Why should we care so much about poverty reduction?



Scan the Slido QR code to participate

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

It is important to reduce poverty because (it)…



Economic Perspective

Minimizes waste of productive potential

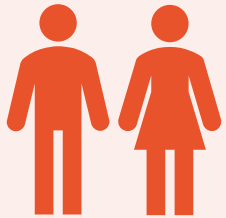
Deficits in nutrition, learning may reduce future earnings

Boosts economic growth

More people can participate in growth-enhancing activities

Reduces repeated recovery costs when shocks occur

Reducing poverty prevents temporary shocks from becoming permanent scars.



Moral / Equity Perspective

Strengthens foundations of a dignified life

Poverty reduction leads to less people experiencing severe hunger, ill health, homelessness, insecurity

Minimizes inequality of opportunity

More people can have better chances to move up the socioeconomic ladder, even if they come from disadvantaged backgrounds

Promotes inclusiveness

Poverty reduction expands people's ability to benefit from development, exercise voice, make meaningful choices.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Extreme poverty has fallen, but other forms of deprivation and vulnerability remain widespread in Developing Asia.

Millions have escaped poverty, yet many remain one crisis, illness, disaster, or economic shock away from falling back



A resident dries their clothes after flooding inundated residential areas in Indonesia.
Image source: ADB Multimedia Library

Monetary Poverty in Asia and the Pacific

66.0%
In 1990 (ADB)

→

3.1%
In 2025 (ADB)

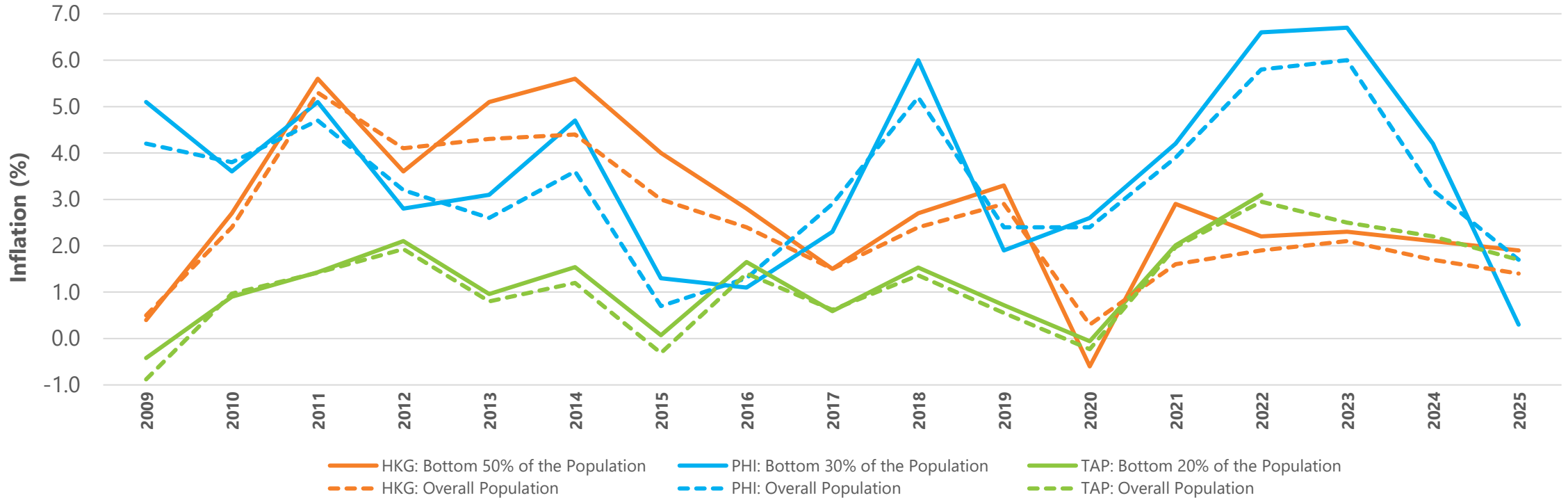
Multidimensional Poverty in Asia and the Pacific

~12%
(Based on UNDP 2025 report)

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

People with lower income often face a higher cost-of-living burden than headline inflation suggests.

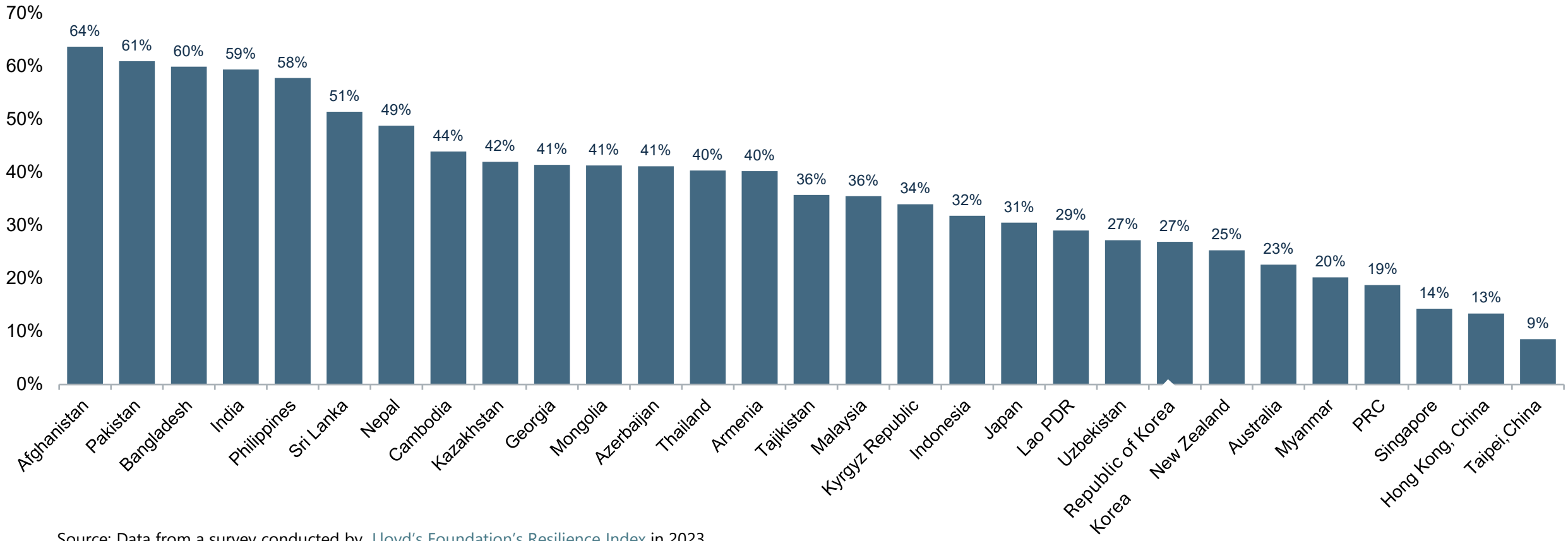
Low-income households devote larger spending on essentials, resulting in different and often more intense inflation experienced.



Sources: For CPI overall population: Asian Development Bank's Key Indicators of Asia and the Pacific 2026. For CPI bottom population, For TAP: Government of Taipei,China. Directorate-General of Budget, Accounting and Statistics; For HKG: The Government of the Hong Kong Special Administrative Region of the People's Republic of China. Census and Statistics Department; For PHI: Philippine Statistics Authority.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Millions of Asians can cover basic needs for only less than a month in the event of a sudden loss of income.



Source: Data from a survey conducted by Lloyd's Foundation's Resilience Index in 2023.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

For millions of families, economic hardship requires a sequence of sacrifices.

For example, when prices go up, households increasingly make difficult trade-offs:

- Reduce food quality or quantity
- Delay healthcare
- Postpone education expenses
- Cut digital connectivity
- Use savings or incur debt



A local market in Nyaung Shwe, Myanmar (Image source: ADB Multimedia Library).

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

To leave no one behind, our poverty metrics must evolve as quickly as our development challenges.

What we chose to measure shapes what we choose to prioritize. By seeing marginalized people more clearly, we can design policies that reach them more effectively.

Preview

Measure deprivation with a multidimensional perspective and at the individual level



Topic # 1

Nowcasting deprivation

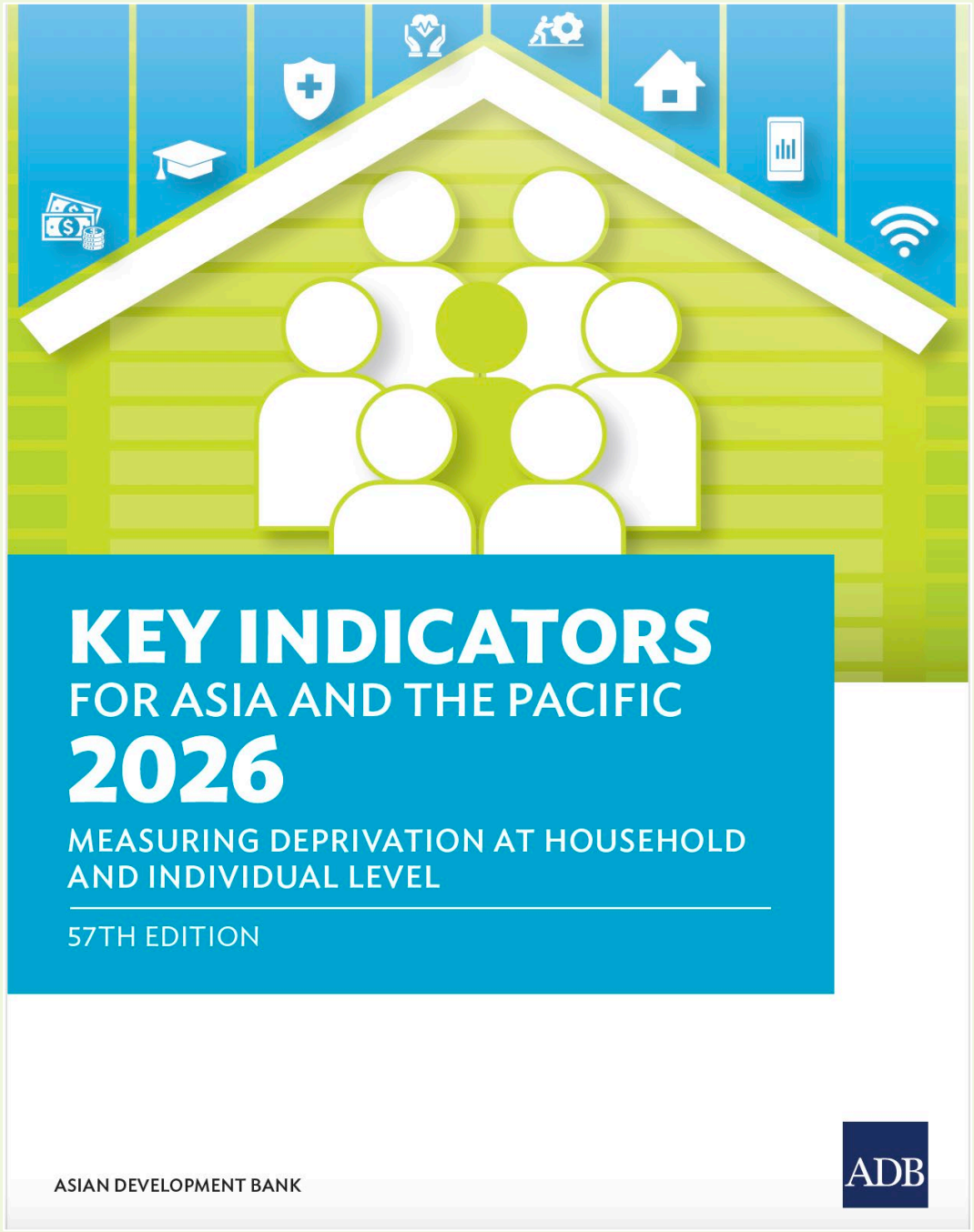


Topic # 2

Measuring deprivation at a geographically granular level



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.



Know more about the Key Indicators for Asia and the Pacific 2026 Report

https://www.adb.org/publications/key-indicators-asia-and-pacific-2026

Scan the QR code

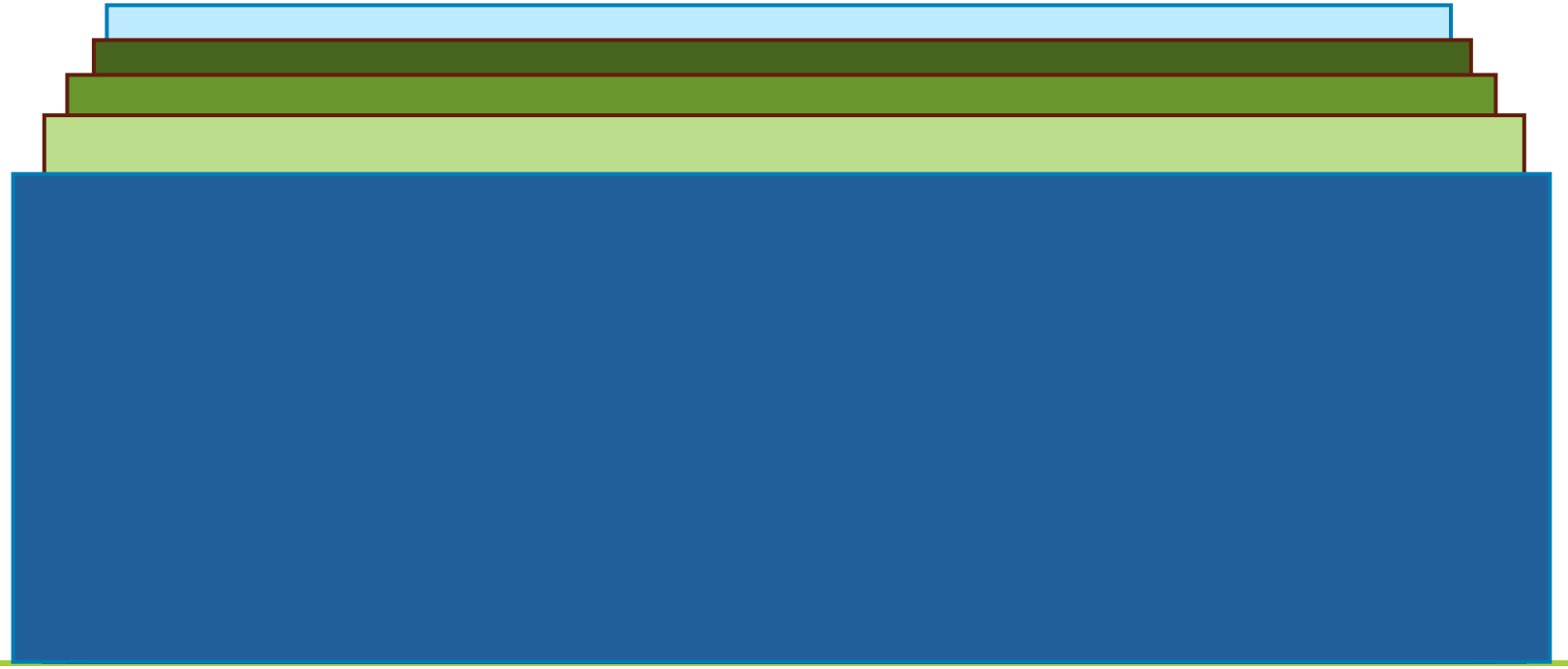
Seeing the Unseen: Sharpening Metrics for People at the Margins of Society

[Introduction to Fundamental Principles of Nowcasting and Mapping of Poverty]

Arturo Martinez Jr. and Joseph Albert Nino Bulan
Data Division
Economic Research and Development Impact Department, Asian Development Bank

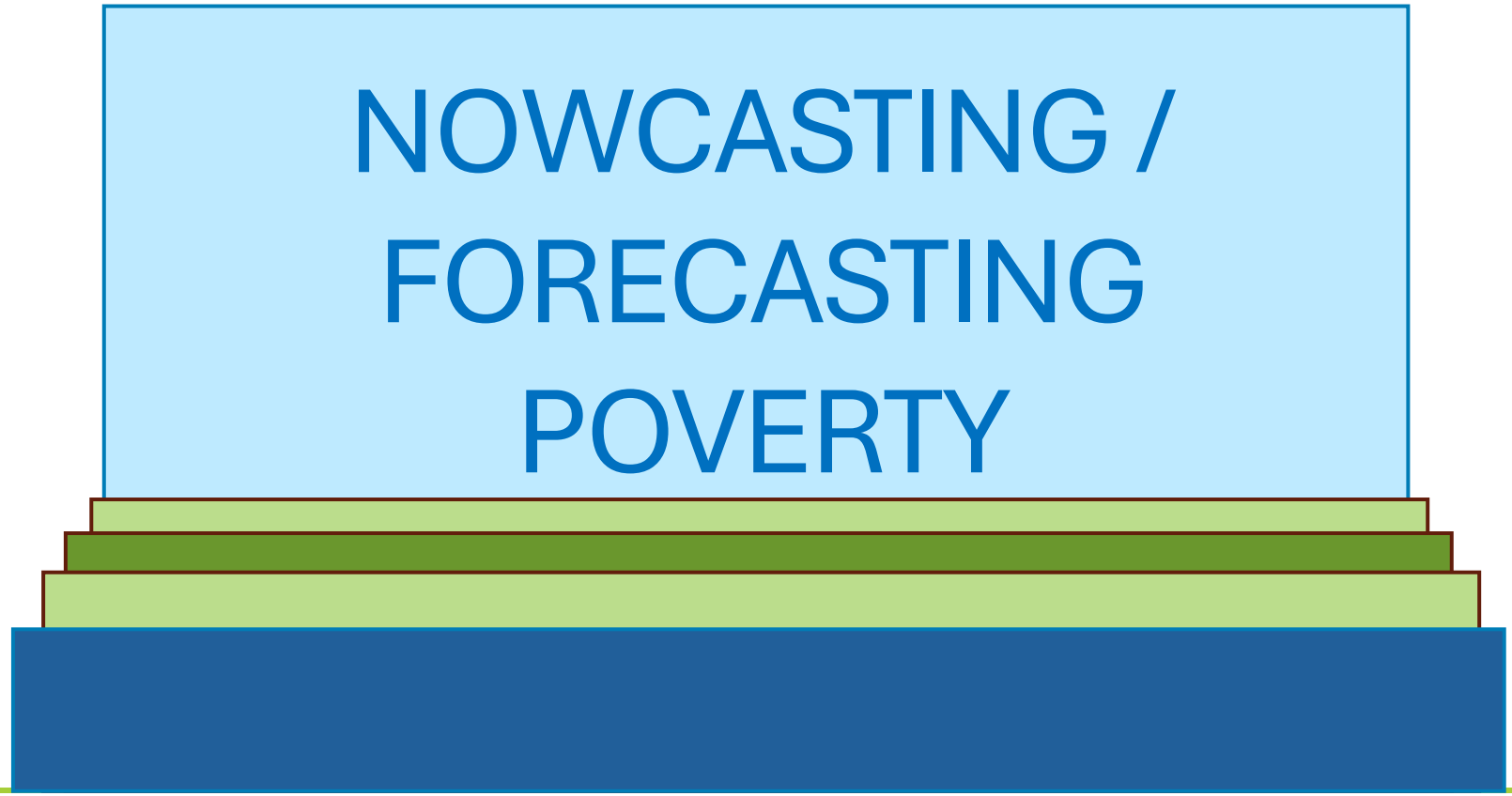
MAST Training (29 October 2026)
Jakarta, Indonesia

TOPIC # 1



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

TOPIC # 1



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

How current is the official poverty estimate for your country?

