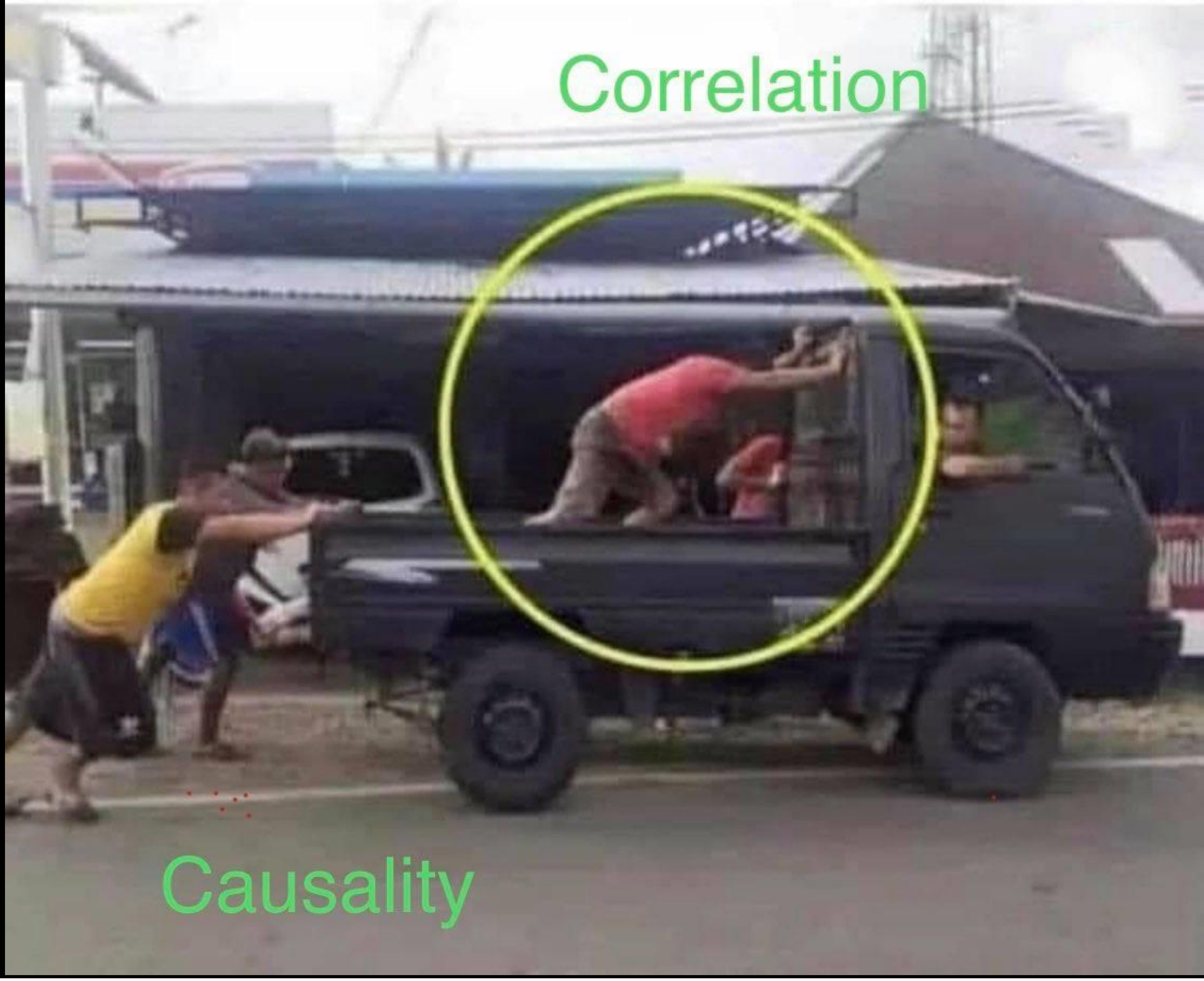
INFO 251: Applied Machine Learning




# Applied ML - start to finish

# Announcements

- Final quiz is on Thursday, 9:40-10:30
  - Closed book, closed notes
  - Available on bCourses
  - I will be in South Hall and on zoom
  - It is cumulative, but weighted toward material since quiz 1
  - There is no other lecture scheduled for Thursday
- I will record and post a ~10 minute lecture on "other methods for dimensionality reduction" later today

# Today's outline

- Applied ML, start to finish
- 5 mins for course evals
- ML harms and ethics

# **Research Agenda**: Overview

My work: Straddles CS (machine learning) and economics (applied micro). Themes:

1. Developing methods to **measure welfare** and **target policies**
   - Real-time measures of poverty and vulnerability (funding from *USAID, Google.org*)
   - Machine learning approaches to targeting emergency humanitarian aid (*today*)
   - Quantifying the impacts of violent conflict (*NSF and ONR/MINERVA*)
2. Understanding the **impact of ICT's** on poor and marginalized communities
   - Large-scale randomized control trials: *Afghanistan, Kenya, Nigeria, Philippines, Tanzania, Togo*
   - Disciplinary econ journal articles: *American Economic Review 2018, J. Development Econ. 2016*
3. **Adapting ML** to economic settings
   - Welfare-Sensitive Machine Learning (*NSF CAREER*)
   - Manipulation-Proof Machine Learning (*Gates Foundation, Amazon MLRA, J-PAL*)
   - Privacy-Preserving Prediction Algorithms (*DARPA*)

# Current focus: Targeting in Togo

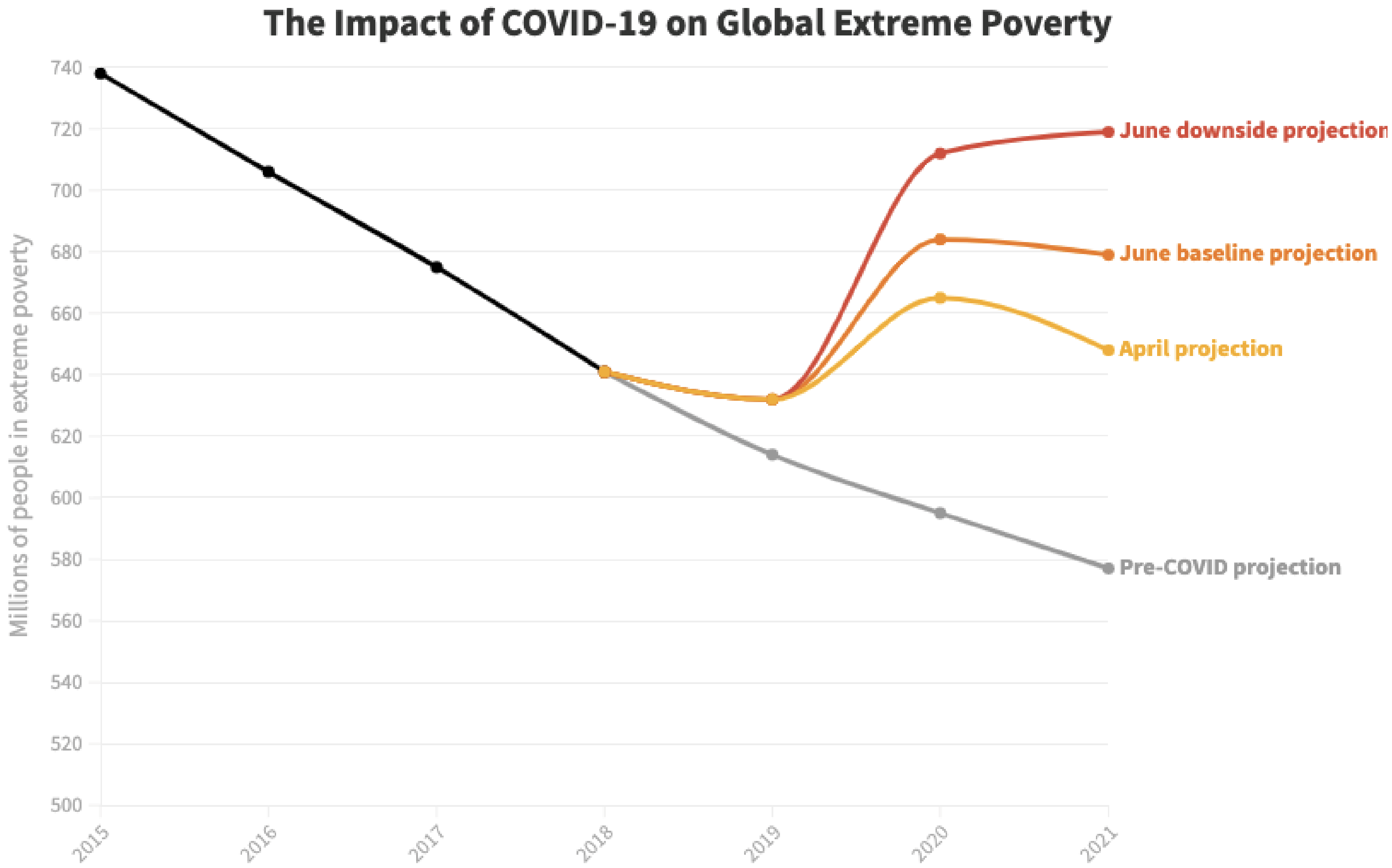
The Togo Team (most of it)


The New York Times

# ‘Instead of Coronavirus, the Hunger Will Kill Us.’ A Global Food Crisis Looms.

The world has never faced a hunger emergency like this, experts say. It could double the number of people facing acute hunger to 265 million by the end of this year.

