



STATISTICS INDONESIA

# Remote Sensing Approaches using **Satellite Imagery** for **Poverty Mapping** in Indonesia

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# 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).

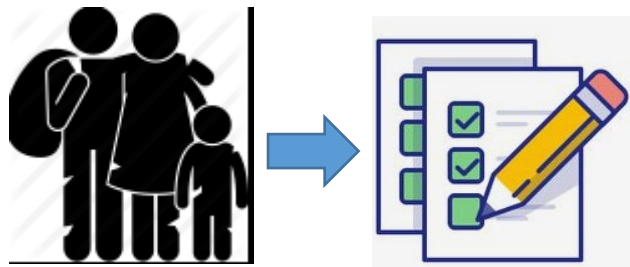


**The non-food poverty line** is the minimum value of spending on housing, clothing, education, health and other non-food basic needs.



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 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: PSE 2005, PPLS) 2008, PPLS 2011, PBDT 2015



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



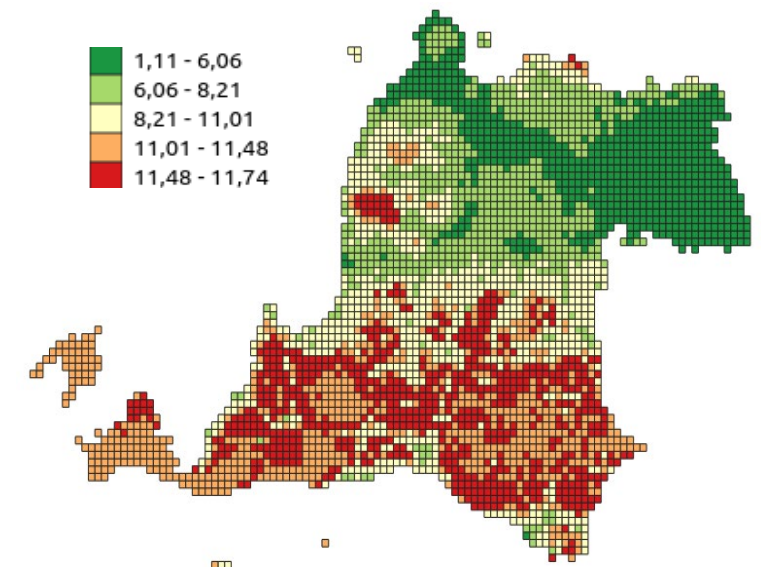
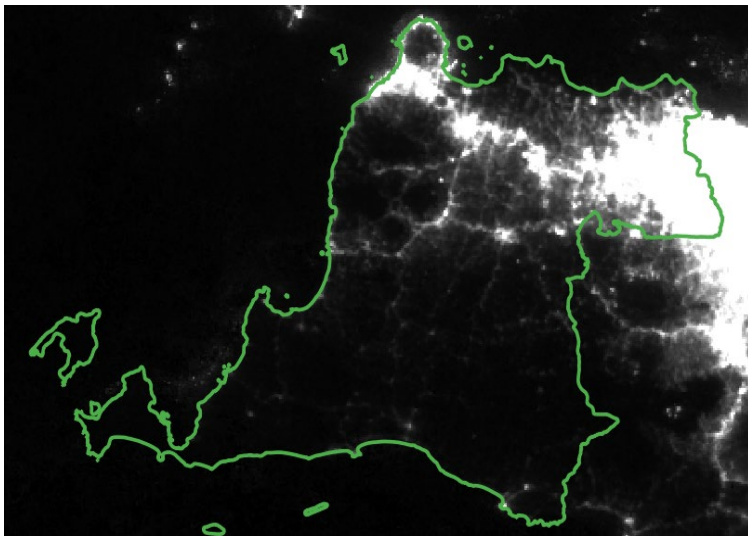
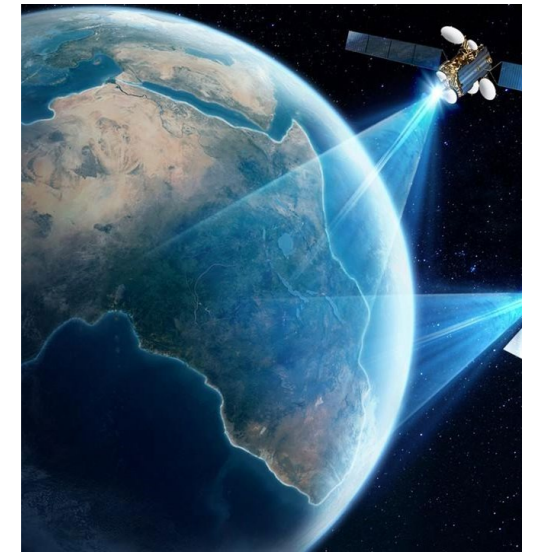
# UTILIZATION OF SATELLITE IMAGES



