# Contextualized Poverty Targeting through Multimodal Spatial Data and Machine Learning in Congo

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## Abstract

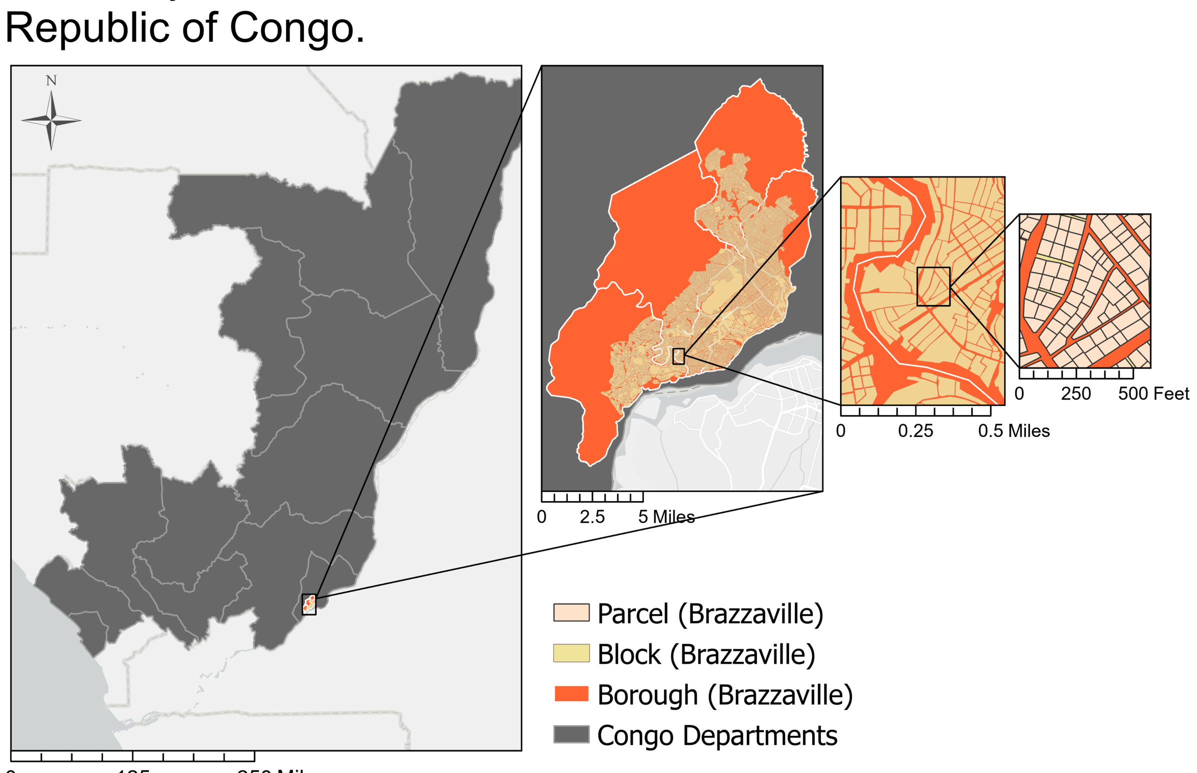
Enhancing targeting accuracy in social welfare programs can lift millions out of poverty without increasing costs. Advancements in this field harness georeferenced data and leverage AI/machine learning (ML) to predict poverty and allocate aid. However, these models that are meant to solve data sparsity are predominantly developed in countries with georeferenced national surveys and for geographic targeting. We demonstrate that micro-targeting can be achieved in data-deficient contexts lacking ground truth. Using the case of Brazzaville in Congo, we leverage intuitive multimodal data to predict multidimensional poverty at the household level. Our ML-based targeting improves traditional methods based on error metrics, targeting errors, and distribution-sensitive poverty indices. Our spatially augmented model, surpassing status quo mechanisms, can promote inclusive social welfare programs at granular levels.

