STATISTICS INDONESIA

THE UTILISATION OF SATELLITE IMAGERY ANALYSIS FOR POVERTY MAPPING IN INDONESIA

Arie Wahyu Wijayanto

UK ONS-UNECE Machine Learning Group 2021 Webinar
November 19, 2021

OUTLINE

- CONCEPT OF POVERTY
- UTILIZATION OF SATELLITE IMAGES
- CASE STUDY OF POVERTY MAPPING
- FUTURE CHALLENGES

POVERTY CONCEPT AND DEFINITION

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).

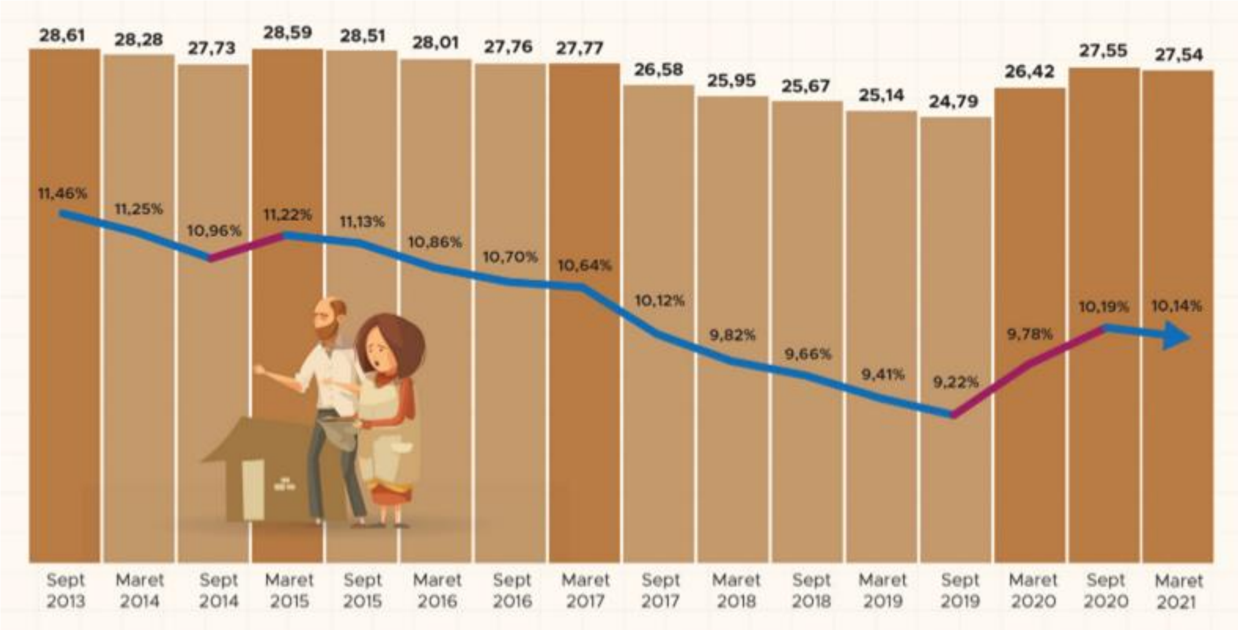
The non-food poverty line is the minimum value of spending on housing, clothing, education, health and other non-food basic needs.

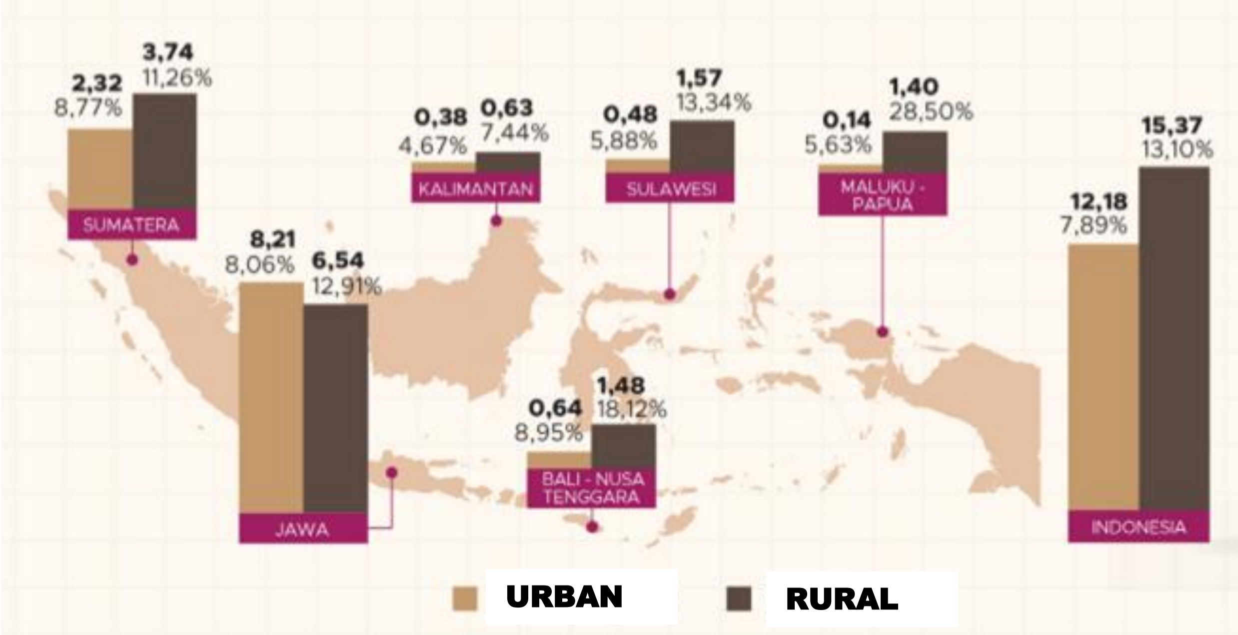
This method has been used by Statistics Indonesia (BPS) since 1998 so that the calculation results are **consistent and comparable from time to time** *(apple-to-apple).*

