Households from Space

Integrating Household Surveys with Geospatial Data Sources for Improved Monitoring of Development Outcomes

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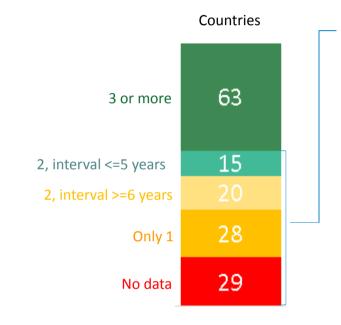


A propitious time for data

- Increased demand for data ...
 - Globally
 - World Bank: new data strategy under Development Data Council
 - At national and sub-national level
 - Increased accountability
 - More evidence-based policy decisions
- Household surveys at core of satisfying this demand



The sobering news: despite increasing demand ...



- 92 low/middle income countries are "Data Deprived"
 - Only 1 point: Mainly in Africa
 - > 5-year interval: 77 countries
 - Irregular survey implementation
- Beyond data deprivation, issues with:
 - Uncertainty of funding: many more (IDA) countries "at risk"
 - Data reliability, comparability and accessibility

Source: Serajuddin et al. (2015)



The SDG provide a unique opportunity, but ...





... need to go beyond indicators!



For evidence-based policy making, need an integrated approach involving ...

- •Integration within same instrument
 - Cost saving
 - Analytical advantages ... but also drawbacks!
- •Integration <u>across</u> data sources
 - Data from space



LSMS–Integrated Surveys on Agriculture (LSMS-ISA)

Technical and financial assistance for the design and implementation of multi-topic panel household surveys, with a focus on agriculture.

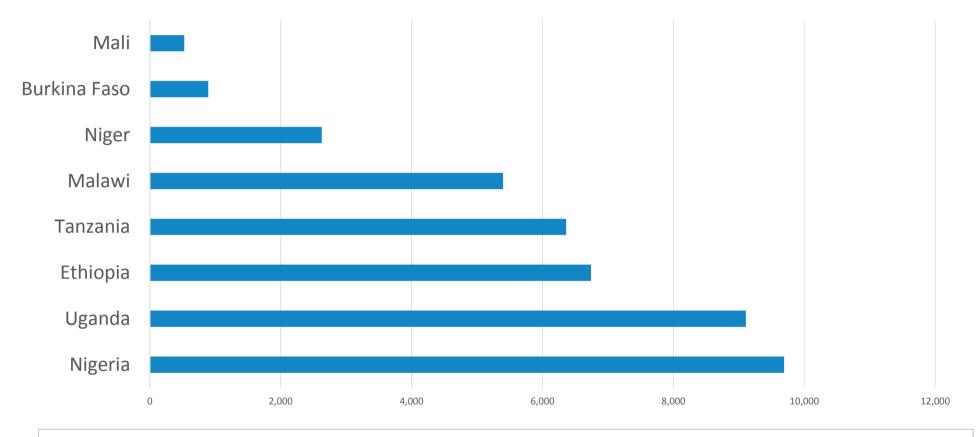
Since 2009, 20+ surveys, which :

- Are integrated into national statistical systems
- Are nationally & regionally representative
- Track households & individuals
- Geo-reference household & plot locations
- Collect individual-level data
- Use field-based data processing (CAPI)
- Are open access





LSMS-ISA Downloads by Country

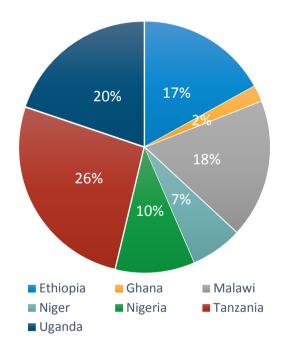


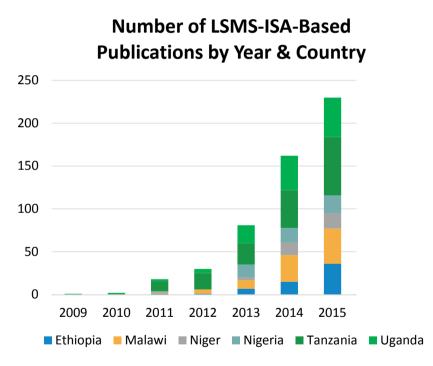
Total of 41,342 for these 8 countries (as of October 24, 2017)

* Lower bound: does not include direct downloads from NSO websites; more than ¾ are downloads of full datasets



LSMS-ISA Research by Country







Examples of cross-country research

Gender & Agriculture

- Partners: IFAD, Africa Gender Innovation Lab, IFPRI, FAO
- World Bank Policy Research Working Papers
- World Bank-ONE Campaign Report Leveling the Field
- <u>Agricultural Economics Special Issue</u>

