



*New generation of risk maps:
multimeric approaches using
routine data and surveys*

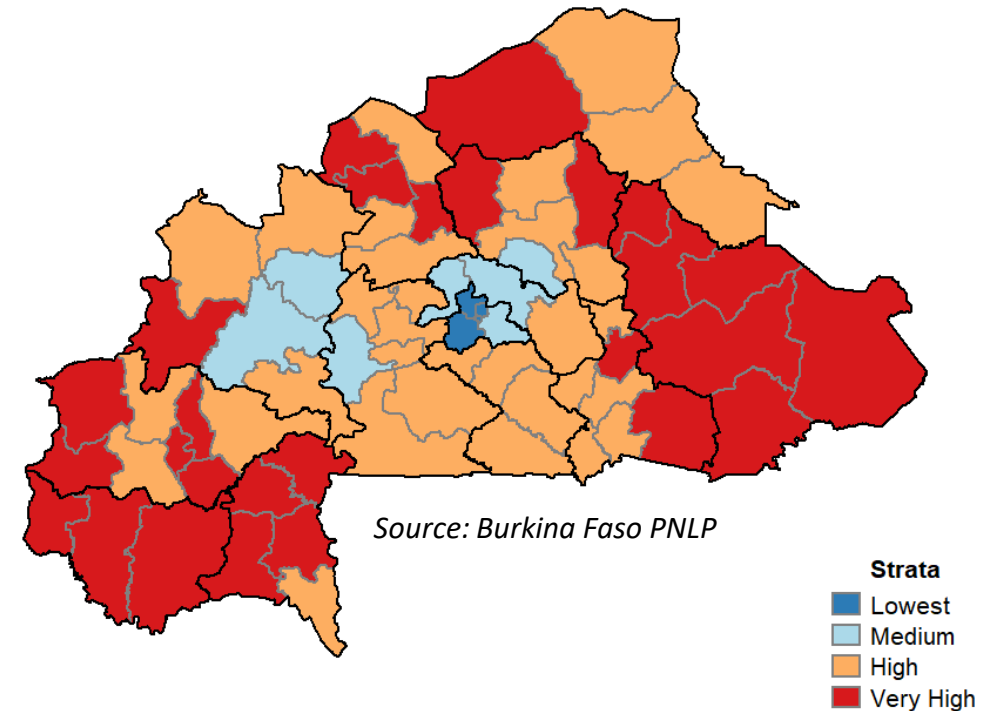
Punam Amratia

SMERG Annual Meeting, Kigali, Rwanda

May 2022

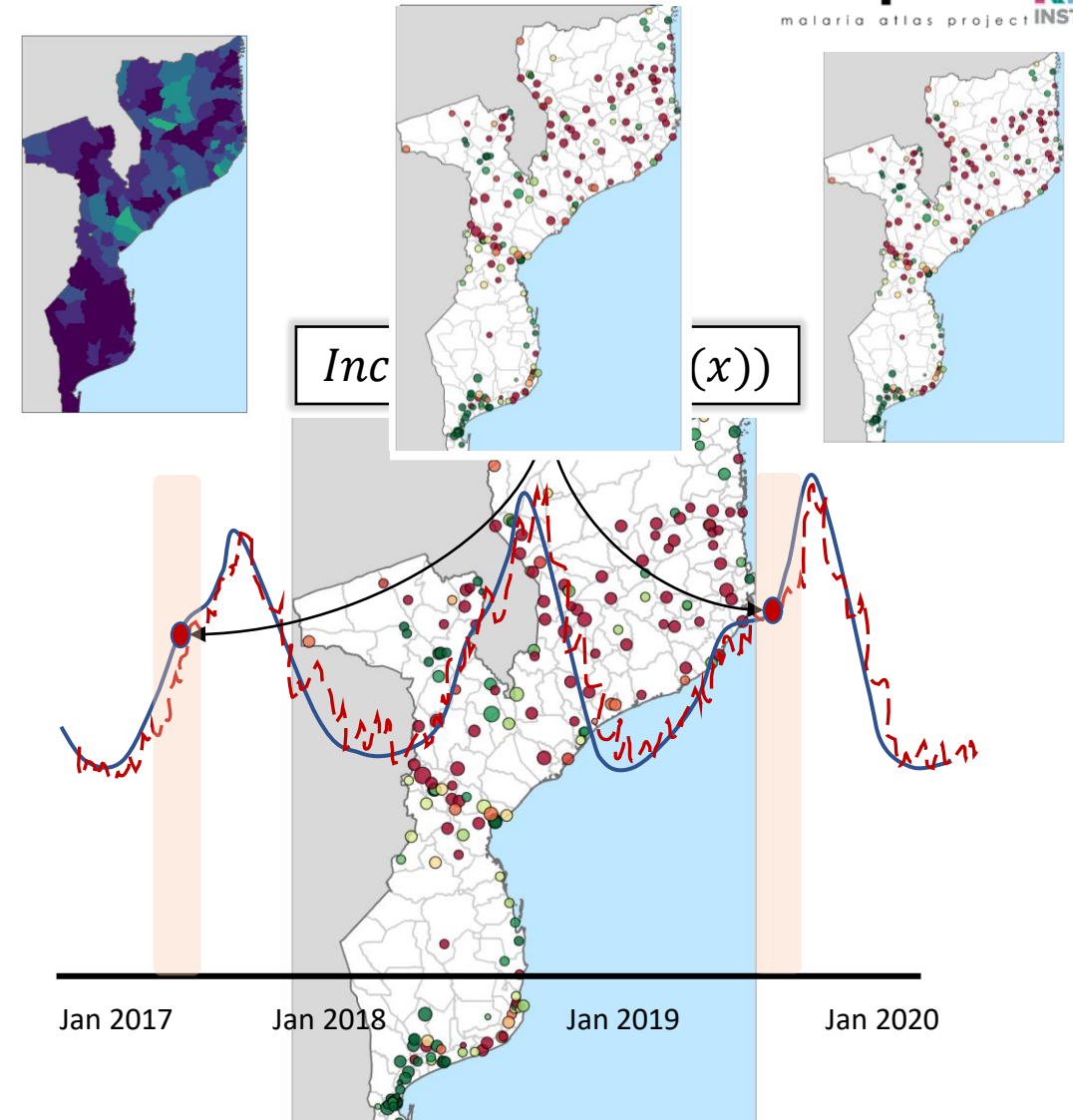
Context

- Malaria stratification involves the classification of geographical areas or localities according to the risk of malaria and has long been recognized as an essential element of efficient resource allocation and a prerequisite for the rational targeting of interventions.
- Robust and accurate maps of disease burden are essential.
- However, often disease metrics of prevalence can have contradictory patterns to incidence.
- Understanding both metrics and their pros and cons is key for robust estimates.



Rationale

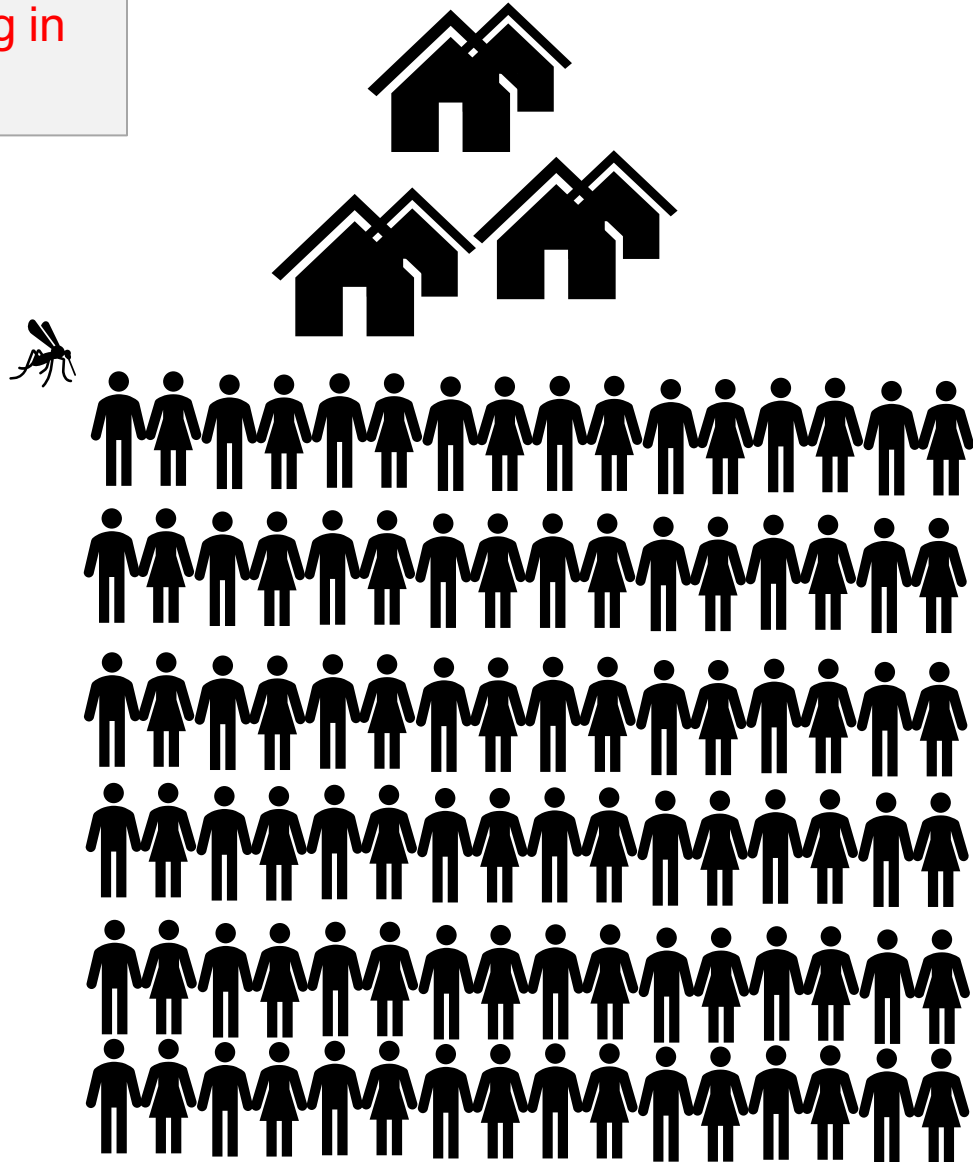
- Cross-sectional parasite surveys:
 - Represent community transmission
 - Standardised measurement, unbiased
 - Spatially sparse (small sample size at cluster)
 - Only a snapshot in time (only every 3-5 years)
 - Not a direct measure of disease burden
- Routine case data (DHIS2):
 - Spatially and temporal rich
 - Measure of disease burden and burden on the health system
 - Not capturing malaria in community
 - Noisy, Less standardised, unknown biases (missingness, test adherence etc.)
- We aim to create **robust/accurate burden estimates for risk stratifications** by combining these two data streams, leveraging the strengths of each to overcome the limitations of the other.



