Welcome to the 2026 MAH Annual Meeting

Jakarta, Indonesia

12 June – Day 3

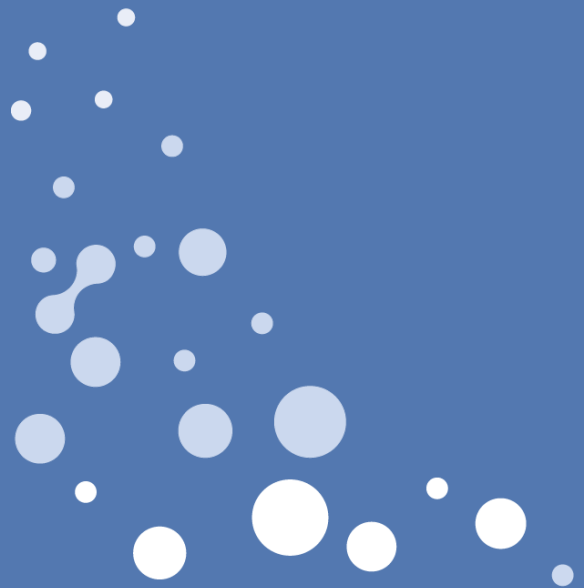
MEASLES
ANALYTICS HUB

Turning Modelling Tools into Decision Support Products

Session Chair: Matt Ferrari

MEASLES
ANALYTICS HUB

Ratnesh Murugan



MEASLES
ANALYTICS HUB

MSP

Measles Strategic Planning (MSP) Tool

Evidence-Based Immunization Planning & Scenario Modelling

Acknowledgement: Prepared with Guidance from Dr. Sudhir Khanal, Regional Advisor, SEARO

Dr. Ratnesh Murugan
WHO India

Introduction of MSP Tool

Background

Developed to evaluate health benefits and cost implications of adjustments to national measles immunization strategies using routinely available data.

Method

Country-specific cohort model estimating measles incidence and mortality via population immunity levels.

Result

Produces valid incidence estimates under low-to-moderate coverage.

Evidence-driven assessment of vaccination strategy impacts.

Conclusion

Identifies strategies that protect against measles at the least cost, supporting evidence-based decisions for effective and comprehensive measles control. ***(cost-effectiveness estimation)***

MSP Tool — Components

1. **Country Selection & Data Entry**
   Load country-specific data from various sources
2. **Measles Case & Coverage Review**
   Validate vaccination coverage and reported measles cases
3. **Age Distribution Analysis**
   Understand measles epidemiology by age group
4. **Vaccination Status Assessment**
   Analyse age-wise vaccination status of measles cases
5. **Immunity Profiling**
   Vaccine-derived & infection-acquired immunity profiles
6. **Scenario Modelling**
   Compare up to 4 vaccination strategies
7. **Core Parameters & Outputs**
   CFR, DALYs, deaths averted, cost-effectiveness

Step 1–2

Country Selection & Data Review

Loading and validating country-specific epidemiological data

1–2

Step 1–2: Country Selection & Data Validation

DATA SOURCES

WHO Vaccine-Preventable Diseases

Monitoring System

WHO/UNICEF Joint Reporting

Form (JRF)

United Nations Population

Division (UNPD)

Local Programme Data

(if available & validated)

VALIDATION & OUTPUTS

✓ Review & Update Population Data worksheet

✓ Review & Update Historical Data worksheet

⟳ Update with local data if available

◎ Country statistics are automatically generated to:

- Assess measles burden
- Estimate potential vaccination impact on child mortality

ⓘ *MSP estimates are model-generated and not official WHO estimates*

Step 3

Measles Cases by Age Distribution

3

Understanding age-specific epidemiology to guide intervention design

Step 3: Age Distribution Analysis

MODEL METHODOLOGY

MSP estimates cases & deaths by age group using:

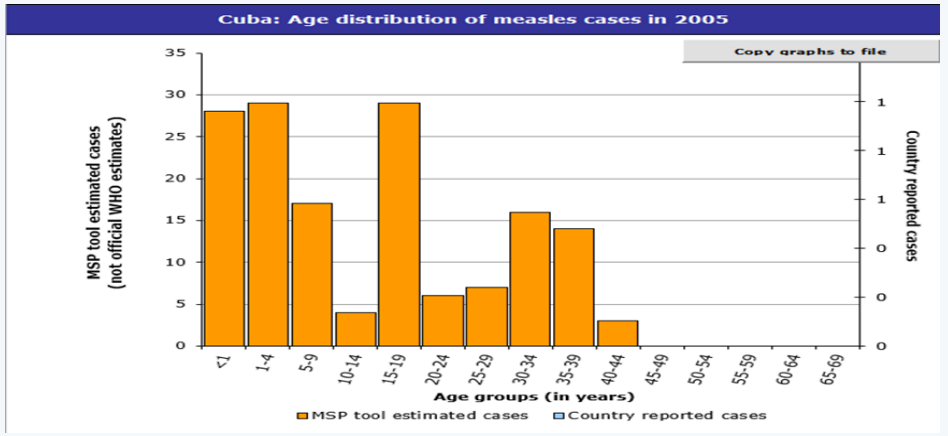
- Historical vaccination coverage data
- Population demographic data by age cohort
- Vaccine-induced immunity models
- Disease-induced (natural) immunity models

Key Analytical Outputs

- Compare reported vs. MSP-estimated cases by age
- Predict impact of future strategies on age-specific disease patterns

Cuba: Measles cases by age distribution in 2005

Year	2005				
Choose Option	Calculations_Baseline				
Age groups (in years)	Country reported measles cases by age group	MSP tool estimated cases by age group	MSP tool estimated deaths by age group	Percent of cases in each age group	Percent of deaths in each age group
<1		28	0	18%	#DIV/0!
1-4		29	0	19%	#DIV/0!
5-9		17	0	11%	#DIV/0!
10-14		4	0	3%	#DIV/0!
15-19		29	0	19%	#DIV/0!
20-24		6	0	4%	#DIV/0!
25-29		7	0	5%	#DIV/0!
30-34		16	0	10%	#DIV/0!
35-39		14	0	9%	#DIV/0!
40-44		3	0	2%	#DIV/0!
45-49		0	0	0%	#DIV/0!
50-54		0	0	0%	#DIV/0!
55-59		0	0	0%	#DIV/0!
60-64		0	0	0%	#DIV/0!
65-69		0	0	0%	#DIV/0!
Total	0	153	0	100%	#DIV/0!



Reviews the **age distribution of measles cases and deaths** to understand measles epidemiology.

Step 4

Vaccination Status of Cases

4

Stratifying reported cases by immunization history

Step 4: Age-Wise Vaccination Status of Measles Cases

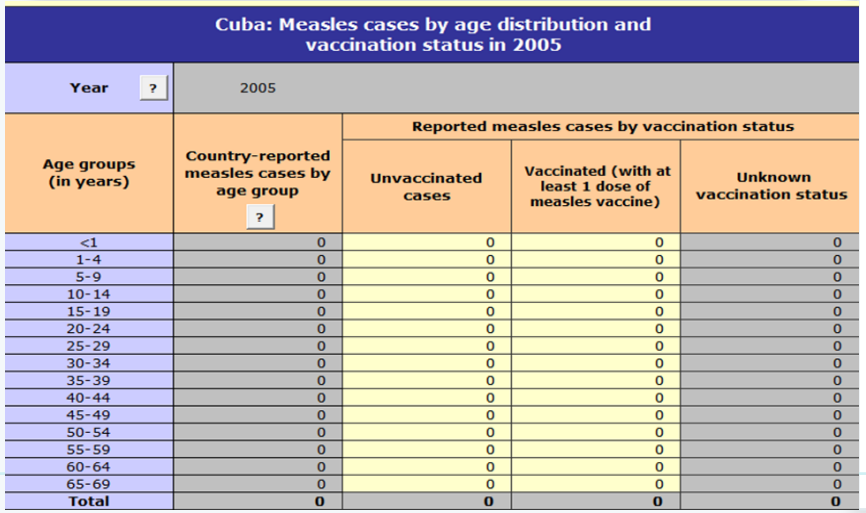
- This worksheet expands on the **age distribution analysis of measles cases**.
- It enables users to **enter and review vaccination status data graphically** for age-specific measles cases.

Data Auto-Import

- Year of analysis
- Country-reported cases by age group
- Age Distribution worksheet data

Manual Data Entry (in Yellow Columns)

- Column D: No. of cases found Unvaccinated
- Column E: ≥1 dose vaccinated cases
- Remaining: auto-classified as unknown



Cuba: Measles cases by age distribution and vaccination status in 2005

Year ? 2005

Age groups (in years)	Country-reported measles cases by age group ?	Reported measles cases by vaccination status		
		Unvaccinated cases	Vaccinated (with at least 1 dose of measles vaccine)	Unknown vaccination status
<1	0	0	0	0
1-4	0	0	0	0
5-9	0	0	0	0
10-14	0	0	0	0
15-19	0	0	0	0
20-24	0	0	0	0
25-29	0	0	0	0
30-34	0	0	0	0
35-39	0	0	0	0
40-44	0	0	0	0
45-49	0	0	0	0
50-54	0	0	0	0
55-59	0	0	0	0
60-64	0	0	0	0
65-69	0	0	0	0
Total	0	0	0	0

Analytical Value

- Identify vaccination failure patterns
- Stratify burden by immune status
- Inform SIA targeting decisions

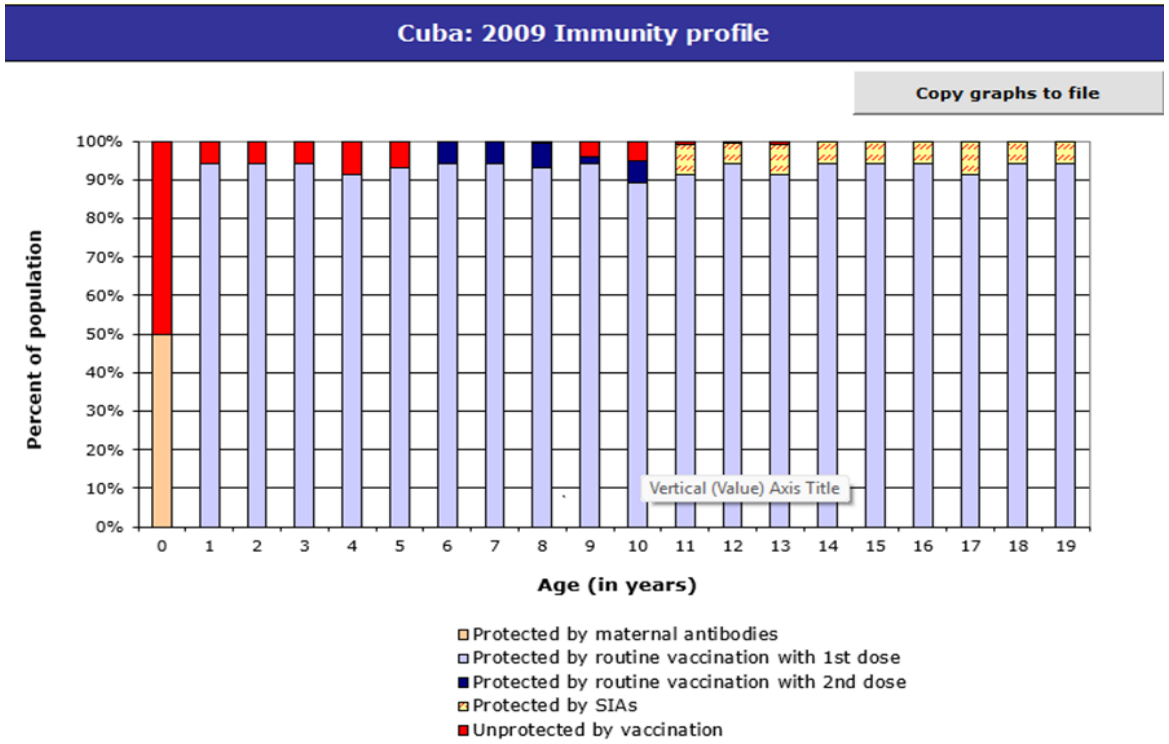
Step 5

Immunity Profile

5

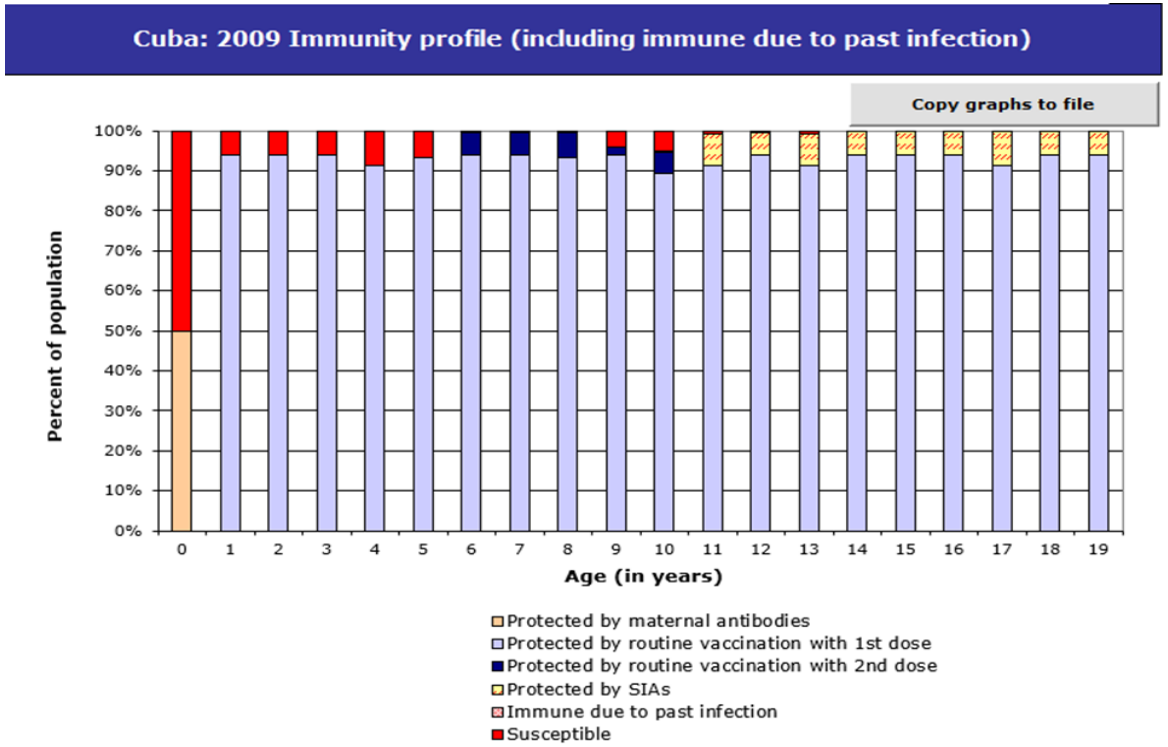
Quantifying protection and susceptibility across age cohorts

Immunity Profile



- The graph represents the **current immunity profile for measles** using programmatic vaccination coverage data from the **Historical Data worksheet**
- It shows the **percentage of the population protected against measles by age group**.

Immunity Profile (Including Immunity due to past Infection)



- The **second immunity profile graph** builds on the first immunity profile graph.
- In addition to vaccine-derived immunity, it includes an estimate of the proportion of people **immune due to prior measles infection**

Step 5: Immunity Profile — Vaccine-Derived & Infection-Acquired

IMMUNITY SOURCES

Maternal Antibodies
Protects infants <9 months

MCV1 — 1st Dose RI

MCV2 — 2nd Dose RI

SIA Coverage

Infection-Acquired Immunity

Unprotected (Susceptible)
Unvaccinated + vaccine failures

OUTBREAK RISK INTERPRETATION

⚠ Outbreak Risk Threshold

Outbreak Risk increases when susceptible children aged 1–4 years equal or exceed the size of an average birth cohort

Tool Applications

- Assess population immunity across all age groups
- Identify immunity gaps and susceptible cohorts
- Evaluate vaccination strategy effectiveness over time
- Support planning of interventions &outbreak prevention
- Detect build-up of susceptibles in older cohorts

Step 6

Vaccination Scenario Modelling

Comparing the probable impact of different evidence-based vaccination strategies

Table 1: Define vaccination options by clicking "yes" or "no" to individual strategies					
Strategies		**Option 1**	**Option 2**	**Option 3**	**Option 4**
Improve routine coverage		**Yes**	**Yes**	**Yes**	**Yes**
Change routine vaccination schedule	- Change age of 1st dose	**No**	**No**	**Yes**	**No**
	- Introduce 2nd dose (only if no 2nd dose in baseline) ?	**No**	**No**	**No**	**No**
	- Change age of 2nd dose (only if 2nd dose is in baseline) ?	**No**	**No**	**No**	**Yes**
	- Include transitional 2nd dose (only if you are changing age of 2nd dose in cell C13) ?	**No**	**No**	**No**	**No**
Conduct SIAs ?		**No**	**Yes**	**No**	**No**

Step 6: Selection & Comparison of Vaccination Strategies

Option 1

RI Strengthening Only

Improve routine immunization coverage rates without additional campaigns

Option 2

RI + MR SIA Campaign

Combine routine strengthening with a measles-rubella supplementary immunization activity

Option 3

RI + Modify MCV1 Age

Change the recommended age for first-dose routine vaccination

Option 4

RI + Modify MCV2 Age

Adjust the timing of second-dose routine vaccination

Step 7

Core Parameters & Model Inputs

7

Fixed assumptions, vaccine effectiveness, and mortality estimates

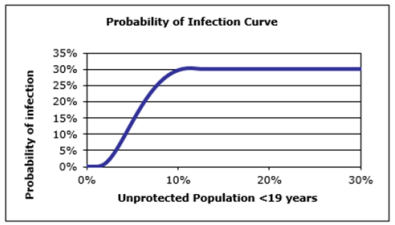
Step 7: Core Parameters for Modelling Measles Infection & Mortality

Cuba:
Core parameters for modelling measles infection and mortality

Vaccine effectiveness < 1 year of age	?	0.85
Vaccine effectiveness > 1 year of age	?	0.95
Initial value of infectiousness	?	0.3
Threshold	?	10.5
Acceleration (inverse)	?	3.5
DalyD	?	0.152
DalyL	?	0.038
K	?	1
DalyC	?	0.166
Dalyr	?	0.030
DalyB	?	0.040
Discount Rate	?	3%

	CFR multiplier	?	<1 year	1 - 4 years
			2	1

CFR 1-4 yrs*	?	0.05%
*Suggested CFR 1-4 yrs	?	0.05%



		<1 year	1 - 4 years	5 - 9 years	10 - 14 years	15 - 19 years
DalyAge	?	0.10	2.60	7.50	12.50	17.50
Male life years lost used for DALY est.	?	82.43	80.27	75.47	70.51	65.55
Female life years lost used for DALY est.	?	82.43	80.27	75.47	70.51	65.55
Average life years lost used for DALY est.	?	82.43	80.27	75.47	70.51	65.55

FIXED MODEL PARAMETERS

Measles Vaccine Effectiveness (< 1 yr)	**85%**
Measles Vaccine Effectiveness (> 1 yr)	**95%**
Infection probability values	**Fixed**
DALY-related fixed values	**Fixed**

ADJUSTABLE PARAMETERS & OUTPUTS

Case Fatality Rate (CFR)

Country-specific CFR for children aged 1–4 years is auto-provided but can be updated with local surveillance data.

Key Outputs per Scenario

- Estimated cases by age group
- Estimated deaths by age group
- Susceptible population (< 15 years)
- Deaths averted per strategy
- Cost-effectiveness comparison
- DALYs averted

Use case for MSP Tool — Practical Applications

Demonstrated Applications in Field Settings

MR SIA Strategic Planning

Used in MR IEAG for MR SIA planning advocacy (2016–2017).

Enabled grouping of states for phased roll-out and identification of highest-benefit geographies.

Target Age Group Identification

Modelled the optimal age groups for MR SIA to maximize immunity impact, enabling evidence-based target population selection.

Rubella Vaccine Introduction — India

Applied for immunity profiling in preparation for Rubella Vaccination Campaign (RVC) and national rubella vaccination introduction.

Age distribution of expected cases– We can customize for any year and we can choose among various options (What happens when there is no vaccination, baseline scenario, we can create our own options for e.g.

- Option 1: my coverage improvement will be 5 to 10% and country will do MR SIA this year in specific age group,
- Option 2 : Only MR SIA
- Option 3: Depend only on RI strengthening
- Option 4: Change RI vaccination schedule

Programme Manager Deliverables: Deaths averted · Economic losses quantified · Summary results across options · Estimated cases & deaths by age group

Limitations & Proposed Enhancements

CURRENT LIMITATIONS

- ☒ Measles-only — no Rubella component
- ☒ Immunity profile limited to age 19 years
- ☒ National-level data only (no subnational)
- ☒ Static model (no dynamic transmission modelling)
- ☒ Data coverage limited to year 2015
- ☒ High-capacity burden for users
- ☒ Difficult to interpret without training

PROPOSED ENHANCEMENTS

- ✓ Extend tool to include Rubella (MR tool)
- ✓ Expand immunity profiling since vaccine introduction
- ✓ Add subnational analysis component
- ✓ Dynamic transmission modelling capability
- ✓ Update data to current years
- ✓ Lighter, more user-friendly interface
- ✓ Outbreak prediction module
- ✓ Extended risk assessment & economic analysis

Key Takeaways

01

Evidence-Based Planning

Compares up to 4 vaccination strategies using real country data.

02

Comprehensive Immunity Profiling

Models vaccine-derived and infection-acquired immunity across all age cohorts to identify susceptibility gaps.

