Predicting poverty from satellite imagery

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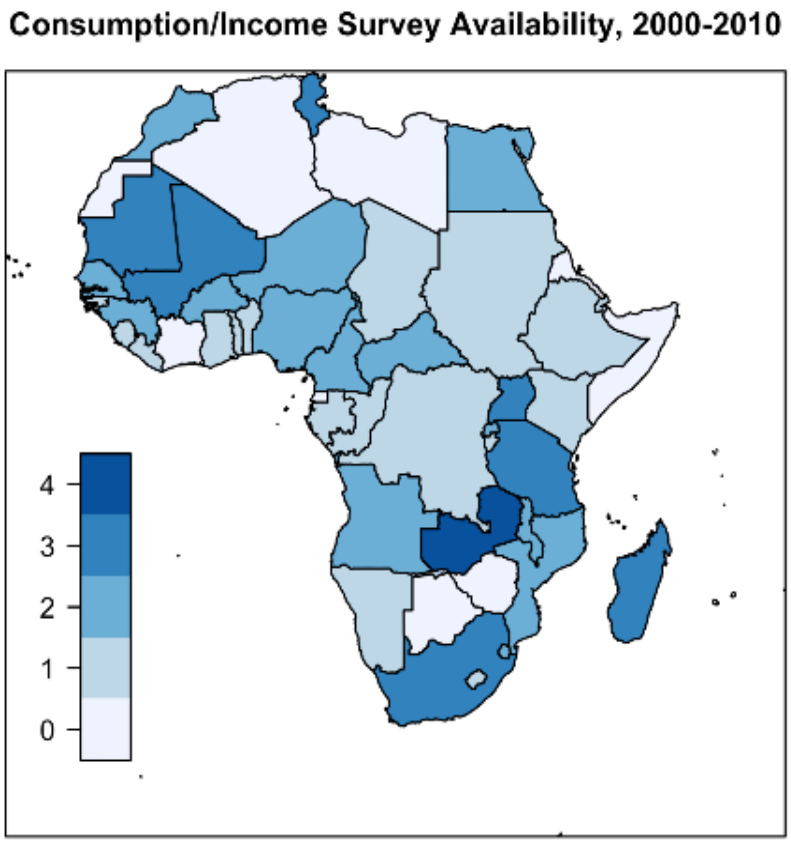
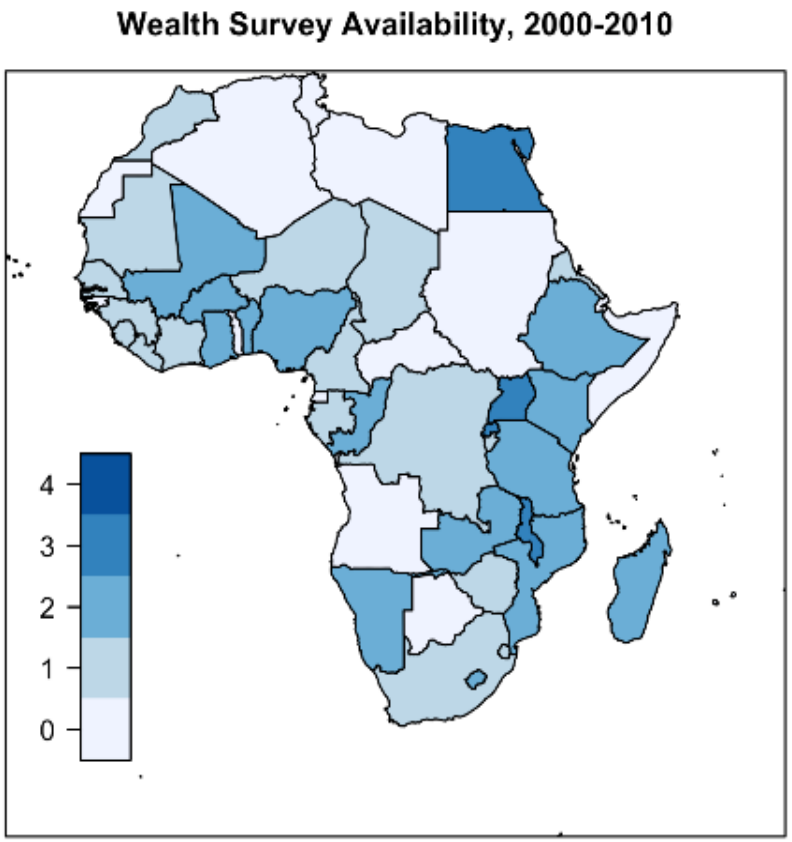
Why poverty?

- **#1** UN Sustainable Development Goal
  - Global poverty line: **$1.90/person/day**
- Understanding poverty can lead to:
  - Informed policy-making
  - Targeted NGO and aid efforts

