*Article*

# Estimation and mapping of sub-national GDP in Uganda using NPP-VIIRS imagery

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**Abstract:** Uganda is one of the poorest nations in the world. To address the developmental challenges and understand social and economic status, it is important to obtain accurate data in a timely manner. Many studies have demonstrated that nighttime lights (NTL) can be used to measure human activities. Nevertheless, methods developed from these studies (1) suffer from coarse resolutions, (2) fail to capture the nonlinearity and multi-scale variability of geospatial data, and (3) perform poorly for agriculture-dependent regions. This study proposes a new enhanced light intensity model (ELIM) to estimate the Gross Domestic Product (GDP) at sub-national scales for Uganda. This model is developed by combining the NTL data from the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS), the population data from the Global Human Settlement Layer (GHSL), and information on agricultural production and market prices across several commodity types. This resulted in a gridded dataset for GDP and GDP per capita for Uganda at 1 km spatial resolution and district level to capture the spatial heterogeneity in economic activity.

**Keywords:** GDP; Nighttime lights; agriculture; development

## 1. Introduction

It is important to obtain accurate socioeconomic in a timely manner to evaluate the current development status in Africa and address developmental challenges. For example, measures like the Gross Domestic Product (GDP) can help us assess the dynamics of urban development. GDP, one of the most widely used metric of national economic progress, measures the total amount of goods and services produced in a country. Nevertheless, only aggregate data measuring national GDP and GDP per capita exist for many African countries like Uganda. There is a clear interest in understanding how GDP and GDP per capita are distributed throughout Uganda at multiple scales to target poverty interventions and bring

greater prosperity to more people. For instance, there is a very strong correlation between GDP per capita and the Human Development Index (HDI), particularly for low-income countries [1].

There are many challenges to measuring GDP accurately. For example, accurate information about the size and distribution of the human population is not available for many regions around the world, and sometimes these data have poor quality [2]. National censuses are not able to capture the human mobility or activity as they are conducted residentially. Additionally, national censuses often release their results with limited resolution below the national level, as is the case with Uganda [3]. Cross-country measurements of GDP lack standardized accounting methods and have inconsistent data collection methodologies [4]. Satellite-based nighttime light (NTL) data can provide us a unique method to visualize and analyze the spatial distribution of socioeconomic environment in a consistent, efficient and low-cost manner. By monitoring the anthropogenic nocturnal light intensity, these satellite image derived data products can help us evaluate human activities at multiple spatiotemporal scales.

In past decades, many studies have utilized the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) NTL data to analyze various socioeconomic indicators like GDP and electric power consumption (ECP). For instance, some researchers used the DMSP-OLS NTL imagery to generate and demonstrate the quantitative relationships between the NTLs and population and energy consumption in the USA [5,6]. Nevertheless, the DMSP-OLS satellite imagery suffers from significant deficiencies like coarse spatial resolution, saturation on bright lights, and the lack of in-flight calibration [7]. On October 28, 2011, the launch of the Suomi National Polar-Orbiting Partnership (NPP) marked a new generation of operational polar-orbiting spacecraft [8]. NPP-VIIRS exceeds its predecessors with its unique features including finer spatial resolution for all bands and a day night band (DNB) that can collect low-light imaging data. Thus, due to the improved NTL detecting ability, NPP-VIIRS have been applied in many fields that were dominated by DMSP-OLS.

The objectives of this study are to utilize the NPP-VIIRS NTL imageries to map sub-national socioeconomic development in Uganda. We conduct our analysis using NPP-VIIRS nightlight imagery covering Uganda for the year 2015, agricultural production and commodity price information [9], and population data from the Global Human Settlement Layer. The structure of the paper is organized as follows: A detailed description of case study area, NTL data, and agricultural production data are presented in Section 2. The data processing and methods used in this study will be described in Section 3. We will then present the estimation results and discuss the performance of our methods by comparing with other existing methods. Finally, we summarize results and draw conclusions in the last section.

**2. Case Study Area and Data**

*2.1. Case Study Area*

This study mainly takes Uganda as the case study area. Uganda is one of the poorest nations in the world and its GDP per capita (current US $) is only $740 [10]. In recent years, the proportion of the population living in poverty is increasing and almost 10 million people are living under the poverty line. In addition, Uganda's economy is heavily dependent on agriculture. Like many other sub-Saharan countries, Uganda has a large rural population. In Uganda, 76 percent of the population lives in rural areas, and 24 percent of the national economy is derived from agricultural activity [10]. The district-level shapefile was obtained from U.S. Agency for International Development (there are 116 district's information in the shapefile, but the total number of districts has increased to 122 as of last summer). The GDP information was obtained from the World Bank database (in constant 2011 U.S. dollars).