03

Decision Support for Programme Managers

Provides deaths averted, cost-effectiveness, and case estimates to support advocacy and resource allocation.

04

Proven Field Applications

Successfully used for MR SIA planning, phased state grouping, and Rubella vaccine introduction in India.

05

Evolving Tool — Modernisation Needed

Dynamic modelling, subnational capacity, Rubella integration and outbreak prediction are priority enhancements.

Alpha Forna

MEASLES
ANALYTICS HUB

Category: Data, modelling, and methodological challenges & innovations

From Tools to Adoption

When should models replace what programmes already use?

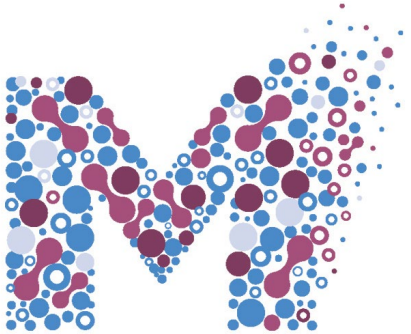
Alpha Forna[1,2,3] on behalf of the measles ML prediction and immunity profile groups

University of Georgia · Johns Hopkins · Penn State

MAH Annual Meeting · Friday Session: Tooling, Adoption, and Sustainability · Jakarta, 13 June 2026

MEASLES
ANALYTICS HUB

When should we advocate replacing a familiar tool with a novel one?

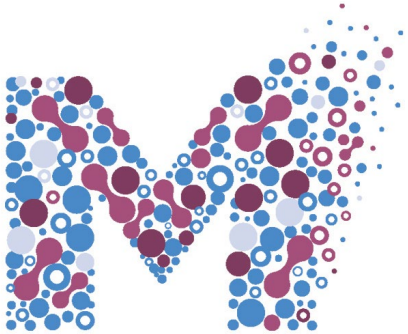


Three questions this talk keeps coming back to:

1. When is well-adopted but imperfect better than well-validated but unused?
2. Who decides what “good enough” means — and at what cost?
3. What does it actually take for a country to switch?

Every modeller in this room has either built a tool no one uses, or sat across from someone whose tool we are trying to replace.

The tools we are going to talk about



Programmatic risk tools

MPRAT (CDC)

Admin-2 risk indicators · widely adopted in country offices · simple scoring rules · low data requirements

Strategic planning tools

MSP-type tools

National programme planning · deterministic scenarios · used to justify campaigns and funding requests

Immunity profile tools

WHO / CDC / Sbarra et al.

Indirect estimates of population immunity · one-off or routine · multiple methodological flavours

Predictive modelling tools

ML approaches (ours + similar)

Probabilistic outbreak risk · country-year · comparative across geographies · validated against baselines

All four exist for the same reason — to help a country decide where to act next. They differ in everything else: who built them, who uses them, what they cost to run, and what they actually predict.

A flexible pipeline applied to 187 countries (RECAP)

Step 1: Collate the data

Step 2: Define prediction target (time step, outbreak definition, prediction horizon)

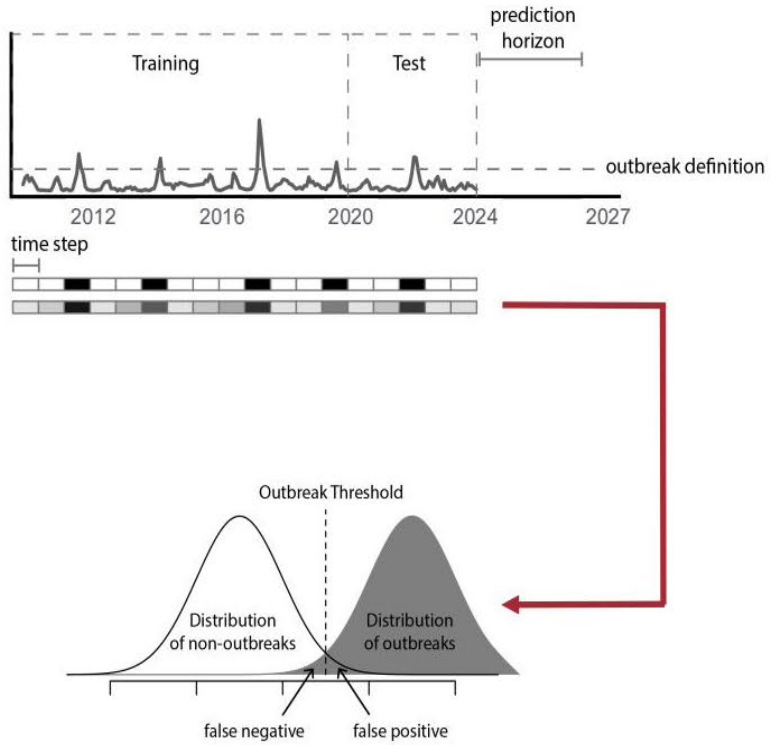
Step 3: Define training, test, and prediction sets

Step 4: Discretize cases by time scale and prediction target definition

Step 5: Quantify the performance of the baseline model

Step 6: Lag and summarize predictors by time step

Step 7: Train ML model on training set and evaluate model performance on test set compared to baseline



We then bins those predicted probabilities into outbreak and non-outbreak time steps by selecting a threshold using the test set that minimizes false positive and false negative classification

Step 3 in practice

Separate years for fitting, tuning, and reporting.

2011–2018

TRAIN

Fit the model with 5-fold cross-validation

2019–2021

TEST

Pick the decision threshold (Youden's index)

2022–2024

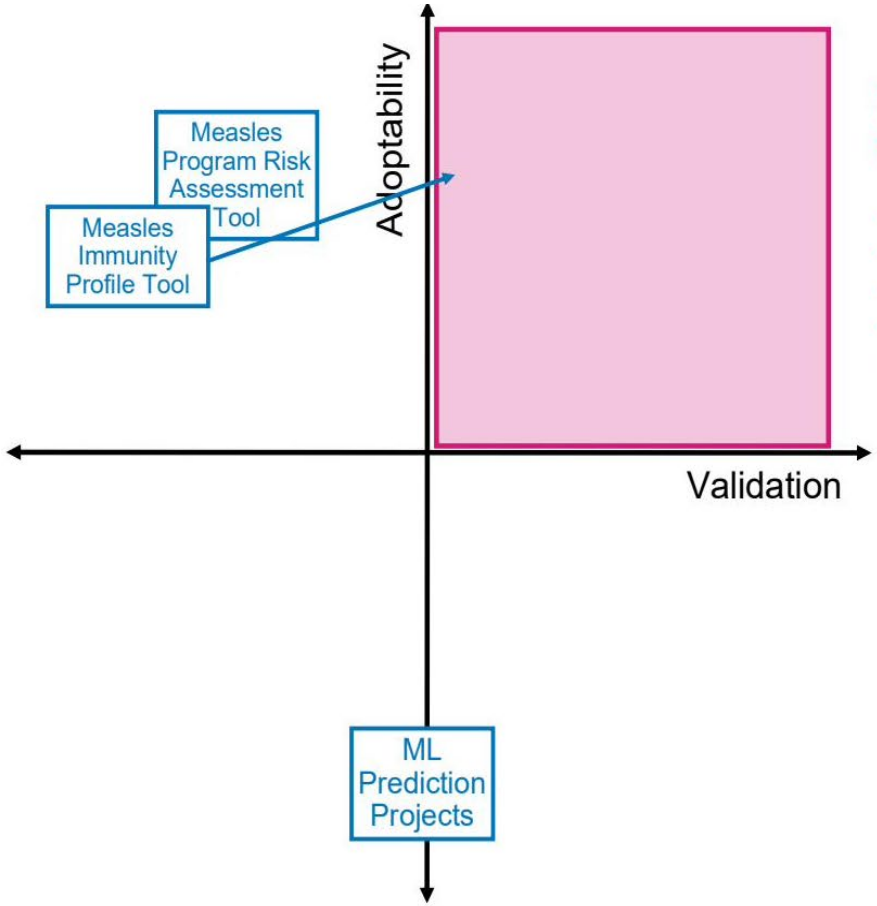
VALIDATE

Report performance on years the model has never seen

MEASLES ANALYTICS HUB

Two axes that decide whether a tool gets used

Where we are:



Where we want to be:

- Well validated
- Trusted/Adopted
- Scalable
- User and purpose-specific

WHERE TOOLS ACTUALLY SIT

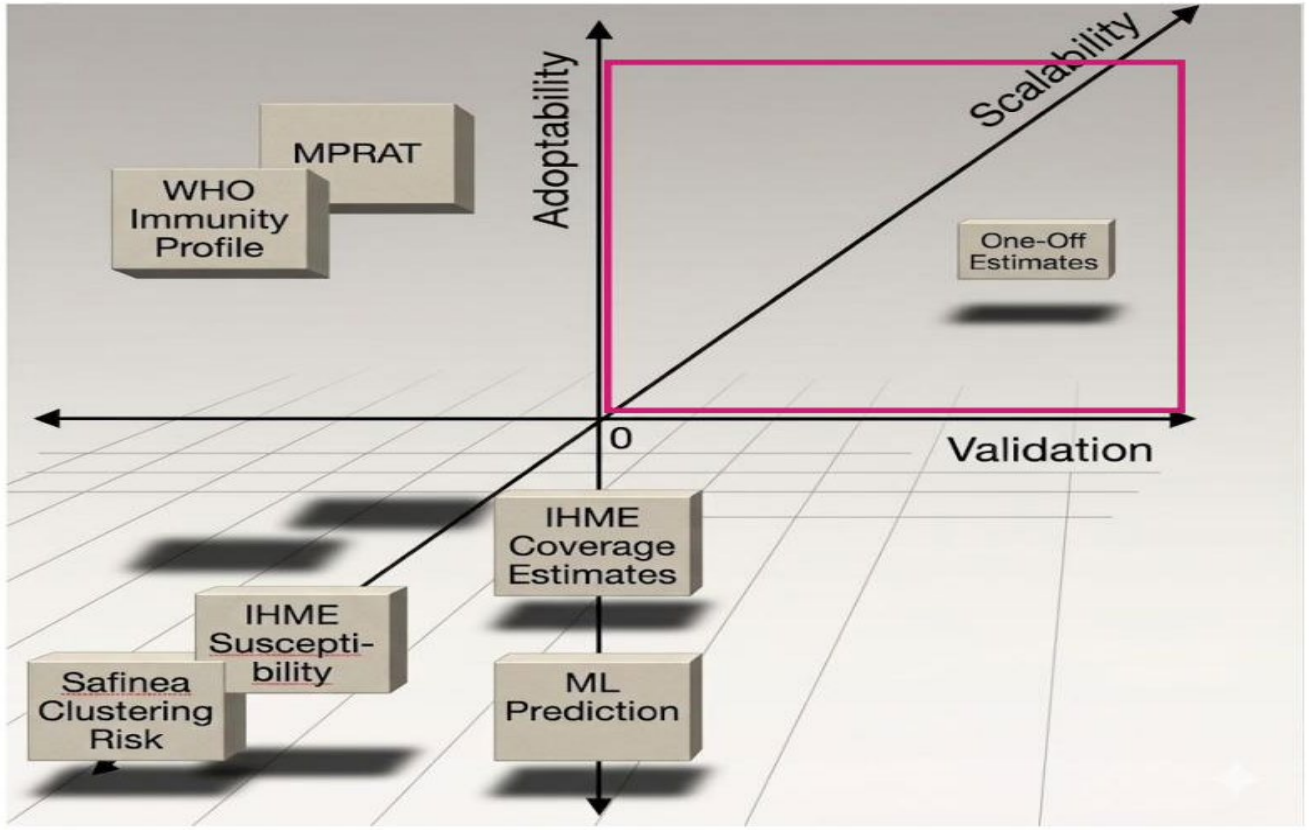
MPRAT, Immunity Profile Tool
→ high adoptability, *lower validation*

ML prediction
→ higher validation, *lower adoptability*

The pink box
→ *where we want to be — and it is almost entirely empty.*

Most tools we have built sit on one axis or the other. The upper-right corner is where we want to be.

Add a third axis: scalability



WHAT SCALABILITY ADDS

One-off estimates

Can be high-validity AND high-adoption — for one country, one year, one user. The moment you ask them to scale, things break.

ML / statistical pipelines

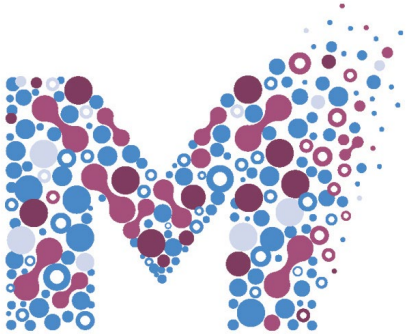
Real scalability advantages — same code runs across 187 countries — but adoption falls off a cliff at exactly the same time.

The pattern

Tools that scale rarely get adopted at the country level. Tools that get adopted rarely scale. We need to bridge this gap.

A tool that works for one country, one year, one user is fundamentally different from one that runs at WPRO scale every year.

What “where we want to be” actually means (Our Experience)



WHERE WE WANT TO BE

Tools that are…

- **Well validated**
- **Trusted / adopted**
- **Scalable**
- **User and purpose-specific**

BUT EACH RAISES A QUESTION

Well validated — against what?

Validation against an internal test set is not the same as validation against the simplest historical baseline. Most novel tools have done the first; few have done the second.

Trusted / adopted — by whom?

MoH staff, WHO regional advisors, donors, and modellers all have different adoption thresholds. A tool can be “adopted” by one and ignored by another.

Scalable — at what level?

National? Sub-national? Across regions? Scaling to more countries is not the same as scaling to finer geography.

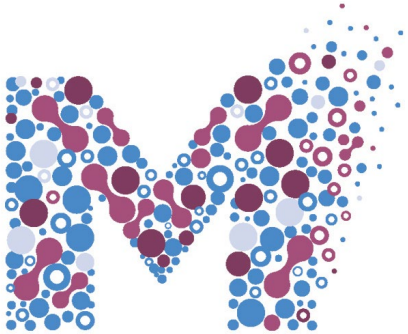
User & purpose-specific — we underrate this one

A tool built for cross-country prioritisation rarely also works for in-country campaign planning. Specificity to use is often what separates adopted from abandoned.

Most disagreements about tools are actually disagreements about which of these four matters most.

Lesson 1: The prediction target is a choice, not a statistical one

What I learned building one of these tools



"What counts as an outbreak?"

20 cases / million / year?

Cases per month, per admin-2 unit?

Above a country-specific endemic baseline?

Each choice changes who gets flagged. A threshold of 20 / million / year calls Indonesia not at risk; a stricter monthly threshold calls Indonesia at risk for half the year.

Which definition is correct depends on what decision you are trying to support — not on what the model can do.

"How far ahead should we predict?"

1 year ahead — what the model can do.

3 months ahead — what programmes need.

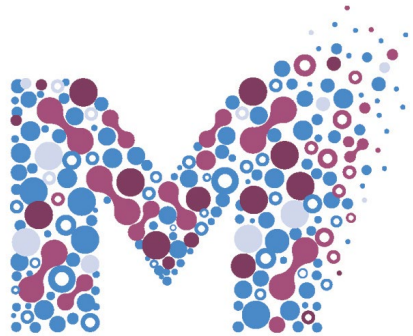
Real-time — what donors and media want.

Modellers pick the horizon that is technically tractable. Programmes need the horizon that fits the response cycle. Donors want the horizon that drives headlines.

These are rarely the same horizon.

Modellers pick what is tractable. Programmes need what is actionable. These are rarely the same.

ML performance depends on chosen prediction target



Number of models (out of 36) that ML or Baseline model performance metric was superior

Performance based on 36 validation sets (Jan 2022 – Dec 2025)

	Sensitivity			Specificity			Accuracy		
	1 year ahead	2 years ahead	3 years ahead	1 year ahead	2 years ahead	3 years ahead	1 year ahead	2 years ahead	3 years ahead
50	−28	−33	−17	21	29	17	12	21	15
48	−27	−31	−15	20	27	13	13	23	15
46	−26	−30	−15	20	29	13	13	21	14
44	−25	−29	−12	14	27	16	5	15	11
42	−21	−28	−15	13	20	14	1	10	13
40	−21	−29	−19	15	22	17	3	11	10
38	−23	−27	−14	9	23	13	−6	5	11
36	−26	−27	−11	14	27	16	−3	7	13
34	−17	−26	−11	8	23	15	−3	8	11
32	−17	−30	−19	12	29	20	2	12	18
30	−20	−31	−16	15	32	20	2	15	16
28	−20	−29	−18	15	32	25	0	20	17
26	−17	−23	−18	7	23	20	1	12	6
24	−17	−26	−18	6	19	21	−3	10	4
22	−17	−24	−20	6	18	20	−4	9	2
20	−20	−25	−19	3	18	19	−3	6	3
18	−18	−25	−22	6	21	22	−5	2	0
16	−17	−19	−19	3	17	22	−3	5	3
14	−20	−23	−11	0	15	18	−4	−3	−1
12	−25	−21	−12	12	14	24	−14	−5	3
10	−30	−21	−15	16	18	17	−8	−4	2

Prediction window

Superiority (non–overlapping CIs)

ML models better in all 36 models

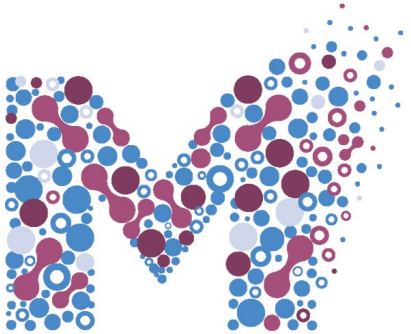
No clear diff

BL model better in all 36 models

The choice of target also affect class imbalance.

Lesson 2: Validation — against what?

What I learned building one of these tools



OUR HONEST FINDING

We benchmarked our ML model against the simplest possible baseline — *"has this country had an outbreak recently?"* At country-year scale, we **barely beat it**. That is not a failure of the model — it is a finding about the ***ceiling*** of country-year prediction with current global data. Simple null proption past outbreak…next year has same chance of outbreak

What this means for tool design

If a new tool cannot beat the simplest baseline, the right response is not to publish anyway. It is to question whether we have chosen the right prediction target — or the right spatial scale, or the right time horizon.

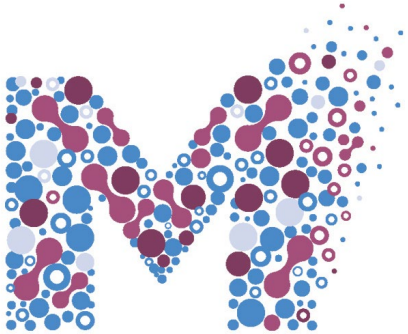
What this means for the field

Novel tools should be benchmarked against the simplest available alternative — not against a random classifier and not against nothing. This is a low bar that an uncomfortable share of published modelling work does not clear.

A well-validated tool that answers a question no one asked is still useless.

Lesson 3: The user is often invisible — until it is too late

What I learned building one of these tools



WHO regional advisors

Wants:

Cross-country comparability · defensible methodology · consistency across years

Pain point:

A tool tuned to one country's context cannot inform a regional priority list.

National EPI managers

Wants:

Actionable · context-aware · locally defensible · fits existing workflows

Pain point:

A global model that flags every country at once tells them nothing they can act on.

Researchers / modellers

Wants:

Flexibility · methodological transparency · code access · publishable

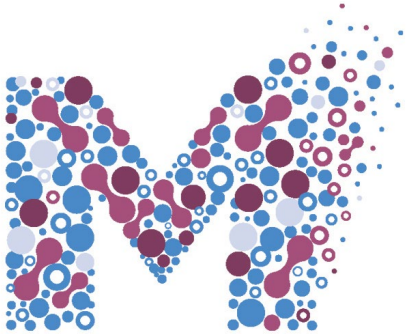
Pain point:

A locked-down operational tool is useless for methods development.

MPRAT works in country offices because it was designed with country office staff. Our ML model works in our group because it was designed in our group.

Lesson 3: And adoption is path-dependent — and that is a feature, not a bug

What I learned building one of these tools



What an existing tool has working for it

(That a novel tool does not)

- Training has already happened.
- Decisions have been justified using it for years.
- Workflows and reporting templates have grown around it.
- Programme staff know its quirks and how to work around them.
- Donors and stakeholders recognise its outputs.

What this means for the change conversation

When we propose to replace MPRAT, we are not just proposing a new tool.

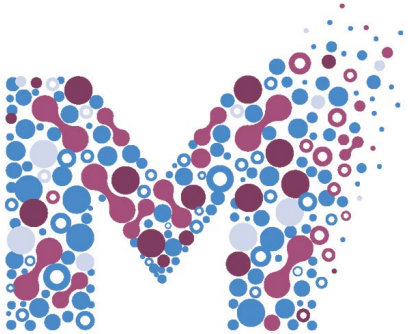
We are asking a country to re-justify every decision they made for the last decade using the old one — to retrain staff, rewrite workflows, recalibrate donor expectations, and absorb the political risk that the new tool will disagree with the old one.

This is rarely a small ask. And it is rarely the modeller's ask to make.

Switching costs are real. They are also why familiar tools deserve more respect than we usually give them.

Lesson 4: Sustainability is a tooling question, not a science question

What I learned building one of these tools



What kills a tool in low-resource settings:

Data dependencies

Surveillance data that arrives because of a donor-funded project disappears when the donor pulls out.

Maintainer turnover

Most modelling work is done by post-docs. The post-doc moves on. The tool goes stale within 18 months.