Think of the poverty estimate your government uses. Is its reference period:

Scan the Slido QR code to participate

A

Less than 12 months old?

B

1 to 2 years old?

C

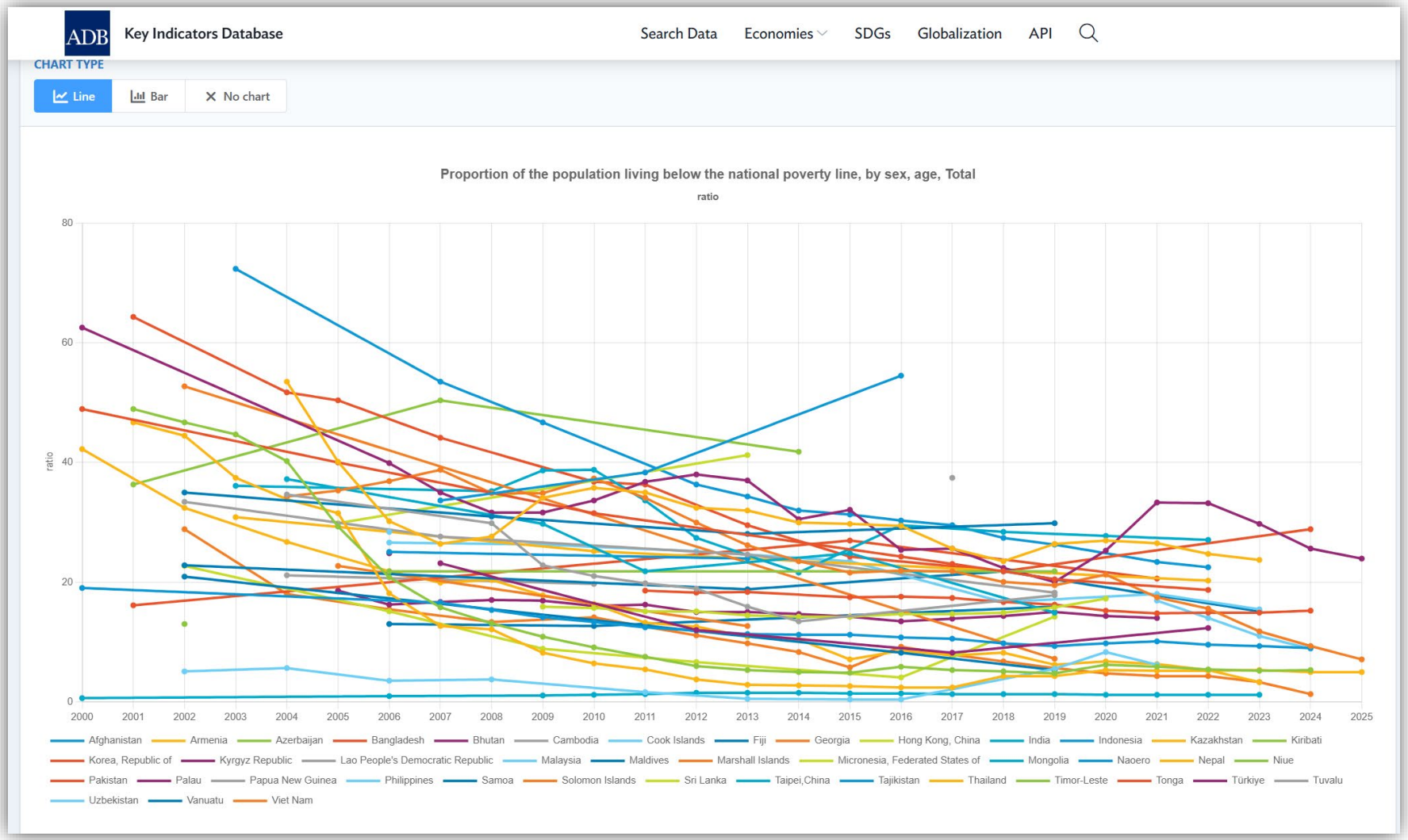
More than 2 years old?

D

Not sure…

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

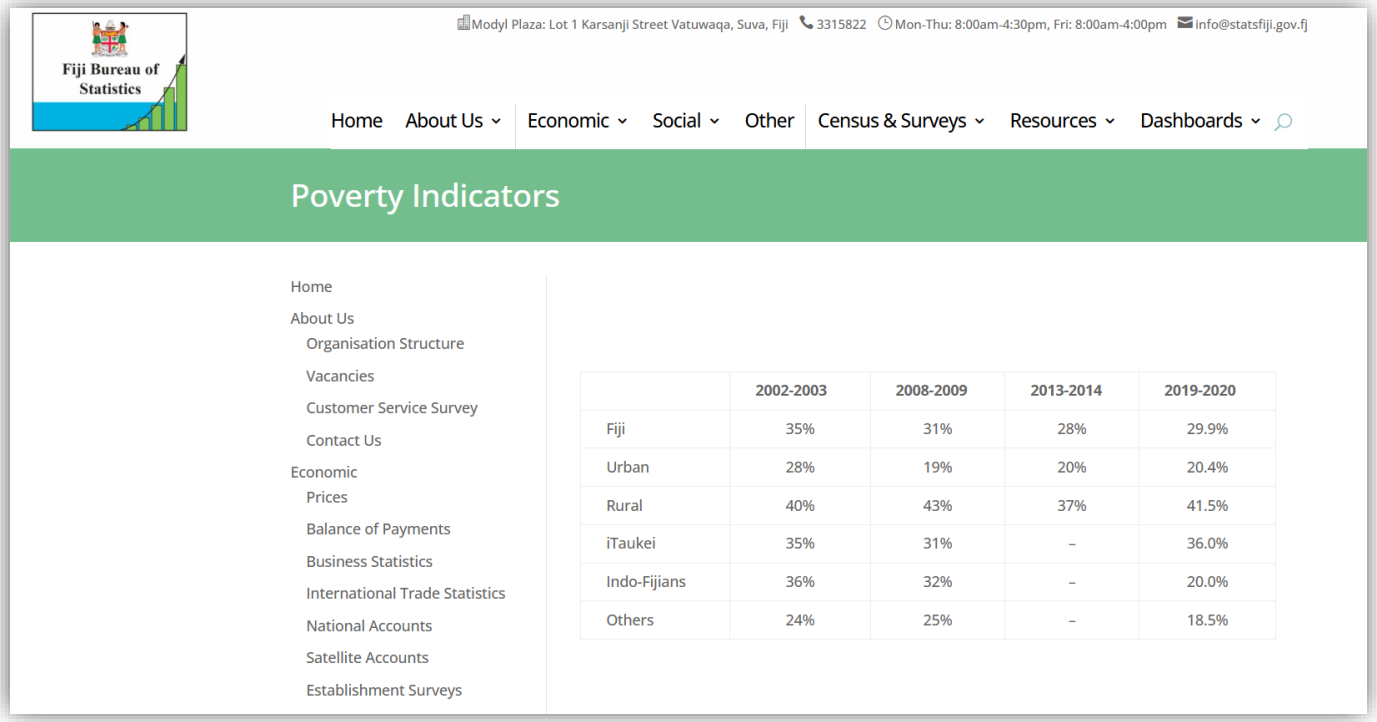
Typically, poverty data has approximately two-year lag.



Source: [Key Indicators for Asia and the Pacific Database]

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Now – how much has changed since then?



	2002-2003	2008-2009	2013-2014	2019-2020
Fiji	35%	31%	28%	29.9%
Urban	28%	19%	20%	20.4%
Rural	40%	43%	37%	41.5%
iTaukei	35%	31%	–	36.0%
Indo-Fijians	36%	32%	–	20.0%
Others	24%	25%	–	18.5%



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

The economy moves every day; official poverty statistics often do not.



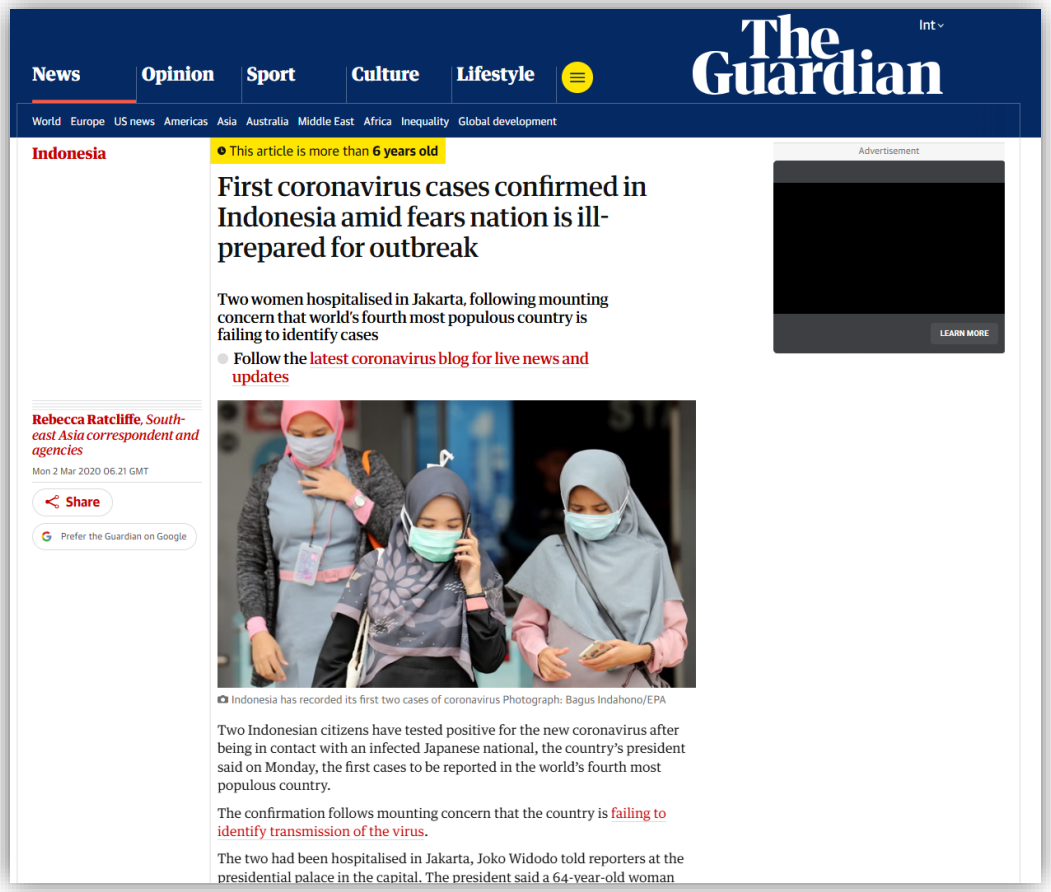
Estimate the current or very recent period using information already observed.

Project a future period using explicit assumptions or scenarios.



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

The economy moves every day; official poverty statistics often do not.



The Guardian

News | Opinion | Sport | Culture | Lifestyle

World Europe US news Americas Asia Australia Middle East Africa Inequality Global development

Indonesia

This article is more than 6 years old

First coronavirus cases confirmed in Indonesia amid fears nation is ill-prepared for outbreak

Two women hospitalised in Jakarta, following mounting concern that world's fourth most populous country is failing to identify cases

Follow the latest coronavirus blog for live news and updates

Rebecca Ratcliffe, South-east Asia correspondent and agencies

Mon 2 Mar 2020 06.21 GMT

Share

Prefer the Guardian on Google

Indonesia has recorded its first two cases of coronavirus Photograph: Bagus Indahono/EPA

Two Indonesian citizens have tested positive for the new coronavirus after being in contact with an infected Japanese national, the country's president said on Monday, the first cases to be reported in the world's fourth most populous country.

The confirmation follows mounting concern that the country is failing to identify transmission of the virus.

The two had been hospitalised in Jakarta, Joko Widodo told reporters at the presidential palace in the capital. The president said a 64-year-old woman

Advertisement

LEARN MORE



THE ASEAN POST

Tuesday, 13 October 2026

Home | Geopolitics | Spotlight | Energy | Markets | Technology | Environment | Opinion

Ensuring Food Security In The COVID-19 Era

T Tiensin, A Kalibata, and M Cole

14 April 2020

Members of the Thai police forces distribute free face masks and food to poor people amid restrictions set up to halt the spread of the COVID-19 coronavirus in Bangkok on 9 April, 2020. (AFP Photo)

COVID-19 has been slowly creeping into our communities. As we seek to ensure our families' health and safety, to many people, food has never seemed so important, both as a source of nutrition and, for many, of comfort. The question is whether, as economic disruption continues, we can stave off a pandemic-related food crisis.

Skyscanner

Manila Ninoy Aquino ✈ Jakarta

from 8,670 PHP Search

Manila Ninoy Aquino ✈ India

from 14,193 PHP Search

TODAY'S STORIES

Tangshan And Xuzhou: China's Treatment Of Women

24 June 2022

Myanmar's Suu Kyi: Prisoner Of Generals

24 June 2022

Philippines Ends China Talks For SCS Exploration

24 June 2022

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

When data are late, policy does not wait – it decides with a blind spot.

Between official survey rounds, governments still must decide:



- whether to expand or retarget social protection;
- where to prioritize disaster assistance;



- whether inflation or labor-market changes are becoming distributional crises;
- which locations or groups require close investigation

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Nowcasting today's poverty by updating the last official survey-based benchmark with today's economic signals



Anchor

Begin with the latest credible source of official poverty data (e.g., household survey and its welfare distribution) – not an algorithm searching blindly for poverty.



Update

Use more timely information such as economic growth or consumption aggregates, prices, employment, administrative records, rapid surveys, or carefully validated alternative data.



Estimate & Test

Produce model-based estimate, validate it against historical survey rounds, quantify uncertainty, and document revisions



Recalibrate

When a new official survey arrives, compare the nowcast with observed outcomes and improve the model

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

The prize is not a faster statistic – it is a faster, better-timed decision.

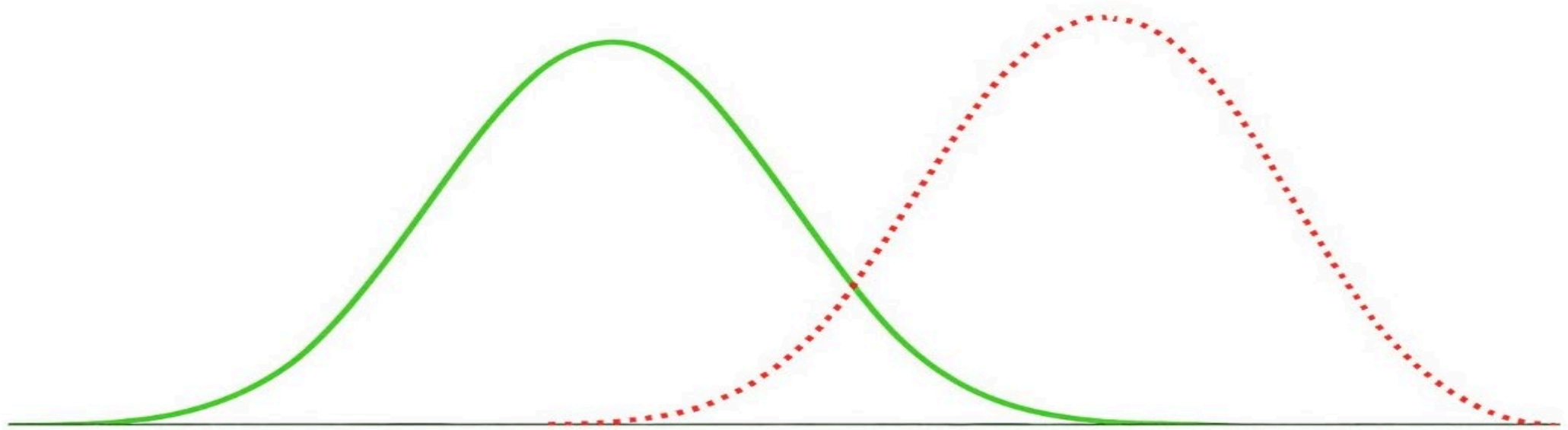
Poverty nowcasts can guide **early investigation, scenario development, temporary program adjustment, and geographic prioritization** – but official surveys remain the authoritative benchmark.



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

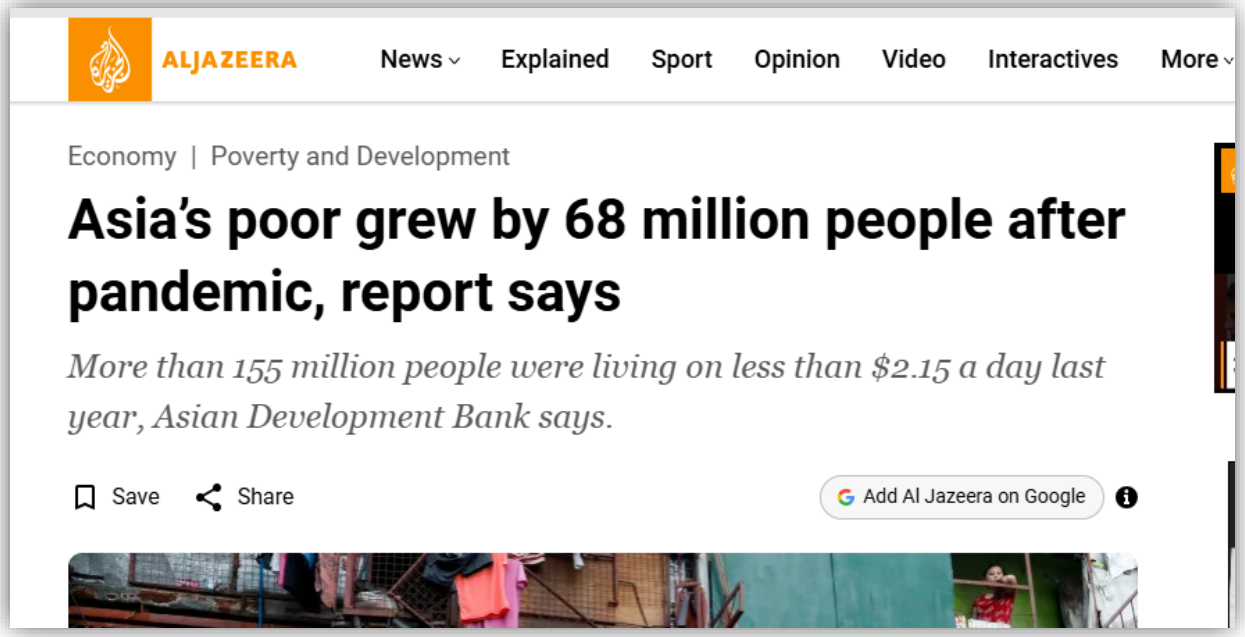
Poverty Nowcasting Approach # 1: Every household income or consumption moves at the same pace proportional to GDP (per capita) growth.

Visual Illustration of Approach # 1: Distribution-neutral growth extrapolation



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Examples of Poverty Nowcasts That Implemented Approach # 1





PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Estimation Procedure at a Glance

Distribution-neutral growth extrapolation – shifts the latest welfare distribution using GDP or household-consumption growth and a pass-through parameter.

Step 1: For each country and survey year, compile mean household consumption or income per capita and the consumption share of each decile (Suggested source: official surveys; or World Bank's Poverty and Inequality Platform)

Step 2: Apply a Lorenz Curve Parameterization to the Mean and Decile Shares. The resulting synthetic distribution allows poverty rates to be estimated at different poverty threshold.