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.

# DATA SOURCES



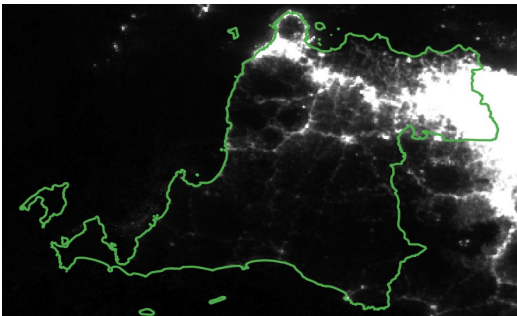
**VIIRS**



**Landsat-8**



**Sentinel-2**



**Publicly available  
30m Resolution  
Night Time  
2011 - present**



**Publicly available  
30m Resolution  
Day Time  
2013 - present**



**Publicly available  
10m Resolution  
Day Time  
2015 - present**

**Official Poverty  
Database**



**PBDT 2015  
National-Scale  
Official Poverty  
Database**

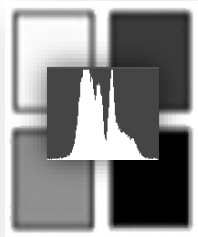


# METHODOLOGY

Input image



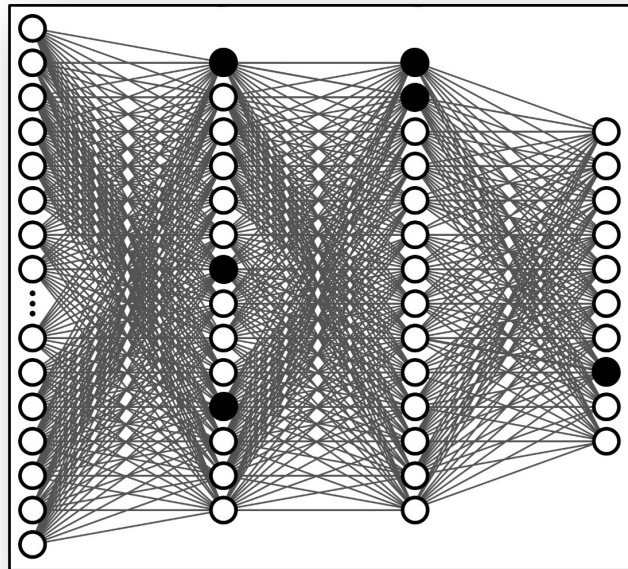
Day time satellite images



Night time light intensities



Extract features using trained machine learning algorithm



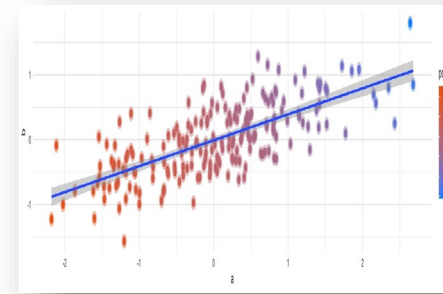
Convolutional Neural Networks (ResNet34)