Update complexity

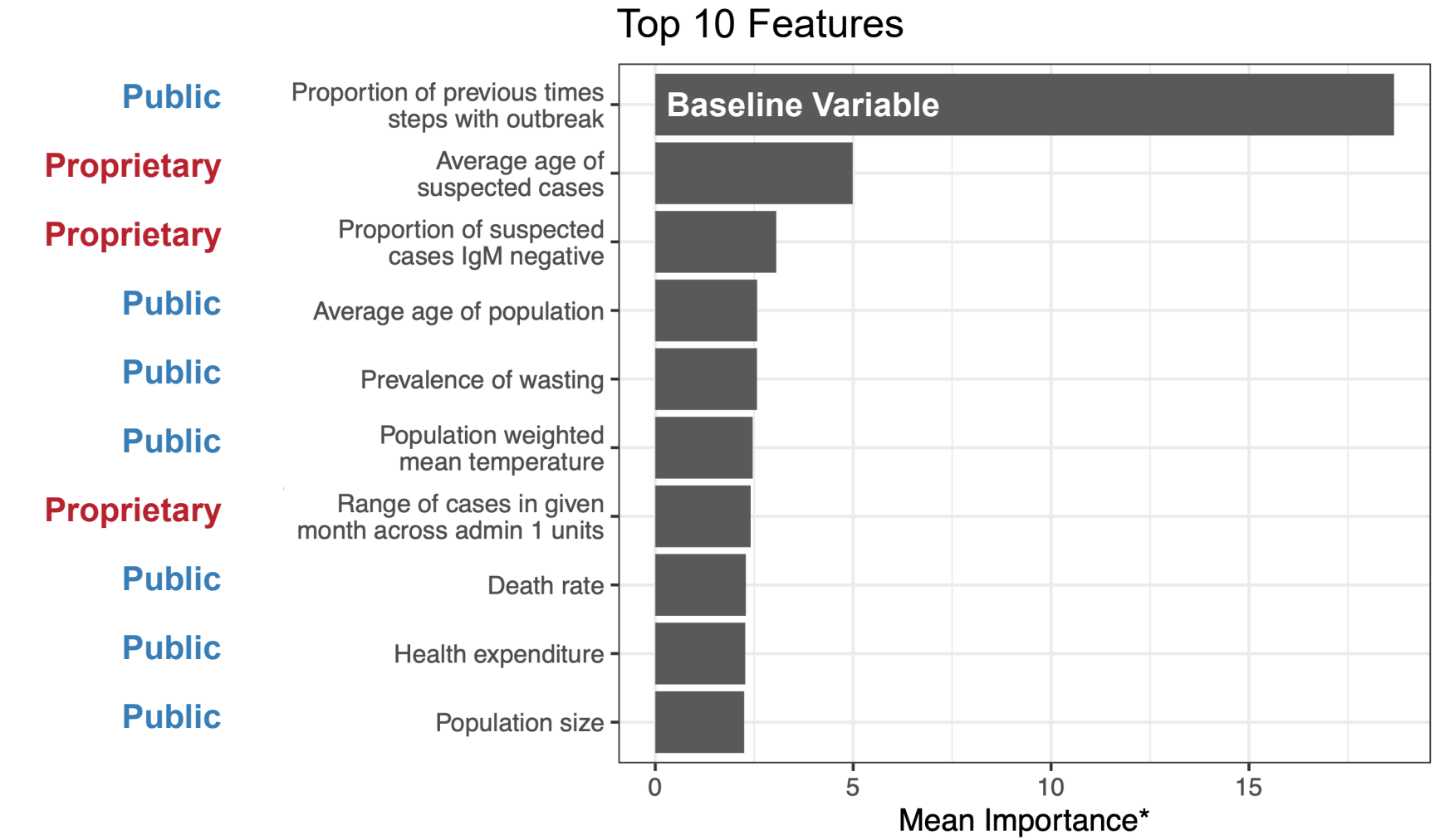
If updating the model requires statistical skill no one in the country office has, the tool only runs when the original authors run it.

Invisible costs

Server time, cloud storage, software licences, training refreshers — rarely budgeted, often the reason adoption ends.

A tool that requires a PhD to update is not a tool — it is a consultancy contract.

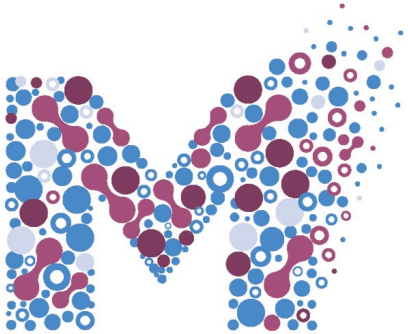
Variable importance plots can be used to quantify the value of measles data streams



*mean across 123 prediction targets and 36 training sets

So when should we advocate for change?

A frame for the discussion — not a prescription



REPLACE

When the existing tool gives a wrong answer to the question being asked

AND the new tool can actually be sustained operationally

e.g. a tool whose underlying assumptions are demonstrably wrong for the new epidemiological regime

AUGMENT

When the existing tool gives a crude answer to the right question

AND the new tool refines it without undermining trust in the workflow

e.g. layering a probabilistic risk model alongside MPRAT, with MPRAT staying the operational anchor

LEAVE ALONE

When the tool is doing its job

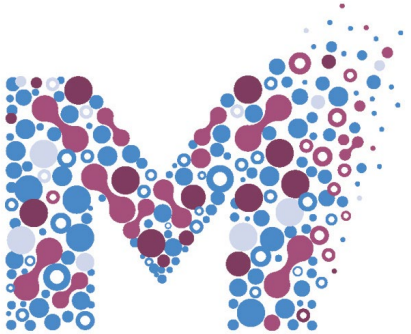
AND the new thing is not materially better at the USER's job

e.g. a tool that beats the existing one on AUC but takes ten times the effort to run

We almost always default to REPLACE. Most of the time, we should be AUGMENTING.

What does the modeller's role look like in each case?

Three modes — most groups default to the first



OUR DEFAULT

Tool-builder

"I write the code. You use it."

Modeller designs and ships a tool. Users adopt it as-is.

Where it fits:

Works when the question is well-defined and stable. Rarely the actual situation in measles programmes.

WHAT WE NEED MORE OF

Decision-support partner

"You frame the question. We build together."

Modeller and user co-design the tool from the start. The question evolves; the model evolves with it.

Where it fits:

Harder, slower, and almost always more useful. Requires modellers who can sit in operational meetings.

EASILY OVERLOOKED

Translator

"You already know things. Let me give them structure."

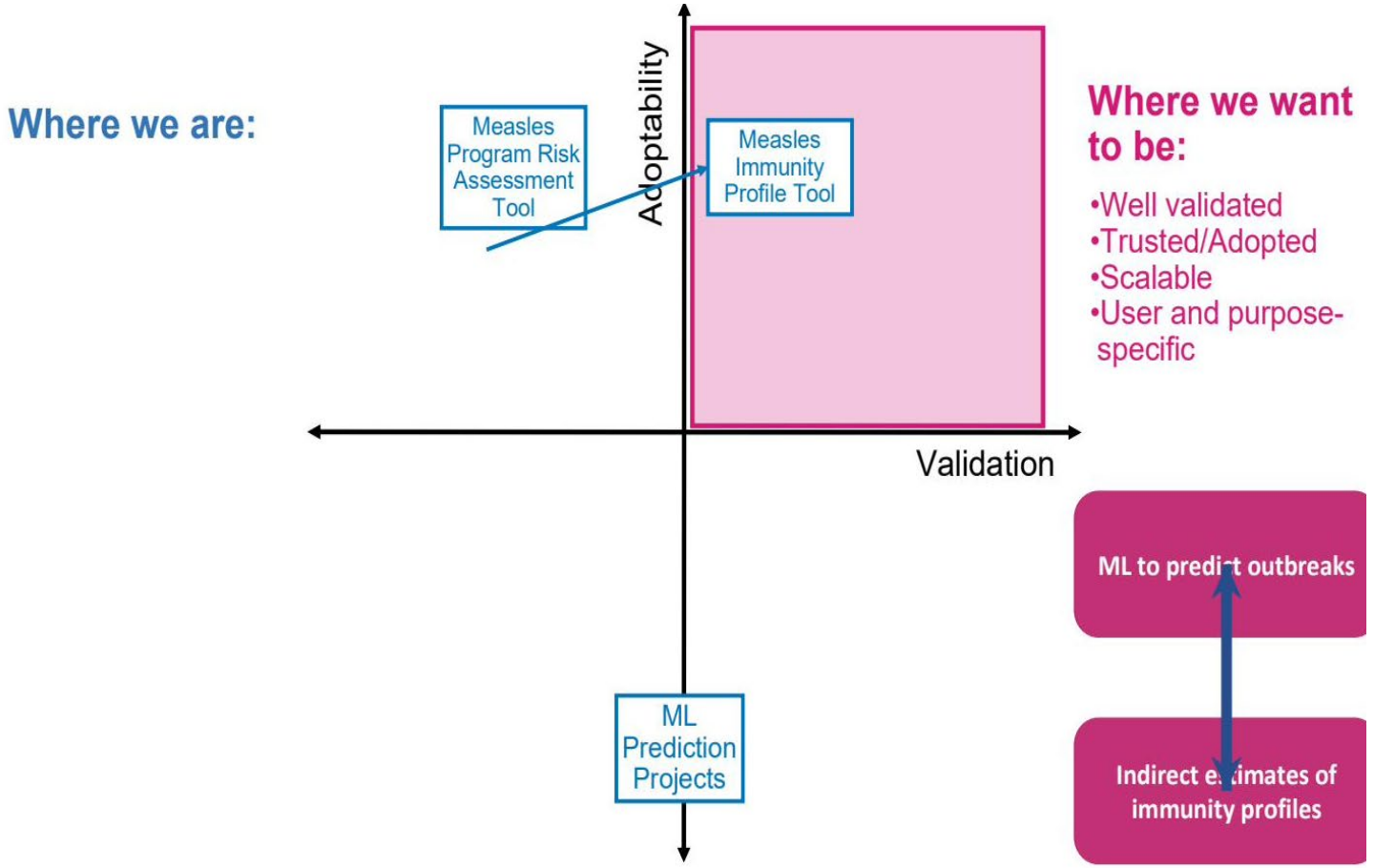
Modeller takes existing programmatic knowledge and adds quantitative scaffolding — not new answers, better articulation of old ones.

Where it fits:

The most under-valued role. It does not look like "modelling" to most modellers.

What role should modellers play in this room's work? That is partly a discussion question.

Where we want to be — revisited, with paths



WHAT THE PATH ACTUALLY LOOKS LIKE

Co-design with users

Start with the decision, not the data. The user is in the room from day one.

External validation

Benchmark against the simplest baseline. Validate in geographies the model has never seen.

Country handover plan

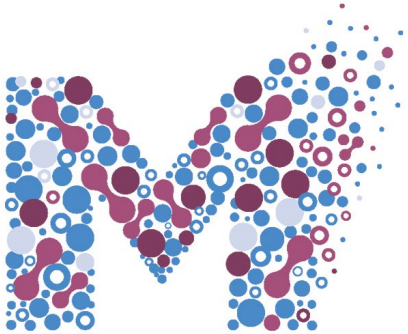
Plan for who runs and updates the tool 3 years from now — at the start of the project, not the end.

Longitudinal maintenance

Budget for maintenance, not just development. The model that ships and is never updated is worse than no model.

The path to the upper-right corner is not a methods question. It is a tooling, partnership, and sustainability question.

Open questions — for this room



1. Who owns the prediction target — countries, WHO, modellers, donors? What happens when they disagree?

2. What does “good enough” mean for routine programmatic use? AUC 0.9? 0.8? 0.7?

3. When is a familiar 0.7 tool better than a novel 0.85 tool?

4. What should modellers stop doing? What should we start doing?

The session is yours from here.

Acknowledgments

None of these tools exist without the people who built them — and the countries that use them.

TOOL TEAMS DISCUSSED

MPRAT · CDC Global Immunization Division

Measles Immunity Profile Tool · WHO / CDC / Sbarra et al.

Strategic planning tools (MSP-type) · WHO and country programmes

ML outbreak prediction · UGA, JHU, PSU (our group)

OUR COLLABORATORS

Alyssa Sbarra (JHU) · Saki Takahashi (JHU)
Bill Moss (JHU) · Shaun Truelove (JHU)
John Drake (UGA) · Matt Ferrari (PSU)
Amy Winter (UGA)

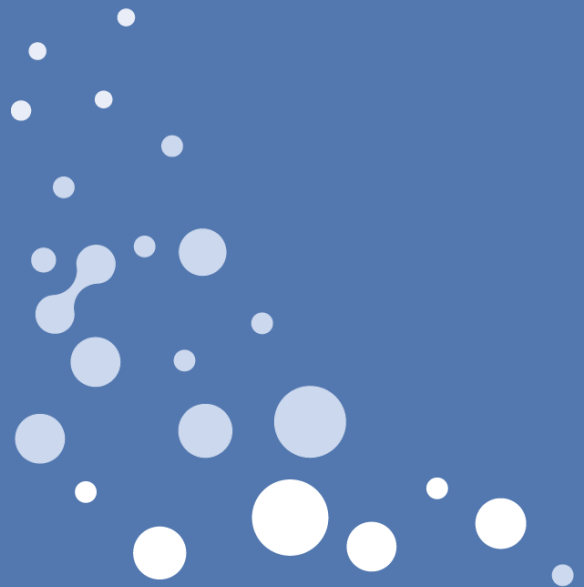
And the country MoH and WHO country office staff who shaped how we think about adoption.

Funding: VIMC, MAH, Gates Foundation

alpha.forna@uga.edu

MEASLES ANALYTICS HUB

Jess Metcalf



MEASLES
ANALYTICS HUB

A foundation model for measles?

Jessica Metcalf
EEB, Princeton University

Max Lau
Department of Biostatistics and Bioinformatics, Emory University

Table 1. Representative foundation models in different domains

Model	Domain	Primary Capabilities
GPT-4 (4)	Language	General-purpose language modeling across diverse domains.
GenCast (5)	Weather Forecasts	Weather forecasting, probabilistic prediction, shared atmospheric structure learning across space and time.
AlphaEarth (6)	Geospatial Modeling	Multi-task geospatial model that captures shared Earth system structure across space, time, and modalities.
FinCast (7)	Finance	Financial forecasting across diverse domains (stocks, crypto, forex) and resolutions; zero-shot generalization; probabilistic uncertainty modeling.
PaPaGei (8)	Photoplethysmography (PPG)	Estimation of cardiovascular health, sleep disorders, pregnancy monitoring, and well-being.
ECG-FM (9)	Electrocardiography (ECG)	Multi-label ECG interpretation, reduced LVEF screening, automated report benchmarking.
BioGPT (11)	Biomedical Language	Biomedical text generation, question answering, biomedical relation extraction.
Galactica (12)	Scientific Text	Molecule property prediction, chemical reaction prediction, citation prediction, etc.
GatorTron (13)	Clinical Language	Clinical concept extraction, classification, question answering, summarization.

Potential

Most epidemic models are still built for one setting, one task.

Country A model

train from scratch

Country B model

train from scratch

Country C model

train from scratch

Can we learn shared epidemic representations of measles across places, and data streams (and other diseases)?

The epidemic data landscape has changed

Epidemic science now produces high-dimensional, heterogeneous signals.

Cases

reported incidence

Mobility

movement and mixing

Genomics

variant dynamics

Wastewater

community signal

EHRs

clinical trajectories

Climate

environmental drivers

The opportunity is not just more data - it is learning across modalities where traditional can struggle

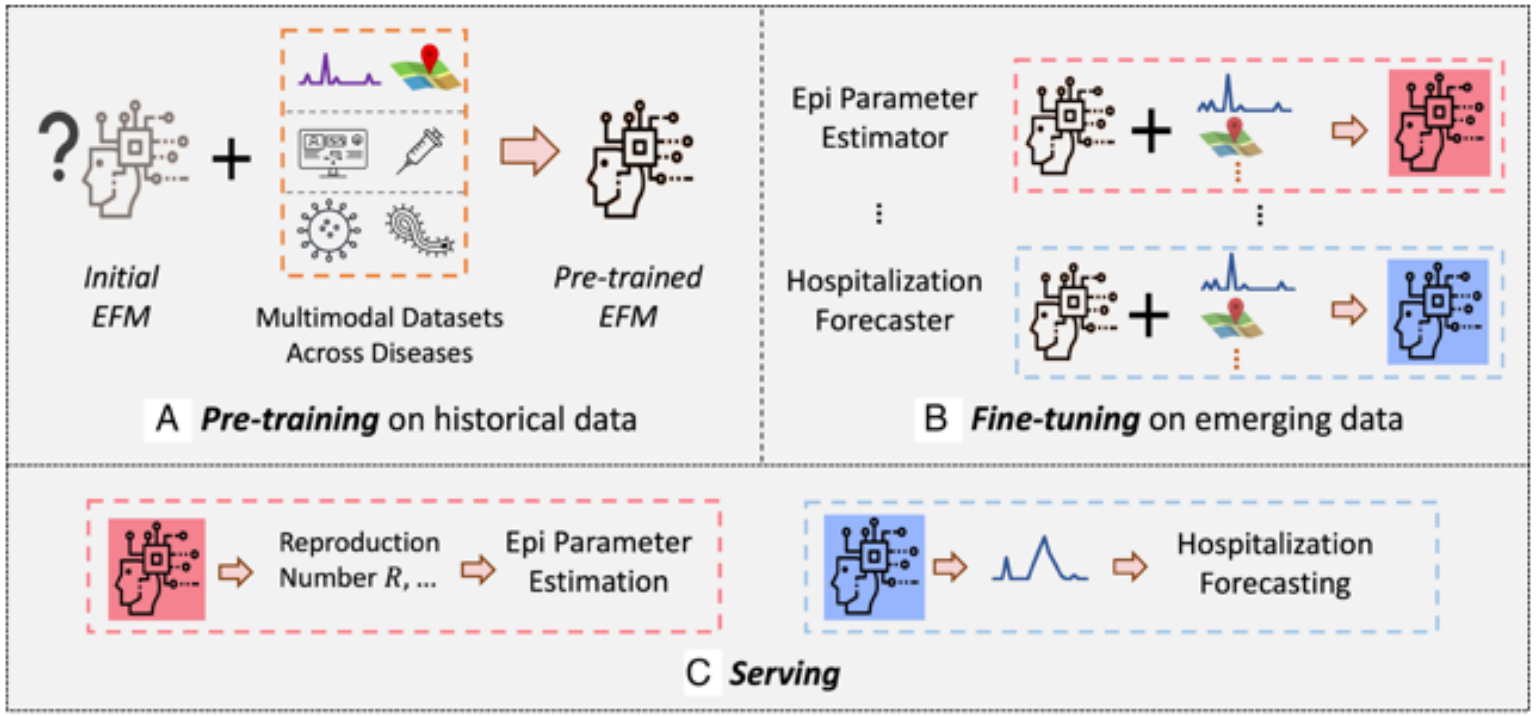
Vision: epidemic foundation models

PNAS PERSPECTIVE OPEN ACCESS

Toward AI foundation models for epidemics: Promise, challenges, and paths forward

Max S. Y. Lau[a,1], C. Jessica E. Metcalf[b], Zewen Liu[c], Bryan T. Grenfell[b,2], and Wei Jin[c,1,2]

Edited by Alan Hastings, University of California, Davis, CA; received October 28, 2025; accepted January 1, 2026



Pretrain on diverse historical outbreaks, then fine-tune to new settings and tasks.

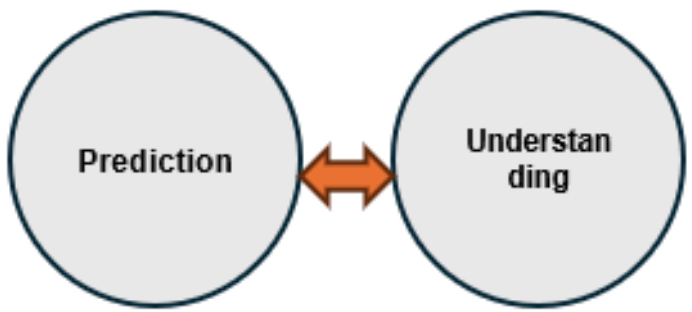
Two approaches to interpretable machine learning

A. Post-hoc interpretation

- Use feature importance to reveal drivers
- Ask: what did the ML/DL model learn?