# For the first time in 20 years, **global poverty is increasing**

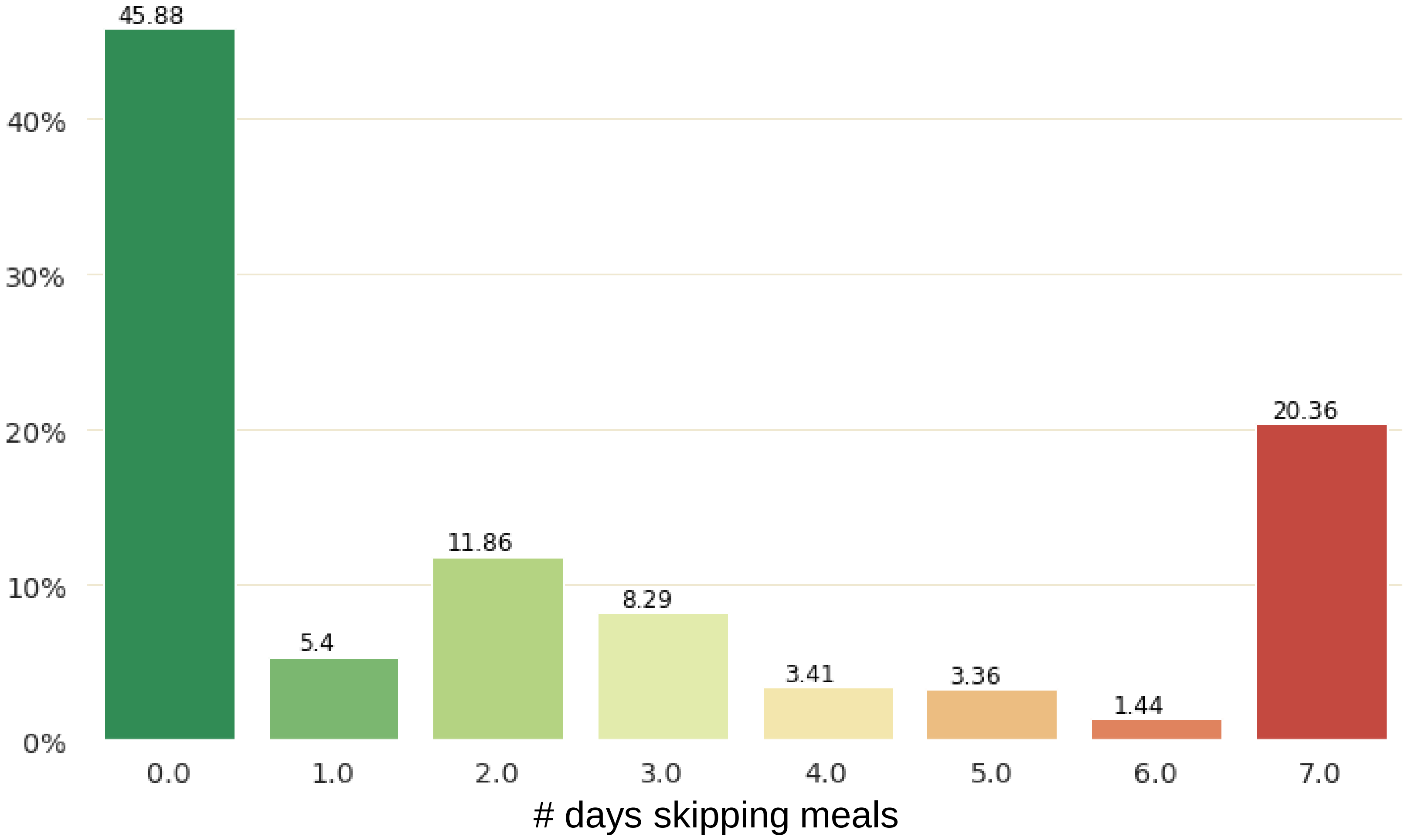



Source: Lakner et al (2020), PovcalNet, Global Economic Prospects, • Extreme poverty is measured as the number of people living on less than $1.90 per day.

# A "Hunger Pandemic"

*"In the past week, on how many days did you or someone in your household have to **reduce the number of meals eaten in a day?**"*

Results from phone survey in Togo, conducted June 2-14, 2020 (*N*=15,107)



# Over 3,300 new social assistance programs launched

# The challenge of *targeting*

**The challenge:** *How to identify those with the greatest need?*

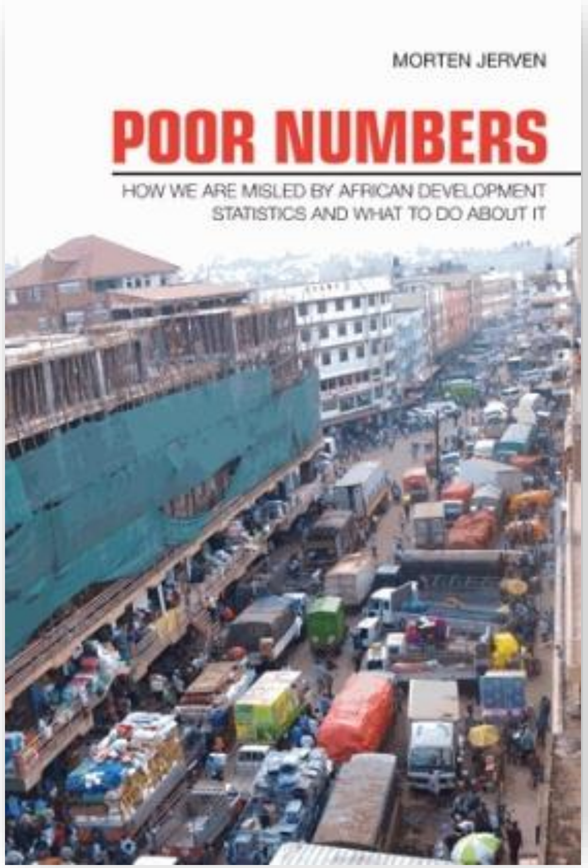



**Table 6.1** Countries with outdated censuses

| Country | Year of last census | Years since last census |
|---|---|---|
| Somalia | 1986 | 28 |
| Congo, Dem. Rep. (planned for 2015) | 1984 | 30 |
| Eritrea | 1984 | 30 |
| Afghanistan (2011 ongoing Socio-Demographic and Economic Survey by province) | 1979 | 35 |
| Lebanon | 1943 | 71 |

# This talk

**Takeaway:** Big data and data science can improve the targeting and delivery of humanitarian aid

## Outline

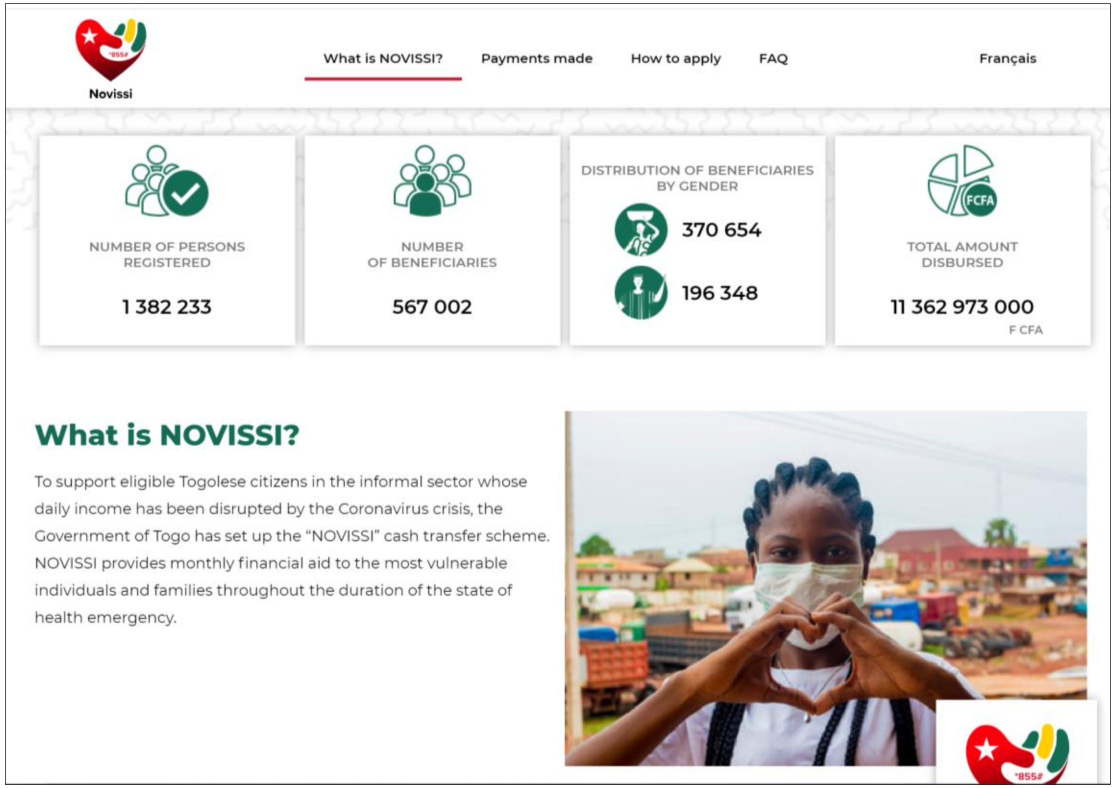
- **Intro: Togo, COVID-19, and Novissi**
- Part 1: Big data from satellites
- Part 2: Big data from mobile phones
- Part 3: The story in Togo
- Discussion: Social, ethical, and practical considerations

# Intro: Togo, COVID-19, and Novissi

# **Background:** Novissi in Togo

**Novissi:** Togo's flagship anti-poverty program, ~1M beneficiaries

- 100% digital registration (USSD) and payment (mobile money)
- Beneficiaries receive bi-weekly payments of roughly $10 USD