POVERTY PROFILE OF INDONESIA

MARCH 2021

The Covid-19 pandemic has driven an increase in the number and percentage of populations living in poverty in Indonesia

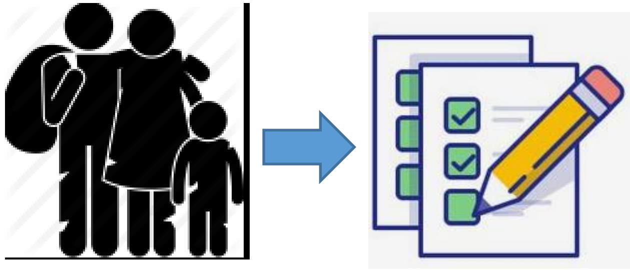




The poverty disparity in rural and urban areas is still high nationally. In total, the poverty are concentrated on the island of Java

Source: Official Release of Statistics, July 15, 2021

POVERTY DATABASE IN INDONESIA



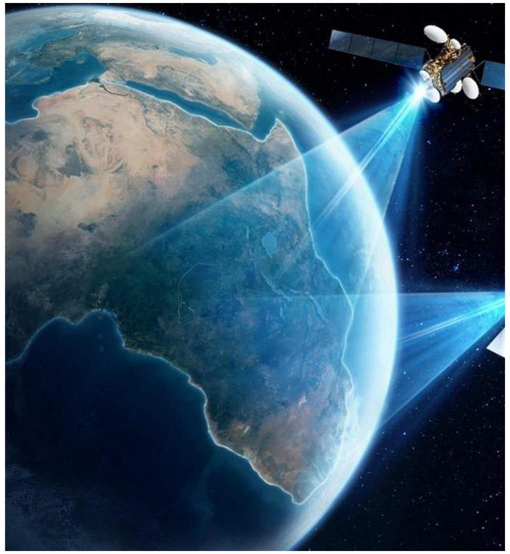
- Eliminating poverty is Indonesia's main target for Sustainable Development Goals by 2030

- 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

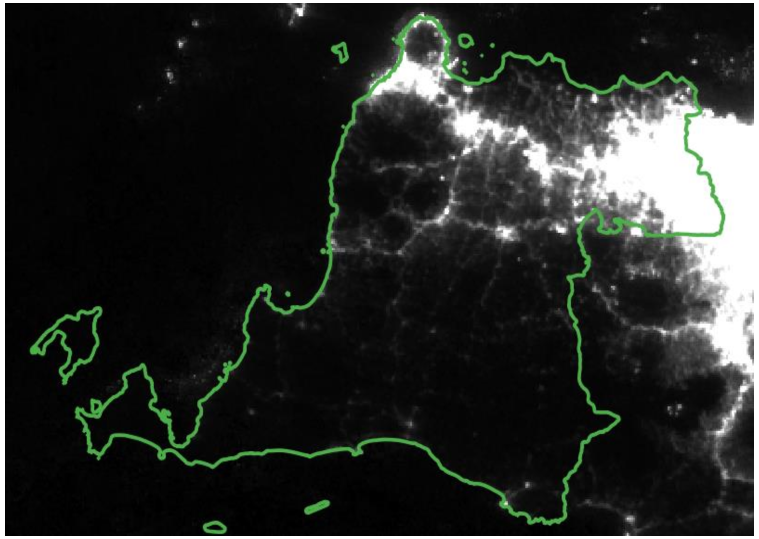
- Poverty data estimation through biannual Households Socio-Economic Surveys (SUSENAS) are only available up to the **regency/municipality level**

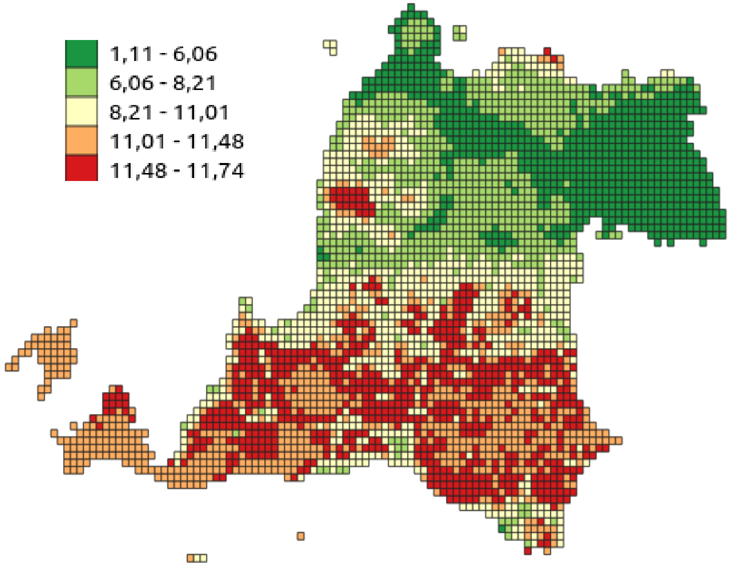
UTILIZATION OF SATELLITE IMAGES



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.