B. Mechanism in the ML/DL model

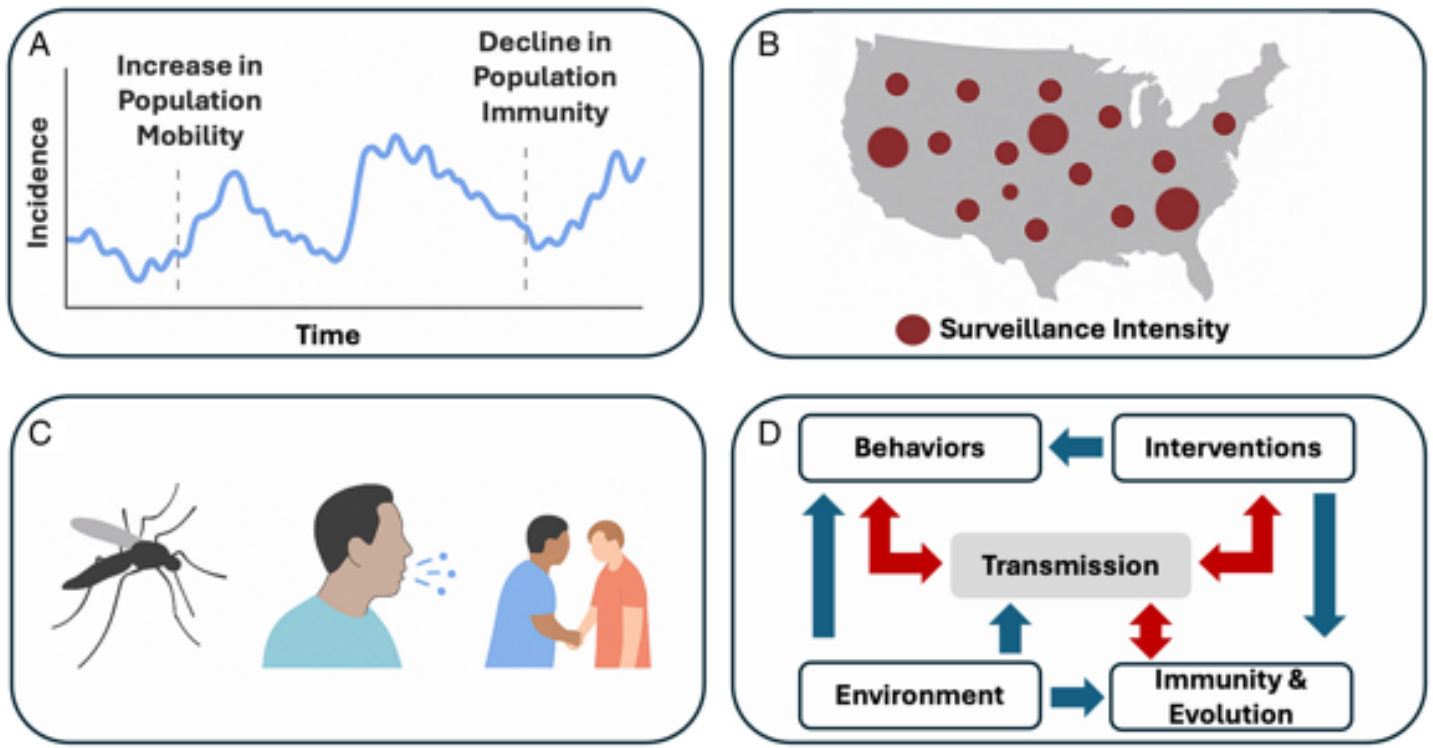
- Embed ODE/SIR constraints directly in ML/DL
- Ask: can ML/DL respect epidemiological principles?



Both aim to bridge the same gap: high predictive accuracy + scientific understanding.

Why epidemic foundation models are hard

Epidemic systems differ from many domains where foundation models have flourished.



1. **Nonstationarity**
2. **Data sparsity + fragmentation**
3. **Diverse dynamical regimes**
4. **Causal and mechanistic feedback**

PLOS Global Public Health

OPINION

Rebalancing power in infectious disease modelling: Toward inclusive and contextual approaches

Justice Moses K. Aheto[1,2*], Megan Auzenbergs[2], Matthew J. Ferrari[2,3], Allison Portnoy[4], Chigozie Edson Utazi[5], Romain Glèlè Kakaï[6], Ezra Gayawan[7], James M. Azam[8], Justice Nonvignon[1]

Thank you

Questions and discussion

Coffee Break

Scale-up, user adoption, training needs etc.

Interactive discussion

MEASLES
ANALYTICS HUB

Lunch Break

Perspectives from AFR region

Networking & icebreaker

MEASLES
ANALYTICS HUB

Introduction to MAH Mentees

MEASLES
ANALYTICS HUB

Esther Arrah

Cameroon

MEASLES
ANALYTICS HUB

MAH Mentee introduction - Cameroon

Measles Analytics Hub Annual meeting

10 – 12 June 2026

Jakarta, Indonesia

MEASLES ANALYTICS HUB

About me

- **Name**: Arrah Esther
- **Nationality** : Cameroonian
- **Position**: Regional Disease Surveillance Officer
- **Organization**: Expanded Programme on Immunization (EPI), Ministry of Public Health, Cameroon
- **Location**: Littoral Region, Douala - Cameroon

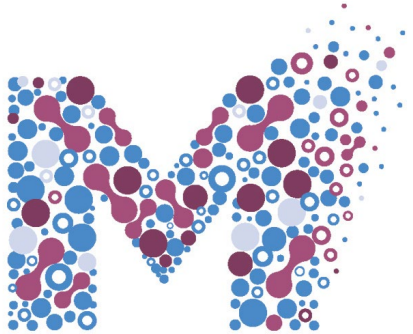
Academics

- B.Sc. in computer sciences
- M.Sc. Data Science
- Diploma in Public Health Administration
- Frontline Field Epidemiology Training Program (FETP)

Fellowship

- SACEMA Policy Modelling Fellowship cohort 2025 (Worked on Transmissions models for measles and immunity estimation for Polio in Cameroon)

My Professional Responsibilities



Disease surveillance and outbreak response.

Monitoring of vaccine-preventable diseases.

Surveillance and immunization data analysis and reporting.

Capacity building and mentorship of healthcare workers.

Surveillance data quality assurance.

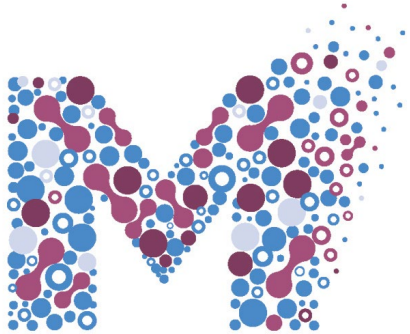
Coordination of specimen transportation and laboratory monitoring.

Mentorship proposed project

Project title

- To generate evidence-based recommendations for optimizing the timing and geographic targeting of measles Supplementary Immunization Activities (SIAs) in Cameroon through epidemiological modelling, thereby supporting progress toward measles elimination.

Why I joined MAH



Strengthen my expertise in measles modelling and analytics.

Learn from leading researchers and practitioners.

Apply modelling approaches to support immunization policy in Cameroon.

Build collaborations within the MAH community.

Contribute evidence for measles elimination efforts in Africa.

Thank you

MEASLES
ANALYTICS HUB

Armand Mutwadi

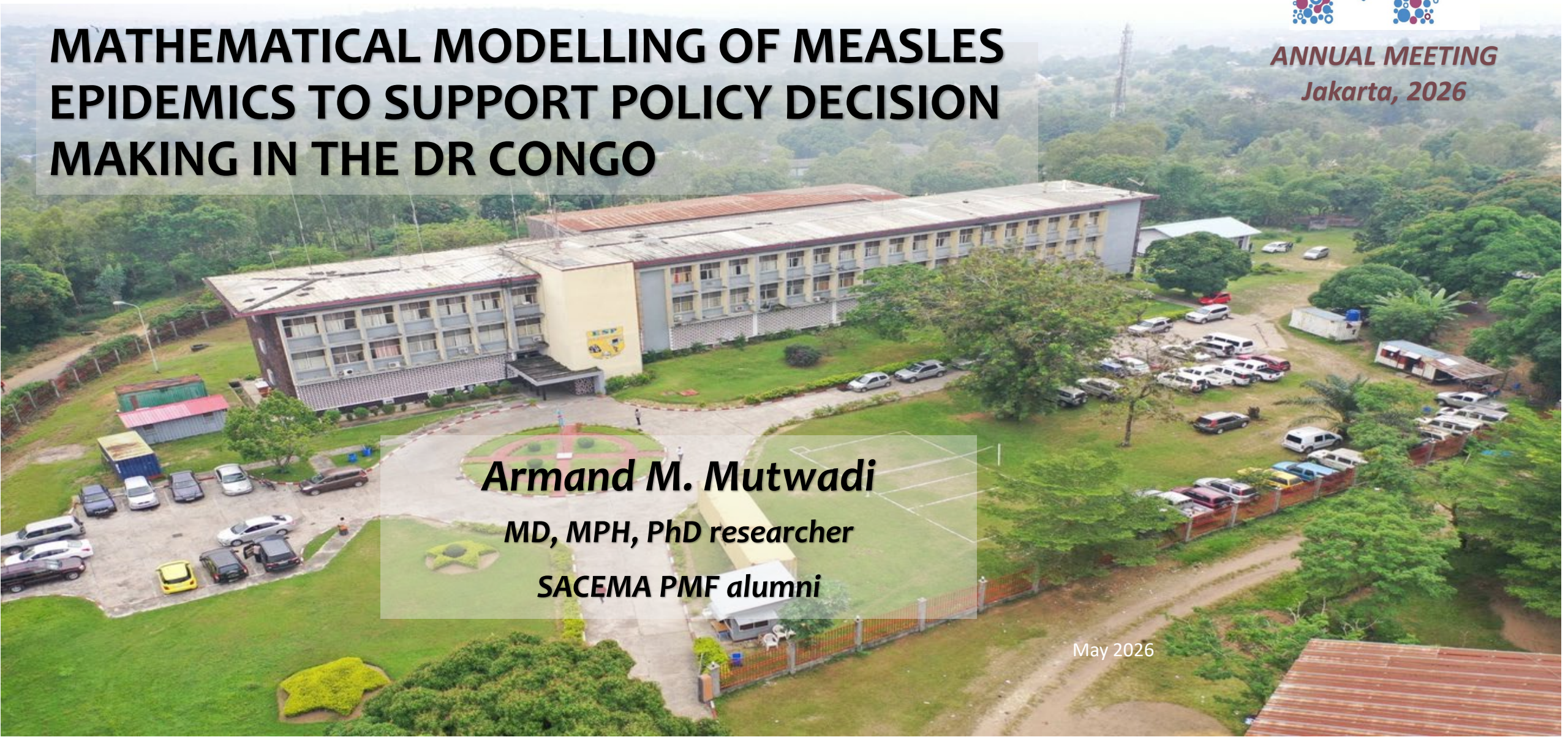
DRC

MEASLES
ANALYTICS HUB

Ecole de Santé Publique de Kinshasa
Kinshasa School of Public Health
UNIVERSITE DE KINSHASA
KSPH

MATHEMATICAL MODELLING OF MEASLES EPIDEMICS TO SUPPORT POLICY DECISION MAKING IN THE DR CONGO

ANNUAL MEETING
Jakarta, 2026



Armand M. Mutwadi

MD, MPH, PhD researcher

SACEMA PMF alumni

May 2026

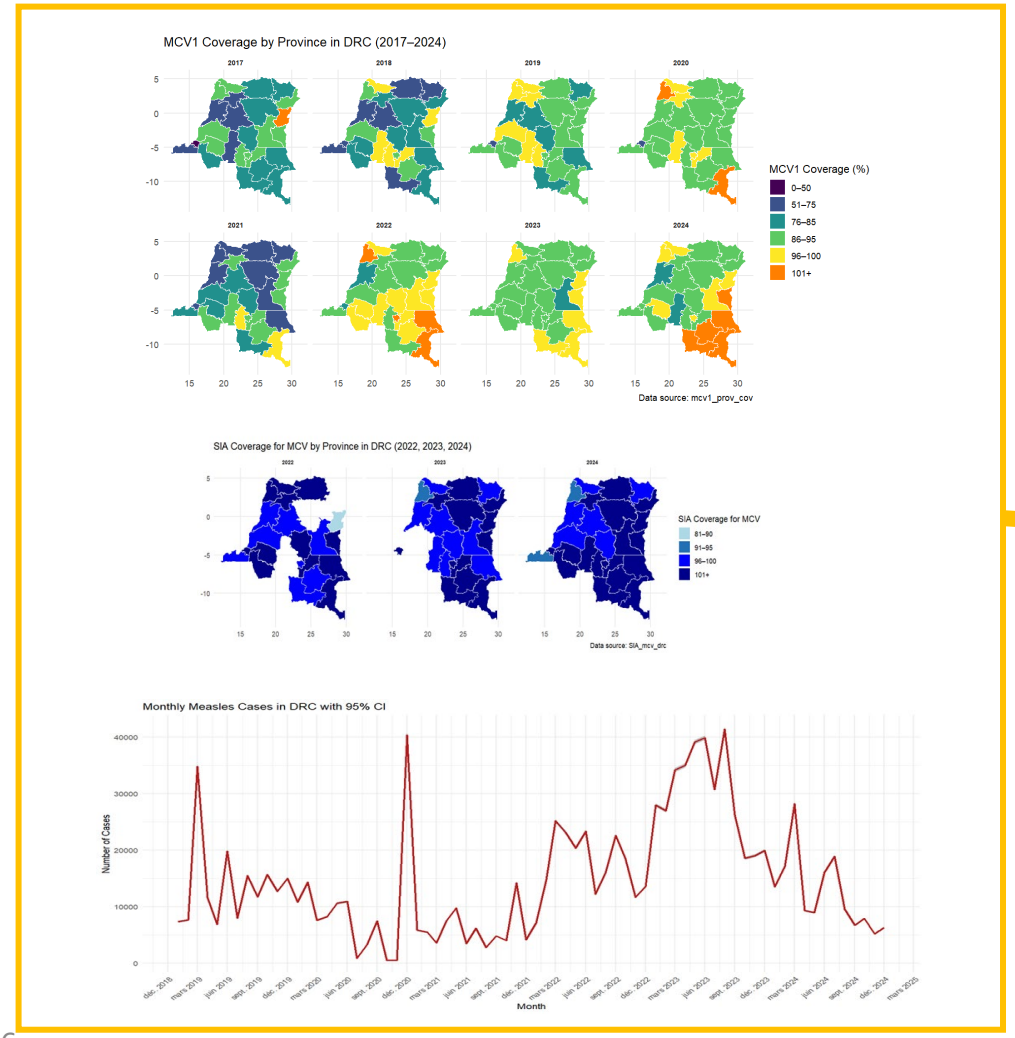
Ecole de Santé Publique de Kinshasa
Kinshasa School of Public Health
KSPH
UNIVERSITE DE KINSHASA