Extracted features



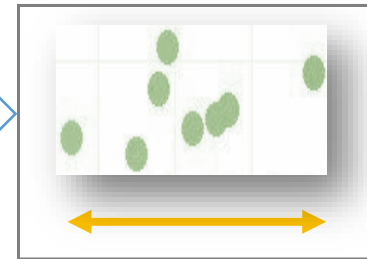
Trained regression model



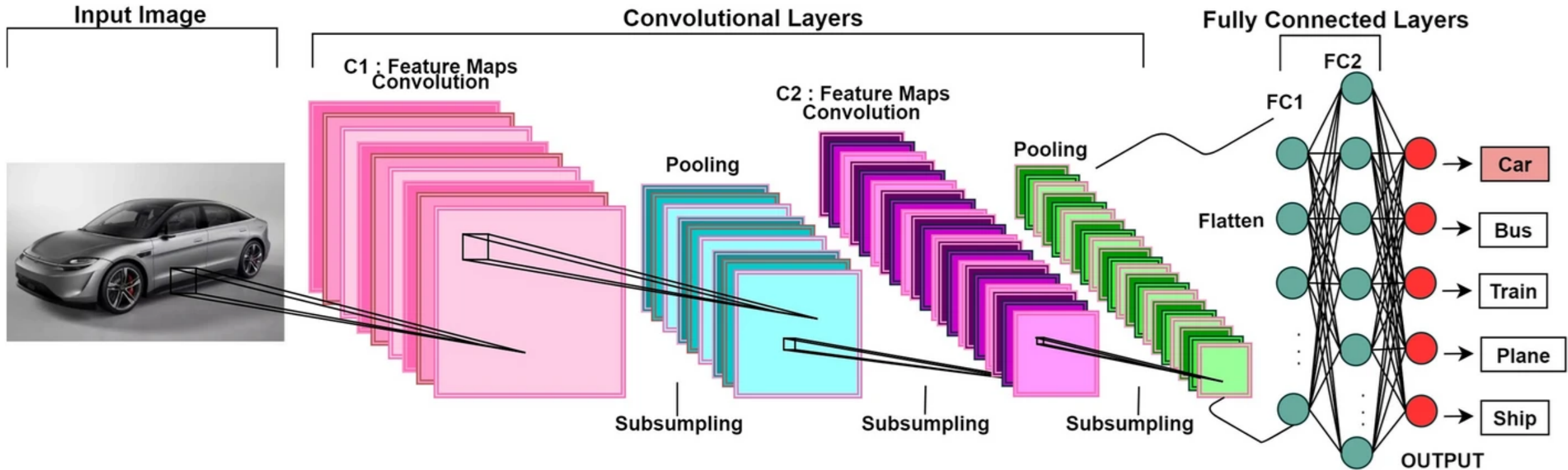
Ridge Regression  
Support Vector Regression



