Malaria, river-blindness and plague: three case studies in spatial modelling of tropical diseases

Emanuele Giorgi and Peter J. Diggle

Lancaster Medical School, Lancaster University, Lancaster, UK

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2. **Spatially structured zero-inflation**: chance finding or disease-free community?
3. **Analysis of spatio-temporal data at multiple spatial-scales**: how to integrate district-level disease case reports with high resolution environmental data?

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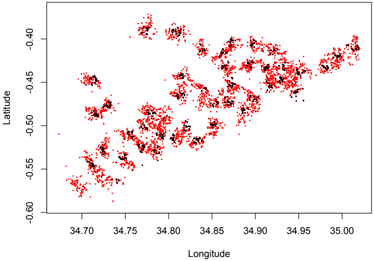
3. **Plague**: spatio-temporal analysis of monthly plague incidence from 2000 to 2007 in Madagascar.

Malaria mapping in Nyanza Province



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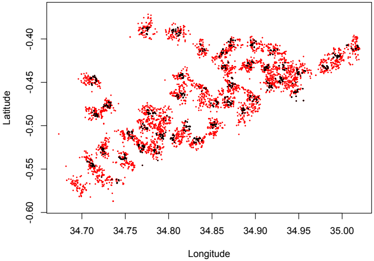

Statistical issues

- Different unmeasured risk factors for malaria.
- Joint model or gold-standard data only?

Accounting for residual spatial bias

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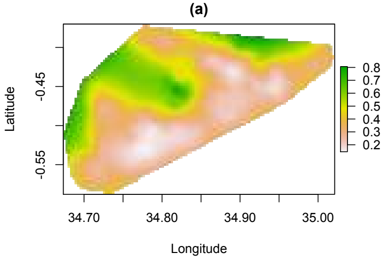
- $Y_{ijk}|S(x_{ij}), B(x_{ij}) \sim$ Bernoulli(p_{ijk}) (i=``survey", $j$=``household", k=```individual'').
- $\log\{p_{ijk}/(1+p_{ijk})\} = d_{ijk}^\top \beta + S(x_{ij}) + B(x_{ij})$;
  $B(x) = 0, \forall x \in \mathbb{R}^2$ if i is ``community''.

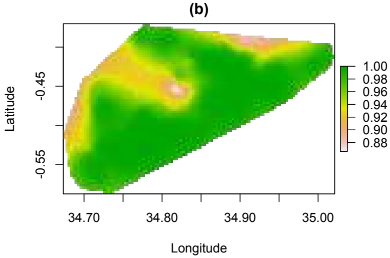
Results (1)

Term	Estimate	95% CI
Intercept	-1.412	(-2.303, -0.521)
Age	-0.141	(-0.174, -0.109)
Rachuonyo District	2.006	(1.228, 2.785)
Socio-Economic-Status	-0.121	(-0.169, -0.072)
School survey	-0.761	(-1.354, -0.167)
Age (bias)	0.094	(0.046, 0.142)

Results (2)

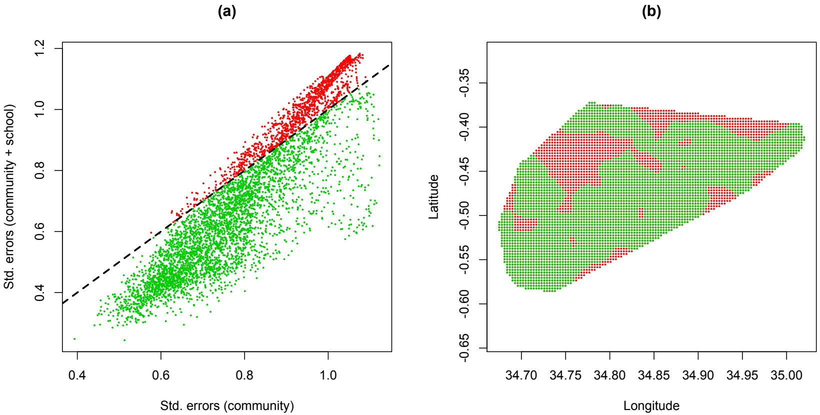
Mapping of (a) $r_c(x)$ and (b) $1 - P(0.9 < r_c(x) < 1.1|y)$.



