Monitoring Economic Development and Effect of Mining: Using Nighttime Lights and Gross Forest Loss Data in Peru

Manav Patel 1 and Alexander Merino 2

1 Saint Peter's University (USA); mpatel4@saintpeters.edu
2 Saint Peter's University (USA); amerino@saintpeters.edu

Abstract

Mining industry is one of the most seasoned businesses which involves extraction of minerals important to deliver many of the items in regular day to day existence. No one can deny the fact that this extraction process has an adverse effect on environment and the local communities. We are trying to identify the correlation and impact of change in Nighttime light intensity and forest loss around large mining area to the overall GDP of the country. Here we apply a novel analytical approach based on satellite data for the period 2000-2012 to estimate the economic impact of the mining companies in Peru. Through the modelling using the Nighttime lights and gross forest loss, we find a positive correlation with the regional economic growth in Peru on a regional level. The nighttime lights have a decreasing trend with distance from the mines. The loss in forest cover trend along the mines provide interesting and different trends around the large mining sites.

Keywords: Nighttime lights, Mining, Peru

1. Introduction

Since Colonization, mining activity have been an important factor from the exploitation of the towns and nature in all Latin America [1]. This was a necessary condition as a basis for the strengthening of a capitalism that has been started [2]. In this phase, Latin America becomes a fundamental metallurgical provider for the economy world, especially gold and silver minerals [2]. During the last century, this activity have been amplified, making available a wide range of minerals, a process that was more beyond the simple extraction of precious metals [2]. That is the reason why mining sector has become a key engine of economic development [3]. Mining Industry contributes to increased tax revenues, greater export incomes, bigger employment opportunities, and better infrastructure development to the host countries (where mining is taking place) [3]. Taking the examples of Peru and Mexico, the first one has become a mining powerhouse, with the mining sector experiencing the fastest growth in modern history and now accounts for over 50% of foreign currency, 20% of tax revenue and 11% of the gross domestic product – a huge economic contributor to say the least, and Mexico's mining sector is Latin America's second largest economy, after Brazil, and has a large number of foreign mining and mining service companies (principally from the US and Canada) are already active and thriving in Mexico's mining and resource sectors [4].

Nonetheless, while the extraction of mineral resources provides developing countries with considerable opportunities for economic development, there is the risk that mining operations can turn into socio-economic enclaves or cause environmental damage [3]. It exists a lot of sources which examines the impact over Latin America societies and economies. However, currently people have realized these data is not enough to know the impact of this activity over this region so recently studies have focused on the ecologic impact [1].

Deforestation currently accounts for approximately 6–17% of global carbon emissions [1,2] and, while forest cover has increased globally in the past 35 years, forest loss is ongoing in the tropics [3,4]. Mining has often been associated with deforestation, land degradation, air pollution, and disruption of the ecosystem (Hilson and Yakovleva 2007). The forest loss becomes a prominent factor in the economic growth prediction as the Peruvian Amazon basin has a large forest cover which is endangered due to the growing mining concessions in Peru.

The previous studies with Nighttime Lights have its relevance with human activities and have shown striking relationships between them. For Example, Imhoff et al. [11] and Small et al. [12] showed distribution and expansion of urban areas in United States and some major cities around the world, Elvidge et al. [8] showed a relationship between spatial distribution of light intensity with economic activity or electricity consumption. Likewise, Dobson et al. [10] showed a relationship with population distribution, Bruederle et al. [5] showed with human development and Ghosh et al. [9] showed with GDP [6 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 [8, 13, 14, 15, 16].

The aim of this research is to obtain a better understanding of the socioeconomic impact of mining extraction on Peru. To achieve this, we will use remote sensing data to estimate the growth (or decline) of economic activities in reference to the mining industry in Peru by comparing estimated levels of nighttime light and forest loss in mining localities. A selection of radius around the mining areas has been developed in order to estimate the level and composition of production as a function of distance from the mining areas [5]. We also have built a predictive model of economic activities in the regional level in Peru using the nighttime lights intensity and total forest loss in the region.

The rest of the paper proceeds as follows. The next section 2 provides a background on the mining industry in Peru. Section 3 reviews the literature on remote sensing and economic activities. Section 4 provides a summary of the methods and data used in the study. Section 5 includes the results from the analysis of the mining sites and the economic growth model. Section 6 concludes the paper.

