UC Berkeley

Final Project

Data-Intensive International Development

# Using Satellite Imagery to Predict Level of Poverty and Education in Nepal, Haiti and Rwanda

*Author:s*
Andrew Head
Melanie Manguin
Nate Tran

*Professor:*
Joshua Blumenstock

May 5, 2017

Berkeley
SCHOOL OF INFORMATION

**Abstract**

Recent advances in applied machine learning ([9]) ([3]) have shown potential for predicting poverty and public health at a high spatial resolution using satellite images. Such techniques could be a cost-effective alternative to collecting fine-grained demographics and health statistics with surveys. However, the method has not been applied to developing countries outside of East Africa. In this study, we show the geographic limitation of the Jean et al.'s transfer learning technique by applying the technique in training and predicting the wealth of developing countries in South Asia and Central America (i.e. Nepal and Haiti). Furthermore, we investigate to what extent in which this method can be used to predict another development index, the education level. We define an education index based on DHS surveys, and apply the same transfer learning technique to predict the education level. Our result shows that the transfer learning method using daytime satellite images outperforms the method of using nighttime light intensities alone in predicting both wealth and education level only in Rwanda, but not in Haiti and Nepal.


# 1 Introduction

Measurement of socioeconomic level of a developing country and its subregions is very critical in policy research and development of that country. It can assist its government to allocate funding and resources more appropriately. Furthermore, continuous tracking and early predicting can support future planning for the country of interested. However, one of the biggest issue regarding socioeconomic research is how to get the accurate measurement in a timely manner with funding constraint. Decision making in the international level (such as foreign-aid) has typically relied on capita GDP. While GDP is an acceptable index in that sense, it is not very useful in the sub-national level, and it does not represent the well-being of the population in general. Another approach to measure the socioeconomic well-being are country-level surveys, such as the Demographic and Health Survey (DHS), a national household survey that provide a wide range of raw data in the areas of population, health, and nutrition. The issue here is although DHS are conducted at a much faster rate than national census, the data is still relatively sparse in the developing world. For example, for the last thirty years, 40 out of 92 countries participate in DHS only have 1 or 2 available dataset, some dated back in 1987, such as Ecuador. This posted a problem for countries and international organization to only rely on DHS survey.

Recent development in machine learning techniques have enable a new method to estimate socioeconomic level of developing country. Mellander et al. demonstrate a technique to predict economic activity of Sweden using Defense Meteorological Satellite Program (DMSP) nighttime light data, achieving high correlation between light intensity and wages income, with $R^2$ equals .700 ([5]). Noor et al. conducted a similar study correlating the nighttime light intensity and asset-based wealth index of 338 Administrative 1 level in 37 African countries([7]). While the nighttime light intensity method performs very well in predicting wealth at the country level, it does so very poorly at the sub-national level, especially in highly developed countries, such as United States and China, due to their higher grade of statistical system([8]). This method also under-performs in low income countries within 'low-output-density regions', because the stable light level is too low to be distinguished from the background lights and therefore is set at zero ([8]). For example, Jean et al. shows that this method cannot distinguish the economic activity of population areas with very low wealth index (or population living below the international poverty line of 1.90 dollars per day.) ([3])

Because of the limitation in using nighttime light data in predicting wealth in developing countries, Jean et al. propose using satellite imagery to predict a region's poverty level for five different countries in East Africa, in a two-step transfer learning process: first, they train a convolution neural network (CNN) to predict night-time light intensity of a region from satellite images; and second, they train a ridge regression model to predict poverty within a region using features from the final layer of this CNN. This study shows that the transfer learning method outperforms the method of only using the nighttime light data, and produce an improvement of at least .1 in $R^2$ value in more than 70% the number of independent trials when correlating with the asset based wealth index.

In this study, we design an experiment that evaluates the performance of the transfer learning technique in developing countries outside of East Africa (i.e. South Asia and Central America). In particular, for easy comparison, we choose to study Nepal, Haiti, and Rwanda, all with similar GDP of \$732.30, \$828.81 and \$697.35 respectively.

