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A Machine Learning Approach to Map the Poor and Non-Poor Buildings in Developing Countries

Bhanu Prasad Chintakindi[1] and Akiyuki Kawasaki[1]

[1]The University of Tokyo

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Abstract

The most reliable way to develop poverty maps is through household surveys. However, in many developing countries, economic data from household surveys are infrequent. As a result, a data gap has emerged, making it impossible to identify and understand the locations of poor people. New approaches that integrate household survey data with non-traditional data sources (such as satellite imagery, call records, Wikipedia, google street view) using machine learning allows for improved resolution and scale in poverty mapping. Nevertheless, these studies developed poverty maps for study areas located in the same geographical region and did not map the location of poor people at the finest level (building level). Integrating income level from household survey data and building footprints from OpenStreetMap data with high-resolution satellite imagery, we extract the building rooftop images and classify them into two classes as poor($<=$ \$5.50/day) and non-poor($>$ \$5.50/day) based on the international poverty lines given by the world bank. We use these rooftop images as training data, develop a deep learning classification model, and estimate whether a building is poor or non-poor. We use physical factors like building area, elevation with rooftop images for transfer learning to contribute to the model's accuracy. We attempt to build a versatile model that maps the locations of poor and non-poor people at the building level by developing, calibrating, and validating the model for Myanmar, Thailand, and Nicaragua study areas. Our findings show that for the model to travel well intra-regionally and inter-regionally, the study areas should be from the same geographical regions with similar roof types and percentages of people living in poverty. Combining the rooftop with income level is a fitting parameter to measure poverty, and roof color plays a crucial role along with the roof texture, shape to increase the model's accuracy. The proposed methodology helps develop poverty maps for different income levels (\$1.90, \$3.20, \$21.70, or any desired income level) from limited household survey data. This research study identifies the location and the total number of poor households living in a specific region which helps plan for effective poverty reduction, urban planning, and disaster prevention tailored to local conditions.

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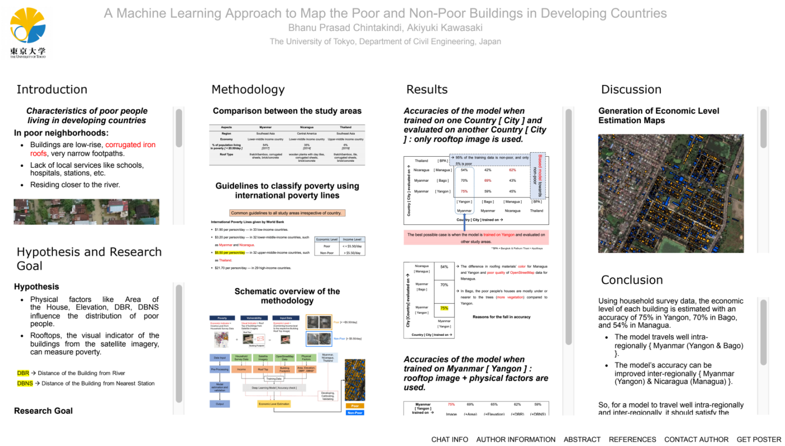

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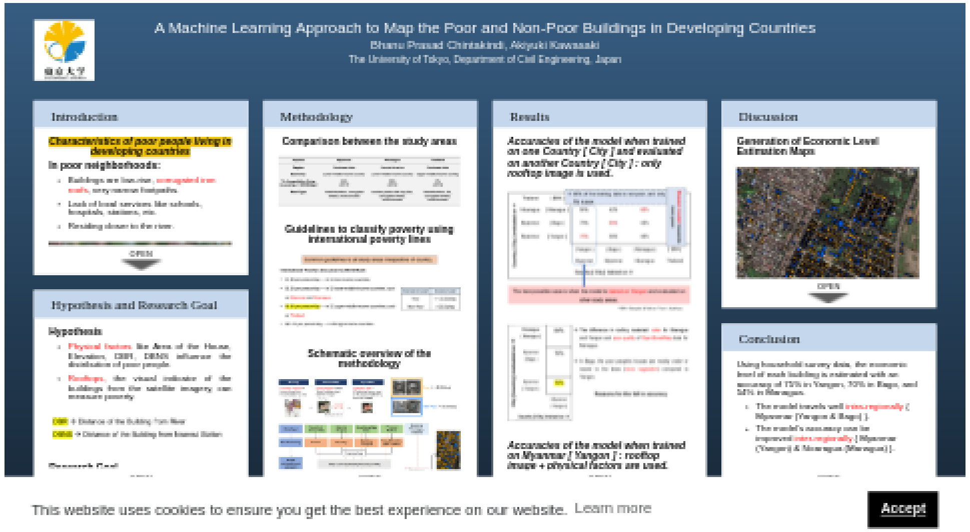

Bhanu Prasad Chintakindi, Akiyuki Kawasaki

The University of Tokyo, Department of Civil Engineering, Japan

PRESENTED AT:

INTRODUCTION

Characteristics of poor people living in developing countries

In poor neighborhoods:

- Buildings are low-rise, corrugated iron roofs, very narrow footpaths.
- Lack of local services like schools, hospitals, stations, etc.
- Residing closer to the river.

In planned areas:

- Buildings are often more significant, brick/concrete roofs, more regularly spaced, gridded road networks.

HYPOTHESIS AND RESEARCH GOAL

Hypothesis

- Physical factors like Area of the House, Elevation, DBR, DBNS influence the distribution of poor people.

- Rooftops, the visual indicator of the buildings from the satellite imagery, can measure poverty.

DBR → Distance of the Building from River

DBNS → Distance of the Building from Nearest Station

Research Goal

- Develop a versatile model to map the locations of poor people based on their living conditions in developing countries.

