Poverty from Space: Using High Resolution Satellite Imagery for Estimating Economic Well-being

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Can features extracted from high spatial resolution satellite imagery accurately estimate poverty and economic well-being? We investigate this question by extracting both object and texture features from satellite images of Sri Lanka, which are used to estimate poverty rates and average log consumption for 1,291 administrative units (Grama Niladhari (GN) Divisions). Features extracted include the number and density of buildings, the prevalence of building shadows (a proxy for building height), the number of cars, density and length of roads, type of agriculture, roof material, and a suite of texture and spectral features calculated using a non-overlapping box approach. A simple linear regression model, using only these inputs as explanatory variables, explains nearly sixty percent of both poverty headcount rates and average log consumption. Estimates remain accurate throughout the GN average consumption distribution. Two sample applications, extrapolating predictions into adjacent areas and estimating local area poverty using an artificially reduced census, confirm the out of sample predictive capabilities.

1. INTRODUCTION

Despite the best efforts of national statistics offices and the international development community, local area estimates of poverty and economic welfare remain rare. Between 2002 and 2011, as many as 57 countries conducted zero or only one survey capable of producing poverty statistics, and data are scarcest in the poorest countries [1]. But even in countries where data are collected regularly, household surveys are typically too small to produce reliable estimates below the district level. Generating welfare estimates for smaller areas require both a household welfare survey and contemporaneous census data, and the latter is typically available once per decade at best. Furthermore, safety concerns may prohibit survey data collection in many conflict areas altogether.

This paper investigates the ability of object and texture features derived from HSRI (High Spatial Resolution Imagery) to estimate and predict poverty rates and consumption at local levels. The area of our study covers 3,500 square kilometers in Sri Lanka, which contain 1,291 administrative units (Grama Niladhari (GN) divisions), which are on average 2.15 sq. km each. For each GN, we extract both object, spectral, and texture features to use as explanatory variables in poverty prediction models. Object features extracted include the number of cars, number and size of buildings, type of agriculture (plantation vs. paddy), the type of roof, the share of shadow pixels (a proxy for building height), road extent and road material. These features are identified using a combination of deep learning based Convolutional Neural Networks (CNN) and eCognition, an object based image processing software. Texture features that characterize the spatial variability in an area or neighborhood within an image were also calculated. These satellite derived features were then matched to household estimates of per capita consumption imputed into the 2011 census for the 1,291 areas.

We investigate four main questions: 1) To what extent can variation in GN economic well-being -- poverty rates defined at the 10 and 40th percentiles of national income and average village consumption -- be explained by high spatial-resolution features? 2) Which features are most strongly associated with these measures of well-being? 3) Can fitted models predict into geographically adjacent areas out of sample? and 4) Are predictions robust to the use of a smaller training sample data sets? We find that: i) satellite features are predictive of economic well-being and explain about sixty percent of the variation in both GN average consumption and estimated poverty headcount rates; ii) Measures of built-up area and roof type strongly correlate with welfare; iii) Predicting into adjacent areas produces less accurate poverty measures, but ranking between true and predicted rates is moderately high; and iv) Using a one percent sample of the census based “ground truth” designed to mimic the sampling strategy of the Household Income and Expenditure Survey has little impact on the accuracy of the prediction.

Daytime imagery has recently emerged as a practical source of information on economic well-being [2]. Advances in Deep Learning such as Convolutional Neural Networks (CNN) have the capability to algorithmically classify objects such as cars, building area, roads, crops and roof type [3]. These objects may be more strongly correlated with local income and wealth than Night Time Lights (NTL) [4]. Furthermore, textural and spectral algorithms provide spatial context [5-6] that may be relevant for poverty estimation. In textural and spectral algorithms, the spatial and spectral variations in imagery are calculated over a neighborhood or non-overlapping block of pixels to characterize the local spatial pattern of the objects observed in the imagery.

Previous researchers [7] have employed a transfer learning approach to estimate poverty, in which a set of 4,096 unstructured features are extracted from the penultimate layer of a Convolutional Neural Network that uses Google Earth daytime imagery to predict the luminosity of NTL. The resulting model predicts well and explains an average of 46 percent of the variation in village per capita consumption, out of sample, across the four

Significance

Estimates of local area poverty remain rare in the developing world. Day-time satellite imagery holds promise for filling data gaps of economic well-being. Using a training site in Sri Lanka, we extract objects (cars, roof type, roads) and textures from satellite images and use these to build models of poverty and income. We find that these models explain 60 percent or more of the variation in poverty or income. The poverty estimates generated by our method are accurate for the poorest villages.

