THE UTILISATION OF SATELLITE IMAGERY ANALYSIS FOR POVERTY MAPPING IN INDONESIA

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To measure the poverty, Statistics Indonesia (BPS) uses the concept of the ability to fulfil basic needs (basic needs approach). Using this approach, poverty is defined as an economic inability to meet basic food and non-food needs as measured by the poverty line (food & non-food).

The poor are people who have an average monthly per capita expenditure below the Poverty Line.

The food poverty line is the value of spending on minimum food needs (equivalent to 2100 kilo calories per capita per day).

The non-food poverty line is the minimum value of spending on housing, clothing, education, health and other non-food basic needs.

This method has been used by Statistics Indonesia (BPS) since 1998 so that the calculation results are consistent and comparable from time to time (apple-to-apple).
The Covid-19 pandemic has driven an increase in the number and percentage of populations living in poverty in Indonesia. The poverty disparity in rural and urban areas is still high nationally. In total, the poverty are concentrated on the island of Java.
Establishing a complete poverty database at national scale is costly.

Currently available of household-level poverty data at national scale:
- Pendataan Sosial Ekonomi (PSE 2005),
- Pendataan Program Perlindungan Sosial (PPLS) 2008, PPLS 2011,
- Pemutakhiran Basis Data Terpadu (PBDT) 2015

Poverty data estimation through biannual Households Socio-Economic Surveys (SUSENAS) are only available up to the regency/municipality level.

Eliminating poverty is Indonesia’s main target for Sustainable Development Goals by 2030.
Estimation of regional poverty using satellite imagery is a new alternative to support poverty alleviation (Chen & Nordhaus, 2011; Henderson et al., 2012; Ivan et al., 2020).

We aim to evaluate the feasibility of estimating the **poverty spatial distribution** and **wealth index development** using satellite imagery and geospatial data to enhance the **cost effectiveness**, **granularity**, and **accuracy** of poverty statistics.
• Most **Spatial Data** has BIG DATA properties.

• **Geospatial analysis** is often a process involving well-defined algorithms.

• **Machine learning techniques** have been used for a long time in the geospatial field.

• The emergence of new types of spatial data from increasingly diverse data acquisition methods: **Social Media**, **Mobile phone data**, **Point Cloud**, **SAR**, etc.
CONVOLUTIONAL NEURAL NETWORKS

Deep learning architecture used to recognize features on objects (e.g. pictures, satellite images, etc.) to be classified into certain labels.
Day time satellite images

Night time light intensities

Basis Data Rumah Tangga Miskin

Landsat 8 Sentinel 2

NPP-VIIRS

National Polar-orbiting Partnership–Visible Infrared Imaging Radiometer Suite

PBDT 2015

Pemutakhiran Basis Data Terpadu 2015
**METODOLOGY**

- **Input image**
  - Day time satellite images
  - Night time light intensities

- **Extract features using trained machine learning algorithm**
  - Convolutional Neural Networks (ResNet34)

- **Extracted features**

- **Trained regression model**
  - Ridge Regression
  - Support Vector Regression

- **Poverty statistics indicators**
ARCHITECTURE: RESNET-34

Convolutional Neural Networks architecture popularized by Fast.AI for image recognition, including day-time and night-time light (NTL) satellite imageries
CASE STUDY: PROVINCE OF DI YOGYAKARTA

Night-Time Lights Luminosity

The capital of Yogyakarta Province and its regencies has a greater luminosity intensity than rural areas and areas outside the city.
The capital of Yogyakarta Province not only has a greater intensity of night-time light but also a lower poverty rate than other areas.
ESTIMATED POVERTY DISTRIBUTION
(COMBINATION OF DAY-TIME & NIGHT-TIME LIGHT SATELLITE)

Poverty Percentage by prediction model with RES34

The resulted model predictions when compared with the Official Poverty Distribution (PBDT 2015)

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE_valid</td>
<td>0.0896</td>
</tr>
<tr>
<td>RMSE_full</td>
<td>0.0861</td>
</tr>
<tr>
<td>R2_valid</td>
<td>-0.5537</td>
</tr>
<tr>
<td>R2_full</td>
<td>-0.4796</td>
</tr>
<tr>
<td>R2_train</td>
<td>0.9247</td>
</tr>
</tbody>
</table>
The results of the model predictions after rescaling are quite good in estimating regional poverty with an RMSE value of 8 percent.
The results of the model predictions with only night-time light (NTL) satellite images are relatively better than if we combine it with the day-time satellite images.
ESTIMATED POVERTY DISTRIBUTION
(NIGHT-TIME LIGHT SATELLITE ONLY)

Using the night-time light (NTL) satellite images, we can estimate the spatial distribution of regional poverty more properly. After rescaling using the population grid, the spatial distribution of poverty is quite well compared with the Official Poverty Database (PBDT 2015).
• The estimation model for poverty mapping using satellite images has been implemented and is quite capable of estimating the spatial distribution of poverty relatively well.
• Area of studies are being expanded to include several other provinces: West Java, South Sulawesi, etc.

ON GOING PROCESS
• Incorporating the use of additional satellite images to capture more geospatial features into the model:
  • **Land Surface Temperature** which represents the Urban Heat Island phenomenon at metropolitan area (Buyantuyev, 2009 and Dissanayake, 2018)
  • **Air Pollution** from CO Emissions (Tariq, 2017)
  • **Built-up Area Distribution** (Faisal, 2016)
  • The **distribution of vegetation area**
• Incorporating small area estimation to sharpen our analysis into smaller areas.
Thank You

"Like slavery and apartheid, poverty is not natural. It is man-made and it can be overcome and eradicated by the action of human beings"

(Nelson Mandela, 2003)