Mining, Economic Activity and Remote Sensing: Case studies from Burkina Faso, Ghana, Mali and Tanzania

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Abstract

Mining is a major economic activity in many developing countries particularly in Africa. Mining operations, whether small- or large-scale, have an impact on local communities. Previous research focus on how the gold mining sector in Africa is dependent on policy reforms in order to enable countries to better benefit from the sector, changing environmental conditions or the structure of the economic activities in the areas surrounding mines. Here, we apply a novel analytical framework based on medium resolution satellite data for the period 2001 – 2012 to estimate the economic effects of mining in Ghana, Mali, Burkina Faso and Tanzania. Through the analysis of nighttime lights, agricultural vegetation dynamics and forest change, we find a positive effect on average economic growth for most mining districts in Mali, Burkina Faso and Tanzania. Moreover, our analysis establishes strong relationship between statistics of agricultural production and vegetation index from satellite data on district level in Mali, Ghana and Tanzania. The effect of mining in Ghana is more complex and the general pattern is that mining has a negative effect on average economic growth on district levels.

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1. Introduction

Mining is a major economic activity in many developing countries particularly in Africa (Weng et. al 2013). Mining operations, whether small- or large-scale, have an impact on local communities. Previous research focus on how the gold mining sector in Africa is dependent on policy reforms in order to enable countries to better benefit from the sector (Gajigo et. al 2012), changing environmental conditions or the structure of the economic activities in the areas surrounding mines (Hilson 2002). Three major factors have been highlighted in relation to the main challenges facing the African mining industry. Low levels of expenditure on exploration and weak downstream processing providing low industrialization of the industry. Many countries are dependent on export earnings from the mineral sector thus vulnerable for external shocks and even despite years of efforts to improve the sector’s competitiveness it have not yet been translated in sustainable economic growth (Hilson 2014). Thirdly, in some African countries, environmental problems and social issues caused by mining have been sources of protests and conflicts between mining companies and communities in mining areas (Campbell 2012). Mining has often been associated with deforestation, land degradation, air pollution, and disruption of the ecosystem (Hilson and Yakovleva 2007).

The aim of this proposed research is to gain a better understanding of the socioeconomic impact of resource extraction on local economic growth with a focus on agricultural production. One important outcome of interest is whether the opening of mines has spillover effects on economic activities within the agricultural sector. Agricultural production could be affected by mining activities in several ways. Mining could lead to a rise in local wages, reduce profit margins in agriculture and lead to exit of many families from farming a localized Dutch disease problem. Negative environmental spillovers such as pollution or local health problems could also dampen productivity of the land and the farmers. Alternatively, mining could create a mini-boom in the local economy—that is, higher employment and higher wages can lead to an increase in local area aggregate demand, including for regional food crops.

The objective of this study is to use remote sensing data to estimate level and growth (or decline) of economic activities in reference to the mining industry in Burkina Faso, Ghana, Mali and Tanzania by comparing estimated levels and changes in agricultural and non-agricultural production in mining and non-mining localities. A selection of radius around the mining areas has been developed in order to estimate the level and composition of production – agricultural and non-agricultural – as a function of distance from the mining areas.

Our study identified 32 mines within the studied countries as prime study areas. A total of 8 mines (2 per country) were chosen to be reported in the analysis. This paper contributes to the literature by studying the effects of natural resources on development using remote sensing data. Moreover, our study investigates the spatial relationship between mining activities by using a vegetation index as a proxy for agricultural production.

Our study is divided into two parts. Firstly, we use time-series analysis of remote sensing data from three different sources in order to estimate change over time in the area surrounding the mines. Nighttime light data from the National Oceanic and Atmospheric Association’s National Geophysical Data Center (NOAA-NGDC) are used to identify artificial light emissions and has previously been used to estimate growth in economic activities. Recent studies conducted by economists have paid attention to human generated night-time light data and tried to associate these with economic growth in order to overcome estimation errors (Elvidge, et al. 1997) (Sutton and Costanza 2002) (Doll, Muller and Morley 2006) (Ghosh, et al. 2010); (Henderson, Storeygard and Weil 2012) (Ebener, et al. 2005) (Chen and Nordhaus 2011). The second data source related to vegetation changes play an important role in the environmental
processes, and is also a sensitive indicator for environmental and global changes (Van Wijngaarden, 1991). The vegetation monitoring can provide useful clues concerning our changing environment and help natural resource management. Traditional method to monitor the vegetation is by field investigation. It is low efficiency and high labor demanding, especially for large scale area, and impossible to conduct continuously. Time-series analyses of satellite data enable the observation of seasonal and annual trends of vegetation cover (Vicente et al, 2004). Our study test the relationship between vegetation index and the actual agricultural production reported by the National Statistics offices in Tanzania, Ghana and Mali by using geographically weighted regression (GWR). Su et al. (2001) pointed out that the results or conclusions for the same area may change with different spatial resolution of research scale. And it is important to understand the effect of different resolution images on the analysis of spatial variation. The selection of radius around the mining areas estimates change of time for 10, 20, 30, 40 50 and 100 kilometers from the mine. Secondly, we look at estimated growth in economic activities on district levels in the studied countries to evaluate growth patterns in districts with a mine, districts neighboring a district with a mine and other districts that are not close to a mine.

The rest of the paper proceeds as follows. The next section (2) provides a background on the gold mining industry in the studied countries. Section 3 provides a summary of the methods and data used in the study. Section 4 reviews the literature on remote sensing and economic activities with particular focus on agriculture. Section 5 includes the results from the analysis of the mining sites and the economic growth model on district levels. Section 6 concludes the paper.
2. Background

Our empirical analysis uses the cases of gold mining in Burkina Faso, Ghana, Mali and Tanzania. The background section provides an overview of the mining sectors in the case countries.

**Fig.1. Case countries with mining locations**

**Burkina Faso**

Comparatively, Burkina Faso does not have a long history of mining activity like other countries in the African sub-region such as Mali and Ghana (Gueye 2001). Gold mining activities have however been known in the southwestern region of the country since ancient times (Kietega 1983), albeit gold deposits were not sufficient enough to attract serious colonial interests (Bantenga 1995). Gold sites in the Gaoua and Poura regions have been exploited by local people for centuries. Customary laws regulated these sites till a decree was passed in 1922 by the colonial government, demarcating zones reserved for artisanal mining by the local people. Exploration activities by a few companies such as the Mining Company of Upper Volta and the Equatorial Mining Company in the Gaoua region were abandoned in 1932 during the economic crisis (Gueye 2001).

In spite of its relative popularity in the southwestern part of the country since ancient times, the importance of gold-mining increased largely during the droughts of the 1980s (Luning 2008). Agricultural activities that constituted an integral part of the rural economy were greatly affected by the droughts and artisanal mining became an alternative source of income for the rural populace (ibid). In 1983, the government made several efforts to restructure the mining sector and make it a major revenue earner for
Burkina Faso. Ownership of the country’s resources was exclusively vested in the state. To ensure that the country had monopoly over the gold market, the Burkinabé Precious Metals Counter (CBMP) was established and it exercised monopoly over the collection, processing and marketing of precious metals (Luning 2008). The mineral sector making it a major contributor to Burkina Faso’s economy as gold has replaced cotton as the country’s main export commodity. After the country opened its first commercial gold mine in 2007, revenues from the mineral sector, in the form of income taxes and royalties, has increased from 0.5% in 2009 and 1% in 2010 to an estimated 1.8% in 2011 (USGS, 2013). These revenues constituted approximately 7% of the total government’s revenues in 2011.

