Linking Pixels and Poverty: Using Satellite Imagery to Map Poverty

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By Ryan Engstrom
Department of Geography, The George Washington University, USA

Introduction

The linking of remote sensing and social science has been a topic of research interest for over two decades. It has made many strides as more and more researchers in a number of disciplines have started to work together. One of the areas where the link is just recently starting to grow is poverty mapping. Ending poverty in all its forms everywhere is UN Sustainable Development goal number one. One of the fundamental requirements for ending poverty, is knowing where it is. Poverty mapping is traditionally performed by either using household survey data or by combining these surveys with census data collected by national statistics offices. This is a time consuming, labor intensive, and costly process that limits the ability to collect data in many areas, with many countries never even collecting the data (Serajuddin et al. 2015). Furthermore, the definition of poverty, the measurements used to calculate it, and the definition of poor persons has a variety of characterizations in development economics (Steele et al. 2017, Chambers 2006, Alkire and Foster 2011). Poverty estimates can be based on monetary metrics such as consumption estimates, or on asset based such as material possessions. Using these different metrics to define poverty can lead to quite different rankings of the same population (Steele et al. 2017).

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 failed to conduct more than a single survey capable of producing poverty statistics, and data are scarcest in the poorest countries (Serajuddin et al., 2015). 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 unstable areas altogether.

In order to fill these gaps, satellite imagery has generated considerable enthusiasm as a potential supplement. The big draw of satellite data is the global coverage available and the timeliness of the continually updating of the data sets. Satellite data can not measure poverty directly as it can only measure the outside of the structures and indicators of development. The most commonly used method in Economics has been to use Night Time Lights (NTL) imagery to map variations in poverty (Henderson et al., 2012, Pinkovskiy and Sala-I-Martin, 2016). The NTL approach works for well for describing large area variations in poverty (i.e., country and continental scales) and has proven useful for comparing poverty between countries. The assumption behind the NTL approach is that areas with greater wealth have higher NTL light emissions and poorer areas have less light emissions. While this approach explains some of the large area variations in poverty, it does not allow for understanding variability at local spatial scales because of the course spatial resolution (1km) of the NTL satellite data. Additionally, this approach is limited in urban areas, as at the within city scale because these areas tend to be relatively bright the NTL observations have relatively little variation as they can reach saturation.

In order to overcome these limitations a recent focus on the use of very high spatial resolution imagery (VHSRI) (spatial resolution less than 5m) has garnered significant attention. In recent years, private companies such as DigitalGlobe and Airbus have rapidly expanded the coverage and availability of VHSRI. Another relative new company, Planet (formerly Planetlabs), currently operates more satellites than any organization other than the US and Russian governments, and just recently, successfully launched 88 dove satellites that will allow for coverage of the entire globe with imagery with a 3 to 5 m spatial resolution on a daily basis. While all of these data are available, the costs of purchasing is still prohibitive for academic researchers and only limited studies have taken place. However, with advances in the technology and the drop in the costs of this type imagery, it should allow social scientists to benefit from this data source in the coming decades.

Poverty Mapping with Very High Spatial Resolution Imagery

Poverty mapping within urban areas using VHSRI imagery, has generally focused on mapping slum versus non-slum areas or informal versus formal housing (Kuffer et al. 2016, Kohli et al. 2016, Taubenbock and Kraff 2014, Kohli et al. 2013, Engstrom et al. 2015). The assumption of this research is that the spatial pattern of buildings, roads and dwelling units allows the ability to differentiate slum from non-slum areas. A number of different approaches have been tested to map slums including simple visual interpretation, object oriented, machine learning based on spectral and spatial features, and others (Kuffer et al. 2016, Kohli et al. 2016, Taubenbock and Kraff 2014, Kohli et al. 2013, Engstrom et al. 2015). While the spatial pattern of the scene model helps to understand what a slum might look like in some contexts, simply visually interpreting slum versus non-slum areas can be difficult due to varying local definitions of slums (Kohli et al. 2016) as well as differing morphologies of slums in different locales (Sliuzus et al. 2008). This has made developing automated methods for mapping slum areas and the transferability of these methods a challenging task.

