Poverty Estimation with Satellite Imagery at Neighborhood Levels

Results and Lessons for Financial Inclusion from Ghana and Uganda

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Creating Markets, Creating Opportunities

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Executive Summary

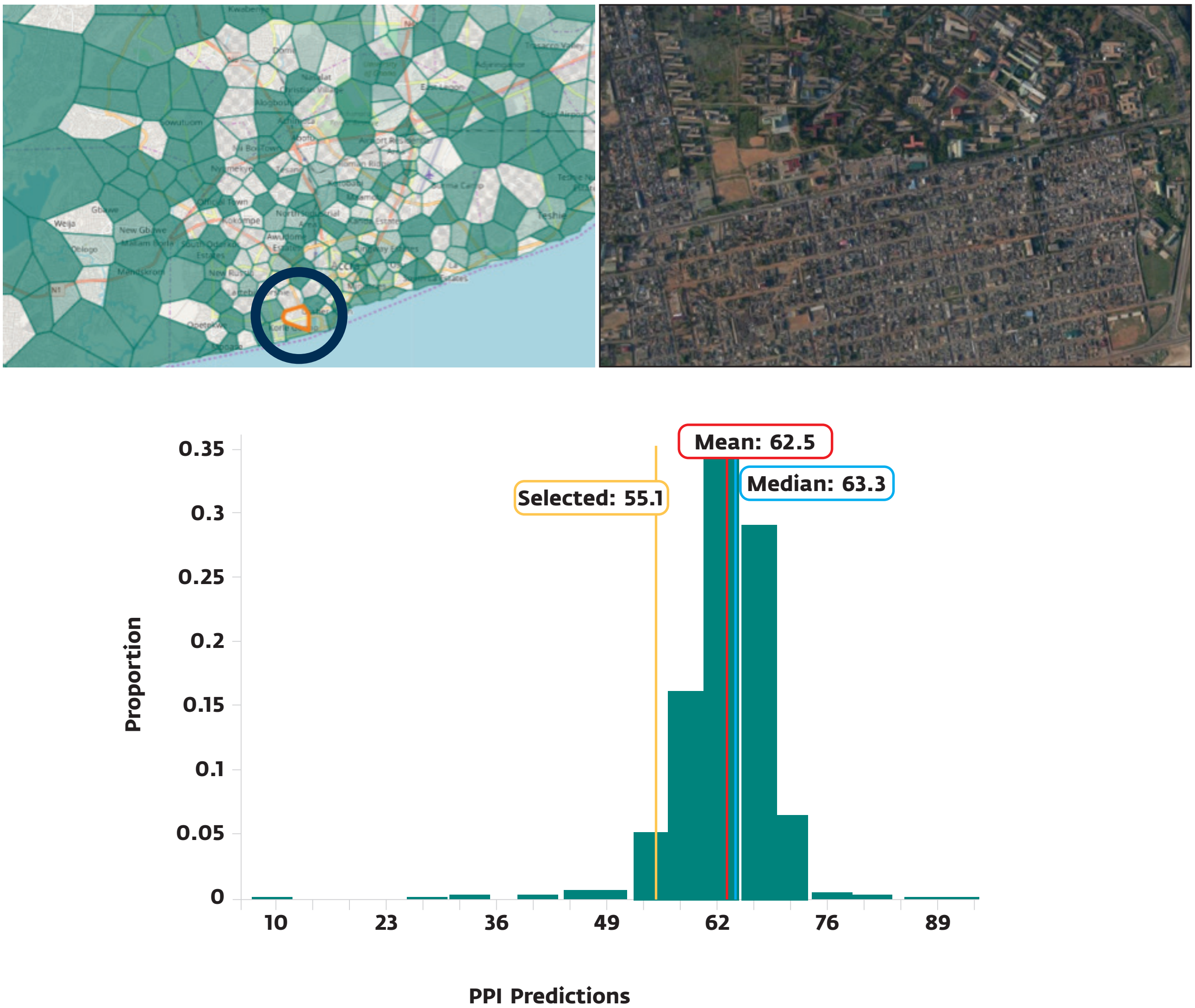
By successfully reaching historically underserved and vulnerable populations such as women, the poor, and people living in rural communities, Digital Financial Services have contributed to unprecedented growth in financial inclusion in Sub-Saharan Africa during the past decade. The adoption and usage of DFS -- and the subsequent financial inclusion that has resulted -- has helped reduce poverty and increase prosperity throughout the region. Still, service providers and development practitioners often lack reliable, detailed, and low-cost poverty data that could help them accurately identify additional communities and individuals who would benefit the most from access to financial services. The lack of data hinders the deployment of services throughout the region and complicates efforts to monitor and evaluate the impact that interventions have on poverty.

Relying on traditional household surveys for poverty data is time consuming and expensive. What's more, by the time the data are collected and analyzed, it is often out of date. But there are alternatives for estimating and mapping poverty with the goal of accelerating and expanding financial inclusion and helping DFS providers target the poorest. Machine learning algorithms can, for example, be trained to predict poverty based on imagery captured by satellites and from call detail records, which document mobile phone usage. For this research study, the IFC-Mastercard Foundation Partnership for Financial Inclusion collaborated with the Stanford University Sustainability and Artificial Intelligence Lab to advance existing poverty prediction models to generate poverty estimates at neighborhood-level resolution, which is much more refined than macro-level estimates produced by research to date. Satellite Imagery and call detail records (CDR), validated by ground-truth surveys, were used to develop models that can predict poverty in Ghana and Uganda.

The study finds that it is possible to make meaningful welfare estimates based on satellite imagery combined with geo-spatial boosting at the neighborhood-level when lower levels of precision are acceptable. The study makes estimates about poverty demographics in regions that are bounded by cell tower locations. Predicting poverty around cell tower locations allows small area welfare estimation in urban environments where cell tower density is high. Above all, daytime satellite imagery proves to be a good basis for poverty prediction, but significant caveats remain. Models may be improved by adding context-specific segmentation that can, for example, detect features such as cars or trees on satellite images in urban areas. This constitutes a future area of research for the community. In lieu of more advanced machine vision feature detection, this study employs spatial boosting techniques, which are found to improve models for estimating poverty in rural areas where there are fewer welfare variations among neighbors than in urban centers. Although, with increased urbanization over time, this is another area that satellite imaging could support. Changes in welfare over time, particularly due to the availability of financial services, are likely to considerably outpace observable infrastructure changes, not least due to the time needed to construct new buildings. Here, changes in financial service usage patterns through provider data are expected to yield stronger implications on financial inclusion and livelihood effects on a year to year basis.

The study compared various statistical poverty estimation methods and identified the Poverty Probability Index (PPI), which yields better results with satellite imagery. Low activity levels and variation of transaction behavior can make it difficult to use phone and mobile money data for poverty prediction. Although, remote sensing poverty estimation models can reduce the sample size for surveys, a broad spectrum of representative ground-truth survey data is essential for developing and training well performing poverty estimation models. In this respect, the research finds that remote sensing and geospatial boosting approaches can be used to improve efficiency and optimization for traditional household survey methods. However, significant work remains before remote sensing models can fully replace ground-based surveys.

This paper also explores the interpretation of predicted poverty scores, using PPI estimators, presenting them on heat maps for Ghana at neighborhood-level granularity and layering atop information about telephone and mobile money activity of users in the same areas to inform targeting and monitoring of interventions for poverty reduction and financial inclusion. This visual layering is proposed as a conceptual strategy for how combining techniques discussed in this study might be used to better quantify financial access, financial inclusion reach and support providers to better understand customer demographics and size their markets.



Executive Summary Visualization of Image Table 8: Mapping PPI predictive scores using the study mapping approach and predictive scores, compared against a satellite image. PPI is the Poverty Probability Index, a standard poverty estimator tool that can translate a PPI score into estimates of multiple benchmarks (eg, $1.90/day or $5/day or access to types of infrastructure).

Introduction

Financial Inclusion empowers underserved individuals to participate in the formal economy, facilitates access to financial services that help businesses grow, and is critical to achieving economic development policies that aim to eliminate poverty. Digital Financial Services support these development interventions by increasing the breadth of delivery channels, variety of services, and affordability of financial access for consumers and companies. DFS are tuned to reaching segments that are historically underserved, such as women, rural individuals and the poor. This is especially evident in Sub-Saharan Africa, where cell phone penetration reached 44 percent as of 2018[1], meaning that nearly half of the one billion adults in the region now have the potential to access financial services through mobile phones. The growing prevalence of DFS on the continent has been a driving factor in enabling financial access for poor and underserved individuals, as mobile money usage has increased from near nil just seven years ago, to 20.9 percent by 2018. Today, financial inclusion is at 43 percent in Sub-Saharan Africa[2]. While marking impressive reach, it is difficult to precisely quantify the extent to which the poorest segments are represented in this growth.

Development strategies to accelerate financial inclusion — and commercial providers seeking to scale Digital Financial Services — lack access to reliable demographic data on poverty. Collecting data using traditional household surveys is time consuming, expensive, and data are quickly outdated by economic changes and population movements. Using remote sensing technology, call detail records and machine learning algorithms provides a solution to close this gap.

Call detail records have been successfully used to predict poverty in some countries; both, for models that attempt to predict welfare based on call activity only, as well as for combined models that include telephone data and remote sensing covariates[3]. However, relying on CDR data for regular poverty measurement may be complicated as these data are privately managed by service providers. Unless data from all main service providers in a country is combined, poverty estimation is likely to be biased or incomplete.

Other methods have also shown promise. Notably, using night time satellite images to view and measure ground-based light emissions that can correlate the magnitude of intensity and coverage area cast by light emissions with economic activity and general well-being of denizens within the coverage zone[4]. While results from night light images are tantalizing, the level of granularity is low.

As light diffuses over large areas, this approach alone provides meaningful interpretation often only at the city-level, or even at more roughly defined coverage areas of larger administrative districts. As demographic and wealth variations are far more granular - both within urban neighborhoods and in rural environments - satellite-based poverty estimation models must deliver much more granular estimates to yield sufficient information for policy makers to target underserved populations; and for commercial DFS providers to better segment their potential customer base and service coverage areas.

