# Final Report: CSMC12300 Group Project

## SateLIFE

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## Description of data

For our analysis we relied on publicly available satellite imagery obtained and pre-processed through the Google Earth Engine (EE) platform, a satellite imagery and geo-spatial analysis platform from Google.

The data we used focused on the Brazzaville and Kinshasha in DRC/Republic of Congo. It consisted of about 1.6 billion total pixels that covered 11 years of 6 bands. The bands are described in more detail below. Each year/band combination was 4,900 by 5,036 pixels each, which resulted in approximately 2GB of data. We also had GeoGSON data from OpenStreetMaps. Our data was too large to push to our repository, but we can provide a USB file if necessary. It is important to note that our code was written with scalability in mind and could easily be applied to larger areas.

### Raw Data

Satellite imagery is a rich form of data with different satellites gathering different information, called bands. We utilized the following data types/bands:

#### Landsat 7

- 30m resolution
- Cleaned yearly composites from 2000-2012
- 3 band RGB (red-green-blue) which yields a traditional image of the area of interest, as it appears to an observer

#### LST

- 1km resolution
- Cleaned yearly composite from 2000-2012
- 1 band quantifying the land surface temperature of the area of interest

#### NDVI

- 30m resolution
- Cleaned yearly composites from 2000-2012
- 1 band, Normalized Difference Vegetation Index, essentially captures the 'greenness' of the land below. This is a measure of the vegetation

### Night_lights

- 1km resolution
- Cleaned yearly composites from 2000-2012
- 1 band, a measure of the average nightime luminosity of the area of interest. This has been shown to be correlated with economic activity and has been widely used as a proxy for economic activity within the development literature

### GeoJSON

- Not obtained through Google but through OpenStreetMaps, a crowd-source mapping platform
- .gpx files (geojson type) containing GPS coordinates describing polygons of the neighborhood boundaries within the city of Kinshasa
- Described in greater detail in "Getting boundaries" below

## Working with the Data

### Cleaning & Exporting Satelite imagery

Raw satellite imagery can be extremely noisy with missingness due to cloud cover, distortions caused when the satellite passes over different areas of the Earth at different times, etc. We utilized the Google EE code editor platform to perform cleaning and rectifying (fitting satellite images together into a clean composite). The EE code editor is written in javascript syntax. The script "geeimage.js" is our script for downloading, processing, and exporting the massive files to Google Drive.

Google EE exports all images as .tiff files, which we then load into Python as numpy arrays. A particular challenge when using any geospatial data is to have the data aligned geographically, so that each pixel within the numpy arrays corresponds to the same geographic location in another .tiff file. Again, we utilized Google EE to ensure the geographic alignment of our raw data.

### Getting Boundaries:

In addition to making statements about the Kinshasa-Brazzaville area, we wanted to make finer-grained statements comparing the two countries, the two-cities, the river between, the city neighborhoods, etc. This required combining the spatial satellite data with GPS indexed boundary data.

OpenStreetMaps, as part of project to map the Democratic Republic of the Congo, provides GPS coordinate data in the form of .gpx (geojson) files which define neighborhoods within Kinshasa. The script "clean_gps.py" parses the .gpx files. However, to be compatible the GPS data needs to be processed through Google EE. Thus, the "clean_gps.py" takes the parsed .gpx files and outputs a .txt file of EE compatible code which builds a tiff image containing the gps boundaries. This txt file is then the foundation for the script "kinshasa_boundaries.js"

Google EE has two image types: raster and feature. The images describe above are rasters and the GPS boundaries are feature types. Again, using EE we convert the GPS boundaries from feature types into raster/image types for compatibility. We also manually draw boundaries where GPS data is not available from OpenStreetMaps. The boundary analsysis is layered, with different codes denoting country differences and different areas within country. Thus, the analysis in EE yields 3 boundary tiff files which are then composited into 1 comprehensive boundary file. This occurs in the "clean_boundaries.py" script

