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Combining satellite imagery and machine learning to predict poverty

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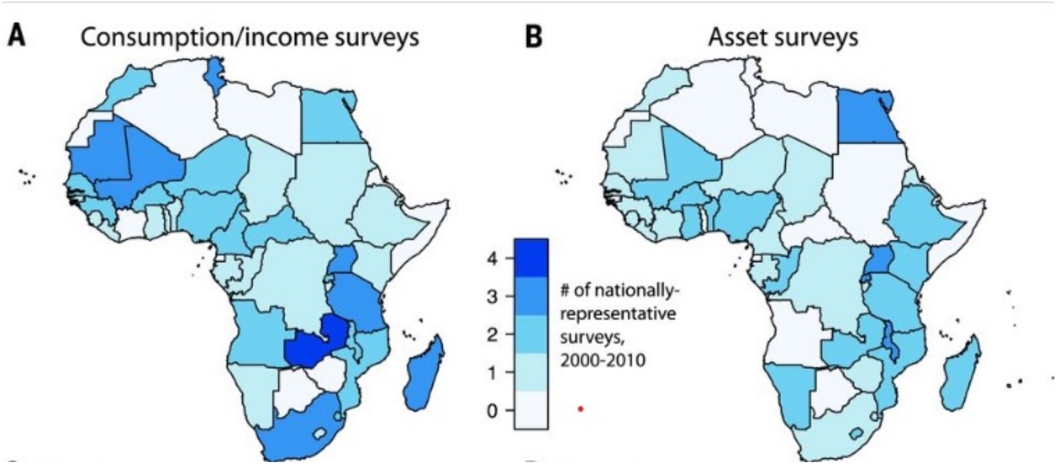
Introduction

- Accurate economic measurements crucial for research and policy
- Despite improvements, data gaps persist in developing countries
- 39 of 59 African countries had fewer than two surveys for poverty measures
- Lack of public domain data from conducted surveys
- Similar limitations in Demographic and Health Surveys (DHS) data



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The need for data

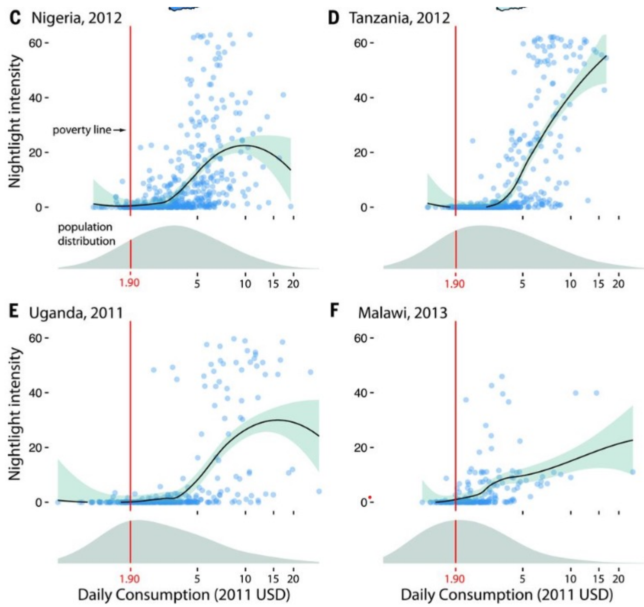
- More frequent surveys suggested, but challenges exist
  - Prohibitively costly and institutionally difficult
- Governments may resist having their performance documented

Alternative approaches

- Scaling up traditional data collection is challenging
- Introduction of alternative approaches using passively collected data
- Examples: social media, mobile phone networks, **satellites**

Limitations of Existing Approaches

- Nightlights technique shows promise but has limitations
- Difficulty distinguishing economic differences in impoverished areas
- Low and uniform luminosity levels in very poor areas
- Tricky to track the livelihoods of the very poor



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And here comes the mighty Machine Learning

- Introduction of a novel machine learning approach:
  - Extraction of socioeconomic data from high-resolution daytime satellite imagery
- Overcomes limitations of existing methods
- Fine-grained poverty and wealth estimates using only public domain data
- Ability to produce detailed poverty and wealth estimates

Difficulties in using CNN

- Recent deep learning methods such as object detection and classification are generally most effective in <u>supervised learning</u>
- In the setting of this paper, labeled data are scarce
  - Individual surveys regarding wealth statistics typically only contain hundreds of locations in the region of Africa
- CNN trained to estimate economic outcomes from satellite imagery directly might be challenging

