Applications of Data & Machine Learning in Economic Research: Part III – Detecting Poverty

BAI 30545 – Foundations of Economic Sciences

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Previous session

Survey results

Thanks to everyone who participated!

Results: About the **same pace** and **same detail**

Pace: In the next lessons, I would prefer the pace to be:

Answer	Choices	Average
Much faster	0/13	0%
Slightly faster	2/13	15%
About the same	10/13	77%
Slightly slower	0/13	0%
Much slower	1/13	8%

Detail: In the next lessons, I would prefer the amount of detail to be:

Answer	Choices	Average
Much more	0/13	0%
Slightly more	4/13	31%
About the same	7/13	54%
Slightly less	1/13	8%
Much less	1/13	8%

Introduction

Research Paper: Jean et al. (2016, Science)

RESEARCH ARTICLES

ECONOMICS

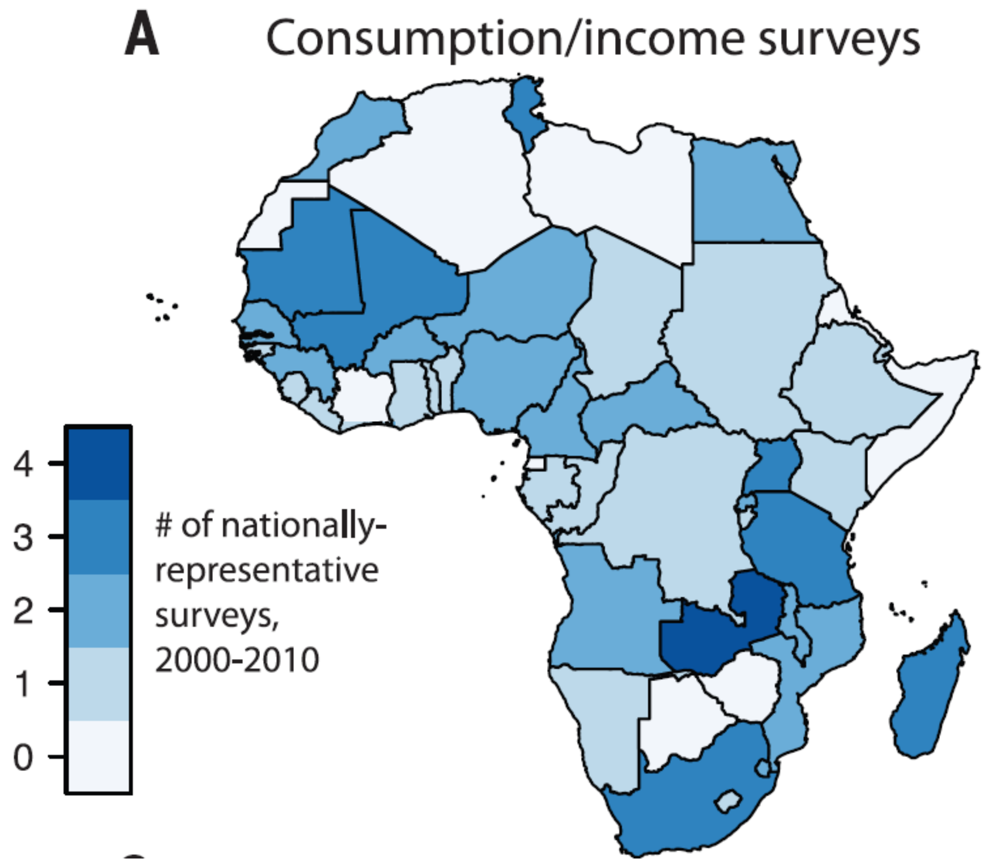
Combining satellite imagery and machine learning to predict poverty

Neal Jean,[1,2*] Marshall Burke,[3,4,5*†] Michael Xie,[1] W. Matthew Davis,[4] David B. Lobell,[3,4] Stefano Ermon[1]

Neal Jean et al.: *"Combining satellite imagery and machine learning to predict poverty"*. Science 353, 790-794 (2016).
DOI: 10.1126/science.aaf7894

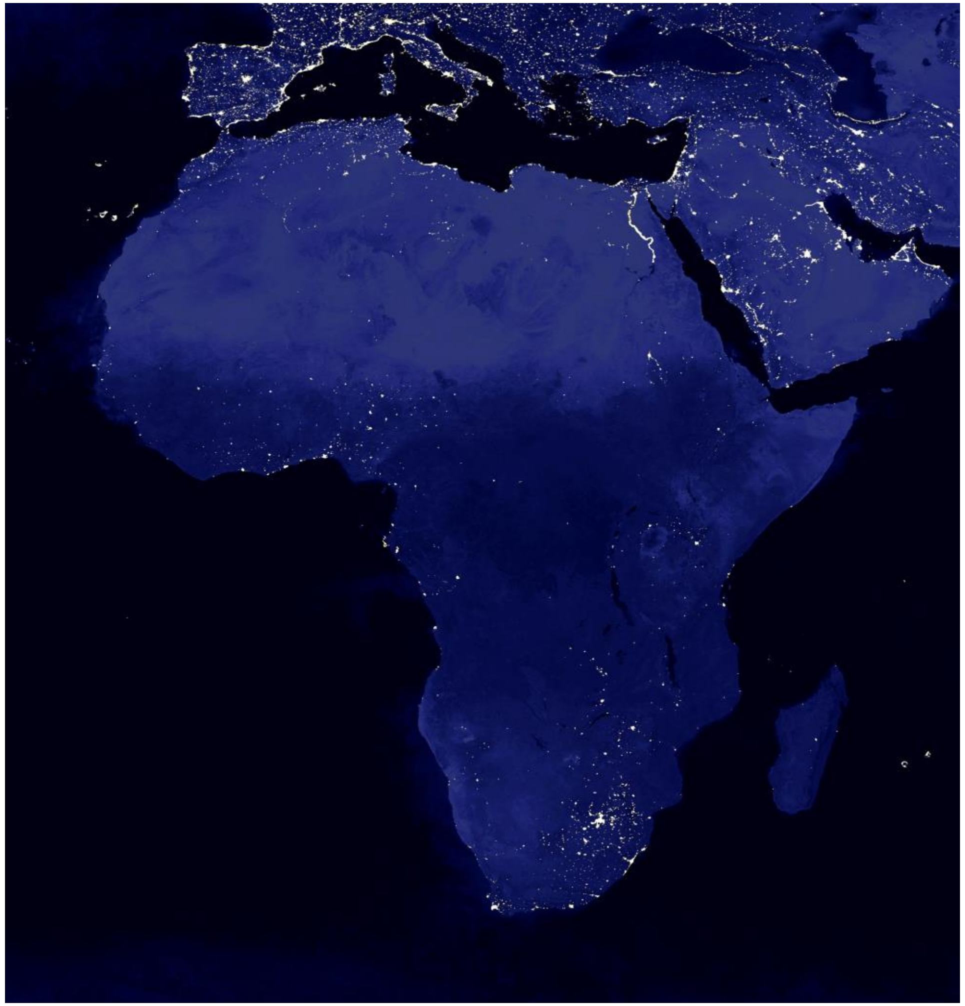
Motivation

- **Accurate measurement of poverty** is crucial to **design policies** and **track their success**
- **Figure:** Only 20 out of 59 African countries have conducted 2+ nationally representative surveys on income / consumption between 2000-2010
- **Implication:** *Limited* geographical data on poverty
- **Problem:** Governments often have little incentive to implement large-scale surveys:
  - Costly
  - Might reveal malpractice / failure / corruption
- **Idea:** Can we use satellite data to identify poor geographical areas?