*2.2. Data Collections*

2.2.1. Nighttime Satellite Imagery

The NPP-VIIRS NTL imagery was used to estimate the urban economic activities for each district in Uganda. The total estimated economic activities attributed to the commercial and industrial activities were calculated based on the total light intensity values within the districts. We selected the NPP-VIIRS "vcm-orm-ntl" product (VIIRS Cloud Mask - Outlier Removed - NTLs, obtained from http://ngdc.noaa.gov/eog/viirs/download_viirs_ntl.html ) for extracting urban and rural regions and estimating productivity from urban locations. This product contains cloud-free average radiance values with outliers (including fires and other ephemeral light) removed. NPP-VIIRS is a stable, cloud-free, NTL intensity data source produced by the National Oceanic Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA). Each square kilometer grid contains relative digital number (DN) values from 0 to $2^{14}$, which indicates the intensity of NTL. Many studies have utilized NPP-VIIRS data for analyzing a range of socioeconomic phenomena from a distance. NPP-VIIRS is suitable for detecting subnational activities because it captures high-radiance images and gathers information at roughly 0.5 km$^2$ level with high dynamic range [11]. Due to the improved NTL detecting ability, NPP-VIIRS have been applied in many fields that were dominated by DMSP-OLS. For example, Shi et al. [12] used NPP-VIIRS to extract built-up urban areas of 12 cities in China and they found that NPP-VIIRS data have higher spatial accuracies than those from DMSP-OLS data for all 12 cities. They concluded that these improvements are due to its high spatial resolution and wide radiometric detection range.

2.2.2. Population and Agricultural Data

The spatial population information was obtained from the Global Human Settlement Layer (GHSL) dataset, which was mapped based on the Landsat imagery to show the global built-up areas and population distribution from 1975 to 2014 [13]. The GHSL framework produces global spatial information in the form of built up maps, population density maps, and settlement maps about the human presence on Earth's surface over time. GHSL population grid shows the distribution and density of population. The population grid information is disaggregated from census or administrative units to number of people per cell (250m and 1km spatial resolution).

This model uses district-level agricultural data to supplement the spatial data in the model. Agricultural activity is not as light intense as commercial activities, so it would be underrepresented in a model based solely on nighttime lights. Taken together, nighttime lights (representing higher value-add economic activity) and agricultural production (an important aspect of Uganda's economy) provide a broad-based estimate of economic activity at the subnational level. This forms the conceptual foundation for the Enhanced Light Intensity Model.

These estimates use data on 16 representative agricultural commodities (production and average market price) to derive an estimate of the spatial distribution of agricultural GDP in Uganda. A mix of annual crops and perennial crops are included as well as cattle, Uganda's primary animal industry. These representative commodities include maize, millet, sorghum, rice, beans, cow peas, soya beans, groundnuts, sim sim, banana, cassava, sweet potatoes, Irish potatoes, coffee, cotton, and cattle. These are representative agricultural commodities and do not constitute the total agricultural output of each district, so national agricultural GDP is used to normalize these estimates.

All district-level crop production estimates are taken from the 2008/09 Census of Agriculture [9]. Data measuring heads of cattle per district are collected from the 2008 Livestock Census [14] and normalized to national-level beef production data from the Food and Agricultural Organization. Cotton production data [15] are sourced from the 2009-2010 Annual Report by the Cotton Development Organization [16].

