Towards Sustainable Census Independent Population Estimation in Mozambique

Isaac Neal[1], Sohan Seth[1]*, Gary Watmough[1], Mamadou Saliou Diallo[2]

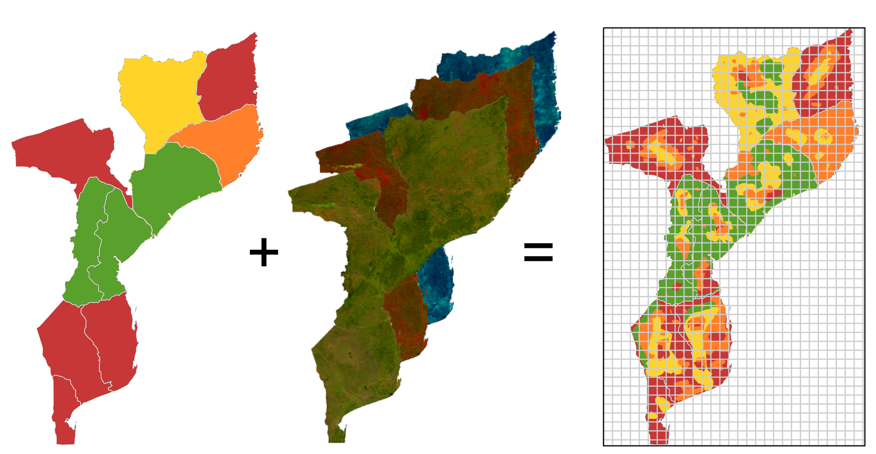
University of Edinburgh[1] and UNICEF[2]

{ineal,sseth,gary.watmough}@ed.ac.uk, mamsdiallo@unicef.org

Need for Population Estimates

Accurate fine scale population estimates serve as a fundamental tool for policymakers. Many decisions involving access to services, distribution of vaccines and disaster relief, tracking of migration, and more are informed