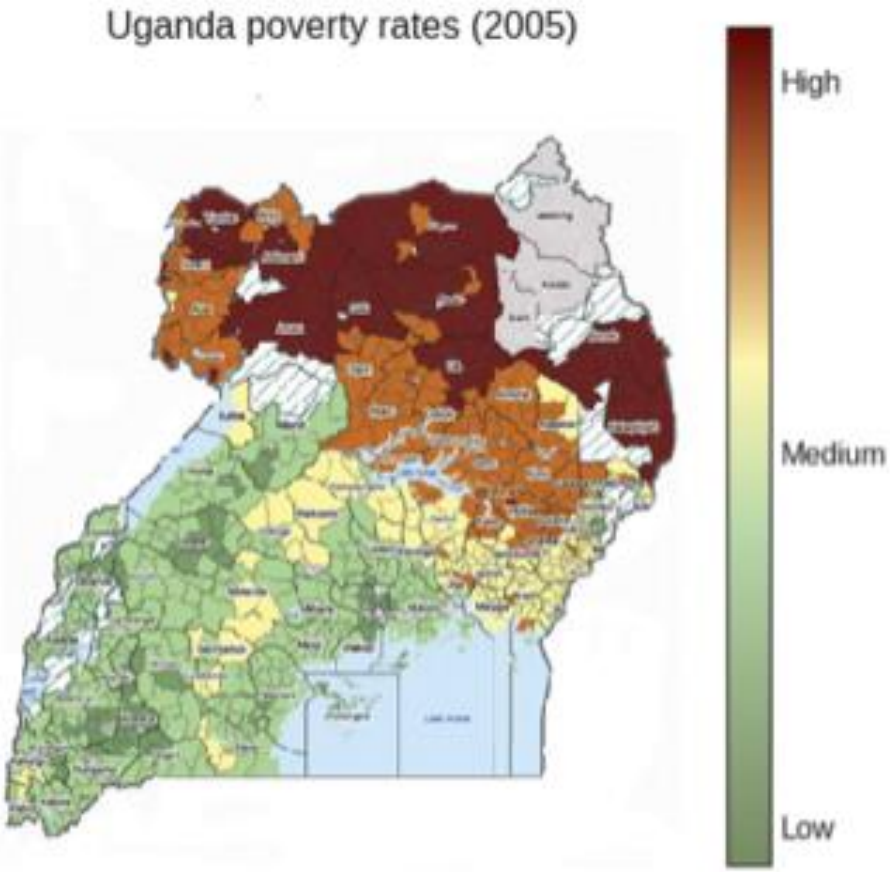
Data scarcity



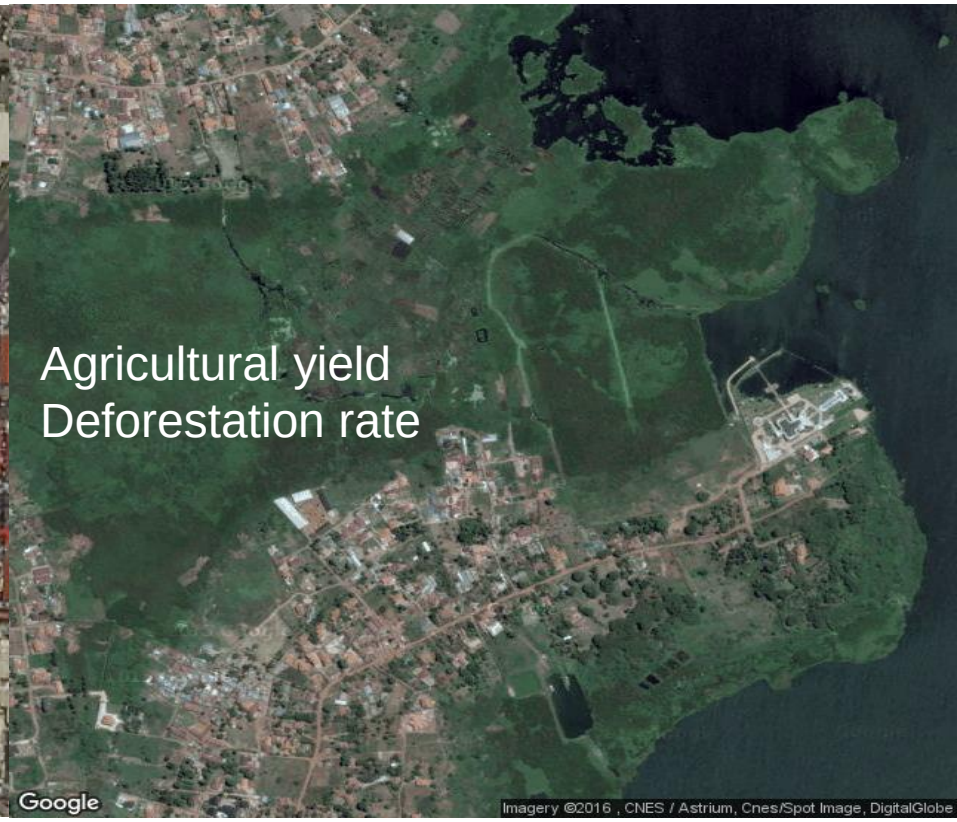


Lack of quality data is a huge challenge

- **Expensive** to conduct surveys:
  - $400,000 to $1.5 million
- **Data scarcity**:
  - <0.01% of total households covered by surveys
- **Poor** spatial and temporal **resolution**



Satellite imagery is low-cost and globally available



Simultaneously becoming **cheaper** and **higher resolution** (DigitalGlobe, Planet Labs, Skybox, etc.)

What if…

we could **infer** socioeconomic indicators from large-scale, remotely-sensed data?

Standard supervised learning won't work

Input

Model

Output

Poverty, wealth, child mortality, etc.

- Very little training data (few thousand data points)
- Nontrivial for humans (hard to crowdsource labels)

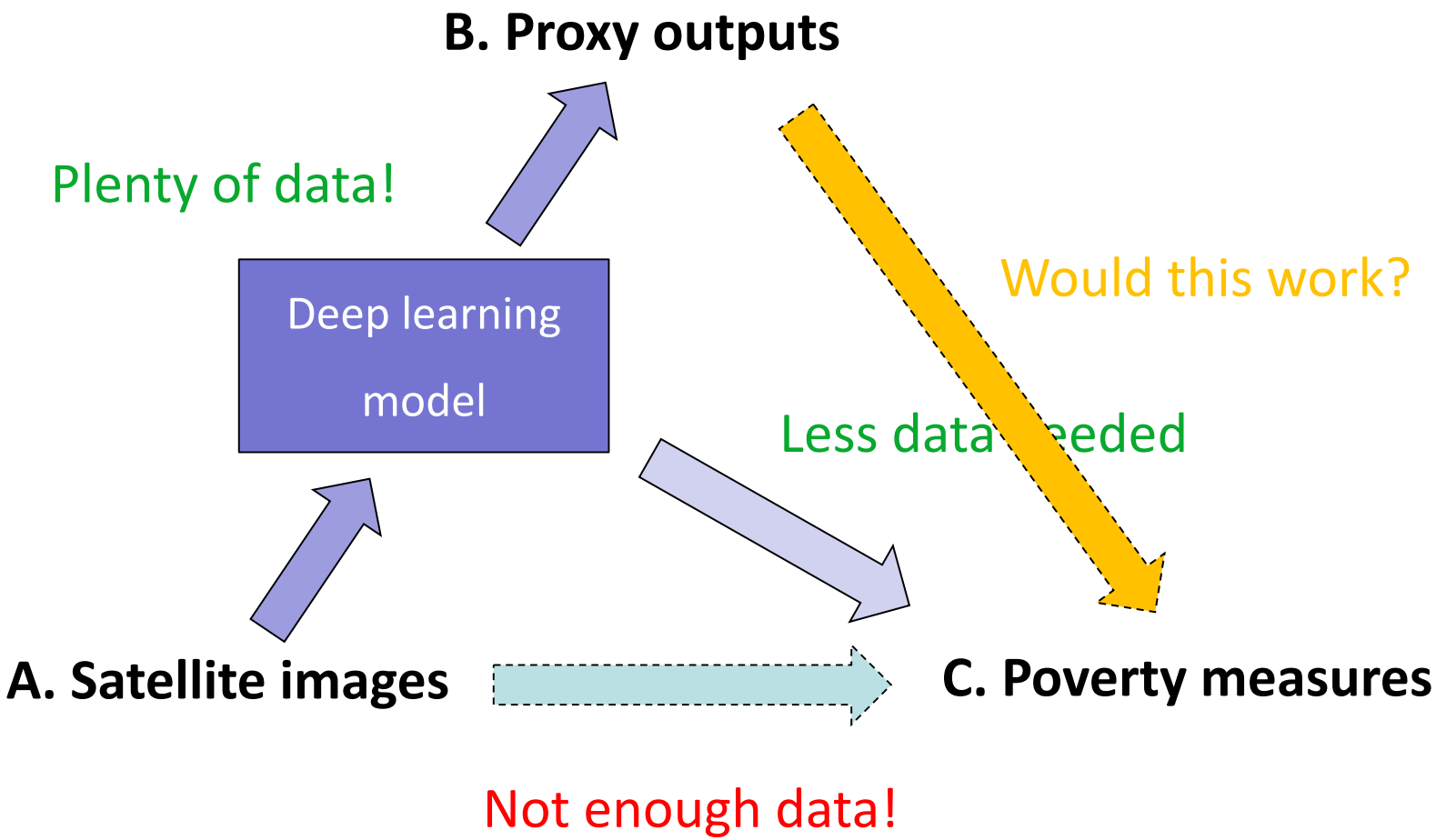
Transfer learning overcomes data scarcity