Using day-time satellite images provides an alternative approach to resolve these granularity issues and deliver results that are more aligned with the data required by policy-makers and DFS providers. This approach was demonstrated by Jean et al. (2016), using a convolutional neural network methodology to identify visible features in high-resolution day-time satellite images, which correlate with demographic data (e.g., roads, agricultural areas, urban environments, building types).

This study expands the approach through a collaboration between Stanford University's Sustainability and Artificial Intelligence Lab and the IFC-Mastercard Foundation Partnership for Financial Inclusion. The study engages questions and areas of further exploration identified in existing literature to specifically look at using day-time satellite imagine methods to predict poverty at the lowest income segments (e.g., below $1.90, or $5.00 per capita per day, using standard poverty threshold benchmarks).

Here, different poverty estimation models are developed for two African countries. Multiple measures of poverty are employed to compare and understand relevance for training models of this nature. The study compares modelling methods and poverty definitions across these two country contexts to learn about trade-offs and optimizations for developing models to predict poverty. The applied research goal is to support DFS providers and financial inclusion policy interventions with a strategy for enhanced information about markets, services and the characteristics of the people who use (or don't use) these services. The approach defines demographic segments geographically, to establish tangible micro-markets as a unit of analysis, and then explores these segments with respect to predicted wealth characteristics, access and usage of digital financial services.

1 *GMSA 2018*
2 *Demirgüç-Kunt et al. 2018*
3 *Steele et al. 2017*
4 *See for example Gosh et al. 2013*

Data and Methods

Ground-Truth Survey data

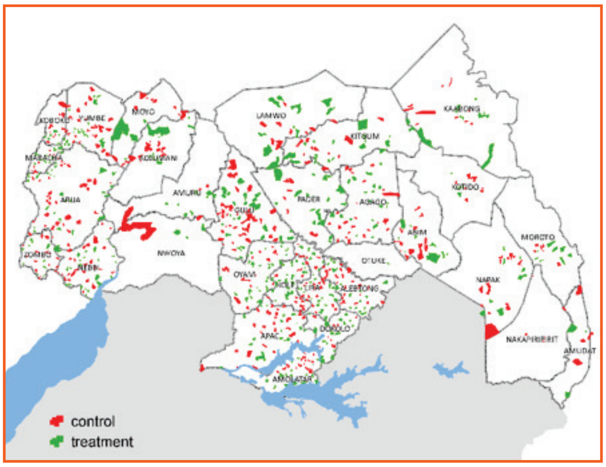
This study was implemented in Uganda and Ghana. In both countries, ground-truth poverty data was collected using household survey instruments. These instruments incorporated modules to assess household poverty and welfare levels. Instead of directly asking household respondents about their consumption levels, which are likely subject to inaccuracies due to seasonal fluctuations and recall bias, different poverty measurement tools were used that eliminated the need to collect detailed consumption data. The survey instrument for Uganda included a SWIFT (Survey of Well-being via Instant and Frequent Tracking) poverty estimation module. Whereas in Ghana, a PPI (Poverty Probability Index) estimation module was used. In addition, information about households' asset ownership was collected in both countries to calculate an asset-based wealth index, using a similar approach as the SustainLab Index used similar research in this area[5].

- PPI is a poverty measurement tool to compute the likelihood that a surveyed household is living below a given poverty line based on answers to 10 country specific multiple-choice questions about household characteristics and asset ownership. Questions can also include visual, observable features such as house roofing material (e.g., is your roof tile, thatch, corrugated metal) or if there is an outdoor latrine. The PPI score is a value between zero and 100; it can be calculated for every household. The lower the score, the higher the likelihood of a given household to be poor. Look-up tables convert PPI scores into likelihoods to fall under different poverty lines in a country and may be interpreted for multiple different poverty threshold benchmarks using the same PPI score.

- The SWIFT methodology was originally developed to monitor one of the World Bank Group's goals of ending extreme poverty. It helps estimate household expenditure data and poverty rates in a simple and cost-effective manner based on answers to 10-15 general household level survey questions (e.g. education levels, asset ownership and household size). SWIFT models for specific regions and countries are derived from existing household budget survey data (multiple rounds of LSMS surveys) indicating which variables are poverty correlates and should be collected in the core SWIFT survey to then estimate consumption and poverty rates.

- The SustainLab Asset-based Wealth Index calculated for this study used principal component analysis on responses to a panel of seven asset ownership questions within a household survey. The largest resulting principal component was used as an index value. The hypothesis was that this index would potentially provide a better method of aggregating different contributions of variables to derive poverty levels than a mere sum of scores that weighs different answers to a list of questions, as the PPI methodology does. This method was previously employed by Jean et al as a poverty predictor in remote sensing models and was therefore used for prediction models in both Ghana and Uganda for consistency.

Figure 1: Enumeration coverage areas in Northern Uganda



The Uganda survey focused strictly on Northern Uganda, one of the poorest areas of the country. In conjunction with another study investigating the adoption and impact of DFS to better scale financial inclusion, IFC collected data between November 2017 and January 2018 for 9,037 households within 926 enumeration areas covering the Ugandan administrative areas of Karamoja, Mid North and West Nile, and Adjumani (see Figure 1).

To ensure ability to tune the satellite image-based modelling, the survey incorporated robust GPS data for each surveyed household, at high levels of precision[6]. This aimed to resolve one of the issues that was previously faced by Jean et al. (2016), which drew on third-party geo-localized survey data that reduced precision by adding up to 10 km of random noise. Here, coordinates were precise within a few meters of survey location.

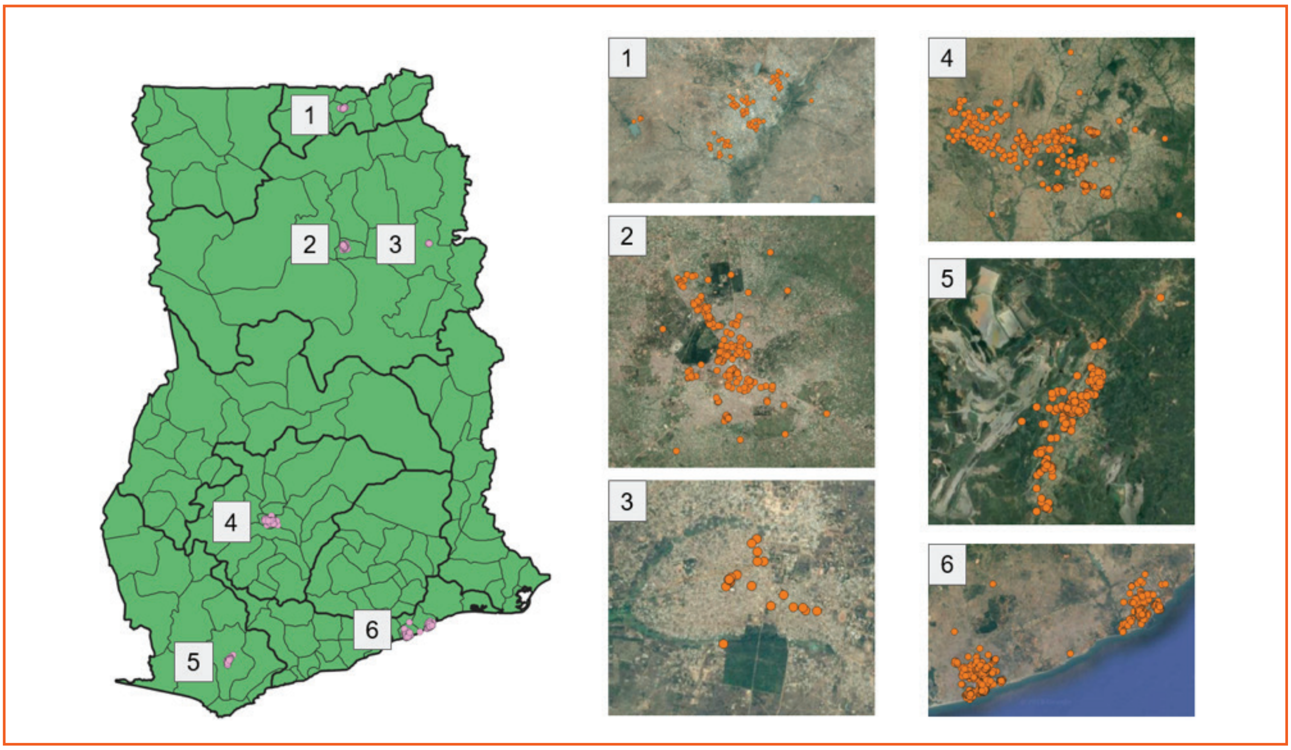
5 *Neal Jean, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, Stefano Ermon. "Combining satellite imagery and machine learning to predict poverty," Science, 19 Aug 2016: Vol. 353, Issue 6301, pp. 790-794*

6 *GPS data achieved high levels of precision overall and the survey data collection methodology implemented robust cross-checking and validation to ensure accuracy and correction of GPS measurement errors. However, due to survey environments in very rural areas, often with farmers, individuals often responded to surveys at community village areas that were proximate to houses but not precisely located at the household for which household information was being reported.*

Similarly, the Ghana survey ensured precise geo-localized survey data. The survey design covered a much larger area, spanning across Ghana, rather than the regional focus implemented in Uganda. Moreover, the enumeration areas were more focused on urban centers and densely populated areas (see Figure 2).

The survey was implemented from December 2017 to February 2018 for 2,165 individuals within six enumeration areas, in which coverage zones ranged between a one and three km radius in seven Ghanaian cities and villages, distributed in five principle administrative regions.

Figure 2: Enumeration coverage areas in Ghana.
Zones are described in terms of their principle regional cities. 1=Bolgatanga, 2=Tamale, 3=Yendi, 4=Kumasi, 5=Tarkwa, 6=Accra + Tema



Call Detail Record and Mobile Money Data

Through IFC project operations, the study incorporated anonymized call detail records and mobile money transaction data from mobile network operators (MNOs) respectively in Ghana and Uganda. Both operators have significant national coverage and the datasets provided customer-level information on numbers of incoming and outgoing calls; SMS volumes; Cash-In transactions; Cash-Out transactions; and transfers between mobile money accounts. Information about the geo-localization of activity through cell tower locations was also provided.