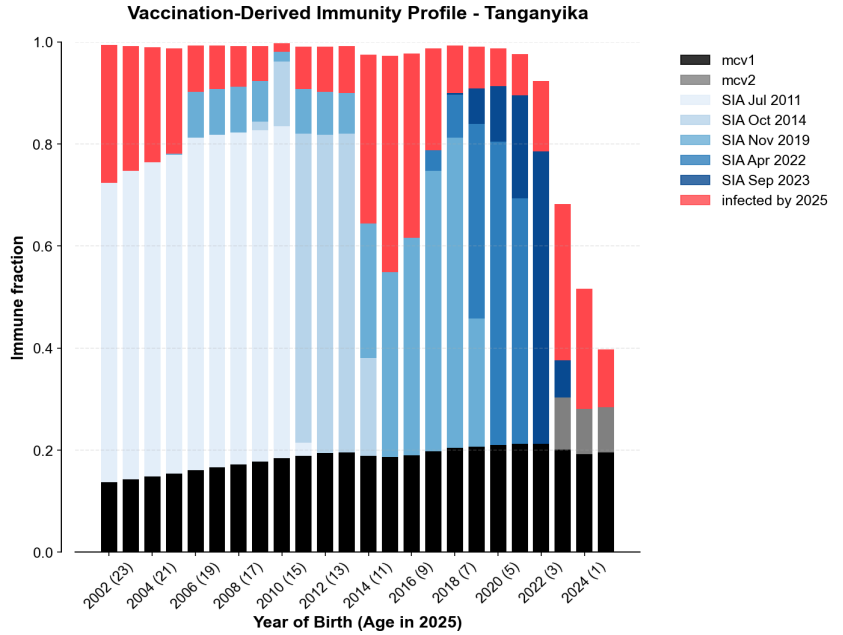
From Policy question → To Model output

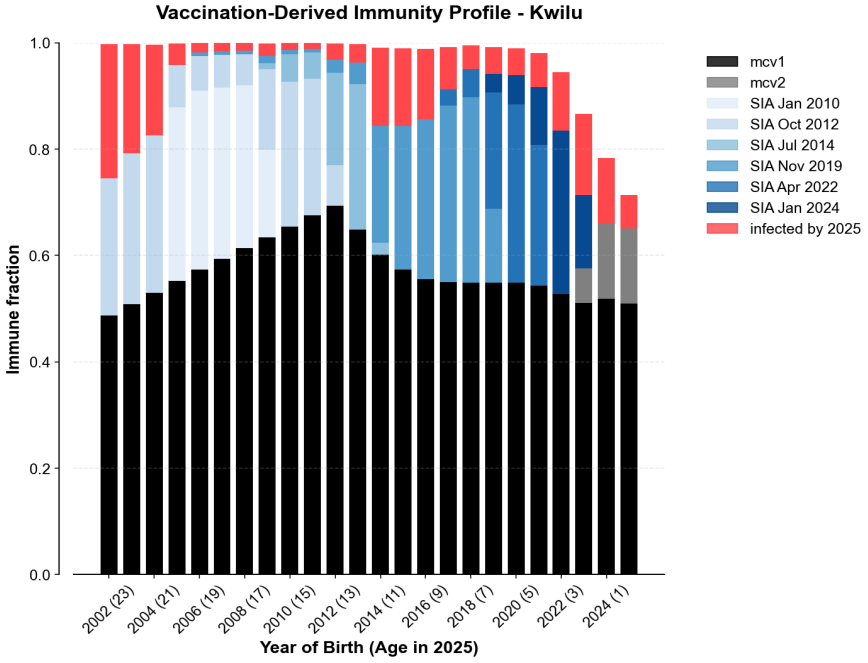
RI coverage

SIA coverage

Measles cases

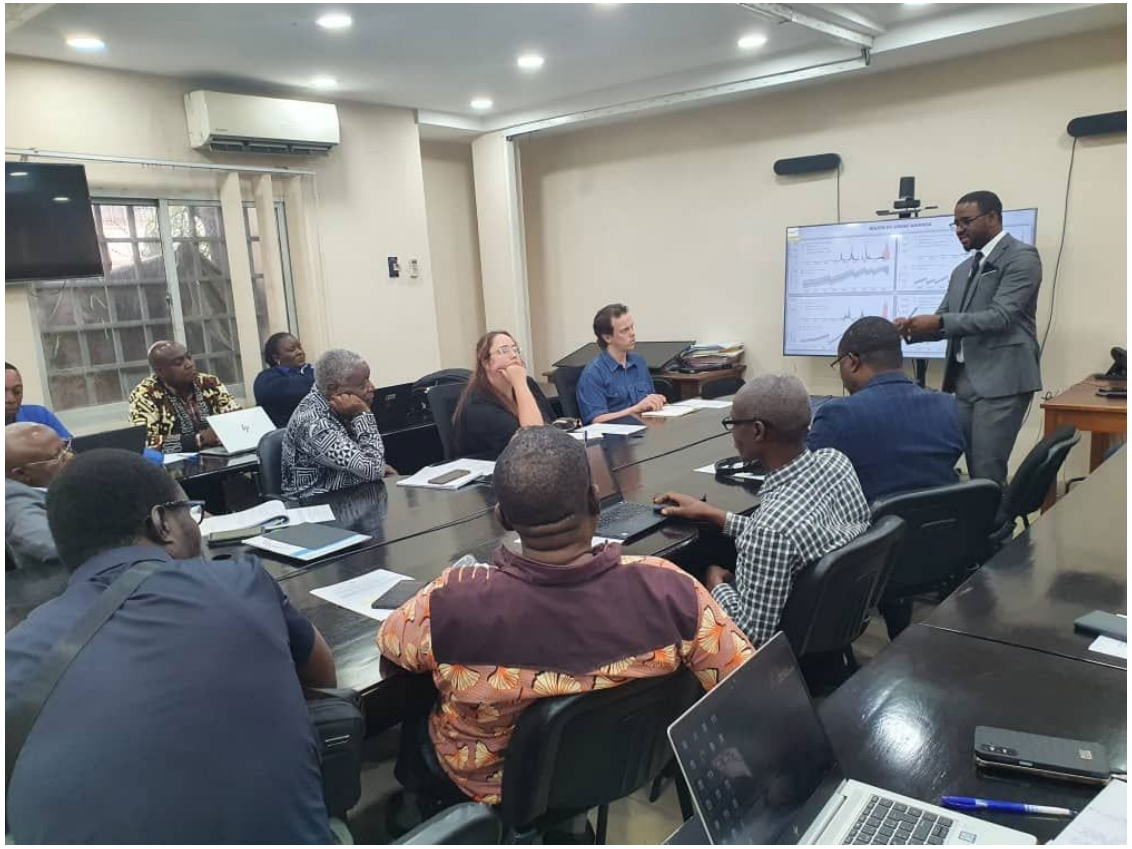




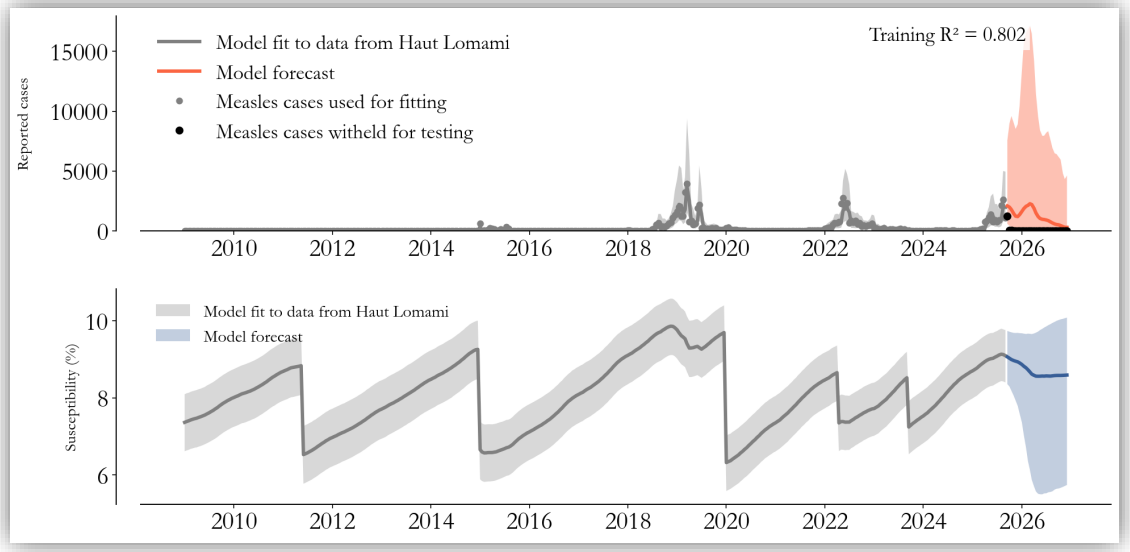


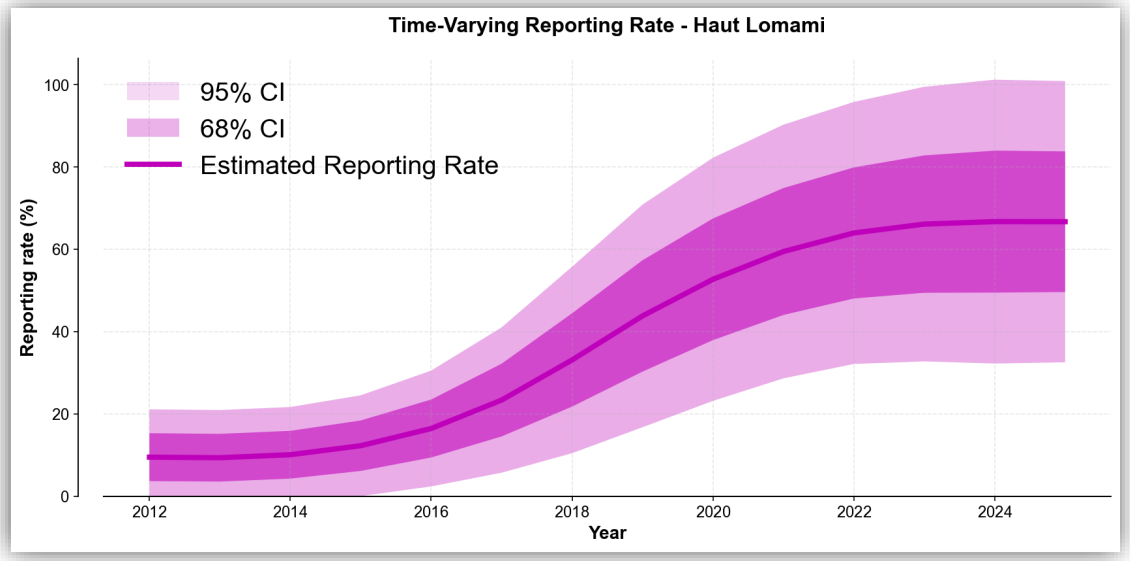
PRESENTATION OF MODELING RESULTS TO MOH & STAKEHOLDERS

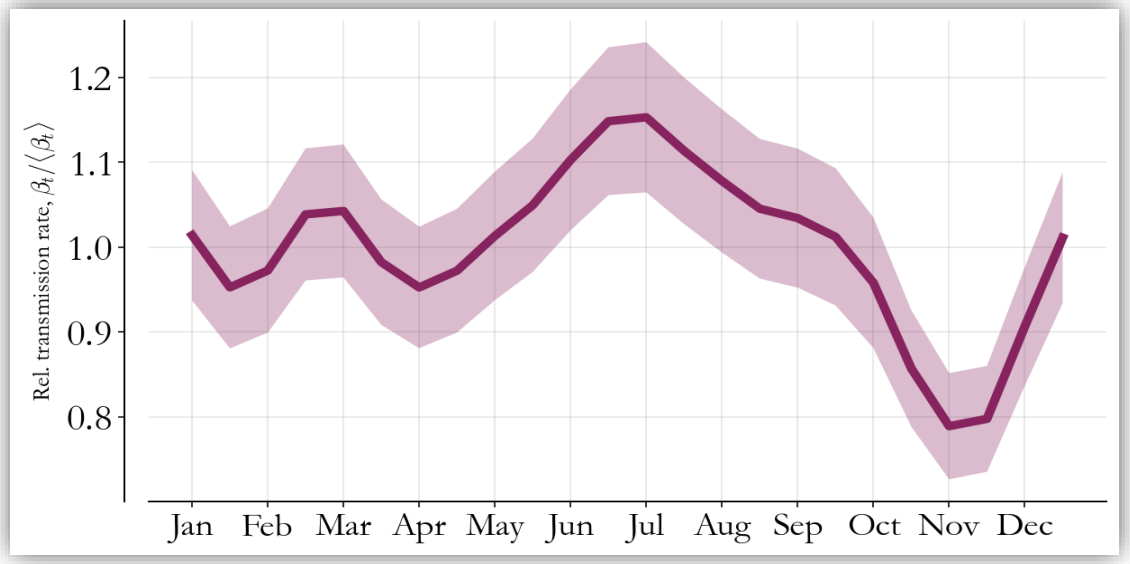
Kinshasa, November 11, 2025

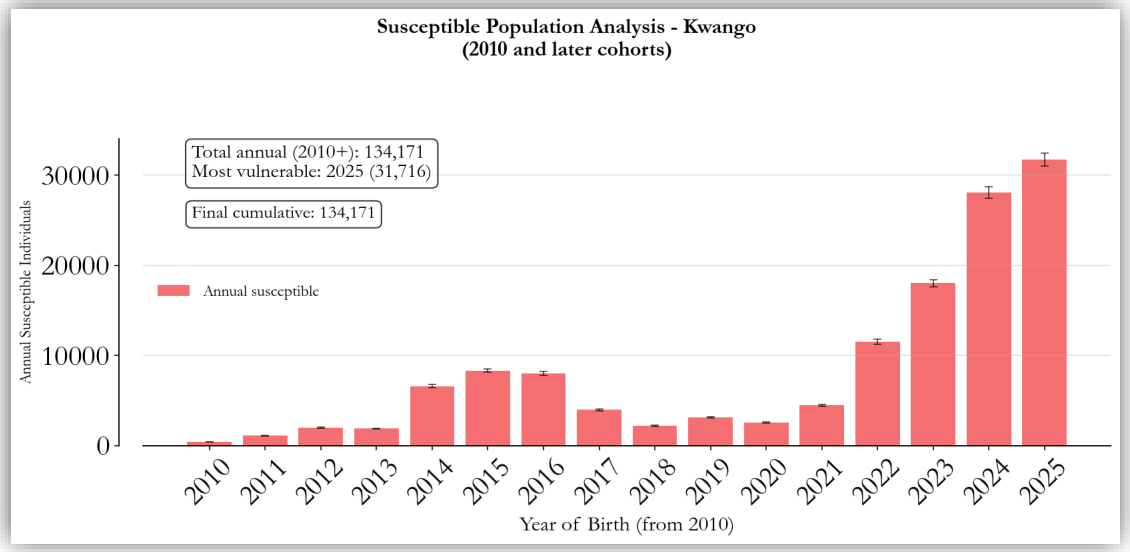


OTHER MODELING OUTPUTS









CURRENT & FUTURE PLANS

- ❑ Leveraging local capacity building
- ❑Strengthened collaboration with MoH on measles fighting strategies using modeling (**mathematical and geospatial**). Extension to others diseases and also ministers
- ❑DSE-MoH division : booked an appointment with the Minister of Health
- ❑Modeling on SIA efficiency by tailoring the age ranges and frequency at the subnational level in the heterogeneous measles transmission dynamic and vaccination coverage context
- ❑***Engagement with the GF to create a center of excellence dedicated to modeling to support the MoH within the KSPH***
- ❑Partner institutions

Institute for Health Metrics and Evaluation
VACCINE IMPACT MODELLING CONSORTIUM
CEMA Center for Epidemiological Modelling and Analysis
UNIVERSITY OF NAIROBI


danke
謝謝
ngiyabonga
teşekkür ederim
спасибо
thank you
gracias
dank je
tapadh leat
bedankt
hvala
mauruuru
dziękuję
mochchakkeram
go raibh maith agat
obrigado
sukriya
kop khun krap
arigatô
takk
dakujem
grazie
terima kasih
merci
мерси
감사합니다
ευχαριστώ

Stephen Ohuneni

Nigeria

MEASLES
ANALYTICS HUB

Stephen Ohuneni

Epidemiologist · Infectious Disease Modeller · Global Health Security Consultant

Global Health Security Consultant

Sydani Group – strategic advisory, health systems strengthening and outbreak preparedness at national scale.

Resident Epidemiologist

NCDC Field Epidemiology Training Programme (FETP) – applied outbreak investigation and disease surveillance.

Infectious Disease Modeller

Develops mathematical and computational models to guide evidence-based public health interventions in Nigeria.

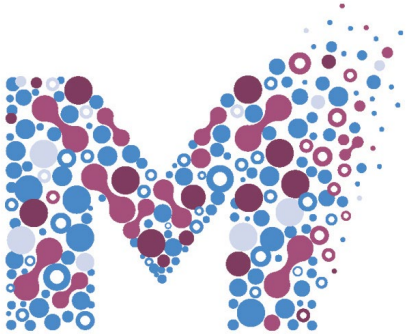
SACEMA Policy Modelling Fellow 2025

South African Centre for Epidemiological Modelling and Analysis – advanced training in quantitative infectious disease policy modelling.

MEASLES
ANALYTICS HUB

Measles Analytics Hub Mentorship Programme

Under the mentorship of Prof. Nafiu Hussaini · Bayero University, Kano



Programme Background

The Measles Analytics Hub Mentorship Programme pairs field epidemiologists with expert modellers to build quantitative capacity in infectious disease epidemiology. Under the mentorship of Prof. Nafiu Hussaini, participants gain hands-on skills in compartmental modelling, statistical analysis, and policy-relevant research to directly support Nigeria's measles control and elimination agenda.

Mentor

Prof. Nafiu Hussaini

Infectious disease modeller | Expert in measles transmission dynamics and vaccination policy modelling in Nigeria.

Programme Goals

Become an Independent Modeller

Build capacity to independently design, parameterise, and interpret infectious disease models without supervision.

Improve Modelling Understanding

Deepen understanding of mathematical and compartmental modelling techniques applied to vaccine-preventable diseases.

Support Measles Catalytic Grant

Generate model-informed evidence to support Nigeria's Measles Catalytic Grant and GAVI-funded immunisation programmes.

Key Activities, Achievements & Future Work

ACTIVITIES & ACHIEVEMENTS

Measles Compartmental Model Design & ODE Writing

Designed a SEIR-type compartmental model structure for measles transmission dynamics. Formulated and wrote a system of Ordinary Differential Equations (ODEs) capturing vaccination, waning immunity, and age-structured mixing. The model underwent structured assessment and peer review.

Longitudinal Statistical Analysis Workshop

Participated in an intensive workshop covering longitudinal data analysis methods including mixed-effects models, GEE, and survival analysis — building statistical competencies essential for interpreting time-series epidemiological data.

PLANNED & FUTURE WORK

Supporting GAVI Application Modelling for NPHCDA

Lead the modelling component of Nigeria's planned GAVI application under IDM guidance, providing epidemiological and health-economic modelling evidence to support NPHCDA's case for sustained measles vaccine financing and programme optimisation.

Expanded ODE Model Calibration & Validation

Complete full calibration, sensitivity analysis, and validation of the measles ODE model against Nigerian surveillance data to produce publishable, policy-ready epidemiological outputs.

Independent Modelling Output

Author an independent modelling manuscript or technical report on measles transmission dynamics and vaccination impact in Nigeria, contributing to the Measles Catalytic Grant evidence base.

ACKNOWLEDGEMENTS

With sincere gratitude to our partners and supporters

Measles Analytics Hub

For providing the intellectual home, mentorship structure, and technical resources that underpin this modelling fellowship, enabling rigorous, policy-relevant research on measles in Nigeria.

Imperial College London

For academic leadership, modelling frameworks, and scientific partnership that drives the Measles Analytics Hub's mission to generate globally impactful epidemiological evidence.

Gates Foundation

For the generous funding and strategic vision behind the Measles Catalytic Grant that supports national-level modelling, GAVI engagements, and vaccine programme optimisation in Nigeria.

Measles Analytics Hub · Imperial College London · Bill & Melinda Gates Foundation · NPHCDA

MEASLES ANALYTICS HUB

Hawult Taye

Ethiopia

MEASLES
ANALYTICS HUB

Introduction to MAH Mentoring Scheme Project Plan

- Mentee: Hawult Taye Adane, AHRI, Ethiopia
- Mentor: Chigozie Edson Utazi, University of Southampton, UK

MEASLES
ANALYTICS HUB

Introduction

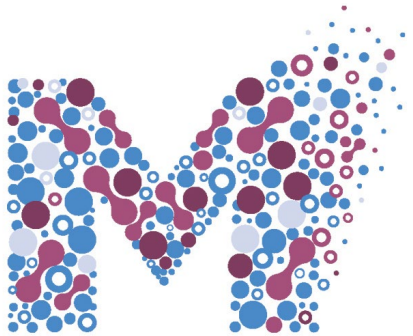
Personal Profile

- Country of origin: Ethiopian/**ኢትዮጵያን**
- Residence : Addis Ababa**፡ አዲስ አበባ**
- Profession : Epidemiologist (MPH, PhD)
- Current Position: Researcher at AHRI

Membership

- Lifetime member of EPHA
- Emory University Almunia
- Member of MAH

Experience and Skills/Interest



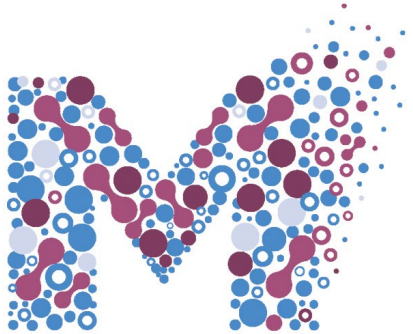
Project Engagement

- Filed Epidemiology/ Surveillance
- Experimental/Clinical trial
- Implementational Research
- Consulting MEAL
  - Community based intervention
  - Gov't Health Program (e.g EPI)
  - R&D Projects by MoH partners

Area of Interest & Skills

- Design Research methodology
- Grant and proposal development
- Data management & analysis
- Meta and Network analyses
- Software: STATA, SPSS, R, Python
- ??? Infectious disease modelling

Project Plan



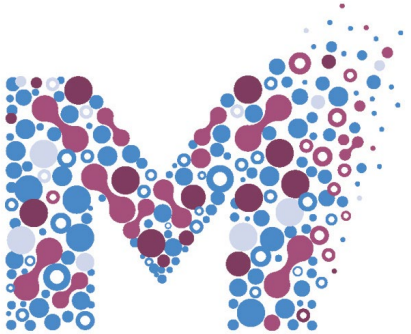
- Scope/AIM: Determine the minimum viable data needed for modelling frameworks to inform targeted SIA design and make reliable decision on alternatives strategies
- Geographic focus Area: Subnational/Districts of Ethiopia
- Rationale
  - Ethiopia – Measle high burden with active outbreak
  - Implemented hybrid and integrated immunization service
  - Persistent geographic inequities (Coverage and incidence)
  - Inconsistent estimates and findings from different sources
  - Lack of quality /complete data

Project Plan

- Primary Data Sources
  - ✓ Measles Case-Based Surveillance (MCBS) – from AFRO
  - ✓ Ethiopian Demographic and Health Surveys (EDHS)
  - District level administrative database (DHIS2),
- Supportive Data sources
  - Integrated National Campaign (SIA -2025) related data
  - Post Campaign Coverage Survey (PMCCS, 2026)
  - National Immunization Program Evaluation Research (NIPE- 2023).

Project Plan

Key Activities	Timeline/ One-year				*Milestones*/Deliverables
	Q1	Q2	Q3	Q4	
1. Preparation & Setup					• Approved final protocol • Accessed all data sources
1.1 Stakeholder engagement					
1.2 Protocol finalization/approval					
1.3 Data access					
2. Data Extraction & Preparation					• Merged and harmonized dataset
2.1 Acquire & clean multi-source data					
2.2 Compilation & harmonization					
3. Model development & Analysis					• Comprehensive SAP • Model formworks • Software codes /tools
3.1 Bayesian model (INLA-SPDE)					
3.2 Spatio-temporal analysis					
3.3 Mathematical Modelling					
4. Calibration & Validation					• Validated & Integrated models • Model outputs and results
4.1 calibration & Integration					
4.2 Validation and sensitivity analysis					
4.3 Visualization & Intervention					
5. Dissemination & Reporting					• Final project report • Policy brief & guideline • Summitted manuscript
5.1 Manuscript preparation					
5.2 Stakeholder workshop					
5.3 Final report & submission					



Thank You!

Esha Kashyap

India

MEASLES
ANALYTICS HUB

Investigating the Impact of Interventions on Measles in India

Esha Kashyap

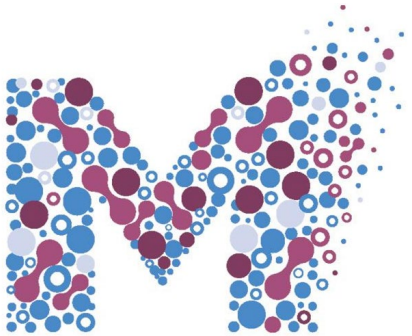
Mentor: Prof. Siuli Mukhopadhyay

Indian Institute of Technology Bombay, India

NDMC
NATIONAL DISEASE MODELLING CONSORTIUM
राष्ट्रीय रोग प्रतिरूपण केन्द्र

MEASLES
ANALYTICS HUB

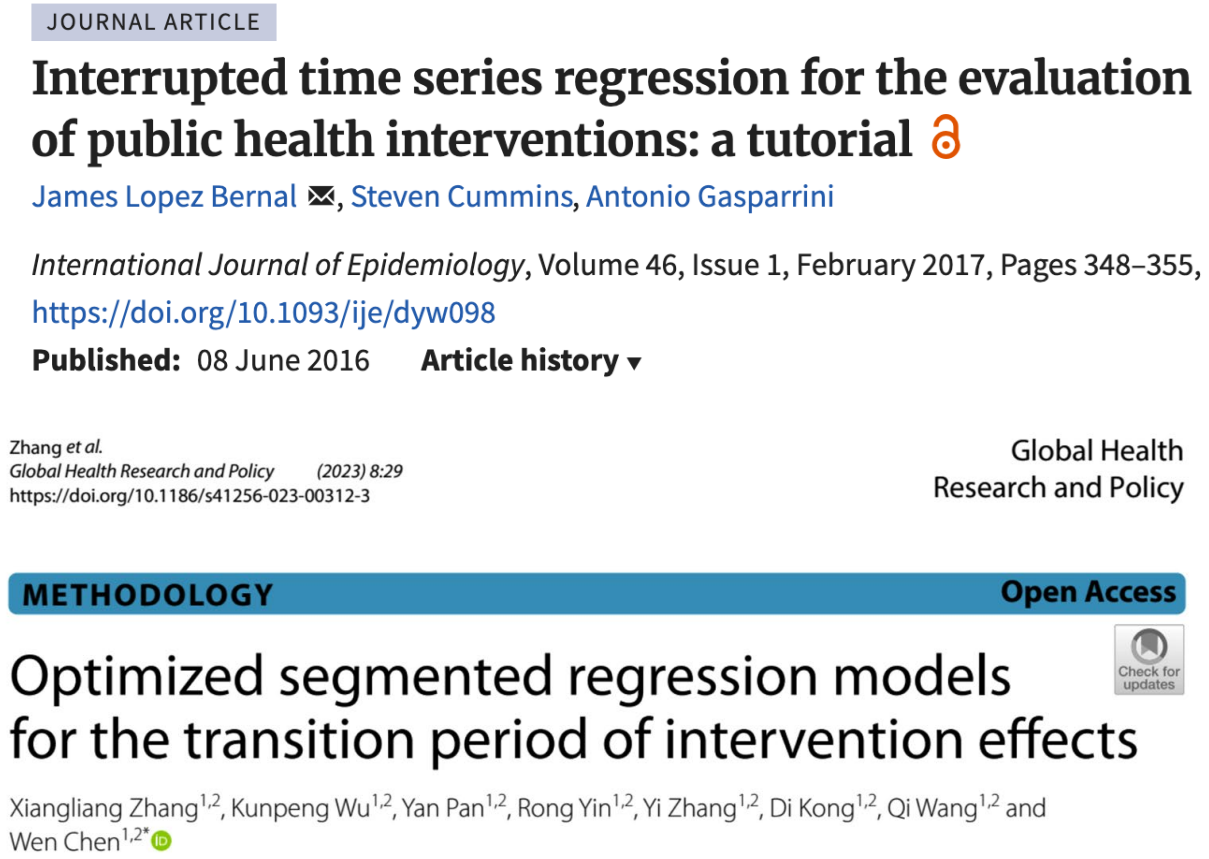
Why evaluate interventions?



- India made substantial progress in measles control through sustained investments in routine and catch-up campaigns
- Multiple catch-up campaigns in India: Supplementary Immunisation Activities, Mission Indradhanush, Intensified Mission Indradhanush, Zero Dose Implementation Plan
- Most evaluation methods focus on immunisation coverage
- There is a need to quantify the real-world impact of catch-up campaigns on measles incidence

Interrupted time series (ITS) regression to account delayed and gradual intervention effects

- A quasi-experimental design used to evaluate the impact of an intervention, policy, or event over time
- Compares outcome trends before and after a clearly defined interruption
- ITS estimates both the immediate impact and the long-term effect of an intervention by analyzing changes in level and trend over time.