To further expanding the use of transfer learning technique in predicting socioeconomic level beyond wealth, we also developed an education index, and train the neural network model to predict education outcome at the sub-country level in Nepal, Haiti and Rwanda. To our knowledge, this is the first attempt of using daytime satellite imagery and nighttime light intensity to measure education outcome. This work can broadens our understanding of the potential of satellite-based poverty prediction techniques by exploring their success in developing regions around the world, and for measurements of development beyond poverty.

# 2 Results

## 2.1 Using nighttime light intensity only

As a baseline for our neural network models, we did a simple regression of the wealth and education over nighttime light intensities, to see to what extent nighttime light alone can predict these indices.

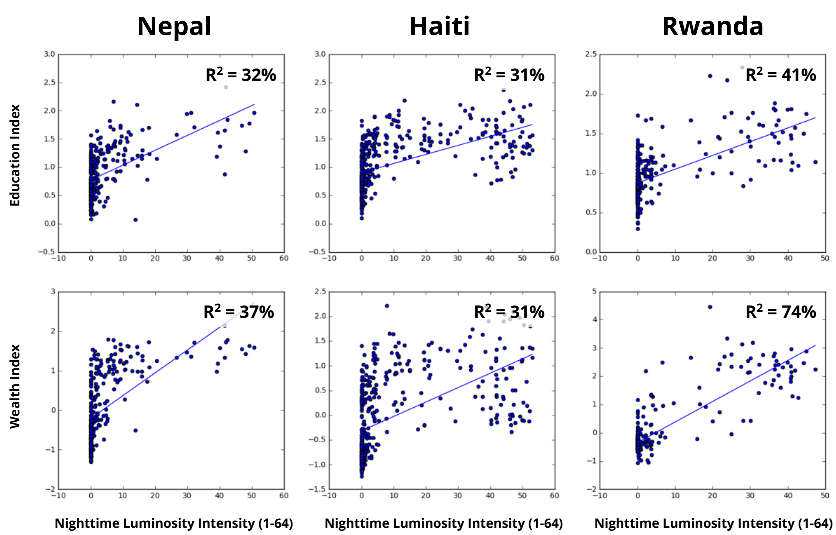


Figure 1: Correlation between nightlights, wealth index, and education index in each country. In most cases, $R^2$ falls between 30 and 40%.

## 2.2 Transfer learning with a neural network

For each country, we trained two convolutional neural networks (see the Methods section). The first neural network included a set of top layers that were trained to predict nighttime luminosity from satellite images. The second network was an adapted version of the first neural network for which the last three convolutional layers were further fine-tuned. We hypothesized that the fine-tuned network would perform the best out of the three models—the regression model, network with trained top, and fine-tuned network.

However, our results did not conform to this hypothesis (see Tables 2.2.1 and 2.2.2). For our models, the best performance was provided by the regression model that used nighttime luminosity to predict wealth index in Rwanda. Most importantly, while the cross-validation accuracy of the convolutional neural network used to predict wealth index in Rwanda was comparable to the accuracy reported in Jean et al.'s [3] work, (see Figure 2), the performance of all other predictors of both indexes in each country was much poorer. In the discussion section, we provide evidence that suggests why the transfer learning method we used may not be successful when applied to education index data, and satellite images from Haiti and Nepal.

### 2.2.1 Wealth index

| Cross-validated $R^2$ | Rwanda | Haiti | Nepal |
|---|---|---|---|
| Regression over nighttime light | 0.741 | 0.304 | 0.362 |
| Standard transfer learning model | 0.558 | 0.362 | 0.320 |
| Fine-tuned model | 0.561 | 0.339 | 0.366 |

### 2.2.2 Education index

| Cross-validated $R^2$ | Rwanda | Haiti | Nepal |
|---|---|---|---|
| Regression over nighttime light | 0.370 | 0.241 | 0.250 |
| Standard transfer learning model | 0.098 | 0.361 | 0.323 |
| Fine-tuned model | 0.084 | 0.372 | 0.323 |