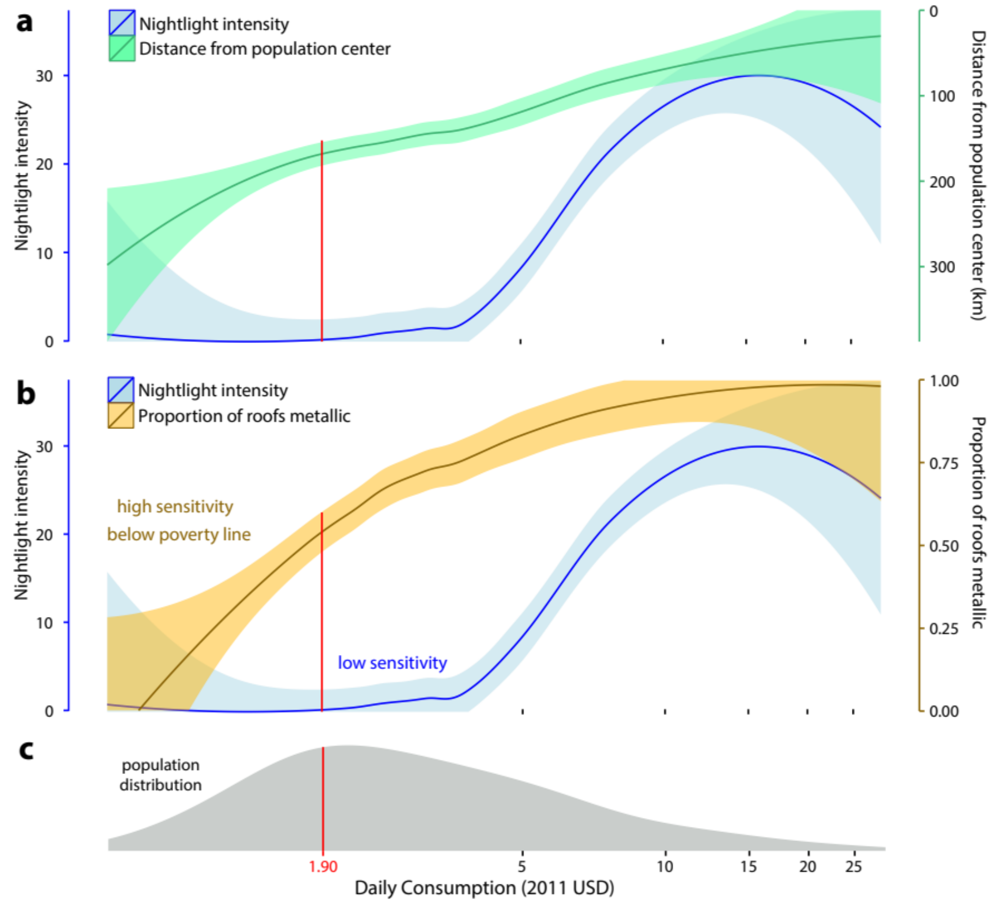
How to overcome it?

- Remember main purpose - Using satellite images to predict poverty
- Poverty indexes:
  - Household expenditure from World Bank's Living Standards Measurement Study (LSMS) surveys
  - Household asset from Demographic and Health Surveys (DHS)
- A useful estimator is needed
- Multistep transfer learning

