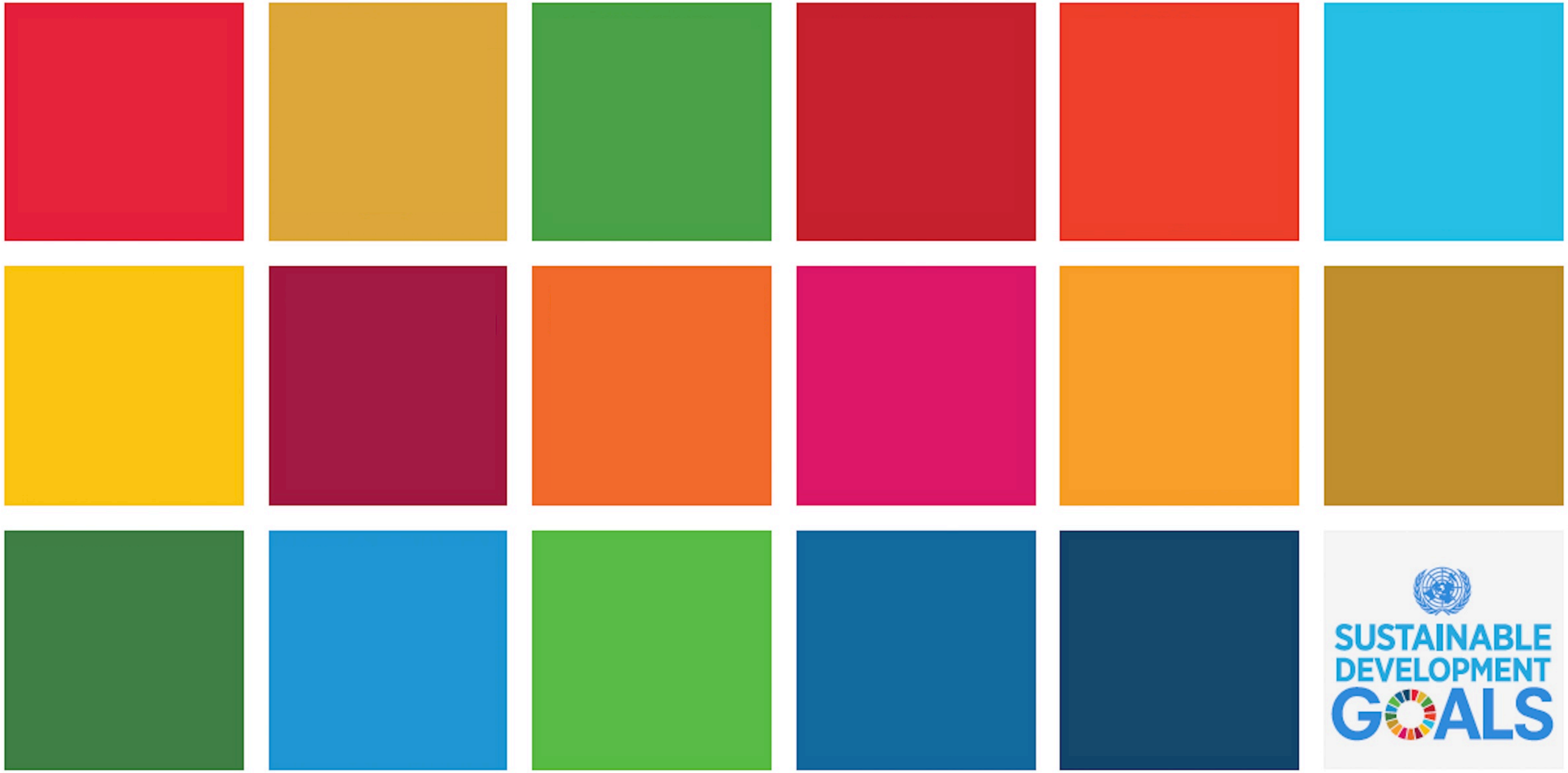


Can Human Development Be Measured with Satellite Imagery?

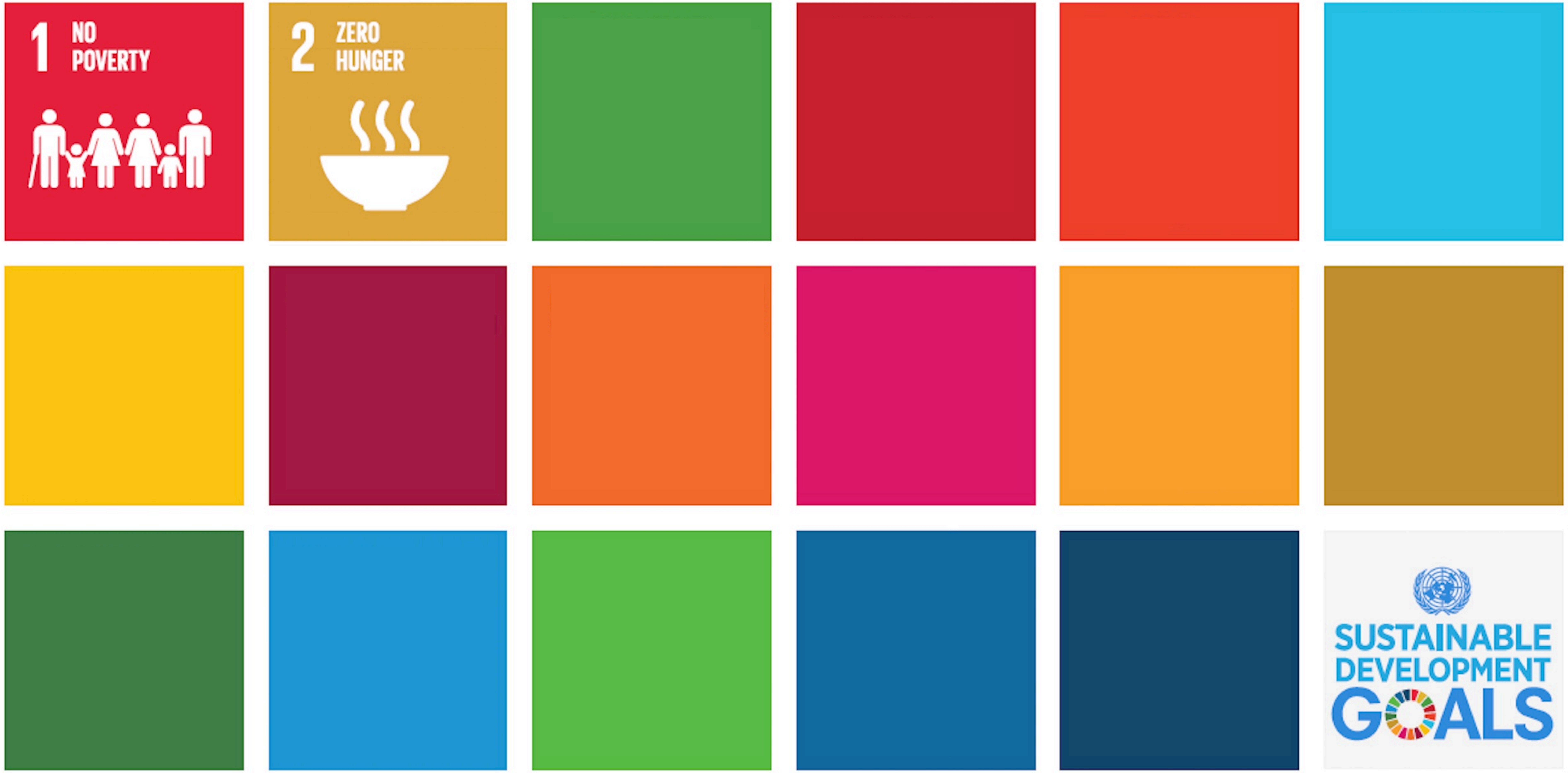
Andrew Head, Mélanie Manguin, Nhat Tran, and Joshua A. Blumenstock
UC Berkeley



SUSTAINABLE DEVELOPMENT GOALS



SUSTAINABLE DEVELOPMENT GOALS



SUSTAINABLE DEVELOPMENT GOALS


SUSTAINABLE DEVELOPMENT GOALS
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
13 CLIMATE ACTION
SUSTAINABLE DEVELOPMENT GOALS


SUSTAINABLE DEVELOPMENT GOALS
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS
SUSTAINABLE DEVELOPMENT GOALS

Quality, accessible, timely and reliable disaggregated data will be needed to help with the measurement of progress and to ensure that no one is left behind.

Transforming our world: the 2030 Agenda for Sustainable Development
United Nations

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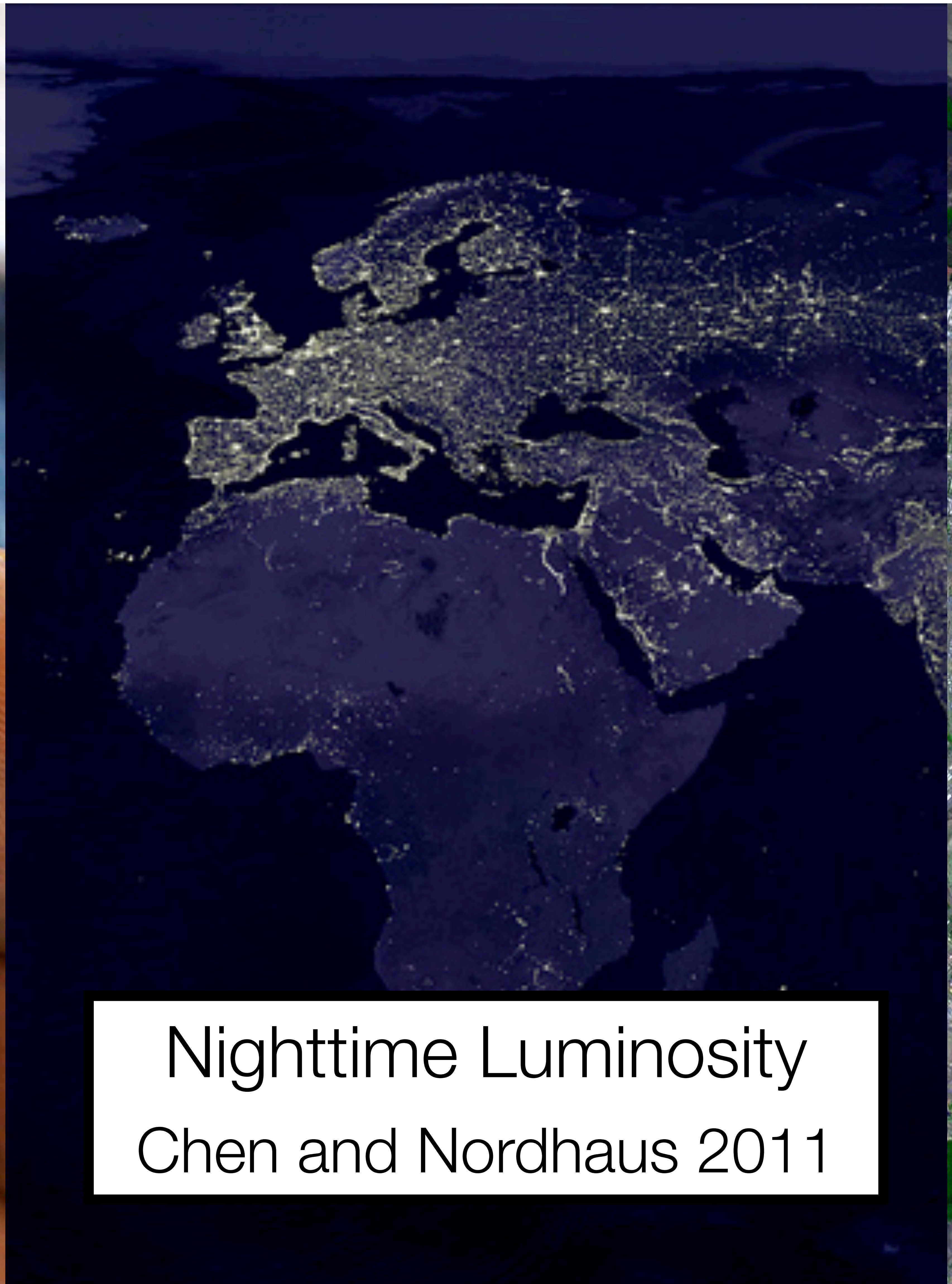
United Nations

Though nationally-representative surveys like the Demographic and Health Surveys requires visits to **more than a year and tens of millions of dollars** to complete.

Measuring Development Outcomes from Existing Data Sources

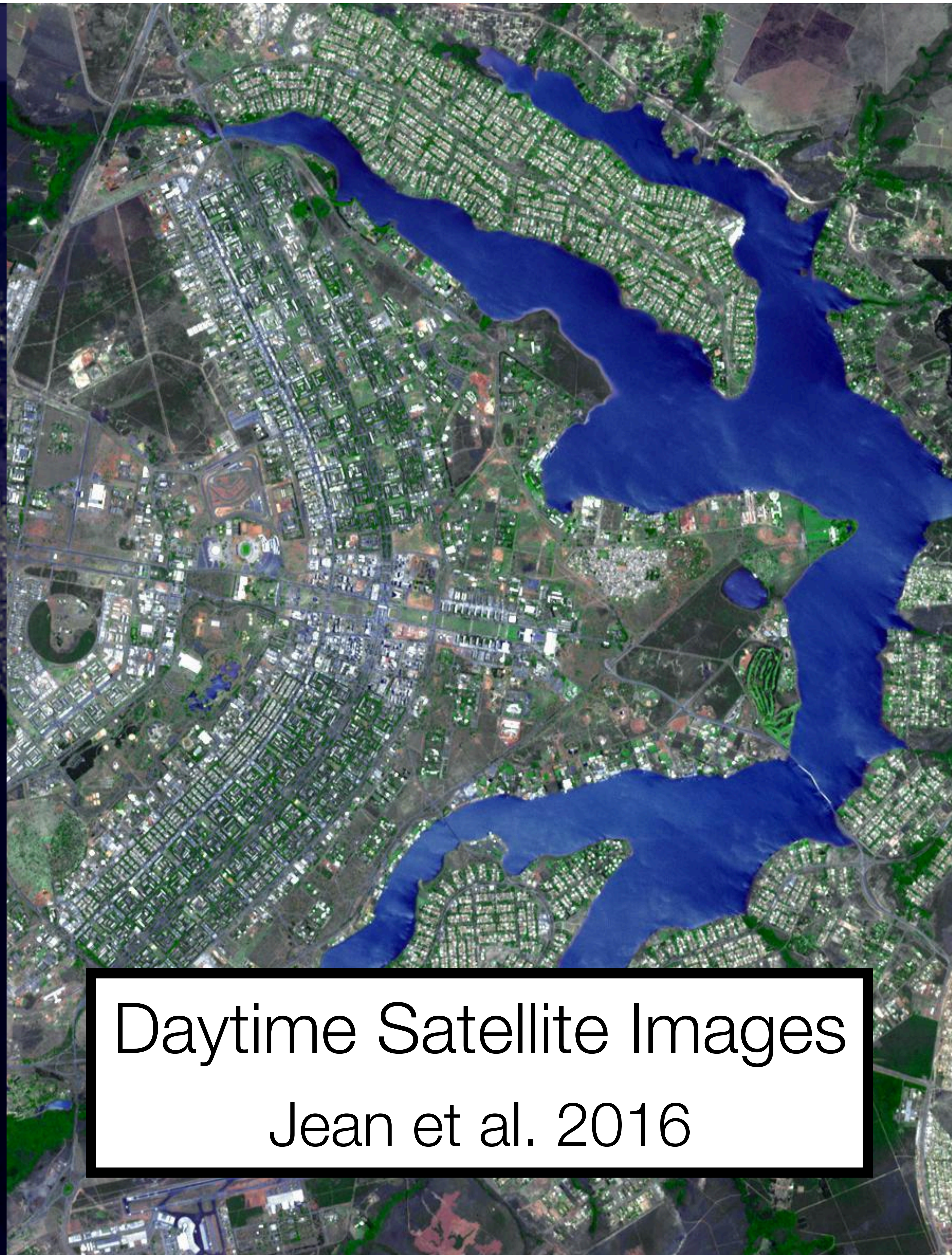
Call Details Records

Blumenstock et al. 2015



Nighttime Luminosity

Chen and Nordhaus 2011



Daytime Satellite Images

Jean et al. 2016

What Can You Estimate Using Daytime Satellite Images?