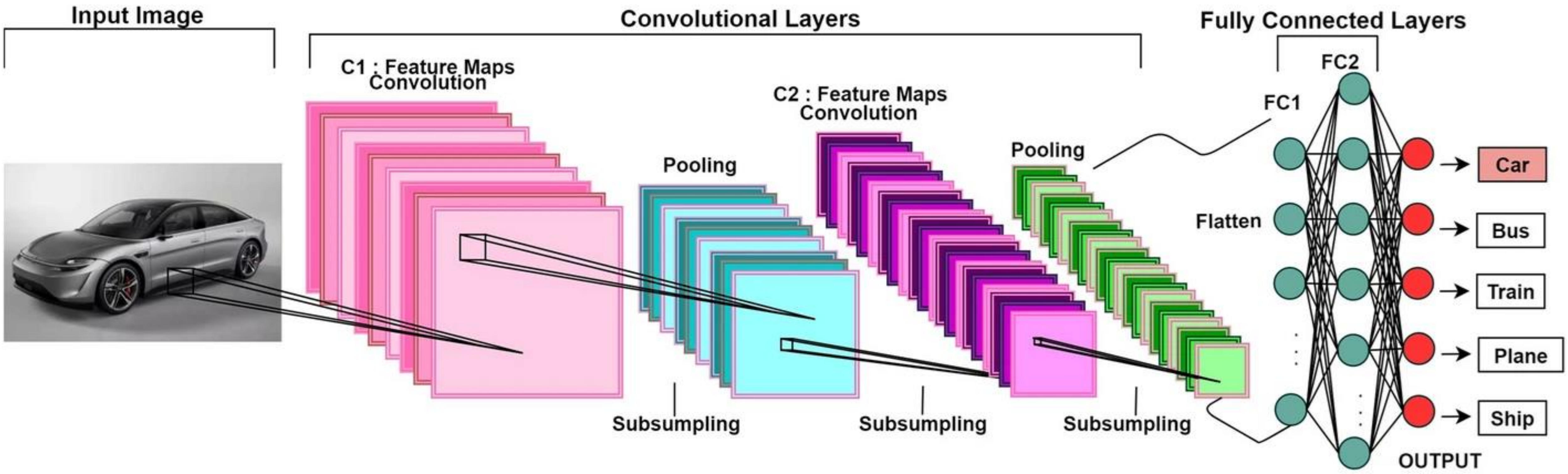




Machine Learning for Geospatial Application

- 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



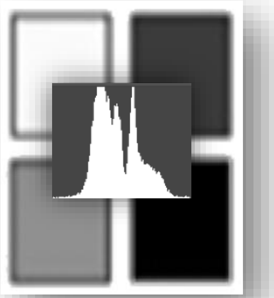
Deep learning architecture used to recognize features on objects (e.g. pictures, satellite images, etc.) to be classified into certain labels.

DATA

Data

Day time satellite images

Landsat 8
Sentinel 2



Night time light intensities

NPP-VIIRS

National Polar-orbiting Partnership–Visible Infrared Imaging Radiometer Suite

Basis Data Rumah Tangga Miskin

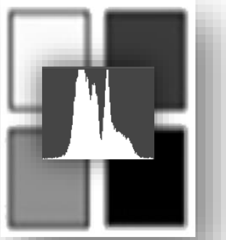
PBDT 2015

Pemutakhiran Basis Data Terpadu 2015

METODHOLOGY

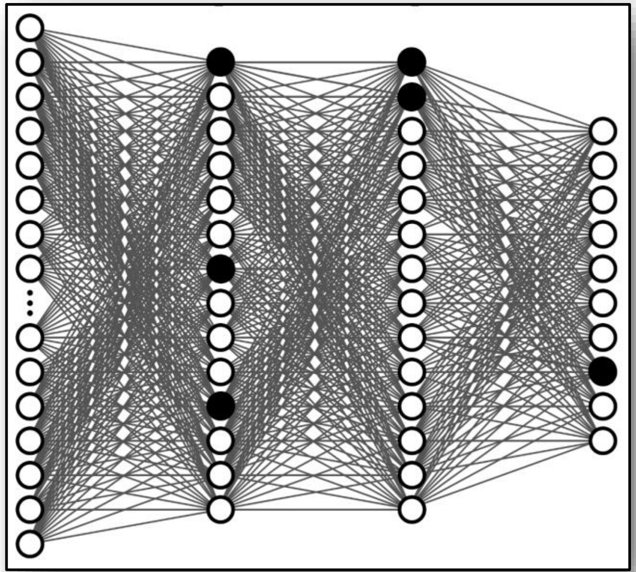
Input image

Day time
satellite images



Night time light
intensities

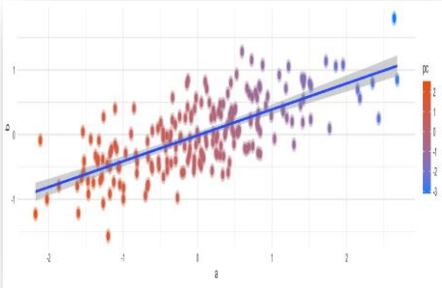
Extract features using trained
machine learning algorithm



Convolutional Neural
Networks
(ResNet34)