## Introduction

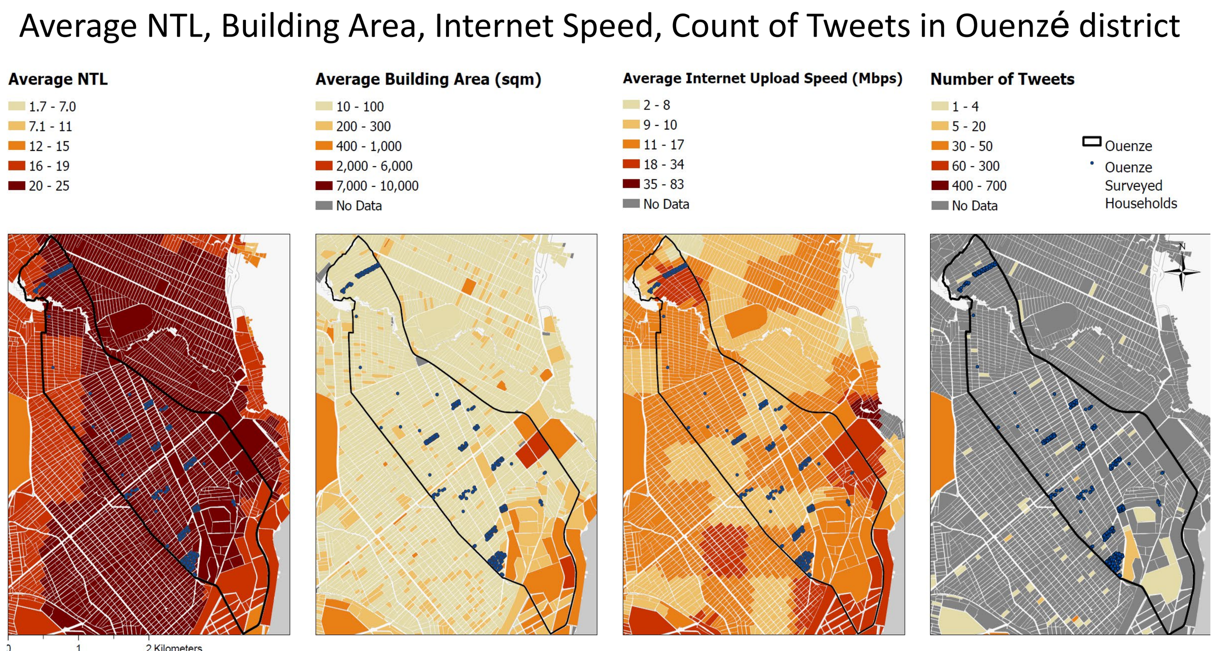
- Ironically, AI/Machine learning (ML)-based poverty models that are meant to solve data sparsity are predominantly developed in countries with georeferenced ground truth, at the national level, and for geographic targeting.
- Our study demonstrates that such a method can be developed for micro household level targeting at a low-tier sub-national scale in 'worse off' contexts, lacking georeferenced surveys.
- We demonstrate a process of developing geolocated ground truth data as well as poverty predictors from satellite imagery, social media, geographic, and administrative data in highly granular, data-deficient contexts.
- We critically examine various high performing ML models to evaluate their simulated impact on poverty alleviation.
- **Research Question:** Do new georeferenced features, when combined with ML techniques, improve upon current targeting methods?