Household assets

Mobile phone ownership

Access to electricity

Level of education

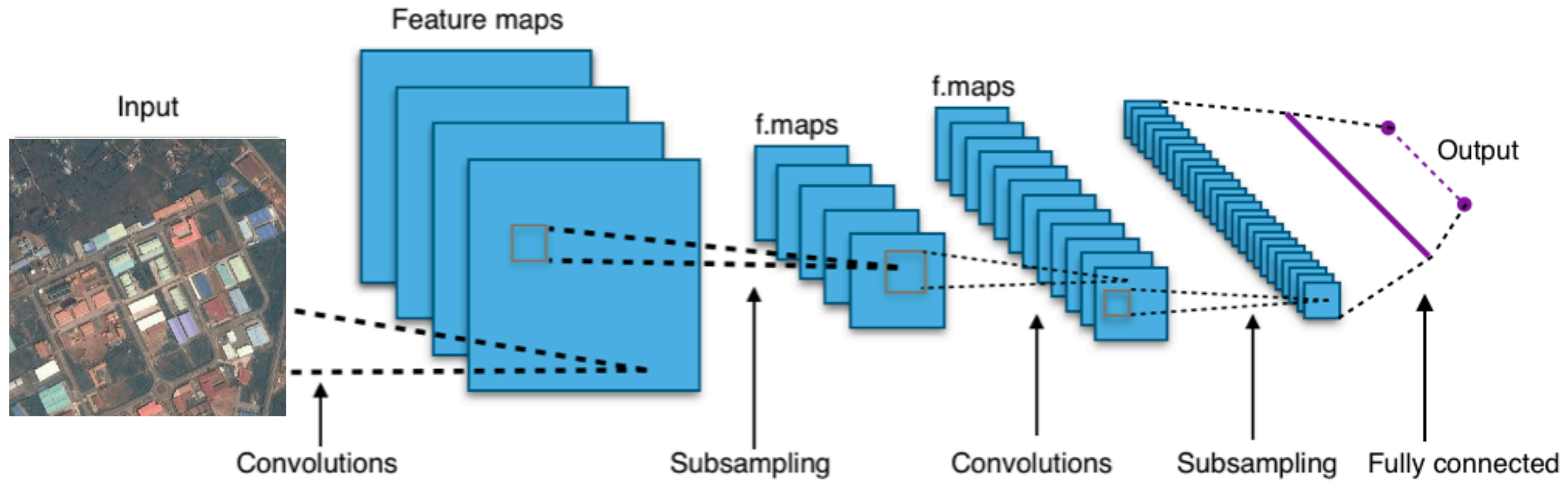
Mosquito nets

Access to drinking water

$$\boldsymbol{x} \mapsto \boldsymbol{y}$$

$$X \mapsto y$$

1 km
400px



Deep neural network + supervised learning on features

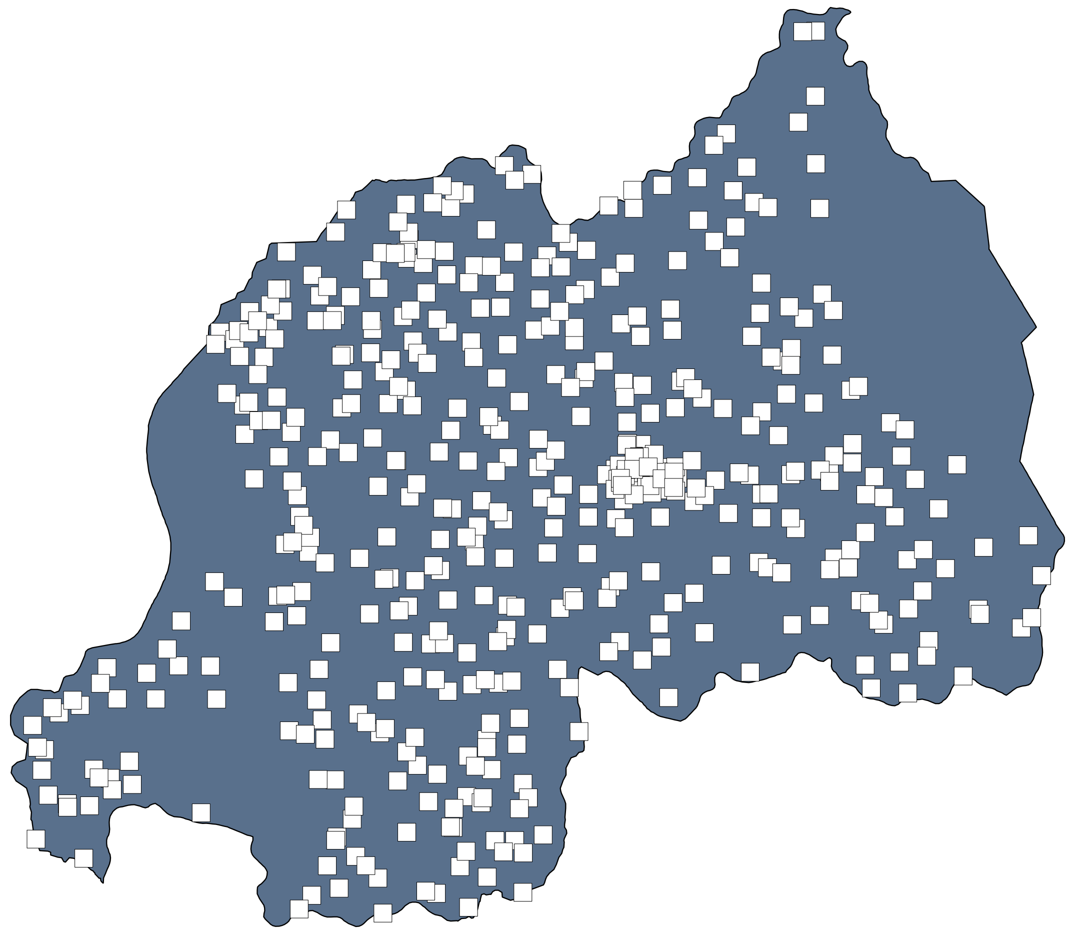
- **household assets**
- **household education**
- **hemoglobin level**
- **... and 8 more**

Estimating "Human Development"

We estimate Demographic and Health Surveys (DHS) Survey Data:

- Large-scale (thousands of surveyed households per country)
- Surveys are nationally representative

492 "clusters" of surveyed households in Rwanda

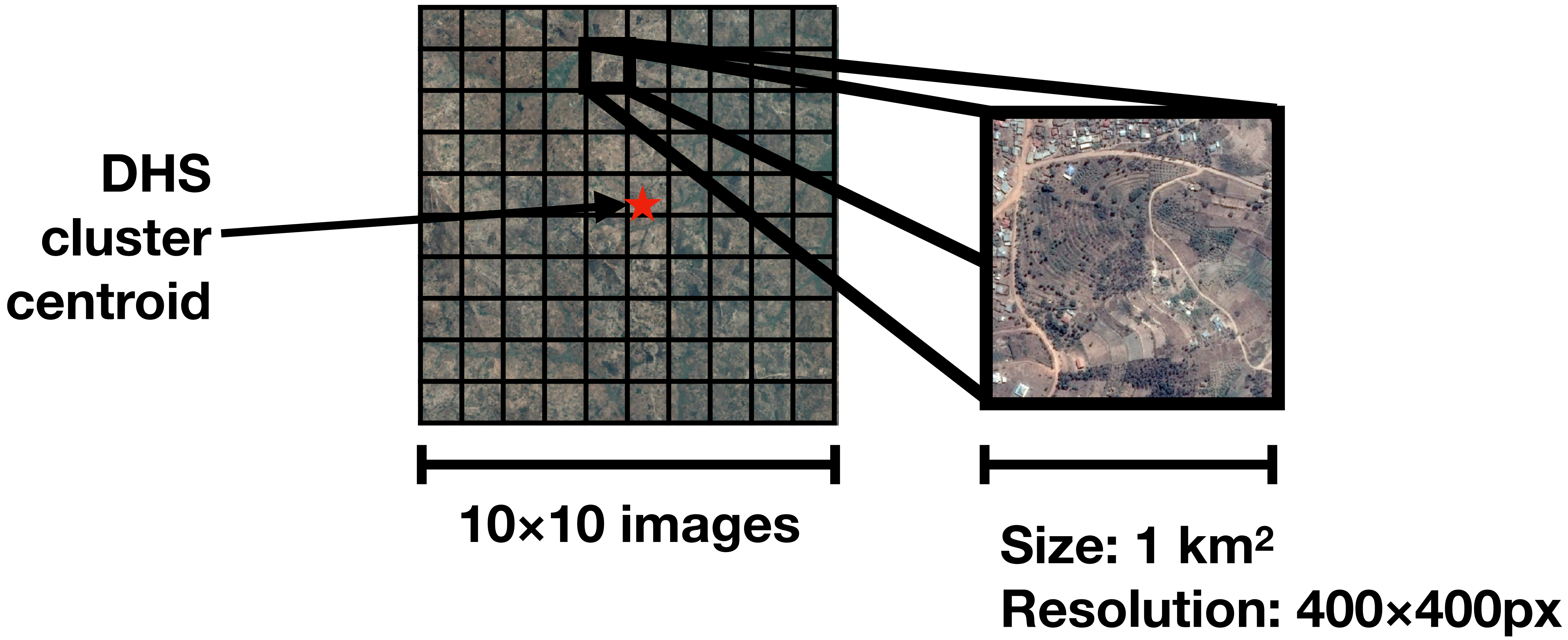


Indicators of development include:

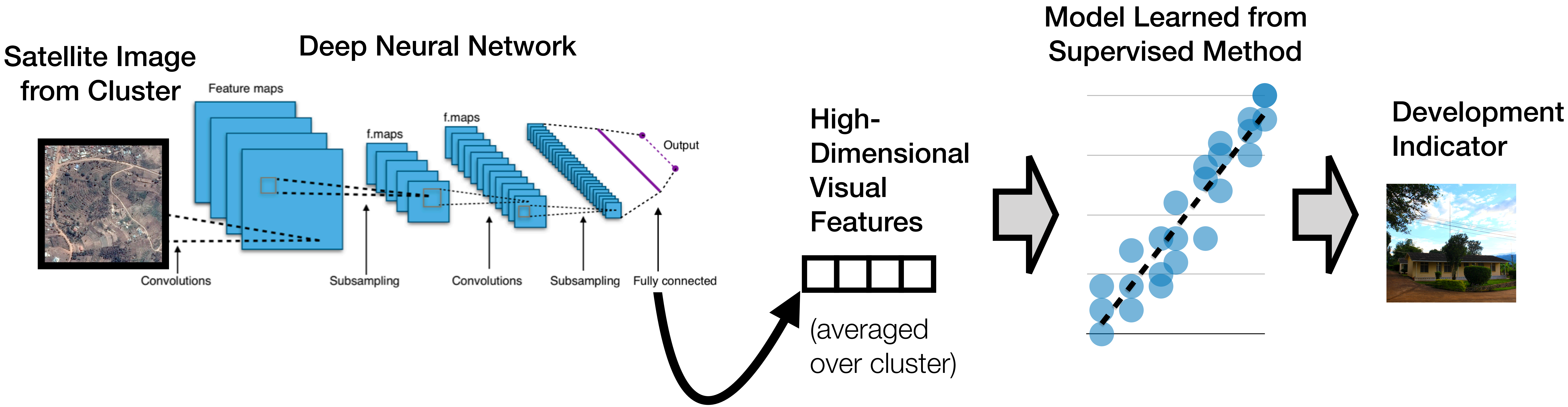
- **Continuous-scale asset index**
- **Level of education attained**
- **Time to reach a source of drinking water**
- **Average hemoglobin level**
- **Average weight-for-height percentile**
- **...**

Daytime Satellite Imagery

We fetched 10,000s of daytime satellite images for 4 countries (2 outside sub-Saharan Africa), using the Google Static Maps API.



Estimating Development from Satellite Images



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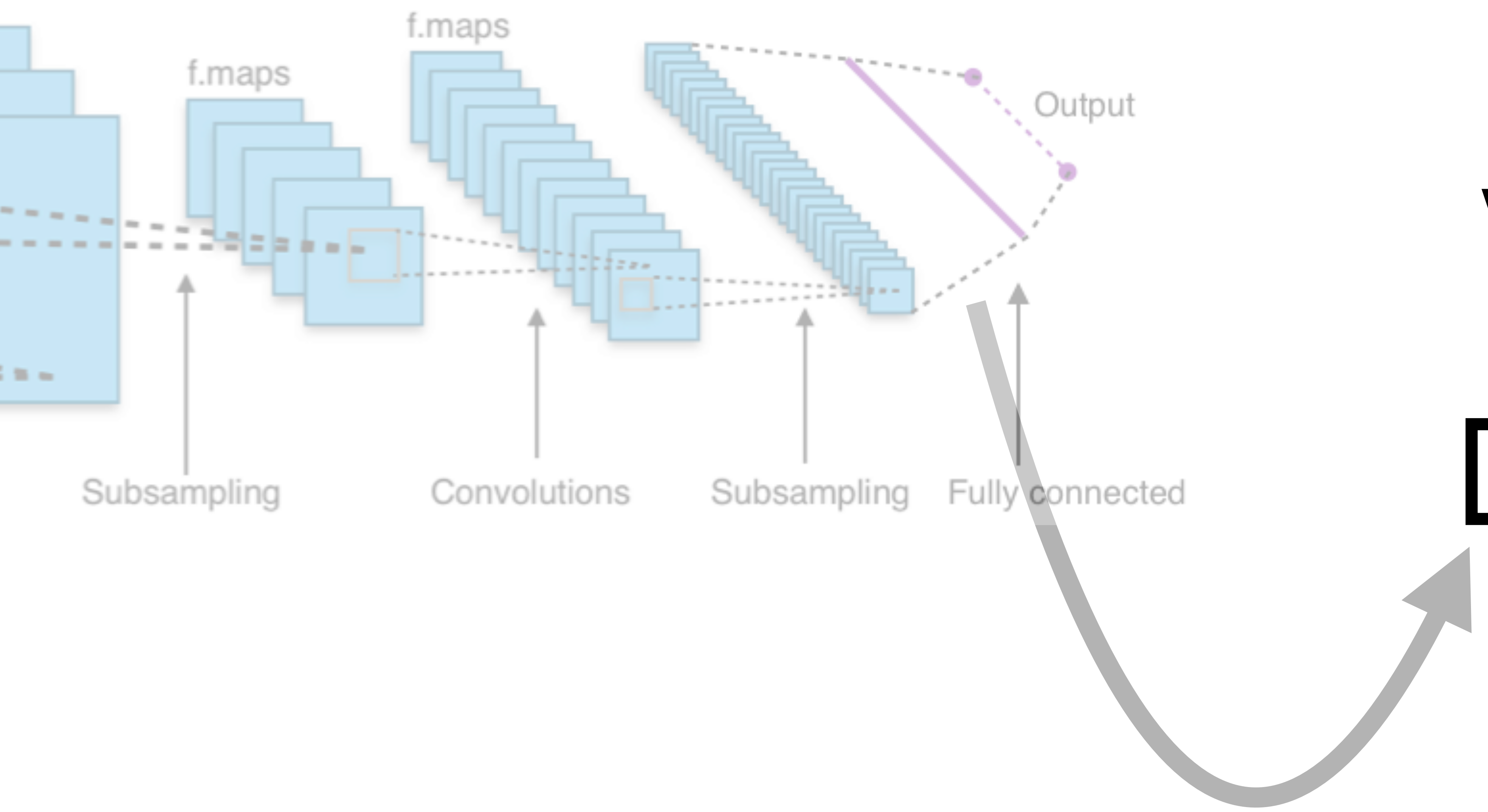
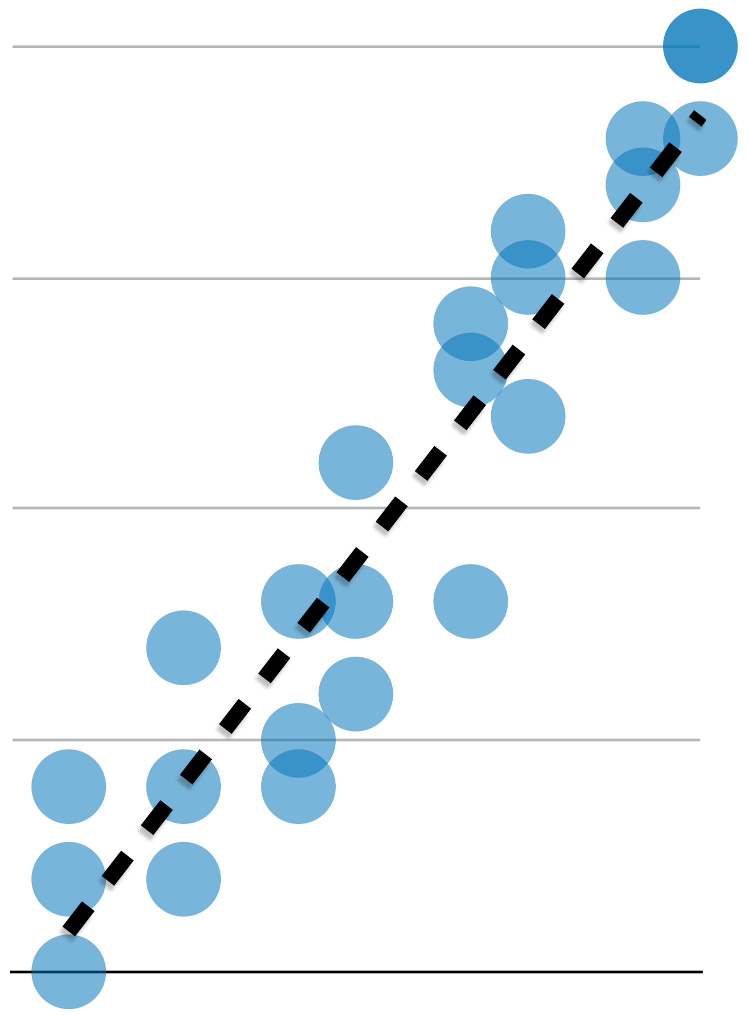


