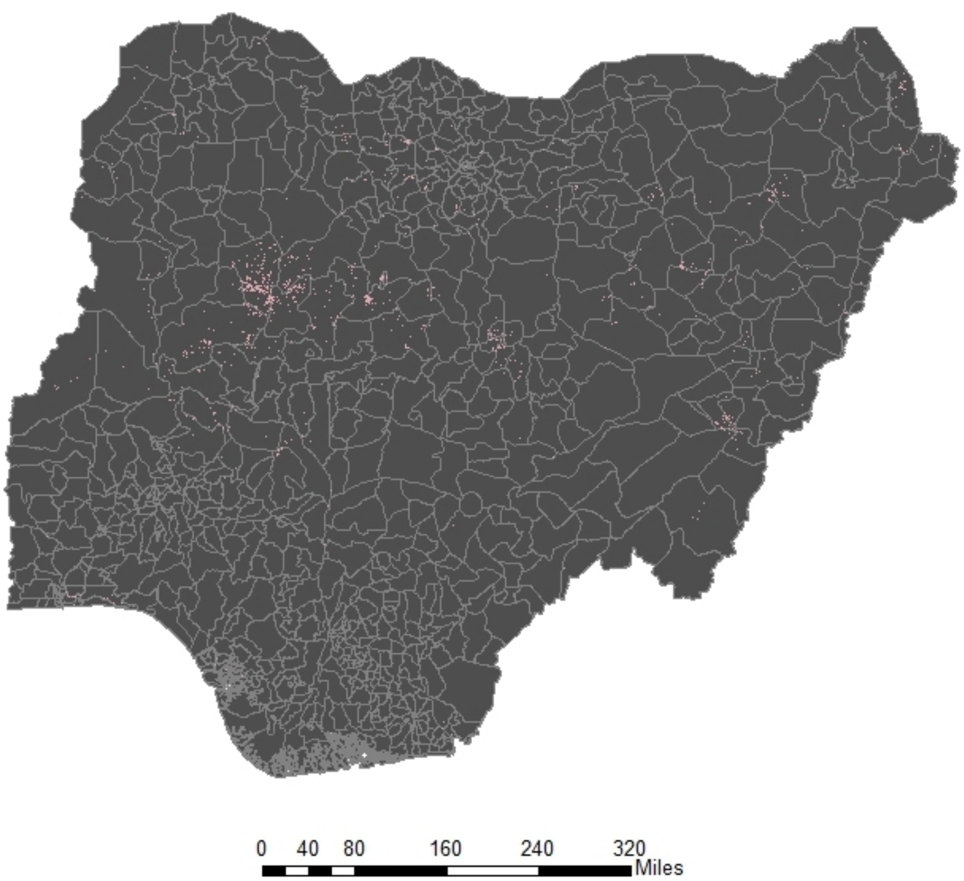

Figure 11. Gain in burned land, areas of interest.

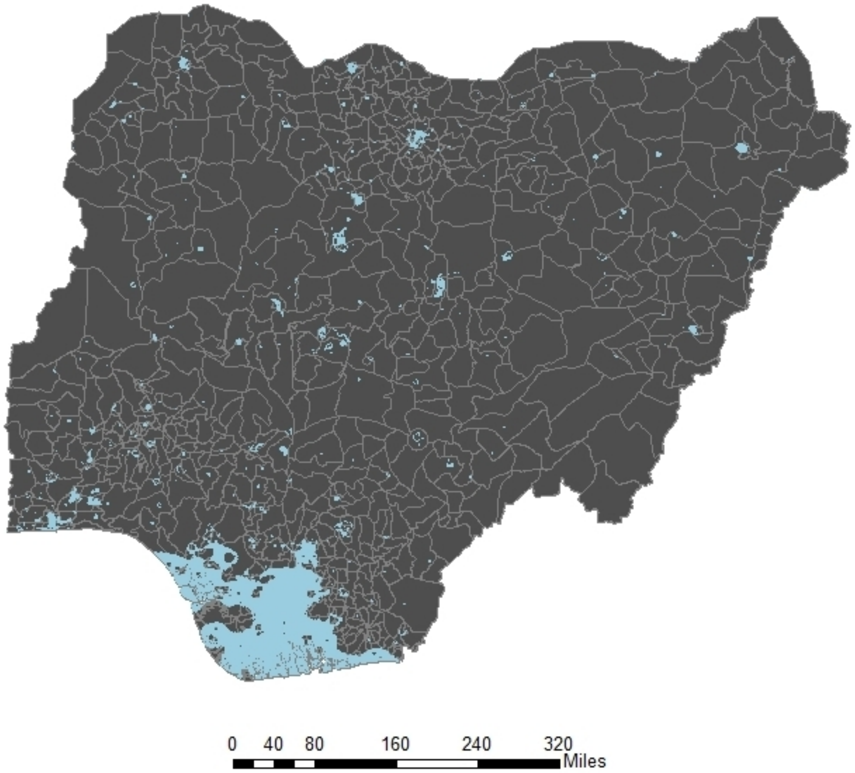

Figure 12. Gain in nighttime lights, areas of interest.