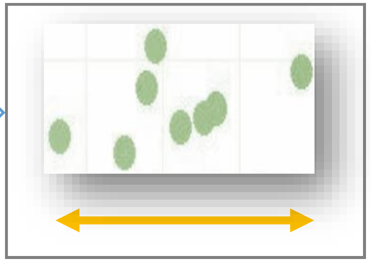
Extracted
features

Trained regression
model

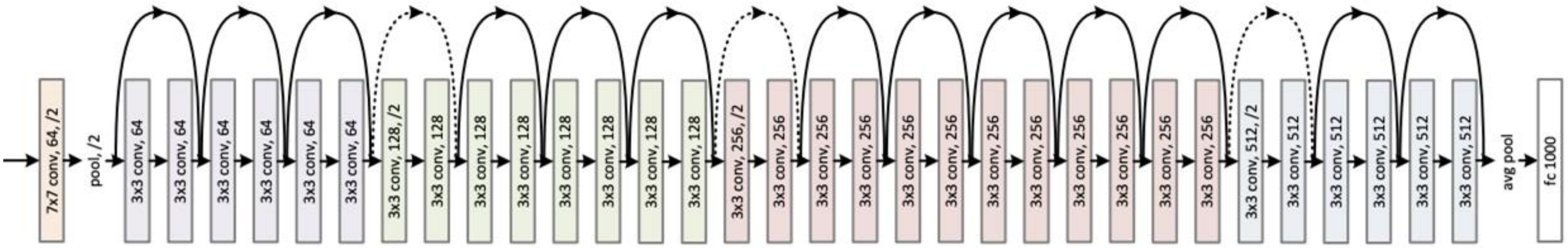


Ridge Regression
Support Vector Regression

Poverty statistics
indicators



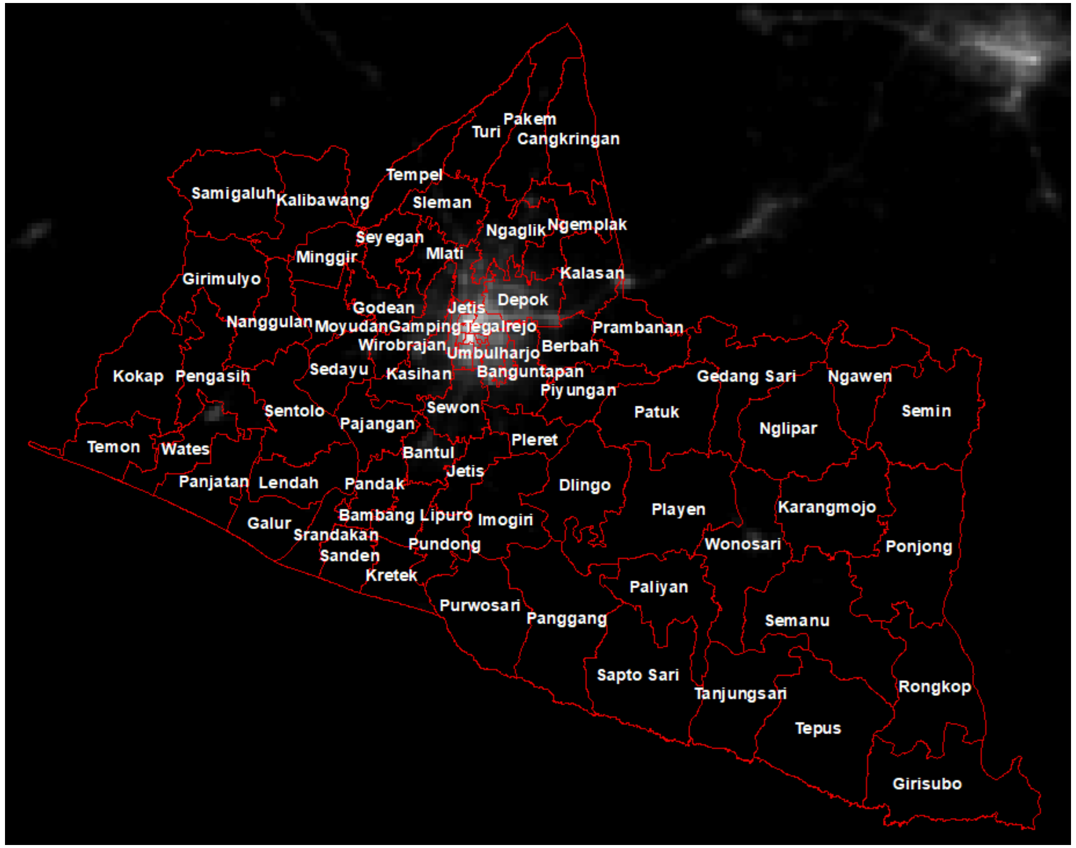
ARCHITECTURE: RESNET-34

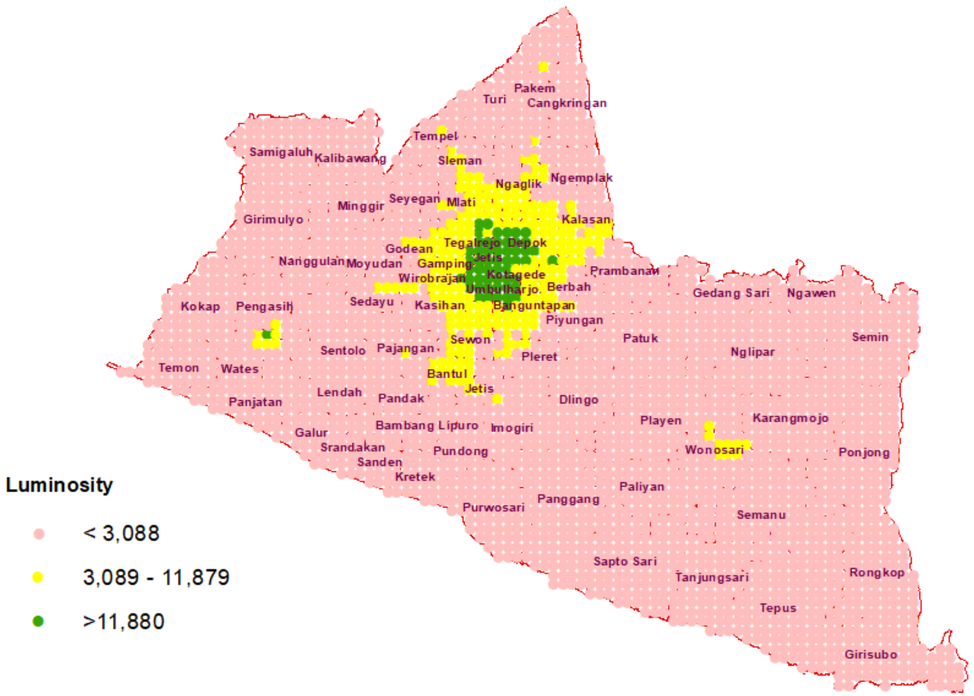


Convolutional Neural Networks architecture popularized by Fast.AI for image recognition, including day-time and night-time light (NTL) satellite imageries