Three-step method

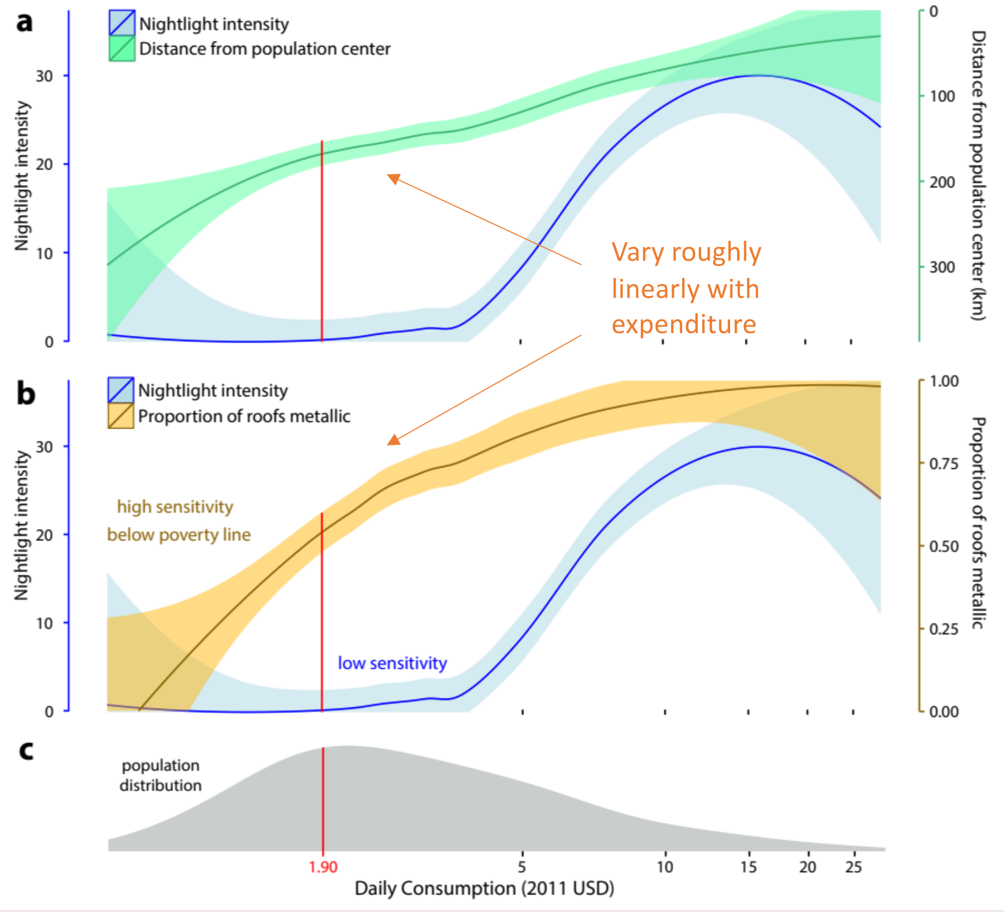
- Step 1: Pretrain a CNN model on ImageNet, which learns to identify common image features (edges, corners, etc.)
- Step 2: Fine-tune the CNN to predict the nighttime light intensities corresponding to input daytime satellite imagery
- Step 3: Use mean cluster-level values from the survey data along with the corresponding image features in CNN to train ridge regression models that can estimate cluster-level expenditures or assets

Discussion: Why useful?



- **Estimator**: Fine-tuned model as a feature extractor for daytime satellite images by **discarding the last layer of the CNN model**

- Nightlights display little variation at lower expenditure levels
- Feature extractor:
  - Predictive ability for nightlights
  - <u>Features visible in daytime satellite imagery</u>



Distinguish between different kinds of features:

It learns on its own that these features are useful for estimating nighttime light intensities without direct supervision.