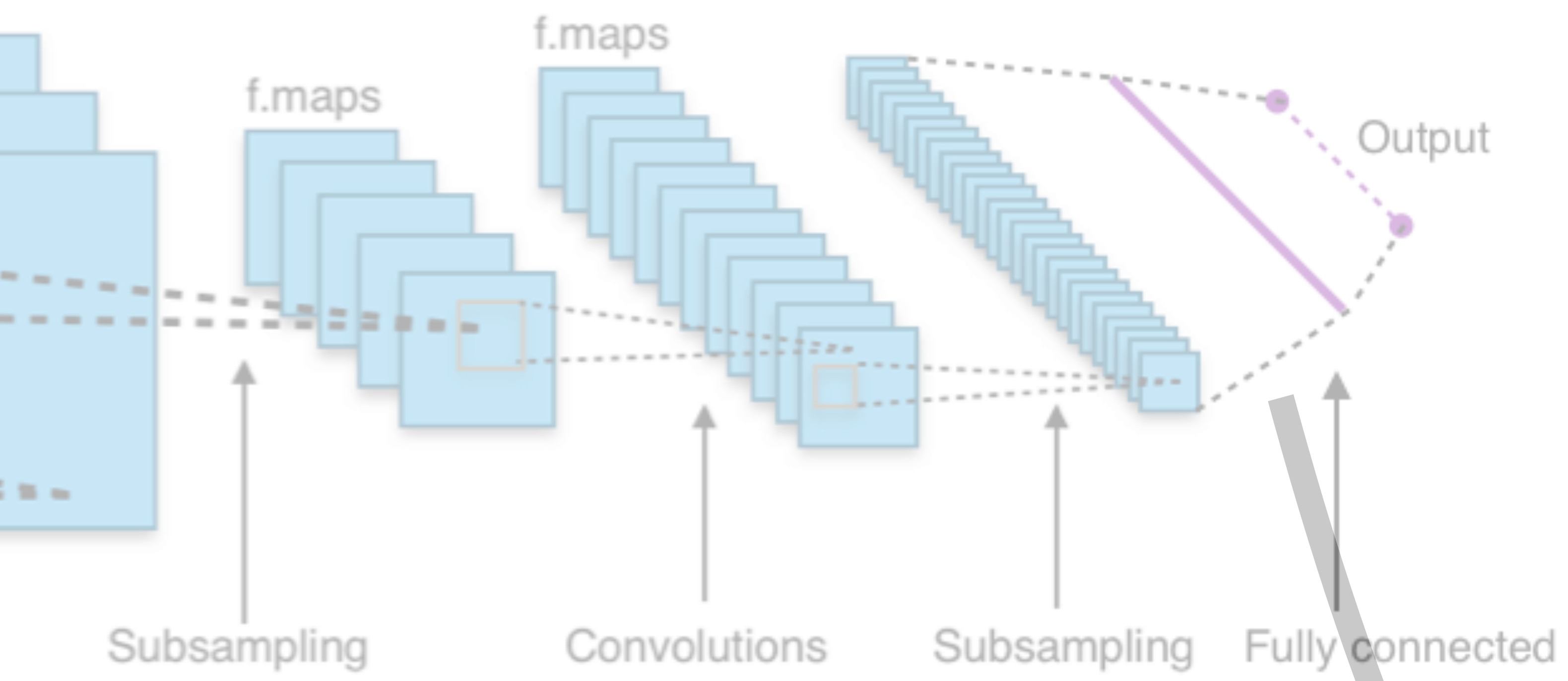
High-Dimensional Visual Features

Supervised Learning Method *M*



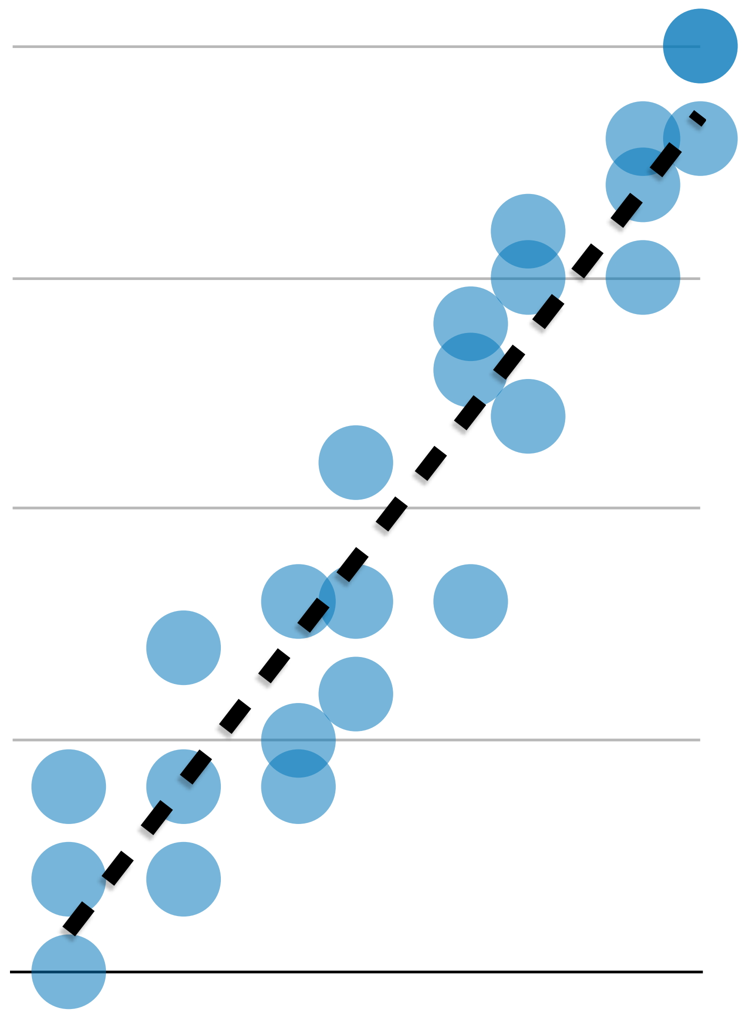
Development Indicator

Estimating Development from Satellite Images



High-Dimensional Visual Features

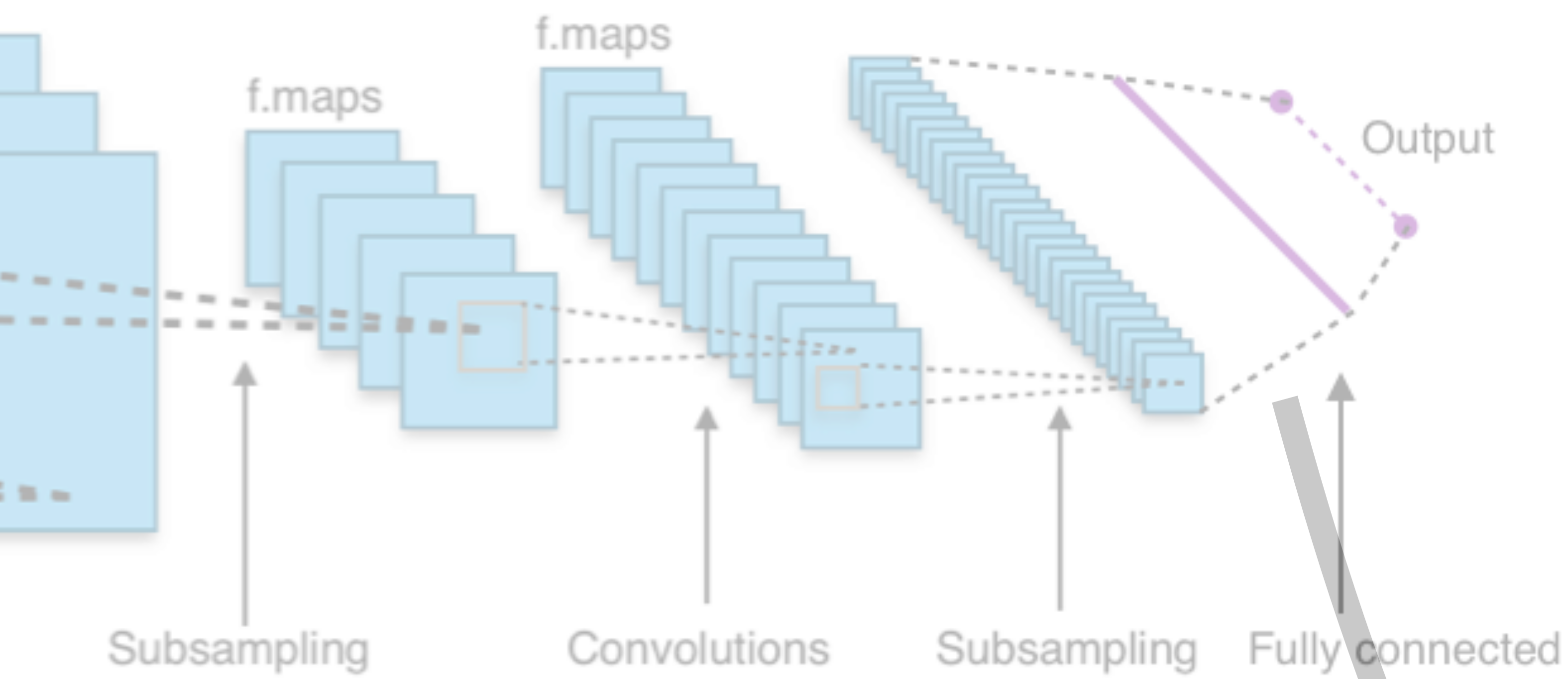
Supervised Learning Method *M*



Development Indicator

(household assets)

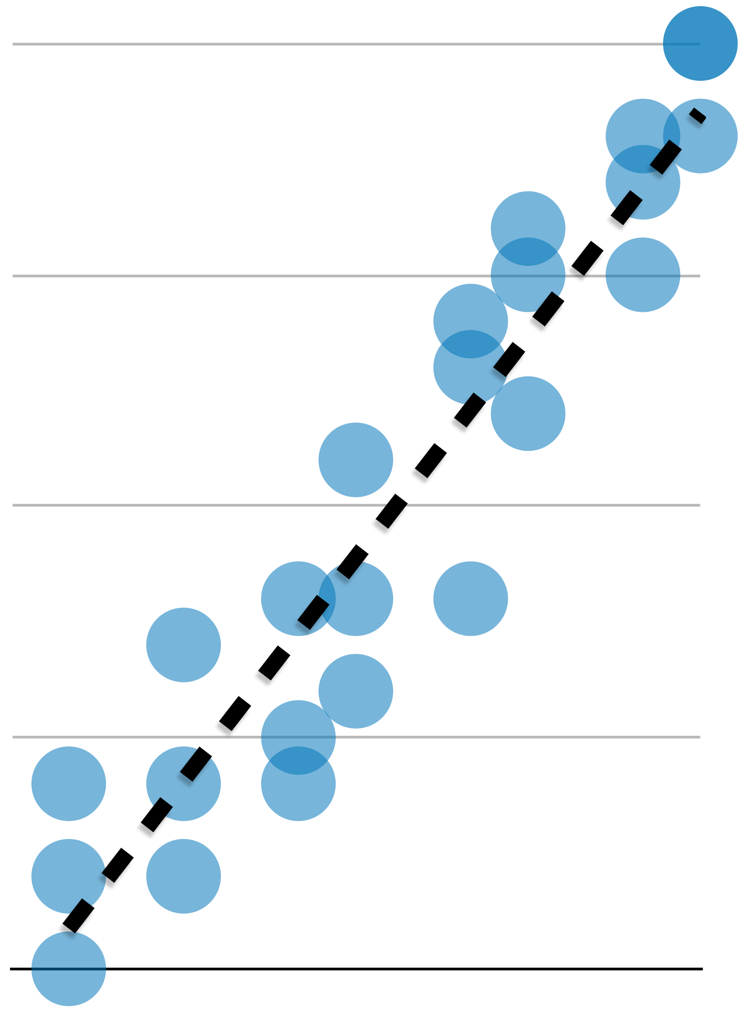
Estimating Development from Satellite Images



High-Dimensional Visual Features

(averaged over cluster)

Supervised Learning Method *M*

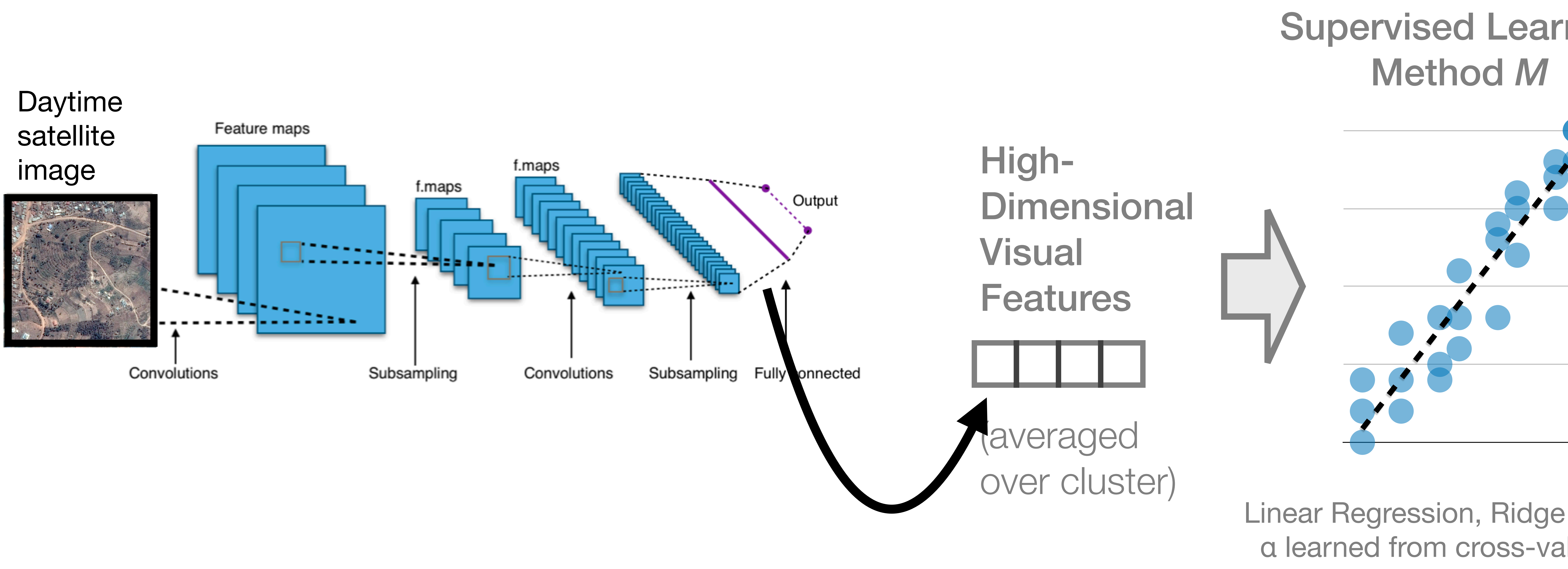


Linear Regression, L2 Penalty,
α learned from cross-validation

Development Indicator

(household assets)

Estimating Development from Satellite Images



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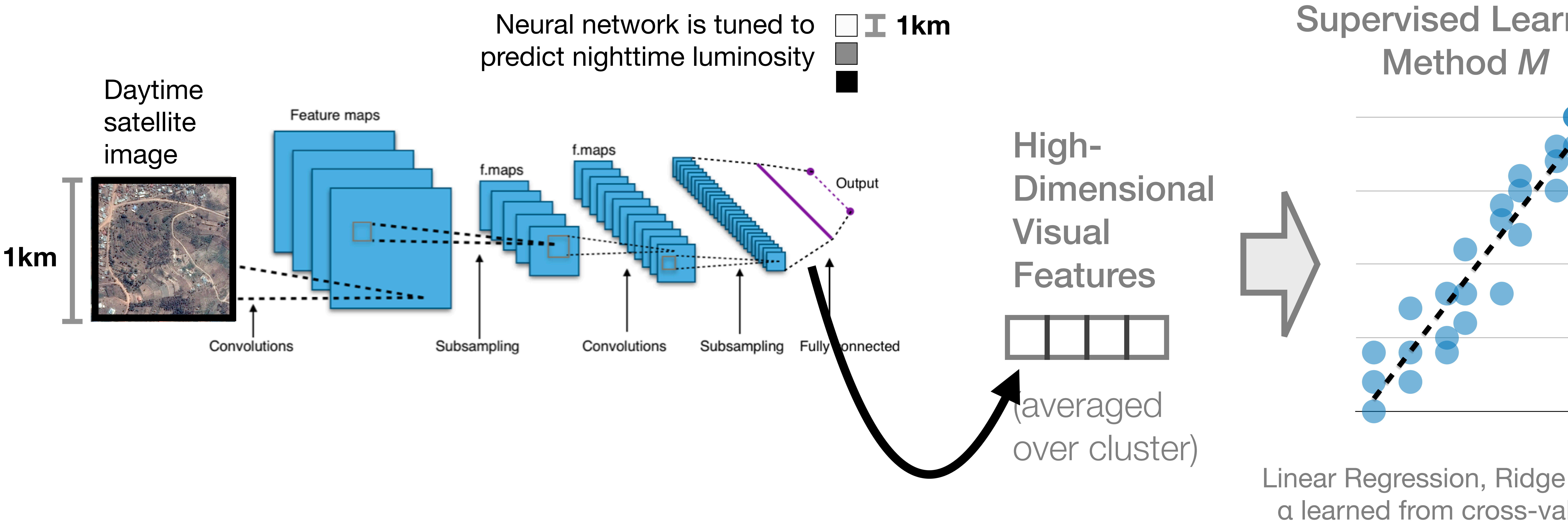

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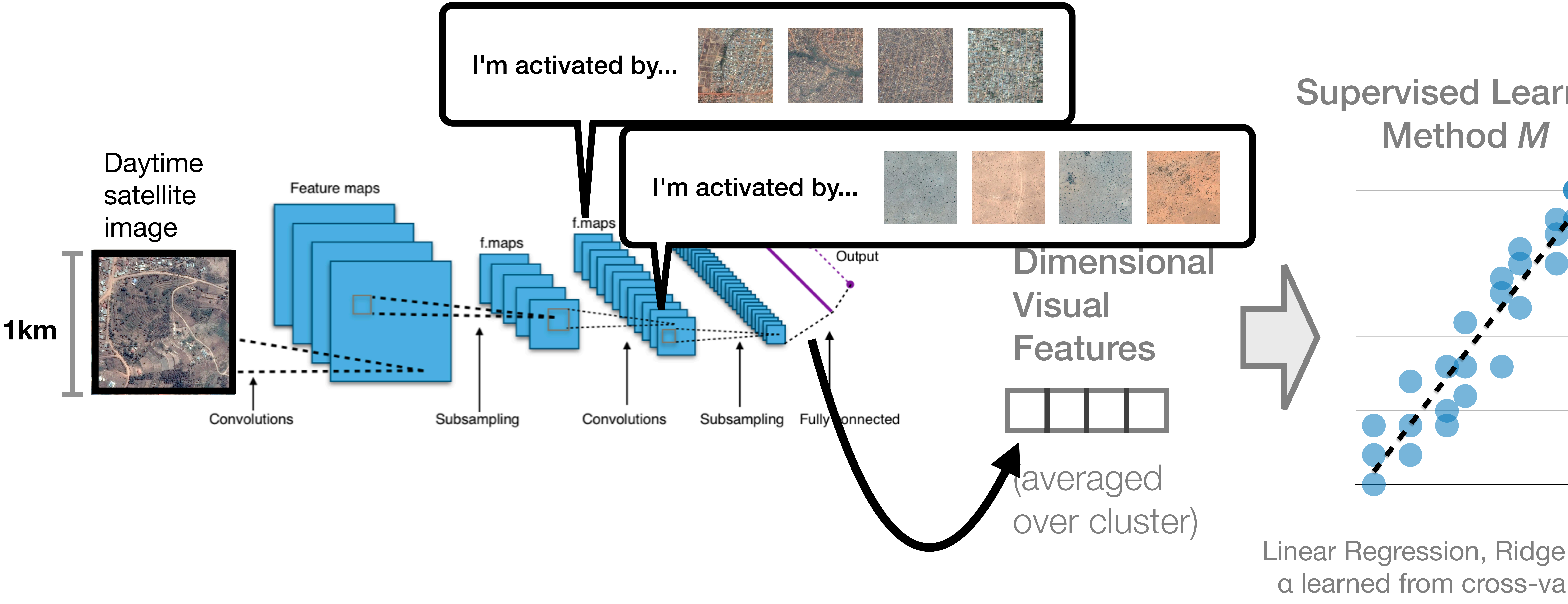
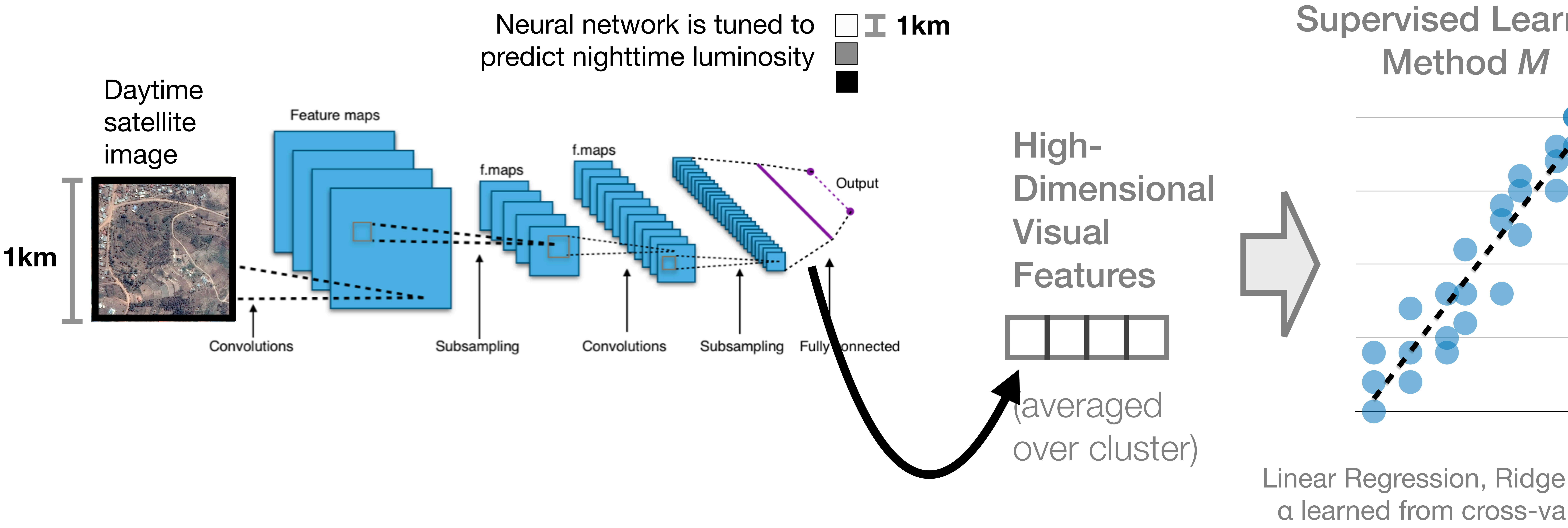