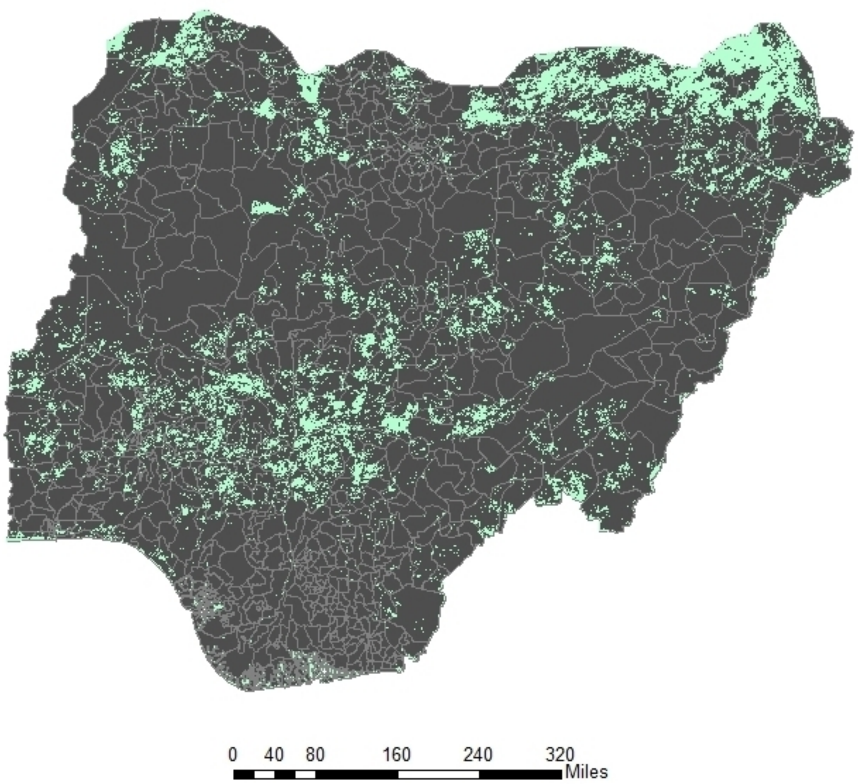

Figure 13. Loss of healthy vegetation, areas of interest.