CASE STUDY: PROVINCE OF DI YOGYAKARTA

Night-Time Lights Luminosity

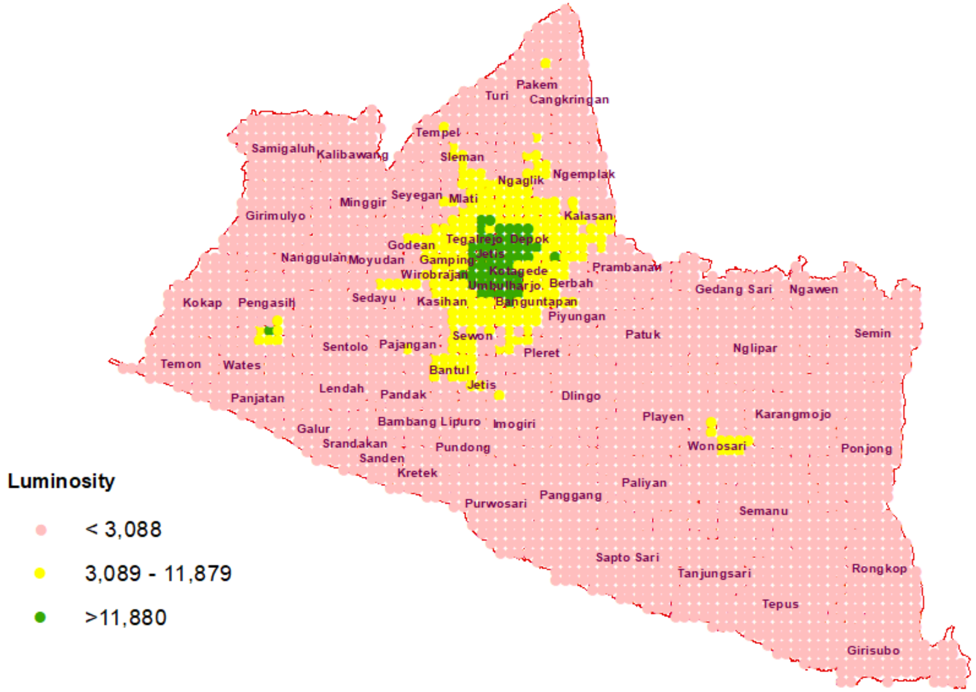




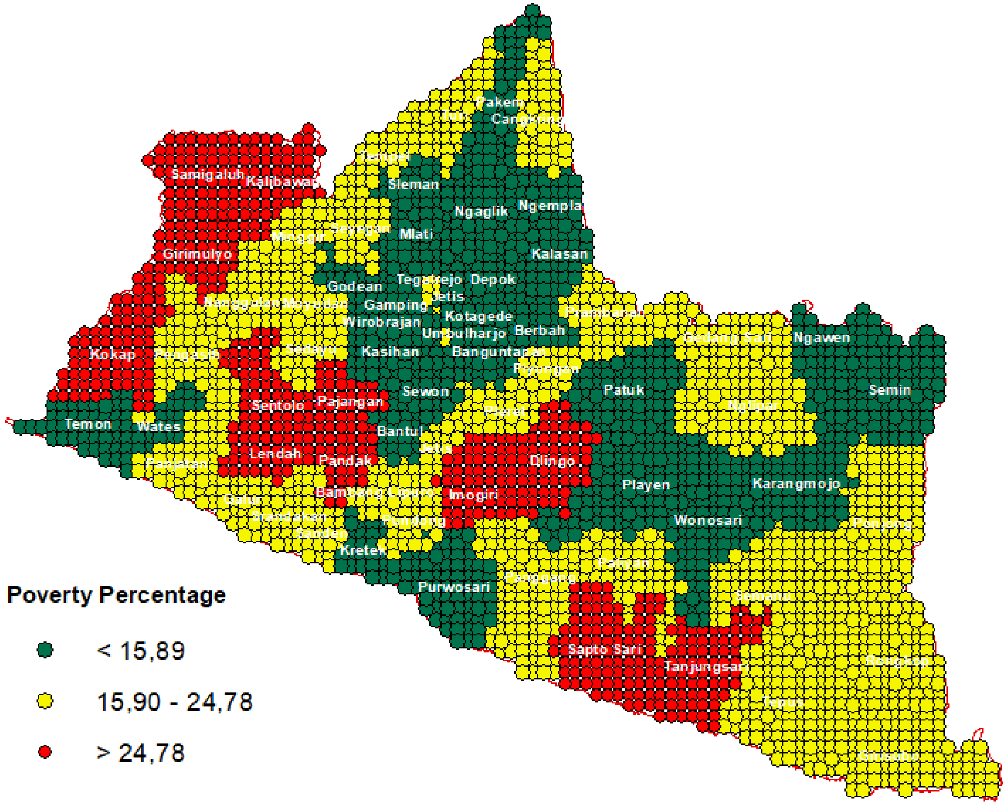
The capital of Yogyakarta Province and its regencies has a greater luminosity intensity than rural areas and areas outside the city.

CASE STUDY: PROVINCE OF DI YOGYAKARTA

Night-Time Lights Luminosity



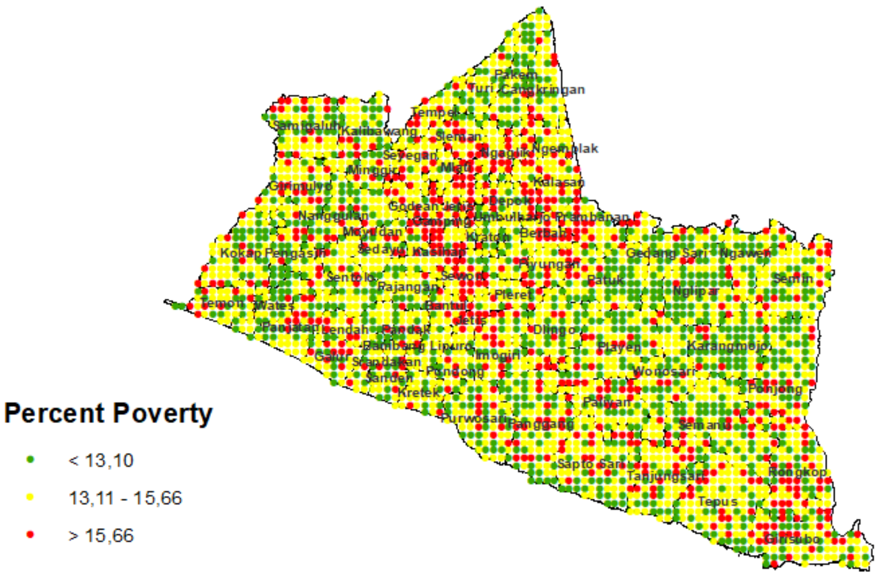
Official Poverty Distribution (PBDT 2015)