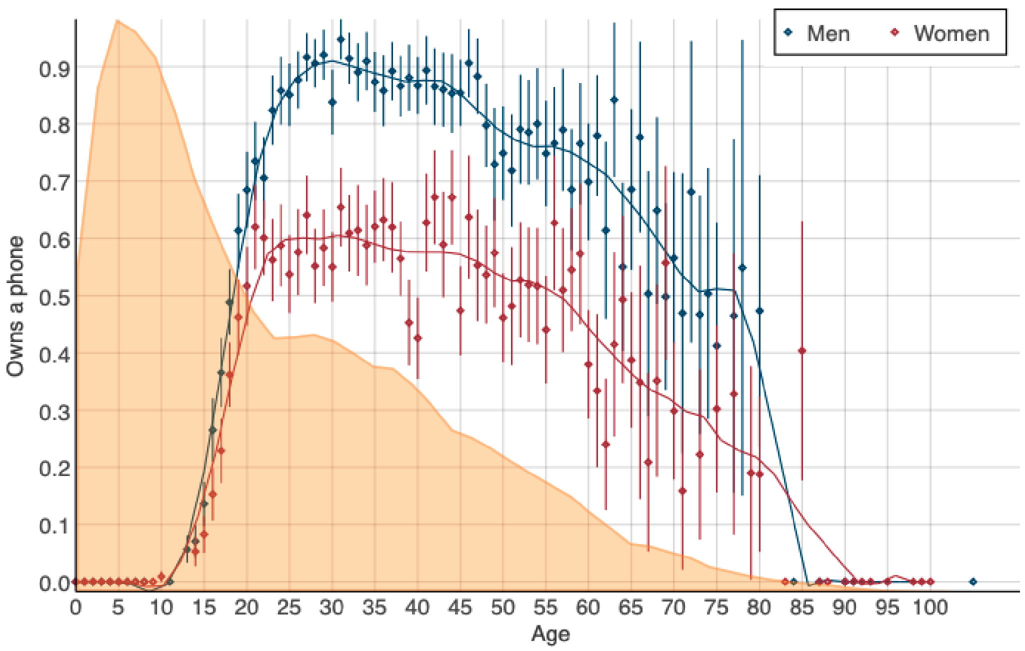

[Details]

# Background: Novissi in Togo

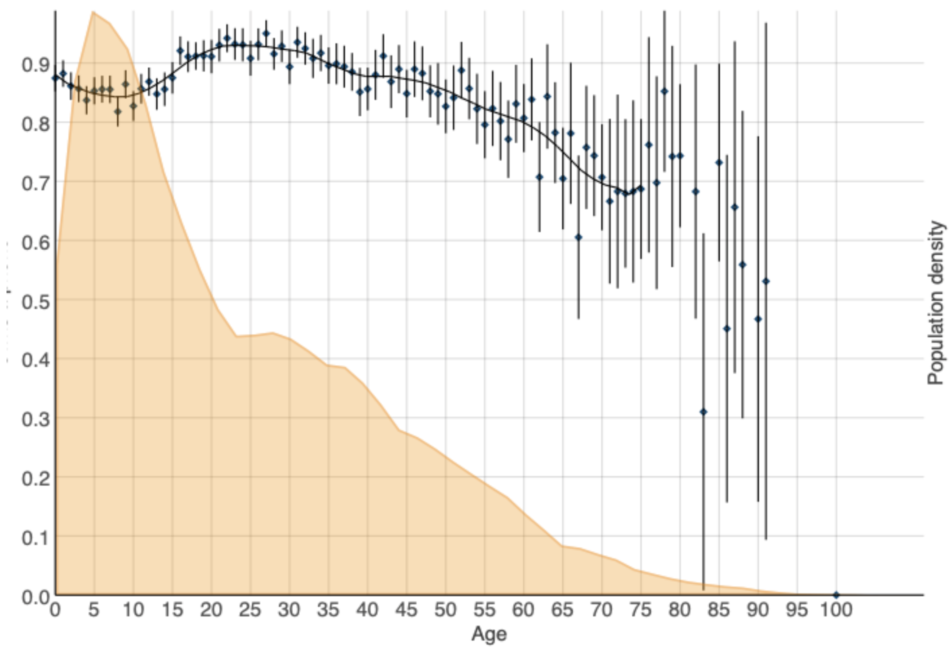
## Mobile phones are widespread, but not ubiquitous

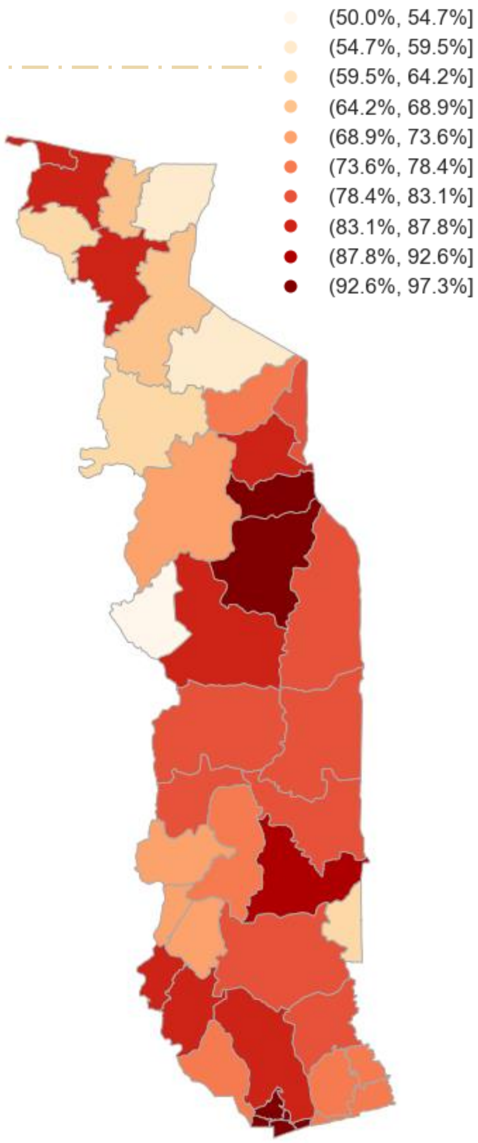
- Household penetration (85%) > individual penetration (65%)
- Novissi registration linked to SIM, not phone
- (SIM penetration increased from 4.2M in 2019 to 6.5M in 2021)

**Individual** phone ownership by age and gender (early 2019)



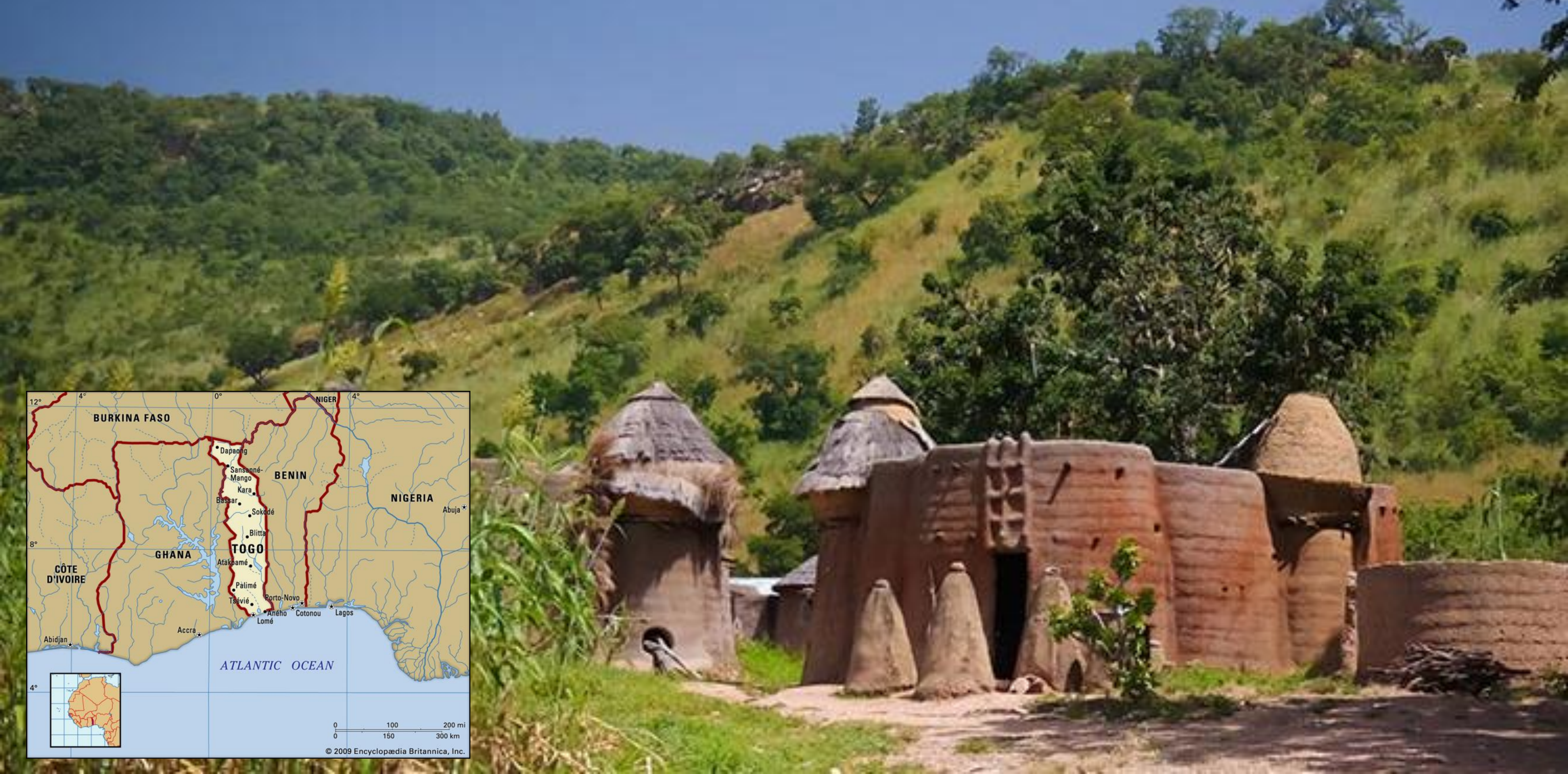

**Household** phone penetration by age (early 2019)




Mobile phone penetration
(by prefecture, early 2019)