Nightlights as indicator for economic activity

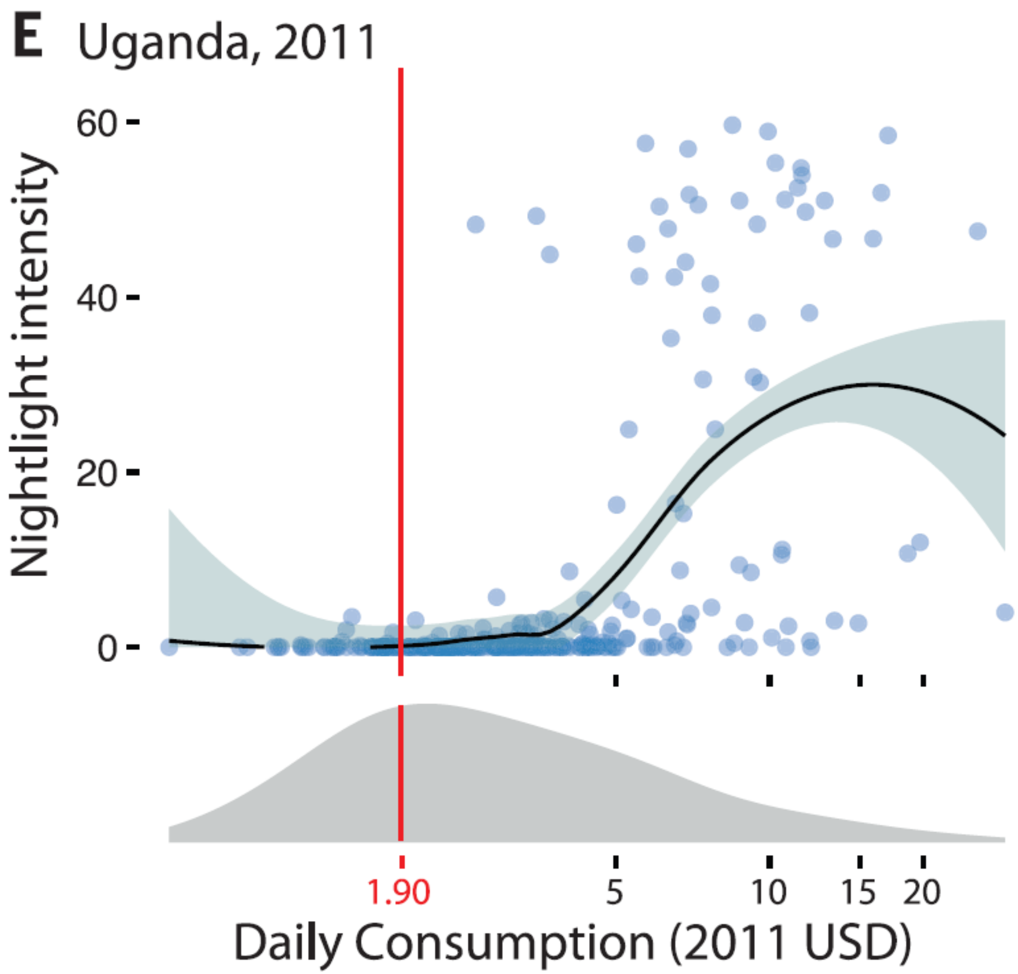
- **Idea:** Economic activity *uses* and *produces* infrastructure that emits light at night (streetlights, industrial plants, ports, airports, etc.)
- **Data** provided by *United States Air Force Defense Meteorological Satellite Program (DMSP)*, publicly, since 1992
- **Measure** the amount of human-generated light every night per *roughly* 1km x 1km grid cell
- Generate **index** by averaging yearly over all clear nights, and scale to 0-63
- **Question:** Can we use nightlights to estimate poverty?



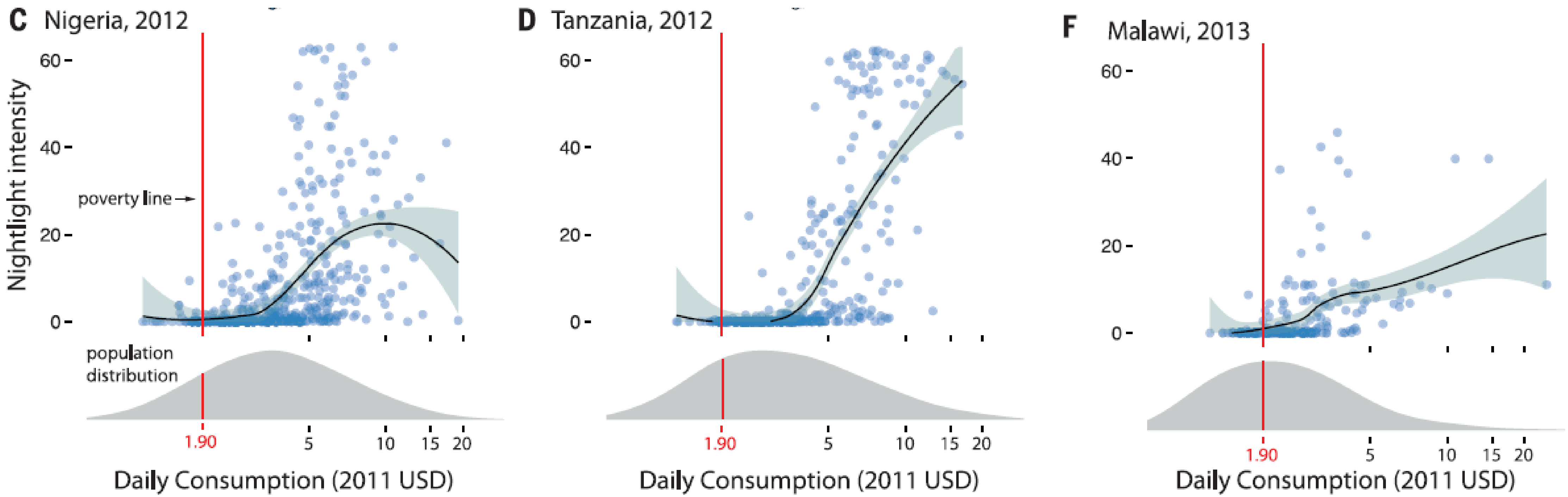
Source: https://commons.wikimedia.org/wiki/File:Africa_at_night_%28Cropped_From_Entire_Earth_Image%29.jpg, last accessed 2025-09-30