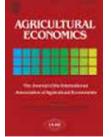
Nutrition & Agriculture

- Partners: BMGF, IFPRI
- World Bank Policy Research Working Papers
- Journal of Development Studies Special Issue

Agriculture in Africa: Telling Facts from Myths

- Partners: AfDB, World Bank Africa CE, Yale, Cornell, Maastricht
- World Bank Policy Research Working Papers
- Food Policy Special Issue









Scope of LSMS-ISA Data



Household

- Dwelling GPS Coordinates
- Demographics
- Education
- Health
- Housing
- Food & Non-Food Consumption
- Off-Farm Earnings
- Asset Ownership
- Anthropometry
- Food Security
- Safety Nets
- Shocks



Agriculture

- Plot GPS Coordinates & GPS-Based Area Measurement
- Parcels : Tenure, Ownership
- Plots: Physical Attributes, Labor
- & Non-Labor Input Use
- Crops: Cultivation, Production (Plot-Crop-Level), & Disposition (Crop-Level)
- Ag Asset Ownership & Use
- Extension Services
- Livestock Ownership & Production



Community

- Demographics
- Infrastructure
- Facilities
- Access to Services
- Facilities
- Collective Action
- Natural Resource Management
- Community Organizations
- Prices



LSMS-ISA Approach to Disseminating Geospatial Data

- Provide Randomly Off-Set, EA-Level Coordinates
 - Average household-level coordinates in a given EA
 - Apply a random offset of 0-2 km in urban, 2-5 km in rural areas
 - Similar to DHS Protocol
- Uses raw GPS coordinates to match household locations with publicly-available geospatial variables, disseminated alongside unitrecord survey data
 - Depending on characteristics of source data, values may be rounded (distance) or ranged (population density) to maintain anonymity of place



LSMS-ISA Geospatial Variables

Theme	Variable	Theme	Variable
Distance	Plot distance to household	Soil & Terrain	Terrain roughness
	Household to nearest main road		Topographic wetness index
	Household to major agricultural market		Landscape-level soil characteristics
	Household to headquarters of district of residence	Rainfall (TS)	Survey year annual rainfall
	Household to nearest city or town with +20,000		Survey year wettest quarter rainfall
	Household to nearest border post		Survey year timing of start of wettest quarter
Climatology	Annual mean temperature	Phenology (TS)	Average total change in greenness within primary ag season
	Mean temperature of wettest quarter		Average timing of onset of greenness increase
	Mean annual precipitation		Average timing of onset of greenness decrease
	Precipitation of wettest quarter		Average EVI value at peak of greenness
	Precipitation of wettest month		Total change in greenness in survey year
Landscape	Land cover class		Timing of onset of greenness increase in survey year
	Density of agriculture		Timing of onset of greenness decrease in survey year
	Population density		Maximum EVI value in survey year
	Agro-ecological zone		Specific crop season NDVI crop season aggregates
Soil & Terrain	Elevation		
	Slope		

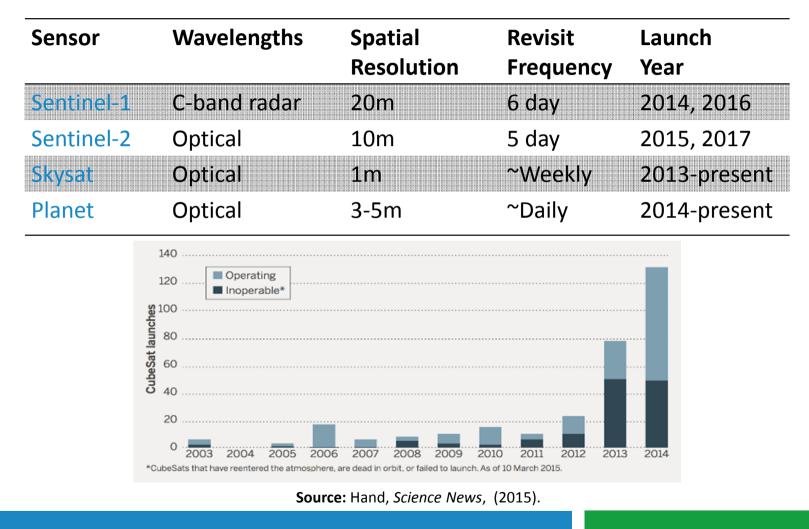


Why are we interested in integrating household survey data with geospatial data?

- At least two reasons...
 - 1. To study the relationships between farms/households/individuals and the environment
 - 1. Obtain higher-resolution/more frequent predictions of economic outcomes, at potentially lower costs
 - Today's highlighted applications will be on poverty and crop yields
 - Common thread: Use of household survey data as "ground truth"



The good news: We have more eyes in the sky than ever before!