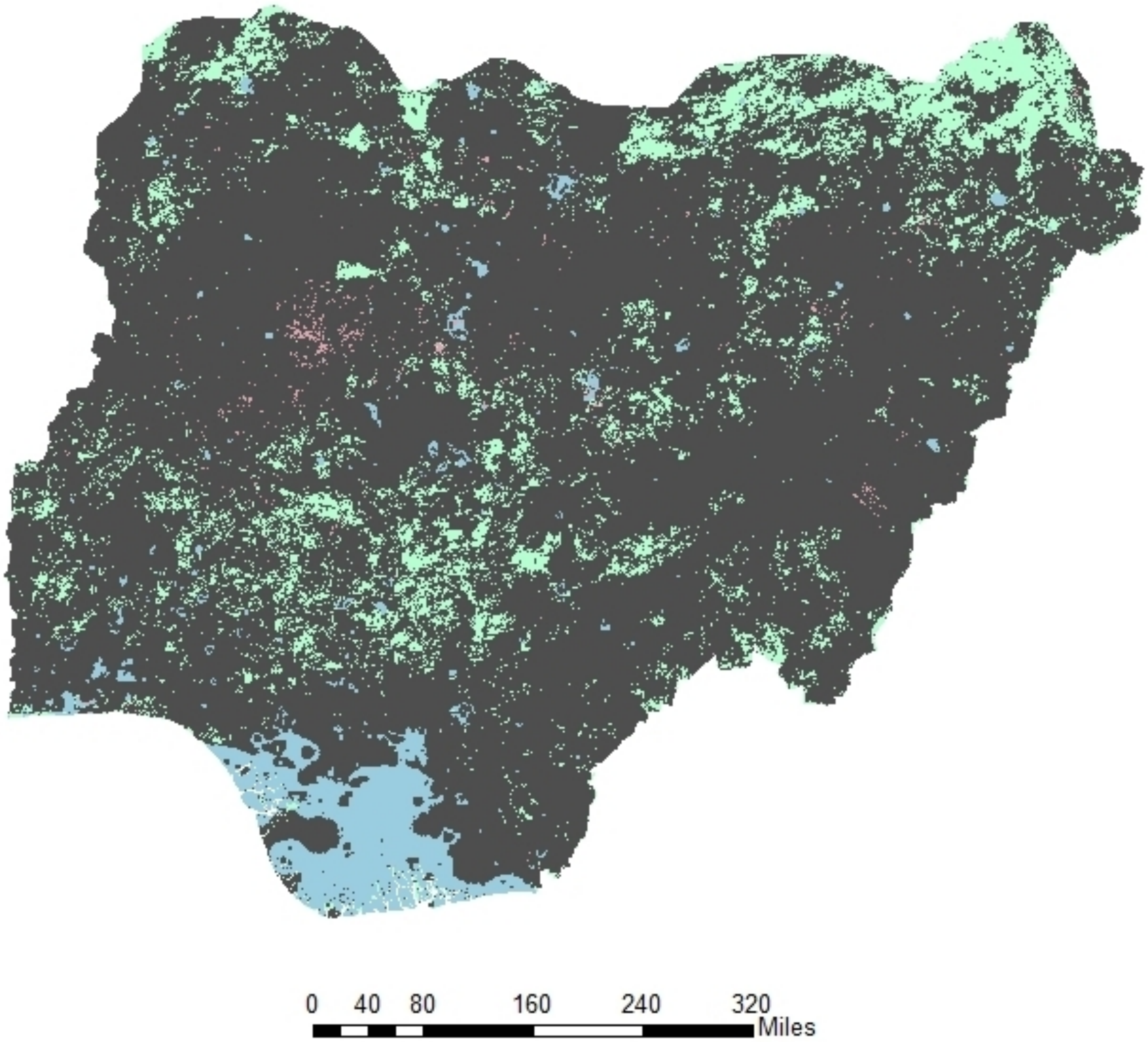

Figure 14. Visualization of all “trending” areas throughout the country. Gain in burned areas characterized by the color pink, gain in nighttime lights in blue, and loss of vegetation in green.

AOI Translation - Administrative Boundaries:

Once we had the resulting raster cells from processing the image collections, we were able to relate those cells to the administrative boundaries in question by creating resulting layers of interest, as depicted in *figures 15, 16, and 17.*

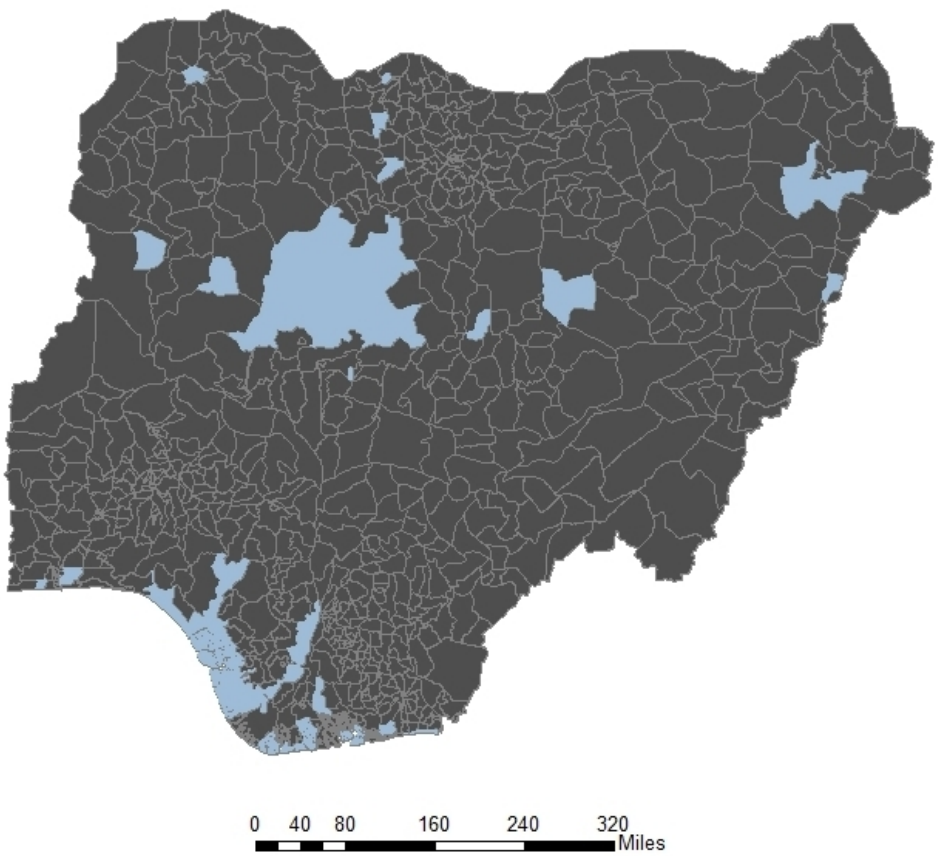

Figure 15. Resulting administrative AOI's from the extraction of cells that featured a **gain in nighttime lights and a gain in burned area.**

