Statistical Methods For Merging Geo-Spatial Maps And Transmission Models

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Geo-Spatial maps: Lancaster, LSHTM

LF models: Oxford/Warwick/Surrey/Birmingham, Erasmus MC, Notre Dame

ModStatSAP

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Outline

Introduction

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- **Geo-spatial maps** of disease prevalence are useful for guiding the planning of reliable spatial control programmes.
- **Mathematical models** can predict the progression of an epidemic $\Longrightarrow$ evaluate potential intervention strategies.
- However, mathematical modelling frequently **ignores spatial heterogeneity**.

Objectives:

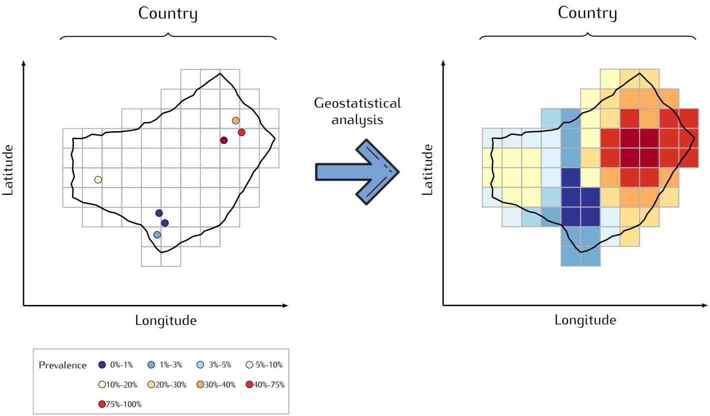
- Develop a method for linking transmission models and geo-spatial maps.
- **Key feature:** Appropriately estimating and communicating the projections with their uncertainty.

Linking Maps with Models

Geo-Spatial Maps

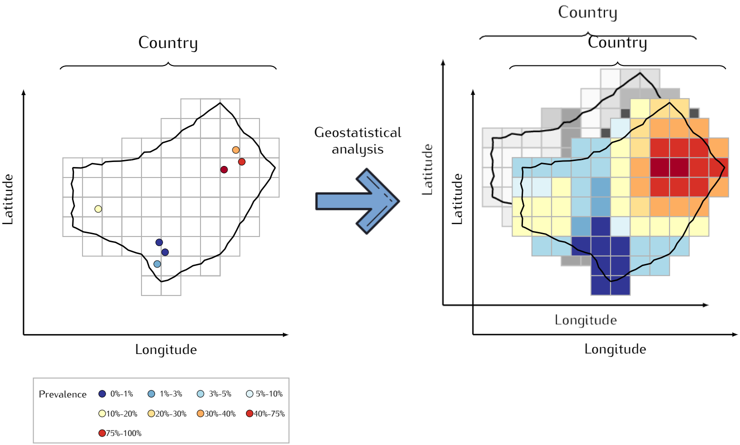
Survey Data

Geo-Spatial Map



Survey Data

Geo-Spatial Map



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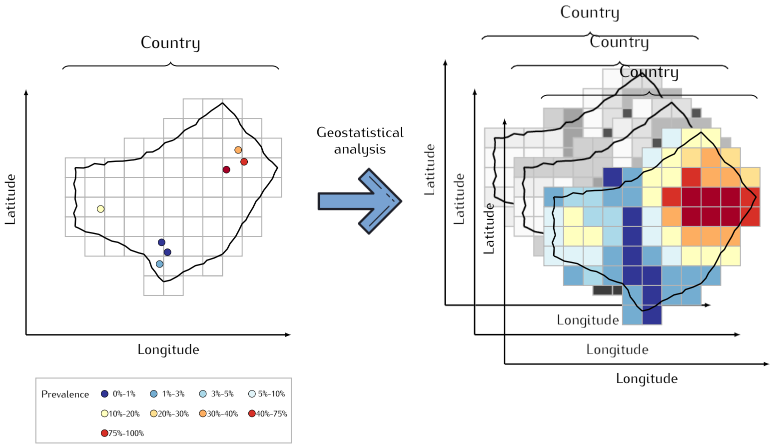
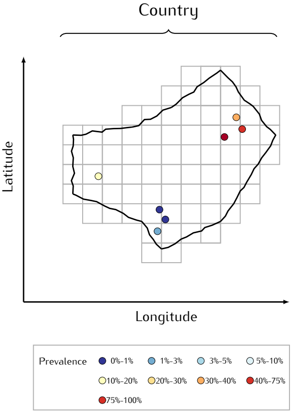
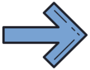


