Data for Better Lives

World Development Report 2021

DEC Policy Research Talk
Part 1 and 2, May 25th, 2021

Robert Cull
Dean Jolliffe
Malarvizhi Veerappan

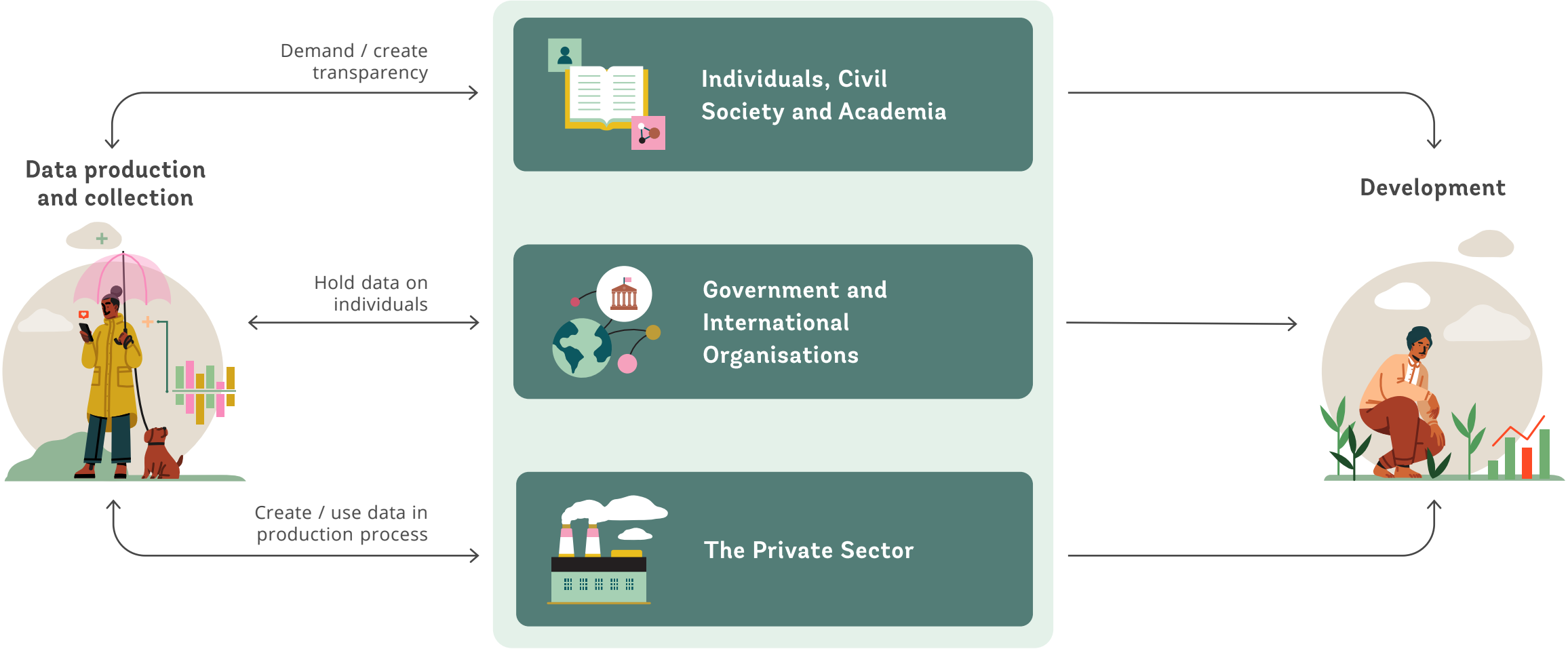
WORLD BANK GROUP

Not just another report on data

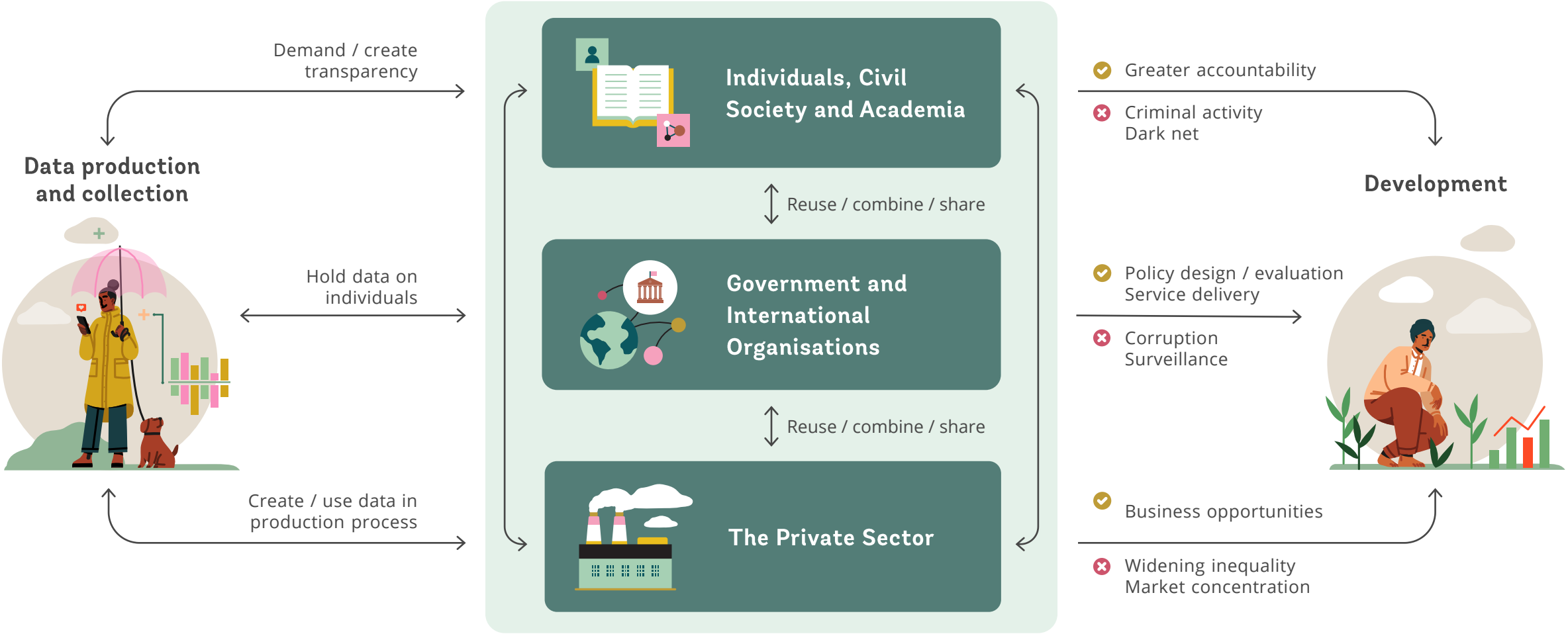
- A **poverty lens** on the value of data
- Prioritising poor people and poor countries

The Government of Madagascar provide 80,000 extreme poor households with regular cash transfers, such as here in Betafo
Photo credit: Mohammad Al-Arief / World Bank

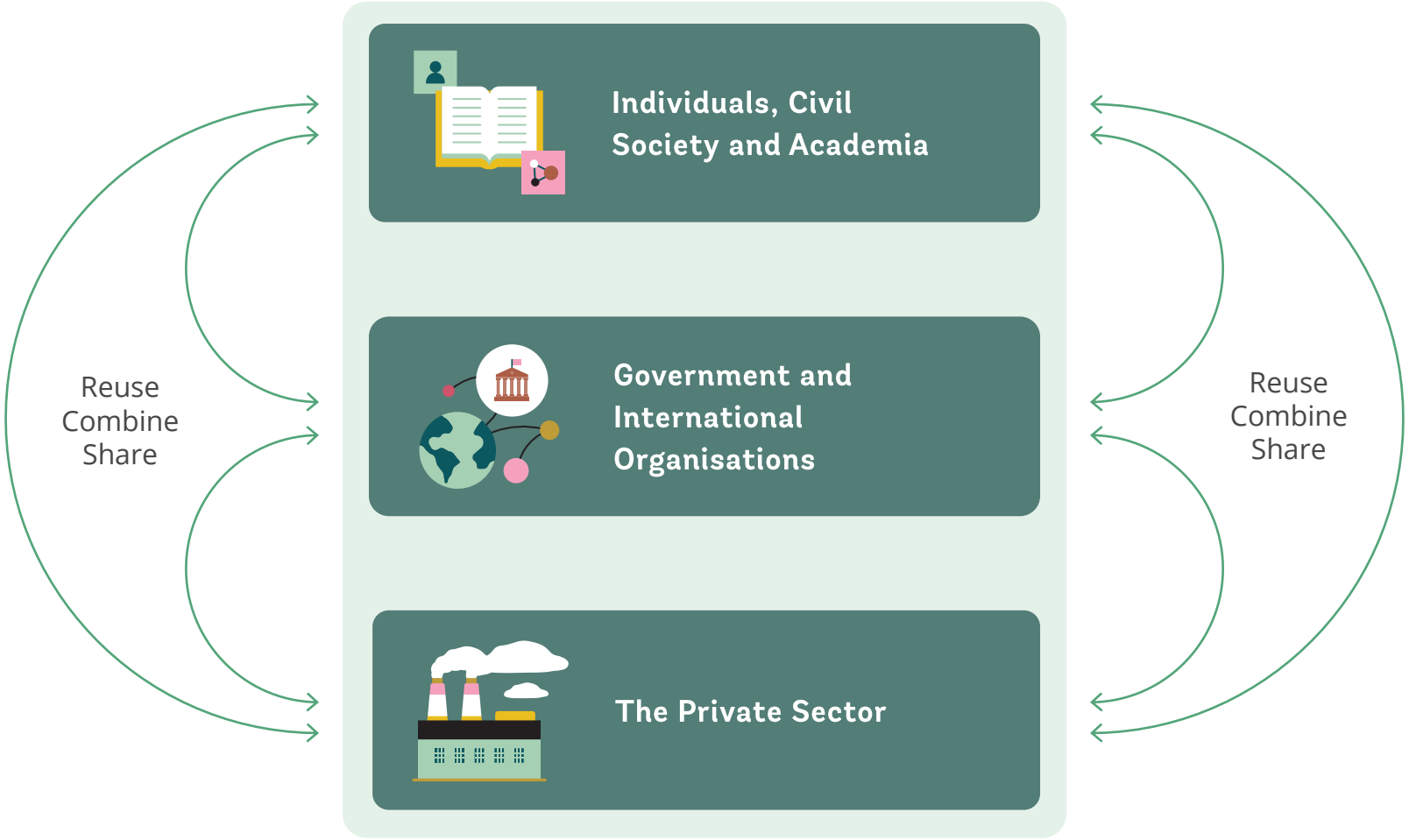
Data for development: 3 pathways



Data for development: 3 pathways



Unlocking potential by reusing data



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WORLD DEVELOPMENT REPORT 2021

Eyes in the Sky, Boots on the Ground

Integrating Surveys and Satellites to Improve **Crop Area** and **Yield** Measurement

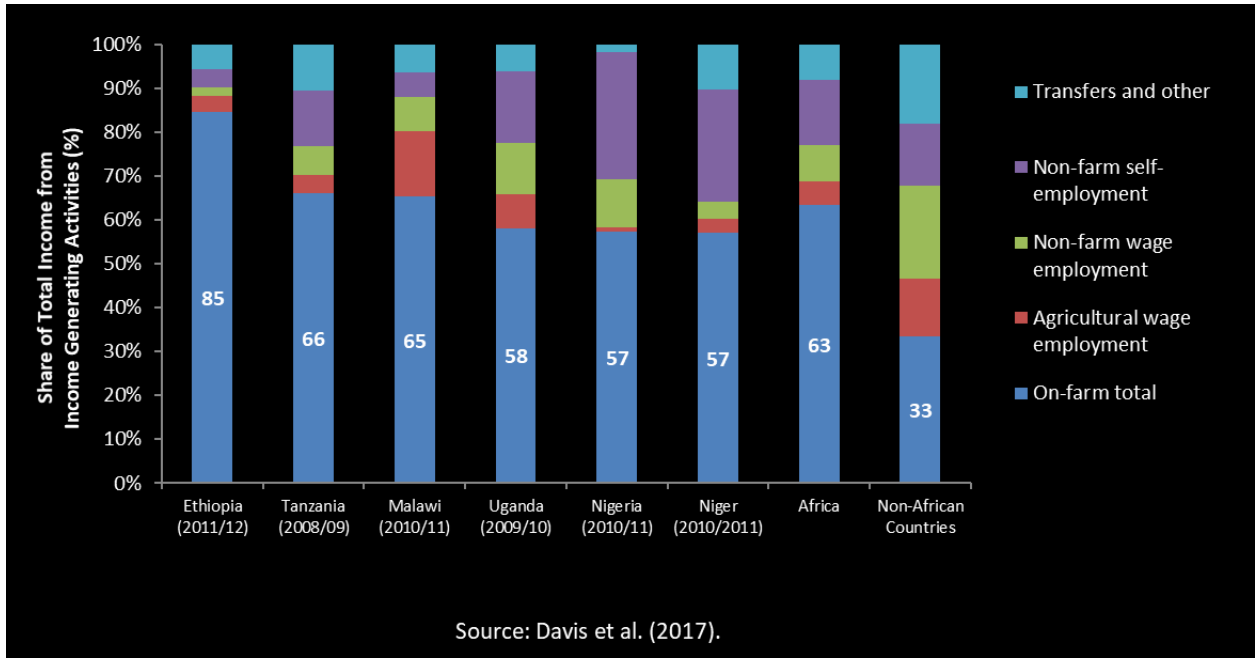
Talip Kilic

DEC Policy Research Talk

May 25, 2021

Background

- Role of agriculture in rural livelihoods (Byerlee et al. 2007, Davis, et al. 2017)

