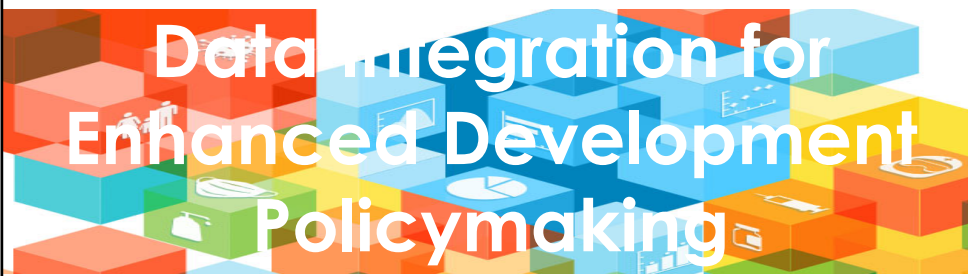


Resilience Month



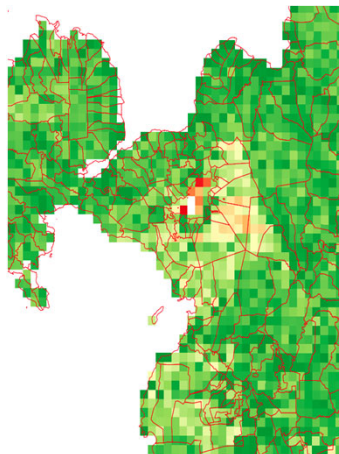
**Data Integration for
Enhanced Development
Policymaking**

**Mildred Addawe, Joseph Albert Nino Bulan,
Ron Lester Durante, Jayzon Mag-atas,
and Arturo M. Martinez Jr.**
Statistics and Data Innovation Unit
Economic Research and Regional Cooperation Department
Asian Development Bank

1

We need accurate, reliable, timely, and granular data!

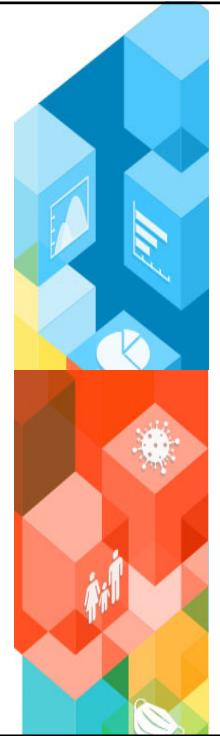
- ❑ Having granular data on poverty can facilitate more targeted poverty intervention programs.
- ❑ Official data on poverty are typically sourced from household surveys on income and expenditure.
- ❑ To enhance its granularity, ideally, sample sizes of surveys need to be increased. However, this is not always a practical option for national statistical systems with limited resources.
- ❑ New types of data can be integrated with traditional sources of poverty data to enhance granularity.



2

Outline

- ❑ Socioeconomic Impact of COVID-19 Pandemic
- ❑ Integrating Multiple Data Sources for Poverty Mapping
- ❑ Using Computer Vision Algorithms to Map the Spatial Distribution of Poverty
- ❑ Key Findings
- ❑ Moving Forward



3



Developing Asia had a remarkable poverty reduction scorecard over the past few decades, contributing less to global poverty.

4



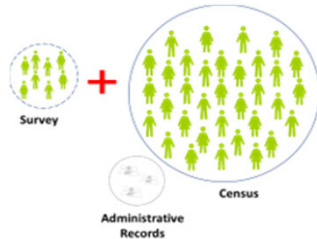
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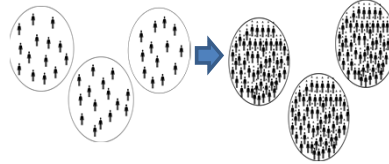
Combining Multiple Data: Small Area Poverty Estimation Approaches

Data Inputs

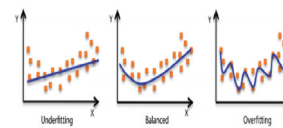


SAE Process

- Which X's are available in both survey and census / auxiliary data?