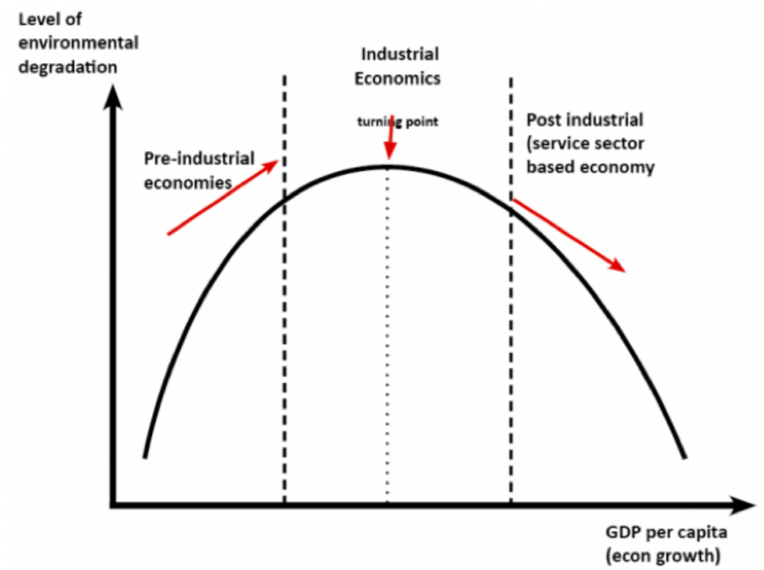
### Class Design

As described in the comments and header of the “util.py” file, the SatData class facilitates the construction and analysis of the satelite tiff image files.

## Hypotheses

### The Kuznets Curve

See the diagram below for an example of the Kuznets curve hypothesis.




Developing nations like DRC & Republic of Congo are expected to be on the left hand side of the graph, and undergo environmental degradation as they develop over time. However, in our data, we found no discernible trend in aggregate means, especially considering that these indices have high standard deviation.

The data we collected corresponds to measures of environmental degradation in the following ways:

- Reduction of green spaces: NDVI - Normalized Difference Vegatation Index
- Light pollution: Night Lights Index
- Urban build-up: Land Surface Temperature

Our hypothesis was that these indices should increase over time.

### A Tale of Two Cities

Brazzaville & Kinshasa are an interesting case study because they are the world’s two most proximate capital cities (ignoring the Vatican City). However, in Kinshasa’s country, DRC, there has been a brutal civil war raging throughout the period. We hypothesized that Brazzaville has seen greater economic development. This can be measured by proxy using the Night Lights Index, as in Mellander et al. (2013). Hence we expect Brazzaville’s Night Lights growth to outstrip Kinshasa’s.

### Neighborhood Variation

We also predict spatial variation between neighborhoods depending on their density, environmental characteristics, location, etc. In order to test this, we found basic statistics for each neighborhood (mean, std, max, min) and looked at differences in magnitude and trend across neighborhoods.

## Algorithms

### Autocorrelation

Autocorrelation is the correlation of a signal with a delayed copy of itself (wikipedia). In other words, it allows us to determine whether the value at a certain pixel within a band is correlated with the value in the next period (or periods). To calculate this, we normalize a each band such that it is mean zero. We then multiply each normalized pixel value in year=t with the corresponding normalized pixel avlue in year=t-k, where k is the level of autocorrelation. Our code currently tests autocorrelations of k=1,2,3 to determine how persistent any correlation is and whether the nature changes with respect to the degree. We then divide by each std deviation and take the expected value of the transformed variable, thus calculating the statistic across the entire band. See “util.py” and “auto_correlation.py” for code.

### K-Nearest Neighbors

This recently added calculation is still a work in progress, but we present it here for its coding usefulness. Unlike many of our other statistics, this calculation is made not across an entire band but across a small k-near-neighborhood of a given pixel. Thus, for any given k x k neighborhood we can calculate a proxy for the spatial correlation within the neighborhood. We essentially slide this neighborhood “filter” across the band calculating with each change, resulting in a new 2D surface. This is very similar to the convolution calculations within a convolutional neural network. See “util.py” and “k_nearest.py” for code.