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countries in which it was trained. While this innovative use of
daytime imagery substantially improves on the use of NTL alone,
it is not necessarily optimal for predicting poverty rates. When the
top two quintiles are excluded from their sample, restricting the
sample to those below twice the international poverty line, the

R-squared falls precipitously, to about 0.12. This illustrates the
challenges this method faces in distinguishing welfare among
the poorest of the poor, who in the African context most likely
live in places of relative darkness.

2. DATA

Our analysis is restricted to a sample area of approximately
3.500 km² in Sri Lanka (see figure S5). National coverage was
not feasible due to the high cost and partial availability of high-
resolution imagery, however these data are rapidly becoming
more available and less expensive as companies such a Planet
and DigitalGlobe expand their archives. We sampled DS Divi-
sions conditional on HSRI being available, drawing areas from
urban, rural, and estate sectors.[1] According to the 2012 census,
population by sector in Sri Lanka is rural (77.4%), urban (18.2%)
and estate (4.4%) [8]. Population by sector in our sample is rural
(45.9%), urban (46.2%) and estate (7.8%).

2.1 Details on Satellite Imagery

The satellite imagery consists of 55 unique “scenes” purchased
from DigitalGlobe, covering areas specified in our sample area.
Each “scene” is an individual image captured by a particular
sensor at a particular time. Images were acquired by three dif-
ferent sensors: Worldview 2, GeoEye 1, and Quickbird 2. These
sensors have a spatial resolution of 0.46m², 0.41m², and 0.61m²,
respectively in the panchromatic band and 1.84m², 1.65m², 2.4m²
respectively in the multi-spectral bands. Pre-processing of im-
agery included pan-sharpening, ortho-rectification, and image
mosaicking. Most imagery was captured in either 2011 or 2012,
although some imagery from 2010 was also used.

2.1.2 Details on Local Area Poverty Training Data

Ideally village poverty and consumption statistics would be
generated directly from the 2012/13 Household Income and Ex-
penditure Survey (HIES), a detailed survey that measures the
consumption patterns of 25,000 households on approximately 400
consumption items. The survey contains an average of 8.4 house-
holds per GN Division in the 47 sampled DS Divisions, making
the HIES insufficient to generate consistent poverty estimates at
the GN Division without supplementary data. We therefore draw
on the most common method to impute welfare estimates [9] into
the 2011 Census of Population and Housing, which is identical to
the method used to generate official poverty estimates at the DS
Division level [10][2]. For each household in the census, per capita
consumption was estimated based on models developed from the
HIES, using household indicators that are common to both
the Census and the HIES.[3] We derive GN headcount poverty
rates using the standard Foster-Greer-Thornbecke method [11],
for two poverty lines: poverty line 1 at the 10th percentile of the
national per capita consumption distribution, and poverty line 2 at
the 40th percentile. This is equivalent to $3.00 and $5.13 per day
respectively in 2011 PPP terms, which compares to an extreme
poverty line in 2011 prices of $1.90 per day.

2.2 Feature Extraction

The derived high spatial resolution features fall into seven
broad categories: (1) agricultural land; (2) cars; (3) building
density and vegetation; (4) shadows; (5) road and transportation;
(6) roof type; and (7) textural and spectral characteristics. In
addition to the satellite features, we use two geographic attributes

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[1] Sri Lanka classifies sectors as urban, rural, or estate. The estate sector refers to
plantation areas of more than 20 acres with 10 or more residential laborers. Except for
sample stratification, the estate sector is grouped with the rural sector.

[2] The term welfare is used interchangeably with per capita household consumption.

[3] Consumption aggregates have been spatially deflated using a district level food price
index constructed from unit values in the HIES survey by the Department of Census and
Statistics.
Table 1. Prediction of local area poverty rates using high resolution satellite features.