2. Background on Mining in Peru

Mining is the dominant sector of the Peruvian economy as it accounts for 12% of total GDP. In 2016 mining exports totalled $23.8bn – consisting of 65% of the country's total merchandise exports [28]. Peru is one of the world's biggest producers of base and precious metals. Peru is the world's third largest producer of copper, silver, zinc and tin, and the seventh largest producer of gold. Peru has 13% of the world's copper reserves, 4% of its gold, 22% of its silver, 7.6% of zinc, 9% of lead and 6% of tin reserves, according to the most recent data of the Peru's Ministry of Energy and Mines [29]. While Peru's economy is diversified compared to other countries in the region, mining is the country's economic engine driver and a disproportionate amount of public funds derive from taxes on the mining sector [30].

Fig.1. Mining Concessions in Peru *Source: Global Forest Watch*

In the website Mining Statistics from Peru Reports [30], there are detailed information about the mining industry in Peru. First of all, it is indicated that Peru's largest copper producers are the Antamina, Toquepala, Cerro Verde, Cuajone and Tintaya mines. The Antamina mine in Ancash is operated by Peruvian company Antamina, a joint venture owned by BHP Billiton, Glencore, Teck and Mitsubishi Corporation. Southern Copper operates Toquepala and Cuajone in Tacna and Moquegua. Freeport operates Cerro Verde in Arequipa. The Tintaya mine in Cusco is owned and operated by Glencore. Second of all, Peru's largest gold producers are Newmont Mining's Yanacocha mine in Cajamarca and Barrick's Lagunas Norte mine in La Libertad. A significant amount of gold is also produced illegally by small-scale operators at the Rio Huaypetue mine in Madre de Dios state. Another point is that Peru's largest zinc producers are the Antamina copper and zinc mine in Ancash, Milpo's Cerro Lindo mine in Ica and Volcan's Chungar mine in Pasco. Related to Peru's silver industry, the largest silver producers are the Antamina mine in Ancash, Buenaventura's Uchucchacua mine in Pasco and Ares's Pallancata mine in Ayacucho. Finally, All of Peru's iron is produced by Shougang's Marcona mine in Ica.

3. Remote Sensing 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 sensors are designed for social science applications [20].

An early identification of the strength of the relationship between nighttime lights and economic development was made by Elvidge, et al. [8], 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 (R2 = 0.97) [19].

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 R2 values ranging from 0.85 to 0.98, and used these to generate a gridded map which estimated GRP at the five kilometer level [19].

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 [19].

Chen and Nordhaus (2011) were one of the first to analyse 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 [19].

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 [19].

One of the most recent applications of nighttime lights dataset in relation to economic activity was by Keola, Andersson and Hall (2015). Their research follows the framework to estimate the economic growth in non-agricultural countries developed by Henderson, Storeygard and Weil (2012). But for the countries where agriculture contributes a large share in its GDP, they didn't find the correlation of nighttime lights with economic growth, hence they modified the Henderson et al. (2012)'s estimation framework to fit in the MODIS land cover data since the data has many different classifications than the nighttime light data. The inclusion of the MODIS land cover data significantly improves their model's estimates for agriculturally dominated regions on the global scale.

Overall, the literature confirms the strong relationship between nighttime lights and economic activity, both in terms of lighted area and intensity and in terms of GDP and GDP growth [19]. There were few time series studies but most of them were for single year. Also, another fact which is highlighted is that the light intensity is used more commonly than lighted area in analysis related to economic activity.

4. 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 than in the natural sciences (Hall 2010). With the improvement in the resolution of sensors and introduction of new quality assessment model to filter input data with global coverage this is about to change. Here, we have applied the framework based on the work of Anderson et al. (2014).

Anderson et al. (2014) used the remote sensing nighttime light data, the MODIS NDVI vegetation cover data and the forest loss data to predict the economic activities in the terms of GDP growth in African countries as they to argued the fact that the nighttime light alone may not explain value- added by agriculture and forestry. They extended the recent statistical framework of Keola et al. (2014) which used the nighttime lights to augment official income growth to account for agriculture and forestry which emitted less or no additional observable nighttime light.