Ghana

Ghana’s mining tradition, particularly gold, dates back to the 15th century (Akabzaa and Darimani, 2001). Notwithstanding the fact that artisanal mining in Ghana predates the first recorded contact with Europeans in 1471, it was not until the late 19th century that capital intensive and large scale-mining by the British and other investors started. This was after British colonial rule was formalized. The mining industry was vibrant in the pre-independence period with Ghana accounting for 36% of total world gold output between 1493 and 1600. With the exception of the early 1960s and 1970s, Ghana saw a decline in the mining industry after independence. This is attributed among other factors to the then prevailing market conditions, investor uncertainty and the effects of state intervention on the sector. Under the post-1983 Economic Recovery Programme, the mining industry was restructured and modernised. Both foreign and local companies are actively involved in mining activities. The large mining companies are owned by foreigners; the government and private Ghanaian investors have less than 15% shares in these mines. The ownership structure of the mining industry has changed over the last three decades as a result of the promotion of foreign investment in the 1980s. Prior to the structural adjustment period, the government of Ghana controlled about 55% shares in all large mining companies. Currently, foreign companies own an average of 70% shares in large scale mines. The government has 10% free share in each mine and may acquire an additional 20% (Akabzaa and Darimani, 2001; Pettersson, 2002).

Mali

Together with Ghana, Mali has one of Africa’s oldest gold mining histories dating back to the Western African empires. It was the introduction of modern commercial mining however, that allowed for a sharp increase in production and export. This increase evolved in the 1990s as a consequence of the new openness to foreign investors, gradual liberalization of trade and the steady rise of the international gold price. Mali has since been the world’s fourth biggest gold producer and having recently reached a production volume of about 50 tonnes per year (with decreasing trend), it has just overtaken Tanzania and become the third largest producer.

Looking at the economic impact of mining (of mainly gold) in regard to symptoms of the Dutch disease, mining can neither said to be blessing or curse as of the present. It has generated crucial revenues but very little spillovers. Strongly dependent on its commodity exports, the most important export goods are gold and cotton. Next to gold, which makes for 95% of all mineral exports, other minerals include phosphate, limestone, rock salt, Iron, manganese and bauxite. Most resources are geologically explored, but not extracted due to a weak infrastructure and insufficient energy supply. Nevertheless, starting in the 1990s, the gold sector has been one of the major sectors attracting FDI, which is why most of Mali’s FDIs are resource-based and not market seeking and thus initially result in higher exports and improved external accounts. The increased share gold in total exports, at 40% in 2002, 75% in 2008 and 80% in 2012 (contribution to GDP 14% in 2008 and 17% in 2012) has made Mali one of the most mining-dependent economies in the world. The long term prospect of gold is declining as some of the biggest mines are to be closed in the coming years. Currently there are 9 active gold mines. As of 2012, the number of people
estimated to be employed in the commercial mining industry was 13,000, while the number for people involved in artisanal mining varies between 200,000 and 400,000. According to Human Rights Watch 2011 estimates 20% of artisanal miners are children. The exact number of artisanal mining sites is unknown, but estimated by the government to be around 350.

Tanzania

Mining in Tanzania has a comparably long history since the first commercial gold mines date back to German colonial rule (1884 – 1918). During that period gold deposits were first discovered around Lake Victoria in the 1890s. Commercial mining commenced in 1909 with gold extraction at the Sekenke mine in the northern part of Singida region, the first and largest mine for decades. Along with South Africa, Mali, Ghana and Guinea, Tanzania is one of Africa’s key gold producers out of 34 African countries engaged in gold mining. From 2005 to 2009 around 9% of Africa’s total gold production came from Tanzania making it the continent’s 3rd biggest gold producer after South Africa and Ghana (as of 2014, it was outranked and placed on fourth rank by Mali). Accounting for more than a third of total exports, gold is Tanzania’s by far biggest export goods with UAE, China and India being the two biggest drivers of demand. The biggest operator, owning three of the country’s five most important gold mines, is Toronto-based African Barrick Gold (ABG). Showing a declining trend, gold currently still accounts for 95% of all mineral exports. Three major factors determine the performance of a gold mine: ore volume, g/t of Gold and the resulting absolute gold production. While local communities have decried numerous cases of spillages like the 2009 cyanide contamination of Tigithe River, media coverage has also focused on police involvement over cases of gold theft at mining sites. Other forms of criticism e.g. concern the general working conditions at mines and lack of health standards, which in some cases have been linked to outbreaks of Tuberculosis, Malaria and other diseases.
3. Methods and Data

Since the early days of satellite remote sensing, its accessibility, quality, and scope of have been continuously improving, making it a rich data source with a wide range of applications (United Nations, 2014). Although there are a few examples of remote sensing to be found in the social sciences, developments have, on the whole, been less pronounced (Hall 2010). With the advent of new medium resolution remote sensing datasets with global coverage this is about to change. Here, we apply a recent framework based in the work of Henderson (2012) and extended by this group (Keola et al., 2015).

In that study we performed estimations of economic activities on global, national, and subnational levels with a focus on developing economies using remote sensing data. Further, it extended the recent statistical framework using nighttime lights to account for agriculture and forestry which emitted less or no additional observable nighttime light. In the study we argued that nighttime lights alone may not explain value-added by agriculture and forestry. By adding land cover data, our extended framework could be used to estimate economic growth in virtually all administrative areas of any sizes.

With that said, the limitations of most global land cover data products are severe (McCallum et al, 2006). Land cover data is conceptually similar to maps and nominal to its character. Classes are derived through a classification process and overall accuracies are generally low. Furthermore, land cover classification is a tedious and expensive process and therefore the temporal resolution becomes very low. This is particularly true for large area mapping such as regional and global land cover data sets.

Here, we further elaborate on the framework by (Keola et al., 2015) by abandoning traditional land cover data in favor of MODIS NDVI which is a global continuous dataset suitable of studying vegetation dynamics at high spatial and temporal resolutions. Our study provides a spatial analysis of the relationship between NDVI and actual agricultural production on districts levels. We find a strong association between actual production of agricultural products and NDVI using spatial regression. An important difference between spatial and traditional (a-spatial) statistics for example OLS regression is that spatial statistics integrate space and spatial relationships directly into their mathematics. Spatial regression methods capture spatial dependency in regression analysis, avoiding statistical problems such as unstable parameters and unreliable significance tests, as well as providing information on spatial relationships among the variables involved. Depending on the specific technique, spatial dependency can enter the regression model as relationships between the independent variables and the dependent, between the dependent variables and a spatial lag of itself, or in the error terms. Geographically weighted regression (GWR) is a local version of spatial regression that generates parameters disaggregated by the spatial units of analysis. This allows assessment of the spatial heterogeneity in the estimated relationships between the independent and dependent variables.