based on the most up to date population estimates for a region. Where these estimates are of insufficient resolution, either spatially or temporally, optimal decision making becomes difficult. Thus, there is a need for accurate and sustainable fine scale estimates of population globally, particularly in response to the COVID-19 pandemic, which requires efficient distribution of vaccines to vulnerable people.

Top-down Estimation



Bottom-up Estimation

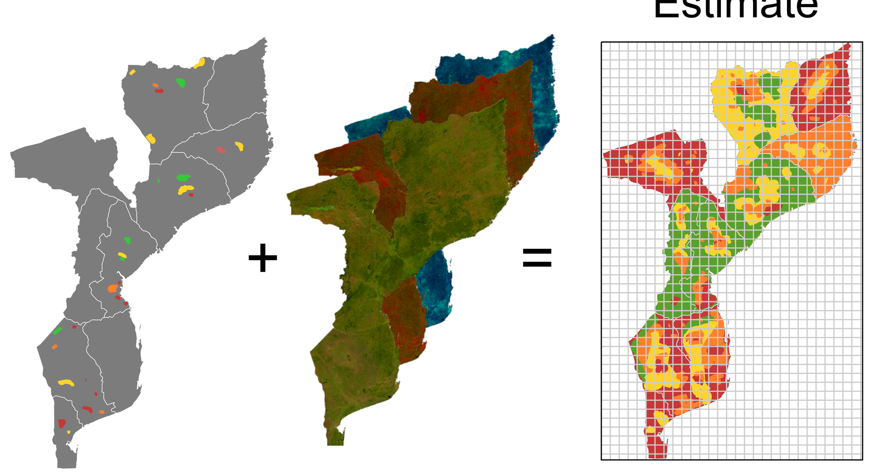
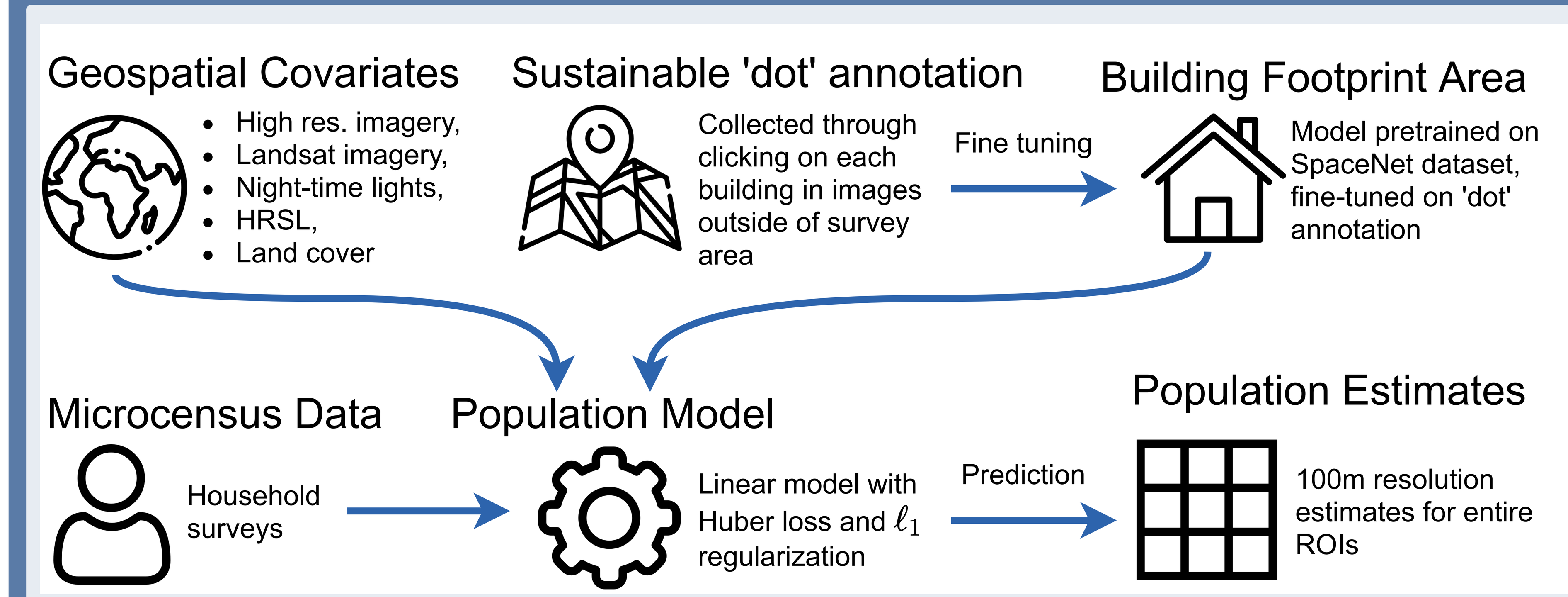