The study expected to identify correspondence between call detail record data and the household survey data from respondent by matching phone numbers across these data sets. The objective was to explore additional CDR-based models for predicting poverty. In both countries, the surveys were conducted using a randomized design; and in both cases, meaningful overlaps were not obtained between the surveyed customers and the CDR data. In Uganda, of the 9,037 survey responses, only 222 matched the CDR data. For Ghana, of the 2,165 survey responses, 166 matched the CDR data. With mobile money adoption levels still lying below the levels of sim card ownership, matching survey and mobile money transaction data was even more difficult. In Ghana only 57 household records matched the respective mobile money dataset. Ultimately, too few observations could be matched directly to train meaningful prediction models. For the CDR models presented in this study, another approach was therefore used for approximation. CDR models were trained with household information that was aggregated and matched with telephone activity data by cell tower catchment area and not by individual household. Results from these models are presented in Table 1 for the sake of completeness, but accuracy figures are unsurprisingly very low and hold little interpretive value due to the poor alignment between survey and provider data and extremely small training sample underlying the model.

Multiple factors may explain the low overlap of survey and mobile network operator data. Different time periods of data collection for survey and MNO data are one factor. Survey respondents may have joined the respective MNO networks after CDR data was extracted or may have churned before. It was moreover determined that survey enumeration areas poorly overlapped with areas where these operators had meaningful market share. Even though service was widely available, other providers dominated these markets. This was confirmed by survey respondents, who reported using other providers. Lastly, in Uganda, the rural-focused survey also found that only one-third of respondents had phones, which considerably limited the pool of potential correspondences between survey and CDR. This yields an important insight for future research: there may be trade-offs between randomized representativeness of a population sample and ability to meaningfully correlate demographic statistics with provider data. A stratified survey approach to deliberately over-sample individuals who are customers of the service provider should be considered.

Satellite Images

Models were developed using both day and night-time satellite imagery. Day-time images were sourced from DigitalGlobe, with a high resolution of 67m2. Night-time images were sourced from VIIRS, at 750m2 resolution. Below, example images are shown for Uganda and Ghana. Survey regions in Uganda were far more rural, by design. Whereas in Ghana, survey coverage included more urban and peri-urban environments across the country. The 'ruralness' in the Uganda survey area is more pronounced in the nightlight images, showing scant light signals in most of the images. The more urbanized regions in Ghana, by comparison, show gradients of deep purple zones (dark, low-light emissions, correlating to low electrification) to bright yellow zones (bright, intense-light emissions, correlating to people using artificial light in homes, offices, cars; general urbanization). These sample images also illustrate the difficulty of using night-time light emission imagery for household-level poverty prediction. At 750m2 resolution, entire neighborhoods can fit under a single pixel, and an entire city within a single image. Even though night-time images were incorporated into the predictive modelling, the coarse resolution of the information yielded little predictive value to improve model accuracy or descriptive power at the granular neighborhood level sought.

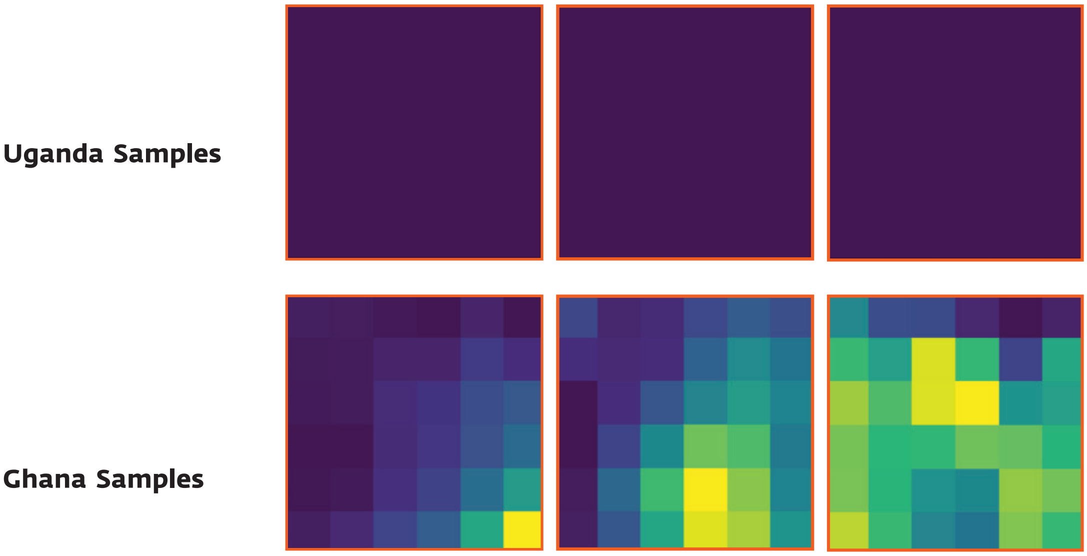
Image Table 1: Daytime satellite sampled images: 67m2 resolution from DigitalGlobe

Uganda Samples

Ghana Samples

Uganda shows increased prevalence of rural features: farms and open space surrounding single-level buildings. Ghana shows mixtures of features and increased urbanization, neighborhood housing configurations, paved roads and multi-story buildings.

Image Table 2: Nighttime satellite sampled images: 750m2 resolution from VIIRS



The random sampling of representative nighttime images aligns with the day time images: the uniformly dark purple images in Uganda indicate extremely little light emission, meaning few people live in the coverage zone, or those that do aren't using lighting at night. Whereas in Ghana, the bright yellow and shades of color depict increased urbanization and peoples' collective usage of lighting within the coverage zone.

Spatial Segmentation

The MNO cell tower data was used to create geographical segments by constructing Voronoi[7] polygons based on the tower locations. As both network operators had national coverage, this provided a useful method of creating spatial zones that covered areas from neighborhoods in densely populated urban areas (where cell tower density is high), up to much larger zones in rural or unpopulated areas (where cell tower density is low, or nonexistent). Although approximate, the technique enables grouping poverty estimates by cell tower coverage zone, and by association, to estimate demographic averages of people living within the coverage zone of their nearest "home" tower. For service providers, this allows interpreting customer demographics in terms of populations living near cell towers.

For developing poverty prediction models, physical images around cell towers were used, rather than the full geographic area covered by the Voronoi polygon. This was for the sake of computational simplicity and the cost of accessing and computationally processing high quality daytime satellite images (Ghana, for example, would be represented by approximately 53 million individual high-resolution image files). In this analysis, satellite images were downloaded from DigitalGlobe and VIIRS, around the geographical areas corresponding to the GPS coordinates collected in the household surveys conducted and the mobile network operator tower sites.

In high-density urban areas, higher tower density results in much smaller polygons, permitting the satellite picture around the tower to suitably represent the demographics of the overall area, typically a neighborhood or even smaller coverage zone. However, in rural areas, the Voronoi polygons are far larger due to low cell tower density. A shortcoming of the methodology is that it may not be reasonable to assume that the area seen on the satellite image around the tower is representative of the broader region. In fact, it may not be: in rural areas, a tower could be placed centrally in a town, while the environs beyond may be entirely uninhabited. In that case, the poverty prediction model would therefore likely over-estimate poverty averages for the associated polygon area. This acknowledged, poverty estimates may still reasonably estimate the average demographics of the individuals within a polygon area, since disproportionally more people are likely to live in a rural town as compared to the very sparsely populated surrounding area.

Spatial Boosting

Granular poverty prediction models based on satellite imagery are challenged by individual images having relatively low-density of signal-rich features in a given image tile. For example, a grassy image might show a green field whose trimmed grass is recently "mowed" by livestock in a sparsely populated rural area. Similarly, an image of trimmed grass might also show the manicured lawn of an upscale residential neighborhood in an urban area. The figure below illustrates this point, comparing top and bottom wealth photo examples in Northern Uganda. Where the wealthier image is similarly rural and depicting agricultural features, it also shows nuances with more refined looking fields, higher quality thatch roofing on out-buildings, and in the bottom-right corner, the cropped portion of a larger building with an angular blue roof. In this sense, it may be unclear if trimmed grass per se; or thatched roofs per se, correlate with income (let alone the ability of machine learning algorithms to identify such features). The problem arises: which visual patterns generate signals to pay attention to.

Image Table 3: Comparing bottom and top wealth images in rural Uganda

Bottom 1% of surveyed wealth

Top 1% of surveyed wealth

7 *A Voronoi decomposition is a method of segmenting space around a set of points such that the borders of the resulting polygon area are equidistant from other adjacent points. Any given point is thereby located at the weighted center of the polygon, in relation to its neighboring points.*

The ideal goal of remote sensing poverty prediction would be to shine a viewpoint over any spot on earth, accurately extract visual information, and derive estimates of the demographic norms of the individuals living in the area. Presently, the technology does not yet permit ex-ante predictions – ground-truth data is necessary to train predictive models with known true data points. Research of this nature therefore requires relatively large survey samples. A challenge – also faced by this study – is that surveys must be representative not only of the demographic population, but also of the visual space. That is, to have data for individuals across the income spectrum – and also to have an additional dimension of the spectrum of visual environments in which they live. For example, what a low-income house and field in a rural area looks like, as compared to a high-income house and field in a rural area.

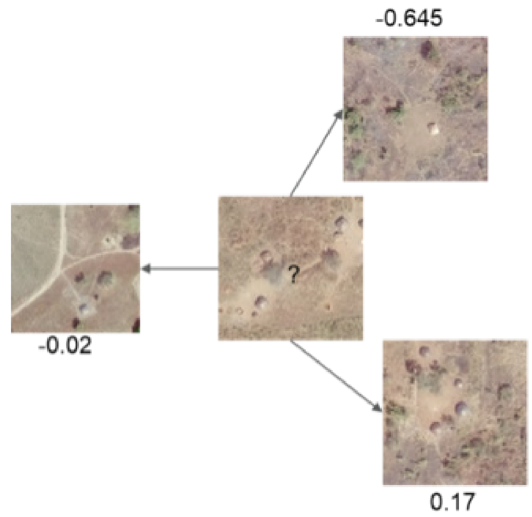
In Uganda, surveys expressly focused on rural low-income areas and generated GPS coordinates for images around low-income households. The result was thin survey data of wealthy comparators with which to train models to differentiate the visual cues associated with the spread of welfare and poverty levels. Somewhat conversely, in Ghana, survey data focused on urban areas, which resulted in fewer samples of what rural demographic variations looked like. However, as Ghana surveys had much broader geographic coverage, surveys and images were far more diverse compared with Uganda and generated a stronger set of features.

