Machine Learning for Social Good

Algorithmic & Data Challenges when working with Vulnerable Populations

Kyriaki Kalimeri

FRONTIER DATA NETWORK

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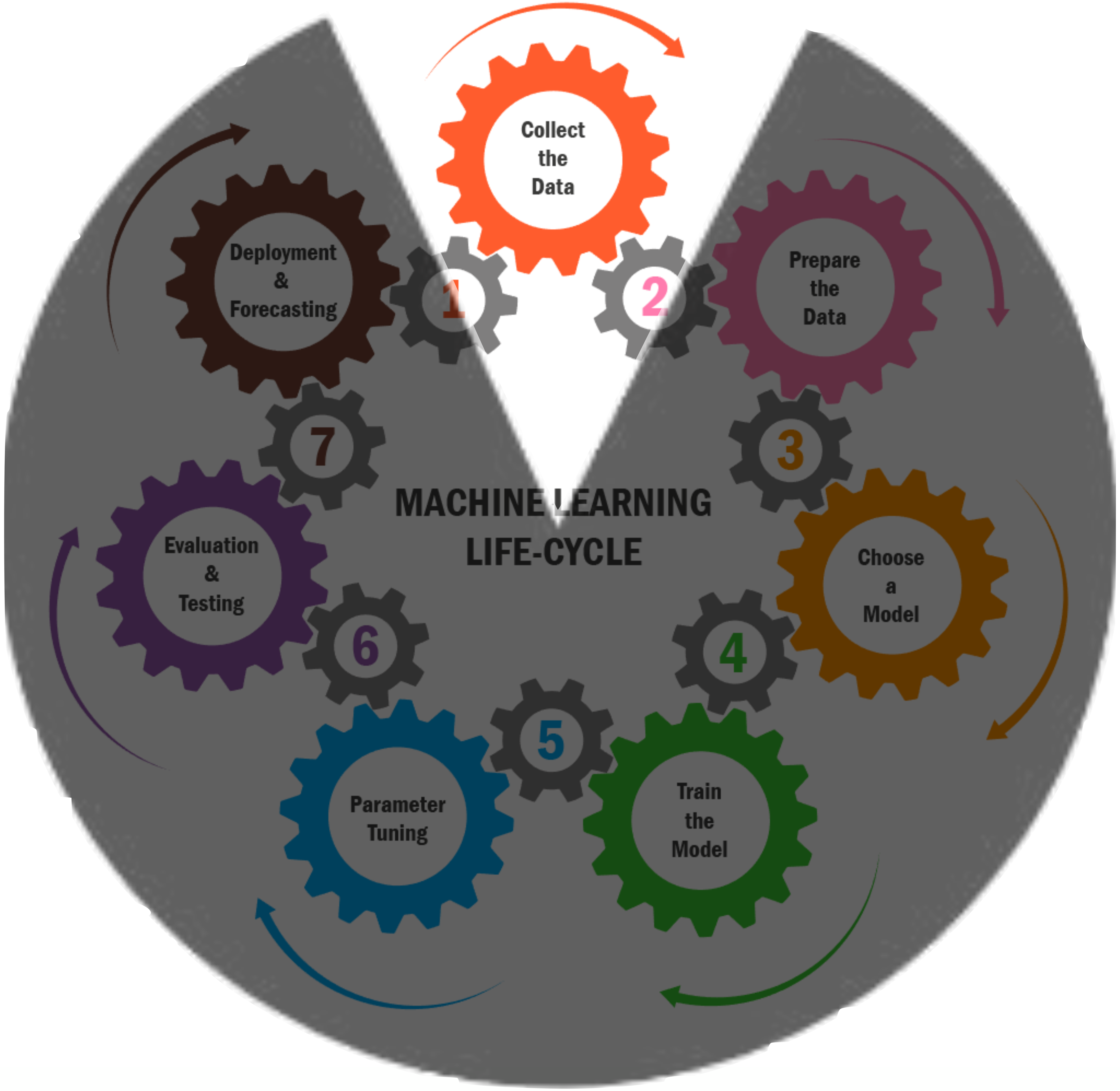
Machine Learning models are increasingly more employed to in the **humanitarian** sector to **inform decision-making**

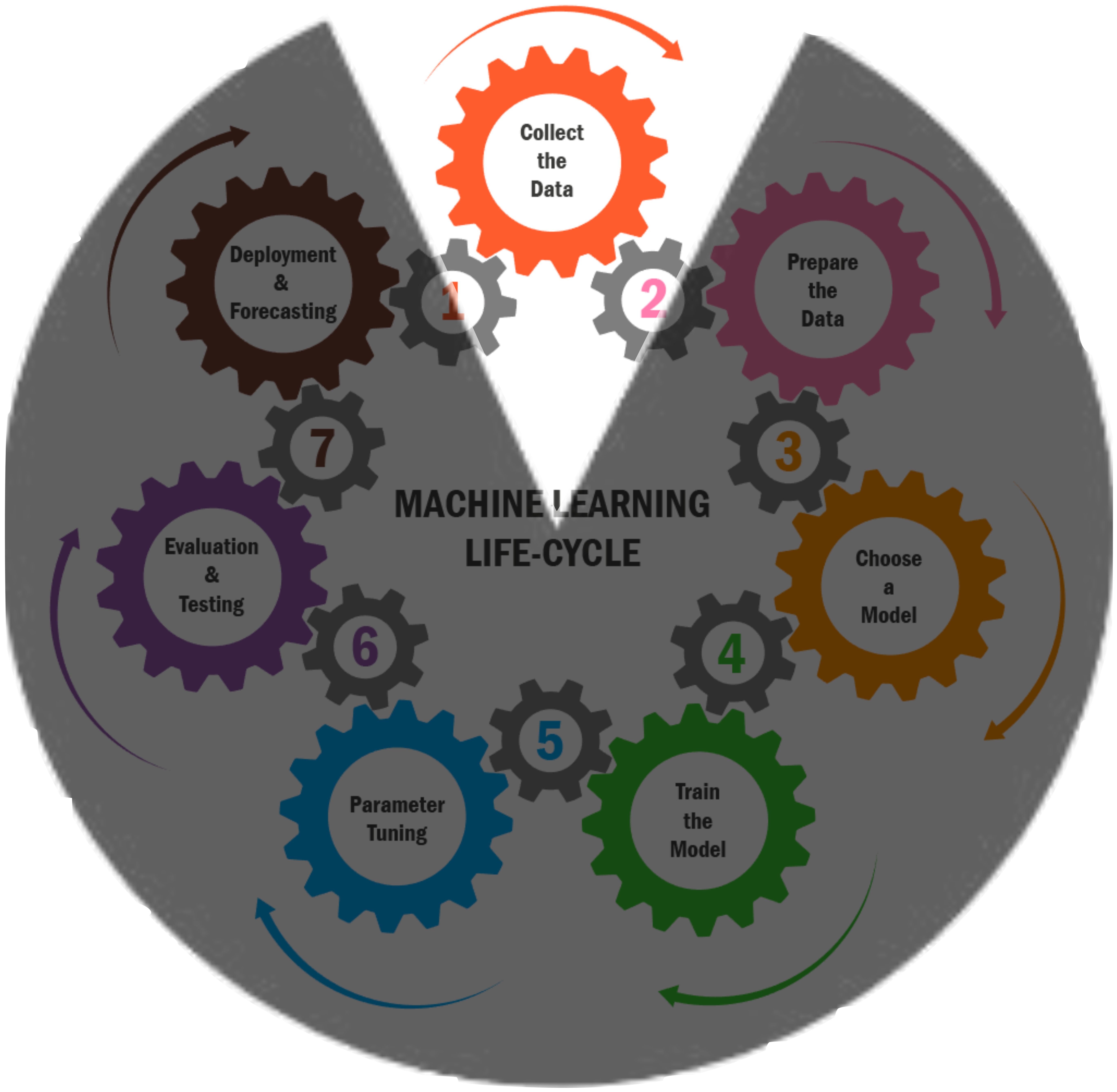
Ensure fairness, transparency, and accountability in model development and deployment

Vulnerability refers to the **susceptibility** of individuals or groups to harm or adverse outcomes due to their specific characteristics, contexts, or **lack of access** to resources and opportunities.


Biases may exist in every step of the pipeline



- ***Sampling & coverage***



MACHINE LEARNING LIFE-CYCLE
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2
Prepare the Data
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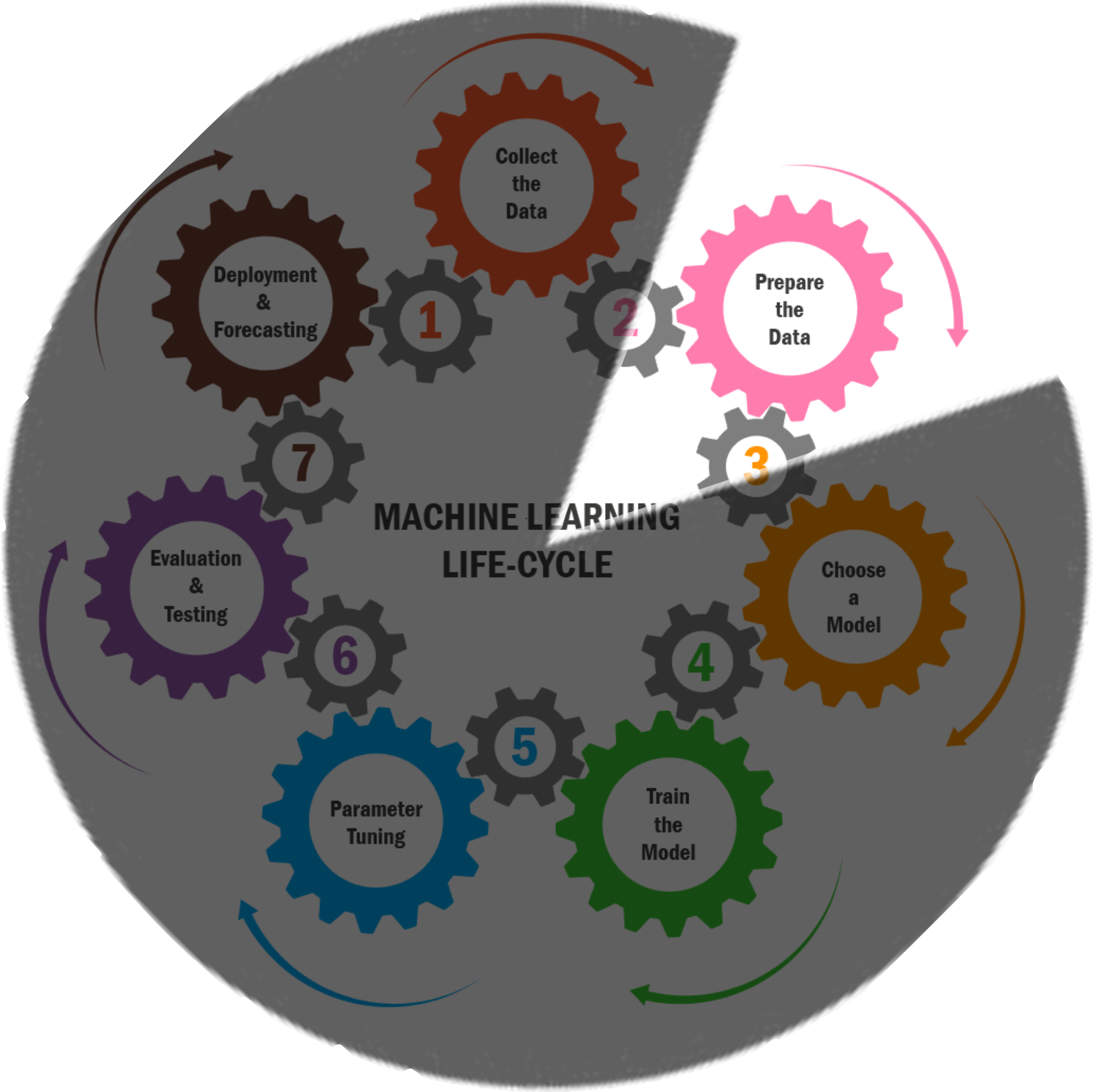
Choose a Model
4
Train the Model
5
Parameter Tuning
6
Evaluation & Testing
7
Deployment & Forecasting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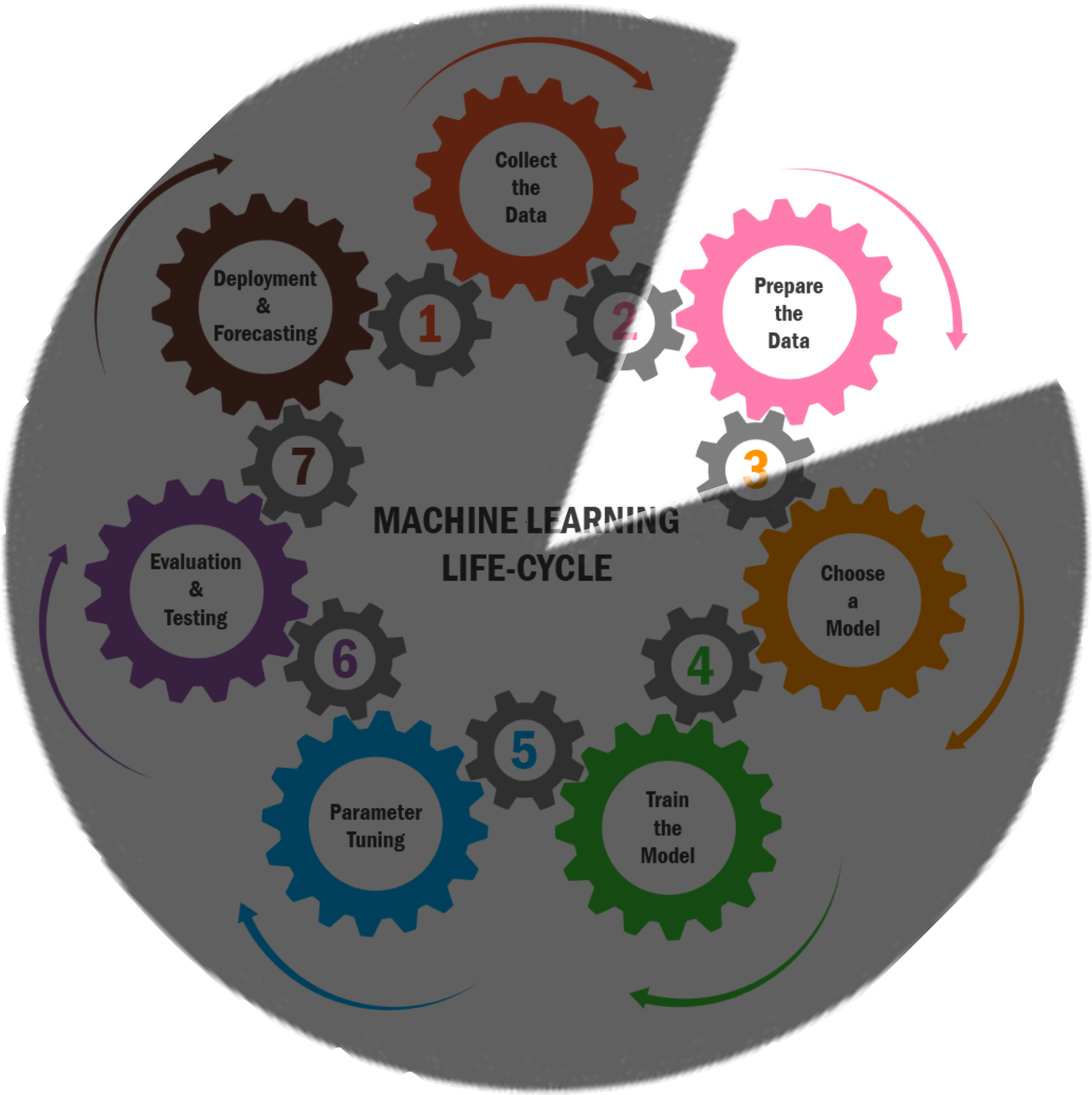
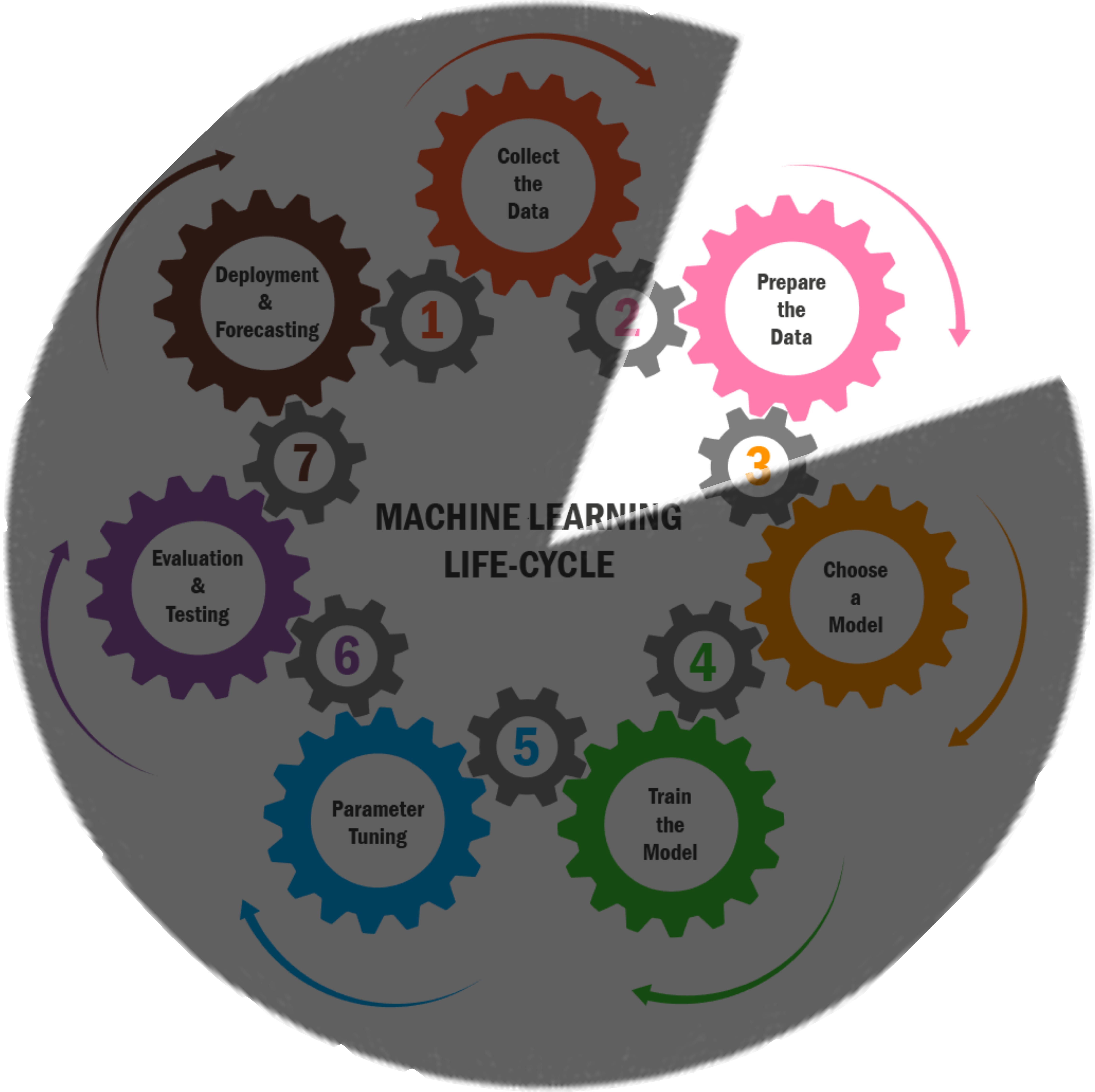


- *Systematic missingness*
- *Sensitive-attribute handling*
- *Bias-aware preprocessing*
- *Harmonisation across silos*



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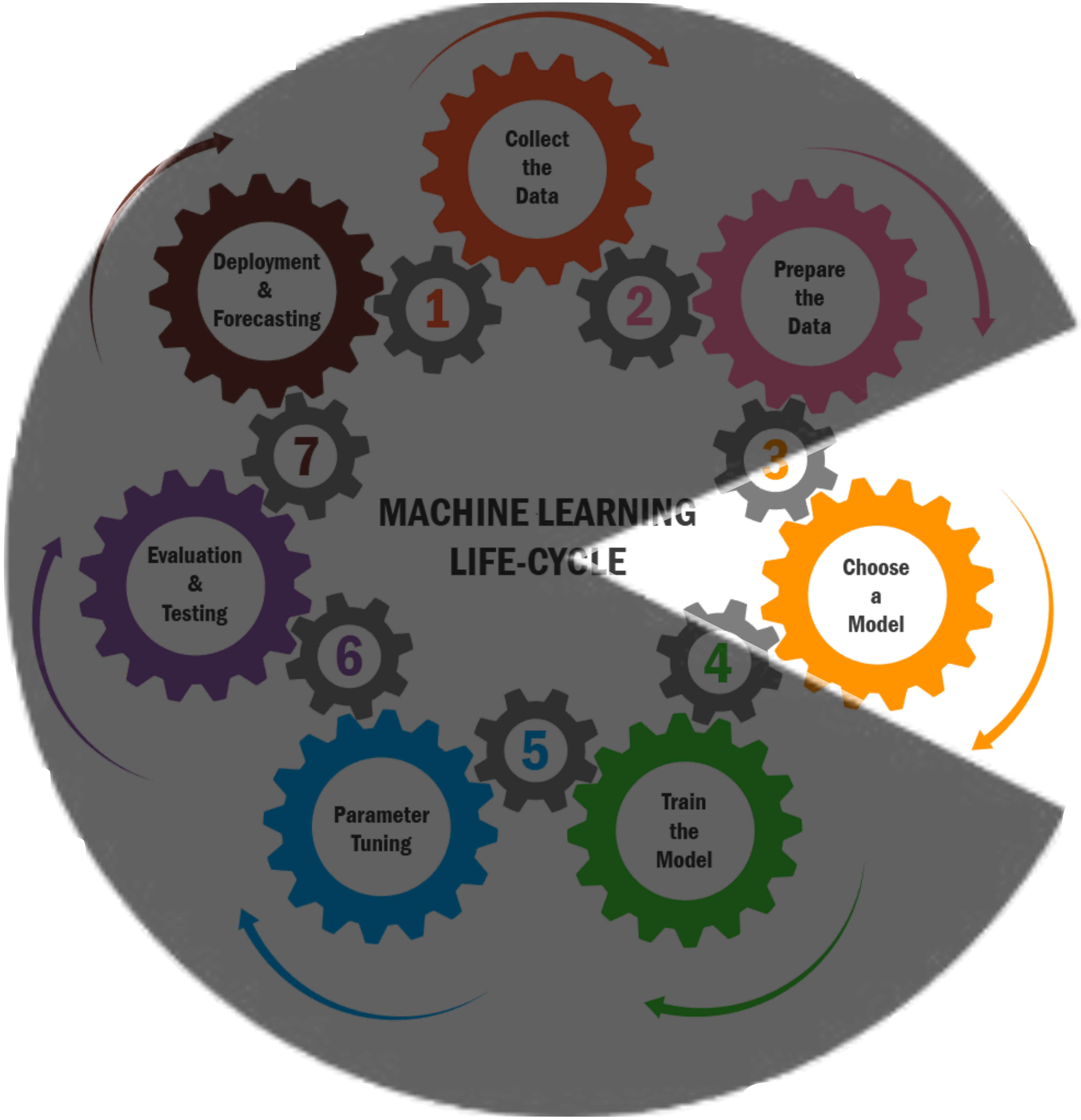
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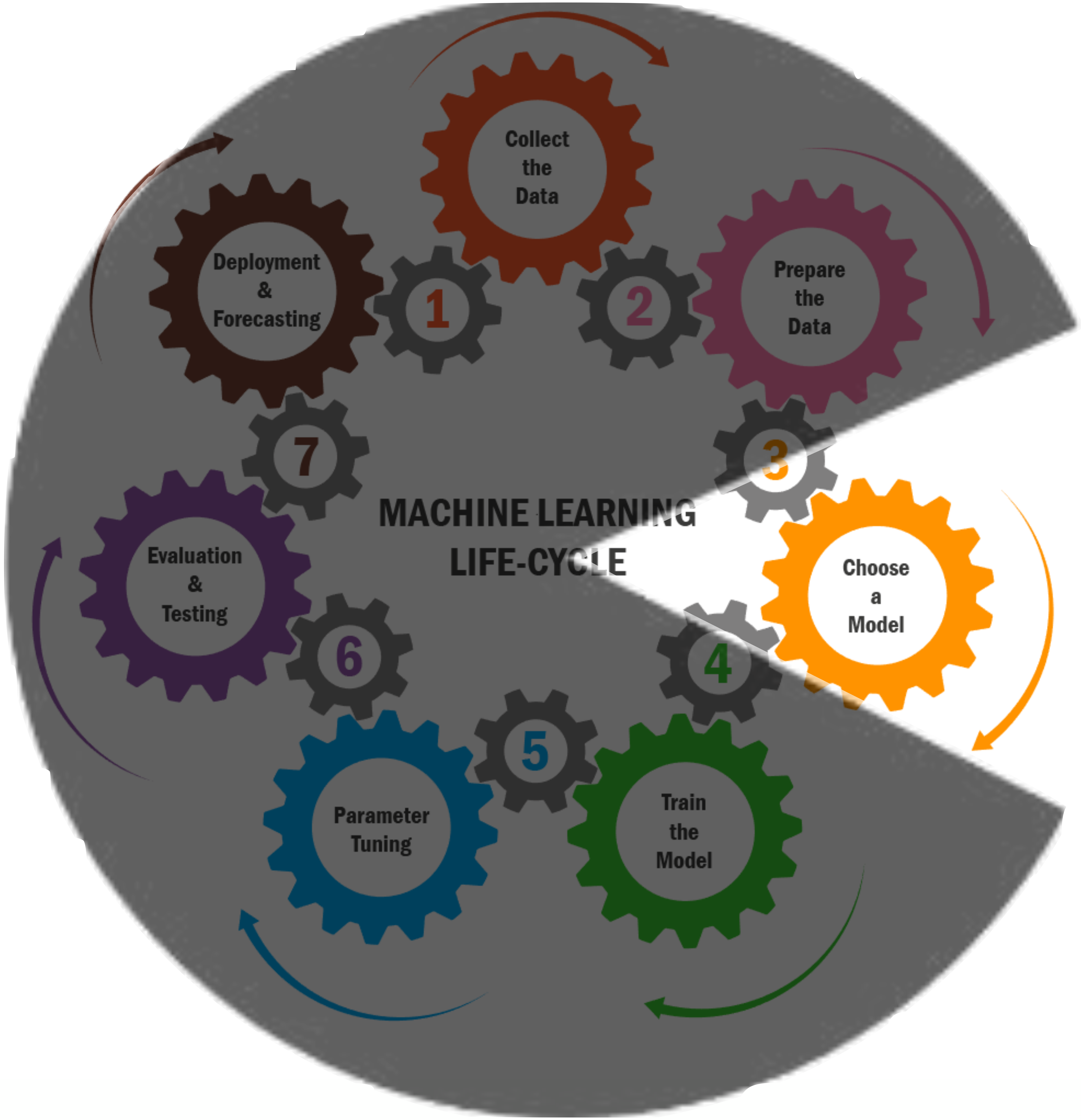
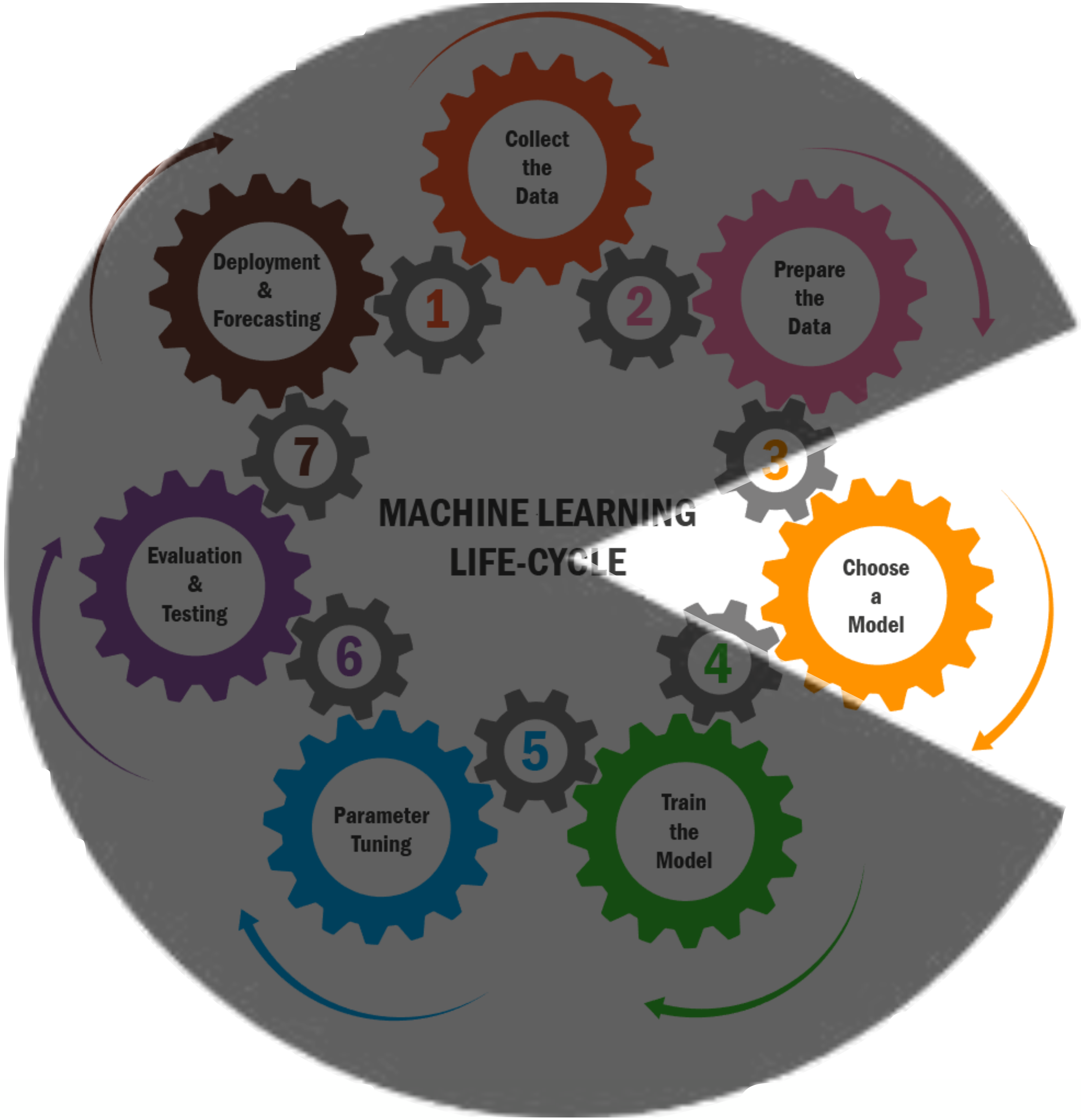


- *Accuracy vs explainability*
- *Fairness constraints*
- *Robustness to imbalance*



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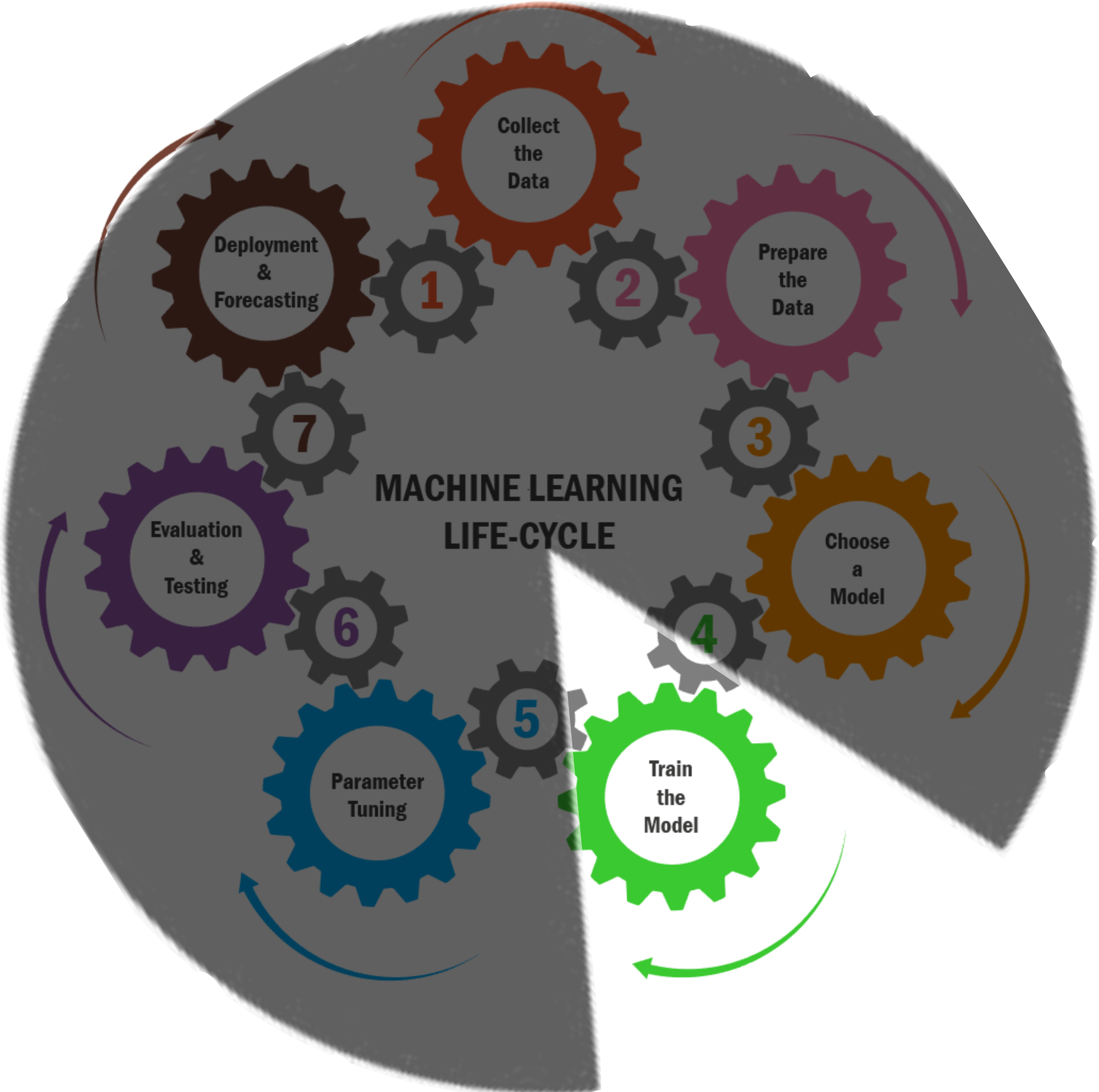
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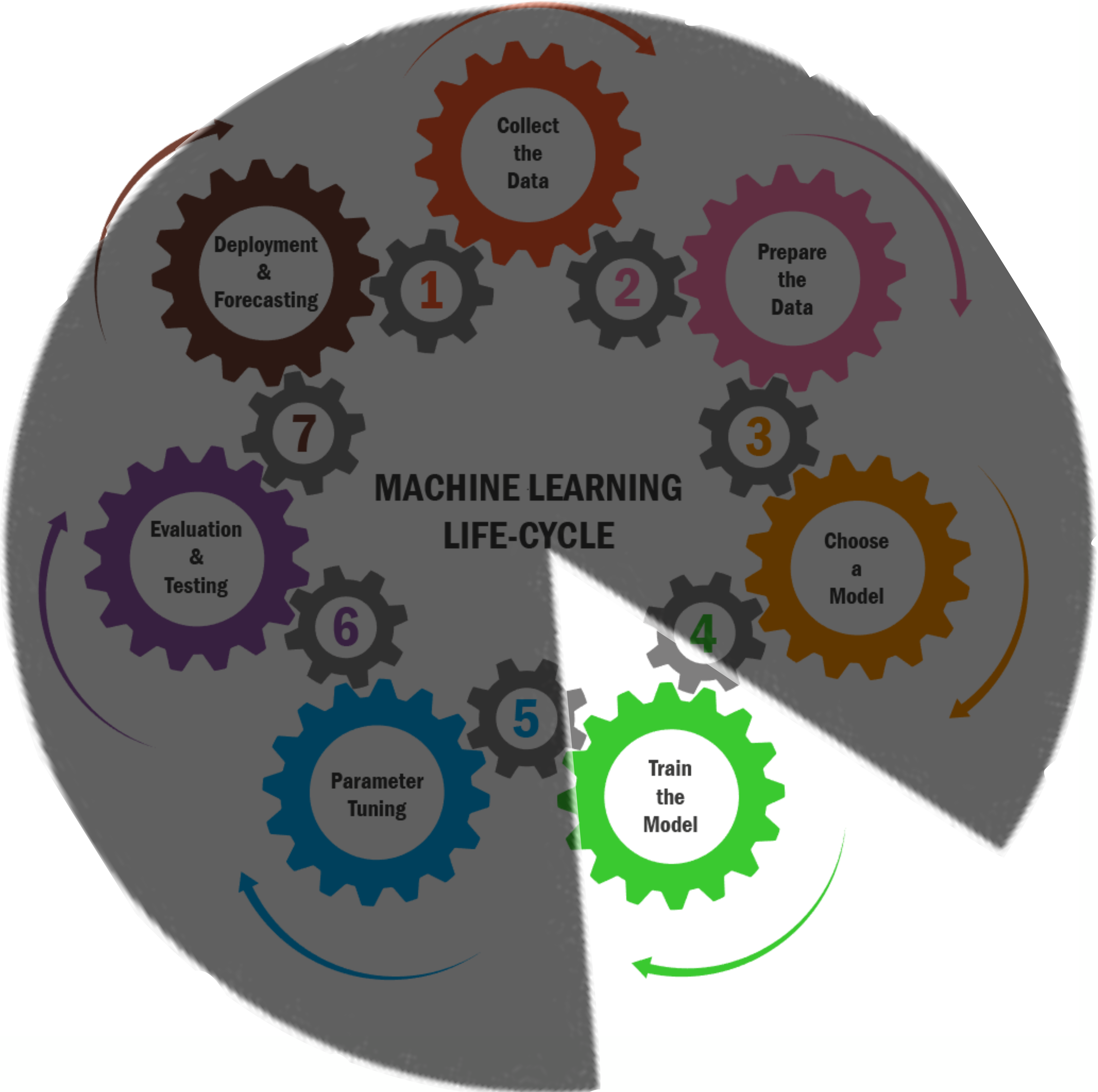
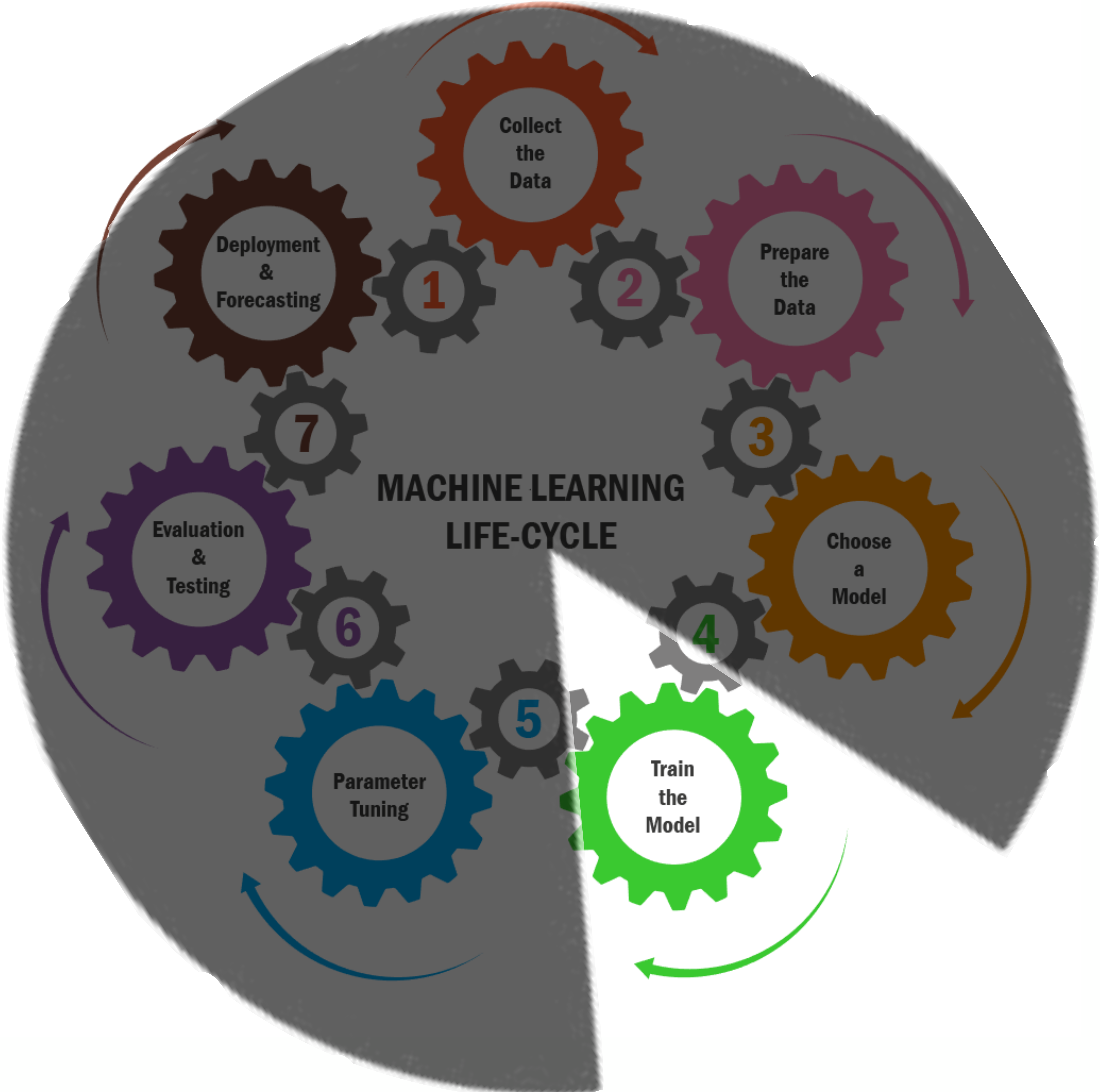


- *Class imbalance & rare events*
- *Fairness–accuracy trade-off*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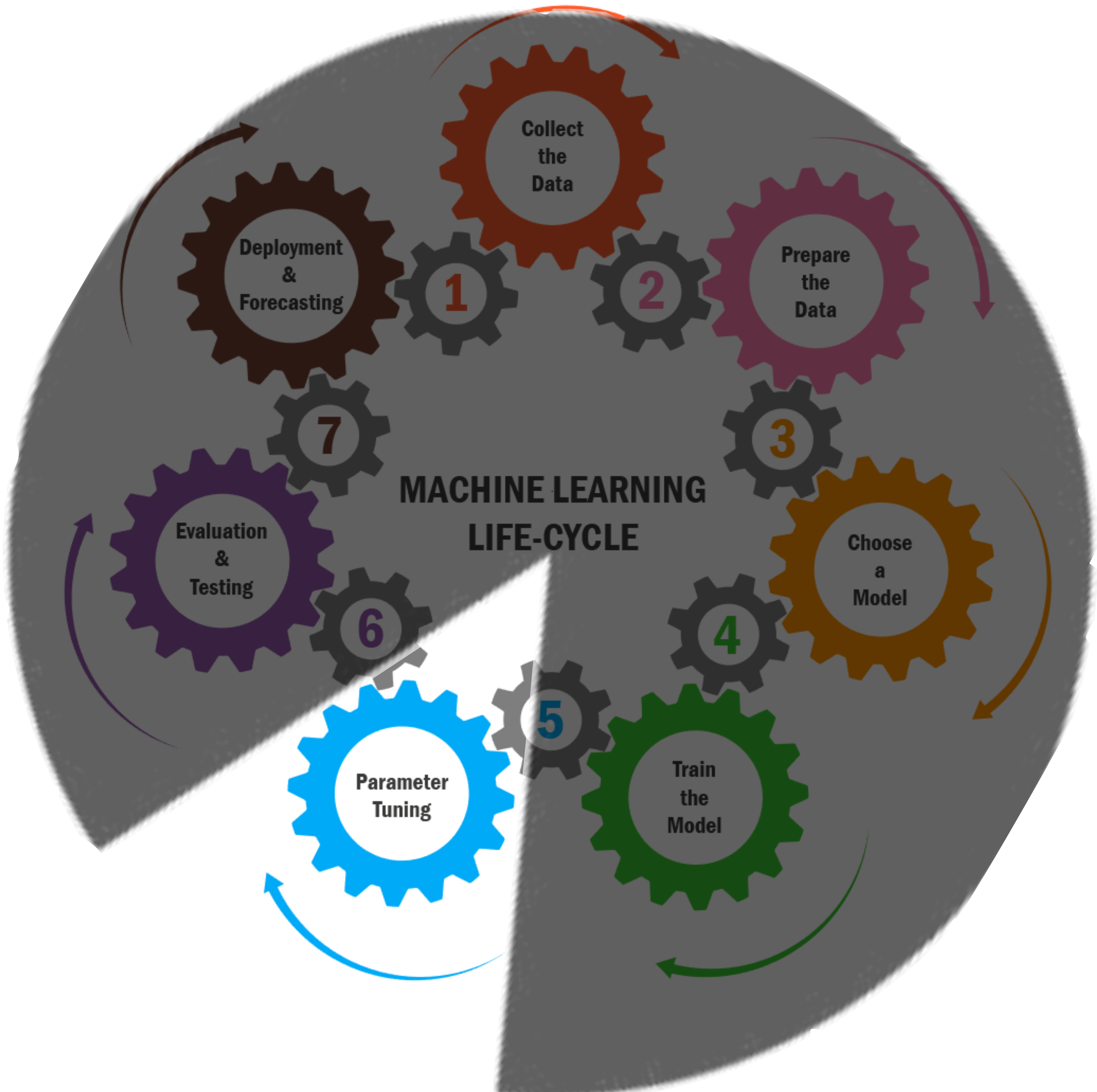

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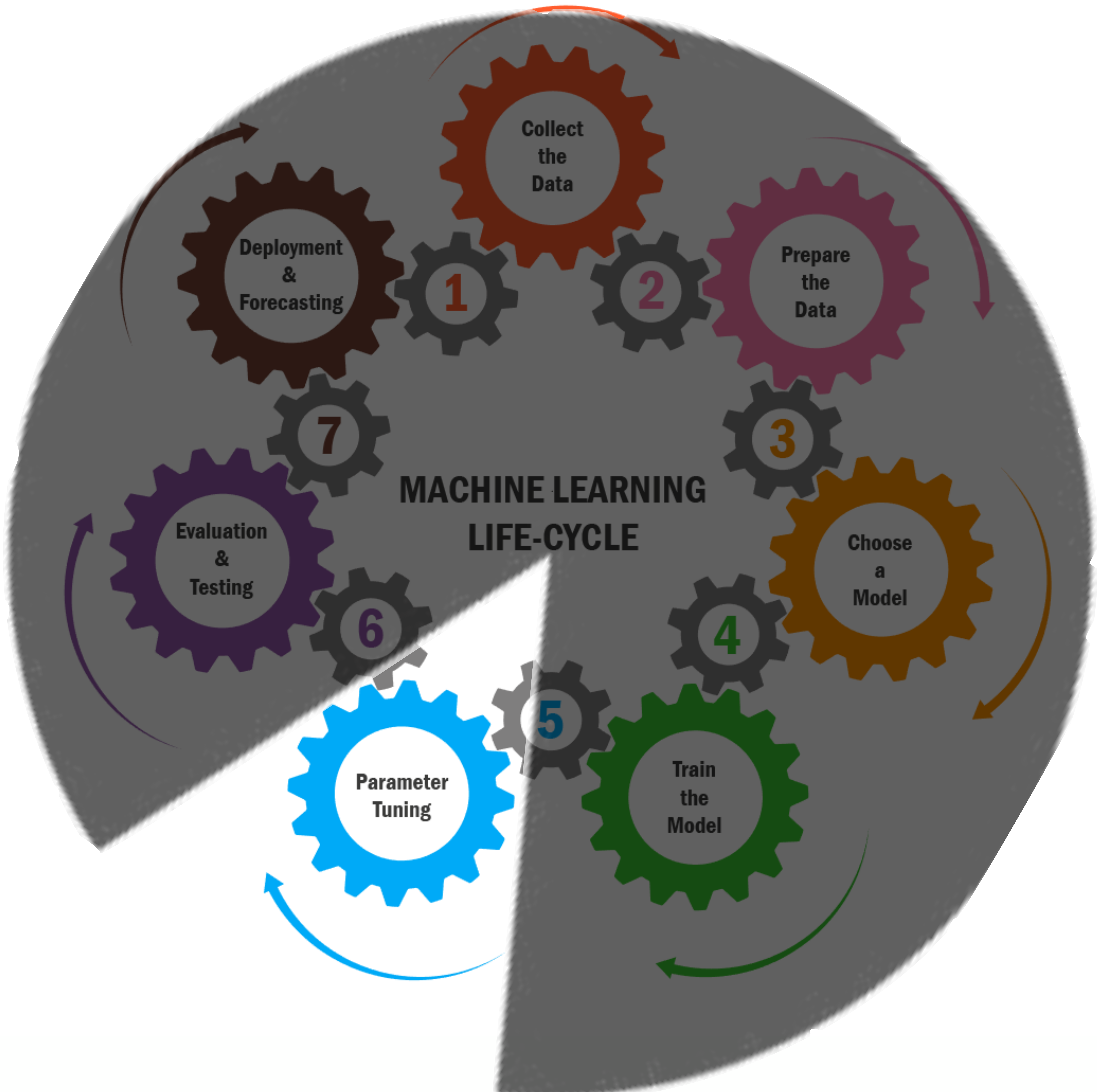
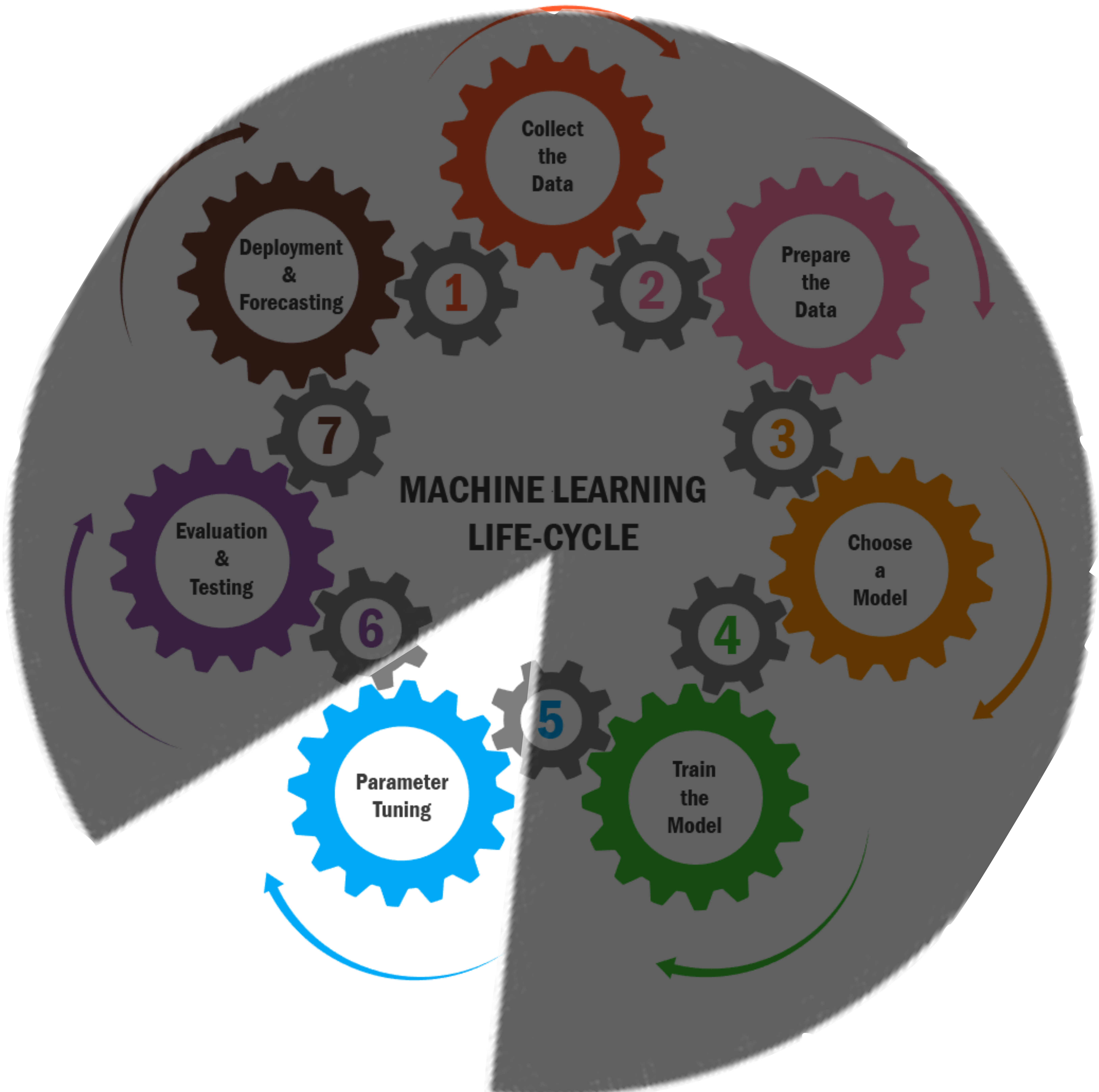