Poverty statistics indicators



# CONVOLUTIONAL NEURAL NETWORKS

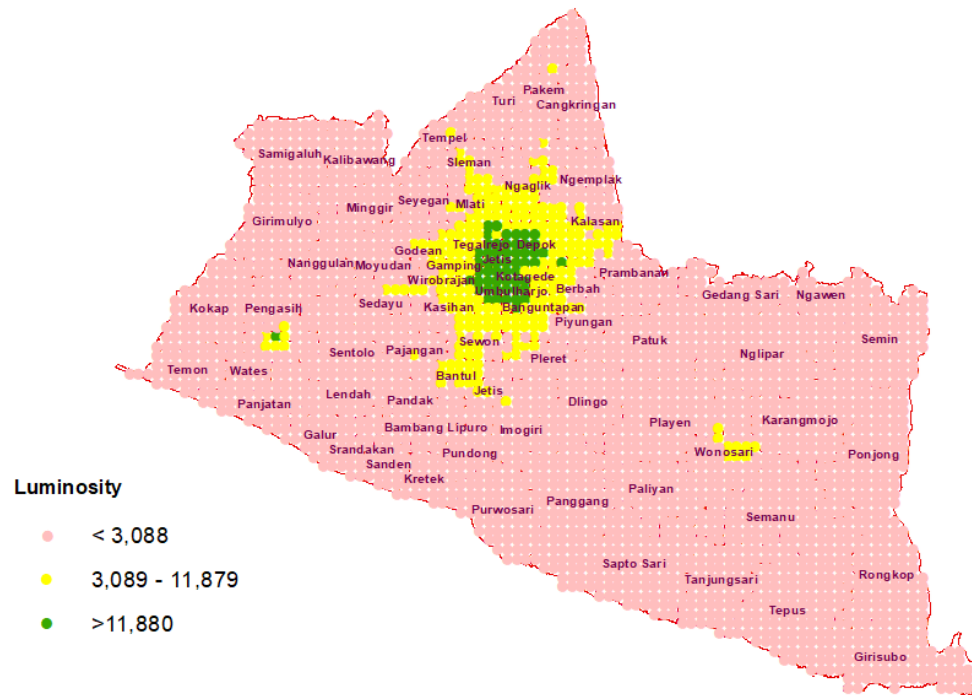


Deep learning architecture used to recognize features on objects (e.g. pictures, satellite images, etc.) to be classified into certain labels.