## Data

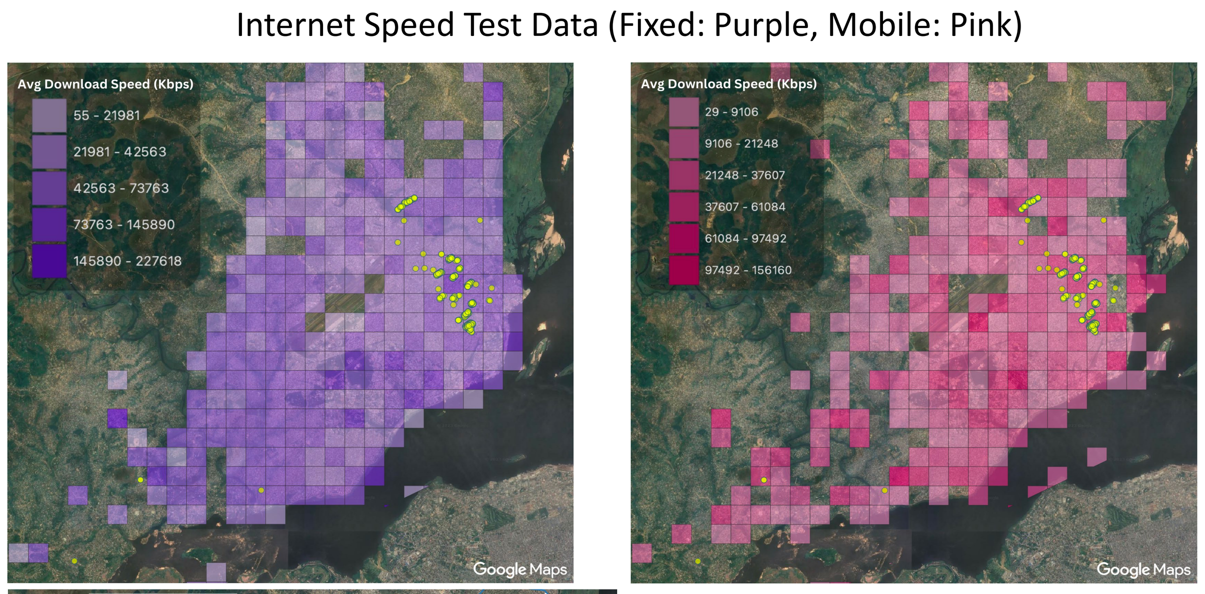
Our study is centered on the Ouenzé district in Brazzaville, Republic of Congo.




Average NTL, Building Area, Internet Speed, Count of Tweets in Ouenzé district



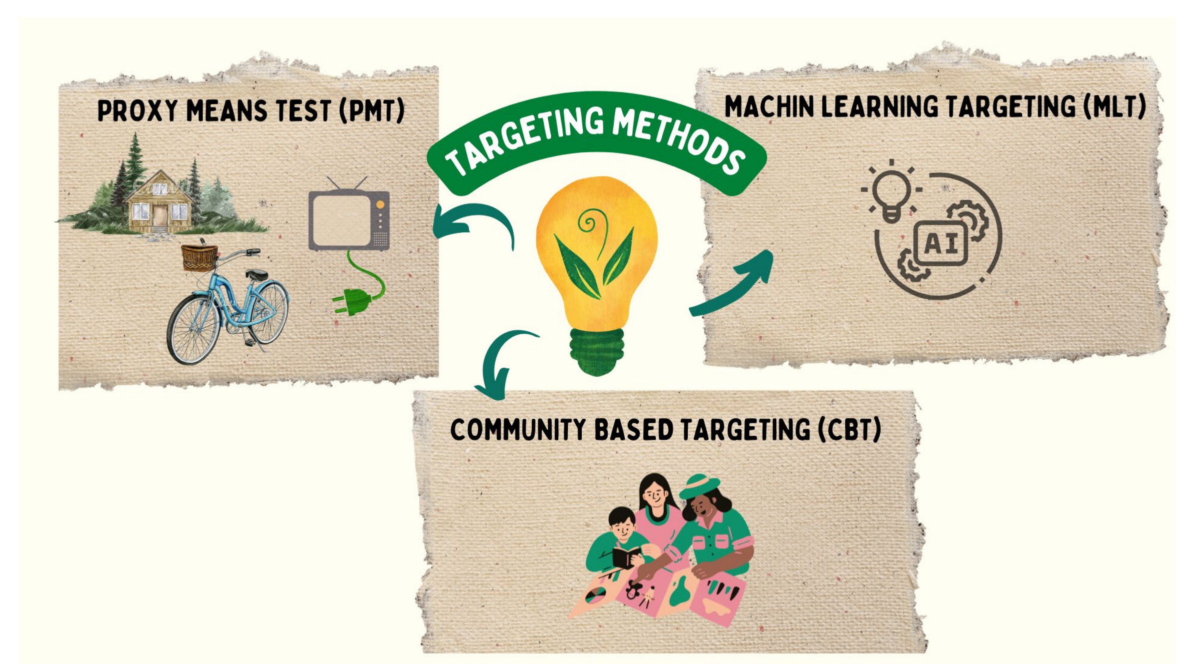

Internet Speed Test Data (Fixed: Purple, Mobile: Pink)