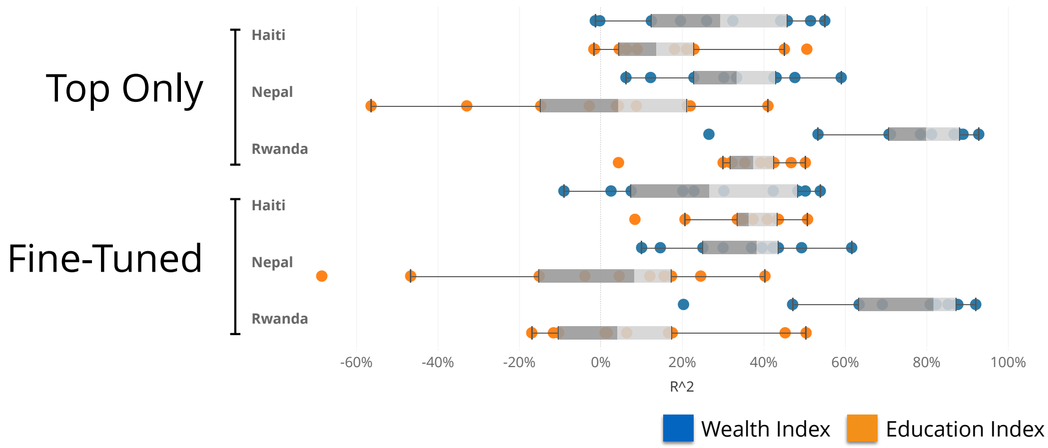


Figure 2: $R^2$ for each of 10 folds of cross validation when training the predictors for wealth and education indexes, using features extracted from the neural network. Note that the median prediction performance for Rwanda is similar to the result achieved by Jean et al. [3]

# 3 Discussion

The weak performance of our models suggest that, at the least, the transfer learning procedure cannot be used as-is with the amount of training we performed to achieve good prediction results beyond Rwanda's wealth index. In the next two subsections, we describe our intuitions of the inherent challenges of using satellite images to predict education index, and to predict wealth index and Haiti and Nepal.

## 3.1 Learning to Predict Nighttime Luminosity from Satellite Images in Haiti and Nepal

It was considerably more time-consuming to achieve a good validation accuracy with the two types of convolutional neural networks for Haiti and Nepal than it was for Rwanda. It took the Rwanda model 8 epochs to achieve $>95\%$ validation accuracy; Haiti required 25 epochs, and Nepal never reached this accuracy. This suggests that there may not be as clear of a relationship between the implicit visual features daytime satellite imagery in Haiti and Nepal and nighttime luminosity to begin with.

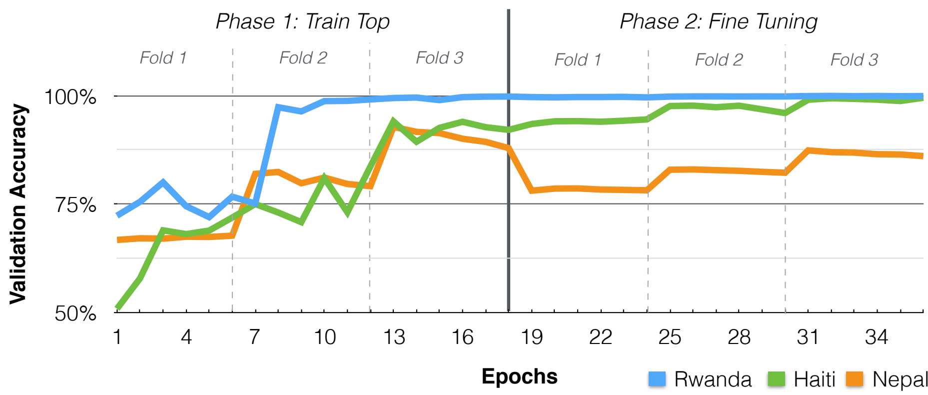


Figure 3: Validation accuracy by epoch as we trained the convolutional neural networks to predict nighttime luminosity.

When reviewing the images that most activated the convolutional layers in the fine-tuned model, we observed that while many of the images that activated a filter for Rwanda shared some common pattern that we observed to be related to economic development (for example, a majority of images with roads or homes, see Figure 4), the groups of images that activated a filter in the Haiti model were more noisy. In the later convolutional layers, it was rare to find more than one image that suggested human presence in the same group of images that maximally activate a layer.