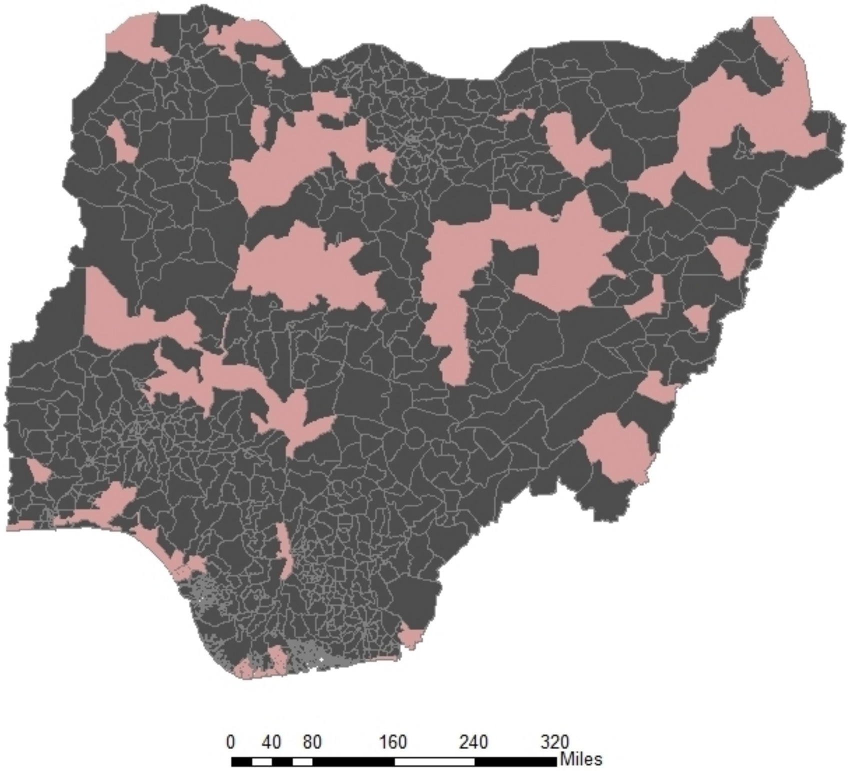

Figure 16. Resulting administrative AOI's from the extraction of cells that featured a **gain in burned areas and a loss in vegetation**.

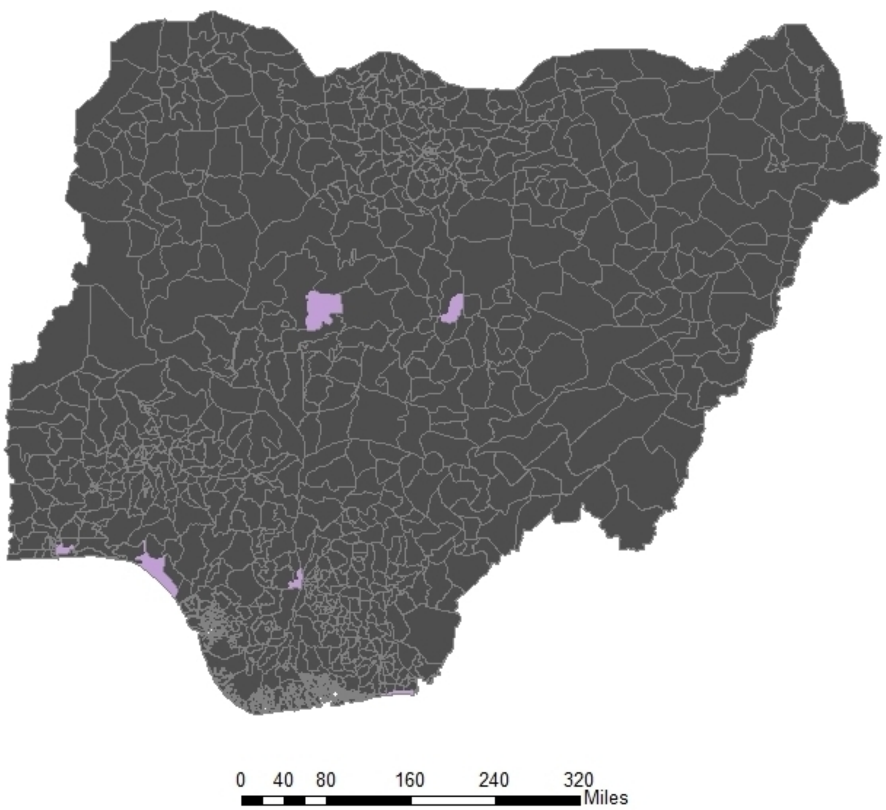

Figure 17. Resulting administrative AOI's from the extraction of cells that featured a **gain in burned areas, a gain in nighttime lights, and a loss in vegetation**