A major hurdle for using VHSRI data for working over larger areas is processing the imagery in an efficient and appropriate manner at scale. Jean et al. (2016) used VHSRI data to map poverty across multiple sub-Saharan African countries at the village level. Their research utilized a convolutional neural network (CNN) approach. CNNs require an enormous amount of training data (Tajbakhsh et al. 2016), so they used a multi-step approach called “transfer learning”. Their transfer learning approach tuned an existing CNN to extract features, which summarize the relationship between NTL intensities and VHSRI data. The properties of the VHSRI imagery that correlated well with NTL were then used to train ridge regression models to predict household expenditures and assets at a village scale. Their results indicate that they were able to explain up to 55% of variation in average consumption and 75% of variation in average asset wealth. While this provides one methodology for mapping poverty over space, the interpretability, amount and type of training data needed for this approach, and repeatability of these results are not that promising as CNNs are difficult to interpret and the relationships between imagery derived values and poverty are somewhat vague.

In previous research we have been testing a new methods for processing VHSRI using spatial and spectral features (Engstrom et al. 2015, Engstrom et al. 2016, Engstrom et al. 2017). In the spatial features approach, instead of mapping objects (buildings, roads, cars etc.) or using a CNN, we characterize the spatial variability in the imagery. Previous research has indicated spectral and spatial features extracted from high resolution imagery are related to potential indicators of poverty, such as informal housing, housing quality, population density, slums, lack of solid waste collection, and lack of improved sanitation at the city scale (Graesser et al. 2012, Sandborn and Engstrom 2016, Engstrom et al. 2015).

Extracting these spatial features is an image processing technique, which derives information related to spatial pattern, structure, orientation, texture, and irregularity from windows of image pixels (Herold et al. 2003). Spatial feature outputs rely on pixel groups, and therefore each spatial feature must be calculated with a specific block and scale size combination for a "neighborhood" (Fig. 1). In figure 1, A represents the individual pixel, B the block size, which becomes the output resolution of the spatial feature, and C is the scale size, also referred to as window size, which represents how many pixels the spatial feature calculation will use to compute the output at the block scale. By using these parameters, a pixel in the output spatial feature layer will represent the relationship between neighborhoods of buildings, roads, vegetation, and other values thus indicating the spatial form of each neighborhood. This block and scale approach allows us to process the imagery in an efficient manner. Additionally, it gathers all of the information from the finest scale (i.e., the pixel) and aggregates it to larger spatial scales, thus reducing the processing time and file sizes. By doing this we can efficiently characterize variations in the landscape over large areas.

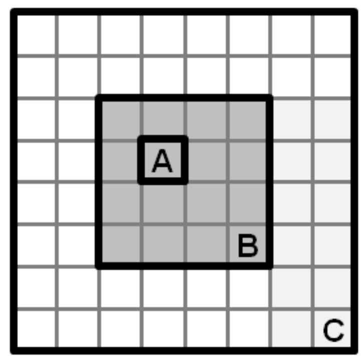

Fig. 1. (A) An individual pixel, (B) Block size of 4x4 pixels, and (C) scale size of 8x8 pixels.

The spatial features we have been examining come from computer vision and have been used in facial recognition software and other applications. Features are: Histogram of oriented gradients (HoG), which captures edge orientations and sorts them into a histogram (Dalal et al. 2005), PanTex, which is a built-up presence index derived from the grey-level co-occurrence matrix (GLCM) (Pesaresi et al. 2008), Line support regions (LSR), which characterize line attributes (Yu et al. 1999), Local binary pattern moments (LBPM), which define contiguous regions of pixel groups and sorts them into a histogram (Wang and He, 1990), Fourier transform (FT) which examines pattern frequency across an image (Smith 1997), Gabor, a linear Gaussian filter used for edge detection (Gabor, 1946), Speeded Up Robust Features (SURF), an algorithm that extracts key points (i.e., edges and corners) from an image through pyramidal Gaussian based decomposition (Bay et al., 2006), the Normalized Difference Vegetation Index (NDVI), the most widely used vegetation index that provides information about the presence and abundance of vegetation (Tucker, 1979), and the mean of the combined spectral bands, and the means of the four individual bands, Blue, Green, and Near Infrared. Together these features characterize information related to the structure and morphology of an area. That spatial and spectral features are related to indicators of poverty is relatively intuitive, as urban morphology and structure are related to socioeconomic conditions (Taubenbock et al. 2009) spatial and spectral features statistical characterize these.