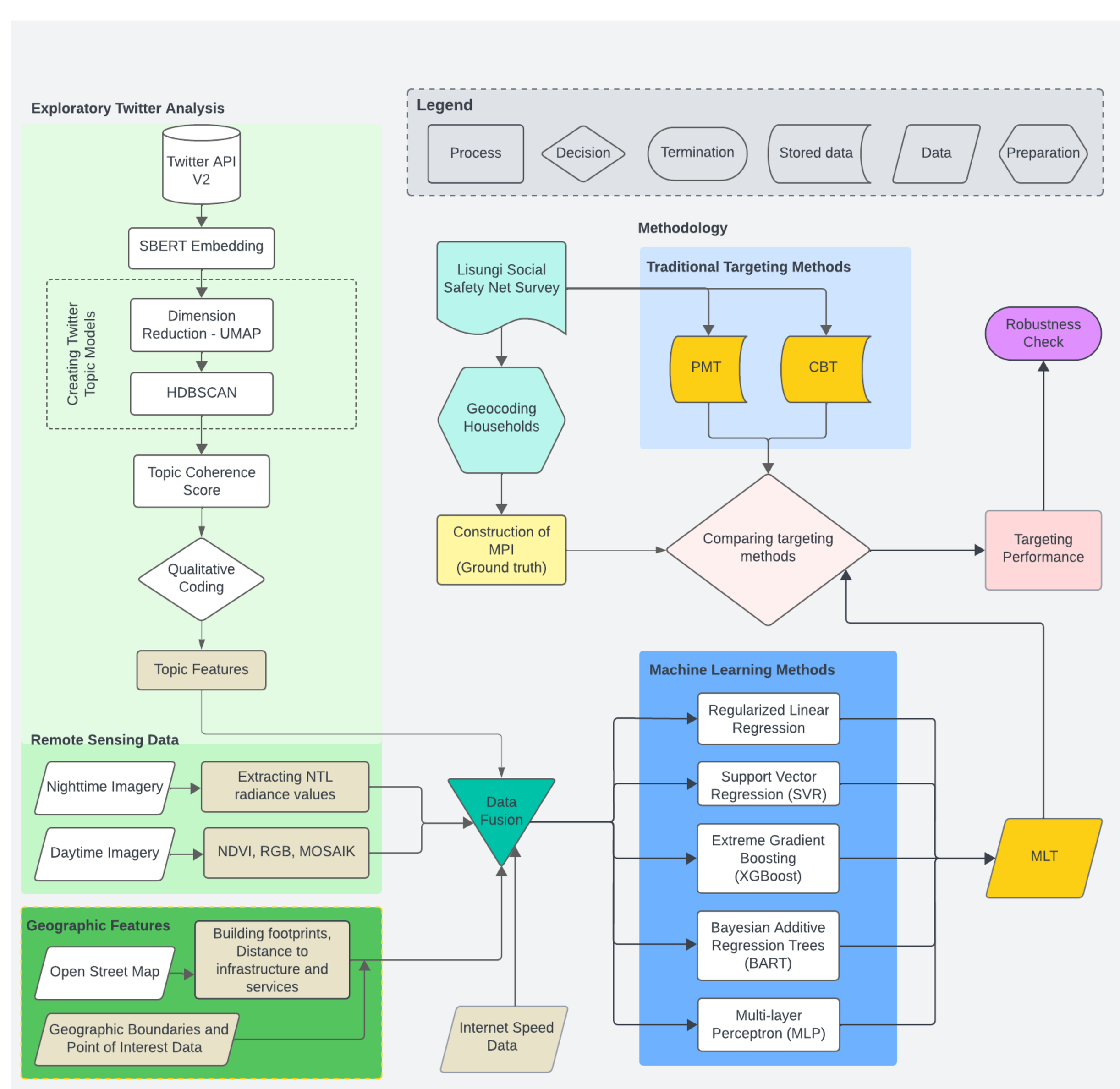




## Data

## Methodology



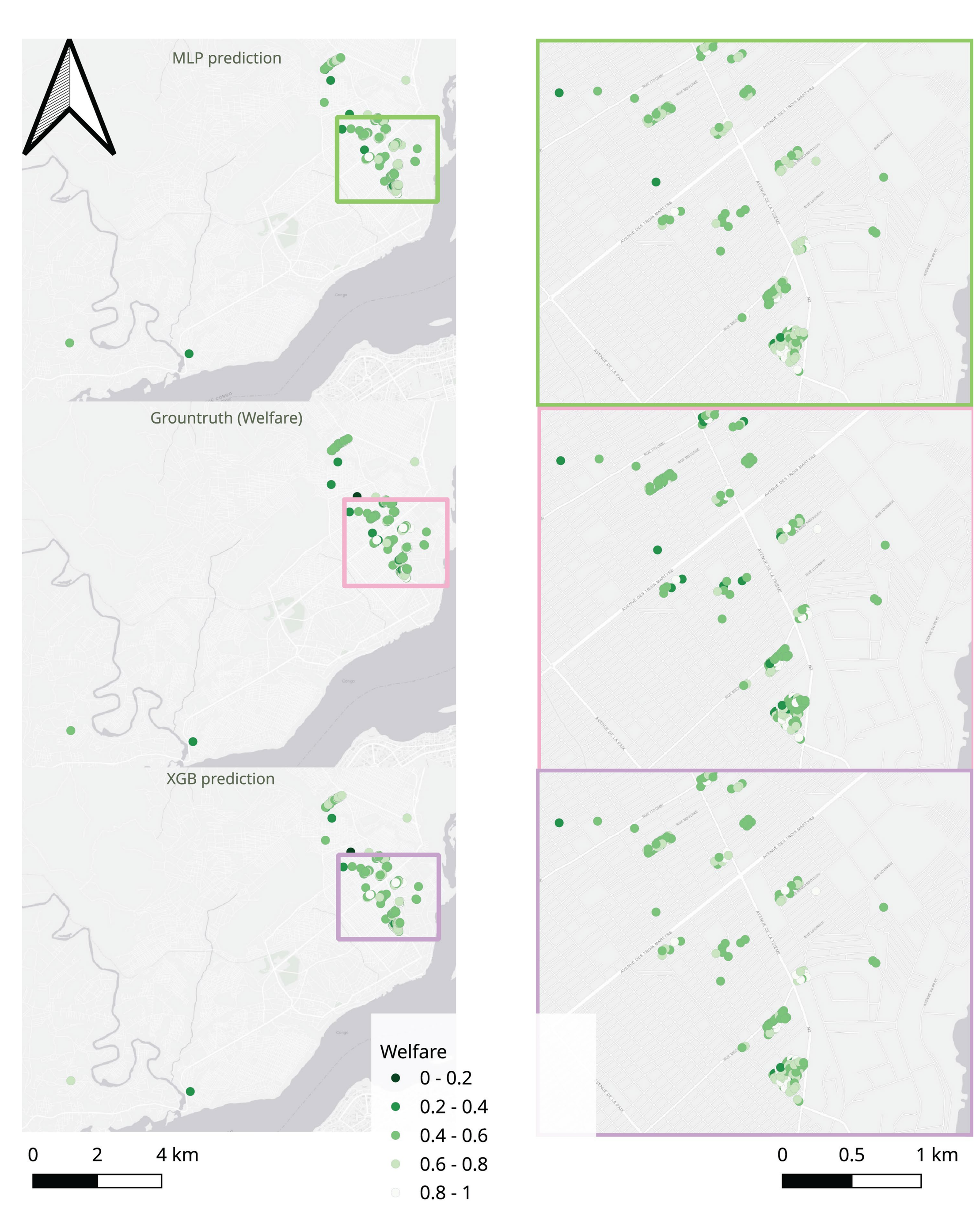

## Results 1: ML Performance

Feature sets used for prediction models

| | Extended+TW | Full | Full+DaySatImg |
|---|---|---|---|
| Family Size | x | x | x |
| CBT | x | x | x |
| PMT | x | x | x |