Nightlights are not a good measure of poverty

- **Figure:** Each point is a region in Uganda in 2011
  - **X-axis:** Avg. daily consumption in USD (including distribution across population)
  - **Y-axis:** Nightlight intensity score
  - **Black line:** Avg. nightlights given consumption level
  - **Red line:** Official international poverty line (1.90$ in consumption / person / day)
- **Goal:** Predict whether a point is to the right or left of red line just using satellite data
- **Observations:** Nightlights are associated with *very high* consumption, but flat for *both low and intermediate* consumption levels
- **Implication:** Cannot estimate poverty from nightlights alone

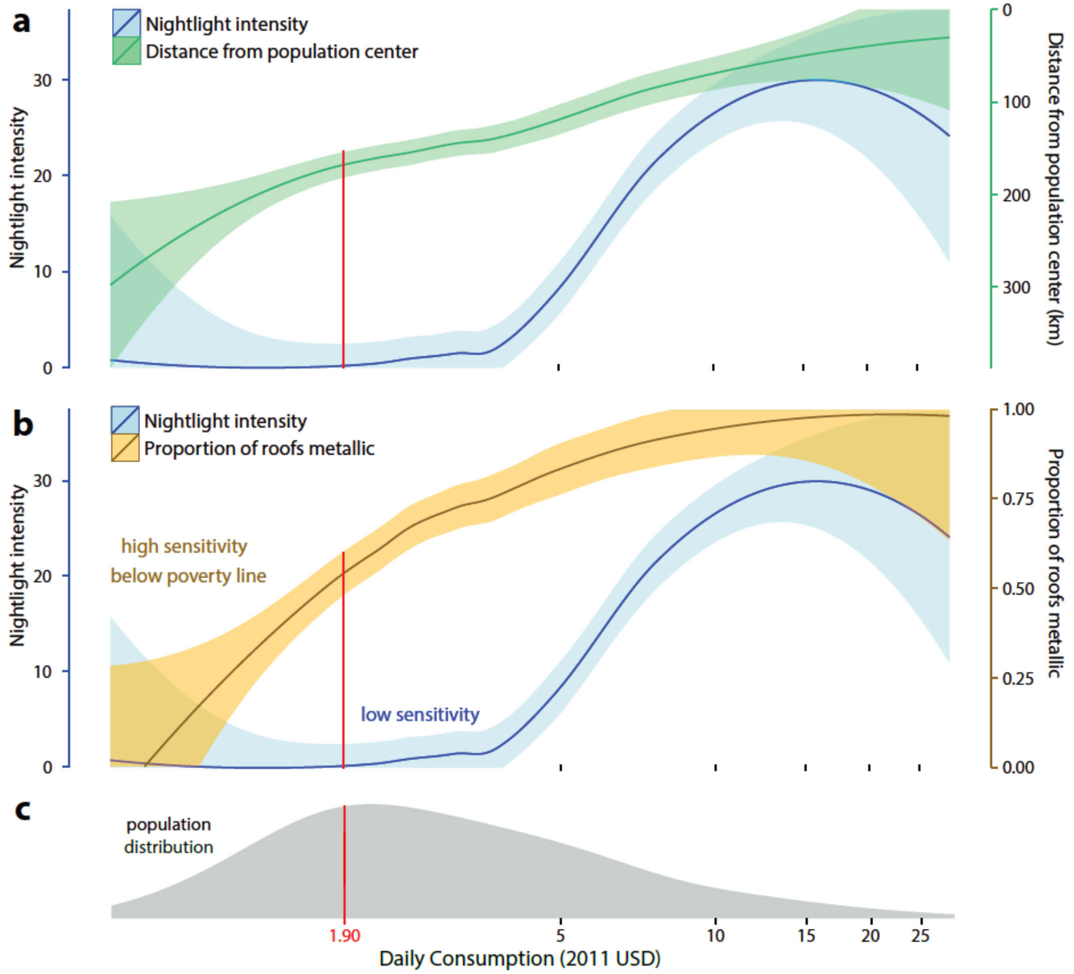


Same for other African countries



Poverty better captured by other features

- **Figures:** Consumption and nightlights vs. other features (Uganda, 2011):
  - a: Distance from nearest population center
  - b: Share of roofs made of metal
  - **Both:** Nightlight intensity
- **Observation:** Both variables better differentiate better between low and high consumption levels *(poverty)* than nightlights
- **Implication:** Want to use also **daylight images** for estimating poverty



This paper

- **Idea:** Estimate poor geographical areas using:
  - **Outcomes:** Survey data on consumption in 5 African countries
  - **Features:** High-resolution satellite images:
    - Night-time: Lights
    - Day-time: Surface features
- **Empirical strategy:** Two steps:
  1. **Detect surface features** on satellite images using deep neural network
     (both natural (lakes) and human-made (infrastructure))
  2. **Predict local consumption levels** from these features

Background and Data

Survey data

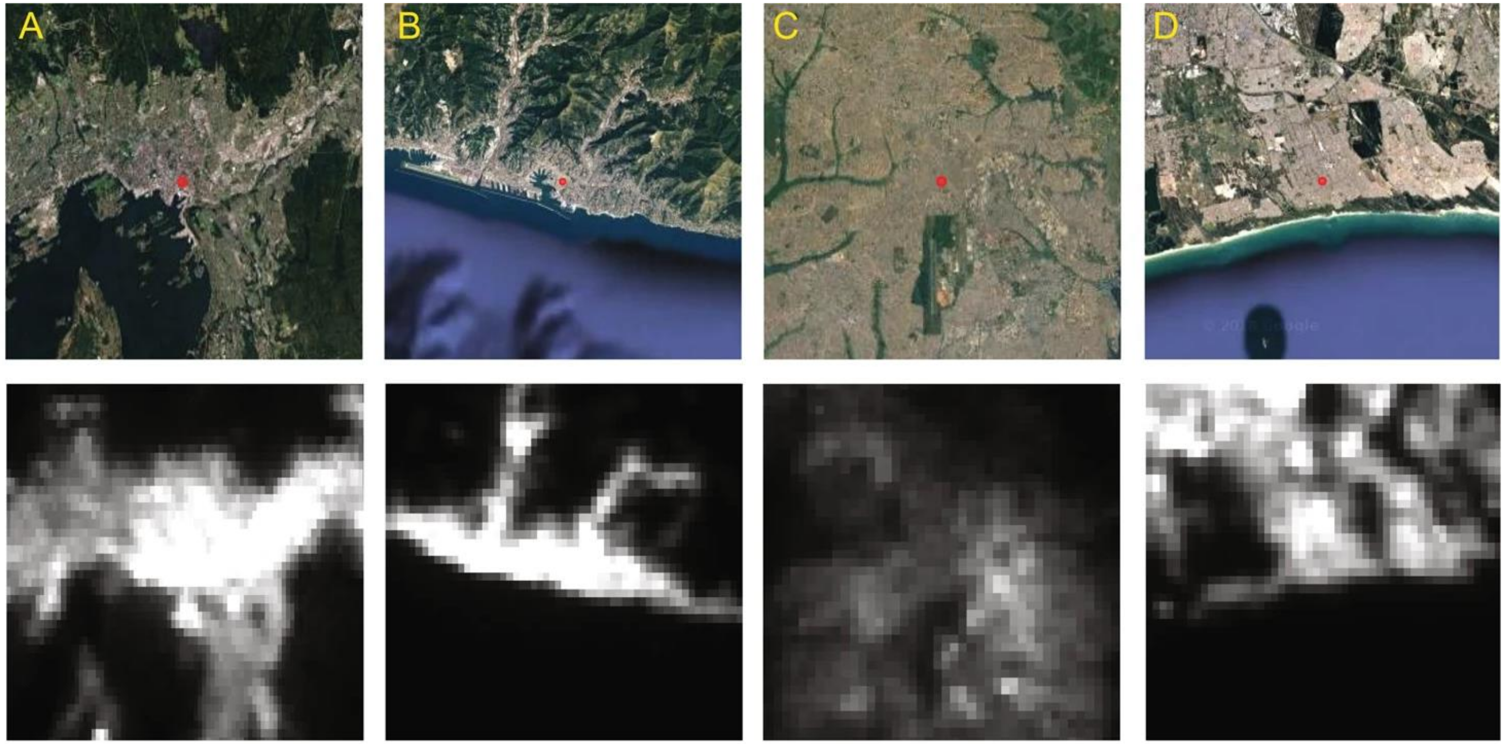
- **5 African countries:** Nigeria, Tanzania, Uganda, Malawi, Rwanda
- **Variables:**
  1. **Consumption expenditure per person,** annually, USD (except Rwanda)
     (World Bank Living Standards Measurement Surveys, LSMS)
  2. **Wealth index per household**, annually, 0-1
     (Demographic and Health Surveys, DHS)
- All variables are averaged over all persons/households within **10km x 10km grid cells (>1,000 clusters)**