Estimating Development from Satellite Images



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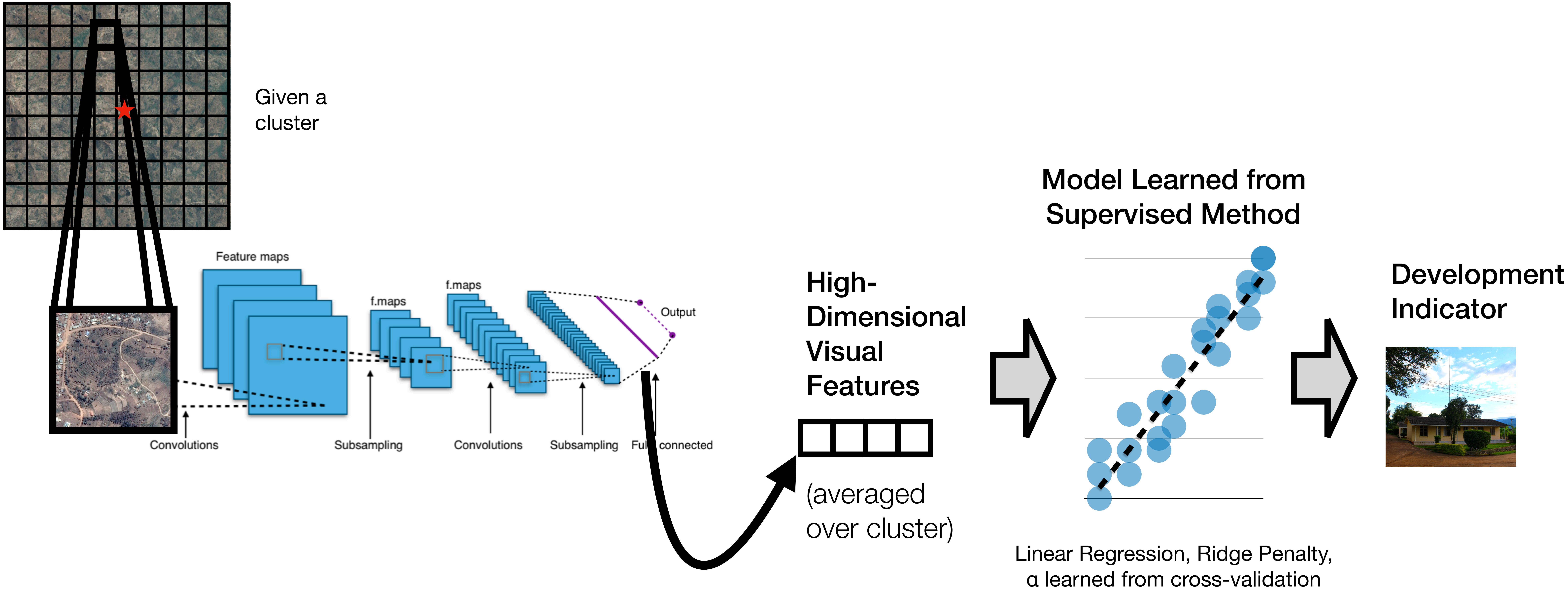
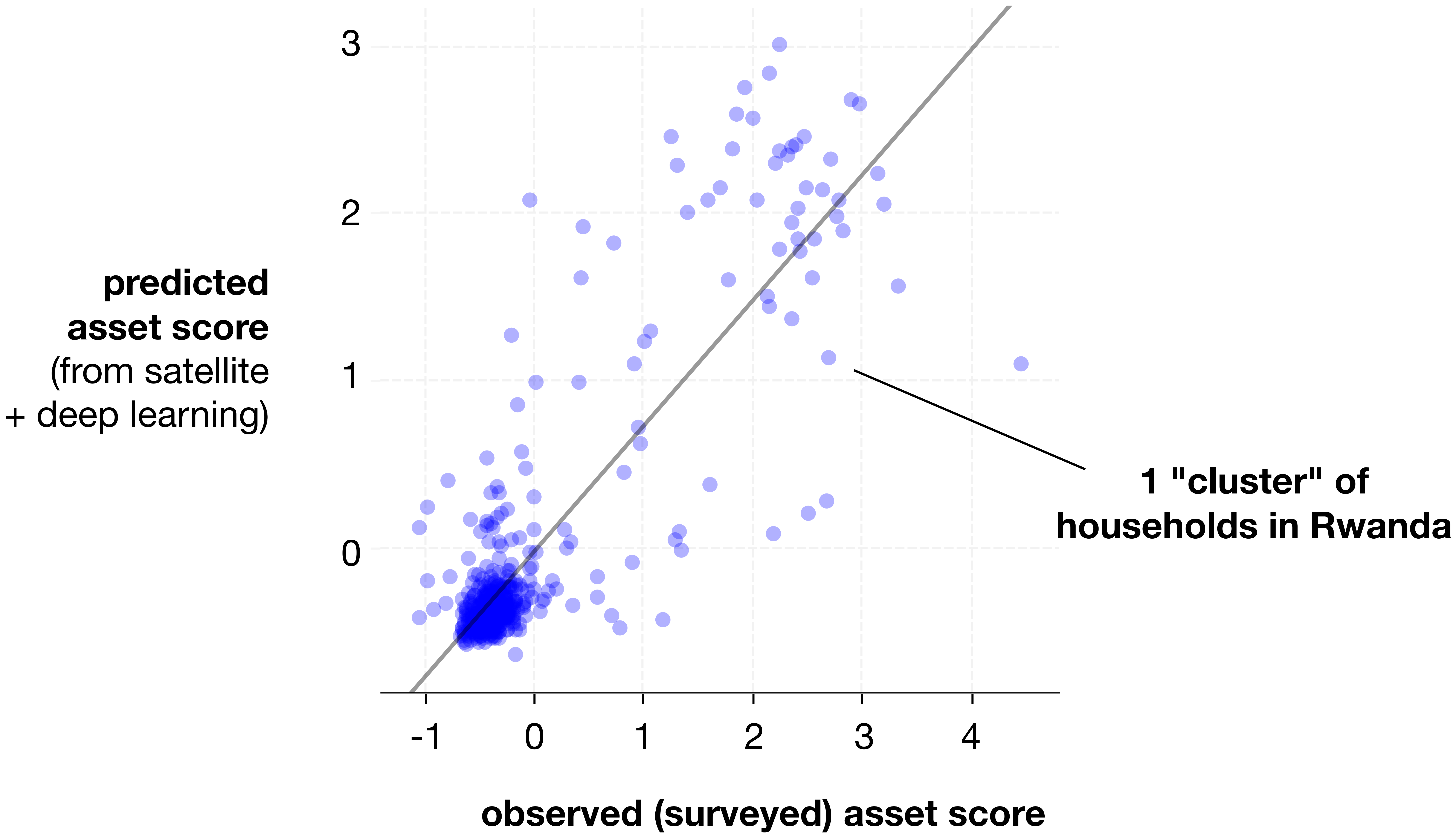


Estimating Wealth in Sub-Saharan Africa



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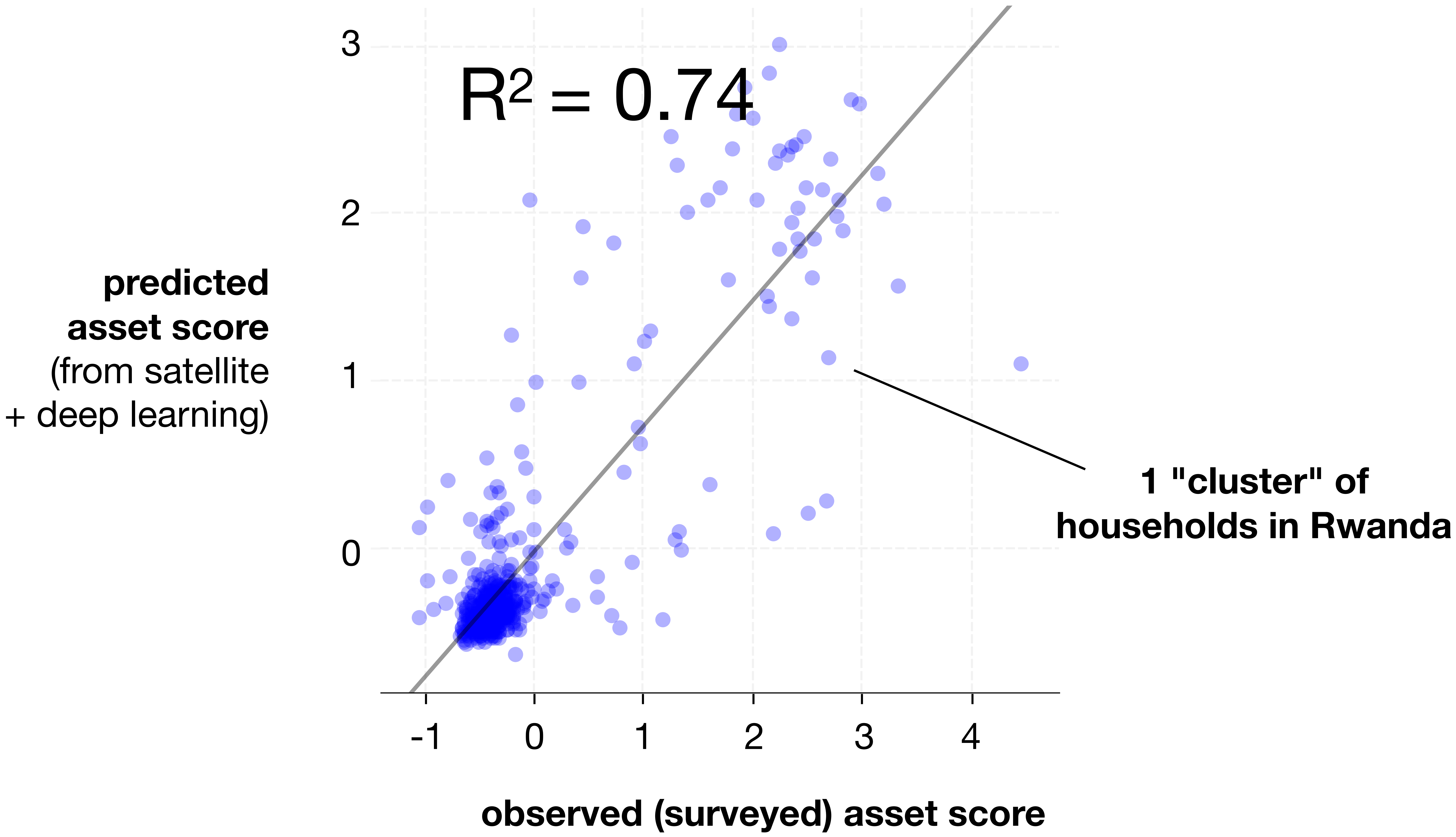

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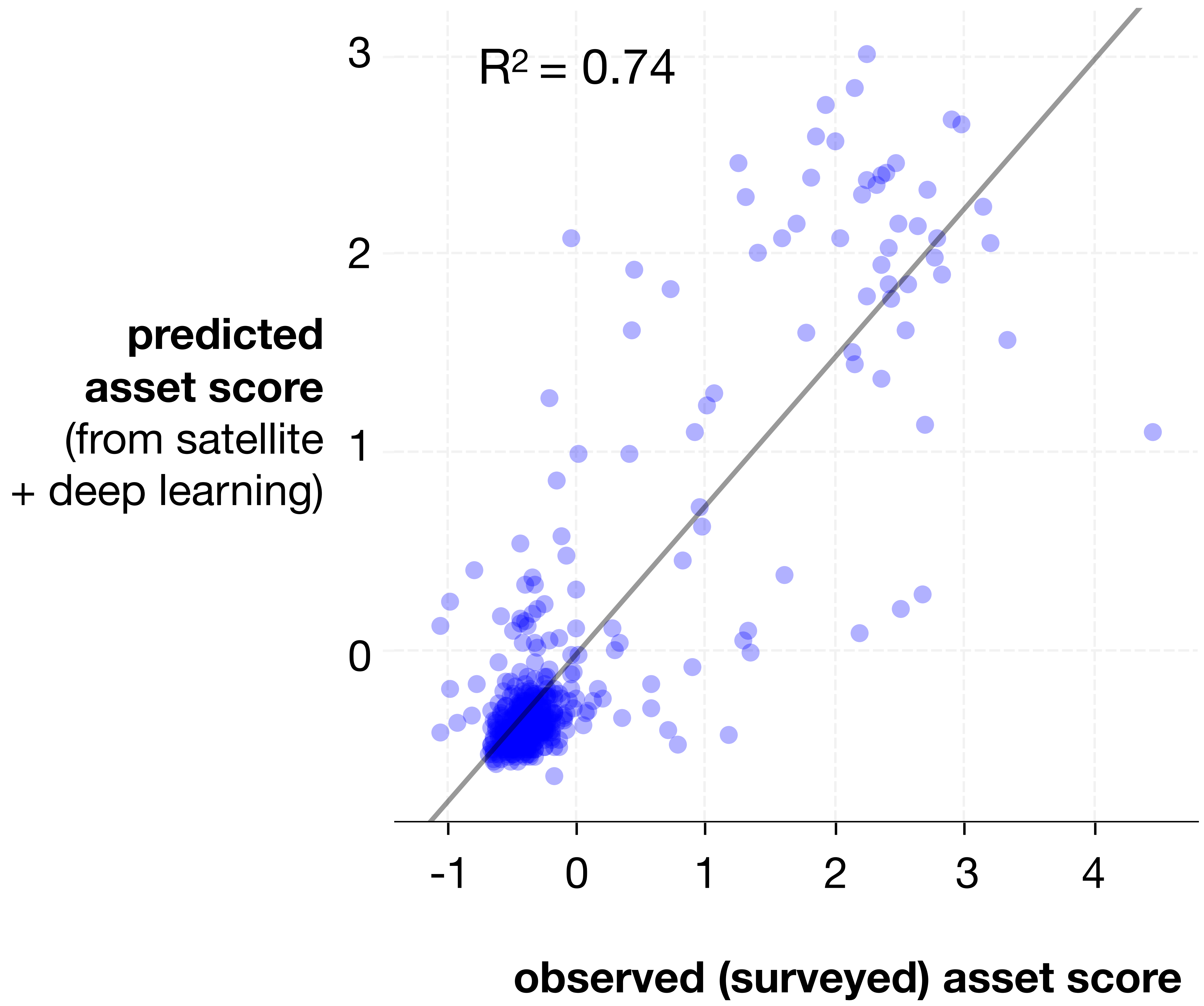