Figure 1: Top-down vs. bottom-up approach

Census-Independent Estimation

Census-independent (or bottom-up) population estimation uses updated demographic information in periodic household surveys, or *microcensuses*, and detailed visual information offered by remote sensing technology to predict intercensal population density in non-surveyed areas.

Pipeline



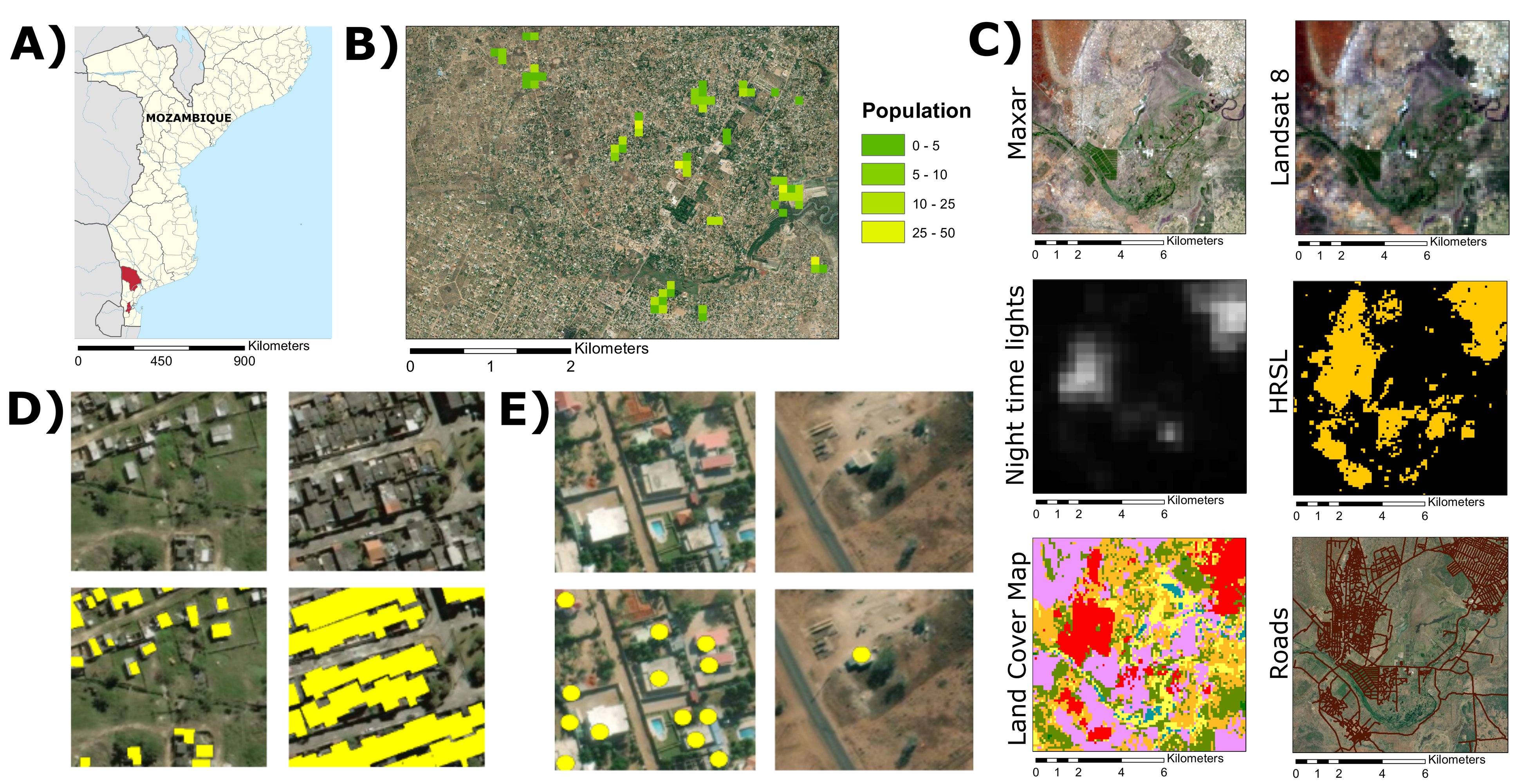


Figure 2: **A)** Regions of Mozambique (red) where microcensus was conducted, **B)** Distribution of gridded microcensus data in Boanne (BOA), **C)** Remote sensing data sources, **D)** Polygon building annotation from SpaceNet (100m tiles), **E)** Dot building annotation from Mozambique (100m tiles).

Recent Literature

Table 1: Summary of recent literature on topic of bottom up population estimation

	[1]	[2]	[3]	[4]
Region of Interest	Nigeria	Sri Lanka	Bo, Sierra Leone	Nigeria
Input Resolution	0.5m (Maxar)	10m (Polygon data) 12-30m (Urban Footprint) 750m (Night time Lights)	30m (Landsat)	0.5m (Maxar), 100m (WorldPop), various (OSM school density, household size)
Output Resolution	90m	Village level	City district level	100m
Input Data Cost	High (Maxar data)	Free (public data) High (Maxar data)	Free (public data)	Free (OSM, WorldPop) High (Maxar data)
Performance				
Validation	eTally data	Train/test split	LOOCV	Train/test split
MeAPE	-	28	11	-
R^2	0.98	0.58	-	0.26

NOTE: LOOCV = leave one out cross validation, MeAPE= median absolute percent error

Evaluation Metrics

The data is split spatially into four approximately equal sized subsets (for each ROI separately), and we reported the error metrics over pooled prediction from the four validation folds. We chose several evaluation metrics:

$$R^2 = 1 - \sum_i (y_i - \hat{y})^2 / \sum_i (y_i - \bar{y})^2$$

Median Absolute Error:

$$\text{MeAE} = \text{median}\, |y_i - \hat{y}_i|$$

Median Absolute Percent Error:

$$\text{MeAPE} = \text{median}\, |y_i - \hat{y}_i| / y_i$$

Adjusted Median Absolute Percent Error:

$$\text{aMeAPE} = \text{median}\, |y_i - \hat{y}_i| / (y_i + 10)$$

Aggregate Percent Error:

$$\text{AggPE}(A) = \left| \sum_{i \in A} y_i - \sum_{i \in A} \hat{y}_i \right| / \sum_{i \in A} y_i$$