Source: https://www.mapchart.net/africa.html, last accessed 2025-09-30

Data

Satellite data

- **Day:** Images of 1x1 km cells at 400x400 pixels from *Google Static Maps API*
- **Night:** *Values* for nightlight intensity between 0-63 in 10x10 km cells from *United States Air Force Defense Meteorological Satellite Program (DMSP)*



A: Oslo, Norway

B: Geno, Italy

C: Lagos, Nigeria

D: Cape Town, South Africa

Li, X., Zhou, Y., Zhao, M. et al.: "*A harmonized global nighttime light dataset 1992–2018*". Sci Data 7, 168 (2020). https://doi.org/10.1038/s41597-020-0510-y

Empirical Strategy

Primer: Convolutional Neural Networks (1/3)

- Type of "deep" neural network often used for image classification
- **Input:** Image as pixels and colors:
  Each pixel as three values: Color as RGB ("red-green-blue")
  => 100x100 pixel image is 100 x 100 x 3 = 30,000 input values
- **Output:** Classification,
  e.g. probability that picture shows a bike
- **Idea:** 3 types of processing steps ("layers"):
  1. **Convolution:** Extract sub-features from image
  2. **Pooling:** Combine into features
  3. **Fully connected:** Make prediction based on features

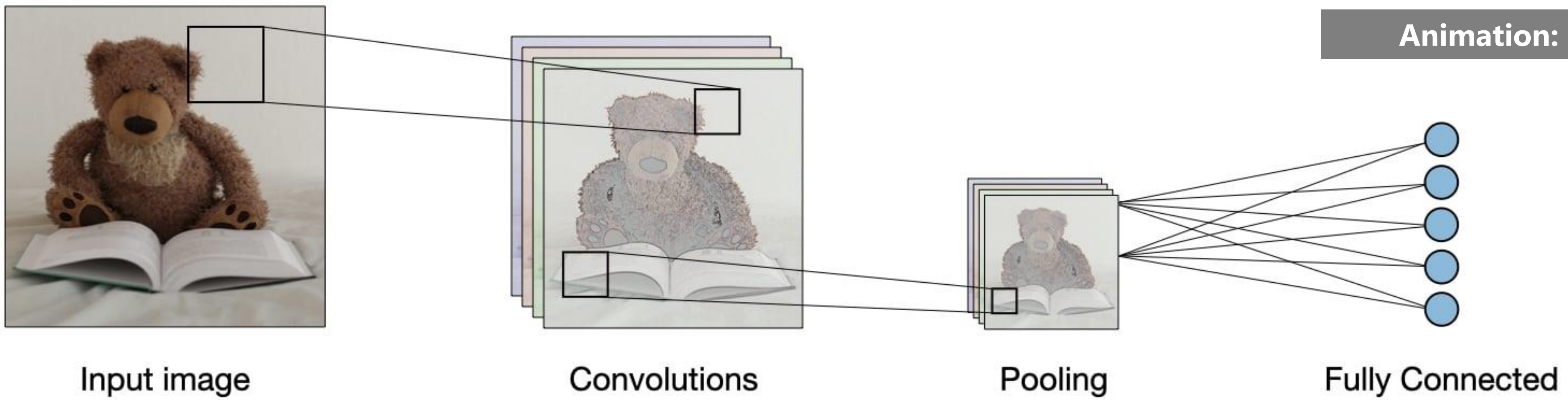
Source: https://www.ibm.com/think/topics/convolutional-neural-networks, last accessed 2025-09-30

Primer: Convolutional Neural Networks (2/3)

1. **Convolution:** Look at each part of the picture and save transformed representation in new layer. Repeat for different *windows* and *step sizes*
2. **Pooling:** Look at convolution layer and combine into features (eyes, ears, etc.)
3. **Fully connected:** Look at all extracted features, decide classification (bear / no bear)