For each districts, a regression coefficient can be estimated using a GWR model (Fotheringham et. al., 2002 and Lloyd for empirical examples ). GWR method allows for analyzing the spatial variability of the local coefficients of the independent variable and can explain spatial heterogeneity. OLS creates a regression coefficient which assumes that the relationship between the studied variables is constant across the landscape. GWR assumes that the relationship between NDVI and the total agricultural production may vary over space.

We also include the recent dataset on forest change by Hansen (2013). Below we present our four datasets and how they were processed. In addition, data has after processing been assembled into a geodatabase with the working title “African Economic Growth, light and vegetation database” (AEG, 2014).
Nighttime Lights

Nighttime lights data from the National Oceanic and Atmospheric Association’s National Geophysical Data Center (NOAA-NGDC) was used. Since the mid-1970s, NOAA-NGDC has operated the Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) and has digitally archived the imagery since 1992 (Baugh, et al., 2010). The sensors are flown on a sun-synchronous, low altitude, polar orbit and are designed to collect global cloud imagery (Baugh, et al., 2010; Elvidge, et al., 2009b; Elvidge, et al., 2004). The sensors have a resolution of 0.56 km; however, on-board averaging of this data into five by five blocks produces a “smoothed” dataset with a resolution of 2.7 km (Baught, et al. 2010; Elvidge, et al., 1999). Each sensor collects 14 orbits daily in 3000 km swaths which provide for complete global coverage four times during the day at dawn, daytime, dusk and nighttime (Elvidge, et al., 2009b; Elvidge, et al., 2004). At night, the visible band is intensified using a photomultiplier tube (PMT), which allows the sensors to detect clouds illuminated by moonlight (Baugh, et al., 2010; Elvidge, et al., 2009b; Elvidge, et al., 2004). The PMT boosts the detection of light and so allows the detection of lights such as human settlements, gas-flares, fires, fishing boats and the aurora (Baugh, et al., 2010; Elvidge, et al., 2009b; Elvidge, et al., 2004).

At a minimum, one satellite is operated each year. However, as the satellites and sensors age, the quality of data produced decreases and they must be replaced. In most years, there are therefore two satellites collecting data (Elvidge, et al. 2009b). The NOAA-NGDC produces three annual nighttime lights products from this data which are freely available to the public: cloud-free, average visible lights and stable lights composites. Additionally, a radiance calibrated and an average lights x pct dataset are produced from this data.4

For this analysis, the annual stable lights composite (version 4) was used (NOAA-NGDC, 2014a). It provides data on the average visible band digital number (DN) values for all cloud-free observations. The DN values range from 0 to 63 and correspond with the brightness of the observed lighting (NOAA-NGDC, 2014b). It is filtered to remove ephemeral lights and background noise (such as auroras, forest fires, lights from fishing vessels and reflections of moon or starlight) so that only persistent surface lights remain (Elvidge, et al., 2013). A series of algorithms are used to select the best data to include within the composite image and the data is reprojected into 30 arc-second grids, between the latitudes of 65° S and 75° N (Baugh, et al., 2010). Baugh, et al. (2010) provides an in depth explanation of the processing required to generate the stable lights composite. The stable lights dataset was selected because it provides a worldwide view of human development from space. It is versatile in that the sensors are able to detect faint light sources from rural areas as well as bright lights from urban areas and, since it contains DN numbers, differentiation between different types of light sources can be made (Elvidge, et al., 2013). Furthermore, it is consistently available on a yearly basis, which is not the case with many of the other nighttime lights products.

Pre-processing

Due to the coarse spatial resolution, high sensitivity and limited dynamic range of the sensors, the DN values saturate over urban areas, meaning that analysis in city centres becomes limited (Baugh, et al., 2010; Doll, 2010b; Elvidge, et al., 2009b). Furthermore, the datasets overestimate the actual size of lighting on the ground, a phenomenon referred to as blooming. Elvidge, et al. (2009b), found that this is due to the large OLS pixel size combined with its ability to detect sub-pixel light sources and to geolocation errors. They also indicated that scattering of light in the atmosphere, reflectance of light on adjacent water bodies and detection of terrain illuminated by scattered light from very bright urban areas

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4 See NOAA-NGDC, 2014b for a description of each of these datasets
could also generate overestimated areas, although they did not test these factors (Elvidge, et al., 2009b). Finally, the OLS has no on-board calibration for the visible band. Each sensor has different detection limits and saturation radiances and degrades at a different rate through time. Furthermore, gain adjustments on individual sensors are not recorded and can therefore not be used for calibration. Thus, DN values have different meanings in each composite and cross-year analysis is not assured (Elvidge, et al. 2013; Elvidge, et al. 2009). Elvidge, et al. (2013; 2009) developed a regression based intercalibration technique to calibrate composites against a base composite and allow for cross-year analysis. This technique was used in this study and will be subsequently explained. Pre-processing of the dataset was required in order to proceed with the analysis. As the OLS has no on-board calibration for the visible band and in-flight gain changes are not reported. Therefore, comparison across composites is not possible since the DN values from each composite have a different base point. The downloaded composites were therefore inter-calibrated for cross-year analysis and then further prepared for this study. The final database covers the whole of Africa.

The first step was to remove gas-flares. Gas flaring is used to dispose of dissolved natural gas from petroleum in production and processing facilities (Elvidge, et al., 2009b). Gas-flares are thus not representative of human settlement and it was deemed appropriate to exclude them from the analysis. While all gas-flares from European countries are located offshore and would therefore not impact the planned analysis directly, they were nonetheless removed so that they would not be present during the inter-calibration procedure. The removal of gas-flares was done using a set of ESRI shapefiles available from NOAA-NGDC which contain polygons outlining the location of gas flares for each country (NOAA-NGDC, 2014d). These locations were identified through analysis of DMSP-OLS nighttime lights imagery, details of which can be found in Elvidge, et al. (2009b).

The second step in the preparation of the nighttime lights dataset was inter-calibration that is, standardizing DN values across composites. The inter-calibration procedure developed by Elvidge, et al. (2009b) was aimed at overcoming the limited comparability of the DMSP-OLS data by calibrating each composite against one base composite. It is a regression based technique that works under the assumption that the lighting levels in a reference area have remained relatively constant over time and can therefore be used as the dependent variable.

First, F182010 was chosen as the base composite because it contained the highest DN values overall. In their study, Elvidge, et al. (2013; 2009b) selected F121999 as the base composite. The difference in the selection is attributed to the fact that Elvidge, et al. (2013; 2009b) were intercalibrating a world-wide dataset while the present study examines only the African case. Of the candidate regions tested, it was determined that Sicily provided the best fit to these criteria, consistent with the findings of Elvidge, et al., (2013; 2009b). Next, a second order regression model was developed for each composite. The calculation is of the following form:

\[ y = C_0 + C_1x + C_2x^2 \]

Table 1 shows the resulting calibration coefficients. These coefficients were applied to each composite so that a new value \(y\) was calculated based on the original value \(x\). Any values over 63 were truncated so that the range of the values remained between 0 and 63.
The result of the averaging was twenty-one composites each representing one year of nighttime lights between 1992 and 2012. Finally, data was re-projected into the Lambert Azimuthal Equal Area projection with a cell size of 1 km².