JOURNAL ARTICLE

Interrupted time series regression for the evaluation of public health interventions: a tutorial

James Lopez Bernal, Steven Cummins, Antonio Gasparrini

International Journal of Epidemiology, Volume 46, Issue 1, February 2017, Pages 348–355, https://doi.org/10.1093/ije/dyw098

Published: 08 June 2016 **Article history**

Zhang *et al.*
Global Health Research and Policy (2023) 8:29
https://doi.org/10.1186/s41256-023-00312-3

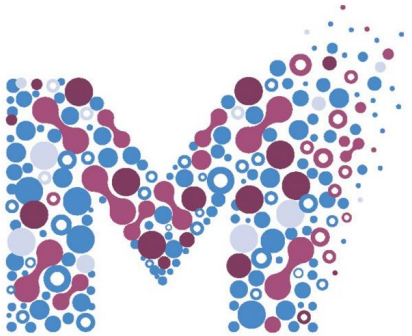
Global Health Research and Policy

METHODOLOGY **Open Access**

Optimized segmented regression models for the transition period of intervention effects

Xiangliang Zhang[1,2], Kunpeng Wu[1,2], Yan Pan[1,2], Rong Yin[1,2], Yi Zhang[1,2], Di Kong[1,2], Qi Wang[1,2] and Wen Chen[1,2*]

Potential outcome



Scientific outcome:

- Quantification of immediate impact of catch-up campaigns
- Estimation of regions with the strongest and weakest programmes

Public health relevance:

- Evidence-based assessment of catch-up campaigns
- Identification of areas requiring intensified immunisation campaign

Deliverables:

- National and subnational impact assessment

Thank you

MEASLES
ANALYTICS HUB

Shakira Babirye
Uganda

MEASLES
ANALYTICS HUB

Shakira Babirye

MAH Mentee Introduction

Mentor: Dr James Azam | LSHTM, UK

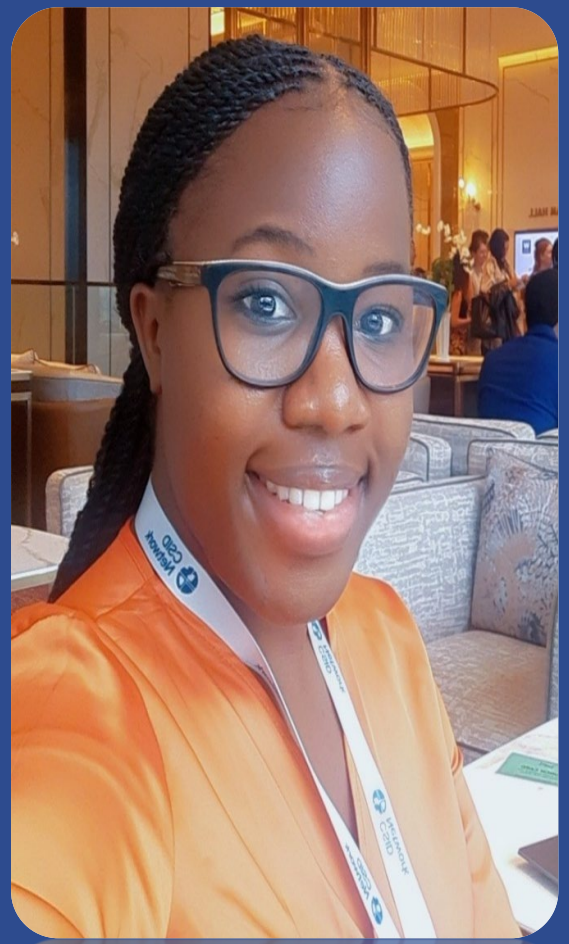
🎓 ***MSc Clinical Epi & Biostatistics***
Makerere University, 2022

💊 ***BSc Pharmacy***
Mbarara University, 2017

📍 ***Kampala, Uganda***

Biostatistician | Infectious Diseases Research Collaboration (IDRC), Uganda

MEASLES
ANALYTICS HUB



github.com/Shakira25
linkedin: shakira-babirye-77135b109

About Me

Pharmacy Roots

BSc Pharmacy (Mbarara Univ., 2017)
Research Pharmacist
Baylor Children's Medicine (2017–2022)

Epidemiology & Biostatistics

MSc Clinical Epi & Biostatistics (Makerere, 2022)
Senior Biostatistician / DS Lead
IDI Makerere (2023–2024)

Key Skills

- R | Python | STATA | SAS
- Machine learning & AI modelling
- Data visualisation (Power BI, R Shiny)
- Epidemiological & mathematical modelling
- QGIS | GeoDa | SQL
- Publications: Lancet Infect. Dis. (2025); Wellcome, BMJ (2026)
- Trainings: G-WAC Pandemic Modelling | Oxford ML | UCSF Clin. Epi.

Current Role

Biostatistician at IDRC (May 2024–present)
Malaria, HIV & infectious diseases; ML/AI
RVF mathematical model (compartmental; ms. in prep.)
IDRC Learning Hub: zero-dose/under-immunised DP

Why am I excited about this?

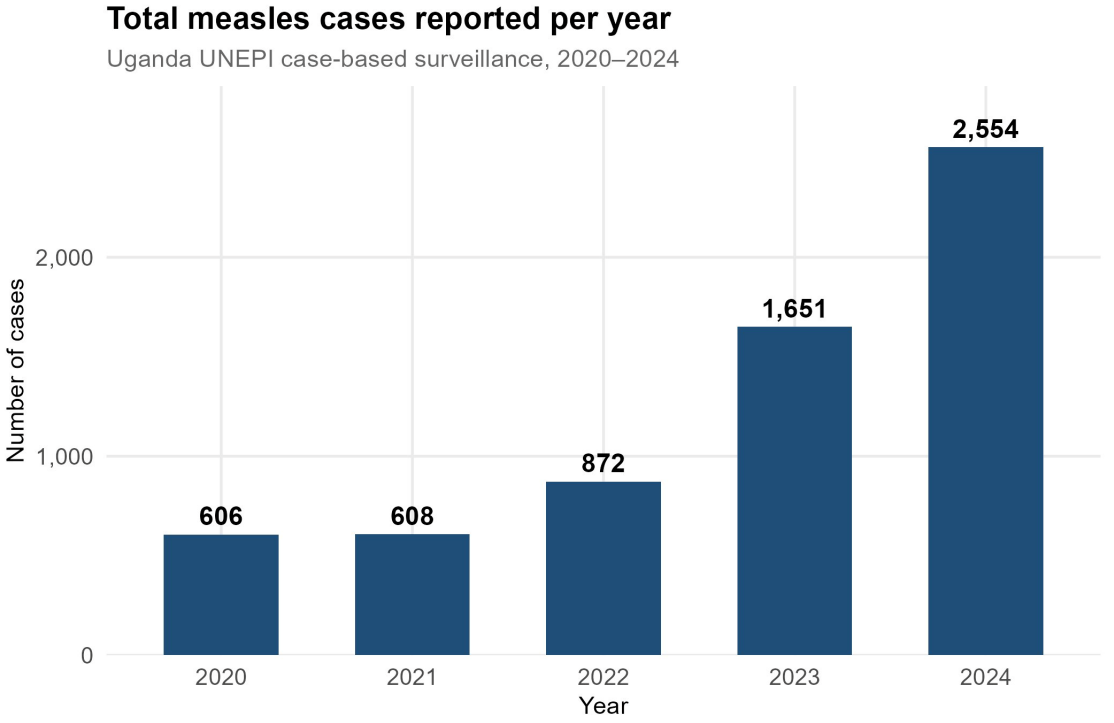
UNEPI case-based surveillance, 2020–2024

6,291
Total cases
2020–2024

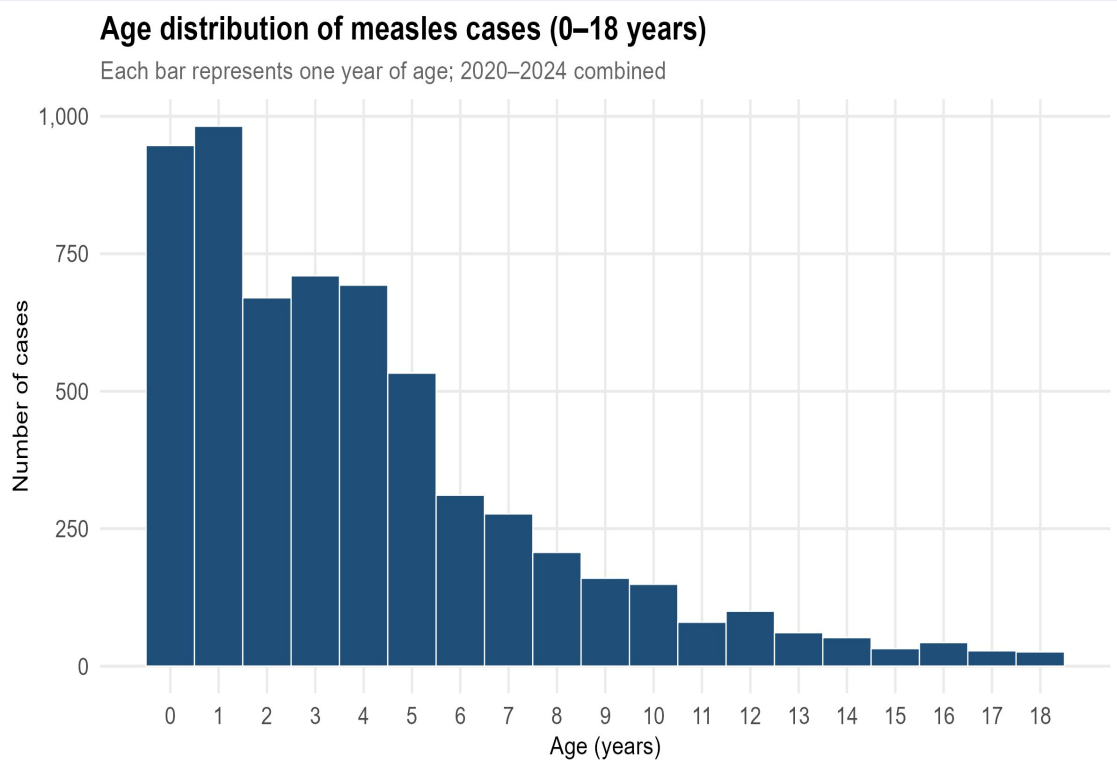
4.2×
Increase
2020→2024

< 5 yrs
Majority of
cases

67
Districts affected
in 2024 alone



Source: Uganda National Expanded Programme on Immunization (UNEPI) case-based surveillance data. Includes confirmed, epi-linked, compatible, and suspected cases across all districts.



Source: UNEPI case-based surveillance data. Cases with recorded age > 18 years are excluded from this chart. 23 cases with missing age are also excluded.

My Project

Beyond the National Average: Regional Measles Immunity Estimation for Uganda Extending & adapting the WHO/CDC MPIP tool for Uganda's regional context

01 Compile & harmonise regional MCV1, MCV2, and SIA coverage from DHIS2, DHS, and MICS; apply multiple imputation methods to address data gaps

02 Extend & adapt the WHO/CDC MPIP tool: relax simplifying assumptions and refine immunisation calculations for Uganda's context using multiple data sources

03 Identify regions with immunity below the 95% herd immunity threshold, capturing subnational heterogeneity masked by national estimates

04 Generate regional immunity profiles and susceptible cohort estimates to guide targeted, regionally tailored interventions a better use of limited time and resources

Analytical Approach

WHO/CDC Measles Population Immunity Profile: Extended & adapted for Uganda regions

1

Data Assembly

Regional MCV1, MCV2 & SIA coverage from DHIS2
Validated vs DHS / MICS surveys

2

Data Quality

Capping implausible values
Triangulation across sources
Consultation with UNEPI team

3

Model Application

Relaxing simplifying assumptions
(e.g. Li et al. dependent assumption, Vaccines 2024)
Uganda-specific VE & cohort parameters

4

Outputs & Action

Regional immunity profiles
Susceptible cohort estimates
Dashboard for UNEPI planning

Reference: Li X, Goodson JL, Perry RT. Measles population immunity profiles: updated methods and tools. Vaccines 2024;12(8):937.

Data Challenges

Implausible & Missing Coverage Values

Administrative DHIS2 data frequently shows coverage >100% in some districts, suggesting denominator errors. Large amounts of missing vaccination history in surveillance records.

Inconsistency Across Data Sources

In case DHIS2 administrative figures and DHS/MICS household survey estimates diverge significantly at regional level. Which source should I prioritise? and when is it required to make programmatic judgement alongside statistical checks?

Sub-national Data Availability & Quality

SIA coverage surveys (PCCSs) may not be available for all campaigns or at regional resolution. Some regions may lack sufficient historical depth to reconstruct cohort-level immunity accurately. How best can I deal with this in the even that I find it present?

Questions I'm curious about

Q1: Have you encountered >100% administrative coverage values in similar work? How did you handle them?

Q2: When DHS/survey and administrative data disagree, which source did you ultimately use and why?

Q3: Any experience reconciling missing SIA coverage data for historical cohorts?

Q4: What tools or processes worked best for UNEPI-level data validation in similar settings

What I Hope to Learn

Learning Goals

- Deepen expertise in subnational measles immunity modelling
- Strengthen practical skills in adapting CDC MPIP to low-resource data contexts
- Develop rigorous multi-source data triangulation approaches
- Build capacity to generate policy-ready visualisations for UNEPI
- Contribute to the evidence base on measles immunity in sub-Saharan Africa

bbrshakira@gmail.com | github.com/Shakira25 | linkedin: shakira-babirye-77135b109

AFRO Perspectives & Regional Priorities

Balcha Masresha &
Ahmadu Yakubu

MEASLES
ANALYTICS HUB

Measles and rubella elimination in AFR

Dr Balcha Masresha

WHO AFRO

May 2026

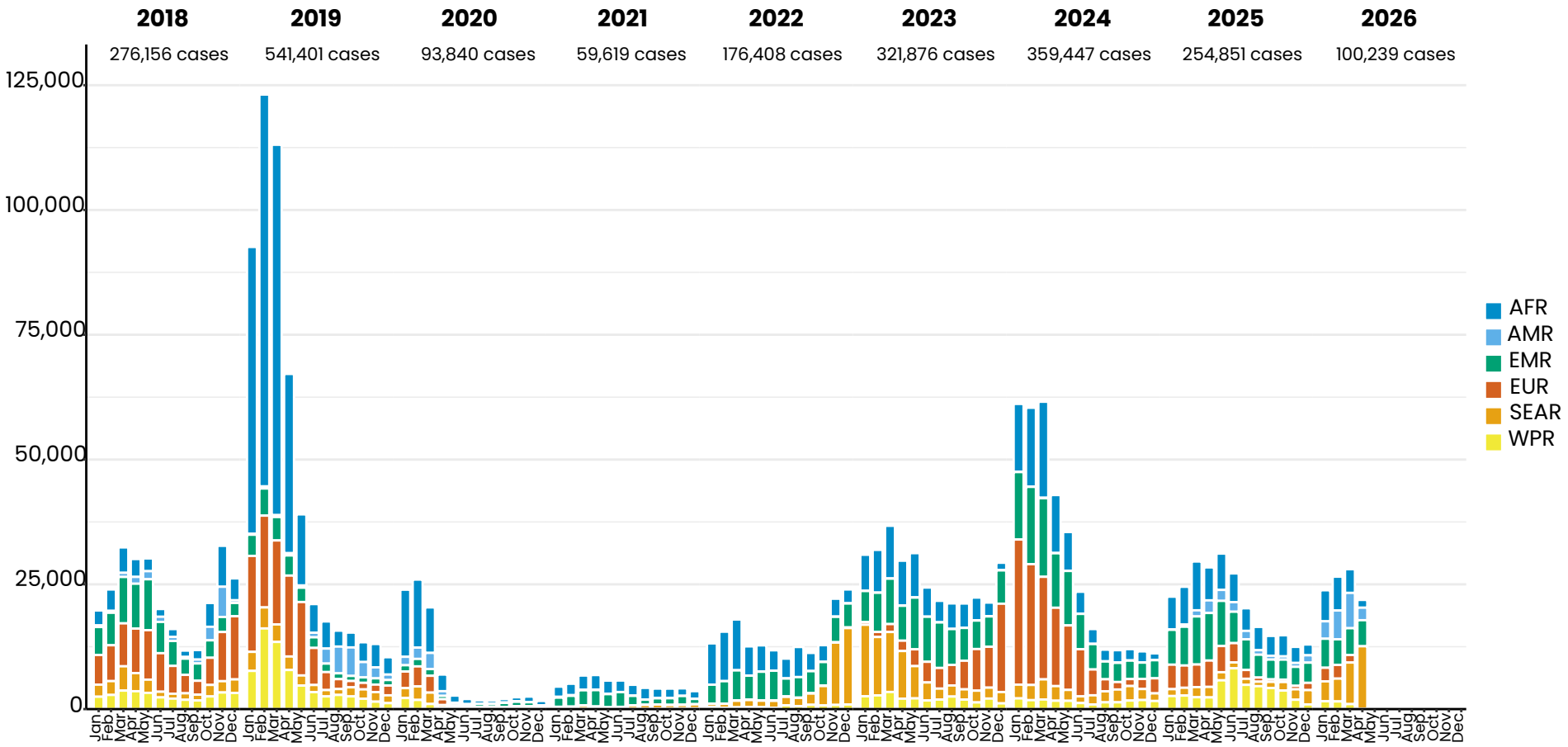
Outline

- Routine MCV/ RCV immunisation
- Supplemental Immunisation Activities
- Measles and rubella incidence in AFR
- Policy questions for modelling consideration

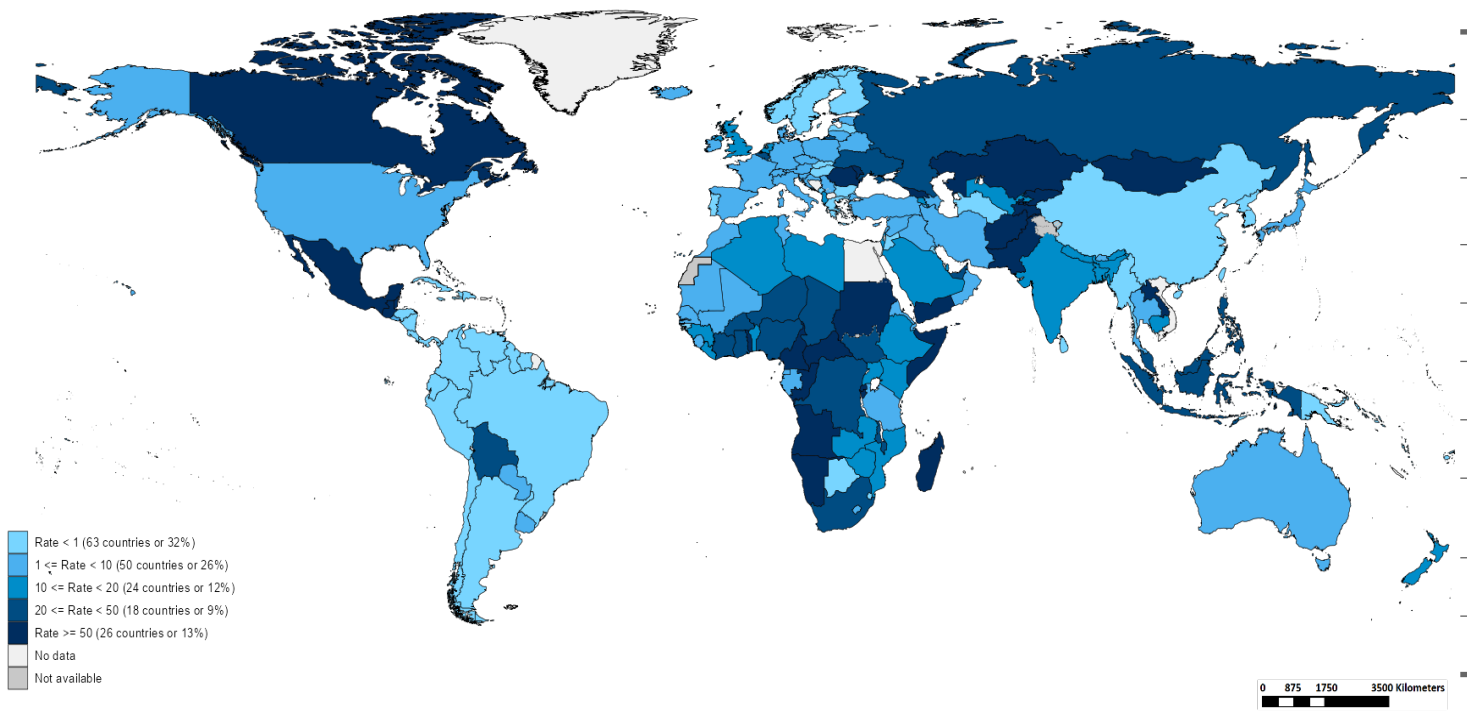
African Regional goal: > 80% countries attain measles and rubella elimination by 2030

- **≥95% MCV1 and MCV2 coverage** at national and district levels
- **≥ 95% coverage in Supplemental Immunisation Activities**
- **incidence of < 1 case / million** population /year (excluding imported cases).
- Achieve the **surveillance performance targets**:
  - *≥ 80% districts investigating one or more suspected measles cases /year,*
  - *a non measles febrile rash illness rate of ≥ 2 per 100 000 population at national level.*