How?

1. What is happening in reality?
 - Drivers of transmission
 - Other diseases circulating
 - Disease progression
 - Care seeking
 - Health system reporting
2. What estimates are important and describe this reality?
 - Clinical incidence in the system
 - Parasite prevalence
3. What data do we have?
 - Surveys
 - Routine case data
4. What adjustments to the data do we need to make?
 - Care seeking
 - Completeness
5. What model would represent this reality in space and time?

1. What's happening in reality?

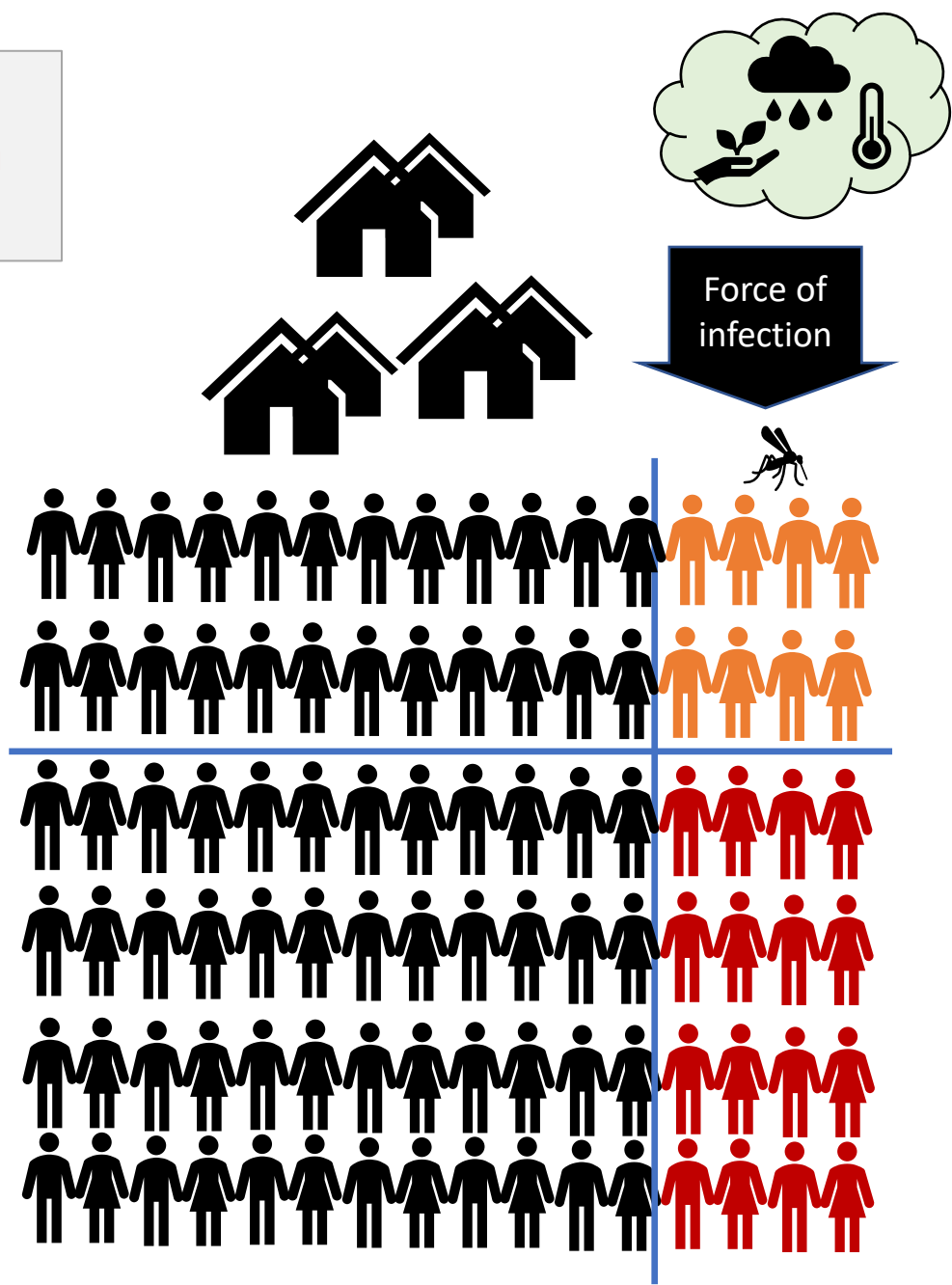


1. What's happening in reality?



1. What's happening in reality?

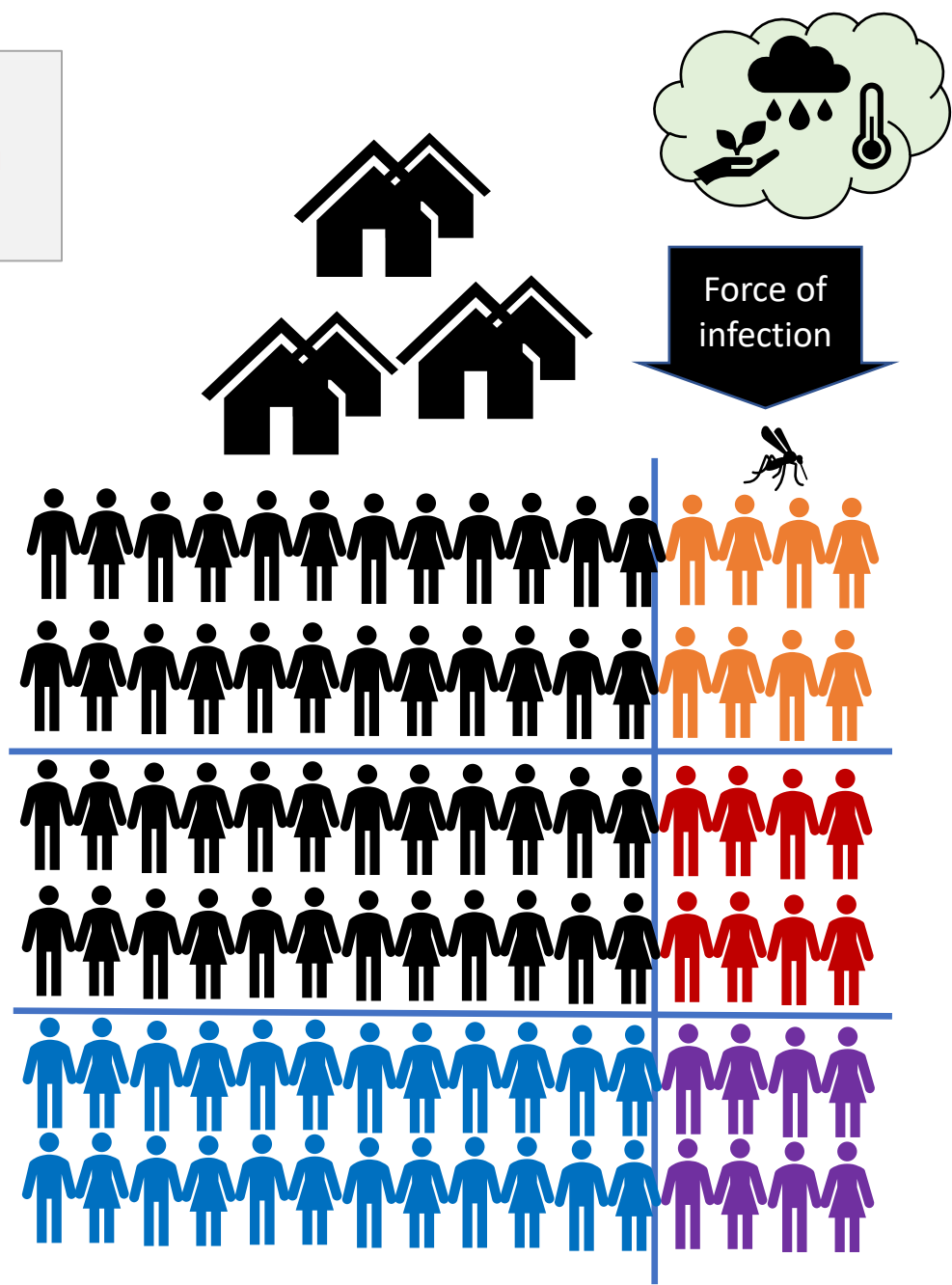
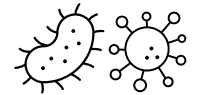
Progression to clinical malaria