The nighttime lights data was aggregated as Sum of Light (SOL), a measure of the total intensity of lighting. It was calculated for all the mining buffers and for each unit of the highest administrative level possible in each country.

**MODIS NDVI**
Normalized difference vegetation index (NDVI) from MODerate Imaging Spectroradiometer (MODIS) vegetation indices product MOD13Q1 were used (ORNL DAAC, 2011). The NDVI data is provided as a global dataset with a 16 day temporal resolution and a spatial resolution of 250 m. NDVI is dimensionless spectral index that relates to the photosynthetic uptake by vegetation (Myneni and Williams, 1994; Sellers, 1985). It is calculated from the near infrared (NIR) and red wavelength bands by using the following relationship:

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}
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<td></td>
<td>2012</td>
<td>0.0122</td>
<td>1.1210</td>
<td>-0.0024</td>
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</tbody>
</table>
\[
\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}
\]

It has previously been shown that NDVI is related to, for example, the vegetation greenness, leaf area index (LAI), and primary productivity of the vegetation (Johnson, 2003; Paruelo et al., 1997). It has, furthermore, been shown that NDVI time series can be used to assess the changes in vegetation cover and responses over time (Hill and Donald, 2003) and that it can be used to estimate agricultural yields (Labus et al., 2010; Ren et al., 2008). This makes it possible, by using remotely sensed NDVI, in regions where field data are sparse, on a large scale, evaluate the vegetation status and the agricultural productivity.

**MODIS NDVI processing**

Since the MOD13Q1 product, for each time step, is acquired as a Hierarchical Data Format (hdf) file it was converted into a raster data format (.rst) that was needed further on in the processing. The 16-day converted NDVI data were, per pixel, filtered and the yearly amplitude were extracted by using TIMESAT. TIMESAT is a specialized software designed to extract information from remotely sensed vegetation time-series (Eklundh and Jönsson, 2012). This was done by, first creating a file list, text file, specifying the location and order of the raster files. Secondly, a TIMESAT settings file was created which pointed to the previous created file list, defined the output and the filtering method, in this case a Savitzky-Golay filter. By running TIMESAT with the created settings file an output file with the filtered data was created. Finally, the yearly amplitude was for each pixel extracted from the filtered data by taking out the difference between the yearly minimum and maximum value. In the case that the peak growing season occurred during Nov-Feb the calendar year was allowed to be flexible. This since a complete growing season must be selected to be able to extract an amplitude value.

Finally, a mask was constructed to exclude land covers that are not part of the agricultural economy. For this purpose, the MODIS Land Cover Type product (MCD12Q1) was used (Friedl et al., 2010). As such, it contains five classification schemes, which describe land cover properties derived from observations spanning a year’s input of Terra- and Aqua-MODIS data. The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP), which includes 11 natural vegetation classes, 3 developed and mosaicked land classes, and three non-vegetated land classes. Here, desired classes from the IGBP classification were Croplands (#12) and Cropland/Natural vegetation mosaic (#14). For classes #12 and #14 Sum of NDVI Amplitude was calculated in the same manner as above.

**Gross Forest Loss**

The recent global dataset of Hansen et al (2013) was used to quantify forest loss annually. They have mapped global tree cover extent, loss, and gain for the period from 2000 to 2012 at a spatial resolution of 30 m. The dataset is remarkable as it improves on existing knowledge of global forest extent and change by being spatially explicit, quantifying gross forest loss and gain, providing annual loss information and quantifying trends in forest loss. Forest loss was defined as a stand-replacement disturbance or the complete removal of tree cover canopy at the Landsat pixel scale.

Annual forest loss data was downloaded from http://www.earthenginepartners.appspot.com/science-2013-global-forest/download.html and a minimum of pre-processing was required. Tiles were merged into larger composites and reclassified into twelve layers, one for each year, thus separating each individual forest loss year. Instead, of SOL, sum of forest loss was calculated in the same way as above.
Agricultural Production

The data used to analyze the relationship between NDVI and agricultural production was obtained from the statistical offices in Ghana, Tanzania and Mali. The data was compiled on district levels and represent all agricultural products produced during one year. Ghana had data for year 2001 to 2012, Tanzania for year 2007 and 2008 and Mali 2002 to 2007.

Gross Domestic Product

Official GDP data were also obtained from the World Bank World Development Indicators open data database (The World Bank Group, 2014). Data were downloaded for each country on a yearly basis from 1992 to 2012. The official GDP data represents the value of the gross output produced in a country minus the value of intermediate goods and services consumed in production. All GDP data are expressed in constant 2005 US dollars (USD). Since the purchasing power of currency changes over time due to inflation, the use of the constant value allowed for time series comparison of the data.
4. Remote sensing and economic activities

Nightlight and economic activities

Satellite remote sensing missions are generally designed for specific applications, often earth sciences related, such as vegetation classification and weather forecasting. Very few, if any, sensors are designed for social science applications (Hall, 2010). The DMSP-OLS sensor, also known as “nighttime lights”, has attracted recent attention due to its capability to depict human settlement and development. It is sensitive enough to detect street lights and even saury fishing vessels at sea (Sei-Ichi, Fukaya, Saitoh, and Semedi, 2010). The light detected by the DMSP-OLS is largely the result of human activities, emitted from settlements, shipping fleets, gas flaring or fires from swidden agriculture. Therefore, nighttime light imagery serves as a unique view of the earth’s surface which highlights human activities. One of the central uses of the nighttime lights dataset is as a measure of and proxy for economic activity. The relationship between economic activity and light has been explored by several authors and all have concluded that there is indeed a positive relationship between the light emitted and the level of economic development within a region. This understanding has been used to estimate both GDP and economic growth.

An early identification of the strength of the relationship between nighttime lights and economic development was made by Elvidge, et al. (1997), who explored the relationship between lighted area and GDP, population and electrical power consumption in the countries of South America, the United States, Madagascar and several island nations of the Caribbean and the Indian Ocean. Using simple linear regression over a single year (1994/1995) they found that GDP exhibits a strong linear relationship with the lighted area ($R^2 = 0.97$).

Elvidge, et al.’s (1997) publication is unique in that it deals with the relationship between economic activity and lighted area. Most other publications related to economic activity examine its relationship with light intensity. Doll, Muller and Morley (2006) were one of the first to apply this relationship to estimating economic activity on a national and sub-national basis. They identified the unique linear relationships between gross regional product (GRP) and lighting for the European Union and the United States using 1996/1997 data and found that one linear relationship was not appropriate since some cities were outliers. With these outliers removed, they were able to generate simple linear regressions for each country, with $R^2$ values ranging from 0.85 to 0.98, and used these to generate a gridded map which estimated GRP at the five kilometer level.