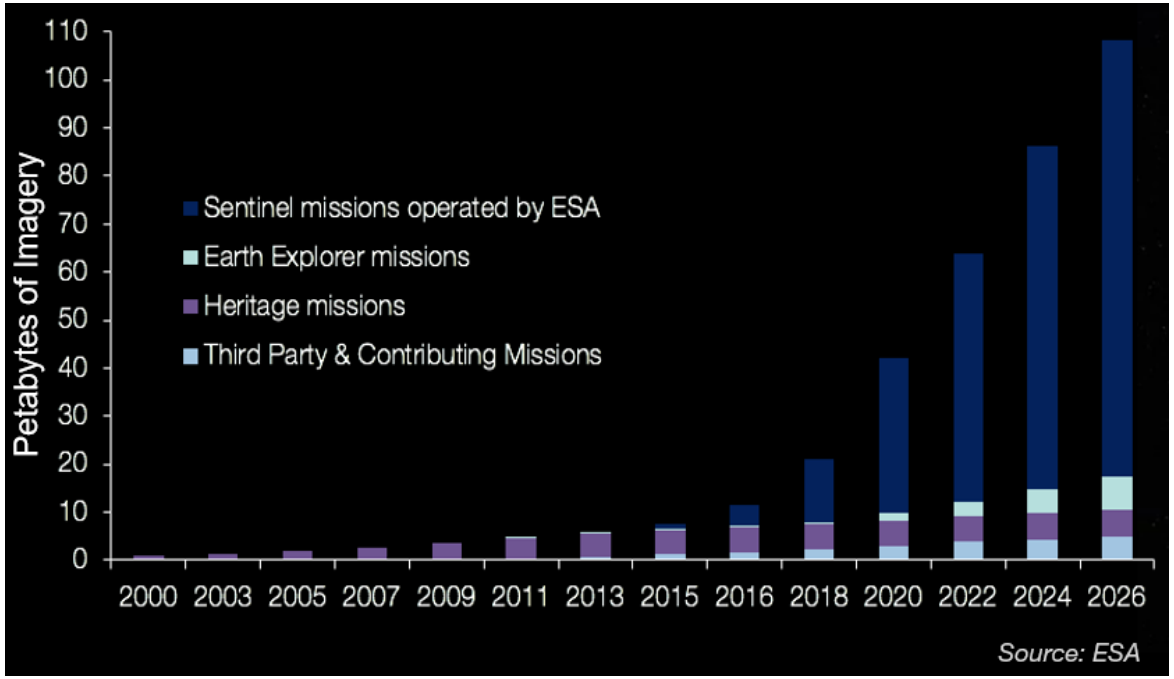


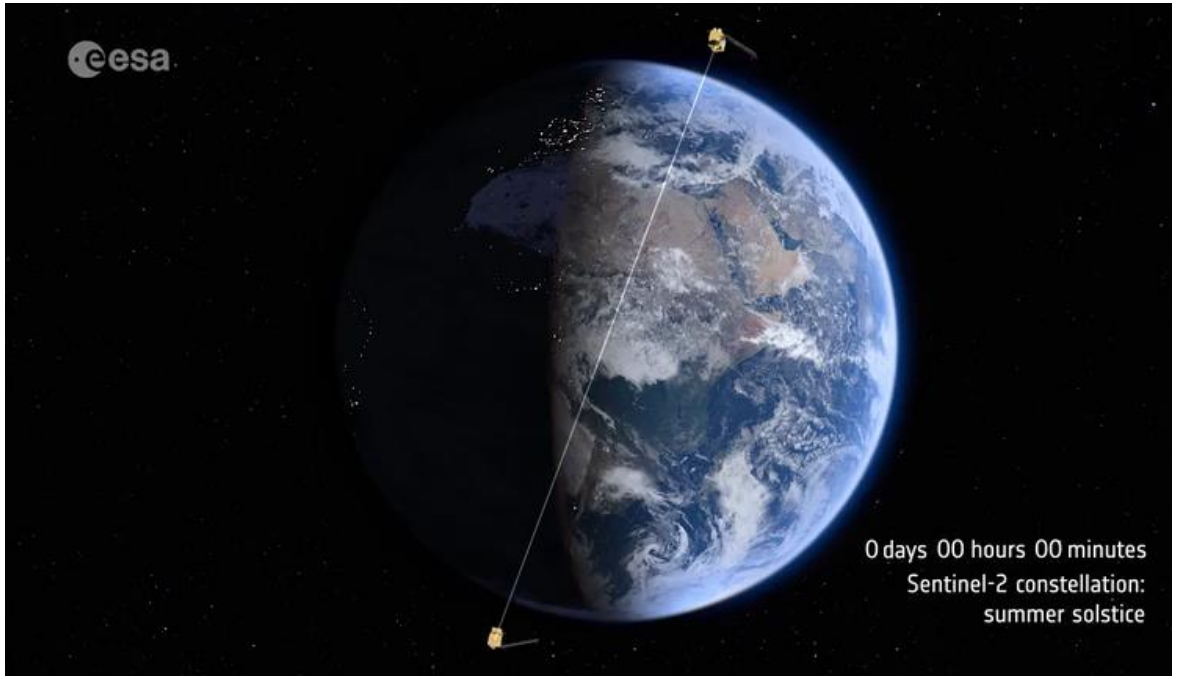
Source: Davis et al. (2017).

SDG Target 2.3.
"By 2030, double the agricultural productivity and the incomes of small-scale food producers…"

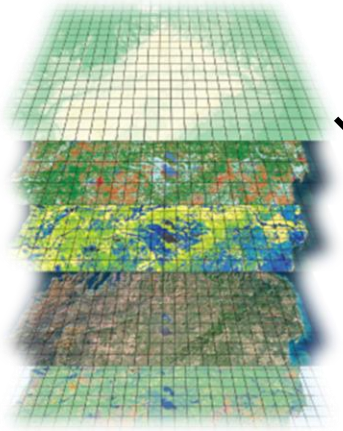
Background

- Role of agriculture in rural livelihoods (Byerlee et al. 2007, Davis, et al. 2017)
- Need for accurate, crop-specific measures of area under cultivation, production and yields – not only at the national-level but with enhanced within-country disaggregation
- Surge in availability of high-resolution satellite imagery



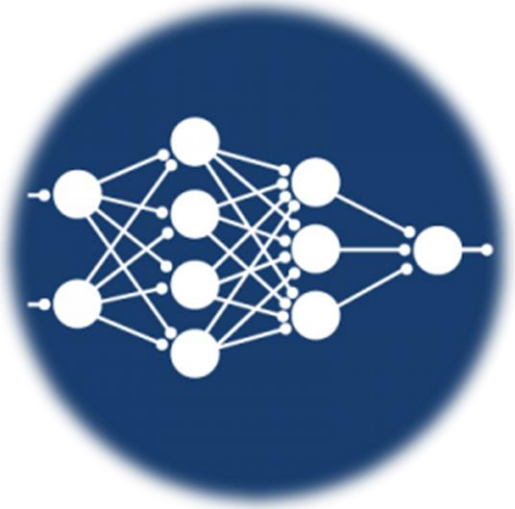


The idea

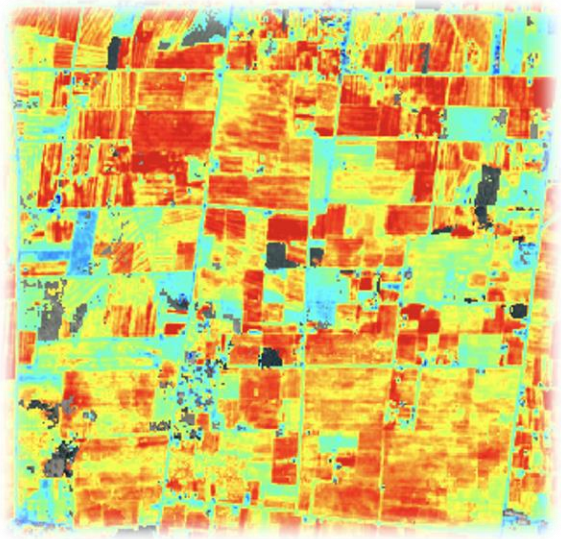


Satellite Data

Ground Truth Training Data



Machine Learning for Classification & Yield Estimation



High-Resolution Seasonal Crop ***Area*** *and* ***Yield*** *Mapping At-Scale*

Research on satellite-based methods for agricultural monitoring in smallholder systems

Training Data Source: Labelled Imagery

Remote Sensing of Environment 221 (2019) 551–568
Contents lists available at ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen2-Agri automated system in various cropping systems around the world

Pierre Defourny[a], Sophie Bontemps[a,*], Nicolas Bellemans[a], Cosmin Cara[b], Gérard Dedieu[c], Eric Guzzonato[d], Olivier Hagolle[c], Jordi Inglada[c], Laurentiu Nicola[b], Thierry Rabaute[d], Mickael Savinaud[d], Cosmin Udroiu[b], Silvia Valero[c], Agnès Bégué[e,f], Jean-François Dejoux[c], Abderrazak El Harti[g], Jamal Ezzahar[h,i], Nataliia Kussul[j], Kamal Labbassi[l], Valentine Lebourgeois[e,f], Zhang Miao[k], Terrence Newby[l], Adolph Nyamugama[l], Norakhan Salh[m], Andrii Shelestov[j], Vincent Simonneaux[e,n], Pierre Sibiry Traore[o], Souleymane S. Traore[p], Benjamin Koetz[q]

Nominal 30-m Cropland Extent Map of Continental Africa by Integrating Pixel-Based and Object-Based Algorithms Using Sentinel-2 and Landsat-8 Data on Google Earth Engine

by Jun Xiong [1,2,*], Prasad S. Thenkabail [1], James C. Tilton [3], Murali K. Gumma [4], Pardhasaradhi Teluguntla [1,2], Adam Oliphant [1], Russell G. Congalton [5], Kamini Yadav [5] and Noel Gorelick [6]

International Journal of Applied Earth Observation and Geoinformation
Volume 89, July 2020, 102087

Multiple factors influence the consistency of cropland datasets in Africa

Yanbing Wei [a], Miao Lu [a], Wenbin Wu [a], Yating Ru [b]

Training Data Source: Ground (Mostly Survey) Data

remote sensing
MDPI
Article

Mapping Smallholder Yield Heterogeneity at Multiple Scales in Eastern Africa

Zhenong Jin [1,*], George Azzari [1], Marshall Burke [1,2], Stephen Aston [3] and David B. Lobell [1]

Remote Sensing of Environment 228 (2019) 115–128
Contents lists available at ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

Smallholder maize area and yield mapping at national scales with Google Earth Engine

Zhenong Jin[a,1], George Azzari[a,1,2], Calum You[a], Stefania Di Tommaso[a], Stephen Aston[b], Marshall Burke[a], David B. Lobell[a,*]

PNAS

Satellite-based assessment of yield variation and its determinants in smallholder African systems

Marshall Burke[a,b,c,1,2] and David B. Lobell[a,b,1]
[a]Department of Earth System Science, Stanford University, Stanford CA 94305; [b]Center on Food Security and the Environment, Stanford University, Stanford, CA 94305; and [c]National Bureau of Economic Research, Cambridge, MA 02138

Edited by B. L. Turner, Arizona State University, Tempe, AZ, and approved January 12, 2017 (received for review October 12, 2016)

Remote Crop Mapping at Scale: Using Satellite Imagery and UAV-Acquired Data as Ground Truth

by Meghan Hegarty-Craver [1,*], Jason Polly [1], Margaret O'Neil [1], Noel Ujeneza [2], James Rineer [1], Robert H. Beach [1], Daniel Lapidus [1] and Dorota S. Temple [1]
[1] RTI International, Research Triangle Park, NC 27709, USA
[2] Independent Agri-Consultant, Kigali 20093, Rwanda
[*] Author to whom correspondence should be addressed.

Remote Sens. **2020**, *12*(12), 1984; https://doi.org/10.3390/rs12121984

Remote Sensing of Environment 216 (2018) 647–657
Contents lists available at ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

Estimating smallholder crops production at village level from Sentinel-2 time series in Mali's cotton belt

Marie-Julie Lambert[a,*], Pierre C. Sibiry Traoré[b,c], Xavier Blaes[a], Philippe Baret[a], Pierre Defourny[a]

Maize Cropping Systems Mapping Using RapidEye Observations in Agro-Ecological Landscapes in Kenya

by Kyalo Richard [1], Elfatih M. Abdel-Rahman [1,2], Sevgan Subramanian [1], Johnson O. Nyasani [1,3], Michael Thiel [4], Hosein Jozani [4], Christian Borgemeister [5] and Tobias Landmann [1,*]

American Journal of Agricultural Economics
Issues JEL Advance articles About

Article Contents
Abstract
Data
Results

Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis

David B Lobell, George Azzari, Marshall Burke, Sydney Gourlay, Zhenong Jin, Talip Kilic, Siobhan Murray Author Notes

remote sensing
MDPI
Article

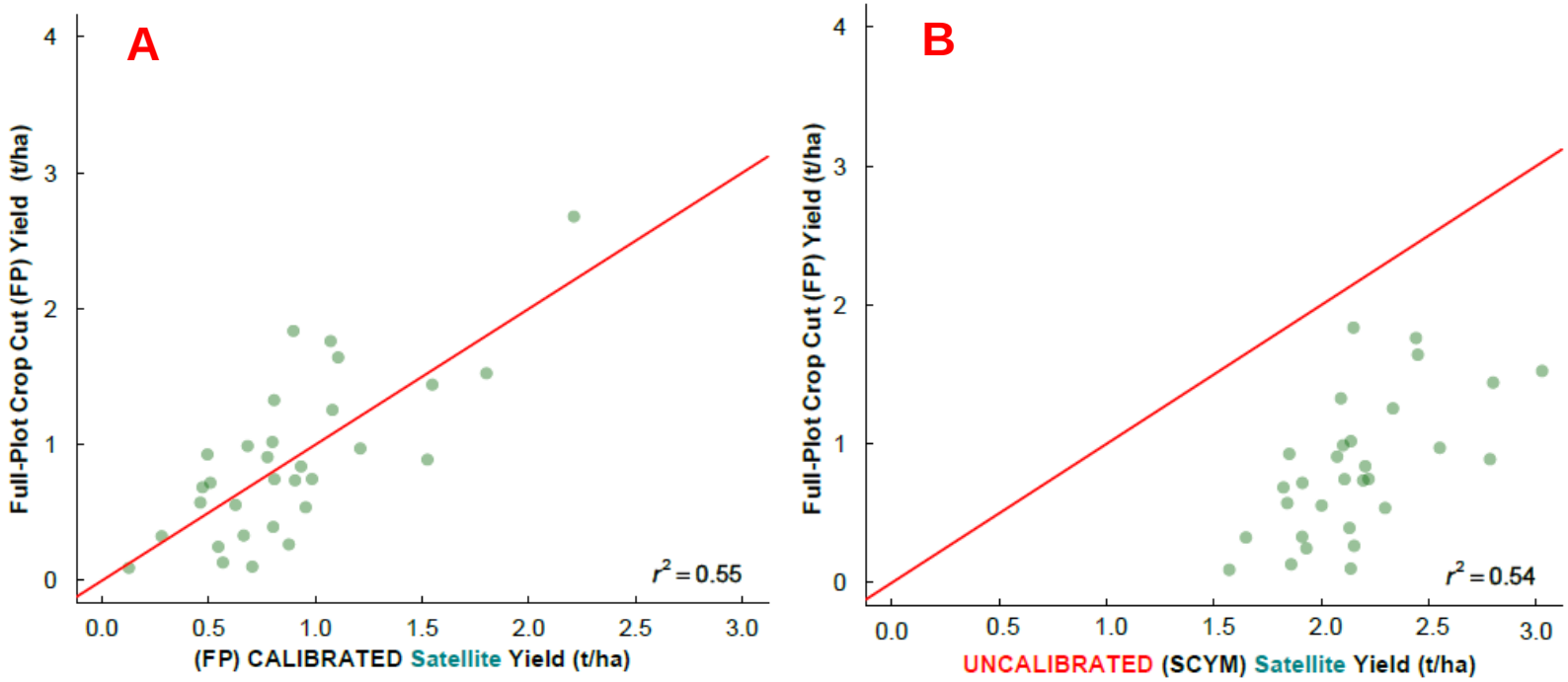
Sight for Sorghums: Comparisons of Satellite- and Ground-Based Sorghum Yield Estimates in Mali