In this study we have performed estimations of economic activities at regional level of Peru using the remote sensing data of nighttime lights and the forest loss data. As discussed earlier the effectiveness of nighttime light data in predicting the economic parameters is well known. We have added the factor of forest loss as a prominent factor in our analysis to take into account the vast forest cover of Peru's Amazon basin which is affected by the extraction companies. Also, we have analysed the time series trends, of change in nighttime lights and the forest cover loss around six different prominent mines in Peru from 2001-2012.

4.1 Night time Light 1992-2012

We have used the Nighttime lights data which was recorded by the Defense Meteorological Satellite Program (DMSP) in the National Geophysical Data Centre (NGDC), now part of NOAA National Centre for Environmental Information (NCEI). The data was collected using polar orbiting satellites that provide full cover of the globe twice a day [31]. The sensors are flown on a sun-synchronous, low altitude, polar orbit and are designed to collect global cloud imagery (Baugh, et el., 2010; Elvidge, et al., 2009b; Elvidge, et al., 2004). The satellites allows them to detect low levels of visible-near infrared radiance at night with a maximum resolution of 250m. With this data, it is possible to detect clouds illuminated by moonlight, lights from cities and towns, industrial sites, gas flares, fires, lightning, and aurora. Since the mid-1970s, NOAA-NGDC has operated the Defence Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and has digitally archived the imagery since 1992 [18]. 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 [17].

Key benefits of these data are the global coverage and the high spatial resolution with pixels corresponding to less than one square kilometre, which allows researchers to aggregate these data at the level of the subnational units they want to study [5]. In addition, nighttime lights are measured with consistent quality across countries with very different institutional capacities, and are not susceptible to politically motivated manipulation [5].

Preprocessing

Due to the high sensitivity, coarse spatial resolution and the limited dynamic range of the sensors, the DN value tend to saturate over urban areas, meaning the nightlight analysis in city centres becomes limited (Baugh, et al., 2010; Doll, 2010b; Elvidge, et al., 2009b). Also, Elvidge, et al. (2009b) found that due to the large OLS pixel size, the ability to detect sub-pixel light sources and the geolocation errors, the datasets overestimate the size of lighting on the ground, a phenomenon called blooming. The overestimation of the illuminated area can also be contributed due to the scattering of the lights in the atmosphere, reflection of light on adjacent water bodies and illumination of terrain by scattered lights from bright areas. But these factors were not tested (Elvidge, et al., 2009b).

The OLS does not have on-board calibration for the visible band and even the gain or loss adjustment on individual sensors are not recorded. Each sensor has a different detection limits and saturation radiances, and it degrades through time. Hence, the DN values have different meanings in each composite and cross-year analysis is not assured (Elvidge, et al. 2013; Elvidge, et al. 2009).

A regression based inter-calibration technique was developed by Elvidge, (2013; 2009) to calibrate composites against a base composite to allow for cross-year analysis and has been widely used for studies related to the nighttime lights. We have used this technique in this study and is explained subsequently. The step wise procedure was followed to inter-calibrate the composites since the DN values of each composite has a different base point which would aid the comparison across the composites for cross-year analysis.

The first step in the preprocessing of the nighttime lights was to standardize the DN values across the composites. The procedure developed by Elvidge et al. (2009b) was aimed at calibrating each composite against a single base composite to ease the comparison between the composites. Since the composite of F18 2010 had the highest DN value, it was considered as the base composite. Also, the regression based technique assumed that the lighting intensity in a reference area has remained constant over time and can be used as the base comparison variable. . Consistent to the Elvidge, et al. (2013; 2009b) findings, the best fit to this criterion was determined to be the Sicily island.

Next, a second order regression model was developed for each composite as per the following form:

$$y = C_o + C_1 x + C_2 x^2$$

The result of the averaging was twelve composites each representing one year of the nighttime lights from 2001-2012. Subsequently, the data 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 6 mining buffers and 6 different regions of Peru.

4.2 Gross Forest Loss 2001-2018

The global dataset of Hansen et al. (2013) was used to quantify the forest loss annually. They have mapped the global tree cover extent, loss and gain for the period of 2000 to 2012 at a spatial resolution of 30m. 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 [19].

The reprocessing of data from 2011 onward in measuring loss, the use of Landsat 8 OLI data 2013 onward, the improvement in sensor quality assessment models to filter input data, Improved input spectral features for building and applying the loss model has led to improvement in data reliability.