Building on this research, Ghosh, et al. (2010) generated a global disaggregated map of economic activity with a spatial resolution of 30 arc seconds (approximately one square kilometer at the equator). They first performed a linear regression between gross state product (GSP), GDP and light intensity for 2006 for various administrative units in the states of China, India, Mexico and the United States to obtain an estimate of total economic activity for each administrative unit. These values were then spatially distributed within a global grid using the percent contribution of agriculture towards GDP, a population grid and the nighttime lights image. Ghosh, et al. (2010) improved on Doll, Muller and Morley (2006) through the use of the population grid and the percent contribution of agriculture as they were able to assign economic activity to agricultural areas which generate economic activity but which are not usually captured by the nighttime lights dataset since they are not often lit.

Chen and Nordhaus (2011) were one of the first to analyze the relationship between economic activity and light using a time series approach. They accomplished this by calculating the weights for light intensity that would reduce the mean squared error for the difference between the true GDP values and the estimated ones in all countries globally for 1992 to 2008. They found that light intensity has a high
potential to add value to GDP estimation in data-poor countries, both at the national and sub-national level. In data rich countries, light intensity data does not add as much value because its measurement error is generally higher than that of the available economic data.

One of the most recent applications of the nighttime lights dataset in relation to economic activity was by Henderson, Storeygard and Weil (2012). Rather than exploring the relationship of lights with GDP, they explored the relationship with economic growth. Like Chen and Nordhaus (2011), they performed an analysis over a time series for the period between 1992 and 2008. They developed a statistical model which estimated GDP growth using country specific economic data combined with light intensity values. Similar to Chen and Nordhaus (2011), they applied different weights for the lighting data and existing economic data based on the quality of the economic data. They found that for “bad” data countries there are often large differences (both positive and negative) between the recorded economic growth and the estimated growth. They also found that their model tended to underestimate economic growth in countries with low growth and overestimate it in countries with high growth.

All in all, the literature confirms that there is a strong relationship between nighttime lights and economic activity, both in terms of lighted area and intensity and in terms of GDP and GDP growth. Most studies have tended to be for single years, although two time-series studies were also discovered. Likewise, light intensity has been used more commonly than lighted area in analyses related to economic activity.

**NDVI and agricultural production**

Numerous methods exist for estimating productivity of the agricultural sector with remote sensing technology. Most approaches rely on measurements of reflected light in red and near-infrared (NIR) wavelengths where vegetation, including crops, is very reflective in the NIR and absorptive at red wavelengths. Combinations of these two wavelengths (i.e. vegetation indices) are good measures of plant vigor and are the mainstay of nearly all approaches to crop yield estimation (Lobell, 2013). Yields are then estimated through establishing the empirical relationship between ground-based yield measures and some vegetation indices, typically Normalized Difference Vegetation Index (NDVI).

Errors in remote-sensing crop-yield estimates vary mainly as a function of sensor properties (spatial-, temporal-, and spectral resolution) and landscape complexity. Classification of crop types is more problematic in regions characterized by multiple crops with similar phenologies, or in regions with intercropped fields (Lobell, 2013). Additional complexity is added with cassava, a major crop for which even farmers themselves have difficulties in estimating yields. This is basically because it is a root crop with staggered harvesting, but also widely differing above-ground architecture. Sometimes overlooked, is the problem of cloud cover in satellite based remote sensing, that could severely limit the number of available observations for a particular geographical region. Yield estimation in mixed cropping systems, characteristic of African smallholder agriculture, should nevertheless be possible, provided correct sensor platform properties.

Long-time scale analysis of NDVI can reveal important information on vegetation anomalies caused by variations in rainfall, temperature and sunlight (irradiance) as well as the trend for a certain location. Phenological metrics, such as start and end of growing season(s), length of season, time for mid of season, seasonal amplitude in NDVI, rate of increase and decrease at beginning and end of season can be related to management and crop yields for individual years as well as longer periods.

The sum of NDVI on district level is used in order to reflect the level of agricultural production. The spatial varying relationship between actual agricultural production measure as output harvested on district level and the sum of NDVI are tested through Geographical Weighted Regression (GWR).
Figure 1 illustrates the varying spatial relationship between our two estimates of agricultural production (NDVI and official statistics covering agricultural production for more estimation details see figure 3 and table 1 in Appendix). The pattern that arises is that there is a strong to medium strong relation between the variables in areas with high population densities. At this point it is difficult to access the quality of the production data in the agricultural production as large shares of production are not commercialized. We also assume that the NDVI-signal becomes more disturbed in areas of low population, less agricultural production and scattered fields.
5. Results
The result section is divided into 2 parts; Part 1 consists of a descriptive analysis of the mining buffers developed from 2 mines in each case country covering 2001 and 2012. Part 2 reports the results from the national and local growth model based on time series analysis covering the period of 2001 to 2012 at district level in the case countries. The districts have been divided into three categories; i) district with mining site, ii) district neighbouring a district with a mining site and iii) other districts.

Analysis of mining buffers
Buffers based on the distance has been created for the three remote sensing datasets to illustrate the changing patterns in terms of intensity in nightlight, forest loss and NDVI based on the distance from the mine location. For each country two mines are selected and included in the analysis.

![Graphs showing the relationship between nightlight intensity and distance from the target mines](image)

**Fig.2.** The relationship between nightlight intensity and distance from the target mines
Fig. 3. The relationship between forest loss and distance from the target mines.
Fig. 4. The relationship between NDVI intensity and distance from the target mines

Burkina Faso

Mana Mine

The Mana Mine with its satellite Siou and Fofina deposits is located approximately 200km west of Ouagadougou, the capital of Burkina Faso. The mine is operated by SEMAFO Inc, a Canadian-based mining company. It owns 90% shares in the mine while the government of Burkina Faso holds the
remaining 10%. The property covers 2,327km² of land over the prospective Houndé belt. Gold production increased by 4.5% from 5,589kg of gold in 2010 to 5,841kg of gold in 2012. The company anticipated to increase annual production capacity of gold to about 9,300kg per year by the end of 2014 through its plant expansion program commenced at the second quarter of 2012.

Nightlight intensity shows a large increase on a radius of 10 to 30 km from the mine thereafter a decrease in the intensity can be observed.

Forest loss for year 2001 is almost on zero levels close to the mine with increasing loss at 50 km distance from the mine. Observations for year 2012 provides a slightly higher forest loss for locations close to the mine and lower levels of forest loss for 40 km and further away.

NDVI intensity is stable both in time and space. However, there is a major difference with a lower intensity during 2012.