# Results: Targeting Evaluation in Togo



# Part 1: Big data from satellites

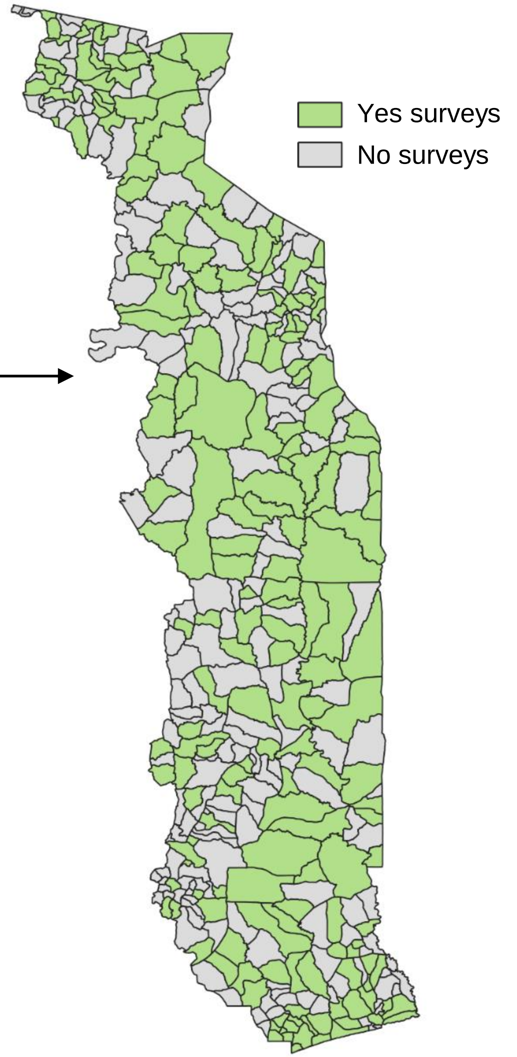
**Details:**

- Chi et al. 2022. "Micro-Estimates of Wealth for all Low- and Middle-Income Countries." *Proceedings of the National Academy of Sciences*
- Smythe and Blumenstock, 2022. "Geographic Micro-Targeting of Social Assistance with High-Resolution Poverty Maps" *Working Paper.*

# **Geographic targeting**: The challenge

**Goal:** Government wanted to target poorest villages

- **But:** They didn't have any data that indicated which villages (or cantons, or even prefectures!) were poorest
  - Only 48% of cantons contain one or more surveyed household




**Map of cantons of Togo**

Togo's predicament is not uncommon:

- <50% of the poorest countries completed a census in past 10 years (Yeh et al. 2020)
- >25% of the world's children under five are not registered at birth (World Development Report 2021)

# **Big data from satellites:** A simple idea

Wealthy regions *look* different from poor regions

Mexico City, Mexico

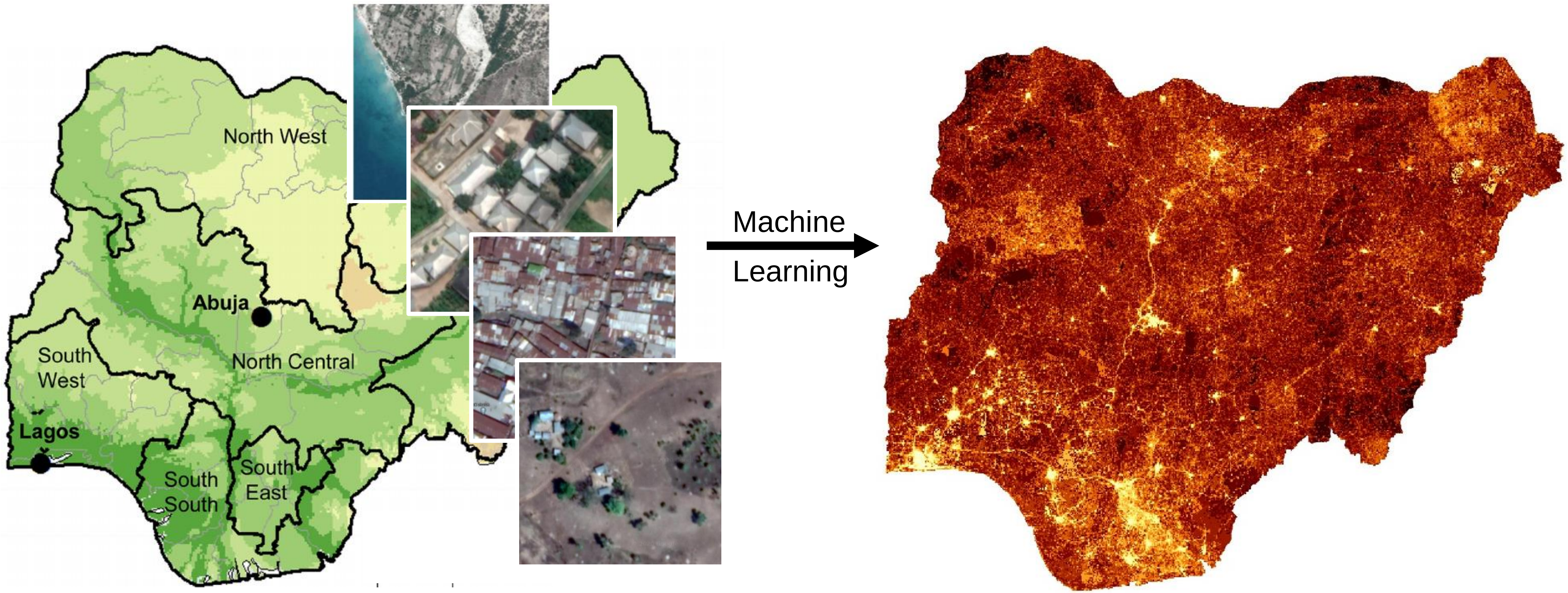
Cape Town, South Africa

https://www.bbc.com/news/in-pictures-45257901

[Details ⮰]

# Can a machine “learn” those differences?

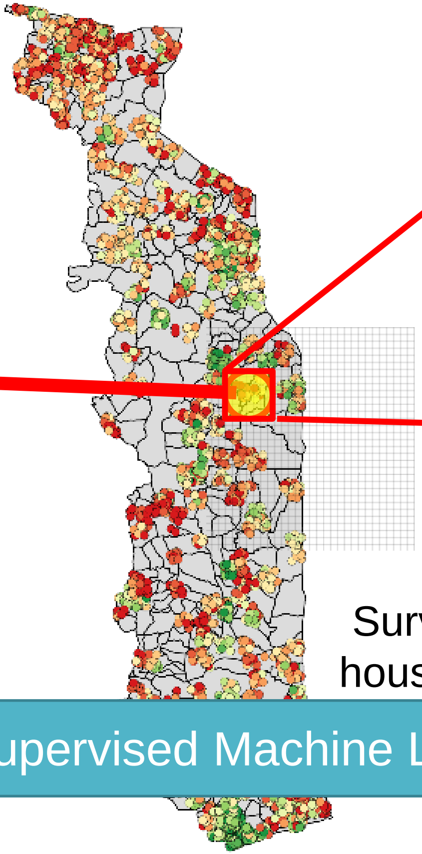
**Yes!** Satellite imagery, processed with AI, can identify the poorest regions of a country, to be prioritized for humanitarian aid



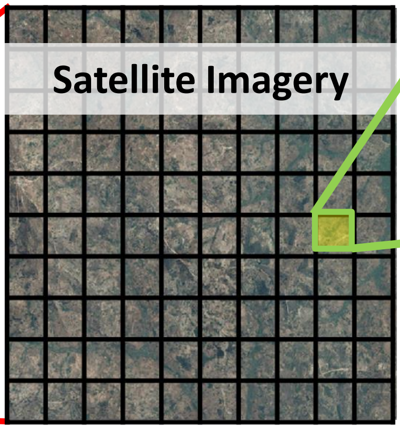
# Big data from satellites: Details

## How does it work? (overview)


- 6,171 households
- In-person survey
- 100's of questions per survey
- Includes "wealth index", PMT, and consumption $(Y_i)$

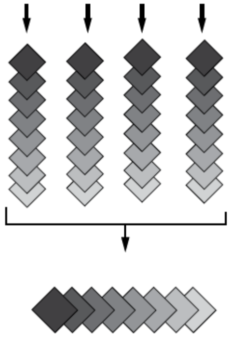


Surveyed households




Size: 1 km$^2$
400×400px

Deep learning "feature extractor"



Village-level image features $(X_i)$

Supervised Machine Learning: $Y_i = f(X_i)$

Details: Chi, Fang, Chatterjee, and Blumenstock, 2022. "Micro-Estimates of Wealth for all Low- and Middle-Income Countries." *Proc. Natl. Academy of Sciences*