To ameliorate the issue of survey visual variation, a method of spatial boosting was employed to estimate income demographic information for visual areas that did not have an explicit survey data point. This was done by creating Voronoi polygons between known household survey GPS coordinates, a strategy similar to the spatial segmentation employed at the level of cell tower locations. Here, images that were not directly associated with household GPS coordinates inferred poverty levels as a weighted average of several closest neighbors, by assuming that households near known survey locations were likely to evidence similar income demographics.

In rural areas that are sparsely populated, this assumption is stronger, as more geographic distance will likely be traveled before large changes are observed in the population income characteristics. In urban areas, a household might also be expected to evidence similar characteristics as immediate neighbors, but the rate of change between a less-wealthy and relatively more-wealthy neighborhood might be more sudden. Indeed, this assumption is borne out in the results, where spatial modelling in Uganda shows a higher R-squared value as compared to Ghana, where the small-scale spatial variation is higher, leading to lower explanatory power.

The spatial boosting approach is depicted in Figure 3 below, where the central satellite image's asset-based wealth index score is estimated by using the nearest neighbors whose scores are calculated using known survey data.

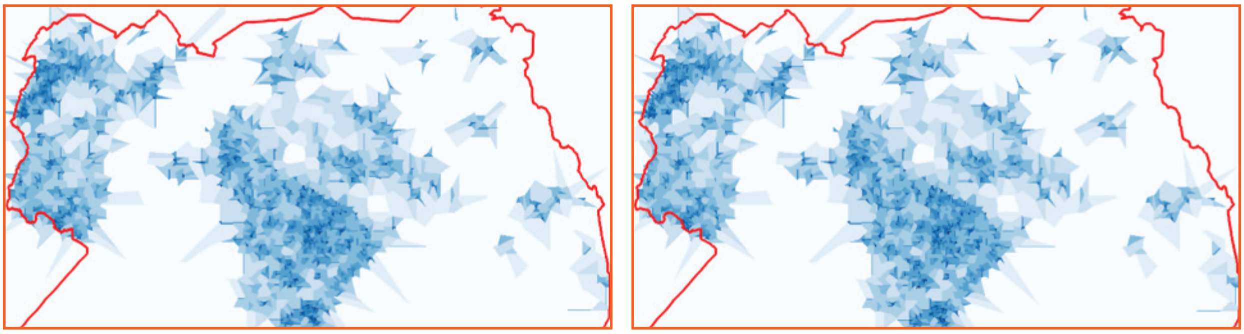
Figure 3: Nearest-neighbor spatial boosting



Aggregating the spatial boosting across the survey enumeration areas is depicted in Figure 3, for Uganda. The strongest signal was detected at an aggregation of 10-nearest neighbors.

In Ghana, 8-nearest neighbors clustering was used. Image Table 4 below compares spatial boosting at the aggregate level of the entire survey coverage area in Uganda: the visual differences are quite small between the actual survey data and the predicted scores at the level of the Voronoi polygons.

Image Table 4: Aggregated spatial boosting in Uganda: comparing survey and predicted values



Ground-Truth Survey Score Gradients | **Poverty Prediction Score Gradients**

Computer Vision Models

The satellite models that are presented in this study are models that predict poverty levels based on features derived from satellite imagery through programmed visual pattern recognition. The models are convolutional neural networks, which are a classification of machine learning algorithms. Meaning, with appropriate training, the computer can effectively learn to "see" relevant features in the associated images.

Convolutional neural networks are neural networks with multiple mathematical layers (between input and output layers) that can recognize visual patterns directly from pixel images with minimal processing since they filter pixel connections by proximity.

The satellite models presented below are so-called ResNet models. ResNet models are convolutional models that through their design address the common challenge when training networks with multiple layers that normally let model performance saturate or decrease with the addition of layers (vanishing gradient problem). For this study, ResNet models were used that had been pre-trained for pattern recognition from generic images and they were further fine-tuned with additional layers and simple extensions based on the relevant country datasets in Ghana and Uganda and the study's objectives to see features that correlate with income demographics.

Results

A variety of prediction methods were explored in the Uganda and Ghana contexts, as well as using different poverty score metrics as dependent variables for the models. A comparative table of key models is shown below (Table 1) specifying each model by listing the category of features that were included in the model (from satellite imagery, through spatial boosting or derived from call detail records) as well as the poverty metric that was predicted respectively. Models that use spatial boosting in combination with satellite imaging yielded the most explanatory power in both countries.

Models

In Uganda, using a combined model approach yielded an R-squared value of 0.28 using an asset-based wealth index as the outcome poverty metric. In Ghana, the highest R-squared value observed was 0.2, using an asset-based wealth index as the dependent variable. In basic terms, this means that the predictive models are able to explain 28 percent and 20 percent of the variation in poverty observed in Uganda and Ghana, respectively. Generally, these figures are not considered especially strong indicators of explanatory power. However, in the context of explaining differences in welfare from one neighborhood to the next, even a small percentage may offer meaningful insight.

Table 1: Comparison of Poverty Prediction Models

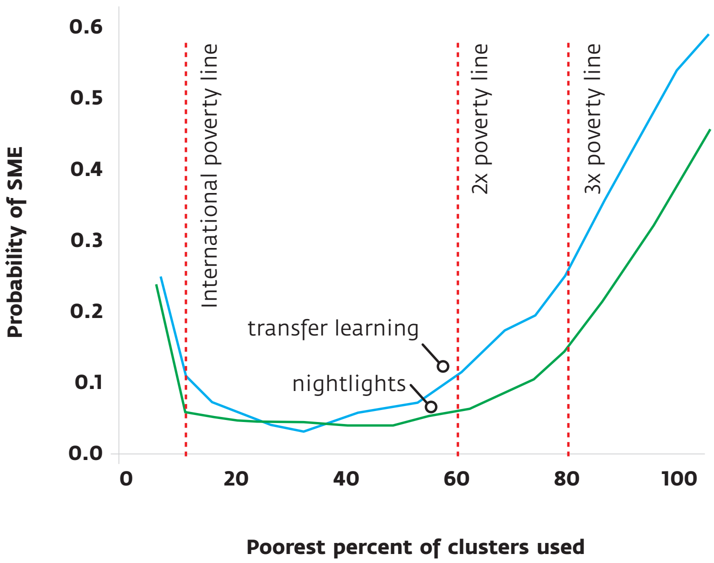
MODEL	POVERTY METRIC	R2
Ghana		
Satellite	Asset-based wealth index	0.01
Spatial	Asset-based wealth index	**0.20**
Satellite + Spatial	PPI	**0.15**
CDR	PPI	0.07
Uganda		
Satellite	Asset-based wealth index	0.14
Spatial	Asset-based wealth index	**0.23**
Satellite + Spatial	Asset-based wealth index	**0.28**
CDR	SWIFT	0.01

Benchmarking

Among the poorest demographics, these results are comparable to previous work conducted by Jean et al. (2016). In that study, the pooled results of the day-time satellite image model yielded R-squared values of approximately 0.10 to 0.25 for the set of poorest clusters below the poverty line of $1.90 per capita per day (see Figure 4).

Explanatory power falls between 1x and 2x poverty line, suggesting difficulty in identifying visual signals to segment gradients of poverty. Noting that the authors' approach yielded scores for larger geographic areas, the model was able to achieve R-squared results of up to 0.6 across all ranges of income demographic clusters, notably increasing explanatory power at levels greater than $5.00 per capita per day income (i.e., approximately 3x and above).

Figure 4: Pooled observations of transfer learning model and nightlights model by Jean et al. (2016)



This research explored poverty estimates at more granular household and neighborhood levels. As previously noted, the CDR-based models were inconclusive due to poor ability to match phone customers and survey responses and acquire a statistically robust sample. Therefore, the models produced results at the relatively granular resolution of neighborhoods, as defined by areas in proximity to cell phone tower locations at a variable resolution of the Voronoi polygons. As spatial resolution of poverty estimates was variable, depending on cell tower density, the results are not directly comparable to the more constant resolution discussed in Jean et al. (2016). Nevertheless, models achieving R-squared values of 0.28 and 0.2 may be considered reasonable, given the nature of the input data and granularity of estimates sought, and that estimates were specifically targeting the lowest clusters of observed income.

Poverty Estimators

Whereas other research has focused on income estimates in a more absolute range across populations (such as predicting a specific income value), this study incorporated different poverty estimation methods, PPI, SWIFT and an asset-based wealth index, to estimate poverty prevalence more generally. The PPI and SWIFT approaches achieve this by providing a statistical estimate that a household is simply above or below a given poverty line. Focusing at more granular spatial levels of urban neighborhoods results in lower power of models to explain the range of approximated levels of household consumption and poverty incidence but the models show a reasonable ability to impute overall prevalence of poverty.

