Reliable Detection of Unelectrified Communities using Night Light Satellite Imagery

Recently, many works have used night-time light (NTL) measured from the Visible and Infrared Imaging Suite (VIIRS) satellite imagery as a proxy for poverty and electricity access [1], [2], [3]. Although NTL has been shown to be a reliable predictor of electrification in municipalities, many have concluded that in deep rural areas, it is not accurate due to high noise readings in VIIRS NTL images and lack of NTL variability in dim rural areas. Still, by complementing with temporal aggregations of VIIRS NTL imagery [4], it has been shown to have reliable accuracy in classifying unconnected communities even in deep rural areas.

This work provides a simpler, more accurate and more explainable method in classifying unconnected but inhabited communities purely based on NTL imagery. It shows that there exists a threshold of noise NTL radiance for which areas with NTL radiance below this level can be classified as unconnected with ~95% confidence. Conversely, it also shows that areas with NTL radiance higher than this noise level can be classified as connected with >80% confidence for areas above 200 households/km^2.

Using our method to classify unconnected communities, it was validated with the ground-truth dataset provided by the Uganda utility company, Umeme, that shows coordinates of ~1.6 million connections all across Uganda, which we used to label areas with less than 5% connection rate (number of connections per 100 household) as unconnected.

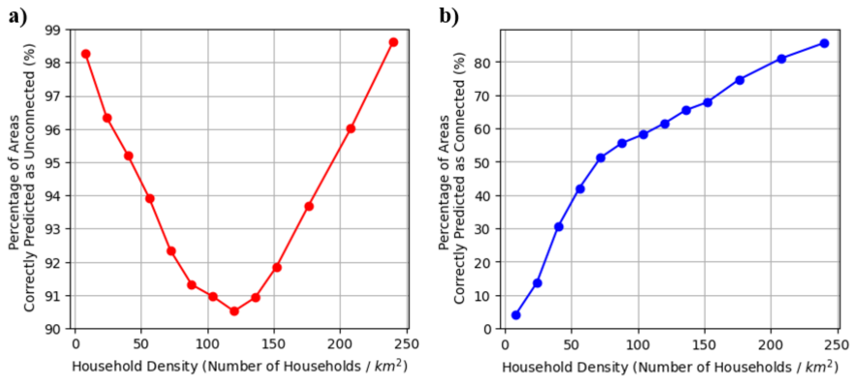

Figure 1: a) True positive rate score (a.k.a. precision) of identifying unconnected communities. b) Negative predictive value score of identifying connected communities. True positive rate is defined as amongst datapoints predicted as non-connected, what is the percentage of correct predictions. Negative predictive value is defined as amongst datapoints predicted as connected, what is the percentage of correct predictions.

Figure 1b shows that at areas with lower household densities, the confidence level is poor but at higher household densities, the confidence reaches above 80% which may be a good method to classify connected communities.

From Figure 1a, it shows that we have about 95% confidence in identifying unconnected communities all across Uganda, with confidence levels reaching 98% for lower and higher household density areas. This shows using just NTL satellite imagery, we are almost certain at identifying unconnected communities. When we plot these unconnected communities on the map (Figure 2), we can even notice that some are actually close to the grid, signifying opportunities to expand the grid infrastructure with minimal cost to reach more customers.

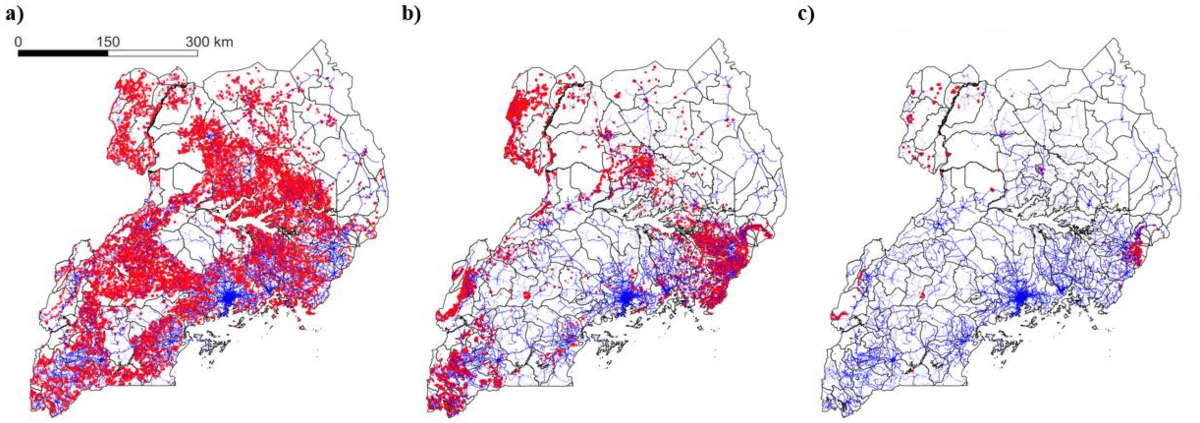

Figure 2: Areas predicted as unconnected with household density a) 30~40 , b) 80~140, c) 160~260 households / km^2 in Uganda. The red scatter plots refer to areas predicted as unconnected. The blue line refers to the Medium Voltage Line.

These results indicate that, in other countries suffering from huge data gaps in electrification records, this method can be a reliable and simple method to identify unconnected communities. On top of this, with household locations (derived from Google's Open Building model detecting man-made structures) this method can pinpoint large communities with poor access to the grid. Supplemented by location of medium voltage lines, opportunities to cheaply expand the grid to large unconnected communities can be presented.

References

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