ESTIMATING HOUSEHOLD-LEVEL ECONOMIC CHARACTERISTICS FROM HIGH-RESOLUTION SATELLITE IMAGERY

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OUTLINE

- MOTIVATION
- DATA REQUIREMENTS & DATA SOURCES
- METHODS
- RESULTS
- FUTURE WORK

caveat:

WIP

MOTIVATION

fine-grained estimates of poverty and vulnerability are important for:

- understanding economic growth and structural transformation
- tax base administration
- land and tenure management
- distribution of social protection

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- understanding economic growth and structural transformation
- tax base administration
- land and tenure management
- distribution of social protection (this work's focus)

MOTIVATION

in previous work, there is a tradeoff between *scale* and *granularity*

national-scale estimates at:

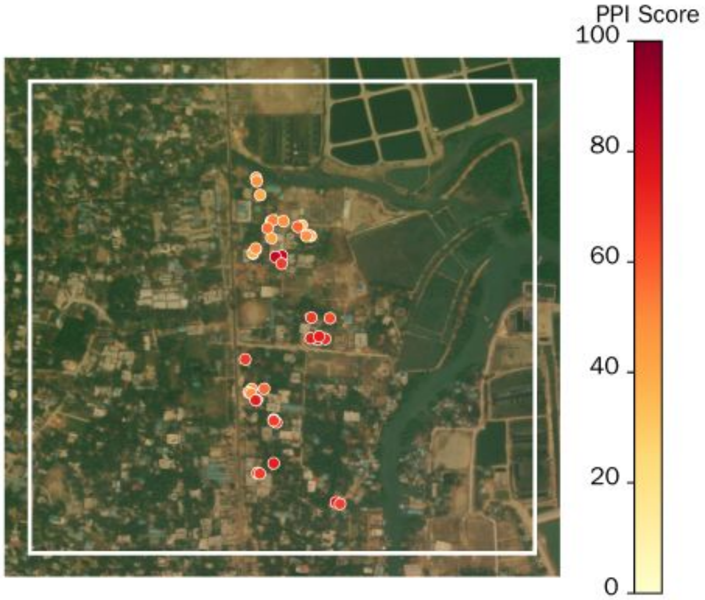
- the village level (Jean et al., 2016; Yeh et al., 2020; Engstrom et al., 2017)
- the neighborhood level (Smythe and Blumenstock, 2022)
- satellite tile level (e.g., tiles that are 1-2 square kilometres in area) (Chi et al., 2022; Rolf et al., 2021)

household-level estimation:

- single village in Kenya; $N = 231$ (Watmough et al., 2019)
- single city in China; $N = 238$ (Han et al., 2021)

No approaches using deep learning at this resolution.

MOTIVATION


PPI Score
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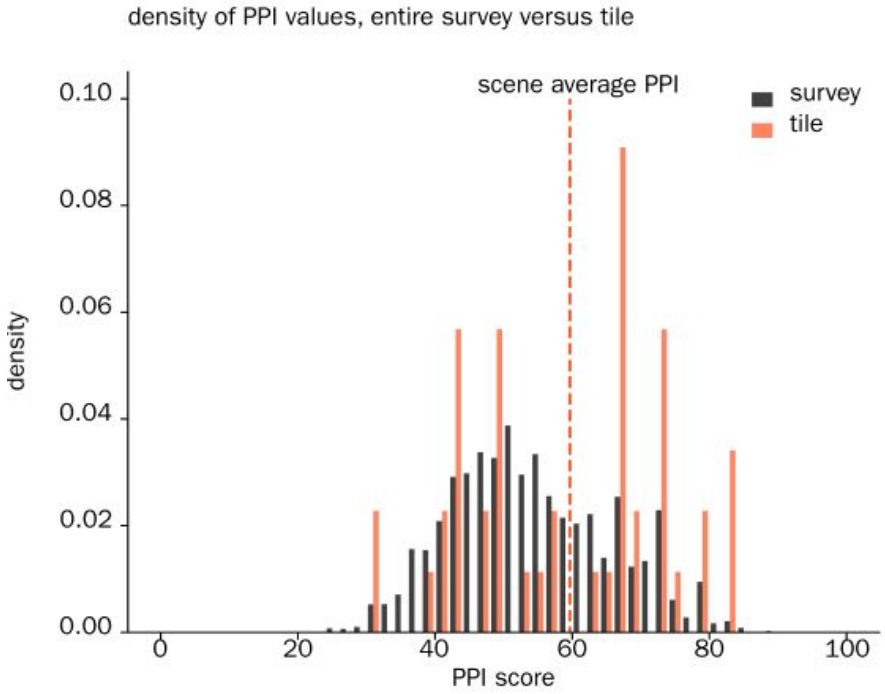
80
60
40
20
0