| Infrastructure (Infra) | x | x | x |
| Building footprints | x | x | x |
| Dist. to closest tweet | x | x | x |
| Tweet count & topics | | x | x |
| Nighttime luminosity (NTL) | | x | x |
| Internet Speeds (Int) | | x | x |
| Daytime satellite imagery (DaySatImg) | | | x |
| Num. of Variables | 15 | 84 | 88 |

Performance Metrics of Models with $R^2 > 0.700$

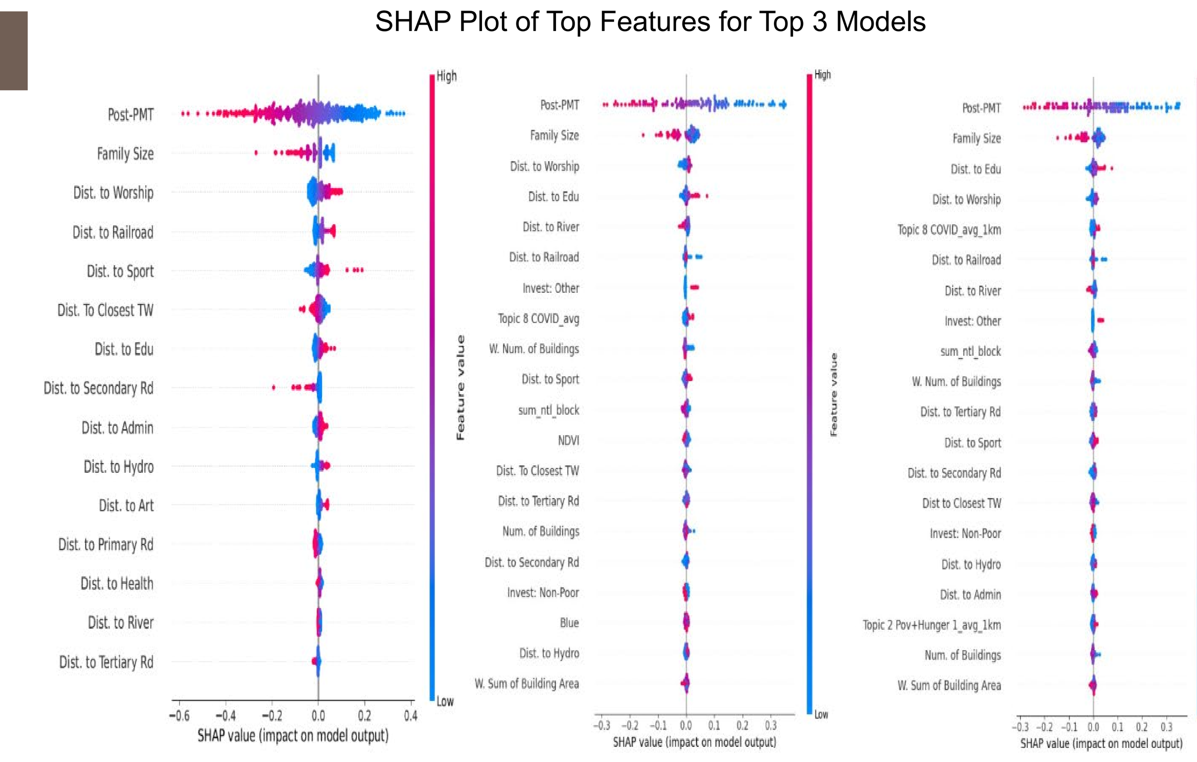
| Model | Algorithm | $R^2$ | mean val MSE | test MSE |
|---|---|---|---|---|
| Extended+TW | MLP | 0.709 | 0.012 | 0.009 |
| Full+DaySatImg | XGBoost | 0.706 | 0.014 | 0.010 |
| Full | XGBoost | 0.703 | 0.014 | 0.010 |