David B. Lobell [1,*], Stefania Di Tommaso [1], Calum You [1], Ismael Yacoubou Djima [2], Marshall Burke [1] and Talip Kilic [2]

Important takeaways from existing research

- Training data does have a bearing on the quality and spatial resolution of satellite-based estimates

Uganda Plot-Level **Ground (Crop Cutting, Survey-Based)** versus **Satellite-Based Maize Yields**
Source: Lobell et al. (2019). "Eyes in the Sky, Boots on the Ground", *AJAE*



Key takeaways from existing research

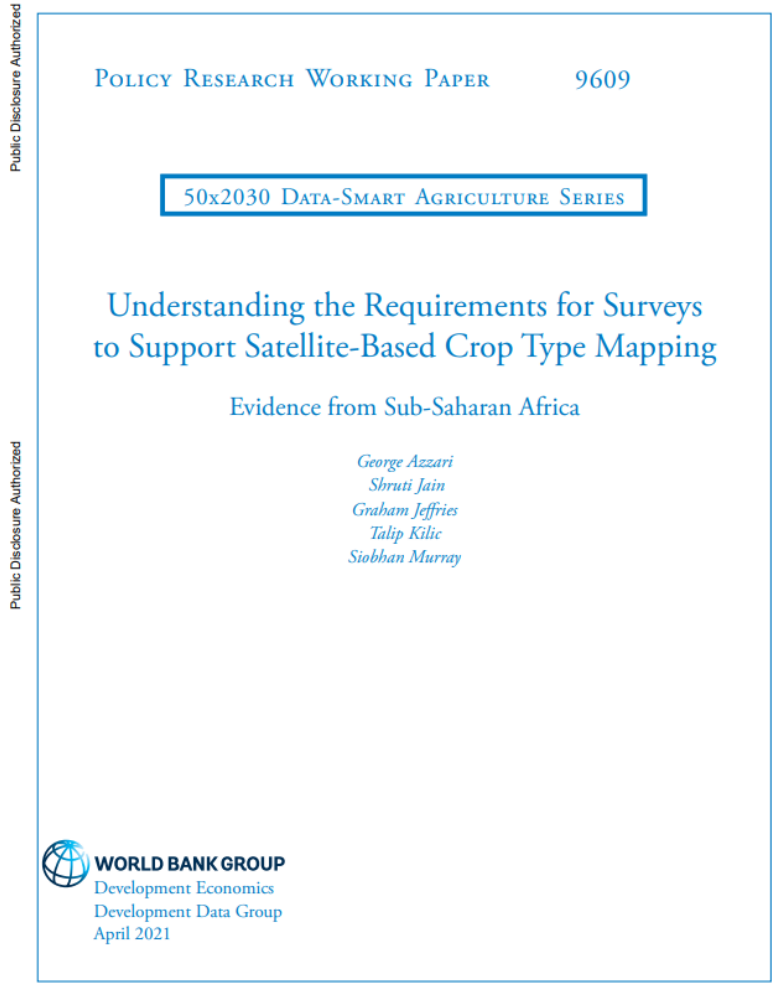
- Training data does have a bearing on the quality and spatial resolution of satellite-based estimates
- Existing research has largely been at sub-national levels, with heterogeneity in the type of and approach to training data collection as part of surveys
- Large-scale surveys *can* address training data needs of earth observation applications on crop area mapping and crop yield estimation in lower-income countries, but…
    - There are no clear recommendations on survey methods and fieldwork protocols that should be adopted to generate the right training data

On-going research to address knowledge gaps

- 50x2030: Data-Smart Agriculture Initiative is supporting research for the development of guidelines for large-scale survey data collection in low- and lower-middle income countries as to meet training data needs of high-resolution satellite-based estimation of **crop areas** and **crop yields**
  - Anchored in peer-reviewed research conducted over the period 2019-2022
  - Focus countries : Cambodia, Ethiopia, Malawi, Mali, and Uganda
  - Focus crops: Maize, wheat, sorghum, millet, barley, and rice
  - Important for assessing the utility of existing georeferenced survey data for earth observation research and for informing the design of future household and farm surveys

On-going research to address knowledge gaps

- Recent work by Azzari et al. 2021 aimed to answer several operational research questions in the context of satellite-based maize area mapping across Malawi and Ethiopia
  - How much training data do we need to reach an acceptable level of accuracy of a crop classification algorithm?
  - How does the approach to georeferencing plot locations in surveys impact algorithmic accuracy?
  - How do the type of satellite data and exclusion of plots under specific area thresholds affect algorithmic accuracy?


Public Disclosure Authorized

Public Disclosure Authorized

POLICY RESEARCH WORKING PAPER 9609

50x2030 DATA-SMART AGRICULTURE SERIES

Understanding the Requirements for Surveys to Support Satellite-Based Crop Type Mapping

Evidence from Sub-Saharan Africa

George Azzari
Shruti Jain
Graham Jeffries
Talip Kilic
Siobhan Murray

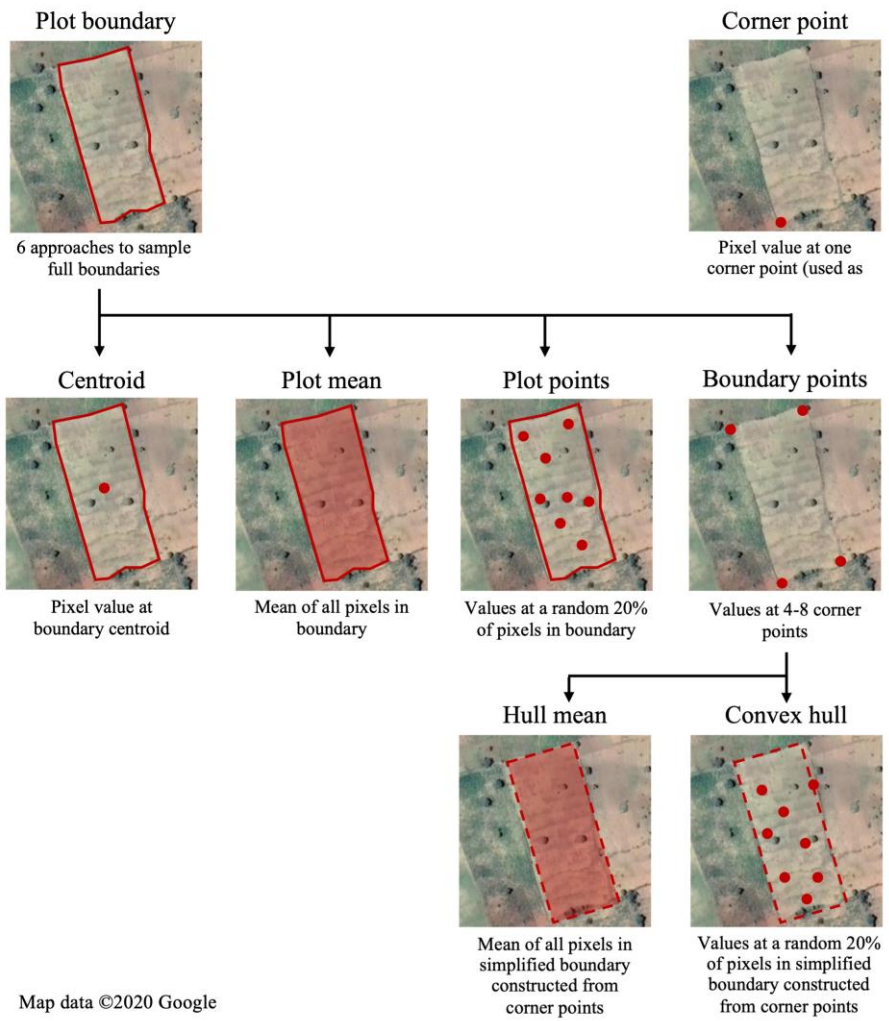
WORLD BANK GROUP
Development Economics
Development Data Group
April 2021

Survey data

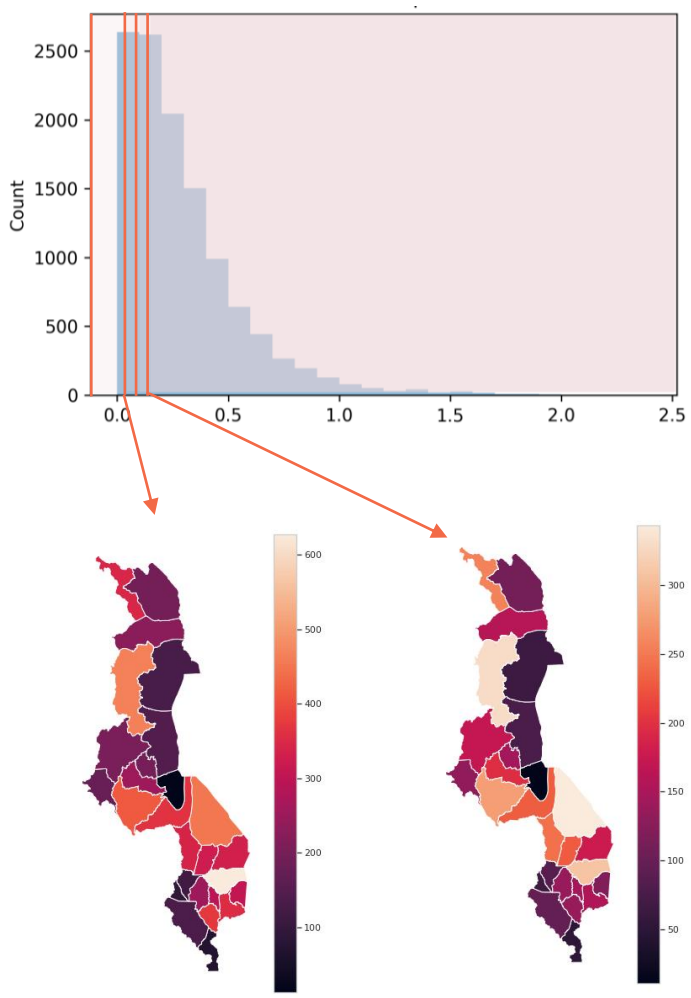
- We use georeferenced plot-level survey data nationally-representative, multi-topic surveys that were implemented by the Malawi NSO and the CSA of Ethiopia under the World Bank LSMS-ISA Initiative
  - Malawi Integrated Household Panel Survey (IHPS) 2019
    - Longitudinal sample, dating back to 2010
    - Reference season: 2018/19
    - Plot-level georeferenced information: Single plot corner point + plot boundaries
  - Malawi Fifth Integrated Household Survey (IHS5) 2019/20
    - Cross-sectional sample
    - Reference season: 2017/18 or 2018/19
    - Plot-level georeferenced information: Single plot corner point + plot boundaries
  - Ethiopia Socioeconomic Survey (ESS) 2018/19
    - Baseline for a new longitudinal sample
    - Reference season: 2018 *meher* season
    - Plot-level georeferenced information: Single plot corner point

Data collection scenarios

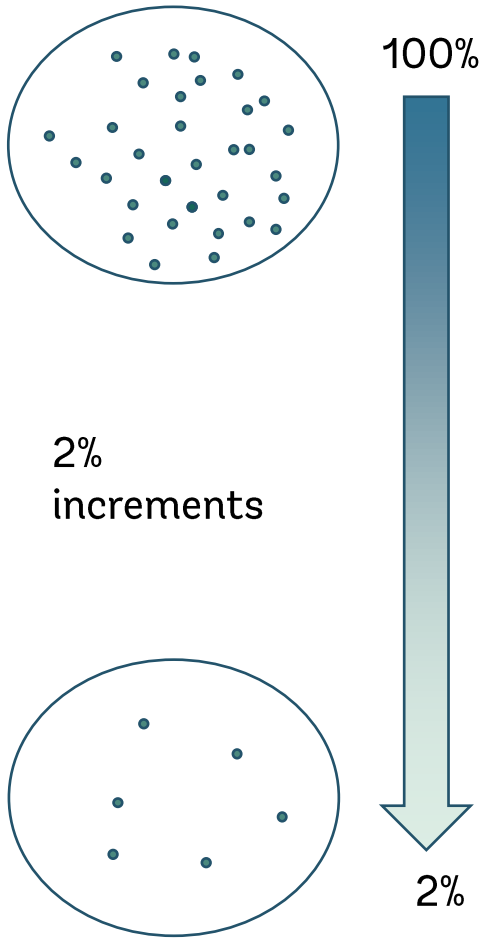
Geolocation



Field Size



Data Pool Size



Data collection scenarios and modeling

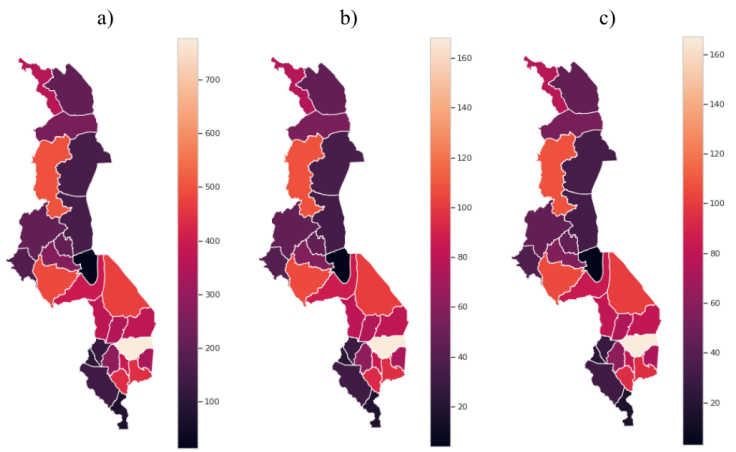
In **Malawi**, we tested a total of **26,250 scenarios:**