- *Sparse validation sets*
- *Overfitting to fairness metrics*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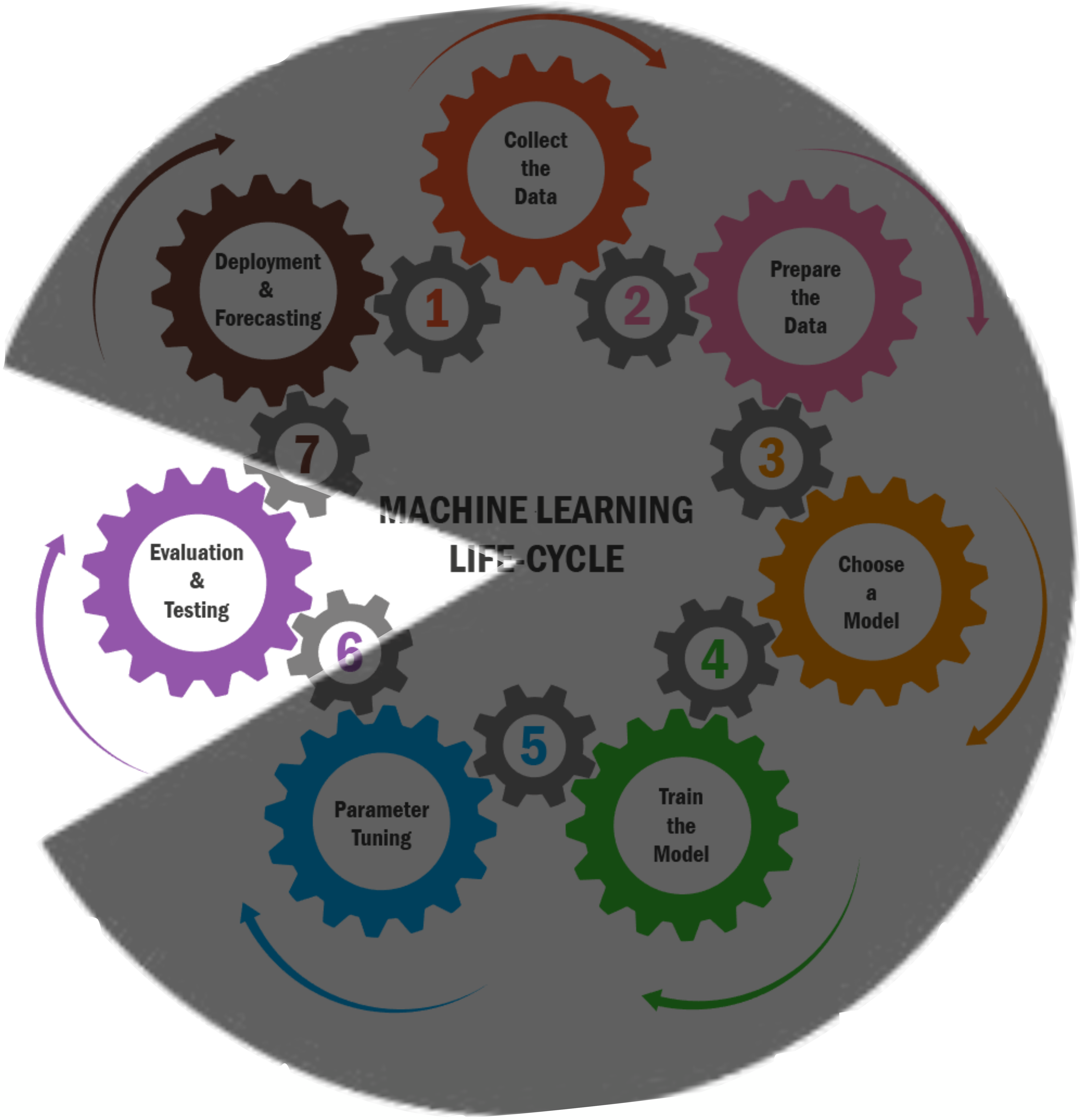

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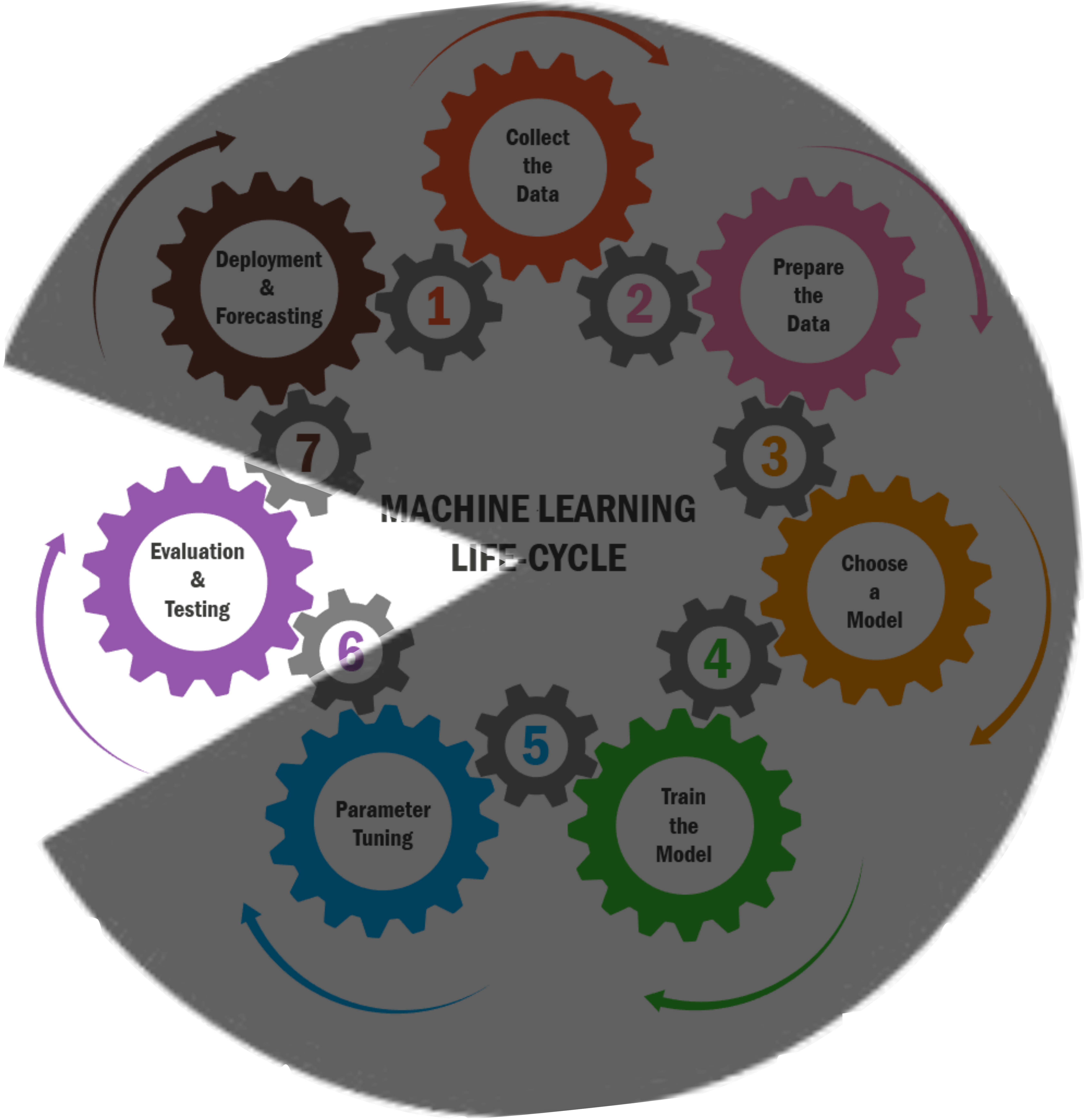
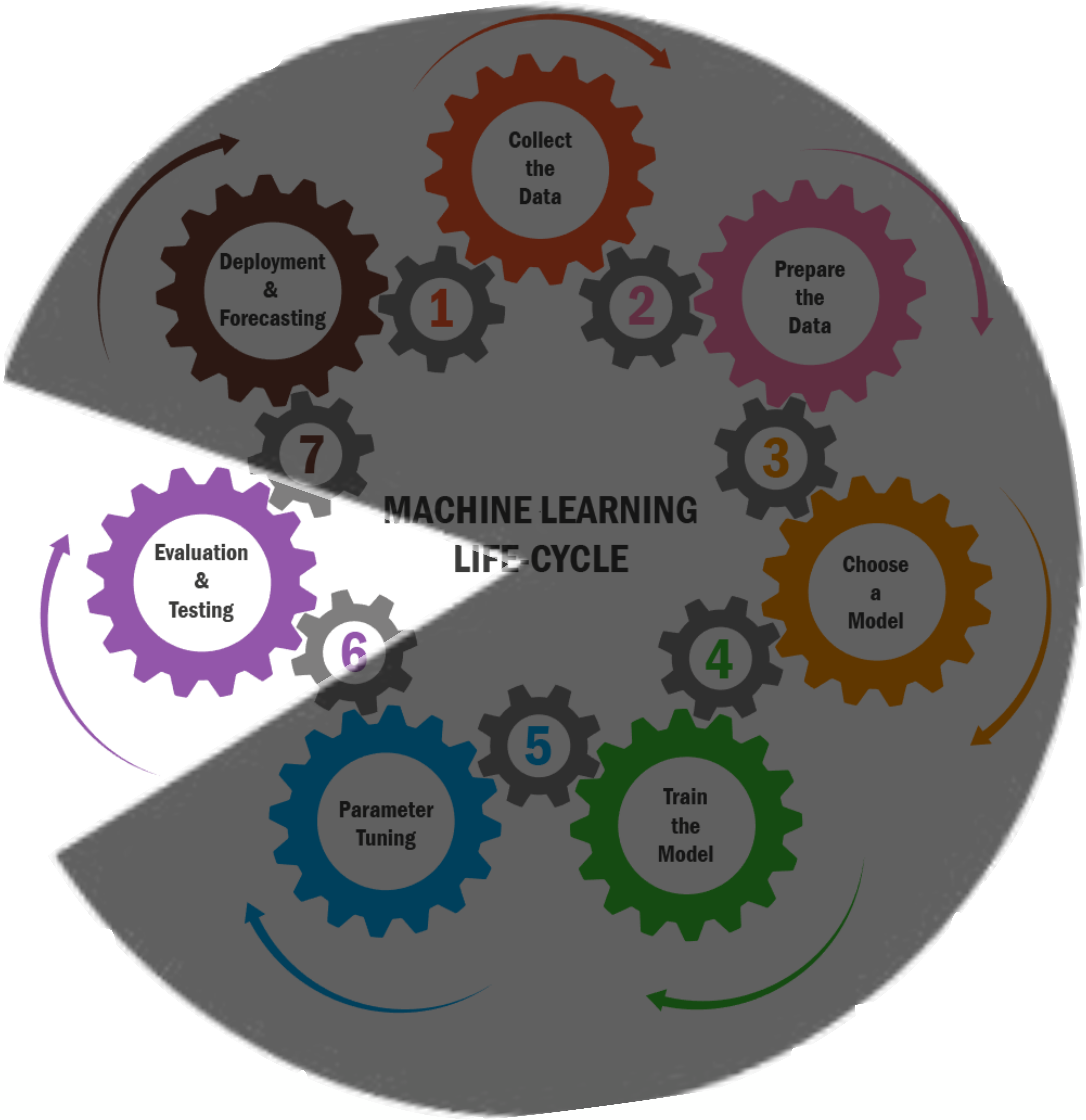


- *Intersectional fairness auditing*
- *External validity*
- *Counterfactual ground truth scarcity*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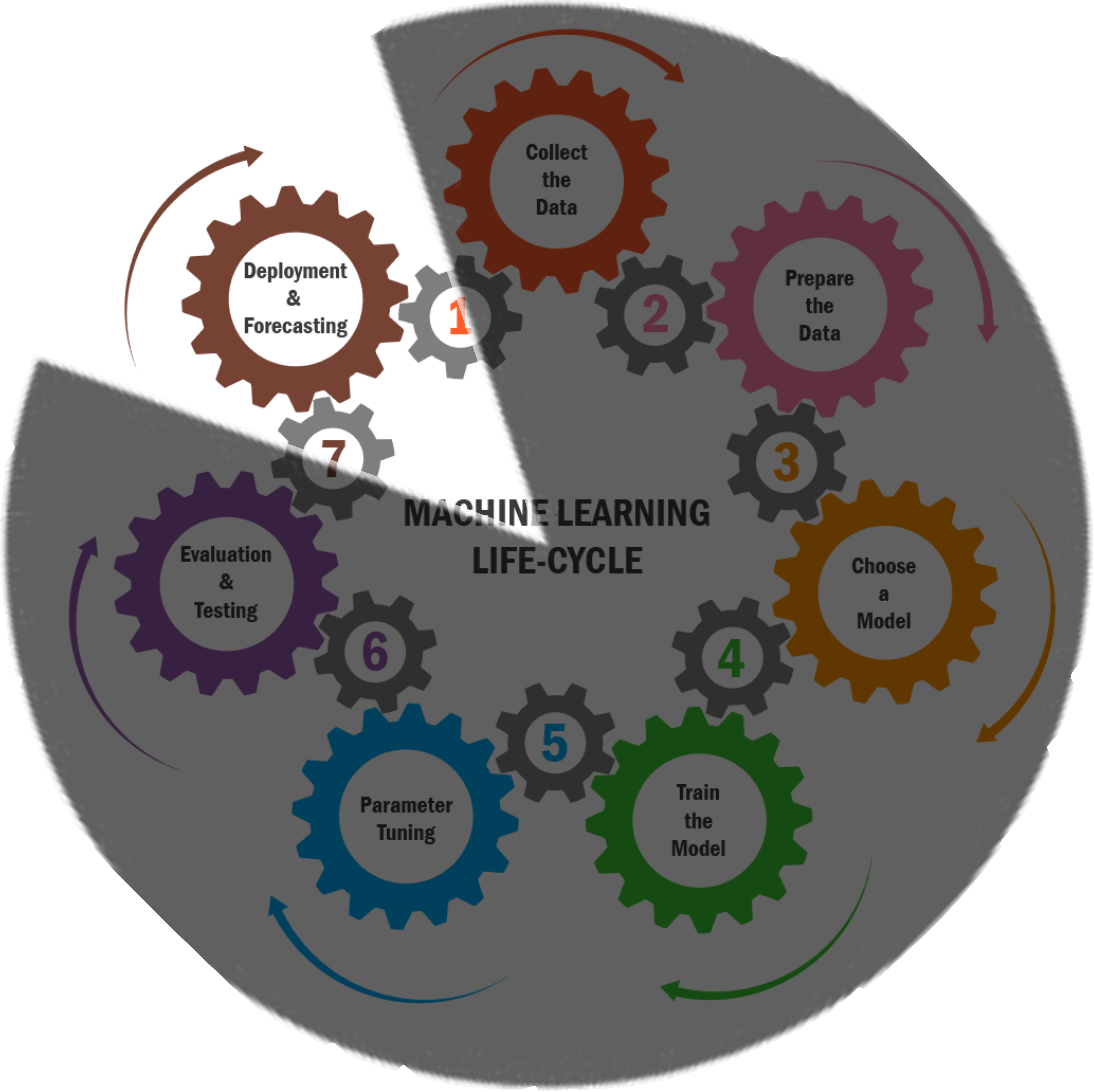
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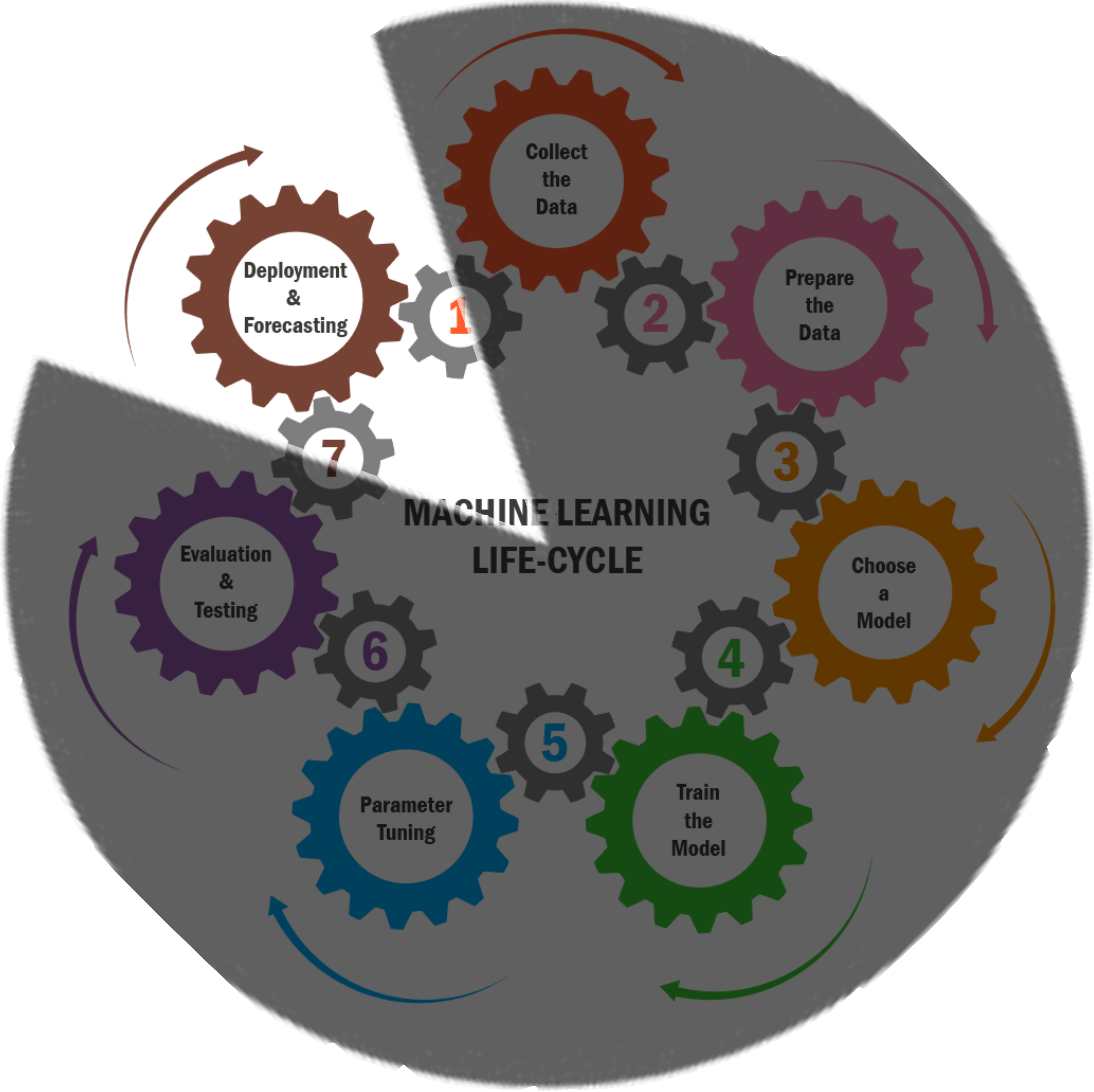


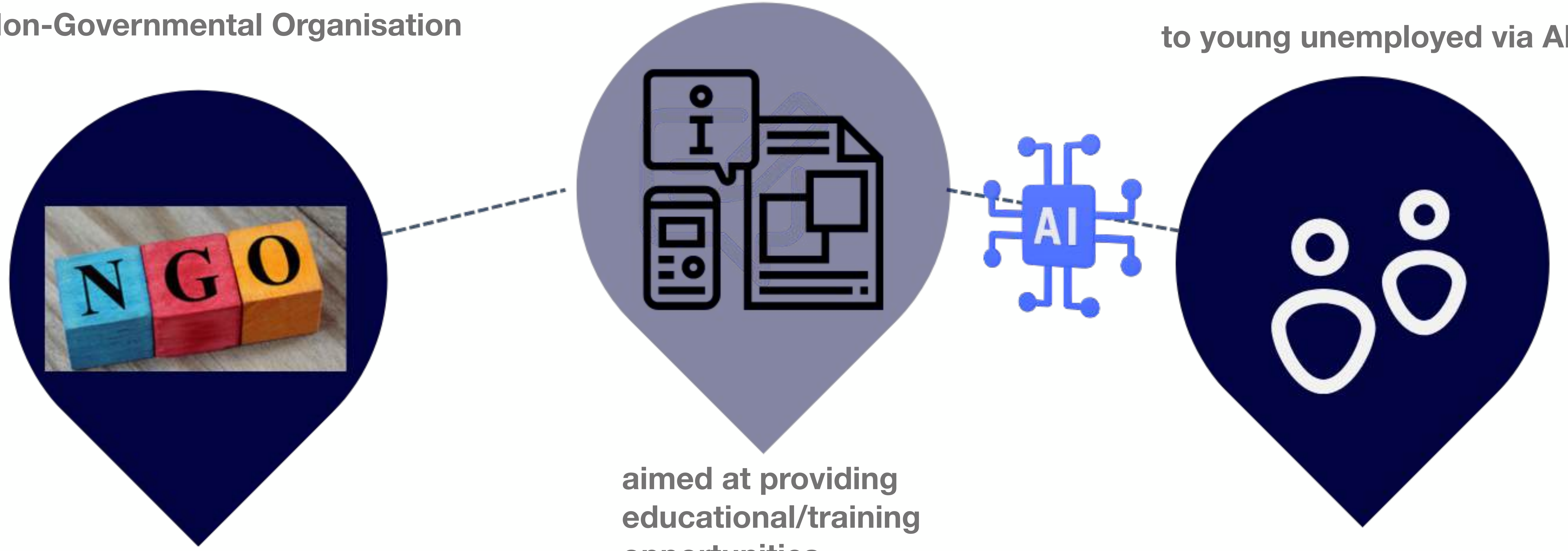
- *Transparency & contestability*
- *Sustainability & hand-off*


"For your own sanity, you have to remember that not all problems can be solved.

Not all problems can be solved, but all problems can be illuminated."

Ursula Franklin

Accuracy versus Fairness

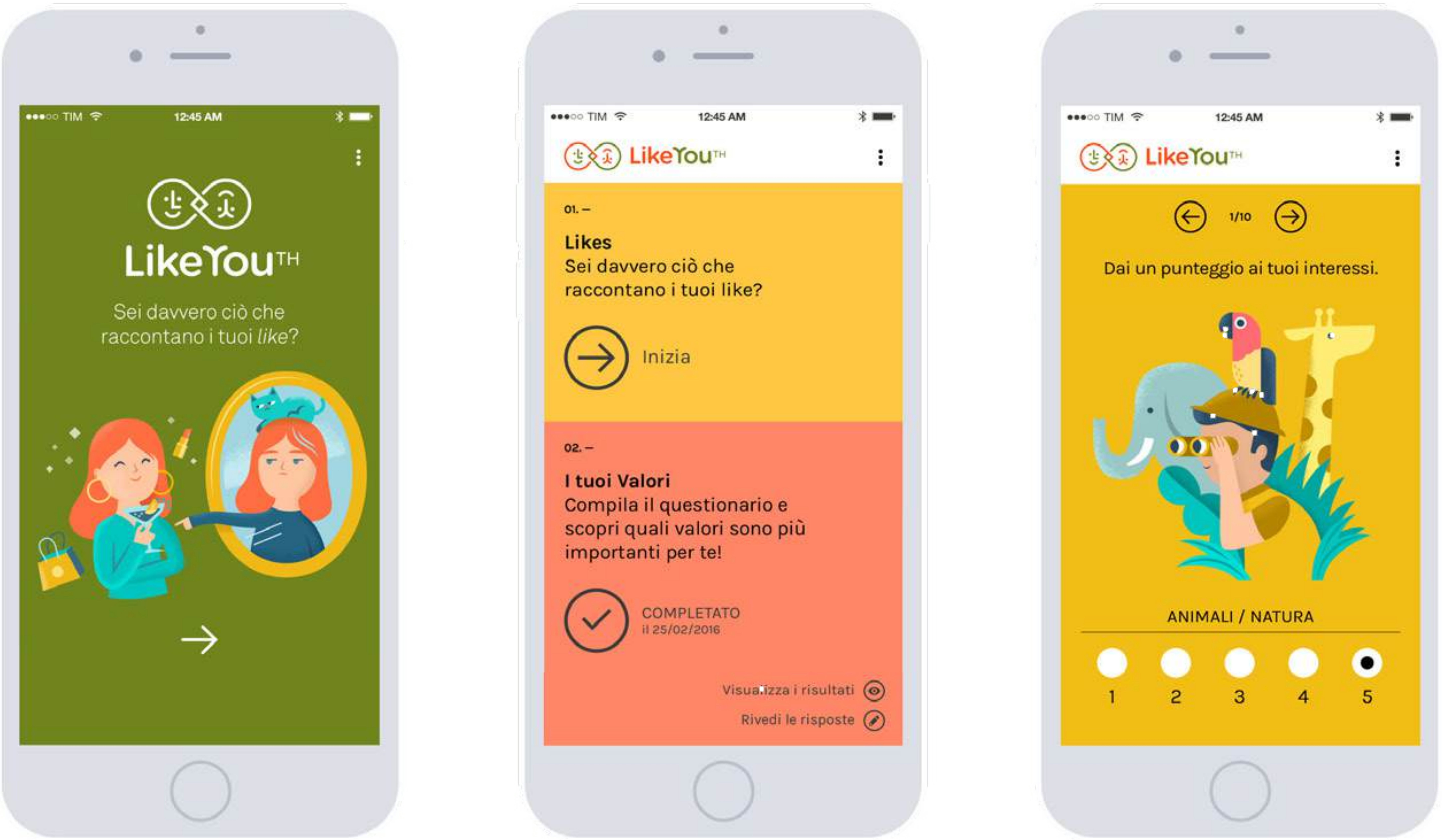


A Non-Governmental Organisation

aimed at providing educational/training opportunities

to young unemployed via AI

Beiró, M.G. and Kalimeri, K., 2022. Fairness in vulnerable attribute prediction on social media. *Data Mining and Knowledge Discovery*, *36*(6), pp.2194-2213.



●●●○○ TIM 12:45 AM
LikeYouTH
Sei davvero ciò che raccontano i tuoi *like*?
●●●○○ TIM 12:45 AM
LikeYouTH
01. –
Likes
Sei davvero ciò che raccontano i tuoi like?
Inizia
02. –
I tuoi Valori
Compila il questionario e scopri quali valori sono più importanti per te!
COMPLETATO
il 25/02/2016
Visualizza i risultati
Rivedi le risposte
●●●○○ TIM 12:45 AM
LikeYouTH
1/10
Dai un punteggio ai tuoi interessi.
ANIMALI / NATURA
1
2
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4
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	Census	Dataset
		n = 11,393
Gender		
Female	51.1%	38.1%
Male	48.4%	61.8%
Age		
17–24	7.9%	43.1%
25–34	11.0%	31.2%
35–44	13.8%	13.6%
45–54	16.1%	7.1%
55–64	13.3%	4.5%
65+	24.5%	0.3%
Occupation		
Employed	77%	43.9%
Unemployed	8.7%	7.4%
Student	14.2%	48.5%

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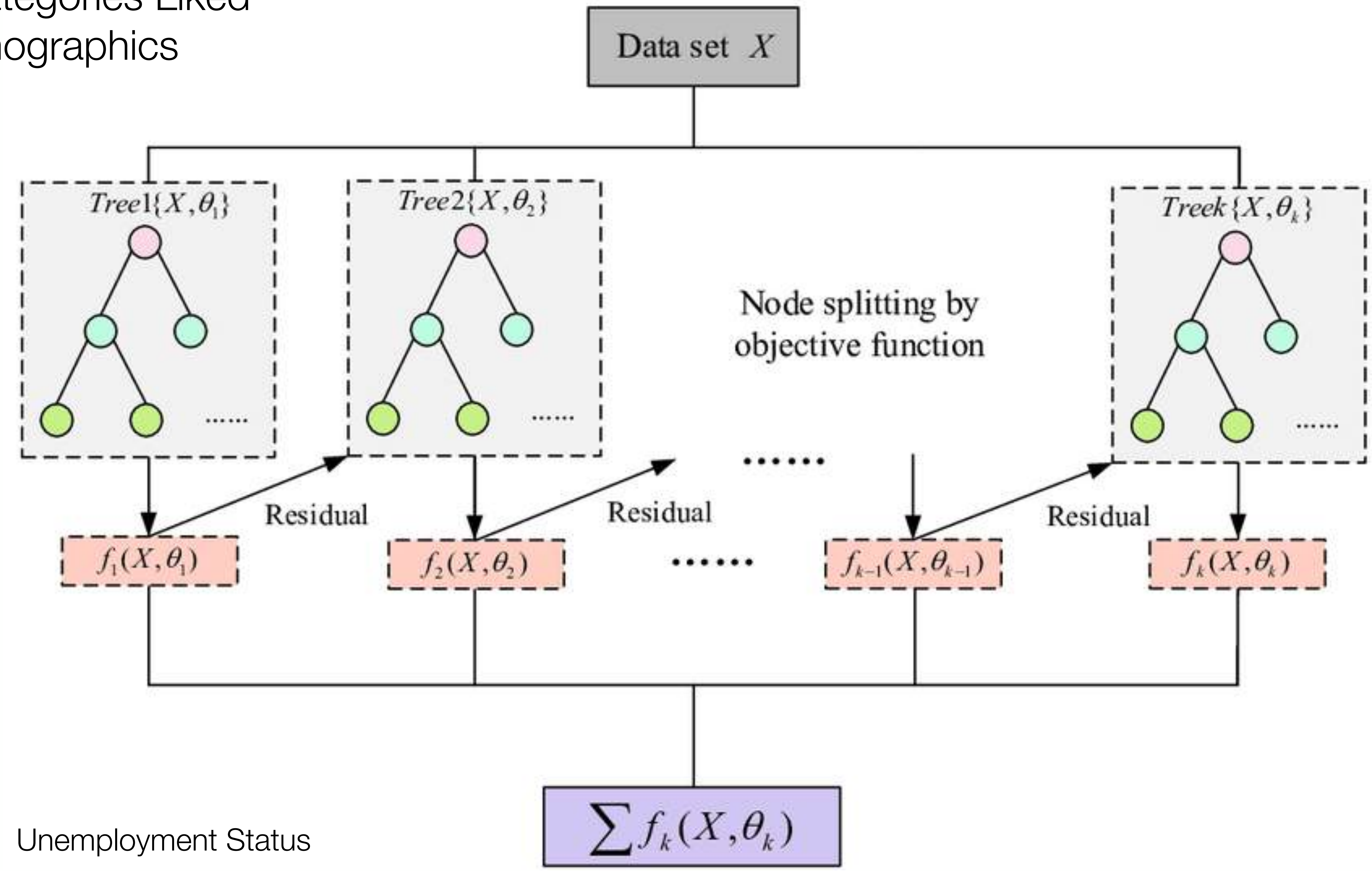
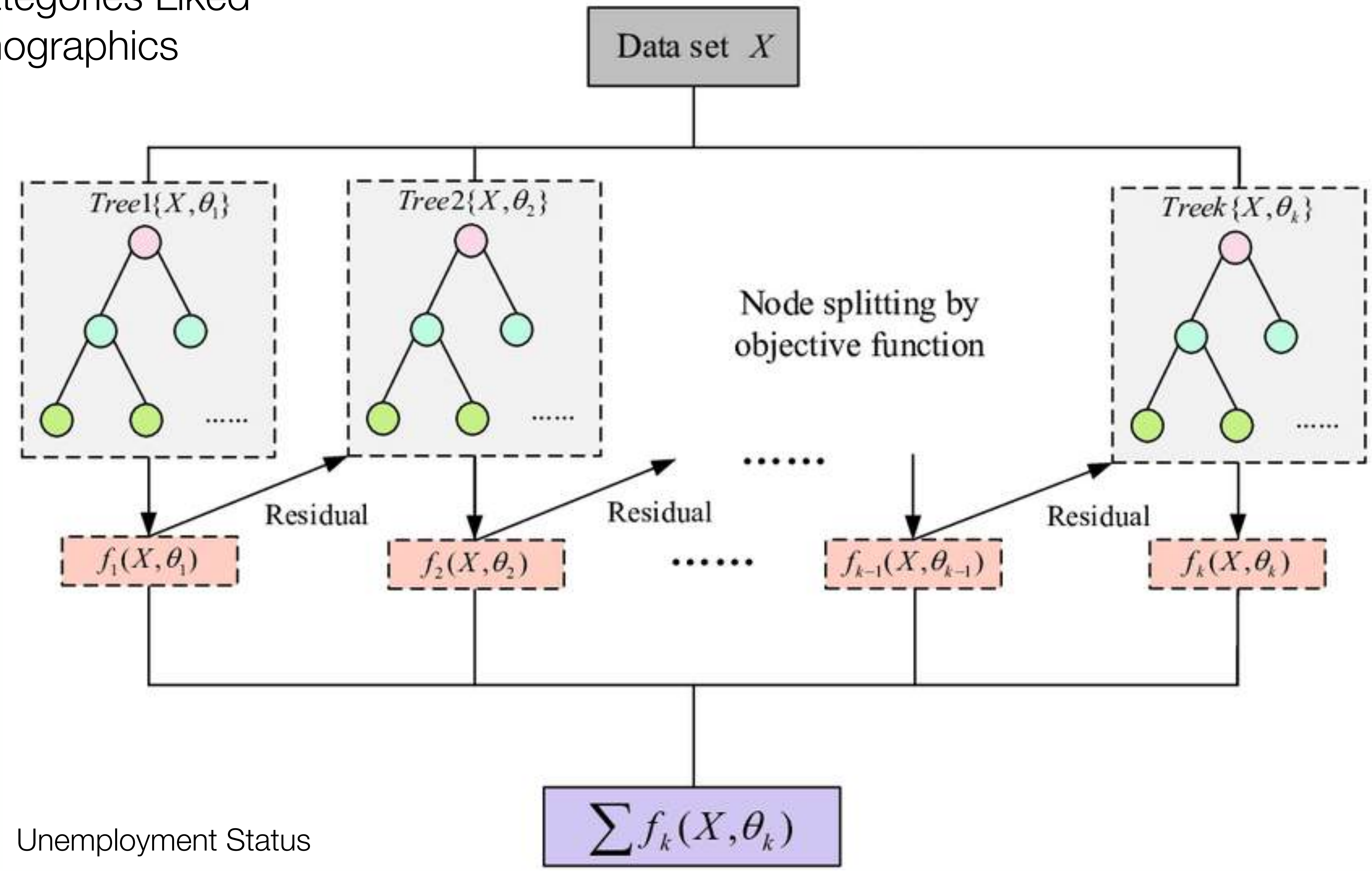
Unemployment rate per Gender:
Male: 5.5%
Female: 9%

Pages Liked
Page Categories Liked
Demographics



Unemployment Status

Pages Liked
Page Categories Liked
Demographics



Unemployment Status

We predict unemployment with 74% AUROC. Cool!

How each model feature contributes to the prediction?

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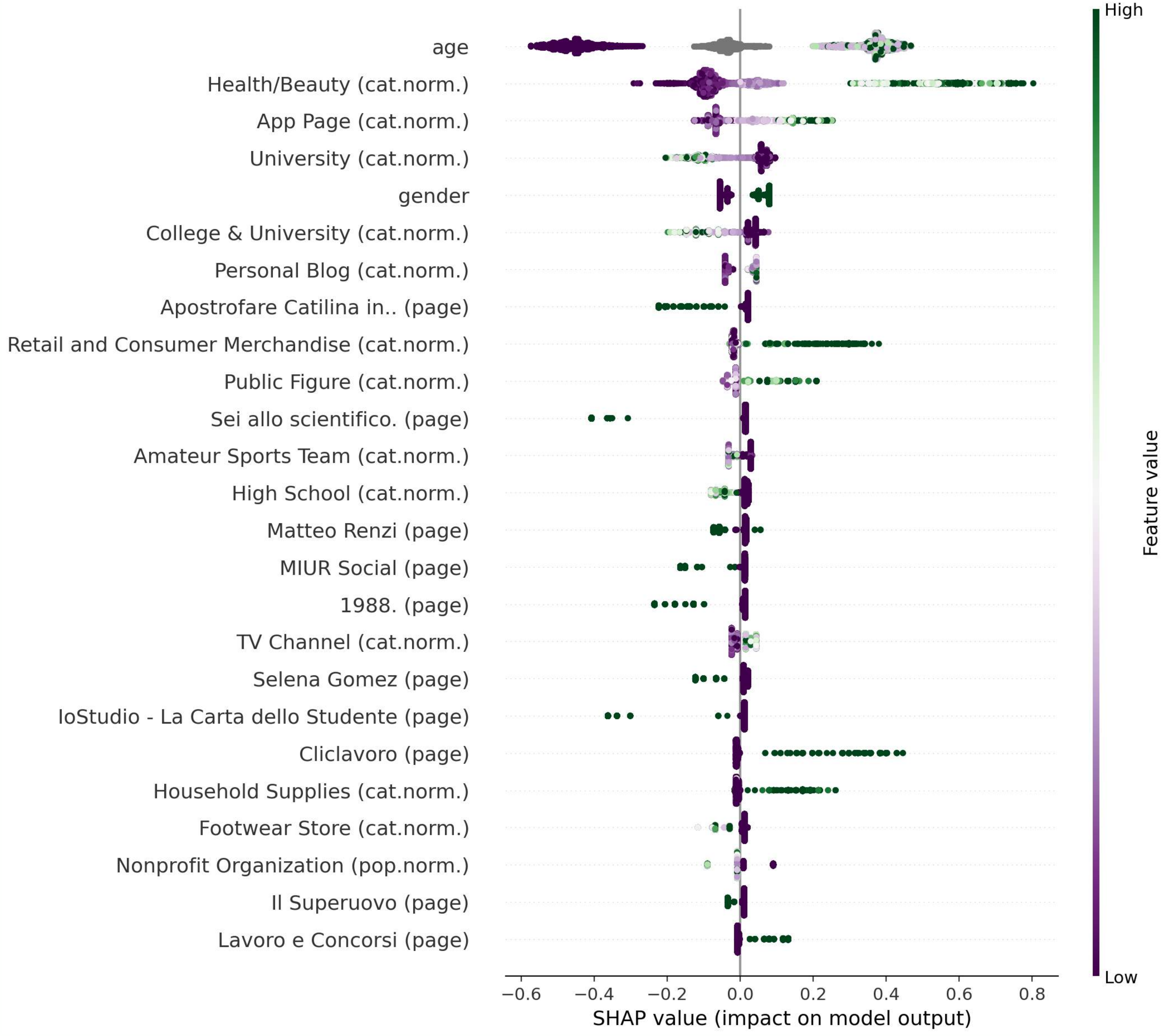

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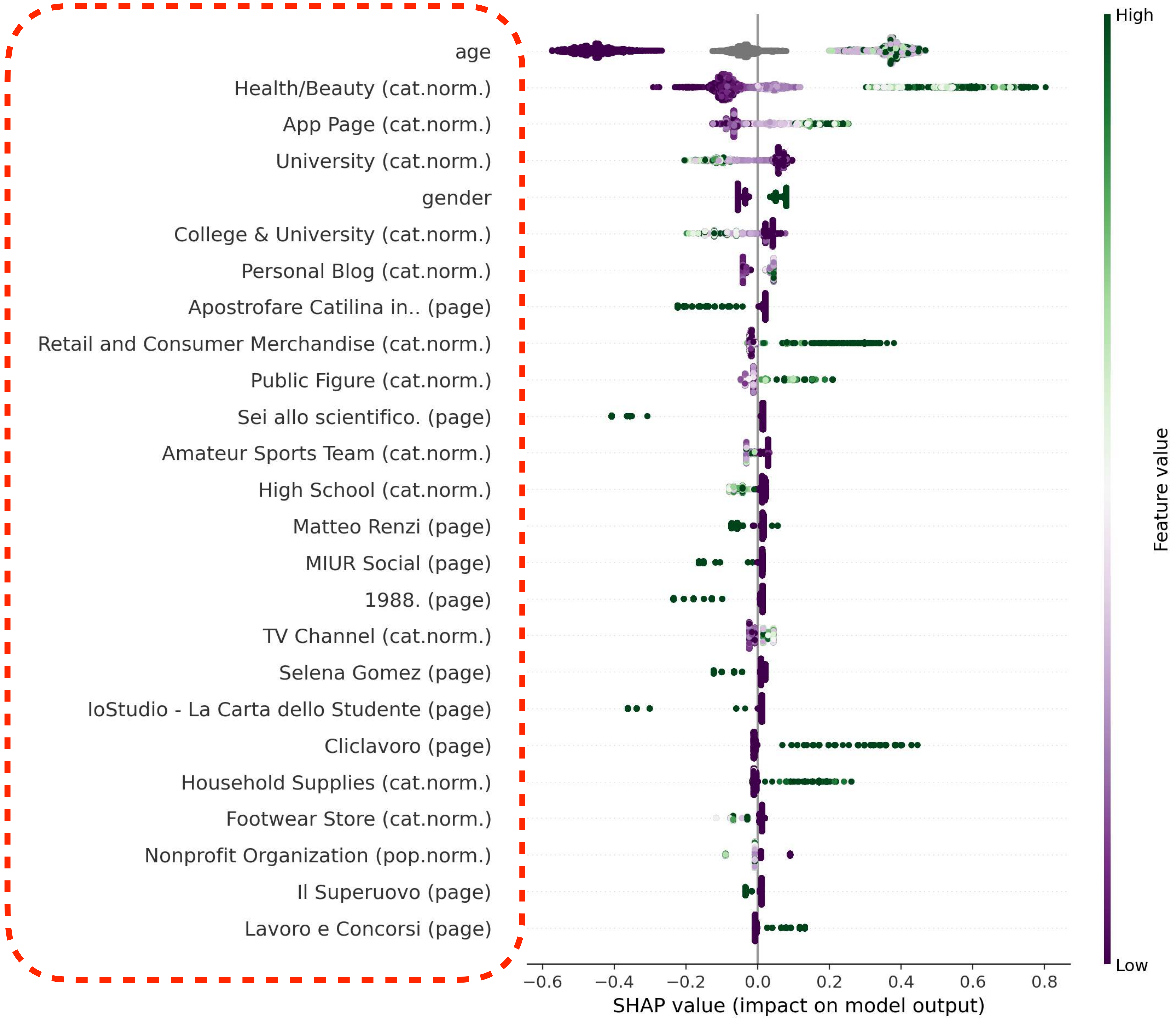

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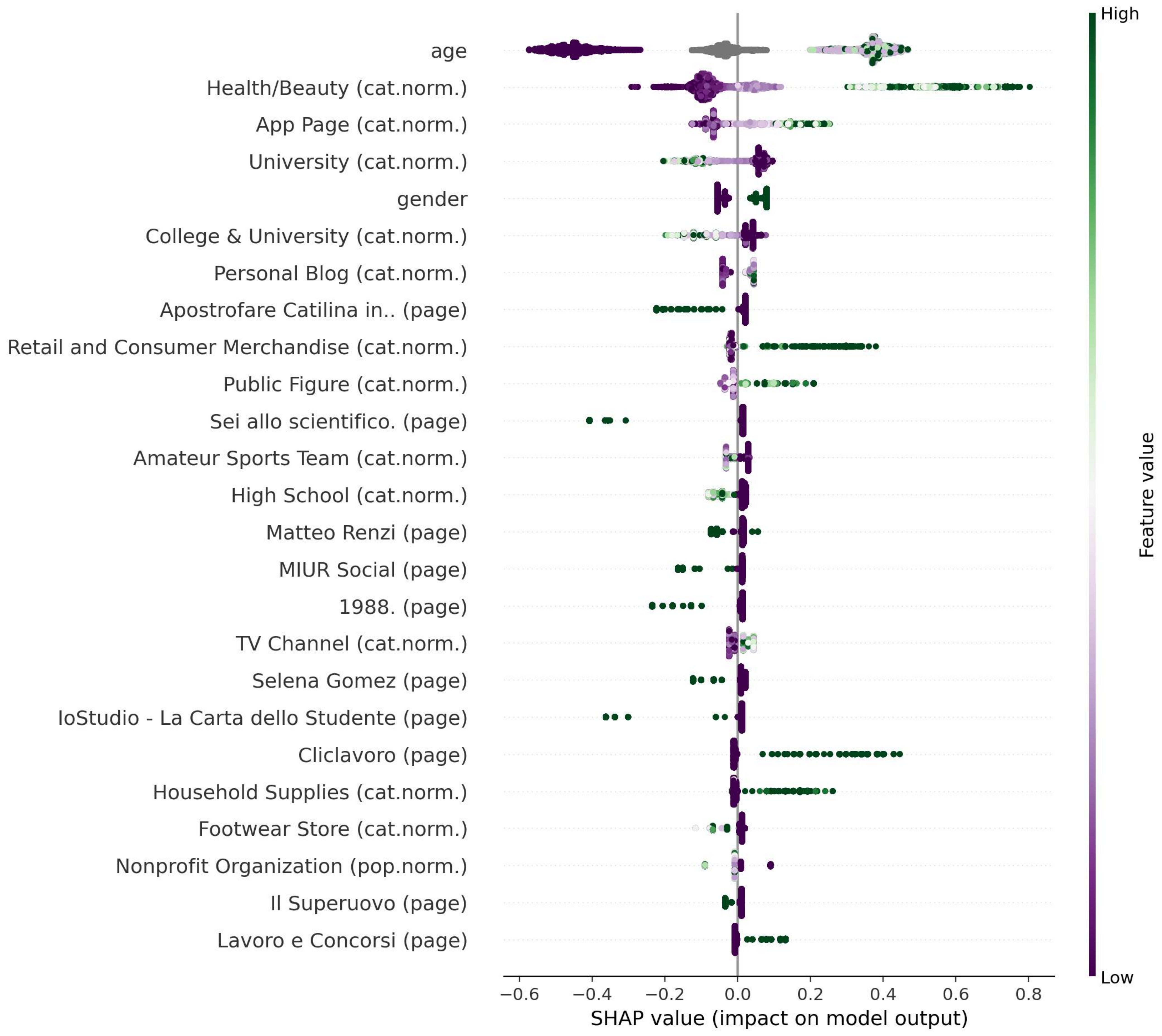