Coffee is Uganda's top export and is divided among arabica and robusta varieties. Production data by district and variety are not readily available, so, in an attempt to estimate the geographic distribution of production value from coffee, a multi-step process is used. Census reports from the Uganda Bureau of Statistics provide information on the share of households engaged in coffee production [17] and the total number of households per district [18]. A map produced by Geo Gecko in 2017 delineates the share of production per district among robusta and arabica among five categories: fully arabica, mostly arabica, fifty-fifty, mostly robusta, and fully robusta [19]. Finally, the 2008/009 Census of Agriculture provides total production data by geographic region for arabica and robusta varieties. These data sources are combined to arrive at a production estimate by district and variety. Price data were derived from average weekly commodity prices recorded at markets in 2015 in Gulu, Mbale, Mbarara, and Kampala, sourced from FIT Insights Group Limited [20]. We chose to use 2015 data for commodity prices, because it was a relatively stable agricultural year. Average coffee prices are taken from the Uganda Coffee Development Authority from October 2014 to September 2015 [21].
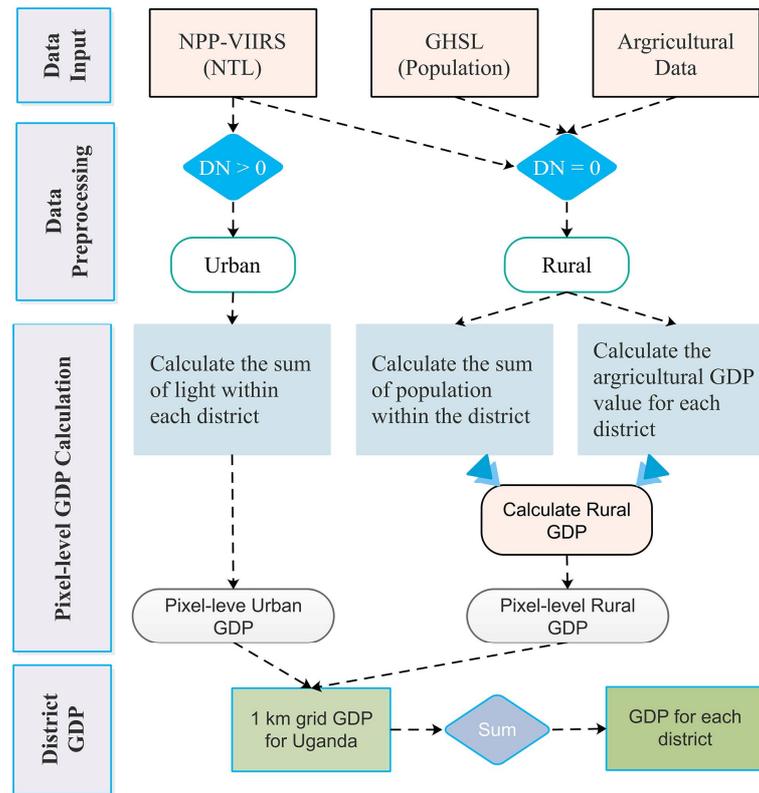
## 3. Methods

### 3.1. Data Pre-processing

The NPP-VIIRS imagery is processed based on the DN values - pixels with DN value of 0 and pixels with positive DN values. Following the method developed by Gosh et al. [22], we assume that: (1) NPP-VIIRS imagery with pixel value > 0 can represent the urban region that mainly consist of secondary and tertiary economic activities, and (2) NPP-VIIRS imagery with pixel value = 0 represents rural regions that mainly consist of agricultural activities. Therefore, the NPP-VIIRS NTL imagery is mainly used to extract and estimate the urban GDP value, whereas the population and agricultural production and price data are used to estimate rural GDP value. In addition, pixels with non-positive DN values are re-assigned to 0.

### 3.2. Model and Simulation of GDP

Many different models, including linear regression models, log-log regression models, and second-order regression models, have been developed to estimate socioeconomic data using NTL [23–27]. For instance, Henderson, Storeygard, and Weil [4] developed a statistical model by combining data from NTLs and income growth to better estimate true income growth. They concluded that satellite imagery can be a useful proxy for estimating economic activity if traditional data is not available or is of poor quality. Shi et al. [12] used simple linear regression model to estimate GDP and EPC at multiple scales. Nevertheless, due to the lack of high quality census data in African countries like Uganda, it is very difficult to develop and validate a statistical model based on these existing methods directly. It is also found that the population data may not fully demonstrate the agricultural activities. For instances, studies have found that there is a weaker association between light and economic activities in agriculture dependent countries [28]. Thus, we have developed an enhanced light intensity model (ELIM) to estimate sub-national GDP in Uganda based on the following steps (Figure 1): (1) using the light intensity to extract urban regions and estimate urban GDP for each district, (2) using population distribution and agricultural value ratios to estimate agricultural GDP for rural regions, (3) the combination of urban and rural GDP can represent the total GDP at sub-national level.

**Figure 1.** Estimating sub-national GDP using ELIM method.

We defined the district agricultural value ratio (DAVR) as follows to measure agricultural production in rural regions,

$$DAVR = \frac{\sum_i^d X_i * Y_i}{NTA} \tag{1}$$

where i is the type of the agricultural product, d is the total number of types of the agricultural product, Xj is the production of the corresponding agricultural product, $Y_i$ is the average crop price of the agricultural product, and NTA is the national total agricultural GDP.

Then, the rural pixel value ($RV_i$) of rural GDP are:

$$RV_i = \frac{PN_{i=1}}{TRP} * AGDP * DAVR \tag{2}$$

where i is the ID of rural pixel (population layer), PNi is the population value of the corresponding pixel, TRP is the total rural population value, and AGDP is the total agricultural GDP of the country

Furthermore, we defined urban GDP pixel value ($UV_i$) as follows:

$$UV_i = \frac{DN_{i=1}}{TNTL} * NAGDP \tag{3}$$

where i is the ID of urban pixel (NPP-VIIRS NTL layer), DNi is the DN of the corresponding pixel, TNTL is the total night time light values of the country, and NAGDP is the total non-agricultural GDP of the country.