- Estimate an income / consumption model



- Fit model parameters into census data
- Predict poverty at small area level

7

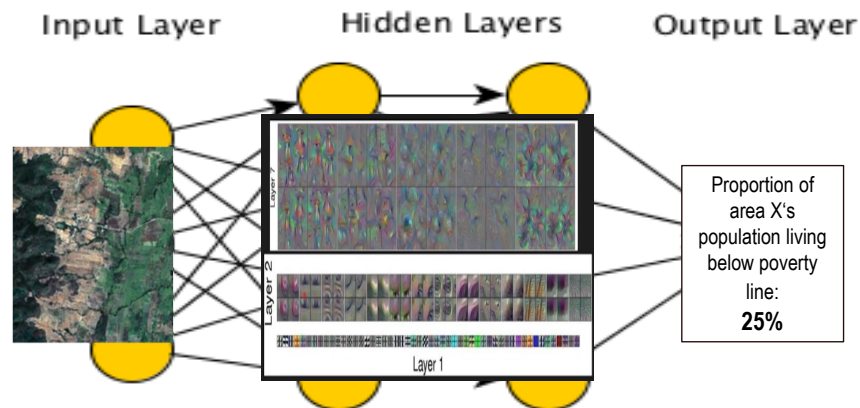
Satellite Imagery provides rich information on poverty in an area.



8

Methods: Using AI for Poverty Mapping

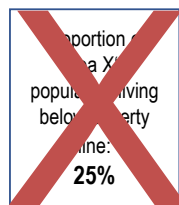
Our objective is to leverage on state-of-the-art computer vision technique, i.e., Convolutional Neural Network, and train it to predict the level of poverty by learning abstract patterns or features from satellite imagery.



9

Methods: Using AI for Poverty Mapping

CNN requires volumes of poverty-labelled images as input data for training which we do not have!



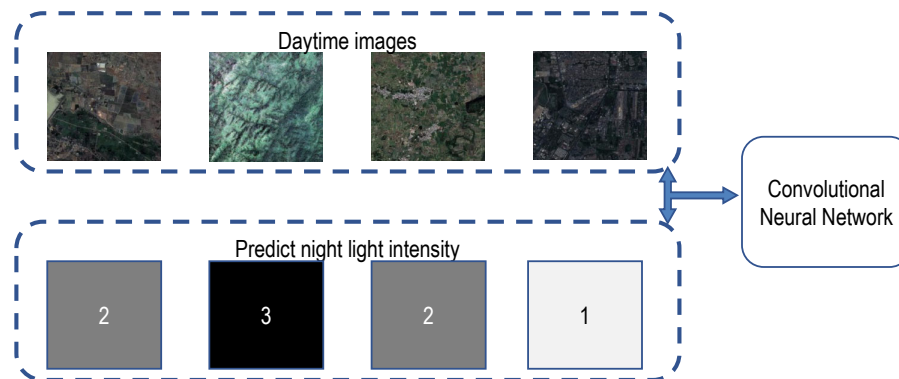
Poverty statistics are typically derived from hhld surveys which are designed to provide reliable estimates at national, regional, or provincial-levels only.

Other countries using small area estimation techniques by combining hhld survey with census to provide village or district-level estimates but SAE has technical complications too, and in some cases, even the number of SAEs is not enough to train a CNN.

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Methods: Using AI for Poverty Mapping



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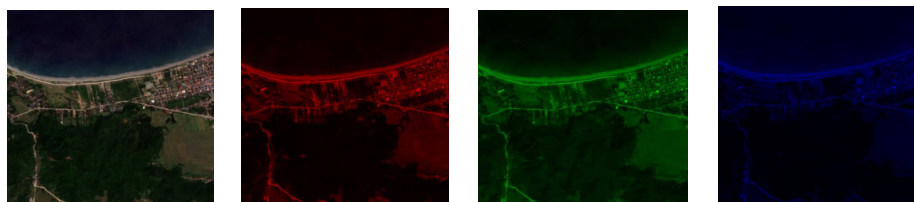
11

Applying on PHI and THA data

We use the estimated proportion of population living below the national poverty line as compiled by the Philippine Statistics Authority and National Statistical Office of Thailand through SAE techniques.

The input data were obtained using georeferenced and tagged image files. These image files are stored in three-dimensional arrays, with each pixel represented in red, green, and blue color bands.