METHODOLOGY

Comparison between the study areas

Aspects	Myanmar	Nicaragua	Thailand
Region	Southeast Asia	Central America	Southeast Asia
Economy	Lower-middle income country	Lower-middle income country	Upper-middle income country
% of population living in poverty *[< $5.50/day]*	54% *[2017]*	35% *[2014]*	6% *[2019]*
Roof Type	thatch/bamboo, corrugated sheets, brick/concrete	wooden planks with clay tiles, corrugated sheets, brick/concrete	thatch/bamboo, tile, corrugated sheets, brick/concrete

Guidelines to classify poverty using international poverty lines

Common guidelines to all study areas irrespective of country.

International Poverty Lines given by World Bank

- $1.90 per person/day — in 33 low-income countries.
- $3.20 per person/day — in 32 lower-middle-income countries, such as Myanmar and Nicaragua.
- $5.50 per person/day — in 32 upper-middle-income countries, such as Thailand.
- $21.70 per person/day — in 29 high-income countries.

Economic Level	Income Level
Poor	< = $5.50/day
Non-Poor	> $5.50/day

Schematic overview of the methodology

RESULTS

Accuracies of the model when trained on one Country [City] and evaluated on another Country [City] : only rooftop image is used.

Country [City] evaluated on →		Myanmar [Yangon]	Myanmar [Bago]	Nicaragua [Managua]	Thailand [BPA]
Thailand	[BPA]				
Nicaragua	[Managua]	54%	42%	62%	
Myanmar	[Bago]	70%	69%	43%	
Myanmar	[Yangon]	75%	59%	45%	

Country [City] trained on →

→ 95% of the training data is non-poor, and only 5% is poor

Biased model towards non-poor

The best possible case is when the model is trained on Yangon and evaluated on other study areas.

**BPA = Bangkok & Pathum Thani + Ayutthaya

City [Country] evaluated on ↑	
Nicaragua [Managua]	54%
Myanmar [Bago]	70%
Myanmar [Yangon]	75%
Country [City] trained on →	Myanmar [Yangon]

→ The difference in roofing materials' color for Managua and Yangon and poor quality of OpenStreetMap data for Managua.

→ In Bago, the poor people's houses are mostly under or nearer to the trees (more vegetation) compared to Yangon.

Reasons for the fall in accuracy

Accuracies of the model when trained on Myanmar [Yangon] : rooftop image + physical factors are used.

Myanmar [Yangon] trained on →	75%	69%	65%	62%	59%
Physical Factors →	Image	(+Area)	(+Elevation)	(+DBR)	(+DBNS)

The model's accuracy has gradually fallen from 75% (only Image) to 69% ~ 59% (Image + Physical Factors), implying that the physical factors do not increase the model's accuracy.

- There is no clear relationship between the household's income with their respective area of the house.
- The relationship between elevation and income changes with the locality because in some cases, poor people live in flood-prone low land areas, while in other cases, they live in mountainous areas.
- In some places, the poor people live closer to the river/station, and in other places, the non-poor people reside closer to the river/station depending upon the economy of that place. This tells us that the relationship between DBR and DBNS with income level is complicated.

Hypothesis and Findings

Hypothesis	Findings
Physical factors like Area of House, Elevation, DBR, DBNS influences the distribution of poor people.	• When physical factors are used, the model's accuracy has fallen. • The distribution of poor people is heterogeneous has been clarified.
Rooftops, the visual indicator of the buildings from the satellite imagery, can be used to measure poverty.	• Rooftop combined with Income Level is a good parameter to measure poverty. • Roof color also plays a crucial role along with the roof texture, shape, etc., to increase the model's accuracy.

DISCUSSION

Generation of Economic Level Estimation Maps

- This township is made up mainly of middle-class and working-class neighborhoods.

- From (Forbes 2019) and (Htay Naing, 1980): It is mentioned that in this area, both poor and non-poor people lived together without segregation historically.

- The results obtained from the model show the same with a combination of blue and yellow buildings with majorly yellow buildings.

Summary

The proposed methodology will help us in

- Combatting poverty and inequality simultaneously by identifying who is most at risk or how support should be prioritized.
  - e.g., Identifying houses that are vulnerable to disasters like floods.
- From our results, we can determine the location and the total number of poor households living in a specific region.
- We can also identify areas with particularly high concentrations of poor people.
- Such information helps plan for effective poverty reduction, urban planning, and disaster prevention tailored to local conditions.
- Our methodology can be used to develop poverty maps for different income levels * ($1.90, $3.20, $5.50, $21.70, or for any desired income level) from a limited number of household survey data.

Therefore, this approach will contribute to effective poverty reduction in many aspects.

CONCLUSION

Using household survey data, the economic level of each building is estimated with an accuracy of 75% in Yangon, 70% in Bago, and 54% in Managua.

- The model travels well intra-regionally { Myanmar (Yangon & Bago) }.

- The model's accuracy can be improved inter-regionally { Myanmar (Yangon) & Nicaragua (Managua) }.

So, for a model to travel well intra-regionally and inter-regionally, it should satisfy the following boundary conditions:

- Study areas should be from the same geographical regions *(like Myanmar and Thailand), which has similar roof type, and

- Study areas should have the same economic levels *(like Myanmar and Nicaragua are the lower-middle-income countries), which has more % of people living in poverty (compared to Thailand, which is an upper-middle-income country).

AUTHOR INFORMATION

Bhanu Prasad Chintakindi, Department of Civil Engineering, The University of Tokyo, Japan

Akiyuki Kawasaki, Department of Civil Engineering, The University of Tokyo, Japan

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