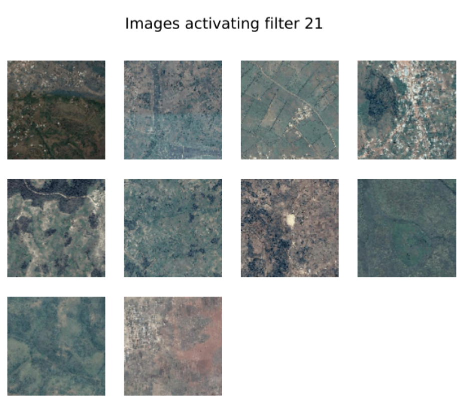


Figure 4: Filter from the fine-tuned Rwanda model that detects well-developed urban areas

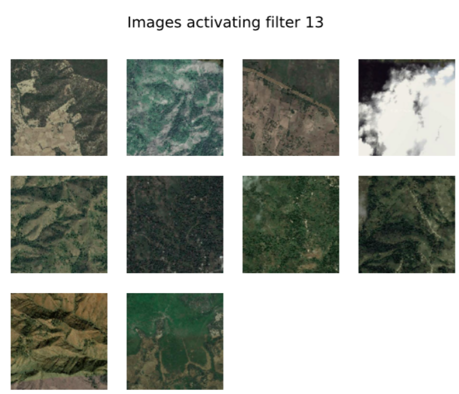


Figure 5: Filter from the fine-tuned Haiti model that detects mountainous wilderness

## 3.2 Relationship Between Nighttime Luminosity and Economic Measurements

We observed that prediction results for wealth were generally much better than for education, especially for Rwanda. We expect that night light intensity may be a better proxy for poverty than for education: it can be more directly linked to economic dynamism than to school infrastructure for instance. In countries where wealth index was predicted with at least an $R^2$ at least a few percentage points better than the education index, the $R^2$ from the linear regression was typically stronger for the wealth index (see Figure 1). The low correlation between night light intensity and education index suggests that any transfer learning procedure that relies on connecting night lights with education index may have limited ultimate accuracy.

# 4 Methods

**Data**

- **Demographic and Health Survey data:** We downloaded the latest version of DHS data for the three countries of interest: Nepal DHS 2011, Haiti DHS 2012 and Rwanda DHS 2010. For testing, we also downloaded Bangladesh DHS 2014, Burundi DHS 2012 and Guatemala DHS 2014

- **Nighttime light data:** We obtained the nighttime light images from the DMSP-OLS website for both F16 and F18 satellites in 2011, 2012 and 2010 to match with the year of the DHS data for Nepal, Haiti and Rwanda respectively.

- **Google Maps daytime satellite imagery data:** We obtained our daytime satellite imagery data from the Google Static Maps API with zoom level 16 (and pixel resolution at 2.5m). We want each image to correspond to a pixel of the nighttime light image (about 1 square km), thus each image is set at 400 pixels x 400 pixels. We created a shapefile for Nepal, Haiti and Rwanda to precisely download the daytime images.

## Retrieving wealth index from DHS data

Each household in the DHS data is assigned to a cluster (or a community). The DHS data of Nepal 2011 has 289 clusters, Haiti 2012 has 445 clusters, and Rwanda has 492 clusters. However, when we extract the shape-file from the GPS Geo-location file provided by DHS for Haiti, 8 clusters have the coordinate (0, 0), so we discard these clusters in our training and analysis. The DHS survey data provides a built-in wealth index, calculated by performing principal components analysis on easy-to-collect data about a household's ownership of selected assets, such as televisions and bicycles; materials used for housing construction; and types of water access and sanitation facilities ([1]). This wealth index is attribute HV 270 in the DHS data file, and is a continuous scale of relative wealth for each household. Finally, for each DHS cluster, we calculate the mean wealth index of all the household within that cluster and assign that as the wealth index of the given cluster.