Comparison of Welfare Prediction Accuracy: MLP vs. Ground Truth vs. XGBoost

## Results 1: ML Performance

SHAP Plot of Top Features for Top 3 Models

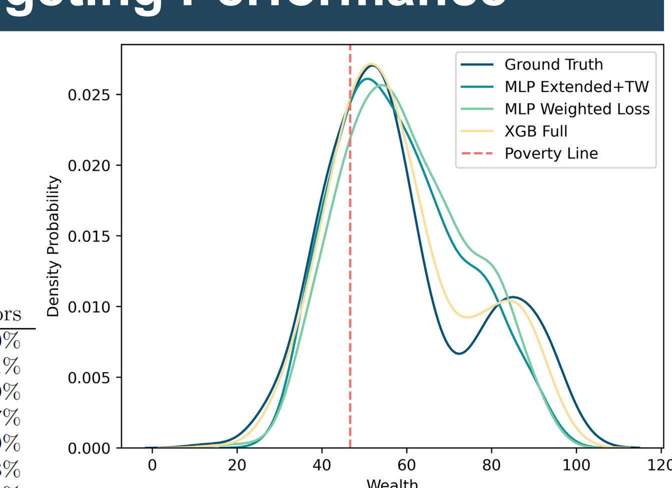


- We construct the ground truth Multidimensional Poverty Index (MPI) based on Social SafetyNet database in Congo Brazzaville and geolocate households.
- We collect and augment spatial features to the traditional targeting method, Proxy Means Test (PMT) as well as demographic information, family size.
- We employ a total of six algorithms to predict MPI using traditional and spatial features: Ridge. ElasticNet, Support Vector Regression (SVR), Extreme gradient boosting (XG Boost), Bayesian additive regression trees (BART), and Multilayer Perceptron (MLP).
- Overall, MLP with household-level distance features (distance to infrastructure, distance to Tweet) achieves the best performance ($R^2$=0.709; test MSE=0.009).
- SHAP plots show that PMT, family size, distance from infrastructure, and distance to closest Tweet features are features commonly employed among top ML models.

## Results 2: Targeting Performance

Lower targeting errors of Machine-learning Targeting (MLT) Models as Compared to Traditional Community-Based Targeting (CBT) and Proxy Means Test (PMT).

| Model | Targeting errors |
|---|---|
| Perfect | 0.0% |
| XGBoost Full | 7.1% |
| XGBoost Full+DaySatImg | 7.9% |
| MLP Extended+TW | 21.7% |
| MLP Baseline | 22.9% |
| Traditional: PMT | 23.8% |
| Traditional: CBT Invest Only | 49.2% |
| Random | 69.9% |
| Universal | NA |




The "Poverty Incidence", "Poverty Gap", "Poverty Severity" Reductions

The XGBoost full model, which uses all features except for Daytime Satellite Imagery features, is the top performer, achieving the lowest targeting error at 7.1%.