density of PPI values, entire survey versus tile
scene average PPI
survey
tile
density
0.00
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0.04
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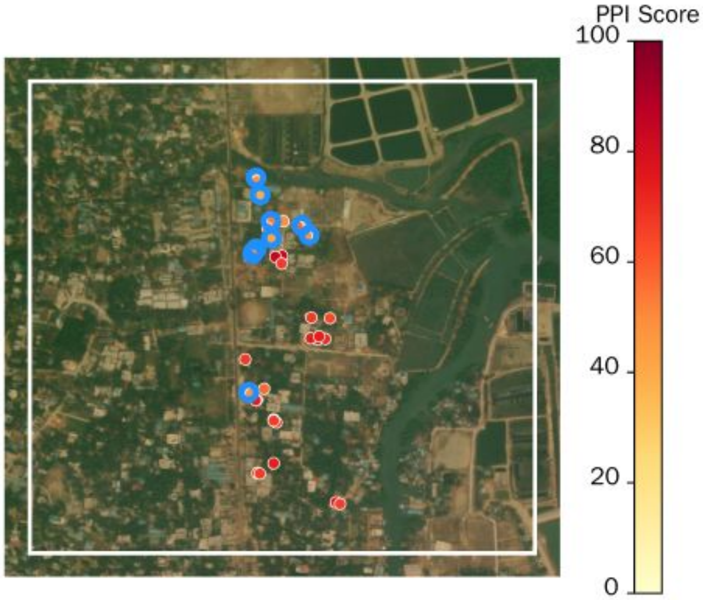
MOTIVATION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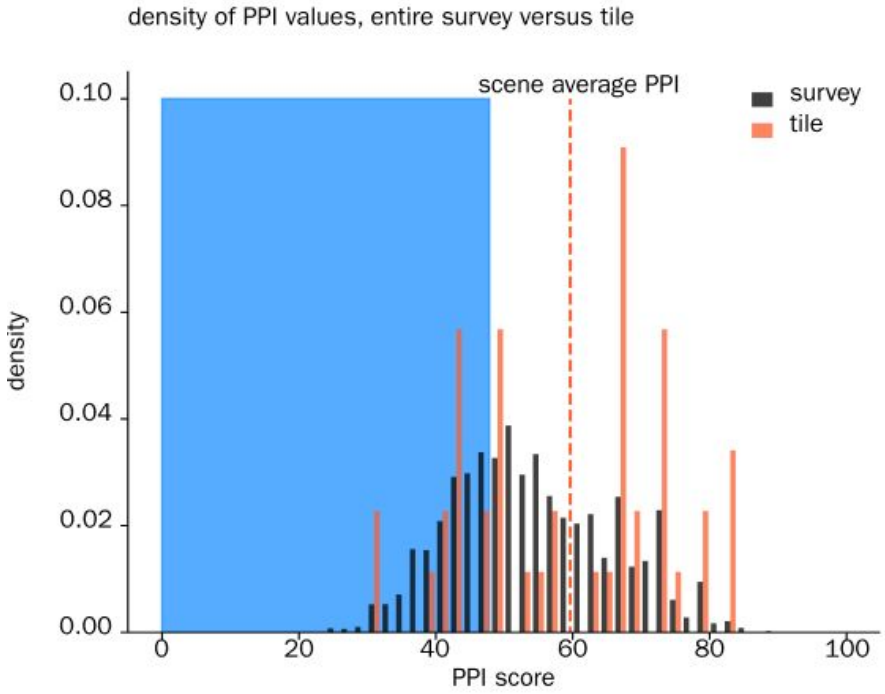
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goal:

compare expert-curated features with deep learning in predicting household level poverty