Table 1. Inter-calibration coefficients for Nighttime lights' values

Satellite	Year	C_o	C_1	C_2
F14	2001	-0.035823459	1.80298828	-0.01370292
	2002	0.26780541	1.69157043	-0.01220747
	2003	-0.016413677	1.78171581	-0.01355786
F15	2001	-0.169807852	1.46330085	-0.00786256
	2002	-0.000173481	1.37342664	-0.00656884
	2003	-0.018291729	1.99846559	-0.01706209
	2004	0.305140215	1.82930082	-0.01425843
	2005	0.054702248	1.77121584	-0.01315809
	2006	0.03963351	1.81313736	-0.01364221
	2007	0.267130555	1.88377815	-0.0148706
F16	2004	0.088767156	1.63095278	-0.01096433
	2005	-0.169918013	1.87248647	-0.01469909
	2006	-0.022101411	1.57387248	-0.00922659
	2007	0.01841716	1.36325477	-0.00632434
	2008	0.052750165	1.43602692	-0.00764044
	2009	0.395733504	1.53013213	-0.00907657
F18	2010	0	1	0
	2011	0.291109528	1.24414498	-0.00511597
	2012	0.090884531	1.12353436	-0.00264093

Annual forest loss data was downloaded from the Department of Geographical Sciences of University of Maryland [21]. A minor pre-processing was required to use the dataset. The tiles were merged into larger composites and reclassified into twelve layers, one for each year, thus separating each individual forest loss year [19]. Instead of the Sum of Lights, the intensity of forest loss was used in this study.

4.3 GDP

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. The official GDP data was obtained from the World Bank World Development Indicators open data database (The World Bank Group, 2014). The data was downloaded from Peru on a yearly basis from 1992-2012.

Since the purchasing power parity of currency is dynamic and changes over time due to several factors like inflation, market etc., the GDP data is expressed in constant 2005 US dollars (USD) to allow for a time series comparison of the available data.

5. Results

The results are divided in two sections. The first section analyses descriptively the datasets of nighttime lights and gross forest loss with mining buffers of companies that began with the mining activity in these regions after 2001 and keep operating after 2012. The second section shows the results of national growth and regional growth based in a linear model.

5.1 Analysis of mines

Buffers were constructed using the datasets we identified previously. The changing patterns illustrated in the following charts are determined by the night time lights and forest loss occurred in different regions of Peru and certain range of time.