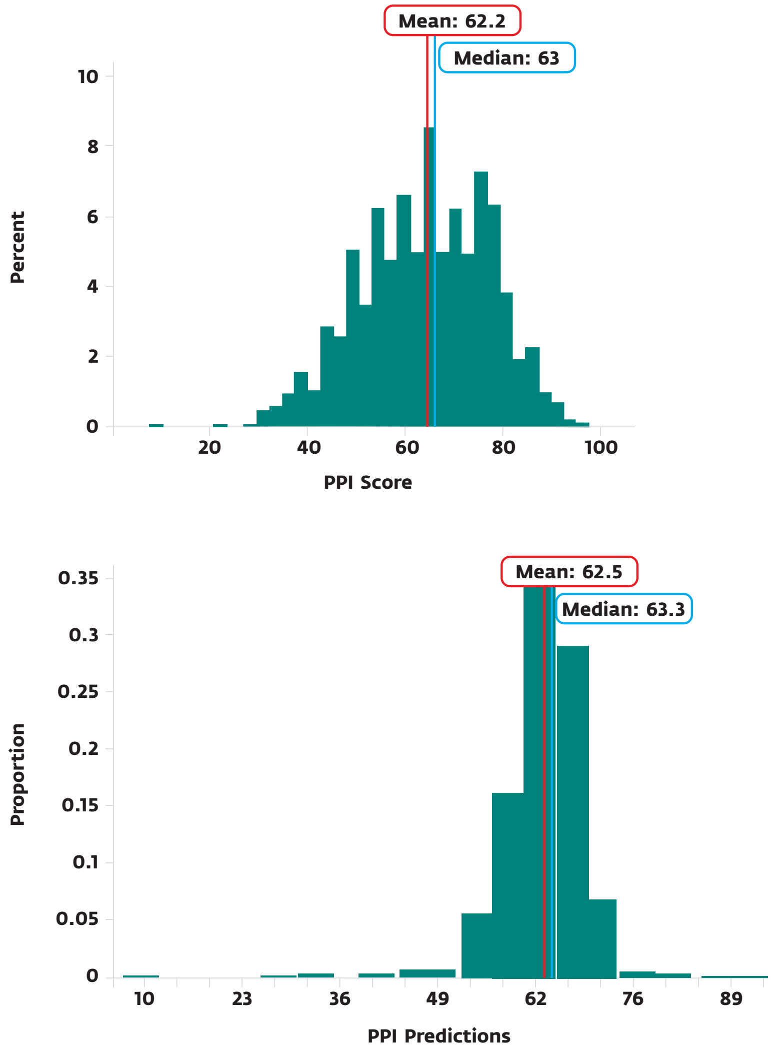
Below, predicted poverty scores, their interpretation, and comparison with actual images are explored and discussed in more detail by the example of the PPI predictions of the Ghana satellite model. Although model results primarily incorporated the SustainLab asset-based index approach and provide some comparability across the Uganda and Ghana contexts, the PPI was considered to offer more interpretive power due to the ability to resolve PPI index scores across multiple poverty benchmarks. Further, in the course of this study, some exploratory analysis suggested the design of the PPI survey might better correspond to visual features that can be resolved by vision models. This may be one area where future research might specifically focus on identifying features that tools like PPI have established as statistically significant poverty estimators.

For Ghana, using the PPI poverty estimator, the predicted distribution compares favorably with the observed PPI results from the survey. Across the 1,262 Voronoi polygon coverage areas in Ghana, the model predicts a median PPI score of 63.3. This is consistent with a median PPI score of 63 observed by the household surveys.[8] Figure 5 shows that the distribution of observed PPI scores and the distribution of predicted scores are very similar, centered around a score value of 62-63, with most score variation happening ten score points below and above this value, and slightly skewed toward higher (non-poor) scores. A score of 60-64 means that nine percent of the population is likely to fall below the \$2.50/day poverty line; and about 52 percent are likely to fall below the higher \$5.00/day poverty line.

8 *Statistical lookup tables that convert PPI scores (here between 60 and 64) into the corresponding likelihoods of falling below different poverty lines in a country are produced by Innovations for Poverty Action and are available here: https://www.povertyindex.org/country/ghana.*

Figure 5: Observed vs Predicted PPI Score Distributions in Ghana

Distribution of: PPI Predictions



Observed PPI distribution:

Median 63

A high PPI score corresponds to a lower probability of being poor.

Predicted PPI distribution:

Median 63.3

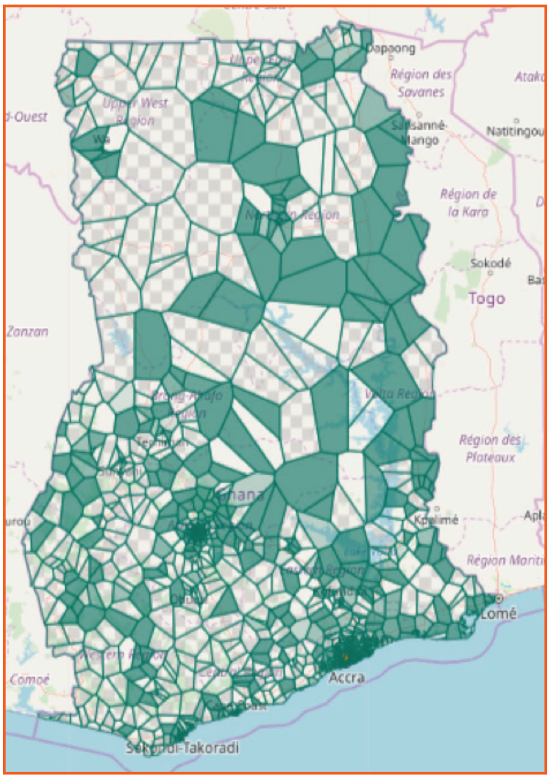
Exploring and Interpreting Poverty Maps

Using the results obtained in this study, poverty maps are presented at varying national, regional and localized scales by using the cell tower geo-segmentation approach. Image Table 5 presents the mapping of predicted PPI poverty scores in Ghana at the country level. A total of 1,262 polygons are visualized, nationally.

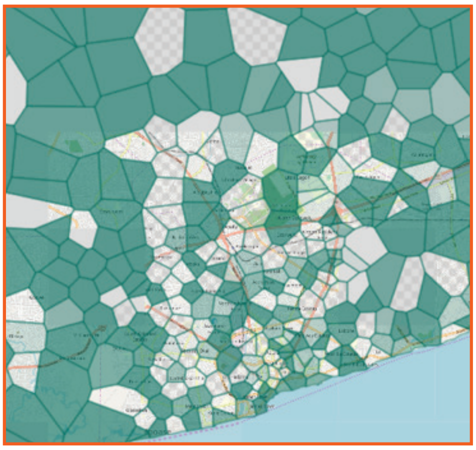
Shaded polygons are established using mobile network provider cell tower locations, where darker shades show estimates of low poverty incidence; lighter shades, higher incidence of poverty. With greater cell tower density to serve more densely-populated urban areas, polygon sizes become more granular, as do predictive score coverage areas.

In this manner, poverty estimation is more granular at a neighborhood level in higher density urban areas; whereas in rural areas, polygons are far larger. Zooming-in on urban centers in Accra and Kumasi shows the granular nature of the polygons, whose geographic area becomes smaller as cell tower density increases. Many map areas do not have predicted poverty levels (they are filled with a gray checked pattern): satellite images were not available country-wide at the resolution used; some areas faced processing errors that resulted in incomplete mapping; and as already discussed, only areas around cell towers attempted generating estimates, as computing several million images far exceeded the coverage of the network and survey data.

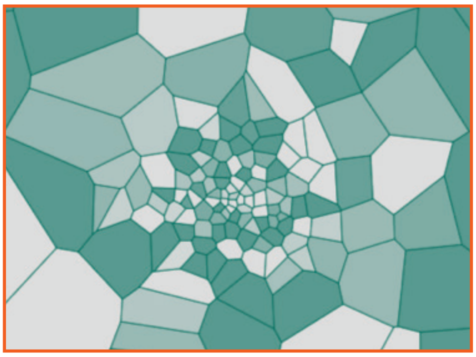
Image Table 5: Satellite image-based PPI Prediction Mapping – Ghana



Map of entire country



Zoom into Accra Municipality



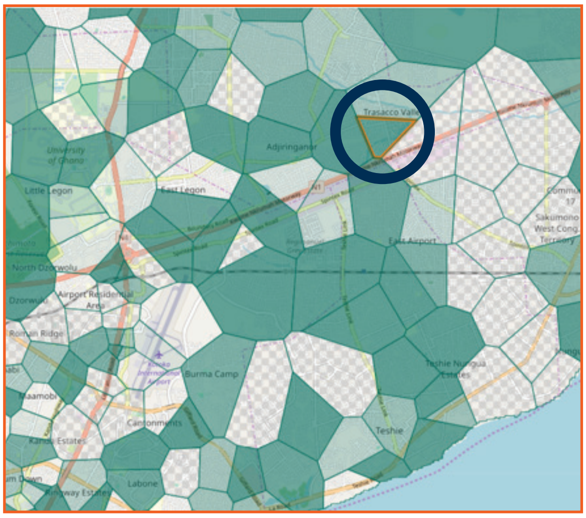
Zoom into Center of Kumasi

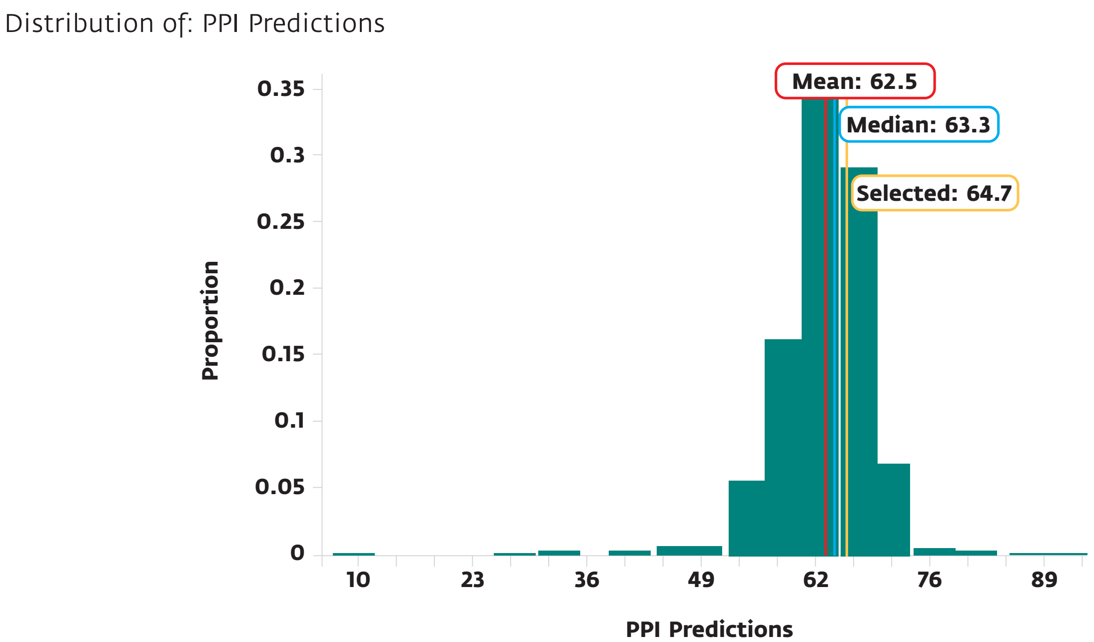
This Image Table visualizes the mapping tool developed for this project, providing shared coverage zones corresponding to the Voronoi polygon segmentation approach. The sequence of images illustrate the ability to zoom-in from country-level to neighborhood-level coverage areas. Here, PPI scores are depicted (darker is higher PPI score prediction, meaning higher wealth; lighter non-checked areas show low scores and therefore increased predicted prevalence of poverty). As discussed elsewhere, the tile-based mapping approach enables layering multiple indicators of interest.