Figure. Image Color Bands within a Georeferenced Image File



Source: Sentinel Images

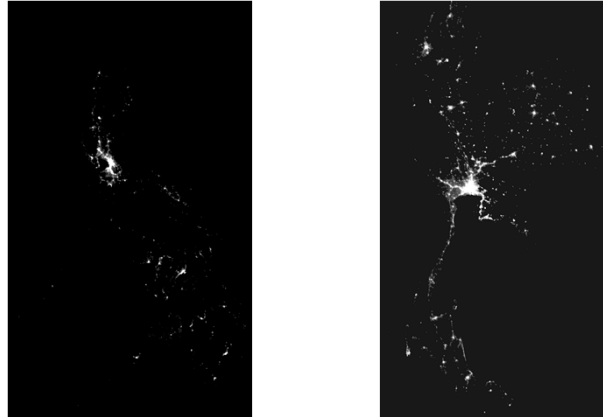
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Applying on PHI and THA data

We use data on night lights compiled by the Visible Infrared Imaging Radiometer Suite (VIIRS). The intensity levels were categorized into discrete groups using combination of Gaussian Mixed Models and heuristic methods.

Figure. Intensity of Night Lights



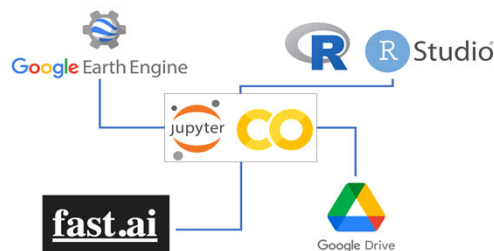
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13

Applying on PHI data

To avoid starting from scratch, we use an off-the-shelf CNN called ResNet34. This algorithm has been pretrained using the ImageNet database to ensure that it is capable of identifying simple features. ImageNet is regarded as a solid benchmark performer in computer vision predictions.

We also leveraged on readily available analytical platforms:



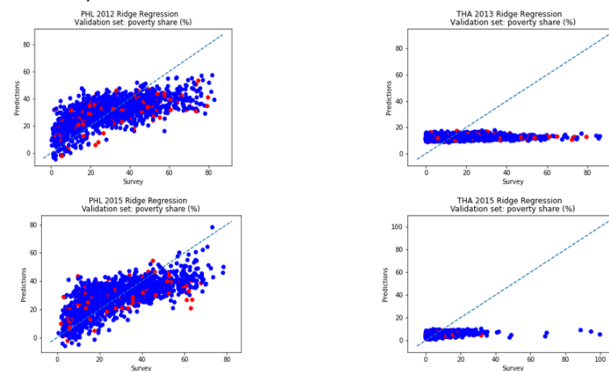
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Key Findings

For each country-year combination, we set aside 90% of the areas for which government-published estimates of poverty are available to constitute the training set. The remaining 10% were used for validation. Within the 90%, we did a further split wherein we used 10-fold cross validation to tune hyperparameters.

CNN's accuracy rate is about 93.5 to 94%

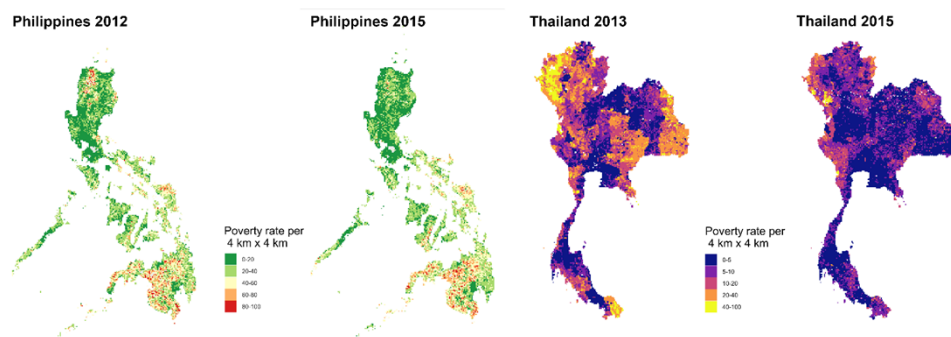


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Key Findings

Calibrated Poverty Maps



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DA How Satellite Data Helped Get Food to the Hungry during COVID-19 | Development Asia

<https://development.asia/explainer/how-satellite-data-helped-get-food-hungry-during-c...>

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EXPLAINER

How Satellite Data Helped Get Food to the Hungry during COVID-19



Leaving no one behind

A COVID-19 emergency food program in the Philippines offered an opportunity to design a targeting program based on granular poverty maps that were compiled using traditional and innovative data sources and artificial intelligence. Photo credit: ADB.