Essakane Gold Mine

The Essakane mine is located approximately 330km northeast of the country’s capital, Ouagadougou. It extends across the boundary of the Oudalan and Seno provinces in the Sahel region of Burkina Faso; situated within 42km east of the nearest large town and the provincial capital of Oudalan, Gorom-Gorom. The mine is located within a 100.02km² mining permit area surrounded by six exploration permits covering a total of 1,383km². From 4,230kg in 2010, production in the Essakane Mine significantly increased to 11,664kg in 2013 mostly due to a streamline of the mine’s processing plant, resulting in a 15% increase in the min’s processing rate. Though commercial production of gold began in 2010, the Essakane deposit had been an active artisanal mining site since 1985. The Office of Geology and Mining of Burkina (BUMIGEB) carried out regional mapping and geochemical programs and financed a program of heap leach test work from 1989 and 1991. From 1992 to 1999, heap leach processing of gravity rejects from artisanal mining activities were undertaken by the Compagnie d’Exploitation des Mines d’Or du Burkina (CEMOB). Upon completion of a feasibility study in September, 2007, GoldFields earned a 60% interest. Orezone Resources reclaimed ownership in October, 2007. In 2009, IAMGOLD Corporation, a Toronto-based international gold producer, acquired Orezone Resources and commenced management of the Essakane project. IAMGOLD has 90% share while the government of Burkina Faso holds 10%, non-dilutable, free-carried interest. The company targets a doubling of hard rock throughput with an expansion project that was expected to begin in 2014. The mine life has been extended to 2025 (IAMGOLD, 2012).

Nightlight intensity shows a large increase in a radius of 10km distance thereafter a sharp intensity decrease can be observed for year 2012 which relates to the opening of the mine in year 2010. For year 2001 almost no emission of light can be observed from the buffers surrounding the location. This is explained by the opening date of the mine being year 2010.

Forest loss for year 2001 and 2012 are on zero levels for both years and at all distances.

NDVI intensity for both years follows the same trend with increased intensity from an already high level from 10 km distance from the mine. The intensity is higher for 2012 than 2001.

Ghana

Ahafo/Subika Mine

The Ahafo Mine is located in the Brong Ahafo region of west-central Ghana, about 30km south of Sunyani and 290km northwest of the capital city of Accra. The mine is wholly owned and operated by Newmont Mining Corporation, a US based gold producing company. Production started from the mine in
2006 and in 2010, 15,450kg of gold were produced. Presently, Newmont Ghana operates four open pits at Ahafo with reserves contained in thirteen pits, over a strike length of 40km. In 2011, the company continued its expansion activities in the neighbouring Subika Mine which will extend the mine life at Ahafo South.

Nightlight intensity shows low levels of nightlight up to distances of 30 km with increase of the intensity up to 50 km from the mine. The trend is similar between the years with higher levels in year 2012.

Forest loss for year 2001 is on stable levels throughout the distance from the mine. Year 2012 follows the same trend but with a higher forest loss.

NDVI intensity is stable both in time and space with a slight decrease over the distance from the mine. However, there is a major difference in a higher intensity during 2012 compared to 2001.

Chirano Mine

Kinross Mining Company acquired 90% ownership of the Chirano mine in September, 2010 after acquiring Red Back Mining Inc. The remaining 10% interest is held by the government of Ghana. Chirano is located in the southwestern part of Ghana, approximately 100km southwest of Kumasi, Ghana’s second largest city. The mine comprises 11 deposits: Akwaaba, Suraw, Akoti South, Akoti North, Akoti Extended, Paboase, Tano, Obra South, Obra, Sariehu and Manna. Both open pit and underground mining methods are employed. The capacity of the mill is approximately 3.5million tones per annum. In 2013, 7,807kg of gold was produced from the mine.

Nightlight intensity shows an increase on a radius of 10km to 20 km distance from the mine thereafter a sharp decrease in the intensity both years follow the same trend.

Forest loss for year 2001 is on stable levels throughout the distance from the mine however with a small decrease when the distance from the mine increases. 2012 follows the same trend but with forest on a higher level.

NDVI intensity is stable both in time and space with a slight decrease over the distance from the mine. However, there is a major difference in a higher intensity during 2012.

Mali

Sadiola mine

Situated in Western Mali, the Sadiola mine lies just 77 km south of Kayes, the capital of Mali’s remote, westernmost administrative region of the same name. It is the only mine for which the government holds a stake of 18% instead of 20%, leaving 41% to Anglogold and Canadian Iamgold each. Mining at Sadiola takes place at five open-pits. The site includes a 4.9million tones per annum carbon-in-leach (CIL) gold plant where ore is eluted and smelted. New regulations introduced in the 1999 Mining Code had made the expansion of Sadiola mine possible as local population had to be resettled in the relatively densely populated Kayes region.

Nightlight intensity for year 2012 shows an increase on a radius of 10km to 20 km distance from the mine with a stable level over 30 to 40 km away from the mine. Interesting to note is that it thereafter show a sharp decrease in the intensity and that both years follows the same trend.

Forest loss for both years is almost on zero levels on close distance to the mine with increasing loss at 60 km distance from the mine. Observations for year 2012 provide a slightly higher forest loss for locations fare from the mine.
**NDVI intensity** for both years follows the same trend with increased intensity from 10 km distance from the mine. There is almost no vegetation close to the mine.

**Syama mine**

Syama mine is located 300 km southeast of Bamako and approximately 30km from the Côte d’Ivoire border in Sikasso region, the southernmost region of Mali. In 2009, the surrounding Fourou Commune (1,340 km²) was home to 41,543 people, a number that had doubled in the course of one decade.

**Nightlight intensity** shows a large increase on a radius of 10km distance thereafter a sharp decrease in the intensity can be observed for both years which corresponds to opening of the mine. No emission of light can be observed 40 km from the mine.

**Forest loss** for year 2001 is on stable levels throughout the distance from the mine. 2012 provides an increase in 10 km to 20 km from the mine. The loss decreases thereafter to the same levels as in year 2001.

**NDVI intensity** for both years follows the same trend with increased intensity from 10 km distance from the mine. There is almost no vegetation close to the mine.

**Tanzania**

**Buzwagi mine**

Located 97 km from Bulyanhulu and 6km south east of the town of Kahama in Shinyanga region, where subsistence is traditionally based around livestock and agriculture development, Buzwagi is the largest single open-pit and second largest mining operation in Tanzania. In 2011, some 2,099 workers (1,004 employee + 1,095 contractor) were employed, of which - according to ABG – 90% were Tanzanian. The mine life is supposed to end in 2022. In the three villages surrounding the mine, Mwendakulima, Chapulwa and Mwime, farming is the predominant economic activity.

**Nightlight intensity** shows a large increase on a radius of 10km distance thereafter a sharp decrease in the intensity can be observed for both years however on lower levels in 2001 compared to 2012. On a distance 40 km from the mine almost no emission of light can be observed from the buffers surrounding the location up until 100 km from the mine.

**Forest loss** for both years is almost on zero levels on close distance to the mine with increasing loss at 50 km distance from the mine.

**NDVI intensity** for both years follows the same trend with increased intensity from 10 km distance from the mine. There is limited vegetation close to the mine.