Geo-Spatial Maps

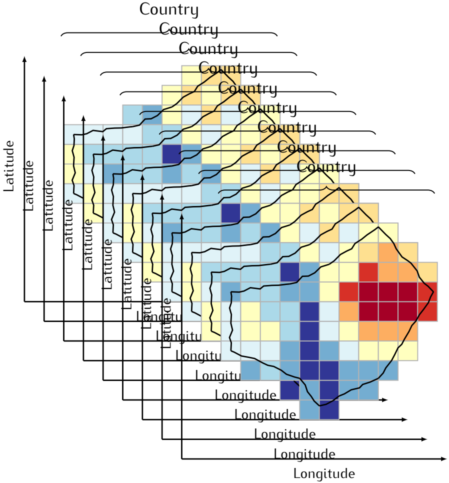
Survey Data



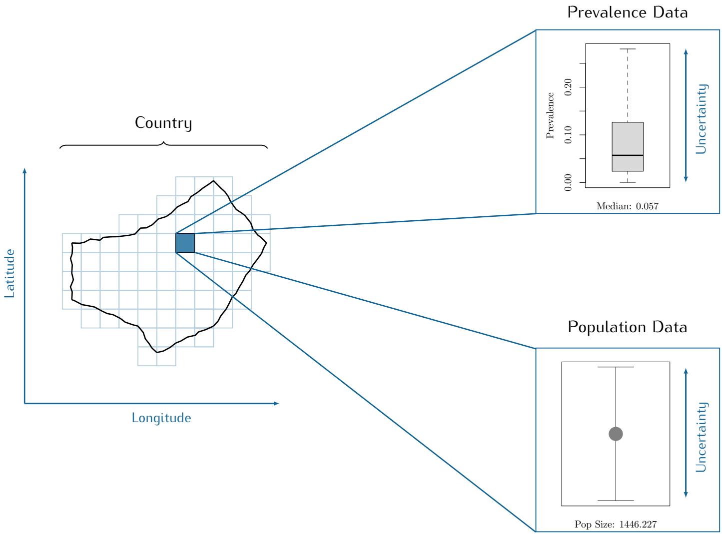
Geostatistical analysis



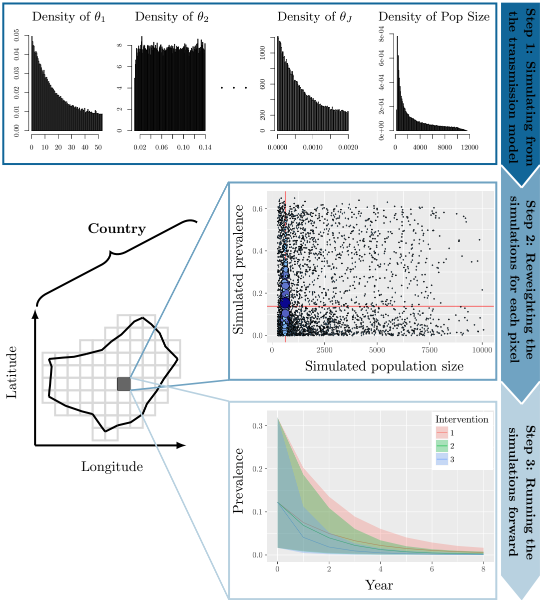
Geo-Spatial Map



Prevalence And Population Data



Methodology: Illustration



Weight The Simulations: Algorithm[1]

For pixel i and simulation j:

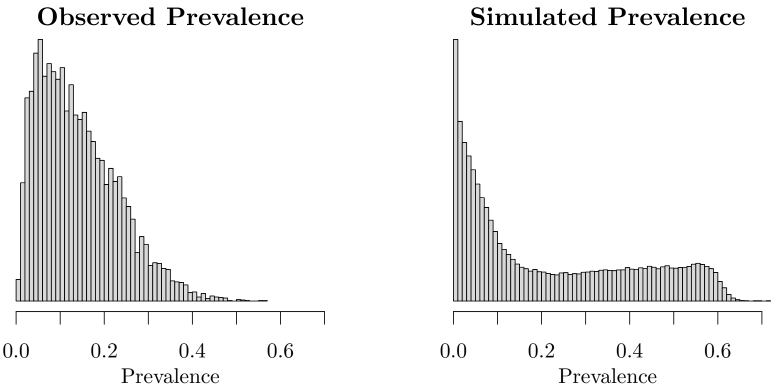
- Calculate:
$$w_{ij}^{(1)} = \pi_i(\boldsymbol{\theta}_j)/q(\boldsymbol{\theta}_j),$$
where $\pi_i(\boldsymbol{\theta})$ is the prior on the model parameters $\boldsymbol{\theta}$ and $q(\boldsymbol{\theta})$ is the proposal distribution over the parameter space.

- Reweigh the simulations to match pixel prevalence distributions:
$$w_{ij}^{(2)} = \frac{f(p_j|\boldsymbol{d}_i)}{g(p_j|\boldsymbol{w}_i^{(1)})} w_{ij}^{(1)},$$
where $\boldsymbol{d}_i = (d_{i1}, \ldots, d_{iM})$ is the posterior samples of prevalences and p_j prevalence of simulation j.

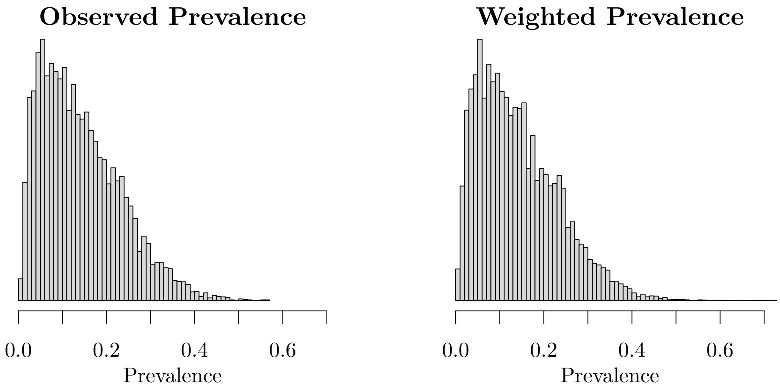
- No closed form $\implies$ Empirical alternatives.

[1] Panayiota Touloupou et al. "Statistical methods for linking geostatistical maps and transmission models: Application to lymphatic filariasis in East Africa". In: *Spatial and Spatio-temporal Epidemiology* (2020), p. 100391.

Weight The Simulations: Illustration



Weight The Simulations: Illustration

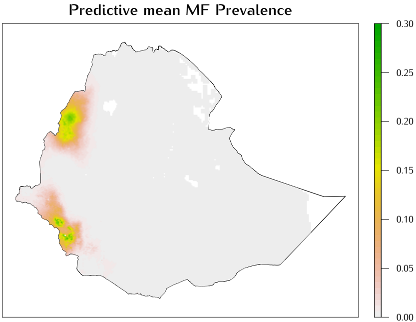


Applications

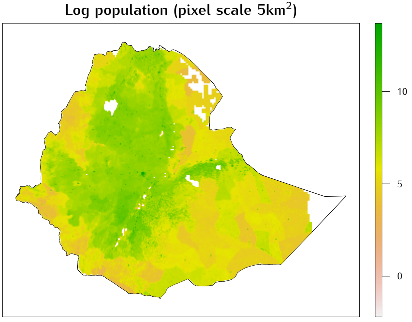
Lymphatic Filariasis (LF) In Africa

- Lymphatic filariasis (also known as elephantiasis) is a parasitic disease caused by filarial worms.
- Vector borne, transmitted by mosquitoes.
- Global efforts for LF elimination as a public health problem:
  - ➢ Prevalence $< 1\%$.
- Use of Mass Drug Administration (MDA).
- New guidelines for 2030.
- **Aim:** Inform policy where elimination efforts should be focused.