## 4. Results and Discussion

### 4.1. District GDP per capita results

Figure 2 shows the GDP and GDP per capita for all 116 districts in Uganda (detailed GDP result and districts information are in Appendix 1). In Figure 2b, the distribution of GDP in Uganda is heavily skewed. Only nine out of 116 districts have GDP per capita values above the national average. This equates to roughly 84% (or about 33 million) of the population is living in districts with GDP per capita estimates below the national average. Kampala has the largest GDP per capita ($3,860), followed by Wakiso ($2,671) and Mpigi ($2,543). Central (the central region dos not include Kampala) and Western Uganda tend to have larger per capita GDP estimates than Western and Northern Uganda.
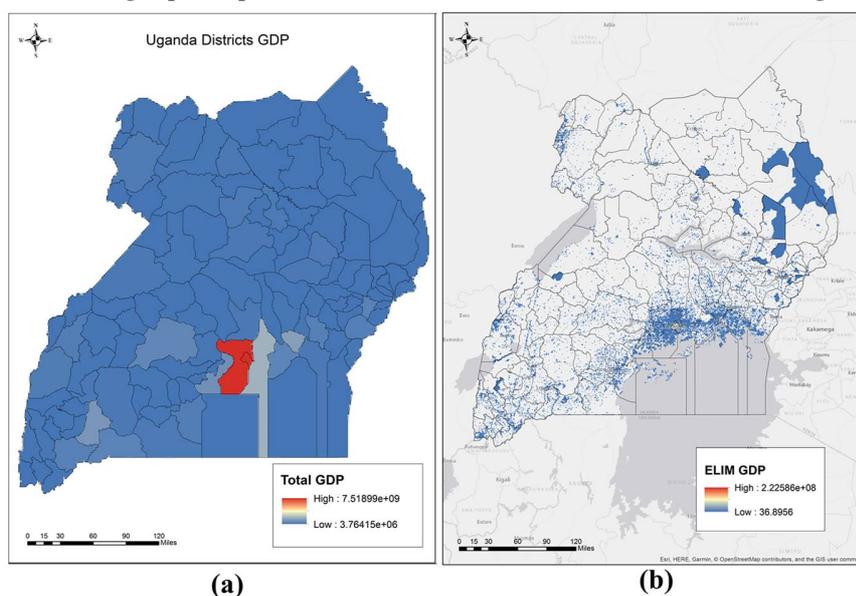


**Figure 2.** Uganda's district level GDP (a) and GDP per capita (b).

In Figure 3, it shows that GDP is heavily concentrated in Central Uganda and Kampala. The ELIM method estimates that Kampala (34.3%), Wakiso (19.7%), and Mukono (4.8%) account for more than half of Uganda's total GDP. Of the ten largest district economies, six are in Central Uganda. Sub-regionally, Kampala and South Central sub-region account for an outsized proportion of Uganda's GDP relative to its population size, meaning that they are significantly more productive sub-regions in Uganda. Kampala is roughly 5% of Uganda's population, but it generates 34.3% of its GDP, whereas the West Nile region comprises 9.5% of Uganda's population and produces 2.1% of the country's GDP. Sub-regionally, Kampala and other Central districts account for an outsized proportion of Uganda's GDP relative to its population size, meaning that they are significantly more productive sub-regions in Uganda. The top 10 district economies in Uganda make up about 71.4% of the total GDP of Uganda, with the remaining 28.6% of the national economy coming from 106 districts. Put another way, these top 10 districts with roughly 18% of the total population and generate more than 70% of the total GDP.
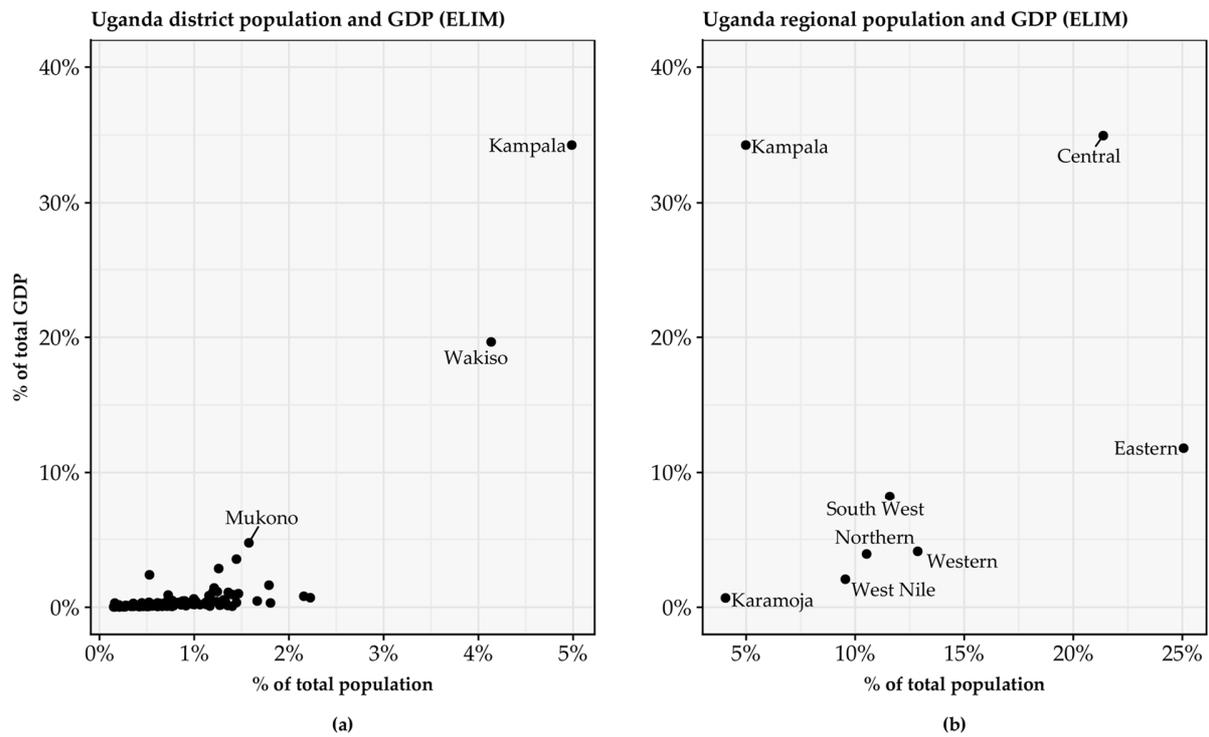
**Figure 3.** Uganda 116 Districts' GDP and Population (a) and Uganda regional GDP and Population (b).