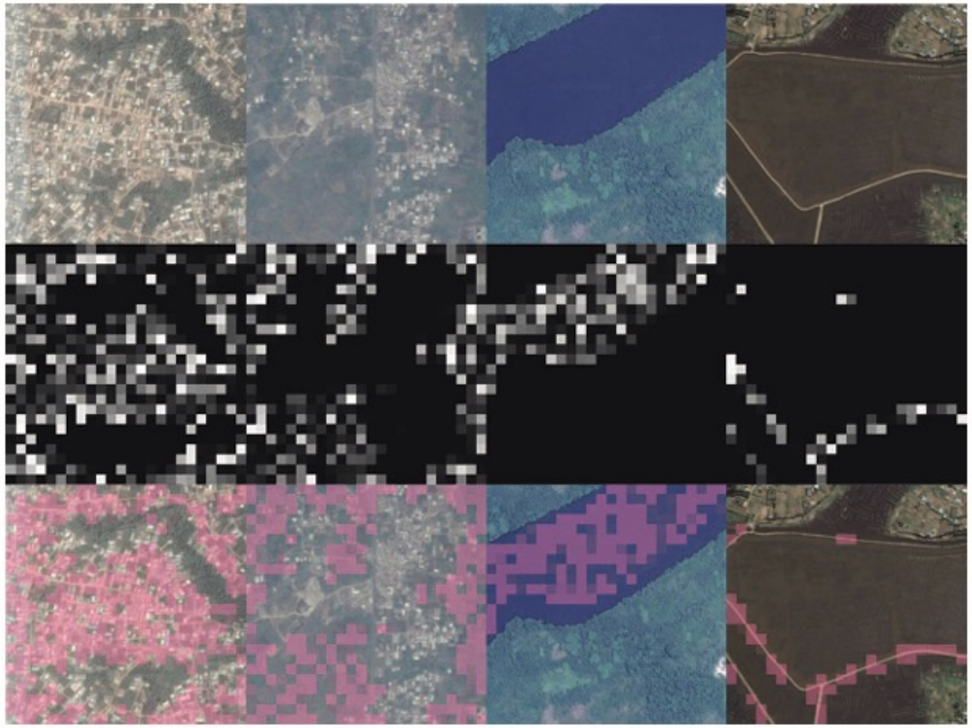


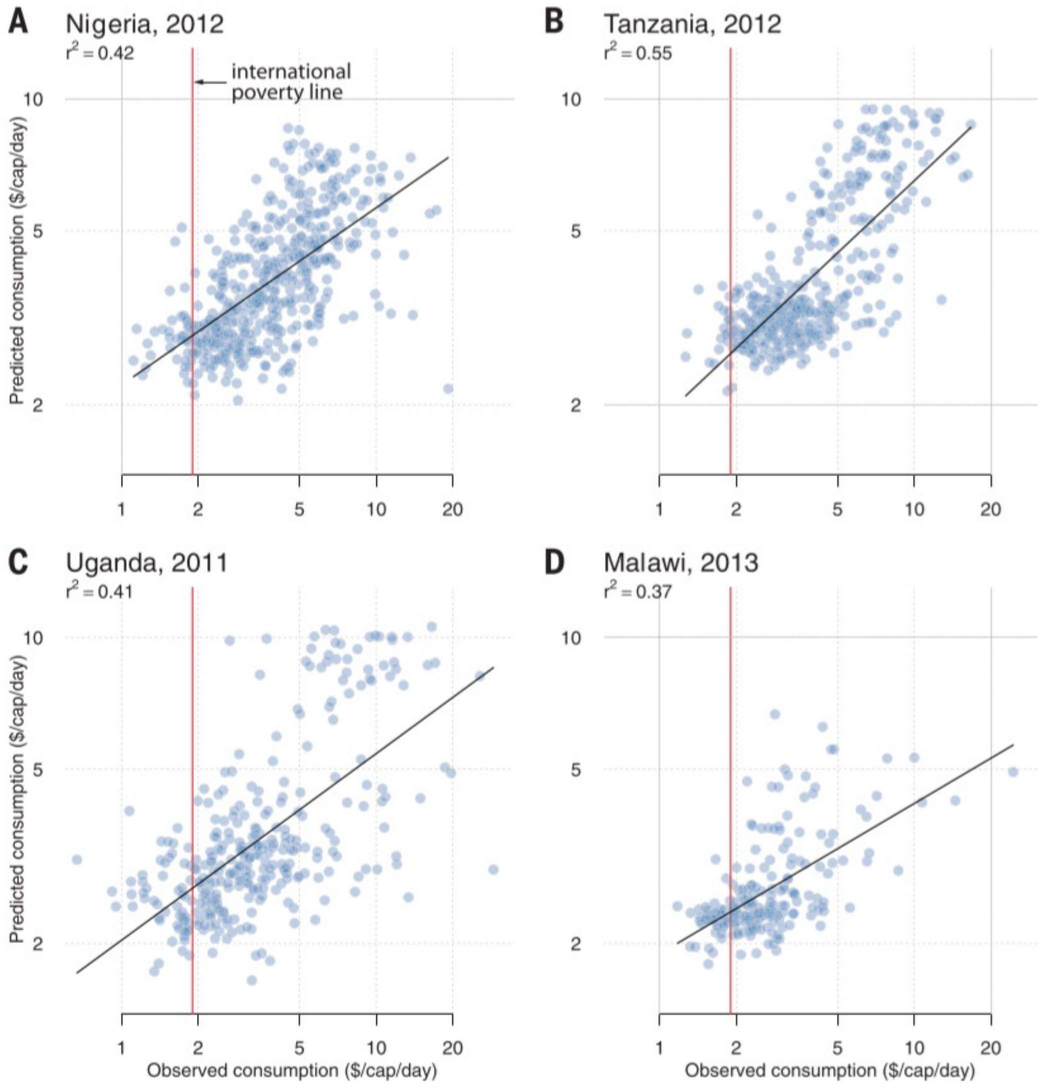
Fig. 2. Visualization of features. By column: Four different convolutional filters (which identify, from left to right, features corresponding to urban areas, nonurban areas, water, and roads) in the convolutional neural network model used for extracting features. Each filter "highlights" the parts of the image that activate it, shown in pink. By row: Original daytime satellite images from Google Static Maps, filter activation maps, and overlay of activation maps onto original images