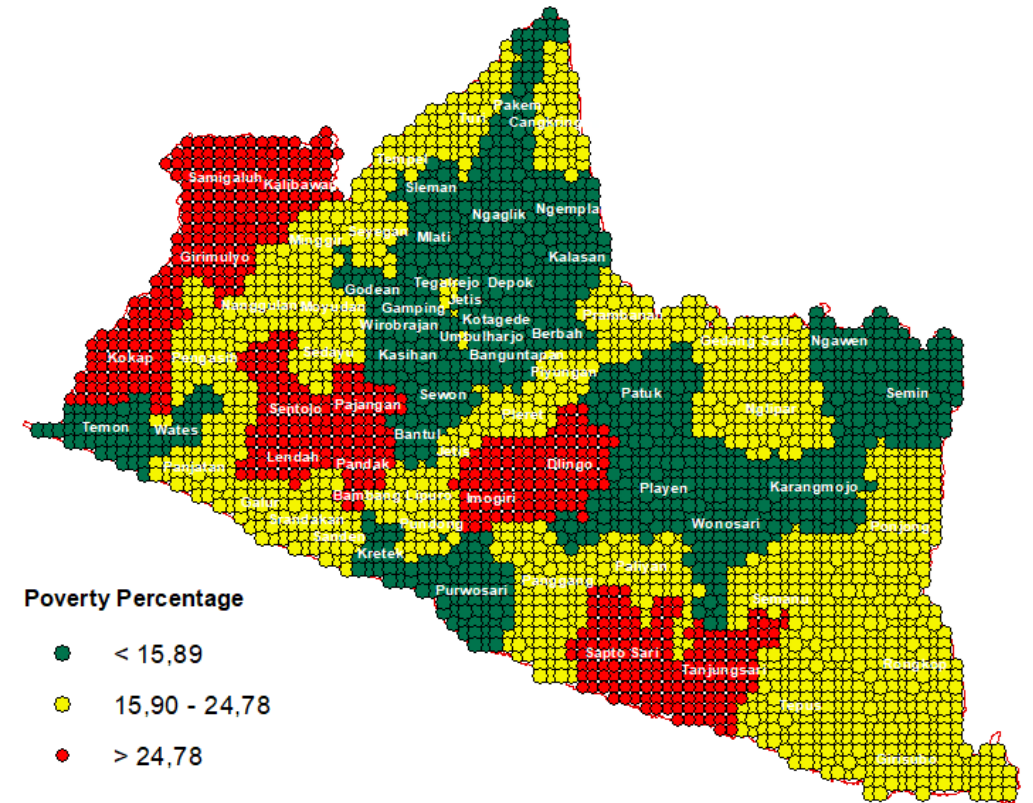


# CASE STUDY: PROVINCE OF DI YOGYAKARTA

## Night-Time Lights Luminosity



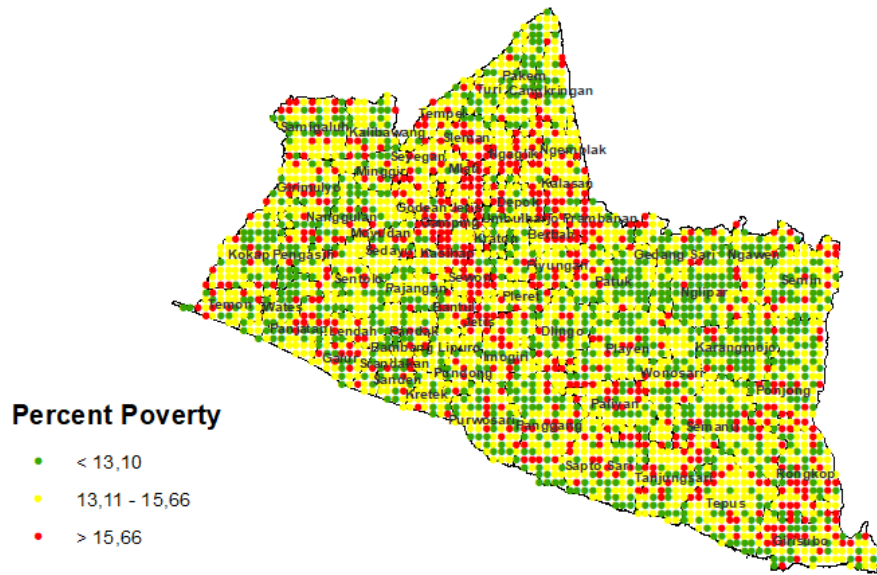
## Official Poverty Distribution (PBDT 2015)