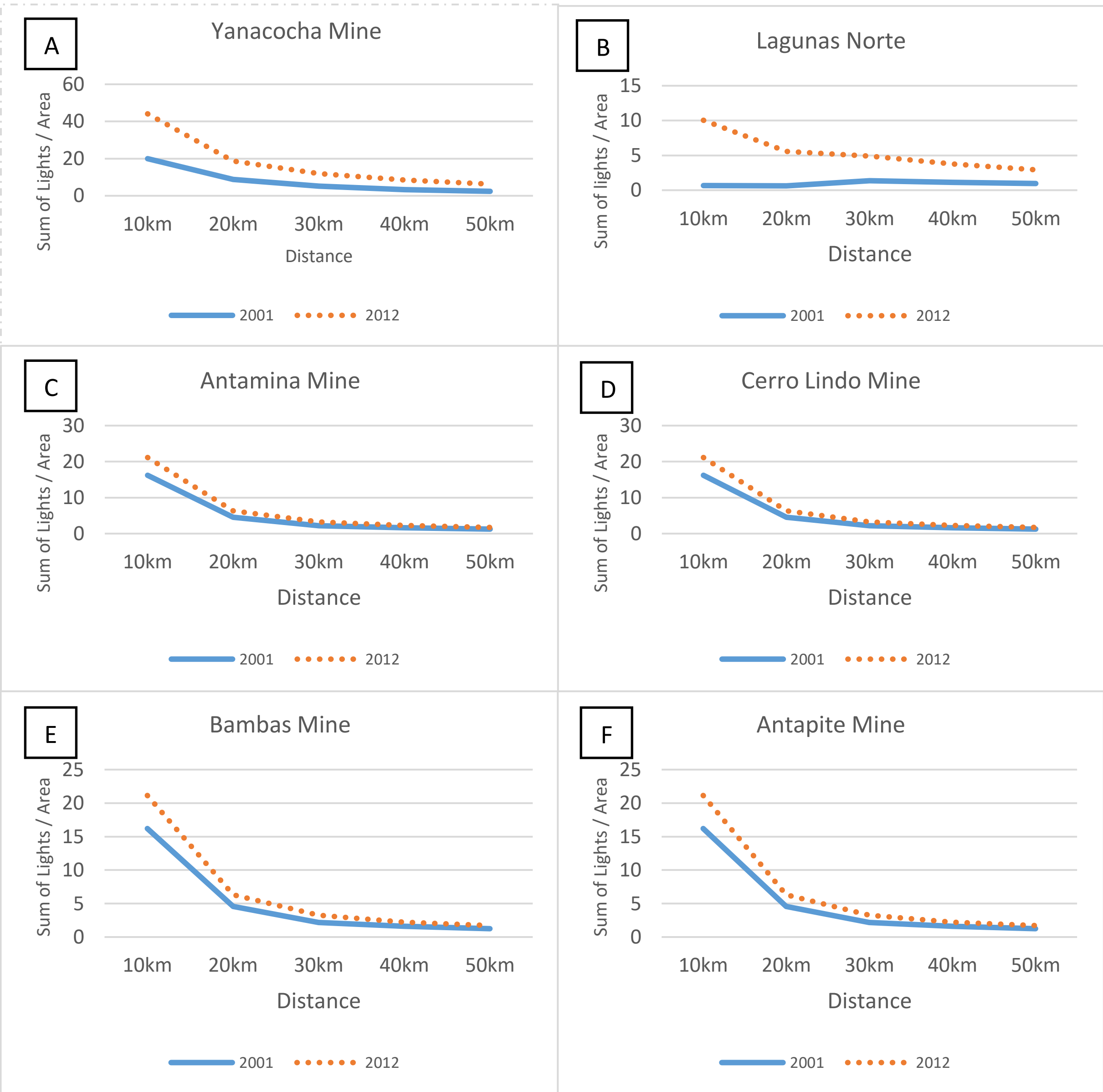

Fig.2. Charts showing the relationship between the sum of lights and certain areas around the mines.