POVERTY FROM SPACE

Engstrom, R., Hersh, J., and Newhouse, D. (2017). "Poverty from space: using high-resolution satellite imagery for estimating economic well-being." World Bank Policy Research Working Paper No. 8284

Feature-Based Approach

- Engstrom et al. (2017) predict poverty rates based on features derived from high-resolution satellite imagery
- 1. Generate features from satellite data
 - Convolutional Neural Networks
 - Identify cars, shadows, built-up area
 - Semi-automated classification
 - Identify road width, dirt vs. paved roads, roof type, roof area, simple land classification
 - Texture features from open-source Sp.Feas program
- 2. Use estimates of poverty and welfare from census-based poverty mapping exercise as "ground truth"
 - 10% and 40% relative poverty rates, and average expected log welfare
- 3. Regress satellite features on census-based welfare and poverty estimates



60 Percent of Variation in Welfare Explained by Satellite Features

Accuracy of Predictions	10% Poverty Rate	40% Poverty Rate	Average GN Log Expected Welfare
Out of sample R ²	0.59	0.60	0.60
Mean Absolute Error	3.2 рр	7.8 рр	0.139
Observations	1291	1291	1291

- Building density, roof type, and shadows are strongest predictors
 - In rural (urban) areas, poor areas have more (less) vegetation
- "Texture features" alone explain 40 to 50 percent of variation



Predictions Remain Accurate When Using Small Sample to Train Model

Out of sample R2	10% Poverty Rate	40% Poverty Rate	Average GN log expected welfare
Full sample	0.59	0.60	0.60
Small sample	0.53	0.59	0.58

- Use case is pairing imagery with a survey, not census
- Drew 1 percent synthetic sample from census
 - Comparable in size to HIES household survey
- Minor loss of performance when using 1 percent subsample





CROP YIELDS FROM SPACE

Preliminary Findings from: "Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-based Approaches to Crop Yield Measurement and Analysis in Uganda" (*Forthcoming*) – DO NOT CITE

Joint w/: David B. Lobell, George Azzari, Marshall Burke, Sydney Gourlay, Zhenong Jin[,] and Siobhan Murray

Objectives

- To test subjective approaches to measurement vis-à-vis objective methods for maize yield measurement, soil fertility assessment & maize variety identification
- To assess potential of using remote sensing for estimating crop yields

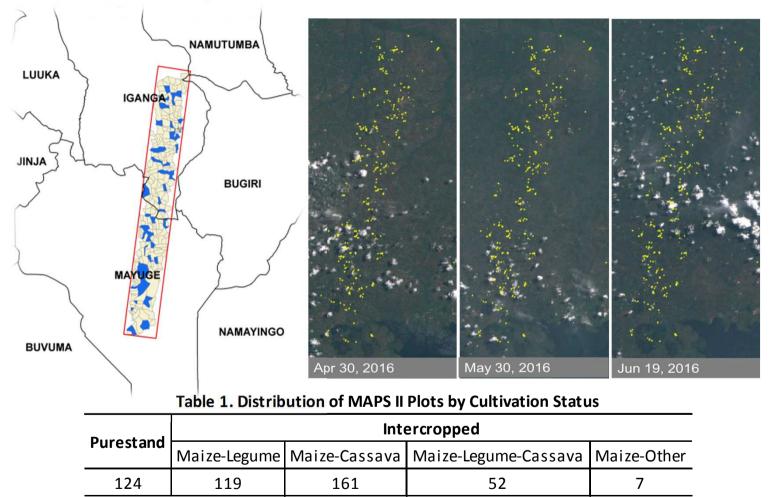


Methods

Methods Tested:			
Maize Production	 Crop-cutting 4m x 4m & a 2m x 2m subplot in Round I 8m x 8m sub-plot in Round II Full-plot crop cut in Round II (1/2 of sample) Remote sensing based on high-res imagery First in testing the method in a smallholder production system against an objective measure Self-reported harvest Conversion of quantities in non-standard unit-condition combos into KG-, dried grain terms ("official" methods) 		
Land Area	 GPS measurement (Garmin eTrex 30 handheld units) Self-reported area 		
Soil Fertility (Round I)	 Conventional Soil Analysis (subsample) Spectral Soil Analysis Self-reported soil quality & attributes 		
Variety Identification	 DNA fingerprinting of grain sampled from the crop-cutting subplot harvest (4x4m in Round I, 8x8m in Round II) Self-reported variety name, type & morphological attributes 		