Animation: Convolution

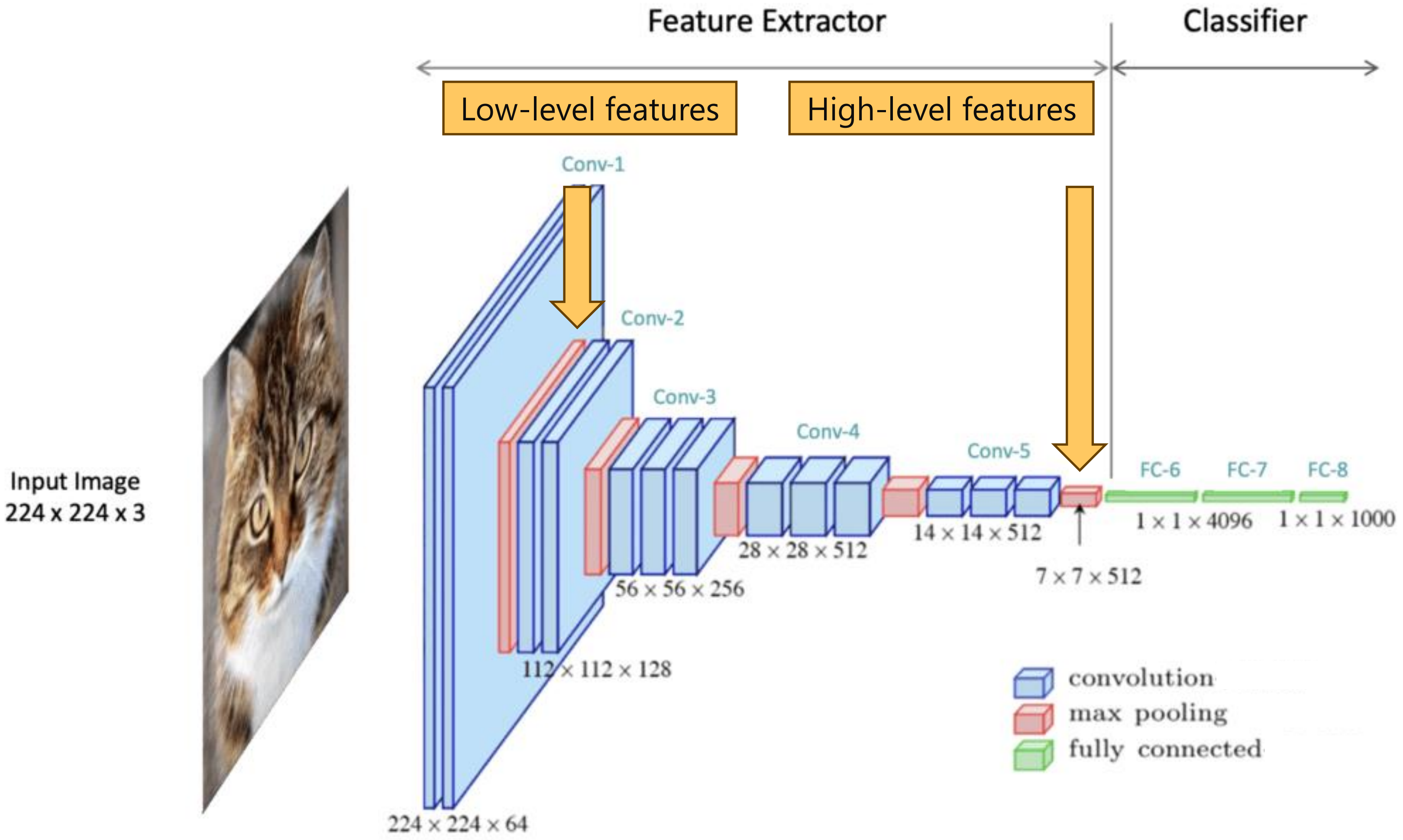
Animation: Pooling



Source: https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks, last accessed 2025-09-30

Primer: Convolutional Neural Networks (3/3)

- Architecture similar to the one used in this paper:
  - 5 pairs of convolutional and pooling layers
  - Output: Predicted probability that picture shows any of 1,000 objects
- First pooling layers contain lower-level features (*parts of* eyes, ears, etc.)
- Last pooling layer contains high-level features (eyes, ears, etc.)



Source: https://learnopencv.com/wp-content/uploads/2023/10/Convolutional-Neural-Network.png, last accessed 2025-09-30

1) Detect surface features (1/3)

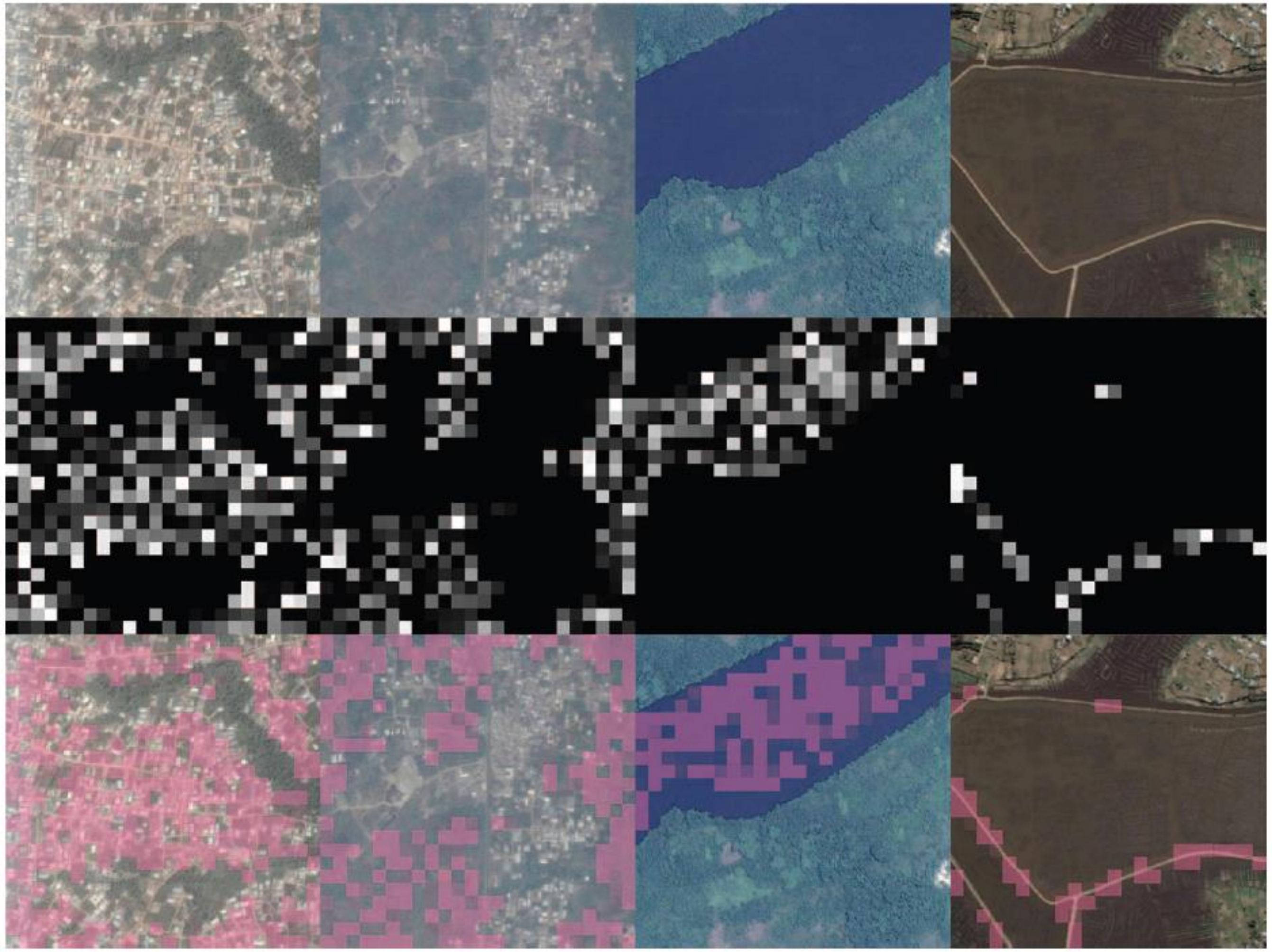
- **Ideally:** Put image data into convolutional neural network (CNN) to classify poverty directly
- **Problem:** CNNs are *data-hungry*: Need lots of training data (= poverty data), which is not available (this is the problem we're trying to solve)
- **Idea:** We don't need the CNN to predict poverty *directly* – instead, **we use it to extract surface features!**

- **Strategy** (and key innovation of this paper):
  Use **daytime satellite images to predict** something similar to poverty - **nightlight intensity!**

  => **Last pooling layer detects surface features** correlated with economic activity (roads, urban areas, etc.)