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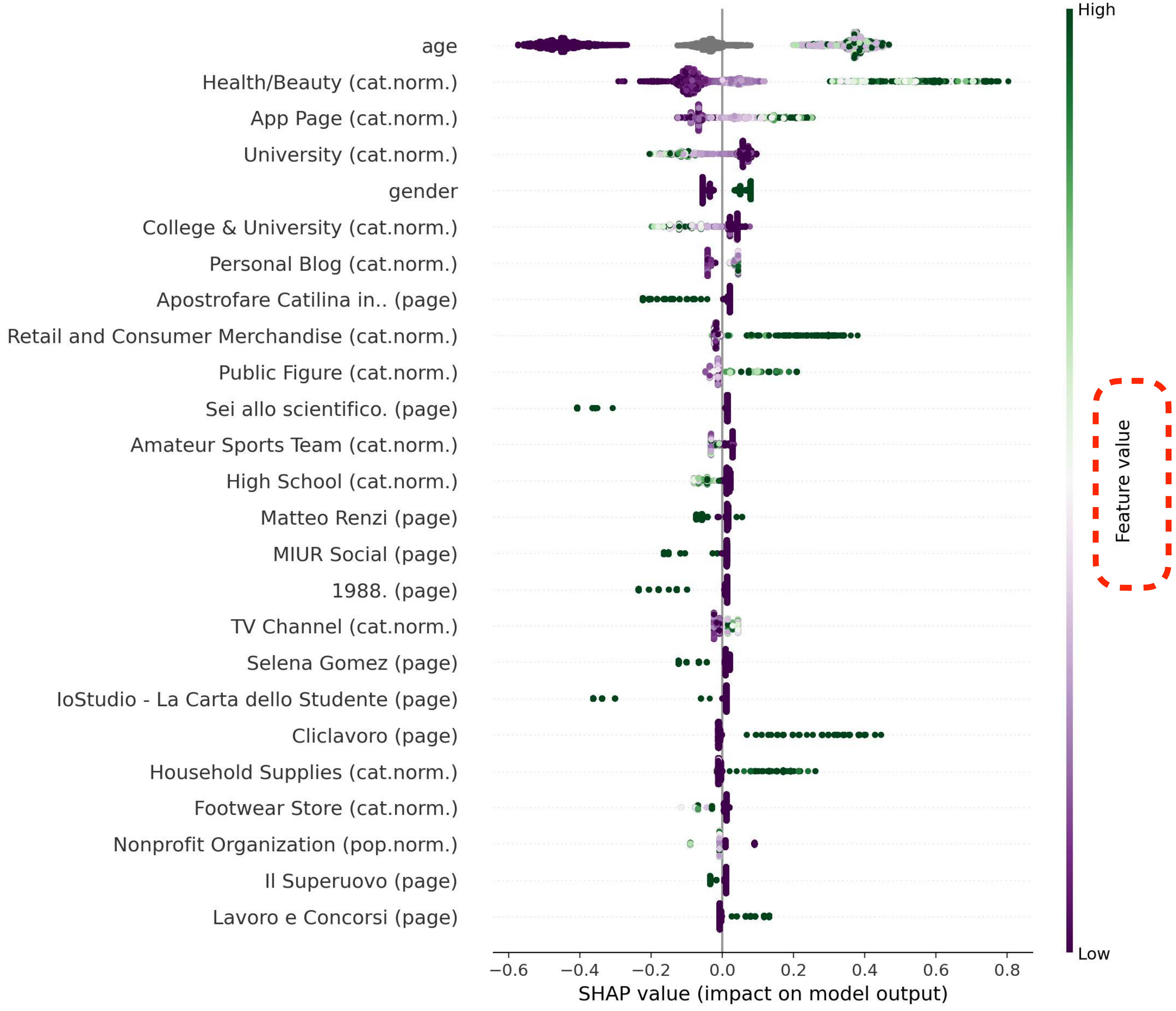

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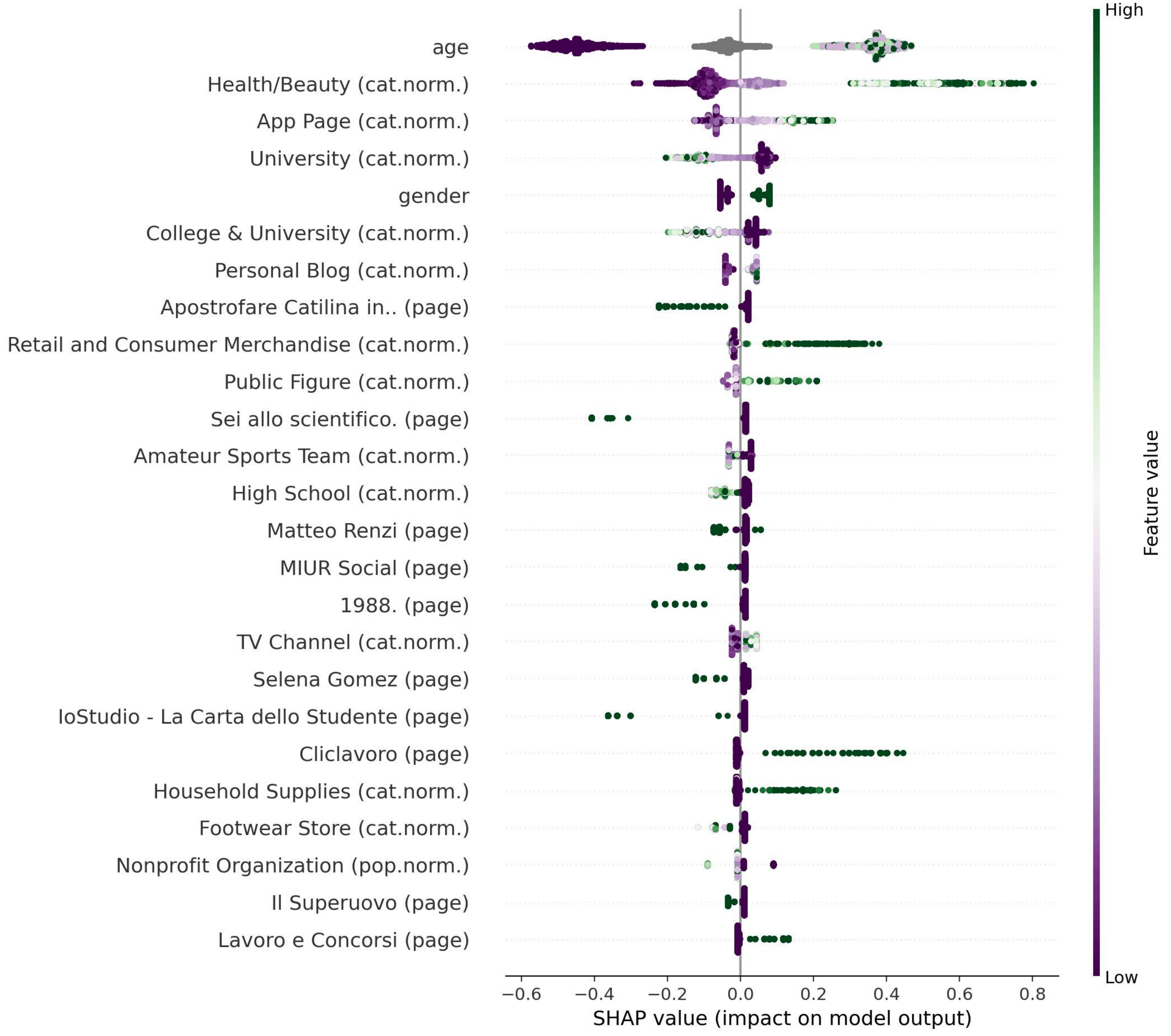

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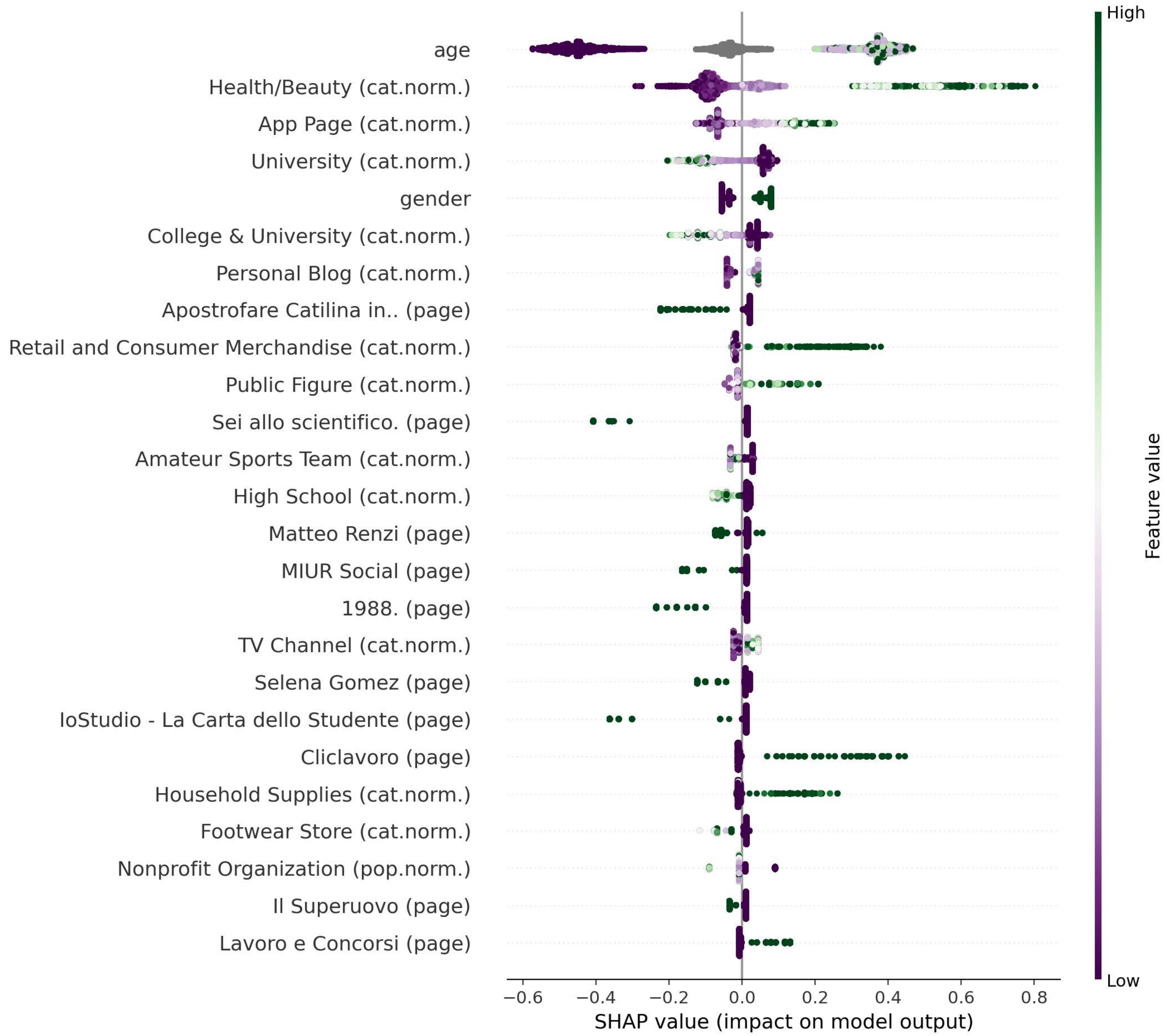

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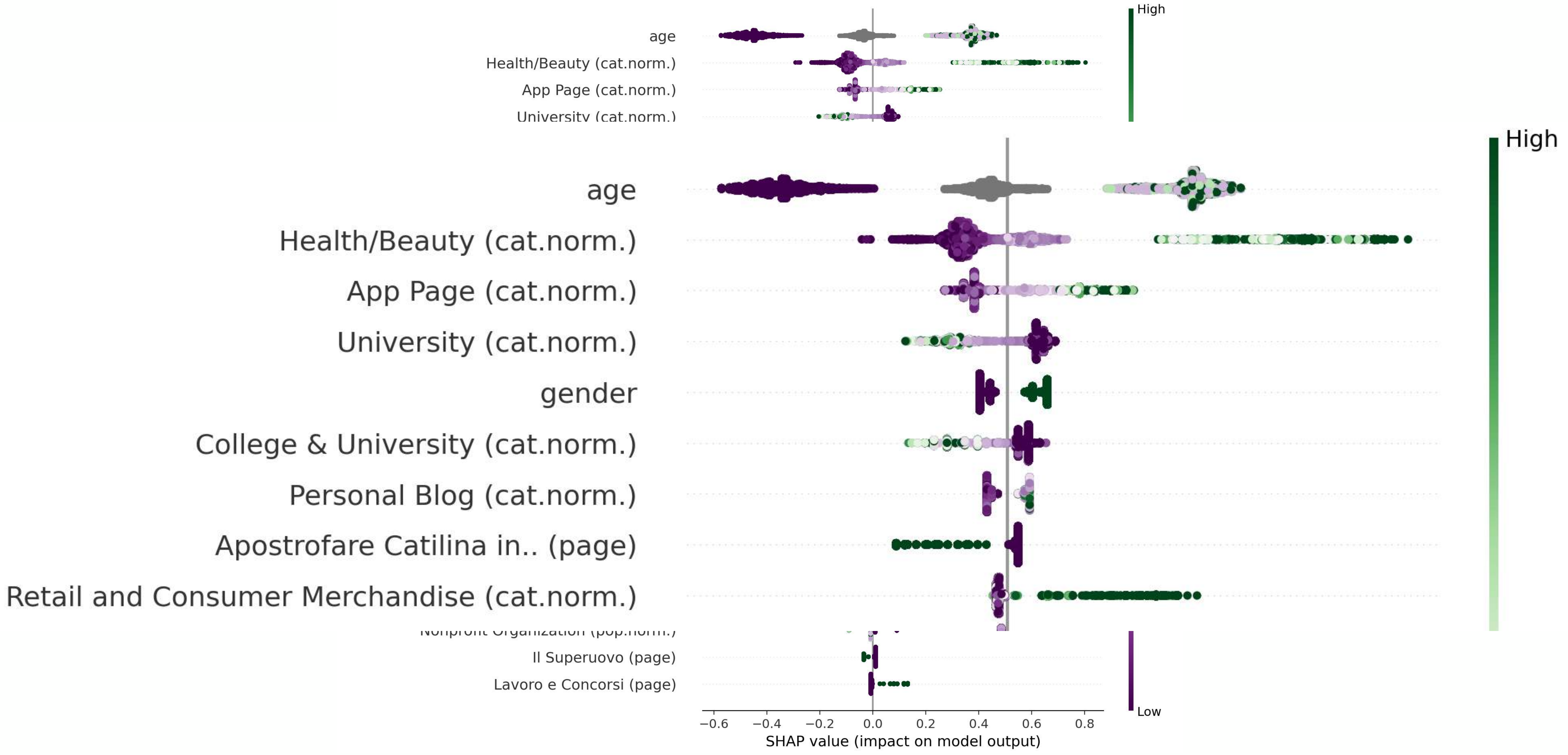

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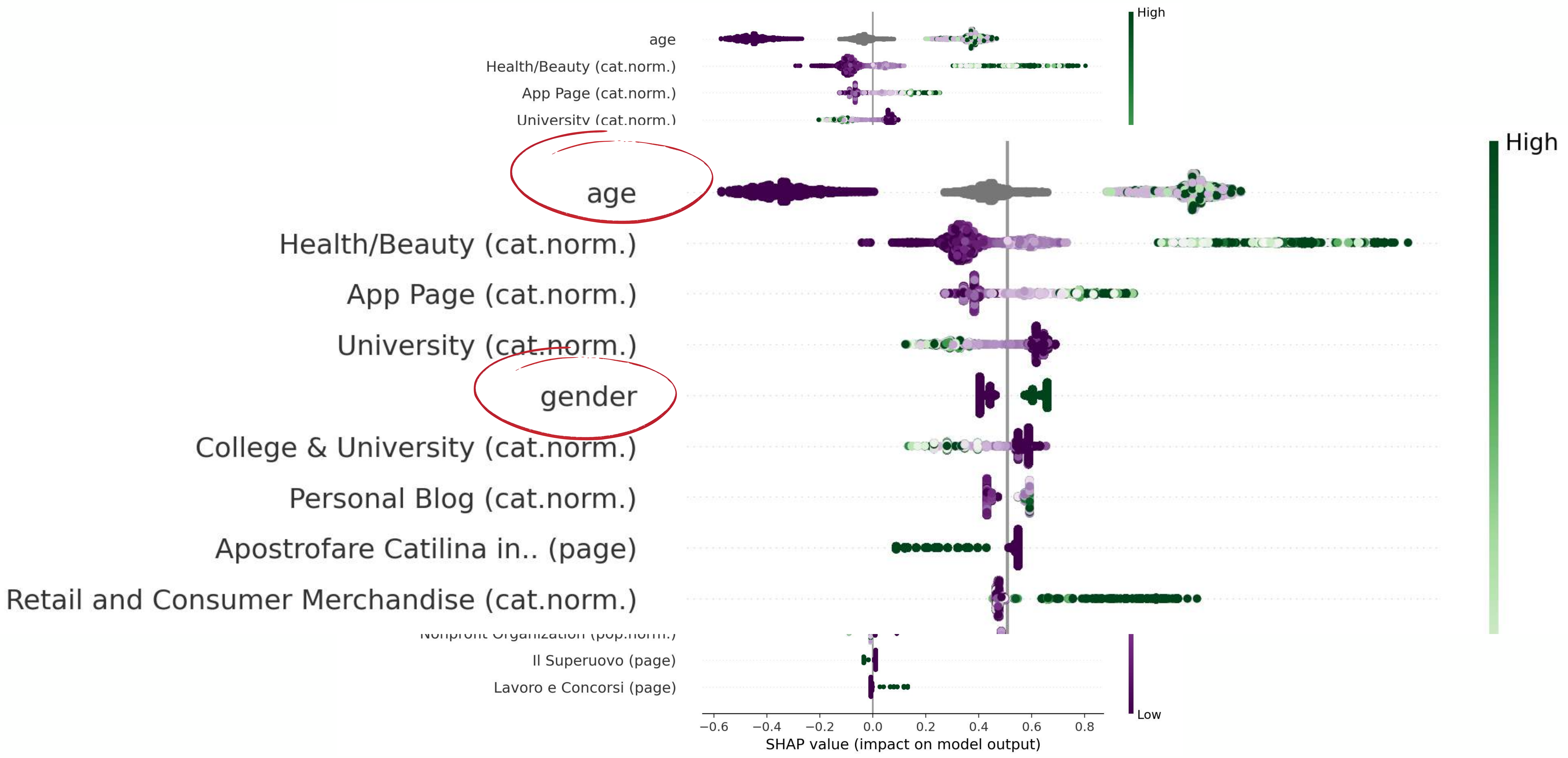

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Non Quantitative Approaches

Awareness of the problem

Spend time understanding models

Team diversity

Don't use ML

Give explanations

Address the root cause

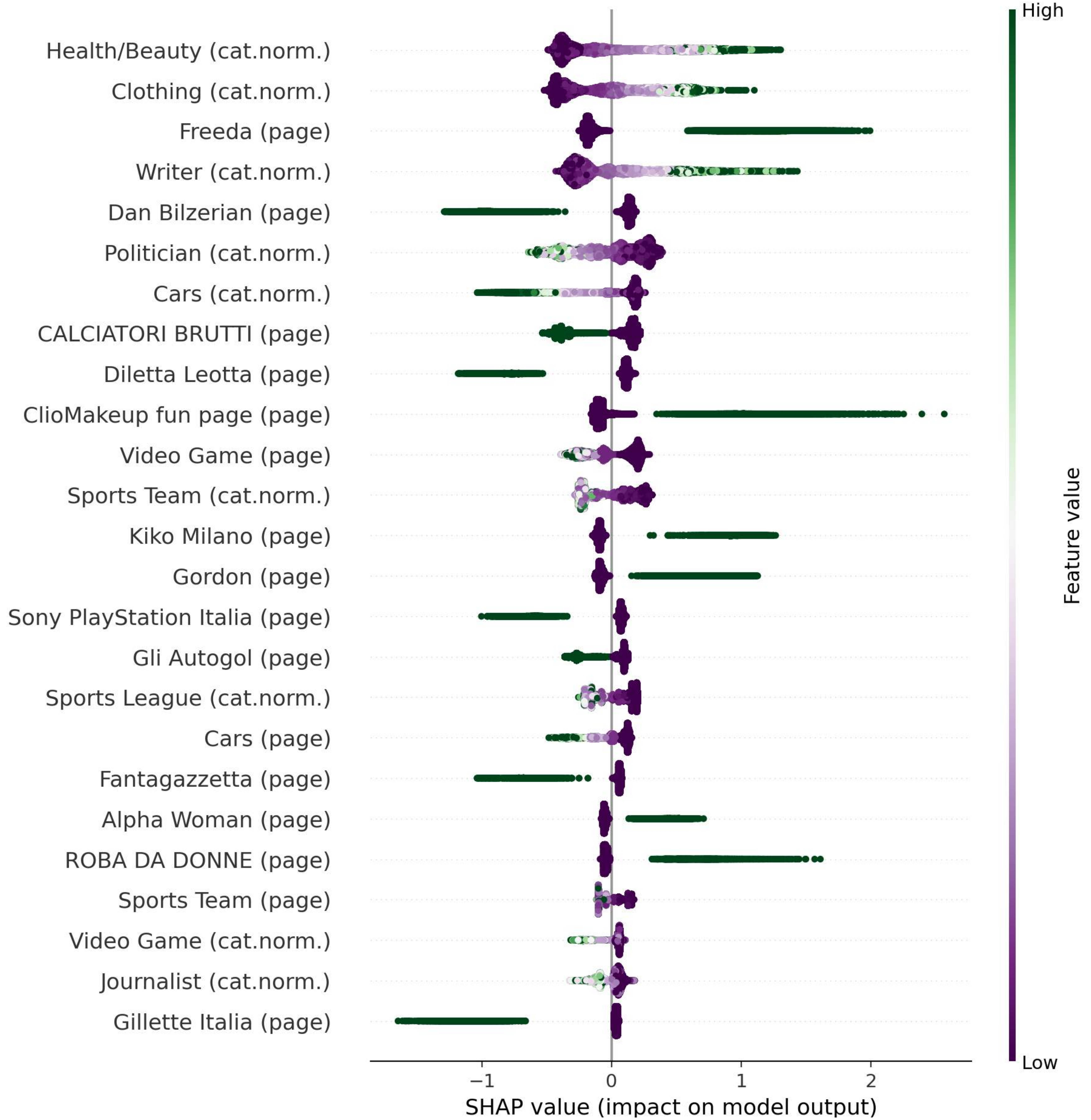
Limit the use of ML

Give opportunity to challenge decisions

Quantitative Approaches

Pre-processing

Modify **data** before training



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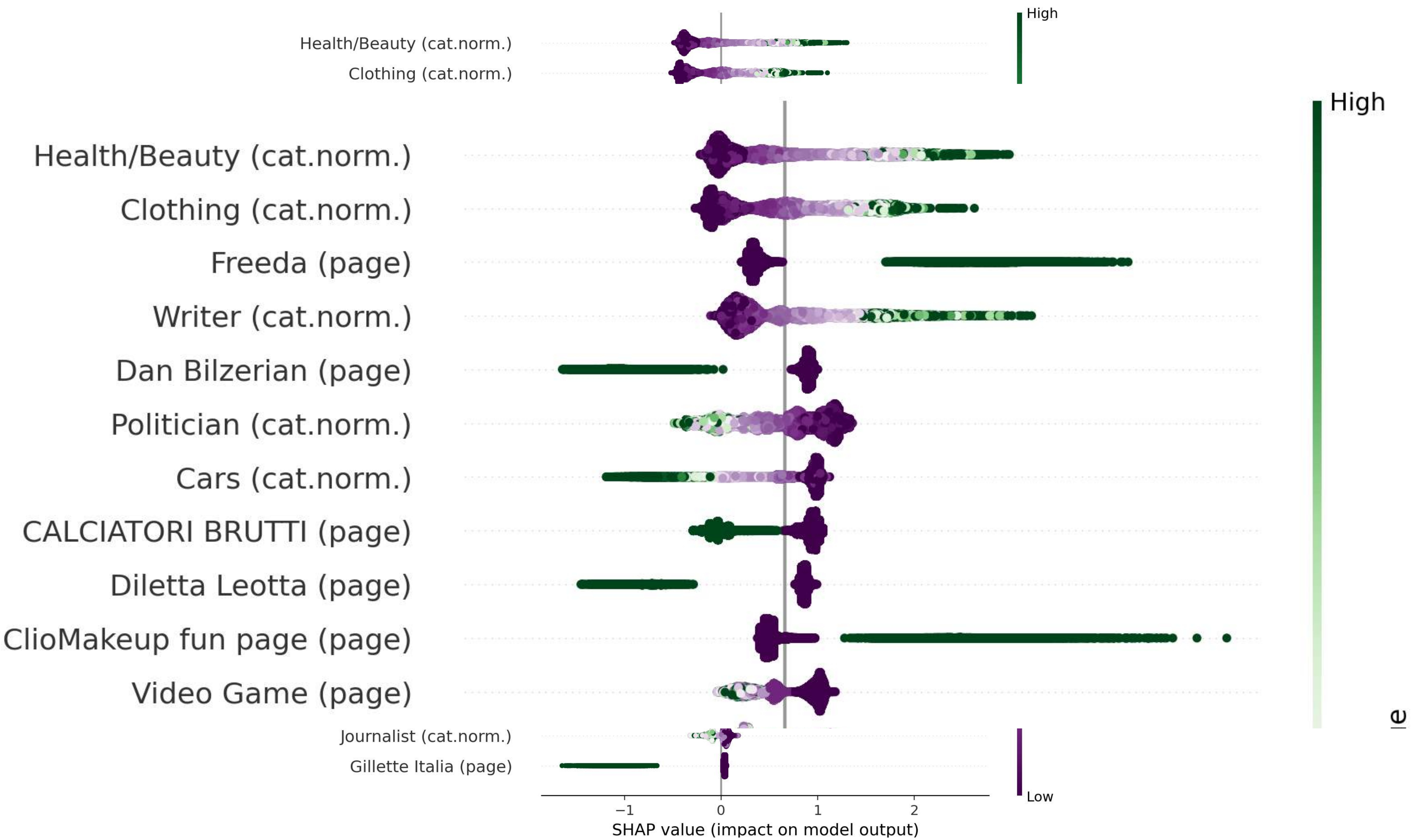

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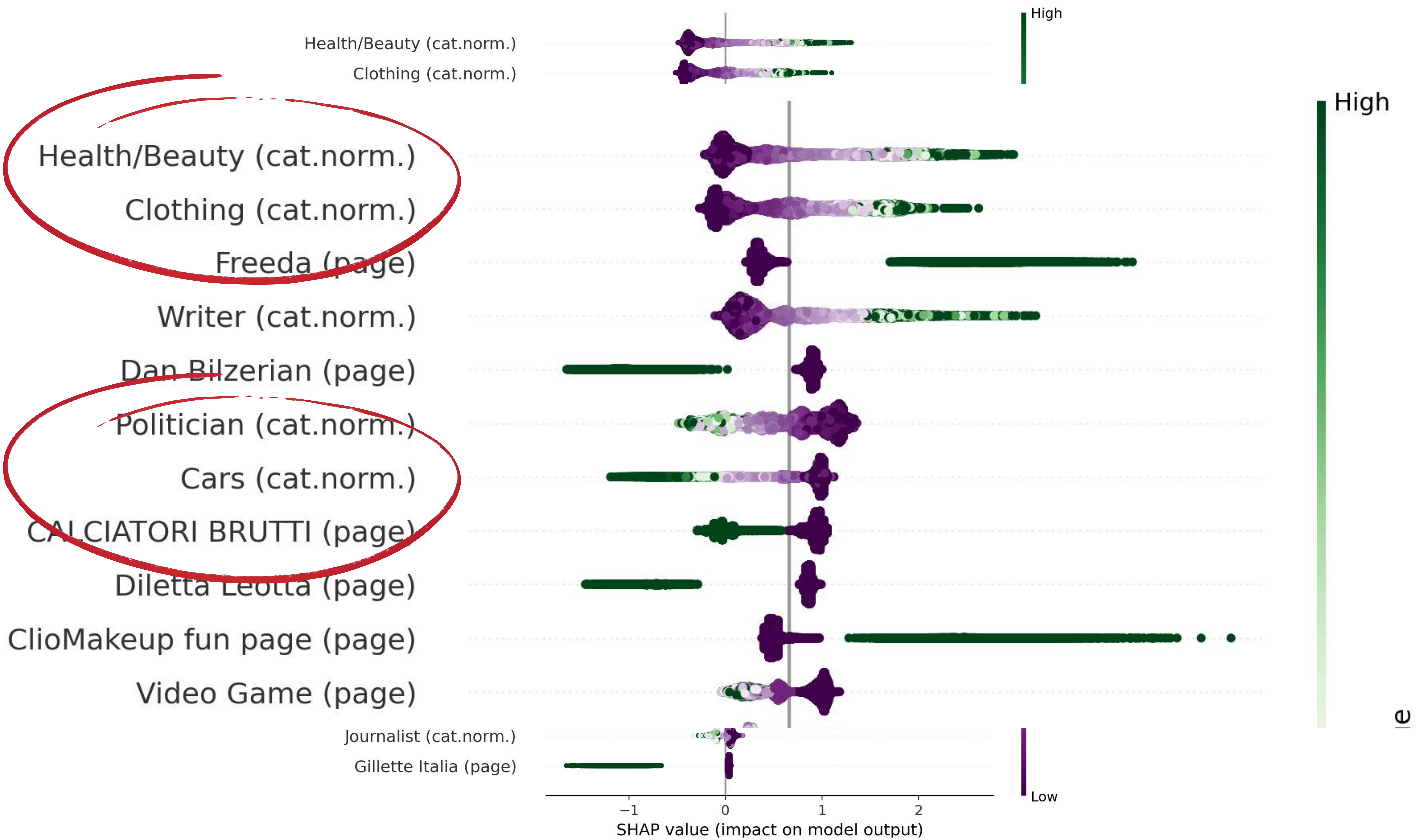

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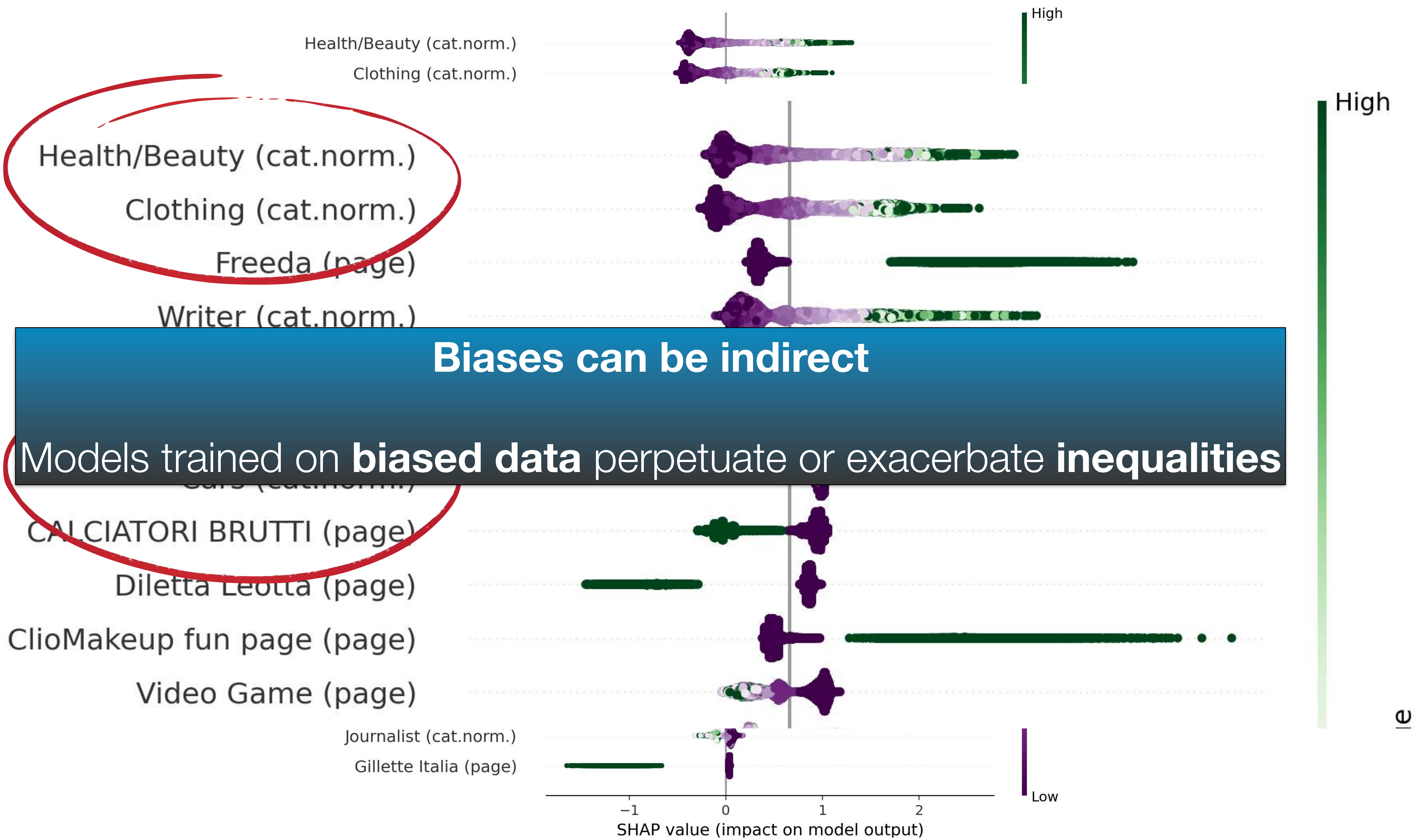

Biases can be indirect

Models trained on **biased data** perpetuate or exacerbate **inequalities**

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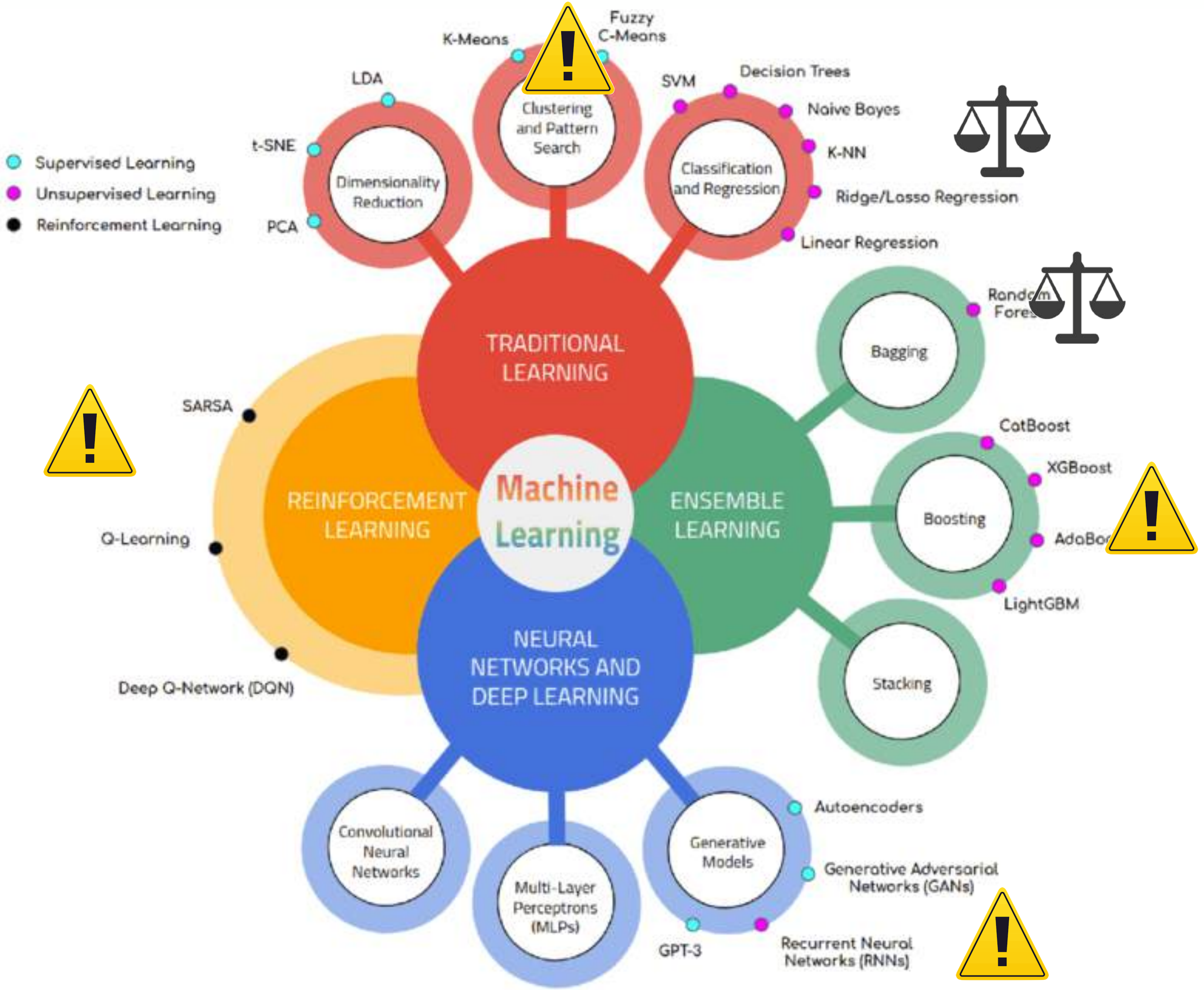
Quantitative Approaches

Pre-processing	Modify **data** before training
In-processing	Modify **algorithm** that is trained

Which models are most appropriate when data are scarce, noisy or sensitive?



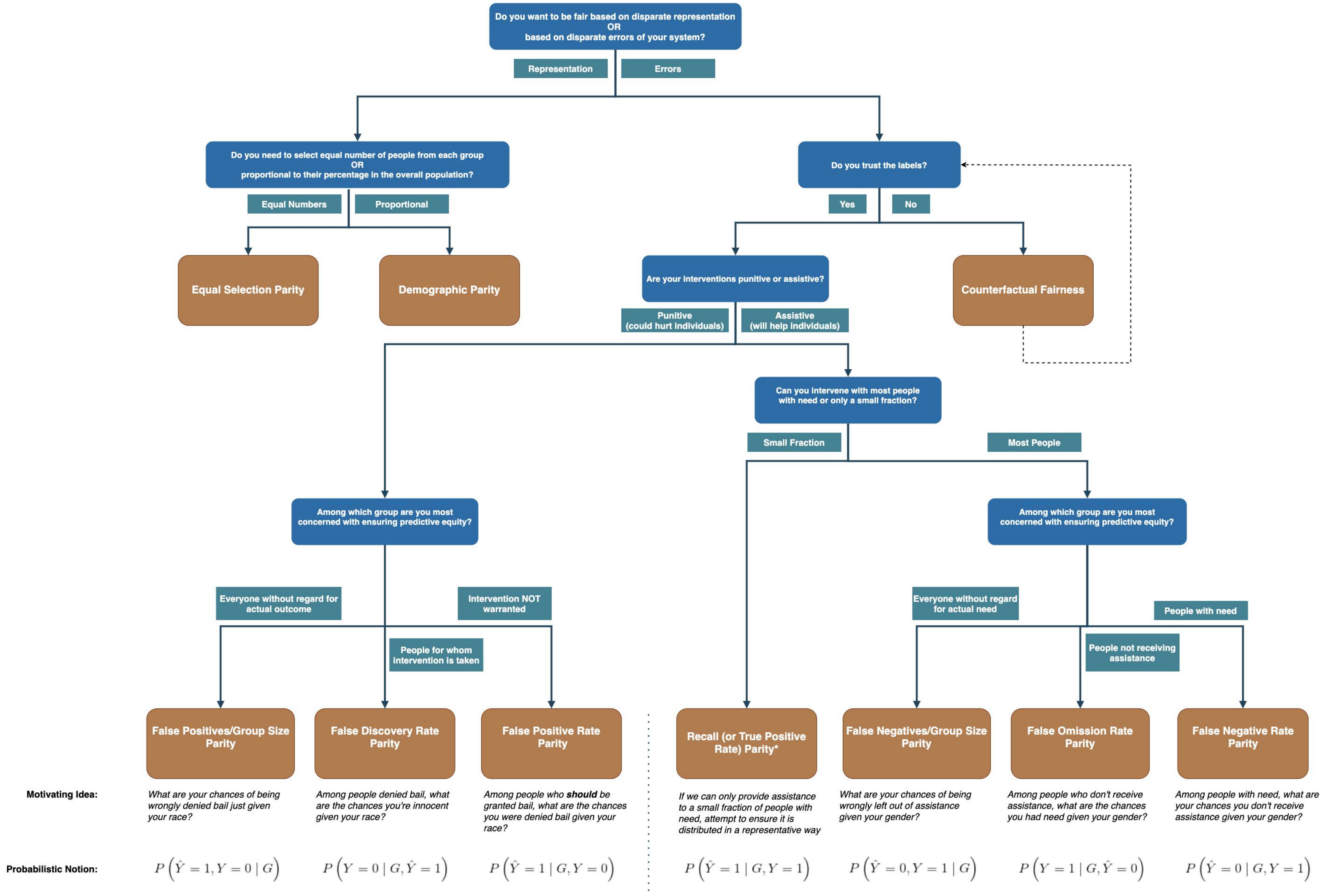
= fairness-constrainable

= for bias

Quantitative Approaches

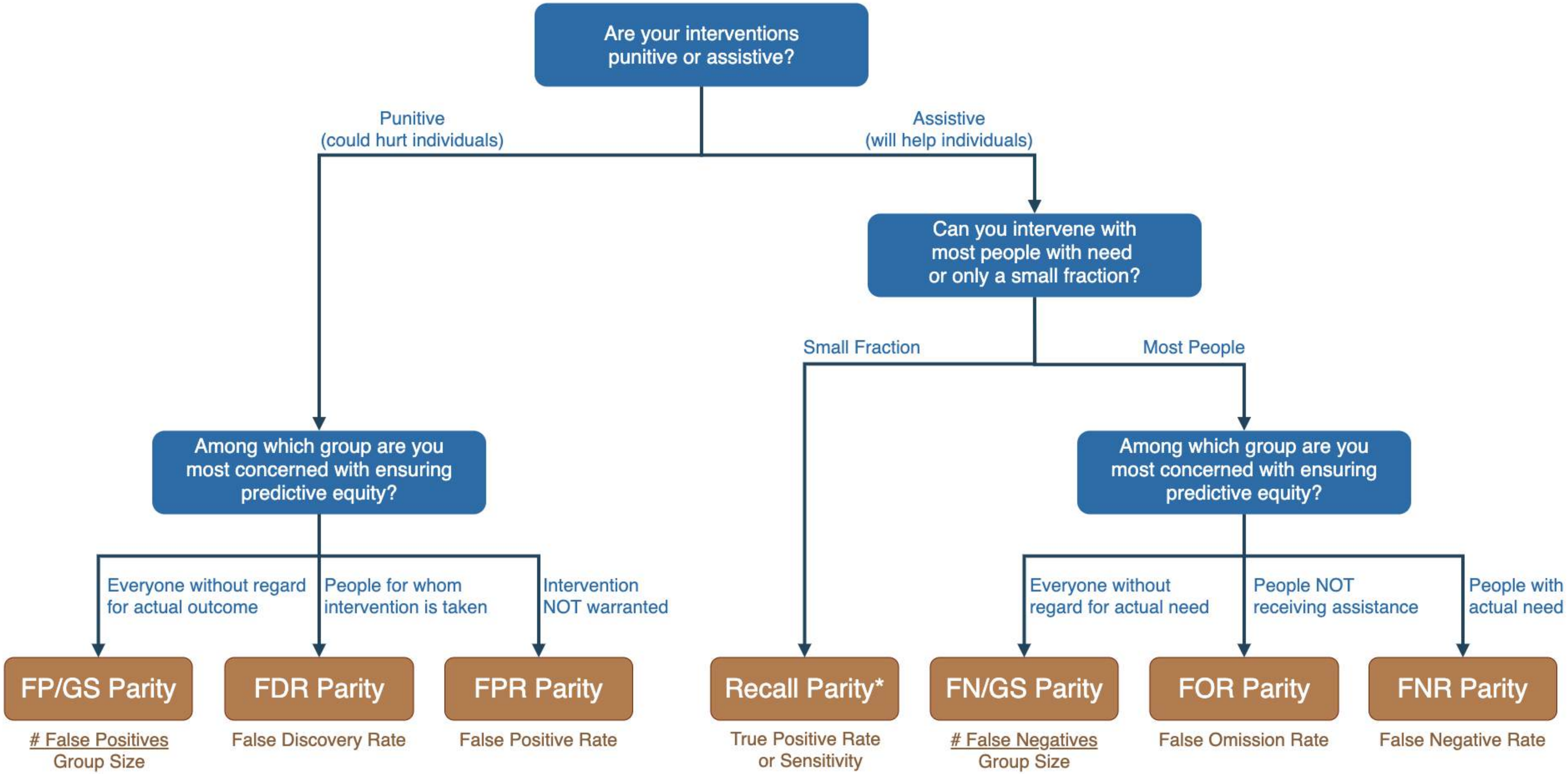
Pre-processing	Modify **data** before training
In-processing	Modify **algorithm** that is trained
Post-processing	Modify **predictions** of model

FAIRNESS TREE



Pedro Saleiro, Benedict Kuester, Abby Stevens, Ari Anisfeld, Loren Hinkson, Jesse London, Rayid Ghani, Aequitas: A Bias and Fairness Audit Toolkit, arXiv preprint arXiv:1811.05577 (2018)

FAIRNESS TREE (Zoomed in)



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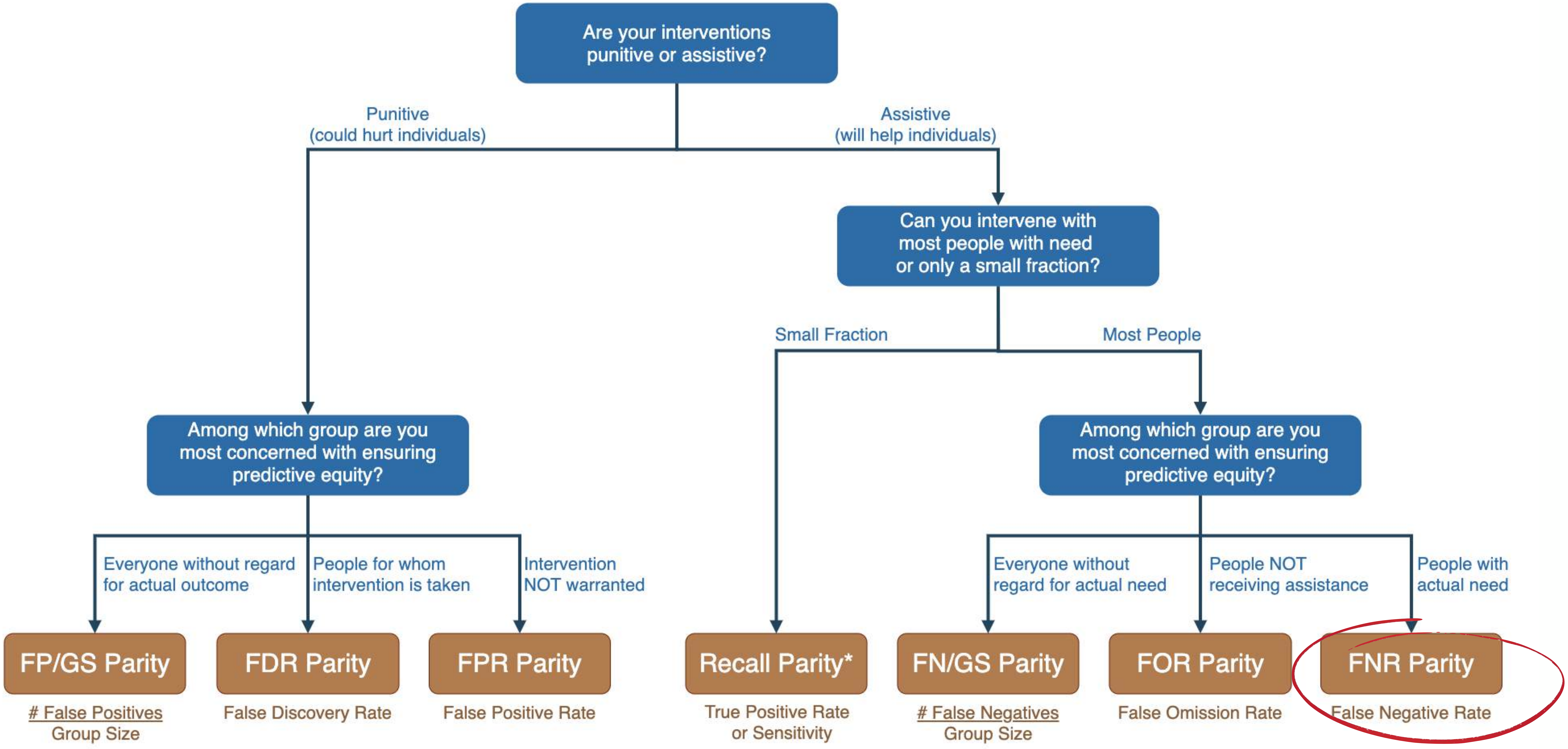

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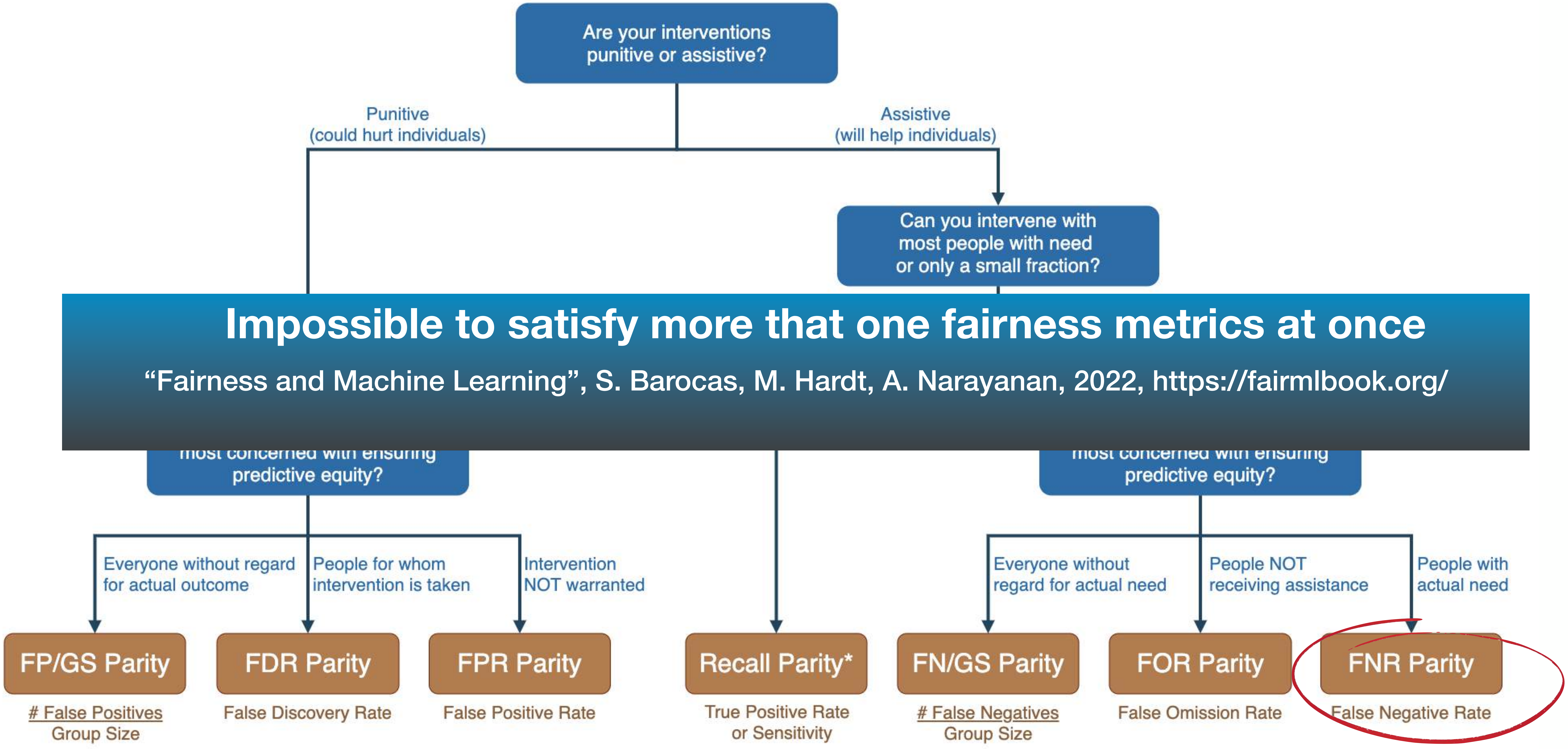