Transfer learning: Use knowledge gained from one task to solve a different (but related) task

Train here

Perform here

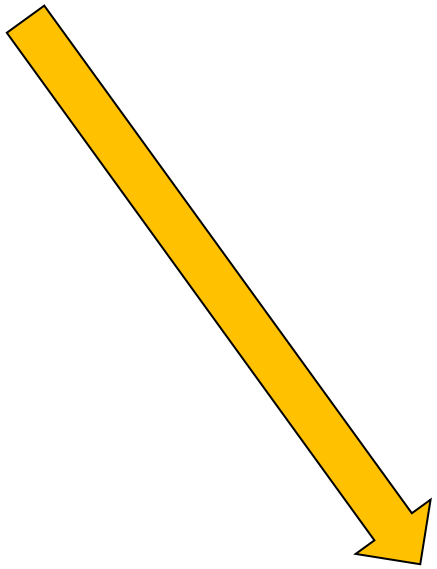
Transfer learning bridges the data gap



Nighttime lights as proxy for economic development

Why not use nightlights directly?

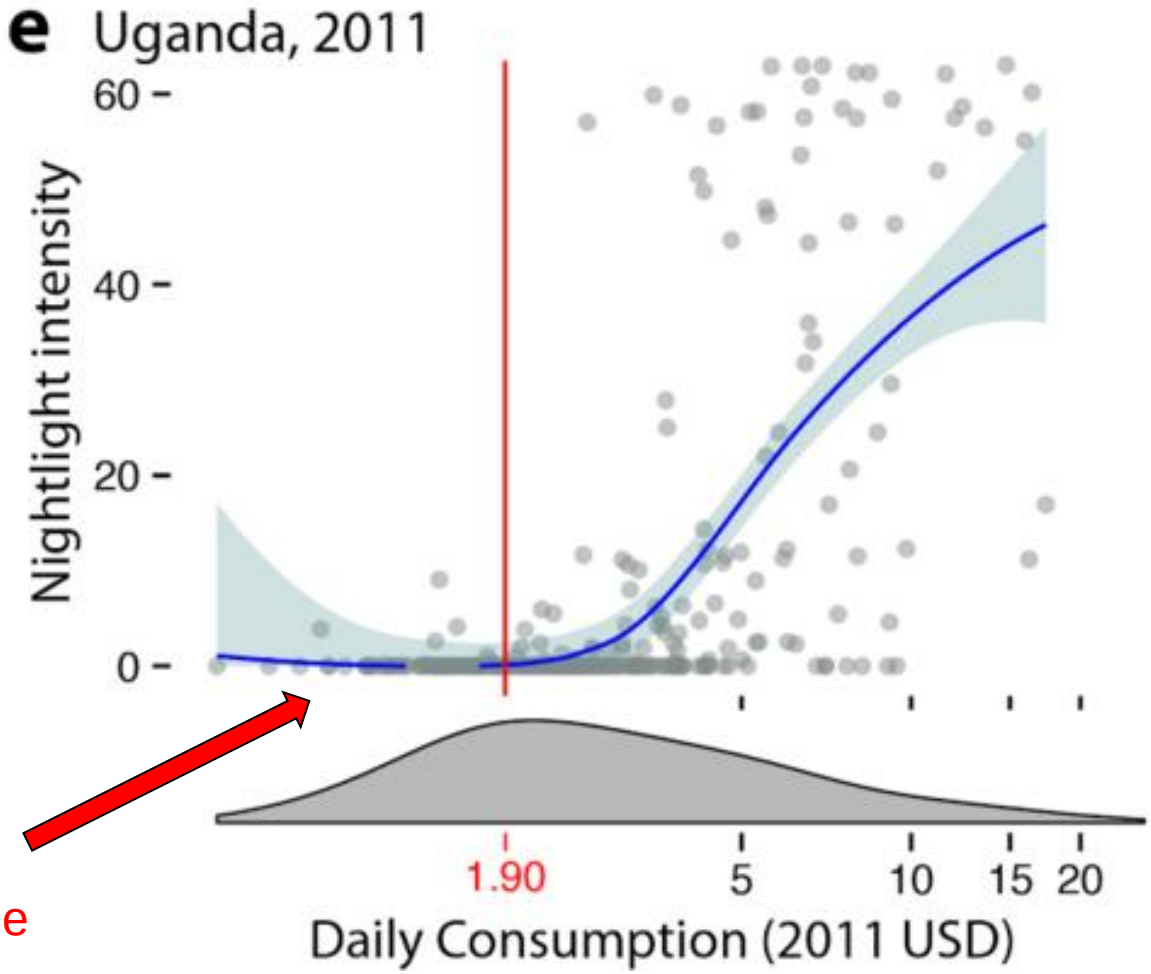
B. Nighttime light intensities