**North Mara mine**

North Mara mine is operated by ABG and as indicated by the name it is located in Mara region, more precisely in Tarime district 100 km east of Lake Victoria and 20 km south of the Kenyan border. The mine consists of four open-pits and, one process plant, waste rock dumps and other related facilities. As of 2012, 2,329 people were employed at the mine, of which the majority of 1,300 were contracted workers. It was opened in 2002 and is estimated to continue production until 2021. Desertification poses a major challenge to the surrounding area in the region, ABG claims to combat desertification through the donation of tree seedlings to different recipients in the local communities. Furthermore, the company has stated that the power line brought to the mining site had provided local businesses and private households with stable access to electricity.
The nightlight observations from year 2001 start on relative high levels around 10 km from the mine then decreases until 30 km and peaks to 40 km then decreases again up to 100 km from the mine. For 2012 the nightlight intensity are low close to the mine with increasing intensity up until 40 km thereafter decreases.

Forest loss for both years is almost on zero levels on close distance to the mine with increasing loss at 50 km distance from the mine. Whereas observations from year 2011 reach an increase in forest loss at 40 km and with sharp decrease in forest loss from 40 to 50 km. 2012 indicate a steady increase of forest loss from 20 and further away from the mine.

*NDVI intensity* for both years follows the same trend with increased intensity from 10 km distance from the mine. There is almost no vegetation close to the mine which confirms the descriptive information from the mine highlighting the problem of desertification around the mine.

**National growth model**

Our basic estimation strategy follows what Henderson et al. (2012) developed. Their framework can be shown as equation (1):

\[ \gamma_{jt} = \hat{\psi} x_{jt} + c_j + d_t + e_{jt} \]

where \( \gamma_{jt} \) is the true GDP of country j in time t. \( x_{jt} \) is the level of observed nighttime light at corresponding country and time. \( c_j, d_t, \) and \( e_{jt} \) stands for country effect, year effect, and error term. The assumption for this model is then that, no matter the type of economic activities on the ground, their aggregated growth results in the same percentage growth of nighttime light observed by satellite plus, country-invariant, time-invariant effects and an error term. The basic regression analysis assumption requires that the error term be a random variable with a mean of zero. However, we have shown through gridded data of land cover and nighttime light that it is possible for agriculture’s value-added to increase without emitting more observable nighttime light into space. If this is the case, then the error term is actually dependent on the agricultural share as the higher the agricultural share the higher the error terms. Randomness of the error term from independent variables is one of the important assumptions of regression analysis. It is therefore desirable to exclude activities that can grow without emitting more nighttime light.

This paper makes full use of the statistical framework in equation (1) and estimation strategy proposed by Henderson et al. (2012). However, we have revised the assumption that all economic growth is captured by growth in observed nighttime light. Our revised assumption is that nighttime light observed in space is the result of growth in only the non-agricultural sector. We therefore divided Henderson et al. (2012) into non-agricultural (eq. 2) and agricultural (eq. 3) parts with a combined model as illustrated in (eq. 4). Based on our discussion in previous sections, previously we introduced MODIS land cover product MCD12Q1 (Keola et al. 2014).

\[ \gamma_{jt}^{na} = \hat{\psi} x_{jt}^{na} + c_j^{na} + d_t^{na} + e_{jt}^{na} \]
(3) \[ \gamma_{jt}^a = (\psi_{a1} \psi_{a2} \ldots \psi_{an}) \begin{pmatrix} l_{jt}^a \\ l_{jt}^{a2} \\ \vdots \\ l_{jt}^{an} \end{pmatrix} + c_j^a + d_t^a + e_{jt}^a \]

In this paper our extended model is refined by changing the categorical variable land cover to estimate agricultural development with using MODIS NDVI and forest cover. A national growth model has for each country been developed using nightlight, NDVI, and forest loss. The models are based on a multiple linear regression between the three variables and national GDP, as can be seen in equation 4.

(4) \[ \text{GDP} \sim \text{Nightlight} + \text{Forestloss} + \text{NDVI} \]

The presented models are developed without allowing for an error (interception) term which is due to an initial analysis that showed that the downscaling, from national growth to district growth, was highly influenced by the error (interception) term hence reducing the model applicability at district scales. The resulting models are for each country presented and analyzed in the sections below.

![Fig. 5. Model results for growth patterns (2001-2012) in case countries.](image)

**Burkina Faso**

For Burkina Faso the resulting national model showed a similar trend as real GDP (figure 5a) but had some inconsistency between years indicating that the model does not manage to completely capture the
country level GDP. The model had a residual standard error of 8.33E+11 which is about 30% of the average national GDP. Furthermore, the model had significant coefficients for nightlight and forest loss which indicates that those two are the best predicting variables for Burkina Faso (table 2).

Ghana

For Ghana the resulting national model showed a good agreement with real GDP (figure 5b). It captured the constant state for the first years and increased from around year 2007. The model had a residual standard error of 1.39E+10 which is about 52% of the average national GDP. Furthermore, the model had significant coefficients for nightlight and NDVI which indicates that those two are the best predicting variables for Ghana (table 2).

Mali

For Mali the resulting national model showed a good agreement with real GDP (figure 5c) by showing approximately the same increase and values as real GDP. The model had a residual standard error of 1.29E+12 which is about 9% of the average national GDP. Furthermore, the model had significant coefficients for nightlight and NDVI which indicates that those two are the best predicting variables for Mali (table 2).

Tanzania

For Tanzania the resulting national model showed a good agreement with real GDP (figure 5d) up until year 2008 and after that showing some inconsistent results. The model had a residual standard error of 9.28E+12 which is about 42% of the average national GDP. Furthermore, the model had a weak significant coefficient for forest loss which indicates that it is the best predicting variable for Mali (table 2).

Table 2

<table>
<thead>
<tr>
<th></th>
<th>Burkina Faso</th>
<th>Ghana</th>
<th>Mali</th>
<th>Tanzania</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nightlight</td>
<td>2.75E+07</td>
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<td>2.46E+06</td>
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<td>4.83E+05</td>
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<td>NDVI</td>
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<td>1.29E+12</td>
<td>-3.68E+03</td>
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

We note that the growth model in some cases produce negative coefficients for NDVI (Table 2). This is caused by varying agricultural production systems and a complicated vegetation mosaic, typical for these regions. We note, for example, that agricultural intensification or expansion not necessarily generates electrification. We know that increase in production often relies on expansion which means clearing of non-agricultural areas, often in forest or semi-forested areas. Low values of NDVI are related to less vegetation, for example, bare soil after clearance, conversion of grasslands to urban fabric, etc. Most probably will the new crop not fully compensate for the loss of biomass by deforestation, unless manure and irrigation systems are utilized which is rare in small holder agricultural systems.
Table 3
Standard error of residuals between model and observed together with average of observed and modeled GDP.