Measles case distribution by month and WHO Region (2018-2026)



Number of Reported Measles Cases (Last 6 months). Data as of 5 May 2026



Highest incidence rates

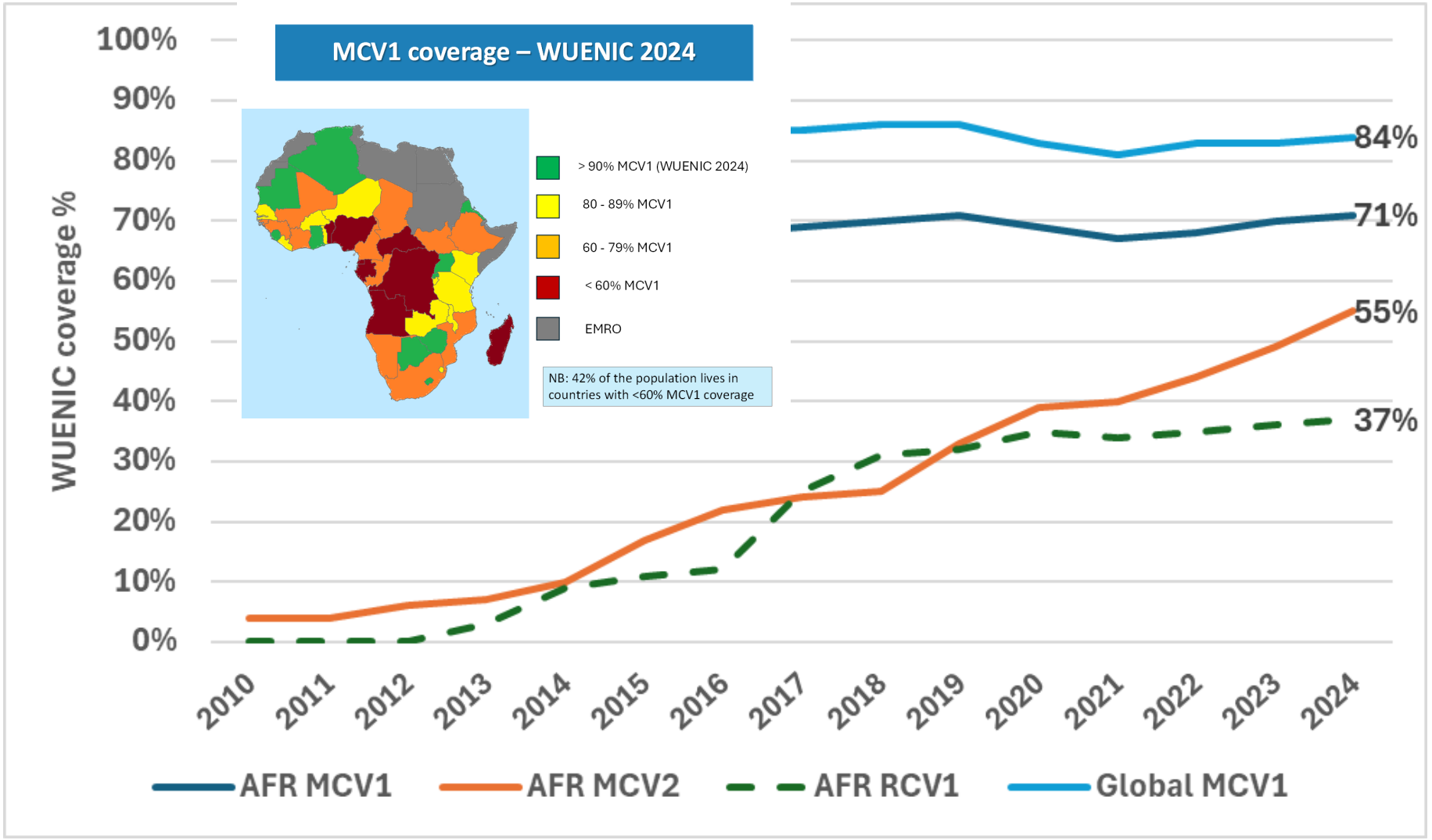
Country	Cases	Rate
Mongolia	13335	3,791.48
Yemen	28925	692.42
Laos	5223	663.40
Kyrgyzstan	3766	516.24
Kazakhstan	8728	418.73
Angola	13419	343.72
Cameroon	8720	291.84
CAR	1505	272.98
Guatemala	4802	256.96
Tajikistan	1783	165.30

World Health Organization

Data source: IVB Database

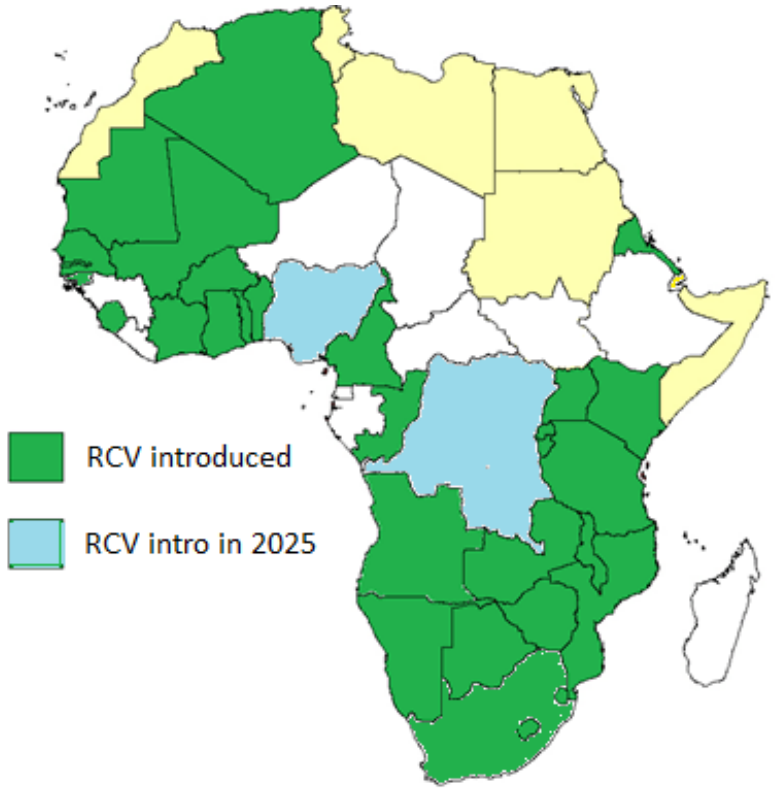
Disclaimer: The boundaries and names shown and the designations used on this map do notimply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Measles and rubella immunisation coverage. African Region. WUENIC. 2014 - 2024



MCV2 and RCV introduction in AFR. Dec 2025

MCV2 introduced nationwide



- 35 / 47 countries introduced RCV in AFR

MCV1 – MCV2 dropout rates. AFR.

(WUENIC 2024)

World Health Organization
African Region

Country	MCV1-MCV2 Drop-out rate
Uganda	44%
Angola	42%
Eq Guinea	42%
Nigeria	39%
Mauritania	37%
Côte d'Ivoire	36%
Congo	35%
Mozambique	32%
Cameroon	31%
Guinea-Bissau	31%
Chad	30%
Liberia	27%
Burkina Faso	26%
Guinea	25%
Malawi	22%
Botswana	21%
Sierra Leone	19%
Ethiopia	18%
Lesotho	18%
Mali	17%
Namibia	16%
Togo	15%
Kenya	14%
Zimbabwe	13%
Zambia	13%
Ghana	12%
Tanzania	12%

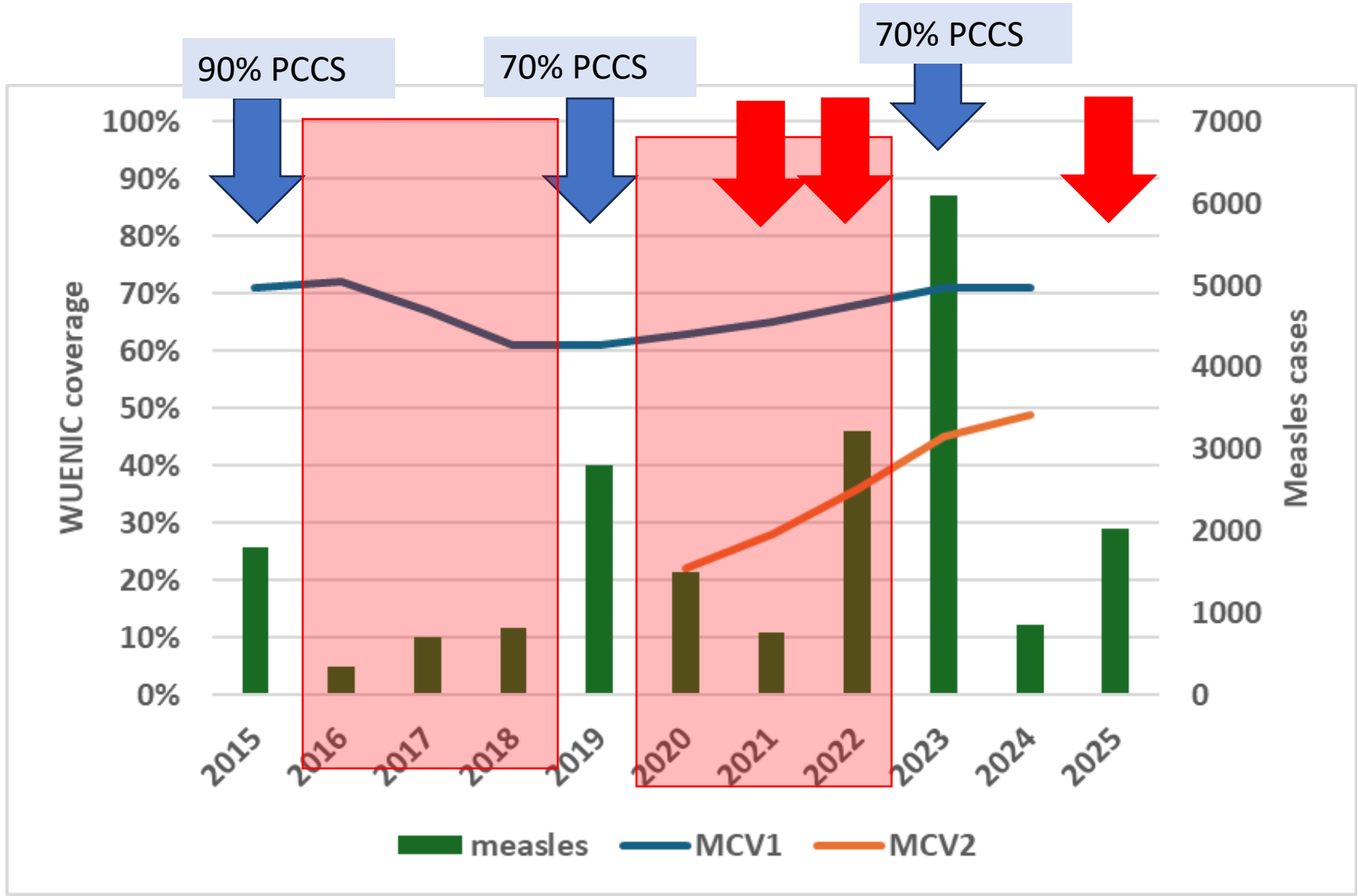
Supplemental Immunisation Activities

- 126.1 million reached in 2025

- Major challenges in recent SIAs:
  - Delayed / inadequate preparations
  - Last minute decisions on “integration”
  - Repeated postponements
  - Low coverage in urban areas
  - Outbreaks shortly after SIAs (CAR, Chad, Togo, Liberia)

World Health Organization
African Region

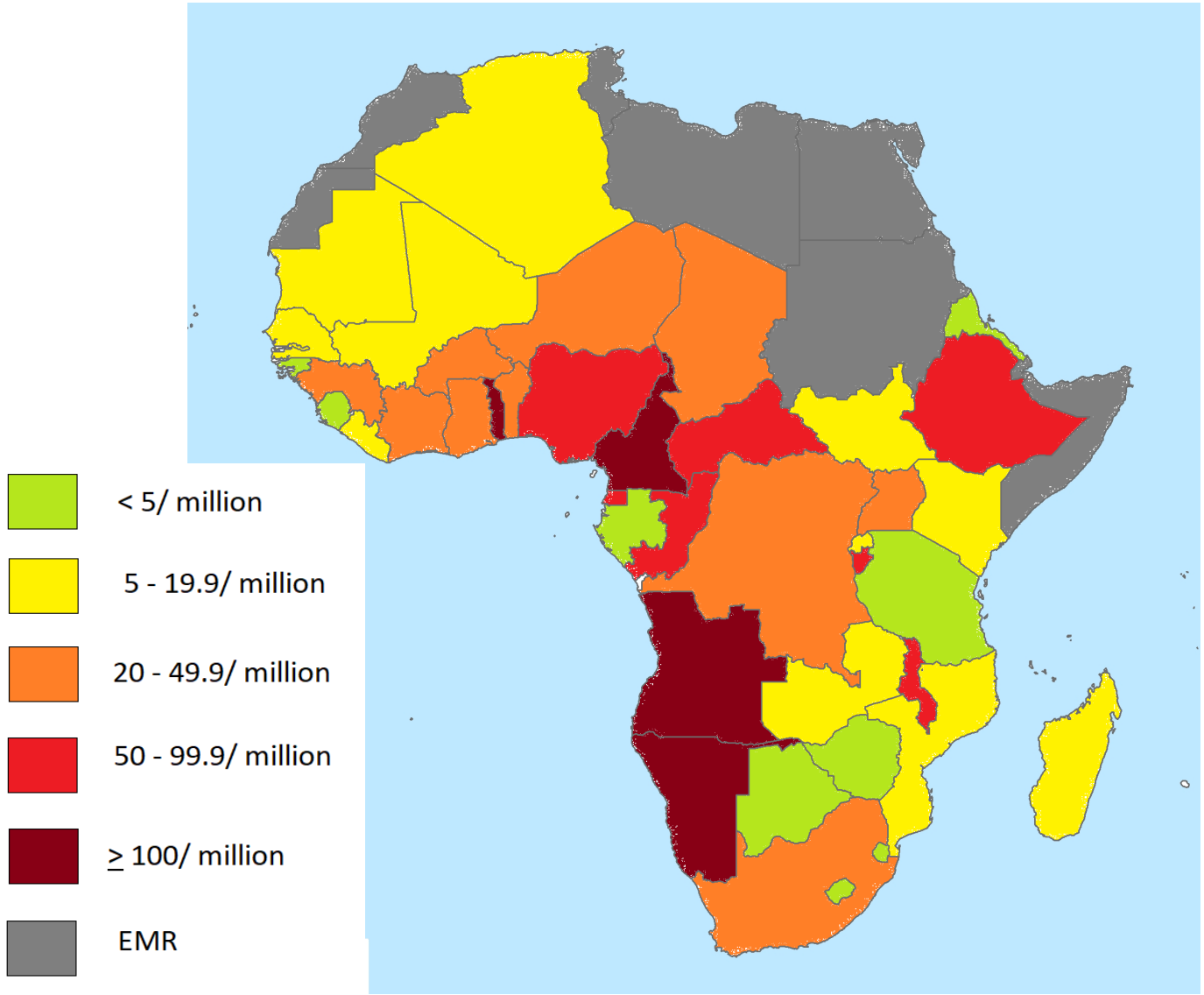
Measles cases, vaccination coverage and SIAs in Cameroon. 2015 - 2025



Measles-rubella surveillance performance in AFR. (2022 –2025). Case based surveillance data.

	2022	2023	2024	2025
Total **suspected measles** cases	114,347	125,957	147,564	110,603
Total **lab specimens collected**	73,457	77,998	95,588	60,693
Total **confirmed rubella** cases	4,319	4,805	14,340	4,700
Total **confirmed measles** cases	52,231	73,094	77,698	61,686
Incidence of confirmed measles / million	51.3	60.3	71	50.5
Number of countries with **Incidence >20/million**	21	26	20	23
% districts reporting suspected cases (≥ 80%)	86%	83%	83%	86%
NMFRI rate (≥ 2:100,000)	3.5	3.7	4.6	3.3

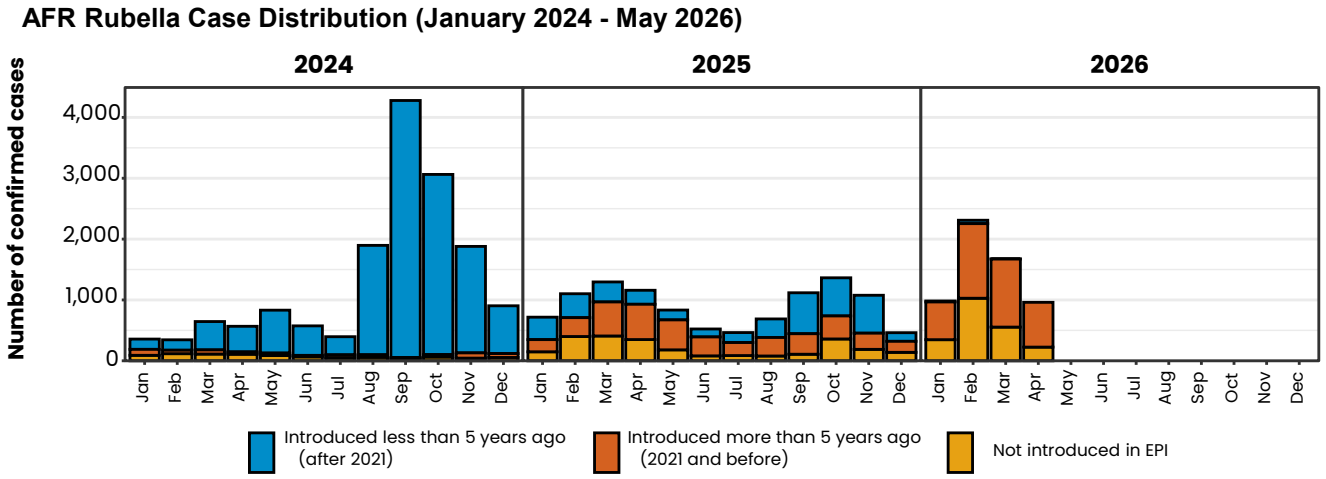
Incidence of confirmed measles in 2025. African Region. [Source: case-based surveillance data]

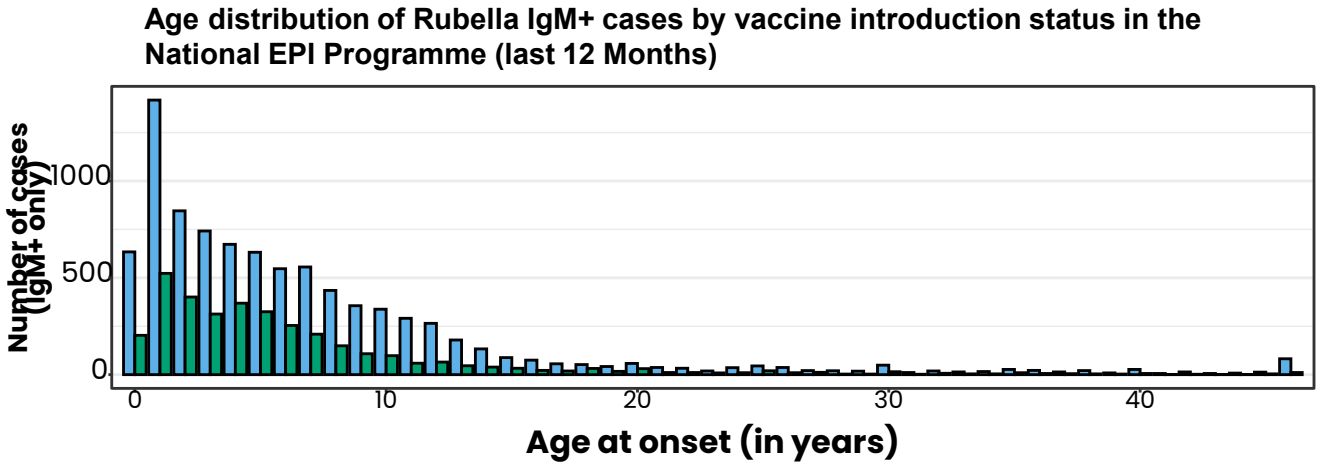


Challenges contributing to measles outbreaks

- Chronically **low MCV coverage**
- **Vaccine stock-outs**
- **Humanitarian contexts** with population displacements
- **Delayed preventive SIAs**
- **Failure to fund** SIAs in middle-income countries
- Measles **susceptibility in school age groups and older** ages while periodic campaigns tend to be limited to under 5s

Rubella cases (AFR)