A. Satellite images

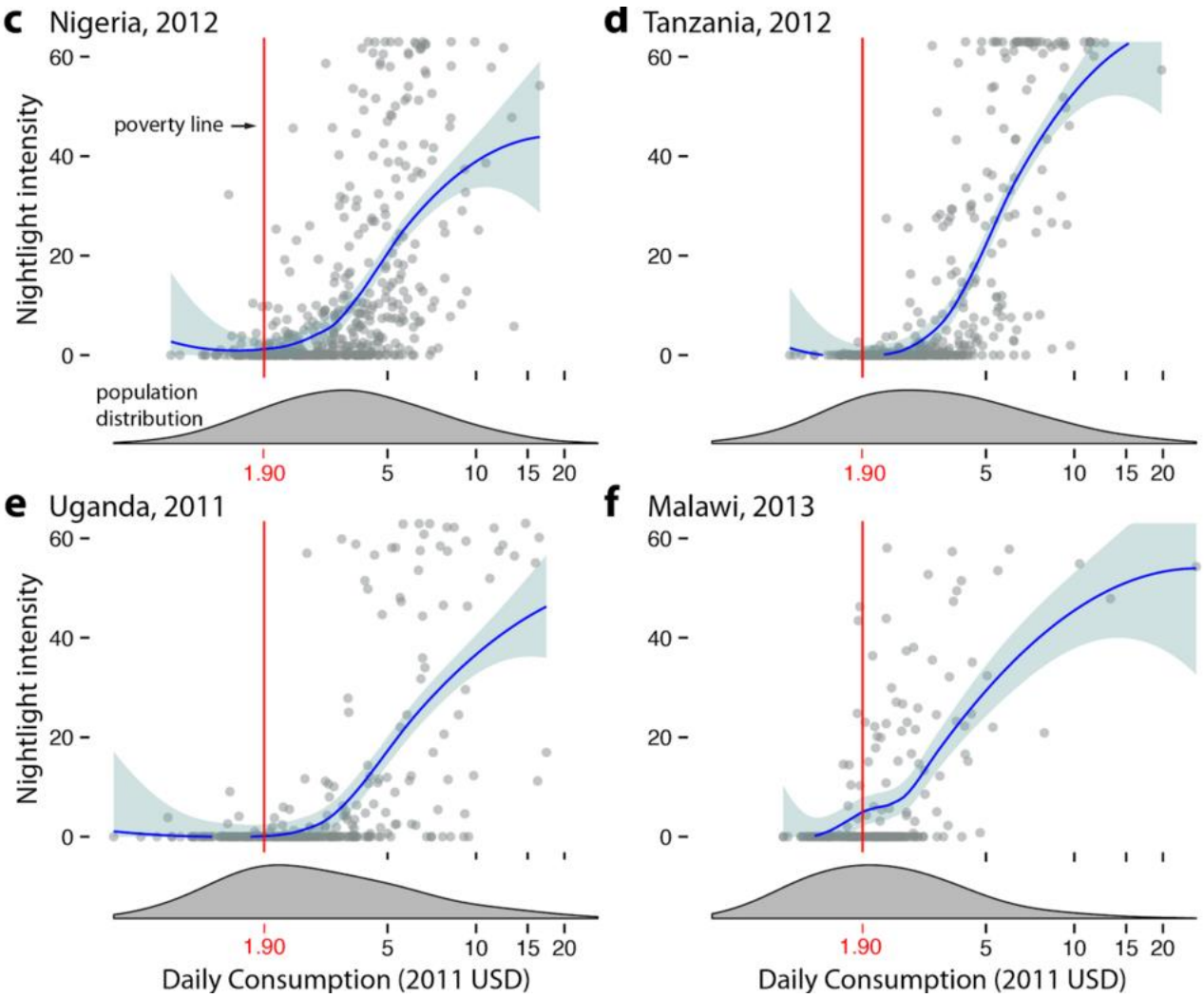
C. Poverty measures

Not so fast…

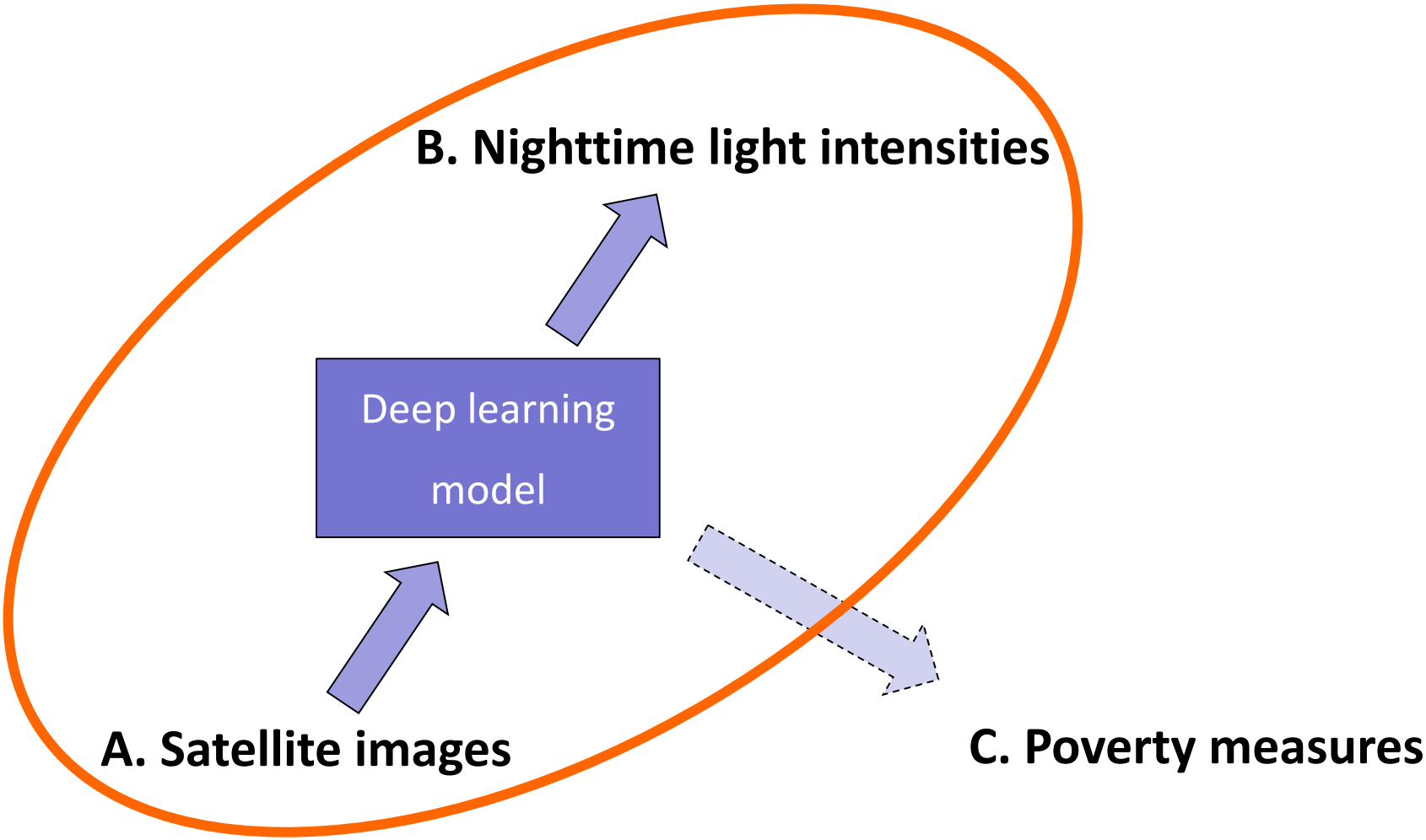


Almost no variation below the poverty line

Lights aren't useful for helping the poorest



Step 1: Predict nighttime light intensities



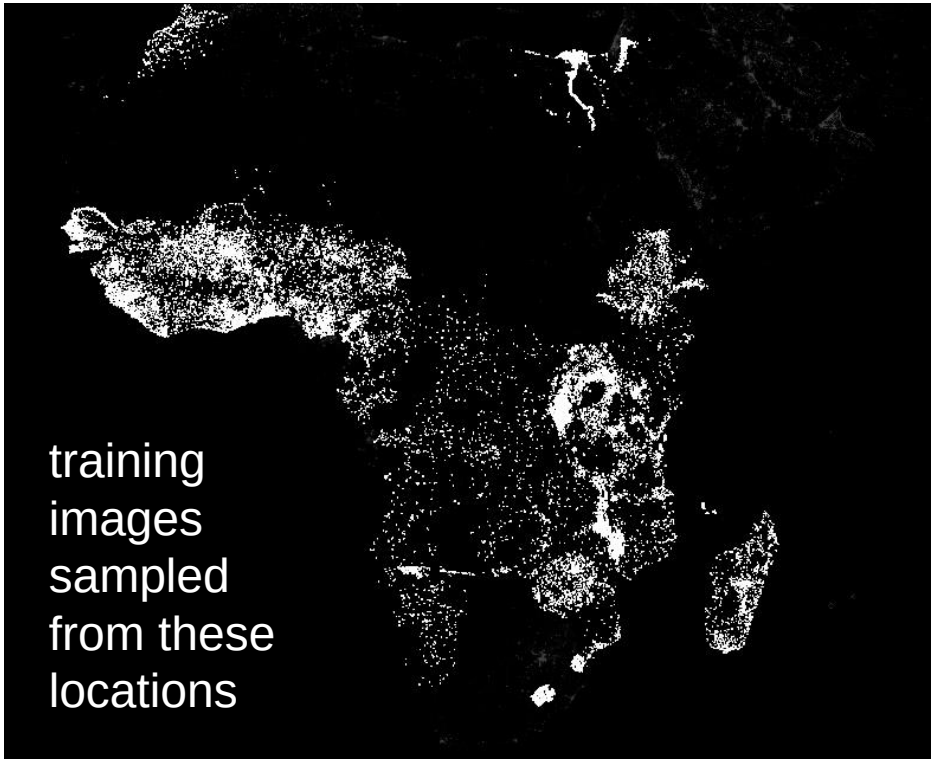
Training data on the proxy task is plentiful