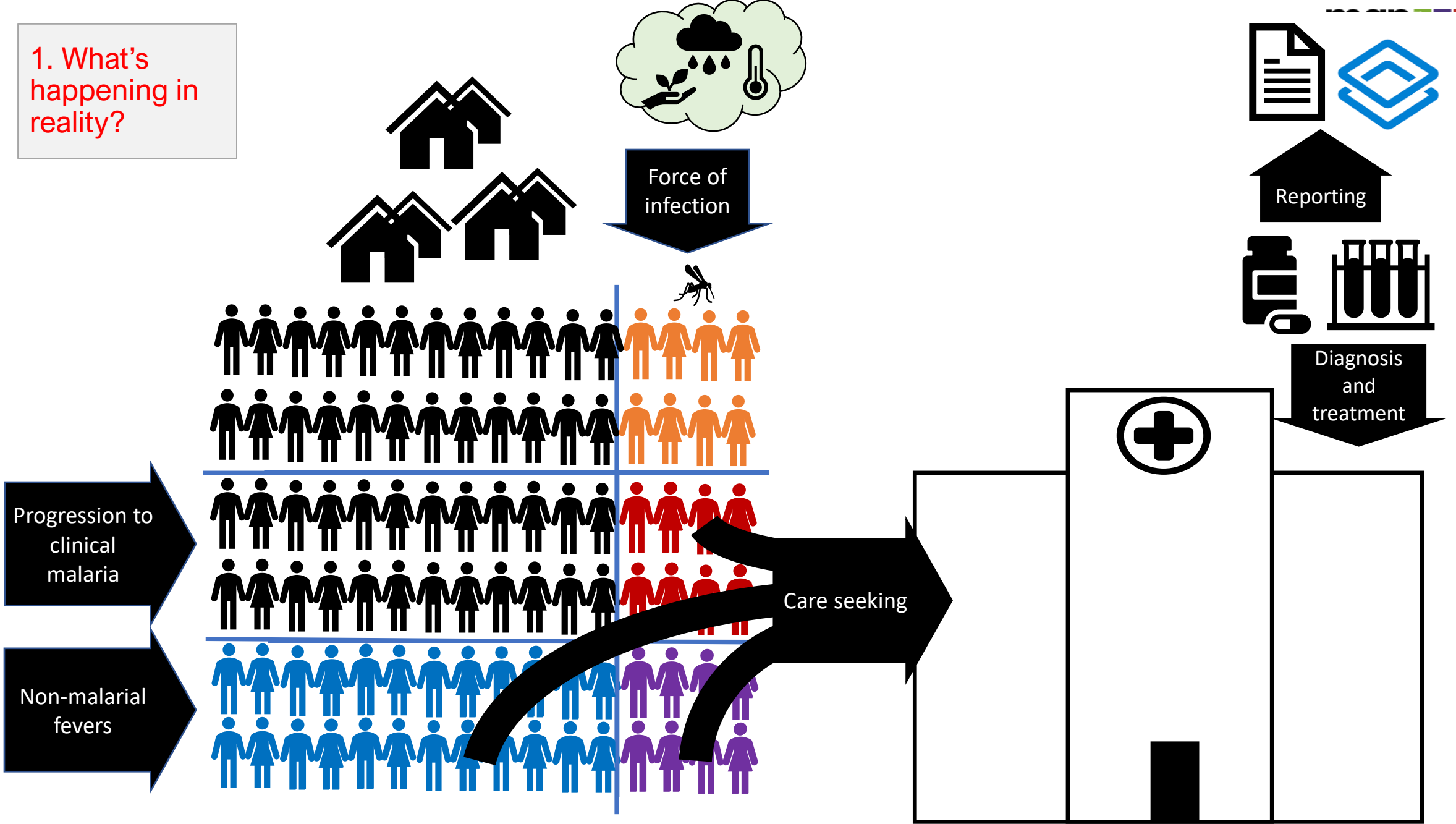
1. What's happening in reality?

Progression to clinical malaria

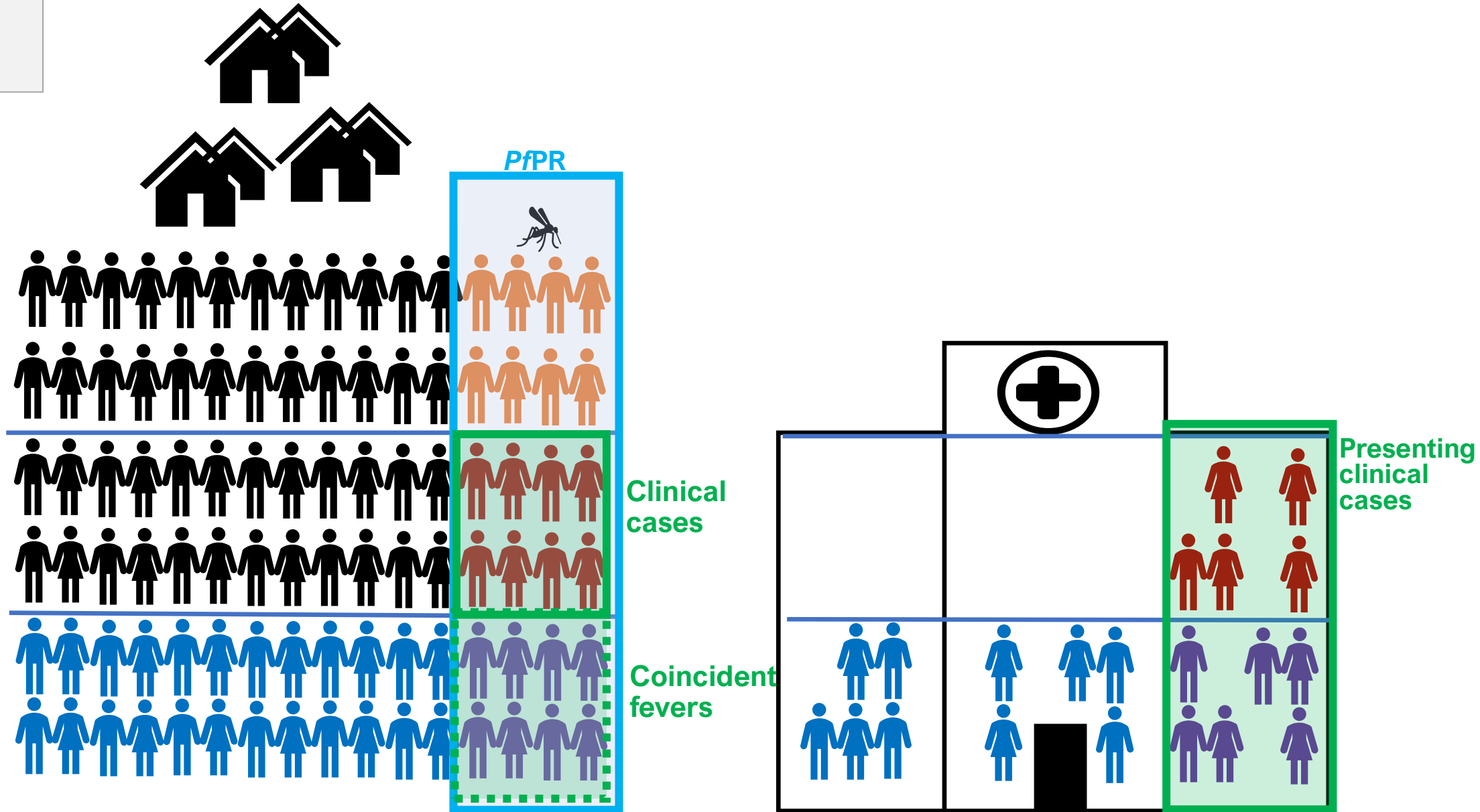
Non-malarial fevers



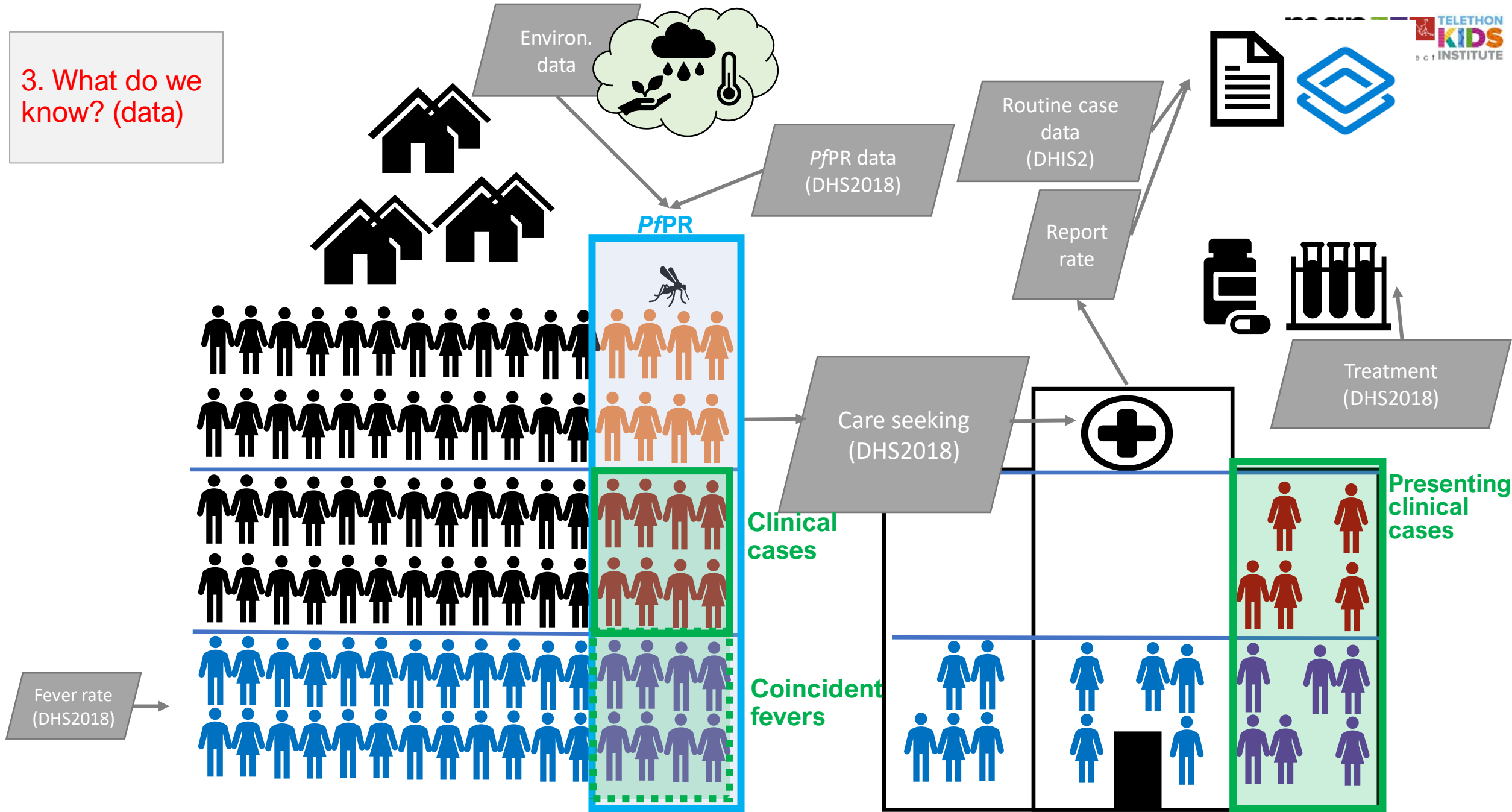
1. What's happening in reality?