Dependent variable is poverty rate using poverty line 1, defined at 10th percentile of national income.

| Variable                                      | Coef  | t-statistic |
|-----------------------------------------------|-------|-------------|
| log Area (square meters)                      | 0.020*| [2.52]      |
| = 1 if urban                                  | -0.023| [-1.80]     |
| % of GN area that is agriculture              | -0.00025| [-1.04]   |
| % of GN agriculture that is paddy            | -0.00033**| [-2.97]   |
| % of GN agriculture that is plantation        | -0.00021**| [-2.84]   |
| % of Total GN area that is paddy             | -0.00019| [-0.58]    |
| Total cars divided by total road length       | -0.31 | [-1.17]     |
| Total cars divided by total GN Area           | 29.6  | [0.54]      |
| log number of cars                            | -0.0059| [-0.89]     |
| log sum of length of roads                    | -0.020***| [-3.64]   |
| fraction of roads paved                       | -0.00035***| [-4.24]  |
| In length airport roads                      | -0.0051| [-1.45]     |
| In length railroads                           | 0.00008| [1.31]      |
| % of area with buildings                      | -0.0027*| [-2.31]     |
| log of Total count of buildings in GN         | -0.0090**| [-2.71]    |
| Vegetation Index (NDVI), scale 64            | 0.061* | [2.04]      |
| Vegetation Index (NDVI), scale 8             | -0.064**| [-2.80]     |
| % shadows (building height)                  | 0.0022*| [2.04]      |
| In shadow pixels (building height)            | 0.016* | [2.51]      |
| Fraction of total roofs that are clay         | 0.00077***| [3.35]   |
| Fraction of total roofs that are aluminum    | 0.00091***| [3.63]    |
| Fraction of total roofs are asbestos          | -0.00033| [-1.08]     |
| Linear Binary Pattern Moments (scale 32m)     | 0.0021**| [2.91]      |
| Line support regions (scale 8m), mean         | -0.66  | [-0.87]     |
| Gabor filter (scale 64m) mean                 | -0.052 | [-1.53]     |
| Fourier transform, mean                       | 0.0017**| [3.42]      |
| SURF (scale 16m), mean                        | -0.0014| [-0.49]     |
| Constant                                      | -0.32**| [-3.03]     |
| Observations                                  | 1291  |             |
| R-sq                                          | 0.610 |             |
| R-sq Adj.                                     | 0.602 |             |
| Out-of-Sample R-sq                            | 0.588 |             |

of the GN Division: whether it is administratively classified as an urban area, and its area in square kilometers. The agricultural land indicators are coarse, and consist only of the fraction of GN agriculture identified as paddy (rice cultivation) or plantation (cash crops such as tea). These sum to one hundred percent for GNs with agricultural land, so the excluded category in subsequent regressions is GN Divisions with no agricultural land. We also calculated the fraction of total GN area that is either paddy, plantation, or any agriculture.

Three car related variables were calculated – the log total number of cars in a GN, total cars divided by total road length, and cars per square kilometer of the GN. Building density variables include the fraction of an area covered by built-up area and the number of roofs identified. Built-up area captures any human settlements – buildings, homes, etc. – regardless of use or condition. These are grouped with two measures of the normalized difference vegetation index (NDVI), a measure of vegetation greenness [12] that indicates a lack of building presence in urban areas. The fifth category are two indicators that capture shadows: the log of the number of pixels classified as shadow as well as the fraction of shadows covering a valid area in a GN.

2.2.1 Object Classification Details

Object features were classified using the assistance of two technical partners: Orbital Insight and LandInfo. Deep learning-based object classification was used for classifying the share of the GN division that is built-up (i.e. consists of buildings), the number of cars in the GN, and the share of pixels in the GN that were identified as shadow pixels (proxy building heights), and crop type. The classification method used is similar to Krizhevsky, Sutskever, and Hinton (2012), which utilizes convolutional neural networks (CNN) to build object predictions from raw imagery. Roof type, paved and unpaved roads of different widths, and railroads were classified using a combination of Trimble eCognition and Erdas Imagine software, utilizing a combination of support vector machines and visual identification.