In terms of satellite imaging, urban areas are also more feature-rich in terms of buildings and roads, while in rural areas there may be more grasslands or uninhabited areas. Yet, urban areas also have much more demographic diversity in smaller areas, meaning neighboring households may be less similar in terms of welfare, despite sharing common visual features in a satellite image.

Visually exploring urban areas in Accra helps to make this point, while also illustrating the application (and challenges) of the poverty estimation models combined with maps segmented by the Voronoi estimation zones. The Image Table 6 depicts one of Accra's wealthiest areas, serving as an empirical example of high-income visual features.

Image Table 6: Empirical Observations Comparing Poverty Scores and Images – Urban Wealth





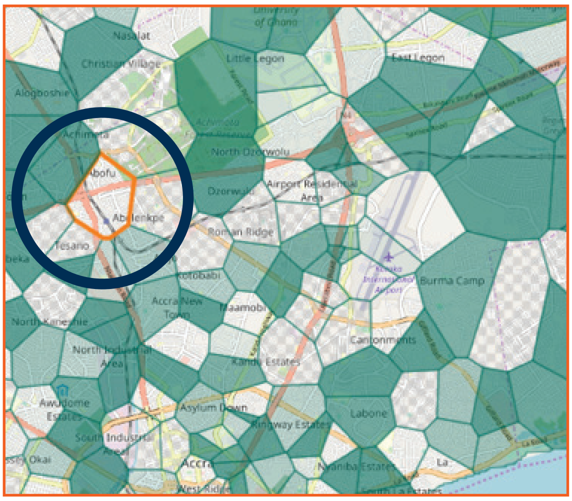
Map: https://earth.google.com/web/@5.65555391,-0.111776,33.42060017a,314.48224383d,35y,0h,0t,0r

Trasacco Valley is recognized as one of Accra's wealthy neighborhoods[9]. Selecting this area specifically on the predicted poverty map shows above-average PPI predicted scores, although only modestly so. This clearly shows limitations of the model's accuracy, with a predicted score of 64.7 – an improbably low prediction corresponding to 43 percent below $5.00/day. This sort of discrepancy may likely be an artifact of the spatial boosting approach combined with satellite imaging. Zooming-in on the coverage area, multi-story single family houses are seen, lawns and swimming pools, which are expected to correlate with near-zero poverty for the coverage area.

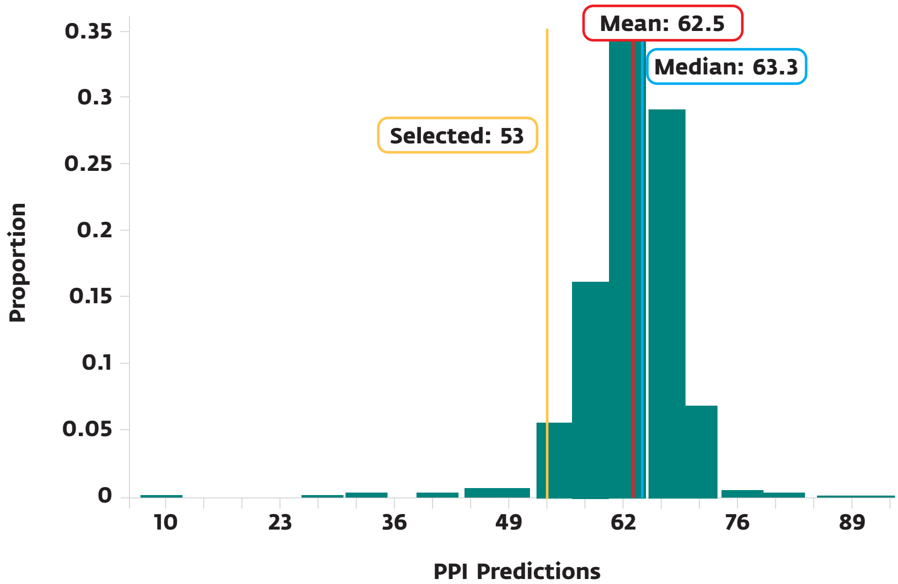
One of the poorest zones predicted within the greater Accra area, depicted below (Image Table 7), includes the Northwest section of the Abelemkpe, a relatively wealthier neighborhood[10]; and also, the Southern area of Achimota, which notably includes the slum area of Abofu (see lightly-shaded low-income estimated coverage area, highlighted with an orange-border polygon area). A satellite image snapshot of the zone covered by Google Maps shows visual differences in the housing density and construction of buildings, particularly clustered around the crossing highways. Identified through the predictive satellite mapping, the predicted PPI score in this area is 53--on the lower end of the distribution of values across the country (see orange line in distribution chart). With a mix of more affluent housing stock and slum areas, this score indicates probability of 68 percent of denizens in this area to fall below the $5.00/day poverty line.

9 *https://www.africa.com/a-million-gets-you-in-ghana/*
10 *https://en.wikipedia.org/wiki/Neighborhoods_of_Accra*

Image Table 7: Empirical Observations Comparing Poverty Scores and Images – Urban Poverty 1



Distribution of: PPI Predictions

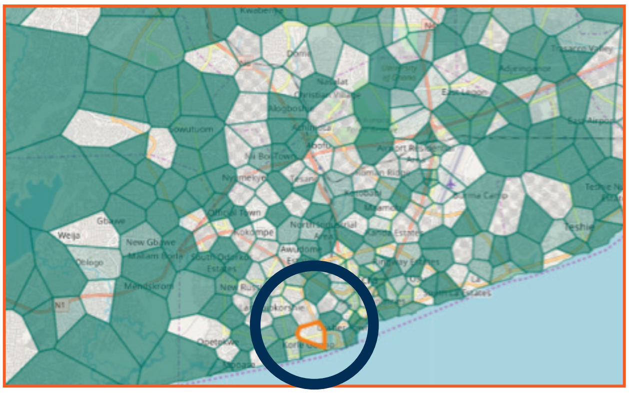


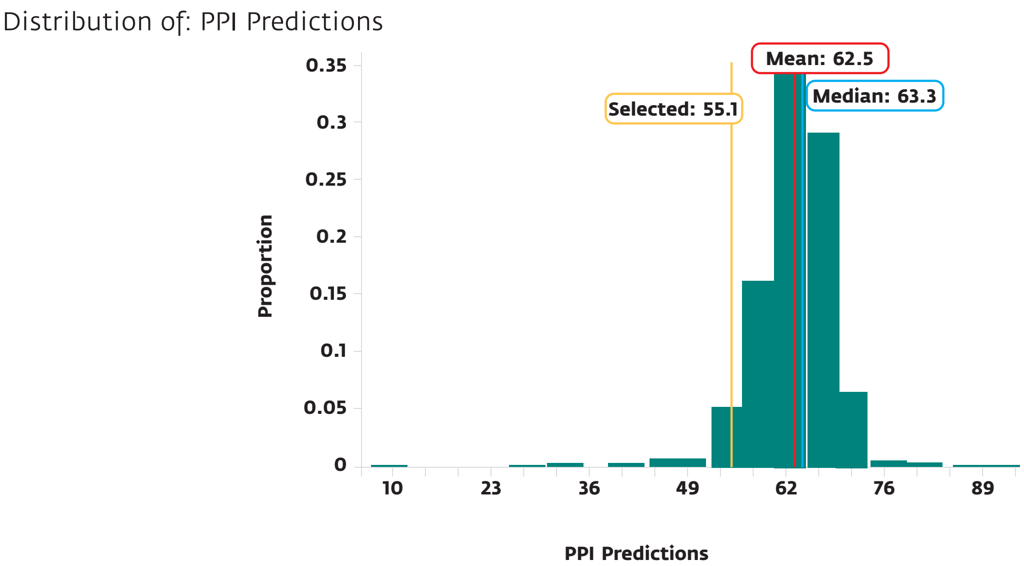
Map: https://earth.google.com/web/@5.61074734,-0.2240724,20.66296749a,1087.02950268d,35y,0h,0t,0r

Another example of a poorer neighborhood in Accra is depicted below in Image Table 8 at different zoom levels. Chorkor is a fishing village at the coastline in Accra. The corresponding satellite image shows a densely populated neighborhood at the coastline in Accra. It is a fishing village struggling with poor sanitation, access to water and power infrastructure, and waste management. The predicted PPI score for this area is 55.1 which corresponds to a 60.3 percent likelihood for the population living there to fall below the $5.00/day poverty line.

Although the predicted poverty level for this area is at the lower end of the distribution poverty scores across the county (see distribution in Image 8), it is not as low as expected for a slum area known for its high levels of poverty and lower access to infrastructure. This result may be explained by a closer look at the Google Maps satellite snapshot. Apart from the slum area at the bottom half, the upper part of the image shows less dense housing structures surrounded by more greenery suggesting higher levels of wealth. Indeed, this upper part of the image shows a university and a hospital campus.

Image Table 8: Empirical Observations Comparing Poverty Scores and Images – Urban Poverty 2





Map: https://earth.google.com/web/@5.5334772,-0.23087813,18.66830879a,2254.39682943d,35y,0h,0t,0r

Both examples of neighborhoods presented above (Image Table 7 and 8) are areas where welfare levels were predicted solely based on the underlying satellite imagery. None of the survey data used for model training was collected in those areas. The fact that both wealthy and poor areas are covered by the polygons respectively, explains moderately low predicted poverty incidence and provides anecdotal evidence that the satellite model for PPI estimation aligns to some degree with observed characteristics.