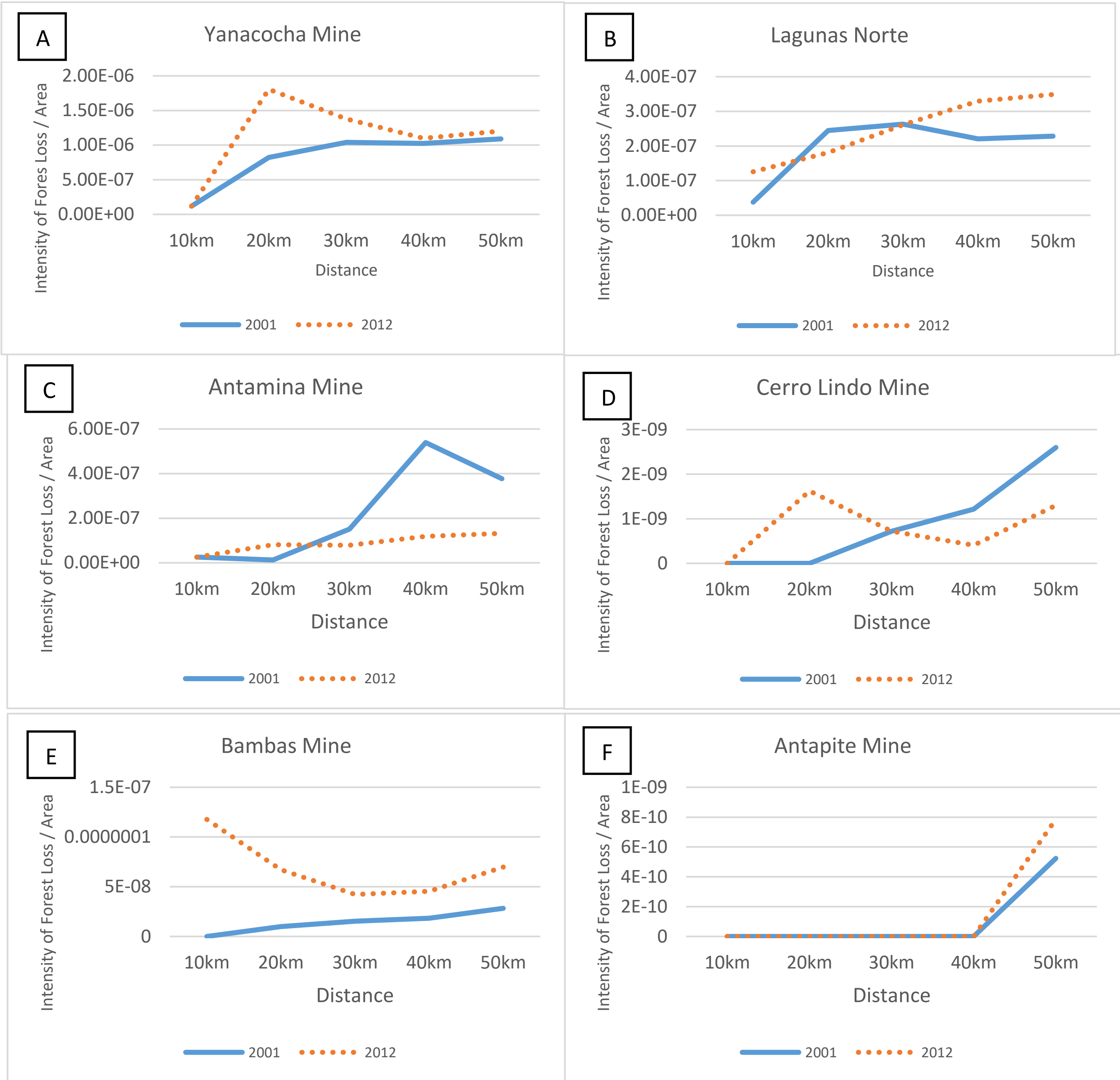

Fig. 3. Charts showing the relationship between the intensity of the forest loss and certain areas around the mines.

Yanacocha Mine

Yanacocha Mine is South America's largest gold mine. It is located in the province and department of Cajamarca, 800 kilometers northeast of Lima, capital of Peru [22]. The mining operations are situated in 4100 meters above sea level. The mine is operated by Newmont (51.35%), Minas Buenaventura (43.65%) and the International Finance Corporation (5%) [22].

Nighttime light intensity in 2001 shows a decreasing trend when the distance is increasing. This trend is the same in 2012. Also, the nighttime lights values finding in these areas have increased in the period 2001-2012.

Forest Loss in 2001 have small values in distances close to the mine but with an increasing forest loss at 20 kilometers of radius. This pattern is the same in 2012, when in 20 and 30 kilometers shows an increasing of forest loss level around the mine.

Lagunas Norte Mine

Lagunas Norte is one of the largest gold mines in Peru and in the world. It is located on the Alto Chicama, 140 kilometers east of the coastal city of Trujillo, in the department of La Libertad [23]. A conventional open-pit, crush, valley-fill heap leach operation, the property lies on the western flank of the Peruvian Andes at an elevation of 4,000 to 4,260 meters above sea level [23].

Nighttime light intensity in 2001 are in the lowest level. In 2012 this pattern changes and collects a great amount of nighttime lights around the mine.

Forest Loss in a radius from 20 to 50 kilometres, the amount of forest loss seems constant. However, in the year 2012, the trend is going up when the distance is increasing.

Antamina Mine

Antamina mine is one of the largest copper/zinc mines in the world. It is located in the Andes mountain range, 200 kilometres of Huaraz, in the department of Ancash. The deposit is located at an average elevation of 4,200 metres [24]. The mine is an open pit, truck/shovel operation. A 302 kilometre slurry concentrate pipeline transports copper and zinc concentrates to the port for shipment to smelters and refineries world-wide [24].

Nighttime light intensity in 2001 shows a decreasing trend when the distance is increasing. The trend has the same pattern in 2012. Besides that, the sum of lights values finding in these areas are increasing in all years.

Forest Loss values around the mine are minimum in the first year, but when the distance increases, the forest loss also increases, having the peak in 40km. However, the forest loss in 2012 follows a constant trend in all the years.

Cerro Lindo Mine

Cerro Lindo Mine is a poly- metallic mine (zinc, lead and copper with some silver) located in Chincha province, in the department of Ica [25]. Cerro Lindo is expected to yield 146,000 tons of zinc concentrates, 39,500 tons of copper concentrates and 14,800 tons of lead concentrates per year [25]. It was purchased by Votoratim, and is currently owned by the Brazilian company Nexa Resources [25].