Labeled input/output training pairs

( , Low nightlight intensity)

…

( , High nightlight intensity)

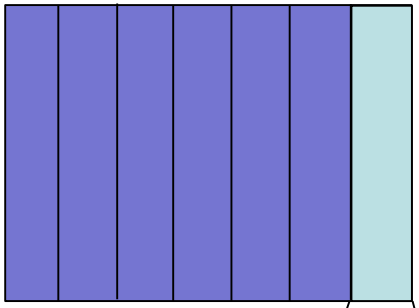


Millions of training images

Images summarized as low-dimensional feature vectors

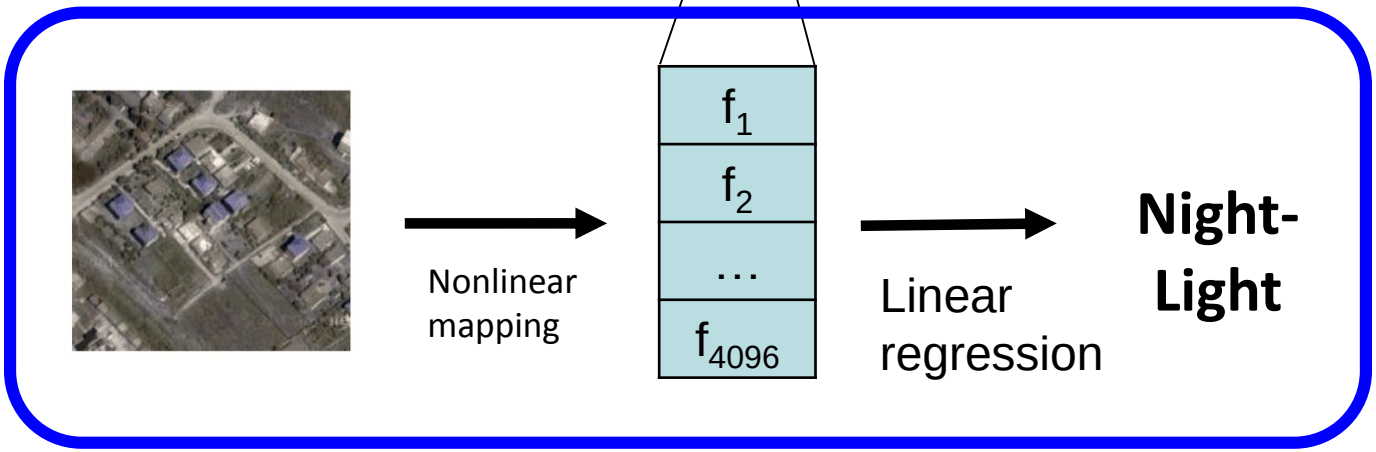
Inputs: daytime satellite images

Convolutional Neural Network (CNN)

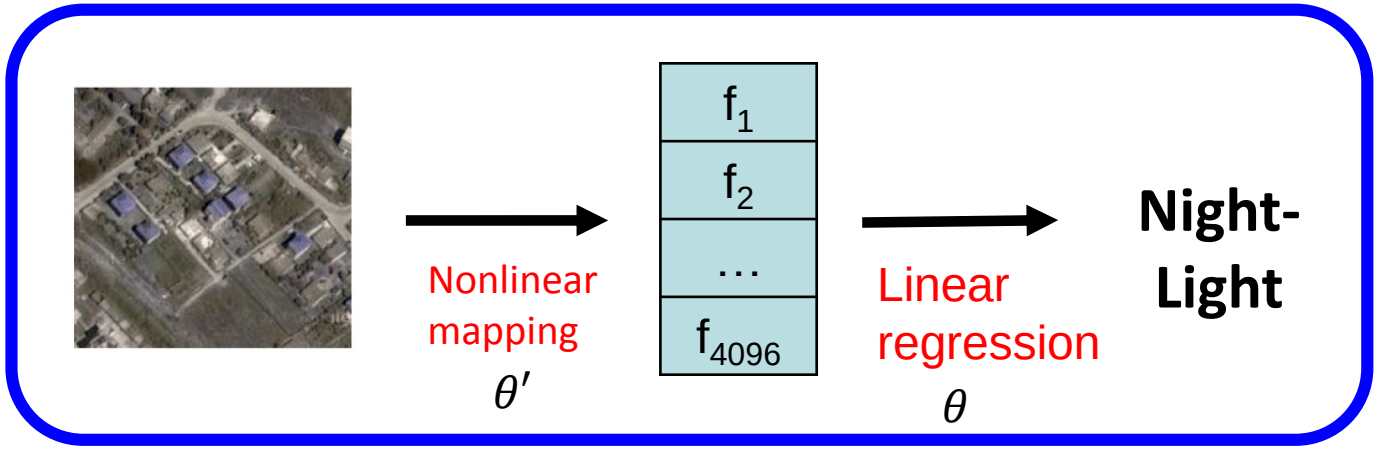


Outputs: Nighttime light intensities

{Low, Medium, High}



Feature learning



$$\min_{\theta,\theta'} \sum_{i=1}^{m} l(y_i, \hat{y}_i) = \min_{\theta,\theta'} \sum_{i=1}^{m} l(\, y_i \,,\, \theta^T f(x_i, \theta'\,))$$

