University of Basel

Presenting the paper: Efficient Poverty Mapping from High Resolution Remote Sensing Images

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Content

- Introduction
- The method
- The conclusion

Introduction

Questions:

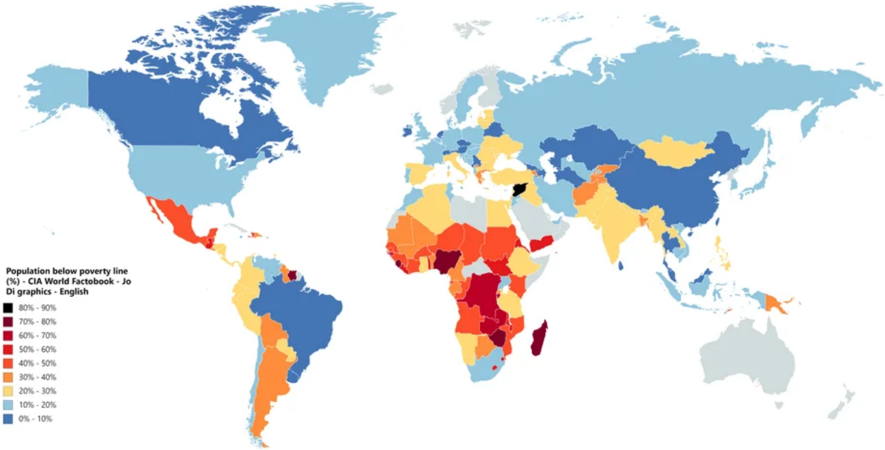
- Why do we need the data?
- How to measure the local poverty level?
- Why this method is by far the most practical and accurate?

Introduction

Different Methods:

- Consumption Expenditure

Introduction



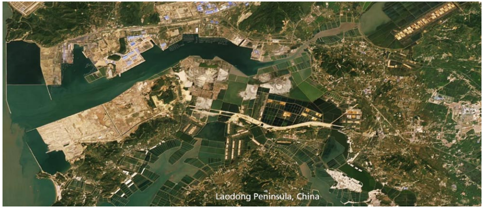
Introduction

Different Methods:

- Consumption Expenditure
- Household Surveys
- Economic Livelihoods (satellite imagery)

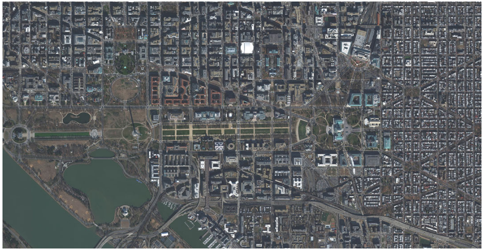
Introduction

Low-resolution satellite images



Introduction

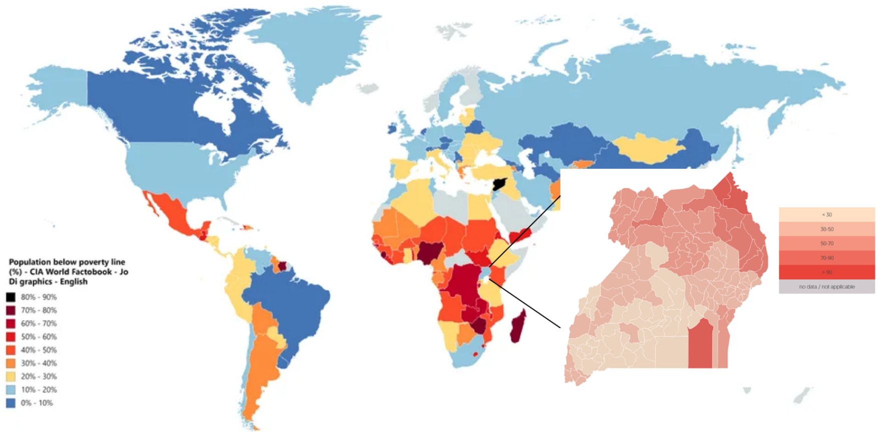
High-resolution satellite images



Introduction

- Feb 2020: *Generating Interpretable Poverty Maps using Object Detection in Satellite Images*
  https://arxiv.org/pdf/2002.01612.pdf
- Jun 2020: *Efficient Poverty Mapping using Deep Reinforcement Learning*.
  First Version of third paper including an appendix
  https://arxiv.org/pdf/2006.04224v1.pdf
- Jan 2021: *Efficient Poverty Mapping from High Resolution Remote Sensing Images*
  https://arxiv.org/pdf/2006.04224.pdf

Introduction



Inputs

Living standard measurement study (LSMS):

- Measuring household expenditure for 2'716 households
- Spatial aggregation for 320 clusters, each of size 10km$\times$10km