Impossible to satisfy more that one fairness metrics at once

“Fairness and Machine Learning”, S. Barocas, M. Hardt, A. Narayanan, 2022, https://fairmlbook.org/

Parity of Opportunity (FNR Parity)

$$\mathrm{FNR}_g \text{ disp.} = \frac{\mathrm{FNR}_g}{\mathrm{FNR}_{ref.group}}$$
$$= \frac{Pr\left[\hat{Y}=0|Y=1 \wedge G=g\right]}{Pr\left[\hat{Y}=0|Y=1 \wedge G=ref.group\right]}$$

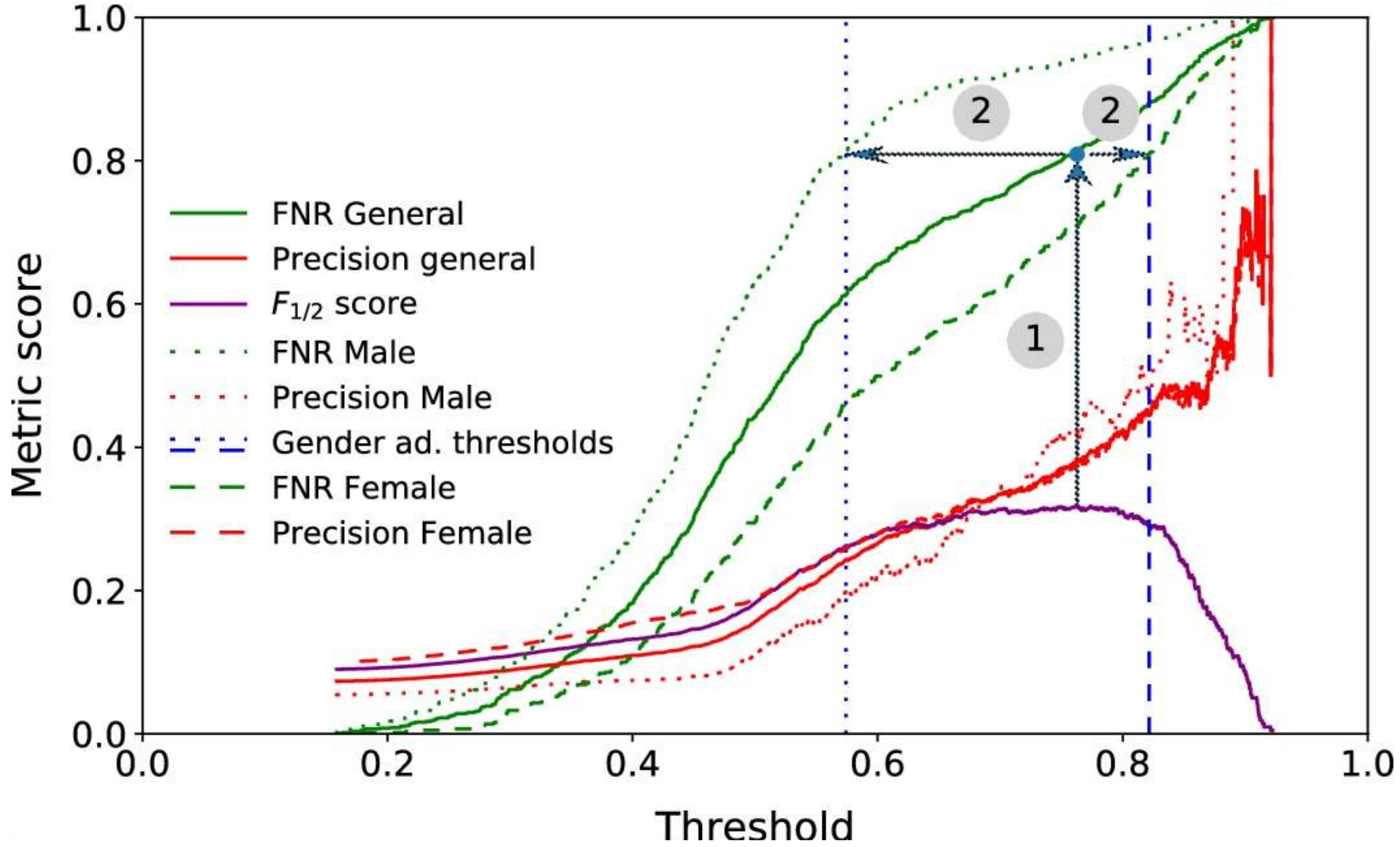
where Y and $\hat{Y}$ represent the real and predicted target values respectively
(“1” represents the unemployed, “0” the employed)

Pragmatic Compromise - ’80% Rule’ - disparity threshold with respect to the reference group

Adaptive Threshold

$$F_\beta = (1+\beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

with β at 0.5 to favour precision



Baeza-Yates R, Ribeiro-Neto B et al (1999) Modern Information Retrieval, vol 463. ACMPress, New York

	Demo	NoDemo	Demo+AT.	NoDemo+AT.
Global Accuracy (Metric: AUC(std))				
Baseline	.50	.50	.50	.50
State of the Art	–	.61(.01) (*)	–	–
Our Approach	.74(.02)	.71(.02)	.74(.02)	.71(.02)
Precision and Recall				
Precision	.16(.02)	.18(.01)	**.26(.05)**	**.25(.03)**
Recall	**.56(.05)**	.48(.02)	.21(.05)	.22(.04)
Demographic accuracy (Metric: AUC(std))				
Gender (M)	.66(.05)	.64(.04)	.66(.05)	.64(.04)
Gender (F)	.78(.02)	.76(.02)	.78(.02)	.76(.02)
Age (17-24)	.70(.08)	.69(.08)	.70(.08)	.69(.08)
Age (25-34)	.66(.05)	.65(.05)	.66(.05)	.65(.05)
Age (35-44)	.74(.09)	.73(.08)	.74(.09)	.73(.08)
Age (45-54)	.61(.17)	.54(.16)	.61(.17)	.54(.16)
Age (55+)	.46(.31)	.46(.29)	.46(.31)	.46(.29)
Fairness (Metric: $\frac{FNR}{FNR_{ref}}$)				
Gender (ref.class: Male)				
Female	.47(.11)	.58(.14)	**1.0(.07)**	**1.02(.14)**
Age (ref.class: 17–24)				
25-34	.35(.08)	.62(.12)	.75(.09)	**.80(.08)**
35-44	.26(.12)	.49(.2)	.71(.09)	.73(.1)
45-54	.41(.24)	**.82(.35)**	**.82(.17)**	**.84(.19)**
55+	.59(.36)	**.99(.42)**	**.82(.18)**	**.91(.19)**

	Demo	NoDemo	Demo+AT.	NoDemo+AT.
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Baseline	.50	.50	.50	.50
State of the Art	–	.61(.01) (*)	–	–
Our Approach	.74(.02)	.71(.02)	.74(.02)	.71(.02)
Precision and Recall				
Precision	.16(.02)	.18(.01)	**.26(.05)**	**.25(.03)**
Recall	**.56(.05)**	.48(.02)	.21(.05)	.22(.04)
Demographic accuracy (Metric: AUC(std))				
Gender (M)	.66(.05)	.64(.04)	.66(.05)	.64(.04)
Gender (F)	.78(.02)	.76(.02)	.78(.02)	.76(.02)
Age ([illegible])	[illegible]	[illegible]	[illegible]	[illegible]
Age (55+)	.46(.31)	.46(.29)	.46(.31)	.46(.29)
Fairness (Metric: $\frac{FNR}{FNR_{ref}}$)				
Gender (ref.class: Male)				
Female	.47(.11)	.58(.14)	**1.0(.07)**	**1.02(.14)**
Age (ref.class: 17–24)				
25-34	.35(.08)	.62(.12)	.75(.09)	**.80(.08)**
35-44	.26(.12)	.49(.2)	.71(.09)	.73(.1)
45-54	.41(.24)	**.82(.35)**	**.82(.17)**	**.84(.19)**
55+	.59(.36)	**.99(.42)**	**.82(.18)**	**.91(.19)**

Gender (ref.class: Male)				
Female	.47(.11)	.58(.14)	**1.0(.07)**	**1.02(.14)**

	Demo	NoDemo	Demo+AT.	NoDemo+AT.
Global Accuracy (Metric: AUC(std))				
Baseline	.50	.50	.50	.50
State of the Art	–	.61(.01) (*)	–	–
Our Approach	.74(.02)	.71(.02)	.74(.02)	.71(.02)
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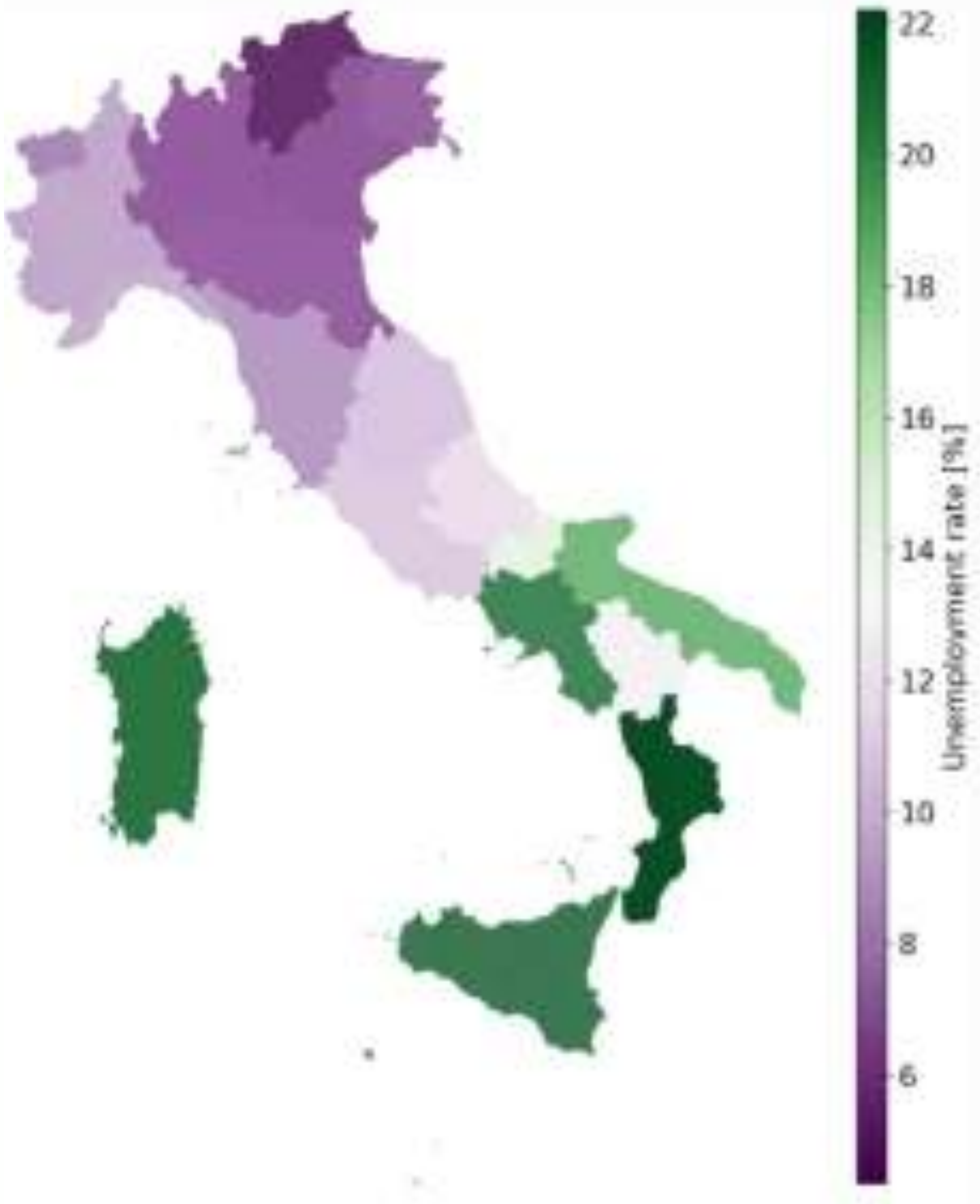
Limitation: Multiple attributes lead to very sparse data points => identification



(c) Unemployment Rate

Gender fairness per region in the NoDemo (left) and NoDemo+Thresh. (right) models. Gender fairness is computed as the FNR of females in relation to that of males. The color extremities are both unfair (Color figure online)


RAW #63
Erikli
adidas
YAMAHA

Can we automatically identify places in humanitarian reports?

Belliardo, E., Kalimeri, K. and Mejova, Y., 2023, September. Leave no Place Behind: Improved Geolocation in Humanitarian Documents. In *Proceedings of the 2023 ACM Conference on Information Technology for Social Good* (pp. 31-39).

Can we automatically identify places in humanitarian reports?

15,661 documents from 45 emergencies from 33 countries

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the extraction of text fragments that may be a location ("toponyms")

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the disambiguation of the toponym to a specific geographic location

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- Total of 11,025 toponyms

Gritta, Milan, Mohammad Taher Pilehvar, and Nigel Collier. "A pragmatic guide to geoparsing evaluation: Toponyms, Named Entity Recognition and pragmatics." *Language resources and evaluation* 54 (2020): 683-712.

Geocoding (identifying geolocations/GPS)

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561 unique document/toponym match pairs from 39 documents, with 474 having non-empty matches, spanning 78 countries

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RoBERTa F1 score .72 (.02) on exact matches and .85(.02) on partial matches.

roBERTa$_{tuned}$	roBERTa$_{baseline}$	Spacy$_{tuned}$	Spacy$_{baseline}$
1. two VOS vessels. Two will be located on board the VOS Theia, two will be located at Aden port, and one will ...			
None ✓	VOS Theia	None ✓	None ✓
2. ... and volatile in June, with tensions between the Syrian Government and 'reconciled' non-state armed groups reported ...			
None✓	Syrian Government	None ✓	None ✓
3. The US Government Congratulates Buhari in Spite of Violent and Corrupt Election			
None✓	None✓	None✓	US
*4. Plateau(5), Taraba(3), Gombe(1), Kaduna(1), **Kwara**(1), FCT(1), Benue(2), Rivers(1) Kogi(1) ...*			
Kwara✓	None	None	Kwara(1
*5. However, clashes intensified in **At Tuhayat and Zabid districts** of Hudaydah city ...*			
At Tuhayat and Zabid districts ✓	At Tuhayat	Tuhayat	None
*6. sources report 17 dead and eight wounded, currently in treatment at **Am-Timan hospital***			
Am-Timan hospital✓	None	Am-Timan hospital✓	None

roBERTa$_{tuned}$	roBERTa$_{baseline}$	Spacy$_{tuned}$	Spacy$_{baseline}$
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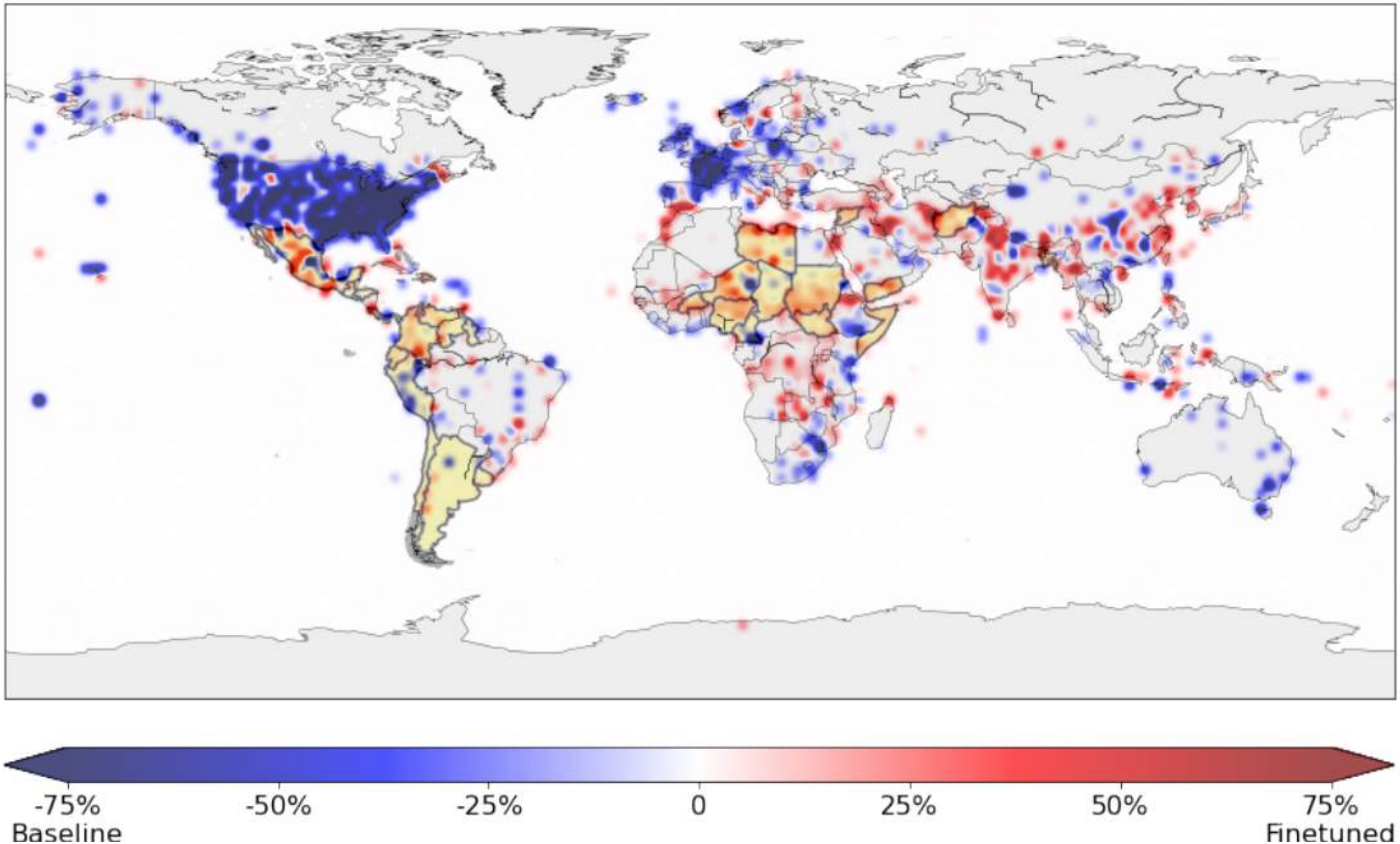
Am-Timan hospital✓	None	Am-Timan hospital✓	None

FineTuned Models F1 score .87 on exact matches and .97 on partial matches.



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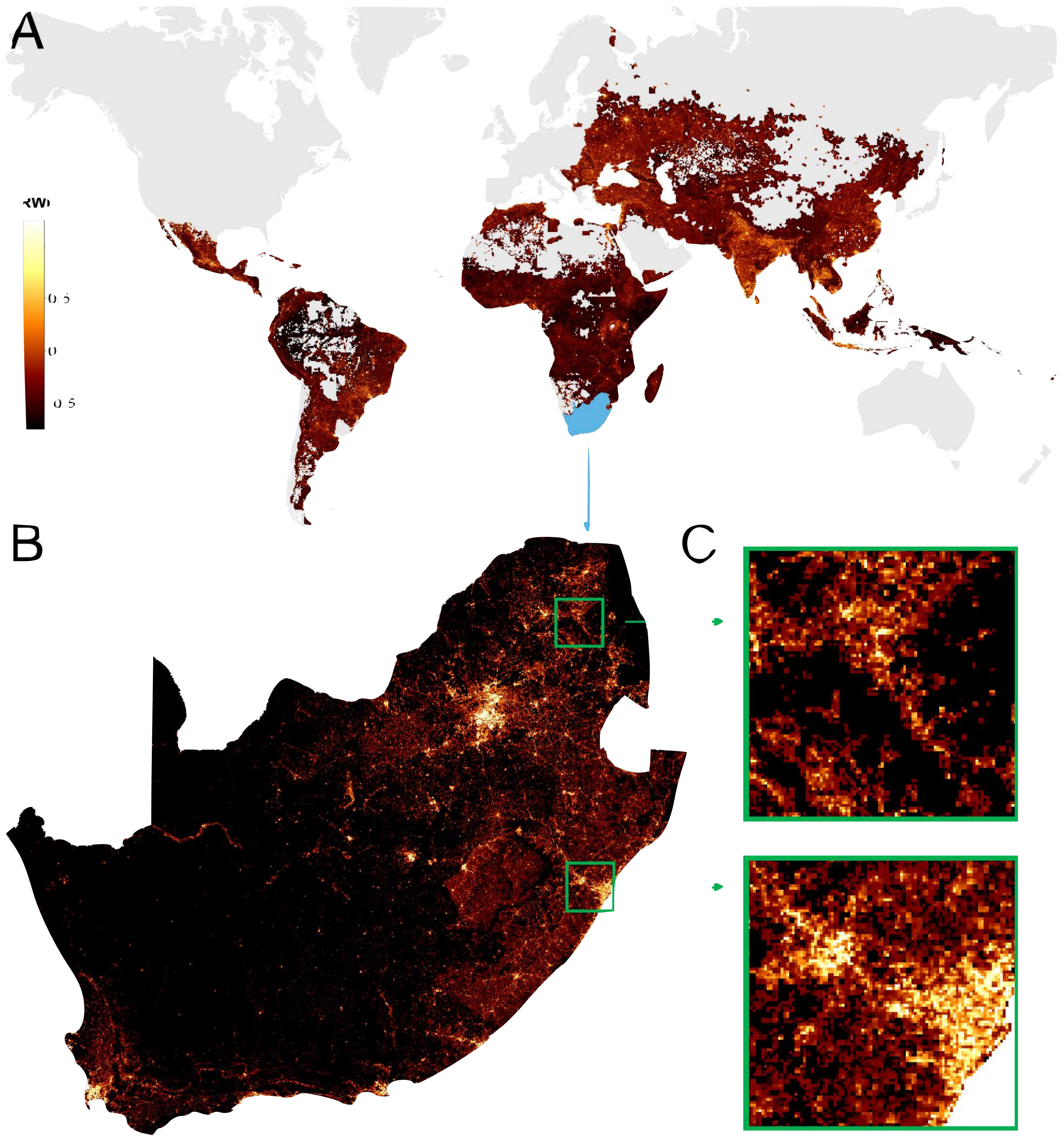
Relative Wealth Index



Chi, G., Fang, H., Chatterjee, S. and Blumenstock, J.E., 2022. Microestimates of wealth for all low-and middle-income countries. *Proceedings of the National Academy of Sciences*, *119*(3), p.e2113658119.

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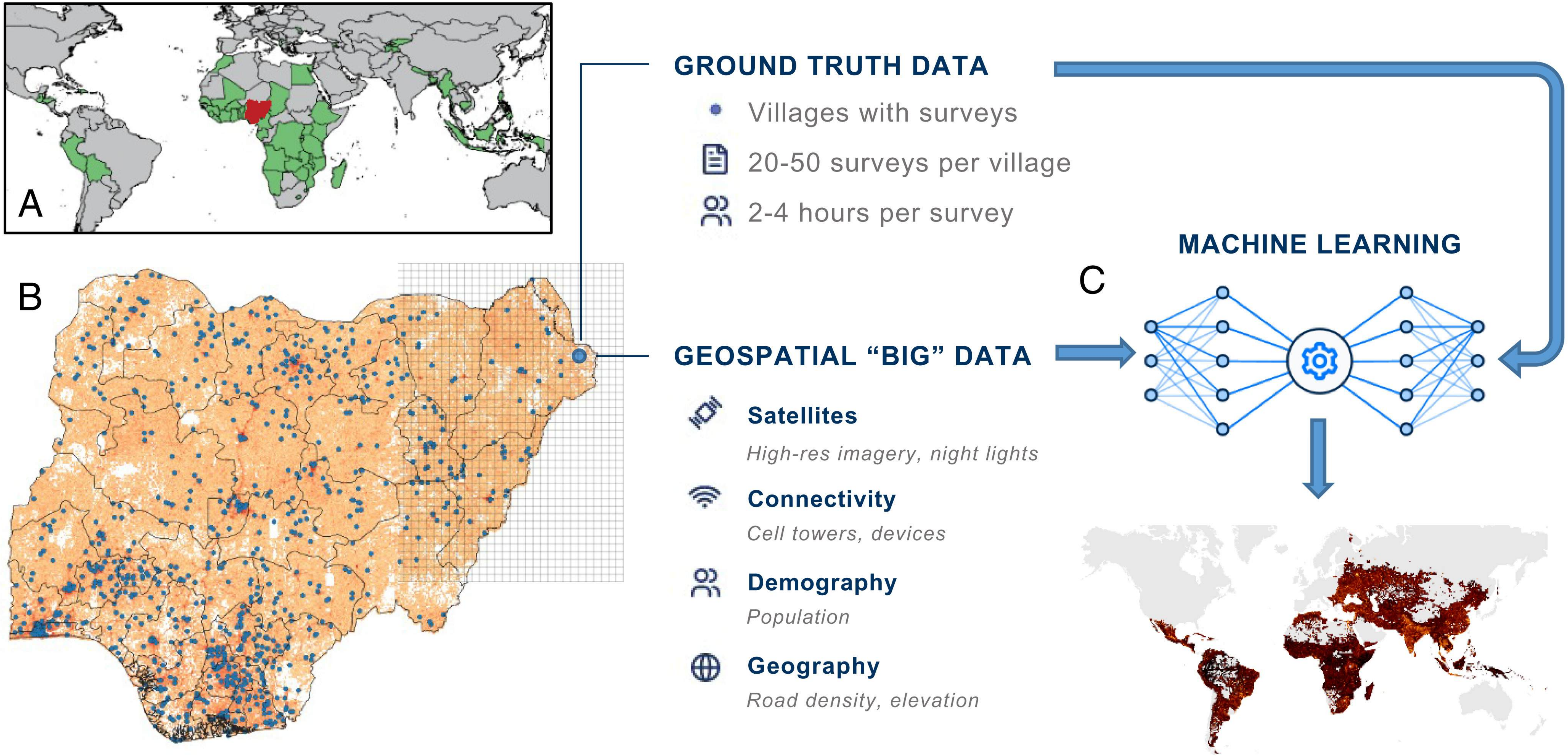

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Could we possibly employ the RWI index in an social assistance programme?

Sartirano, D., Kalimeri, K., Cattuto, C., Delamónica, E., Garcia-Herranz, M., Mockler, A., Paolotti, D. and Schifanella, R., 2023. Strengths and limitations of relative wealth indices derived from big data in Indonesia. *Frontiers in big Data*, *6*, p.1054156.

About the Social Protection Card

The Social Protection Card (KPS) is a card issued by the government to poor households.

As a marker of poor households, the KPS card is useful for accessing government assistance as part of the Subsidised Rice for the Poor Programme, more commonly known as Raskin. Moreover, KPS can also be used to access the Cash for Poor Students (BSM) and Unconditional Cash Transfers (BLSM).

The government issued KPS to 15.5 million poor and vulnerable households, equivalent to 25 percent of households with the lowest socio-economic status in Indonesia.

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Poverty Surveys

- not always measuring the same **aspects** of poverty (DHS, SUSENAS)
- Index estimation methods are **not standard**
- Different **time frequency** and **spatial aggregation**

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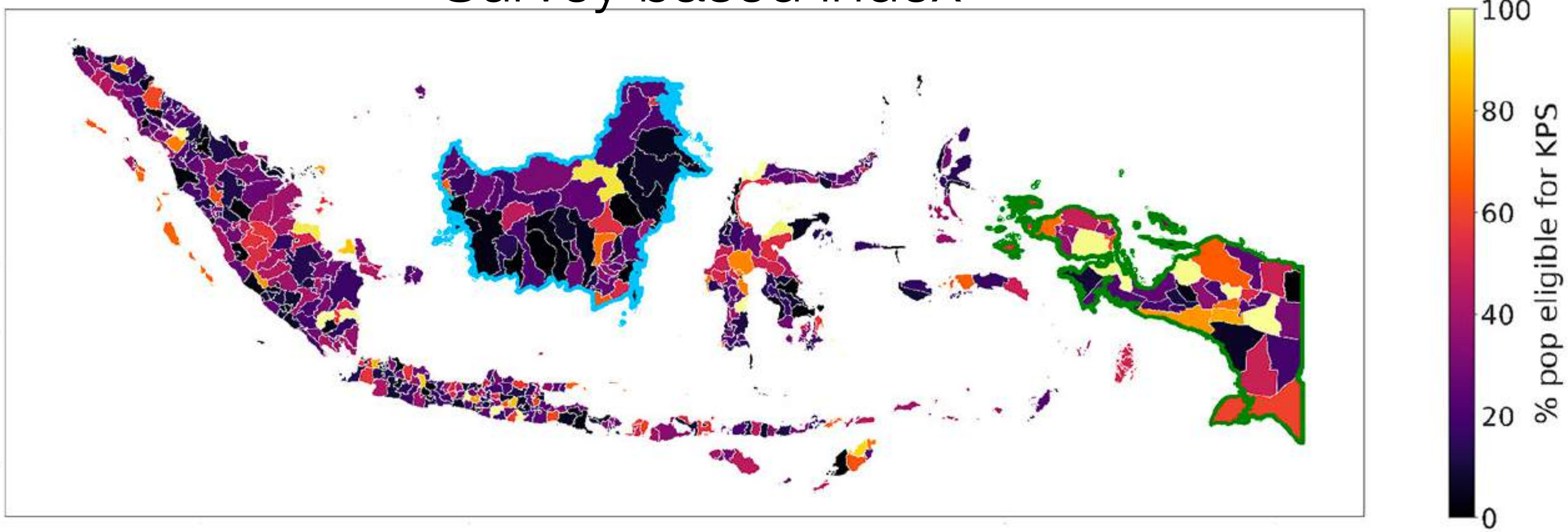
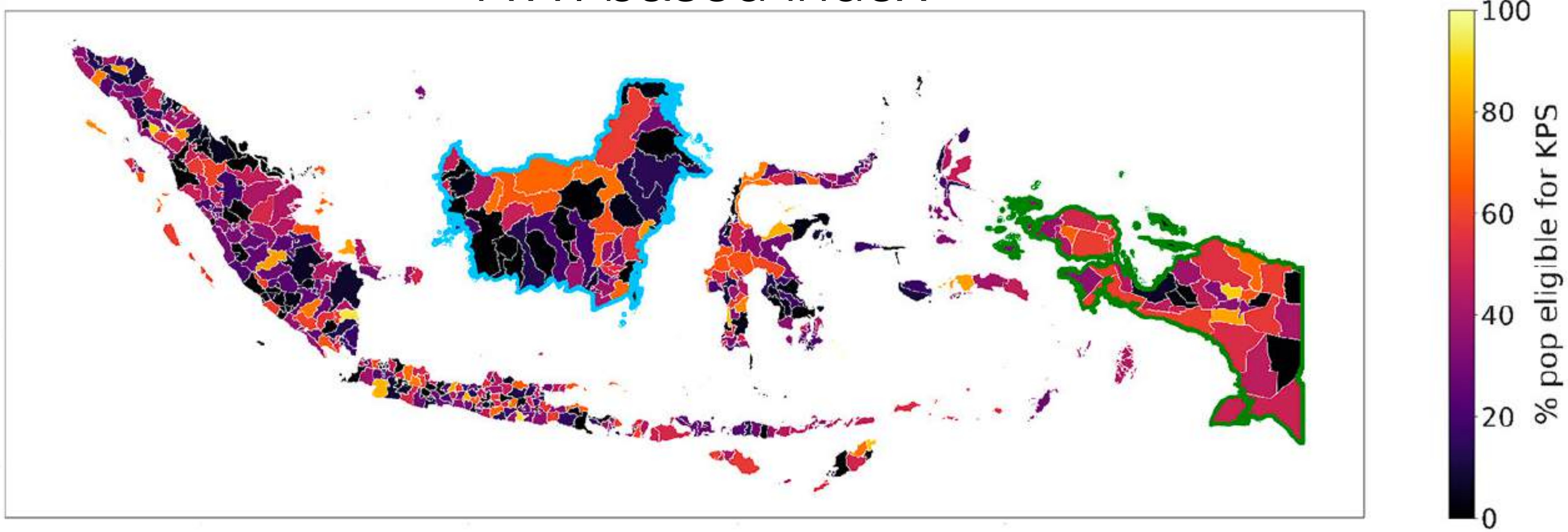
Lack of a unique “ground-truth”

Survey based index



RWI based index



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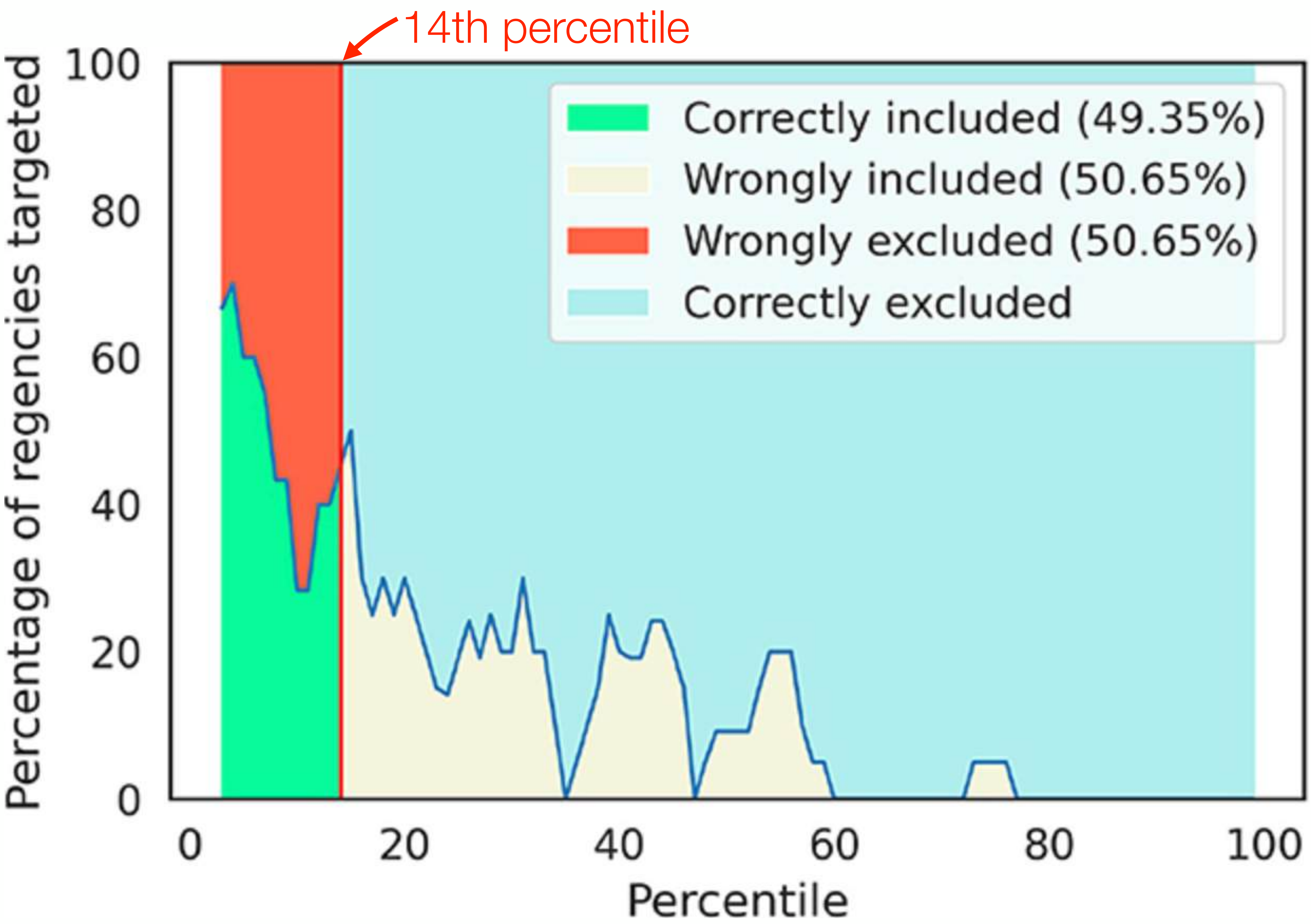
Accuracy vs Fairness

- Good performance in population prediction (ranked correlations rho= .70 - .75) between the Survey and RWI indices

- Good spatial representation with .72 -.79 AUROC in province and regency aggregations


14th percentile
Percentage of regencies targeted
Percentile
Correctly included (49.35%)
Wrongly included (50.65%)
Wrongly excluded (50.65%)
Correctly excluded
0
20
40
60
80
100

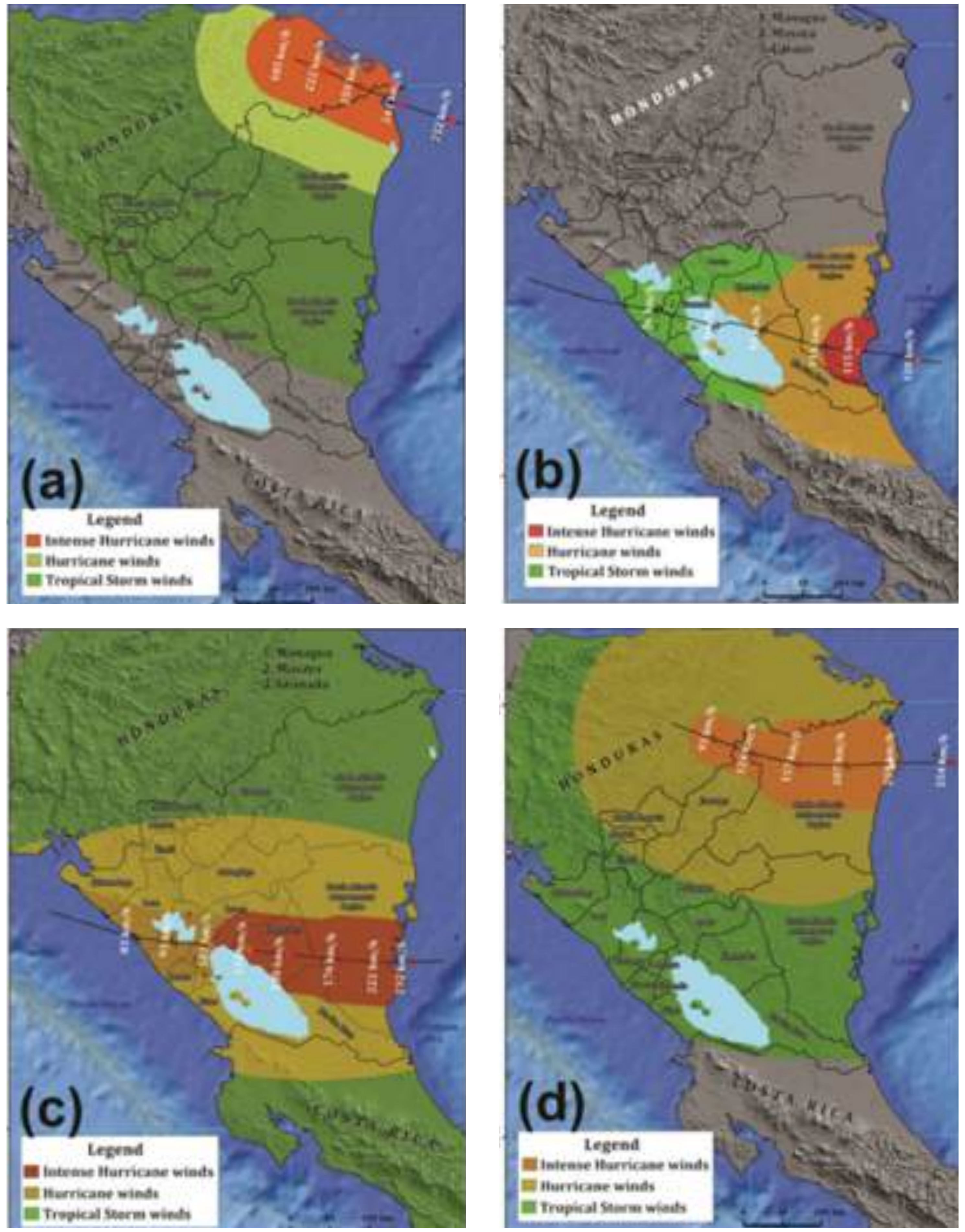

When considering the 14% poorest quantile
18 out of 36 million people wrongly excluded
Sartirano, D., Kalimeri, K., Cattuto, C., Delamónica, E., Garcia-Herranz, M., Mockler, A., Paolotti, D. and Schifanella, R., 2023. Strengths and limitations of relative wealth indices derived from big data in Indonesia. *Frontiers in big Data*, *6*, p.1054156.
© UNICEF

Can we have an early alert system for tropical cyclone impact?

Kooshki Forooshani, M., van den Homberg, M., Kalimeri, K., Kaltenbrunner, A., Mejova, Y., Milano, L., Ndirangu, P., Paolotti, D., Teklesadik, A. and Turner, M.L., 2024. Towards a global impact-based forecasting model for tropical cyclones. *Natural Hazards and Earth System Sciences*, *24*(1), pp.309-329.

IPCC, 2023: Sections. In: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, pp. 35-115, doi: 10.59327/IPCC/AR6-9789291691647

CURRENT APPROACH



Method

- Uses forecast error cones from hurricane predictions, like the Esri Disaster Response Program/NOAA overlaid with population density maps.

Shortcomings

- **Limited Hazards Considered:** Only tracks hurricane path and intensity; lacks surge, rainfall, and multi-hazard data.
- **No Infrastructure Impact:** Only population exposure; does not account for infrastructure damage estimates.
- **Misleading population at risk estimates:** Early cyclone error cones are too wide for an accurate estimation of humanitarian support.

Informing humanitarians worldwide 24/7 —a service provided by OCHA

Philippines

Anticipatory Action Framework Philippines, 2021-2022

Manual and Guideline • **Source:** OCHA • **Posted:** 15 Sep 2021 • **Originally published:** 15 Sep 2021

Executive summary

The Framework outlines an approach to a collective anticipatory action delivered at scale as an innovative attempt to pilot typhoon response in the Philippines. The document includes details about the forecasting trigger (the Model), the preagreed action plans (the Delivery) and the pre-arranged financing (the Money). As this is a learning pilot an investment will be made in documenting evidence and learning (the Learning). CERF has allocated $7.5 million for this pilot in typhoon season 2021/2022.

Primary country:
Philippines

Source:
UN Office for the Coordination of Humanitarian Affairs

Format:
Manual and Guideline

Theme:

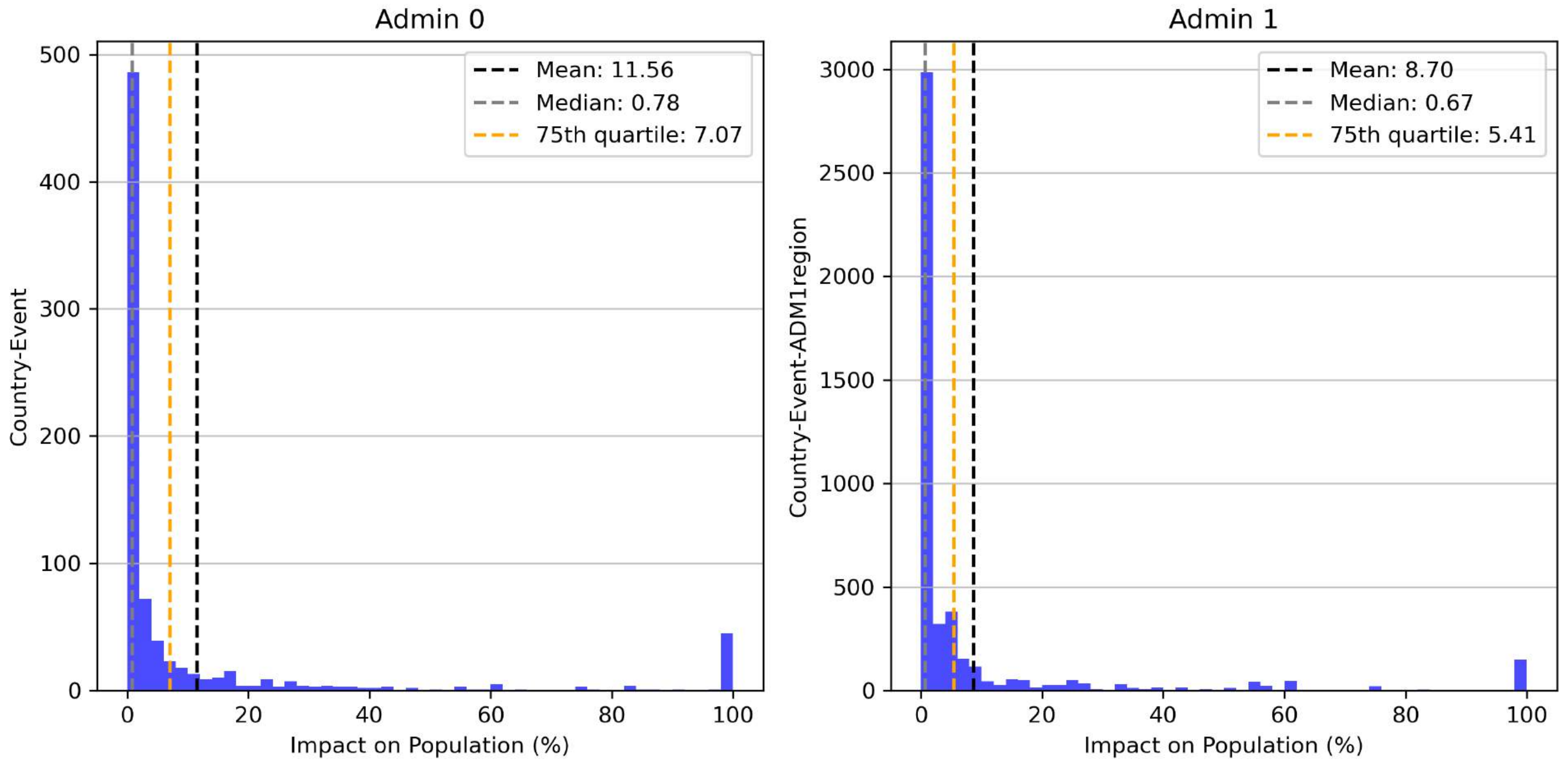
Optimised the 510 model

- model evaluation
- feature selection
- cross validation
- explored different ML models

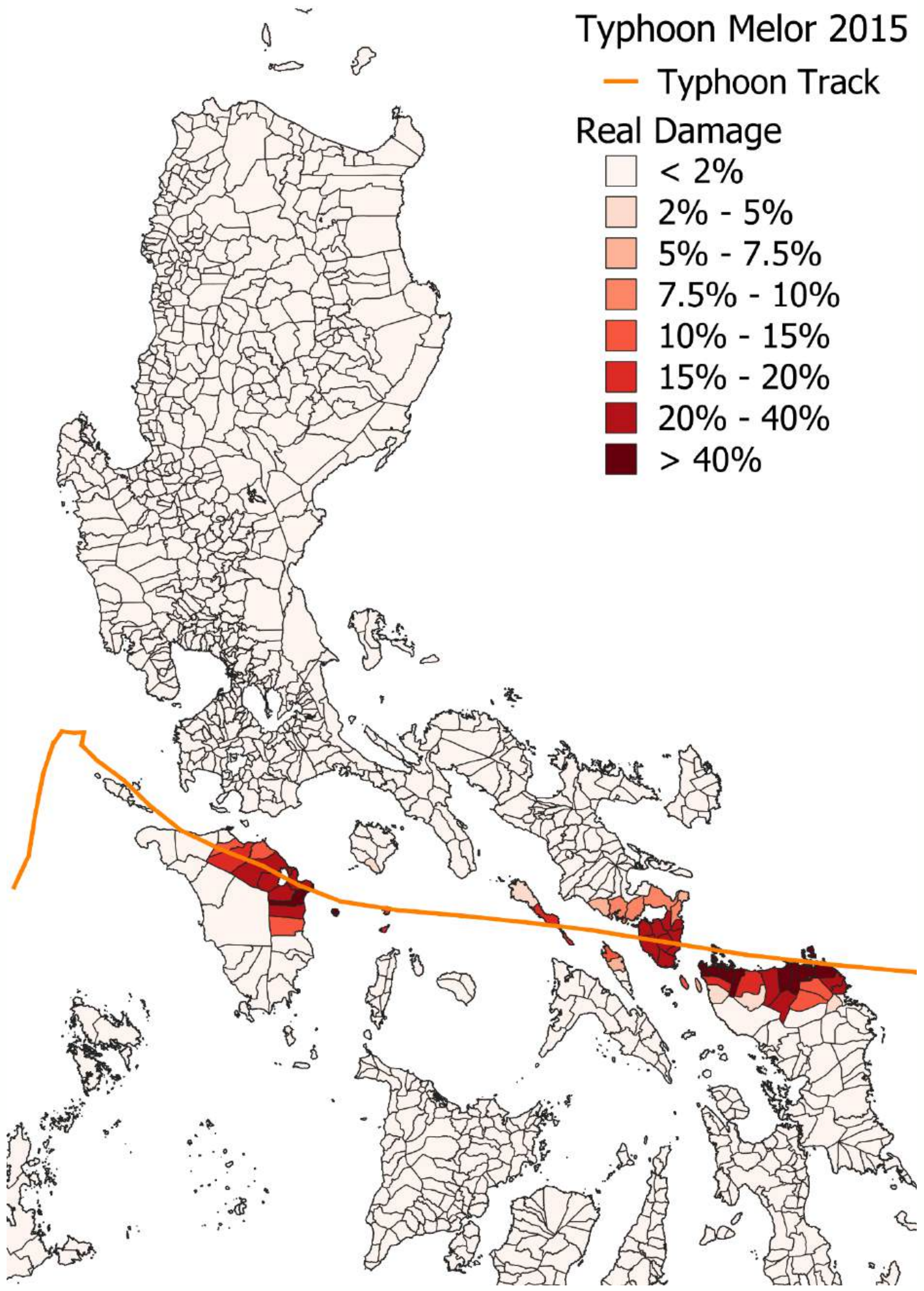
RMSE	Average of 100 random shuffle split	
	XGBoost regression model (M1)	Combined model
bin_1: [0,1)	1.04(±0.09)	1.25(±0.10)
bin_2: [1,10)	4.36(±0.31)	5.40(±0.49)
bin_3: [10,20)	8.99(±0.53)	7.58(±0.71)
bin_4: [20,50)	17.49(±1.10)	13.86(±1.15)
bin_5: [50,101)	31.83(±4.11)	28.18(±3.84)