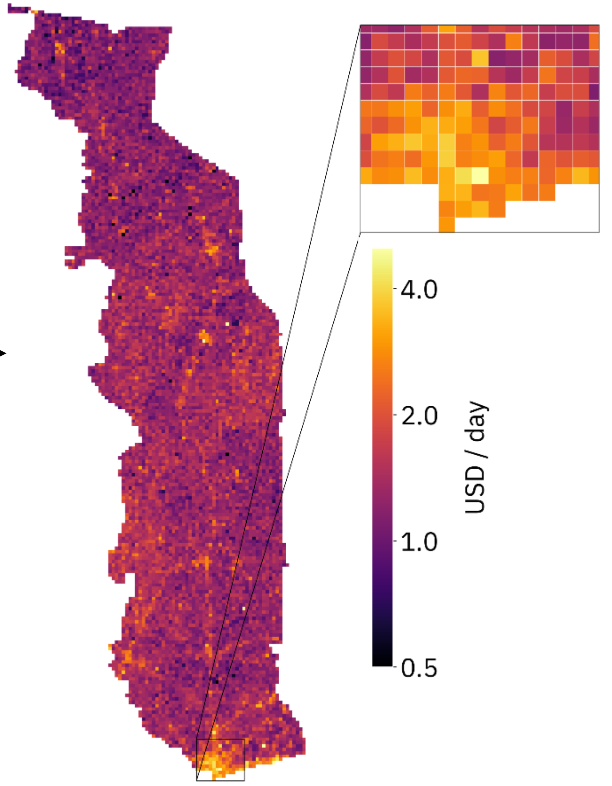
[Details ⮰]

# Big data from satellites: Relevance in Togo

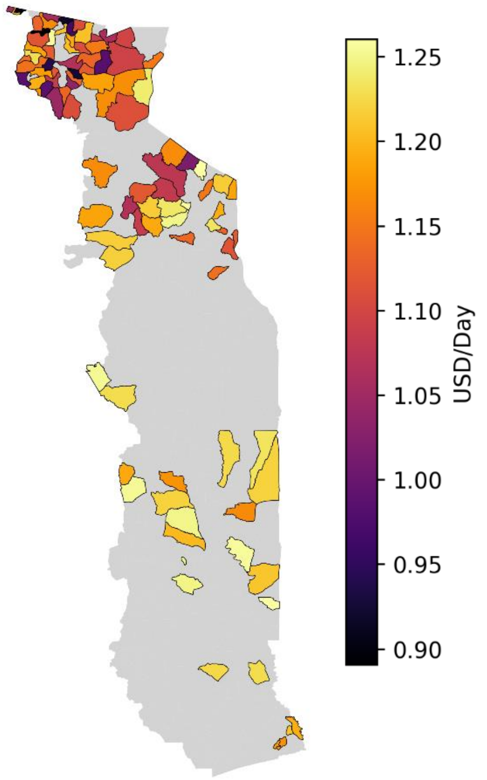
Satellite-based poverty maps enabled the government to concentrate benefits in the 100 poorest counties of Togo

High-resolution satellite imagery

Machine Learning [details ⮰]




ML-based poverty maps



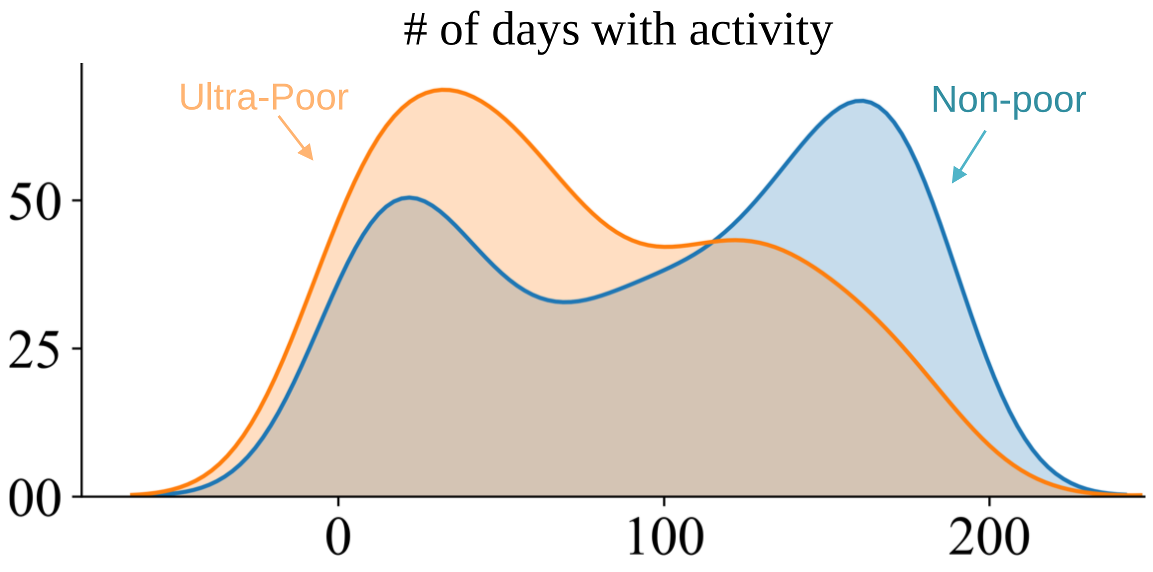

Eligible cantons

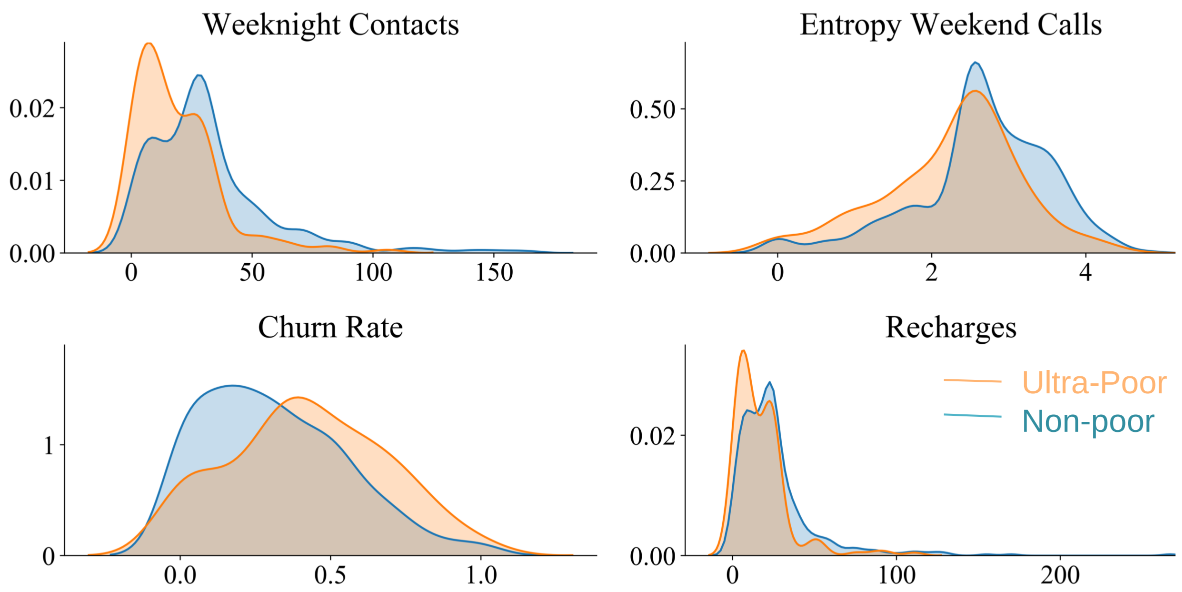
# Part 2: Big Data from Mobile Phones

# Big data from mobile phones: A simple idea

Wealthy people use their phone differently than poor people

- These differences can be used to *predict* which subscribers are wealthy and poor



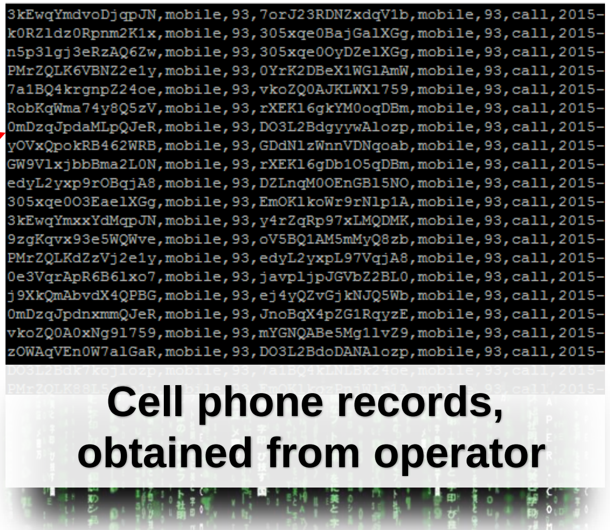



# Big data from mobile phones: Details

[Details]