- **7 geolocation methods** - boundary points, centroid, convex hull, corner, hull mean, plot points, and plot mean.
- **50 data subsets** - 2% to 100% subsets of training data, at an increment of 2% points.
- **5 area thresholds** - 0, 0.05, 0.1, 0.15, and 0.2 ha.
- **3 feature types** - optical only, radar only, both optical and radar.
- **5 replications** to capture variability due to random sampling

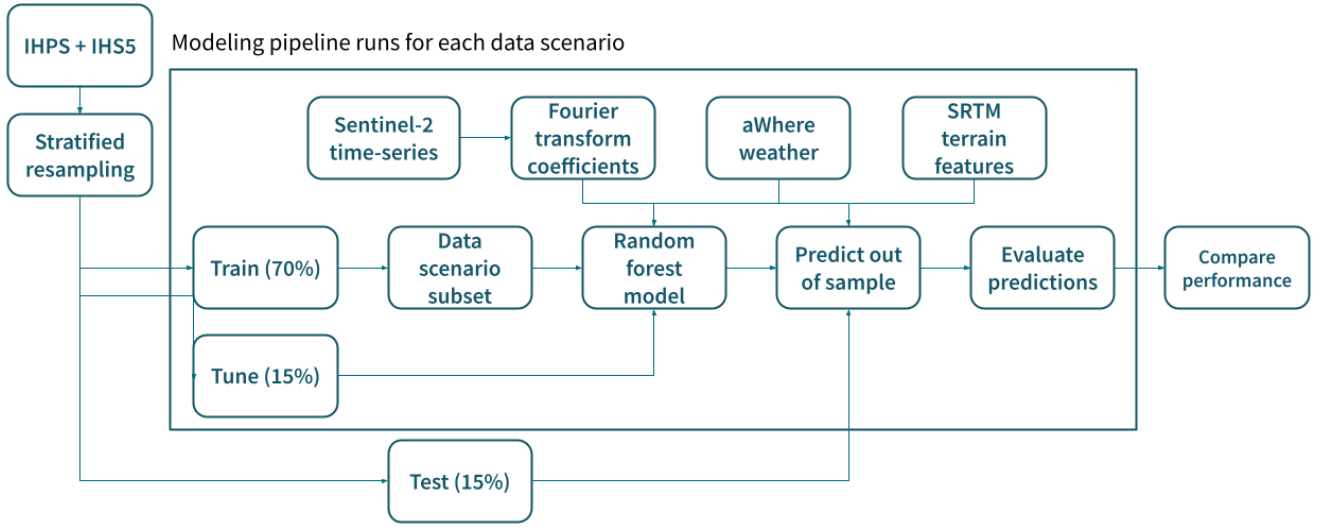
In **Ethiopia**, we tested a total of 250 scenarios – based on findings from Malawi and availability of only corner points:

- **1 geolocation method** – corner point
- **50 data subsets** - 2% to 100% subsets of training data, at an increment of 2% points.
- **No area threshold**, with optical data only
- **5 replications** to capture variability due to random sampling

Figure 4: Distribution of plots across districts in a) train, b) validation, c) and test subsets

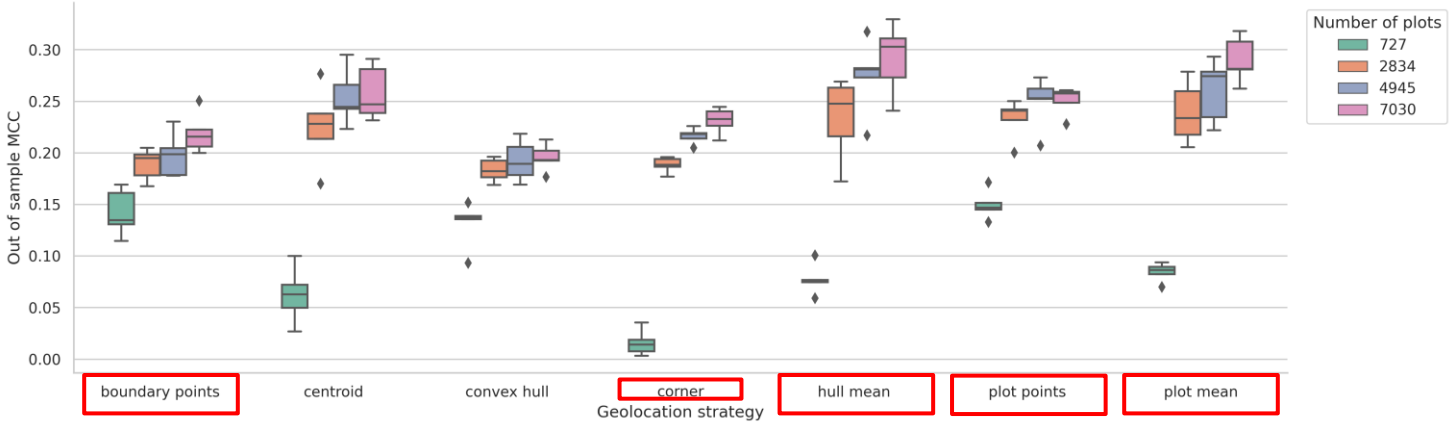


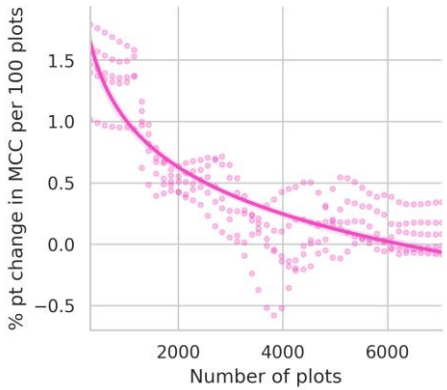
Notes: Color indicates number of plots.

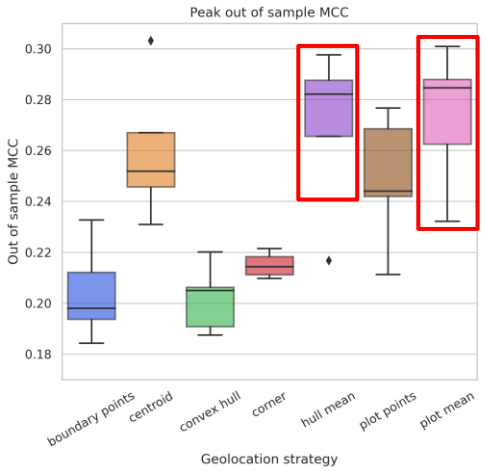


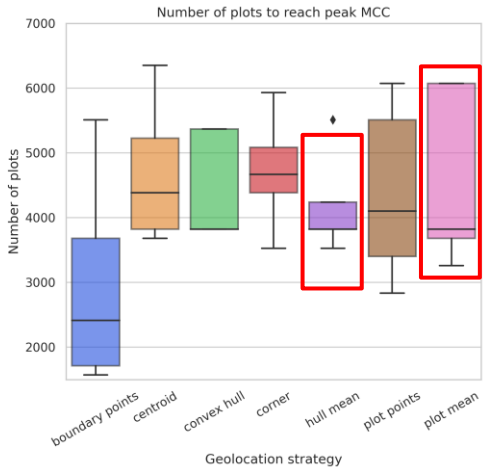
Headline findings

- < 1,000 plots: multi-point approaches perform better
- 2,000+ plots: aggregation approaches - plot mean (based on plot boundary) & hull mean (based on all corner points) - outperform all
- Need ~7,000 plots with a single corner point to reach performance with ~3,000 plots under aggregation approaches
- Aggregation approaches had the fastest learning
- Peak performance can be achieved with ~ 60% of training data (~4,000 plots) under plot mean **(preferred)** and hull mean **(second best).**
- Centroid method outperforms the single corner point method. If only a single georeferenced point can be collected, it should be near the center of the plot **(third-best).**









Small differences, large consequences

- Small differences in model performance may lead to large differences in estimated areas.
- Aggregated methods yielded most conservative estimates.
- Multi-points methods tended to "overclassify" the most.
- There is value in achieving small performance gains with better training data.

Malawi Total Maize Area Estimates, by Classification Model

Classification model	Out of sample MCC	Total maize area - 2018/19 rainy season (million ha)
Boundary points	0.21	2.27
Centroid	0.24	2.17
Convex hull	0.21	2.46
Corner	0.23	2.15
Hull mean	0.25	1.94
Plot points	0.24	2.41
Plot mean	0.26	1.99
Mean across models	0.23	2.19

Classification model	Difference in out of sample MCC	Total area with disagreement (million ha)
Boundary points	-0.05	0.84
Centroid	-0.02	0.48
Convex hull	-0.05	0.69
Corner	-0.03	0.95
Hull mean	-0.01	0.22
Plot points	-0.02	0.55

Key takeaways

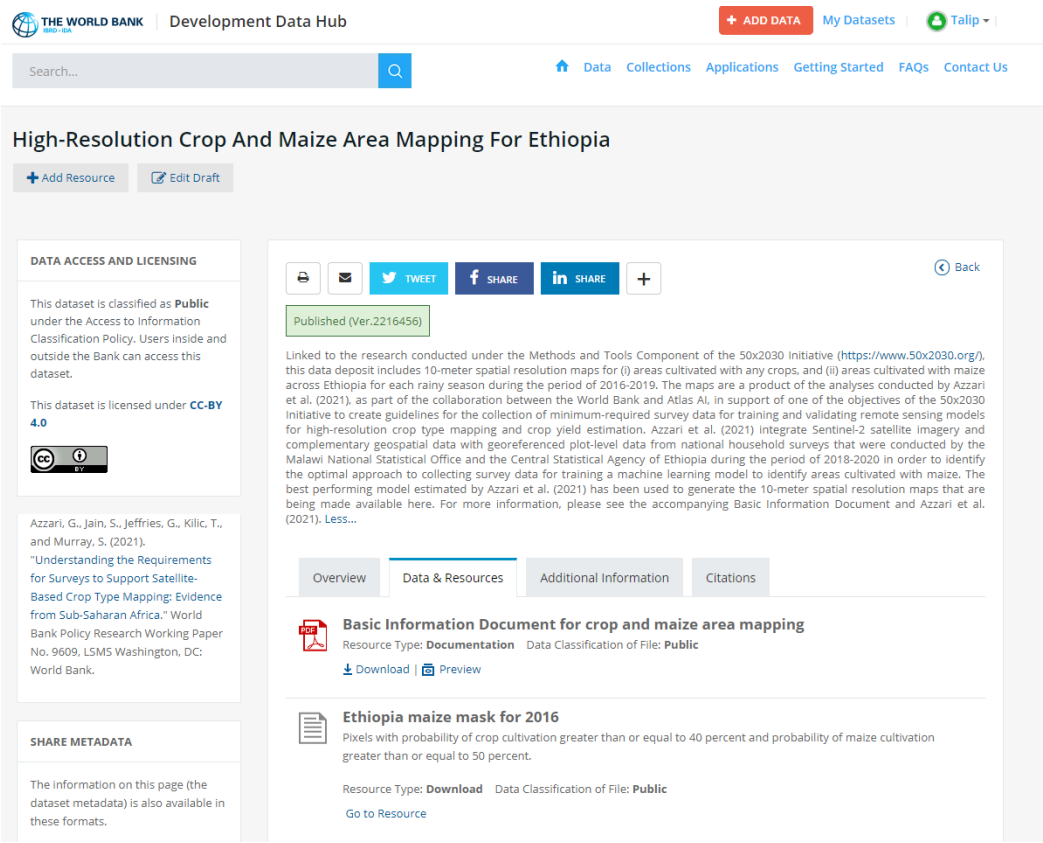
- Collecting a **complete plot boundary** is preferable to competing approaches to georeferencing plot locations in large-scale household surveys.
- Seemingly-small erosion in maize classification accuracy under less preferable approaches to georeferencing plot locations **consistently results in total area under maize cultivation to be overestimated** - in the range of **0.16 to 0.47 million hectares** (8 to 24 percent)
- Collecting **GPS coordinates of the complete set of plot corners is a second-best strategy**, can approximate full plot boundaries and can in turn train models with comparable performance
- **Classification performance peaks with ~60% of the training data** under preferred and second-best approaches to georeferencing plot locations
- If only a single GPS point can be collected, it should be near the plot center rather than at the plot corner. With large datasets, performance could be comparable to that of complete plot boundaries.
- No plot observations should be excluded from model training based on a minimum plot area threshold
- Optical features alone can provide sufficient signal to maximize prediction quality

Looking forward

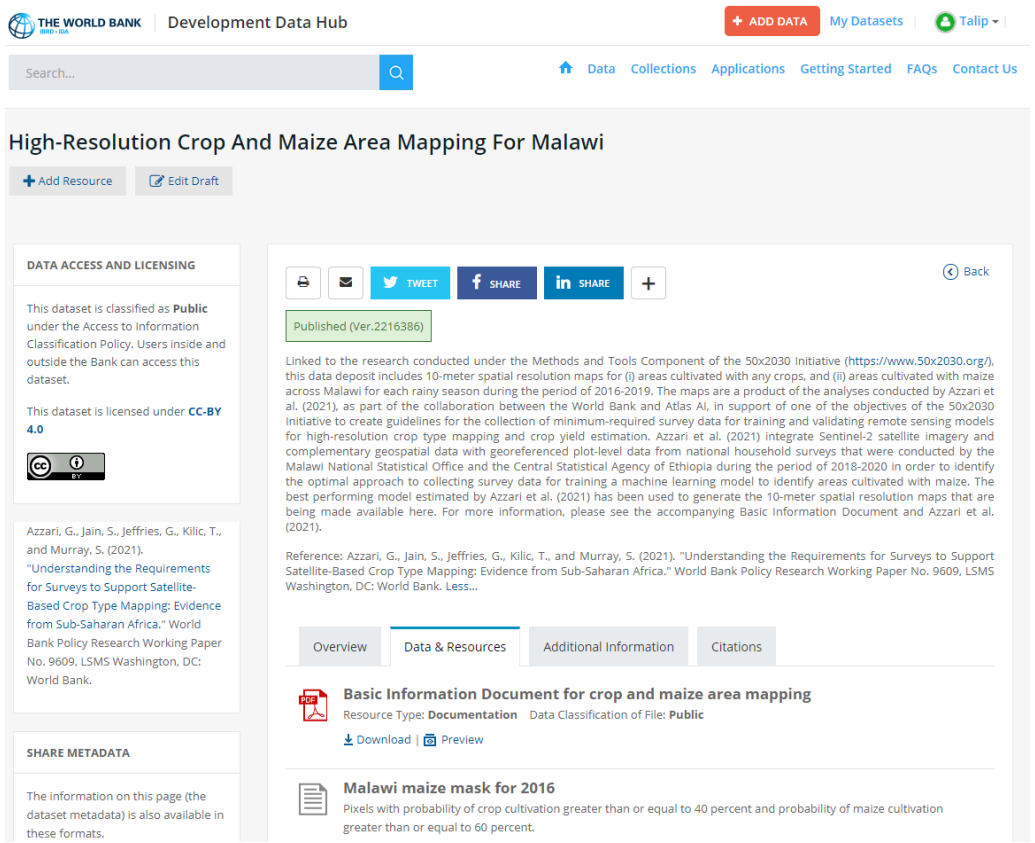
- Continuing 50x2030-supported research to formulate the guidelines for large-scale surveys to fulfill training data needs of satellite-based crop area mapping and yield estimation in smallholder farming systems
  - Leverage additional existing large-scale survey data from Mali, Malawi and Uganda – with georeferenced plot outlines and objectives measures of yields based on crop cutting – to:
    - Expand crop classification to new countries & new cereals: barley, millet, rice, sorghum & wheat
    - Identify training data requirements for high-resolution yield estimation for maize & new cereals
  - Gauge sensitivity of recommendations to the choice of model (e.g., RF vs. CNN) & geospatial covariates
  - Document accuracy of out-of-season predictions & inter-temporal decay in model accuracy
  - Conduct research on object-based classification and automated detection of plot boundaries
  - Depending on the COVID-19 pandemic, conduct additional survey experiments in 2022 in non-African settings