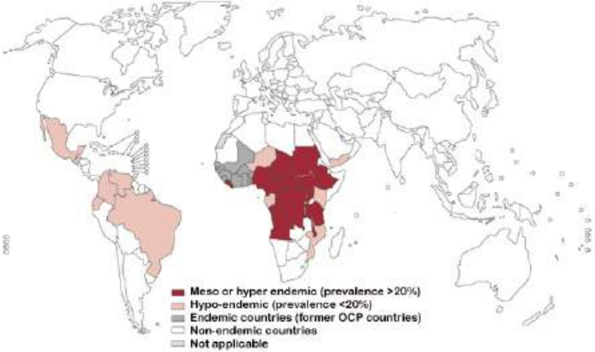


Results (3)

Gain/loss in the accuracy for the estimates of $S(x)$.

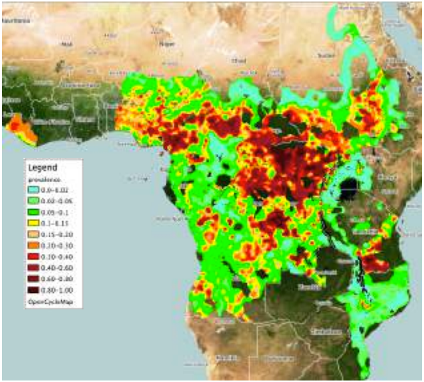


River blindness



Rapid epidemiological mapping of onchocerciasis

Prevalence estimates in the 20 APOC countries



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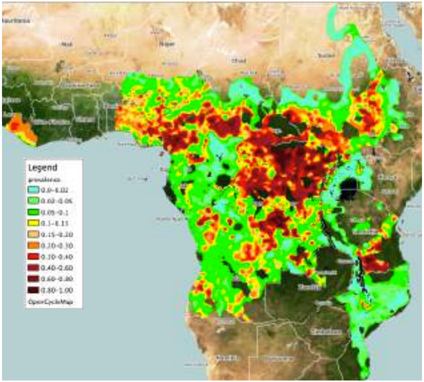

Statistical issue

1. $3,320$ villages with no case and $11,154$ villages with at least one case.
2. Accounting for zero-inflation: how to identify disease-free areas?

Extending the standard geostatistical model

- **Standard model**: $Y|S(x) \sim \text{Bin}(\cdot; n, p(x))$ where

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$$P(Y = y|S_1(x), S_2(x), D(x)) = \begin{cases} \pi(x) + (1-\pi(x))\text{Bin}(0; n, p(x)) & \text{if } y = 0 \\ (1-\pi(x))\text{Bin}(y; n, p(x)) & \text{if } y > 0 \end{cases}$$