17



TA 6721: Using Frontier Technology and Big Data Analytics for Smart Infrastructure Facility Planning and Monitoring

- Instead of using sensors, a new and more cost-effective approach is being explored which leverage from the use of very high-resolution satellite imagery to collect road quality metrics.
- The idea is to develop computer vision algorithm that can predict IRI from satellite imagery of roads or transport infrastructure.
- The algorithm will require satellite imagery tagged with known road IRI

Gabriel Cadamuro, Aggrey Muhebwa, and Jay Taneja. 2019. **Street smarts: measuring intercity road quality using deep learning on satellite imagery**
<https://doi.org/10.1145/3314344.3332493>



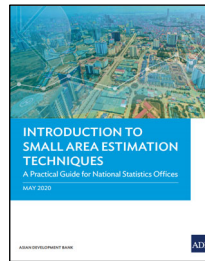
ADB Photo

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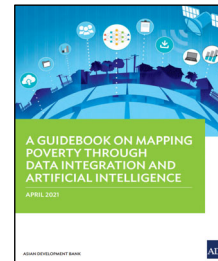
References



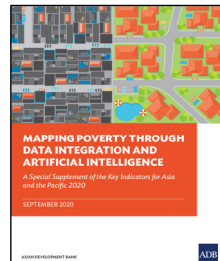
[Key Indicators for Asia and the Pacific 2021 \(adb.org\)](https://www.adb.org/publications/key-indicators-for-asia-and-the-pacific-2021)



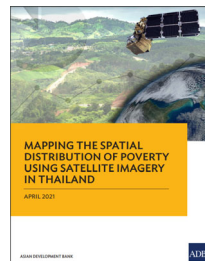
[A Guidebook on Mapping Poverty through Data Integration and Artificial Intelligence \(adb.org\)](https://www.adb.org/publications/introduction-to-small-area-estimation-techniques)



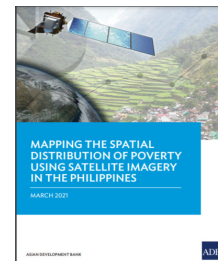
[A Guidebook on Mapping Poverty through Data Integration and Artificial Intelligence \(adb.org\)](https://www.adb.org/publications/a-guidebook-on-mapping-poverty-through-data-integration-and-artificial-intelligence)



[Mapping Poverty through Data Integration and Artificial Intelligence: A Special Supplement of the Key Indicators for Asia and the Pacific \(adb.org\)](https://www.adb.org/publications/mapping-poverty-through-data-integration-and-artificial-intelligence)



[Mapping the Spatial Distribution of Poverty Using Satellite Imagery in Thailand \(adb.org\)](https://www.adb.org/publications/mapping-the-spatial-distribution-of-poverty-using-satellite-imagery-in-thailand)



[Mapping the Spatial Distribution of Poverty Using Satellite Imagery in the Philippines \(adb.org\)](https://www.adb.org/publications/mapping-the-spatial-distribution-of-poverty-using-satellite-imagery-in-the-philippines)