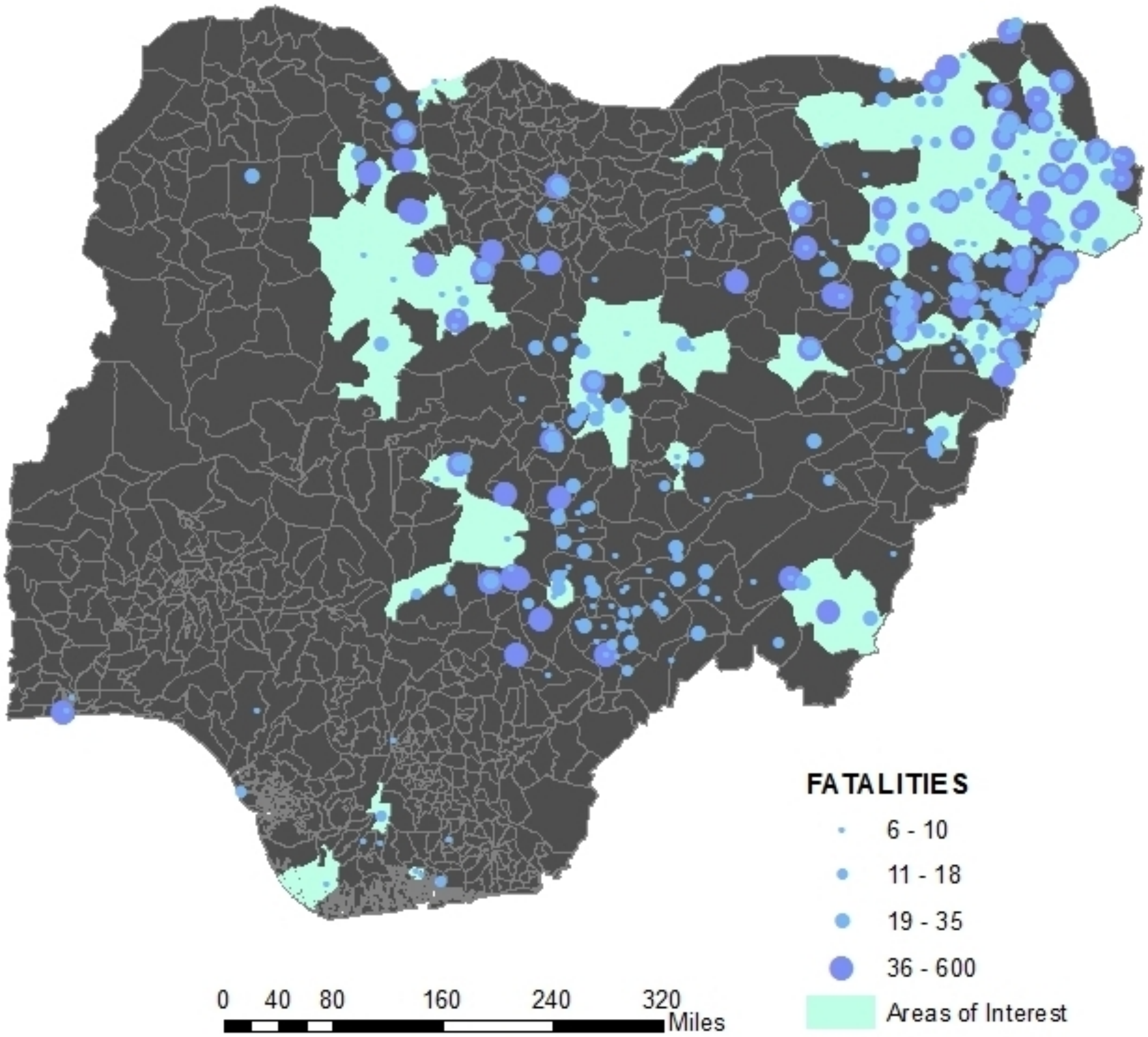

Figure 18. Distribution of ACLED event points with greater than 6 fatalities, coupled with the combined AOI's for burned area, nighttime lights, and EVI.

Outcomes:

Figure 18 shows the distribution of ACLED event points from 2015-2016 with greater than 6 fatalities coupled with the combined AOI's, and *figure 19* compares those events and AOI's with the photo of "Nigeria's Insurgent North", featuring events from 2009-2014. Results were quite good for this analysis—the breakdown of events successfully "predicted" by each trending area within 20 miles of an AOI are as follows:

- 38/38 **(100%)** of ACLED events with 100+ fatalities
    - (34/38 **(89.5%)** of ACLED events with 100+ fatalities located *fully* within an AOI)
- 731/793 **(92%)** of ACLED events with 6+ fatalities

There is a great deal of additional work could be done to gain insight on finer details of this study in relation to exactly which combination of AOI "signatures" best suits a region. This case study sought to test the ability of our predictive regions to accurately predict violent events, and in this pursuit, it yielded very good results.