## Building an education index from DHS data

From the DHS survey data per household, we found several education attributes : HV106 : Highest level of education the household member attended, HV107 : Highest year of education, HV108 : Education in single years, HV109 : Educational attainment and HV110 : Whether the household member is still in school. We found out much data was missing for all attributes, except for HV106 which had a good completion. HV106 is a standardized variable providing level of education in the following categories: No education, Primary, Secondary, and Higher. Any member below the lower age limit for the education questions is classified in the "No education" category. We assign value of 0, 1, 2 and 3 respectively for the categories No education, Primary, Secondary and Higher. For each DHS cluster, we take the average of all the category values and assign that as the education index of the given cluster. *N.B : While the education index per household is an ordinal value, taking its average per cluster yields a floating value that we assume as a continuous variable, that we can regress.*

## Extracting nighttime light luminosity data

The NOAA nighttime light intensity data includes digital luminosity level from 0 to 63, with 0 being the darkest pixel. We average the two satellites F16 and F18's data using ArcGIS software and remove gas flare effect by excluding gas flare data shapefile obtained from the NOAA library [?]. Once data cleanup is performed, we match the DHS year with the respective nighttime light images year to provide a more accurate training model. For Bangladesh and Guatemala, the available DHS data is in 2014 and 2015 respectively, and we choose to use the nighttime light images of 2013 for the training. To verify that the temporal effect of nighttime light images in two consecutive year is negligible, we map the histogram of Guatemala and Bangladesh in both 2012 and 2013. Then we did a Chi-square test to compare the two temporally different data. Our Chi-square test has a p value of less than .001, which shows that the temporal effect is negligible for Guatemala and Bangladesh. For each cluster of the DHS data in Nepal, Haiti and Rwanda respectively, we find the cluster's location in the nighttime light data using its coordinate. We take the min, max, median, mean and std of the nighttime light intensity of a 10 x 10 square centered at that coordinate. These values will become the nighttime light attributes for each cluster of a given country, and will be used later to predict wealth and education level.

## Extracting satellite images features

We fine-tune a pre-train 3-layer convoluted neural network (VGG 16) of the ImageNet dataset and use the daytime satellite images to classify nighttime light intensity. To do this, we prepare nighttime light data for all the countries of interest, and instead of using the numerical luminosity values, we categorize these into three distinctive luminosity classes: low for pixel intensity from 0 to 2, medium for 3 to 34, and high for 35 to 63. This is the same class range that Jean et al. used in their transfer learning approach, and we used this because we observed that the pixel intensity distribution of both Nepal and Haiti resemble that of Rwanda (with three dominant modes - the three classes listed above.) The model is trained and fitted using the daytime satellite images (described above) and its corresponding nighttime light luminosity (1 daytime image per a single nighttime light pixel.) Finally, the satellite images features are extracted from the last layer of the Convoluted Neural Network using this trained model as an extractor.

### Predicting wealth and education using transfer learning

For each country, we fitted and trained a neural network on the satellite images of this country for the specific task of predicting nighttime light intensity levels. We use the same neural network for both the education and the wealth index. Then, following Jean et al's method [3], we extract the final layer features and use them as the weights of a regression model for the education and the wealth index. This method is called **transfer learning** : we train a neural network for an intermediate task and use the results of this task as inputs for our ultimate goal, which is to predict wealth and/or education. The architecture of the neural network was built following the work of Xie et al. [2], and the network setting includes the following parameters: batch-size=100, learning-rate=.0001, and epochs=6

Finally, in order to achieve higher accuracy and better computational efficiency in our model, we followed a **fine-tuning** method described in a blog post on keras website ([4]), which consists in two phases: First, extract the bottleneck features of a pre-trained neural network (vgg16) and only train the top layers; and Second, retrain only the end of top of the net and the last convolutional block

## 5 Conclusion

We conducted this project in order to investigate two questions : to what extent the Jean et al.'s [3] method could be replicated to other geographical regions than their country of study, Rwanda, and to other economic indicators such as education level. From our results, we are tempted to answer negatively to these two questions, but further work on the tuning of the transfer learning model, or more precise data for education could yield more accurate results. First, we explain poor performances in predicting wealth on other countries compared to Rwanda by the difference in the distribution of the wealth index: Rwanda has a particular 'peaked' distribution of wealth that matches its nighttime light distribution very well, while other countries have smoother wealth distributions that nighttime light intensity, whether taken directly or indirectly from transfer learning, fails to explain. Secondly, while it has been proven in related work that nighttime light intensity is a good proxy for economic activity [5] and wealth [3], the correlation with education level is harder to draw. We suggest that this is mainly due to the lack of a more complete education index, or to the intrinsic nature of these two variables.