Open access data assets

10-m resolution crop area and maize area maps for Malawi and Ethiopia for each agricultural season from 2016 to 2019 on **World Bank Development Data Hub**



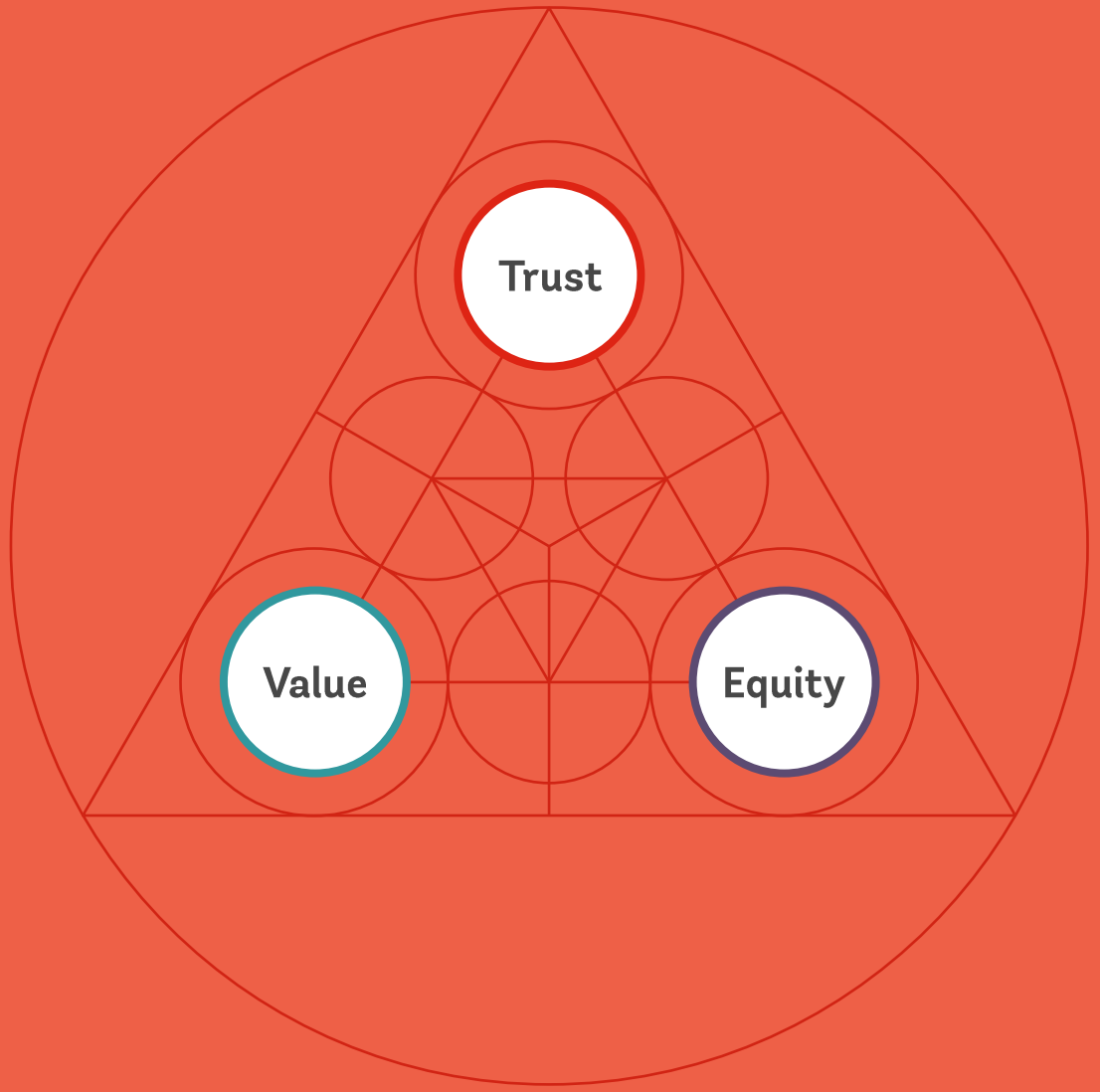
http://bit.ly/ethiopiamaps



http://bit.ly/malawimaps

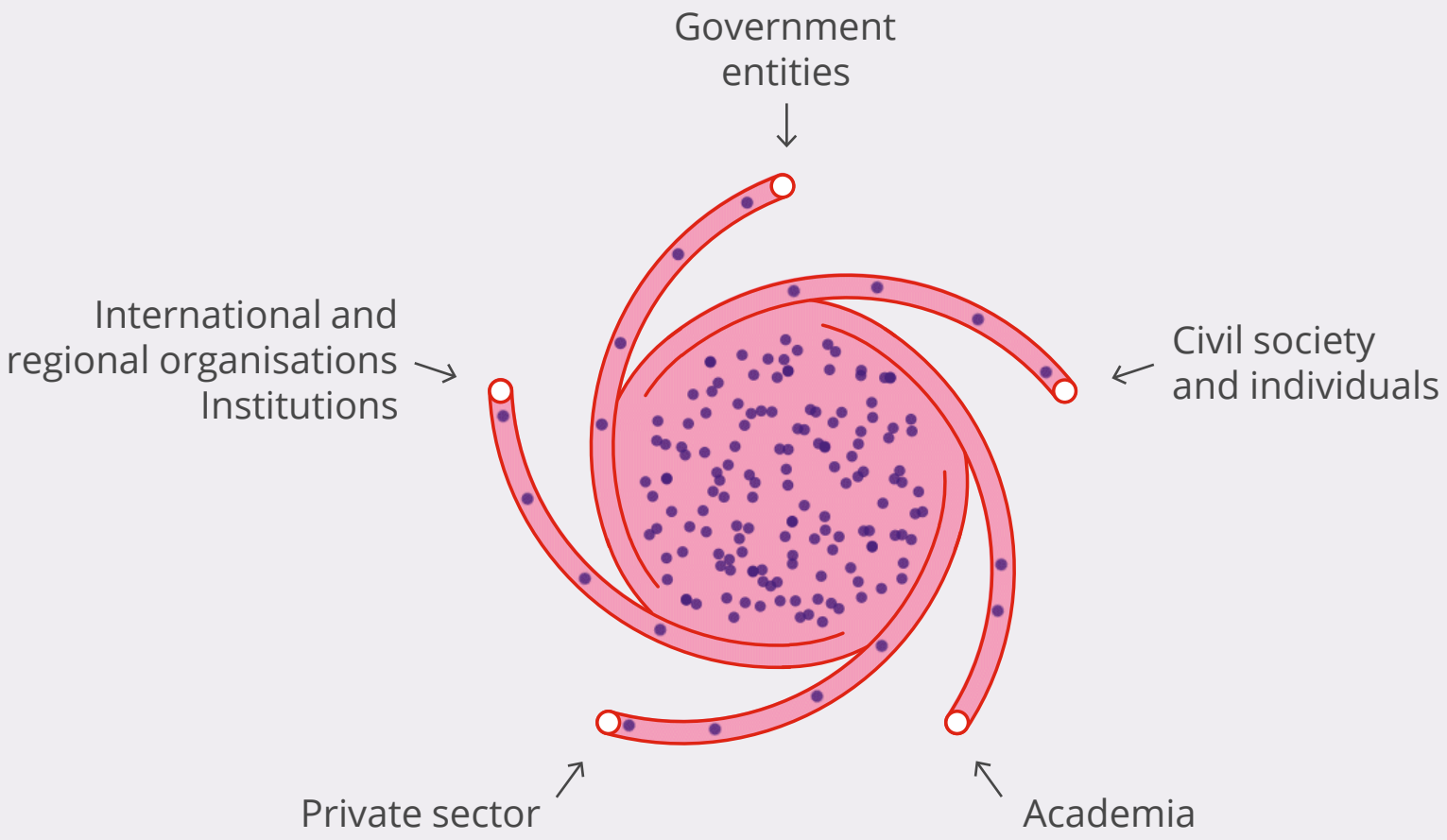
The social contract for data

The three elements of a social contract for data: Value, Equity and Trust

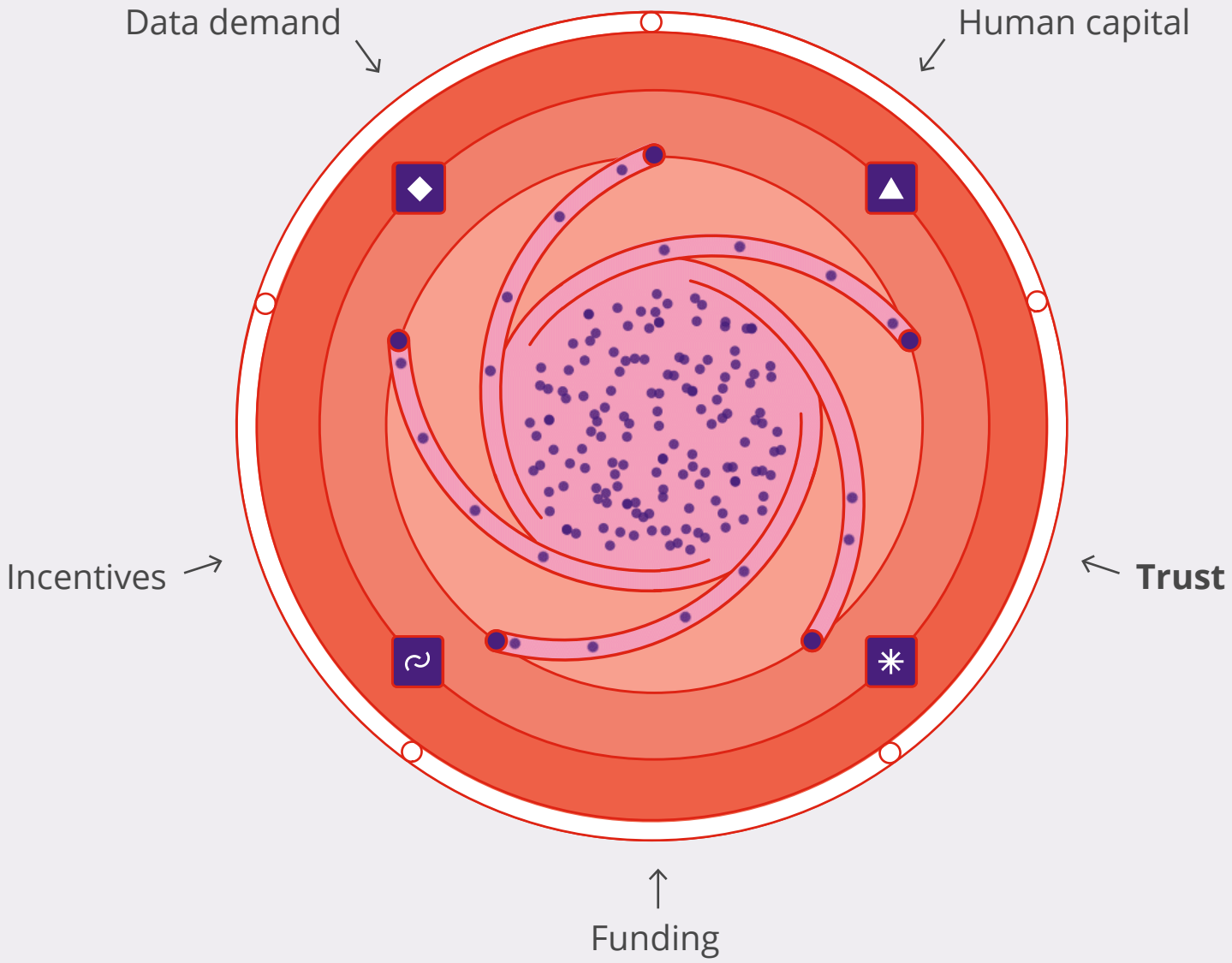


Working towards an integrated national data system (INDS)

Participants in the INDS create and share data



Five foundations sustain the INDS



Trust

1. Trust that the information created from data is credible.

   => test new methods and data (data quality)

   => monitor data systems (e.g. transparency, access, SPI)

2. Pillars (Infrastructure, Policies, Institutions, Governance)

   => participants need to trust that they won't be harmed from sharing data and that they will share in some of the benefits