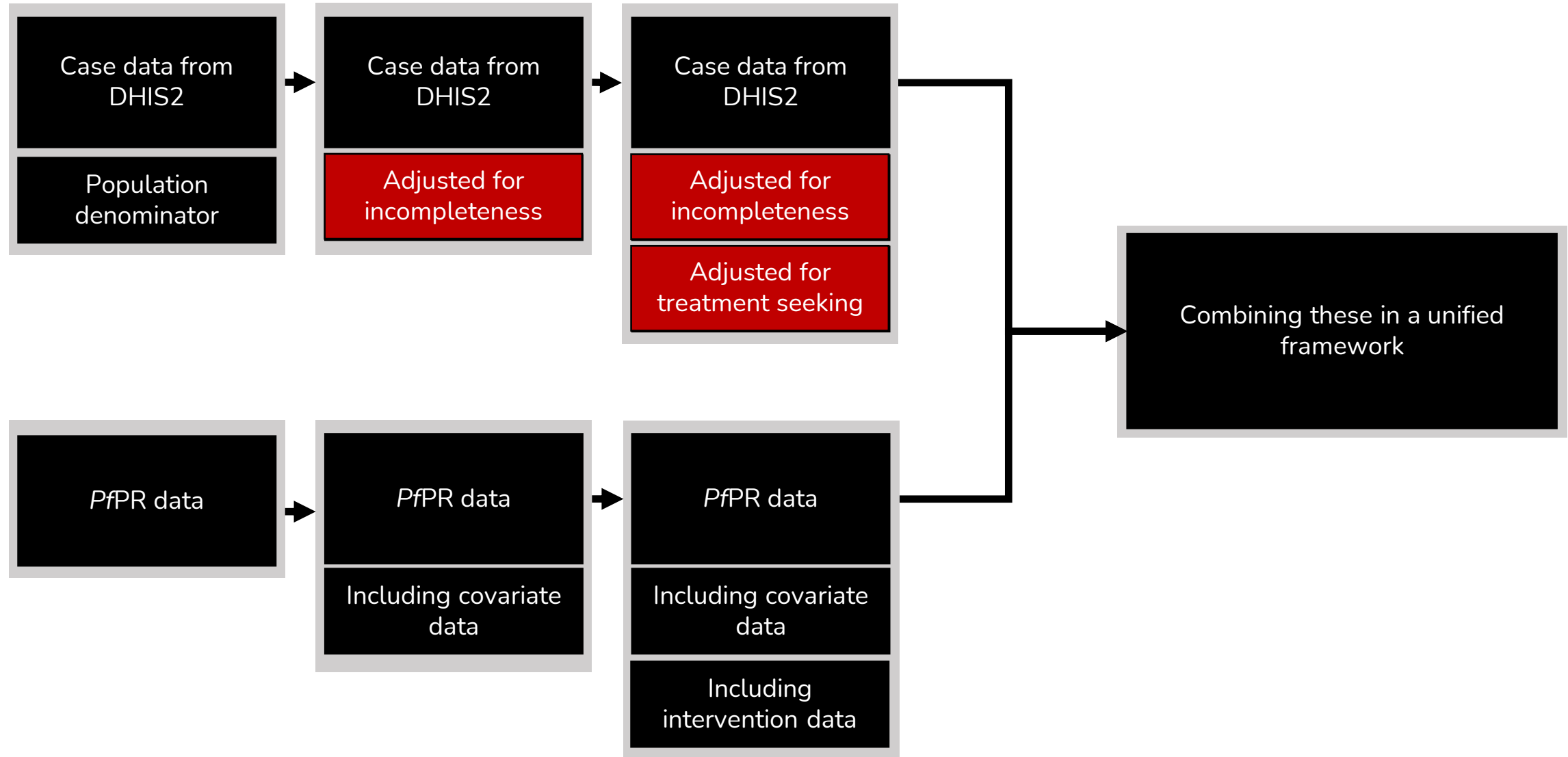
2. What do we want to estimate?



3. What do we know? (data)



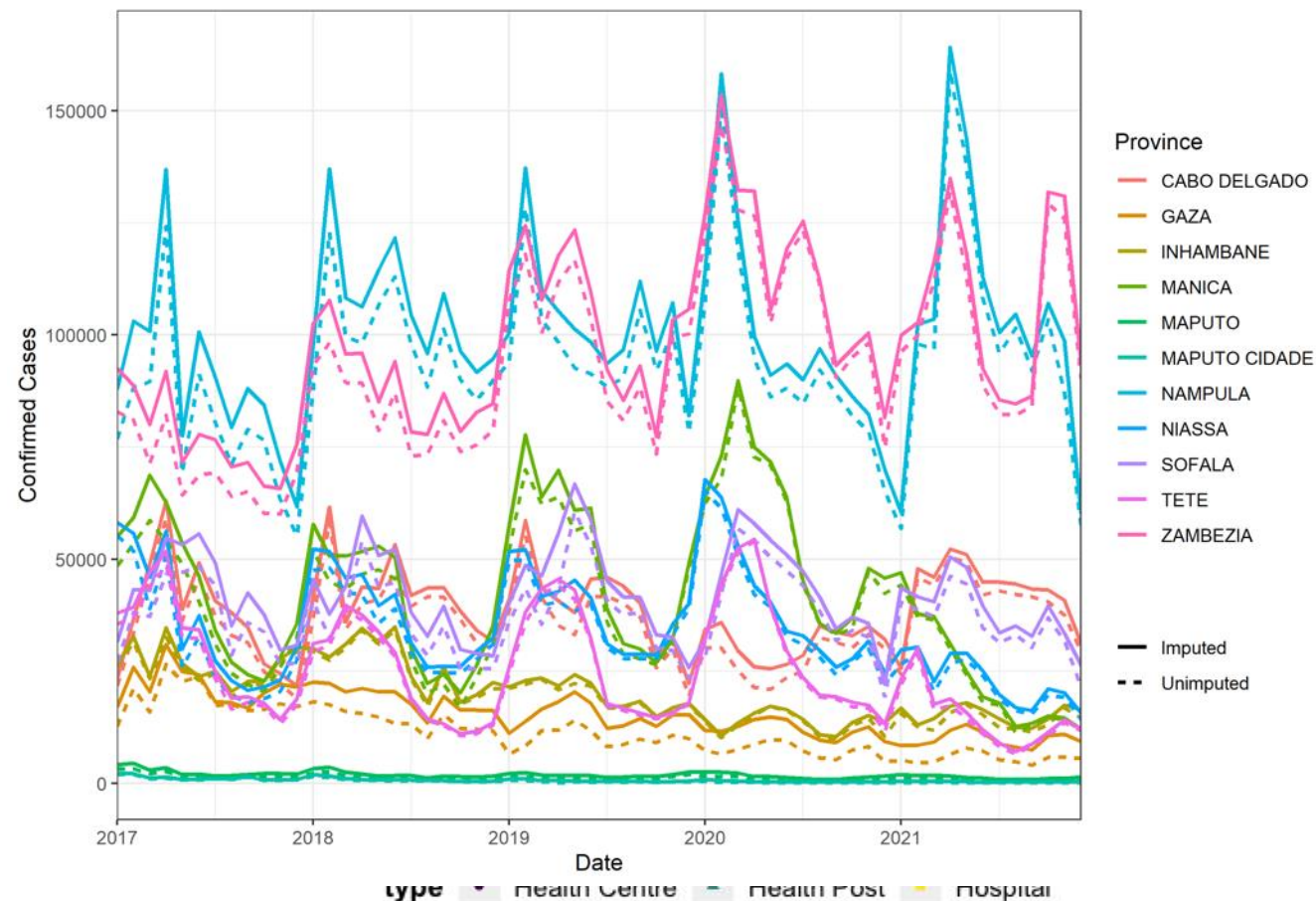
4. What adjustments need to be made?