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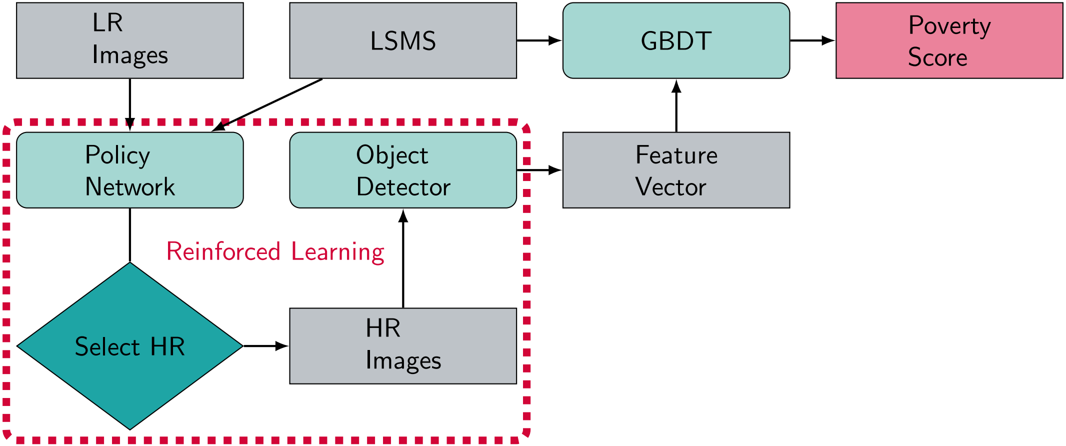
Satellite Images:

- HR image with 1000$\times$1000 pixels, 0.3m resolution
- Thus a cluster consists of $34 \times 34 = 1156$ tiles
- LR image with 1014$\times$1014 pixels, 10m resolution, divided into tiles corresponding to each HR image

Overview


LR
Images
LSMS
GBDT
Poverty
Score
Policy
Network
Object
Detector
Feature
Vector
Reinforced Learning
Select HR
HR
Images

Architecture and Training

Policy Network:

- ResNet with 32 layers, residual Networks include skipping connections
- Trained with freely available *xView* dataset: http://xviewdataset.org/

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GBDT:

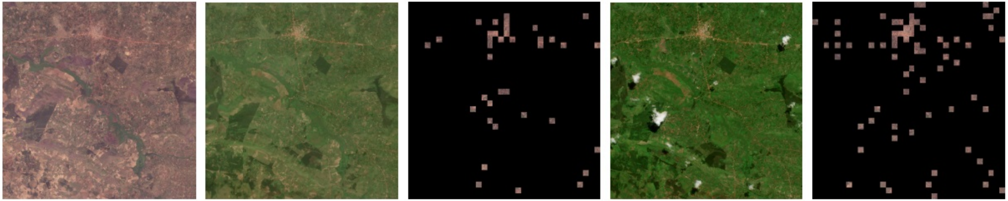
- Trained on raw object counts for 10 object classes using HR tiles and poverty score from LSMS

Results and conclusions

- Analysis based on Season.
- Quantitative Analysis.
- Impact on Interpretability.
- Cost saving.

Analysis based on Season

The presence of greenery during **wet season** allows a better identification of regions containing objects of interest, than during **dry season**.



Quantitative Analysis

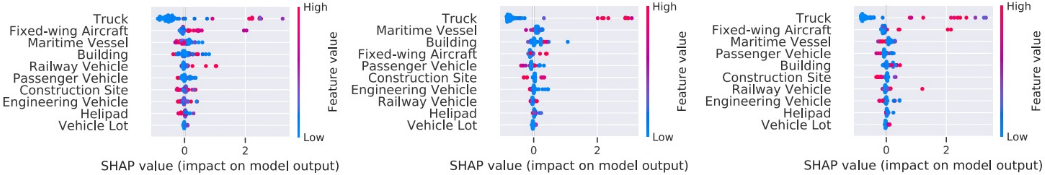
Some results of poverty prediction in Uganda.

	No Dropping	Fixed-18	Random-25	Stochastic-25	Green	Counts Pred.	Sett. Layer	Nightlights	Ours (Dry sea.)	Ours (Wet sea.)
r^2	0.53	0.43	0.34	0.26	0.33	0.49	0.45	0.45	0.51 ± 0.01	$\mathbf{0.61} \pm \mathbf{0.01}$
MSE	1.86	2.20	2.67	3.13	2.56	1.91	2.16	2.17	1.89 ± 0.02	$\mathbf{1.46} \pm \mathbf{0.02}$
Explained Variance	0.54	0.43	0.33	0.27	0.36	0.48	0.46	0.45	0.50 ± 0.01	$\mathbf{0.63} \pm \mathbf{0.02}$
HR Acquisition.	1.0	0.18	0.25	0.25	0.19	0.19	0.19	0.12	0.19	**0.19**

Our model outperforms the "No Dropping" model, using more or less **80 percent** fewer HR images.
Also relying on data layers such as **settlement** and **nightlights**! (+ **0.16** r^2)

Impact on Interpretability

An important contribution of Ayush et al's method was to introduce **model interpretability**: that allows successful application in different domains.



(a) No Dropping (b) Ours (Dry Season) (c) Ours (Wet Season)

Our method obtains practically the **same** SHAP values of the "No Dropping" method, for every feature.

Cost saving

Considering that:

- Current pricing for HR RGB imagery: **10-20 dollars per km^2**.
- Land area of Uganda: **240k km^2**.

If we set 15 dollars, an average imagery price, for each km^2...

Cost saving

...we reach a cost save of roughly **2.9 million dollars**!

This represents a potentially larger cost saving if our approach is scaled at a country or continent scale.

Connection to our seminar

- Computational sustainability?
- AI?
- Social Good?

Connection to our seminar

- Computational sustainability?

  $\Rightarrow$ Yes
- AI?

  $\Rightarrow$ Yes
- Social Good?

  $\Rightarrow$ Yes

Questions?

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