3. INDS

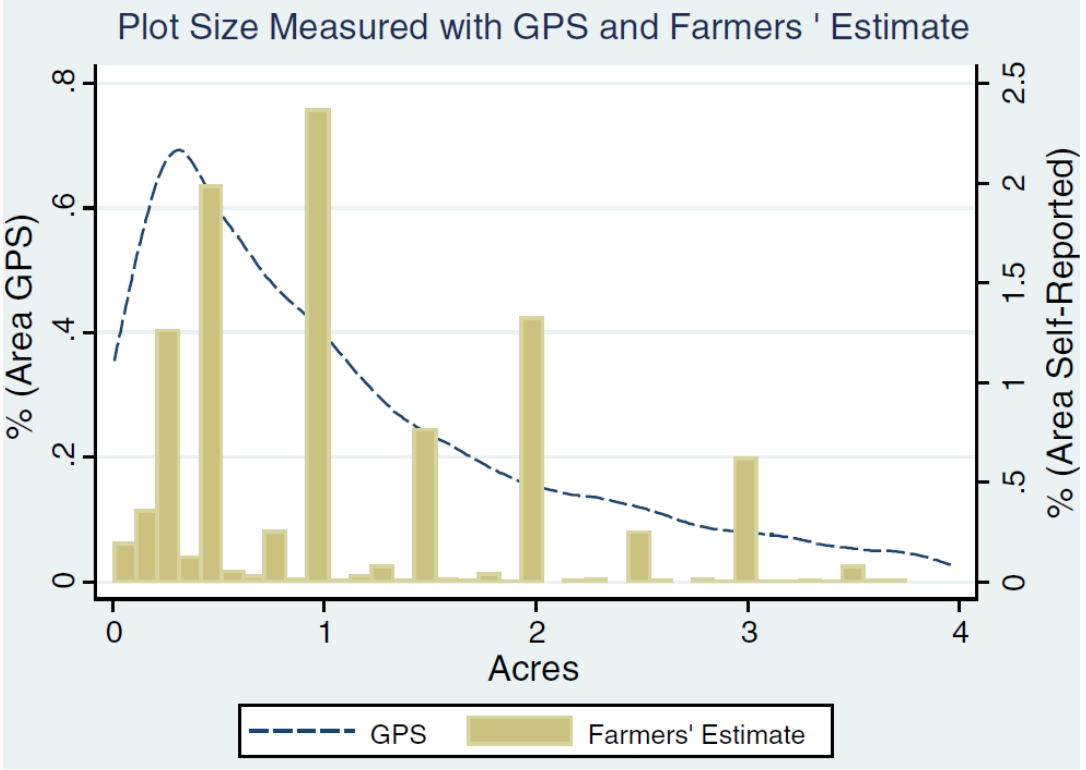
   => steps to create trust

Data experiment example, Plot Size

Within-subject design: Two measures of plot size. Malawi, Uganda, Tanzania, Niger.
(Self-report – GPS) / (GPS)

ha <0.5	Error 103%
0.5-1	23%
1-2	6%
2-5	-1%
>5	-33%
Tot	*-0.04%*

Uganda: GPS (density) & Self reports (histogram)

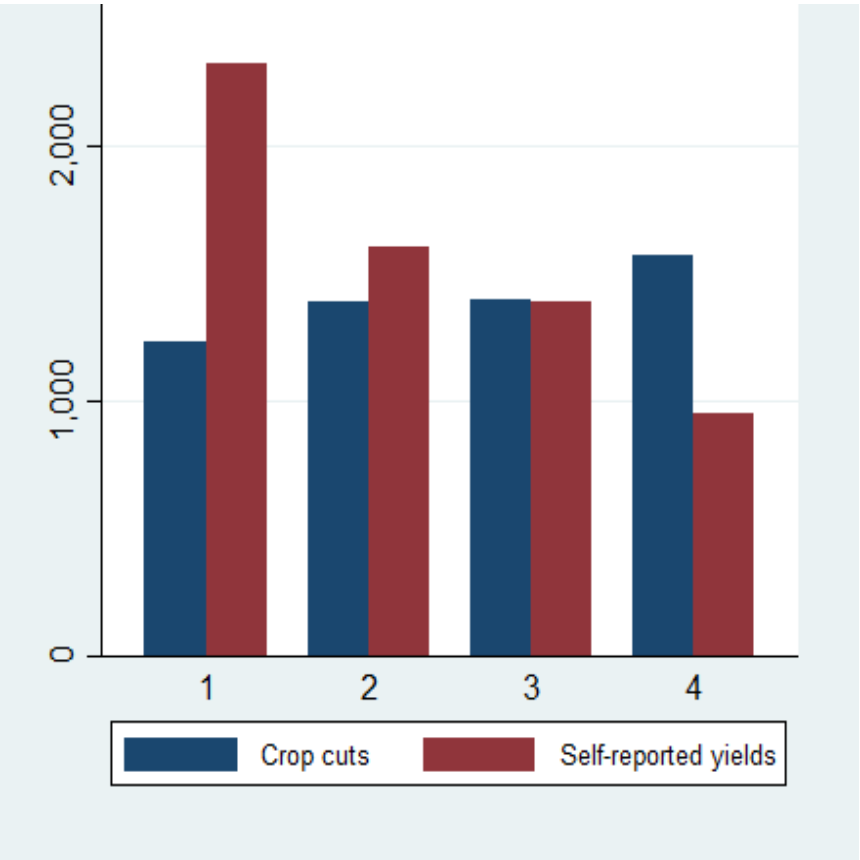


Carletto, Calogero, Sara Savastano, and Alberto Zezza. 2013. “Fact or Artifact: The Impact of Measurement Errors on the Farm Size–Productivity Relationship.” Journal of Development Economics 103 (July): 254–61.

Data experiment example, Crop Yields

- Ethiopia Socioeconomic Survey
- Within-subject design: Two independent measures of crop yields for the same plot (n= 5,000).
- External validity: Nationally representative, two points in time, 23 crops.
- Plot size measured with GPS (denominator)
- 5248 plots with both **crop cuts and self-reported production**

Median maize yields (kg/ha) by plot size



Desiere, Sam, and Dean Jolliffe. 2018. "Land Productivity and Plot Size: Is Measurement Error Driving the Inverse Relationship?" *Journal of Development Economics* 130 (January): 84–98.

WDR2021 Data and analysis – wdr2021.worldbank.org

Data and analysis

Download and explore the data behind the WDR 2021.

Statistical Performance Indicators (SPI)
The indicators measure statistical performance across 174 countries. They are grouped into five dimensions, which capture whether foundations such as financing, skills, and governance needed for a strong statistical system are in place. Under each dimension is a set of indicators to measure performance providing a time series extending at least from 2016 to 2019 in all cases, with some indicators going back to 2004.

Global Data Regulation Survey
The Global Data Regulation diagnostic is a comprehensive assessment of laws and regulations on data governance. It covers both the enabler and safeguard regulatory practices in 80 countries. The questionnaire comprises 37 questions designed to determine if a country has adopted good regulatory practice on data governance.

Data Governance Indicators
The DGI dataset is a subset of the Digital Government/GovTech Systems and Services (DGSS) dataset. The indicators are categorized based on WDR2021 report's four pillars of data governance framework (infrastructure, laws & regulations, policies, and institutions). They aim to inform a maturity model (MM) approach to data governance and contain both qualitative and quantitative metrics to monitor the state of the data governance practices within the public sector.

The World Development Report 2021 (WDR2021) Dataset Collection
This data catalog collection provides access to all available source data and R/STATA replication files (for specific figures) necessary to create the figures and maps that appear in the report.

Background research

The World Bank working papers on WDR 2021 topics.

Measuring the Statistical Performance of Countries: An Overview of Updates to the World Bank Statistical Capacity Index
Hai-Anh Dang, Mustafa Dinc, Juderica Diaz, Hiroko Maeda, John Pullinger, Umar Serajuddin, Brian Stacy, and Dereje Wolde.
National statistical systems are facing significant challenges. These challenges arise from increasing demands for high quality and trustworthy data to guide decision making, coupled with the rapidly changing landscape of the data revolution. To emphasize the urgent need for transformation and to help create a mechanism for learning amongst national statistical systems, the World Bank has developed new Statistical Performance Indicators (SPI) to monitor the statistical performance of countries.

Policy Choices Can Help Keep 4G and 5G Universal Broadband Affordable
Edward J Oughton, Niccolo Comini, Vivien Foster, and Jim W. Hall.
The United Nations Broadband Commission has committed the international community to accelerate universal broadband, but the costs of meeting these objectives in the context of rapid technological change are not well understood. This paper compares the global cost-effectiveness of different infrastructure strategies for the developing world to achieve universal 4G or 5G mobile broadband.

Change in global data landscape requires new measurement and benchmarking tools

Statistical Performance Indicators

Forward looking

Measures less advanced systems, and more advanced systems

Open Data + Open Code

Gives countries incentives to build modern data and statistical systems

5 pillars, 22 dimensions and 51 indicators

Pillars	Dimensions				
Data Use (User Types)	Legislature	Executive	Civil Society	Academia	International Bodies
Data Services (Service Types)	Quality of Data Releases	Richness and Openness of Online Access	Effectiveness of Advisory and Analytical Services Related to Statistics	Availability and Use of Data Access Services	
Data Products (Topics)	Social	Economic	Environmental	Institutional	
Data Sources	Statistical Office (Censuses and Surveys)	Administrative Data	Geospatial Data	Private Sector Data/ Citizen Generated Data	
Data Infrastructure	Legislation and Governance	Standards and Methods	Skills	Partnership	Finance (Domestically and from Donors

Uses Indicators from various sources

Publicly available data + Open code

Partners

International Monetary Fund

FAO FIAT PANIS

WORLD BANK GROUP

OPEN DATA WATCH

ILO

Foreign, Commonwealth & Development Office

PARiS21

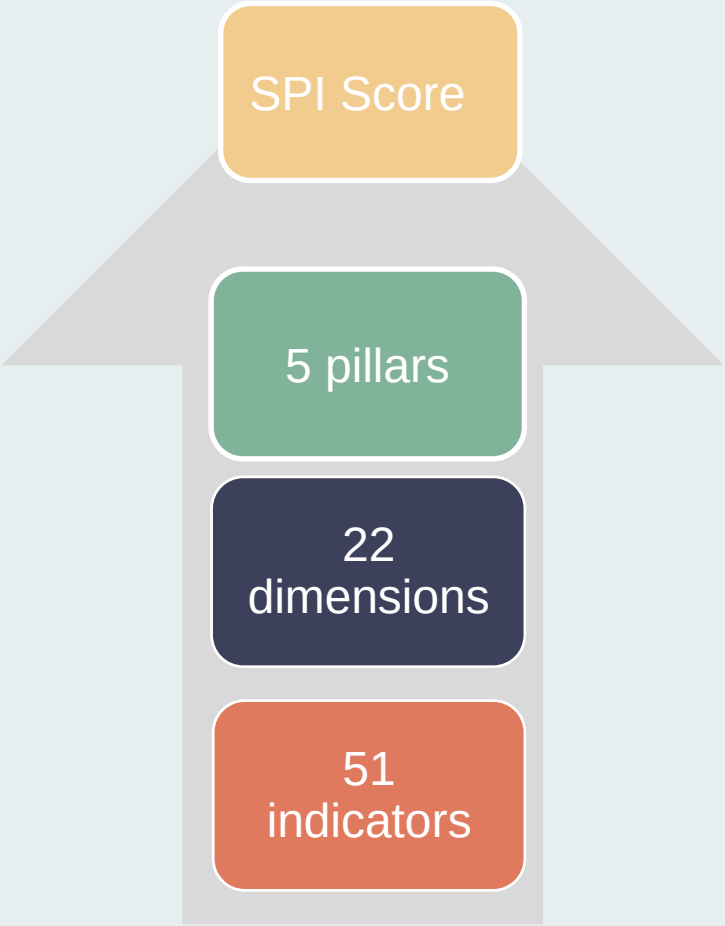
IHSN International Household Survey Network

UNESCO United Nations Educational, Scientific and Cultural Organization

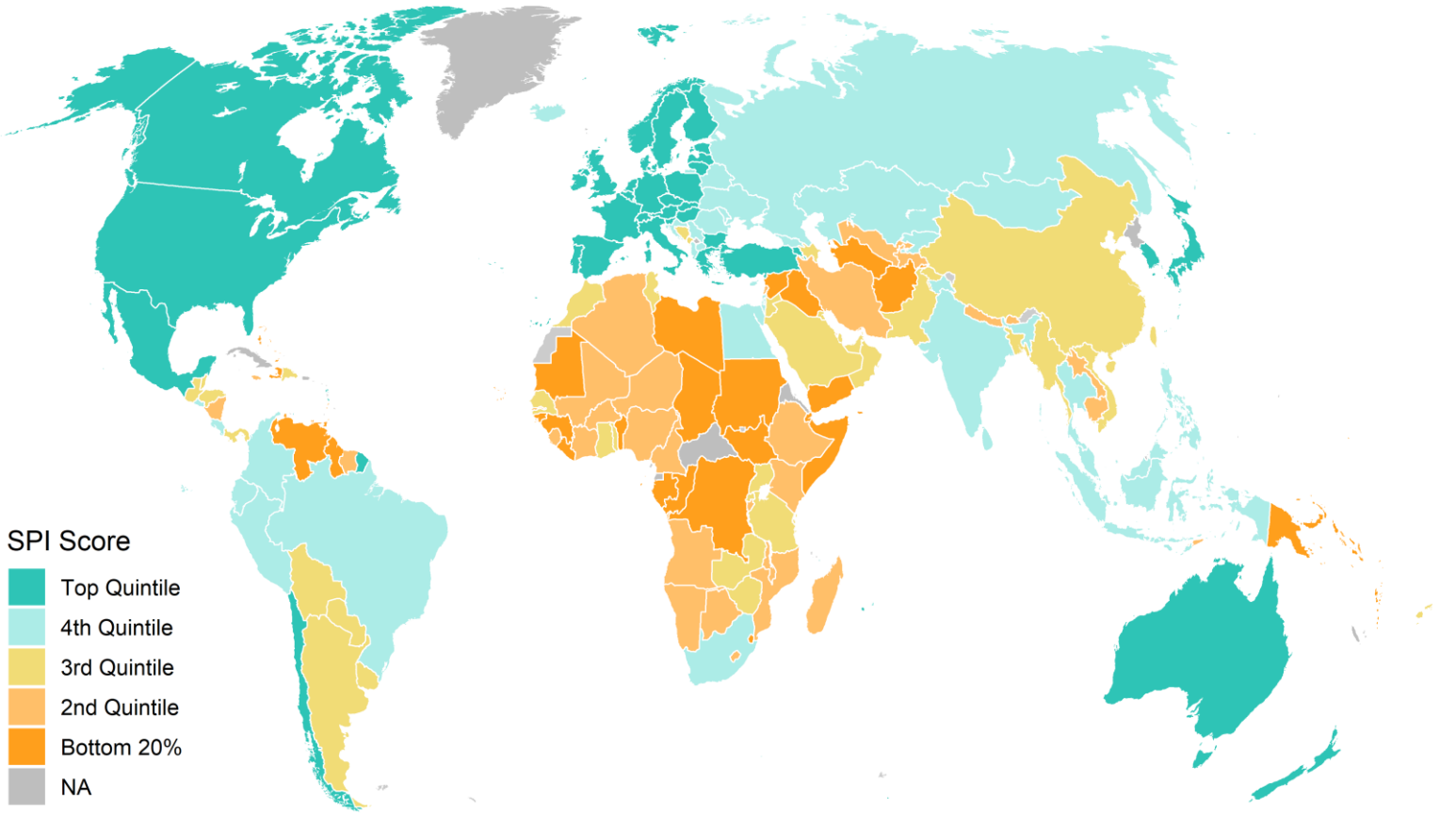
UNESCO INSTITUTE FOR STATISTICS

Index Methodology

- SPI score = sum of statistical performance indicators
- Index can be broken into components to see where a country leads and lags
- Nested structure allows for symmetry, monotonicity, and subgroup decomposability