We have found that they are strong indicators of not only variables related to poverty, such as informal housing, housing quality, population density, slums, lack of solid waste collection, and lack of improved sanitation (Graesser et al. 2012, Sandborn and Engstrom 2016, Engstrom et al. 2015) but also poverty measures themselves at the city scale (Engstrom et al. 2017). Additionally, when they are added to other remote sensing derived data sets, they can help explain poverty over large parts of countries explaining greater than 60% of the variance in poverty (Engstrom et al. 2017 and Engstrom et al. in Review). This indicates that we may be able to scale these types of analyses to much larger spatial areas.

Concluding Remarks

Combining the uncertainty in poverty values, with the lack of census and survey information for many countries, and the issues with obtaining satellite data, makes the mapping of poverty with satellite data a very rich field for research and exploration. While satellite data can not directly measure poverty, the ability to characterize either the lights from settlements or the infrastructure and spatial patterns of the landscape appears to be a good proxy for explaining the spatial patterns of poverty. NTL has proven to be successful over large areas while information extracted from VHRSI appear to work at finer spatial scales and may be scalable to large areas. Next steps include determining how to scale these appropriately, testing the ability of combing VHSRI and cell phone record data (i.e., Steele et al. 2017), and other ways of extracting information from the data. Finally, the ability to detect changes in poverty through time is only just beginning to be a possibility as there is an increase in the amount of both satellite imagery and georeferenced survey and census data available to test this.

References:

Alkire S, and Foster J. Understandings and misunderstandings of multidimensional poverty measurement. Journal of Economic Inequality. 9, 289–314.(2011).

Bay, Herbert, Tinne Tuytelaars, and Luc Van Gool. "Surf: Speeded up robust features." In European conference on computer vision, pp. 404417. Springer Berlin Heidelberg, (2006).

Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), vol. 1, pp. 886893. IEEE, (2005).

Chambers R. What is poverty? Who asks? Who answers? Poverty in Focus December 2006, UNDP International Poverty Centre. See http://opendocs. ids.ac.uk/opendocs/handle/123456789/120 (2006).

Engstrom, Ryan, Avery Sandborn, Qin Yu, Jason Burgdorfer, Douglas Stow, John Weeks, and Jordan Graesser. "Mapping slums using spatial features in Accra, Ghana." In 2015 Joint Urban Remote Sensing Event (JURSE), pp. 1-4. IEEE, (2015).

Engstrom, R., Copenhaver, A. and Qi, Yang. Evaluating the use of Multiple Imagery Derived Spatial Features to Predict Census Demographic Variables in Accra, Ghana. International Geoscience and Remote Sensing Symposium (IGARSS), Beijing, China (2016) 10.1109/IGARSS.2016.7730909

Engstrom, R., Copenhaver, A., Newhouse, D., Hersh, J., and Haldavanekar, V. Evaluating the Relationship between Spatial and Spectral Features Derived from High Spatial Resolution Satellite Data and Urban Poverty in Colombo, Sri Lanka. Joint Urban Remote Sensing Event (JURSE 2017) Dubai, UAE. DOI: 10.1109/JURSE.2017.7924590 (2017)

Engstrom, Ryan; Hersh, Jonathan Samuel; Newhouse, David Locke. Poverty from space : using high-resolution satellite imagery for estimating economic well-being (English). Policy Research working paper; no. WPS 8284. Washington, D.C. : World Bank Group (2017).

Engstrom Ryan; Hersh, Jonathan Samuel; Newhouse, David Locke. Poverty from space : using high-resolution satellite imagery for estimating economic well-being (*In Review*)

Gabor, Dennis. "Theory of communication. Part 1: The analysis of information." Electrical Engineers-Part III: Radio and Communication Engineering, Journal of the Institution of 93, no. 26 (1946): 429-441.

Graesser, Jordan, Anil Cheriyadat, Ranga Raju Vatsavai, Varun Chandola, Jordan Long, and Eddie Bright. "Image based characterization of formal and informal neighborhoods in an urban landscape." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 5, no. 4 (2012): 1164-1176.