Step 3: Use a model that predicts average household consumption or income growth from GDP per capita growth. Apply the model to the baseline and scenario-based GDP growth estimates

$$y_{h,t+1} = y_{h,t}(1 + \lambda * g_t)$$

where g_t is real per-capita GDP or household-consumption growth and λ is the survey-to-national-accounts pass-through rate.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Neutral Growth Extrapolation of Poverty

When everyone's consumption grows at the same rate, how does poverty change?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume full pass-through to household consumption $\lambda = 1$.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1		
2	70	1		
3	85	1		
4	92	1		
5	98	1		
6	105	0		
7	120	0		
8	145	0		
9	180	0		
10	250	0		

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Neutral Growth Extrapolation of Poverty

When everyone's consumption grows at the same rate, how does poverty change?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume full pass-through to household consumption $\lambda = 1$.

STEP 1: Calculate each household's updated consumption.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	60.5	
2	70	1	77	
3	85	1	93.5	
4	92	1	101.2	
5	98	1	107.8	
6	105	0	115.5	
7	120	0	132	
8	145	0	159.5	
9	180	0	198	
10	250	0	275	

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Neutral Growth Extrapolation of Poverty

When everyone's consumption grows at the same rate, how does poverty change?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume full pass-through to household consumption $\lambda = 1$.

STEP 2: Identify which households remain below the poverty line.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	60.5	1
2	70	1	77	1
3	85	1	93.5	1
4	92	1	101.2	0
5	98	1	107.8	0
6	105	0	115.5	0
7	120	0	132	0
8	145	0	159.5	0
9	180	0	198	0
10	250	0	275	0

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Neutral Growth Extrapolation of Poverty

When everyone's consumption grows at the same rate, how does poverty change?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume full pass-through to household consumption $\lambda = 1$.

STEP 3: Calculate the baseline and updated poverty headcount rates.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	60.5	1
2	70	1	77	1
3	85	1	93.5	1
4	92	1	101.2	0
5	98	1	107.8	0
6	105	0	115.5	0
7	120	0	132	0
8	145	0	159.5	0
9	180	0	198	0
10	250	0	275	0

Poverty Rate$_{t+1}$ = 3/10 = 30%

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Neutral Growth Extrapolation of Poverty

When everyone's consumption grows at the same rate, how does poverty change?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume pass-through to household consumption **$\lambda = 0.7$**.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	58.85	1
2	70	1	74.9	1
3	85	1	90.95	1
4	92	1	98.44	1
5	98	1	104.86	0
6	105	0	112.35	0
7	120	0	128.4	0
8	145	0	155.15	0
9	180	0	192.6	0
10	250	0	267.5	0

Poverty Rate$_{t+1}$ = 4/10 = 40%

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Methodological Features: Distribution-Neutral Growth Extrapolation of Poverty

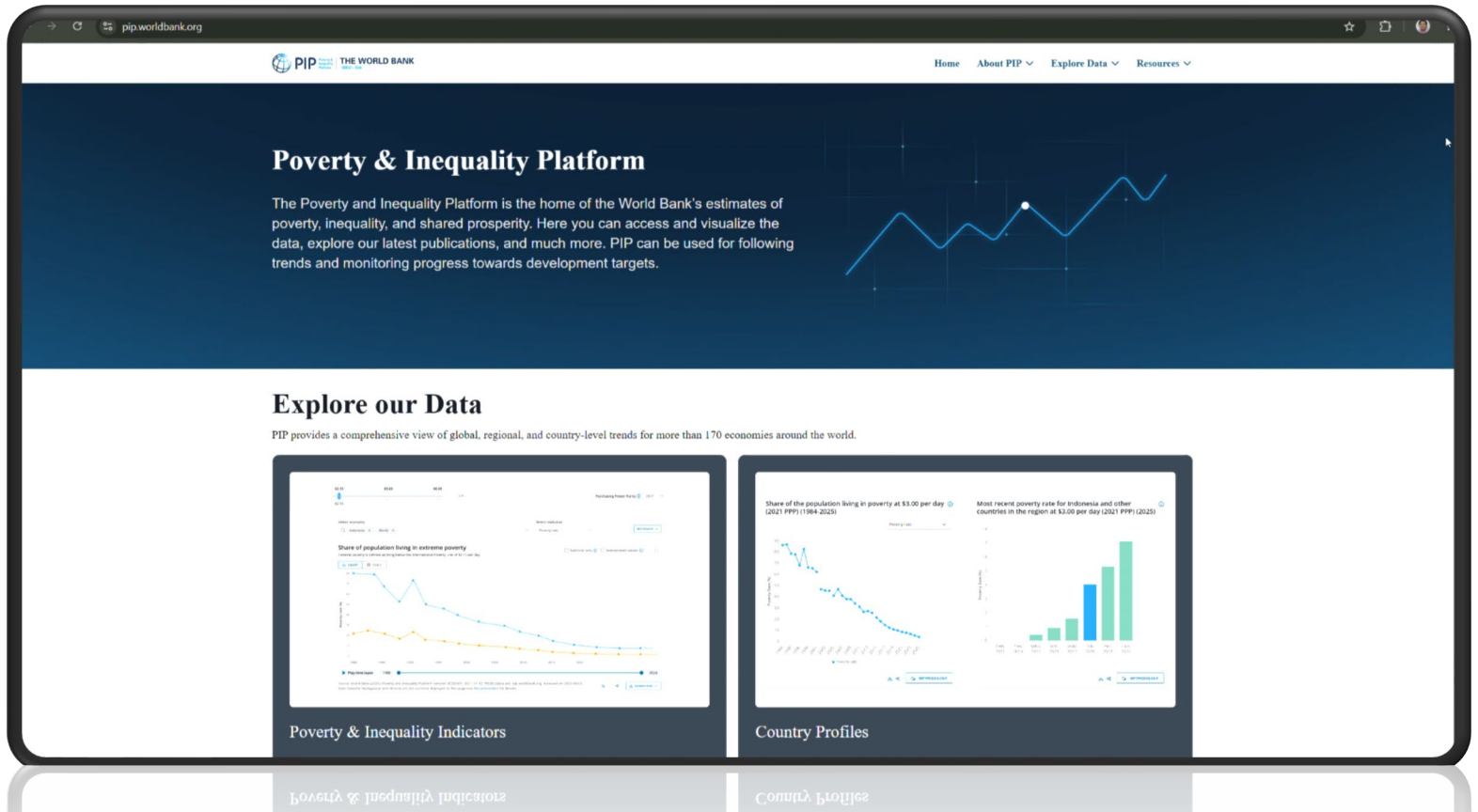
- Everyone's income or consumption changes by the same percentage.
- The relative distribution, and therefore inequality, remains unchanged.
- The poverty estimate depends on:
  - the baseline welfare distribution;
  - projected GDP or consumption growth;
  - the pass-through rate, λ; and
  - how many households begin close to the poverty line.

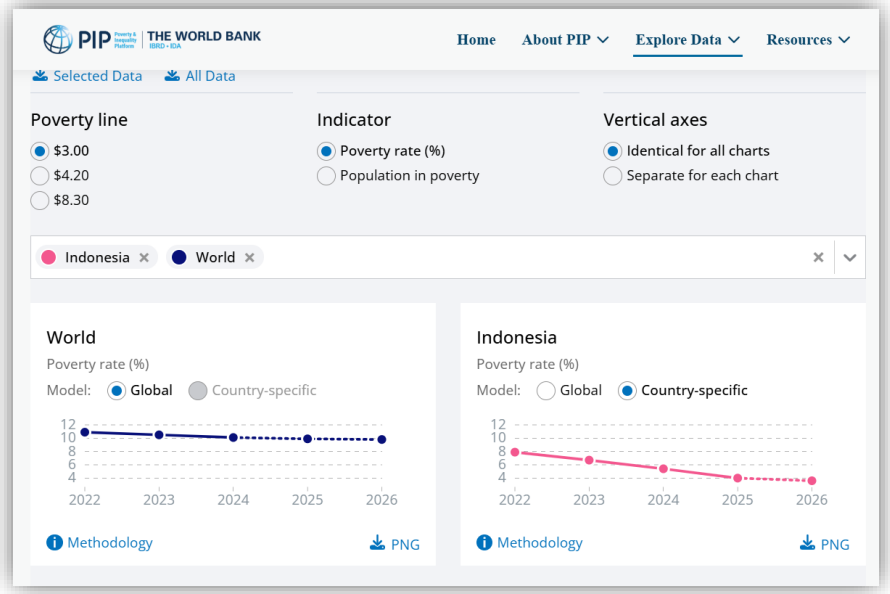
Points to remember when interpreting results:

- A transparent and scalable benchmark, but not a claim that all households actually experienced the same change.
- It cannot capture differences across sectors, locations, occupations, or income groups.
- Interpret the result as: "poverty under unchanged inequality and the stated pass-through assumption."

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Tool(s) applying variants of methods operationalizing Approach # 1



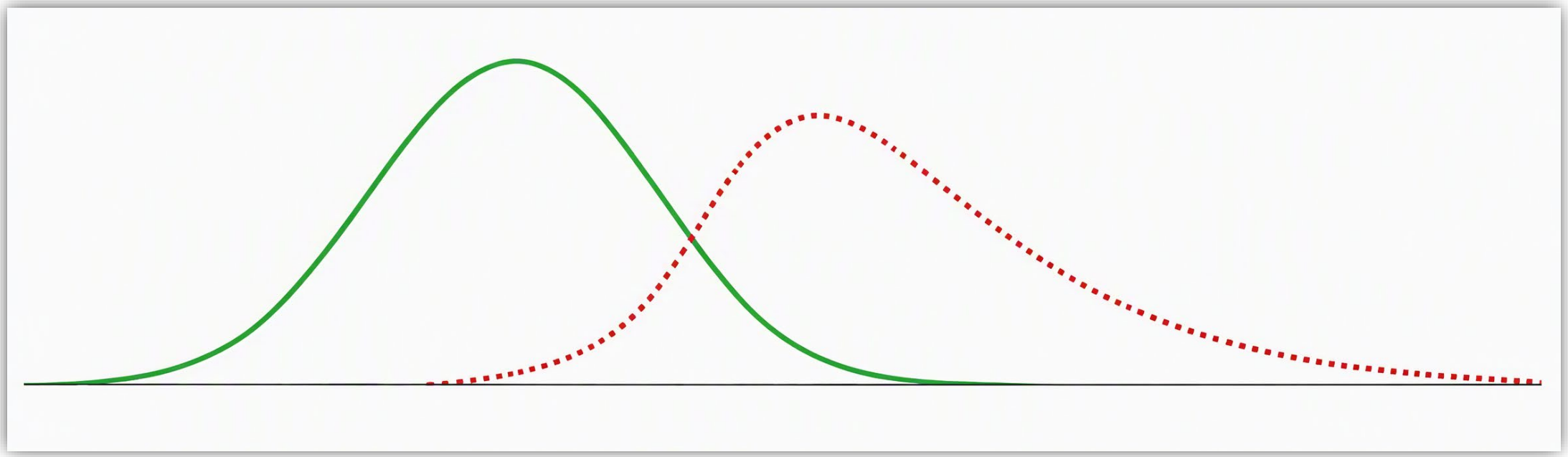


Source: [WB's Poverty and Inequality Platform / Nowcasts]

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Poverty Nowcasting Approach # 2: Average household income or consumption moves at a pace proportion to GDP (per capita) growth but bottom X% grew faster / slower than the upper (100 – X)%.

Visual Illustration of Assumption # 2



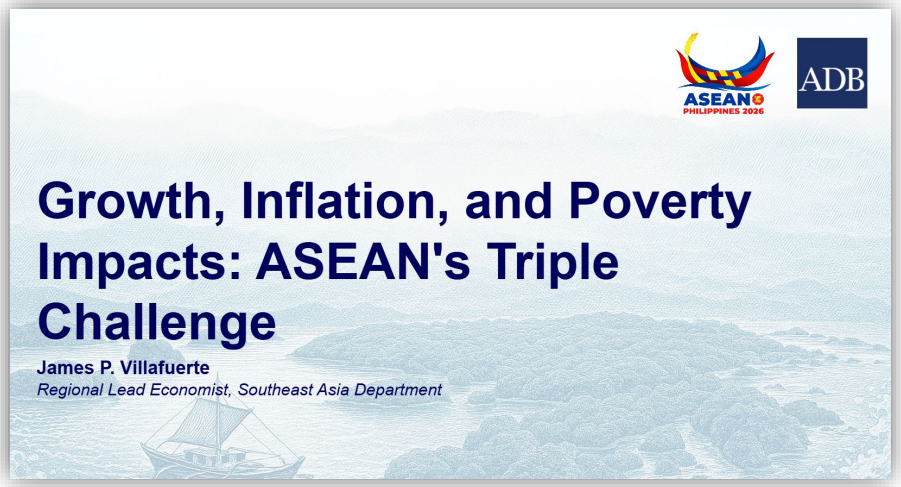
PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

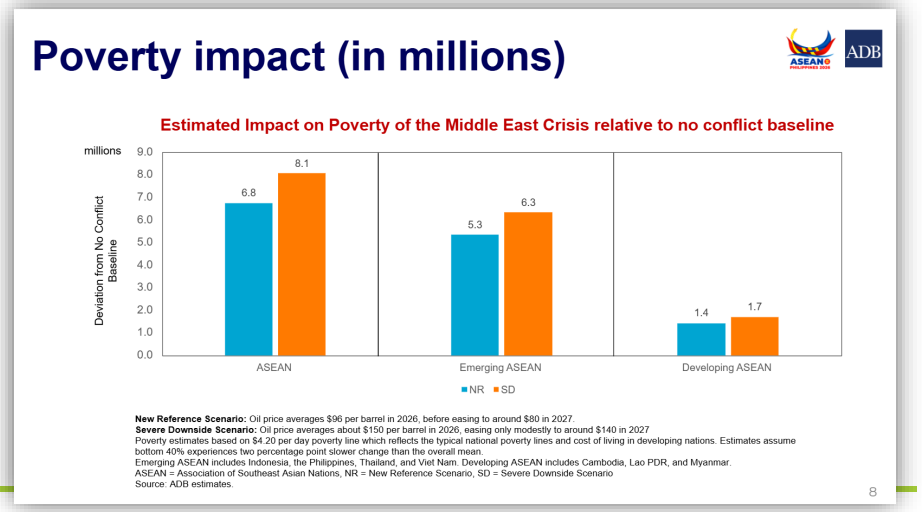
Examples of Poverty Nowcasts That Implemented Approach # 2











PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Estimation Procedure at a Glance

Similar to Approach # 1 but does not assume all households have experienced the same growth since the last survey by also predicting inequality – either directly or by predicting change in inequality (i.e., distribution-sensitive growth).

$$poverty_{t_{n,AS}}\left(\hat{\mu}_{t_n}, \widehat{gini}_{t_n}\right) = F[welfare_{h,p,t_s}\left(1 + g_{p,t_s,t_n}\left(\hat{\mu}_{t_n},, \widehat{gini}_{t_n}\right)\right) < poverty\ line]$$

where $g_{p,t_s,t_n}\left(\hat{\mu}_{t_n},, \widehat{gini}_{t_n}\right)$ are percentile-specific growth rates, which are determined such that the resulting distribution matches the predicted mean and Gini;

AS – refers to the assumed distribution of welfare

Source: Mahler, D., Aguilar, A., and Newhouse. 2022.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Sensitive Growth Extrapolation of Poverty

Can the same average growth produce different poverty outcomes?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume pass-through to household consumption $\lambda = 0.7$.

Progressive growth: bottom 50% grows by 20%; overall mean grows by 10%*0.7 = 7 % → top 50% grows by X%?

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1		
2	70	1		
3	85	1		
4	92	1		
5	98	1		
6	105	0		
7	120	0		
8	145	0		
9	180	0		
10	250	0		

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Sensitive Growth Extrapolation of Poverty

Can the same average growth produce different poverty outcomes?

- B= baseline consumption total of the bottom group
- T= baseline consumption total of the top group
- g= required aggregate or mean consumption growth
- g_B= bottom-group growth
- g_T= top-group growth to be solved

$$B(1+g_B)+T(1+g_T)=(B+T)(1+g)$$

$$g_T = \frac{(B+T)g - Bg_B}{T}$$

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Sensitive Growth Extrapolation of Poverty

Can the same average growth produce different poverty outcomes?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume pass-through to household consumption $\lambda = 0.7$.

Progressive growth: bottom 50% grows by 20%; overall mean grows by 10%*0.7 = 7% → top 50% grows by 0.5%.

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	66	1
2	70	1	84	1
3	85	1	102	0
4	92	1	110.4	0
5	98	1	117.6	0
6	105	0	105.525	0
7	120	0	120.6	0
8	145	0	145.725	0
9	180	0	180.9	0
10	250	0	251.25	0

Poverty Rate$_{t+1}$ = 2/10 = 20%

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Sensitive Growth Extrapolation of Poverty

Can the same average growth produce different poverty outcomes?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume pass-through to household consumption $\lambda = 0.7$.

Regressive growth: bottom 50% grows by 0%; overall mean grows by 10%*0.7 = 7 % → top 50% grows by X%?

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1		
2	70	1		
3	85	1		
4	92	1		
5	98	1		
6	105	0		
7	120	0		
8	145	0		
9	180	0		
10	250	0		

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Distribution-Sensitive Growth Extrapolation of Poverty

Can the same average growth produce different poverty outcomes?

Ten equally weighted households have the baseline consumption levels shown below. The poverty line is 100 consumption units. Real GDP per capita increases by 10%, and assume pass-through to household consumption $\lambda = 0.7$.