**In practice:** Requires *training data* that maps CDR → wealth


Each respondent



Feature engineering

to construct predictors $X_i$

Principal component analysis

to construct labels $Y_i$

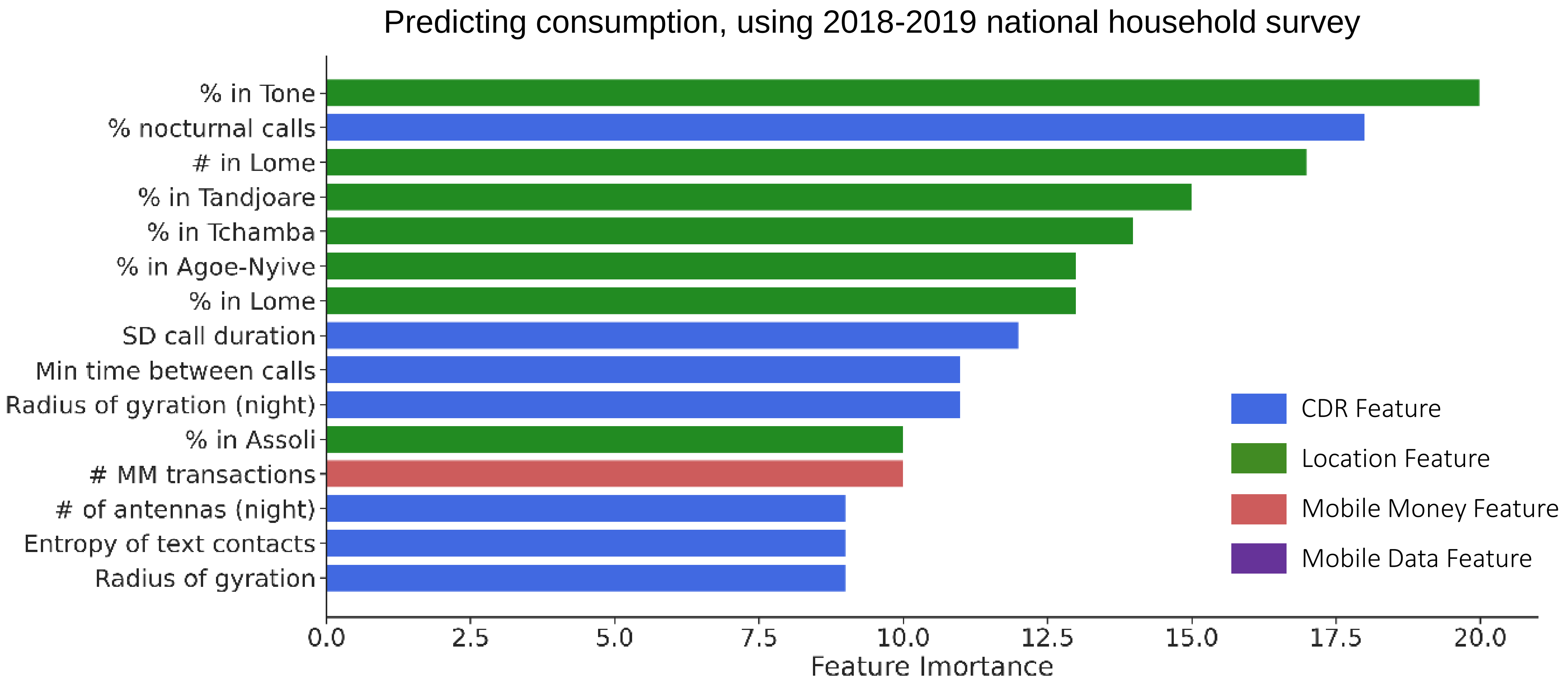
**Supervised Learning**

Fitted model $f$

predicts wealth $\widehat{Y}_i$ from CDR $X_i$

# Big data from mobile phones: Details

## Top predictors (in mobile phone data) of consumption in Togo




[Rwanda]

[2020 importances]

# Targeting with phone data and machine learning

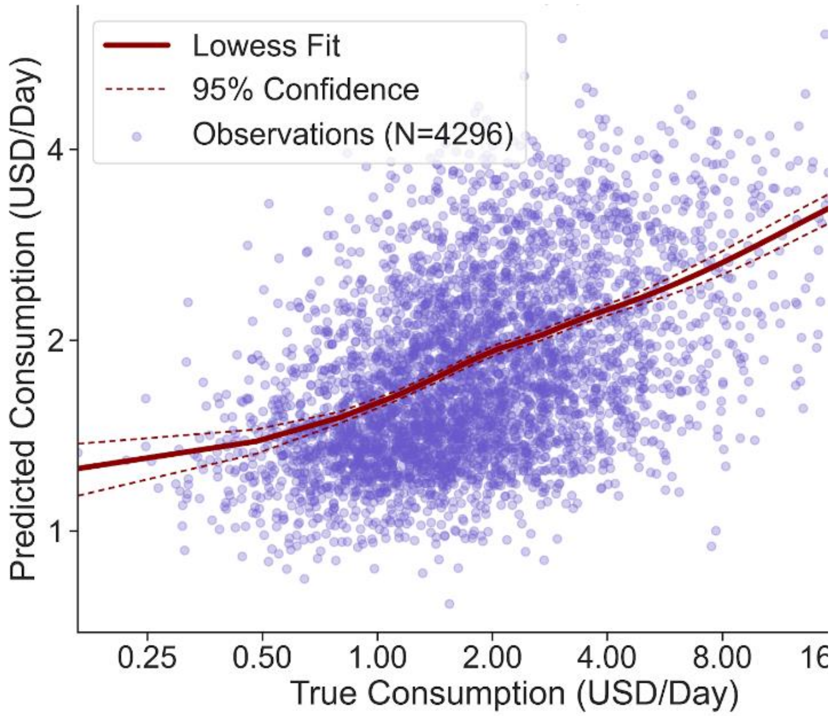
[Dynamics]

[Validation]

## Accuracy of phone-based predictions (in Togo)

| Asset | Consumption | PMT | Asset Index |
|---|---|---|---|
| *Panel A: 2018-2019 Field Survey (N = 4,171)* | | | |
| ML | 0.46 | 0.62 | 0.74 |
| Single Feature | 0.13 | 0.16 | 0.11 |
| *Panel B: 2018-2019 Field Survey, Rural Only (N = 2,306)* | | | |
| ML | 0.31 | 0.44 | 0.51 |
| Single Feature | 0.09 | 0.12 | 0.08 |
| *Panel C: 2020 Phone Survey (N = 8,915)* | | | |
| ML | -- | 0.41 | 0.40 |
| Single Feature | -- | 0.13 | 0.14 |
| ML trained in 2019 | -- | 0.35 | -- |

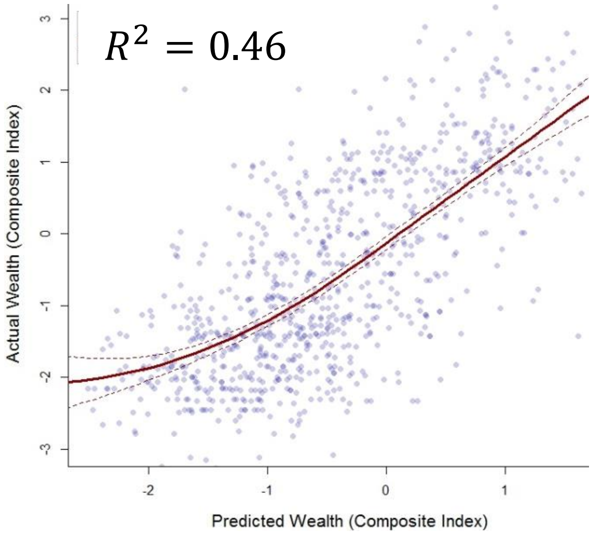
2018-19 household survey



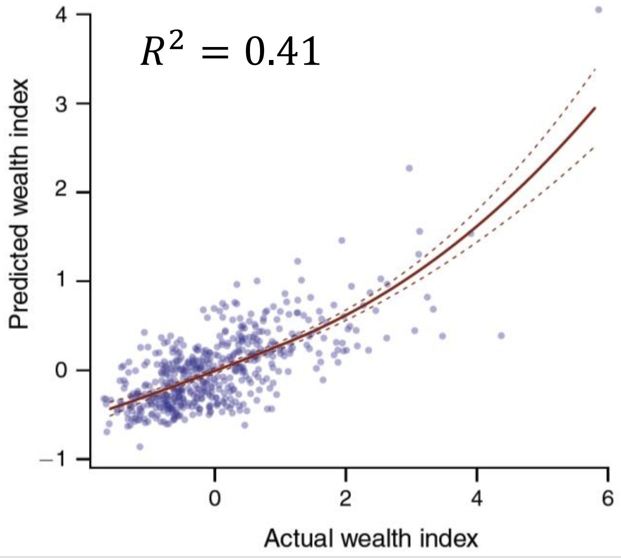
# Targeting with phone data and machine learning

Across countries, phone data capture 25-50% of economic status

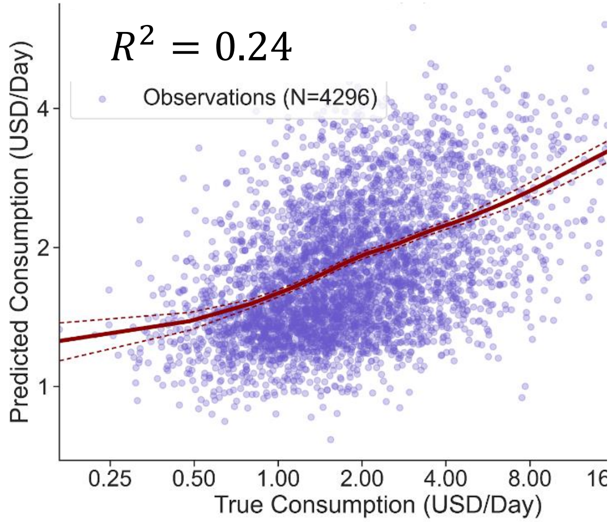
Rwanda 2010 (*N*=856)



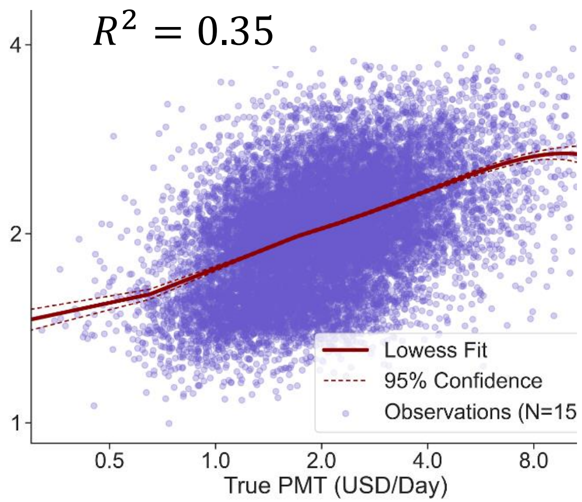

Afghanistan 2015 (*N*=1,234)