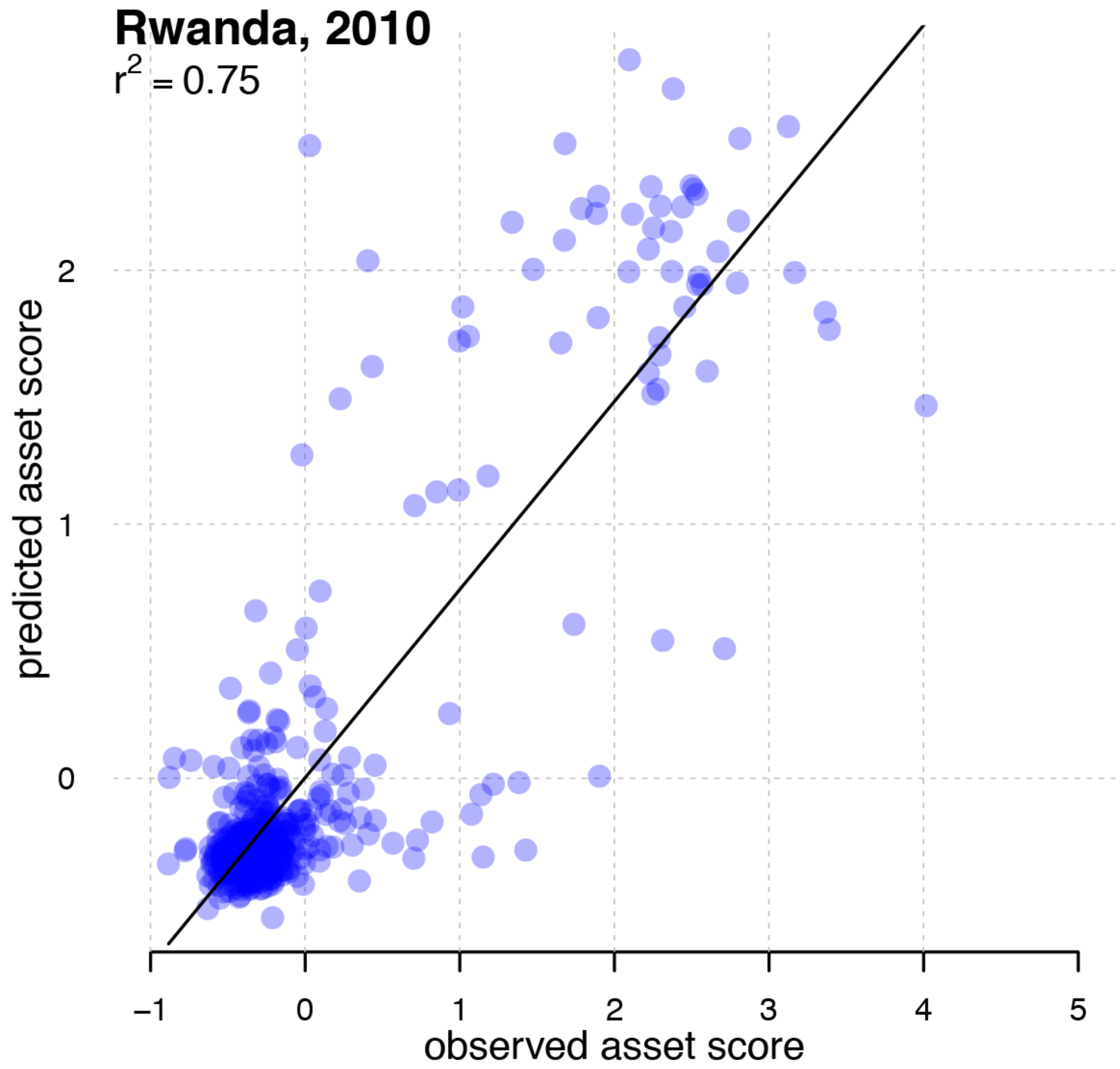

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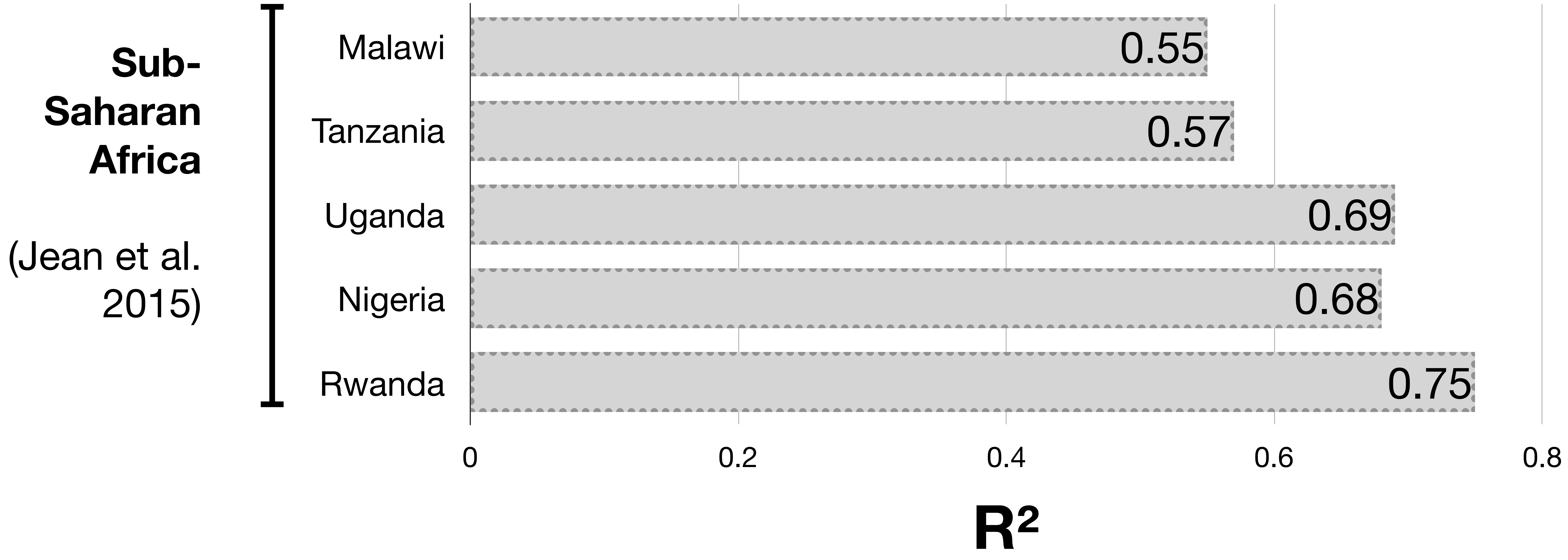
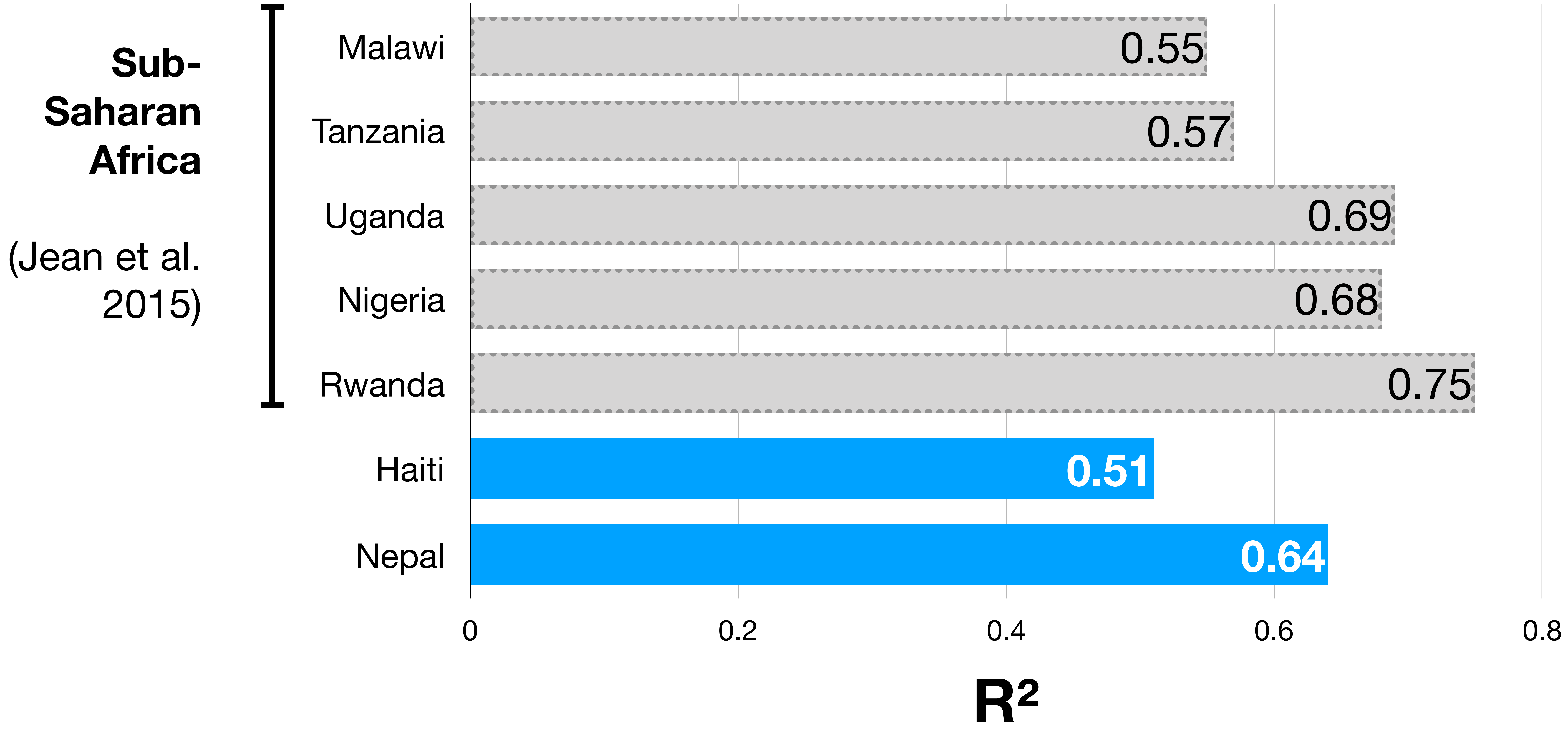
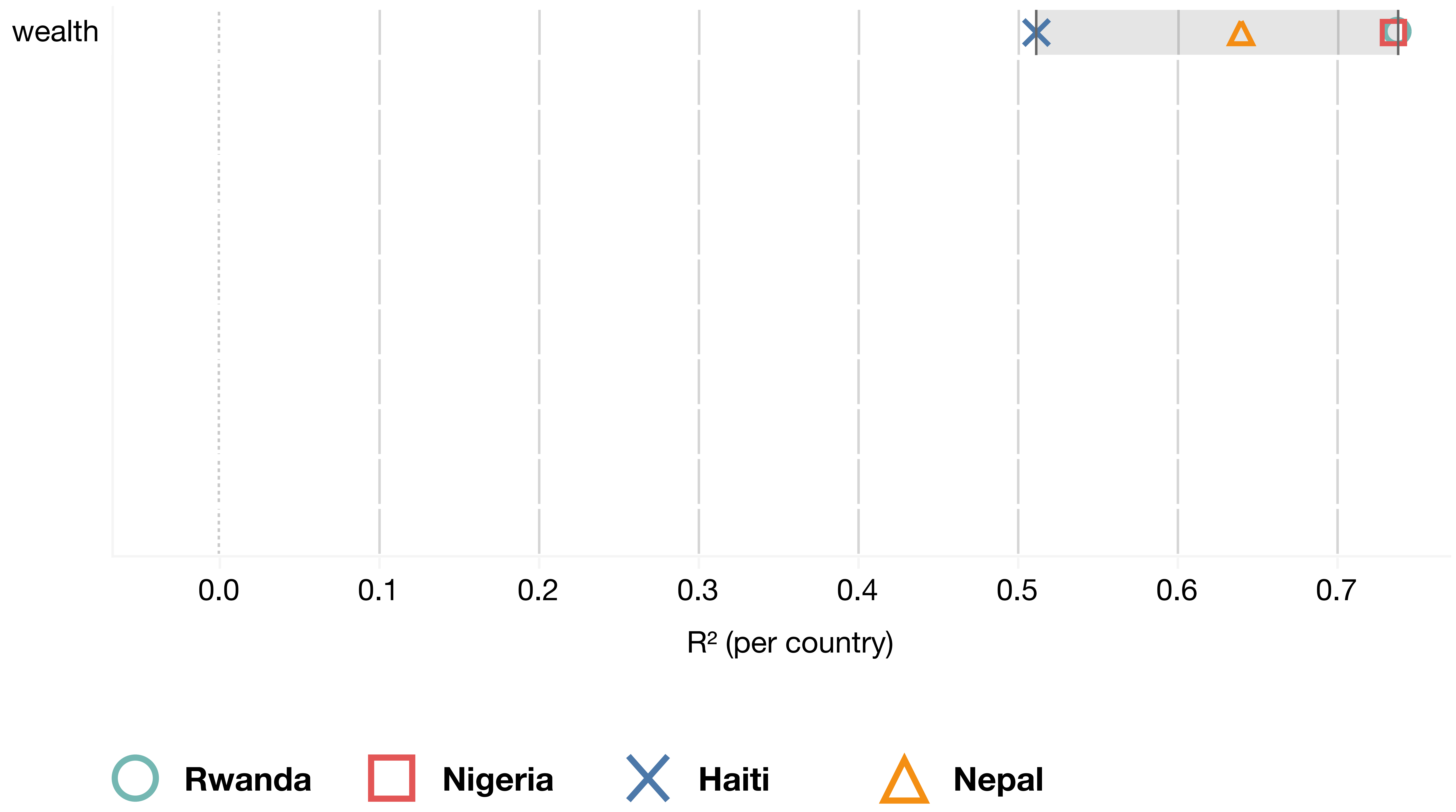
Estimating Wealth Outside Sub-Saharan Africa



Estimating Wealth Outside Sub-Saharan Africa



Estimating Development Indicators Everywhere



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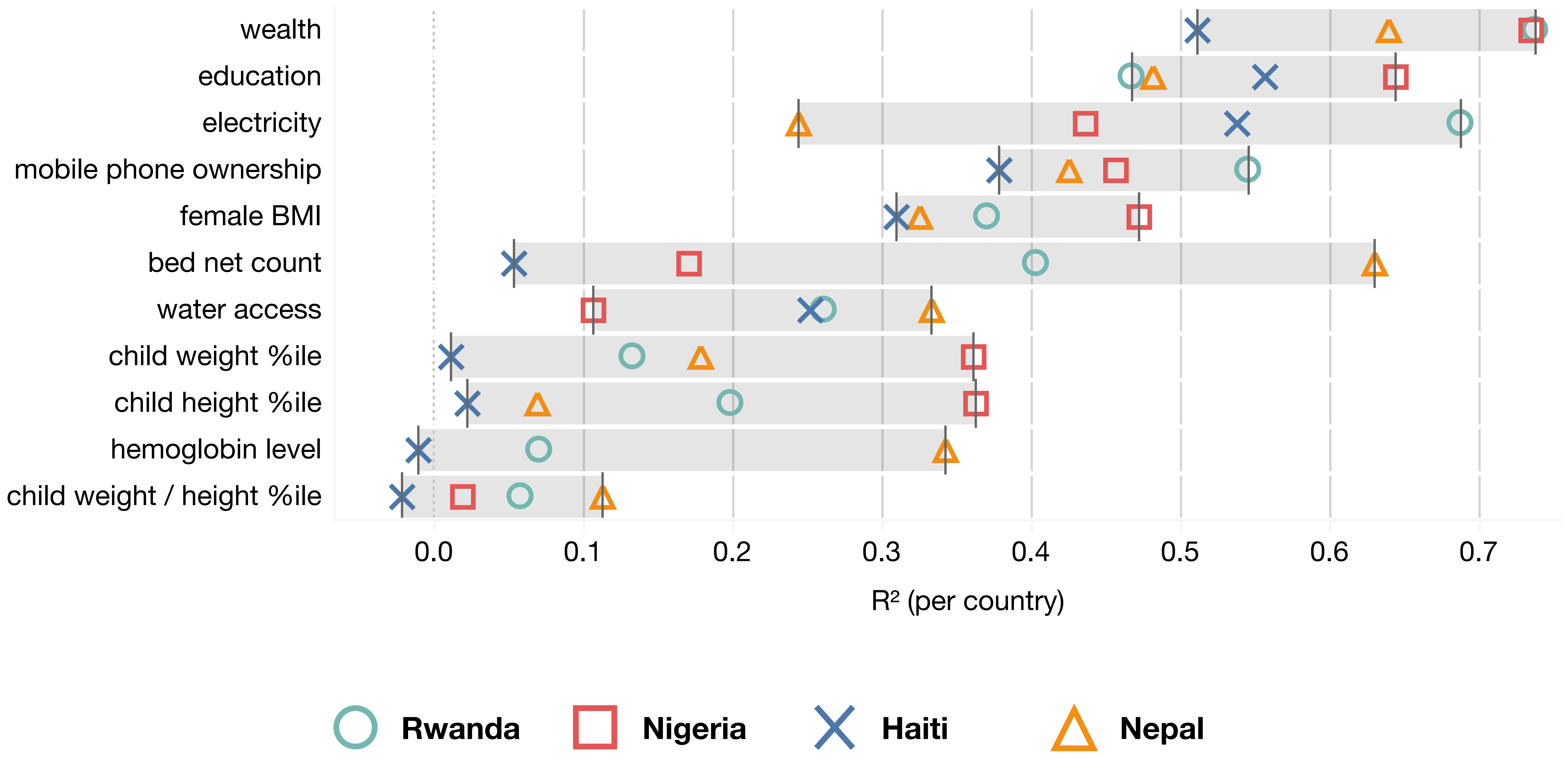
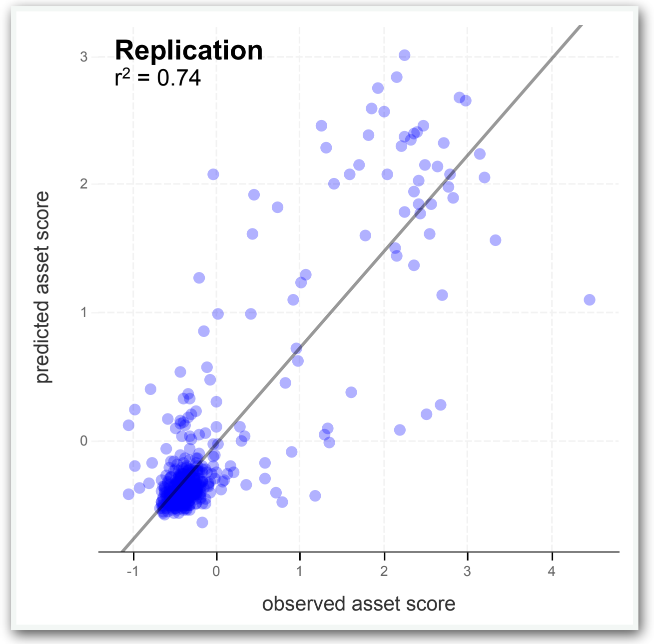