Model Improvements

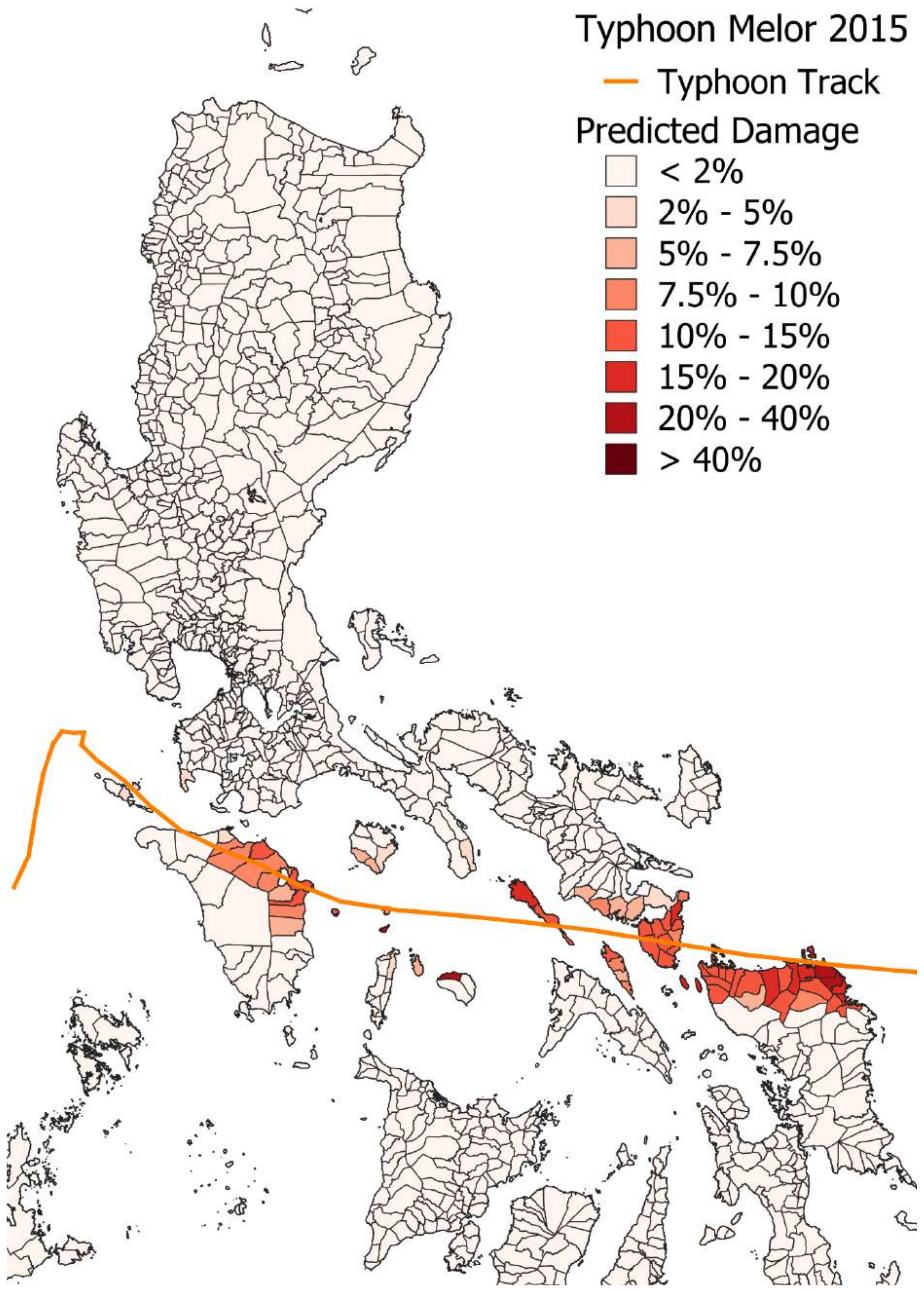
- Used only global, grid-based features
- Added social and vulnerability features
  - relative wealth index (from Meta)
  - %houses-damaged in the last 5 years
  - %grid classified as rural, urban or water (from GHSL)
- Compared to the municipality based model
  - XGBoost regression model
  - Compare to a naive baseline model
  - Transform output to the municipality level
- Applied feature importance



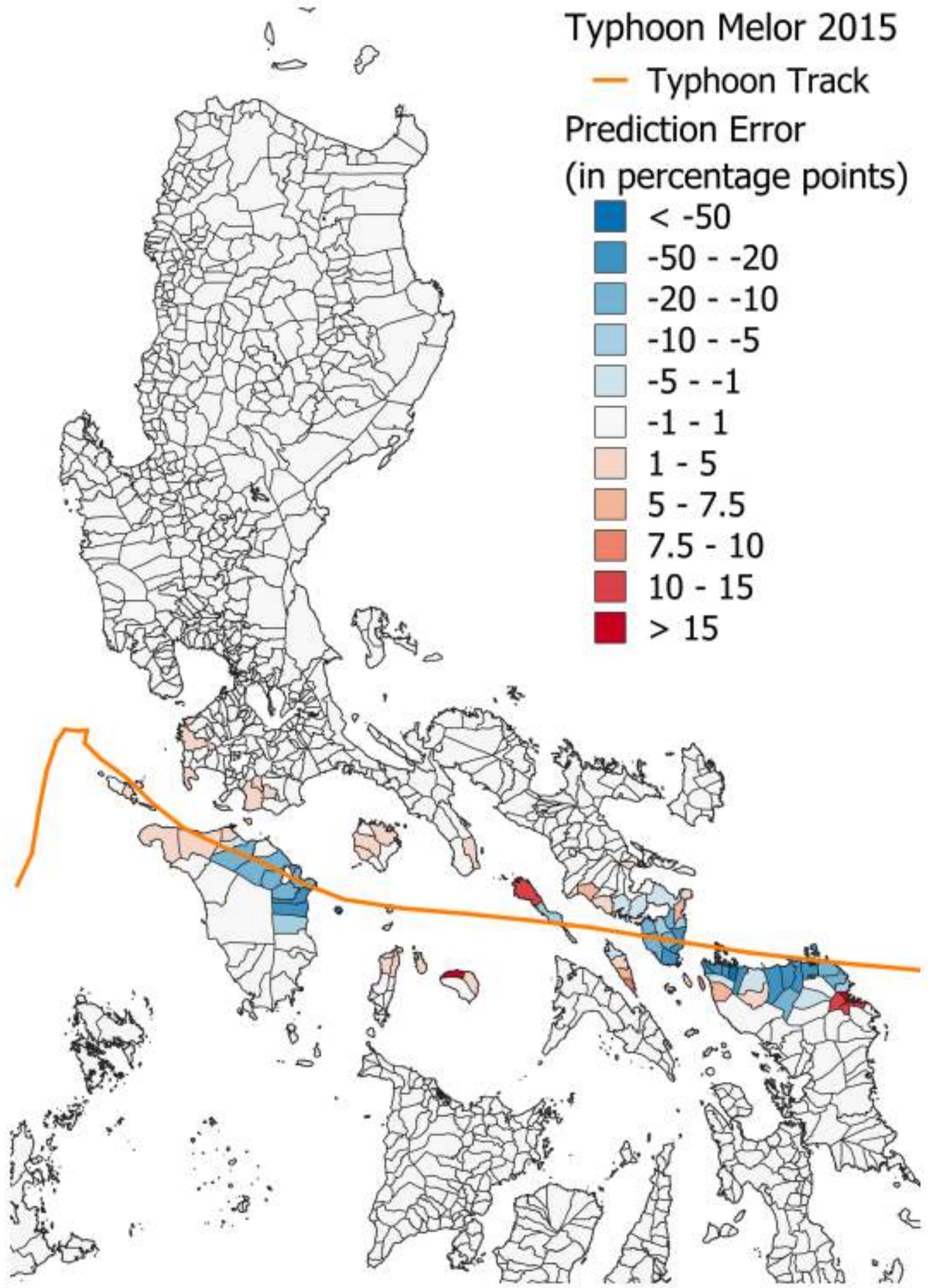
Case Study: Typhoon Melor, 2015



Actual Damage per municipality



Predicted Damage by the 2SG-Global+ model (F1 .64)
35/41 correctly identified municipalities vs 25/41 of old model

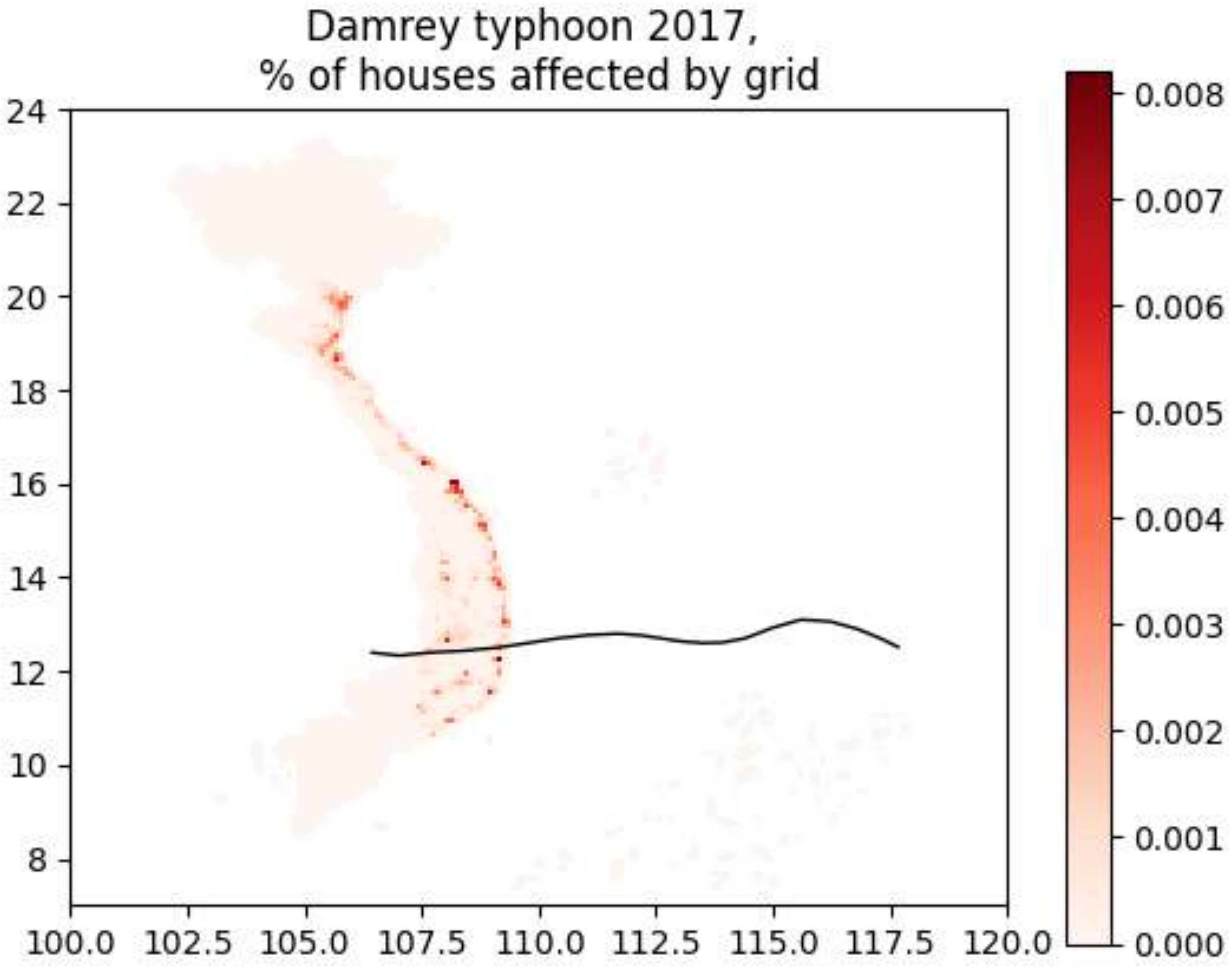


Prediction Error

On an average $145,000 cost per municipality, the saving from 4 fewer false alarms is **more than half a million dollars.**

But OCHA doesn't just "save" money – it **reallocates** it from mistaken early actions to people who actually suffer ≥10 % housing destruction, **sharpening the value-for-money of each dollar.**

Example of Questionable Groundtruth data - Vietnam



Example of Questionable Groundtruth data - Vietnam

OCHA Services

centre for humdata

FOCUS AREAS STORIES PRESS RESOURCES ABOUT US GET INVOLVED

Home / Resource Library / The State Of Open Humanitarian Data 2024

Resource Library February 27, 2024

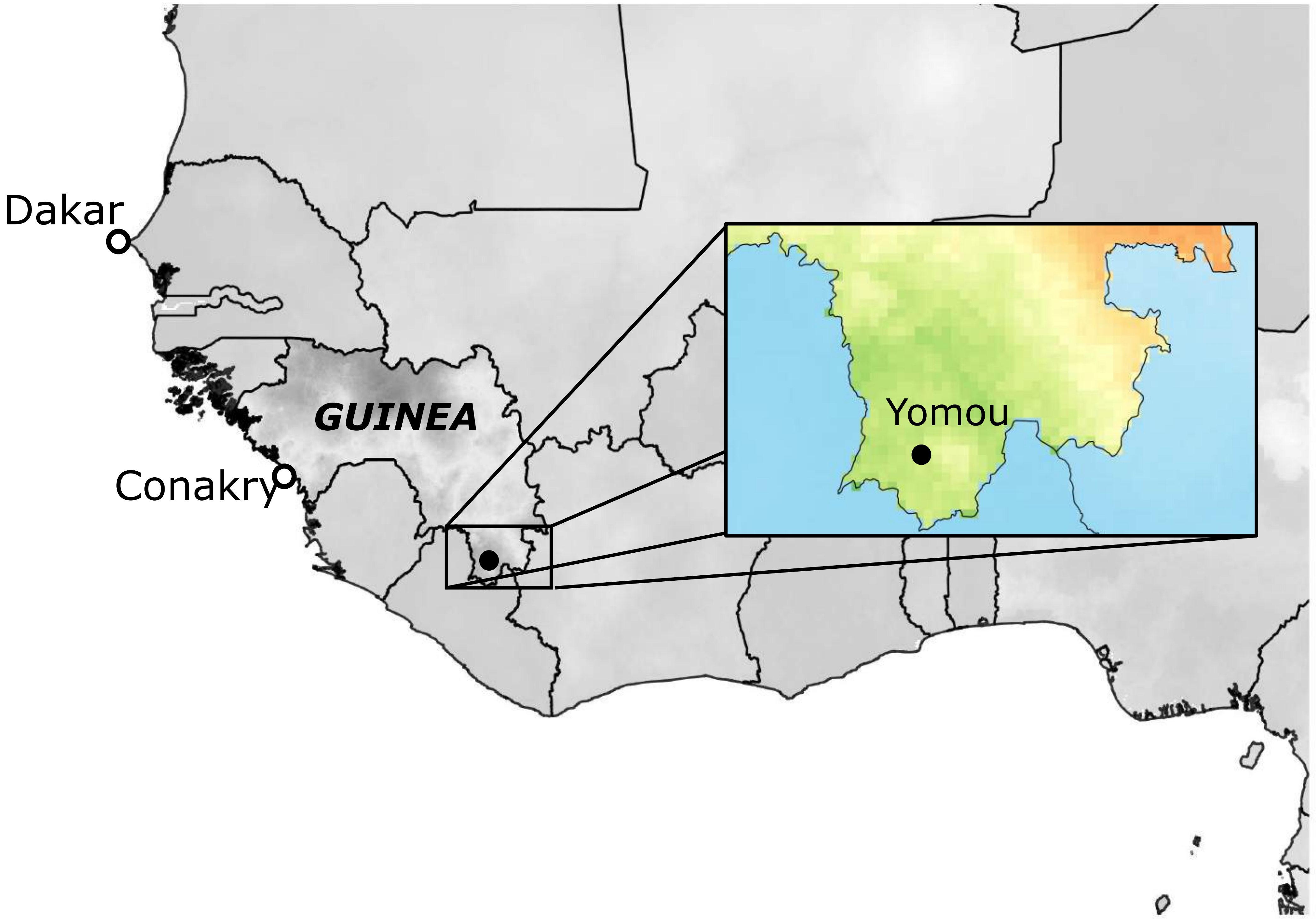
The State Of Open Humanitarian Data 2024

In 2023, the demand for humanitarian data reached a record level as the world contended with the effects of war, climate shocks, food insecurity, displacement and disease in crises ranging from Gaza to Sudan. At the same time, data availability across priority humanitarian operations remained steady.


"*The extent and complexity of the problem does not matter as much as the willingness to solve it*" - Ralph Marston

In search of zero dose children in remote districts of Guinea

REACH THE UNREACHED
LOCATE AND LINK UNREACHED CHILDREN WITH IMMUNIZATION AND BIRTH REGISTRATION



slide credit Martin Bogaert & Tommaso Salvatori

REACH THE UNREACHED

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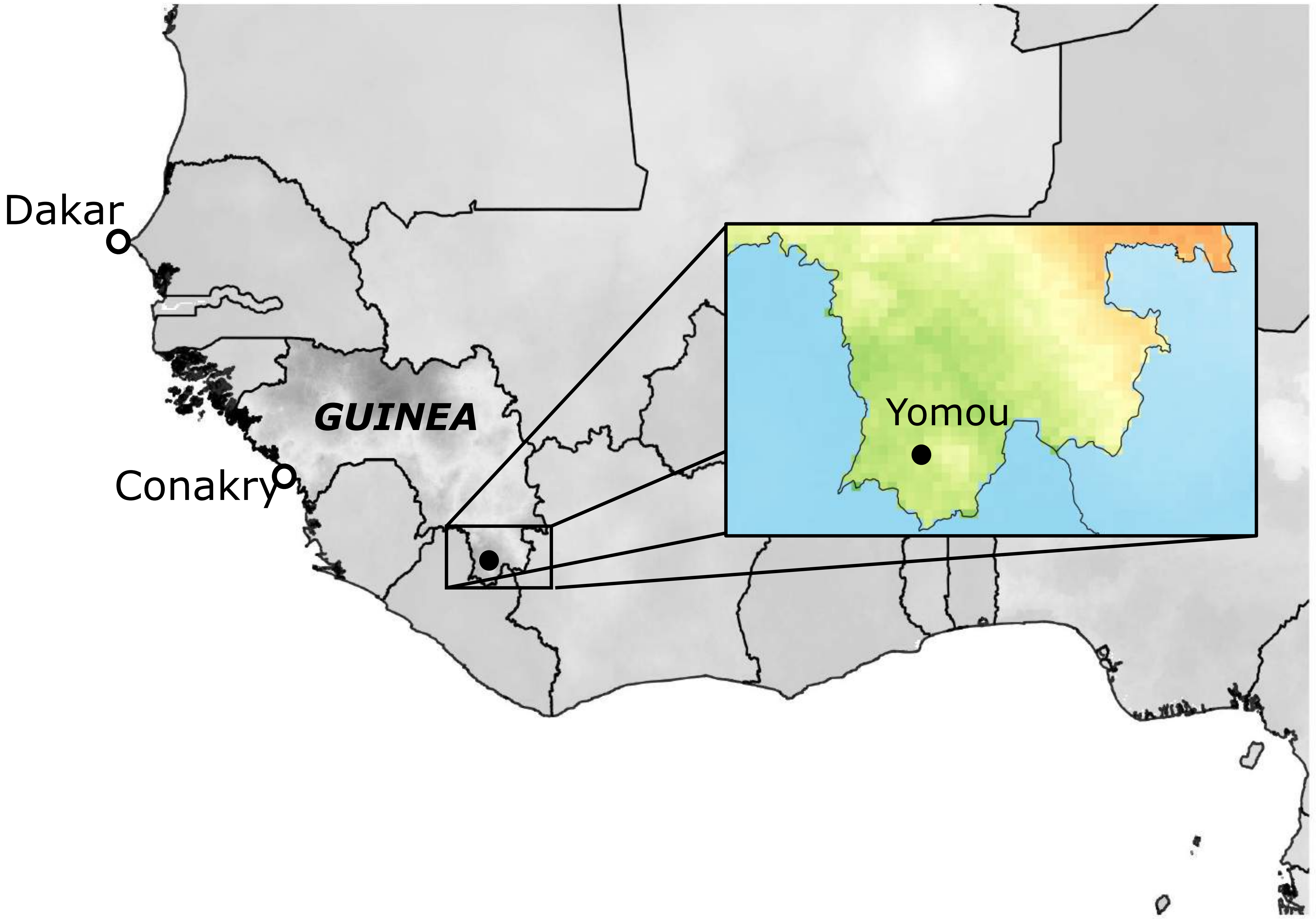
In search of zero dose children in remote districts of Guinea



1 out of 10

children do not reach the age of five

slide credit Martin Bogaert & Tommaso Salvatori

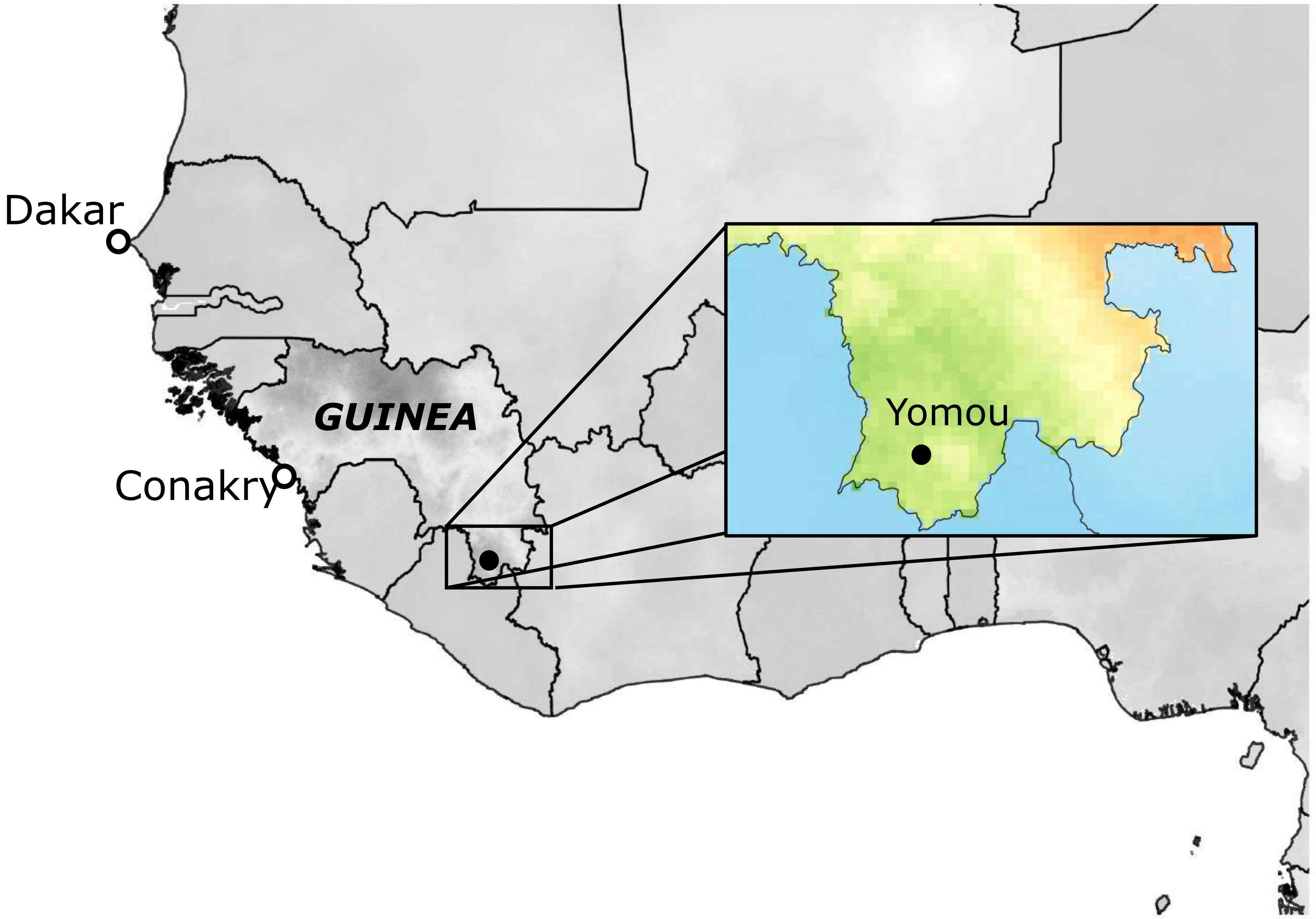
REACH THE UNREACHED

LOCATE AND LINK UNREACHED CHILDREN WITH IMMUNIZATION AND BIRTH REGISTRATION

In search of zero dose children in remote districts of Guinea

190k

children have never received a single vaccine



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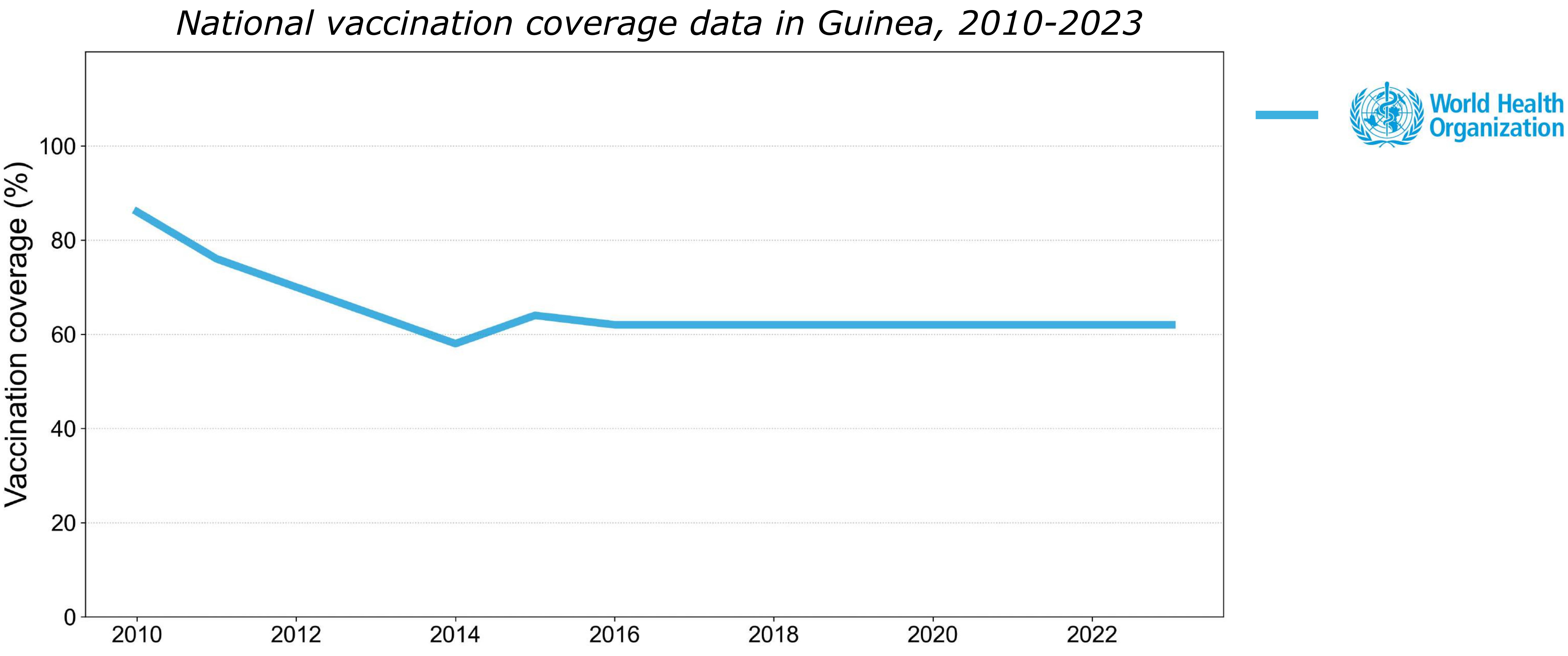
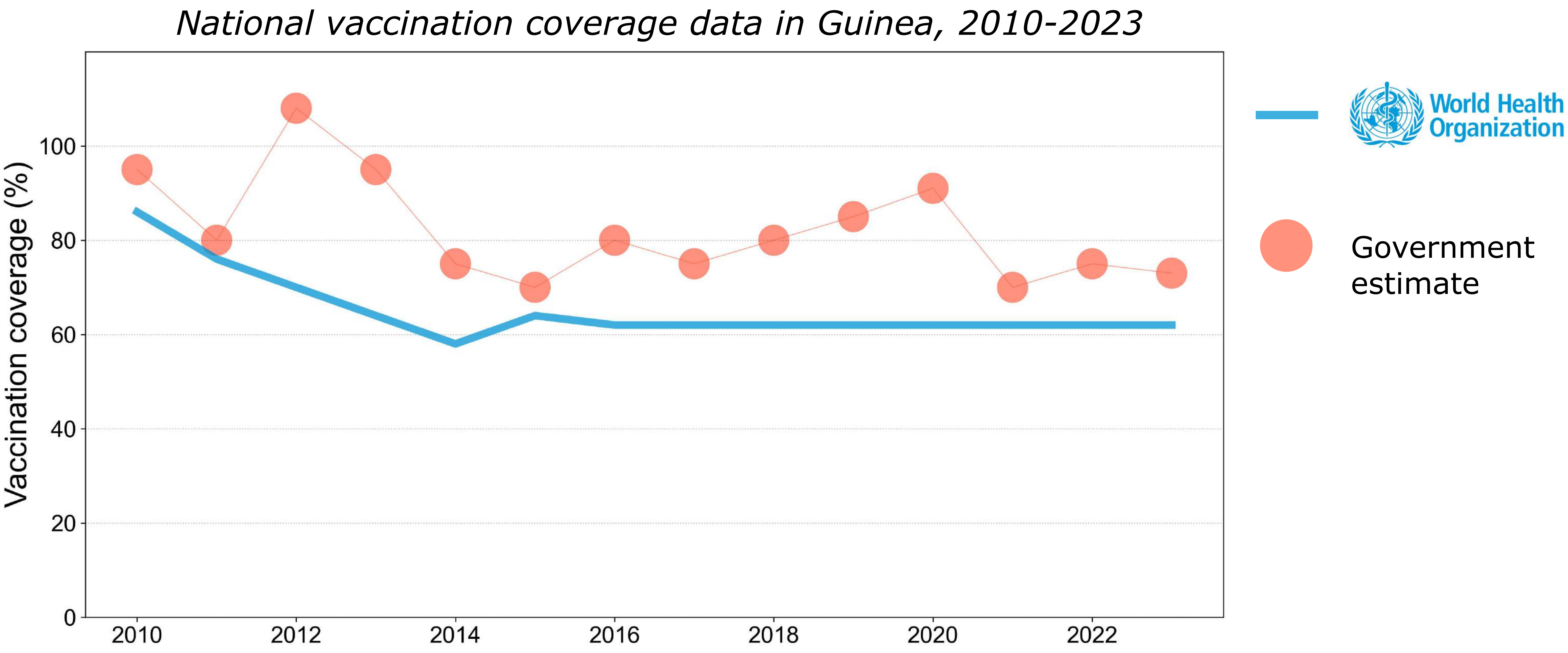
Administrative data reporting is prone to errors



Source: WUENIC Trends

slide credit Martin Bogaert & Tommaso Salvatori

Administrative data reporting is prone to errors

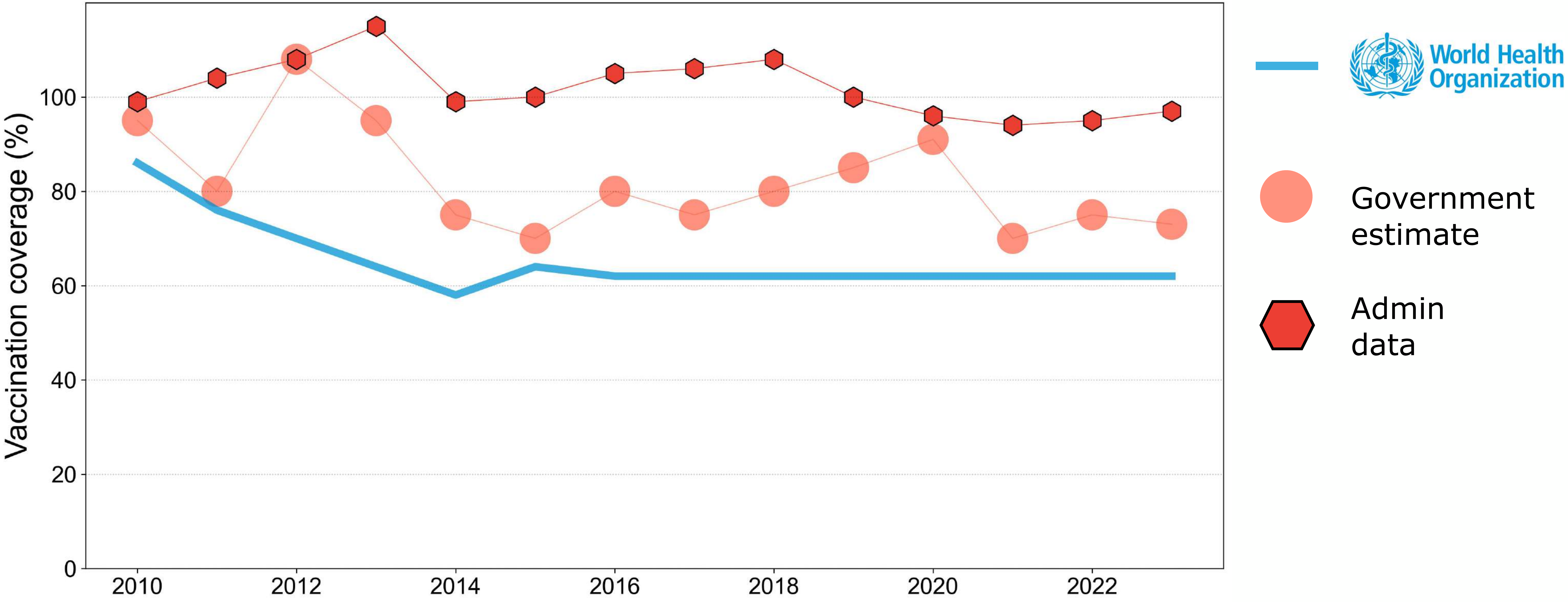


Source: WUENIC Trends

slide credit Martin Bogaert & Tommaso Salvatori

Administrative data reporting is prone to errors

National vaccination coverage data in Guinea, 2010-2023



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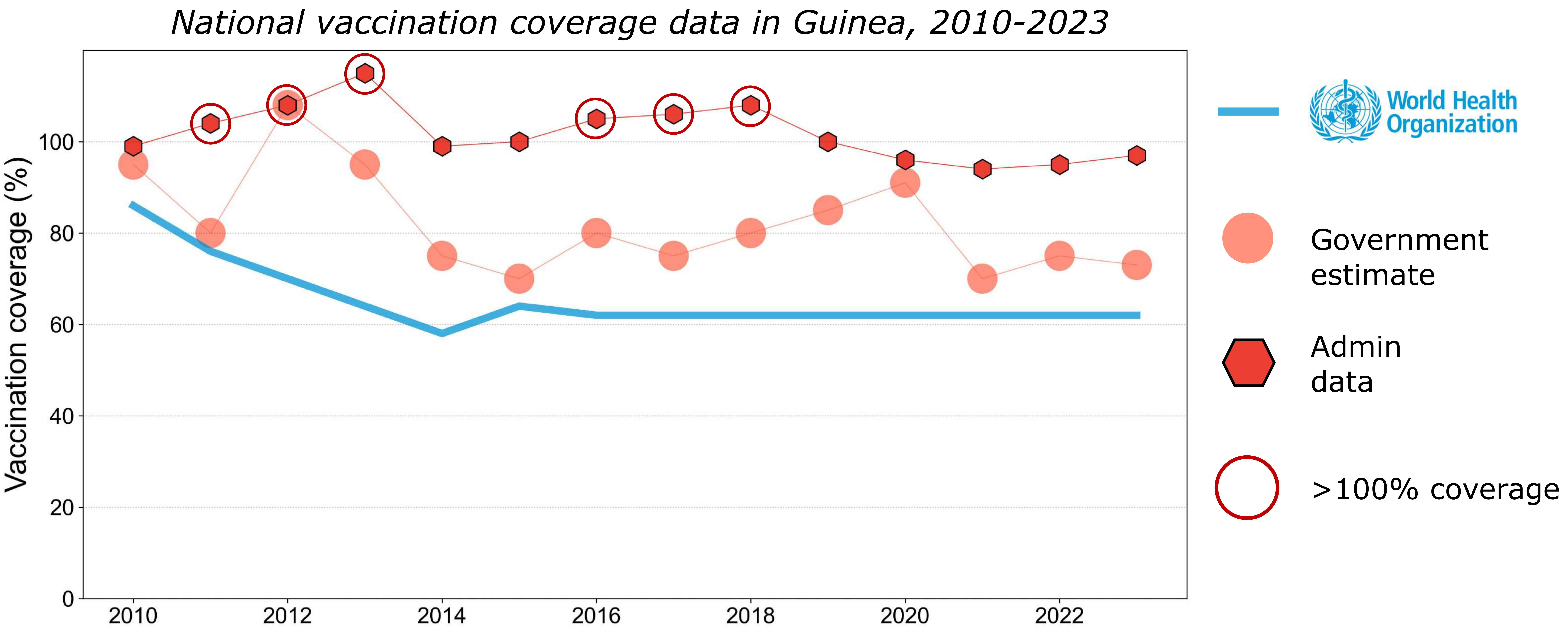
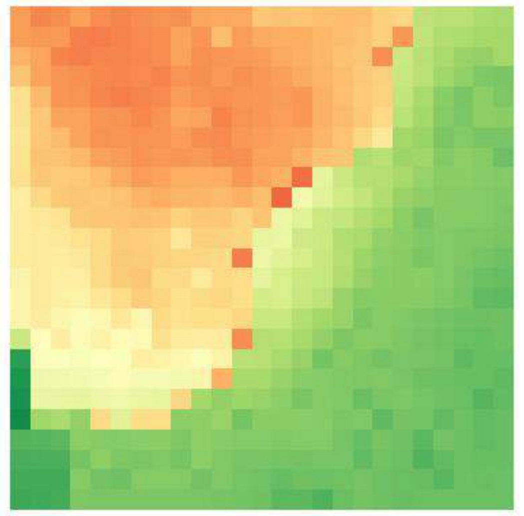


Source: WUENIC Trends

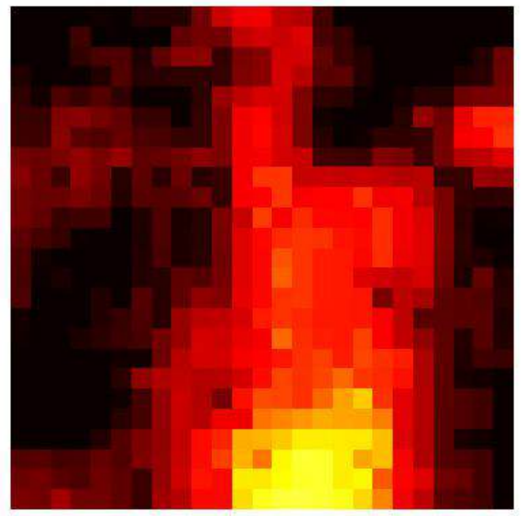
slide credit Martin Bogaert & Tommaso Salvatori

To estimate zero-dose children, we need both vaccination and population maps

Vaccine coverage

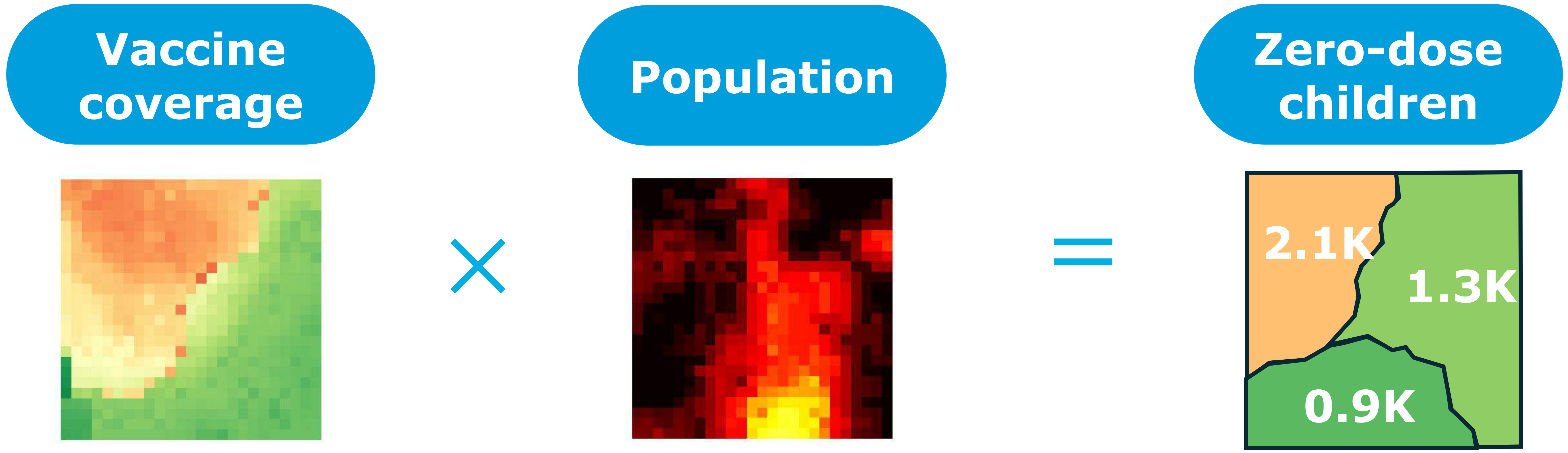


Population



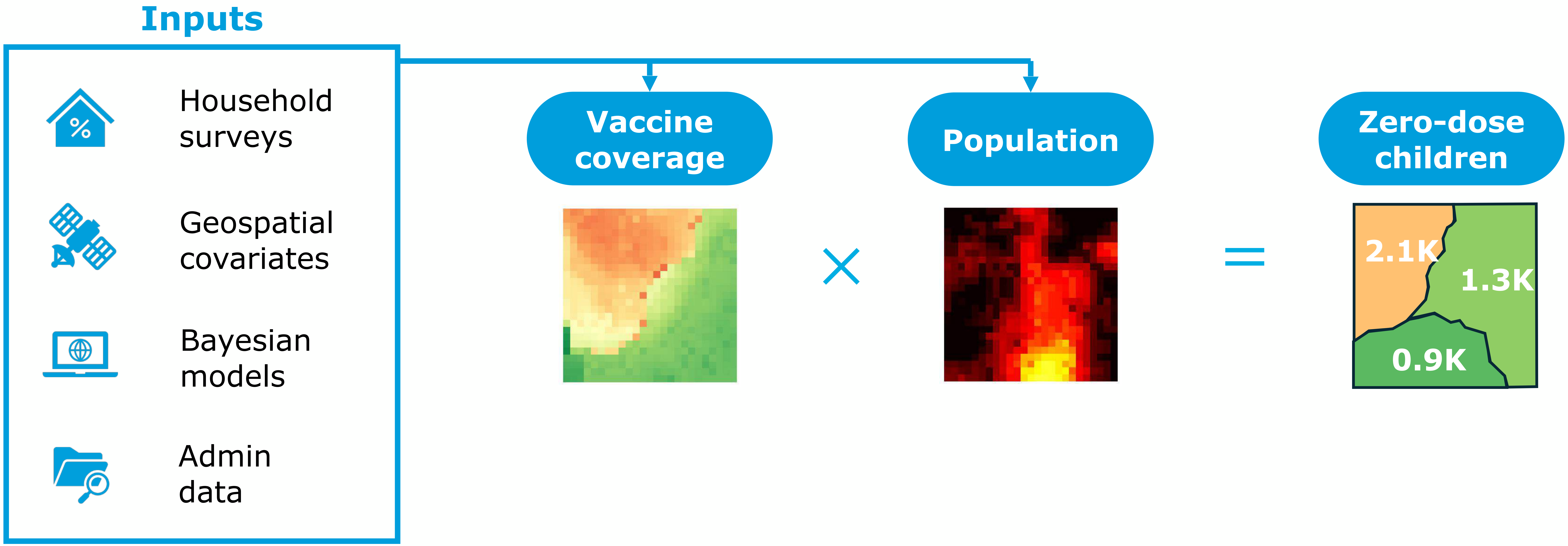
slide credit Martin Bogaert & Tommaso Salvatori

To estimate zero-dose children, we need both vaccination and population maps



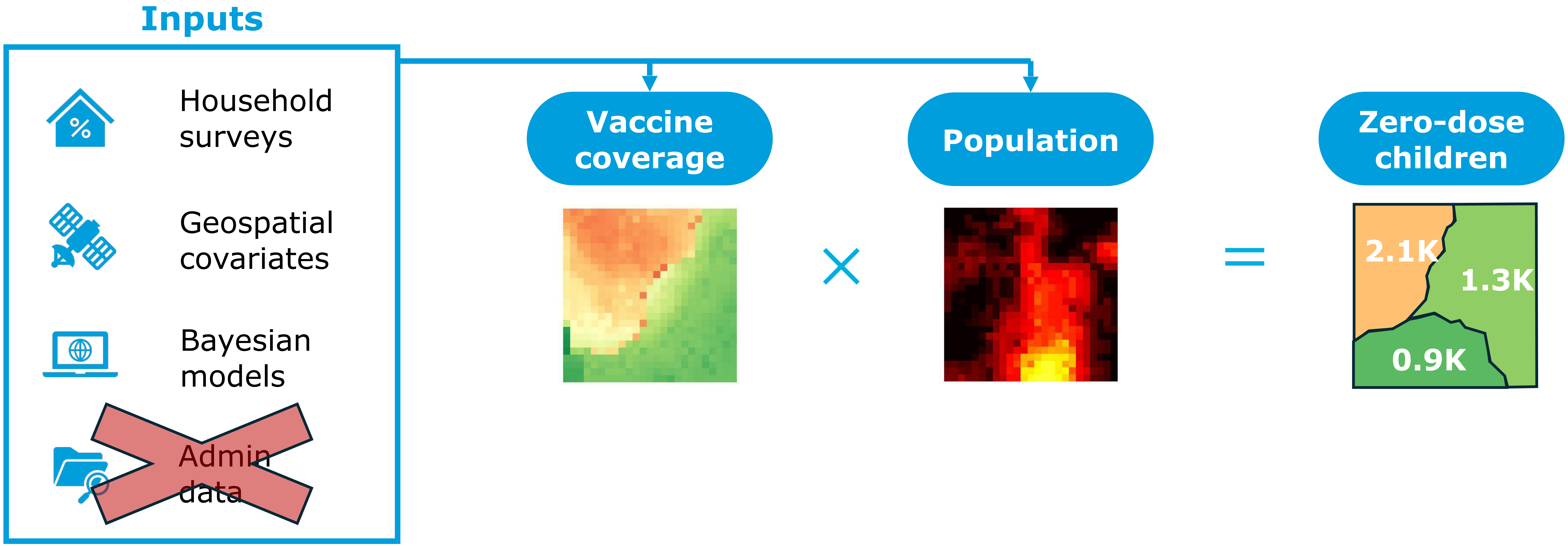
slide credit Martin Bogaert & Tommaso Salvatori

To estimate zero-dose children, we need both vaccination and population maps



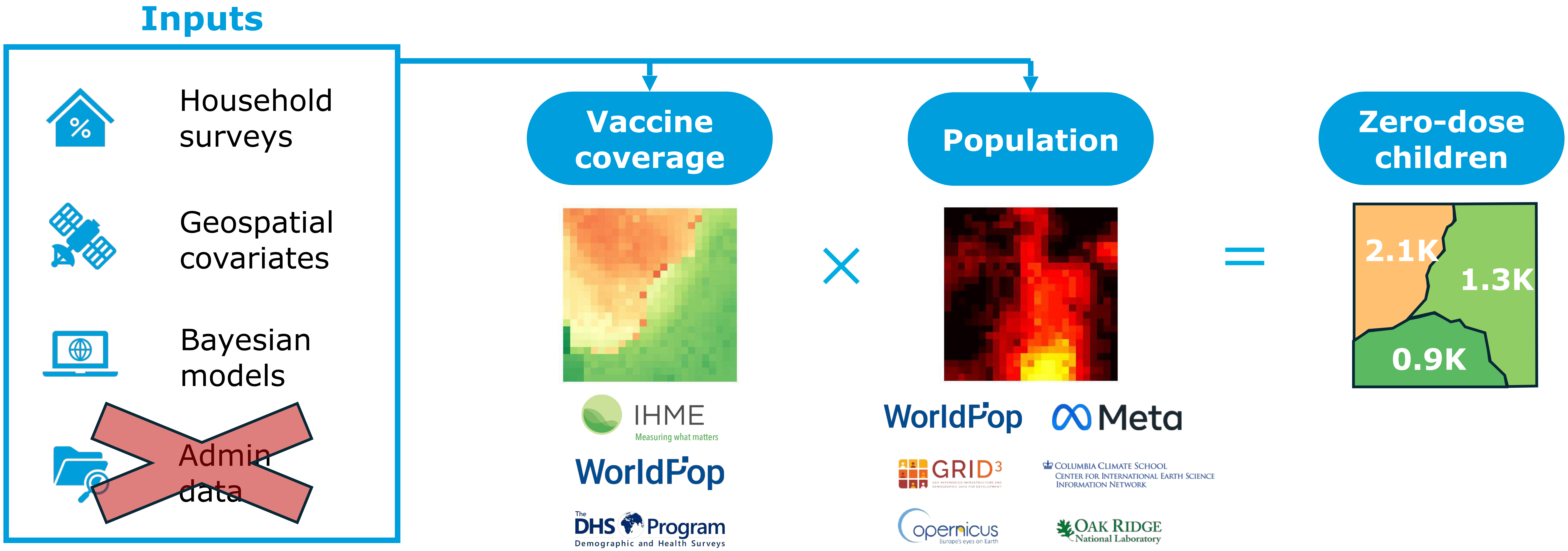
slide credit Martin Bogaert & Tommaso Salvatori

