# A Bayesian geospatial modelling framework for the synthesis of point prevalence and health facility catchment data

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## Introduction

Sources of clinical incidence data on malaria:

(**A**) malaria attributable fever: **MAF**

(**B**) non-malaria febrile illness with asymptomatic *P. falciparum (Pf)* infection: **$NMFI_{Pf+}$**

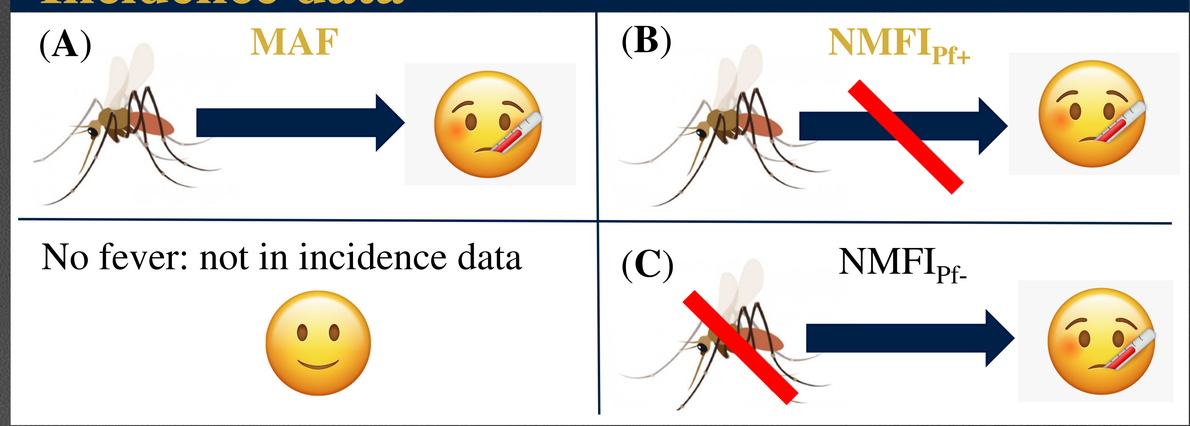
- Incidence data alone cannot distinguish (**A**) from (**B**)
- *Pf*PR-to-incidence relationship based on PR survey data alone can only estimate (**A**)

## Aim

Predict pixel-month and pixel-annual malaria incidence along with:

- uncertainty quantification on predicted incidence
- predicted prevalence and background fever surfaces
- estimated proportion of **MAF** and **$NMFI_{Pf+}$** cases
- estimated probability to visit a specific health facility (catchment model)

## Incidence data




## Model overview

THREE GAUSSIAN PROCESSES jointly fit

(1) MALARIA PREVALENCE *Pf*PR

classical geostatistics approach with logit-transformed prevalence fit as a linear function of spatio-temporal covariates and a spatio-temporal random effect given by a second Gaussian process $GP(\text{lat}, \text{lon}, \text{t})_{\psi}$ which captures the variability unexplained by the covariates;

(2) *Pf*PR-TO-INCIDENCE relationship

Gaussian process ($GP_{\phi}$) allows for a smooth but complex, non-linear, *Pf*PR-to-incidence relationship to be learned statistically;

(3) BACKGROUND FEVER PREVALENCE $BFPR_{Pf+}$

modelled very similarly to the *Pf*PR surface (1) with a Gaussian process $GP(\text{lat}, \text{lon}, \text{t})_{\rho}$. The covariates for $BFPR_{Pf+,i,t}$ are chosen from the same pool as for *Pf*PR, but are selected independently.

## Model structure

- MODELLING FRAMEWORK: Bayesian hierarchical geospatial model
- DATA: prevalence survey data $y_{i,t}^{PR}$ and health facility incidence count data $y_{i,t}^{inc}$ = **MAF** + **$NMFI_{Pf+}$**
- INCIDENCE DATA MODEL: $y_{i,t}^{\text{inc}} \sim \text{Poisson}\left(\sum_j C_{j\to i} \times \text{inc}_{j,t} \times \text{pop}_j \times TS_j\right)$ composed of:
  - population at risk estimated as population $pop_j$ multiplied by probability of treatment seeking $TS_j$
  - catchment model for each health facility $j$: $C_{\text{j}\to\text{i}} \propto \frac{M_j}{d_{j\to i}^2}$ based on a modified gravity model
  - incidence rate $inc_{i,t}$ given as a transformation of the prevalence fields [1]:
    $$inc_{i,t} = \alpha PfPR_{i,t} \exp f\left(PfPR_{i,t}\right) + \gamma BFPR_{Pf+,i,t}$$
    - *Pf*PR-to-incidence modelled as a function of a Gaussian process: $f \sim GP_{\phi}$
    - $BFPR_{Pf+,i,t}$ as background fever prevalence ($BFPR$) times malaria prevalence ($PfPR$):
      $$BFPR_{Pf+,i,t} = BFPR_{i,t} \times PfPR_{i,t}$$
- DATA MODEL for *Pf* PR: $y_{i,t}^{PR} \sim Binomial(PfPR_{i,t}, N_{i,t})$, with $N_{i,t}$: tested cases
- LINEAR PREDICTOR for $PfPR$ and $BFPR$: Gaussian process $GP(lat, lon, t)_{i,t}$ + covariates $\boldsymbol{X}$:
  $$logit\left(PfPR_{i,t}\right) = GP(lat, lon, t)_{i,t,\psi}\boldsymbol{X}\beta + c$$
  $$logit\left(BFPR_{i,t}\right) = GP(lat, lon, t)_{i,t,\rho}\boldsymbol{X}\beta' + c'$$
- PRIORS set for: prevalence-incidence $\alpha, \gamma$, Gaussian processes $\phi, \psi, \rho$ prevalence surface slopes $\beta, \beta'$ and intercepts $c, c'$
  $$\alpha, \gamma, \phi, \psi, \rho, \beta, \beta' c, c' \sim \pi$$

## Future results

MAPS
- pixel-month and pixel-year
- incidence rate and case counts
- jointly-fit surfaces of *Pf*PR and $BFPR_{Pf+,i,t}$

UNCERTAINTY
- quantification of the model uncertainty based on non-spatial bootstrapping method as an alternative to computationally expensive posterior sampling methods.

DISENTANGLE **MAF** AND **$NMFI_{Pf+}$**
- estimates of the proportion of cases which are malaria-attributable (**MAF**) vs non-malarial febrile illnesses co-incidence with a *P. falciparum* infection (**$NMFI_{Pf+}$**) complementary to [2].

## Summary

- Modelling framework that distinguishes incidence cases coming from malaria (**MAF**) and non-malaria attributed fever (**$NMFI_{Pf+}$**)
- Joint model that fits together incidence rate and prevalence in space and time
- Joint fit of several data sources: incidence & *Pf*PR & background fever prevalence

## References

[1] Cameron et al., 2015. Defining the relationship between infection prevalence and clinical incidence of Plasmodium falciparum malaria. *Nature Com.* 6, 8170.

[2] Dalrymple, U. et al., 2019. The Contribution of Non-Malarial Febrile Illness Co-Infections to Plasmodium Falciparum Case Counts in Health Facilities in Sub-Saharan Africa. *Malaria J. 18(195).*

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