The CNN classification algorithm involved four steps:
1. Ingestion/tiling
2. Model development
3. Classifying all pixels using the trained model
4. Aggregating prediction results to GN division level

The tiling stage splits the large images into many small images or tiles, in order to make the modeling computationally scalable, as each tile could be distributed to a different GPU core for greater efficiency. In the model development stage, the classification model was trained and tuned. Model building began by manually classifying or labeling a sub-sample of the imagery as a positive or negative value for a given object using a crowdsourced campaign. The classified data was split into an 80% training and a 20% testing set, where the training set was used to build the model. This allowed sample prediction metrics to be calculated using the withheld test set. Training was run for 60,000 iterations using the Nesterov solver method, a variant of stochastic gradient descent.

Figure 1 shows an example of a developed area building classification, with raw images shown at the top and CNN classification accuracy shown below. On the bottom panel, true positives are
coefficients for all three models estimated with the three separate dependent variables.

The model's explanatory power is high, summarized in the in-sample $R^2$ of 0.610, out-of-sample $R^2$, estimated using ten-fold cross-validation [23], is 0.588, indicating the model is not likely to be overfit. In words, a simple linear model that includes only the geographic size of the GN Division, whether it is urban, and remotely sensed information explains 61 percent of the variation across GNs in headcount poverty rates. Figure 3 plots predicted against true average GN consumption, with colors assigned by province in which the GN is located. A LOWESS smoothing line is shown with associated confidence interval. The model has a tendency to under-predict for GNs with very high average incomes. While there is noise, the predictions tend to straddle the 45° line indicating a high degree of agreement between the predicted and true welfare values. Figure S10 presents a map of predicted and true values for a sample area.

3.1 Decomposition of Feature Explanatory Power

The results above do not distinguish the degree to which individual indicators improve the model's predictive power. To address this question, we use a Shapley decomposition [24] to decompose the model's explanatory power. The Shapley procedure calculates the marginal $R^2$-squared of a set of explanatory variables as the amount by which $R^2$-squared declines when removing that set from the set of variables. The results (table S4) confirm that measures of building density – built up area, number of buildings, shadow pixels, and to a lesser extent vegetation – are powerful contributors to predictive power. Collectively, these three sets of variables account for 37 to 40 percent of the model's explanatory power. NTL, including average, squared, cubed, and average standard deviation of NTL, explain between 7 and 12 percent of the variance in per capita consumption or poverty, suggesting that HRSF capture approximately an additional 90 percent of on the ground poverty or income in comparison to NTL.

3.2 Model Performance at Varying Income Levels

To verify the model performs well for the very poor, we divide the sample of GN Divisions into quintiles based on the mean predicted per capita consumption of census households, and re-estimate the main model for log per capita consumption on the subsample of the bottom 80, 60, 40, and 20 percent of the distribution. Model performance across income quintiles are shown in Table 2. Overall, the model continues to predict well within the poorest subsamples, as the adjusted $R^2$-squared declines only mildly from 0.60 in the full sample to 0.579 when only considering the bottom decile. Given that the poorest decile of GNs have an average welfare of $84,67 per day, this represents a little more than double the international poverty line. This suggests that this approach for estimating welfare from high-resolution satellites images is accurate for fairly poor contexts.

4. APPLICATIONS

4.1 Estimating Poverty Using a Reduced Census

The standard small area estimation technique used to model poverty combines a smaller household survey with a population census. We can combine satellite features with a smaller household survey alone to produce sufficiently precise small area estimates? To assess this, we examine whether the predictive power of satellite imagery remains when it is calibrated using a census extract, of approximately the size of the Household Income and Expenditure Survey, rather than a full census.

We produce several simulations of the dependent variable (either per capita consumption or GN poverty rate) using subsamples of the census intended to mimic the size of a household survey. For each subsample only 20% of GNs are sampled. The number of households within each subsample that are "surveyed" (i.e., used to produce the training set's poverty statistic). We sample either 5%, or 100% of the actual households in the GN. For each simulated sample we build a model of poverty...
using HRSE, producing estimates of poverty that we can then compare to actual estimates. The poverty rate of a GN in the training data will become less precise the fewer households that are sampled per GN, although survey costs increase with the number of households surveyed.

Figure 4 plots the results of the simulation exercise, where we have plotted R-squared values between predicted welfare rates and true welfare rates, both in-sample (GNs within the subsample) and out-of-sample (GNs excluded from the subsample), and mean absolute error. Average R-squared values between predicted and true values do not depreciate significantly when using the sample consisting of 20% of GNs and 5% of households within those GNs.