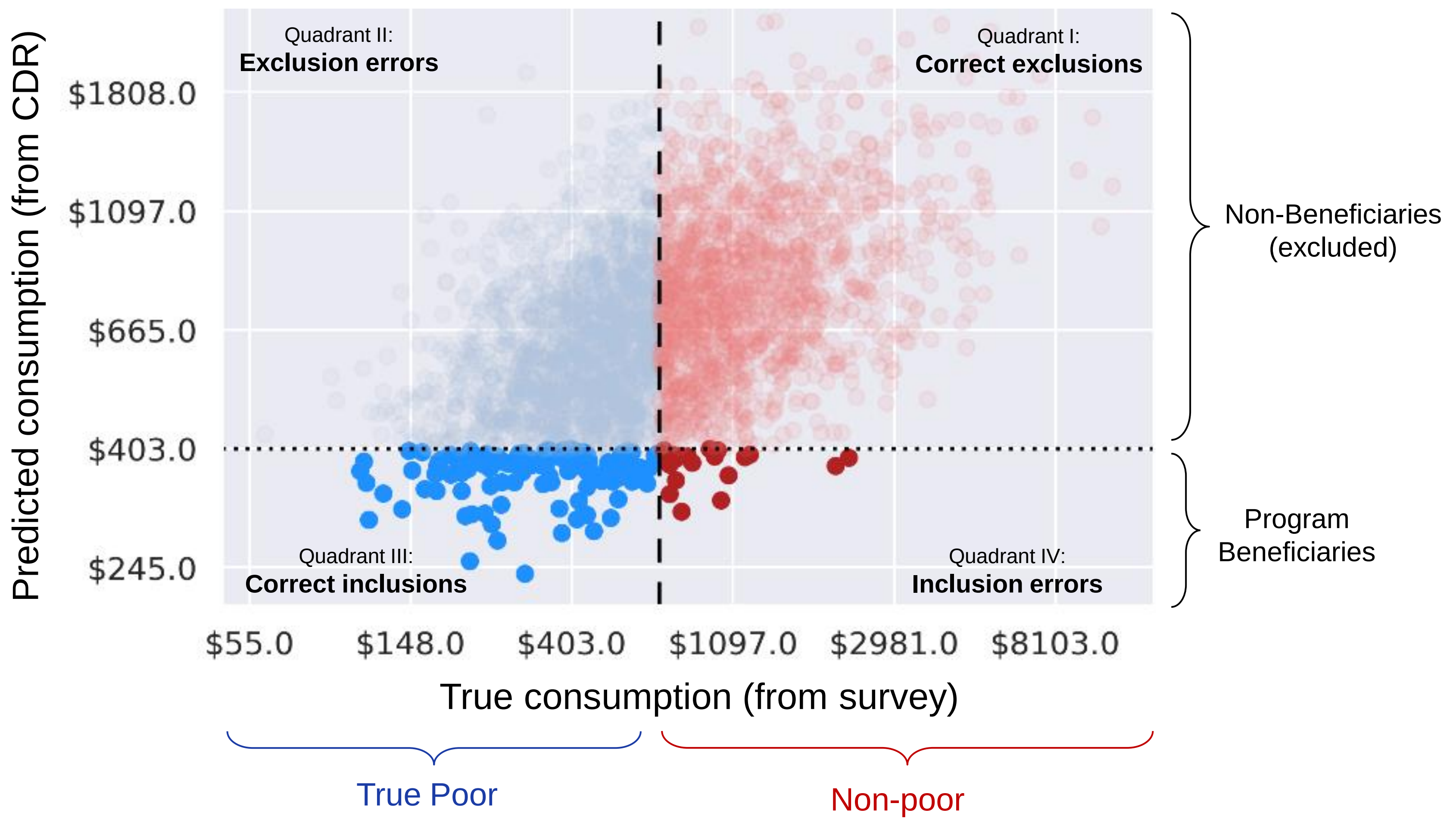

Togo 2018 (*N*=4,296)




Togo 2020 (*N*=15,044)



# But… can big data help target aid?



# **Evaluation:** ML vs. Traditional Targeting

Main question: How does targeting with phone data compare to alternative targeting mechanisms in Togo?

**Evaluation in Togo**: Compares feasible and infeasible approaches

1. Occupation-based targeting
2. Geographic targeting
3. Mobile phone-based targeting
4. Asset-based index
5. Proxy means test

Feasible in Togo

Infeasible

[Related work ⮰]

**Details:** Aiken, Bellue, Karlan, Udry, Blumenstock (2022, forthcoming). Machine Learning and Mobile Phone Data Can Improve the Targeting of Humanitarian Assistance. *Nature*.

[Details]

# **Togo evaluation:** Data

## Scenario 1: **Targeting the Novissi program in rural areas**

- Evaluated using a phone survey of Togo's 100 poorest cantons
- Conducted in September 2020, immediately prior to Novissi expansion
- $N$ = 8,915 using a 40-minute survey instrument. *No consumption data*
- *This survey was also used to train the ML algorithms used in Novissi's deployment*

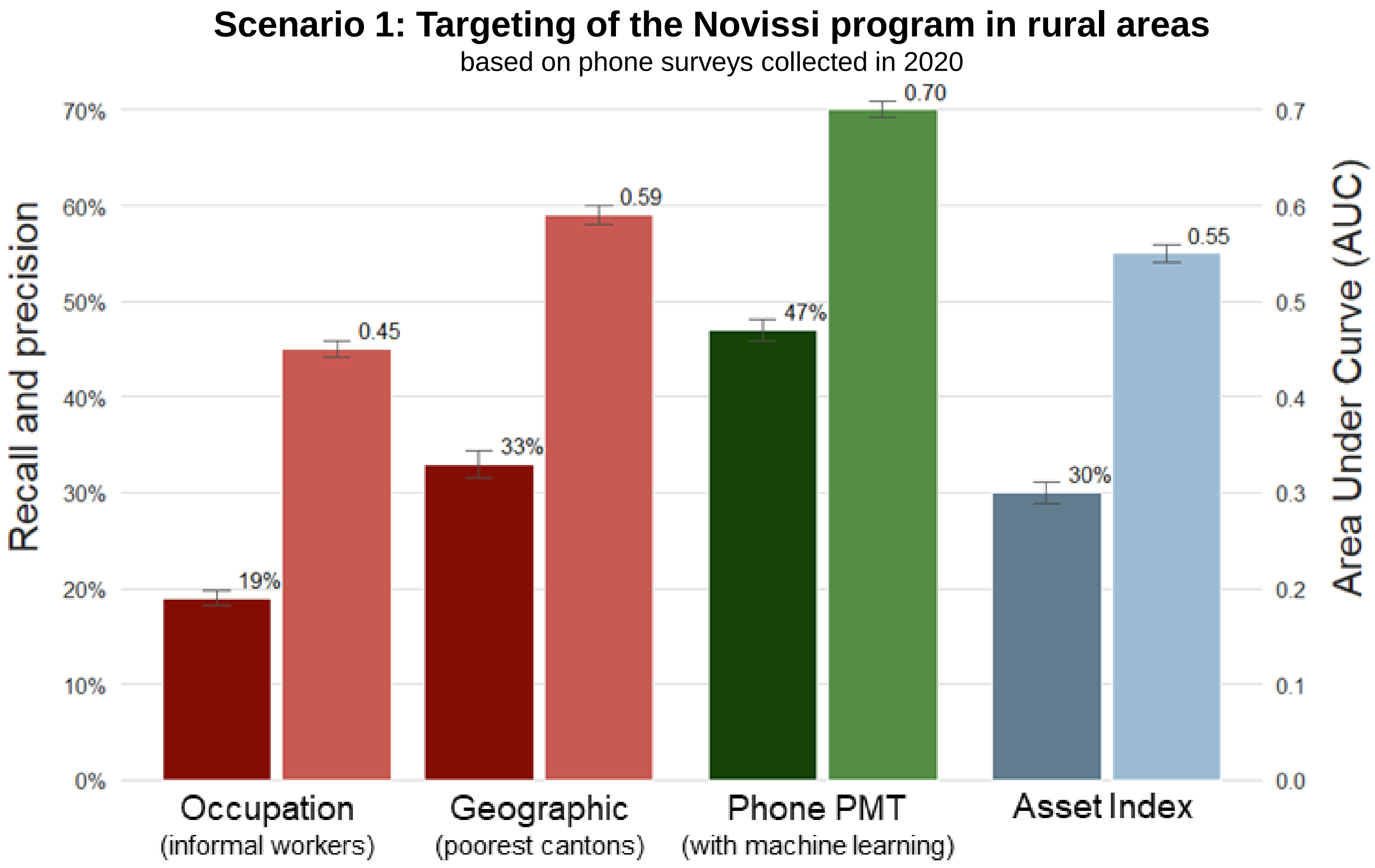
## Scenario 2: **Targeting a nationwide Novissi program**

- Evaluated using a national in-person survey
- Conducted in 2018-2019 by national statistical agency of Togo (INSEED)
- $N$ = 6,171 using a 3-hour survey instrument with consumption data
- $N$ = 4,171 where head of household has a phone number that matches to CDR

[Details ⮰]
[Alternative thresholds ⮰]