DATA: REQUIREMENTS & FUSION

	THIS WORK	OTHER OPTIONS
satellite imagery 	Google Static Maps	Maxar, DigitalGlobe, SkySat

DATA: SATELLITE IMAGERY SCALES

$z = 21$

$z = 20$

$z = 19$

DATA: REQUIREMENTS & FUSION

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satellite imagery	Google Static Maps	Maxar, DigitalGlobe, SkySat

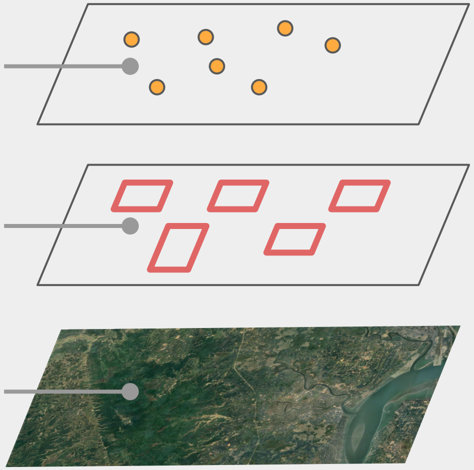
DATA: REQUIREMENTS & FUSION

building footprints

satellite imagery

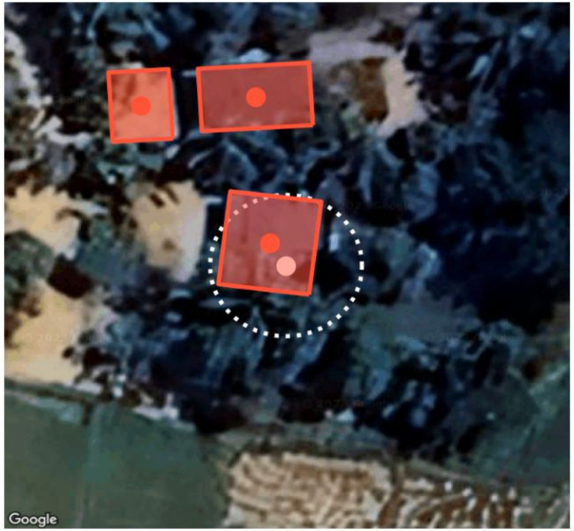
	THIS WORK	OTHER OPTIONS
building footprints	OpenBuildings	OSM, MSFT buildings, custom segmentation
satellite imagery	Google Static Maps	Maxar, DigitalGlobe, SkySat

DATA: REQUIREMENTS & FUSION

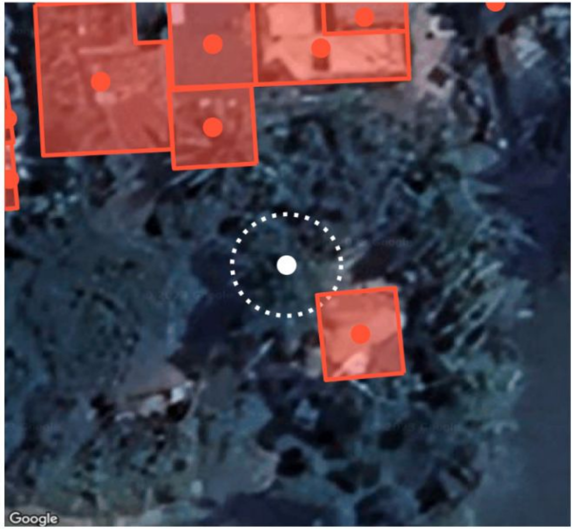


	THIS WORK	OTHER OPTIONS
ground truth labels	GiveDirectly asset survey $N_0 = 100{,}000$	LSMS, DHS
building footprints	OpenBuildings	OSM, MSFT buildings, custom segmentation
satellite imagery	Google Static Maps	Maxar, DigitalGlobe, SkySat