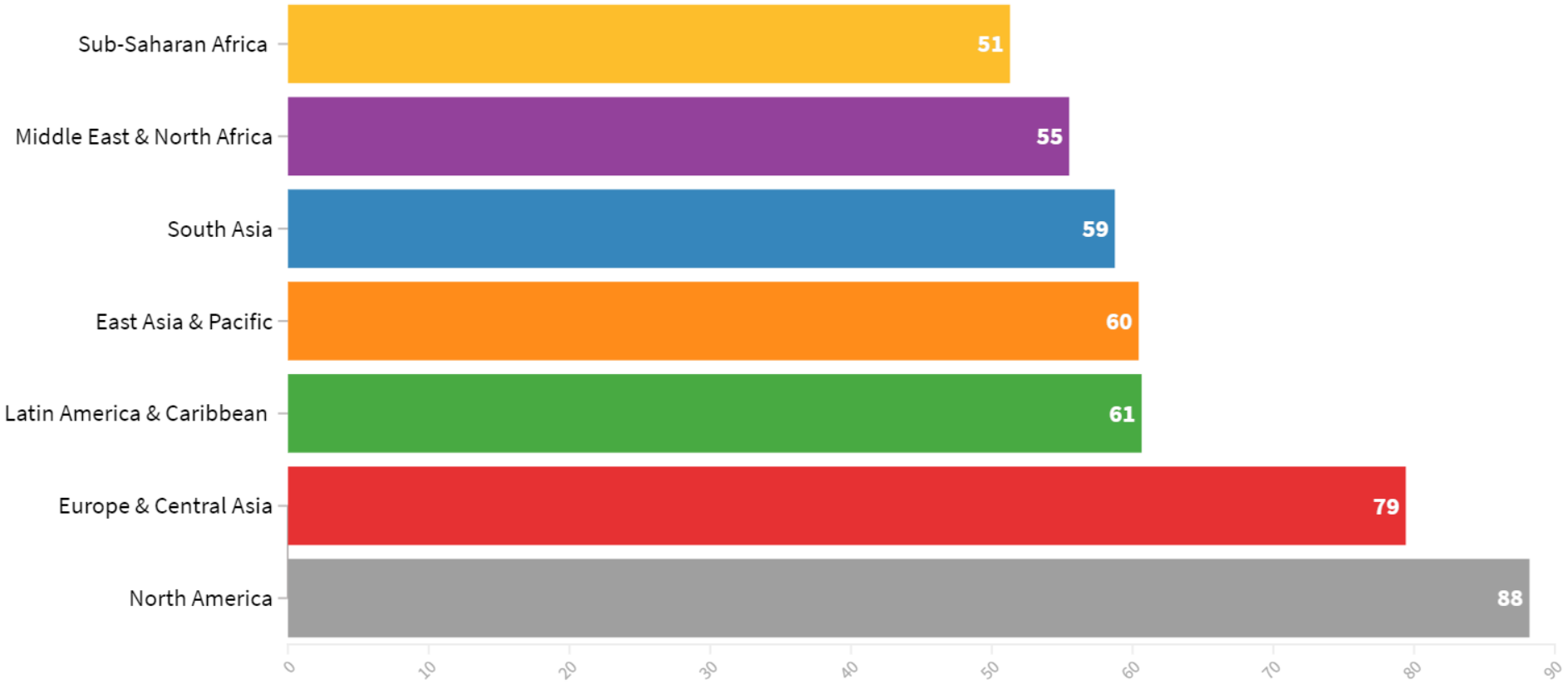


Global Landscape of Statistical Performance



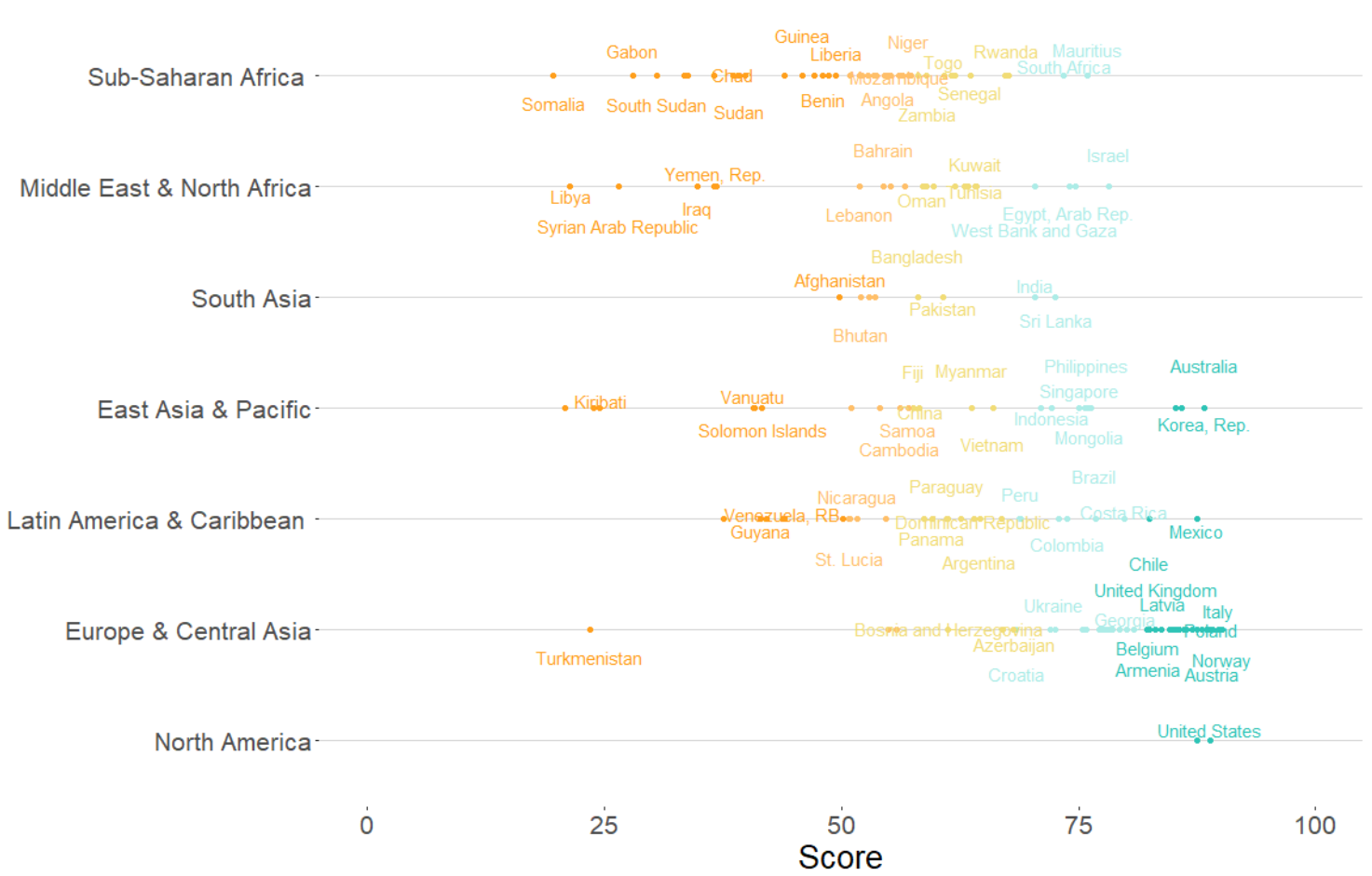
Source: World Bank. Statistical Performance Indicators

Regional scores



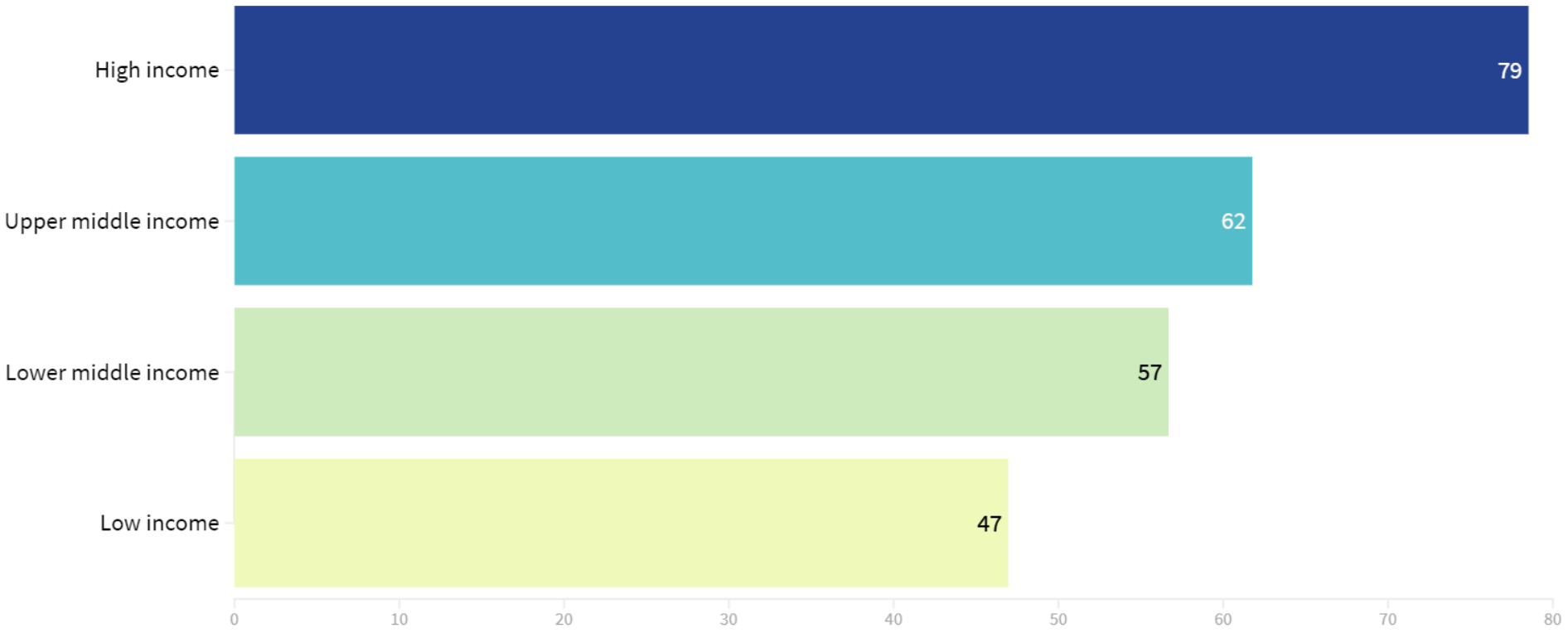
Source: World Bank Statistical Performance Indicators

Country performance varies tremendously within regions



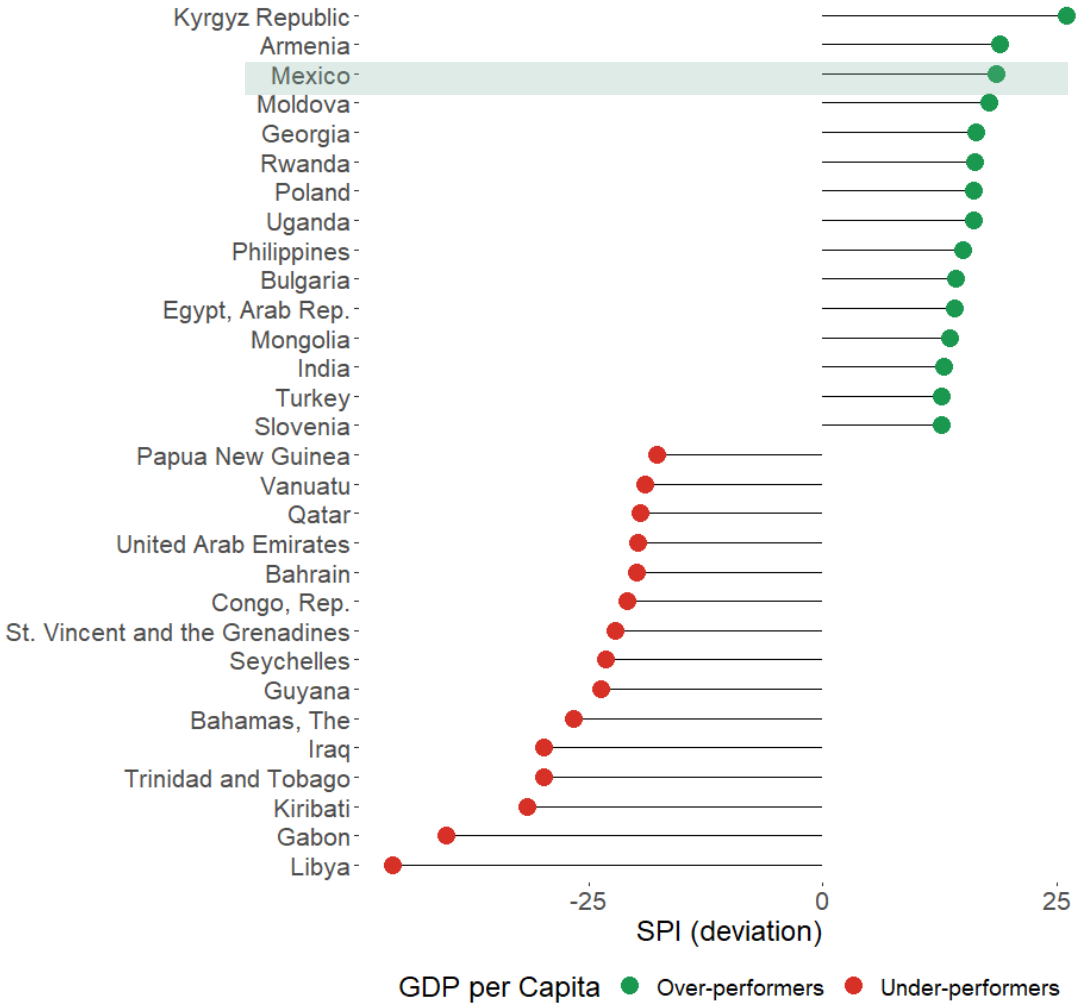
Source: World Bank Statistical Performance Indicators