4.2. Data Comparisons

We have compared our results with publicly-available census data. Nevertheless, there are no sub-national-level GDP estimates in Uganda that can be used for direct comparison. Other researchers have produced sub-national-level GDP estimates based on remotely sensed imagery. For instance, Nordhaus [29] had produced the G-Econ database, which measures the global economic activity at a 1° latitude by 1° longitude scale (Figure 4a). Due to the coarse resolution, the G-Econ cannot sufficiently reflect the sub-national economic activities within districts. Kummu, Taka, and Guillaume [30] have produced global GDP and Human Development Index (HDI) at sub-national level with higher resolution (Figure 4b). However, their data is unable to consider the nonlinearity and multi-scale variability of geospatial data, and the GDP values are mainly derived from population per pixel and GDP per capita at national level. This dataset is insufficient to justify the sources of economic activities and the variation of productivities within districts. For instance, Figure 4c shows that the difference between ELIM result and the Gridded Global GDP data from[30]. Figure 5 shows the comparison between Gridded Global GDP data and the ELIM results. The Gridded Global GDP data has significantly underestimated GDP from districts like Kampala, Wakiso, and Mukuno since the subnational calculation is mainly based on the sub-national population, not the heterogeneous productivity across rural and urban landscapes.
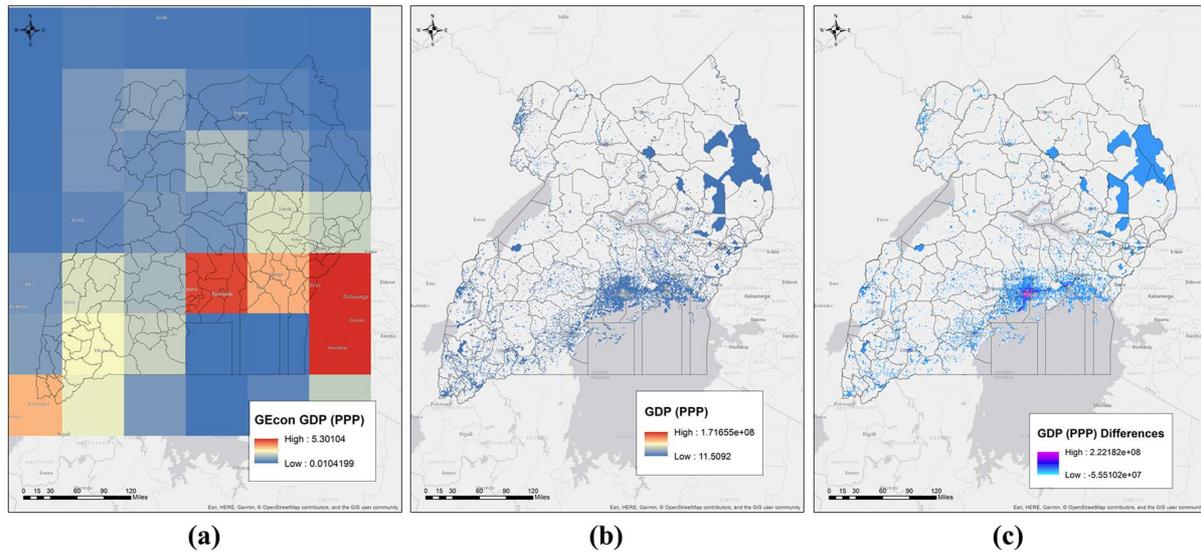
**Figure 4.** Comparisons of (a) G-Econ data from [31], (b) Gridded Global GDP (PPP) data from [30], and (c) the difference between the ELIM and Gridded global GDP data.