# References


[1] Demographics and Health Survey. Standard Recode Manual.DHS-VI Recode Manual.

[2] Michael Xie et al. 2015. Transfer learning from deep features for remote sensing and poverty mapping. arXiv preprint, 2015.

[3] Jean, Neal, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, and Stefano Ermon. "Combining satellite imagery and machine learning to predict poverty." Science 353, no. 6301 (2016): 790-794.

[4] Francois Chollet. 2016. Building powerful image classification models using very little data. Keras Blog.

[5] Mellander, C.; Stolarick, K.; Matheson, Z.; Lobo, J. Night-Time Light Data: A Good Proxy Measure for Economic Activity. CESIS Electronic Working Paper Series, The Royal Institute of Technology, Centre of Excellence for Science and Innovation Studies (CESIS).

[6] Glewwe, P., & Kremer, M. (2006). Chapter 16 Schools, Teachers, and Education Outcomes in Developing Countries. Handbook of the Economics of Education, 2, 945-1017.

[7] A. M. Noor, V. A. Alegana, P. W. Gething, A. J. Tatem, R. W. Snow, Population Health Metrics 6, 5+ (2008).

[8] Chen, X. & Nordhaus, W. D. Using luminosity data as a proxy for economic statistics. Proceedings of the National Academy of Sciences 108, 8589-8594 (2011). URL http://dx.doi.org/10.1073/pnas.1017031108.

[9] Ford, Timothy E., Rita R. Colwell, Joan B. Rose, Stephen S. Morse, David J. Rogers, and Terry L. Yates. "Using satellite images of environmental changes to predict infectious disease outbreaks." Emerg Infect Dis 15, no. 9 (2009): 1341-1346.

# 6 Acknowledgments

# 7 Appendix

## 7.1 The three countries of focus and some statistics

The 3 countries we chose show high variation in the distribution of education and wealth index. While Rwanda has a wealth index pretty low and constrained in a small range, Nepal wealth is overall higher and has a smoother distribution, same as for Haiti. Concerning education level, most of the Rwandan population (66%) falls into the primary education category, while the Nepalese population is less educated (49% of the population has no education), and Haitian population is more equally partitioned into no education, primary and secondary education. Below, we include some graphs that illustrate these differences. Finally, nighttime light intensity follows pretty much the same distribution for each of the three countries : very concentrated in the low intensity levels, even though Haiti shows more higher nighttime light intensities. This huge imbalance is a challenge we had to deal with while training our models.

### 7.1.1 Rwanda

We used data from the 2010 DHS household survey, that gathered responses from about 12,500 respondents.

**7.1.1.1 Rwanda wealth level** The wealth index in Rwanda is concentrated in a very small range around -0.5.

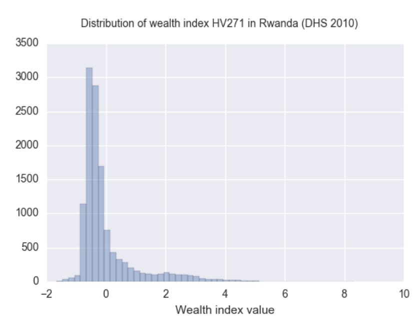


Figure 6: Distribution of wealth index in Rwanda (by geographical clusters)

**7.1.1.2 Rwanda education level** The top category is by far the 'Primary education level', which concerns 66% of the respondents.

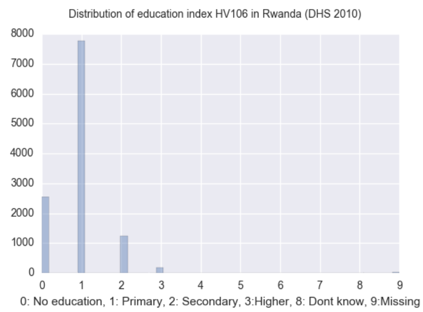


Figure 7: Distribution of education index in Rwanda (by geographical clusters)

**7.1.1.3 Rwanda nighttime light** Here we show the distribution of nighttime luminosity in Rwanda

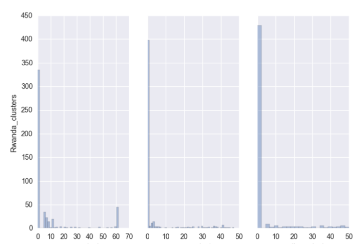


Figure 8: Distribution of max, mean, median nighttime light intensity values)

### 7.1.2 Haiti

**7.1.2.1 Haiti wealth level** The wealth index in Haiti is concentrated in a small range around -0.5 but is more evenly distributed compared to Rwanda.