Low- and Middle-Income Countries have some way to go

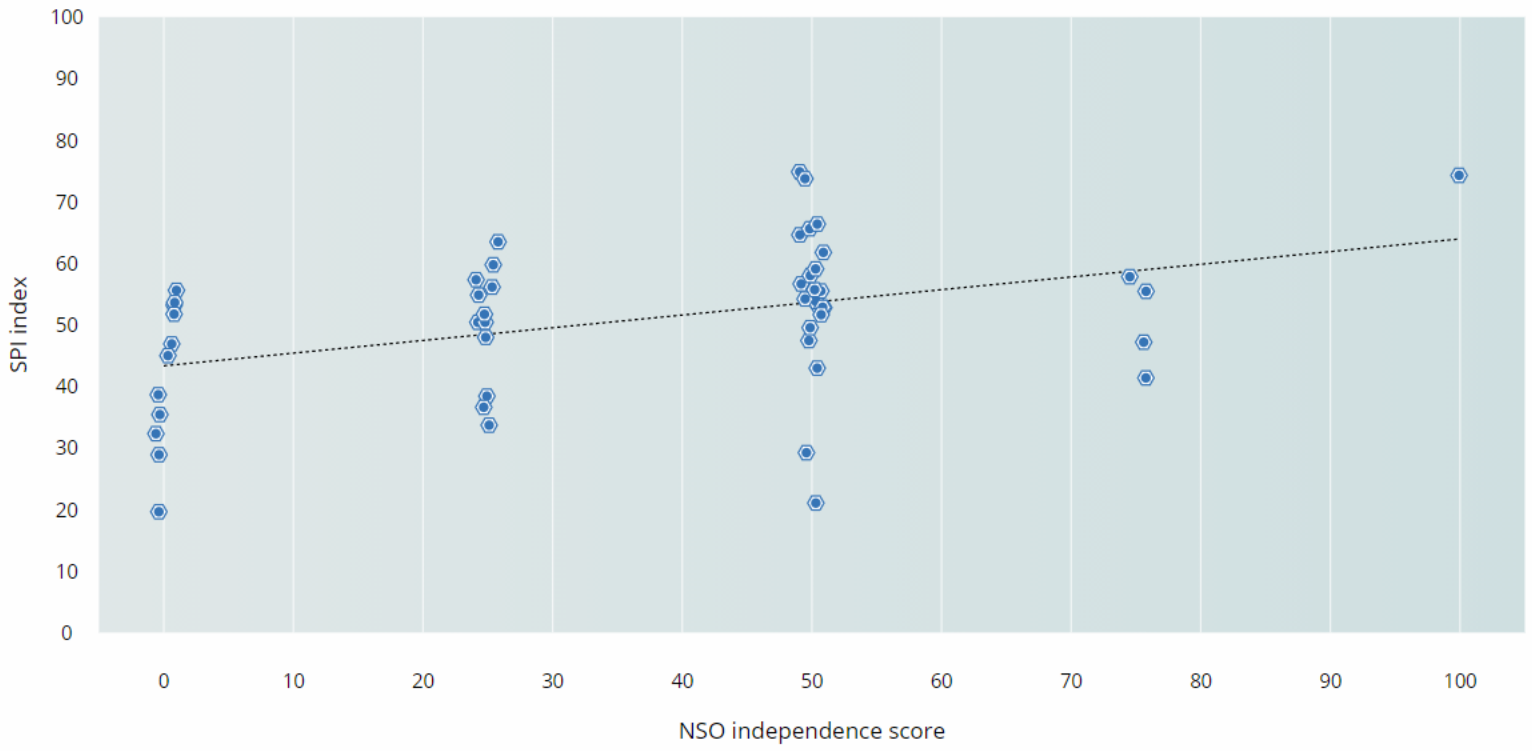


Source: World Bank Statistical Performance Indicators

Over/Underperformers



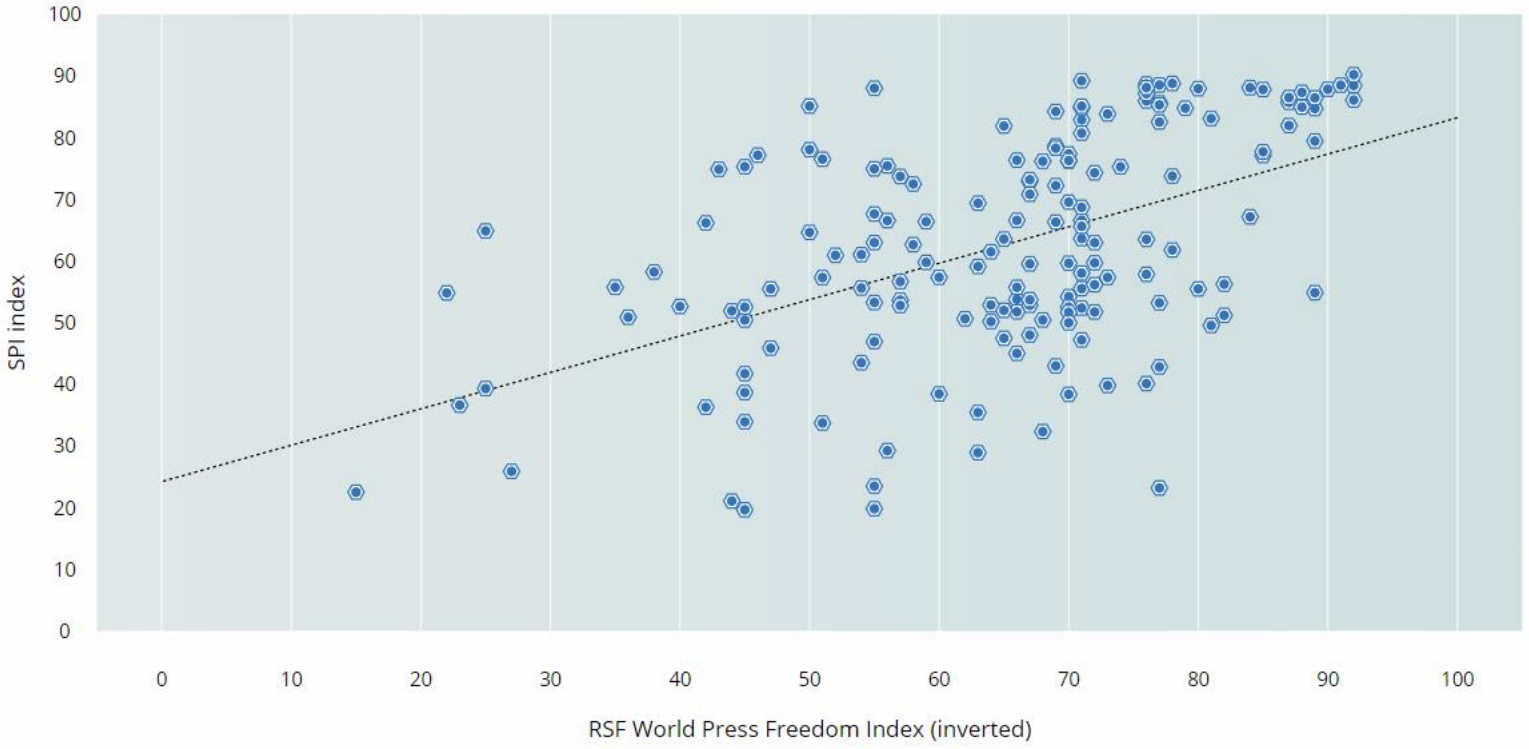
Higher NSO independence score correlates with higher statistical performance



Source: WDR 2021 team calculations based on Ibrahim Index of African Governance and the World Bank's Statistical Performance Indicators.

Note: The values in the chart are jittered to make them more readable.

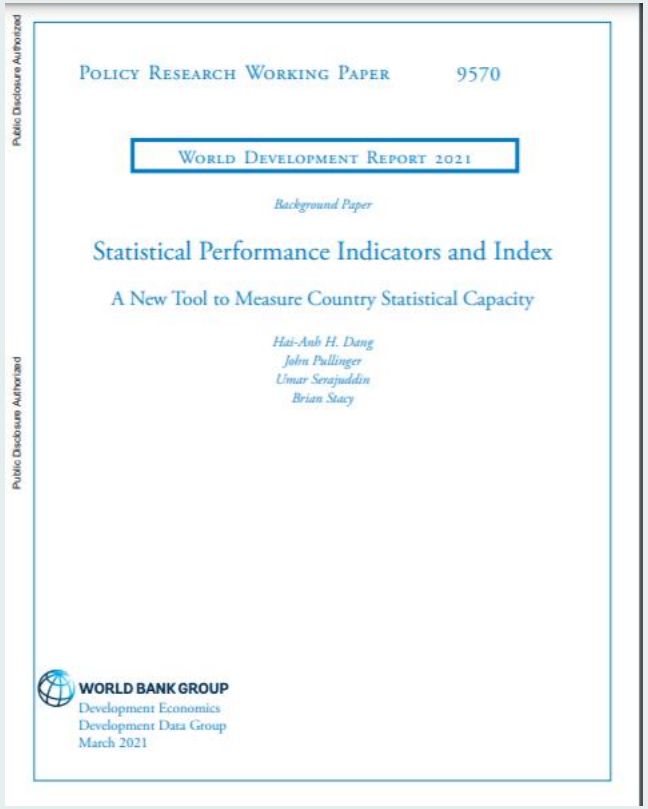
Greater press freedom correlates with higher statistical performance



Source: WDR 2021 team calculations based on World Press Freedom Index and the World Bank's Statistical Performance Indicators.

Learn More - https://www.worldbank.org/spi

Github: https://github.com/worldbank/SPI/ **SPI Data Explorer:** https://datanalytics.worldbank.org/SPI/



Public Disclosure Authorized

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Policy Research Working Paper 9570

World Development Report 2021

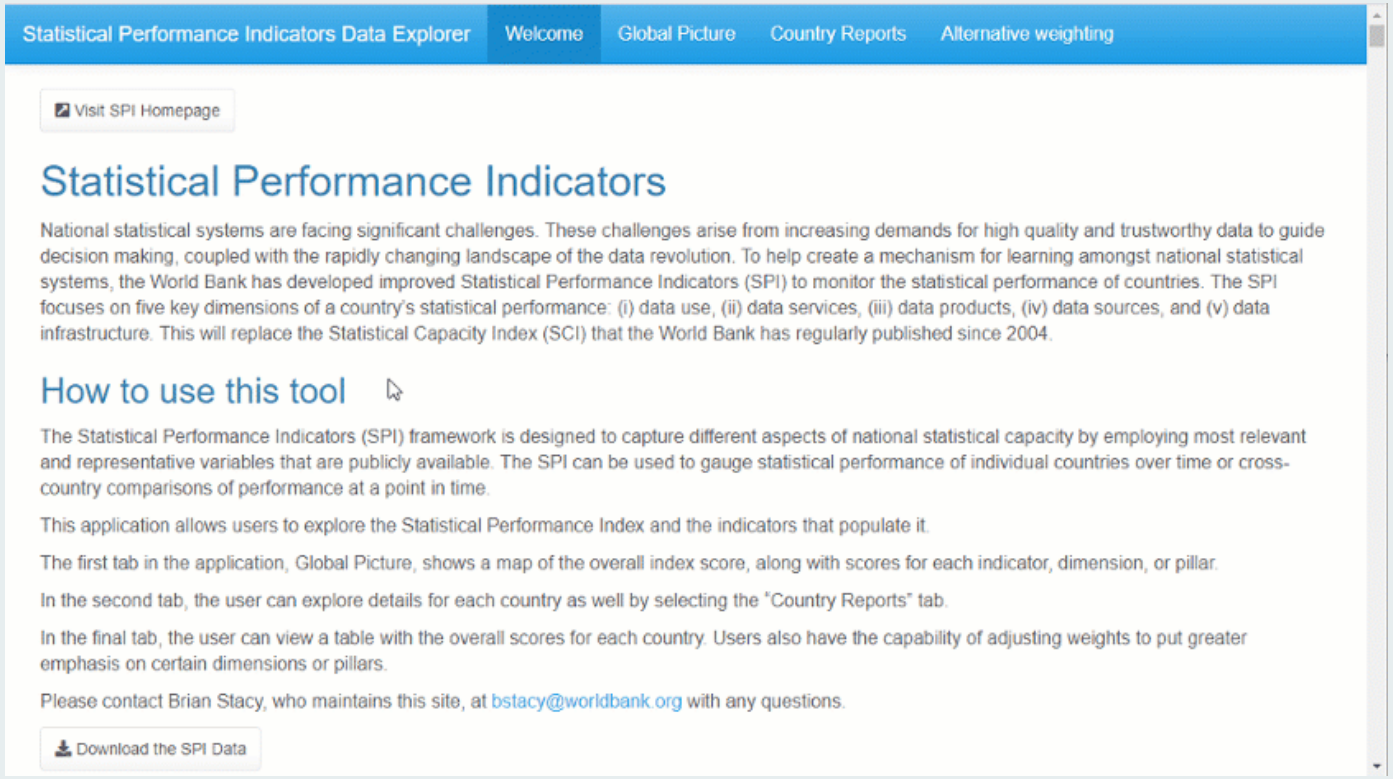
Background Paper

Statistical Performance Indicators and Index

A New Tool to Measure Country Statistical Capacity

Hai-Anh H. Dang
John Pullinger
Umar Serajuddin
Brian Stacy

WORLD BANK GROUP
Development Economics
Development Data Group
March 2021



Statistical Performance Indicators Data Explorer | Welcome | Global Picture | Country Reports | Alternative weighting

Visit SPI Homepage

Statistical Performance Indicators

National statistical systems are facing significant challenges. These challenges arise from increasing demands for high quality and trustworthy data to guide decision making, coupled with the rapidly changing landscape of the data revolution. To help create a mechanism for learning amongst national statistical systems, the World Bank has developed improved Statistical Performance Indicators (SPI) to monitor the statistical performance of countries. The SPI focuses on five key dimensions of a country's statistical performance: (i) data use, (ii) data services, (iii) data products, (iv) data sources, and (v) data infrastructure. This will replace the Statistical Capacity Index (SCI) that the World Bank has regularly published since 2004.

How to use this tool

The Statistical Performance Indicators (SPI) framework is designed to capture different aspects of national statistical capacity by employing most relevant and representative variables that are publicly available. The SPI can be used to gauge statistical performance of individual countries over time or cross-country comparisons of performance at a point in time.

This application allows users to explore the Statistical Performance Index and the indicators that populate it.

The first tab in the application, Global Picture, shows a map of the overall index score, along with scores for each indicator, dimension, or pillar.

In the second tab, the user can explore details for each country as well by selecting the "Country Reports" tab.

In the final tab, the user can view a table with the overall scores for each country. Users also have the capability of adjusting weights to put greater emphasis on certain dimensions or pillars.

Please contact Brian Stacy, who maintains this site, at bstacy@worldbank.org with any questions.

Download the SPI Data

Download the report and explore Data Stories at
https://wdr2021.worldbank.org/

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