### Basic Statistics on Multiple Levels

We founds the mean, min, max, and std for entire region and by neighborhood. We also found a simple difference between years.

- Bands Collapse (look at the mpi_bands_collapse.py code for specific implementation). The output for this can be found in bands_collapse_data.
- Neighborhood Analysis (look at the mpi_neighborhood.py code for specific implementation). The output for this can be found in neighborhood_data. The neighborhood dictionary that maps neighborhood numbers to names is in util.py.
- Geographical Differences Over Time (look at the mpi_geography.py code for specific implementation). The output for this was too large to store on git, so it is stored locally on each machine.

## Big Data

### Automation via Bash Scripts

In order to maximize our use of MPI via the Google Cloud VM platform while avoiding the tedium of manually initializing, preparing, and linking instances/nodes, we wrote a handful of Bash scripts that would automate the process. For `gcloudsetup.sh`, the user simply runs the script specifying the nubmer of VM instances desired, and the shell, using the `gcloud` command-line interface, will create those instances, send over requisite files/data via `SCP`, and install necessary software and packages. From within each node, the script also calls `chain.sh`, which connects each node to each other nodes via `SSH` to facilitate MPI. Finally, `update.sh` serves to automate the process of sending files and directories to all nodes at once. Look within the scripts for explicit documentation.

### MPI and Numpy

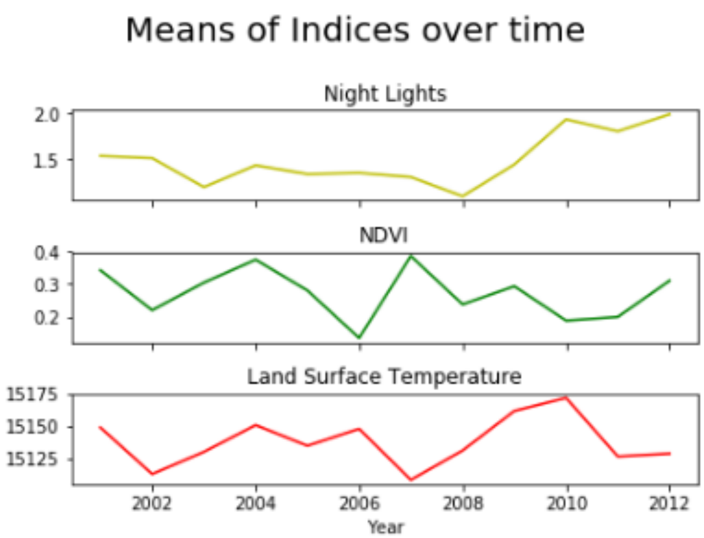
We used MPI to parallelize computation on different nodes. Because our data was in tiff format and it was easy to represent it as a numpy array, we were able to split the data and do many calcuations using numpy functions. We split our analyses into five different scripts depending on the type of analysis we were doing. Our five MPI codes are: mpi_bands_collapse.py, mpi_neighborhood.py, mpi_geography.py, k_nearest.py, and auto_correlation.py.

## Results

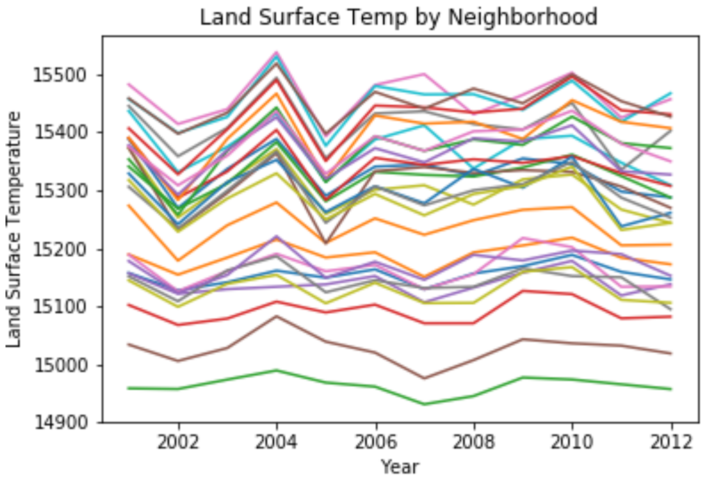
Our data anlalysis was conducted using jupyter notebooks, which facilitated quick and easy graphing.