# **Results:** Summary

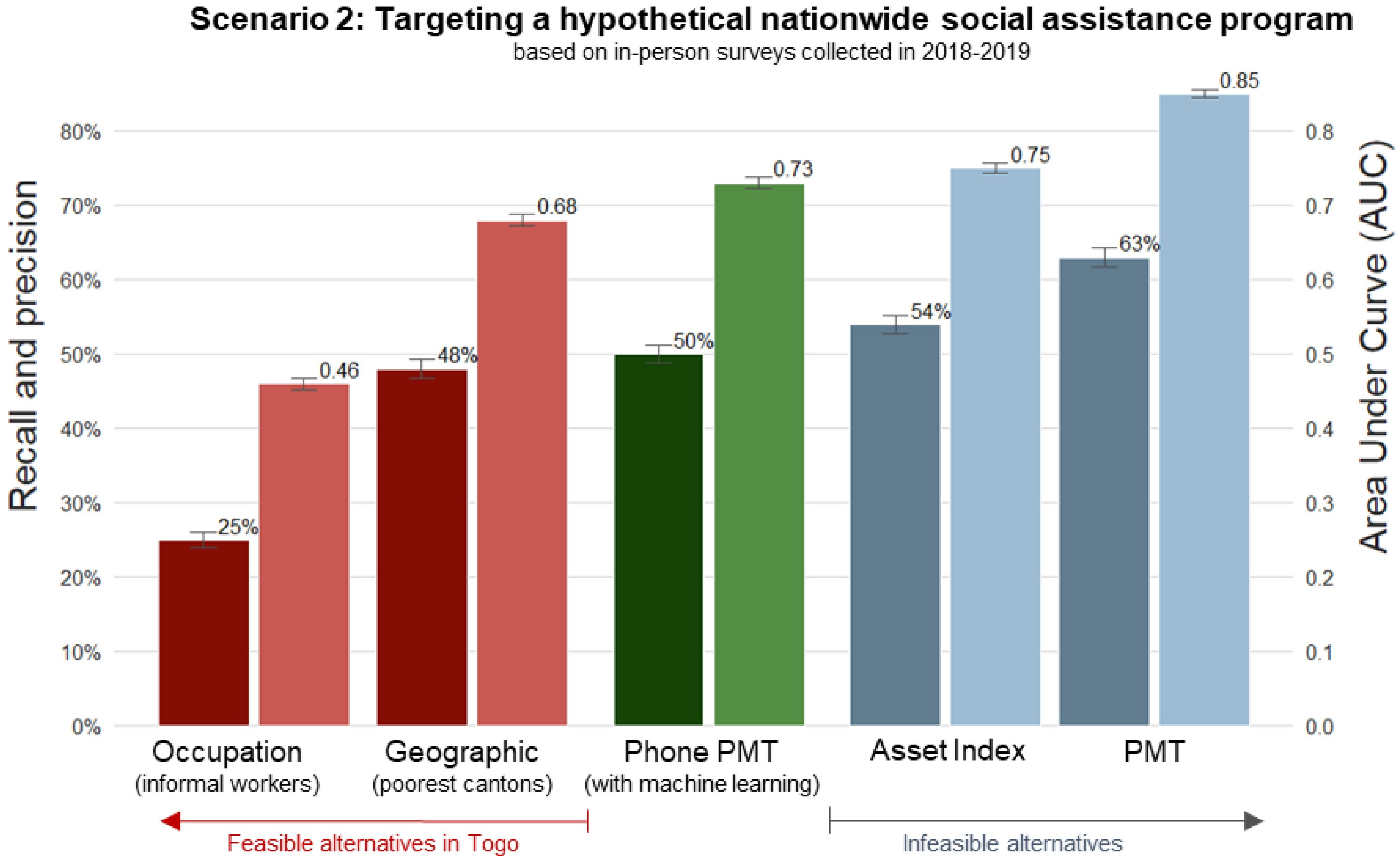
**Key results:** The phone-based approach performs better than other methods available in Togo during the COVID-19 crisis.



[Details ⮰]
[Rural / national differences⮰]

# **Results:** Summary

**Key results:** BUT, it does not perform as well as methods with a comprehensive social registry – especially in national program



[Details ⮰]

# **Results:** Exclusion errors

Key considerations: What causes **exclusion errors**?

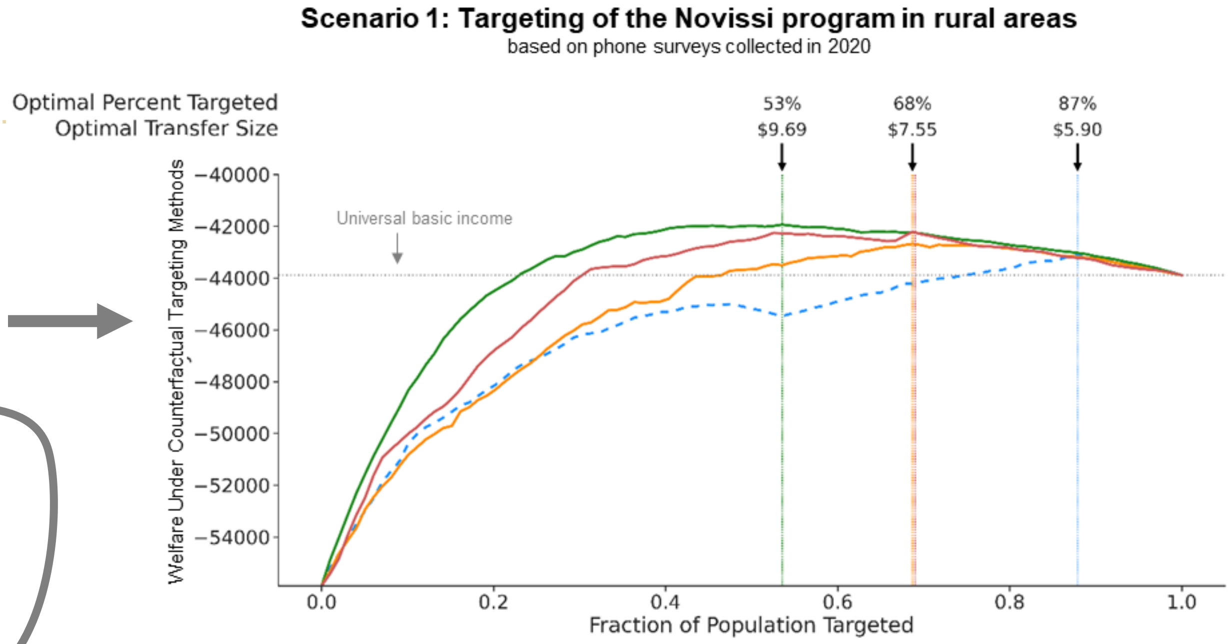
1. Must be **registered to vote** in an eligible canton (87% of adults ⮰)
2. Must have a **SIM card**, and access to a mobile phone (85% of households ⮰)
3. Must “**self-target**” and attempt to register (40% of voters ⮰)
4. Must succeed in **registering** (72% success rate ⮰)
5. **ML-predicted consumption** below $1.29/day (47% recall ⮰)

Note: These sources of exclusion are not independent. See attrition funnel ⮰ for details

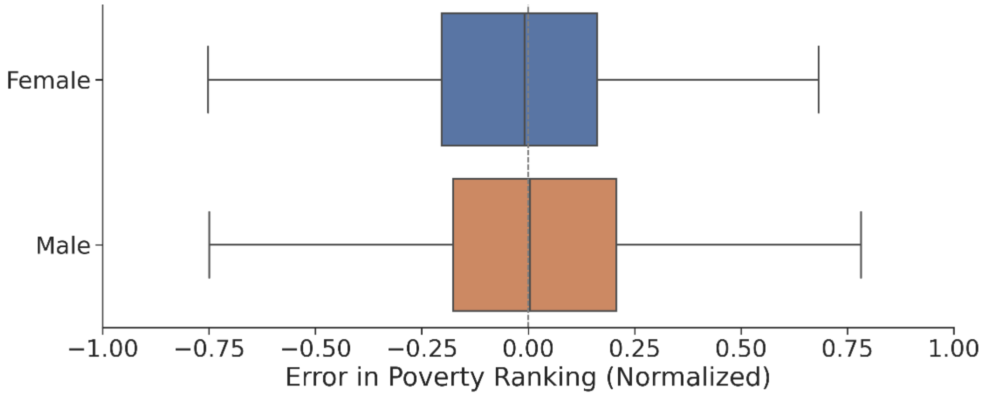
# Results (summary)

## Other key results

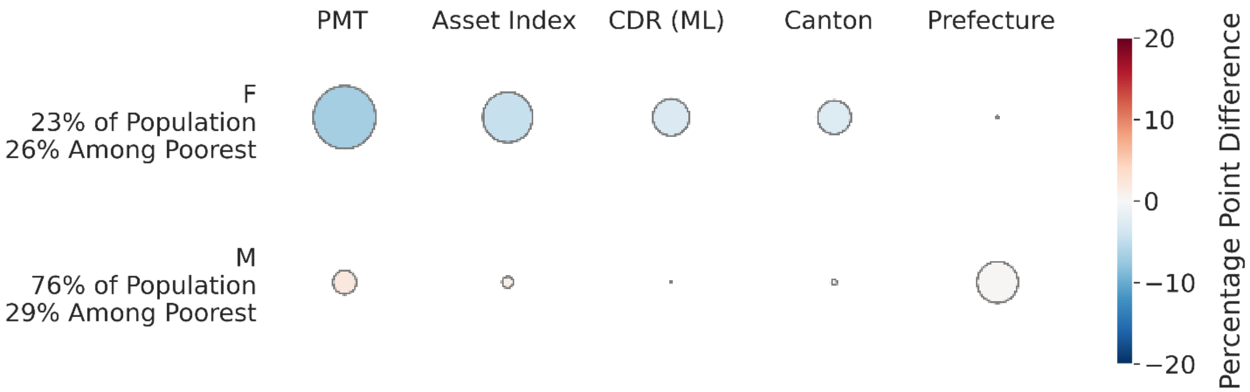
- [Welfare analysis & comparison to UBI]
- [Fairness audits and algorithmic bias]
- [Temporal stability]




**Targeting errors, by gender (phone-based approach)**




**Demographic parity by gender (all targeting approaches)**



# Discussion: Social, ethical, and practical considerations

# Discussion

This approach was accurate, fast, and cheap, particularly in a crisis

- In Togo, it improved the targeting of cash transfers

But, it is imperfect. What concerns you?

- Reaching people without phones
- Data access and data privacy
- Algorithmic biases and population representativity
- Informed consent, appeals and recourse
- Community perceptions and values
- Safeguarding against future (mis)use

Takeaway: it should **complement, not replace**, existing methods