Addressing incompleteness

- Could use district level reporting rates, BUT – assumes equal missingness across facility types. We chose to apply an imputation model that considers facility characteristics
- The DHIS2 data were first name-matched to most up-to-date master-facility list available to remove duplicate entries. We additionally extract information on facility types and ownership
- Imputation model based on GLMMs is run accounting for facility types, ownership, location
- *Key assumption: all facilities in DHIS2 are active throughout the modelling period and report. information on date of activation would be useful to reduce over-estimations if this is un-realistic.*

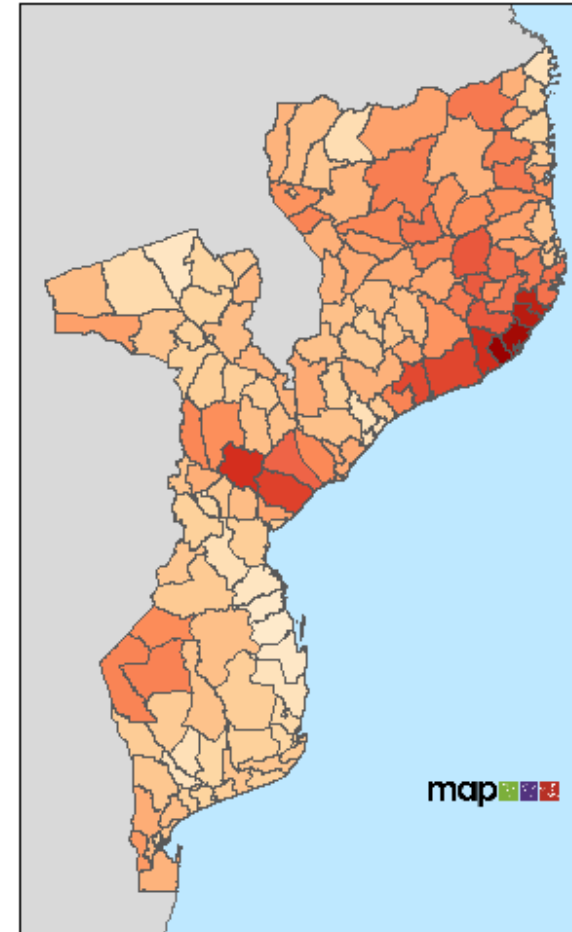
Imputation results for routine case data: Mozambique



Understanding treatment-seeking

- We mainly used the under 5s treatment seeking data from MIS 2018
- A geostatistical model jointly estimates pixel-level probability of treatment seeking from any source and from 'DHIS2 facilities' as defined in the mapping.
- The covariates used:
 - access to cities;
 - nighttime lights;
 - population density.
- Overall treatment seeking regardless of DHIS2 or nonDHIS2 averages between 63 – 75% nationally

From any source, u5

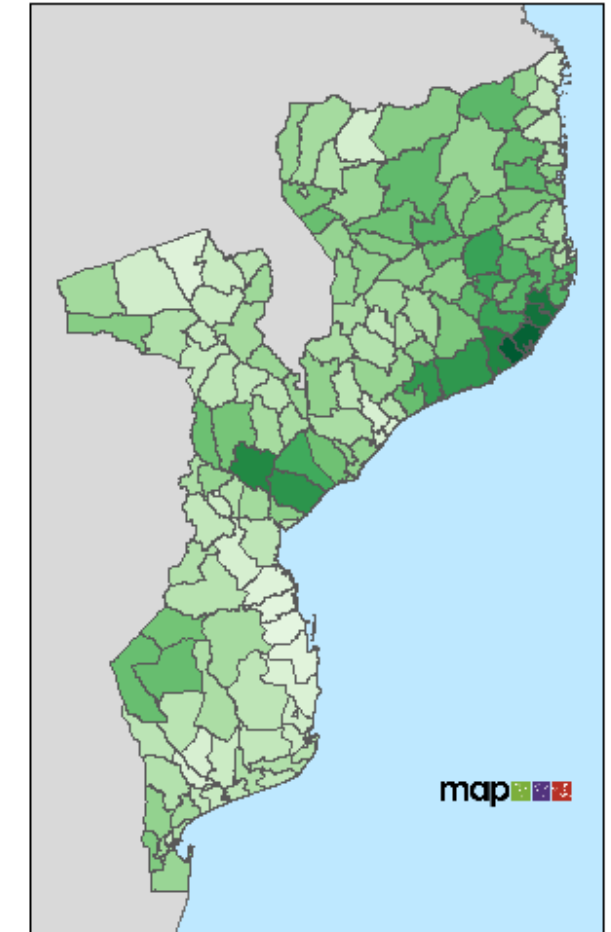


Probability of treatment seeking



0.4 0.6 0.8

From a DHIS2 facility, u5

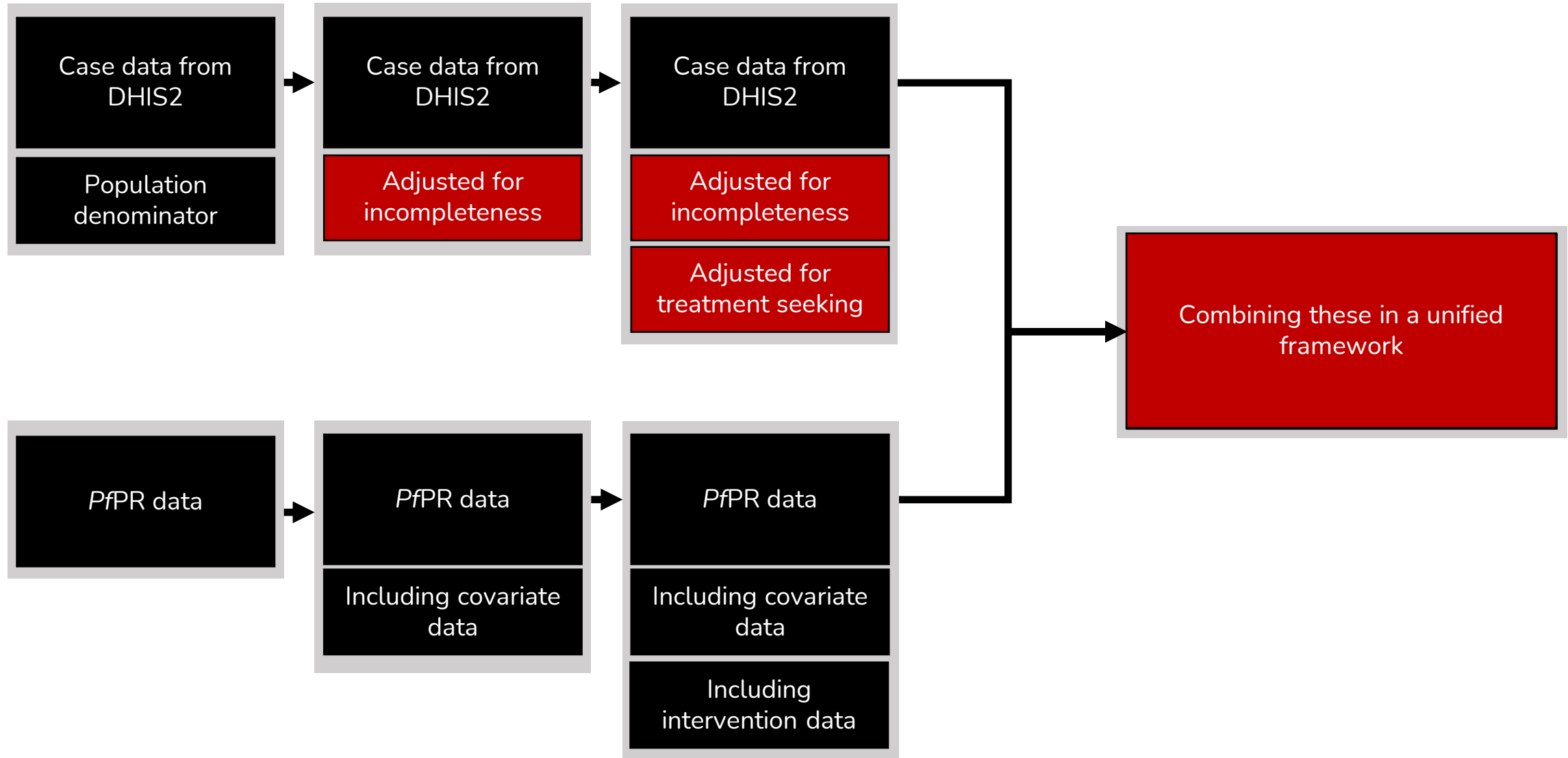


Probability of treatment seeking



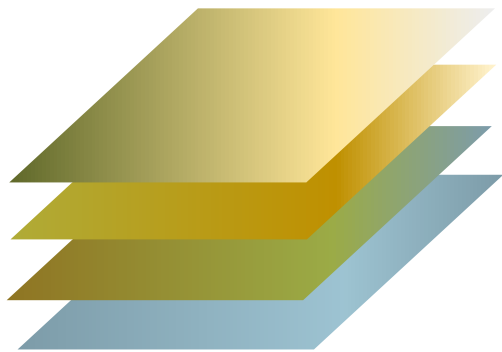
0.4 0.6 0.8

4. What adjustments need to be made?



Unified Framework

5. What model would depict this reality in space and time?



1. Environmental + Intervention covariates inform spatio-temporal forces of infection

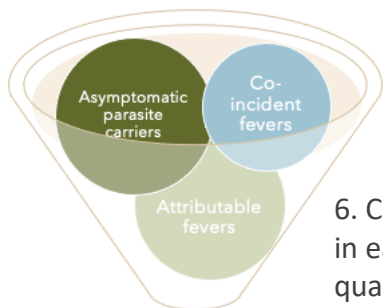
$$p_{fe} = \alpha_0 + \alpha_1 FOI + \alpha_2 \sqrt{FOI}$$

2. Force of infections converted to probability of fever using parametric form (with learnt parameters)

3. A Markov model of febrile disease aetiology allocates population to possible disease states and evolves through time and space

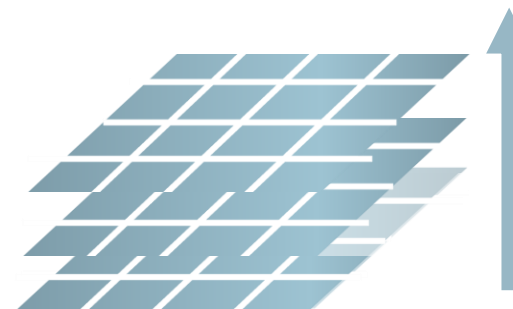


4. Transitions between states determined by forces of infection, treatment status, parasite clearance rates (treated and untreated), etc.