## Comparison between Gridded Global Data and ELIM results
Percent of GDP by district
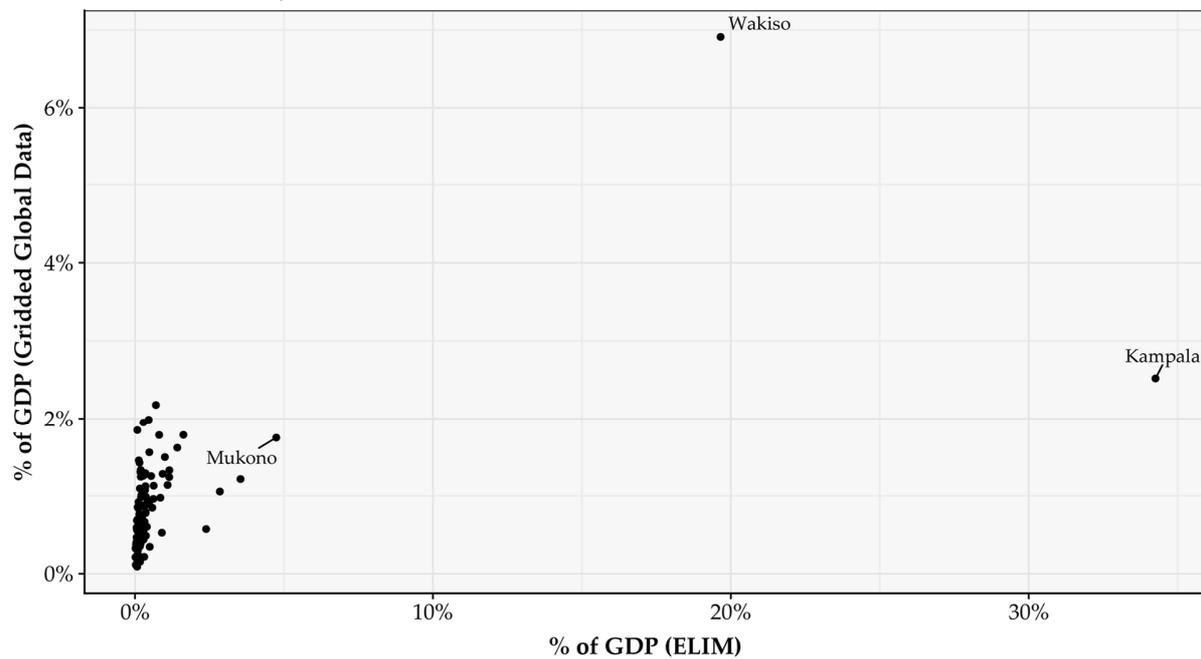


**Figure 5.** Comparison between the ELIM and Gridded Global GDP data.

## 5. Discussion

The NTL imagery can record the dynamics of human activities by monitoring the artificial light on the Earth's surface. Therefore, we support the idea that in migrating from DMSP-OLS to NPP-VIIRS data sources, the NTL imagery is an improved and more accurate source for estimating GDP. Nevertheless, the traditional DMSP-OLS imagery has a coarse spatial resolution and this may limit its applications for estimating human activities at sub-national levels [32]. In addition, Bundervoet et al. [28] found that the correlation between lights and economic activity is stronger in places where agriculture is a less significant component of the national GDP. Therefore, many traditional methods for estimating GDP with NTL may not be suitable for countries dependent on agriculture like Uganda. Following this rationale, in this study, instead of using population data only for estimating agricultural GDP, we proposed a simple process for estimating the rural GDP values by combining the population and agricultural value ratios within the districts of Uganda.