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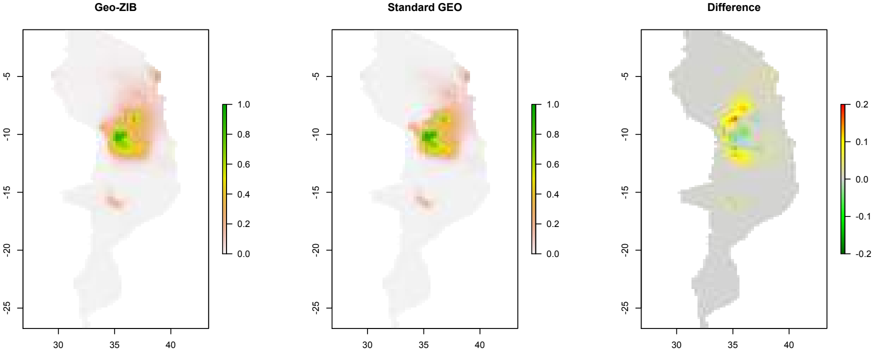
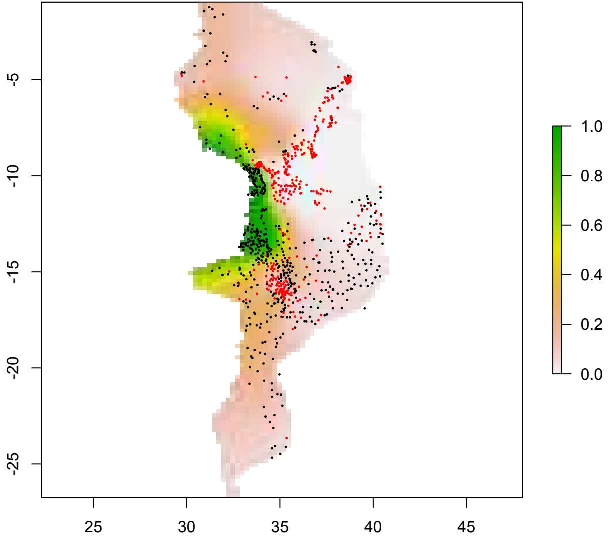
- In the next example $D(x) = 0, \forall x$.

Mapping in Mozambique - Malawi - Tanzania (1)

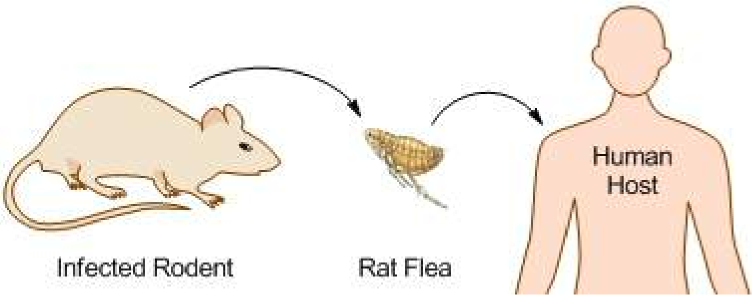


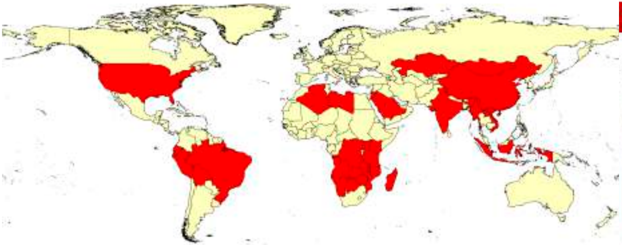
Mapping in Mozambique - Malawi - Tanzania (2)

Mapping of $\pi(x)$.



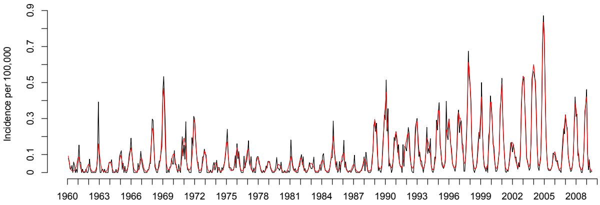
Plague

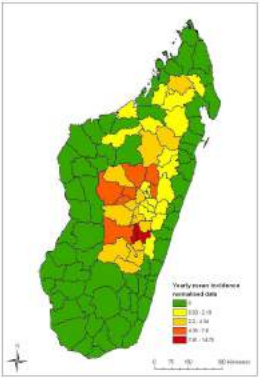

Infected Rodent
Rat Flea
Human
Host




BBC
NEWS
Madagascar plague outbreak kills 40, says WHO

Plague in Madagascar





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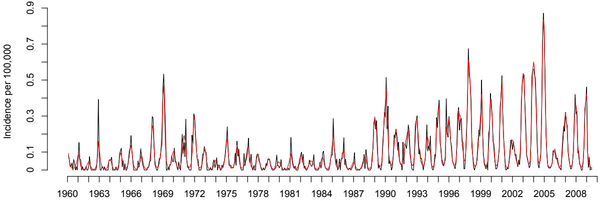