Nighttime light intensity have the same decreasing trend when the distances increase. However, 2012 values are higher than the ones in 2001.

Forest Loss values around the mine are close to zero, but when the distance increases, the pattern is going up. The peak in 2012 is showed in 20km but then, the forest loss is decreasing.

Bambas Mine

Las Bambas is one of the largest coppers mine located in Apurímac, Peru. It is an open-pit mine located at altitude of about 4000 meters above sea level [26]. Las Bambas is a joint venture project between the operator MMG (62.5%), Guoxin International Investment (22.5%) and CITIC Metal (15%) [26].

Nighttime light values in 2001 are decreasing when the distances are moving away from the mine. The same pattern occurs in 2012.

The forest loss values are minimum in 2001. However, values in 2012 change having the maximum peak around the mine (10 km) and seems to decrease drastically in the next distances.

Antapite Mine

The Antapite mine is a gold/silver mine located in the city of Antapite, department of Huancavelica, 434 km southeast from city of Lima at an altitude of approximately 3,350 metres above sea level [27]. It consists of an underground mine [27].

Nighttime light values in 2001 have a decreasing trend all over the distances. The same trend occurs in 2012.

There is no forest loss in the first year (2001) around the mine. In 2012 occurs the same pattern. However, after 40 km seems to increase the amount of forest loss.

5.2 National Growth Model

We are using the framework that used Andersson, Olen and Hall (2014). We are assuming that economic growth will develop by using nighttime lights and gross forest loss. Therefore, instead of using the same national growth model, we decide not to include NDVI. Hence, we construct our linear regression model with two variable Nightlights and Forest Loss, as can be seen in equation 1.

1) **GDP ~ Nightlight + ForestLoss**

Because this model was used and already proved that worked in African countries (Andersson, 2014), we decide to use it in Peru and downscaling from national growth to regional growth. Below, the results are shown for the regional level in different cities of Peru where is located different mines.

Regional Growth Model

The analysis of the results of the model applied to the regions are shown in the Figure 3. These results are the GDP of these regions impacted in different periods of time. The explanation to each region will be showed below.