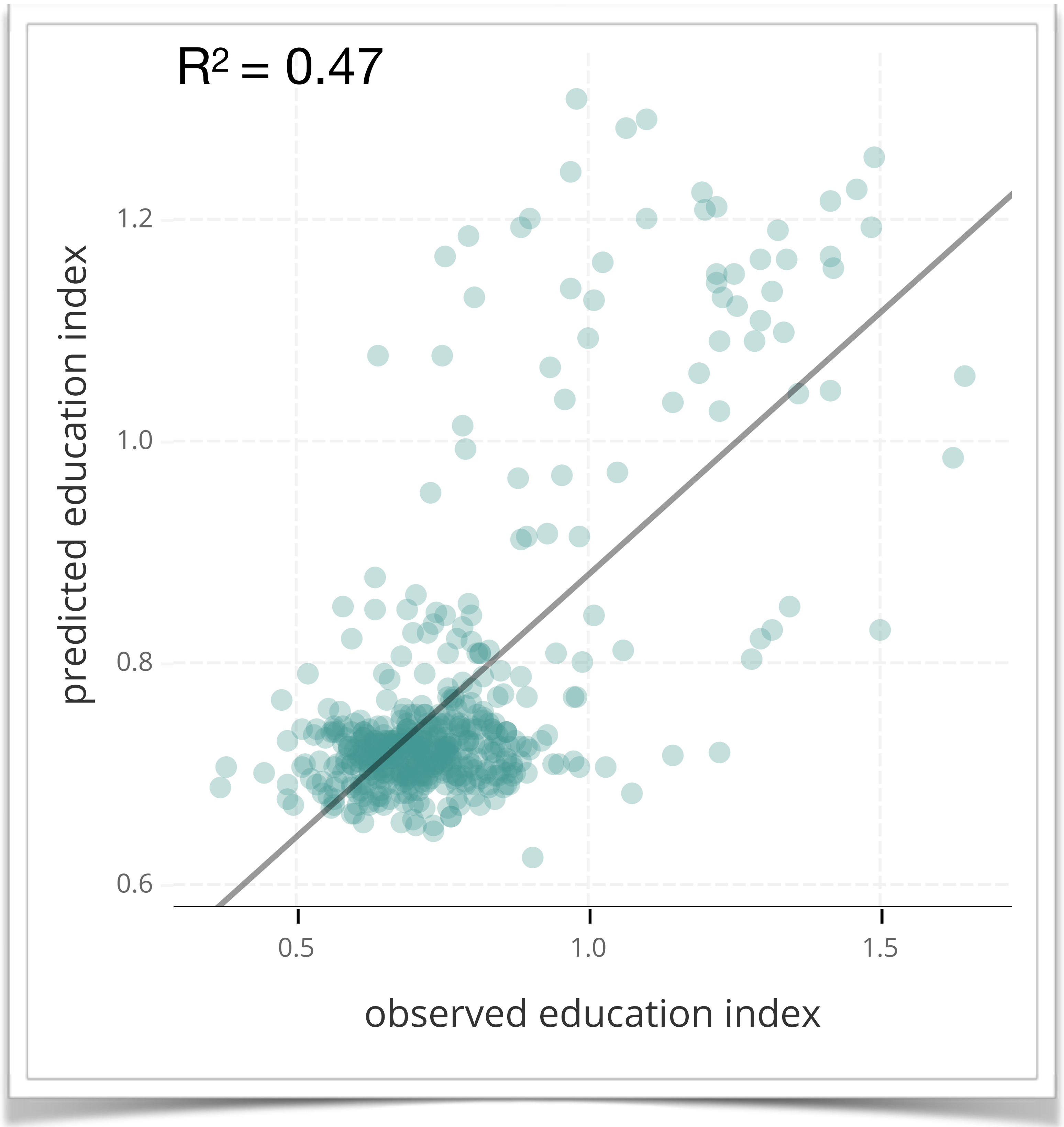
Mileage Varies When Estimating Other Development Indicators

Reference: Estimating Wealth

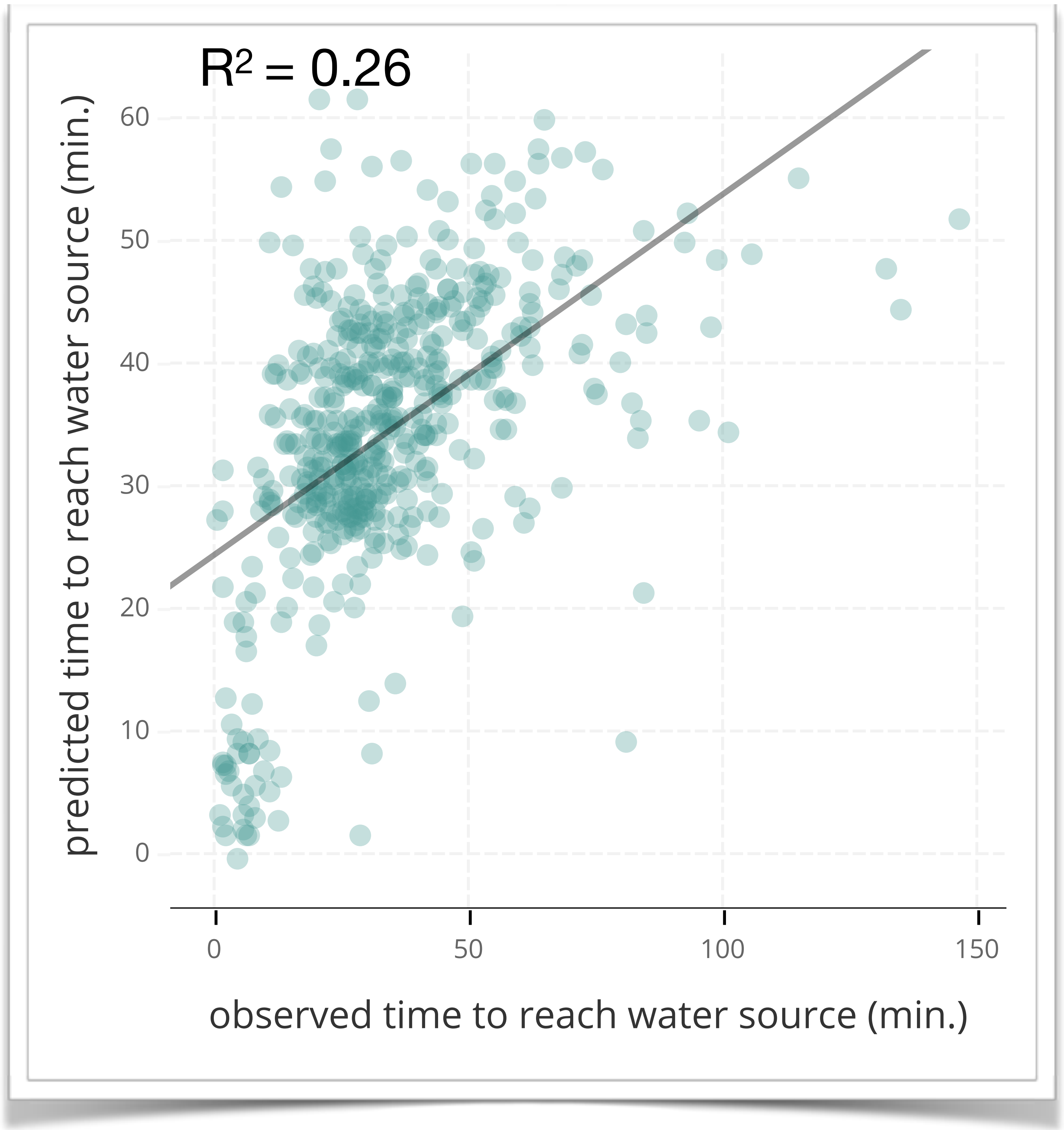
$R^2 = 0.74$



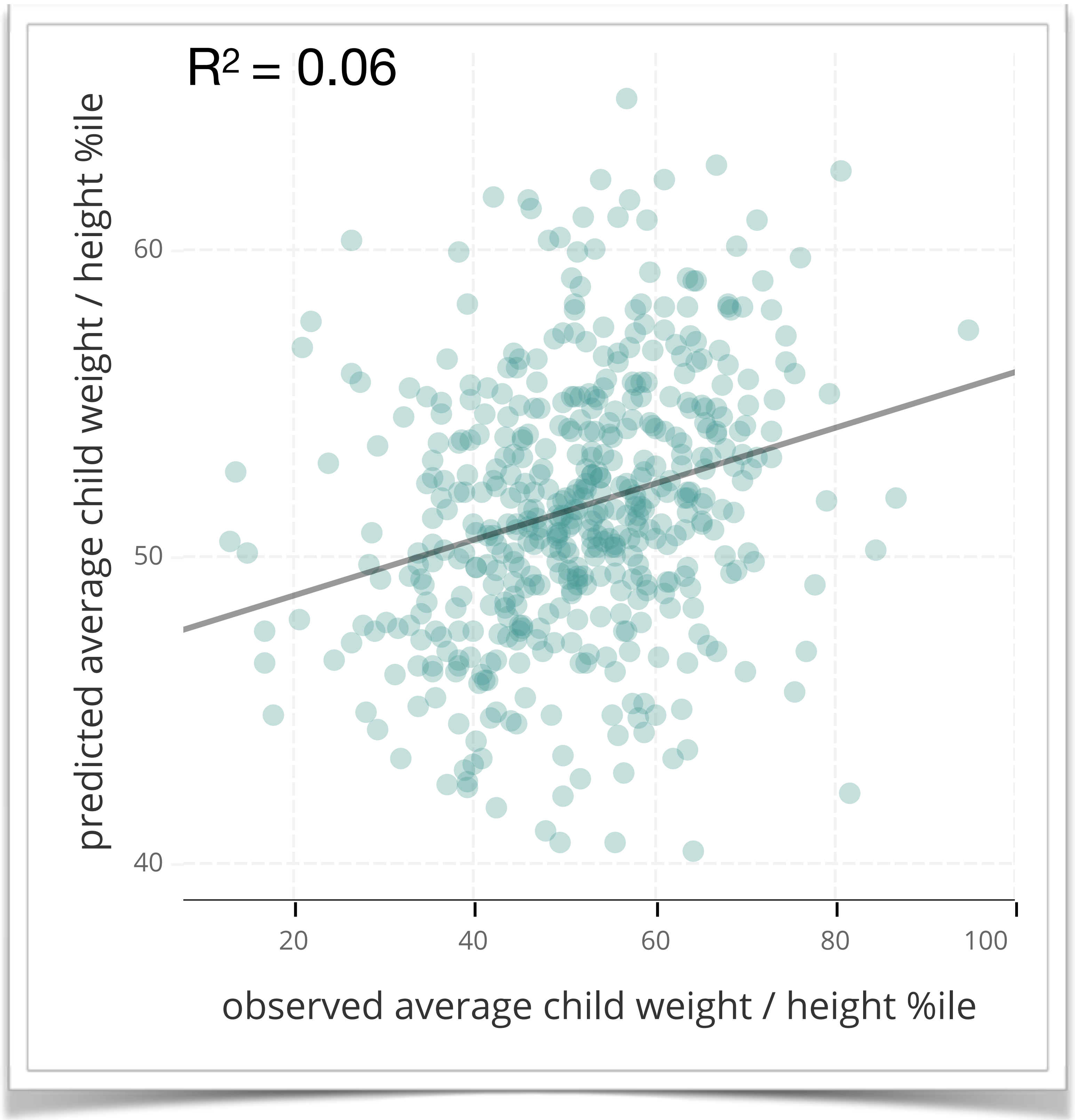
Household Level of Education



Access to Drinking Water



Child Weight / Height Percentile



Taking Stock of Estimating Development with Satellite Imagery

This approach works well for estimating wealth in sub-Saharan African ($R^2 \approx 0.55$–0.75)

And the approach works pretty well for two countries outside sub-Saharan Africa ($R^2 \approx 0.5$–0.65).

However, the approach does not trivially generalize to other measures of human development ($R^2 \approx -0.02$–0.65).

Are There Fundamental Obstacles to Estimating Indicators using Satellite Images?

- *Insufficient visual signal?* Satellite images may lack cues for predicting more "invisible" measures of development
- *Noise by design*: Ground truth data has built-in noise
- *Hard-to-learn features?* Other methods to define features may be more suitable (e.g., Gros and Tiecke, for population density)

Estimation Might Improve With Additional Effort

- *Neural Network Tuning*: Another categorical variable for tuning the network (besides night-time luminosity)

- *Machine learning design*: network architecture, hyperparameters, non-linear model, data augmentation, image resolution



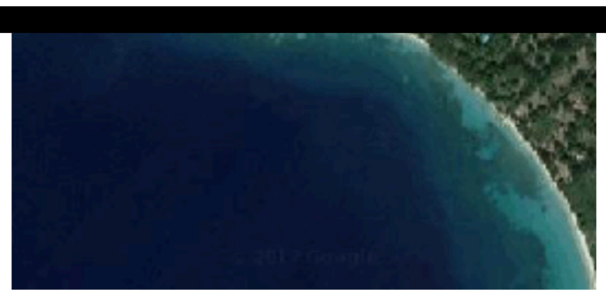
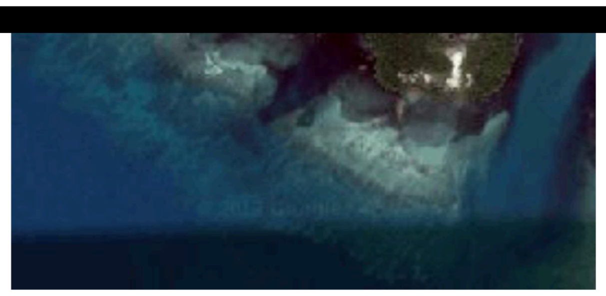
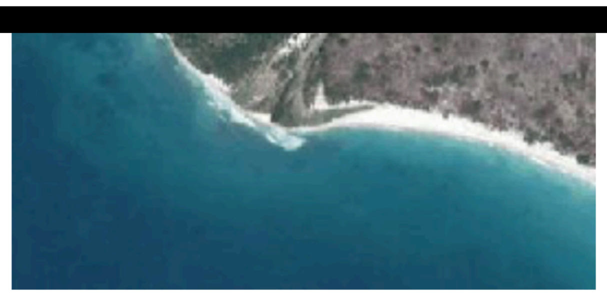
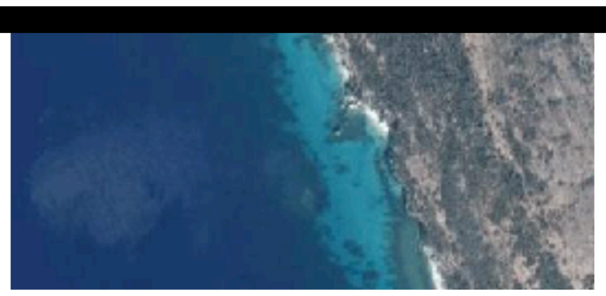


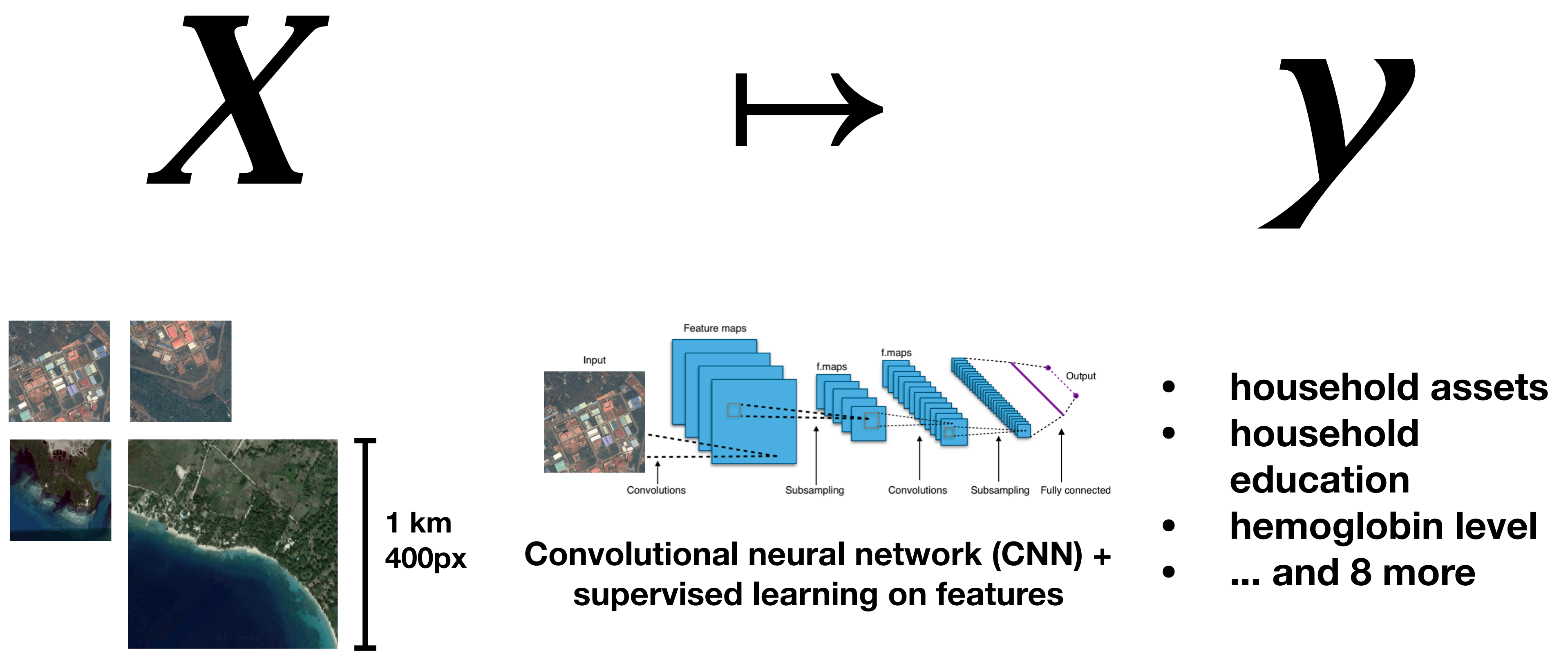

Key Takeaway

This exact framework—retraining a deep neural network on night-lights data, and then using those features to predict the wealth of small regions in sub-Saharan African—shows promise even outside sub-Saharan Africa.