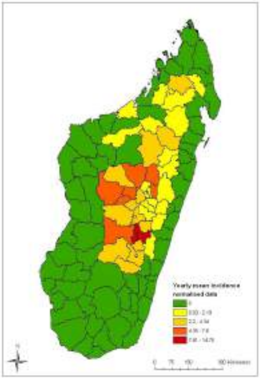

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- $\mathcal{X}_{i,t} = \{X_{j,t} \in A_i\} | N_{i,t} = n_{i,t}$ has multinomial distribution with probabilities

$$p_k = \frac{\lambda(x_k, t)}{\sum_{j=1}^{n_{i,t}} \lambda(x_j, t)}, \text{ for } k = 1, \ldots, n_{i,t}.$$

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V(t) &\mid V(t-1), \ldots, V(0) = V(t) \mid V(t-1)
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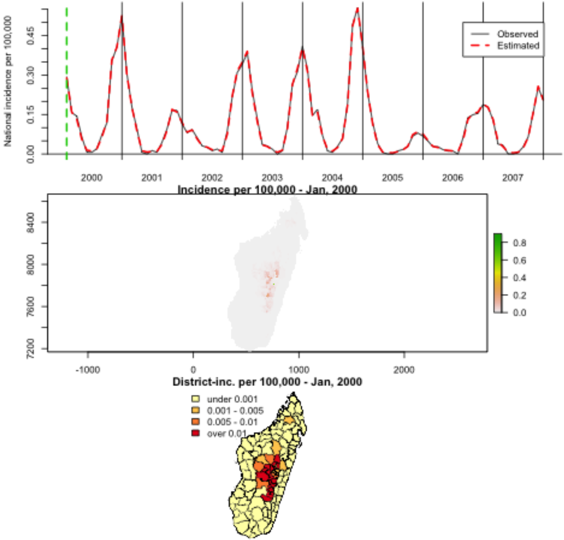
Results (1)

Term	Estimate	95% CI
β_1	-41.301	(-54.246, -30.104)
β_2	0.055	(-0.008, 0.125)
β_3	0.028	(-0.009, 0.061)
β_4	22.241	(10.566, 35.322)
β_5	0.027	(0.011, 0.043)
β_6	-0.024	(-0.041, -0.008)
β_7	0.069	(0.014, 0.140)
β_8	0.735	(-0.103, 1.444)
β_9	-0.293	(-0.314, -0.269)
β_{10}	0.025	(-0.003, 0.053)
β_{11}	5.017	(4.513, 5.498)
β_{12}	0.040	(0.007, 0.078)
β_{13}	-0.026	(-0.063, 0.013)

Results (2)



National incidence per 100,000
0.00
0.15
0.30
0.45
Observed
Estimated
2000
2001
2002
2003
2004
2005
2006
2007
Incidence per 100,000 - Jan, 2000
8400
8000
7600
7200
-1000
0
1000
2000
0.8
0.6
0.4
0.2
0.0
District-inc. per 100,000 - Jan, 2000
under 0.001
0.001 - 0.005
0.005 - 0.01
over 0.01

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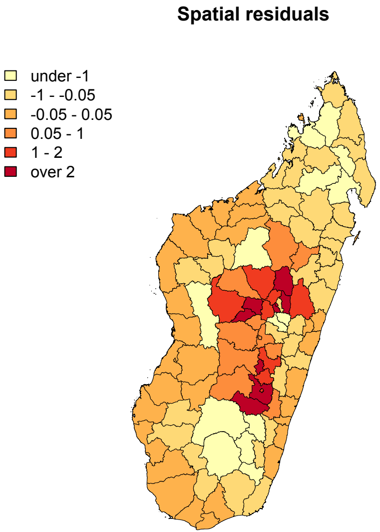

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Thanks for your attention.