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

# ESTIMATED POVERTY DISTRIBUTION

Poverty Percentage by prediction model using ResNet34 Model



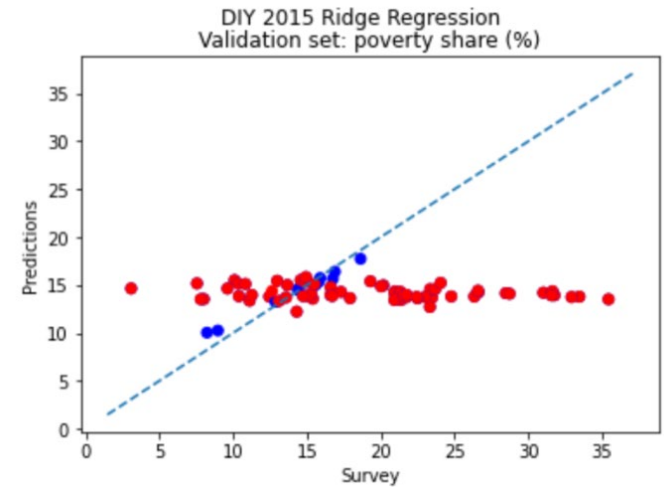
CNN Model Testing and Evaluation

Confusion matrix

	0	1	2	3
0	88	37	26	1
1	44	44	8	2
2	7	11	23	11
3	0	0	6	19
	0	1	2	3

Actual

Predicted

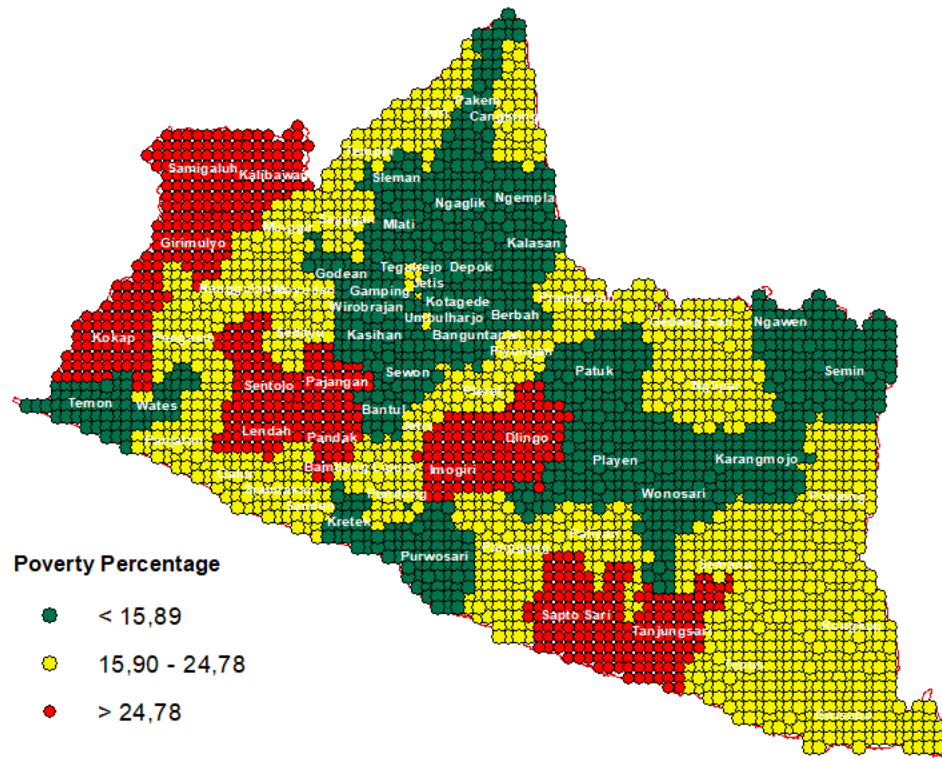


RMSE_valid	0.0896
RMSE_full	0.0861
R2_valid	-0.5537
R2_full	-0.4796
R2_train	0.9247

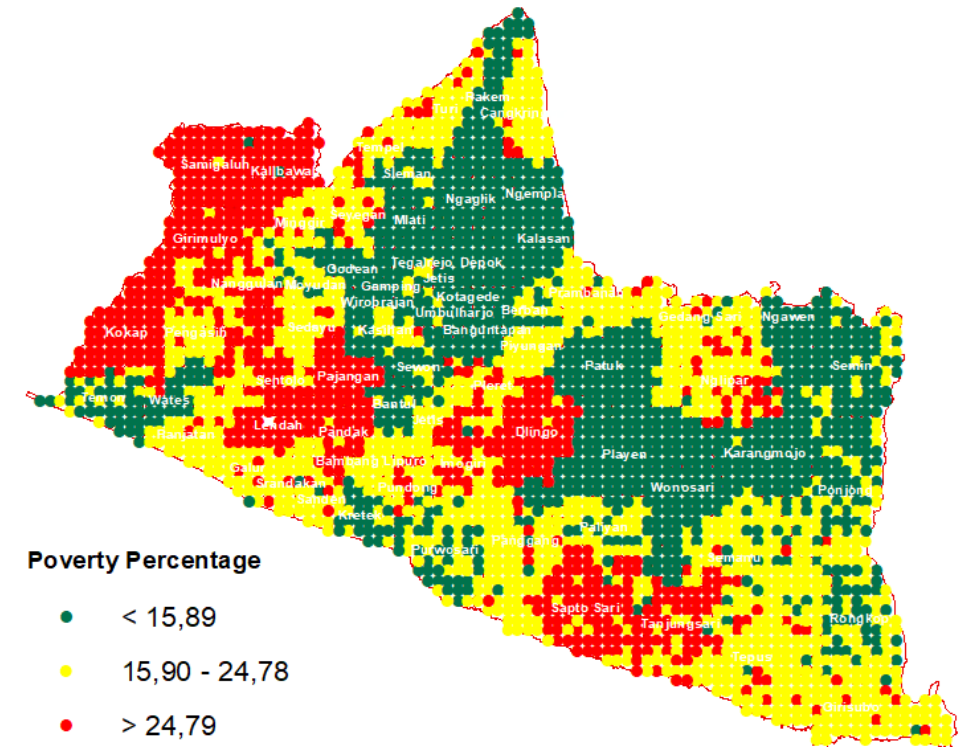
The resulted model predictions when compared with the Official Poverty Distribution (PBDT 2015)