<table>
<thead>
<tr>
<th></th>
<th>Burkina Faso</th>
<th>Ghana</th>
<th>Mali</th>
<th>Tanzania</th>
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<tbody>
<tr>
<td>Average GDP</td>
<td>2.83E+12</td>
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<td>1.44E+12</td>
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<td>Average model GDP</td>
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<tr>
<td>Residual standard error</td>
<td>8.33E+11</td>
<td>1.39E+10</td>
<td>1.36E+11</td>
<td>9.28E+12</td>
</tr>
</tbody>
</table>

Growth model on district levels
The results from the national growth models for each country are used to determine individual country models to estimate growth on district levels. The models are based on the regression results presented in Table 1. When developing the growth model for districts several methods were used in order to provide an accurate local dimension of the local economy. Population data, and average household expenditure on district levels were included as weights in the model estimating local growth patterns. However, population on district level was highly correlated with nightlight intensity on district levels and average household expenditure was highly correlated with GDP (for details on the correlation analysis see Appendix) and therefore removed from the estimations.

The analysis of the results from the district growth model are divided into three parts; i) a spatial analysis reported in thematic maps dividing the districts into positive, negative or no growth districts in order to highlight the geographical patterns of district growth in each country, ii) graphs illustrating the average growth based a on categorization of the districts analyzed in order to compare districts with a mine (category I), with districts neighboring a mine (category II) and with districts with no mines (category III), iii) graphs illustrating all districts average growth levels.
Fig. 6. Spatial analysis of average growth in districts (2001-2012) estimated by growth model.
Fig. 7. Average district growth separated in categories (2001-2012).

**Burkina Faso**

Burkina Faso shows spatially fragmented growth on district levels with large parts of the country indicating average growth as seen in Figure 6a. However, the northeastern part of the country high growth patterns can be identified possible through the large size of the districts in that area of the country. The southern parts of the country account for lower levels of growth. The effects of having a mine located in the district are evident in the case of Burkina Faso as seen in (Category I, Figure 7a). The country as a whole account for low levels of growth where the three districts with mines we are analyzing account for considerable higher growth. The possible causal link between mining location and growth can be problematic in this case as we only base our conclusions on three mines. Figure 8a highlights Bobo-Dioulasso the country’s second largest city with an expanding mining industry as the district with the highest levels of growth in the country. Interesting to note is that the district with lowest levels of growth is located on close distance to Bobo-Dioulasso namely Siderdougou.

**Ghana**

The patterns of growth in Ghana shows a spatial distribution to the southern parts of the country where high growth districts are located on the coastline. The northern parts of the country provide lower levels of growth as shown in Figure 6b. Ghana is the only studied country where districts with a mine is associated with negative growth patterns as indicated in Category I, Figure 7b. However, the country as a whole indicates stable positive growth. The areas with highest growth figures are found in Figure 8b which indicates the capital Accra and a district with a mine named Atwima. Overall growth patterns distributed on district levels show positive level with a few as indicated in Category I, Figure 7b.
Fig. 8. Average district growth in each country (2001-2012).

**Mali**

Mali shows a high growth both in the northern and southern part of the country, as seen in Figure 6c. In the southern part this is proposed to be due to a combination of the urban area of Bamako and the location of the mines. However, in the northern part the higher growth is mainly due to a spatial size dependency of the model which most likely generated a falsely estimated high growth. This since the area mostly consists of desert. However, it is also influenced by the urban areas in the southern part of the district close to river Niger. It can be seen that districts with a mine (Category I, Figure 7c) shows a higher growth than average and that districts neighboring to a mine (Category II) shows a lower than average growth. It can be seen, overall, that almost all the districts in Mali shows a positive trend in the economic growth.
(Figure 8c). The high growth in the northernmost district Timbuktu, shown in Figure 8c, is again proposed to be due to model errors and the urban areas in the southern part of the district.

**Tanzania**

Tanzania shows spatially fragmented growth between the districts, as can be observed in figure 6d. Most of the mines are, however, located in or close to districts with high growth. This finding is further supported with that Category I and II shows a slightly higher growth than the average (whole), as can be seen in Figure 7d (Category I + II). Interesting to note is that districts neighboring to a mine (Category II) shows on average a higher growth than districts with a mine (Category I). The district growth model was able to correctly identify the urban region Lushoto as a district with high growth (Figure 8d). However, Bukombe which is a mining district was identified as a district with negative growth (Figure 8d) which was an unexpected result. However this could be due to the location of the mine which is on the border to a high growth region (Figure 6d, westernmost mine).
6. Conclusions

The objective of this study was to use remote sensing data to estimate level and growth (or decline) of economic activities in reference to the mining industry in Burkina Faso, Ghana, Mali and Tanzania by comparing estimated levels and changes in agricultural and non-agricultural production in mining and non-mining localities. Our study identified 32 mines within the studied countries as prime study areas. The analysis was divided into 2 parts. Firstly, 8 mines (2 per country) were chosen and studied using spatial analysis using three types for remotely sensed data namely nightlight intensity, NDVI intensity and forest loss intensity based on the distance. Secondly, the paper estimated growth in economic activities on district levels in the studied countries to compare economic growth patterns in districts with a mine, districts neighboring a district with a mine and other districts that are not close to a mine. The remote sensing data sets used in the study covered a period from 2001-2012 providing not only high spatial resolution but also a time series perspective in order to account for change over time and a validation vegetation index from satellite images with agricultural production statistics from the ground.

The data used in the study has after processing been assembled into a geodatabase with the working title “African Economic Growth, light and vegetation database” (AEG, 2014).

Results from the first section provide detailed information about the relationship between distance to a mine and the intensification of vegetation, forest loss and nightlight. Among the studied 8 mines we can observe individual patterns where the mines located in Mali and Tanzania are located in areas with almost no vegetation with an increasing intensification with the increased distance from the mine. The trends are identical from 2001 and 2012. However, for Ghana and Burkina Faso our result indicates that the studied mines are located in areas with high intensity of vegetation. Particularly, Ahafo and Chirano provide interesting results in terms of increasing levels of vegetation from year 2001 to 2012. The levels of intensification are stable with the distance from the mine.

A clear pattern in terms of nightlight is that the intensification increases during the years associated with an establishment of a mine. This confirms knowledge from the ground saying that activities omitting nightlight are common during the establishment of a mine.

Results from the second part of the analysis focusing on modelling growth on districts levels in each of the studied countries using remote sensing data to account for non-agricultural activities (nightlight) and agricultural activities (NDVI and forest loss). The objective is this part is to compare districts with a mine and districts neighboring a district with a mine with districts without a mine. Our results show that districts with a mine account for higher growth than districts without a mine – this result holds for Burkina Faso, Mali and Tanzania. Ghana provides results in opposite direction giving lower growth for districts with mines.
References


Appendix

**Fig. 1.** Correlation between GDP and household expenditure per capita levels for Ghana year 1991/1992 and 2005/2006

**Fig. 2.** Correlation between nightlight intensity and population on districts levels for Ghana year 2010
Source: DMSP-OLS processed by authors and population data provided by the World Bank
Fig. 3. GWR – Local R-squared for relationship between Dependent variable Total agricultural production by district and Independent variable NDVI Intensity sum by district
Source: NDVI processed by authors and agricultural production data provided by the World Bank
Table 1. GWR – Local R-squared for relationship between Dependent variable Total agricultural production by district and Independent variable NDVI Intensity sum by district
Source: NDVI processed by authors and agricultural production data provided by the World Bank