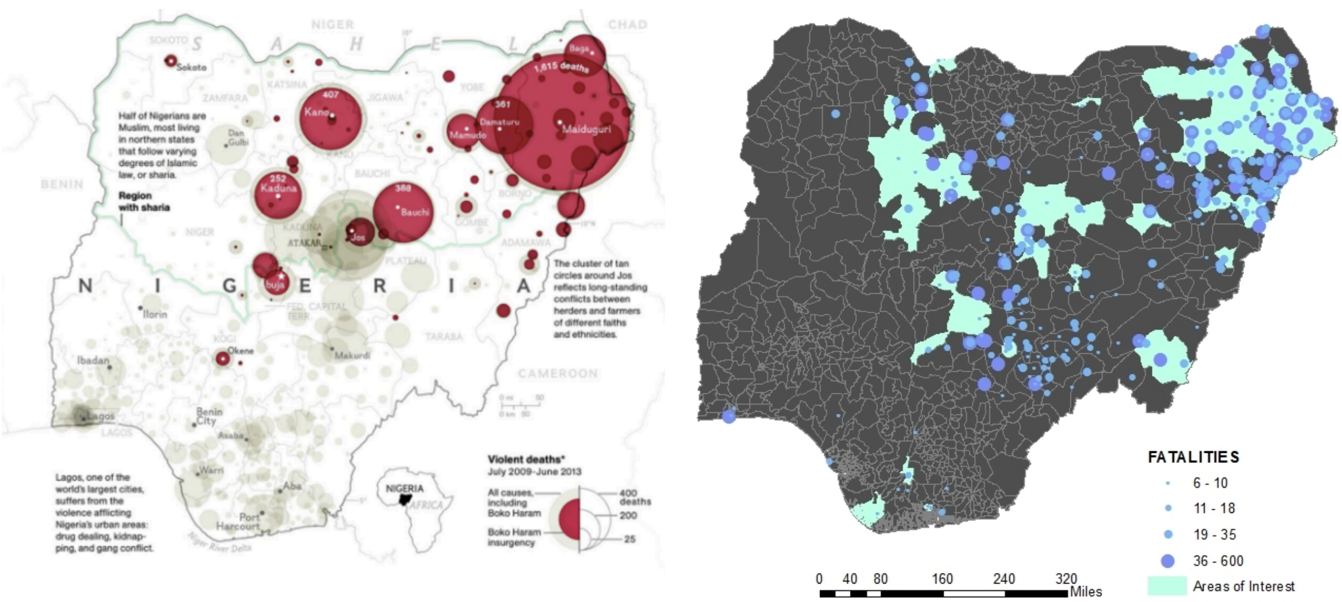

Figure 19. Comparison of event maps.

Project Testing and Revisions

The main changes between the first and final iterations of my project focused mainly on the manipulation of each image collection to its' final binary product and then to extract meaningful values. By this, we mean that the only argument to map() in Google Earth Engine is a function which takes one parameter: an ee.Image. The mapped function is then limited in the operations it can perform. Specifically, GEE can't modify variables outside the function; it can't print anything; it can't use JavaScript 'if' or 'for' statements. As such, ee.Algorithms.If() should be used to perform conditional operations in a mapped function.

Google Earth Engine provided the meaningful linear regression transformations on each image collection to an extent, and we followed up by exporting these images and re-mapping them in relation to our points of interest in ArcGIS. Originally, we had planned to bypass this issue by doing some of the initial operations on image collections in GEE. In the interest of making use of the information available via ACLED in a timely manner, however, we chose to use a combination of Google Earth Engine and ArcGIS for trend analysis.

As the use cases for Google Earth Engine are inherently different than those for ArcGIS, the decision to use GEE for broad analysis coupled with ArcGIS for fine-tuned analysis worked quite well. Generally speaking, GEE is very good for fast analysis of large areas. When looking for "trending" areas as they relate to conflicts or violence, one would likely want more detail than GEE can provide. As such, the product works quite well for projects such as this example of trend analysis—where individual pixel values do not matter as much as the simple space that the AOI occupies. As this project exhibits, once the AOI's have been established, it is then quite easy to compile these regions and to relate them to events/points of conflict.

The most important way to test this information would really be to determine our trending areas in near real-time from the data available in GEE, and to test them against events that occur shortly after—therein lies the real "predictive" power of determining AOI's from raster cells and areas of interest. To continue to test the outcomes of this project, it would take a predetermined workflow to ingest and process imagery and a clear methodology for the analysis—this case study has laid much of that groundwork, enabling future analyses (for Nigeria, at least) to run smoothly.

Conclusions

The AOI's, established via image processing by means of a linear regression reducer, delivered very interesting insights in terms of "predictive" power. The cells extracted from our trending areas of interest, overlaid onto the smallest level Nigerian administrative boundaries, provide a very close indication of previous violent events in Nigeria. As noted in our outcomes, there is a strong visual connection between the most violent events throughout the country and the AOI's that our analysis provided. This analysis really demonstrates a strong connection to the ACLED event data, especially as the importance of the number of fatalities increases.