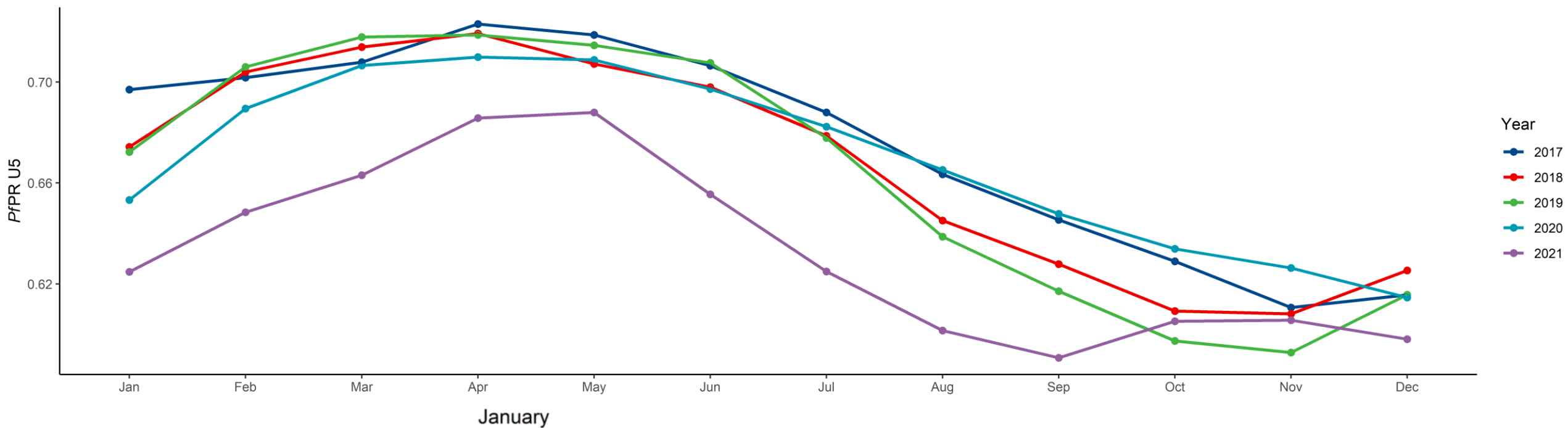


6. Counting proportion of population in each state at each time converts to quantities observed in data allows us to recalculate modelled incidence and prevalence at monthly scale

5. Iterate through time to obtain spatio-temporal cube of each disease state

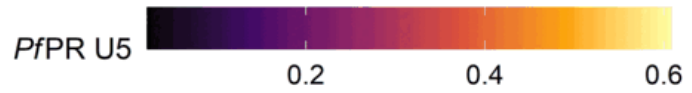
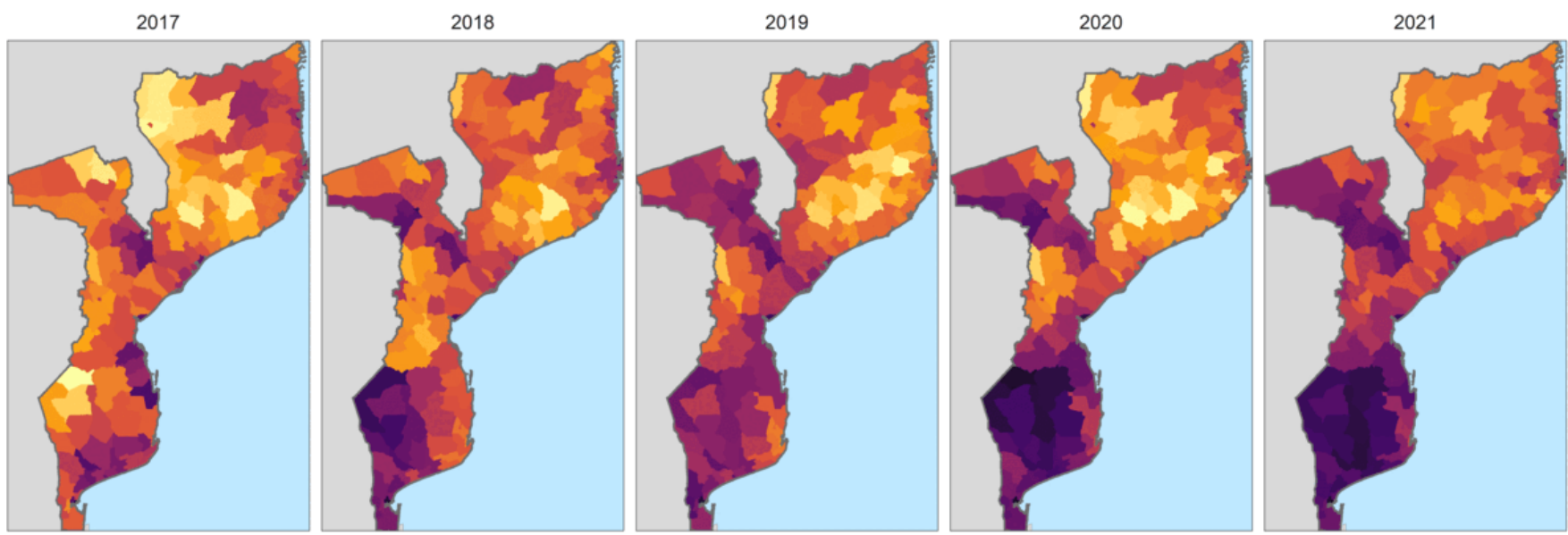


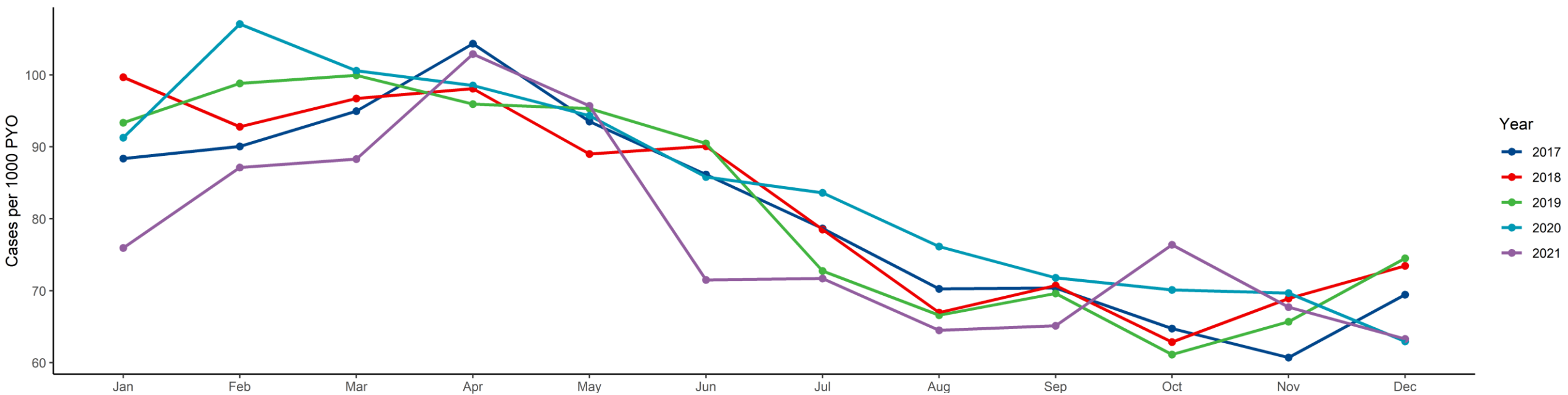
Resulting maps



January

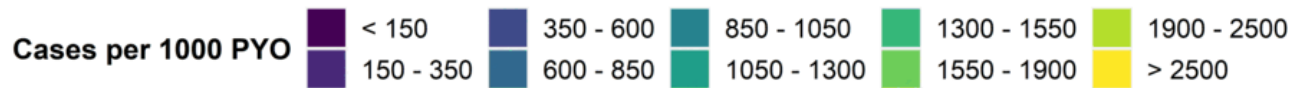
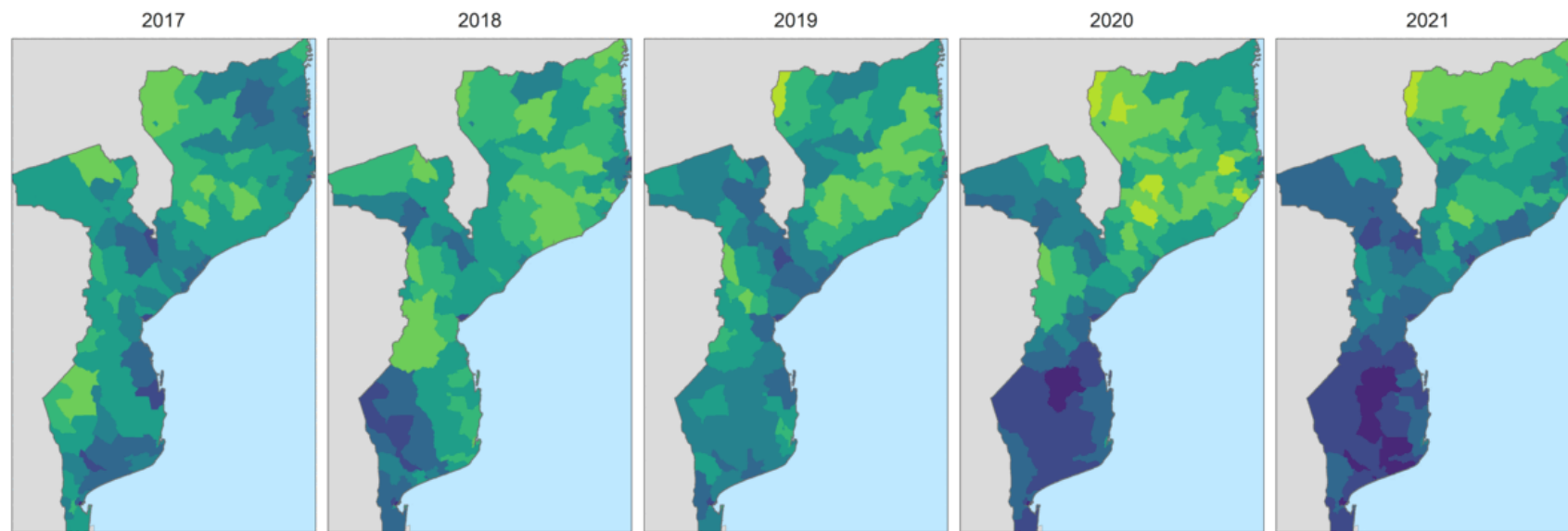
These new generation maps allow us to predict monthly outputs for long periods of time allowing us to build a seasonal profile