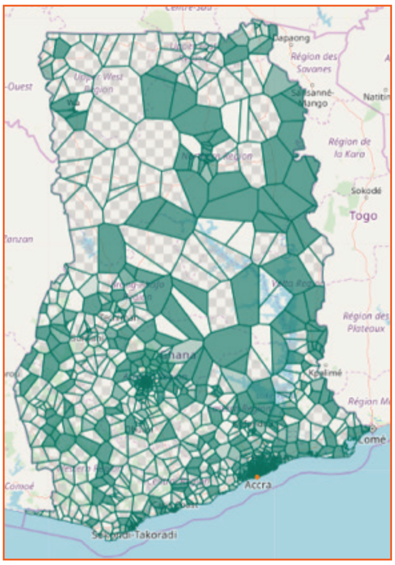
These two examples also illustrate the complexity in generating granular neighborhood-level estimates, especially in more urban environments precisely because of the rapid changes that may occur between low- and high-income segments, the visual features that characterize them, and general lack of border boundaries (e.g., a political or administrative line).

Ultimately, the goal of this research is to explore the interplay of poverty and Digital Financial Services. Image Table 9 shows how poverty heat maps can be meaningfully compared to layers of telephone and mobile money activity. Three metrics are selected for comparison:

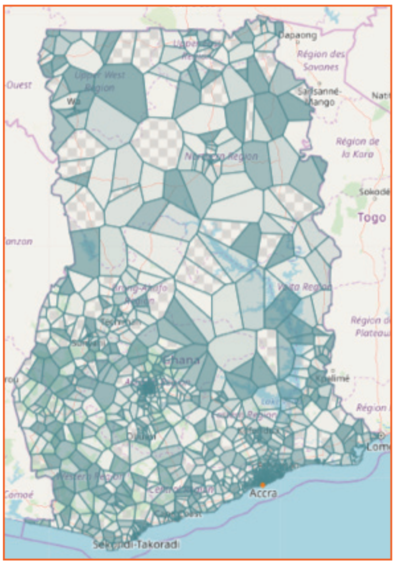
- Map A.1 depicts the satellite-based predicted PPI scores for Ghana. Darker shades visualize higher scores in respective areas, which translate into lower predicted poverty incidence in those polygons.
- Map B.1 visualizes call activity for users of a Ghanaian mobile network operator. The map shows gradients of telephone calls incoming to respective smaller areas. Darker areas depict relatively more calls received.
- Map C.1 shows mobile money transaction activity. The map shows gradients of the total value of transfers that are being sent and received in a respective area. The higher the value of transfers per month, the darker the shade.

Image Table 9: Layering poverty predictions, telephone and mobile money activity in Ghana

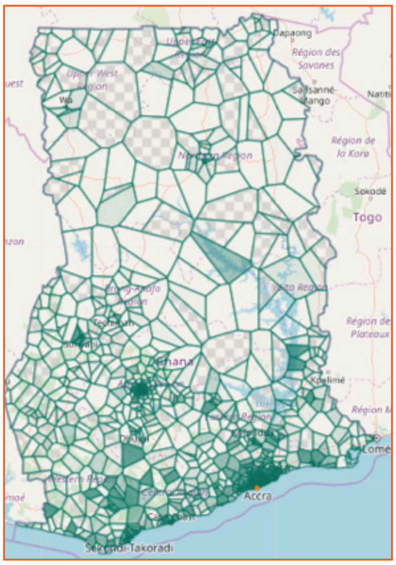
Map A.1–Poverty Prediction
(PPI score) (Lighter=Poorer)



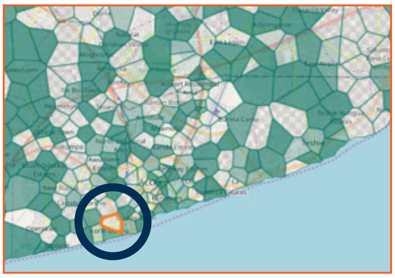
Map B.1-Telephone Activity
(Number of Incoming Calls)



Map C.1-Mobile Money Activity
(Total Value of Transfers)

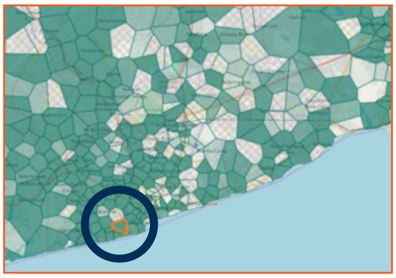


Map A.2 – Zoom into Accra



Map B.2 - Zoom into Accra

Map C.2- Zoom into Accra



Across the maps, the same polygon areas are shaded,[11] enabling the ability to directly layer transactional data atop poverty estimates. Moreover, as polygons are approximating mobile network operator service areas, insights are equally valuable to providers seeking a better understanding of consumer segments with respect to their service areas.

Regarding call behavior and mobile money transaction activity, nationally, darker-shaded urban areas show increased activity, as would be expected. This is most pronounced for the mobile money activity layer as adoption levels are still largely lacking behind cell phone ownership. Zooming-in on urban areas (see for example Map B.2 zoomed into Accra in Image Table 9) shows again the granular nature of the polygons, whose geographic areas become smaller as cell tower density increases. As a result, these urban zones also show significant gradients of calling and mobile money activity between them at this level of resolution.

11 *Polygons with missing data are again filled with a gray checked pattern. Different reasons can explain missing data. No available high-resolution satellite imagery, processing errors or no recorded call or mobile money activity during given time period in respective polygon.*

To illustrate the feature layering approach with a concrete example, one area that was discussed before (capturing parts of the poor village of Chorkor in Accra) is again highlighted with orange boarders (Image Table 9). Table 2 lists the corresponding poverty, telephone, and mobile money activity metrics for the selected areas, comparing them to the median values across locations in Ghana. By definition each Voronoi polygon constitutes a geographic area with a single cell tower at its geometric middle. Therefore, values may be interpreted in terms of volume of activity per tower per month.

Table 2: Predicted Poverty Statistics, Telephone and Mobile Money Activity (per tower per month) in Chorkor

METRIC	EXAMPLE POLYGON ZONE (PART OF CHORKOR)	GHANA MEDIAN
Poverty Statistics		
Predicted PPI Score	55.1	63.3
$5.00/day poverty rate - PPI interpretation	60.3%	**52.1%**
$1.90/day poverty rate - PPI interpretation	3.6%	**1.5%**
Telephone Activity		
Number of outgoing calls per month (per month and user)	104	47.5
Number of incoming calls (per month and user)	41	**15**
Outgoing call duration (total tower minutes per month)	129 hours	**69 hours**
Incoming call duration (total tower minutes per month)	61 hours	29 hours
Number of incoming SMS per month (total per tower)	26,600	7,900
Number of outgoing SMS per month (total per tower)	81,000	39,000
Mobile Money Activity		
Mobile money transfer (average amount per month)	$21	$19.5
Mobile money cash in (average amount per month)	$13	$15
Mobile money cash out (average amount per month)	$17	$16

The predicted poverty incidence in the selected polygon is with an estimated 60.3 percent of the population living below the $5.00/day poverty line, which is an eight percentage point higher poverty rate than the median value in Ghana. But despite low welfare levels, the area still shows high levels of telephone activity. Across all call activity metrics, the values for the specific polygon are more than twice as high as the median values. In other words, the cell tower in this area hosts a highly active userbase, as compared to tower and user communities elsewhere.

Regarding mobile money activity, results differ depending on the metric. Mobile money activity in the area is higher than the countrywide median with respect to the volume of cash-outs and mobile money transfers; whereas the average cash-in amount is lower than in the majority of other polygons across the country.

Overall, this shows that in this specific area, a community with higher poverty prevalence also shows much higher telephone usage; and similar mobile money activity patterns (slightly biased toward cash-out, suggesting net inflows into the community).

As previously observed, this neighborhood shows a mix of features that expect to correlate with higher and lower poverty prevalence (eg., slum areas adjacent to areas with single family homes and lawns). It is impossible to identify wealth characteristics at the individual user level to know if the telephone and mobile money patterns are driven by wealthier demographics or poorer demographics or evenly distributed across all users. However, what is known – and what is important from the perspective of both providers and policy makers is this: the community depicted here shares a common infrastructure.

Telephone statistics are reported in terms of the traffic served by the tower at the geometric center of the polygon; cash-in and cash-out statistics are similarly reported in terms of the tower that intermediated the agent float balances to facilitate the service transaction. Consequently, any commercial or developmental interventions designed to expand financial access will reach communities that access those services via this shared infrastructure. It is therefore meaningful to articulate the reach of financial services with respect to the demographic make-up of the communities to share the "home" network tower in their neighborhood.

The Chorkor neighborhood discussed here was selected simply by having a low-scoring PPI prediction for the sake of exemplifying a layered analytic approach between poverty models, GSM and DFS activity. Overall, a refined computational approach that explores relationships among these types of data would identify "hot spots" of interest according to specific strategic interests for providers or policy-makers. Digital financial service providers and donors might use the layering approach to compare even static or slowly changing poverty baseline estimates with a variety of different indicators that help to monitor and identify areas for targeted interventions to reduce poverty and to increase financial inclusion. Remittance rates as well as other metrics of (net) financial inflows and outflows of neighborhoods, and especially population numbers that better estimate financial reach and micro-market sizing, are interesting indicators for layering atop of poverty rates.

Discussion

Lessons for Estimating Welfare with Satellite Imagery and Call Detail Records

It is necessary to measure welfare and poverty levels regularly, at high spatial resolution, at high temporal frequency, and at low cost. The increasing availability of day- and night-time satellite images and powerful deep learning algorithms has introduced new methods to predict poverty and welfare levels. This research aimed to further these methods, specifically by increasing the granularity of analysis to smaller areas.

Overall, the study finds that it is possible to identify meaningful welfare estimates at neighborhood-level resolution. However, these estimates are likely to lack precision. A joint spatial/satellite model provides the highest explanatory power, which combined interpolated geo-marked survey data with machine vision feature identification. This demonstrates that there are components of estimated wealth that are detectable through satellite imagery. While ground surveys are still necessary to develop country-specific models, adding remote-sensing information can reduce the sample sizes needed for detailed poverty estimation.

The following are key lessons learned from this study about different data sources, methods, and challenges depending on context and targeted levels of granularity:

1. Evaluating welfare at neighborhood levels and with high spatial resolution may be valuable when lower levels of precision are acceptable. A rough understanding of income can meaningfully segment geographic areas that are below (or above) specific poverty threshold, such as in this case where poor versus not-poor can characterize neighborhoods or provide estimators for service reach to demographic segments. More so, when rough estimates can help to describe highly variable wealth demographics among neighbors in densely populated areas, it may be possible to approximate general poverty preponderance within that neighborhood, rather than a specific per-household value.