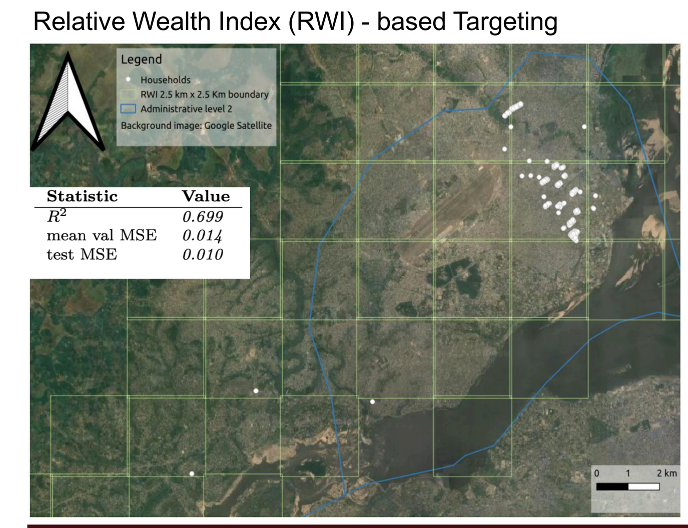
## Results 3: Poverty Reduction Impact

| Model | Features | Poverty Index (P) | Mean |
|---|---|---|---|
| Perfect | | $P_0$ | 29.49 |
| | | $P_1$ | 3.27 |
| | | $P_2$ | 0.94 |
| **XGBoost Full** | All Traditional+Infrastructure+TW+NTL+Int | $P_0$ | 27.65 |
| | | $P_1$ | 3.21 |
| | | $P_2$ | 0.93 |
| XGBoost Full+DaySatImg | All Traditional & Spatial Features+DaySatImg | $P_0$ | 27.50 |
| | | $P_1$ | 3.21 |
| | | $P_2$ | 0.93 |
| MLP Extended+TW | Family+PMT+Infrastructure & TW Dist | $P_0$ | 22.43 |
| | | $P_1$ | 2.95 |
| | | $P_2$ | 0.89 |
| MLP Baseline | Family+PMT | $P_0$ | 21.51 |
| | | $P_1$ | 2.93 |
| | | $P_2$ | 0.89 |
| Traditional: PMT | | $P_0$ | 21.51 |
| | | $P_1$ | 3.00 |
| | | $P_2$ | 0.90 |
| Traditional: CBT | CBT Investigator | $P_0$ | 13.83 |
| | | $P_1$ | 2.08 |
| | | $P_2$ | 0.68 |
| Universal | | $P_0$ | 16.28 |
| | | $P_1$ | 1.55 |
| | | $P_2$ | 0.53 |
| Random | | $P_0$ | 8.76 |
| | | $P_1$ | 1.03 |
| | | $P_2$ | 0.32 |

- Our XGBoost Full model is near the hypothetical perfect targeting method with a poverty incidence reduction of 27.65%.
- Our best MLT model makes a substantial difference in terms of simulated reduction of poverty incidence, gap, and severity.

## Robustness Check

Relative Wealth Index (RWI) - based Targeting




| Statistic | Value |
|---|---|
| $R^2$ | *0.699* |
| mean val MSE | *0.014* |
| test MSE | *0.010* |

XGBoost Full + DaySatImg Variations

| Model | R2 | Mean Val MSE | Test MSE |
|---|---|---|---|
| Sentinel-2 | 0.690 | 0.015 | 0.010 |
| 1km buffer Landsat-8 | 0.700 | 0.014 | 0.010 |
| 1km buffer Sentinel-2 | 0.702 | 0.014 | 0.010 |
| MOSAIKS | 0.645 | 0.015 | 0.012 |

Our model surpasses RWI, MOSAIK-based targeting and current actual targeting method in Congo.

Status Quo Targeting Performance

| Targeting methods | Targeting error rates |
|---|---|
| Perfect method | 0.0% |
| Status Quo | 2.6% |
| XGBoost Full | 1.1% |
| PMT | 2.4% |
| Random method | 6.7% |
| Universal method | NA |

## Conclusion

- Targeting drawn from ML techniques and geospatial features generates sizable improvements in predicting wealth.
- Machine Learning-based Targeting (MLT) also leads to considerably improved targeting error, poverty headcount, poverty gap, and poverty severity reductions.
- The accuracy of poverty prediction is greatly increased by including intuitive and fine-grained geographical data sources.
- The best predictive model may differ from the model with the best policy outcomes when evaluating models based on poverty effect measurements, such as poverty indices.
- The robust performance of our model suggests the potential of data-augmented MLT to design and scale social welfare programs in larger areas with greater spatial variation.