# ESTIMATED POVERTY DISTRIBUTION

Distribution poverty percentage by PBDT 2015



Poverty Percentage by prediction model with ResNet34 after it is rescaled by population grid

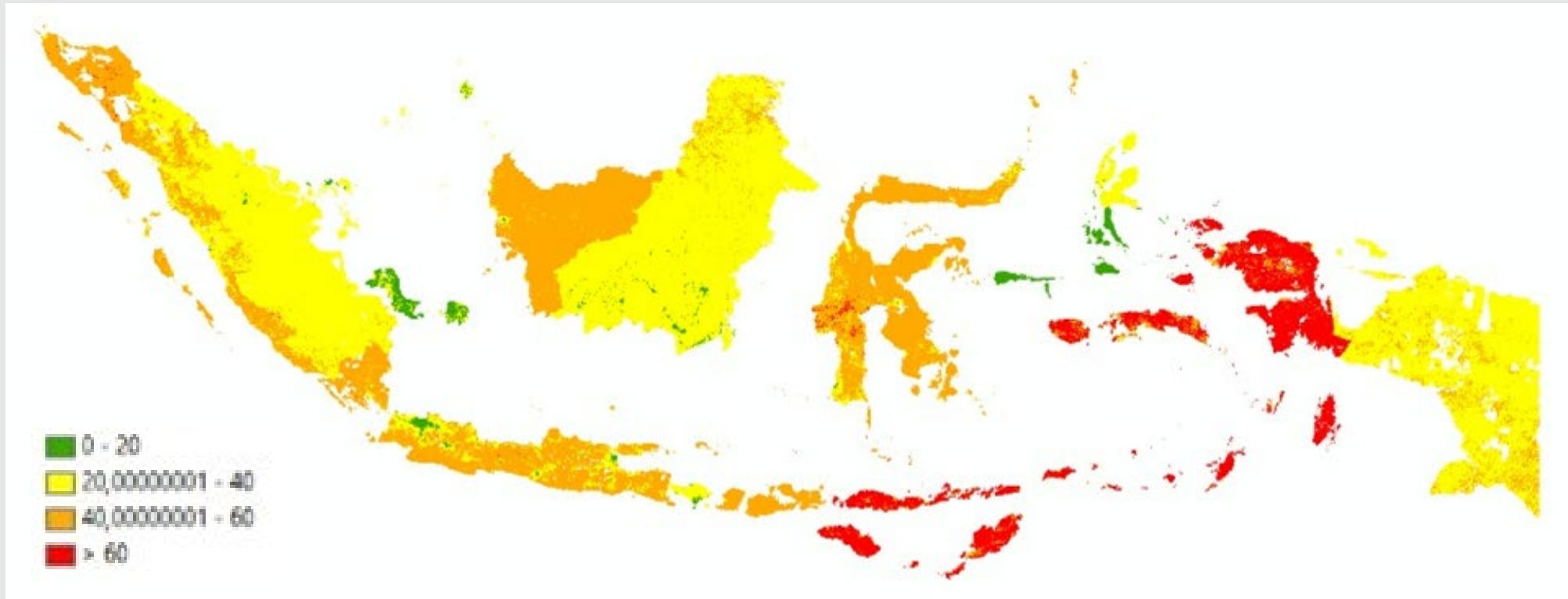


The results of the model predictions after rescaling are quite good in estimating regional poverty with an RMSE value of 8 percent



# NATIONAL-SCALE POVERTY MAPPING

## Preliminary National-Scale Poverty Mapping of Indonesia



\*) Preliminary national-scale mapping using only night-time satellites data (without day-time data) due to the current limitation of computing resources.

## SUMMARY

- The estimation model for poverty mapping using satellite images has been implemented.
- The model is quite capable to estimating the spatial distribution of poverty.
- Ground checking have been carried out to ensure that the satellite imagery at these locations correctly represents the local economic activity.

## CHALLENGES

- The need for high performance computing resources.
- Huge amount of data requires efficient processing pipelines.
- Improvement of the prediction model
- Incorporating small area estimation to sharpen our analysis into smaller areas.



# Thank You

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"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)