Regressive growth: bottom 50% grows by 0%; overall mean grows by 10%*0.7 = 7 % → top 50% grows by 10.5%

Household	Baseline: Consumption$_t$	Poor at time = t?	Consumption$_{t+1}$	Poor at time = t+1?
1	55	1	55	1
2	70	1	70	1
3	85	1	85	1
4	92	1	92	1
5	98	1	98	1
6	105	0	116.025	0
7	120	0	132.6	0
8	145	0	160.225	0
9	180	0	198.9	0
10	250	0	276.25	0

Poverty Rate$_{t+1}$ = 5/10 = 50%

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Methodological Features: Distribution-Sensitive Growth Extrapolation of Poverty

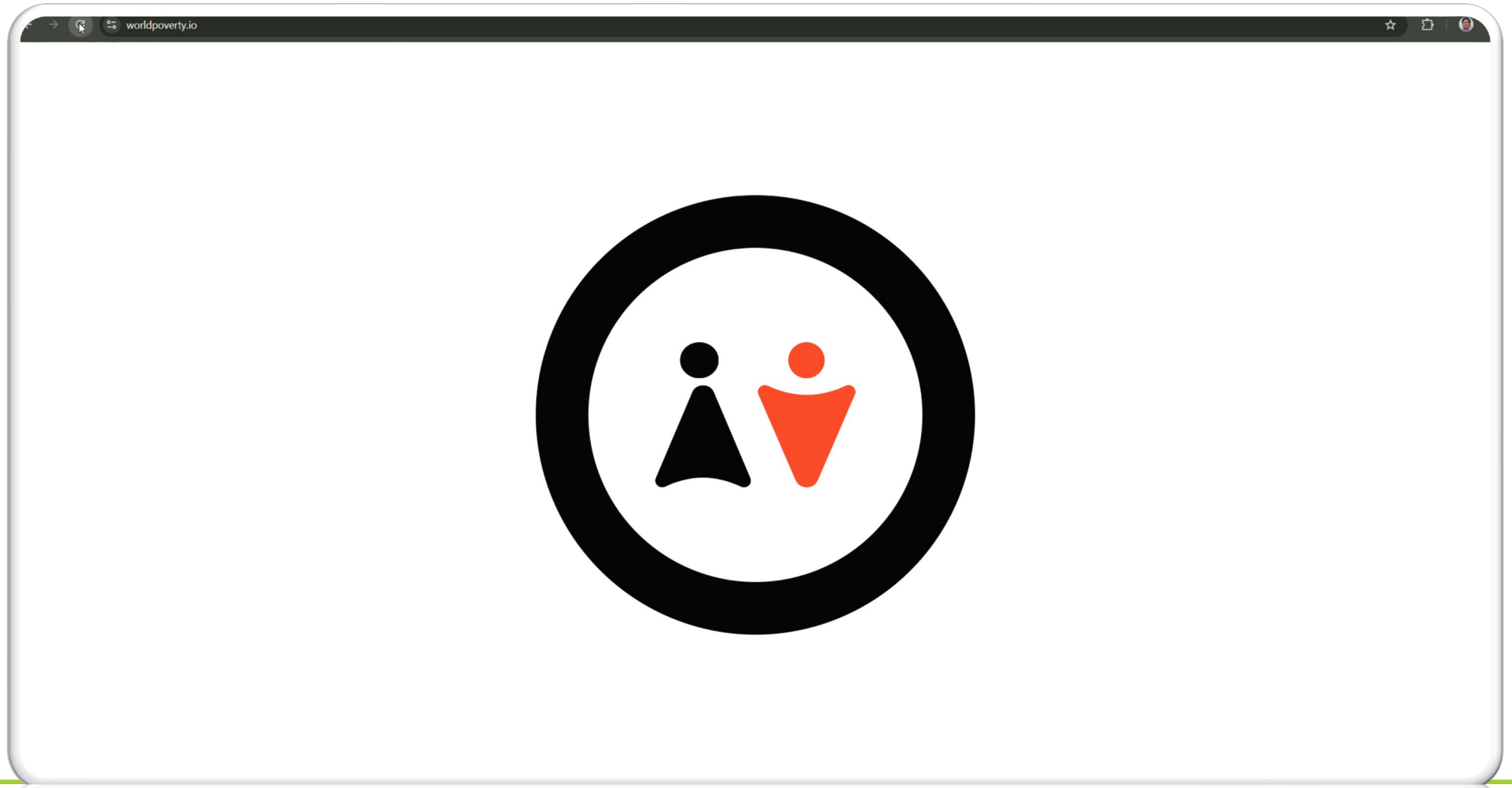
- Households or population groups can experience different rates of welfare growth.
- The method therefore requires an additional assumption or prediction about how growth is distributed.
- Poverty now depends on both:
  - how much average welfare changes; and
  - how different households receive the gains or losses.

Points to remember when interpreting results:

- Progressive growth can produce substantially more poverty reduction than the distribution-neutral benchmark.
- Regressive growth can leave poverty much higher, even when the economy records the same average growth.
- The approach may be more realistic, but its results are also more sensitive to assumptions about who gains.
- Present distribution-sensitive estimates as clearly labeled scenarios, or with uncertainty ranges, unless distributional changes are supported by timely evidence.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Tool(s) applying variants of methods operationalizing Approach # 2



Source: World Data Lab's World Poverty Clock.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

A Note About Data Requirements

Both the distribution-neutral and distribution-sensitive approaches for extrapolating (or nowcasting/forecasting) poverty have minimal data requirements. They can be implemented even without access to micro-level data, using only grouped distribution data (averages, percentiles, etc.).

The next approach is more data-demanding and typically requires access to micro-level data.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Poverty Microsimulation

Reduced-form macro-micro microsimulation: Changes individuals' employment status, sector, earnings, remittances, transfers, and prices to match macro scenarios.

CGE-microsimulation / structural macro-micro models: a CGE or input-output model first generates sectoral prices, wages, employment, and factor returns that are mapped onto survey households.

Price-and subsidy-focused household microsimulation: applies commodity-specific price changes to household expenditure baskets, sometimes with indirect input-output effects.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Estimation Procedure at a Glance

Constructs a model-based distribution of household income or consumption by updating the last observed household survey using macroeconomic evidence or projections for factors such as economic growth, population changes, jobs, wages, remittances and prices.

Step 1. Divide people into different groupings (e.g., age-education) and change their survey weights so that the survey resembles the population for the time for which nowcasts, forecasts, or alternative scenarios are meant to produce.

Step 2. Using latest survey, classify people into analytically useful groups, especially by age, education / skills, sector of employment, and other relevant grouping, to establish the baseline distribution against which nowcasts, forecasts, or alternative scenarios will be based upon.

Step 3. Map macro changes (e.g., based on CGE models, or other relevant models) describing how large the economic becomes, which sectors expand or contract, how relative wages change, what happens to prices, etc. Extract the "linkage aggregate variables": overall growth, sectoral employment, relative earnings by skills and sector, factor returns, consumer prices, etc. Implement these macro changes to the household model sequentially.

Step 4. Update household income components, household size, consumption information, and the poverty line, per population sub-group in Step 2, using macro changes described in Step 3.

Step 5. Calculate poverty and other distribution-based measures.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Two Specific Examples of Poverty Microsimulation

Step 1. Household survey baseline
Household consumption, income, demographics, education, labor supply, etc.

Step 2. Reweight demographic population groups
Adjust survey weights to match target population structure (e.g., age x education)

Step 3. CGE model generates growth, sector jobs, relative wages and consumer prices
General equilibrium model produces macroeconomic and sectoral changes.

Step 4. Reallocate workers and adjust wage / factor returns
Shift employment across sectors and update wages and returns based on CGE results

Step 5. Rebuild counterfactual welfare distribution and poverty / inequality results
Simulate household welfare under the scenario and compute poverty and inequality indicators

Source: Narayan. Olivieri, Sanchez-Paramo. 2010 .

Step 1. Household survey baseline
Household consumption, income, demographics, education, labor supply, etc.

Step 2. Add external macro scenarios and population growth
Incorporate external macroeconomic scenarios (e.g., global crisis) and demographic projections

Step 3. Reassign employment / sectors and earnings
Update the sectoral employment and individual earnings consistent with macro scenarios.

Step 4. Update remittances, other income and poverty-line
Adjust remittance inflows, non-labor income and consumer prices, including the poverty line if necessary

Step 5. Rebuild counterfactual welfare distribution and poverty / inequality results
Construct welfare distribution for each scenario and compare poverty and inequality outcomes

Source: Bussolo, Hoyos, Medvedev. 2010.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Poverty Microsimulation

Household	XXXXX	Baseline: Consumption$_t$	Poor at time = t?	XXXXX	XXXXX	Consumption$_{t+1}$	Poor at time = t+1?
1		55	1				
2		70	1				
3		85	1				
4		92	1				
5		98	1				
6		105	0				
7		120	0				
8		145	0				
9		180	0				
10		250	0				

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Poverty Microsimulation

How do sector-specific performance affect households differently according to their main livelihood and position in the welfare distribution?

Ten equally weighted households have the baseline consumption levels and main livelihoods shown below. The poverty line is 100 consumption units. Assume sector shocks / growth of -10% in agriculture, -8% in manufacturing, and +2% in services. Apply the livelihood and percentile-specific pass-through parameter to each sector shock/growth to nowcast poverty at t+1.

Household	Main Livelihood	Baseline: Consumption$_t$	Poor at time = t?	Sector Shock/Growth	$\lambda_{livelihood,percentile}$	Consumption$_{t+1}$	Poor at time = t+1?
1	Agriculture	55	1	-10%	0.8		
2	Agriculture	70	1	-10%	0.8		
3	Manufacturing	85	1	-8%	1		
4	Manufacturing	92	1	-8%	1		
5	Services	98	1	2%	0.9		
6	Agriculture	105	0	-10%	0.8		
7	Manufacturing	120	0	-8%	0.8		
8	Manufacturing	145	0	-8%	0.8		
9	Services	180	0	2%	1		
10	Services	250	0	2%	1		

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Worked Example: Poverty Microsimulation

How do sector-specific performance affect households differently according to their main livelihood and position in the welfare distribution?

Ten equally weighted households have the baseline consumption levels and main livelihoods shown below. The poverty line is 100 consumption units. Assume sector shocks / growth of -10% in agriculture, -8% in manufacturing, and +2% in services. Apply the livelihood and percentile-specific pass-through parameter to each sector shock/growth to nowcast poverty at t+1.

Household	Main Livelihood	Baseline: Consumption$_t$	Poor at time = t?	Sector Shock/Growth	$\lambda_{livelihood,percentile}$	Consumption$_{t+1}$	Poor at time = t+1?
1	Agriculture	55	1	-10%	0.8	50.6	1
2	Agriculture	70	1	-10%	0.8	64.4	1
3	Manufacturing	85	1	-8%	1	78.2	1
4	Manufacturing	92	1	-8%	1	84.64	1
5	Services	98	1	2%	0.9	99.764	1
6	Agriculture	105	0	-10%	0.8	96.6	1
7	Manufacturing	120	0	-8%	0.8	112.32	0
8	Manufacturing	145	0	-8%	0.8	135.72	0
9	Services	180	0	2%	1	183.6	0
10	Services	250	0	2%	1	255	0

Poverty Rate$_{t+1,\ All}$ = 6/10 = 60%
Poverty Rate$_{t+1,\ Agri}$ = 3/3 = 100%
Poverty Rate$_{t+1,\ Mfg}$ = 2/4 = 50%
Poverty Rate$_{t+1,\ Svcs}$ = 1/3 = 33.33%

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Other Variants of Poverty Nowcasting Methods

Target Outcome Variables

Target variable	Approach for estimating poverty
(1) Poverty rates	Predicted directly
(2) Changes in poverty rates	Apply the predicted change to the most recent poverty rate
(3) Mean welfare	Scale the past distribution to the predicted mean welfare
(4) Growth in mean welfare	Scale the past distribution by 1+ the predicted growth in mean welfare
(5) Mean welfare and Gini coefficient	(i) Assume the distribution is log-normal or log-logistic or (ii) apply a growth incidence curve from the past distribution to match the predicted mean and Gini
(6) Growth in mean welfare and Gini coefficient	(i) Apply the predicted growth in the mean and Gini to the past mean and Gini and assume that the distribution is log-normal or log-logistic or (ii) apply a growth incidence curve to the past distribution with the predicted growth in the mean and Gini

Source: Mahler, Aguilar, and Newhouse (2022)

Potential Explanatory Variables

- Macroeconomic variables (such as inflation, government debt, unemployment, etc.)
- Other socioeconomic indicators
- Remote sensing data (night lights, rainfall, land surface temperature, impervious surface, cropland, normalized difference vegetation, snow, water indices, etc

Estimation Methods

- Lasso Regression, Post-lasso, Random Forest, etc.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Other Variants of Poverty Nowcasting Methods

Predicting socioeconomic wellbeing using mobile phone data

Rationale: People with different levels of socioeconomic well-being (asset wealth, multidimensional poverty status, etc) often communicate, move, recharge airtime, and use digital services differently. A supervised model learns the statistical relationship between these patterns and survey-measured welfare.

Step 1: Capture metadata of calls and SMS: time, direction, duration, frequency, cell tower; or depending on availability: airtime recharges, mobile data, mobile money, handset characteristics, communication volume, timing, number and diversity of contacts, number of towers visited, home-location concentration, mobile-money activity, etc.

Step 2: Use information from Step # 1, to estimate a prediction model of wellbeing (typically for a smaller subset of subscribers)

Step 3: Apply the fitted model to other subscribers, to predict poverty status of the wider population.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Other Variants of Poverty Nowcasting Methods

Updating poverty estimates without repeating a full consumption survey

Step 1: Use the latest full household consumption survey to estimate how consumption is related to variables that are cheaper to collect—such as demographics, employment, assets, housing, or selected expenditures.

Step 2: Collect the same variables in a more frequently collected survey.

Step 3: Impute a current household consumption distribution, then calculate the share below the poverty line.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Hands-on Exercise #1

A hypothetical country is preparing for the potential impacts of El Niño and energy-related inflation. The Ministry of Welfare is considering expanding its existing financial assistance program, which currently provides approximately 10 currency units per poor household.

The Ministry would like to estimate the additional budget required to extend the same assistance to households that are newly pushed below the poverty line as a result of these shocks.

Assume that GDP per capita contracts by 1%. Estimate the additional budget requirement under each of the following scenarios:

- *Scenario 1: Uniform impact. All households are assumed to be affected by the GDP contraction. Use $\lambda = 0.7$ to translate the change in GDP per capita into a change in household consumption.*

- *Scenario 2: Larger shock among vulnerable households. Households that are both in rural areas and in the bottom 20% of the income distribution experience a 5% decline in real consumption due to the combined effects of El Niño and the energy crisis. Consumption of all other households are affected uniformly. Use $\lambda = 0.7$.*

- *Scenario 3: Differentiated impacts. Households that are in the agriculture sector, live in rural areas, and belong to the bottom 20% of the income distribution experience a 5% decline in real consumption. All households in the middle 60% of the income distribution experience a 3% decline in real consumption. Consumption of all other households are affected uniformly. Use $\lambda = 0.7$.*

For each scenario, estimate:

- **The number of additional households newly pushed below the poverty line**; and
- **The additional budget required to provide these newly poor households with financial assistance of 10 currency units per household**.

If you were to improve the current nowcasting and/or forecasting method by incorporating additional types of big data, what data would you use, and how would you integrate them into the method?

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Hands-on Exercise #1: Answers

A hypothetical country is preparing for the potential impacts of El Niño and energy-related inflation. The Ministry of Welfare is considering expanding its existing financial assistance program, which currently provides approximately 10 currency units per poor household.

The Ministry would like to estimate the additional budget required to extend the same assistance to households that are newly pushed below the poverty line as a result of these shocks.

Assume that GDP per capita contracts by 1%. Estimate the additional budget requirement under each of the following scenarios:

- *Scenario 1: Uniform impact. All households are assumed to be affected by the GDP contraction. Use λ = 0.7 to translate the change in GDP per capita into a change in household consumption.*
- *Scenario 2: Larger shock among vulnerable households. Households that are both in rural areas and in the bottom 20% of the income distribution experience a 5% decline in real consumption due to the combined effects of El Niño and the energy crisis. Consumption of all other households are affected uniformly. Use λ = 0.7.*
- *Scenario 3: Differentiated impacts. Households that are in the agriculture sector, live in rural areas, and belong to the bottom 20% of the income distribution experience a 5% decline in real consumption. All households in the middle 60% of the income distribution experience a 3% decline in real consumption. Consumption of all other households are affected uniformly. Use λ = 0.7.*

For each scenario, estimate:

- The number of additional households pushed below the poverty line; and
- The additional budget required to provide these newly poor households with financial assistance of 10 currency units per household.

Baseline number of $poor_t$: 7; Baseline $Poverty_t$: 7%
Baseline $Cost_t$: 7*10 = 70

Scenario 1
Number of $poor_{t+1}$: 9; $Poverty_{t+1}$ = 9%
Number of people who were non-$poor_t$ *but* $poor_{t+1}$: 2
Additional cost for people who were non-$poor_t$ *but* $poor_{t+1}$: 2*10 = 20
% cost increase relative to baseline cost = (90/70) – 1 = 28.57% higher than baseline cost

Scenario 2
Number of $poor_{t+1}$: 15 ; $Poverty_{t+1}$ = 15%
Number of people who were non-$poor_t$ *but* $poor_{t+1}$: 8
Additional cost for people who were non-$poor_t$ *but* $poor_{t+1}$: 8*10 = 80
% cost increase relative to baseline cost = (150/70) – 1 = 114.29% higher than baseline cost

Scenario 3
Number of $poor_{t+1}$: 14 ; $Poverty_{t+1}$ = 14%
Number of people who were non-$poor_t$ *but* $poor_{t+1}$: 7
Additional cost for people who were non-$poor_t$ *but* $poor_{t+1}$: 7*10 = 70
% cost increase relative to baseline cost = (140/70) – 1 = 100% higher than baseline cost

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Additional References

ADB. 2026. Key Indicators for Asia and the Pacific 2026 – Measuring Deprivation at Household and Individual Level.

ADB. 2023. Key Indicators for Asia and the Pacific 2023.

Bussolo, M. Hoyos, R., Medvedev, D., 2010. Economic Growth and Income Distribution: linking Macro-Economic Models with Household Survey Data at the Global Level.

Labeaga, J. 2023. CHIPS Microsimulation model: A tool to evaluate effects on inequality and poverty.

Dovonou, V., and Xie, Z. 2023. The Distributional Impact of Inflation in South Asia. WB Policy Research Working paper No. 10527.

Habib, B., Narayan, A., Olivieri, S., and Sanchez-Paramo, C. 2010. Assessing Ex Ante the Poverty and Distributional Impact of the Global Crisis in a Developing Country. WB Policy Research Working Paper No. 5238.

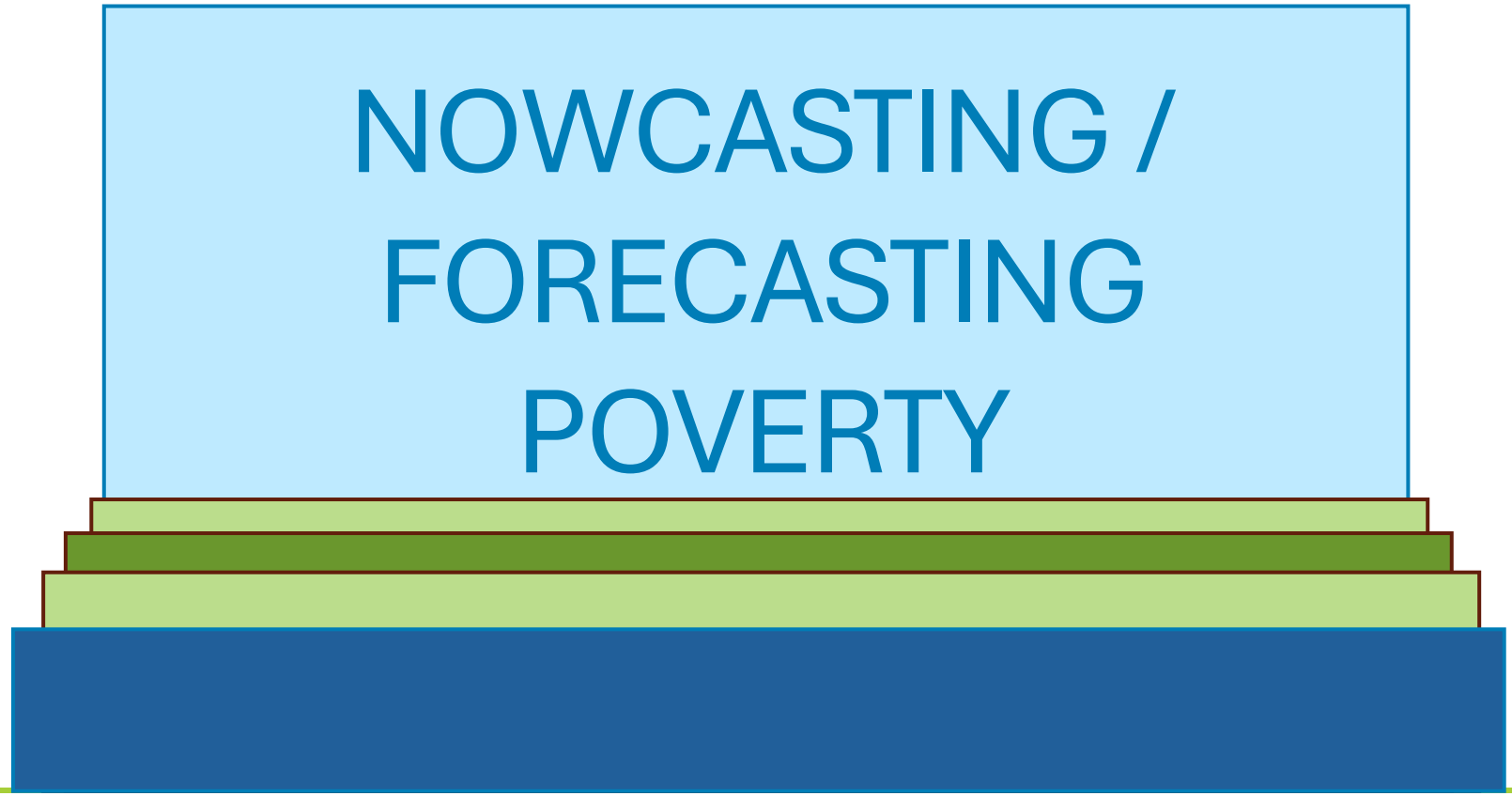
Mahler, D., Aguilar, R., and Newhouse, D. 2022. Nowcasting Global Poverty. The World Bank Economic Review, 36(4), 835 – 856.