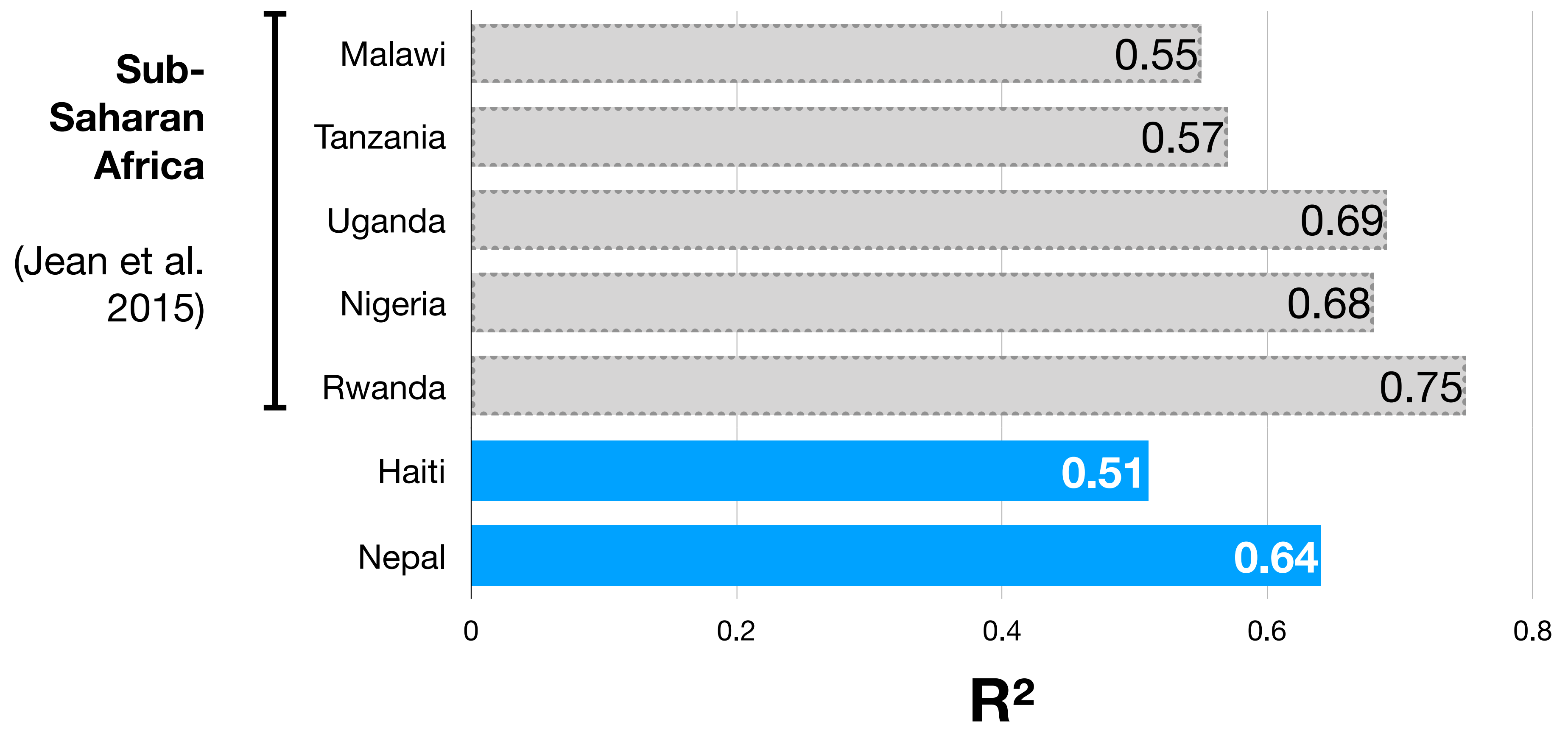
Though it cannot be applied directly to estimating arbitrary indicators in any country with uniformly good results.





Estimating Wealth Outside Sub-Saharan Africa



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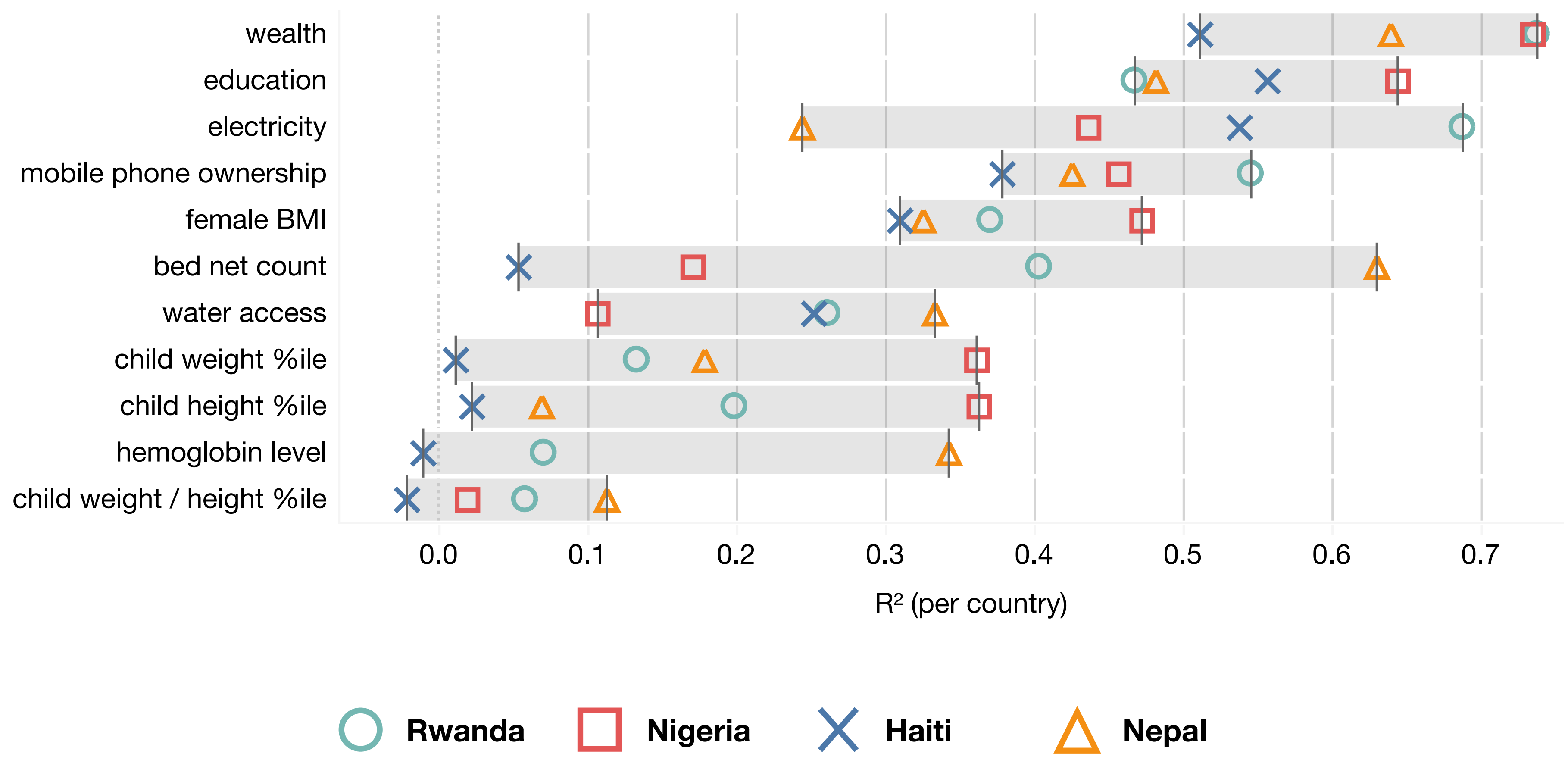

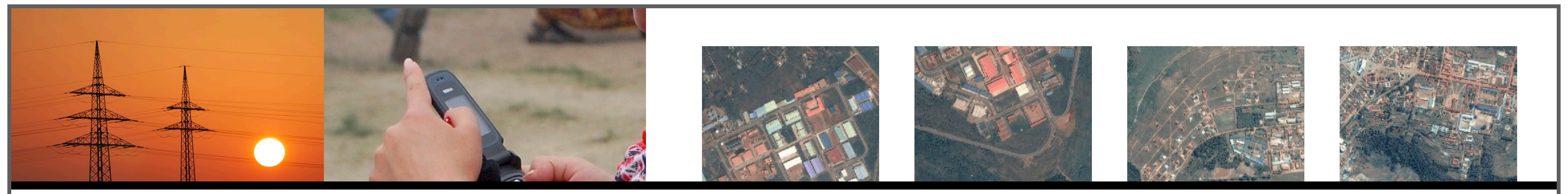

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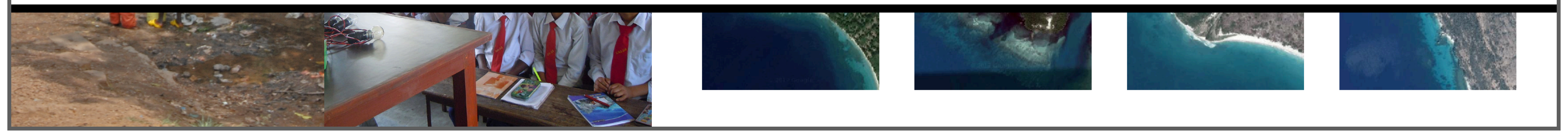


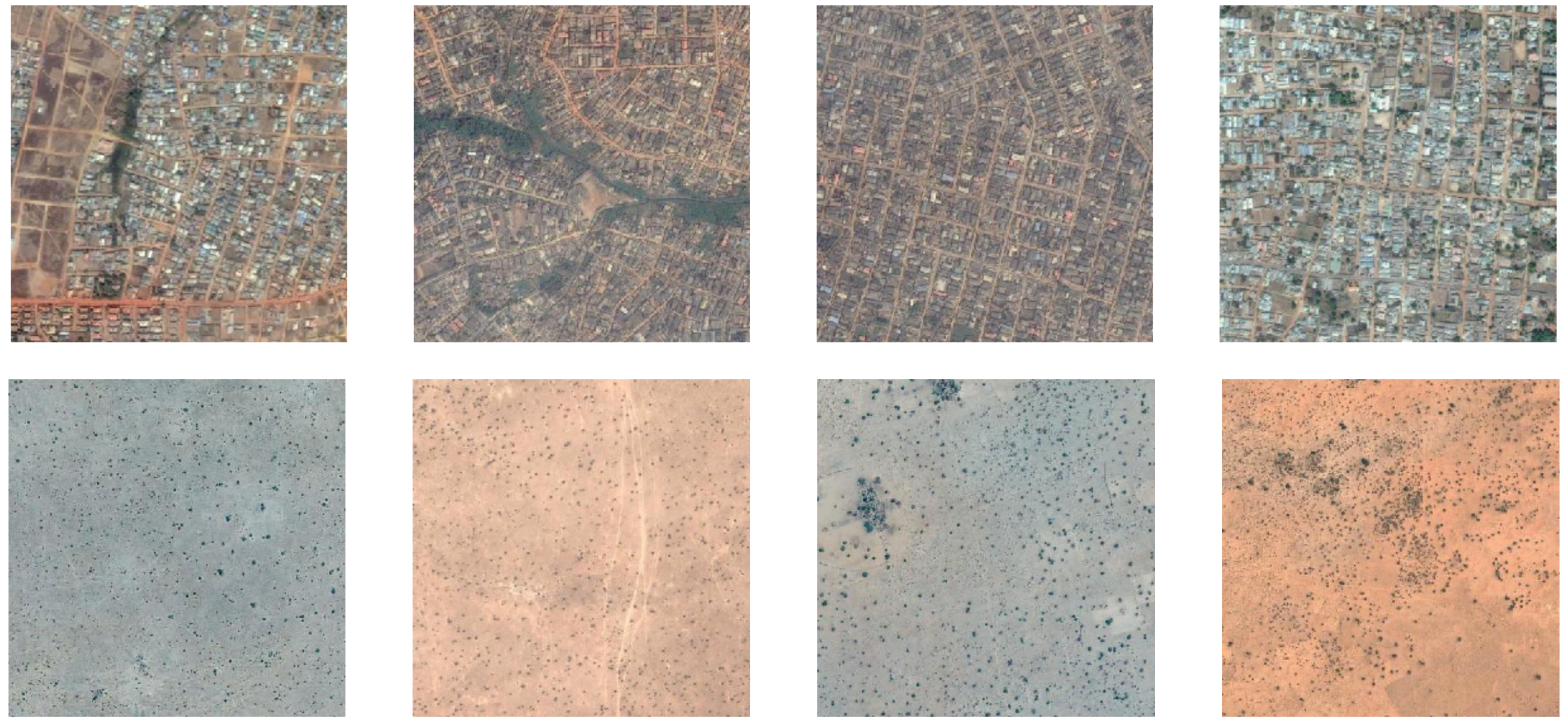
Paper: `http://tinyurl.com/ictd17-satellites`