1) Detect surface features (2/3)

- **Figure:** Features extracted from predicting nightlights from daytime satellite images
- **Panels:** 4 examples:
  - **Top:** Satellite image
  - **Middle:** Pattern identified by second-to-last layer of NN
  - **Bottom:** Top and middle, overlaid
- **Result:** NN learns to identify features of interest relevant for predicting nightlights: **urban areas, non-urban areas, water, roads, etc.**



2) Predict local consumption levels from surface features

- **Data:** For each 10x10 km grid cell:
  - **Outcome:** Avg. consumption level measured by survey
  - **Features:** 4,096 variables capturing presence of surface structures
- **Example:**

	Roads	Water	Urban	...			
Cell 1	0.8	0.1	0.9	0.5		...	=> Many roads, little water, many urban areas
Cell 2	0.1	0.7	0.1	0.3		...	=> Few roads, much water, few urban areas

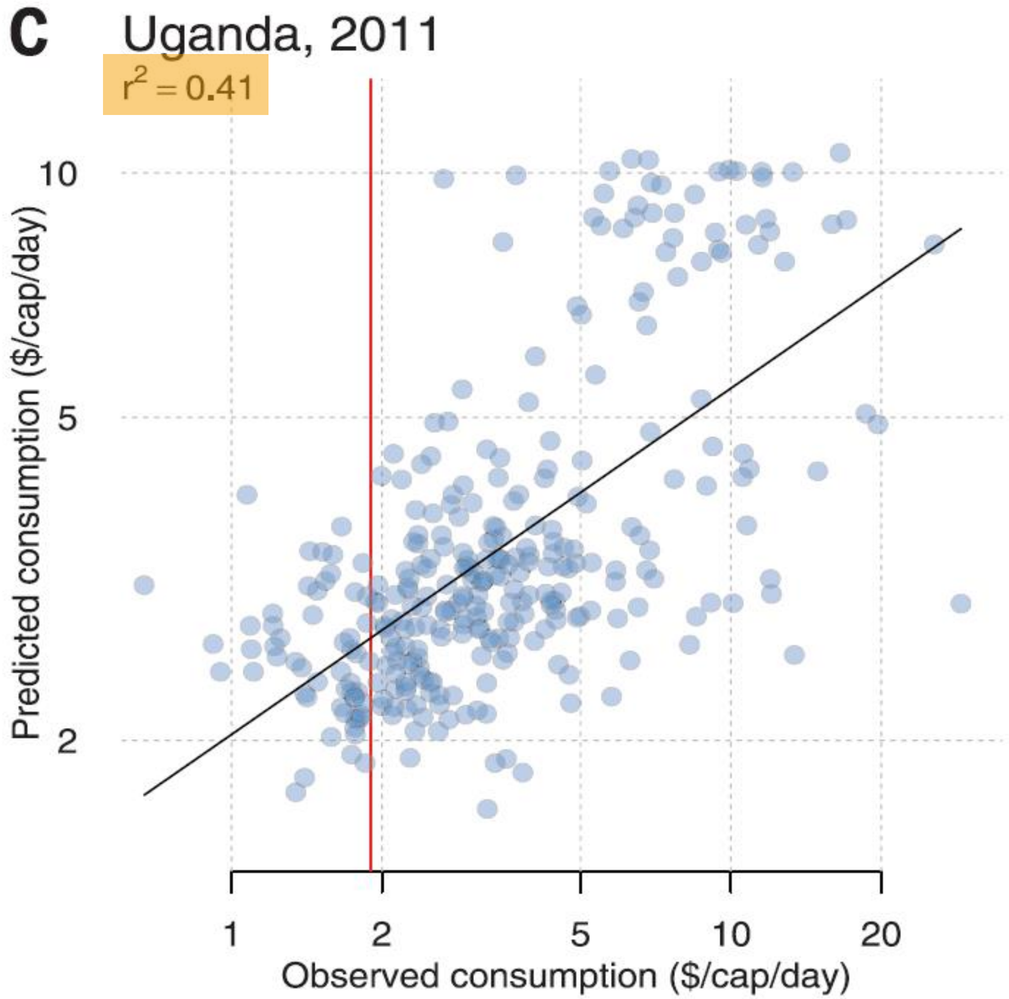
- **Prediction using Linear Regression**

  (include ridge penalty that accounts for high dimensionality of feature vector)

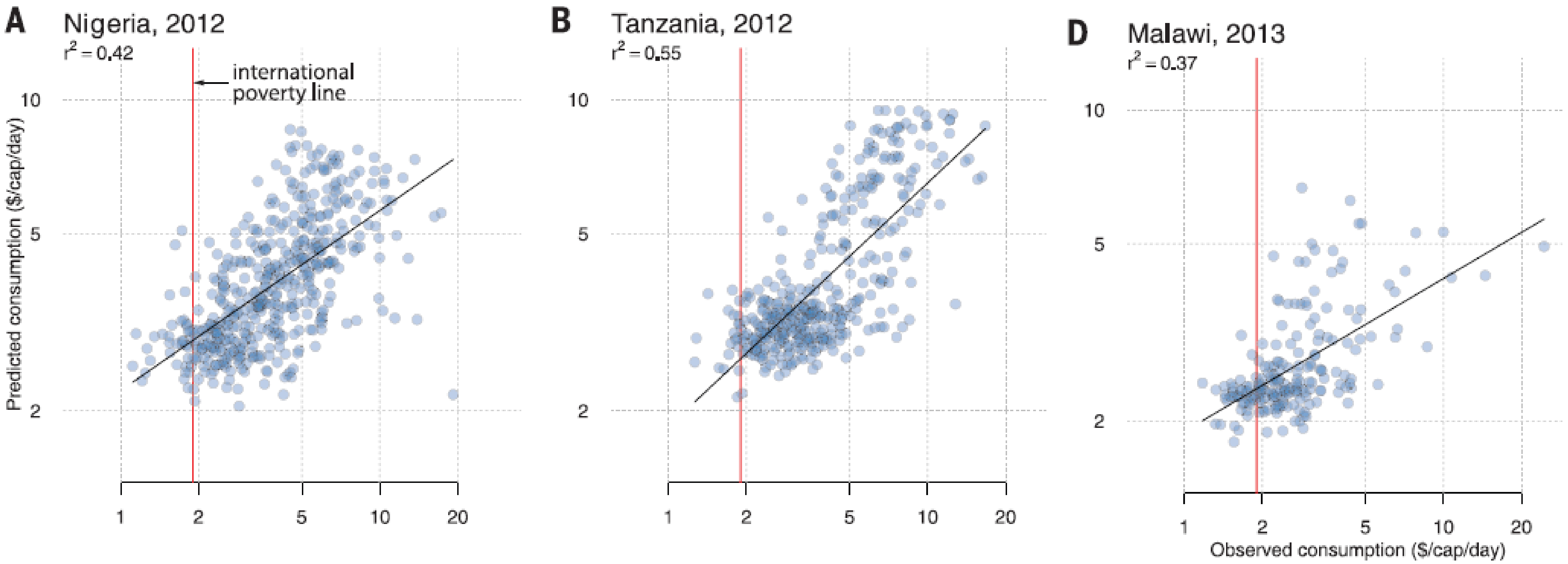
Results

Satellite images predict 41% of variation in consumption (Uganda)