Tiberti, L., Cicowiez, M., and Cockburn, J. 2017. A top-down behavior (TBD) microsimulation toolkit for a distributive analysis: A manual; download other files: here

World Bank's Macroeconometric Model (MfMod) and Macro Poverty Outlook

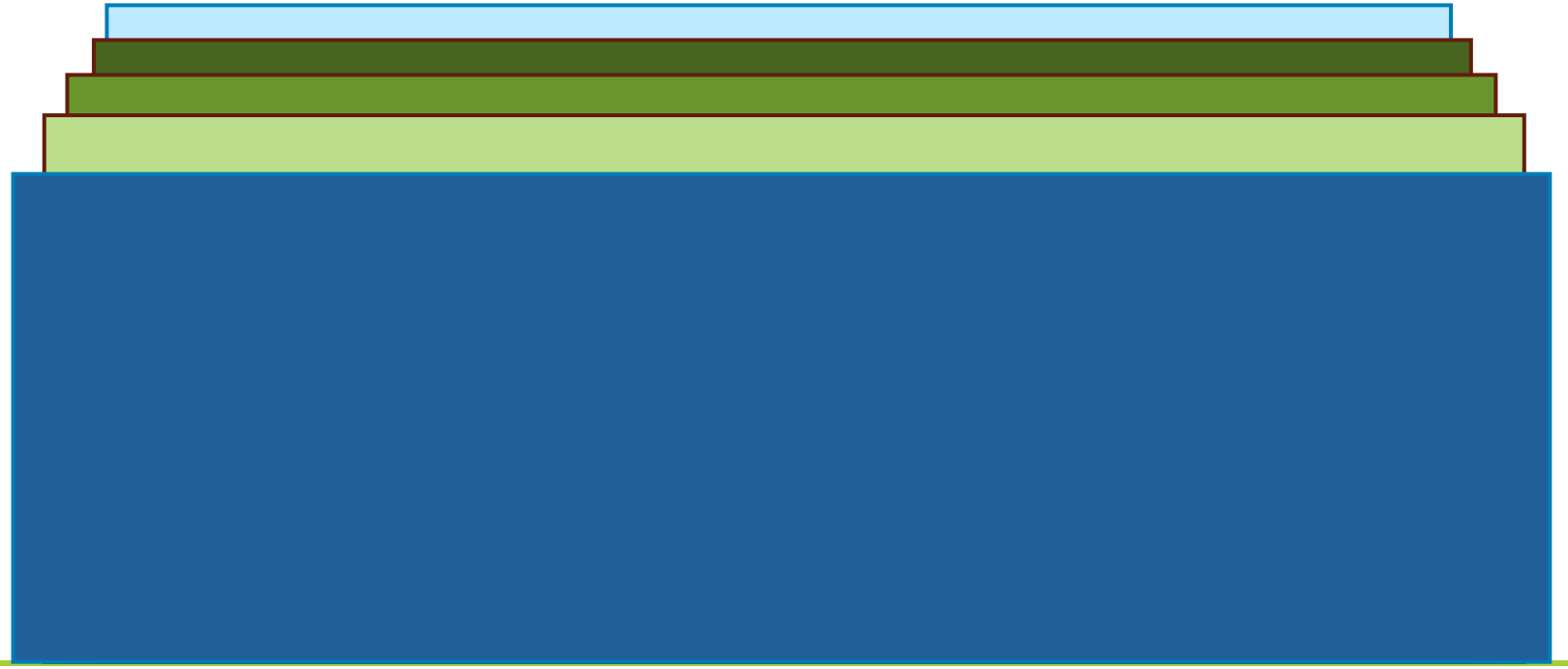
PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

TOPIC # 1



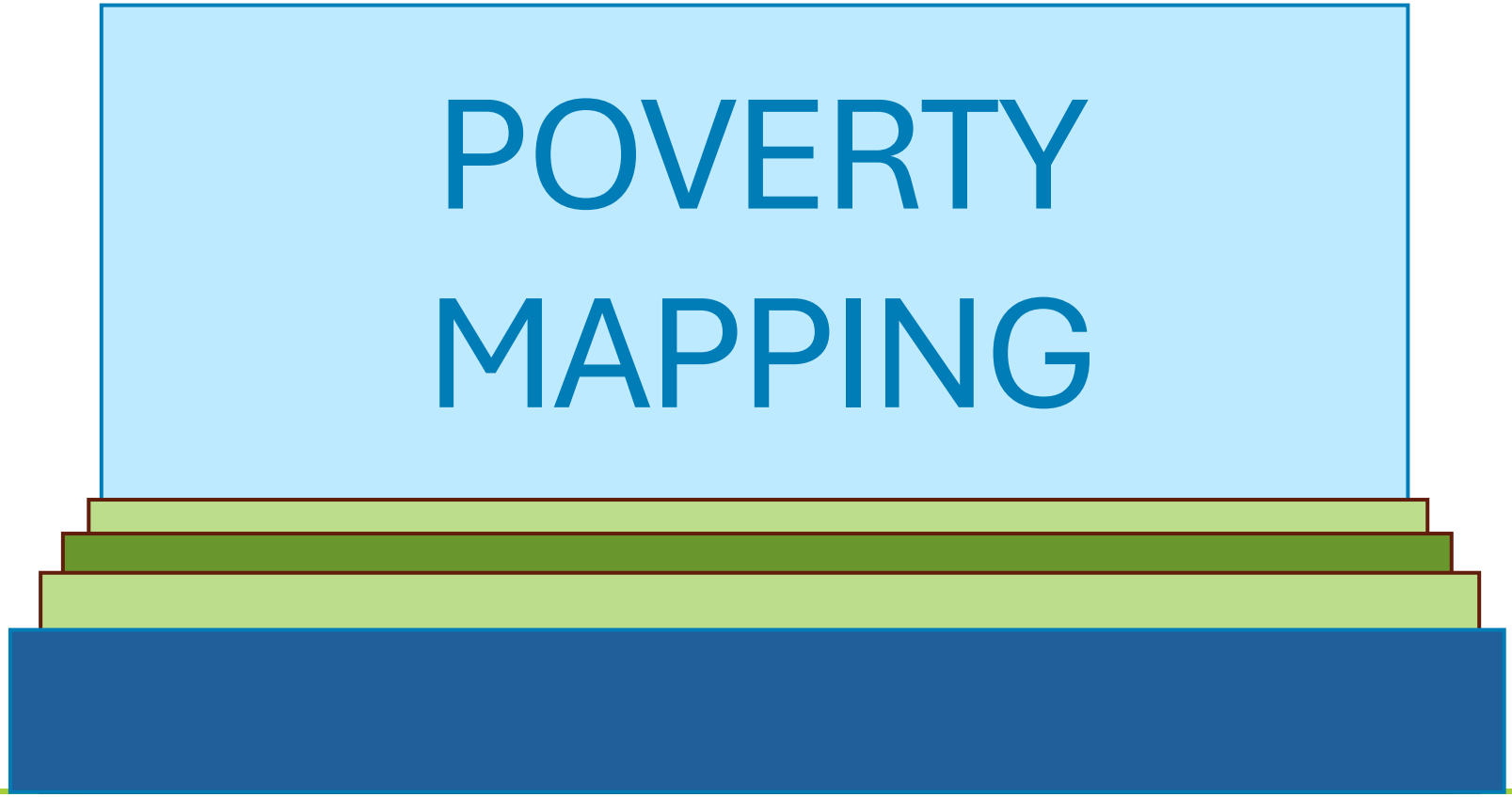
PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

TOPIC # 2



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

TOPIC # 2



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Two regions, one poverty rate – but should the response be the same?

Poll: Two regions have the same population and the same poverty rate: 20%. Each region has 10 local areas. Your government can fund intensive support in only 10 local areas. What is the most defensible approach?

A

Select 5 local areas from each region.

B

Prioritize the region with the larger land area.

C

Use existing knowledge about each local area to identify priority areas.

D

Repeat the previous year's allocation.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Which poverty data would be most useful for a place-based program?

Poll: If your country could improve one poverty data, which would most strengthen targeting and resource allocation?

A

A more precise national poverty rate

B

More frequent estimates for broad regions

C

Reliable estimates for the geographic areas where programs are delivered.

D

The most detailed map possible – even if some estimates are not reliable.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

National poverty rates can conceal pockets of severe deprivation.

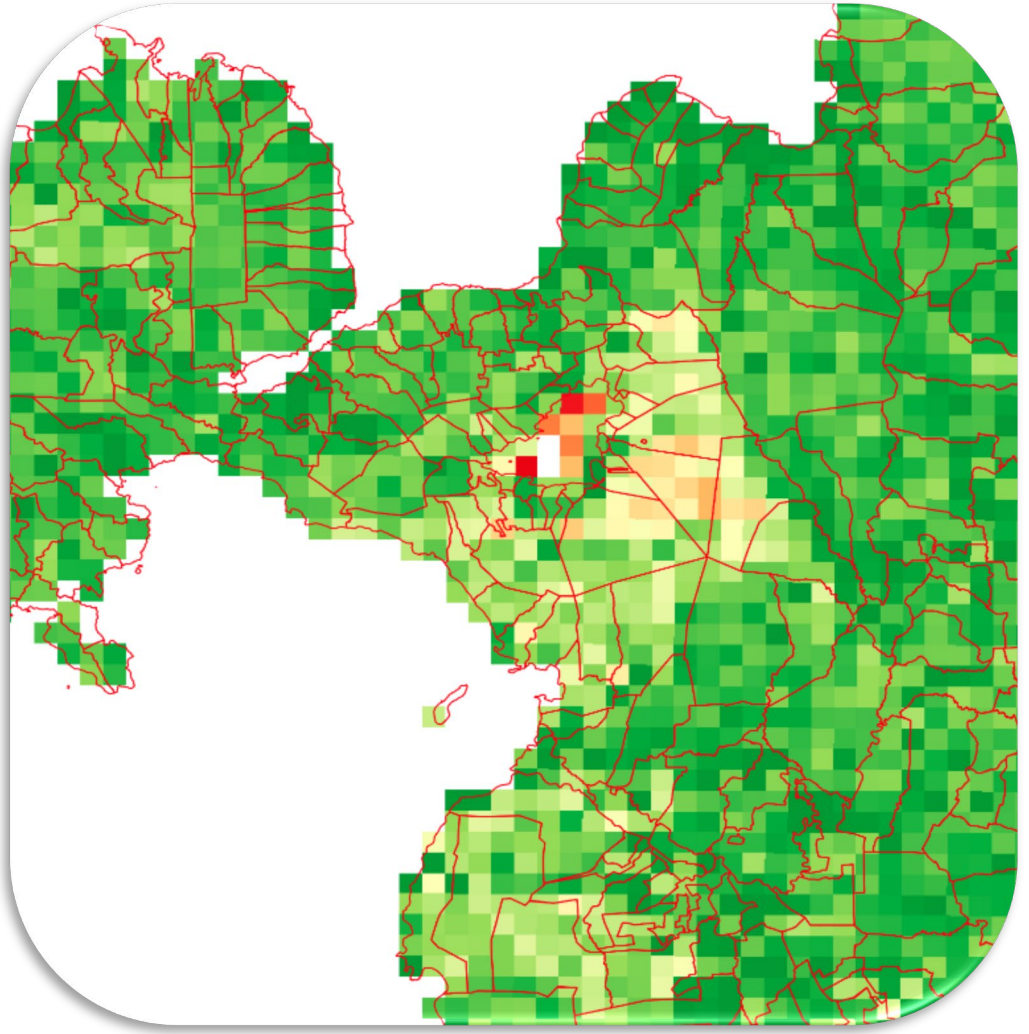
A local estimate can turn lived hardship into a policy signal. Data can mobilize attention… and drive policy action!



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Importance of Geographically Granular Poverty Maps

- ✓ 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.



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Household surveys used to produce official poverty estimates are typically designed to provide aggregate, 'big-picture' measures of poverty.



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

In addition to ‘big-picture’ numbers, policymakers also need more ‘zoomed-in’ statistics.



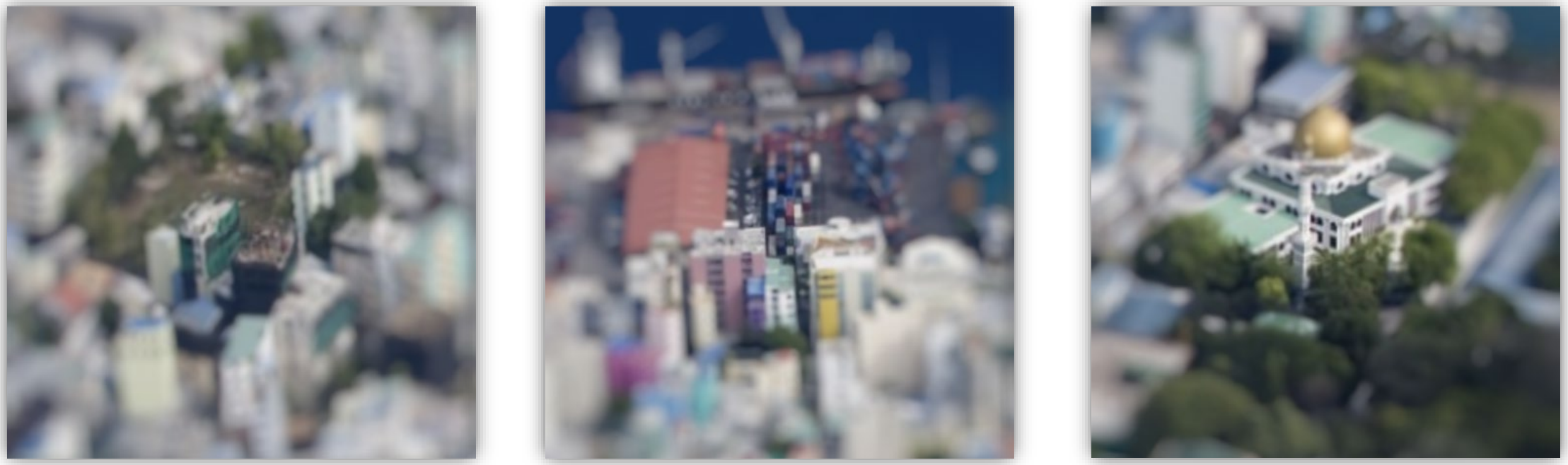




Expectation

PUBLIC. This information is being disclosed to the public in accordance with ADB’s Access to Information Policy.

In addition to ‘big-picture’ numbers, policymakers also need more ‘zoomed-in’ statistics.

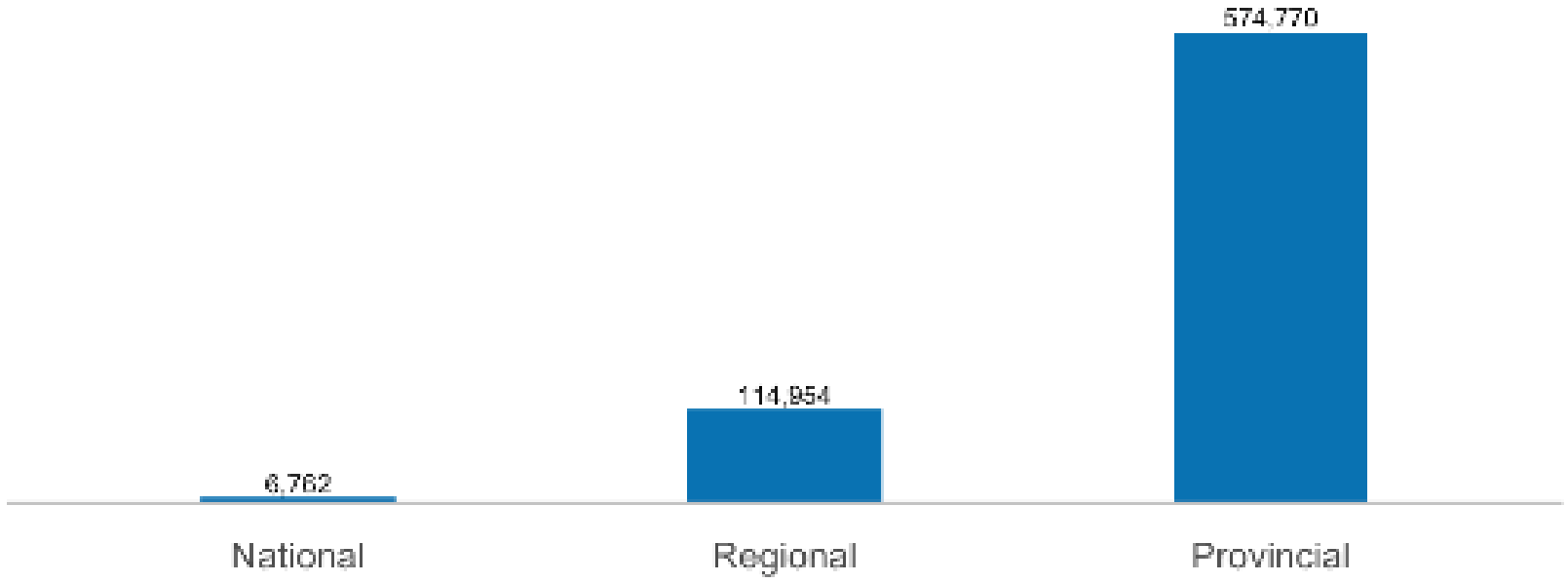


vs. Reality

PUBLIC. This information is being disclosed to the public in accordance with ADB’s Access to Information Policy.

If we want our poverty data to be representative at finer geographic levels, why can't we simply increase household survey sample sizes?