To estimate zero-dose children, we need both vaccination and population maps



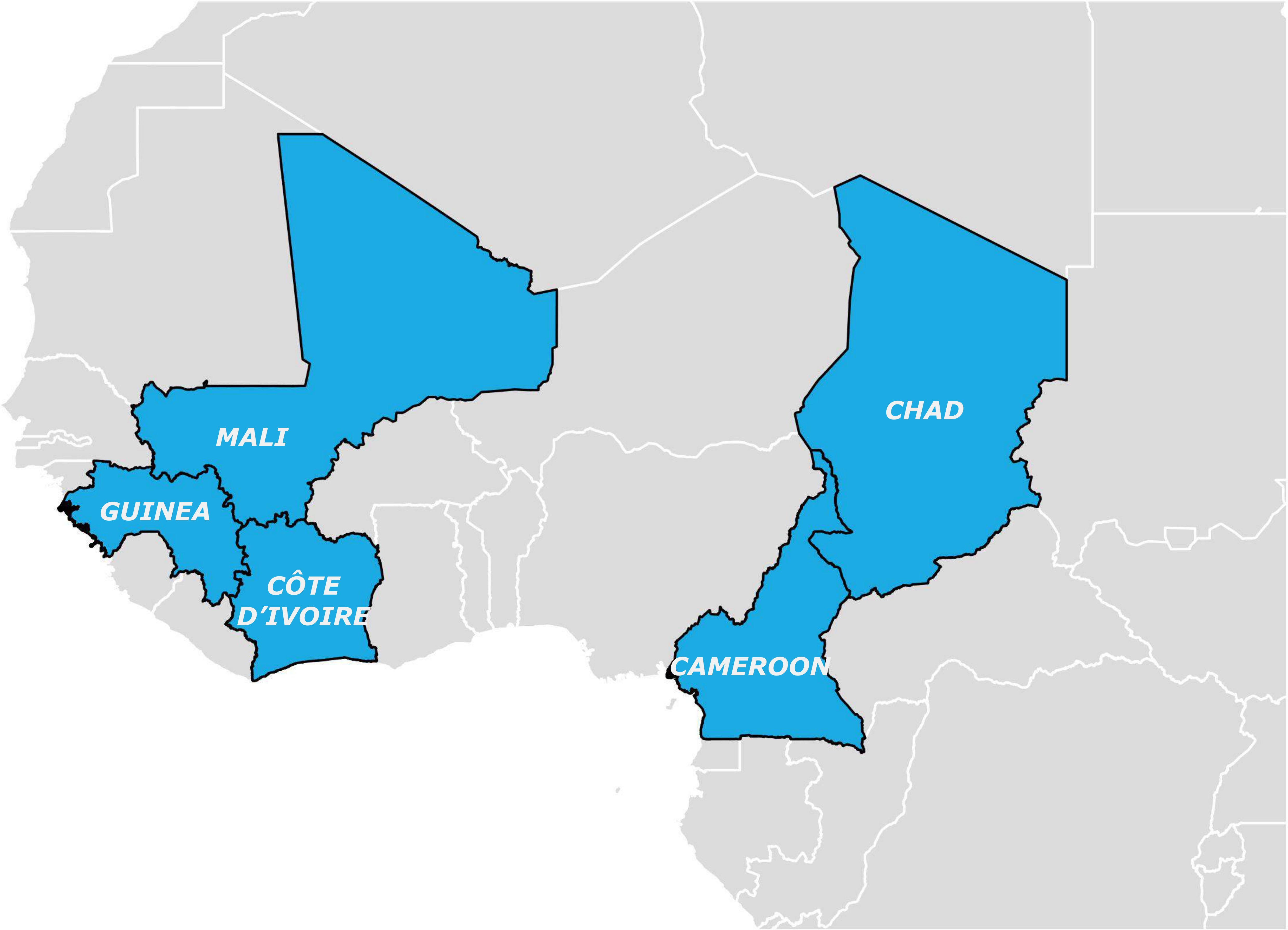
slide credit Martin Bogaert & Tommaso Salvatori

To estimate zero-dose children, we need both vaccination and population maps



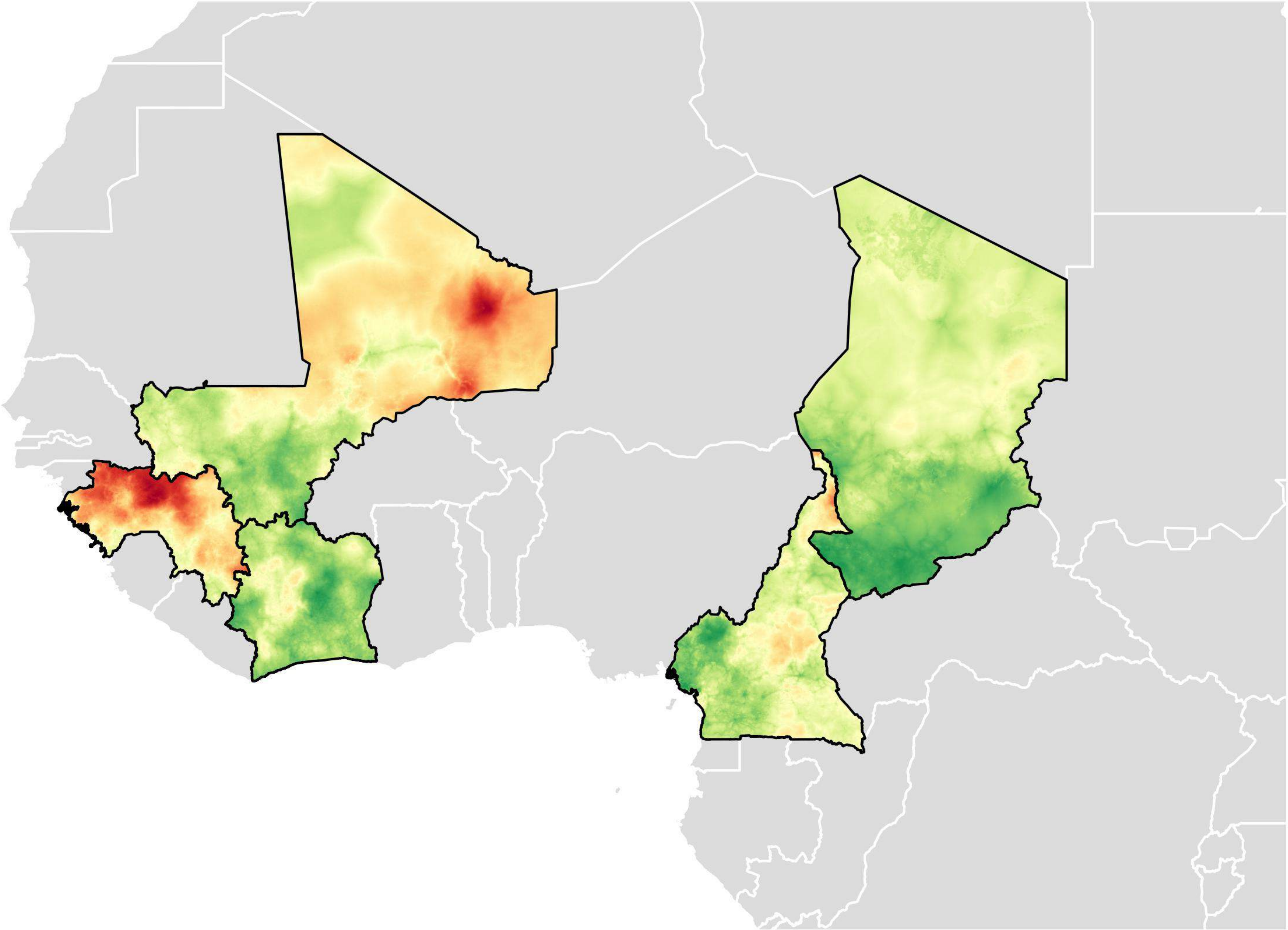
slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage



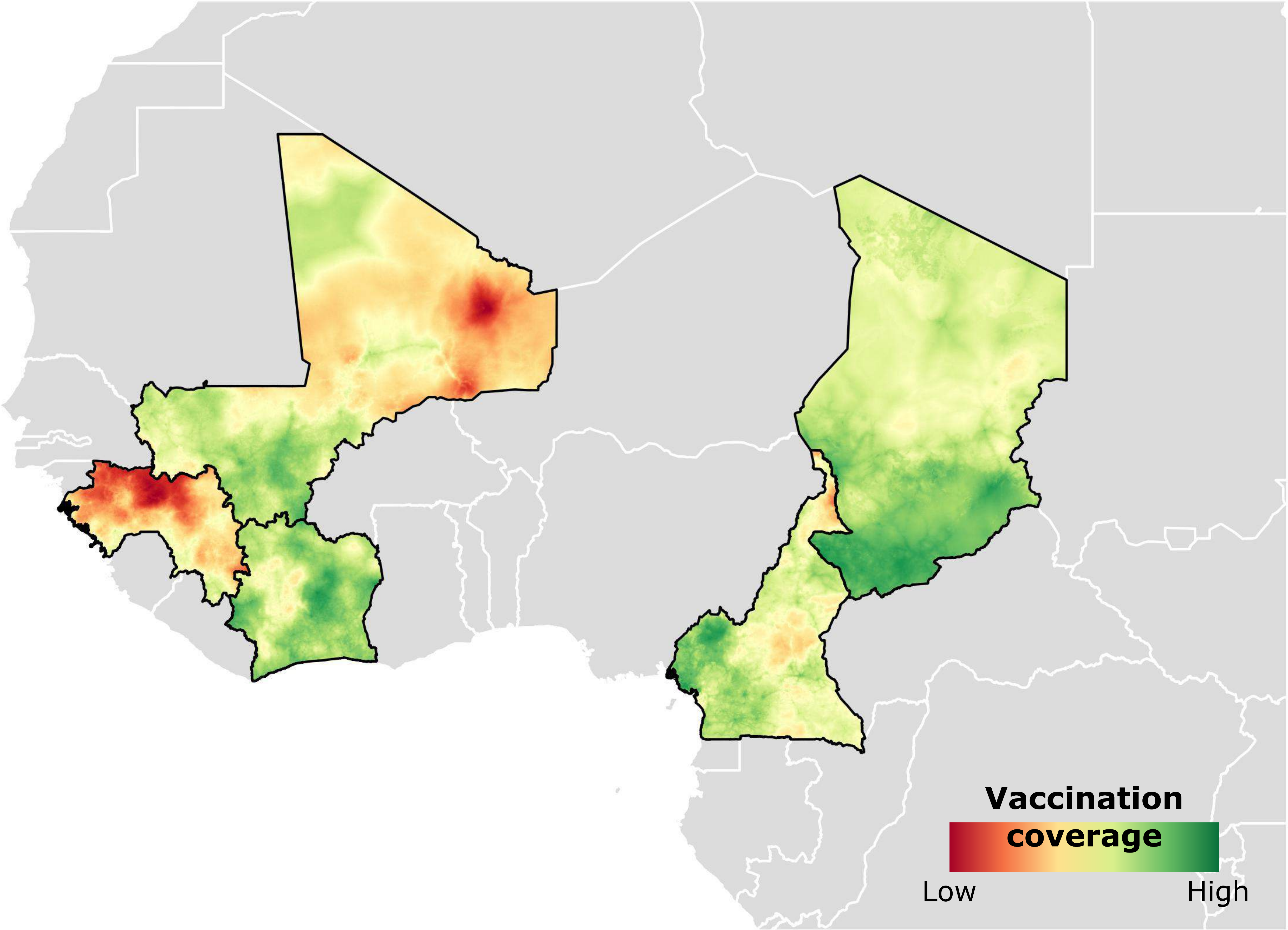
slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage



slide credit Martin Bogaert & Tommaso Salvatori

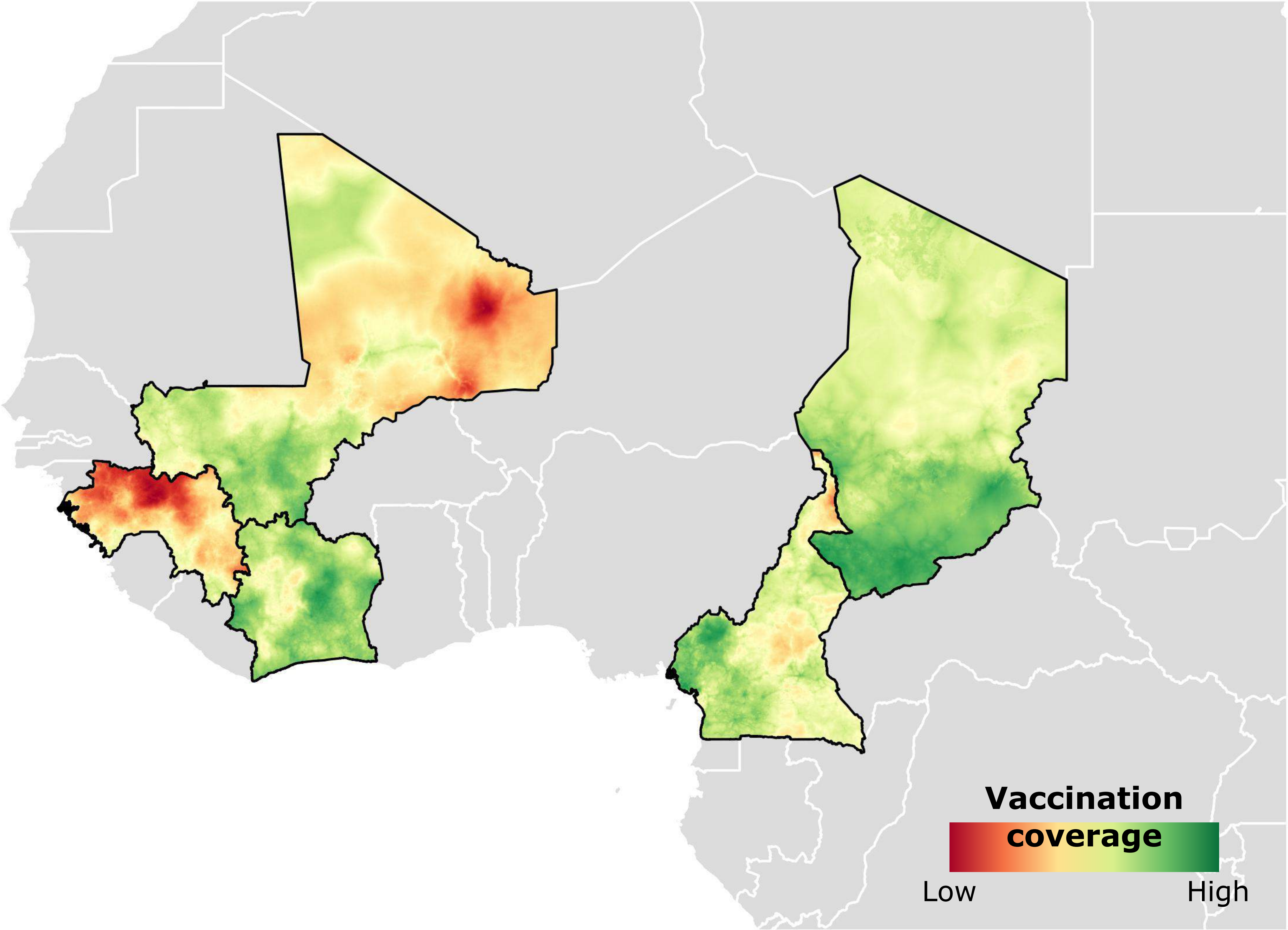
Alternative ways to estimate subnational coverage



slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage

Suitable for use in unique national contexts

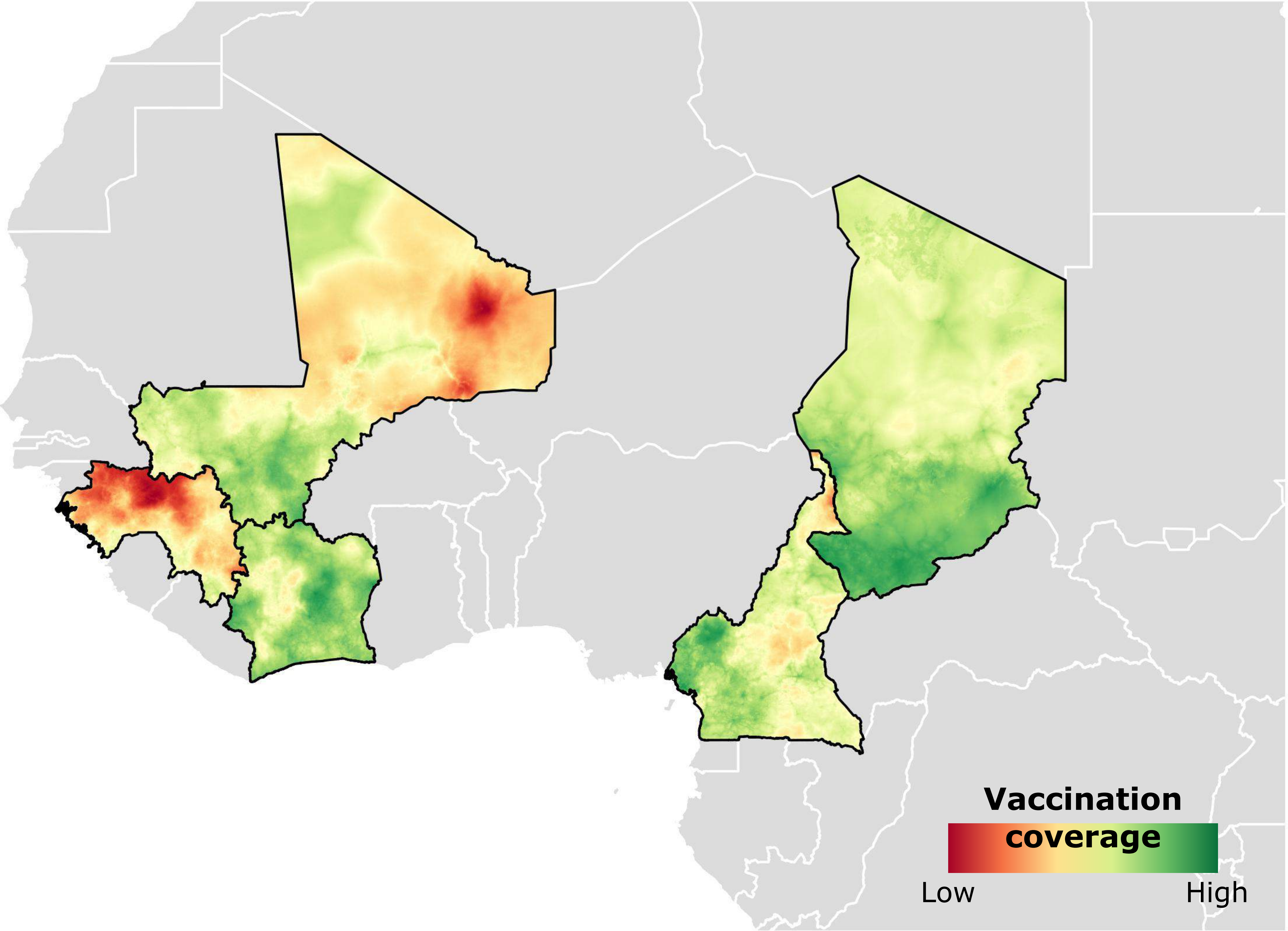


slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage

Suitable for use in unique national contexts

Consistent with trusted WHO estimates



slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage

slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage

Understand methodologies and identify sources of variability

Alternative ways to estimate subnational coverage

Understand methodologies and identify sources of variability

Compare pre-existing models and quantify variability

slide credit Martin Bogaert & Tommaso Salvatori

Alternative ways to estimate subnational coverage

Understand methodologies and identify sources of variability

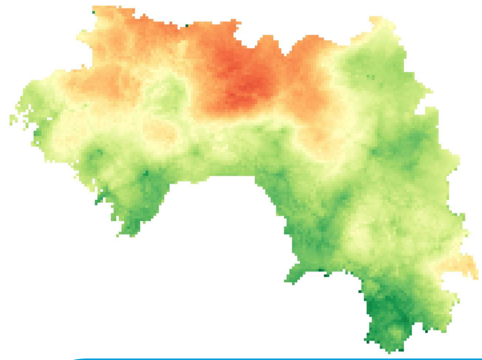
Compare pre-existing models and quantify variability

Evaluate validity of UNICEF's strategy

slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

Inputs

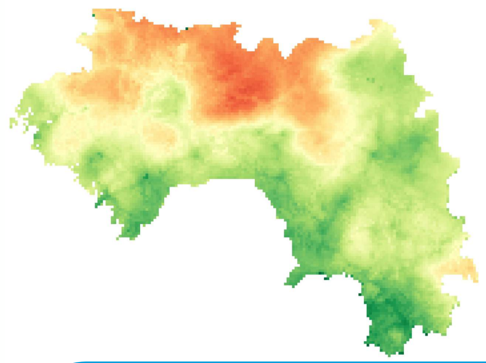


Vaccination

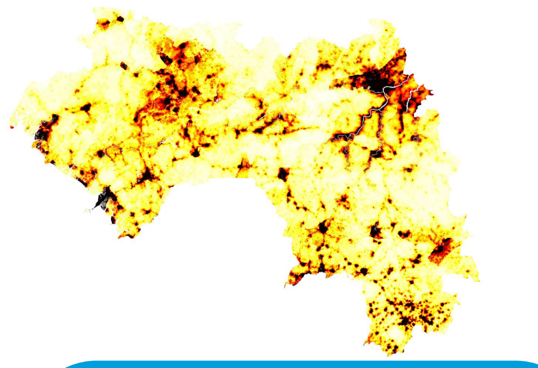
slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

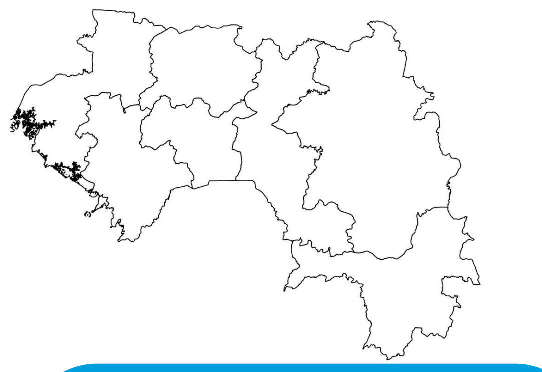
Inputs



Vaccination



Population

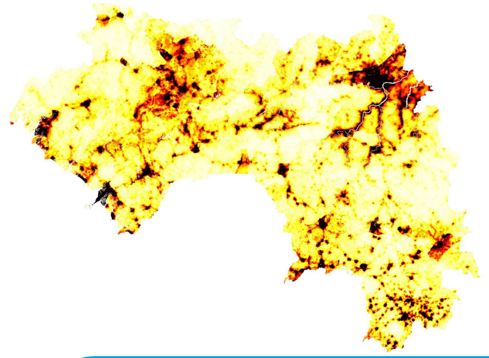


Regions

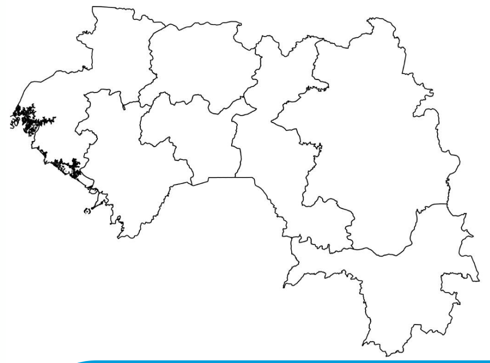
These vaccination maps can be used to locate zero-dose children

Inputs

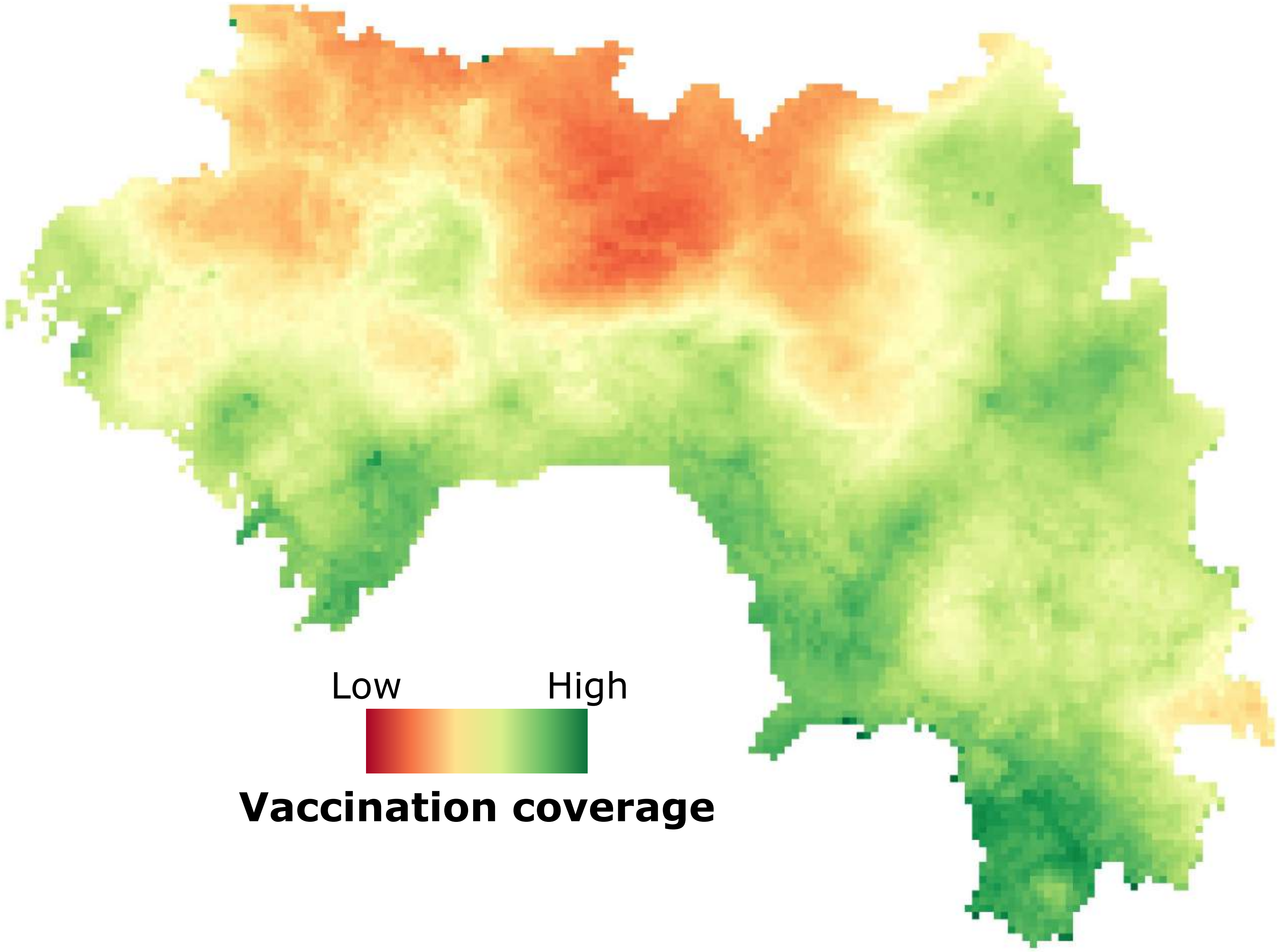
Vaccination



Population



Regions

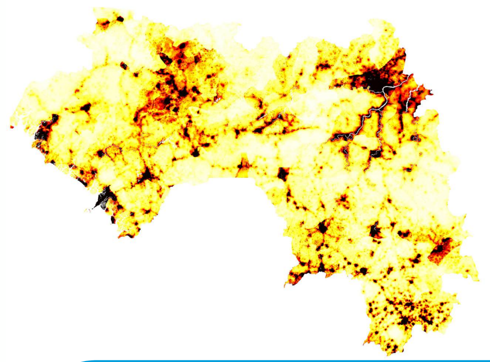


slide credit Martin Bogaert & Tommaso Salvatori

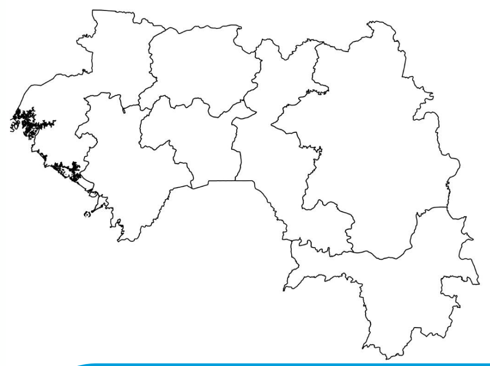
These vaccination maps can be used to locate zero-dose children

Inputs

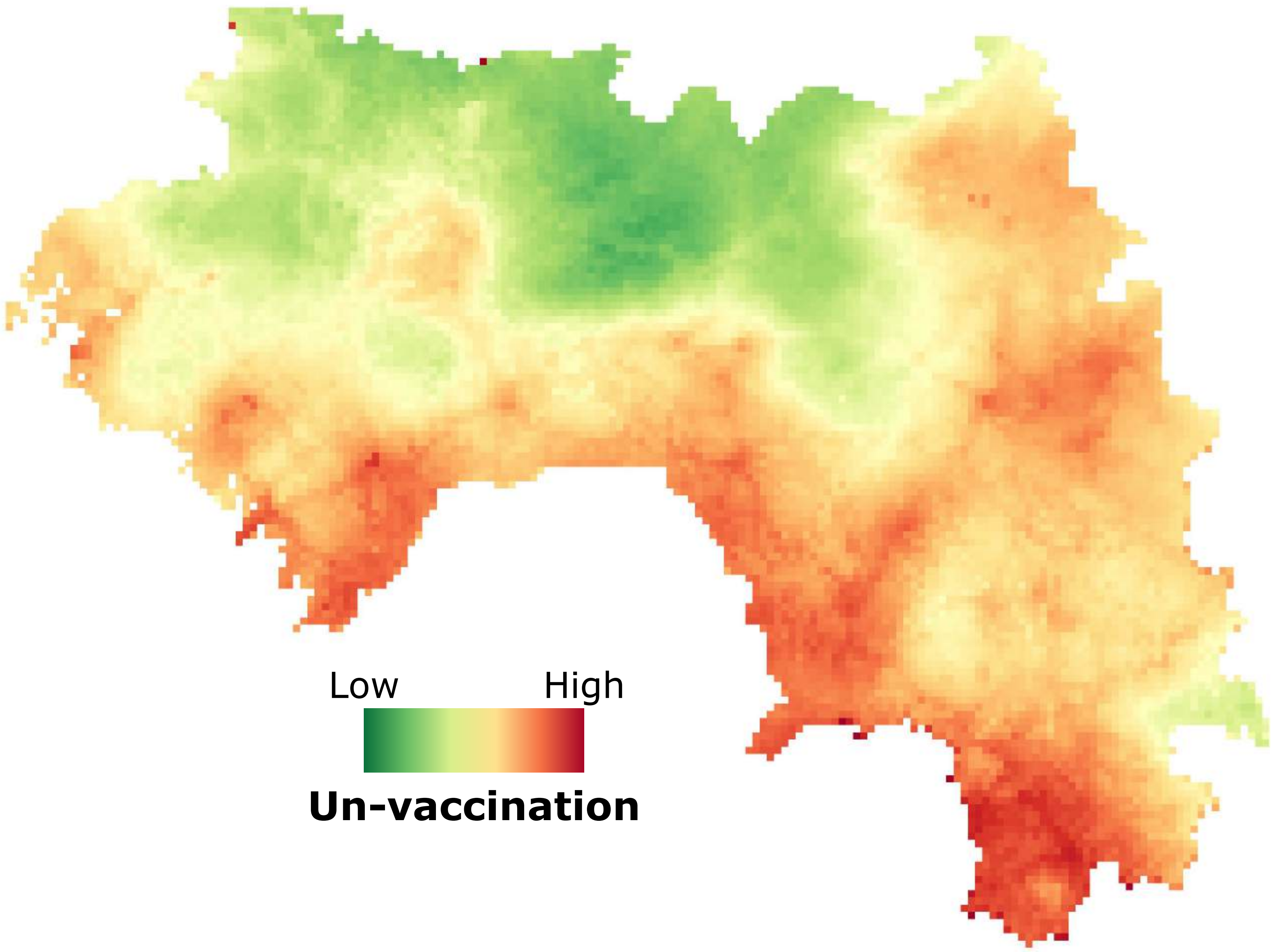
Vaccination



Population



Regions

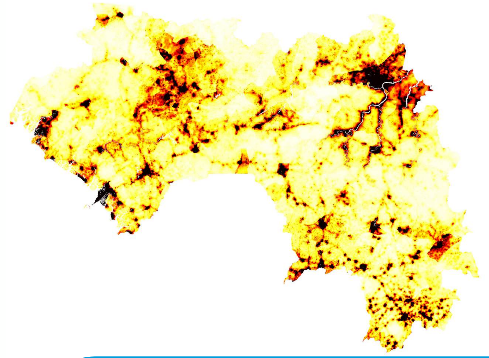


slide credit Martin Bogaert & Tommaso Salvatori

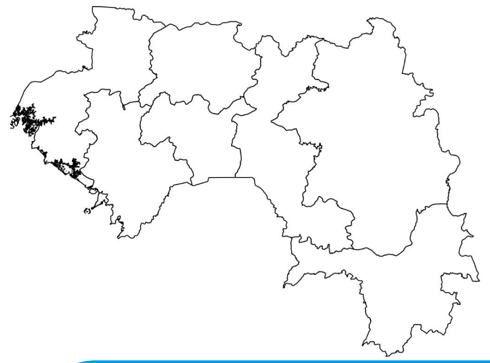
These vaccination maps can be used to locate zero-dose children

Inputs

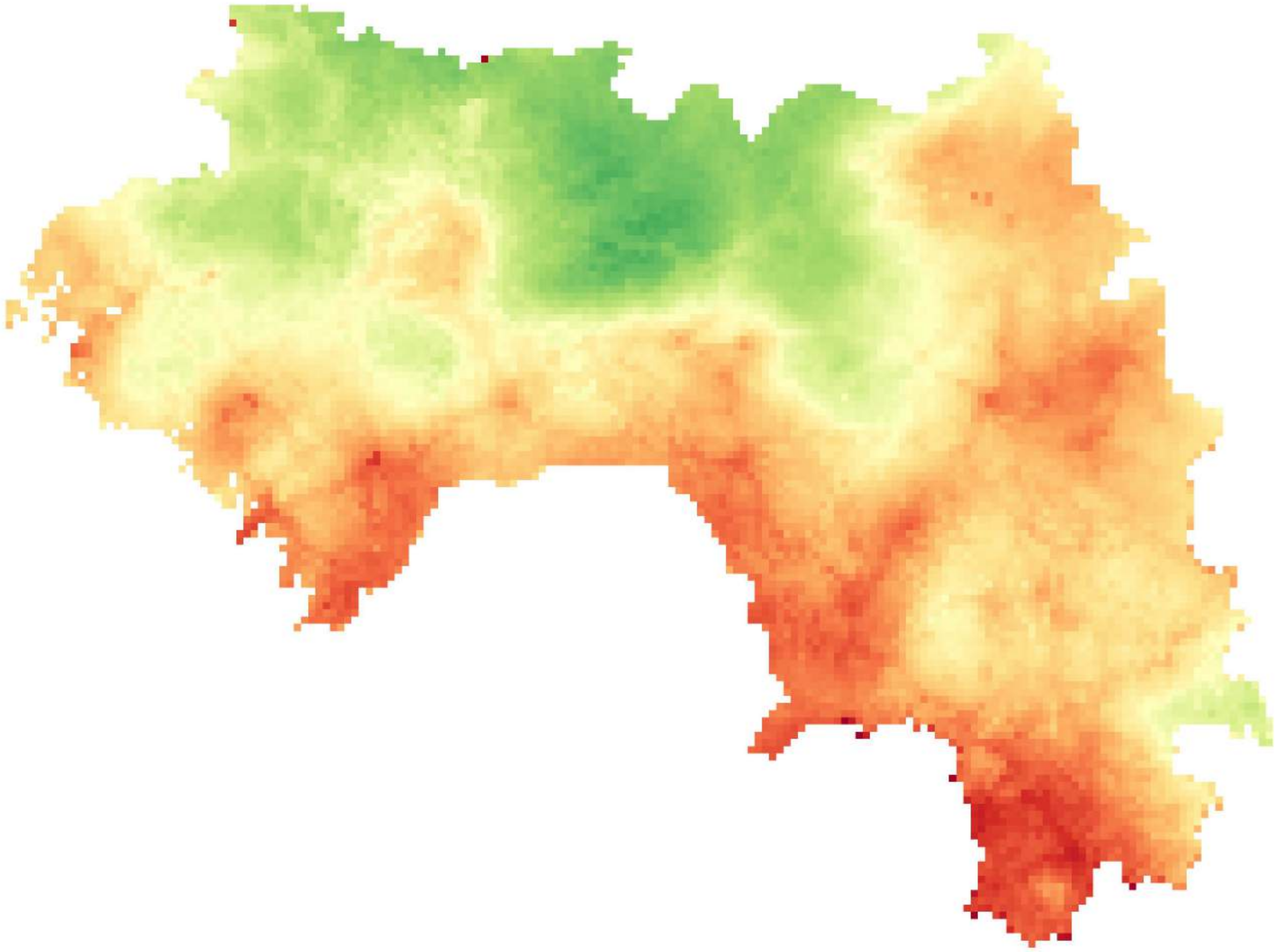
Vaccination



Population



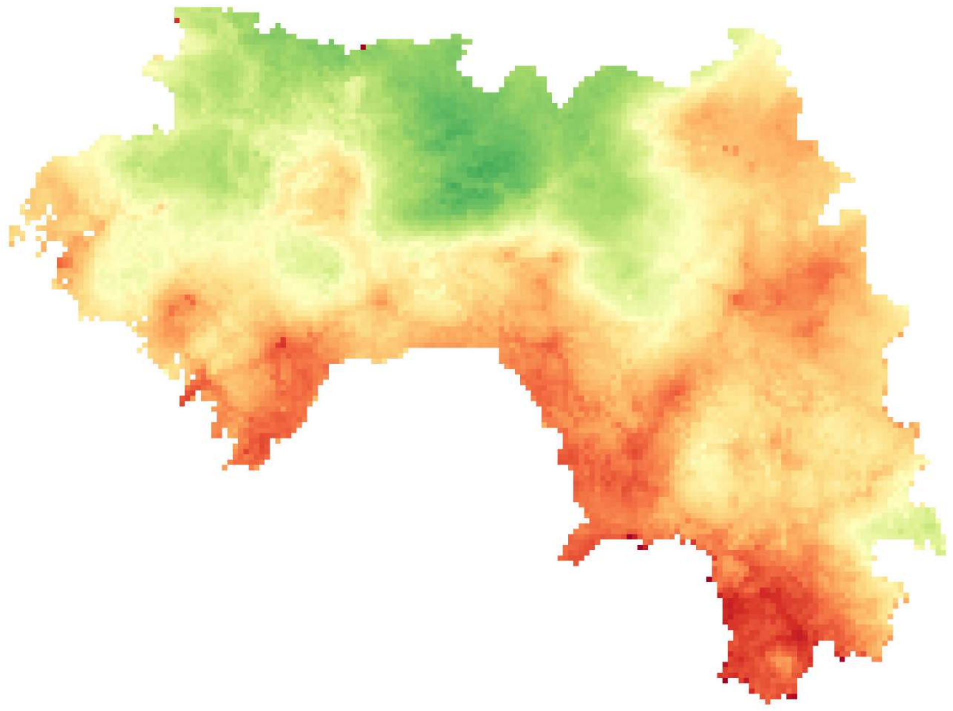
Regions



slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

Inputs



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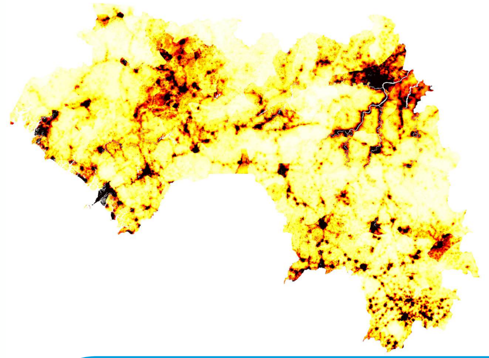
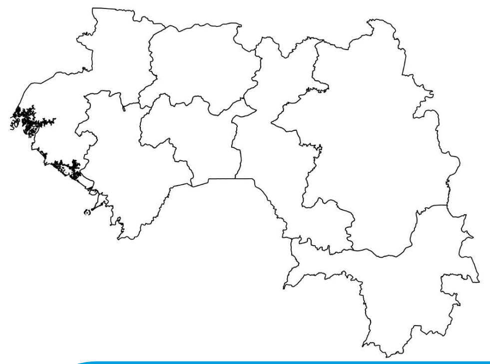


Population



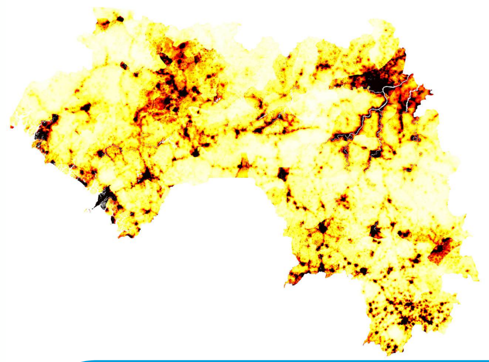
Regions

slide credit Martin Bogaert & Tommaso Salvatori

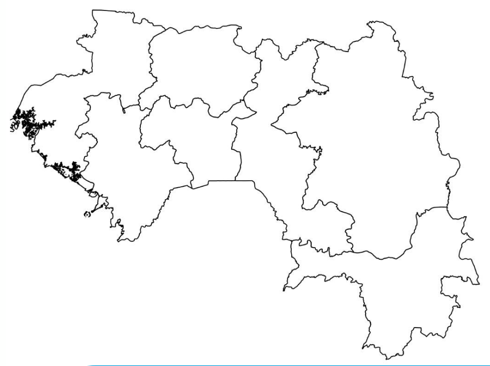
These vaccination maps can be used to locate zero-dose children

Inputs

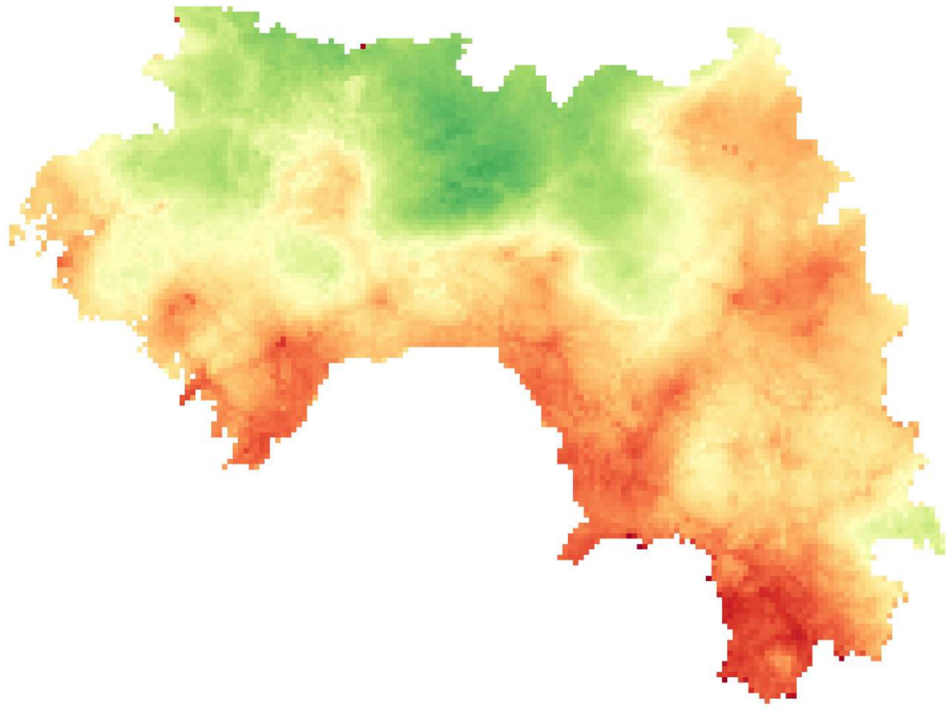
Vaccination



Population



Regions



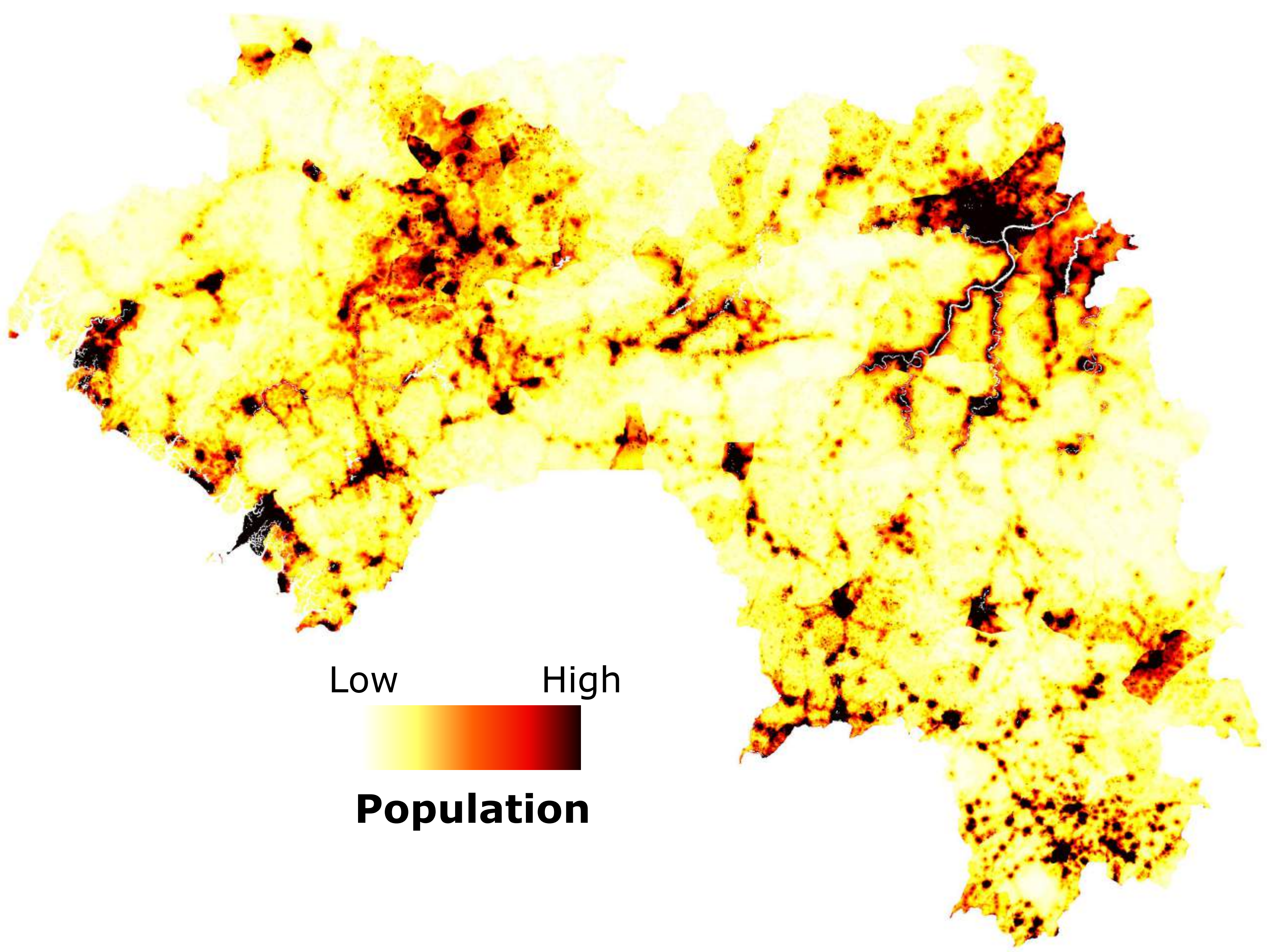
slide credit Martin Bogaert & Tommaso Salvatori

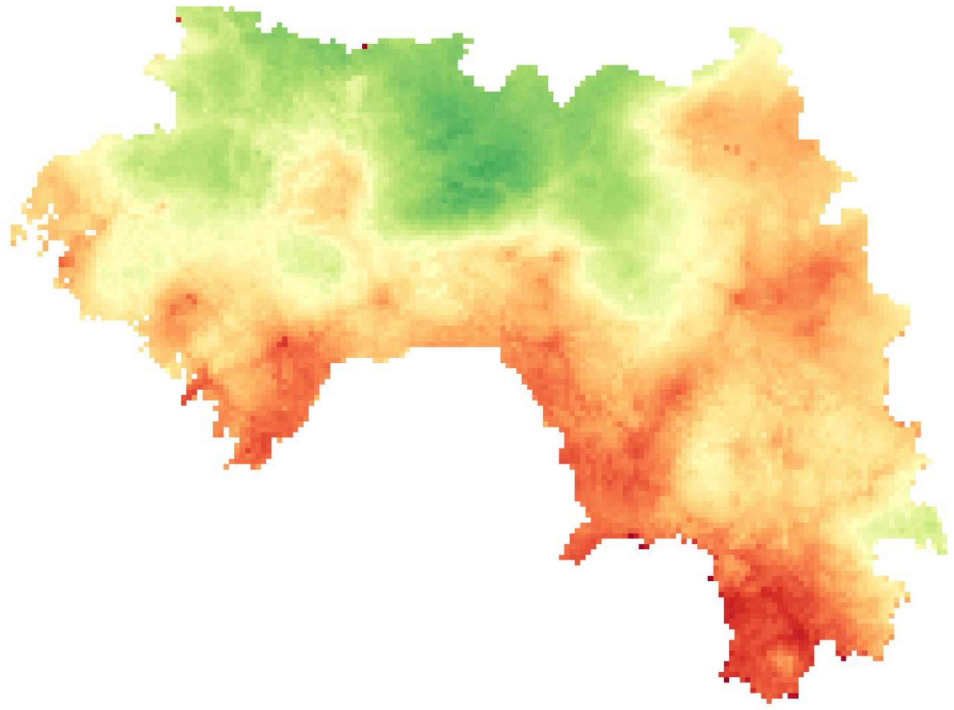
These vaccination maps can be used to locate zero-dose children