Over 50 million parameters to fit

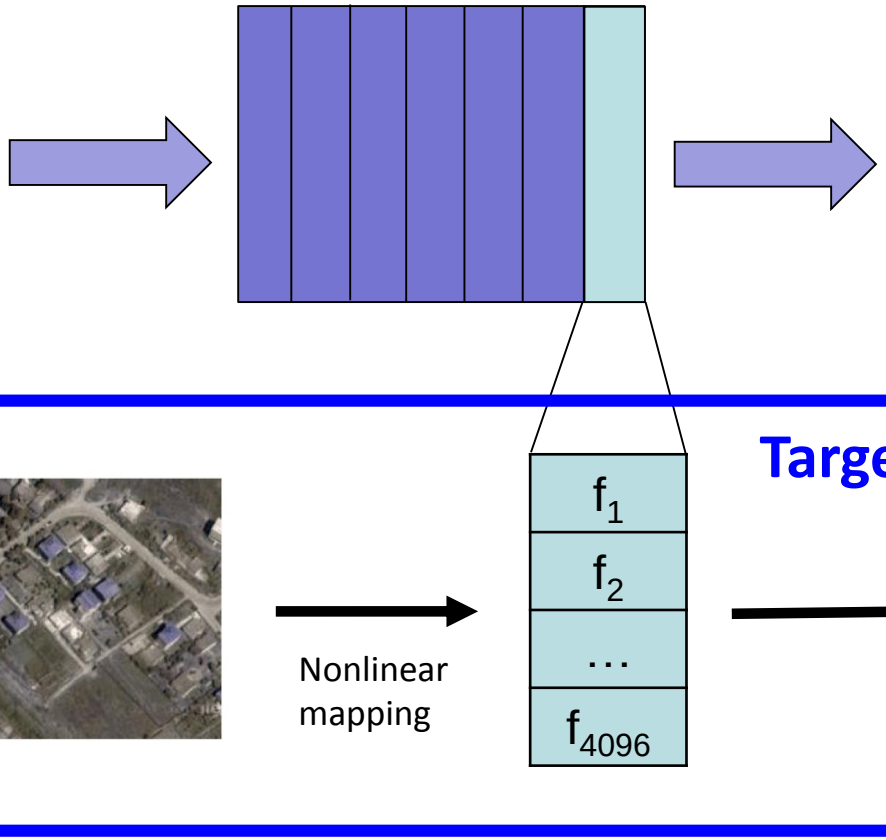
Run gradient descent for a few days

Transfer Learning

Inputs: daytime satellite images

Feature Learning

Outputs: Nighttime light intensities



Have we learned to identify useful features?

Model learns relevant features automatically

Satellite image

Filter activation map

Overlaid image

Target task: Binary poverty classification

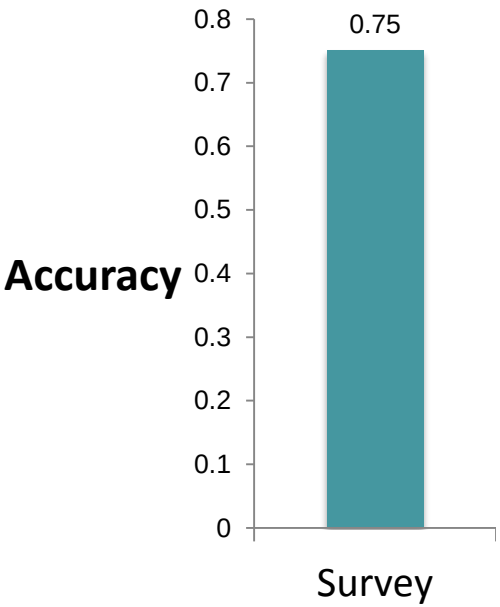
- Living Standards Measurement Study (LSMS) data in Uganda (World Bank)
  - Collected data on household features
    - Roof type, number of rooms, distance to major road, etc.
  - Report household consumption expenditures

- **Task**: Predict if the majority of households in a cluster are above or below the poverty line

How does our model compare?

Survey-based model is the gold standard for accuracy but…

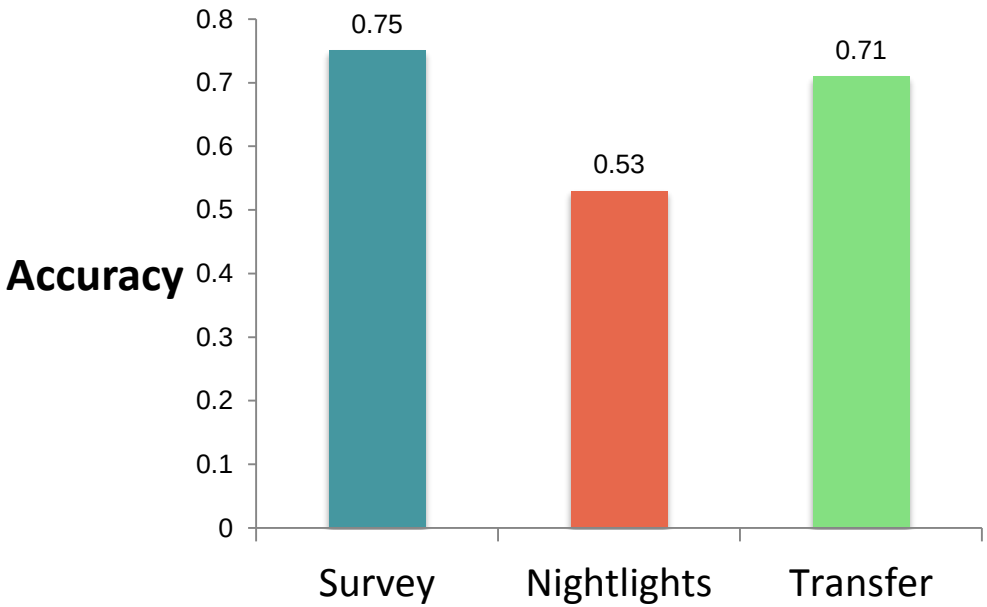
- Relies on expensively collected data
- Is difficult to scale, not comprehensive in coverage



Transfer learning model approaches survey accuracy

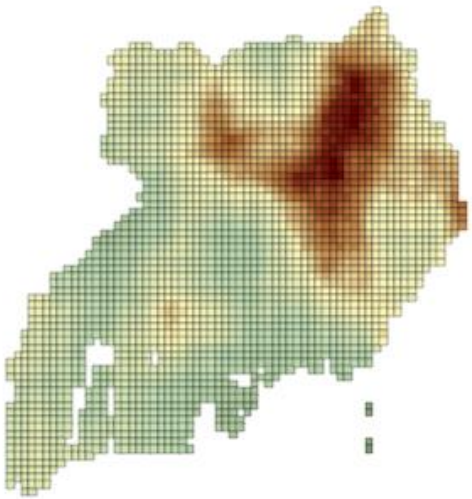
Advantages of transfer learning approach:

- Relies on inexpensive, publicly available data
- Globally scalable, doesn't require unifying disparate datasets