Hypothetical Example of Required Sample Size by Varying Level of Required Disaggregation

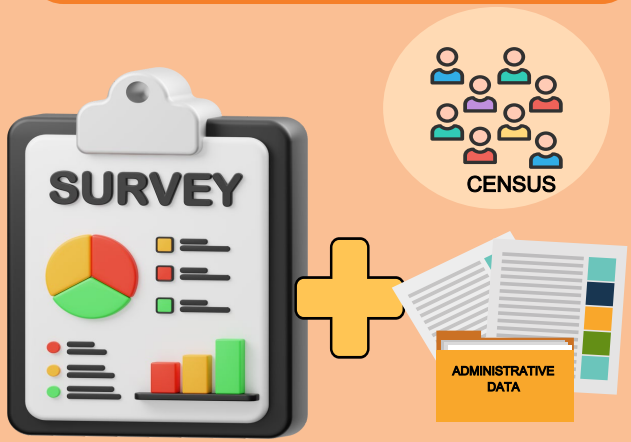


In simple random sampling, the sample size increases (approximately) by a factor equal to the desired number of analysis groups.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Two Ways of Producing Geographically Granular Poverty Maps

Small Area Estimation for Poverty Mapping



SAE combines the survey data with other types of auxiliary data (e.g., administrative data or census data or big data) that have wider coverage to enhance the survey estimator.

Machine Learning Based Poverty Maps

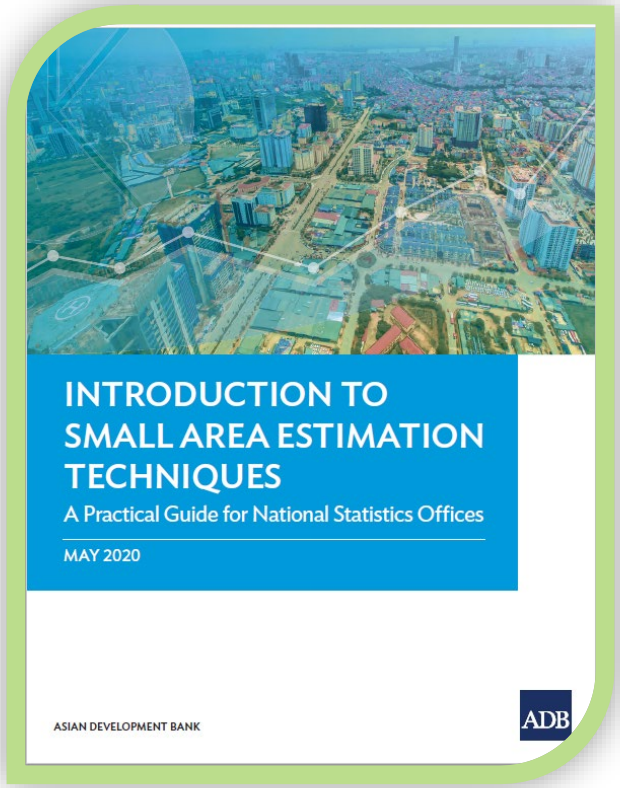


Integrating conventional data sources like surveys with innovative data sources such as satellite imagery, call data records, etc.

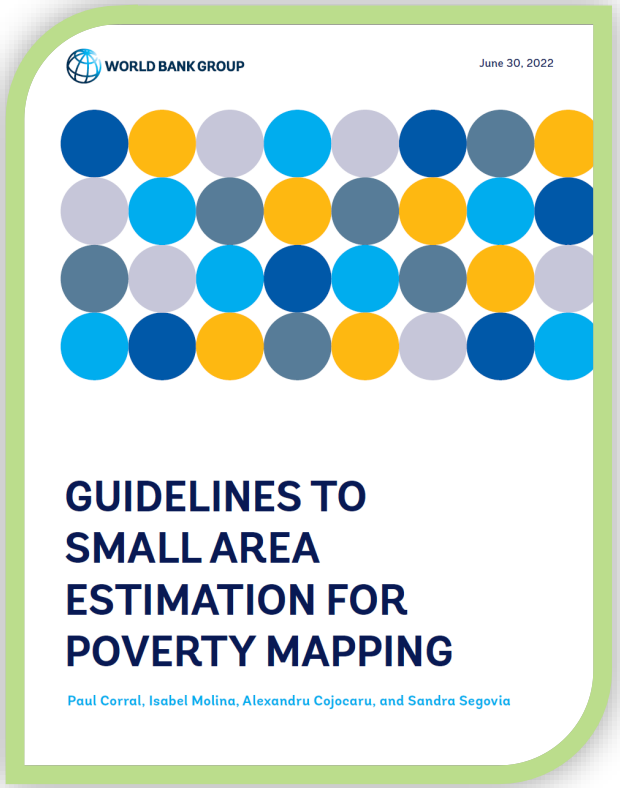
Computer vision techniques and machine-learning algorithms can be used to process unstructured data from images.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

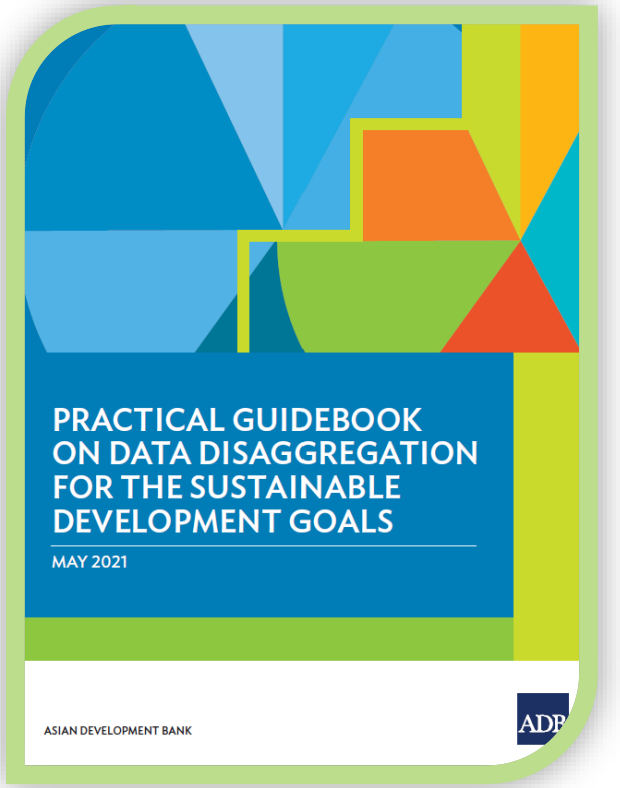
Guides on Small Area Estimation



Introduction to Small Area Estimation Techniques



Guidelines to Small Area Estimation for Poverty Mapping



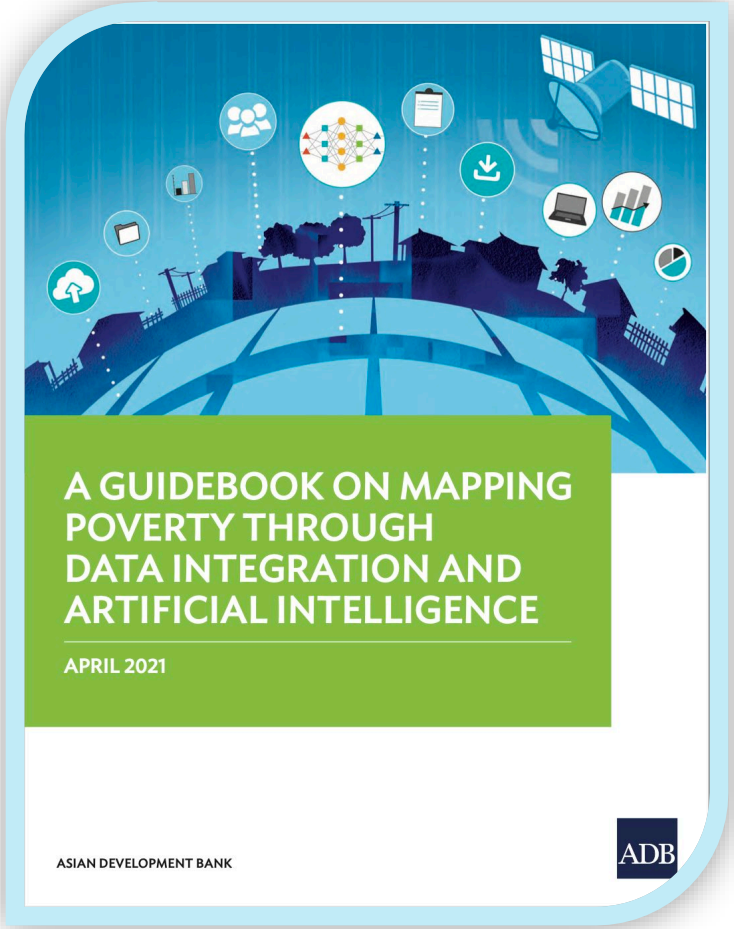
A Practical Guidebook on Data Disaggregation for the Sustainable Development Goals

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Today's Focus: Poverty Mapping Using Satellite Imagery and Machine Learning Techniques



Source: Martinez and Mehta. How Satellite Data Helped Get Food to the hungry during COVID-19



https://www.adb.org/publications/guidebook-mapping-poverty-data-integration-ai

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Different Types of Information from Geospatial Data and Satellite Imagery

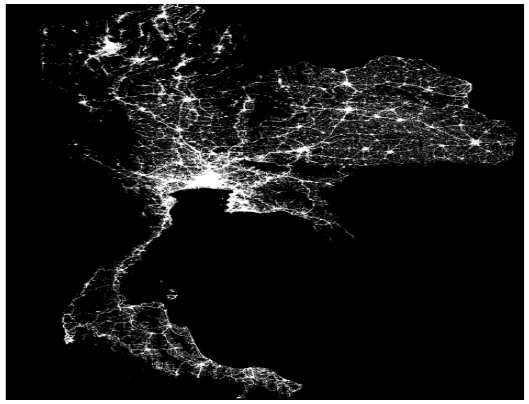


Image Source: VIIRS

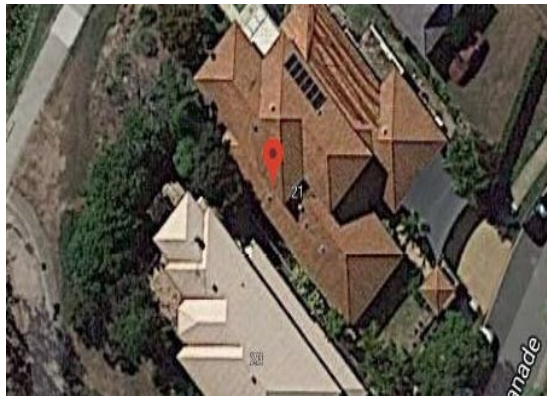


Image Source: Solar Quotation

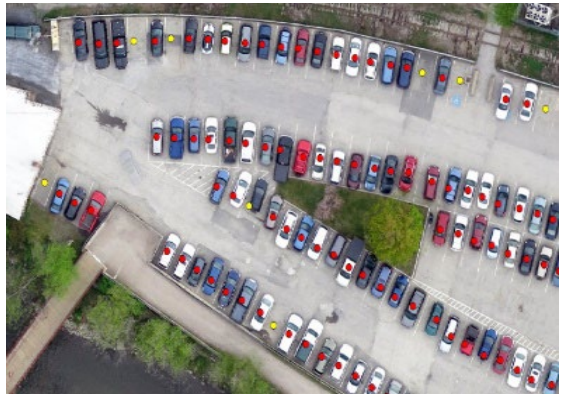


Image Source: Earth Imaging Journal

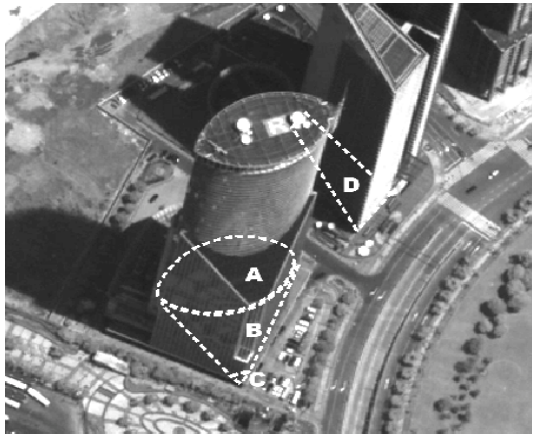


Image Source: Pan et al., 2008



Image Source: AgriLand

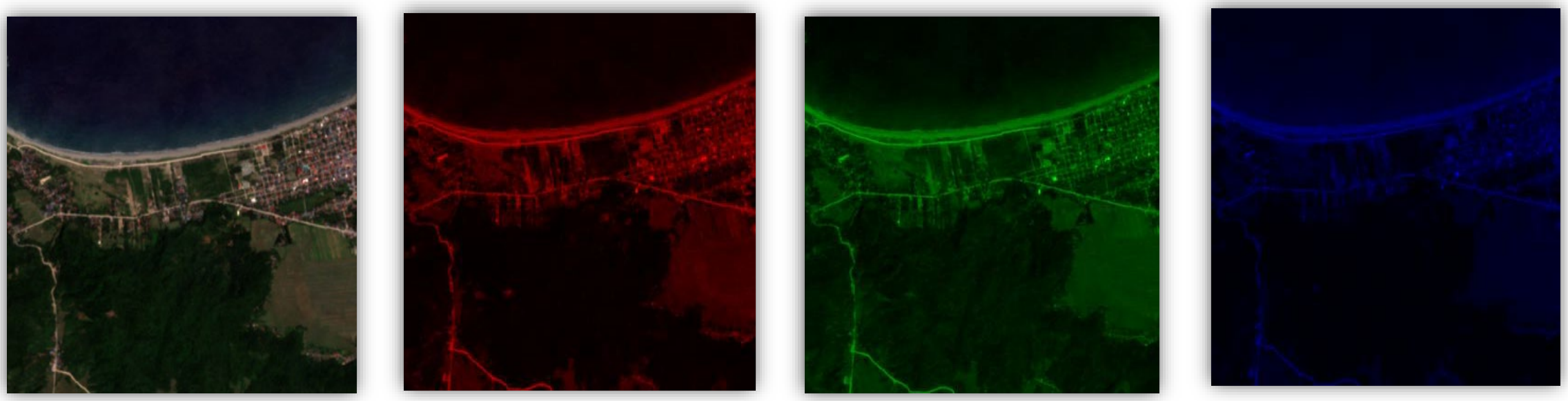


Image Source: Wang et al., 2016

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

Image Color Bands within a Georeferenced Image File



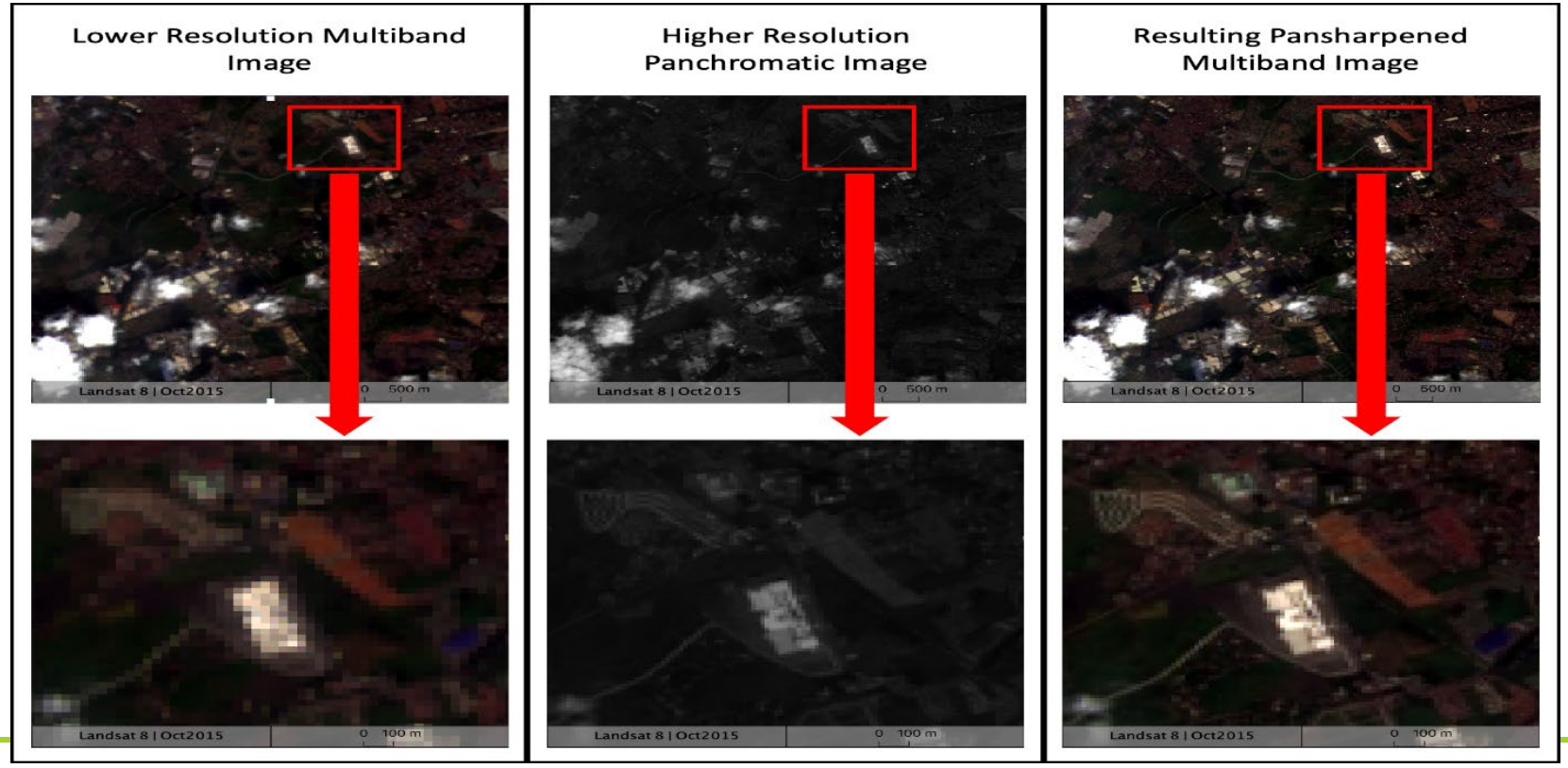
Source: Sentinel Images

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

We enhance the resolution through pansharpening.

Figure. Pansharpening Images To Improve Their Resolution

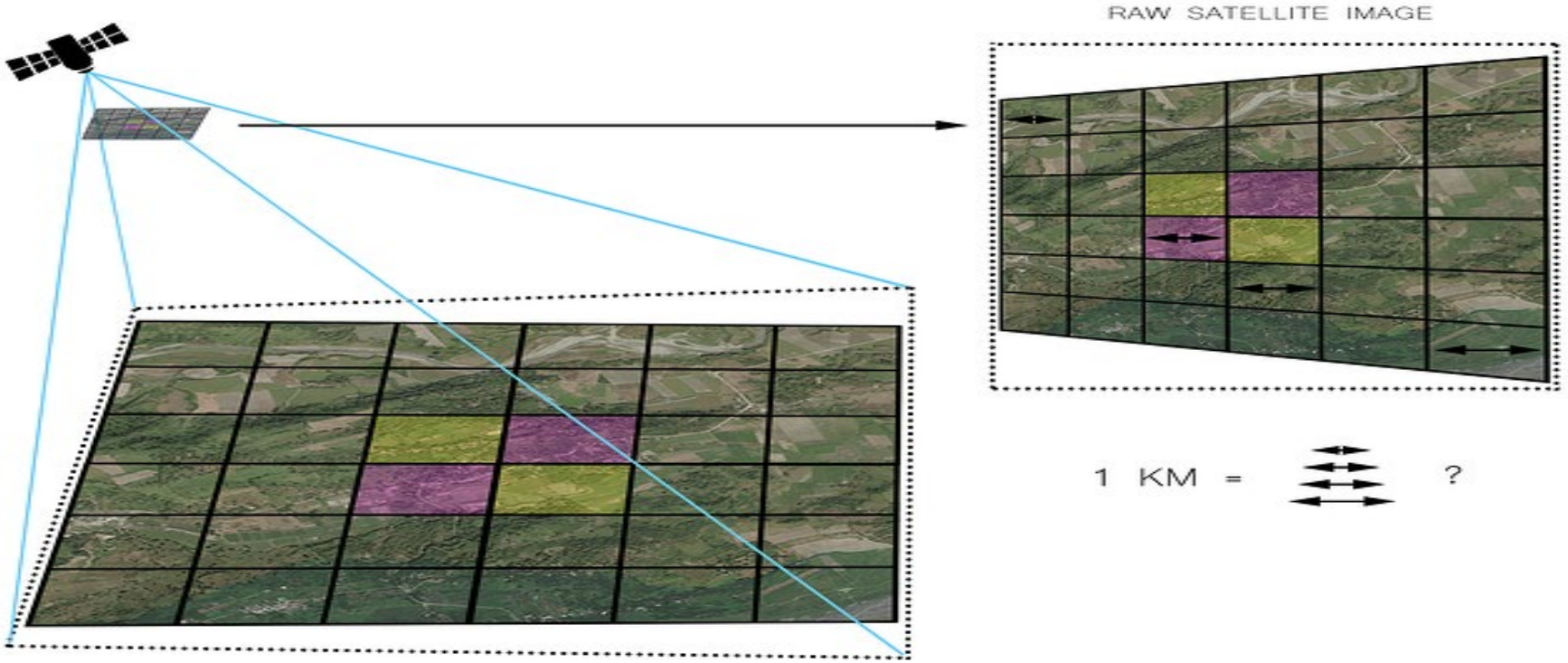


PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

Addressing perspective distortion through orthorectification.