Inputs

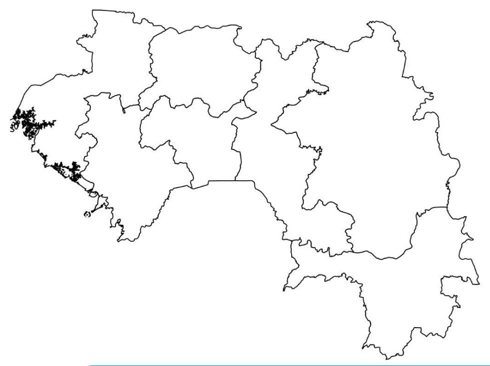
100 × 100m

Vaccination





Population



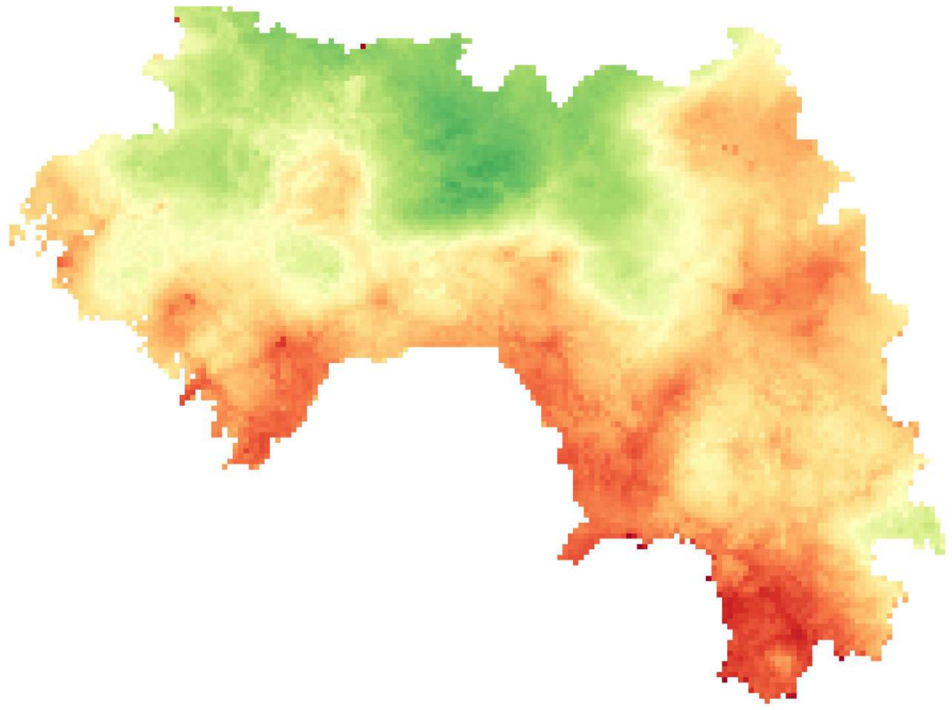
Regions

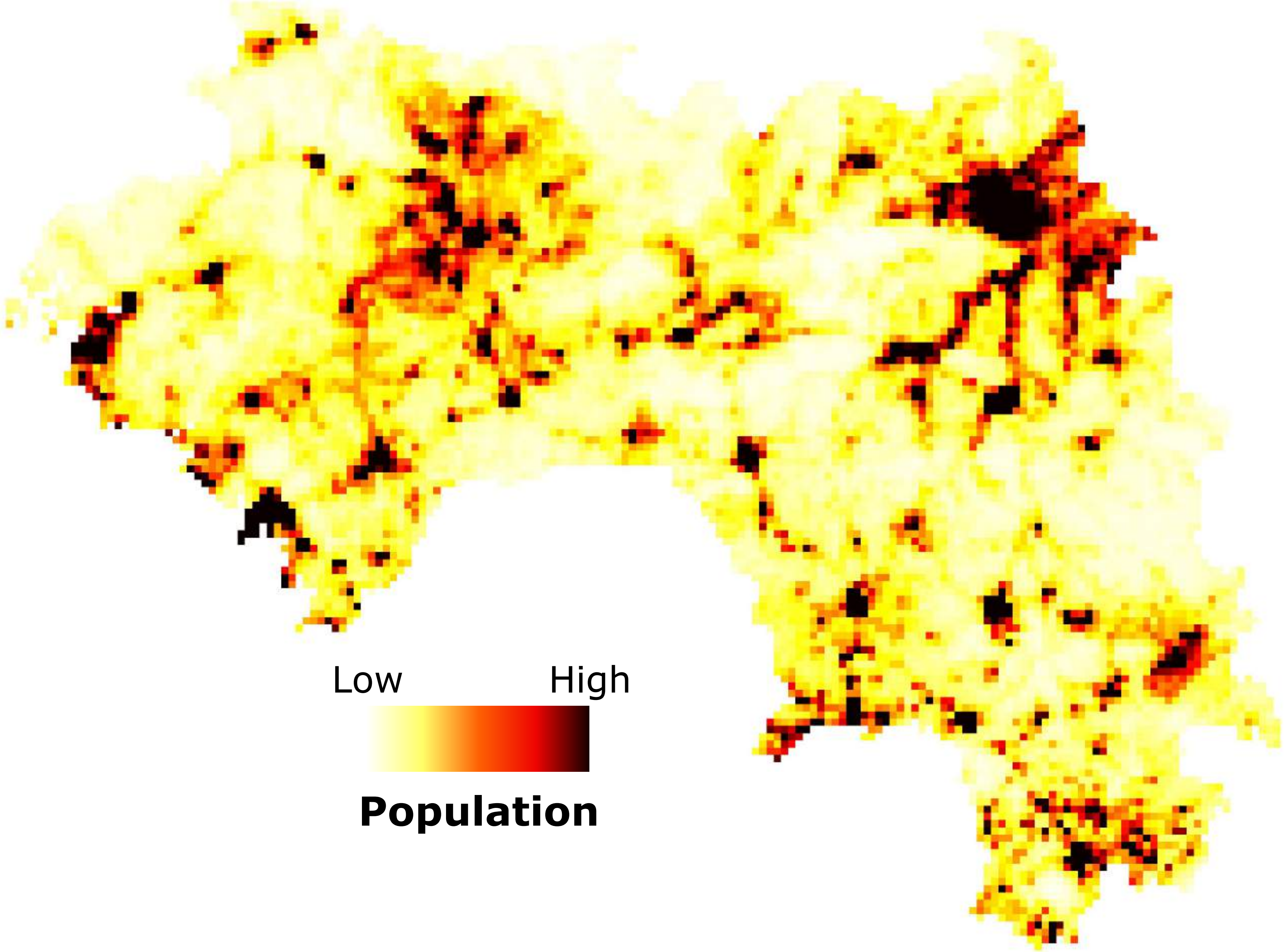
slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

Inputs

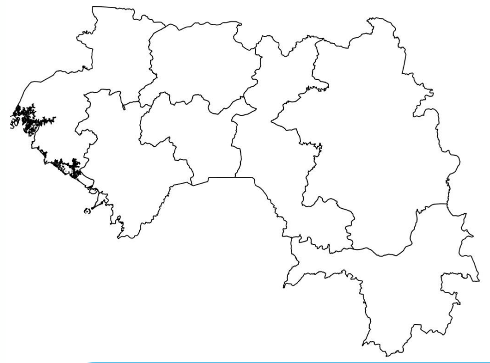
5 × 5km





Vaccination

Population



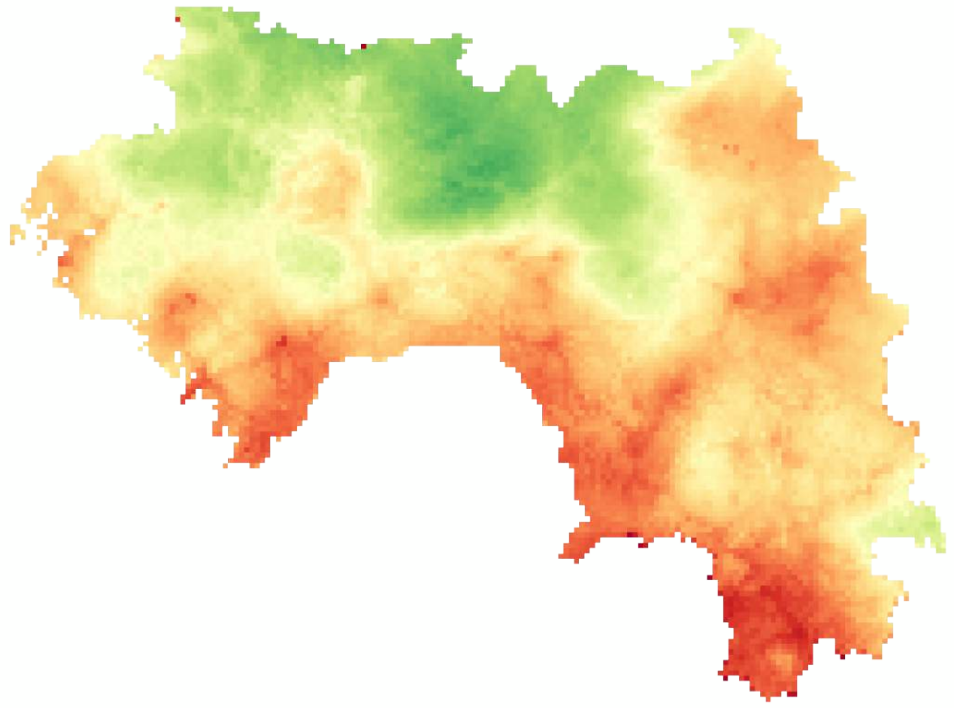
Regions

slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination



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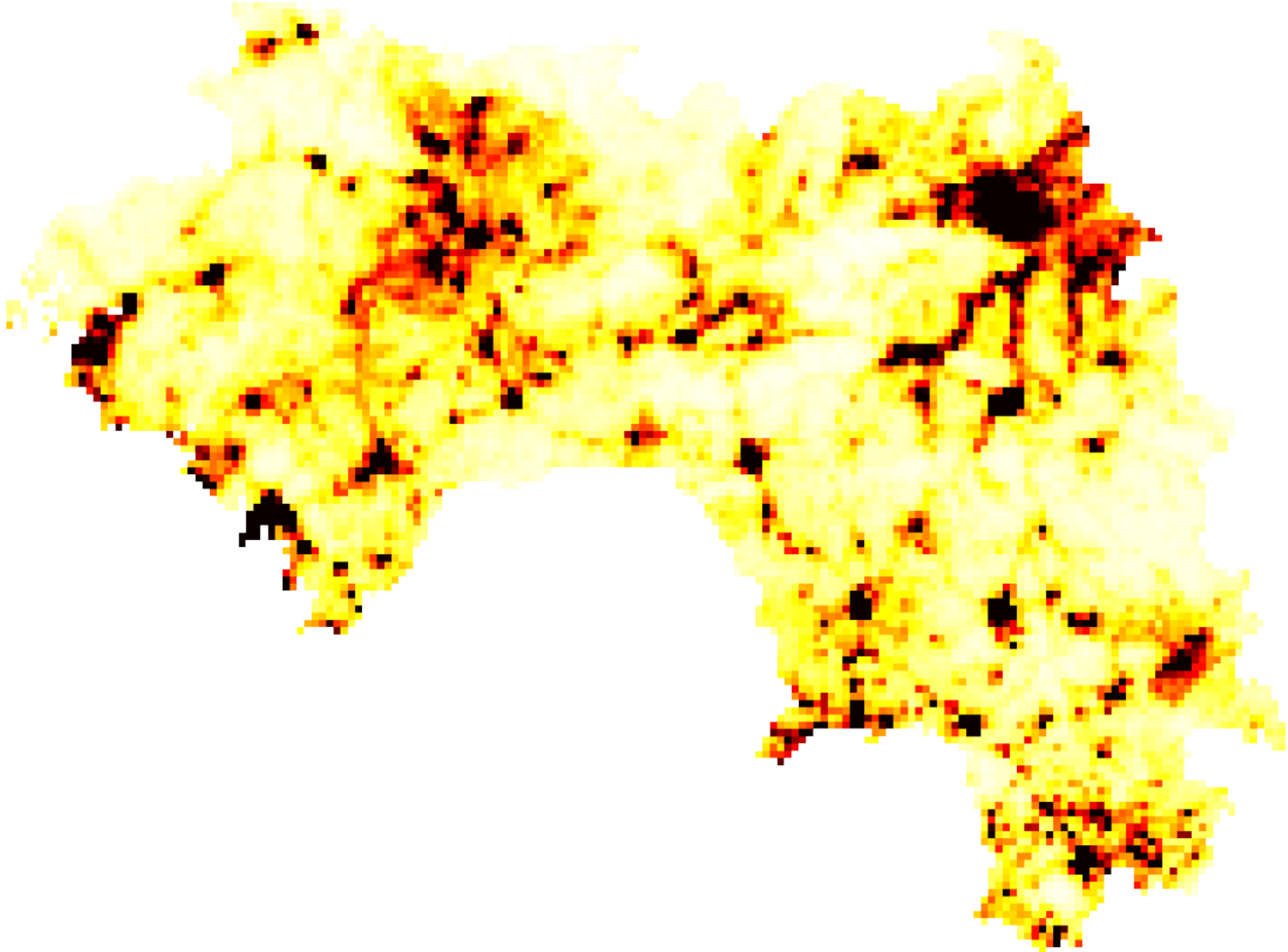

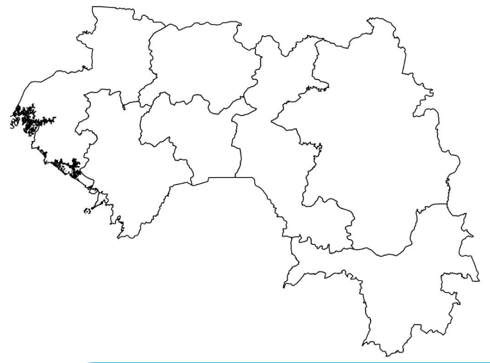

Regions

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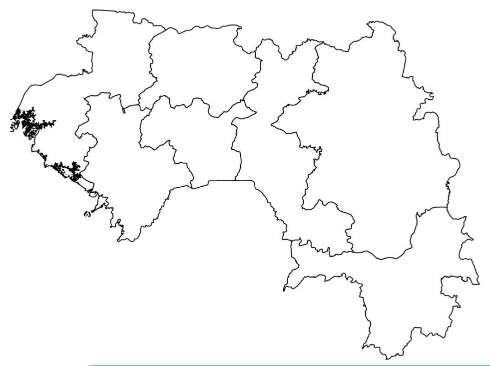
These vaccination maps can be used to locate zero-dose children

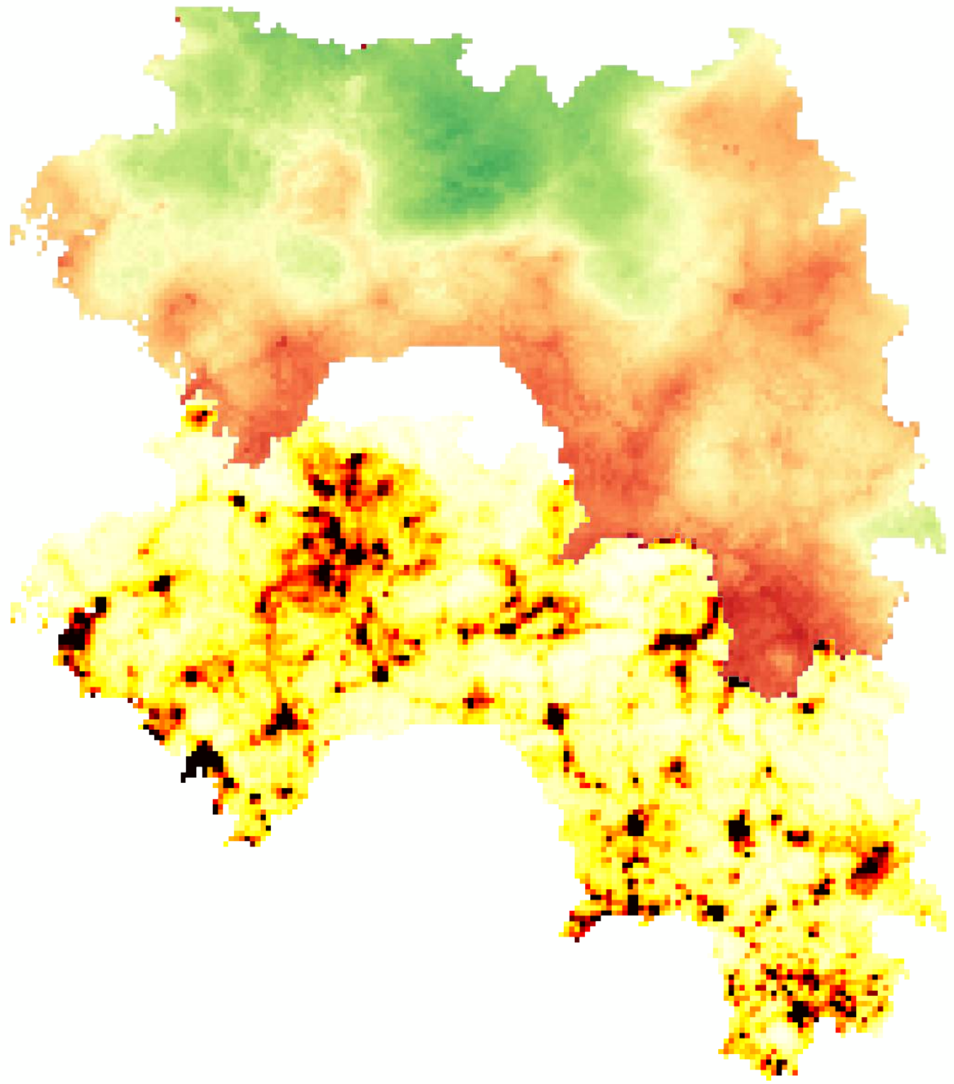
Inputs

Vaccination

Population



Regions



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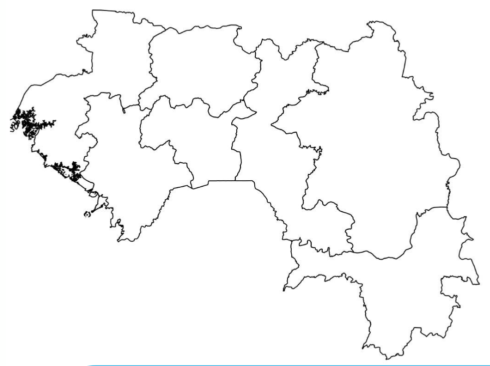
These vaccination maps can be used to locate zero-dose children

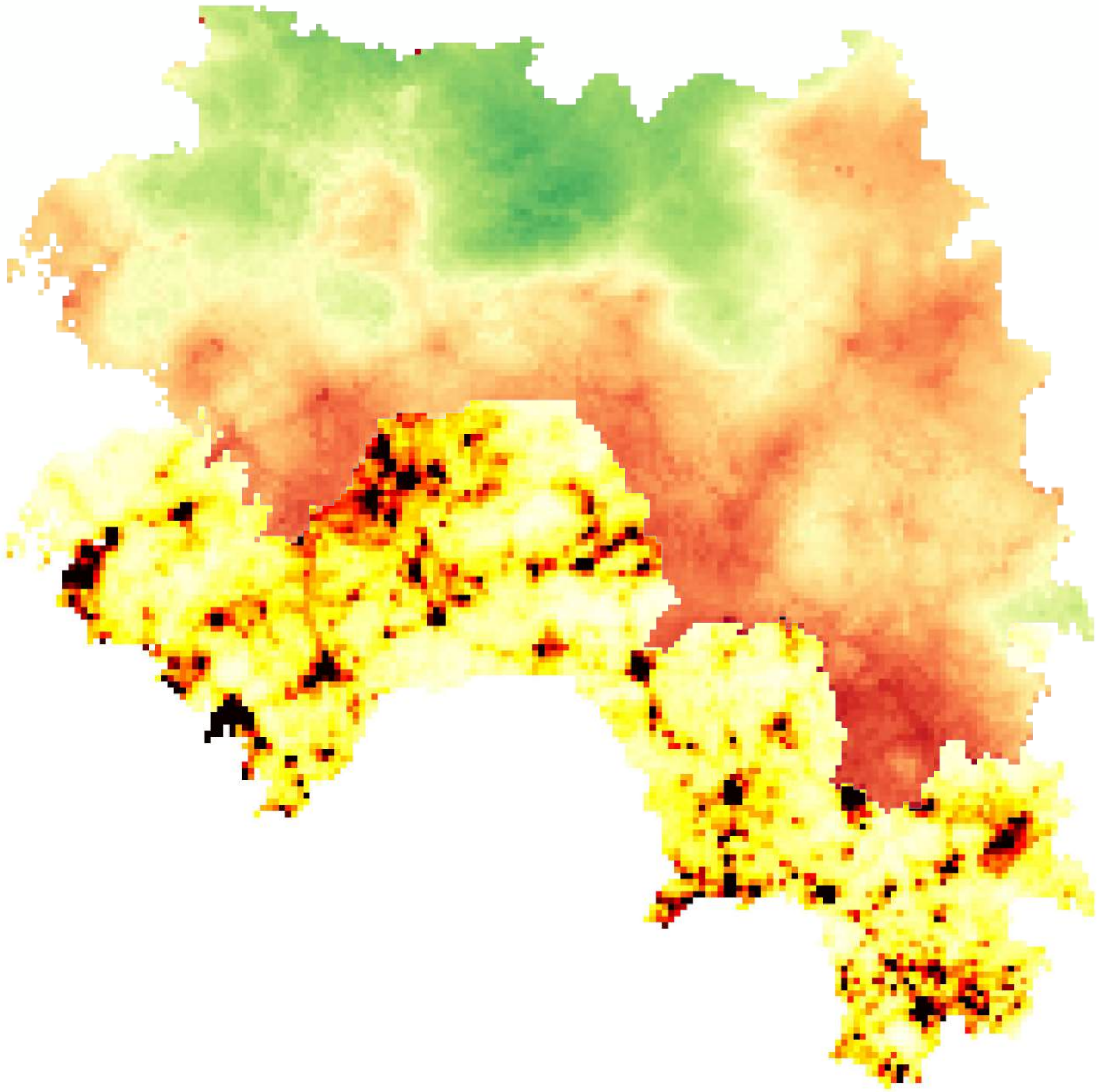
Inputs

Vaccination

Population



Regions



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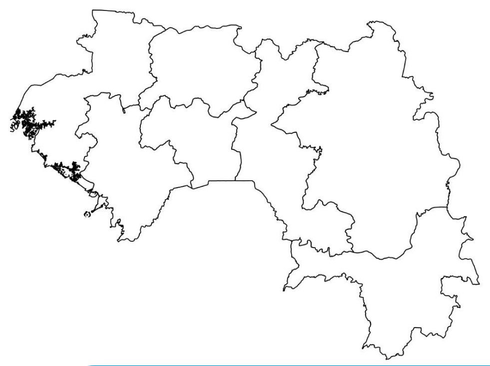
These vaccination maps can be used to locate zero-dose children

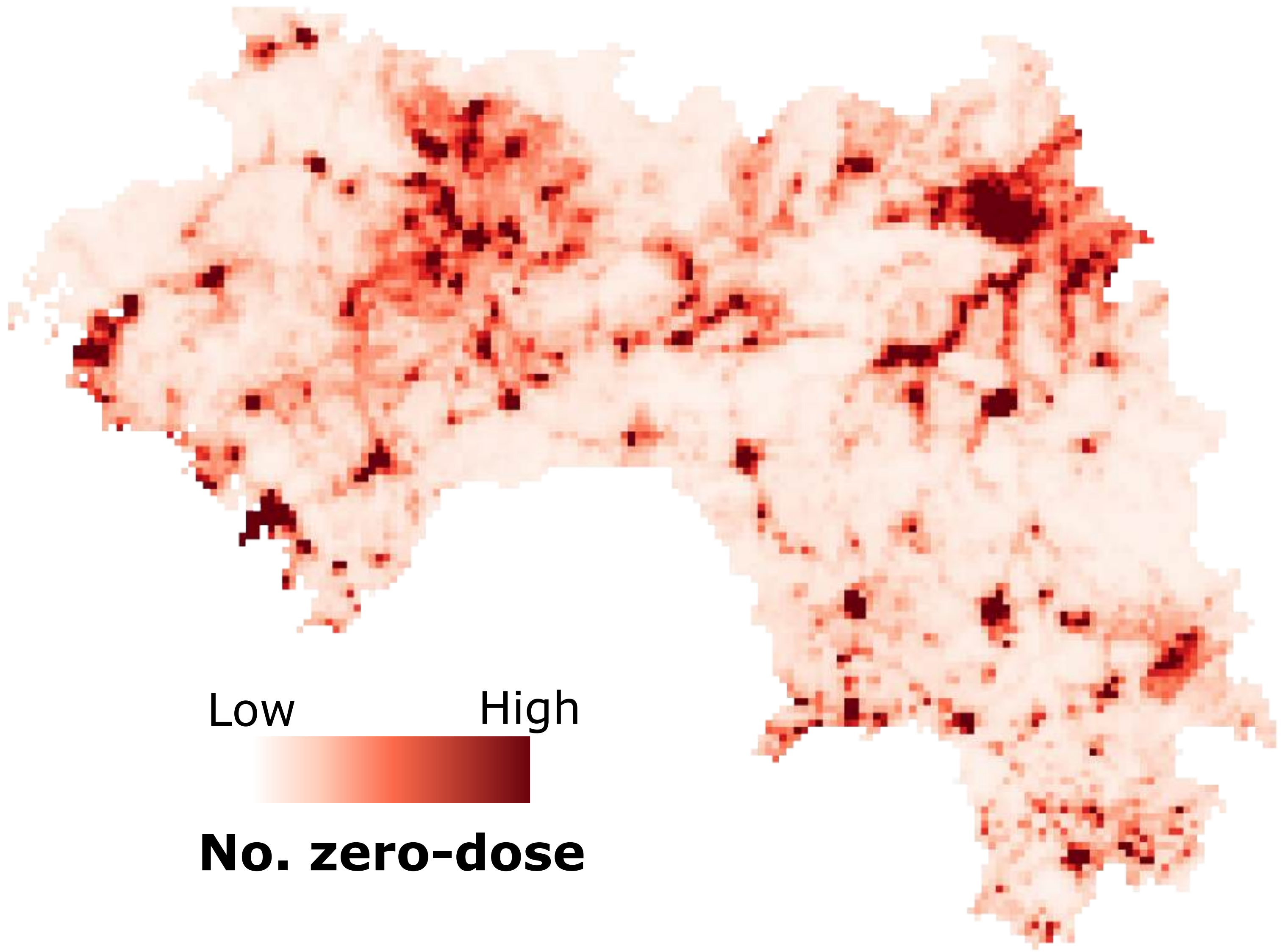
Inputs

Vaccination

Population



Regions

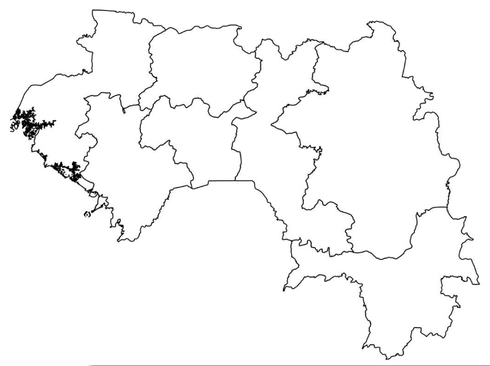


These vaccination maps can be used to locate zero-dose children

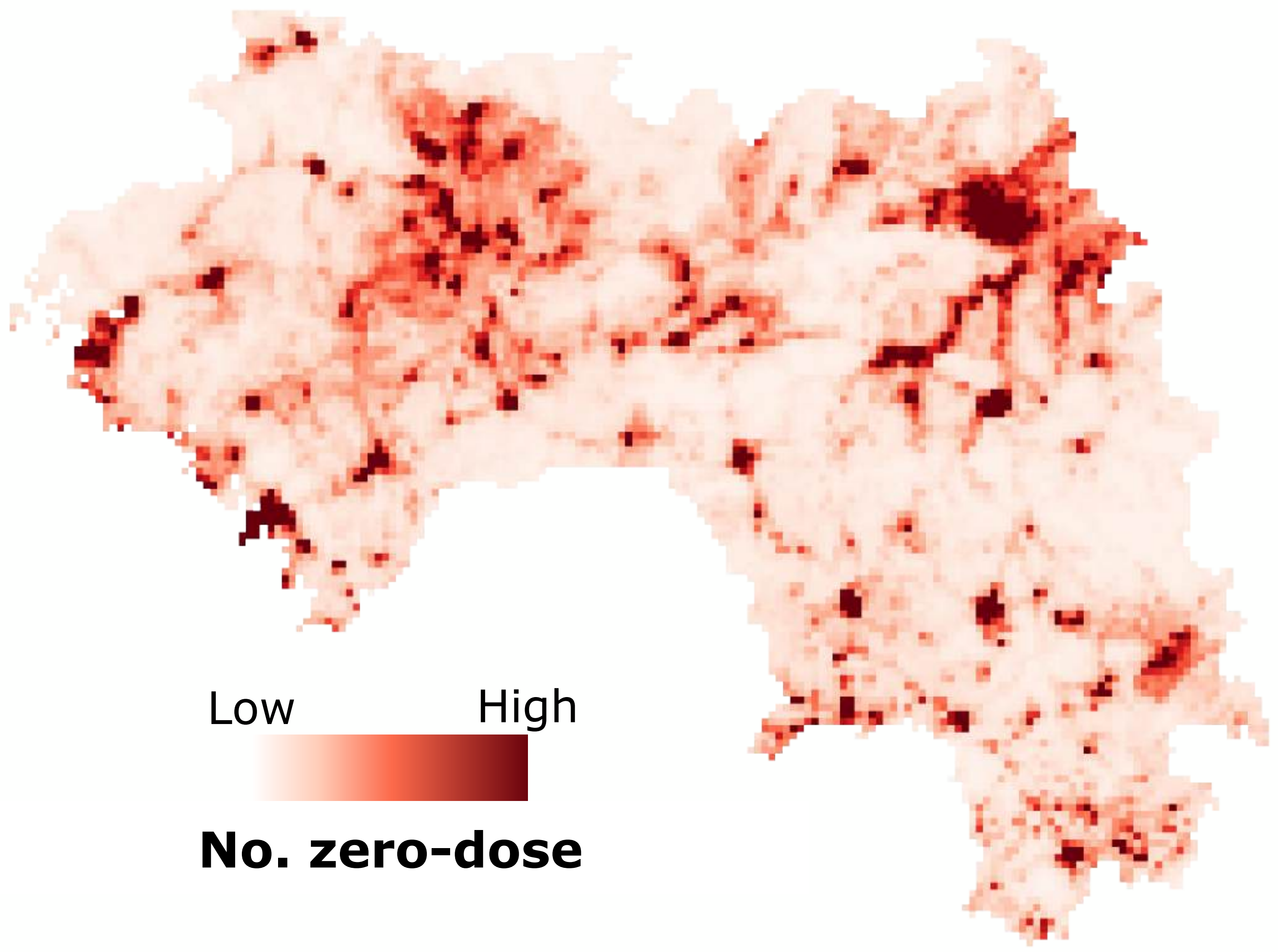
Inputs

Vaccination

Population



Regions



slide credit Martin Bogaert & Tommaso Salvatori

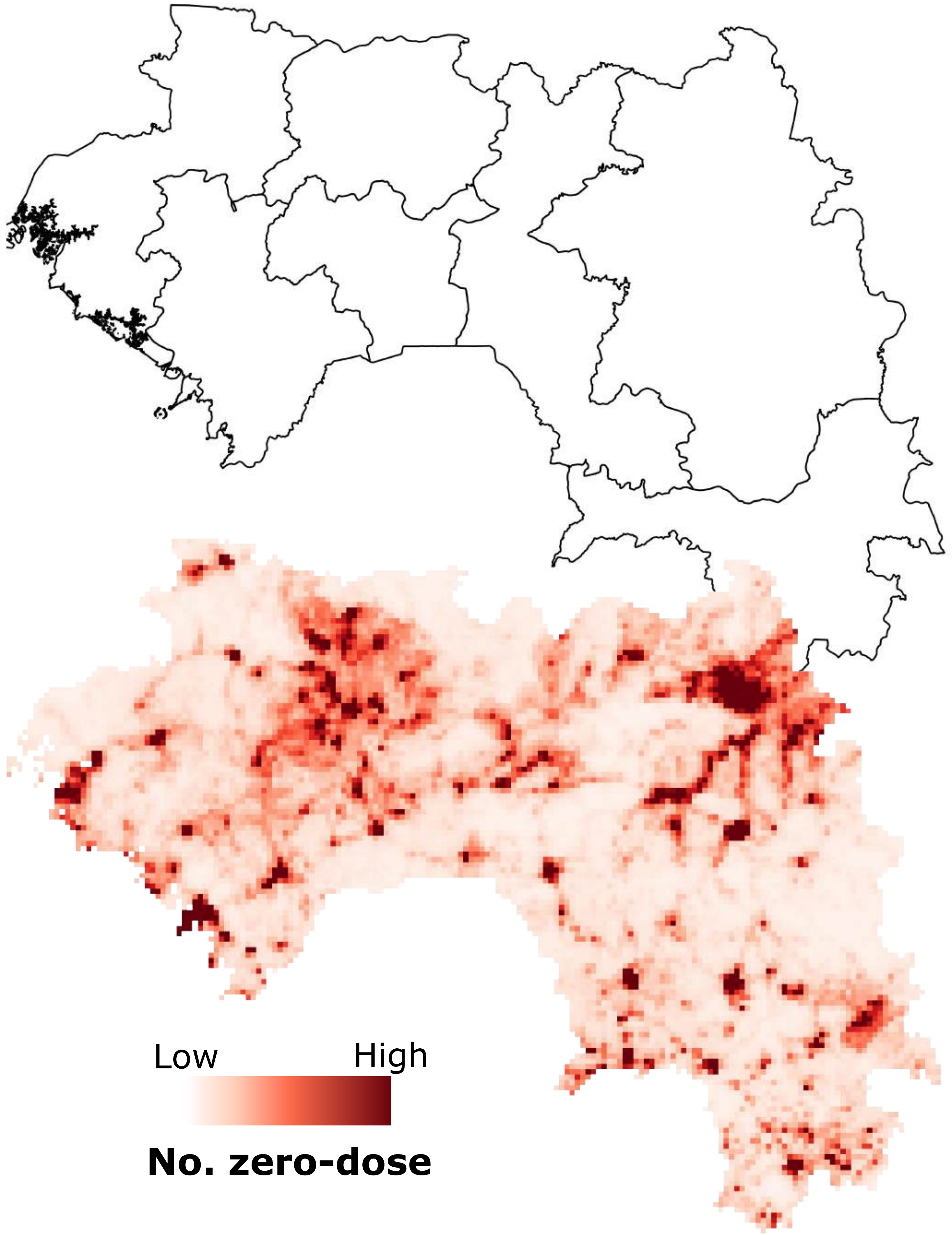
These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination

Population

Regions



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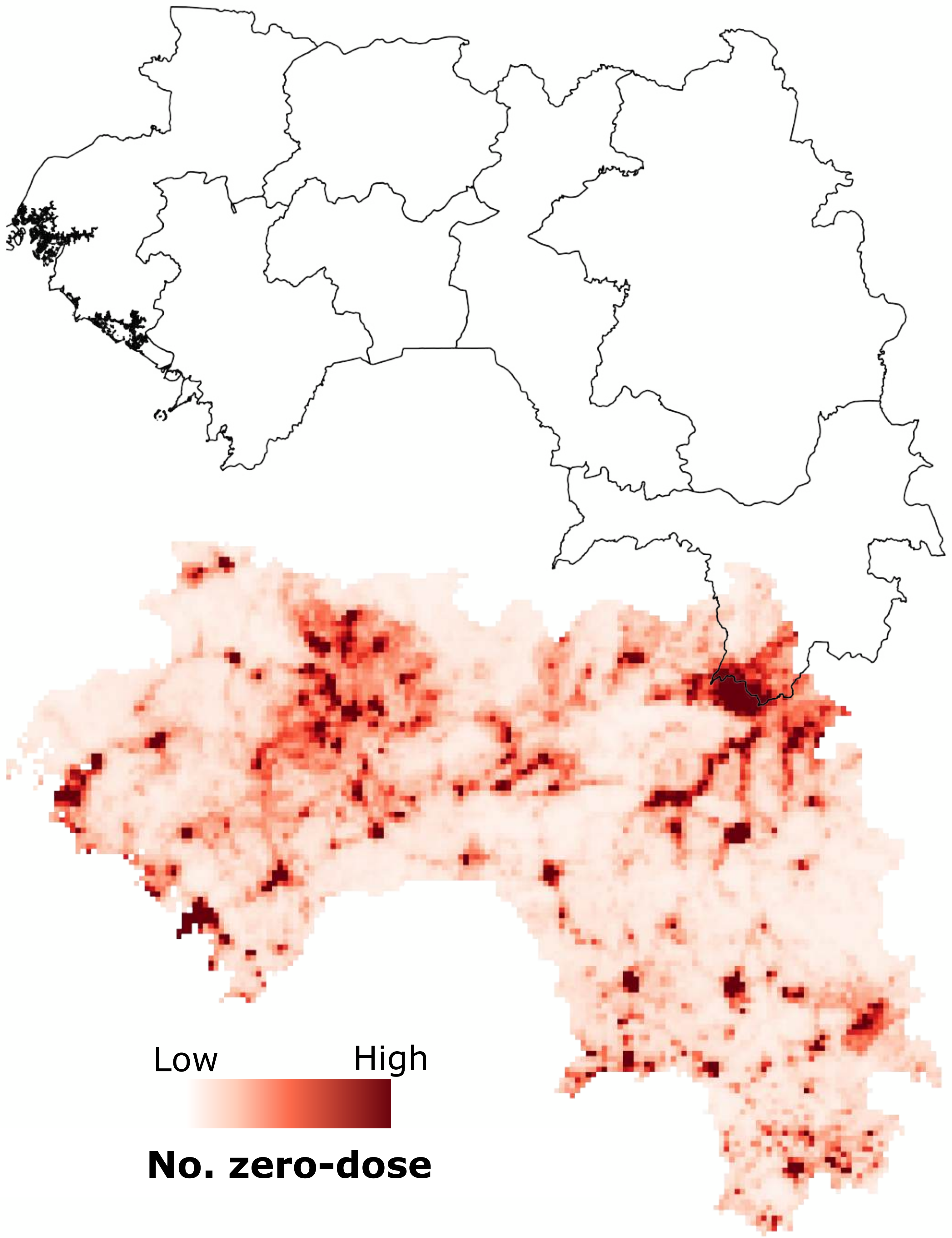
These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination

Population

Regions



slide credit Martin Bogaert & Tommaso Salvatori

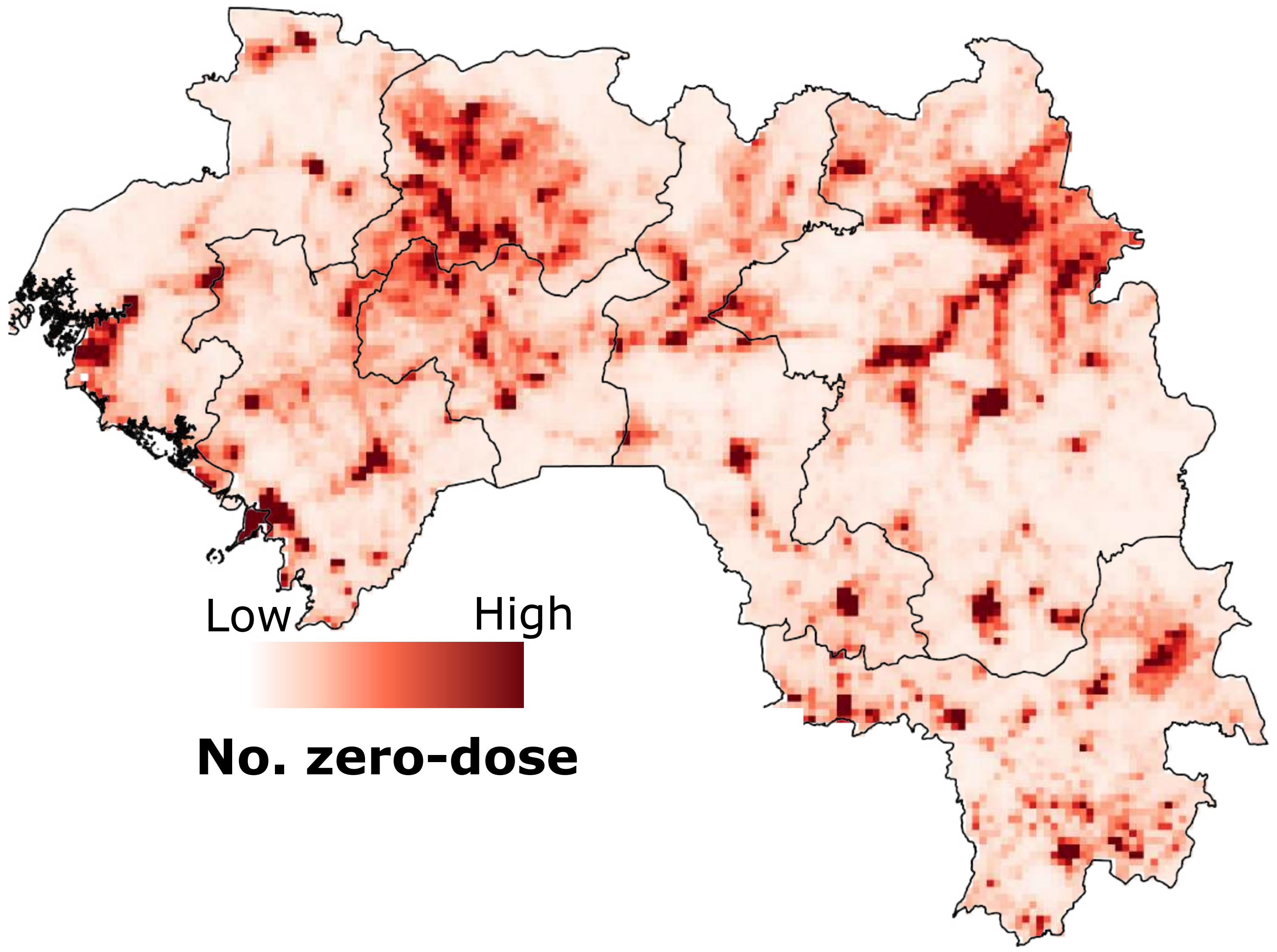
These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination

Population

Regions



slide credit Martin Bogaert & Tommaso Salvatori

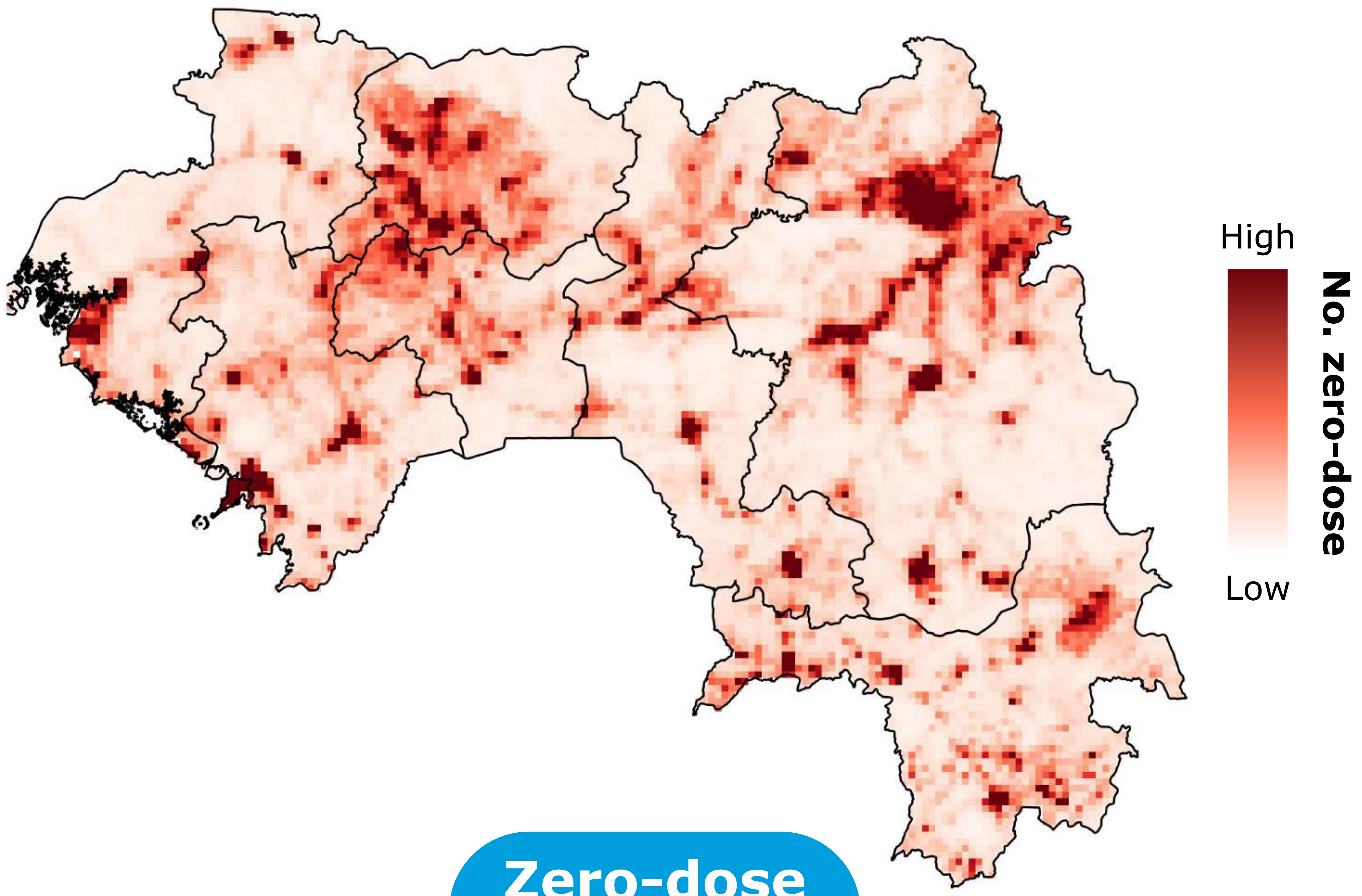
These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination

Population

Regions



Zero-dose (regional)

slide credit Martin Bogaert & Tommaso Salvatori

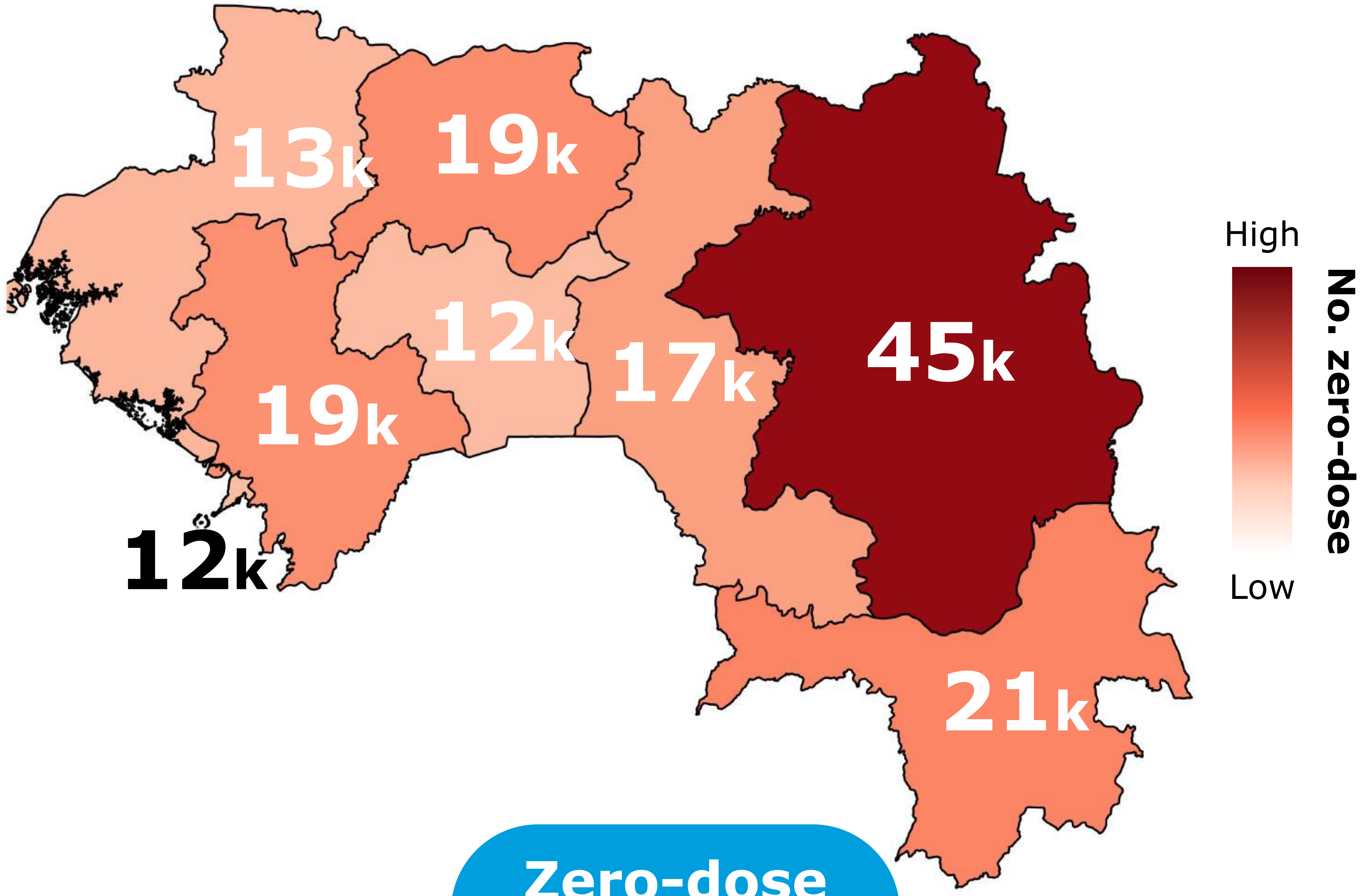
These vaccination maps can be used to locate zero-dose children