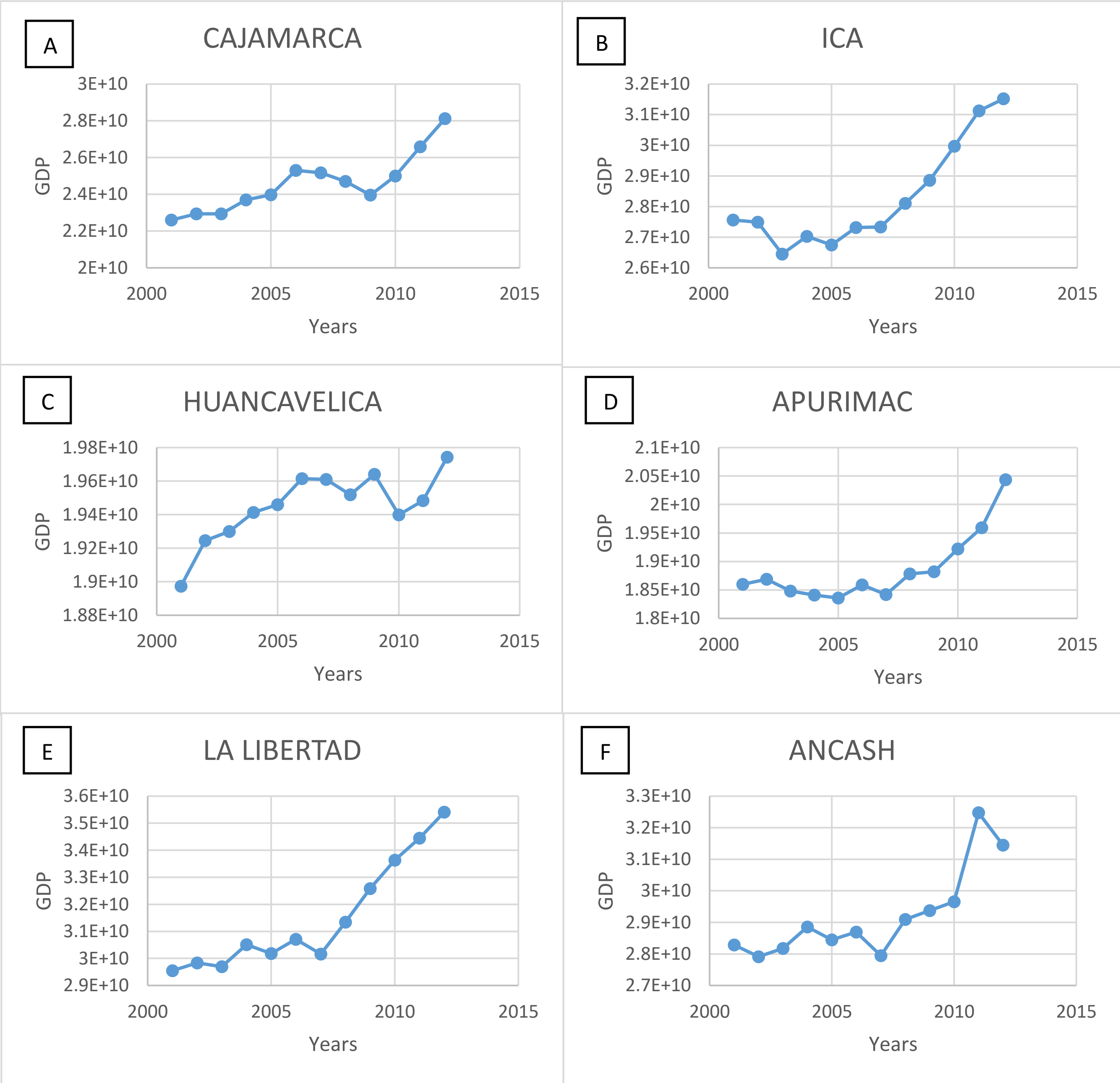

Fig. 3. Model results in Peru (2000 to 2012) applied to regional level

CAJAMARCA

In figure 3.A, the region of Cajamarca shows an increasing pattern over the years. However, the values from 2016 to 2018 achieved low levels as expected, but after this drop, the values continue having the right pattern.

ICA

In figure 3.B, the region of Ica shows the lowest level in the first years. However, after 2007, the trend is going up having the highest values in the last years.

HUANCAVELICA

In figure 3.C, the region of Huancavelica shows an increasing pattern over the first years. However, in 2017 begins a random pattern, increasing and decreasing until 2011 where it seems follow an increasing trend.

APURIMAC

In figure 3.D, the region of Apurimac shows an increasing pattern over the years. In 2007 shows a light drop but recovers in the next years, having an increasing trend in the last years.

LA LIBERTAD

In figure 3.E, the region of La Libertad shows an increasing pattern over the years. In 2005 and 2007 are shown low values. However, in the next years, the trend seems to go up.

ANCASH

In figure 3.F, the region of Ancash shows an increasing pattern over the years. There are drops in 2005 and 2007 but seems to recover in the next years.

6. Conclusion & Discussion

The objective of this study was to use the remote sensing data to estimate level and growth (or decline) of the economic activities on the regional level in Peru by comparing the estimated levels and changes in nighttime light intensity and forest loss on a regional level. Our study also focused on spatial trend analysis of the level and changes in the nighttime light intensity and gross forest loss around six mining areas (one per region) based on distance in Peru. Furthermore, the paper estimated growth in economic activities on regional levels in Peru to compare economic growth patterns in the mining regions. 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.

Results from the first section provide detailed information about the relationship between distance to a mine and the forest loss and nightlight. Among the studied six mines we can observe individual patterns where the Yanacocha, Antapita and Lagunas Norte mines show almost similar forest loss trends in 2001 and 2012 with increasing distance from the mines. However, the Antamina and Cerro Lindo mine gives us an interesting trend where the forest loss has decreased in 2012 as compared to 2001. The 10km radius from the Lagunas and Bambas mines has high forest loss in 2012 as compared to 2001.

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 includes focusing on the growth modelling on regional levels in Peru using the remote sensing data of nighttime lights and forest loss. The result shows us a positive trend with the growing GDP of Peru.

The existing model could be done better by adding the factor of vegetation cover data in the region. It would also provide great insights into the spatial trends of vegetation cover change in areas surrounding the mines and also give us a perspective on the whole regional agricultural economic situation and changes with increasing mining activities. Also, the regional contribution to GDP over time would be a great factor in comparing the actual change and trends in the regional economy rather than comparing it with the national GDP.

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