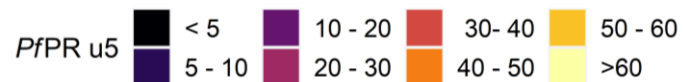


January

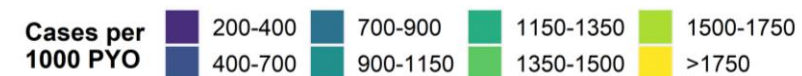
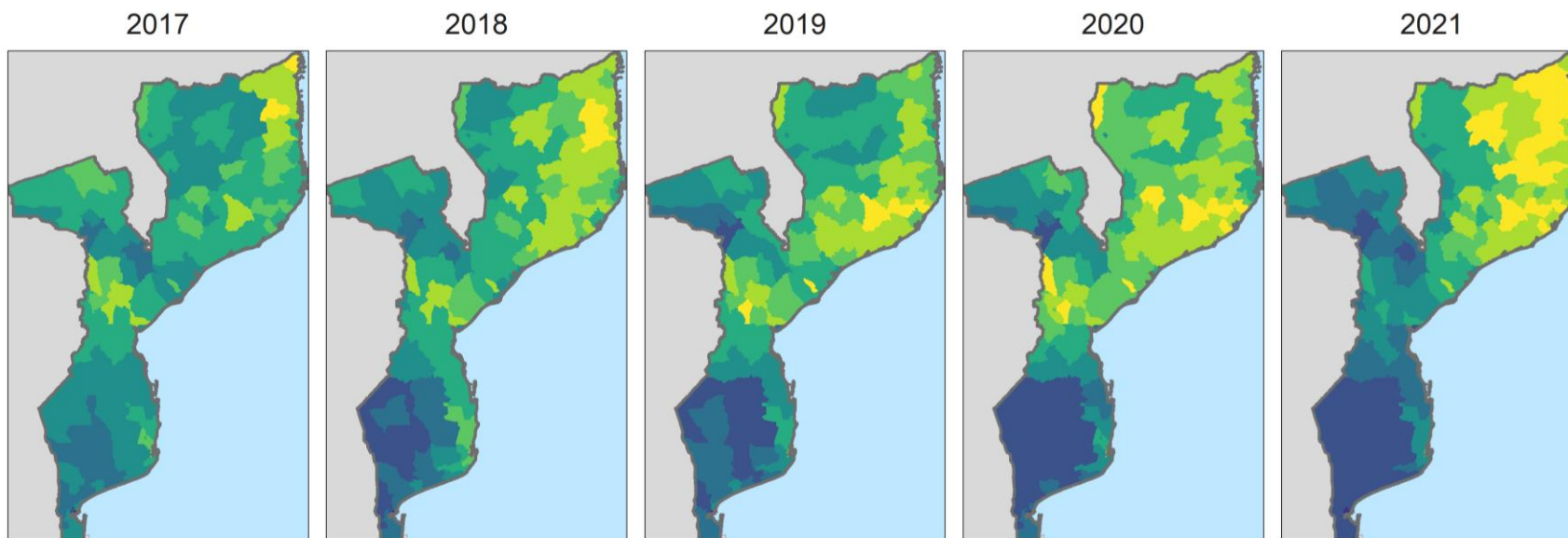
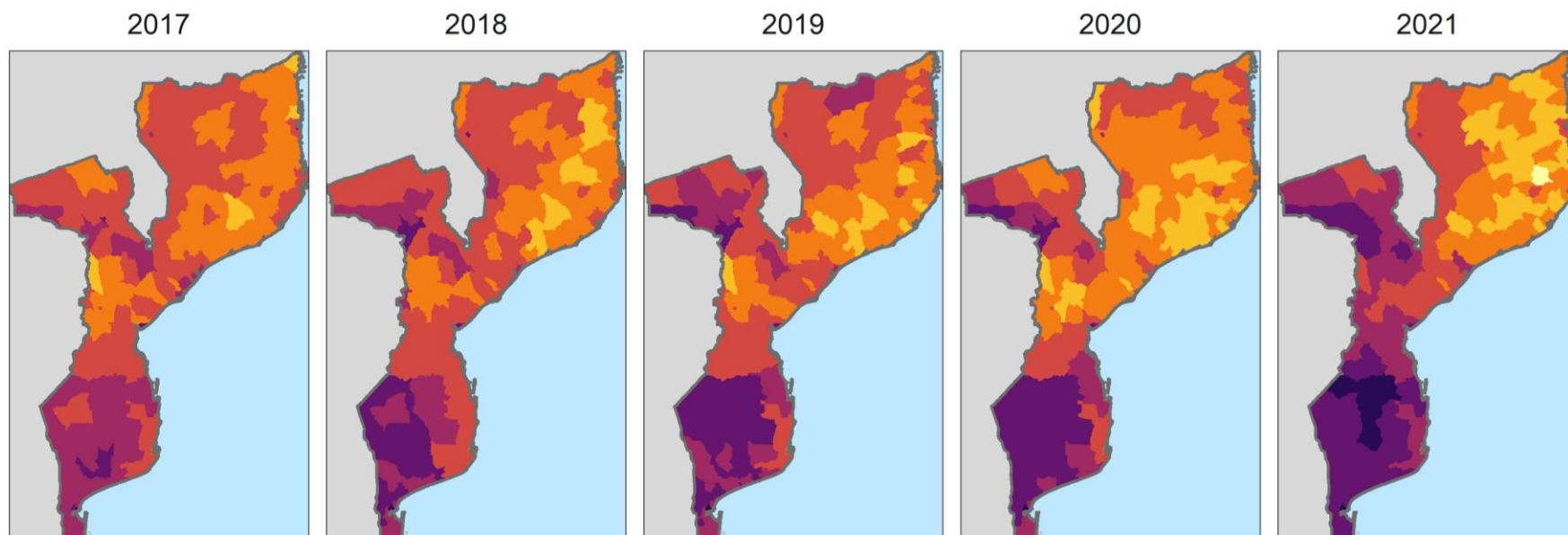
incidence are more coherent with prevalence using the model, allowing us to see more signal in clinical burden estimates



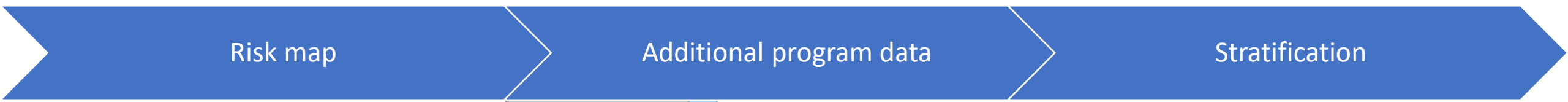
Annual average risk maps



Overall declines are achieved in the south; 2021 reflects some gains from areas where New Nets Project exists



How this risk map can inform stratification



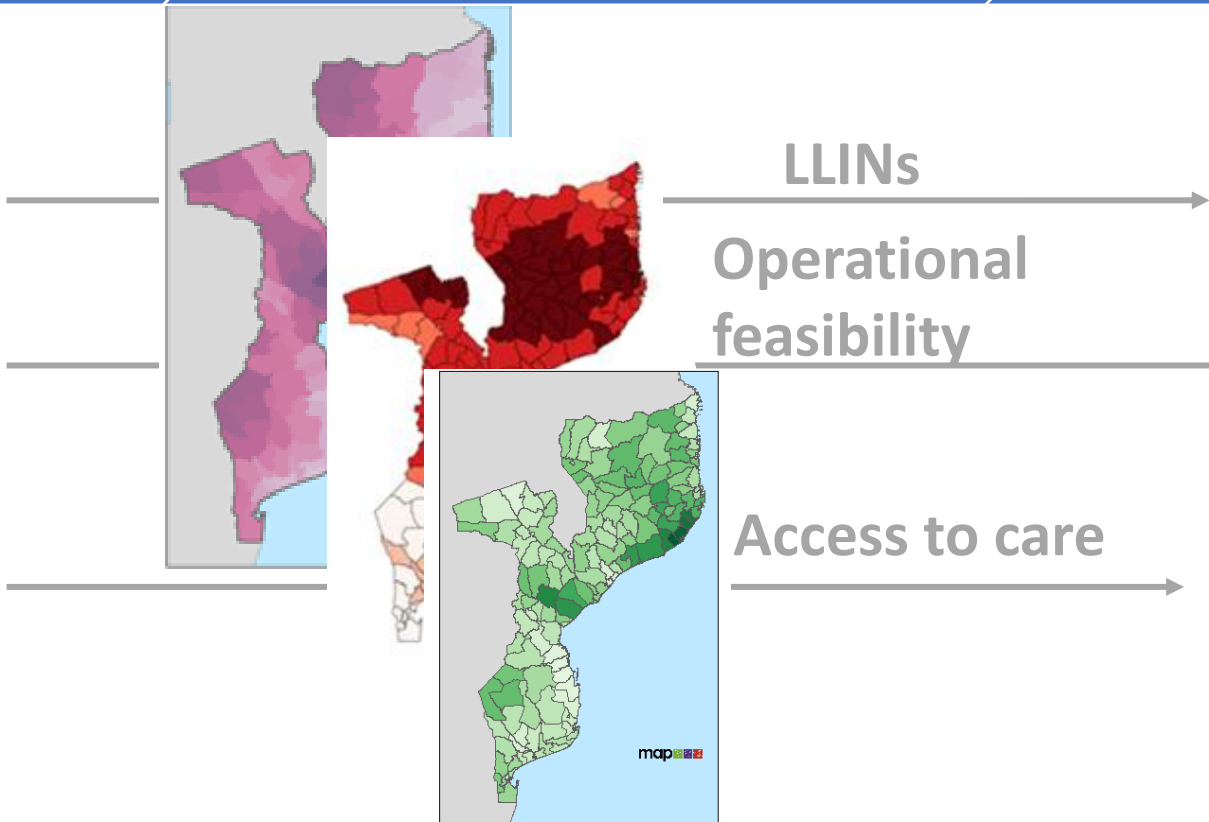
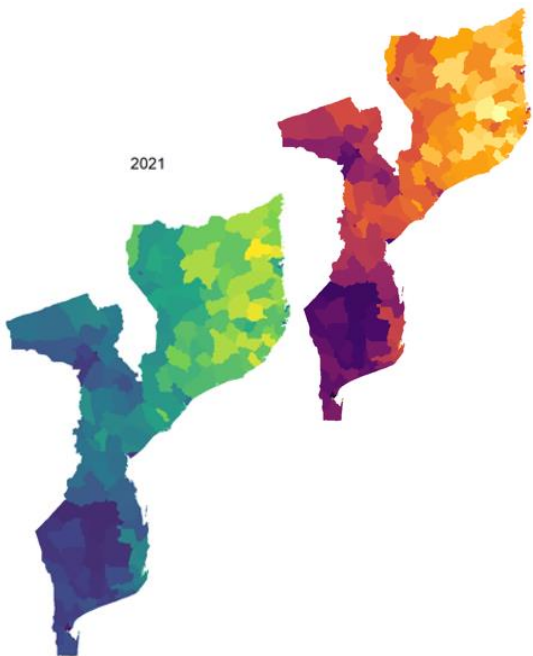
Risk map