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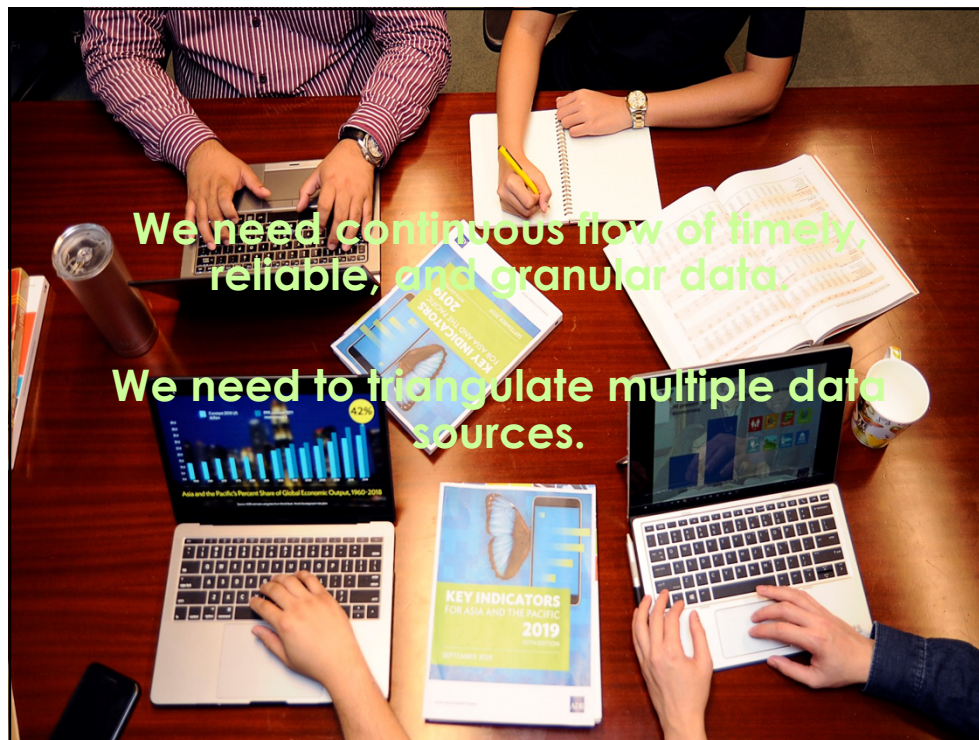
<https://www.adb.org/news/events/webinar/asian-impact>

<https://development.asia/insight/using-machine-learning-satellite-images-map-poverty>

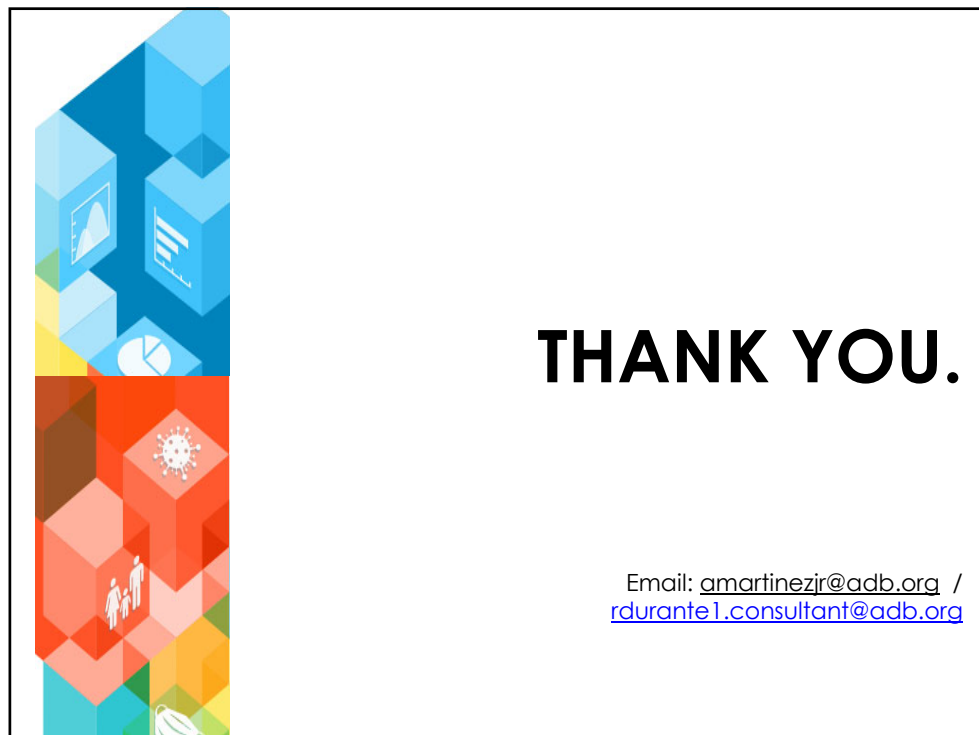
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