Henderson, J. V., Storeygard, A., & Weil, D. N. Measuring economic growth from outer space. The American Economic Review, 102(2), 994-1028 (2012).

Herold, Martin, XiaoHang Liu, and Keith C. Clarke. "Spatial metrics and image texture for mapping urban land use." Photogrammetric Engineering & Remote Sensing 69, no. 9 (2003): 991-1001

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

Kohli, Divyani, Pankaj Warwadekar, Norman Kerle, Richard Sliuzas, and Alfred Stein. "Transferability of object-oriented image analysis methods for slum identification." Remote Sensing 5, no. 9 (2013): 42094228.

Kohli, Divyani, Alfred Stein, and Richard Sliuzas. "Uncertainty analysis for image interpretations of urban slums." Computers, Environment and Urban Systems 60 (2016): 37-49.

Kuffer, Monika, Karin Pfeffer, and Richard Sliuzas. "Slums from Space—15 Years of Slum Mapping Using Remote Sensing." Remote Sensing 8, no. 6 (2016): 455

Pesaresi, Martino, Andrea Gerhardinger, and François Kayitakire. "A robust built-up area presence index by anisotropic rotation-invariant textural measure." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 1, no. 3 (2008): 180-192.

Pinkovskiy, Maxim, and Xavier Sala-i-Martin. "Lights, Camera… Income! Illuminating the National Accounts-Household Surveys Debate." The Quarterly Journal of Economics 131.2 (2016): 579-631.

Sandborn, A. and Engstrom, R Determining the Relationship Between Census Data and Spatial Features Derived From High Resolution Imagery in Accra, Ghana. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS)* Special Issue on Urban Remote Sensing. DOI 10.1109/JSTARS.2016.2519843 (2016)

Serajuddin, Umar, Hiroki Uematsu, Christina Wieser, Nobuo Yoshida, and Andrew Dabalen. "Data deprivation: another deprivation to end." World Bank Policy Research Working Paper 7252 (2015).

Sliuzas, Richard, and Monika Kuffer. "Analysing the spatial heterogeneity of poverty using remote sensing: typology of poverty areas using selected RS based indicators." Remote Sensing–New Challenges of High Resolution, Bochum (2008): 5-7.

Smith, Steven W. "The scientist and engineer's guide to digital signal processing." (1997).

Steele, Jessica E., Sundsøy, Pål Roe, Pezzulo, Carla, Alegana, Victor A., Bird, Tomas J., Blumenstock, Joshua, Bjelland, Johannes, Engø-Monsen, Kenth, de Montjoye, Yves-Alexandre, Iqbal, Asif M, Hadiuzzaman, Khandakar N., Lu, Xin, Wetter, Erik, Tatem, Andrew J., Bengtsson, Linus “Mapping poverty using mobile phone and satellite data.”, Journal of The Royal Society Interface 14, 127 (2017).

Tajbakhsh, Nima, Jae Y. Shin, Suryakanth R. Gurudu, R. Todd Hurst, Christopher B. Kendall, Michael B. Gotway, and Jianming Liang. "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?." IEEE transactions on medical imaging 35, no. 5 (2016): 1299-1312.

Taubenbock, H., M. Wurm, N. Setiadi, N. Gebert, A. Roth, G. Strunz, J. Birkmann, and S. Dech. "Integrating remote sensing and social science." In 2009 Joint Urban Remote Sensing Event, pp. 1-7. IEEE, 2009.

Taubenböck, Hannes, and N. J. Kraff. "The physical face of slums: a structural comparison of slums in Mumbai, India, based on remotely sensed data." Journal of Housing and the Built Environment 29, no. 1 (2014): 15-38.

Tucker, Compton J. "Red and photographic infrared linear combinations for monitoring vegetation." Remote sensing of Environment 8, no. 2 (1979): 127-150.

Wang, Li, and Dong-Chen He. "Texture classification using texture spectrum." Pattern Recognition 23, no. 8 (1990): 905-910.

Yu, Won Pil, Gil Whoan Chu, and Myung Jin Chung. "A robust line extraction method by unsupervised line clustering." Pattern recognition 32, no. 4 (1999): 529-546.