Figure. Perspective Distortion



Source: https://www.intermap.com/blog/orthorectification-in-a-nutshell

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

We use publicly accessible daytime satellite imagery from Landsat 8 (30-meter resolutions reduced to 15-meter resolutions after pansharpening) and Sentinel 2 (10-meter resolutions).

Low-Quality Satellite Images Isolated from Training

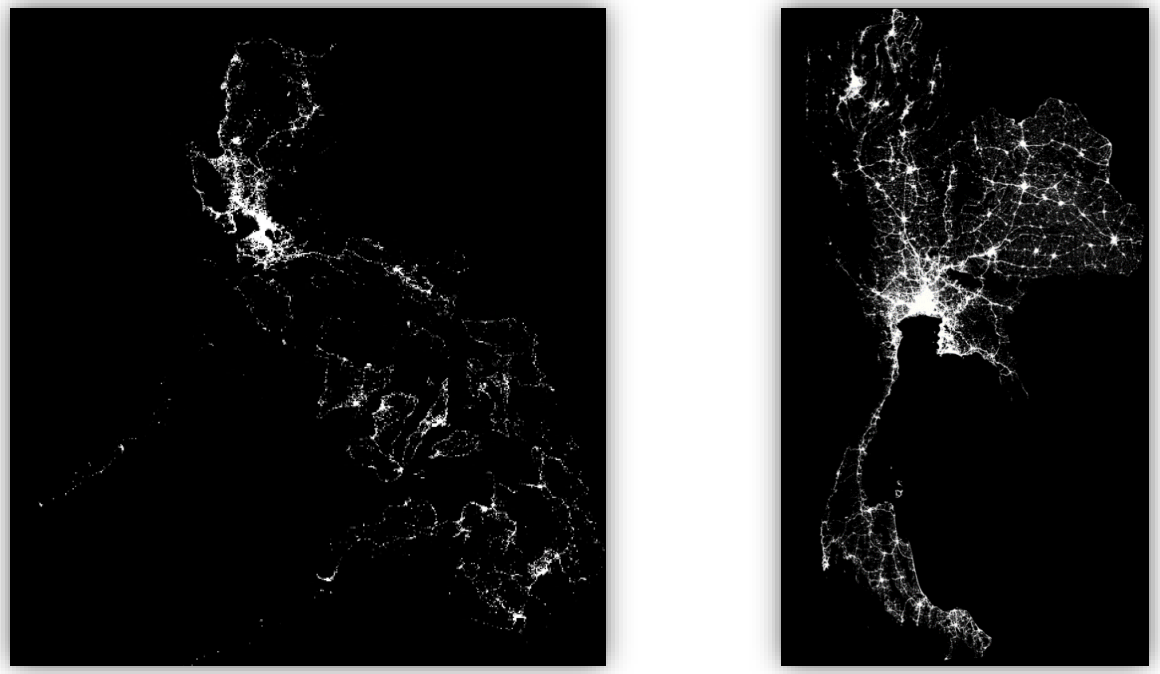


PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

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



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



Image courtesy of https://www.pcmag.com/news/what-is-computer-vision



Image courtesy of https://www.pinterest.co.uk/pin/89579480066620720/?autologin=true

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



Night lights used to ‘label’ each image as a proxy measure of socioeconomic activity

PUBLIC. This information is being disclosed to the public in accordance with ADB’s Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

$\bar{X}$ 1
$\bar{X}$ 2
$\bar{X}$ 3
:
:
:
$\bar{X}$ p

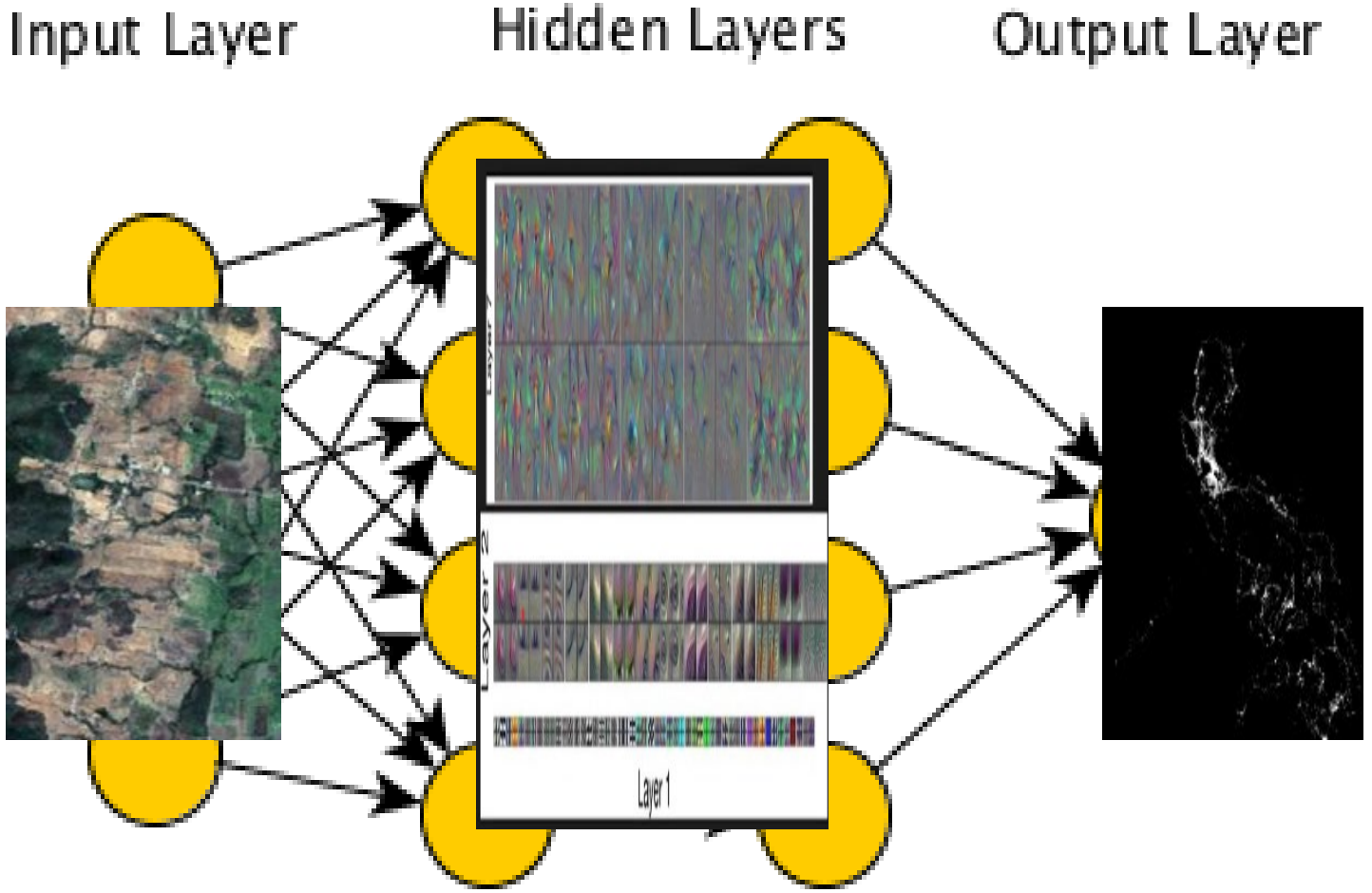




$$Y = \beta \bar{X} + \varepsilon$$

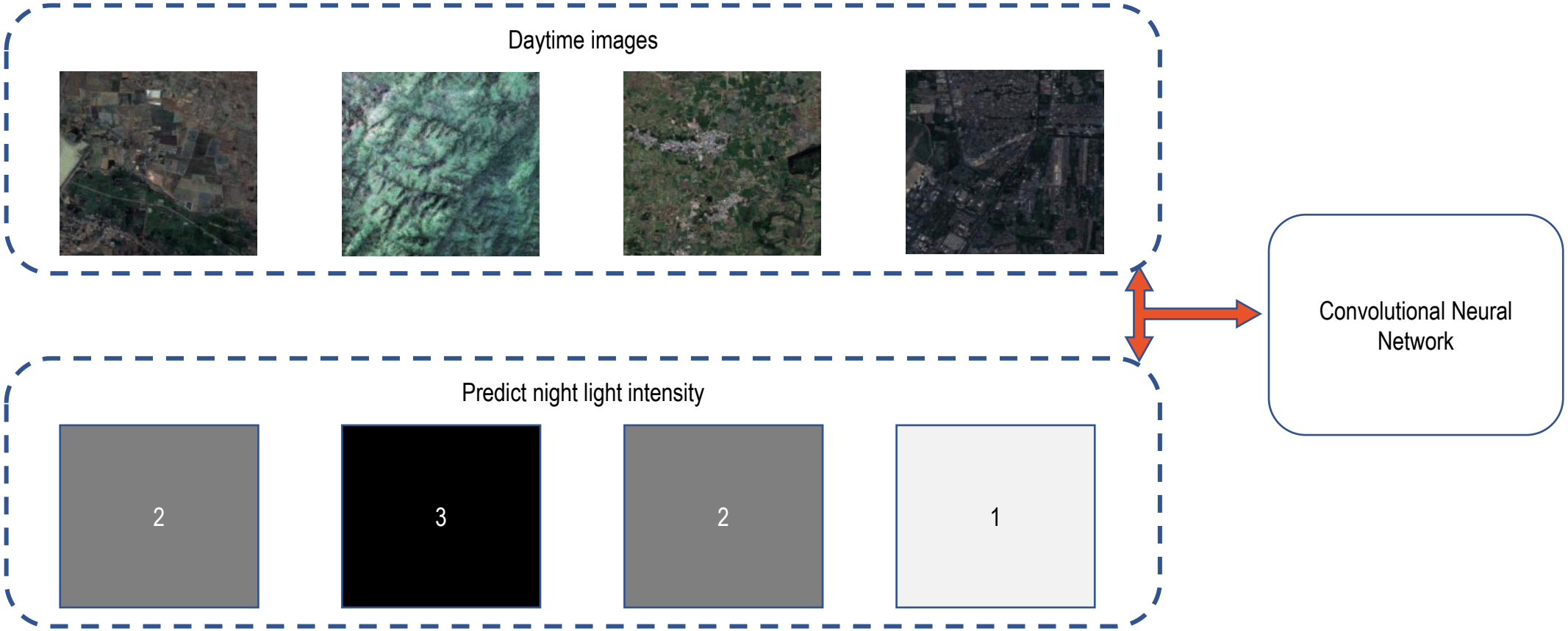
PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

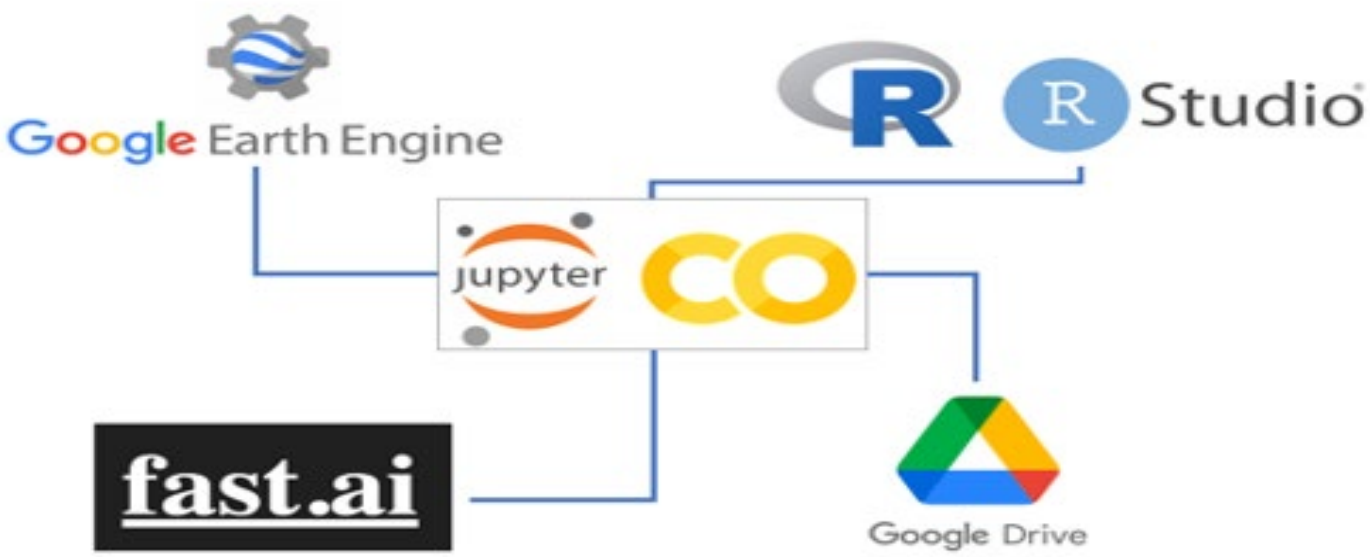


PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty

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:

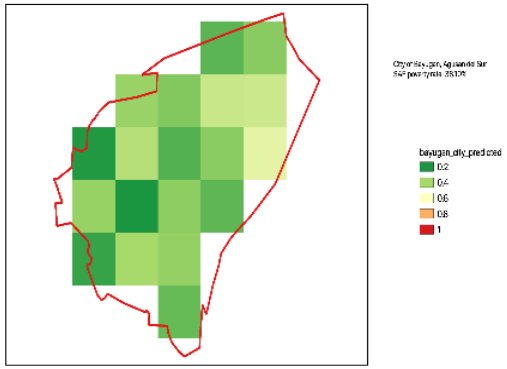


PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Some Results from ADB's Poverty Mapping Initiatives