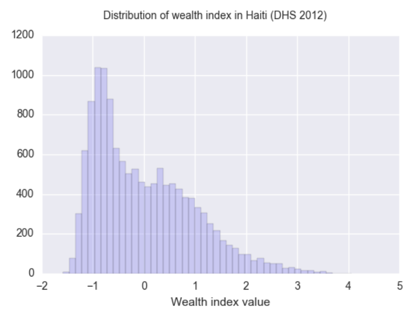


Figure 9: Distribution of wealth index in Haiti (by geographical clusters))

**7.1.2.2 Haiti education level** The top category is the 'Primary education level', which concerns 46% of the respondents.

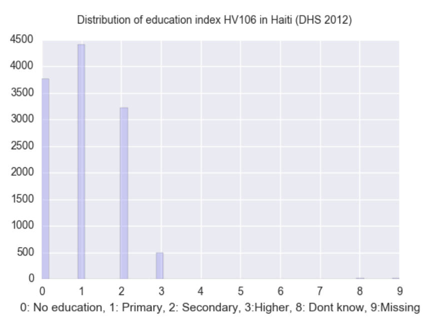


Figure 10: Distribution of education index in Haiti (by geographical clusters))

**7.1.2.3 Haiti nighttime light** Here we show the distribution of nighttime luminosity in Haiti

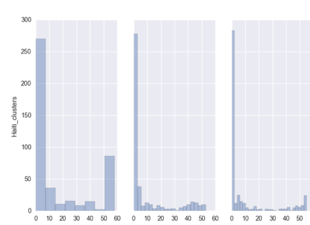

Figure 11: Distribution of max, mean, median nighttime light intensity values in Haiti)

#### 7.1.3 Nepal

**7.1.3.1 Nepal wealth level** The wealth index in Nepal is concentrated in a small range around -0.1 but is more evenly distributed compared to Rwanda.

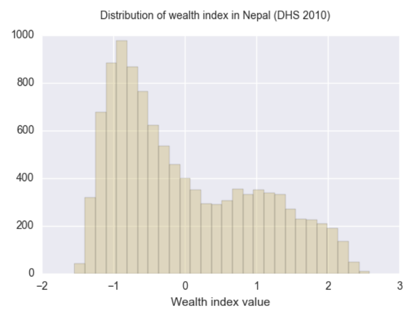


Figure 12: Distribution of wealth index in Nepal (by geographical clusters))

**7.1.3.2 Nepal education level** Top category is 0 no education : for 49 percents of population

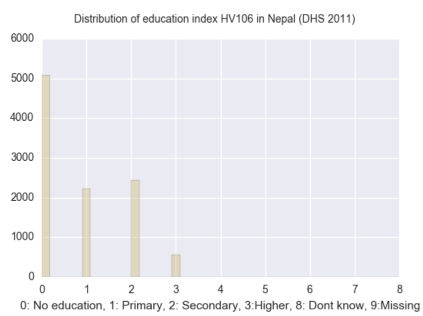


Figure 13: Distribution of education index in Nepal (by geographical clusters))

**7.1.3.3 Nepal nighttime light** Here we show the distribution of nighttime luminosity in Nepal

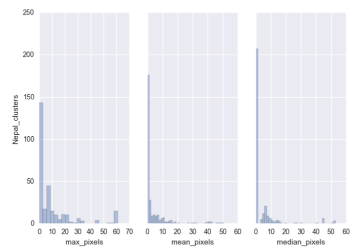


Figure 14: Distribution of max, mean, median nighttime light intensity values in Haiti)

## 7.2 Other images that maximally activate particular neurons

### 7.2.1 Rwanda


Figure 15: Rwanda : remote villages


Figure 16: Haiti : rural towns