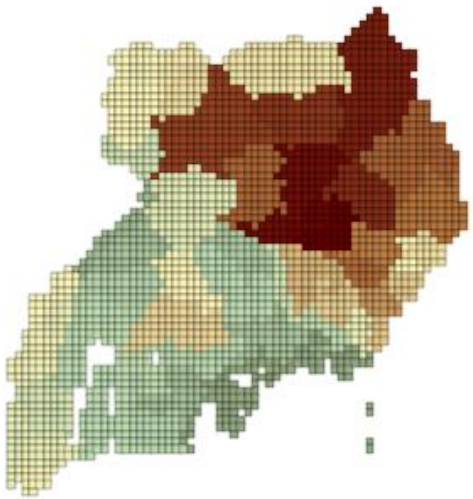


Our model maps poverty at high resolution

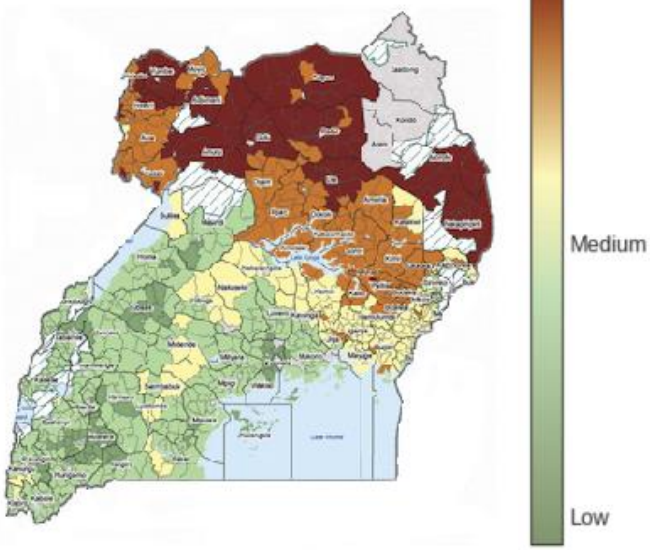
Smoothed predictions



District aggregated



Official map (2005)



<u>Case study</u>: Uganda

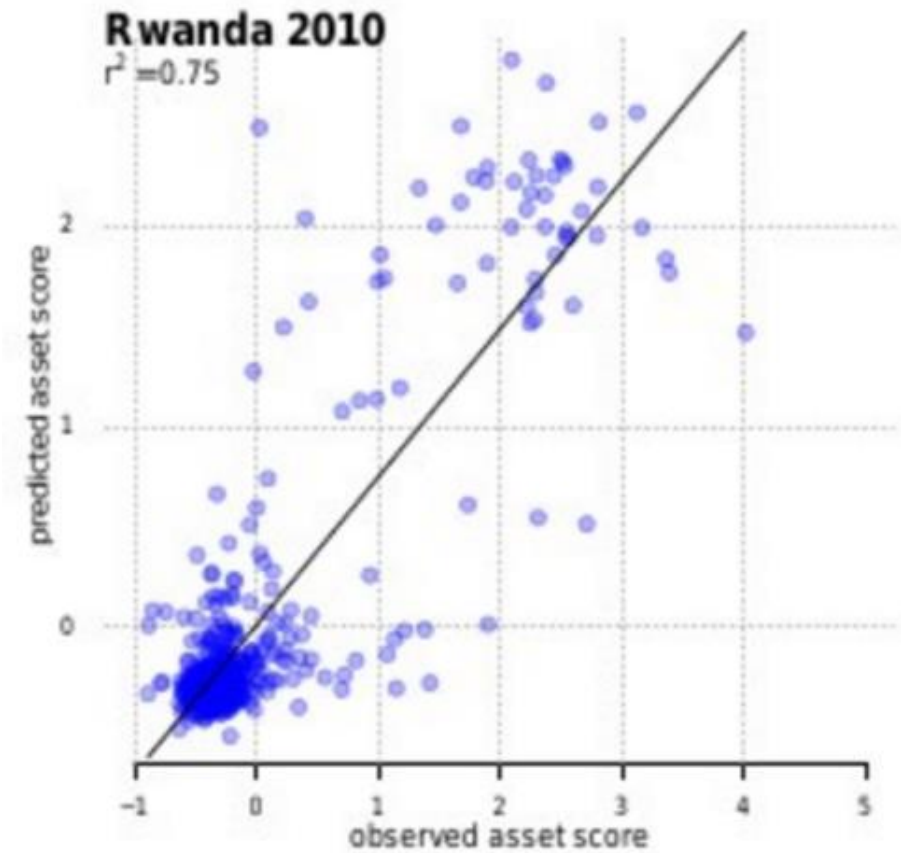
- Most recent poverty map over a decade old
- Lack of ground truth highlights need for more data

We can differentiate different levels of poverty

<u>2 continuous measures of wealth</u>:

- Consumption expenditures

- Household assets



We outperform recent methods based on mobile call record data

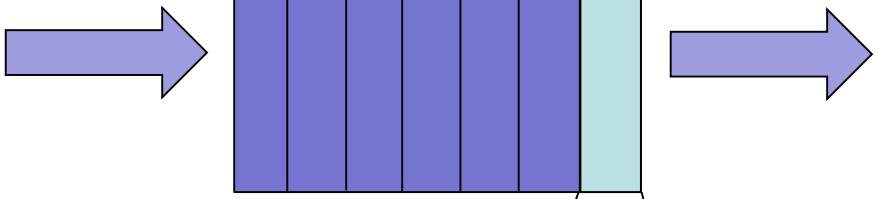
Blumenstock et al. (2015) Predicting Poverty and Wealth from Mobile Phone Metadata, *Science*