Results and discussion

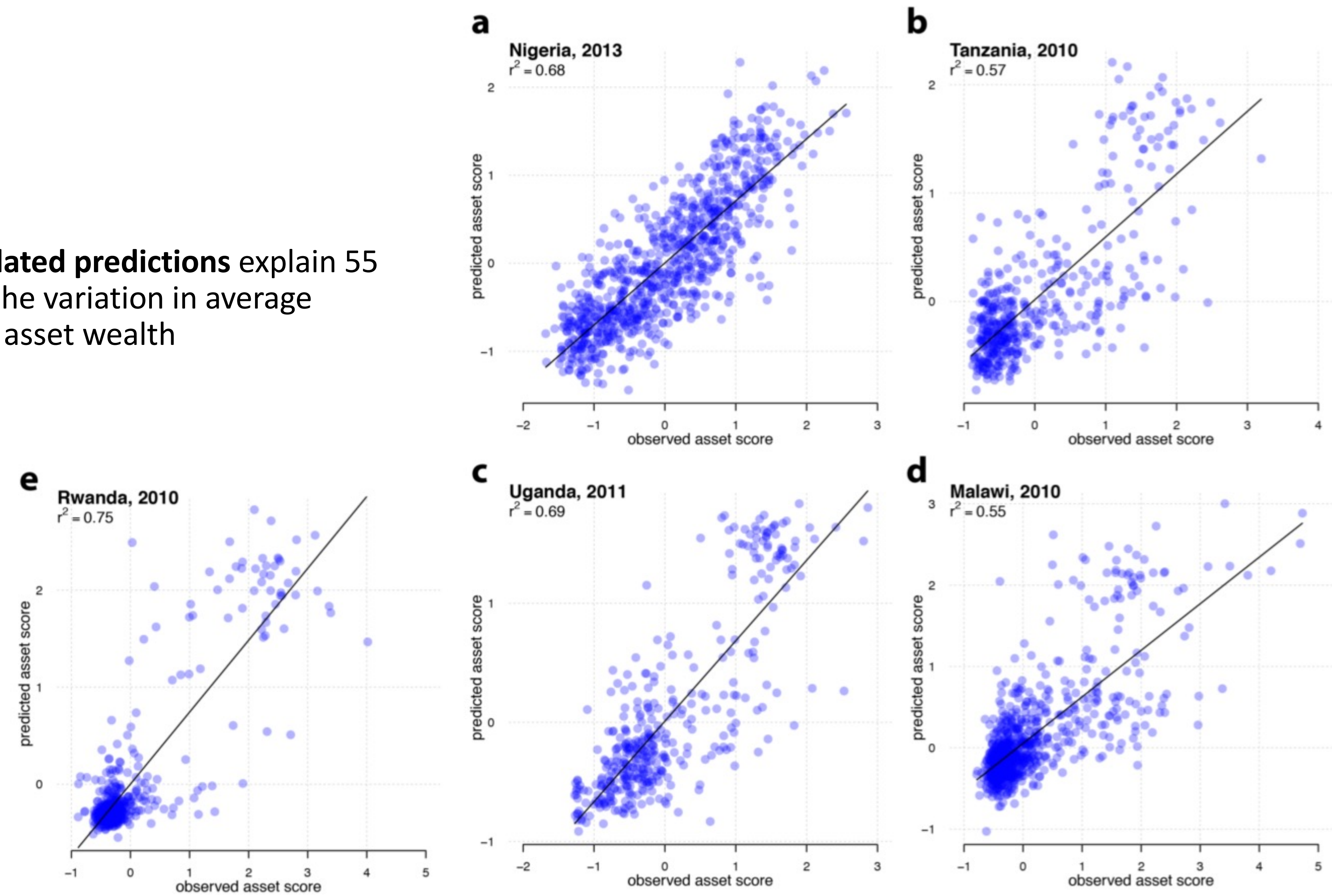
Strongly predictive of:

- Average household consumption expenditure
- Asset wealth

- **Cross-validated predictions** explain 37 to 55% of the variation in average household consumption



- **Cross-validated predictions** explain 55 to 75% of the variation in average household asset wealth