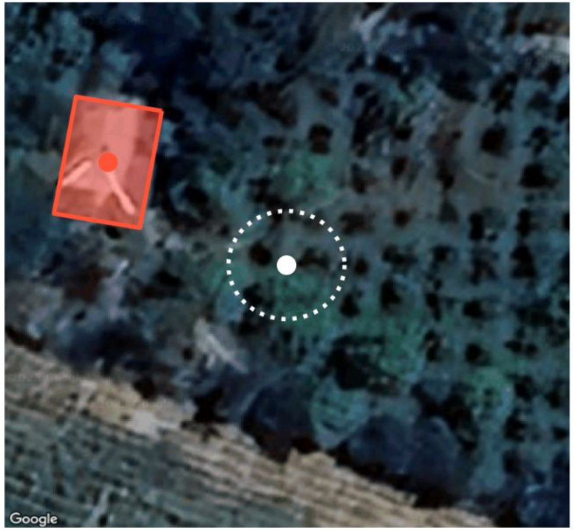
DATA: LINKING SURVEYS TO BUILDINGS



point-in-polygon



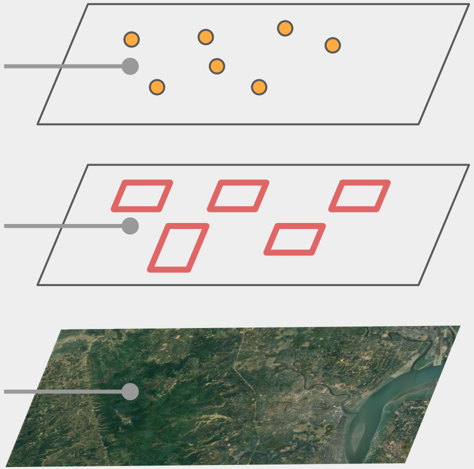
GPS buffer intersection



scene heuristic

Matched dataset: $N = 20{,}000$

DATA: REQUIREMENTS & FUSION



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METHODS: FEATURIZATION

Manually-curated features:

1. building footprint size
2. total count of buildings in scene
3. minimum distance to nearest neighboring building
4. average distance to nearest 4 neighboring buildings
5. spectral band: Red
6. spectral band: Green
7. spectral band: Blue
8. RGB 16-bit composite

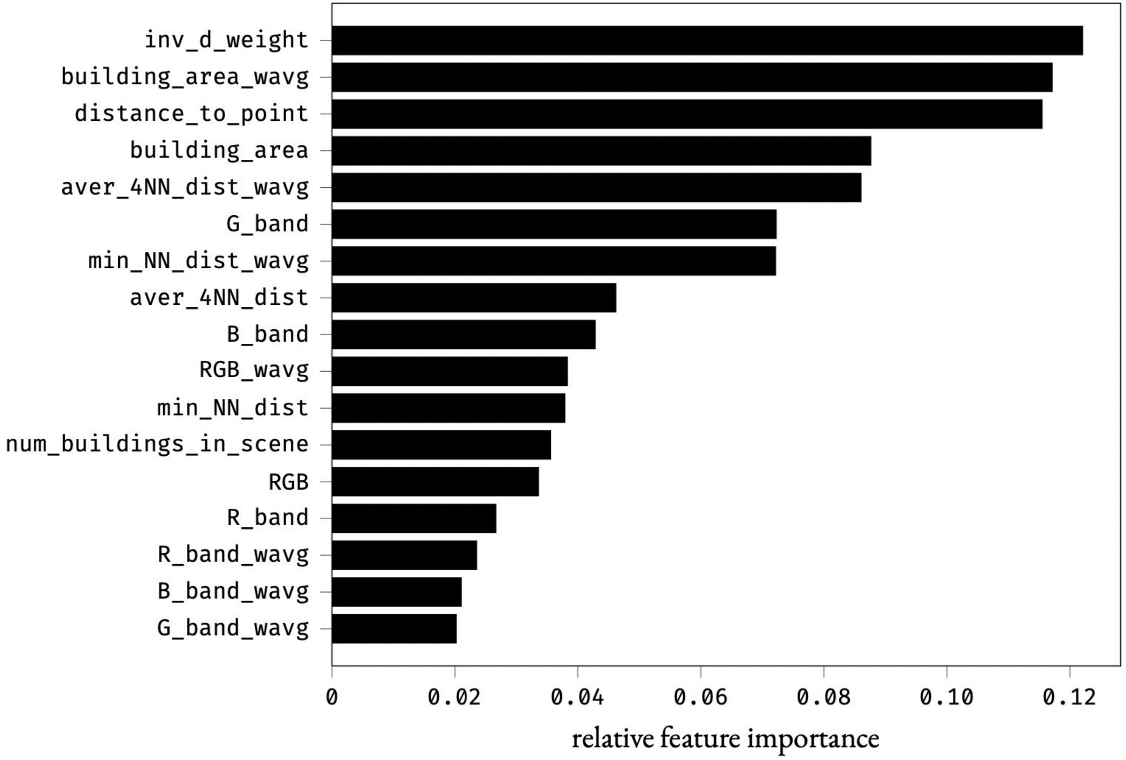
Deep-learning based approach:

- Artificial neural network image classification models trained on ImageNet fed satellite images as input
- Intermediate representations of classifier used as features
- No manual curation

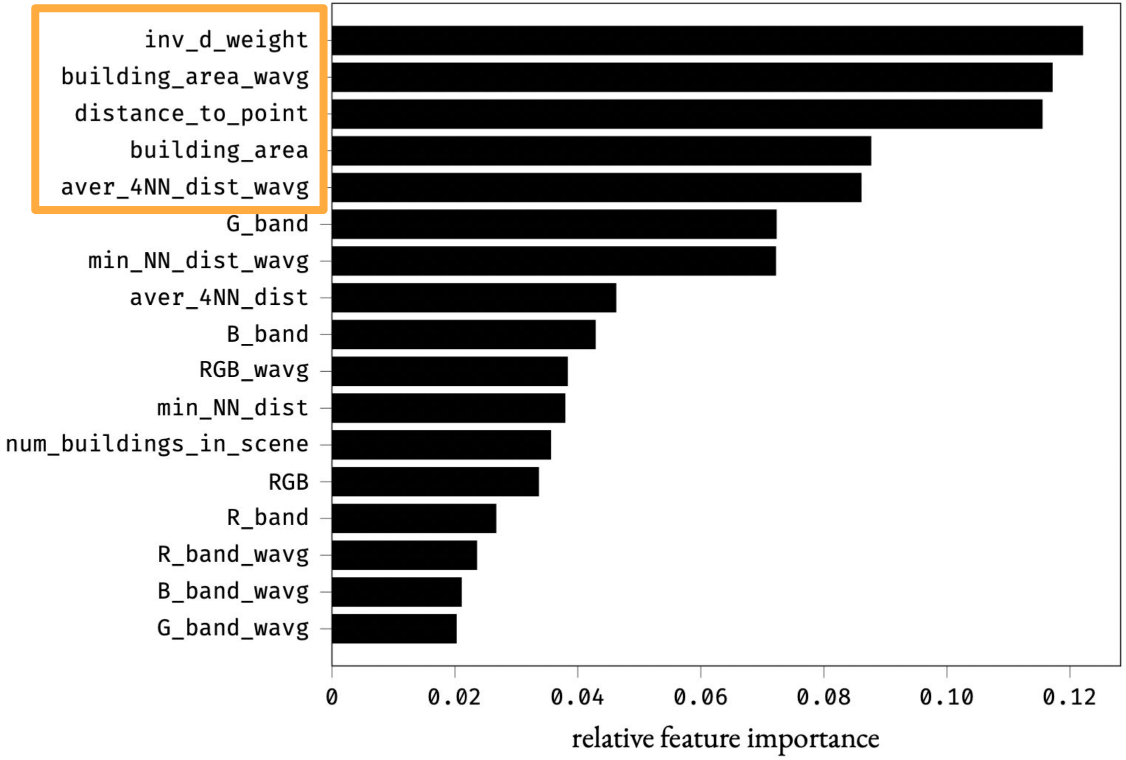
RESULTS: AGGREGATE PERFORMANCE

feature set	performance		optimal hyperparameters		
	R^2	MSE	# estimators	learning rate	maximum tree depth
explicit featurization	0.1199	121.09	100	0.1	3
ConvNeXt-featurized	0.1182	121.34	5000	0.01	none
ResNet18-featurized	0.0188	135.01	1000	0.01	1

RESULTS: FEATURE IMPORTANCE



RESULTS: FEATURE IMPORTANCE



FUTURE WORK

- Higher-resolution satellite imagery
- More manual features
- Further refinement of deep-learning (fine-tuning, apply regression heads)
- Apply techniques to similar datasets in Togo

thank you!

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Q+A