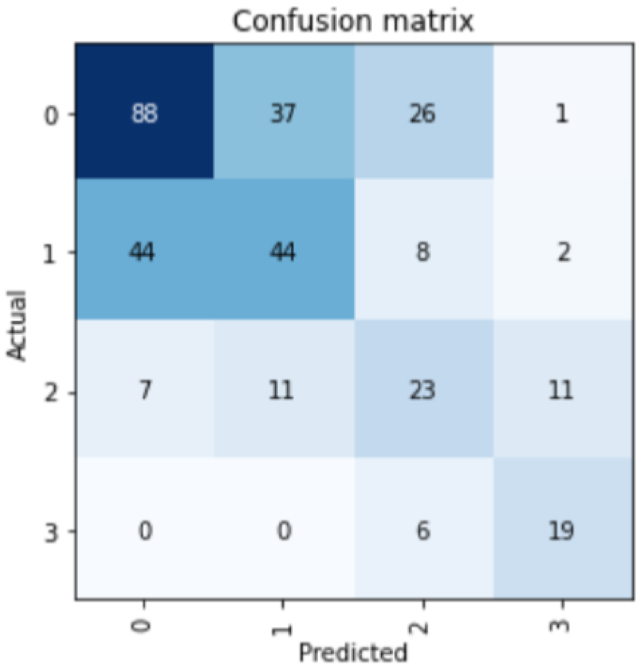
The capital of Yogyakarta Province not only has a greater intensity of night-time light but also a lower poverty rate than other areas.

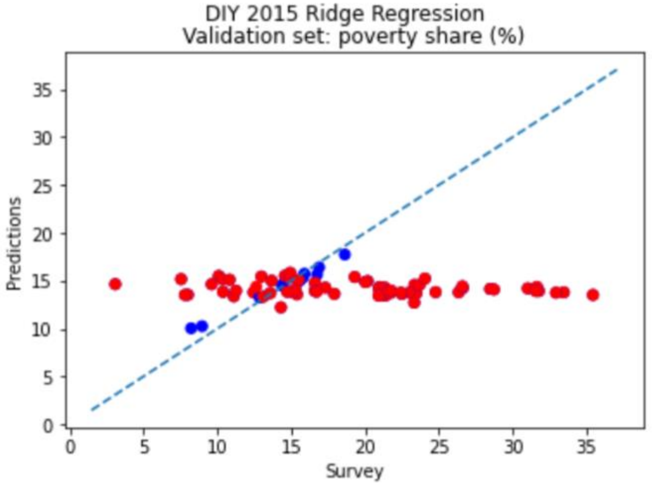
ESTIMATED POVERTY DISTRIBUTION
(COMBINATION OF DAY-TIME & NIGHT-TIME LIGHT SATELLITE)

Poverty Percentage by prediction model with RES34



CNN Model Testing and Evaluation



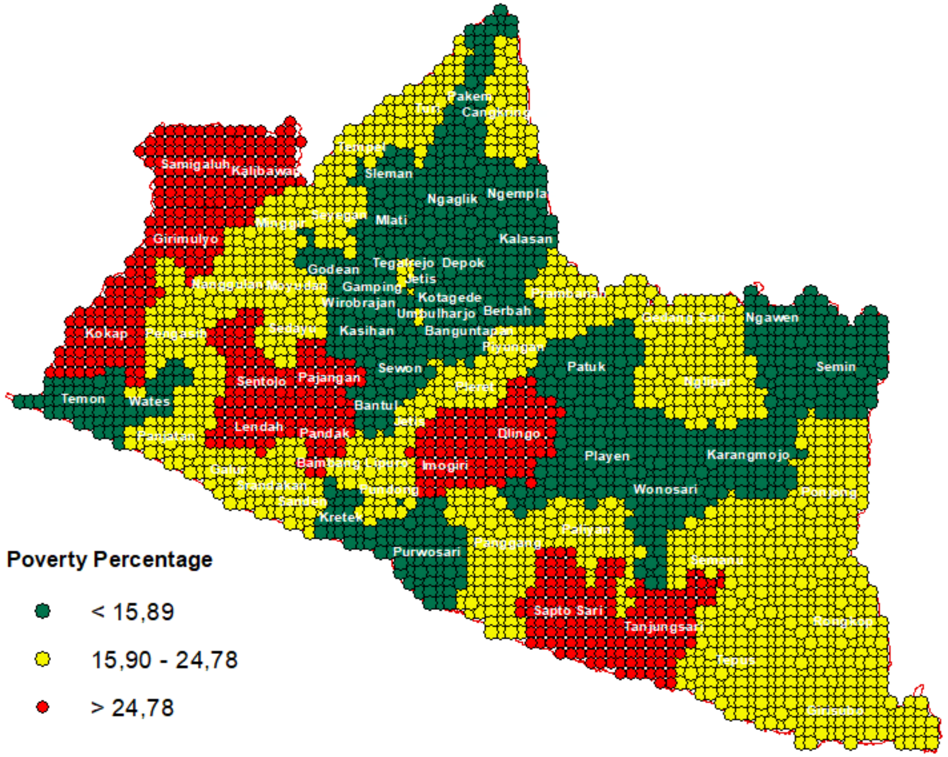


RMSE_valid	0.0896
RMSE_full	0.0861
R2_valid	-0.5537
R2_full	-0.4796
R2_train	0.9247