100% of ACLED points with over 100 fatalities were located within 20 miles of an area of interest, and ***89.5%*** of ACLED points were located directly within an area of interest. Results were still quite strong with the event points representing only 6+ fatalities, where ***92%*** of events were located within 20 miles of an area of interest. As noted, it will be more significant to test these AOI's in near-real time with only new and evolving events in order to test true "predictability". That said, the combination of image processing techniques using a linear regression reducer for various image collections in Google Earth Engine, coupled with additional analysis in ArcGIS, did provide favorable out comes. Although a predetermined workflow, much like this project has developed, will make analysis much faster, it would be ideal to be able to do the entire analysis within Google Earth Engine—that will be a task for future case studies.

The goals outlined in this project focus on providing advanced situational intelligence to policymakers and humanitarian aid workers, among others. This project does give people a measurable description of where events are occurring, and how environmental factors and "signatures" noted in imagery analysis and processing can provide additional insight into some of those issues. Further use cases for this project include the trend analysis of very specific "signatures", such as burning, which can be particularly helpful in determining exactly which provinces or AOI's to focus on for outbreaks of violent events. One of the key benefits of GEE for analysis (as opposed to other spatial analysis and image processing software packages) is the ease of use, and sheer amount of imagery available to the user. These factors allow for very creative and fast paced analytical work, which takes on utmost importance when it comes to situational intelligence. This case study, though exploratory in nature, provides measureable groundwork for the continuation of satellite imagery trend analysis, especially as a means to take some of the guesswork out of the world's most pertinent crisis situations. Although this project in particular blends environmental occurrences with political instability, we can appreciate how such work might be useful in a variety of situations. From geopolitics to oil spills and earthquakes, we expect this type of rapid, advanced imagery processing and analysis to become increasingly significant and influential in terms of innovative crisis prediction and mitigation techniques.