2. Poverty prediction at the level of Voronoi polygon-based cell tower locations allows small area welfare estimation in urban environments. Predicting poverty at lower than regional levels raises the question of how to segment space – simply, where do boundaries exist? Political or map boundaries may or may not exist in a national context, especially for smaller towns. More importantly, how political boundaries are drawn is unlikely to reliably characterize demographic features of people who live within that zone. Using cell towers to segment geographies is beneficial, as the Voronoi polygon approach groups populations in terms of proximity to nearest tower[12]. It is reasonable to assume that tower density is proportional to population density (or at least provider subscriber density). That is, providers are incentivized to put more towers where increased service is need. Doing so refines coverage polygons into smaller geographic spaces, importantly characterized by the people using the shared access point. The area defined by the Voronoi polygon therefore describes the DFS usage statistics of the denizens since the tower intermediates transactions performed by users and agents.

3. Daytime satellite imagery improves poverty prediction, but caveats remain. Nightlight satellite imagery can provide baseline estimates for regional poverty, but they are less useful in rural areas that do not have much variation or nightlight signals due to lower levels of electrification. Daylight satellite imagery provides a better alternative in many cases, although high-resolution imagery is not always available for all regions in a country and individual high-resolution satellite images are unlikely to have uniformly distributed features that carry meaningful signals of poverty or wealth. Enough variation in wealth exists across the visual space to make wealth estimation with day time satellite imagery difficult without a robust ability to detect and identify the features that characterize the visual space. There is room for ample improvement for granular level poverty estimation, especially for urban neighborhoods. In this study, higher R-squared values for rural Uganda are due to the relatively lower rate of change across adjacent satellite images. Urban Ghana's rapid feature changes across smaller geographic space results in fewer salient features (or conflicting features) in the visual space. Here, further research might focus on specialized feature detection, such as models that can detect cars, prominent urban characteristics and other indicators of wealth.

In the course of this research, it was conjectured that additional feature detection research might prioritize identifying features that correspond to visually-identifiable features of poverty survey tools. Specifically, the PPI methodology uses some statistical measures that have strong visual determinants (such as a building's roof material, or whether there is an outdoor latrine). While a challenging problem to solve, it is nevertheless reasonable to train a visual model to see a thatch roof or metal roof or tile roof, for example, and perhaps recognize features like community washrooms or cisterns for potable water. Whereas poverty survey tools driven by consumption data, ownership or household expenditure provide less direct opportunity to "see" these types of features in the visual space and interpret them accordingly.

12 Cell tower location data is available publicly or may be purchased by independent organizations that map infrastructure locations, globally, such as OpenCellID (https://www.opencellid.org/).

An area of future research might therefore seek to train visual models specifically to recognize observable features present in PPI (or other methods) to improve prediction accuracy.

4. Spatial boosting is particularly helpful to improve models for rural poverty estimation. The ostensible goal of using remote-sensing to estimate poverty is to reduce the time and expense of ground surveys. This study found that using spatial boosting helps to address this, as meaningful estimates can be inferred for non-surveyed image locations by weighting surveyed observations from nearest-neighbors. This approach was found to be more effective in rural areas that are less likely to have substantial variations in welfare over short distances. Whereas in urban areas, large disparities of wealth were observed among neighbors, posing a significant challenge for training machine vision models.

5. Representative sampling may not meaningfully overlap with provider data. This study also tried to predict poverty levels in neighborhoods with call activity data, expecting randomly selected survey respondents to be sufficiently represented in provider data to model CDR usage and wealth demographics. For both countries, the survey results effectively showed that providers had relatively low market share in the enumeration zones. Although results are presented in Table 1 for the sake of completeness, there is little interpretive value due to very low coincidence between CDR users and survey respondents. Therefore, future similar research should conduct minimal baseline surveys to understand general market share when attempting to use provider data and then design the full survey to over-sample in a statistically controllable manner to ensure adequate coincidence between data sets.

6. Broad-spectrum representative ground-truth survey data is essential for training poverty estimation models. Breadth here implies that ground-truth welfare data encompasses the range of economic well-being within the population. Data should come from households with sufficient geographical dispersion so that the number of areas they fall in are high enough to train machine learning models if the variance is too small. Additionally, breadth also implies that images selected also encompass the range of buildings, roads, fields, farms and relevant features that are representatively associated with the spectrum of welfare. The variation should ensure sufficient feature capture to identify and differentiate a wealthy household's manicured lawn from a poorer household's adjacent pasture, for example; equally for urban areas, to ensure that the variety of visual features are captured along with the variety of wealth segments that may correlate with those features. This problem was evident in this study's focus in rural Uganda, particularly since (by design) surveys focused on the poorest households, but this also resulted in a relative lack of wealthy households against which to compare and train models.

Application of Poverty Estimation Findings – Financial Inclusion and Beyond

Research shows that telephone usage[13] and increased social network size[14] are strong predictors for active uptake and use of Digital Financial Services. Moreover, Digital Financial Services boost financial inclusion and contribute to poverty reduction and improved livelihood indicators. DFS tend to be adopted first among higher income demographics, particularly urban youth. They scale by diffusing from early adopters and are likely to grow along remittance corridors or social networks (such as urban laborers who send money home to families in rural areas).[15] Identifying these corridors is key, and normalizing the use of DFS is a means of scaling financial inclusion. Tracking financial flows into (or out of) areas with low-income welfare estimates may help to monitor the reach of financial inclusion and help target areas of greatest need.

Given that DFS can play a significant role in diminishing poverty, it is important to be able to accurately identify locations where the poor live for the purpose of deploying targeted financial inclusion strategies, as well as for monitoring the use of financial services, and observing the impact they have on the population. Current national survey methods are slow and costly, meaning that observing and measuring reach and change is likely to take place on multi-year time lines. Even techniques that employ remote-sensing perfectly, while less expensive, may also be slow to observe poverty changes. However, indicators of financial empowerment represented through provider data change much faster, at the rate of usage and uptake.

Layering heat maps of poverty, telephone usage and financial activity

Financial inclusion insights can therefore be obtained from comparing different data layers of telephone usage, financial transaction activity and poverty levels to deepen the understanding of how they are interconnected. A base layer of poverty estimates is fundamental to drive these types of insights, which can benefit providers and policy makers alike.

The maps presented in this report depict single-variable layers to illustrate the approach. But further research is necessary to computationally aggregate population, income and financial activity estimates to quantify the reach and scale of financial inclusion meaningfully at the national-level and at a more granular scale. Population layers are also critical to further this approach and should be considered equally in further research.

13 *IFC 2016; Blumenstock et al. 2015.*
14 *Mattson and Stuart 2018*
15 *IFC et al. 2017, Aga and Martinez Peria 2014*

Increasing impact by identifying areas of biggest need and largest reach

This research finds that satellite imaging can be used to meaningfully segment welfare levels at neighborhood-level granularity, although with relatively low precision. While these models offer only modest ability to explain the variation in wealth at granular levels, the ability to segment and rank poverty estimates can identify key areas to focus on, potentially advancing both commercial and financial inclusion strategies. Further, layering poverty estimate data can identify financial inclusion engagement opportunities (i.e., high cell coverage, low welfare) or populations that are particularly underserved that donors may seek to strategically target (i.e., low cell coverage, low welfare). In this manner, poverty estimates such as those obtained through this study can provide viable insights, despite the low precision of results: relative rank of welfare estimate is sufficient to provide directional information on financial inclusion targeting and reach, as does a categorical assessment of poverty prevalence above-or-below a given threshold.

Improved understanding of the financial behavior and needs of the bottom of the pyramid

Comparing poverty estimates with financial activity data helps to explore the scale of financial inclusion among the poorest income demographics. Providers seeking to better understand their own markets and customer demographics may gain insight into how services are used across geographies and income demographics. Such as whether money is sent and received from high-to-low predicted poverty areas or vice versa; or to quantify the volume of activity with respect to these parameters or relative per-capita metrics within coverage areas. Do these wealthier and poorer segments make phone calls to each other? Do remittances flow from one to another? If so, to what degree? If not, how may remittance and communication corridors be described in terms of the demographic characteristics of sender and receiver zones?

Application beyond financial inclusion

This study was more specifically focused on identifying poverty as a basis to compare and assess with respect to the prevalence of Digital Financial Services. However, the need for regular and granular poverty prediction with the help of satellite imagery and call activity data goes of course beyond financial inclusion. Layering publicly-available population information[16] onto cell-tower location-based polygons allows for example to approximate estimates for how populations with different income demographics access Digital Financial Services. Applications in other domains is also possible, by assessing the proximity to access different services as well as the coverage density provided to populations within an area of interest. Other areas of application include for example agriculture and infrastructure.

16 *Such as Center for International Earth Science Information Network https://www.ciesin.columbia.edu/data/hrsl/ or WorldPop http://www.worldpop.org.uk/data/summary/?doi=10.5258/SOTON/WP00098*

Conclusion

Neighborhood level poverty estimation with satellite imagery is possible, although aided significantly by spatial boosting techniques that draw on traditional survey data. Combined, the coverage of surveys is effectively increased substantially, enabling smaller sample sizes to yield more information. While the precision of poverty estimates is limited, the ability to segment and rank geospatial areas in terms of welfare is nevertheless insightful. Further work is needed to refine the models developed in this study and to develop research of this nature into insights for service providers. However, the basic building blocks are here to start using them. Even directional information on estimates of wellbeing can help to direct better understanding of financial inclusion reach.

The ability to map small area poverty estimates and to combine them with layered financial transaction data, as explored in this study, provides opportunities for development professionals and Digital Financial Services providers alike to identify and quantify engagement, particularly among the poorest individuals. Equally, to identify opportunities where high engagement on telephone channels or other demographic characteristics may signal opportunities to strategically engage underserved markets that are likely to adopt and benefit from improved services.

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ACKNOWLEDGMENTS

IFC and the Mastercard Foundation Partnership for Financial Inclusion are grateful to Marshall Burke and Joshua Blumenstock for their scientific input and oversight of the model development for this research project. To the Bill & Melinda Gates Foundation for supporting the research engagements whose data are included in the analyses. Additional appreciation to Shafique Jamal for his support in mapping and visualizing poverty predictions and to Gary Seidman and Lesley Denyes from IFC for their editorial support.