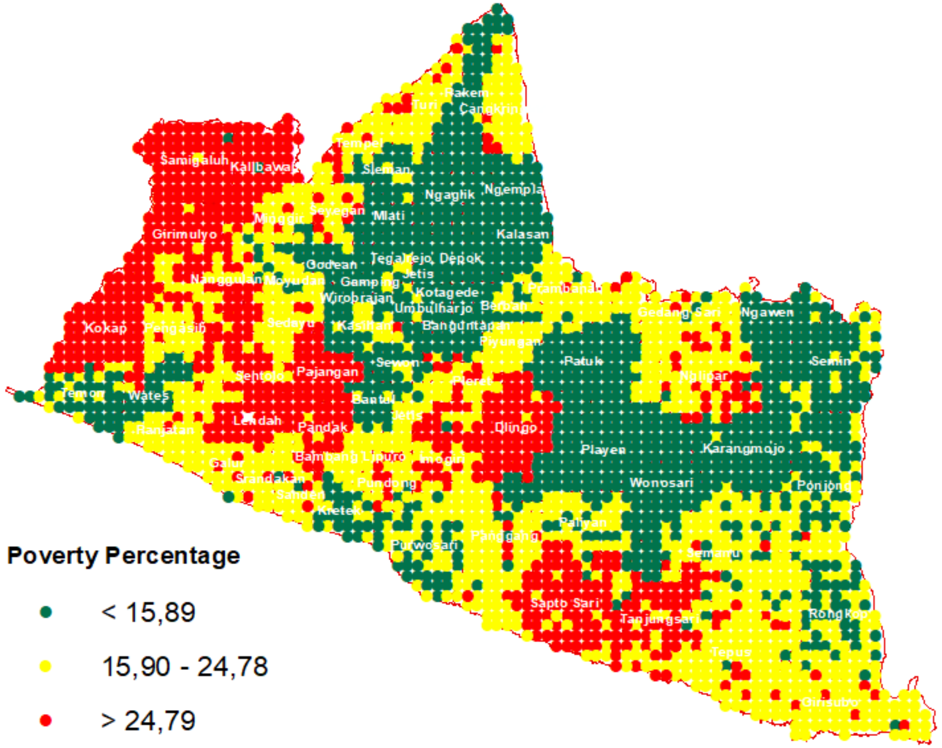
The resulted model predictions when compared with the Official Poverty Distribution (PBDT 2015)

ESTIMATED POVERTY DISTRIBUTION
(COMBINATION OF DAY-TIME & NIGHT-TIME LIGHT SATELLITE)

Distribution poverty percentage by PBDT 2015

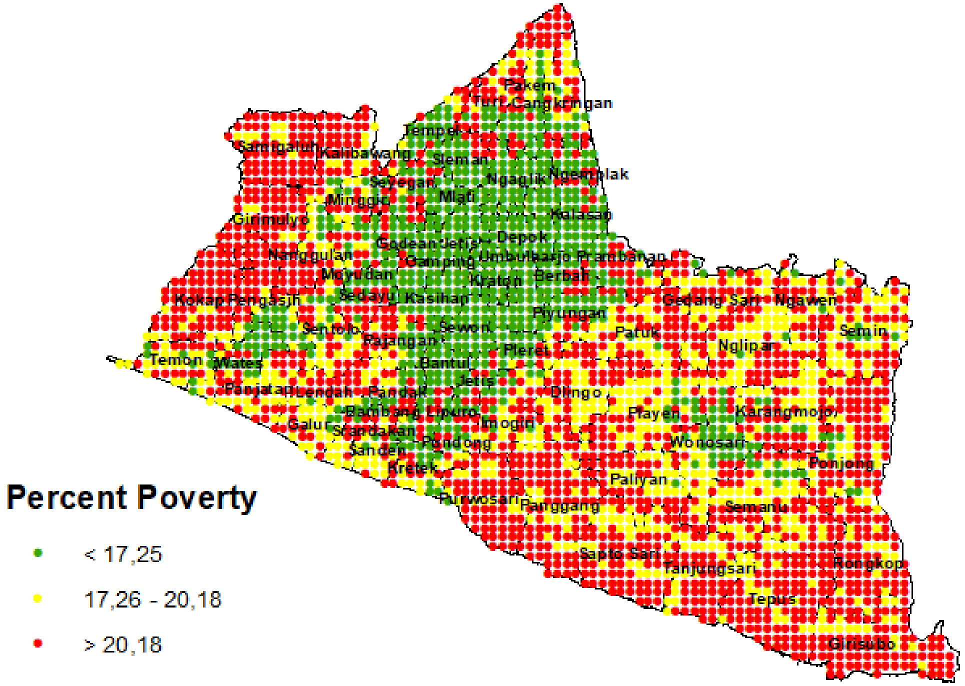


Poverty Percentage by prediction model with RES34 after it is rescaled by population grid

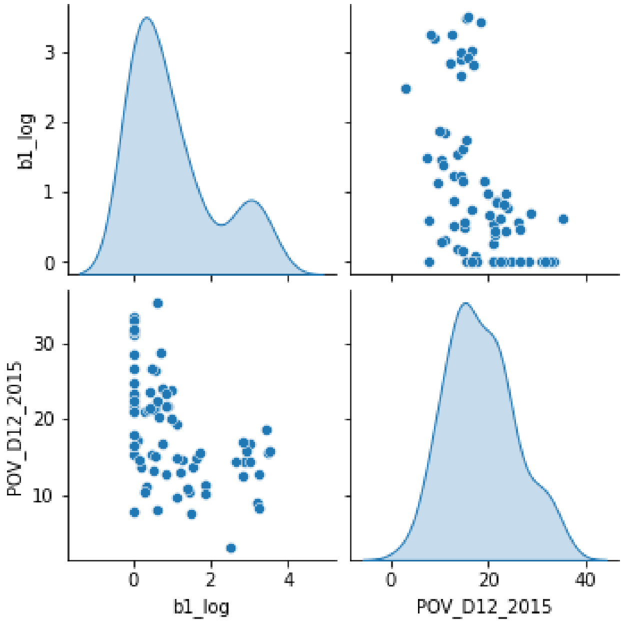


The results of the model predictions after rescaling are quite good in estimating regional poverty with an RMSE value of 8 percent