There are still limitations for this method. First, due to the resolution restriction of NPP-VIIRS NTL, the NTL imagery is not likely to accurately demonstrate the dynamics of economic activities at a finer spatial resolution. Second, since the NPP-VIIRS was only launched in 2012, there is a limited amount of time series data available. NPP-VIIRS may be combined with DMSP-OLS to cover a longer period of time to demonstrate the dynamics of economic activities in Africa. Thirdly, due to the relatively coarse resolution of NPP-VIIRS imagery, it may not be able to accurately define the urban regions and separate some agricultural activities from other secondary and tertiary sectors of the economy.

## 6. Conclusion

Africa is experiencing rapid urbanization due to fast population growth. It is estimated by the United Nations that more than 50% of global population growth between now and 2050 will occur in Africa [33]. This rapid population growth is causing fast expansion of megacities, small cities, and towns; and, putting great pressure on Africa's sustainable development objectives by causing the loss of biodiversity, environmental degradation, and natural resource depletion. It is important to obtain timely and accurate information to evaluate the impacts of urbanization and promote sustainable development in countries like Uganda. Nighttime stable light data from the DMSP-OLS and the NPP-VIIRS can be used to reveal the dynamics of urban expansion in Africa. In this study, we have developed a new method for extracting the dynamics of sub-national-level economic activities based on nighttime stable light data using a combination of population data from GHSL and agricultural value ratios. In this study, a sequence of preprocessing procedures is implemented to estimate economics activities from different industries in urban and rural regions.

The results of the ELIM indicate some emerging themes for those interested in district-level policy in Uganda. First, the distribution of economic activity is heavily concentrated in Central Uganda. Three districts (Kampala, Wakiso, and Mukono) account for nearly half of Uganda's total GDP, while comprising only about 10% of Uganda's population. Second, the top 10 district economies in Uganda make up about 71.4% of the total GDP, leaving the remaining 28.6% of the national economy coming from 106 districts. Through a case study of Uganda, this research investigates the ability of NPP-VIIRS data to estimate sub-national GDP using multi-source data that not only improve the resolution of dataset, but also captures the spatial heterogeneity of socioeconomic activities. By comparing our results with other publicly available data sources, data generated from the ELIM model can better capture the variations of GDP within the sub-national administrative boundaries. The GDP is also allocated based on the types of economic activities, instead of just based on the simple averaged values of population and GDP per capita, thus capturing heterogeneous productivity across rural and urban landscapes. Due to the limited availability of calibrated and processed NPP-VIIRS data, it is important to produce multiple years of NPP-VIIRS NTL data analysis

in the future to further compare and improve the model performance. Moreover, obtaining accurate and relevant ground truth data is important for validation to produce better-quality results.

**Author Contributions:** Conceptualization, All Authors; methodology, All Authors; validation, X.W. and M.R.; formal analysis, X.W. and M.R.; investigation, X.W. and M.R.; data curation, X.W., M.R, and P.S.; writing—original draft preparation, X.W. and M.R.; writing—review and editing, All Authors.; visualization, X.W. and M.R.; funding acquisition, M.R. and J.M.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

**Table A1.** GDP and GDP per capita Results

| DNAME | Region | GDP (million US$) | GDP per capita (US $) |
|---|---|---|---|
| Abim | Karamoja | 5.89 | 100 |
| Adjumani | West Nile | 62.08 | 136 |
| Agago | Northern | 26.10 | 73 |
| Alebtong | Northern | 15.47 | 60 |
| Amolatar | Northern | 19.06 | 133 |
| Amudat | Karamoja | 14.65 | 106 |
| Amuria | Eastern | 27.95 | 53 |
| Amuru | Northern | 80.25 | 394 |
| Apac | Northern | 93.14 | 234 |
| Arua | West Nile | 154.09 | 177 |
| Budaka | Eastern | 12.12 | 61 |
| Bududa | Eastern | 41.24 | 202 |
| Bugiri | Eastern | 41.86 | 83 |
| Buhweju | South West | 26.09 | 227 |
| Buikwe | Central | 311.52 | 659 |
| Bukedea | Eastern | 30.97 | 144 |
| Bukomansimbi | Central | 36.71 | 224 |
| Bukwo | Eastern | 36.96 | 458 |
| Bulambuli | Eastern | 20.04 | 130 |
| Buliisa | Western | 13.41 | 150 |
| Bundibugyo | Western | 26.11 | 85 |
| Bushenyi | South West | 78.71 | 284 |