### Kuznets curve

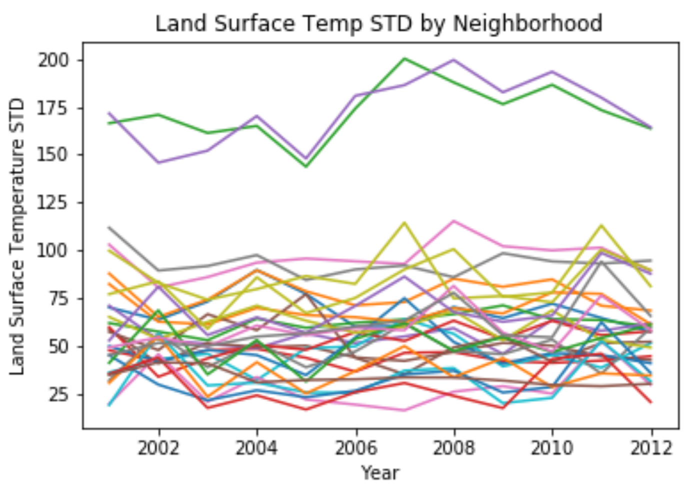
Our results do not support the Kuznets Curve hypothesis.




However, we do see variation by neighborhood that is intuitive. For example, in the below graph, river/marsh areas are the lines with the lowest LST:

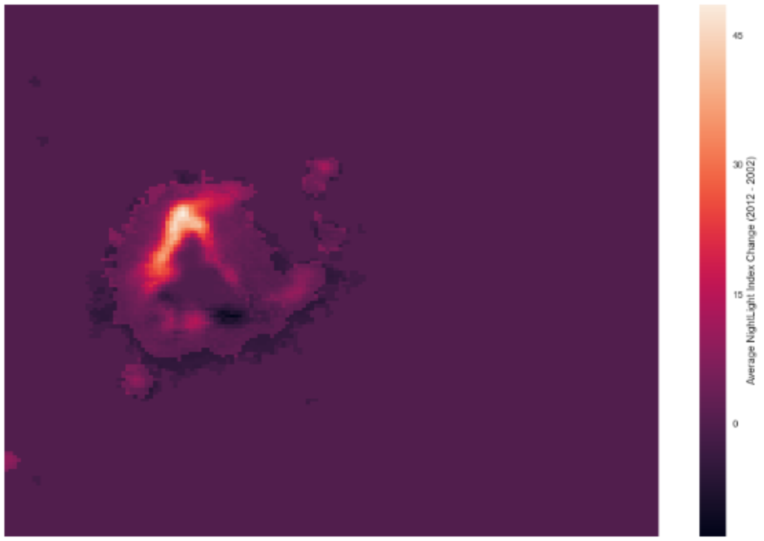



Additionally, the variance in the data showed trends between neighborhoods. For example, the two neighborhods with the highest standard deviation in the LST graph below include both marshland and concentrated urban areas, so their variation in temperature is high.




**Cities**

Brazzaville's nightlights increased more over the period, in line with our prediction, as visualized below. However, the other indices did not have the same general upward trend.:




## Challenges

Initially, downloading the data from Google Earth Engine was difficult. Our group needed to learn basic javascript syntax in order to work with the data. Additionally, Google Earth Engine makes it very easy to work with the data on their site, but downloading was very slow.

We also frequently tested our code using the google cloud servers, and because we were opening up 4-8 nodes at once, the setup for MPI was slow and tedious. To overcome this, we set up a bash script that would automatically set up the number of nodes proviced. We also created a update script to update any file on which we were working on all the open nodes.

We also faced issues of lack of complexity: because we were working with numpy arrays, finding simple statistics was very quick even without using MPI. To try to make our project more complicated, we did a neighborhood analysis, which involved looping over the data, and k-nearest neighbors and autocorrelation analyses. We also built approaces that could be scaled up to larger datasets.