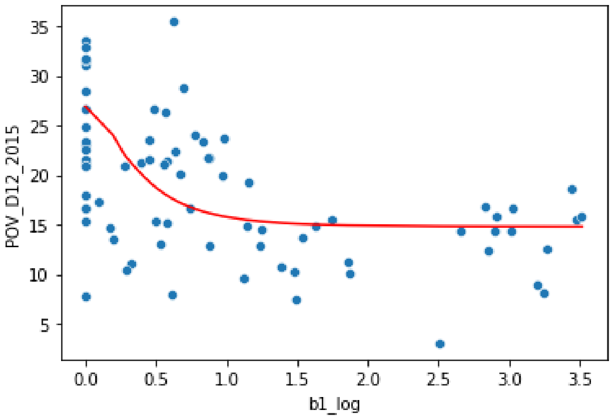
ESTIMATED POVERTY DISTRIBUTION
(NIGHT-TIME LIGHT SATELLITE ONLY)



Using log transformation for transformation luminosity intensity to normal value distribution



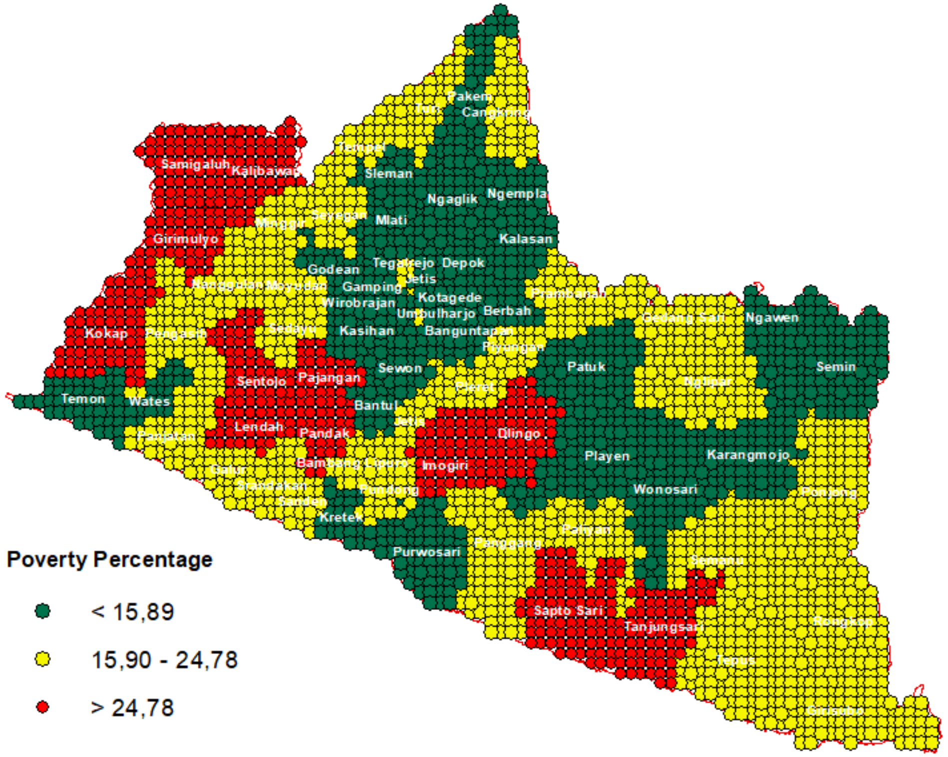
Support Vector Regression



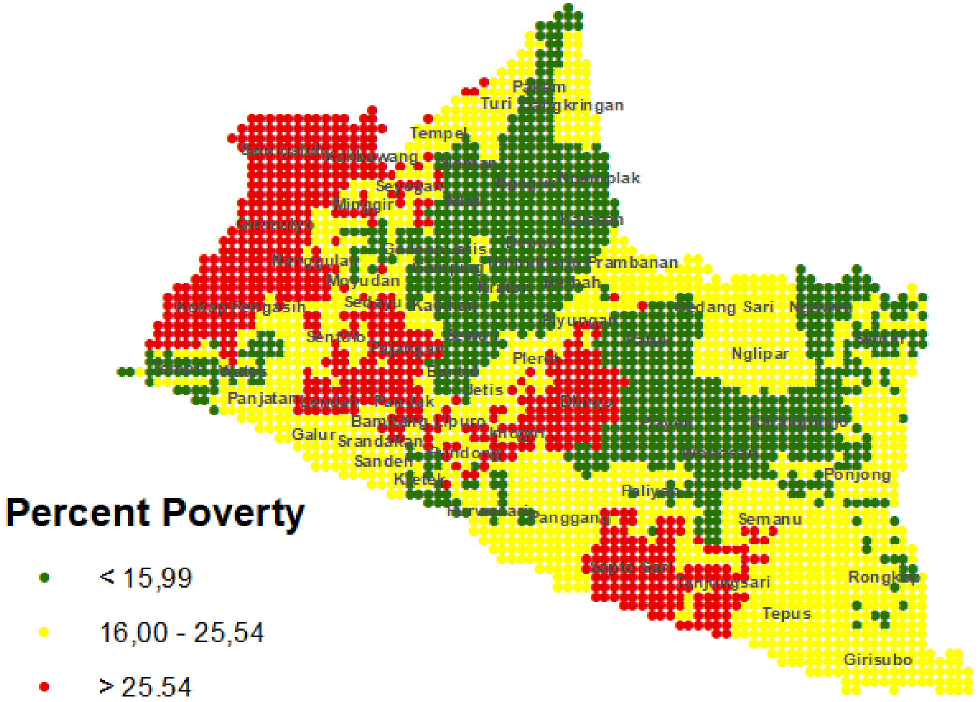
The results of the model predictions with only night-time light (NTL) satellite images are relatively better than if we combine it with the day-time satellite images.

ESTIMATED POVERTY DISTRIBUTION
(NIGHT-TIME LIGHT SATELLITE ONLY)

Official Poverty Distribution (PBDT 2015)



Poverty Percentage by prediction model with SVR after it is rescaled by population grid



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).

SUMMARY

- 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.

STATISTICS INDONESIA

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)