Email: andrewhead@berkeley.edu

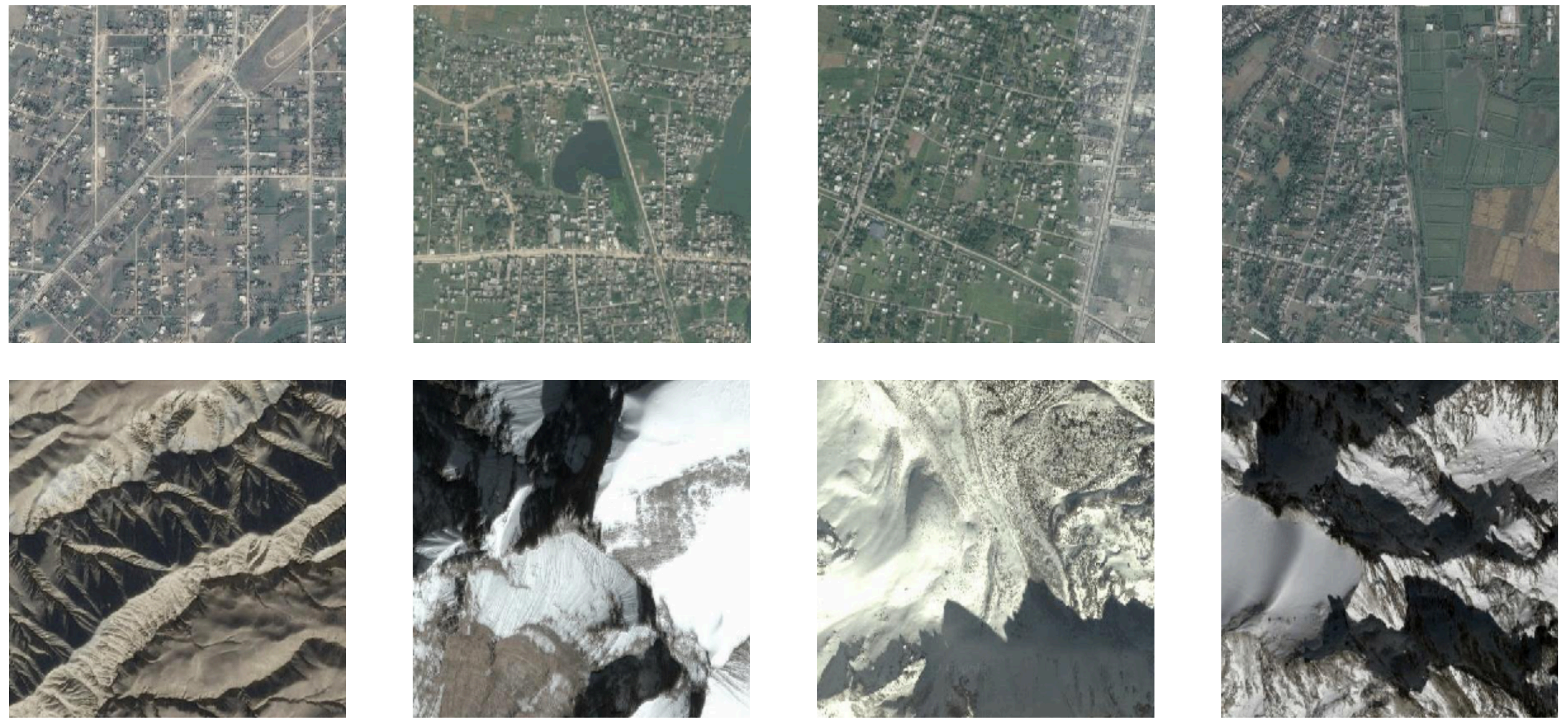
Rwanda

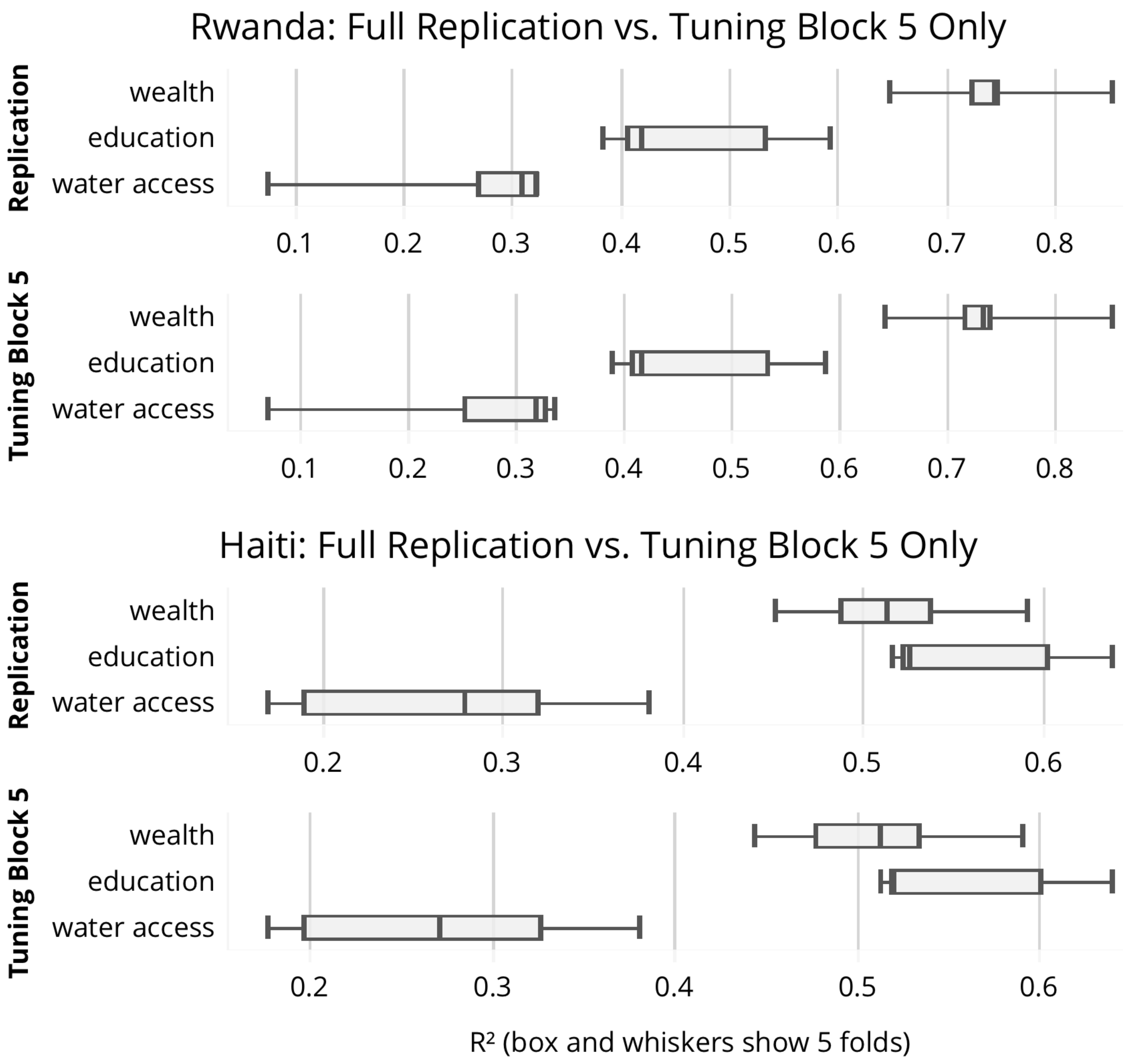
Haiti

Nigeria



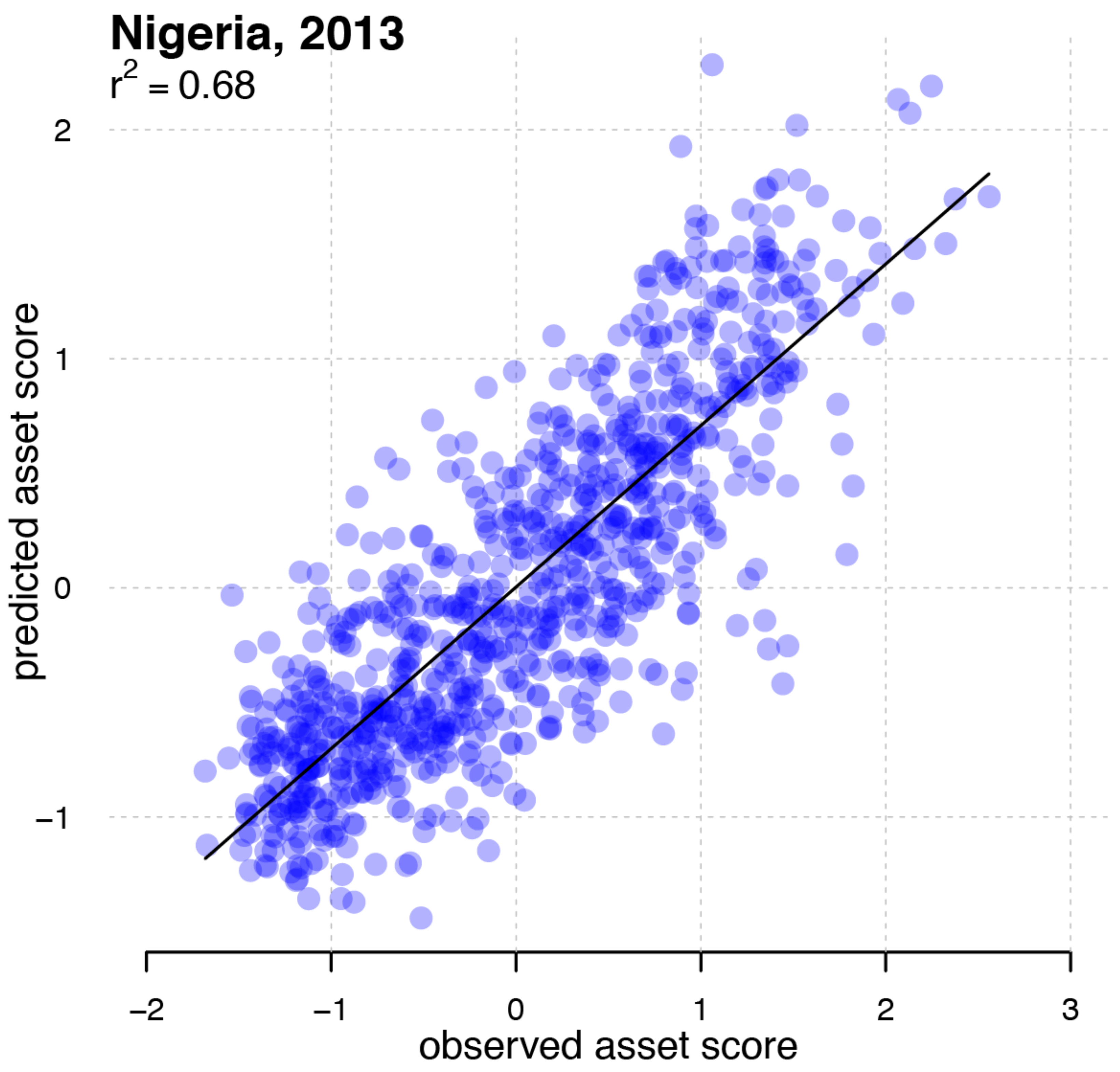
Nepal

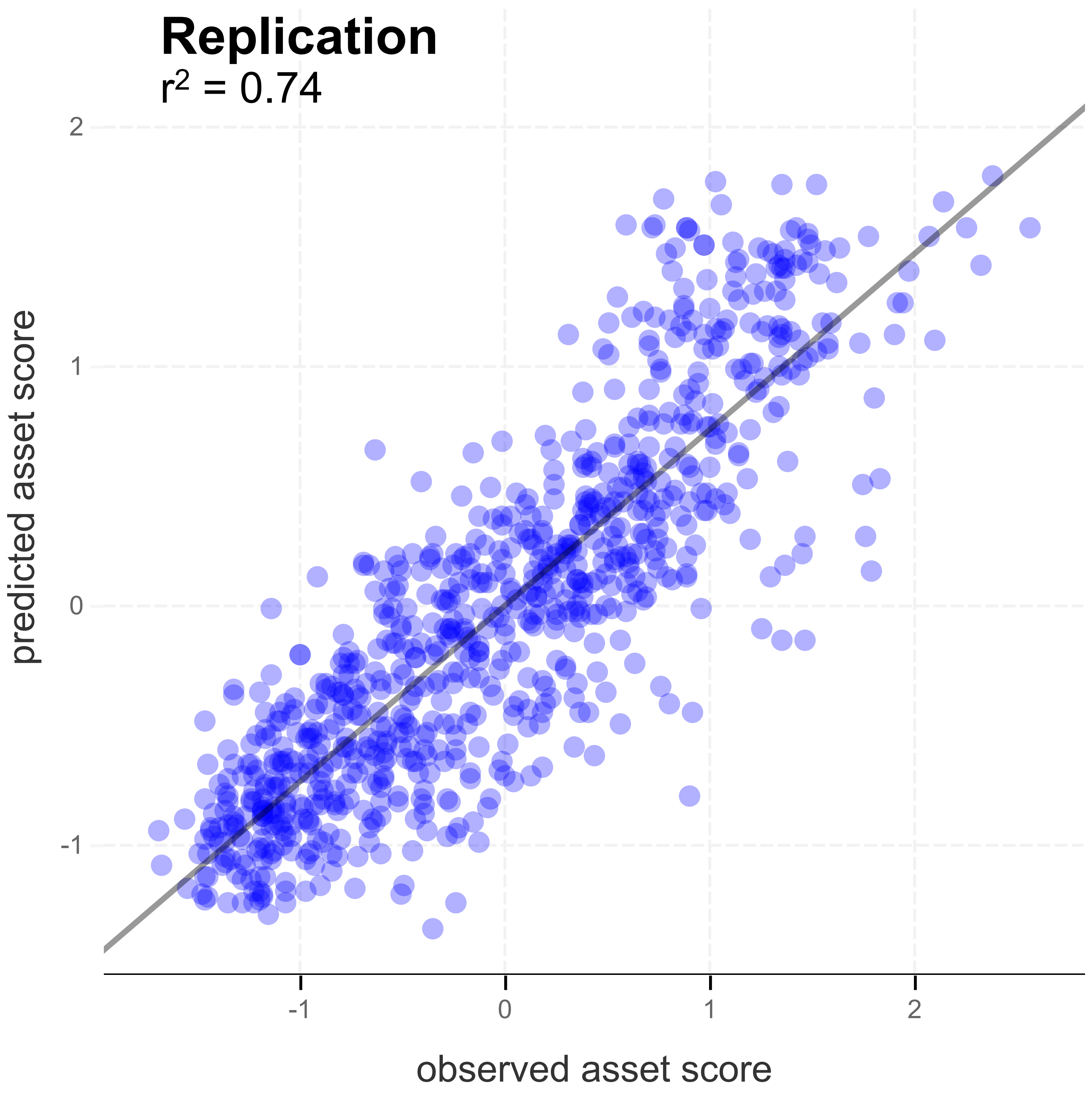




Rwanda: Full Replication vs. Tuning Block 5 Only
Replication
wealth
education
water access
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Tuning Block 5
wealth
education
water access
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Haiti: Full Replication vs. Tuning Block 5 Only
Replication
wealth
education
water access
0.2
0.3
0.4
0.5
0.6
Tuning Block 5
wealth
education
water access
0.2
0.3
0.4
0.5
0.6
R² (box and whiskers show 5 folds)

Replicating Nigeria Wealth Estimation





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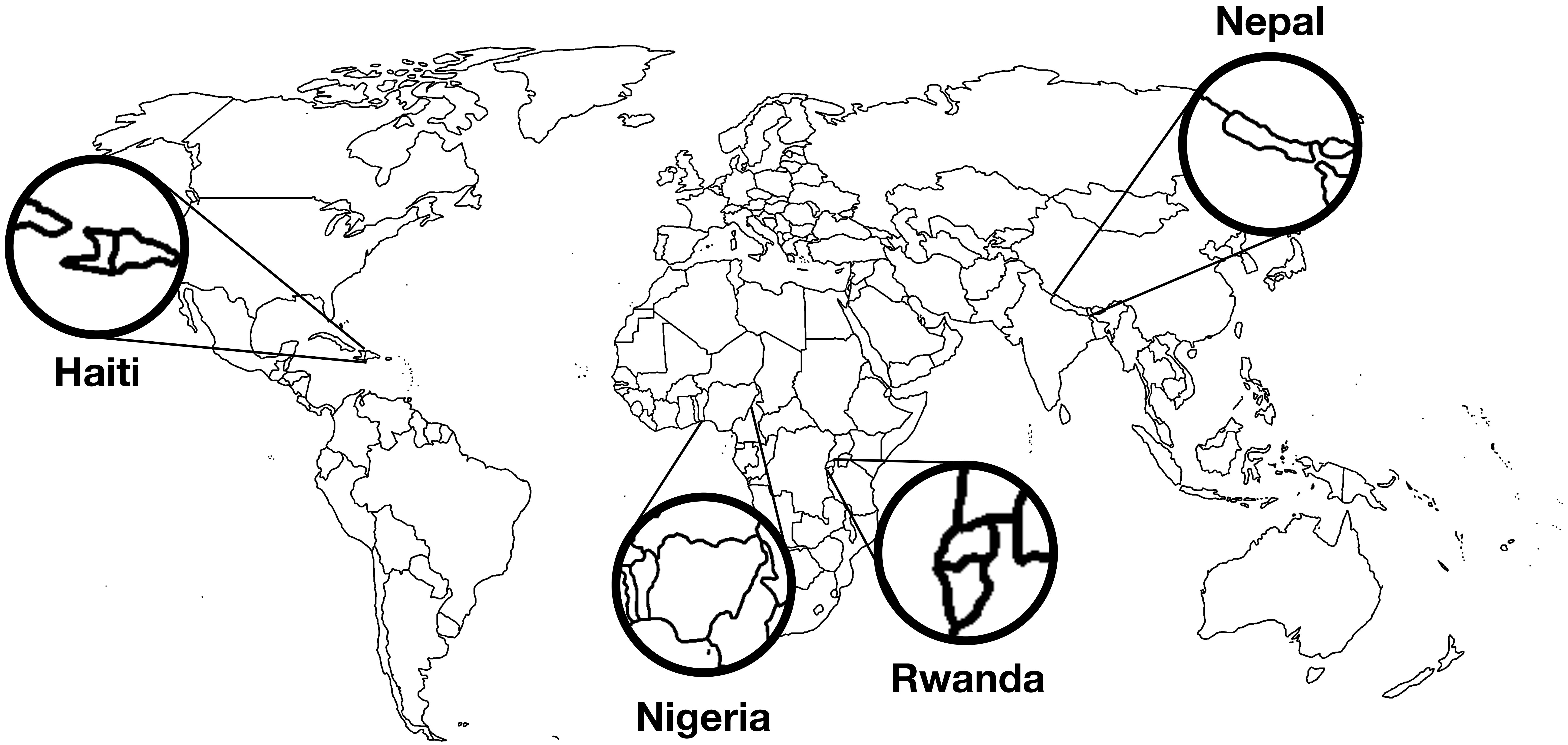
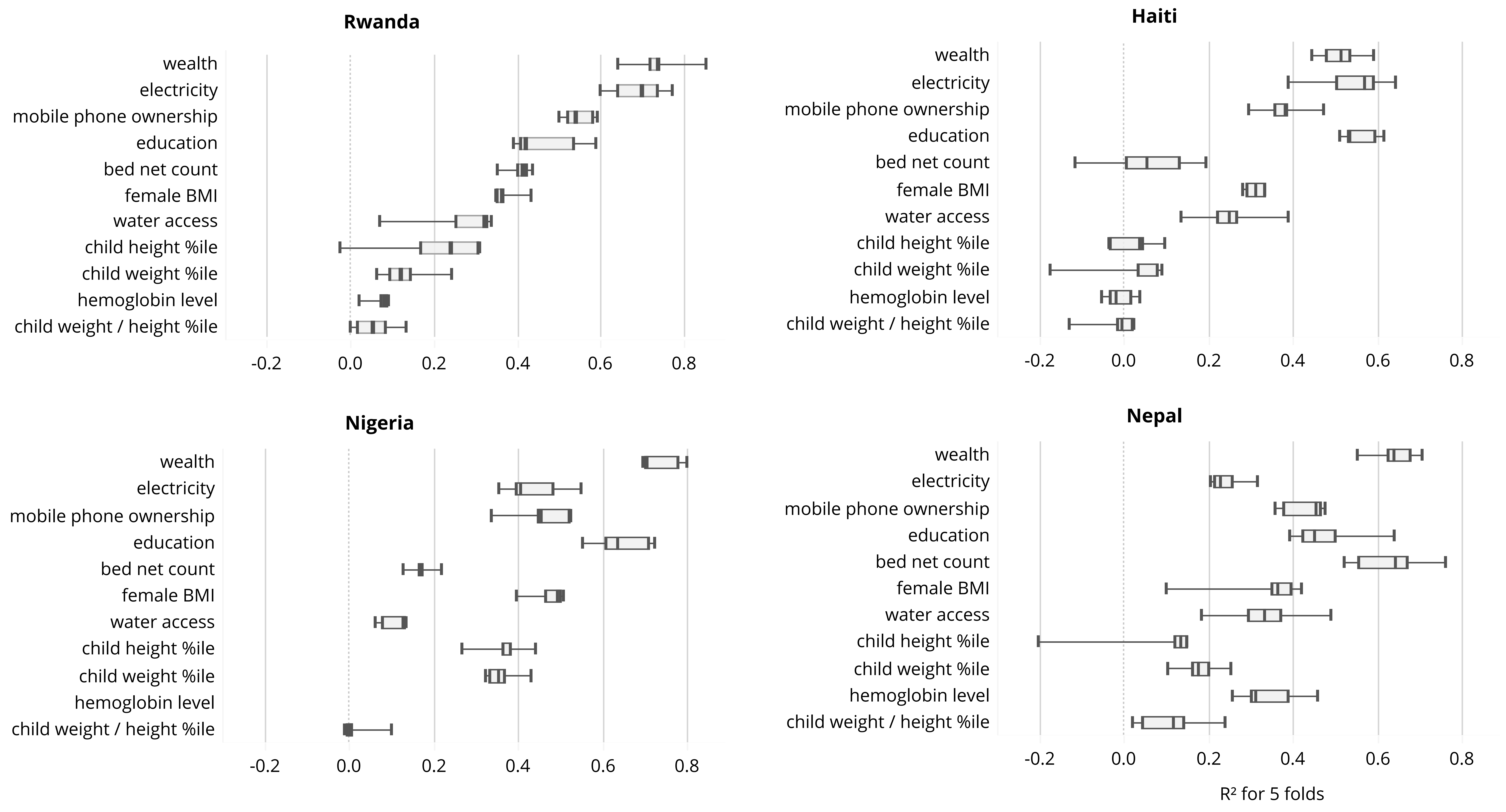
... And Beyond Sub-Saharan Africa





Rwanda
wealth
electricity
mobile phone ownership
education
bed net count
female BMI
water access
child height %ile
child weight %ile
hemoglobin level
child weight / height %ile
-0.2
0.0
0.2
0.4
0.6
0.8
Haiti
wealth
electricity
mobile phone ownership
education
bed net count
female BMI
water access
child height %ile
child weight %ile
hemoglobin level
child weight / height %ile
-0.2
0.0
0.2
0.4
0.6
0.8
Nigeria
wealth
electricity
mobile phone ownership
education
bed net count
female BMI
water access
child height %ile
child weight %ile
hemoglobin level
child weight / height %ile
-0.2
0.0
0.2
0.4
0.6
0.8
Nepal
wealth
electricity
mobile phone ownership
education
bed net count
female BMI
water access
child height %ile
child weight %ile
hemoglobin level
child weight / height %ile
-0.2
0.0
0.2
0.4
0.6
0.8
R² for 5 folds

A Brief Fine-Tuning Experiment

		$\alpha = 1$		tuned α	
		$\lambda = 0$	$\lambda = 5\times10^{-4}$	$\lambda = 0$	$\lambda = 5\times10^{-4}$
Asset-Based Wealth Index	LR = 10^{-6}	**0.38 ± 0.10**	**0.38 ± 0.10**	**0.51 ± 0.06**	**0.51 ± 0.06**
	LR = 10^{-4}	**0.36 ± 0.11**	**0.35 ± 0.13**	**0.51 ± 0.06**	**0.51 ± 0.05**
Average Child Weight / Height %ile	LR = 10^{-6}	**-0.51 ± 0.06**	**-0.51 ± 0.06**	**-0.02 ± 0.06**	**-0.02 ± 0.06**
	LR = 10^{-4}	**-0.55 ± 0.09**	**-0.55 ± 0.11**	**-0.02 ± 0.06**	**-0.02 ± 0.06**