GOOGLE EARTH ENGINE SCRIPT

```
// This script helps to assess & visualize trending areas of interest
// In observing crisis trends, it considers 3 factors:
// (1) MODIS Burn Data (2) Night-time lights (3) MODIS EVI

// ----------------AREA & EVENTS OF INTEREST

// Load Nigerian border/provinces and GDELT data

var NGAadmin = ee.FeatureCollection("ft:14e9fO8qoweTROMXUZfYsdzAcB7mygYe5U6VBsmuZ");
var NGAacled = ee.FeatureCollection("ft:1CnsFMinbTVCNuMIxEmHVdqQ6Ke59HG_0DnXM1z0k");

Map.addLayer(NGAacled);
Map.addLayer(NGAadmin,{color:'000000'},'NGA Admin');

var acledFilt = NGAacled.filterBounds(NGAadmin);
Map.addLayer(acledFilt,{color: 'FF0000'},'ACLED Points');

///////////////////////////////////////////////////////////////////////////////


// ----------------LIGHTS TREND ANALYSIS

// Compute the trend of night-time lights

// Adds a band containing image date as years since 2011 (this marks the //beginning
of the conflict, we need to be careful to specify dates, //particularly in trend
analysis). Unfortunately,Wedid not realize until //later thatWeshould have used
ee.Algorithms.If() for full functionality of //modeling variables outside the
function.

function createTimeBand(img) {
var year = ee.Date(img.get('system:time_start')).get('year').subtract(2011);
return ee.Image(year).byte().addBands(img);
}

// Map the time band creation helper over the night-time lights collection

var collection = ee.ImageCollection('NOAA/DMSP-OLS/NIGHTTIME_LIGHTS')
    .select('stable_lights')
    .map(createTimeBand);

// Perform linear regression using reducer

var theReducer = collection.reduce(ee.Reducer.linearFit());

//This helps to visualize brightness in green and a linear fit trend line in red/blue
```

```
//Use this to observe trends if you want to create thresholds on the resulting
indices

Map.addLayer(theReducer);
Map.addLayer(collection.reduce(ee.Reducer.linearFit()),
{min: 0, max: [0.18, 20, -0.18], bands: ['scale', 'offset','scale']},'stable lights
trend');

// Clip the resulting trend data to our border

var clipped = theReducer.clip(NGAadmin);
//Add the layer for visual analysis
Map.addLayer(clipped);

///////////////////////////////////////////////////////////////////////////////

// ----------------VEGETATION TREND ANALYSIS

// This function adds a band representing the image timestamp mentioned //previously


var addTime = function(image) {
  return image.addBands(image.metadata('system:time_start')
    .divide(1000 * 60 * 60 * 24 * 365));
};

// Now we load the MODIS collection, and again map the time band over it to
//assist with looking at the long term linear trend over the collection

var collection = ee.ImageCollection('MODIS/MYD13A1').map(addTime);

// We select the bands to model with the independent variable first

var trend = collection.select(['system:time_start', 'EVI'])

  // We then compute the linear trend over time
  .reduce(ee.Reducer.linearFit());

// After again performing linear regression with the reducer we clip the
//resulting image to our area of study

Map.addLayer(trend);
var clipTrend = trend.clip(NGAadmin);
Map.addLayer(clipTrend);

// Display the trend with increasing slopes in green, decreasing in red

Map.setCenter(8.0000, 10.0000, 5);
```

```
Map.addLayer(
    clipTrend,
    {min: 0, max: [-50, 15, 4000], bands: ['scale', 'scale', 'offset']},
    'EVI Clipped');

///////////////////////////////////////////////////////////////////////////////

// ----------------BURN TREND ANALYSIS

// This function adds a band representing the image timestamp mentioned //previously

var addTime = function(image) {
  return image.addBands(image.metadata('system:time_start')
    .divide(1000 * 60 * 60 * 24 * 365));
};

// Now we load the MODIS collection, and again map the time band over it to
//assist with looking at the long term linear trend over the collection

var collection = ee.ImageCollection('MODIS/051/MCD45A1').map(addTime);

// We select the bands to model with the independent variable first

var trend = collection.select(['system:time_start', 'burndate'])

  // We then compute the linear trend over time
  .reduce(ee.Reducer.linearFit());

// After again performing linear regression with the reducer we clip the
//resulting image to our area of study

var burnTrend = trend.clip(NGAadmin);
Map.addLayer(burnTrend);

// Display the trend with increasing slopes in green, decreasing in red

//Map.setCenter(8.0000, 10.0000, 5);
Map.addLayer(
    burnTrend,
    {min: 0, max: [-50, 50, 4000], bands: ['scale', 'scale', 'offset']},
    'Burn Clipped');

///////////////////////////////////////////////////////////////////////////////

// ----------------CREATING BINARY IMAGES FROM THRESHOLDS ON INDICES
```

```
var geometry =
ee.Geometry.Rectangle([2.6769318581,4.0690956116,14.6779823303,13.8856458664]);

// We take our first clipped trend (lights) and choose a threshold based on
//the visualizations the original images provided showing the decreasing trends

var lightsbare = clipped.lt(5);
Map.addLayer(lightsbare,{color:''},'Lights Threshold');

// Create visualization layers.
var lights = lightsbare.visualize({bands: ['scale', 'offset']});

Export.image(lights, '1', {
      crs: 'EPSG:4326',
      maxPixels: 1e13,
      region: geometry
});

// We then take our second clipped trend (vegetation)
//and choose a threshold based on the original visualizations

var modisbare = clipTrend.lt(1);
Map.addLayer(modisbare,{color:''},'Modis Threshold');

var evi = modisbare.visualize({bands: ['scale', 'offset']});

Export.image(evi, '1', {
      crs: 'EPSG:4326',
      maxPixels: 1e13,
      region: geometry
});

//We then take our third clipped trend (burn data) and choose a threshold based on
the original visualizations

var burnbare = burnTrend.lt(5);
Map.addLayer(burnbare,{color:'FFFFFF'},'Burn Threshold');

var burn = burnbare.visualize({bands: ['scale', 'offset']});

Export.image(burn, '1', {
      crs: 'EPSG:4326',
      maxPixels: 1e13,
      region: geometry
});
```

Works Cited

ACLED Armed Conflict Location & Event Data Project. (n.d.). Retrieved April 23, 2016, from http://www.acleddata.com/

Black, I. (2015). Satellites capture how the lights have gone out in Syria. Retrieved March 12, 2016, from http://www.theguardian.com/world/2015/mar/12/satellites-capture-how-the-lights-have-gone-out-in-syria

Jones, S., & Mark, M. (n.d.). Boko Haram: Satellite images reveal devastation of massacre in Nigeria. Retrieved April 24, 2016, from http://www.theguardian.com/world/2015/jan/14/satellite-images-reveal-devastation-boko-haram-massacre-nigeria

Linear Regression. (n.d.). Retrieved April 12, 2016, from https://developers.google.com/earth-engine/reducers_regression

Nigeria's Insurgent North. (n.d.). Retrieved May 01, 2016, from http://ngm.nationalgeographic.com/2013/11/northern-nigeria/insurgent-north-map

Remote Sensing for Human Rights. (n.d.). Retrieved March 04, 2016, from http://www.amnestyusa.org/research/science-for-human-rights/remote-sensing-for-human-rights

Satellite Imagery Assessment of the Crisis in Ukraine: Part Two: Border Deployments. (2014). Retrieved March 04, 2016, from http://www.aaas.org/page/satellite-imagery-assessment-crisis-ukraine-part-two-border-deployments