Study Area & Sentinel-2 Imagery





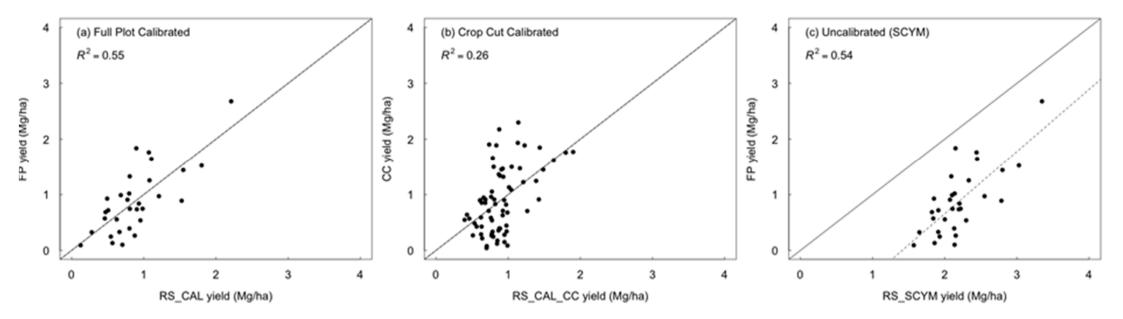
Vegetation Indices (Vis)

Name	Equation	Equation using Sentinel-2 bands	Reference
NDVI			(Power et al 1072)
(Normalized Difference Vegetation Index)	$(R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$	(B8 – B4) / (B8 + B4)	(Rouse et al., 1973)
GCVI			(Gitelson et al., 2003)
(Green Chlorophyll Vegetation Index)	(R _{NIR} / R _{GREEN}) – 1	(B8/B3) - 1	
MTCI	(R _{NIR} – R ₇₀₅) / (R ₇₀₅ – R _{RED})	(B8-B5) / (B5 – B4)	(Dash and Curran, 2004)
(MERIS Terrestrial Chlorophyll Index)			
NDVI705	(R _{NIR} – R ₇₀₅) / (R _{NIR} + R ₇₀₅)	(B8 – B5) / (B8 + B5)	(Viña and Gitelson, 2005)
(Red-Edge NDVI ₇₀₅)			
NDVI740	(D	(B8 – B6) / (B8 + B6)	(Viña and Gitelson, 2005)
(Red-Edge NDVI740)	$(\kappa_{NIR} - \kappa_{740}) / (\kappa_{NIR} + \kappa_{740})$		

Table 2. Spectral Vegetation indices (VIs) Used

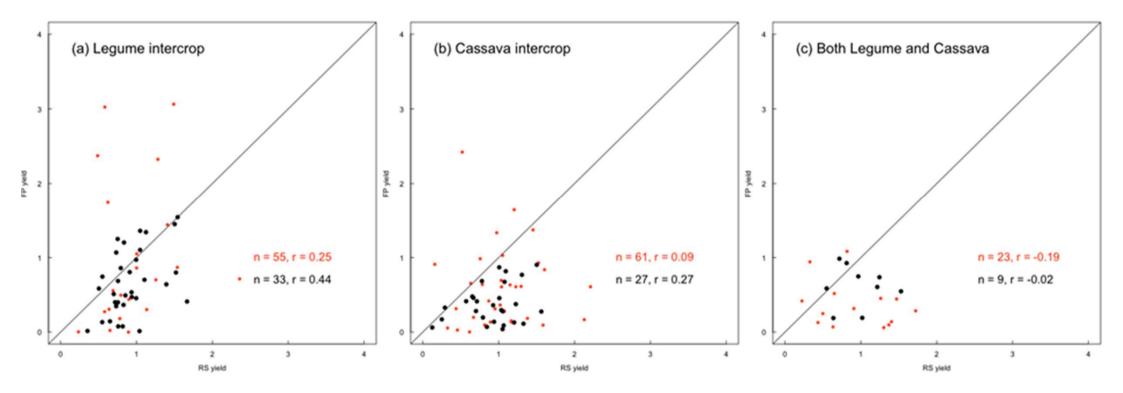


Remotely-Sensed vs. Ground-Based Yields on Purestand Plots





MAPS II Remote Sensing Performance on Intercropped Plots





Key Takeaways

On poverty...

- Tough to get R² above 0.5 when predicting welfare or poverty at large scale using integrated household survey and geospatial data applications
- Need to better understand strengths and weaknesses of different methods in different contexts
 - Feature-based approach by Engstrom et al. (2017) vs. Transfer learning approach by Jean et al. (2016) in Africa (Not reviewed here, uses LSMS-ISA data)
- Are satellite predictions better than census-based poverty maps? Not sure yet...

On agriculture...

- Promising performance of public-use, high-frequency 10m resolution imagery and remote sensing techniques in predicting maize yields at plot-level
- Importance of calibration using survey data



Some final thoughts

- Great potential for value addition of using data from space to inform policy research
- With increased availability of free/inexpensive spatial data, it will only get better!
- Household surveys remain indispensable source, including for validation
- Need to work on a global methodological research agenda to make value addition of integration more reliable and scalable
- Access to household-level geo-referenced data still problematic



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