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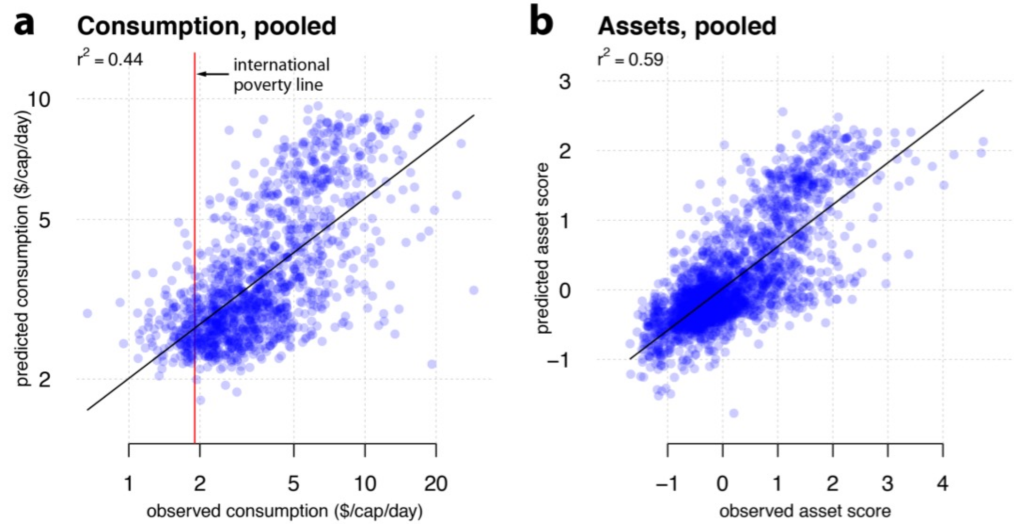
- **Pooled model** with **cross-validated predictions** explain 44 to 59% of the variation in average household asset wealth



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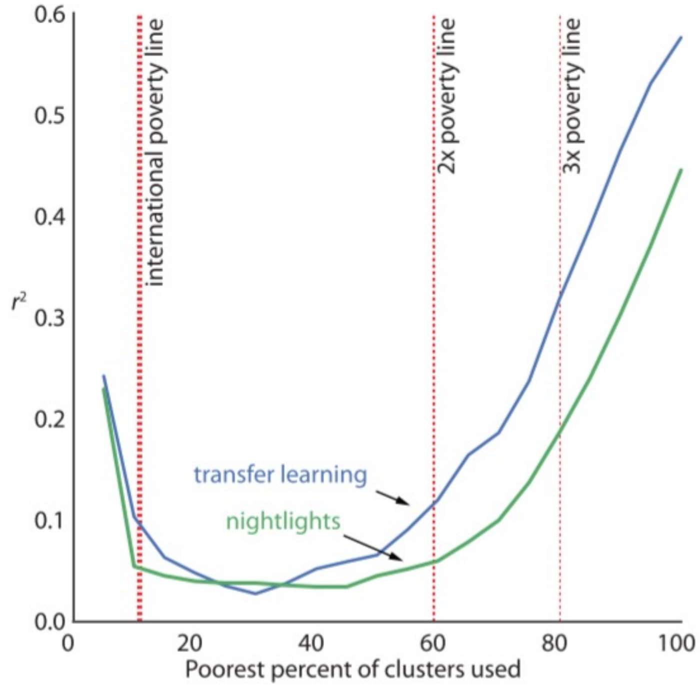
High Overall Predictive power

- High overall predictive power is achieved
- Better than using cell phone data
- Predictive power for assets is better than for consumption
  - Asset index is believed to be a better proxy
  - Certain assets in the index are identified in the extracted features