Transfer Learning

Inputs: daytime satellite images

Feature Learning

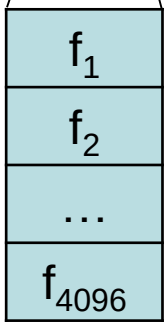
Outputs: Nighttime light intensities



{Low, Medium, High}

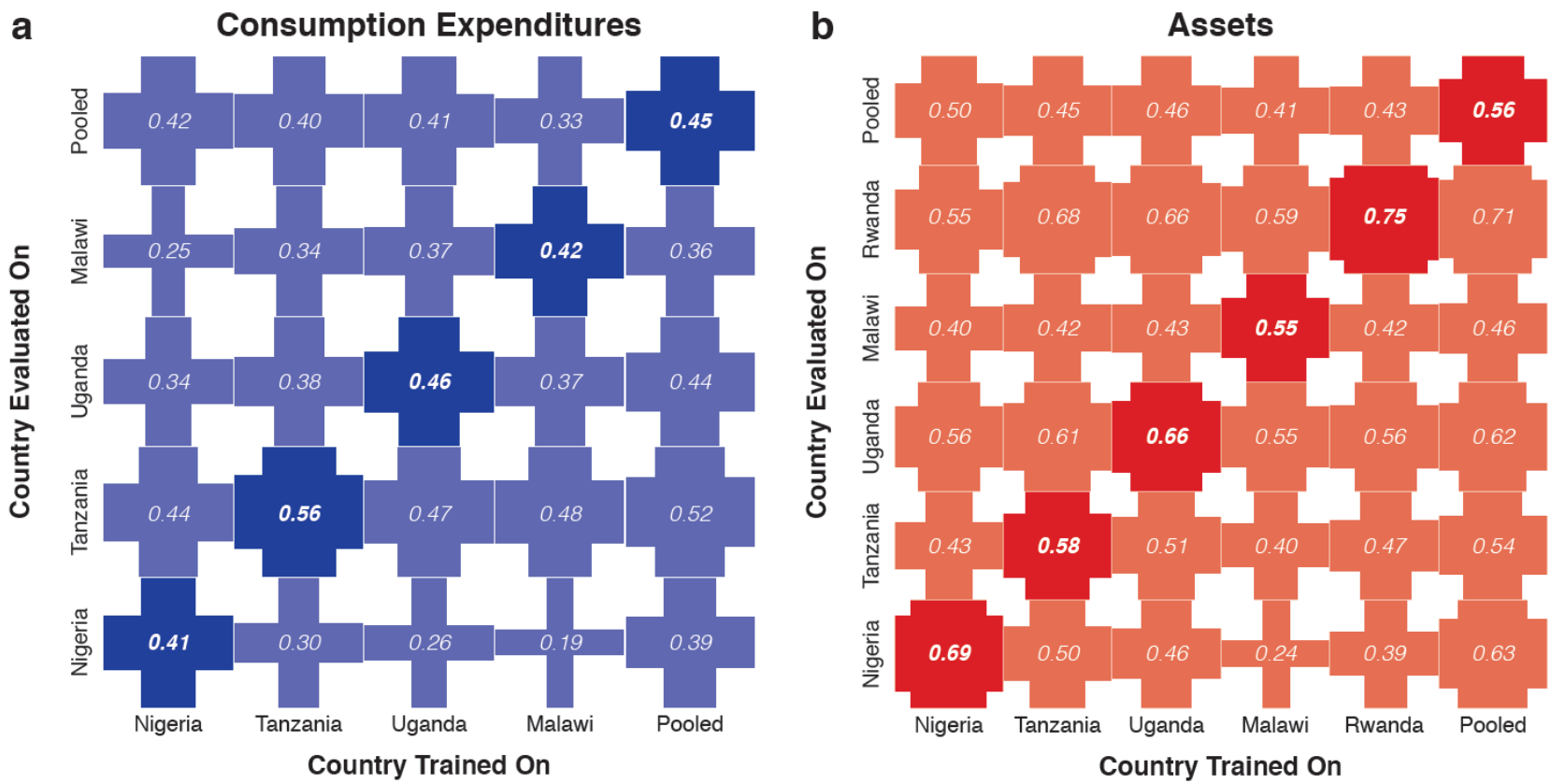
Target task

Nonlinear mapping



Expenditures
Assets

Models travels well across borders

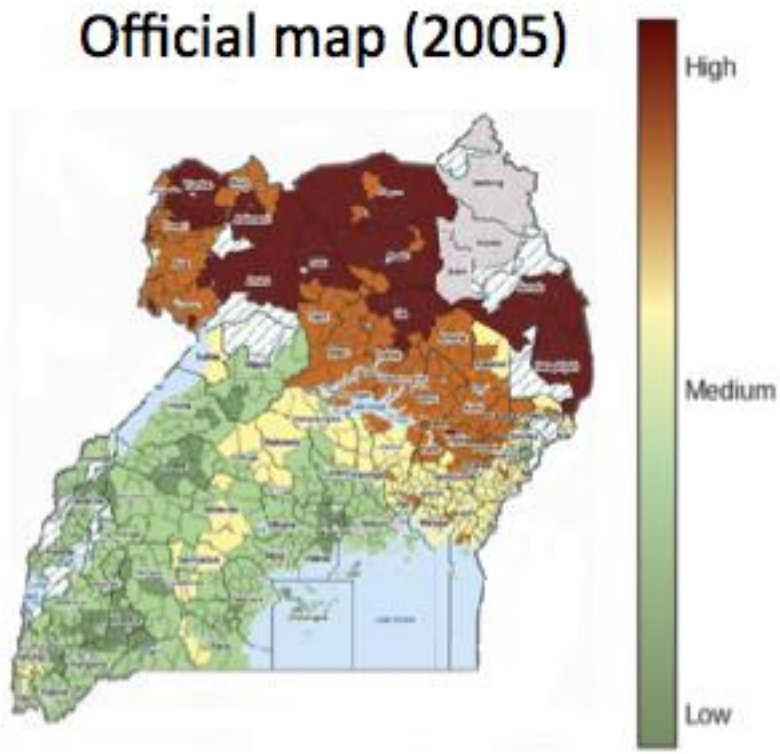


Models trained in one country perform well in other countries

Can make predictions in countries where no data exists at all

What do we still need?

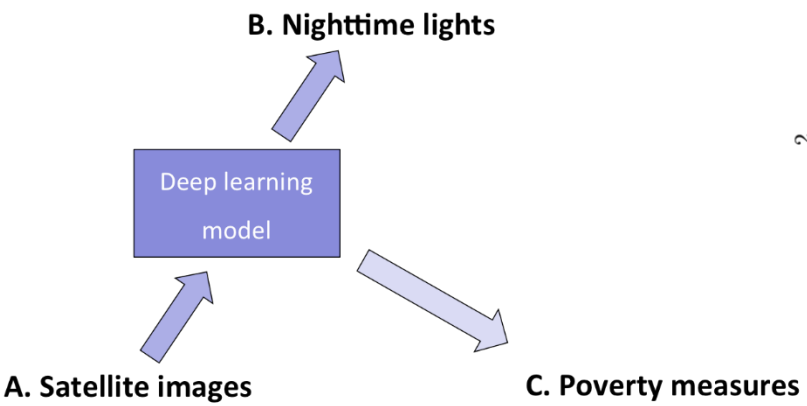
- Develop models that account for spatial and temporal dependencies of poverty and health

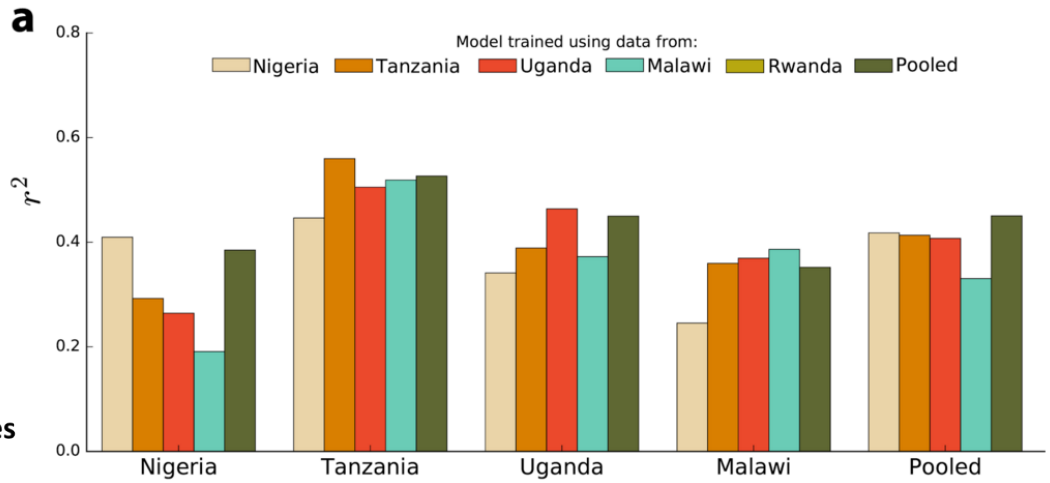


Take full advantage of incredible richness of images

A new approach based on satellite imagery

We have introduced an **accurate**, **inexpensive**, and **scalable** approach to predicting poverty and wealth





The Upshot The New York Times

Satellite Images Can Pinpoint Poverty Where Surveys Can't

Economic View

By SENDHIL MULLAINATHAN APRIL 1, 2016