Additional program data

Stratification

Modeled prevalence and incidence rate

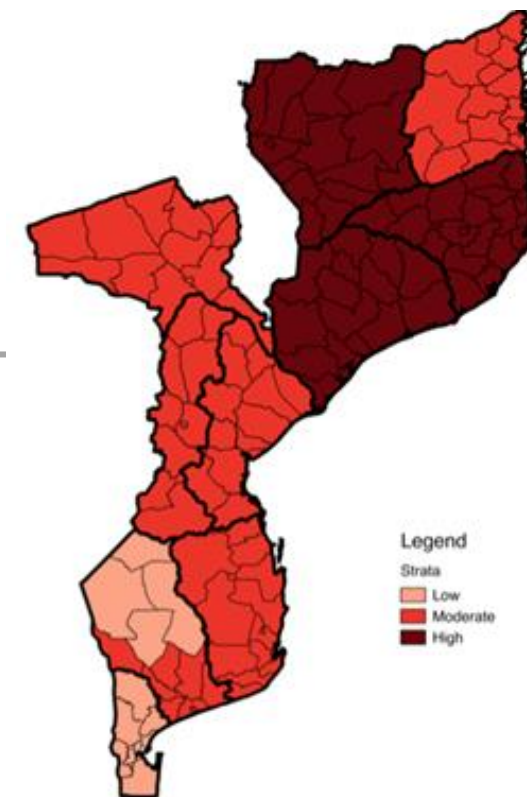
2021



LLINs

Operational feasibility

Access to care



Legend

Strata

Low

Moderate

High

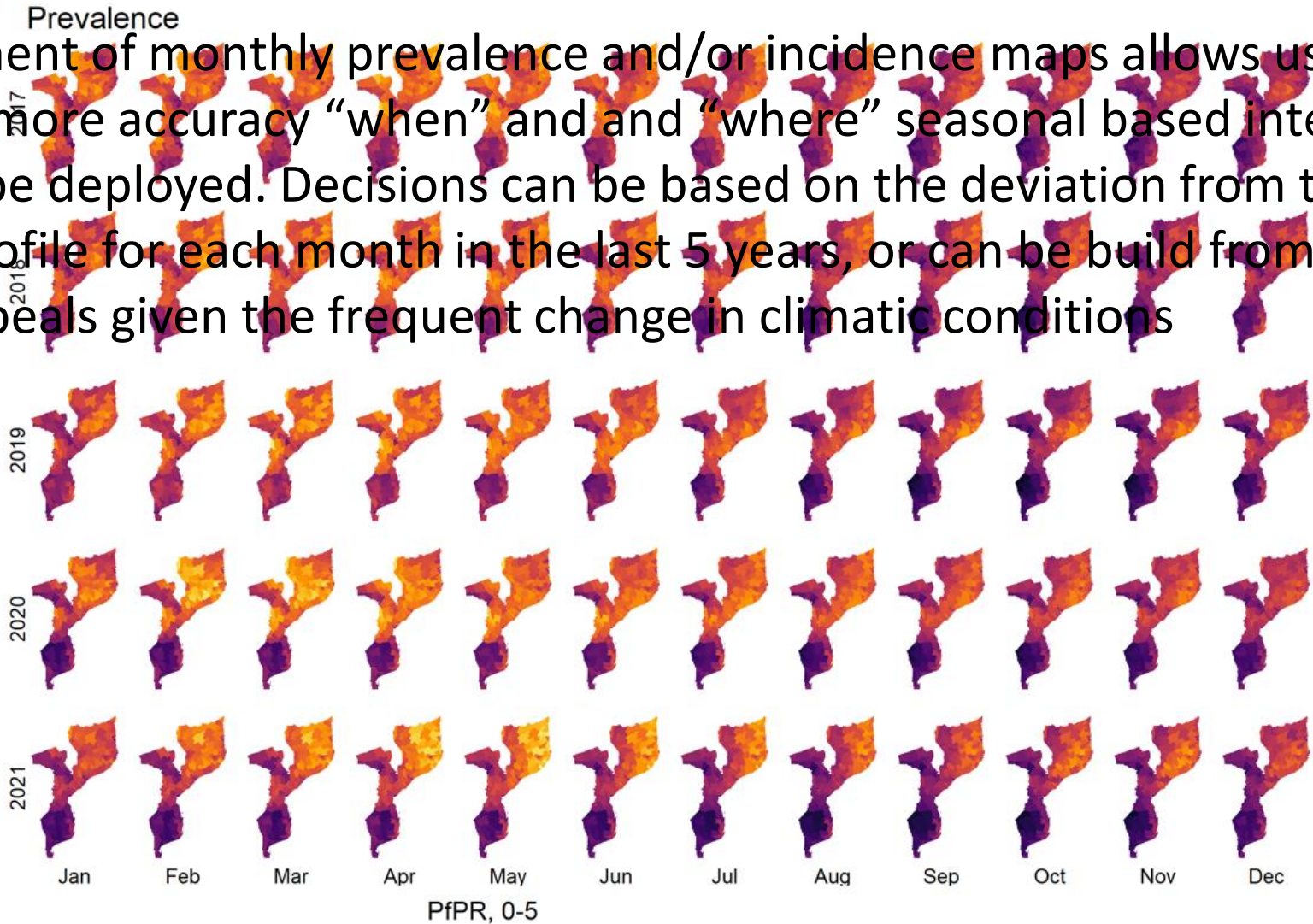
1. The risk map describes where burden is highest, and interventions are most needed

2. Additional data (e.g., vector distribution, insecticide resistance, access to care) show what interventions would be most effective

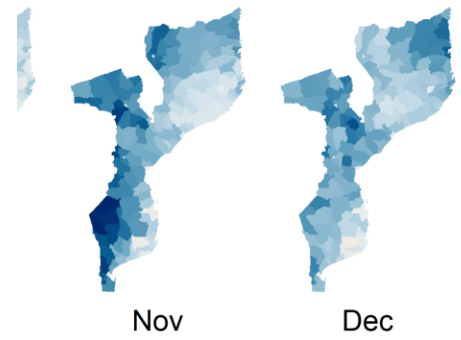
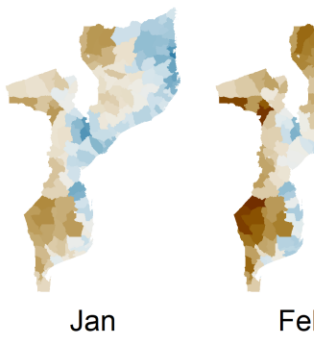
3. Intervention packages are identified based on where they are most needed and what package would be most effective

Other uses: SMC, Vaccine roll out?

The development of monthly prevalence and/or incidence maps allows us to begin estimating in more accuracy “when” and “where” seasonal based interventions (e.g. SMC) should be deployed. Decisions can be based on the deviation from the average prevalence profile for each month in the last 5 years, or can be build from the last years transmission peaks given the frequent change in climatic conditions



Prevalence, 0-5



Additional activities

- Vaccine rollout initiative?
- Retrospective analysis: reflecting at the spatio-temporal trends
- Feeds into models for intervention scenarios (e.g. OpenMalaria)
- Estimations of commodity needs

Future activities

- Begin handover of modelling to country teams, develop risk mappers within Mozambique to support the program

Acknowledgments

- No work is done in solitude!



Dr. Tasmin Symons (lead modeler)
Dr. Ewan Cameron
Dr. Susan Rumisha
Mark Connell



Dr. Balthazar Candrinho



Dominic Lucero
James Coborn
Abigail Ward



Dr. Abdisalan Noor

Spatial training

Making useful maps

- Have you ever wanted to make a map using the data you have? Always wondered how risk maps are made? Malaria Atlas Project will take participants through best data handling practices, introduction to GIS techniques, how to build your own geostatistical model and interpreting results.
- We will focus on key surveillance data sets such as DHIS2 and DHS surveys.
- **Priority will be given to participants from LMICs and National Malaria Control Programs**