- **Figure:** Observed and predicted consumption levels
  - **Points:** Each point is a 10x10 km grid cell
  - **Black line:** Linear average
  - **Red line:** International extreme poverty line
- **Important:**
  - R^2
    = Share of variance in consumption
    that is predicted by our model
    = 41 %
  - => 41% of variation in consumption is "explained" by our model



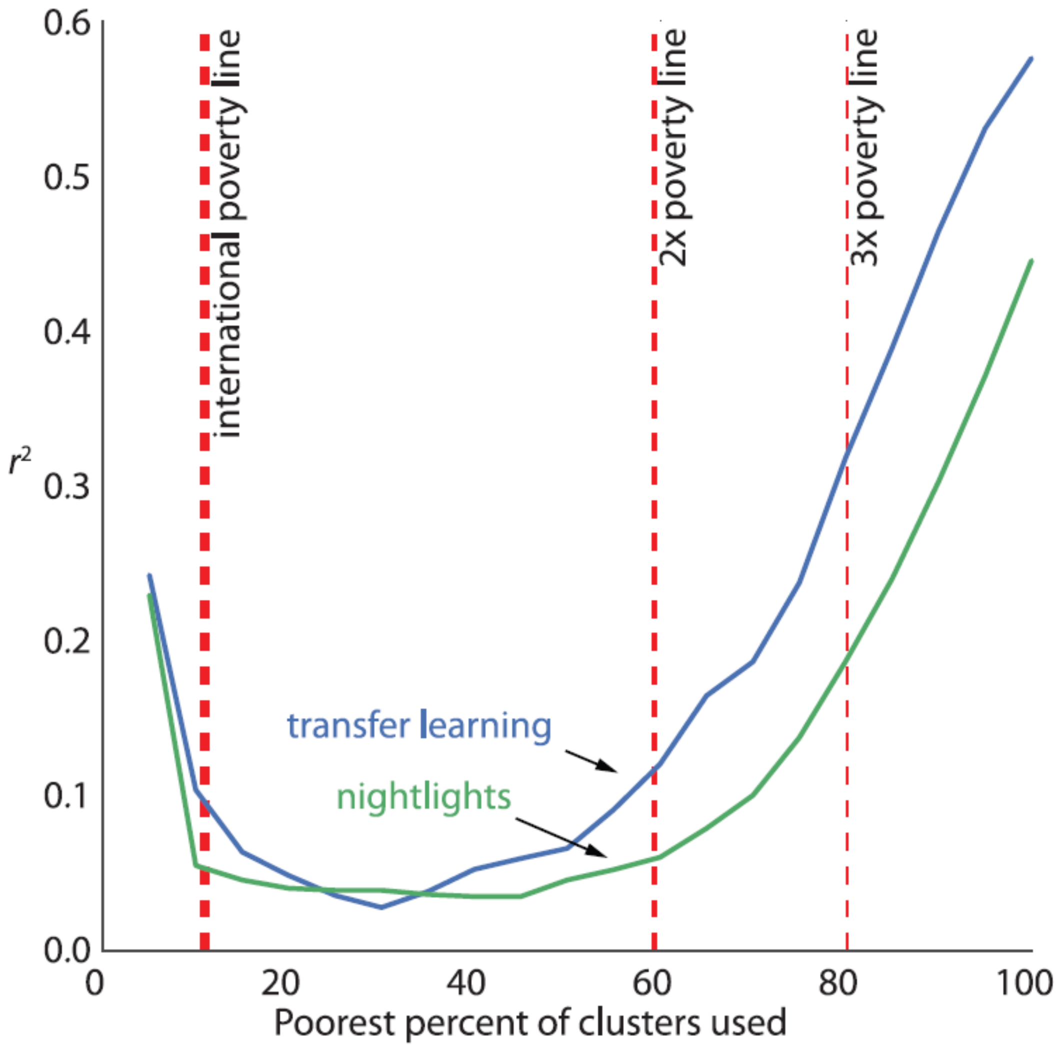
Good prediction performance also for other countries



Results

Consumption: Improvements compared to nightlights data

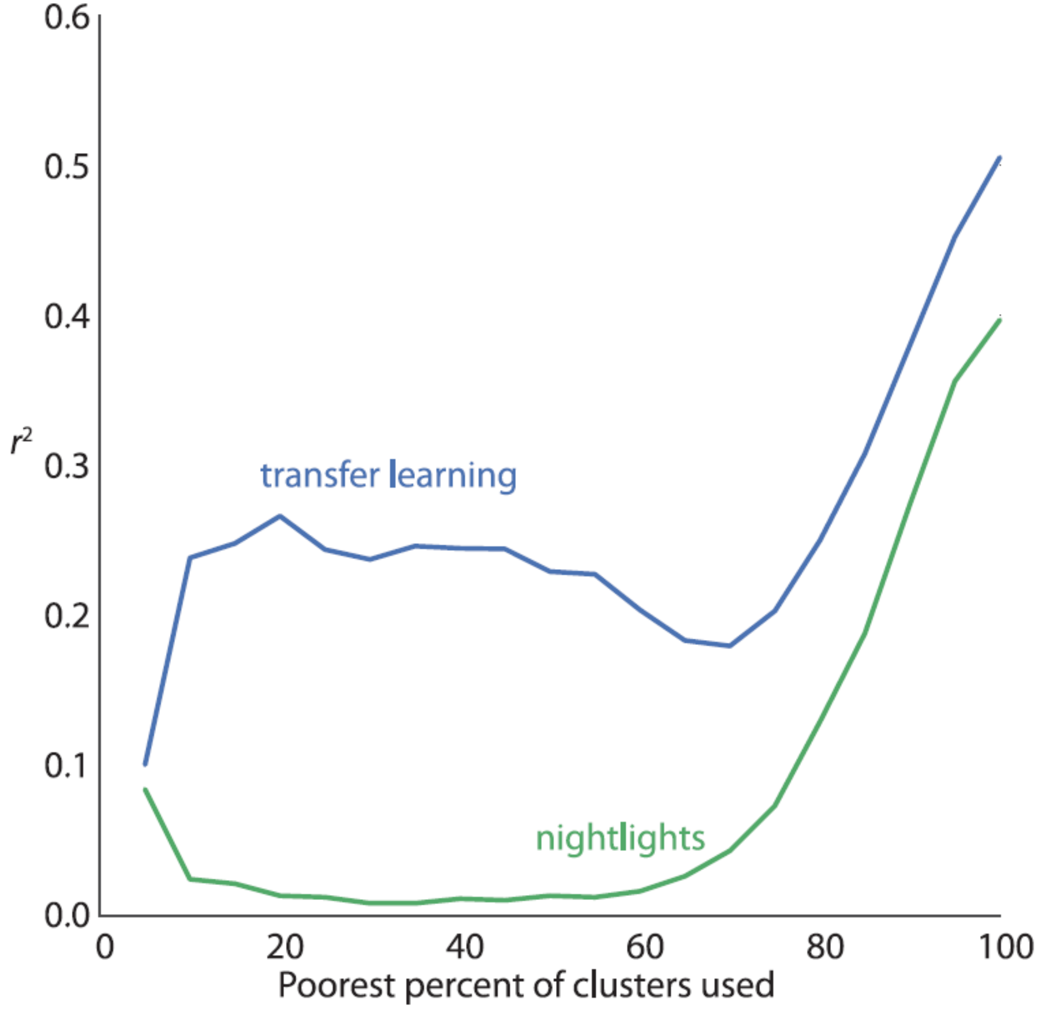
- **Figure:** R^2 when training the model using only the poorest x% of grid cells (all countries)
  - **Each line** reflects a model trained as described here ("transfer learning") and using only nightlights
  - **Each point** of the lines uses only the poorest x% of grid cells for training the model (e.g., at x=50, use the poorer 50% of cells)
  - **Red vertical lines** indicate multiples of the international poverty line (i.e., 1.9, 3.8, and 5.7 USD/person/day)
- **Result:** Daytime images are usually better than nightlight values, and more so for more data