Example Building Footprints

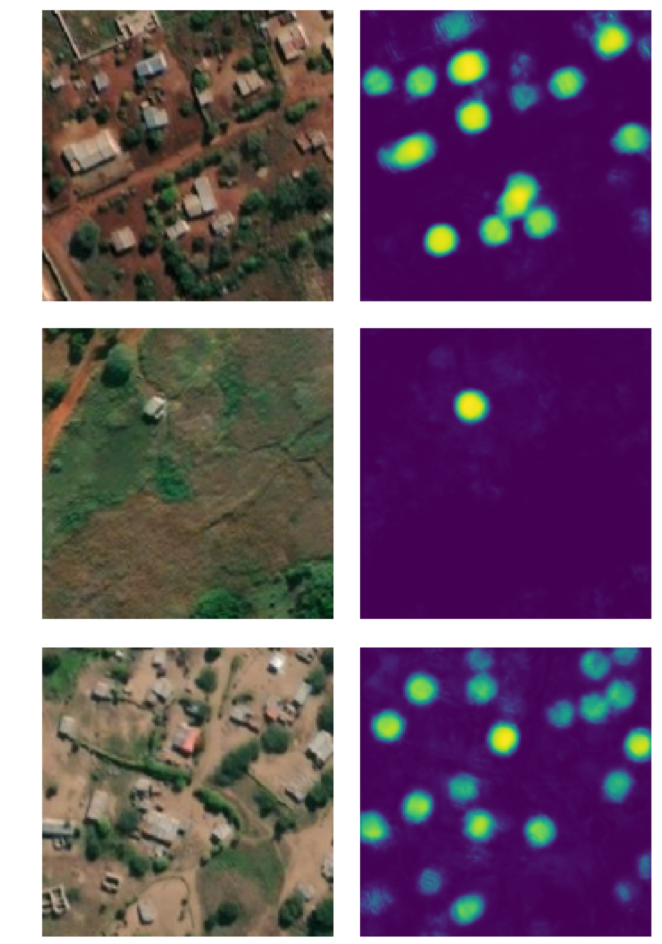


Figure 3: Example grid cells and their footprints

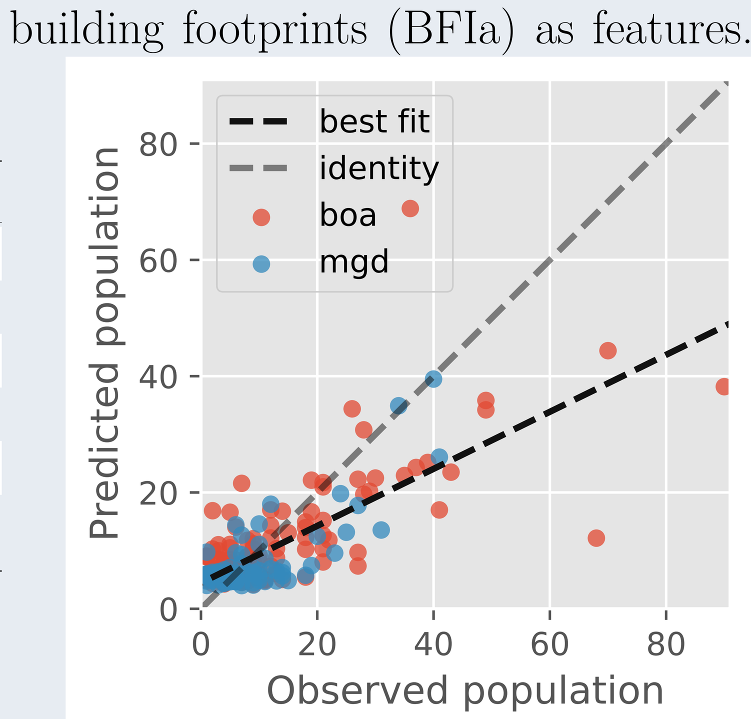
Results

We observe that the model can effectively predict population, and outperforms the null model. The model performs the best with either public and fine-tuned building footprints (BFIb) as features, or only BFIb as features, and the performances are similar. A loss in accuracy is incurred when using either public only or public and pre-trained building footprints (BFIa) as features.

Table 2: Summary of model performance

Features used	R^2	MeAPE	aMeAPE	MeAE	AggPE
Public	0.05	51.8%	0.23	3.84	25.4%
BFIa	-0.08	59.9%	0.25	4.02	32.1%
BFIb	0.54	39.2%	0.20	3.41	14.9%
Public + BFIa	0.05	50.1%	0.23	3.97	27.3%
Public + BFIb	0.53	42.1%	0.19	3.45	13.2%
Null Model	-0.12	76.45%	0.41	7.57	1.68%

See **Evaluation Metrics** above for metric definitions. BFIa and BFIb are pre-trained and fine-tuned building area estimates respectively. Predicted vs. observed plot (**right**) summarizes the results for Public + BFIb.



Takehomes

- *Census-independent* approaches have grown in popularity in an effort to address limitations of census data
- Existing literature relies heavily on features generated through human supervision
- Inexact fine-tuned building footprints can still produce high quality population predictions with limited human intervention
- A small amount of sustainable 'dot' annotation is sufficient for this fine tuning

References

[1] M Weber et al., Remote sensing of environment, 204:786–798, January 2018.

[2] R Engstrom et al. PLOS ONE, 15(8):e0237063, August 2020.

[3] R Hillson et al. International Journal of Health Geographics, 18(1):16, July 2019.

[4] D Leasure et al. PNAS, 117(39):24173–24179, September 2020.