4.2 Estimations of Poverty via Geographic Extrapolation

A major motivation for using satellite imagery is to extrapolate poverty estimates into areas where survey data on economic well-being do not exist. While most of the data deprivation that characterizes the developing world occurs at the country level, it is also common for surveys to omit selected regions, due to political turmoil, violence, animosity towards the central government, or prohibitive expense. For example, from 2002 through 2009/10, Sri Lanka’s HIES failed to cover certain districts in the North and Eastern part of the country due to civil conflict, and Pakistan’s HIES exclude the Federally Administered Tribal Areas, Jammu and Kashmir.

To assess how well a model “travels” to a different geographic area, we fit a series of models, where in each model we exclude a single Divisional Secretariat (DS), a larger administrative area, from the model, and use the estimated model to predict into that excluded area. This is a form of ‘leave-one-out cross-validation’ (LOOCV), a common method used to infer statistical out-of-sample performance [25]. We estimate both linear models and random forest models[4] to predict out of sample to determine if more flexible model specifications perform better out-of-sample.

Table S5 shows model performance at predicting into adjacent areas, comparing normalized root mean squared error, normalized mean absolute error, and the correlation between predicted and true welfare rates using both random forest and linear models to fit HRSE models. The adjacent prediction error rates are larger than when predicting randomly out of sample using cross-validation. Normalized error rates divide average error by the average value of welfare, therefore the error rates can be interpreted as fractions of average welfare. Mean absolute error is estimated at 2.5% of log household consumption, 45% of the average poverty rate at the lower poverty line, and 30% of the average poverty rate at the higher poverty line using linear models to estimate and predict into adjacent areas. The error rates are lower when using random forests to estimate and predict into adjacent areas. When predicting and predicting using random forest models mean absolute error declines to 1.5% of log household consumption, 38% of the average poverty rate at the lower poverty line, and 25% of the higher poverty line.

While these error rates imply adjacent predictions will be too imprecise for producing welfare measures intended as official statistics, they may be sufficient for generating rank ordering of villages by poverty or income. We conclude from these results that HRSE cannot yet be used to predict accurately into adjacent areas for official statistics, but the accuracy may be acceptable for targeting or other applications.

5. DISCUSSION

Traditionally, given the prohibitive cost of conducting surveys sufficiently large to produce accurate statistics for small areas, generating small area poverty estimates requires pairing a welfare survey with a census or intercensus survey. Census and inter-census data is expensive to collect and therefore produced relatively infrequently. It is also usually disseminated with a lag, making it difficult to rapidly assess changes in local living standards. The results above show that indicators derived from high spatial resolution imagery, when paired with survey data, generate accurate predictions of local level poverty and welfare, and that by large the conditional correlations are of sensible signs and magnitudes. Furthermore, predictions based on specific features accurately predict mean per capita consumption throughout the welfare distribution. While the welfare consequences of more frequent measures of poverty and inequality are unknown, they may be large given the many applications of frequent local measures of economic well-being, ranging from impact evaluation, to budget allocation to social transfers.

These findings raise questions for further work, and contribute to an ongoing discussion regarding the use of predictive

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4] For each random forest model we use 1000 decision trees, sampling 13 of the predictors with replacement.
methods in public policy [26]. The most immediate of these is whether satellite indicators can substitute for census data in different contexts and for different indicators. Second, it is important to better understand the extent to which these results generalize to different social and ecological environments, such as Africa, the Middle East, and other parts of Asia. There is no guarantee that the predictive power of building density, shadows, and other features documented above will hold in all environments.

A second line of research could explore whether changes in satellite imagery could be used to forecast changes in economic well-being across space and time. Poverty surveys are typically collected every three years and the most recent global estimates are produced with a three-year lag. Therefore, the ability to “now-cast” measures of economic well-being by combining frequently updated satellite imagery with the most recent survey-based measures of poverty has great potential. Additional research can shed light on identifying the best way of predicting into adjacent areas not covered by surveys. Overall, the inevitable increase in the availability of imagery and feature identification algorithms, in conjunction with the encouraging results from this study, implies that satellite imagery will become an increasingly valuable tool to help governments and stakeholders better understand the spatial nature of poverty.

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