Results

Assets: Very large improvements compared to nightlights data

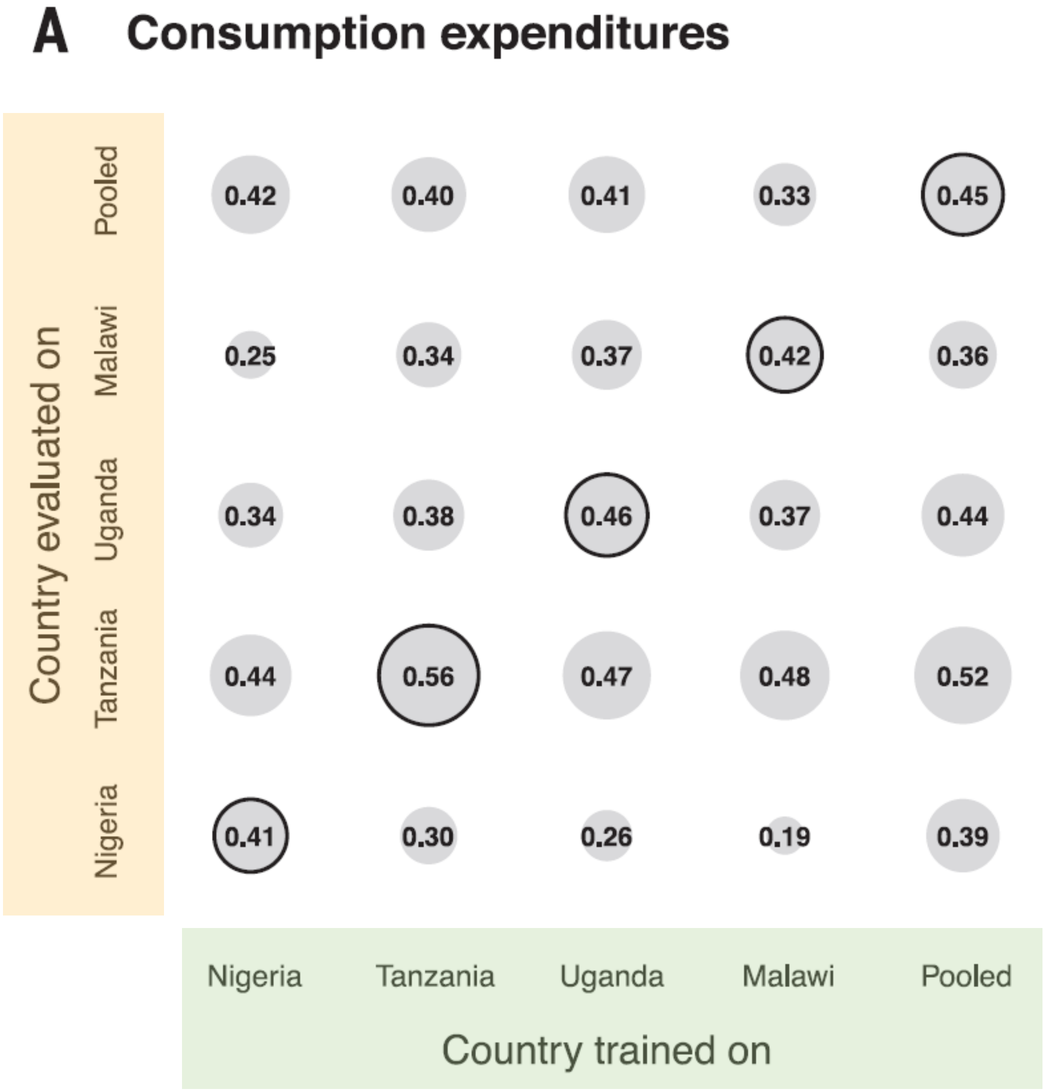
- **Figure:** As previous, but using the model to predict **assets** (wealth) rather than **consumption**
- **Result:** Our approach does *a lot* better, especially for poorest regions!
- **Why?** Wealth better observable from space (e.g., metal roofs)?



Results

Model generalizes across borders

- **Figure:** R^2 for different combinations for training and testing data
  - **Columns:** Data used for training
  - **Rows:** Data used for evaluation
  - **Example:** Top-left value indicates that a model trained on Nigeria and evaluated on *all* countries achieved explained 42% of variation in consumption
- **Result:** Consistently high out-of-sample performance
- **Implication:** Model might generalize well to countries where no survey data is available (the point of this study!)



Discussion

Conclusion

- Used neural network to **detect surface features** from daytime **satellite images** that **predict average consumption and assets** in 10x10 km cells

- Model **improves upon current methods**, and **generalizes well** to unseen countries

- Useful for **estimating poverty**, even in regions where no survey data is available
  => Basis for targeting welfare-enhancing policies

Advantages

- **Remote:** No ground intervention necessary
- **Cheap:** No additional infrastructure required on top of existing satellites
- **Large-scale:** Feasible for entire continent
- **Public data:** Does not rely on proprietary data (social media, cellphone usage, etc.)

Discussion

Open questions

- **Expert opinions:** How much is the improvement compared to prediction from "expert opinions": If you would ask a person on the ground to point out poor areas, would they do better?
- **Explainability:** Which features predict poverty?
- **Heterogeneity:** Where are our predictions better? Where worse?

Discussion

Key limitation

- **Generalizability:** Selected sample: Countries where high-quality survey data is available. Results generalize *within* this sample, but unclear how well they generalize to poorer countries

Discussion

Further avenues

- **Finer grids:** Currently, lots of noise due to imprecise location in survey (for privacy reasons). In principle, could make much better use of high-resolution image data
- **Combine with other sources:** Usage of phones, internet, social media
- **Time series:** Check how well method tracks changes in poverty over time