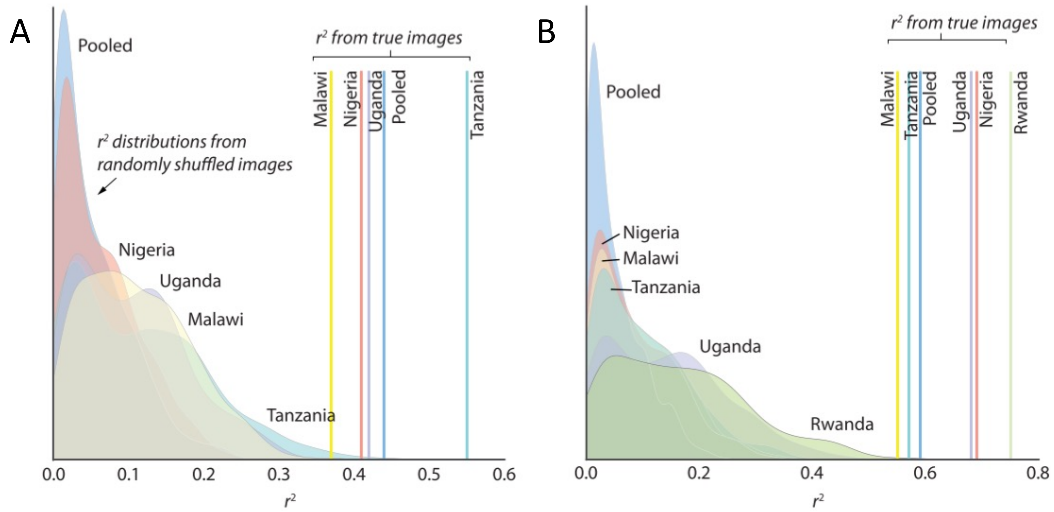
Compare with Nightlights Alone and other Methods

- **Pooled setting**, this model outperforms nightlights alone
  - in 81.3%, below international poverty line
  - in 98.5%, below 2 times the poverty line
  - in 99.5%, below 3 times the poverty line
- **Individual country**, results are similar
- Better than color histograms, histograms of oriented gradients, and using data from past surveys



Statistical Significance of the Results

- Randomly reassign daytime imagery to survey locations and retrain the model on these incorrect images



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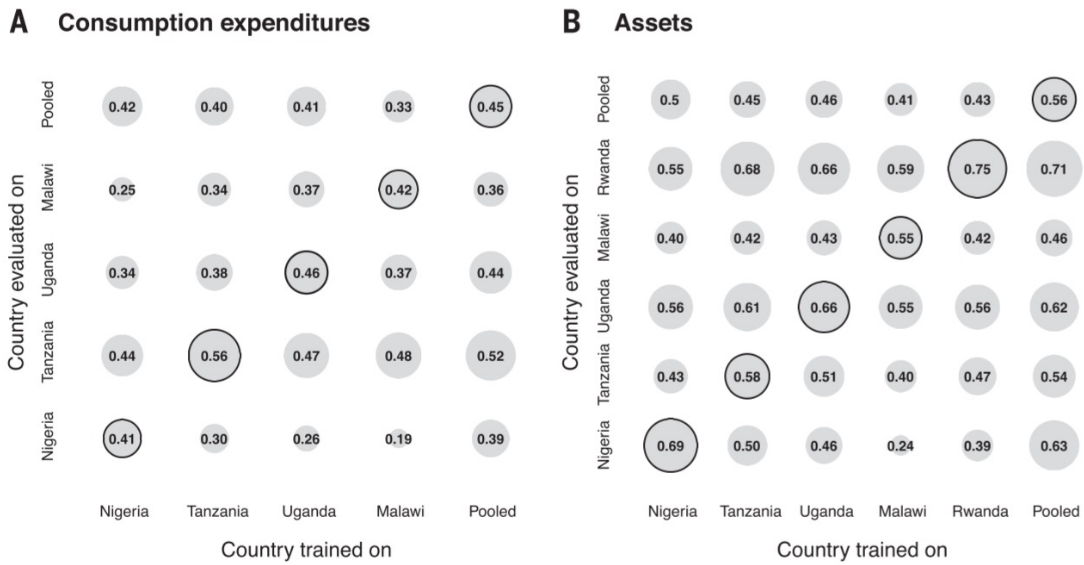
- Common determinants of livelihoods are revealed in imagery
- Commonalities can be leveraged to estimate consumption and asset outcomes in countries where survey are unobserved



Conclusions

- High-resolution satellite imagery predicts economic well-being
- Applied across five African countries
- Robust performance despite challenges in data precision

Model Performance and cross-country predictions

- Model accuracy remains high with inexact timing and location data
- Precision improvements likely to enhance performance
- Demonstrates adaptability and resilience with imperfect data

- Effective estimation of consumption or assets across different countries
- Highlights commonalities in determinants of livelihoods
- Addresses data gaps resulting from poor survey coverage

Future directions

- Future improvements through new sources of ground truth data
- Opportunities for data integration and finer resolution predictions
- Broader implications for global development goals and SDGs

Questions