| | | | |
|---|---|---|---|
| Busia | Eastern | 68.43 | 207 |
| Butaleja | Eastern | 31.41 | 125 |
| Butambala | Central | 16.28 | 126 |
| Buvuma | Central | 3.96 | 63 |
| Buyende | Eastern | 43.94 | 146 |
| Dokolo | Northern | 29.92 | 143 |
| Gomba | Central | 25.70 | 156 |
| Gulu | Northern | 108.59 | 362 |
| Hoima | Western | 100.76 | 155 |
| Ibanda | South West | 87.30 | 315 |
| Iganga | Eastern | 220.13 | 384 |
| Isingiro | South West | 252.22 | 519 |
| Jinja | Eastern | 777.38 | 1,376 |
| Kaabong | Karamoja | 32.97 | 66 |
| Kabale | South West | 77.37 | 238 |
| Kabarole | Western | 186.91 | 414 |
| Kaberamaido | Eastern | 21.98 | 95 |
| Kagadi | Western | 19.38 | 43 |
| Kakumiro | Western | 20.69 | 95 |
| Kalangala | Central | 3.76 | 46 |
| Kaliro | Eastern | 63.12 | 255 |
| Kalungu | Central | 43.92 | 234 |
| Kampala | Kampala | 7518.99 | 3,860 |
| Kamuli | Eastern | 76.53 | 136 |
| Kamwenge | Western | 74.15 | 199 |
| Kanungu | South West | 63.95 | 233 |
| Kapchorwa | Eastern | 21.53 | 162 |
| Kasese | Western | 177.87 | 211 |
| Katakwi | Eastern | 18.77 | 93 |
| Kayunga | Central | 44.59 | 114 |
| Kibaale | Western | 62.99 | 451 |
| Kiboga | Central | 49.91 | 230 |
| Kibuku | Eastern | 22.93 | 111 |
| Kiruhura | South West | 100.80 | 294 |
| Kiryandongo | Western | 39.52 | 117 |
| Kisoro | South West | 38.64 | 145 |
| Kitgum | Northern | 18.46 | *67* |
| Koboko | West Nile | 14.25 | 48 |

| | | | |
|---|---|---|---|
| Kole | Northern | 61.03 | 232 |
| Kotido | Karamoja | 51.91 | 180 |
| Kumi | Eastern | 25.20 | 84 |
| Kween | Eastern | 15.68 | 120 |
| Kyankwanzi | Central | 38.45 | 199 |
| Kyegegwa | Western | 38.10 | 208 |
| Kyenjojo | Western | 59.01 | 135 |
| Lamwo | Northern | 12.28 | 62 |
| Lira | Northern | 127.40 | 277 |
| Luuka | Eastern | 77.48 | 262 |
| Luwero | Central | 92.09 | 190 |
| Lwengo | Central | 77.53 | 278 |
| Lyantonde | Central | 30.22 | 281 |
| Manafwa | Eastern | 46.56 | 106 |
| Maracha | West Nile | 49.62 | 222 |
| Masaka | Central | 197.81 | 698 |
| Masindi | Western | 77.17 | 176 |
| Mayuge | Central | 105.57 | 204 |
| Mbale | Eastern | 253.21 | 540 |
| Mbarara | South West | 625.36 | 1,272 |
| Mitooma | South West | 40.19 | 193 |
| Mityana | Central | 70.29 | 213 |
| Moroto | Karamoja | 9.43 | 57 |
| Moyo | West Nile | 17.09 | 31 |
| Mpigi | Central | 524.23 | 2,543 |
| Mubende | Central | 356.64 | 510 |
| Mukono | Central | 1040.68 | 1,689 |
| Nakapiripirit | Karamoja | 22.17 | 112 |
| Nakaseke | Central | 27.39 | 124 |
| Nakasongola | Central | 70.39 | 403 |
| Namayingo | Eastern | 19.61 | 71 |
| Namutumba | Eastern | 48.83 | 201 |
| Napak | Karamoja | 13.06 | 54 |
| Nebbi | West Nile | 48.29 | 125 |
| Ngora | Eastern | 14.05 | 78 |
| Ntoroko | Western | 7.39 | 70 |
| Ntungamo | South West | 240.08 | 452 |
| Nwoya | Northern | 67.73 | 1,074 |

| Omoro | Northern | 35.79 | 252 |
|---|---|---|---|
| Otuke | Northern | 7.15 | 73 |
| Oyam | Northern | 137.45 | 301 |
| Pader | Northern | 20.82 | 73 |
| Pallisa | Eastern | 42.75 | 103 |
| Rakai | Central | 119.13 | 233 |
| Rubanda | South West | 15.58 | 76 |
| Rubirizi | South West | 27.64 | 203 |
| Rukungiri | South West | 78.85 | 225 |
| Serere | Eastern | 102.67 | 292 |
| Sheema | South West | 50.15 | 207 |
| Sironko | Eastern | 27.20 | 104 |
| Soroti | Eastern | 135.27 | 348 |
| Ssembabule | Central | 70.38 | 294 |
| Tororo | Eastern | 203.84 | 371 |
| Wakiso | Central | 4314.70 | 2,671 |
| Yumbe | West Nile | 69.28 | 98 |
| Zombo | West Nile | 38.11 | 155 |

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