Inputs

Vaccination

Population

Regions



Zero-dose (regional)

slide credit Martin Bogaert & Tommaso Salvatori

These vaccination maps can be used to locate zero-dose children

Inputs

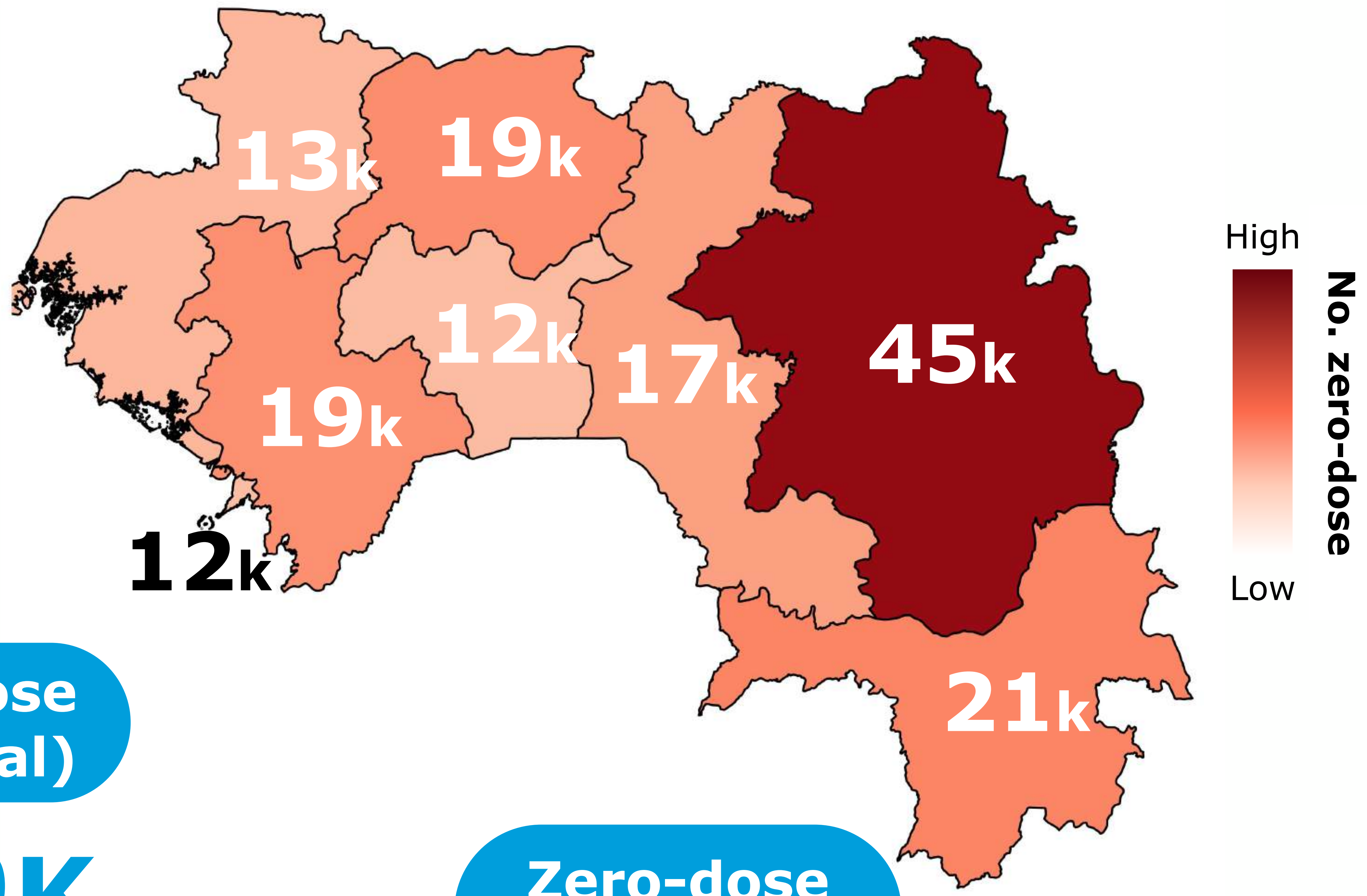
Vaccination

Population

Regions

Zero-dose (national)

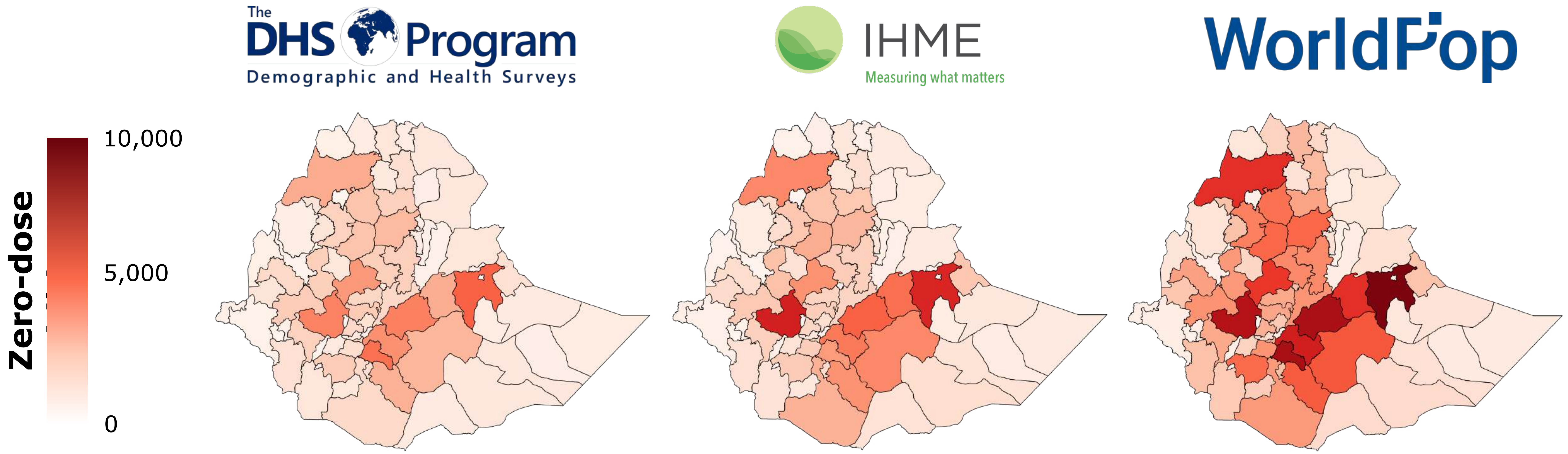
159K



Zero-dose (regional)

slide credit Martin Bogaert & Tommaso Salvatori

Consider Ethiopia: existing models disagree by as much as 1M children



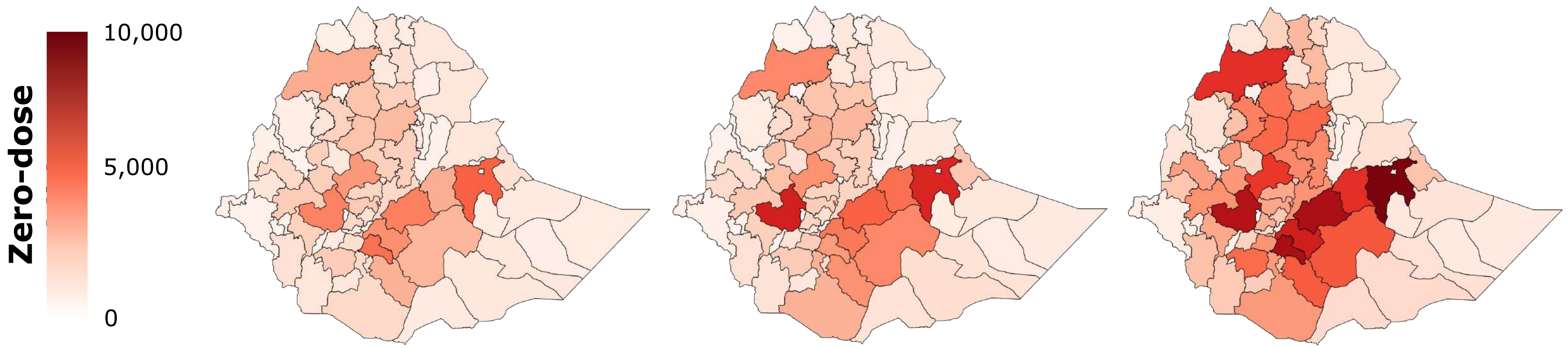
0.96M **1.15M** **1.96M**

No. zero-dose children*

slide credit Martin Bogaert & Tommaso Salvatori

Consider Ethiopia: existing models disagree by as much as 1M children

The DHS Program Demographic and Health Surveys | IHME Measuring what matters | WorldPop



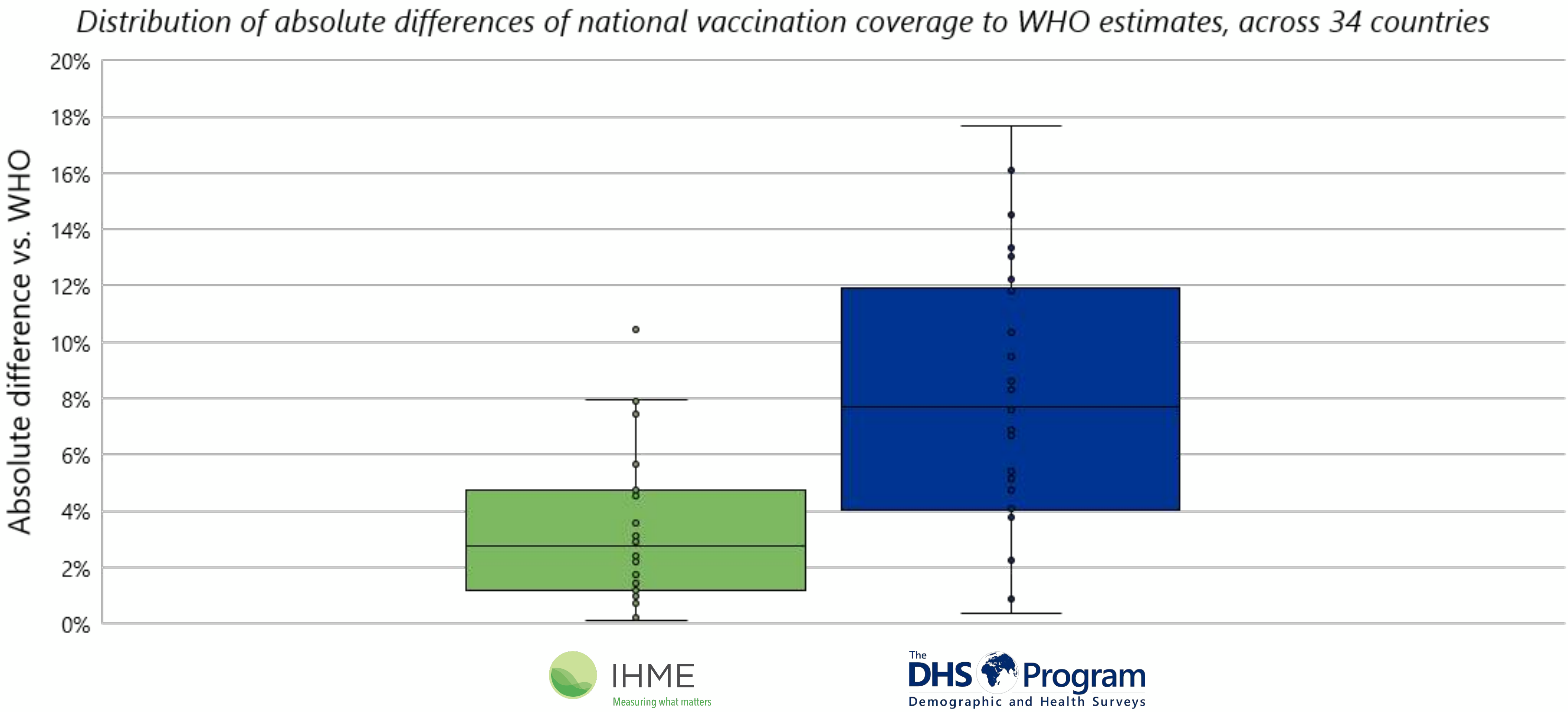
0.96M | **1.15M** | **1.96M**

No. zero-dose children*

±1M zero-dose children

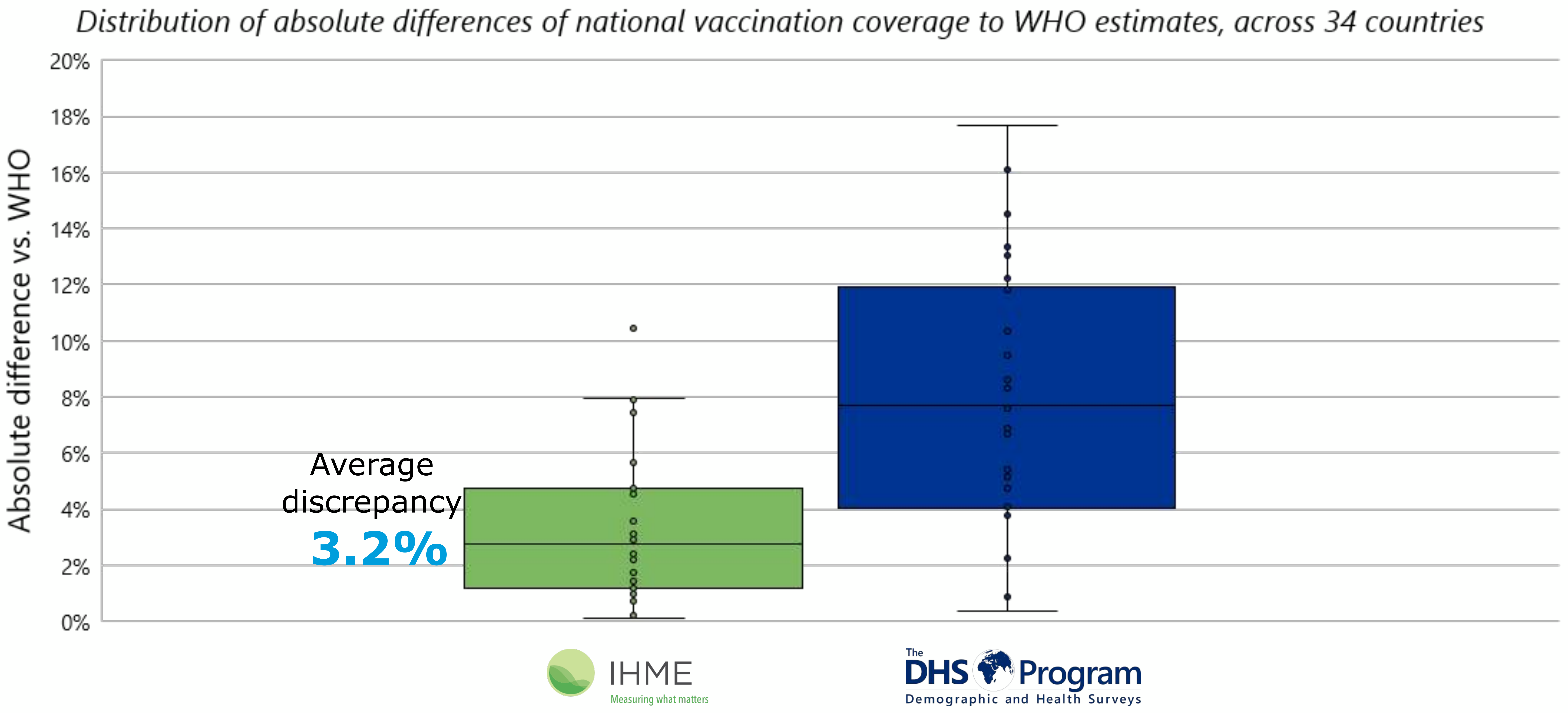
slide credit Martin Bogaert & Tommaso Salvatori

This discrepancy is systemic, making it hard for decision-makers to know which model to trust



slide credit Martin Bogaert & Tommaso Salvatori

This discrepancy is systemic, making it hard for decision-makers to know which model to trust



slide credit Martin Bogaert & Tommaso Salvatori

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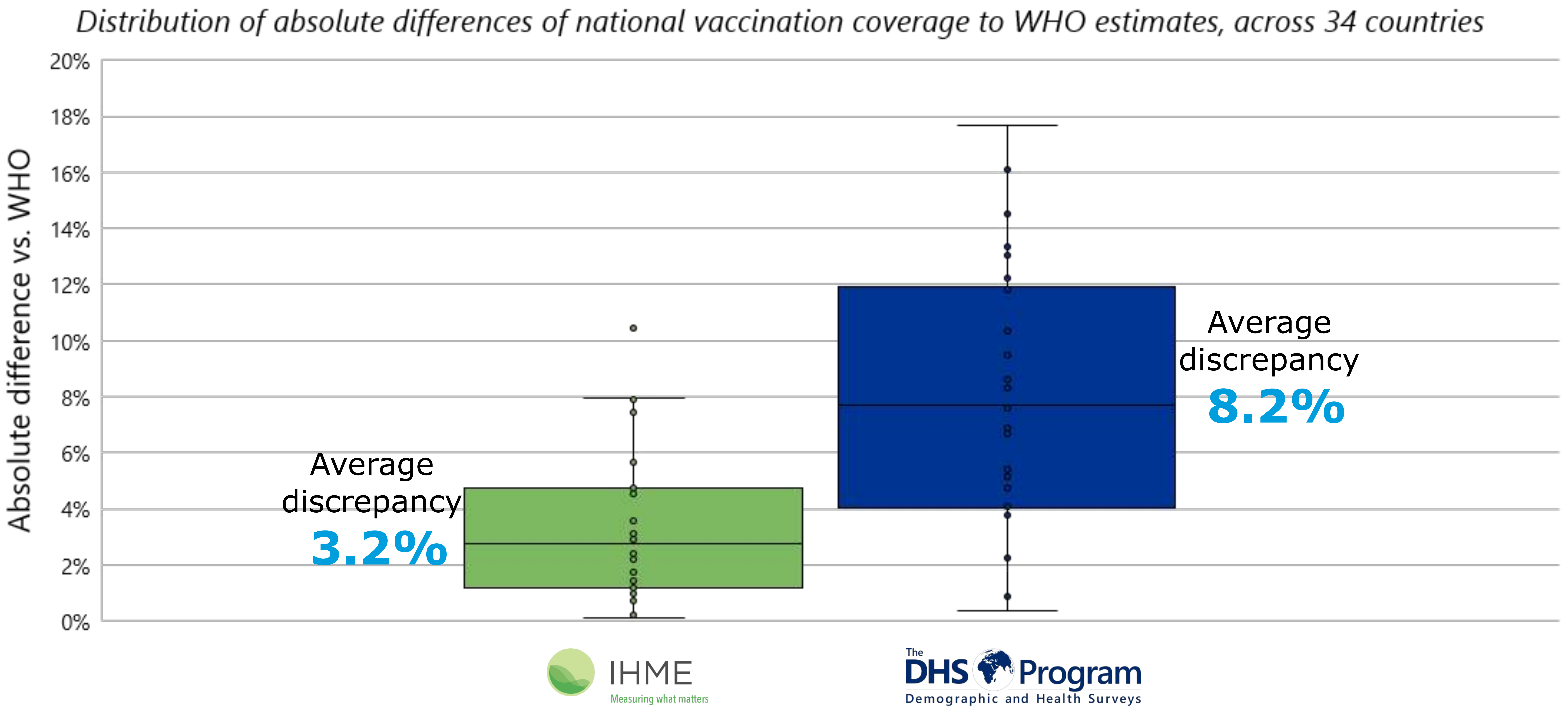

slide credit Martin Bogaert & Tommaso Salvatori

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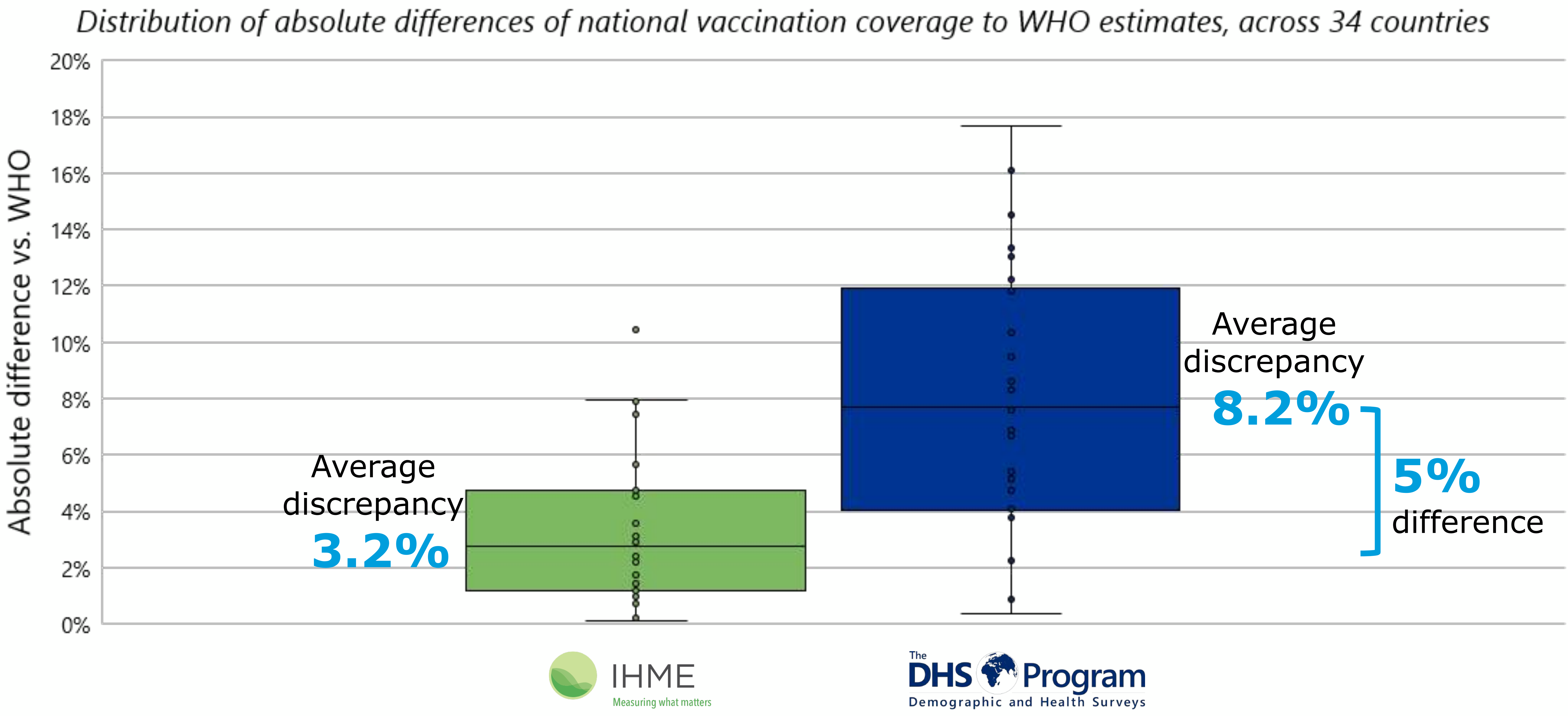
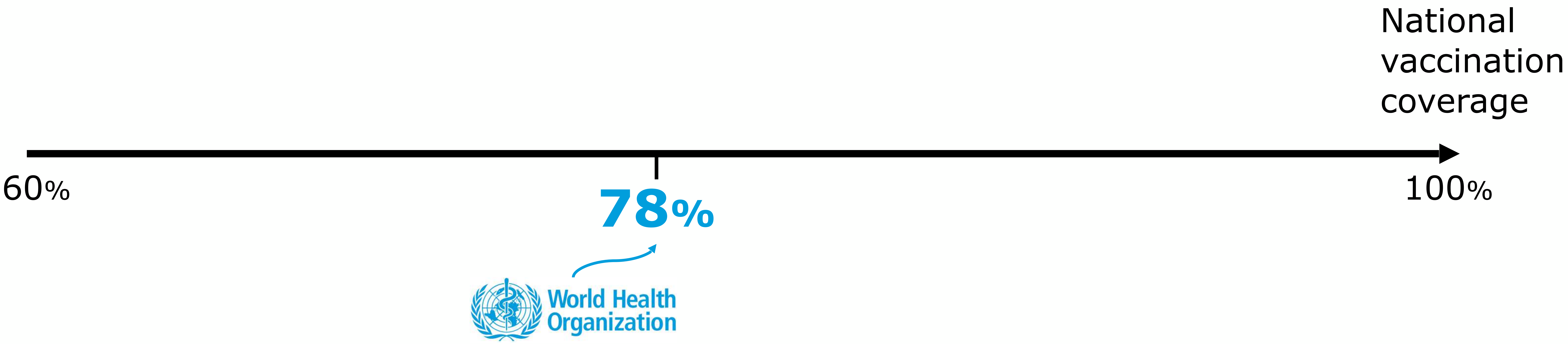
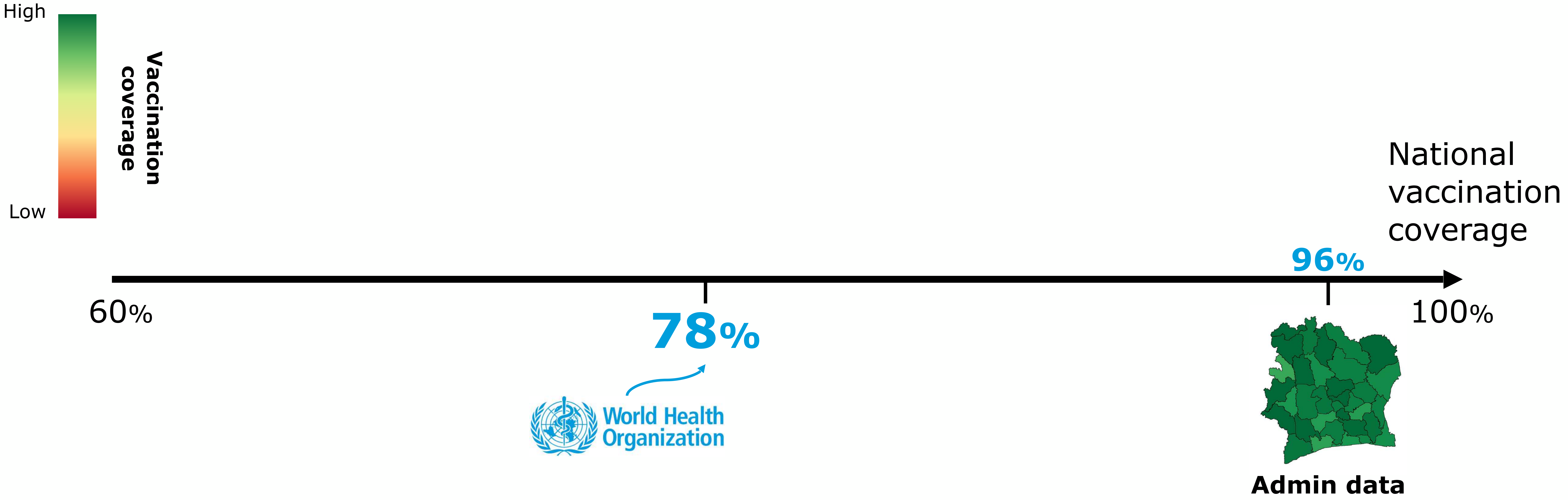


slide credit Martin Bogaert & Tommaso Salvatori

Case study: Côte d'Ivoire

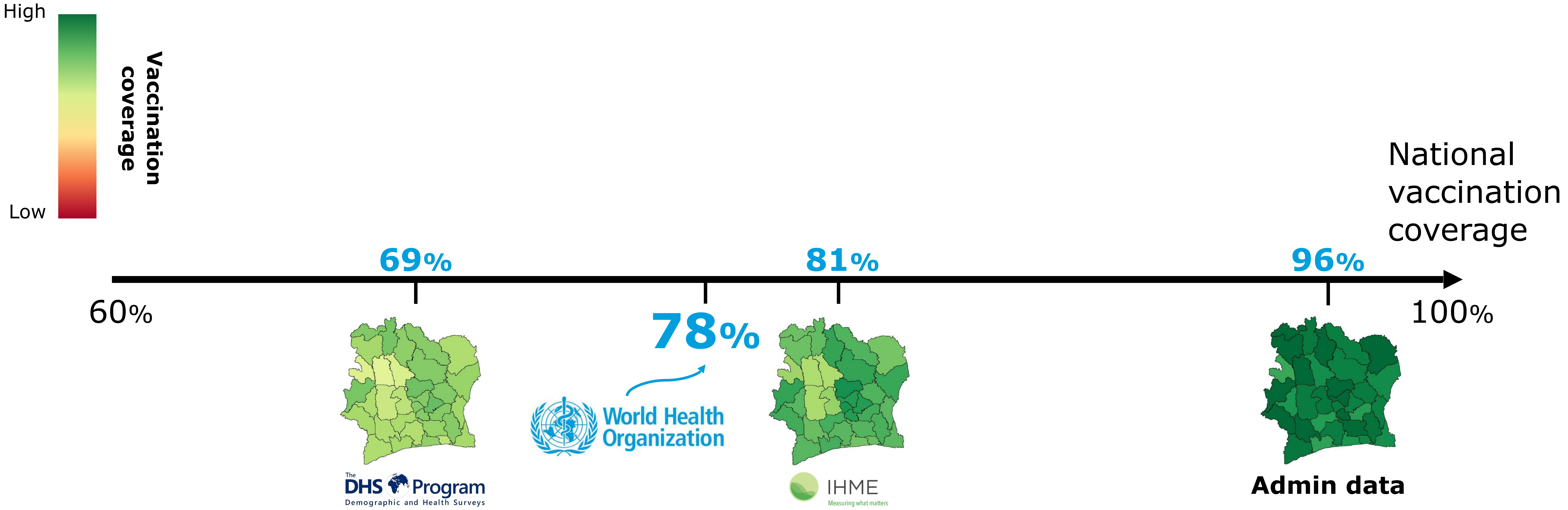


Case study: Côte d'Ivoire



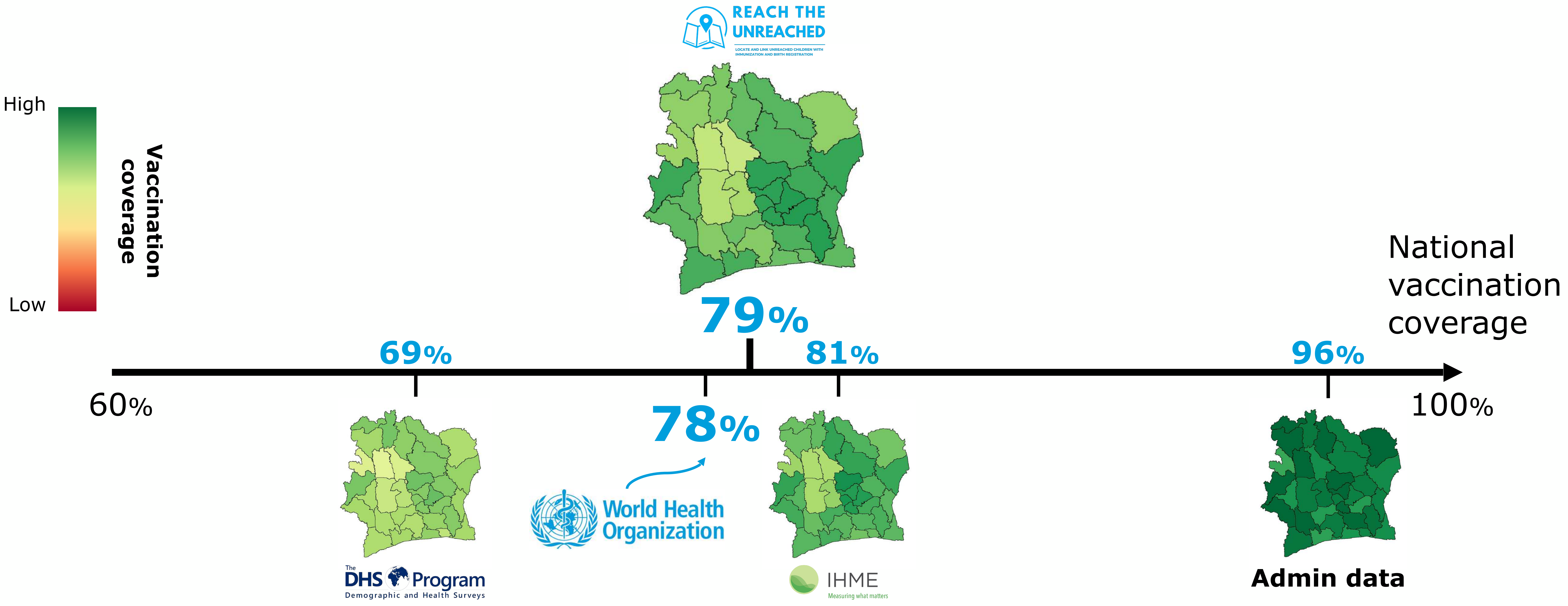
slide credit Martin Bogaert & Tommaso Salvatori

Case study: Côte d'Ivoire



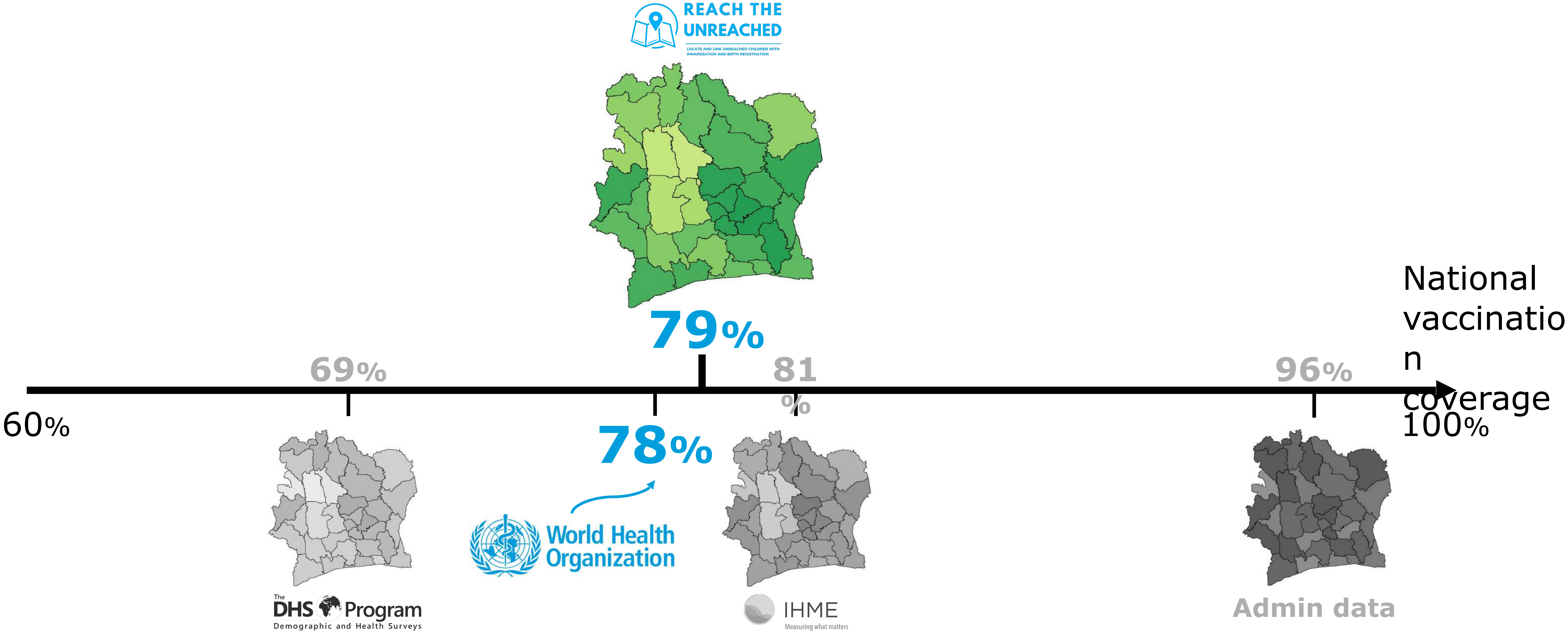
slide credit Martin Bogaert & Tommaso Salvatori

Case study: Côte d’Ivoire



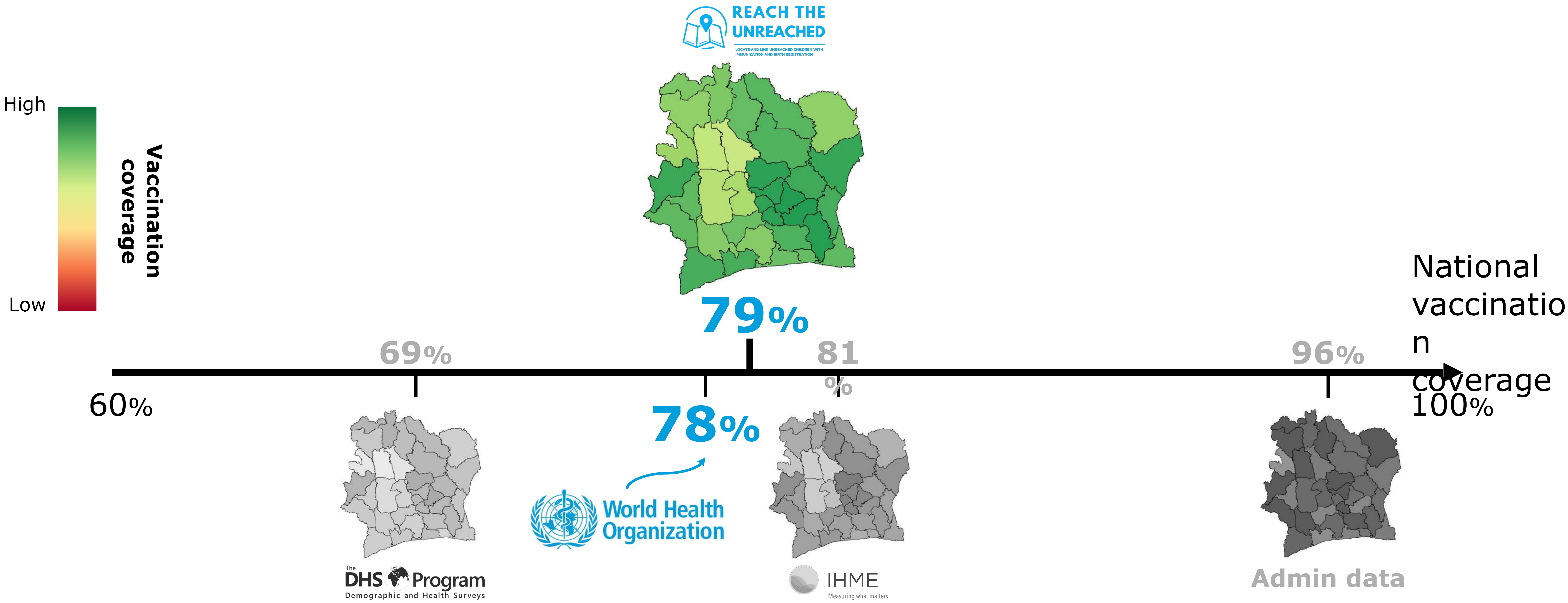
slide credit Martin Bogaert & Tommaso Salvatori

RtU’s model aligns the closest with WHO estimates



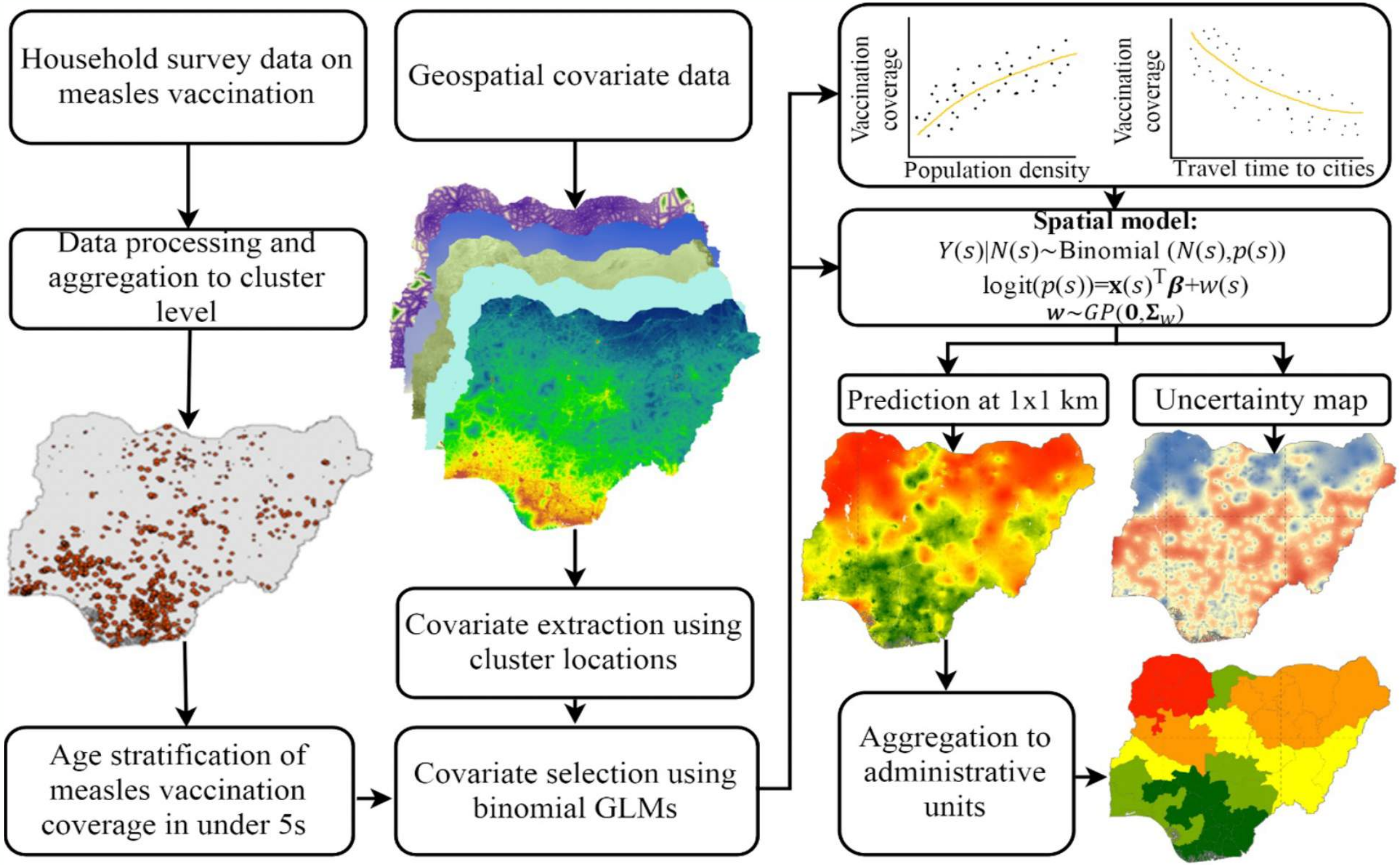
https://data.unicef.org/resources/reaching-the-unreached-with-life-saving-vaccines-through-data-science-and-geospatial-technologies/

RtU's model aligns the closest with WHO estimates



https://data.unicef.org/resources/reaching-the-unreached-with-life-saving-vaccines-through-data-science-and-geospatial-technologies/

WorldPop

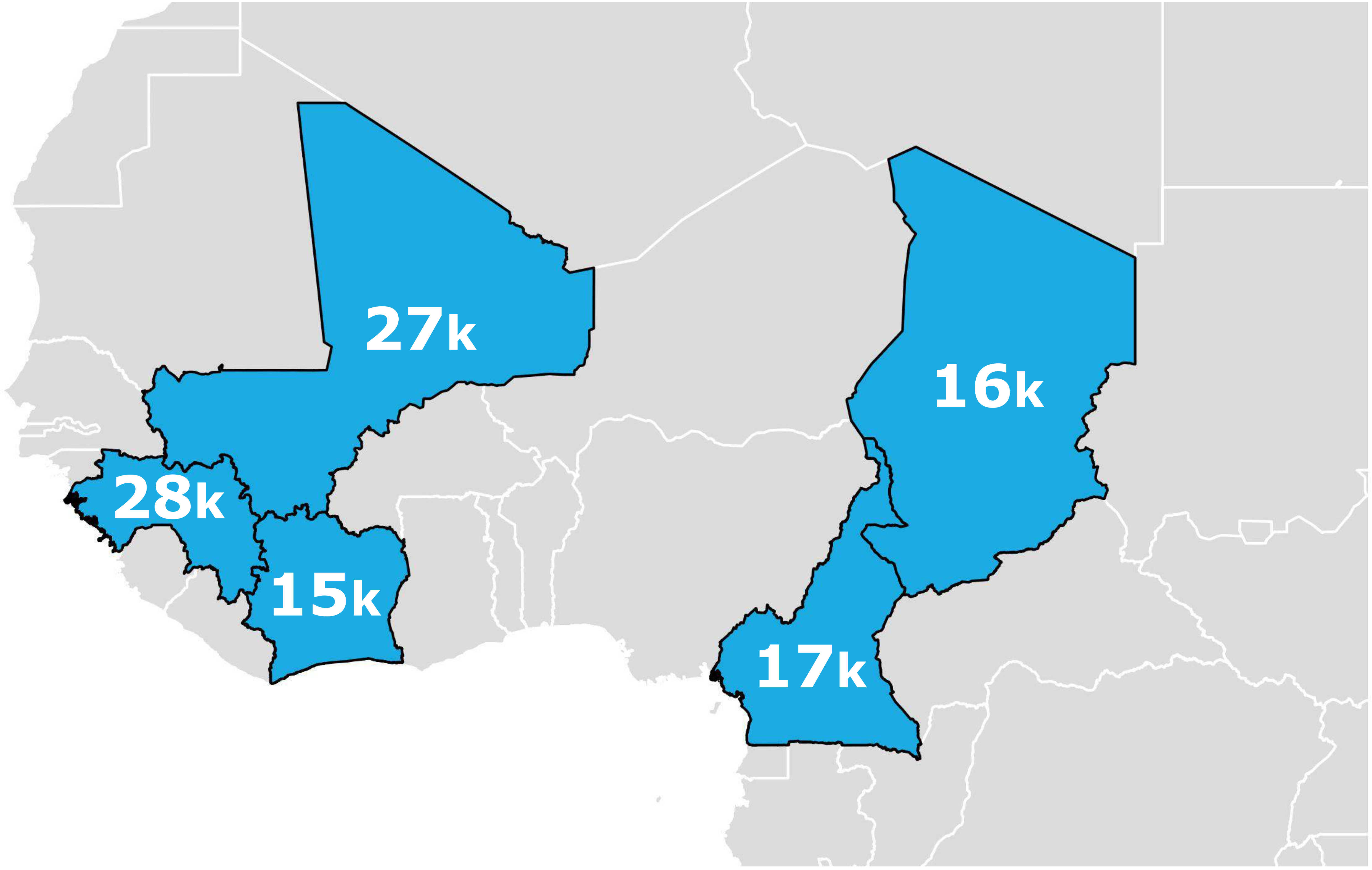


https://github.com/wpgp/RtU_vaccination_modelling/tree/main

What's at stake?

103,000

child deaths could be avoided every year in the 5 countries by achieving 95% coverage



Estimated number of under-five children lives saved by achieving 95% vaccination coverage by country

slide credit Martin Bogaert & Tommaso Salvatori

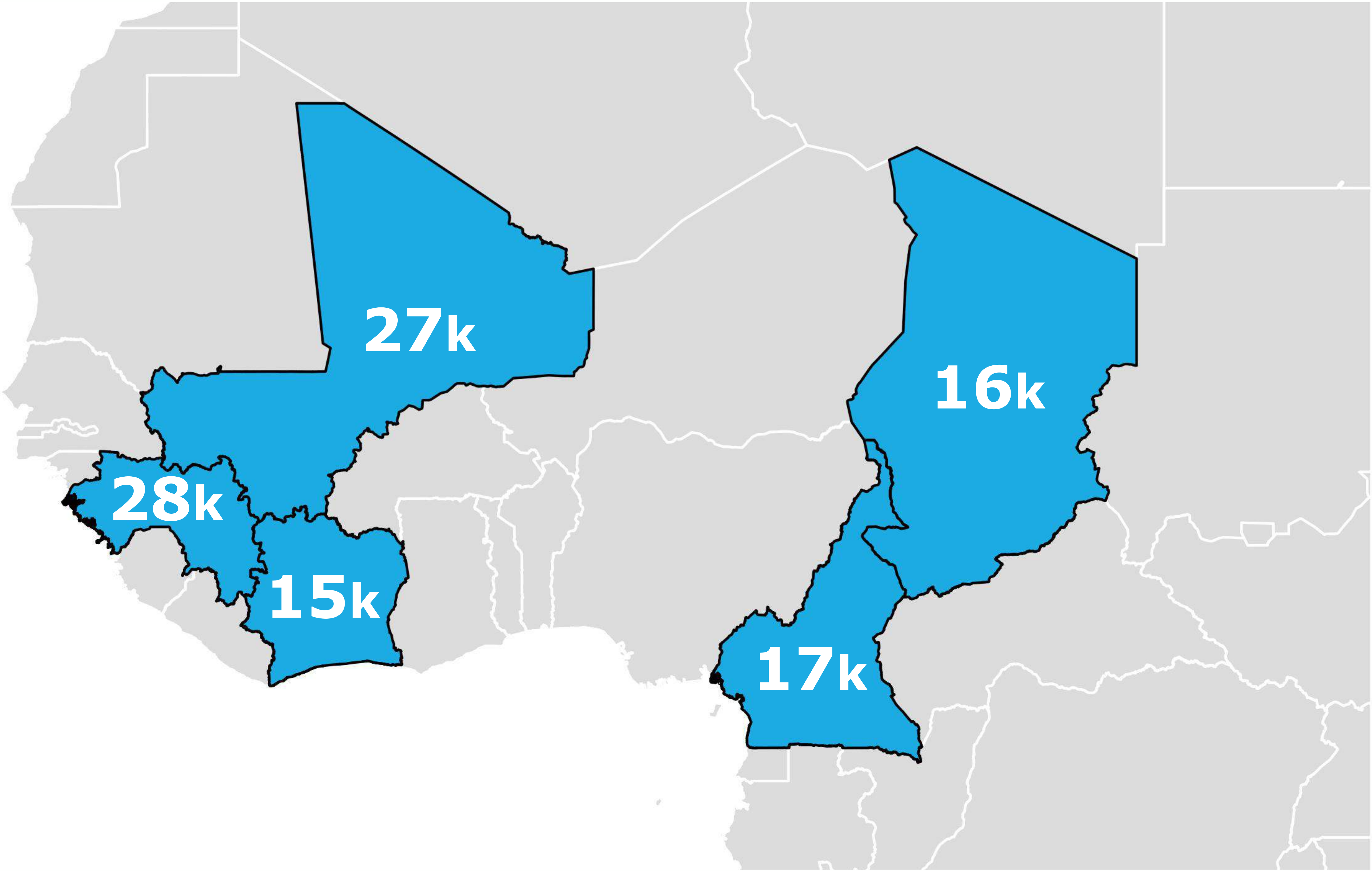
What's at stake?

103,000

child deaths could be avoided every year in the 5 countries by achieving 95% coverage

6,400

child deaths could be prevented for every 1% increase in vaccination coverage



Estimated number of under-five children lives saved by achieving 95% vaccination coverage by country

slide credit Martin Bogaert & Tommaso Salvatori

Take Aways

Vulnerability is multifaceted

The "It works!" trap - Accuracy vs Fairness

Data & Tools you employ are likely not originally thought to address the problem you tackle

Social Good problems are complex **-** often there is time pressure but make sure to thoroughly observe your models' outputs

Carefully consider the **tradeoffs**


All models are wrong but some are useful
- George E. P. Box
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Interesting Reads

- https://developers.google.com/machine-learning/foundational-courses
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