Measuring economic well-being from

space

Marshall Burke Stanford University

* With thanks to SustainLab collaborators David Lobell, Stefano Ermon, Neal Jean, Tony Duan, and others

UN ITU AI for Good | Geneva, May 16 2018

1. Ground data are very infrequent



- 1. Ground data are very infrequent
- 2. Humans can distinguish well-being in imagery





- 1. Ground data are very infrequent
- 2. Humans can distinguish well-being in imagery
- 3. Computers are getting really good at image recognition tasks





- 1. Ground data are very infrequent
- 2. Humans can distinguish well-being in imagery
- 3. Computers are getting really good at image recognition tasks
- 4. There is a lot of new imagery to play with

New sources of satellite data



Sensor	Wavelengths	Spatial Resolution	Revisit frequency	Launch year
Sentinel-1	C-band radar	20m	6 day	2014, 2016
Sentinel-2	Optical	10m	5 day	2015, 2017
Skysat	Optical	1m	~weekly	2013- present
Planet	Optical	3-5m	~daily	2014- present

Some results: poverty in Africa

Outcome: village-level consumption (LSMS) **Input**: ~3m RGB **Model**: CNN/ transfer learning

Some results: poverty in Africa

Outcome: village-level consumption (LSMS) **Input**: ~3m RGB **Model**: CNN/ transfer learning



Jean, Burke et al Science, 2016

Data from: N. Jean, M. Burke, M. Xie, W.M. Davis, D. Lobell, S. Ermon., "Combining satellite imagery and machine learning to predict poverty". Science, 2016 For more info, visit sustain.stanford.edu

3

Some results: poverty in India (rural)

Outcome: village-level consumption **Input**: 10m radar + 30m multispectral **Model**: CNN

Some results: poverty in India (rural)



Some results: smallholder agriculture

Outcome: plot level maize yields **Input**: 10m Sentinel **Model**: regression/SCYM

Some results: smallholder agriculture



Jin et al. (2017), Remote Sensing

Some results: access to electricity

Outcome: Village-level electricity (Afrobar.)

Input: 30m Landsat

Model: CNN

Some results: access to electricity

Outcome: Village-level electricity (Afrobar.)

Input: 30m Landsat M

Model: CNN



label	balance	nightlights	OSM	oracle	Landsat 8
Electricity	0.66	0.79	0.73	0.89	0.85
Pipedwater	0.60	0.73	0.73	0.89	0.86
Sewerage	0.35	0.75	0.77	0.89	0.74
Road	0.53	0.67	0.68	0.79	0.76
Postoffice	0.24	0.56	0.64	0.92	0.70
Marketstalls	0.65	0.50	0.62	0.84	0.65
Policestation	0.33	0.54	0.63	0.90	0.62
Bank	0.24	0.57	0.70	0.93	0.68

Economic well-being from space

We are getting better at measuring development outcomes with satellites.

The next few years will see huge advances, and we are working on scaling these estimates.

We want to work with policymakers and practitioners to operationalize satellite-based estimates.

Thank you!

Marshall Burke mburke@stanford.edu

Extra slides

Are these useful measurements?

R₂ < 1

Are these useful measurements?

$R_2 < 1$ But this could be because of error in either ground or satellite data (or both).



 $R_2 < 1$ But this could be because of error in either ground or satellite data (or both).

Attempt at diagnosing source of error:

- We have two measurements of the same outcome
- See how well they relate to known inputs
 - Agriculture: fertilizer/ hybrid seed
 - *Poverty*: roads, climate, independent wealth estimates
- "Better" outcome measurement is that which correlates more strongly with input

Results: agriculture

Relationship between inputs (fertilizer, hybrid seed) and outputs the same for the two outcome measures



Burke and Lobell, 2017, PNAS

Results: poverty



Satellite-based predictions Survey-based measurements

Suggests that, at minimum, there is no more error in satellite-based measures than ground measures