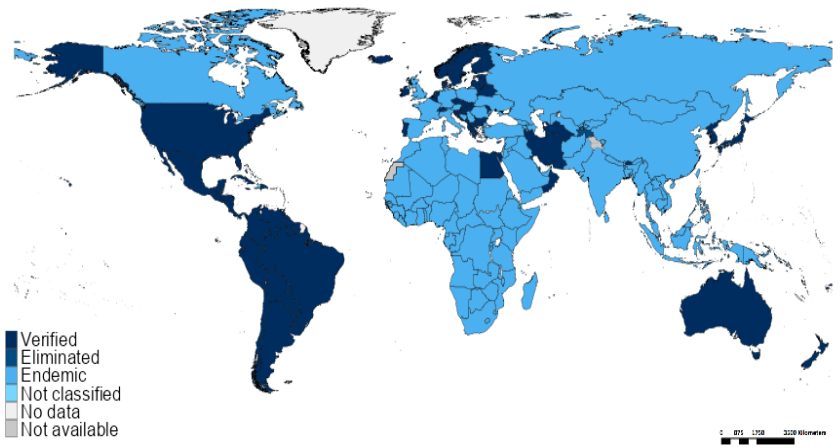


Top 10 countries (last 12 M)			
Country	**RCV in RI**	**Cases**	**% of Total**
Burkina Faso	2015	2942	24
DR Congo	No	1630	13
Nigeria	2025	1469	12
South Africa	2024	1400	11
Angola	2018	1302	10
Others	-	1113	9
Niger	No	890	7
Mozambique	2018	780	6
Ethiopia	No	338	3
Guinea	No	327	3
Kenya	2017	267	2

Measles/rubella verification of elimination status. May 2026

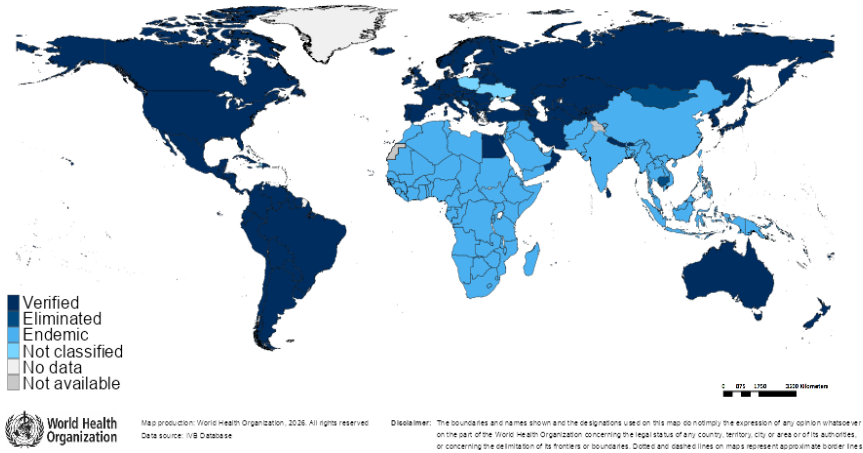
Measles

Region	Member States	Verified	% Verified	Eliminated	Endemic*	Not classified
AFR	47	3	6	0	44	0
AMR	35	33	94	0	1	1
EMR	21	4	19	2	15	0
EUR	53	32	60	1	19	1
SEAR	10	4	40	0	6	0
WPR	28	19	68	0	9	0
GLOBAL	**194**	**95**	**49**	**3**	**94**	**2**



Rubella

Region	Member States	Verified	% Verified	Eliminated	Endemic*	Not classified
AFR	47	3	6	0	44	0
AMR	35	34	97	0	0	1
EMR	21	4	19	2	15	0
EUR	53	49	92	0	0	4
SEAR	10	6	60	0	4	0
WPR	28	19	68	2	7	0
GLOBAL	**194**	**115**	**59**	**4**	**70**	**5**



Way forward

- Support more countries to **shift to 5-dose vials and assess impact**
- Advocacy and support for **RCV uptake in the remaining countries**
- Support for **strengthening the vaccination platform in the 2nd year**
- Advocacy and technical support for **timely and high quality SIAs,**
- **Verification of measles/rubella elimination** in high performing countries

Some policy questions for consideration in modelling studies

- How best to use **subnational data to better tailor preventive activities – subnational targeting, PIRIs…**?
- How to **determine the appropriate target age range, geographic scope and frequency of preventive SIAs** to achieve rubella/CRS and measles elimination?
- How can we **estimate the threshold population size and susceptible density required to sustain measles** virus transmission in various settings?
- Estimating the **magnitude of natural infection and immunity** across birth cohorts
- What is **the role of measles and rubella among adolescents and adults in sustaining transmission** in settings with suboptimal coverage?
- What is the **impact of different types of interventions** in terms of contribution to population immunity and/ or deaths averted in different settings?

Rebalancing Scales in Infectious Disease Modelling: Reactions and Reflections

Justice Moses K Aheto

MEASLES
ANALYTICS HUB

Rebalancing the Scales: The Measles Analytics Hub as a Model for Equitable Global Health Modelling

Prof Justice Moses K Aheto

MAH Scientific Co-Chair

Annual Meeting

12th June 2026

MEASLES ANALYTICS HUB

Outline for today

- Motivation for the commentary
- Problem 1: Power imbalance is systemic
- Problem 2: Analyses don't reflect on-the-ground realities
- Problem 3: AI tools risk reinforcing existing inequities
- MAH as a best practice example
- *A call to action*

- Motivation for the commentary
- Problem 1: Power imbalance is systemic
- Problem 2: Analyses don’t reflect on-the-ground realities
- Problem 3: AI tools risk reinforcing existing inequities
- MAH as a best practice example
- *A call to action*

Motivation

- Inspired by: ‘Pai M et al: **Shifting power in global health will require leadership by the Global South and allyship by the Global North**. The Lancet 2024.’
  - Call for “genuine partnerships with people who have lived experience and local expertise”
    - Emphasising that sustainable global health leadership must be driven by the Global South with meaningful allyship from the Global North
  - Further engagement with FairerGH – a group based at Boston University with Allison Portnoy that advocates for fairer partnerships in global health
- *Through these discussions, we realised that the MAH serves as a best practice example of a global health initiative that addresses this call to action…*

Motivation for the commentary

Problem 1: Power imbalance is systemic

Problem 2: Analyses don't reflect on-the-ground realities

Problem 3: AI tools risk reinforcing existing inequities

MAH as a best practice example

A call to action

Problem 1

- Infectious disease modelling for low- and middle-income countries (LMICs) is often led by institutions in high-income countries (HIC), **limiting local ownership** and **contextual relevance** of evidence used for decision-making.
- Structural inequalities in **funding**, **data access**, and **modelling capacity** constrain researchers in high-burden settings from leading modelling efforts
  - Much of the analytical infrastructure, funding streams, and advanced methodological tools are concentrated in high-income institutions

Motivation for the commentary

Problem 1: Power imbalance is systemic

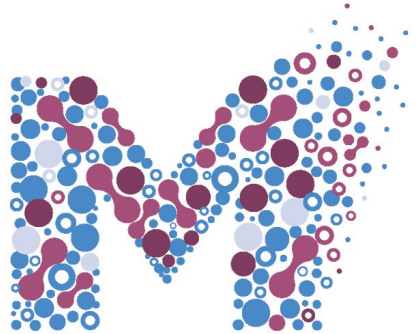
Problem 2: Analyses don’t reflect on-the-ground realities

Problem 3: AI tools risk reinforcing existing inequities

MAH as a best practice example

A call to action

Problem 2



- There is insufficient integration of **local expertise** and stakeholder input in modelling processes, **resulting in analyses that may not reflect on-the-ground programme realities or priorities.**
  - Modellers often exist in these settings, so the skills are there, but sometimes local researchers are under-utilised, and their local expertise is overlooked

Motivation for the commentary

Problem 1: Power imbalance is systemic

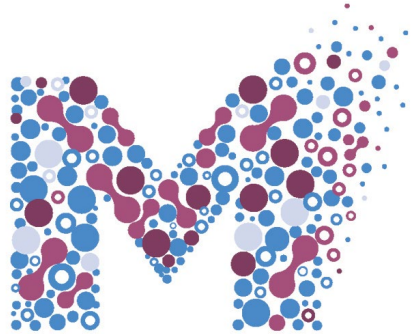
Problem 2: Analyses don’t reflect on-the-ground realities

Problem 3: AI tools risk reinforcing existing inequities

MAH as a best practice example

A call to action

Problem 3



- The growing use of Large Language Modelling (LLM) and AI tools **risks reinforcing existing inequities** if capacity, resources, and decision-making power are not more equitably distributed.
  - Limited access to high-cost AI subscriptions and computing resources restricts LMIC researchers from conducting advanced modelling.
  - And, this also brings us back to problems 1 & 2: models developed externally often lack local validation and contextual input, reducing relevance for in-country decision-making.

Motivation for the commentary

Problem 1: Power imbalance is systemic

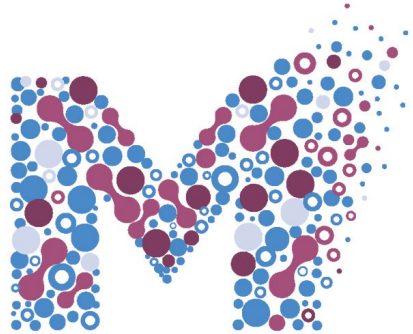
Problem 2: Analyses don’t reflect on-the-ground realities

Problem 3: AI tools risk reinforcing existing inequities

MAH as a best practice example

A call to action

MAH as a best practice example

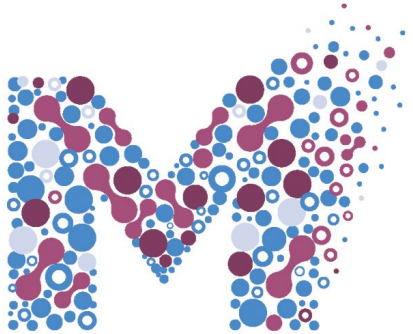


- The MAH is already doing many of the things that Pai et al. called for in their commentary…
  - Direct funding to modellers based in high burden countries
  - Enable authorship and visibility for modellers in high burden countries
  - Leadership within high burden countries for research projects and agenda setting
  - Equitable access to conferences and meetings
  - Fund local partners as leaders of knowledge production and ensure bidirectional partnerships in grants

Equitable access to funding

- MAH provides financial support for modellers in high-burden countries to be first time PIs, or build their own modelling teams
  - Tremendous support from HIC modellers to 'pass the torch' to modellers based in high measles burden countries with local expertise
  - Although not a requirement, all funded RfPs to date have included a local workshop or stakeholder engagement component, underscoring the value placed on local expertise.
    - RfP currently under review: Modelling Alternatives to Current Measles SIA Strategies and Pathways for Their Evolution

Competing stakeholder priorities



- Decades of model development and policy engagement have resulted in a dependency on HIC groups, creating a positive feedback loop that favours established relationships over new voices from high measles burden countries.
    - Global partners often default to HIC institutions because of trust and familiarity, even when technically qualified LMIC experts are available.
    - Breaking this cycle requires more than funding and technical training—it needs deliberate relationship-building, cultural understanding, and mentorship to help LMIC researchers navigate global policy networks
- One approach of MAH – Technical Vetting Committee
    - Ensure that tools developed in high burden settings are validated/peer reviewed ahead of time, so more modellers can respond to acute requests

Motivation for the commentary

Problem 1: Power imbalance is systemic

Problem 2: Analyses don’t reflect on-the-ground realities

Problem 3: AI tools risk reinforcing existing inequities

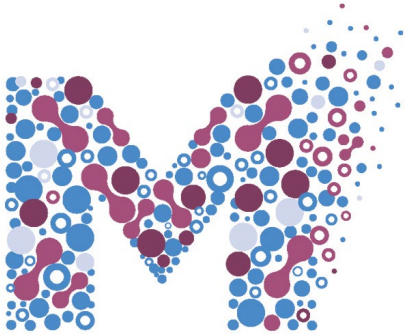
MAH as a best practice example

A call to action

Call to Action

- Facilitating a successful transition to LMIC leadership is a **shared responsibility**.
- HIC researchers must use their access to global partners to create space for LMIC colleagues. This cannot be an LMIC-only effort; it **requires joint commitment**.
- Initiatives like the MAH are essential—not only for technical support but also for convening diverse actors and maintaining focus on equitable research partnerships.
  - Funders and global health agencies must recognise these barriers and invest in mechanisms that prioritise **trust-building**, **mentorship**, **and locally autonomous research outputs**.

Bringing it all together



REBALANCING POWER IN INFECTIOUS DISEASE MODELLING

Toward Inclusive and Contextual Approaches

3 KEY OUTCOMES

From PLOS Global Public Health
(DOI: 10.1371/journal.pgph.0006220)

1 POWER IMBALANCE IS SYSTEMIC

- Decision-making power is concentrated among institutions in high-income countries.
- Local researchers and communities are often underrepresented or excluded.
- Leads to inequities in knowledge production and policy influence.

OUTCOME: Persistent inequities in knowledge production and policy influence.

2 CONTEXT-BLIND MODELS REDUCE EFFECTIVENESS

- Over-reliance on generalized assumptions.
- Limited incorporation of local data and lived experience.
- Weak alignment with implementation environments.

OUTCOME: Policies derived from these models can be less effective or misaligned with community needs.

3 INCLUSIVE CO-PRODUCTION IMPROVES MODELLING QUALITY

- Engage local experts, policymakers, and communities.
- Build equitable research partnerships.
- Share data, tools, and decision-making authority.

OUTCOME: More accurate, trusted, and actionable models that support equitable public health responses.

THE BIG PICTURE

Current state — Centralized power + weak context → **Problem** — Inequitable & less effective policy outputs → **Solution** — Inclusive, locally grounded modelling → **Result** — Better health decisions + equity gains

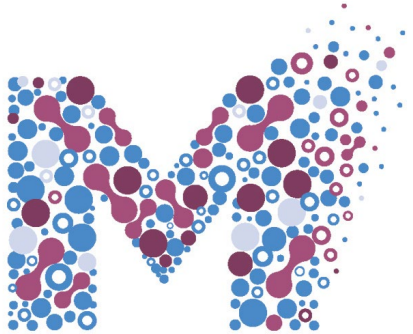
Image source: WorldPop

Panel discussion with co-authors

Prof Ezra Gayawan
Dr Edson Utazi

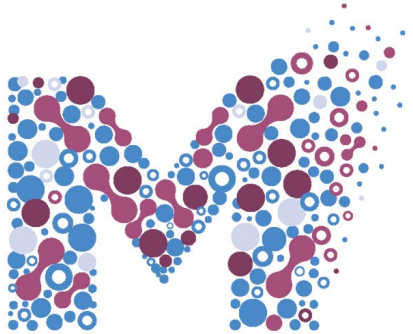
MEASLES
ANALYTICS HUB

Equity & Power Dynamics



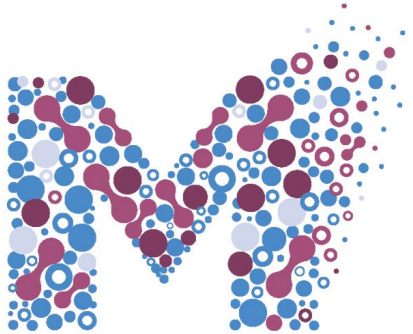
- How can global health modelling move from being “data extracted from low-income countries” to genuinely co-owned by the countries generating the data?
- What mechanisms ensure that local researchers and ministries have equal decision-making power in platforms like the Measles Analytics Hub?
- How do we prevent modelling tools from reinforcing existing inequities in funding and vaccine allocation?
- What does “equitable modelling” look like in practice beyond representation in authorship?

Data Quality & Trust



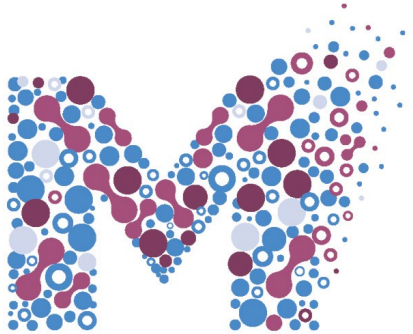
- How does the Hub address gaps in surveillance data from under -resourced regions without penalizing those countries in model outputs?
- What strategies help build trust among policymakers when models produce uncertainty or conflicting projections?
- How can countries with weak health information systems still benefit meaningfully from advanced analytics platforms?

Local Capacity Building



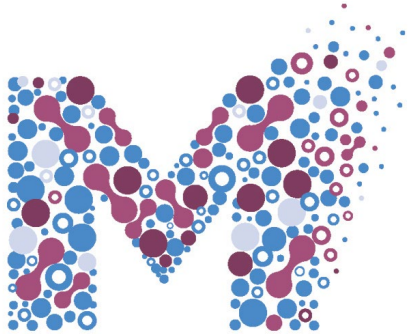
- What investments are most critical for enabling African and other LMIC institutions to lead—not just participate in—global disease modelling?
- How can universities and public health agencies in the Global South be positioned as long-term modelling hubs rather than temporary project partners?
- What role should mentorship and technology transfer play in the sustainability of initiatives like the Measles Analytics Hub?

Ethics & Governance



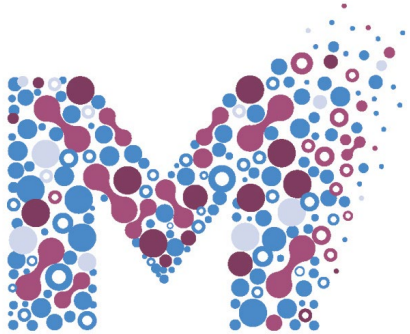
- Who owns the data, models, and insights generated through multinational collaborations like this?
- Should there be global standards for transparency and accountability in infectious disease modelling?
- How do we balance rapid outbreak response with ethical concerns around data sovereignty and consent?

Policy Impact



- Can you share an example where modelling directly changed measles vaccination strategy or outbreak response policy?
- What barriers still exist between model outputs and real-world public health decision-making?
- How can analytics platforms better communicate findings to non-technical policymakers and communities?

Future-Oriented / Provocative Questions



- Could the Measles Analytics Hub become a blueprint for modelling other diseases such as cholera, malaria, or pandemic preparedness?
- What would success look like 10 years from now if equitable global health modelling truly becomes the norm?
- If funding for global modelling shifted entirely to regional leadership, what would improve—and what challenges might emerge?
- What is one uncomfortable truth the global health community still avoids discussing about inequity in disease modelling?

Special Issue

AI and Geospatial Modeling for Vaccination Strategies in LMICs

Message from the Guest Editors

This Special Issue focuses on the growing role of geospatial analysis, artificial intelligence, and mathematical modelling in informing childhood vaccination strategies in low- and middle-income countries. It aims to showcase innovative methodological and applied research that leverages geospatial data, machine learning, epidemiological modelling, and advanced statistical approaches to answer relevant programmatic questions and address persistent challenges in immunization systems. Topics of interest include high-resolution mapping of vaccination coverage and zero-dose children, modelling of outbreak risk and population immunity, optimization of vaccination campaigns, integration of routine administrative and survey data, forecasting approaches, and the use of novel data streams to support immunization planning and monitoring. By bringing together contributions from multiple disciplines, the Special Issue seeks to highlight how data-driven approaches can support more equitable, targeted, and effective vaccination strategies, and ultimately contribute to disease control and elimination efforts in resource-constrained settings.

Guest Editors

Name: Dr. C. Edson Utazi

Affiliation: WorldPop, School of Geography and Environmental Science, University of Southampton, Southampton, United Kingdom

Name: Dr. Oghenebrume Wariri

Affiliation: London School of Hygiene & Tropical Medicine, London, United Kingdom

Name: Prof. Justice Moses K. Aheto

Affiliation: University of Ghana, Accra, Ghana

Deadline for manuscript submissions

Vaccines

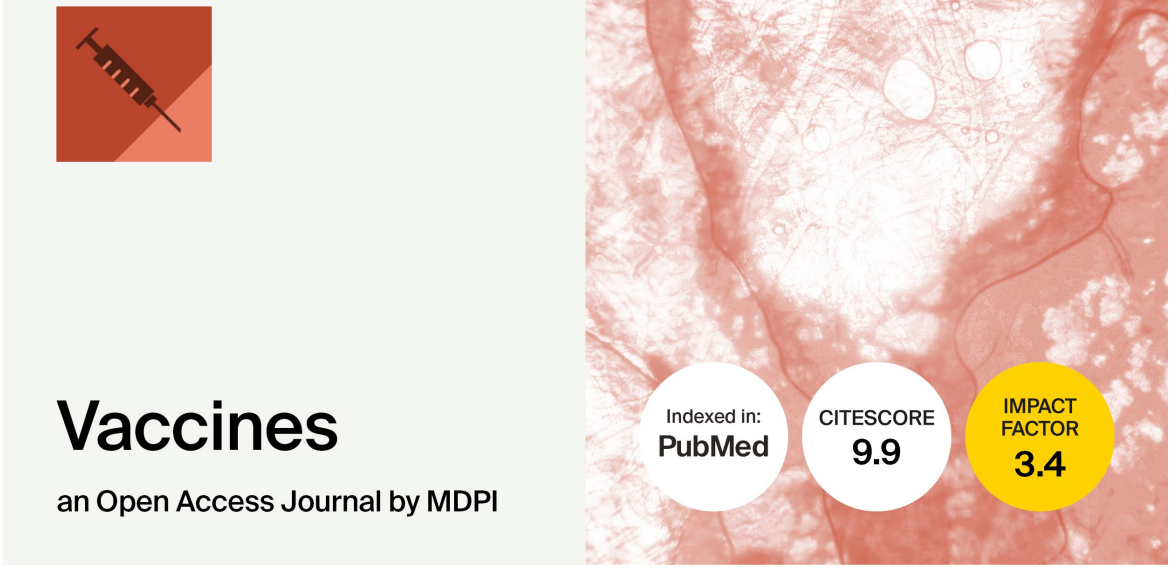
an Open Access Journal by MDPI

Impact Factor 3.4
CiteScore 9.9
Indexed in PubMed

Vaccines
Editorial Office
MDPI, Grosspeteranlage 5
4052 Basel, Switzerland
Tel: +41 61 683 77 34
vaccines@mdpi.com

mdpi.com/journal/vaccines

MDPI



Thank you

MEASLES
ANALYTICS HUB

Closing Remarks