Calibrating Poverty Maps

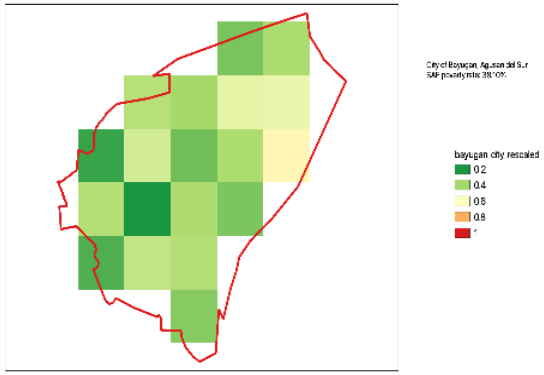
ML Predictions

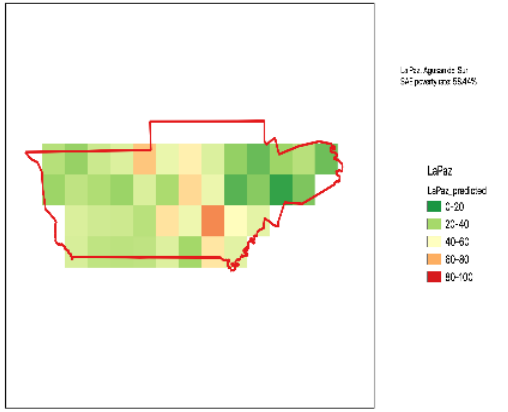


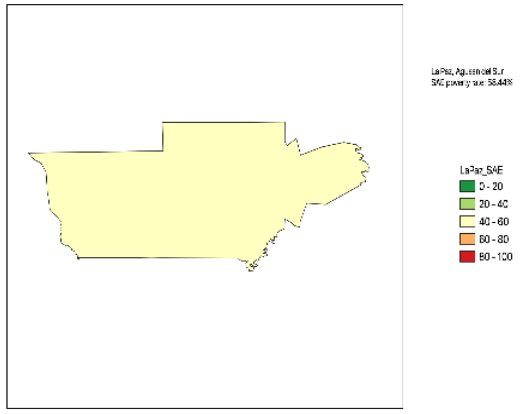
Published

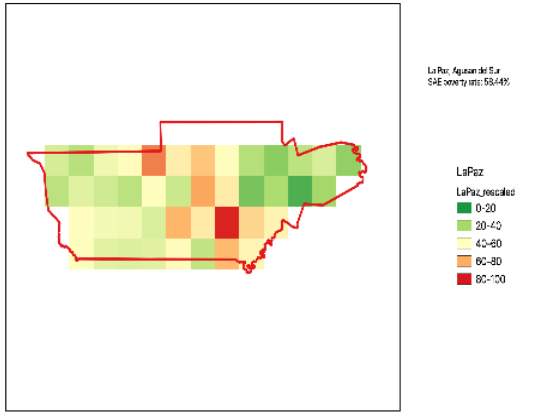


Calibrated





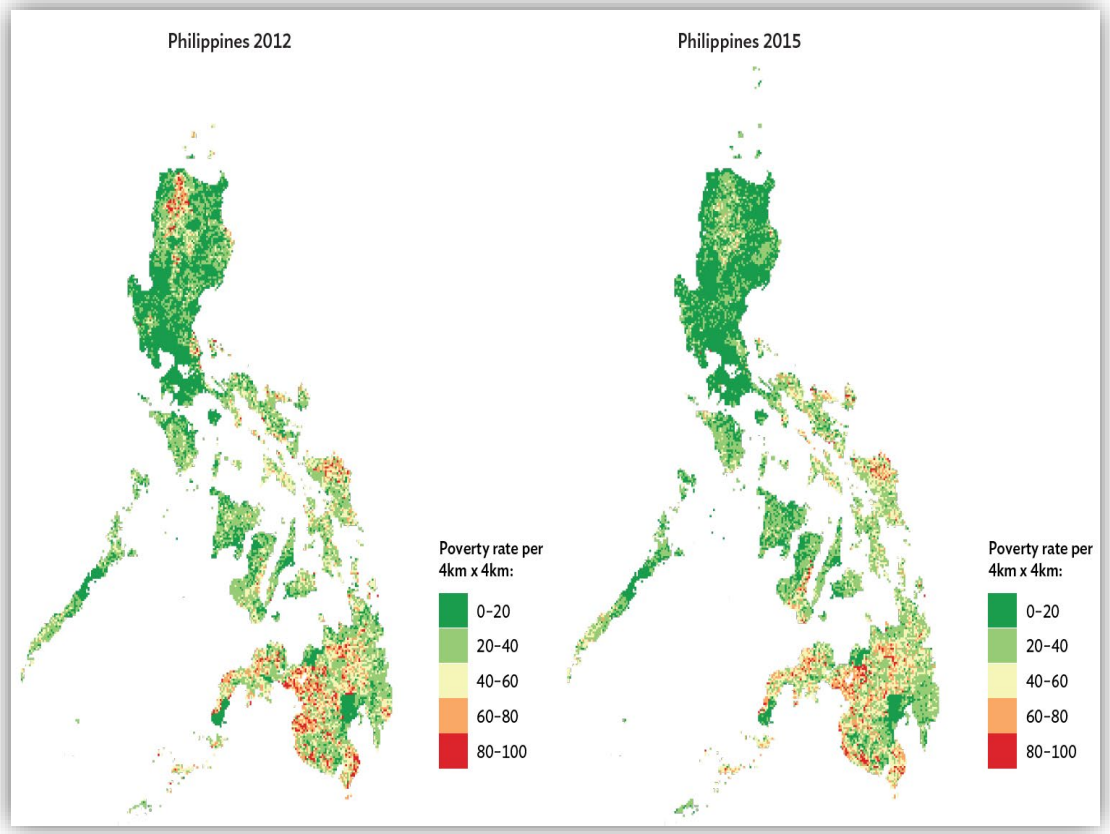


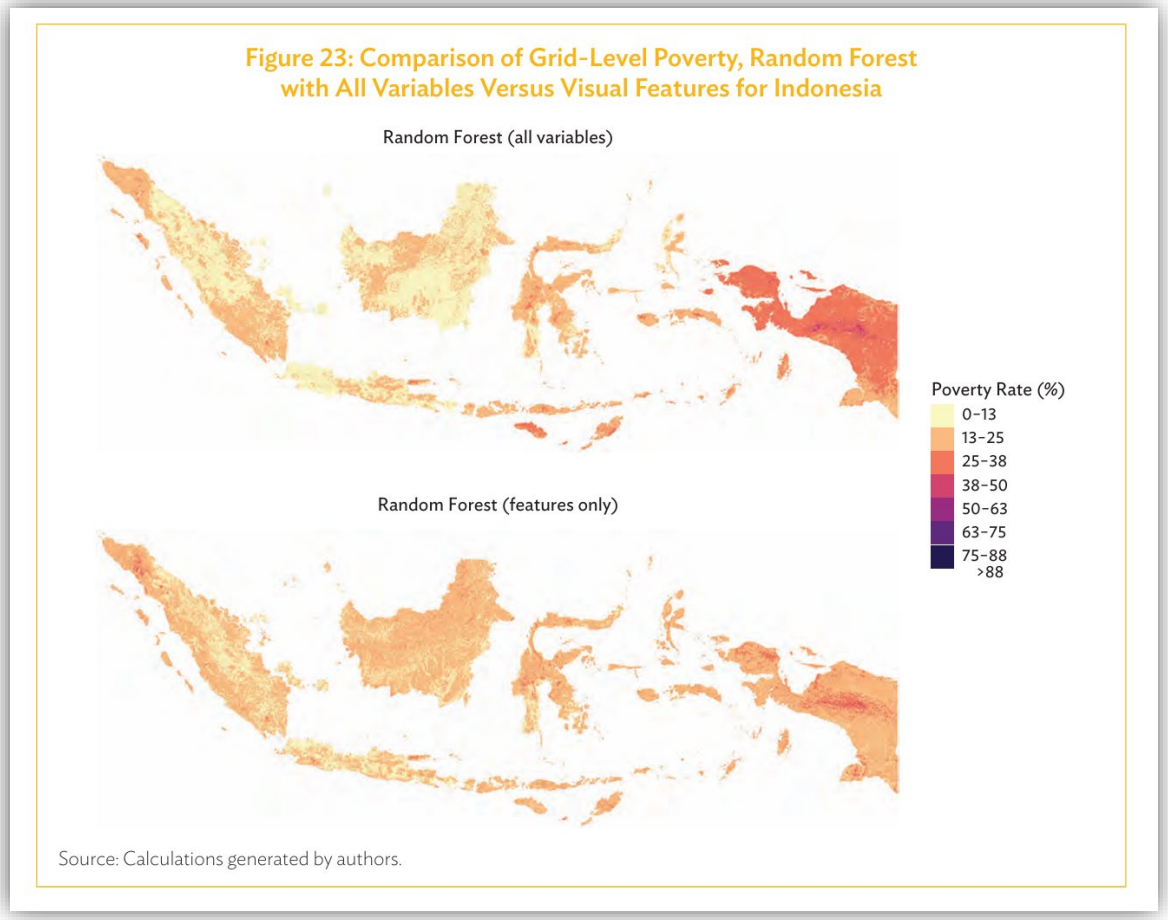


PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Some Results from ADB's Poverty Mapping Initiatives

Calibrated Poverty Maps





PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



Step 1. Assemble and align data sources.
Prepare cloud-free daytime satellite images, night-light observations, and government-published small-area poverty estimates, ensuring that they cover the same locations and reference periods. The satellite data show what places look like, while the conventional poverty statistics provide the authoritative benchmark.



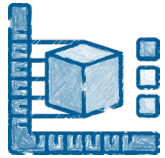
Step 2. Train the model to recognize visible signs of development.
Using transfer learning, train a convolutional neural network (CNN) to predict night-light intensity from daytime images; in doing so, the model learns to recognize spatial patterns—such as settlements, roads, and agricultural land—that may also be associated with economic well-being.



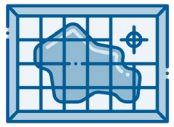
Step 3. Convert the learned image patterns into area-level profiles.
Extract the numerical features identified by the CNN and average them across each village—the same geographic level at which the government poverty estimates are available.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Training a Computer Vision Technique to Predict Poverty



Step 4. Link the satellite-derived profiles to observed poverty.
Use ridge regression or random trees (or other suitable data science technique) to estimate the relationship between the aggregated image features and government-published poverty rates, while setting aside part of the data to test whether the model predicts areas it has not seen during training. Apply the resulting relationship to smaller satellite-image grids to generate more geographically detailed poverty estimates.



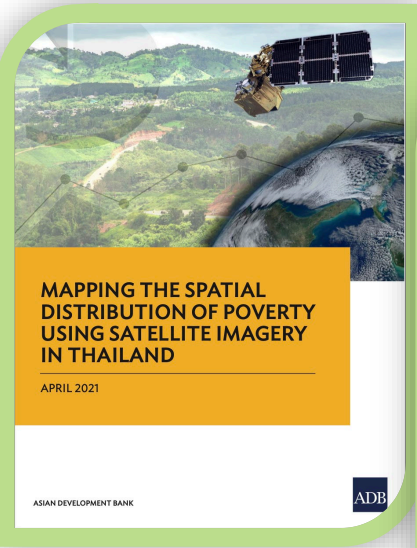
Step 5. Validate, calibrate, and produce the granular poverty map.
Compare the grid-level predictions with government estimates and, where appropriate, calibrate them so that their aggregated values remain consistent with published statistics; population estimates may then be combined with the predicted poverty rates to calculate poverty headcounts.

References:

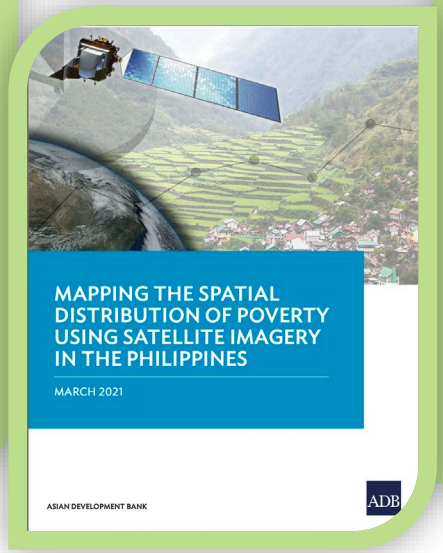
ADB. 2020. Mapping Poverty Through Data Integration and Artificial Intelligence – A Special Supplemnt of the Key Indicators for Asia and the Pacific 2020.
ADB. 2021. A Guidebook on Mapping Poverty through Data Integration and Artificial Intelligence.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

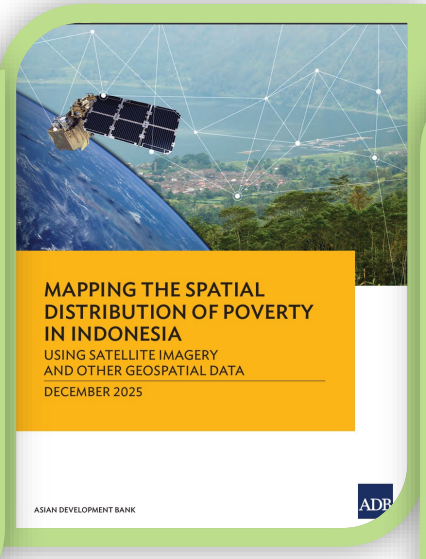
To learn more about machine learning-based poverty mapping, check these resources:



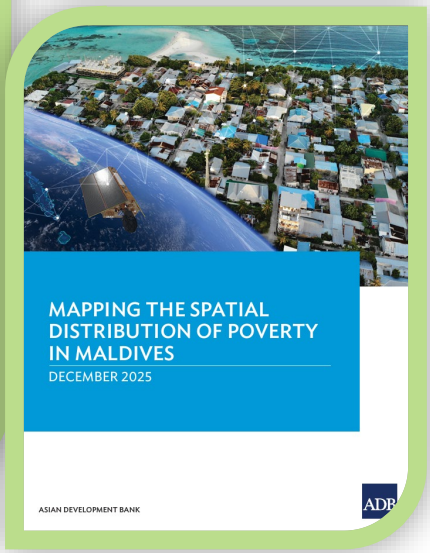
https://www.adb.org/publications/mapping-poverty-satellite-imagery-thailand



https://www.adb.org/publications/mapping-poverty-satellite-imagery-philippines

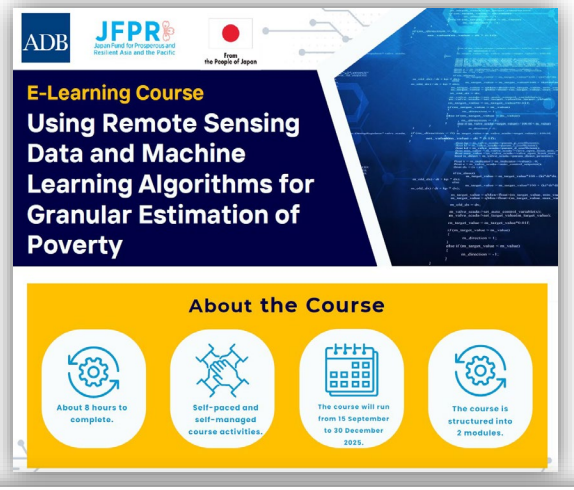


https://www.adb.org/publications/mapping-poverty-satellite-imagery-indonesia



https://www.adb.org/publications/mapping-poverty-satellite-imagery-maldives

Self-paced e-learning courses (concluded)





PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Hands-on Exercise #2:
Can nighttime lights help flag district allocations that may warrant review?

Scenario: Conditional cash transfer resources for poor households are lodged with provincial governments, which must allocate the available resources across districts. The existing allocations are based on district-level poverty estimates produced through rigorous field and technical work several years ago. Before deciding whether the allocations should be reviewed, provincial leaders want a rapid diagnostic using more recent nighttime light intensity as a complementary signal. The purpose is not to replace the existing poverty estimates or automatically reallocate resources, but to assess whether the broad pattern across districts still appears plausible and to flag substantial departures for further investigation.

Note: Refer to the Excel file provided, which contains data for 100 districts in 7 provinces on:

- **Poverty incidence**—higher values indicate higher poverty; and
- **Nighttime light intensity**—higher values indicate brighter areas.

Tasks:

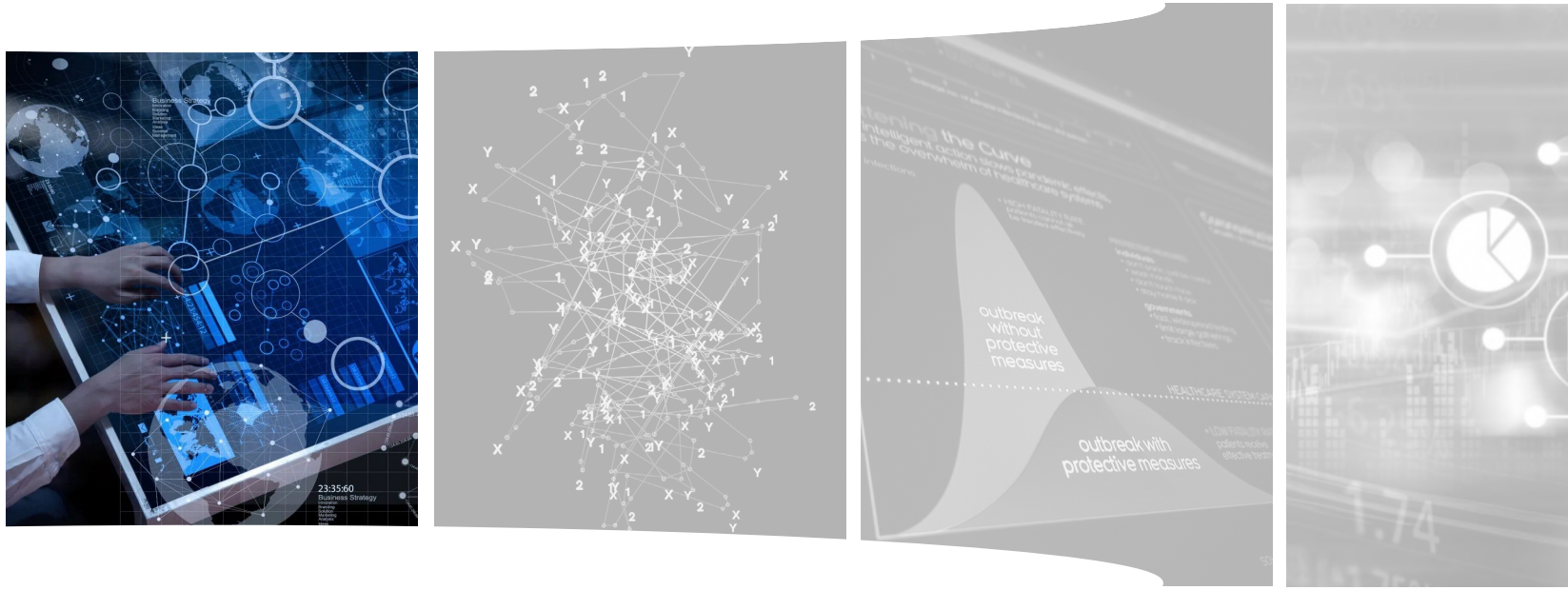
1. Compare district poverty incidence and nighttime light intensity.
2. Calculate the correlation coefficient between the two indicators.
3. Plot their relationship using a scatter plot.
4. Interpret the direction and strength of the relationship, noting any districts that depart substantially from the overall pattern.

Policy discussion:

What does the observed relationship imply about using nighttime lights as a rapid screening signal for whether district allocations may warrant review? Which substantial departures—or apparent changes in district ordering—should prompt more thorough investigation?

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

There is an abundance of untapped potential of data.

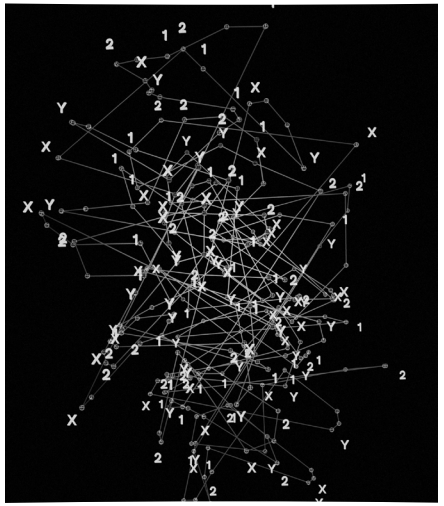


Advances in technology and digital systems have generated vast volumes of structured and unstructured data.

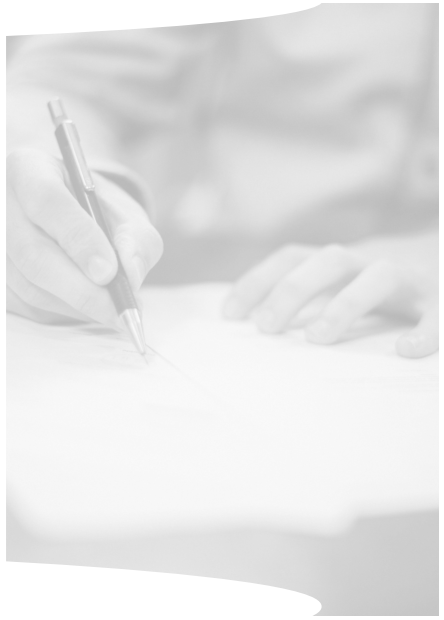
PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Data integration is key











The real challenge lies in combining diverse data sources—administrative, survey, geospatial, and big data—for richer analysis.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Unlocking deeper insights



Integrated data enables more comprehensive and nuanced understanding of complex development issues.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Improved targeting and policy relevance

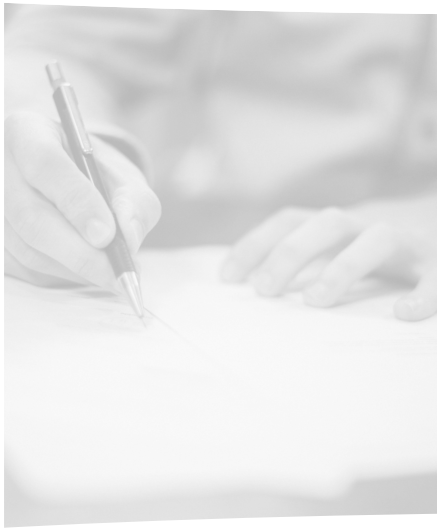


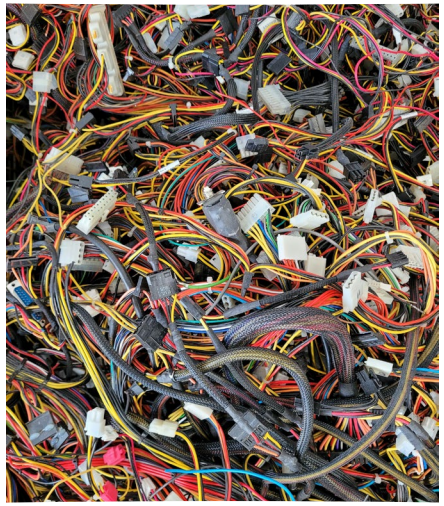
Integrated dataset help identify hidden disparities and better target interventions. They enhance the relevance and timeliness of evidence for decision-making too.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Capacity gaps remain







Many institutions still lack the tools, skills, and systems to effectively link and analyze multiple data streams.

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.

Thank you!

Find out more about Data Division's
Knowledge Products and Capacity Building

ERDD Webpage

Contact Details:

Arturo Martinez Jr. – amartinezjr@adb.org
Joseph Albert Nino Bulan – jbulan@adb.org

PUBLIC. This information is being disclosed to the public in accordance with ADB's Access to Information Policy.