Application 1: LF In Ethiopia

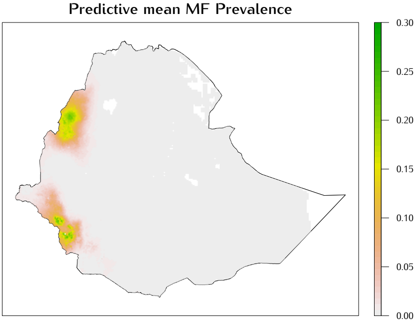


(a) Geo-spatial map provided by Emanuele Giorgi (pixel scale 5km^2).

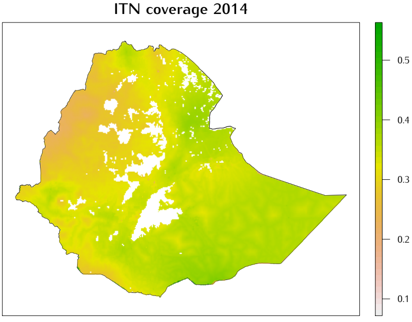


(b) Worldpop population estimates.

Bednet Coverage

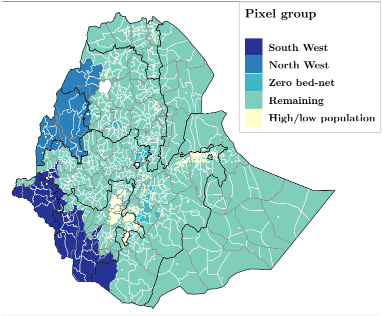


(c) Geo-spatial map provided by Emanuele Giorgi (pixel scale 5km^2).

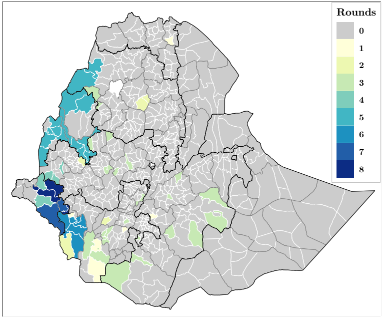


(d) Extracted from the Malaria Atlas Programme (Jorge Cano).

Historic Interventions



(e) Pixel Groups.

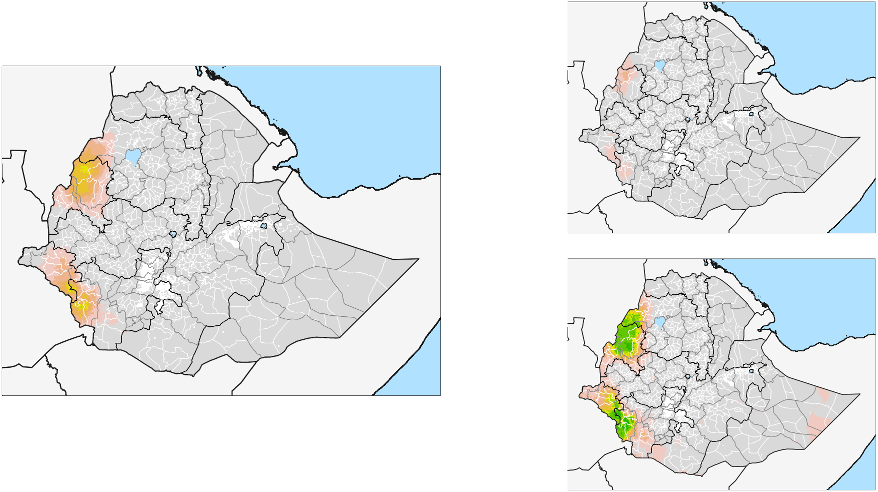


(f) Historic MDA.

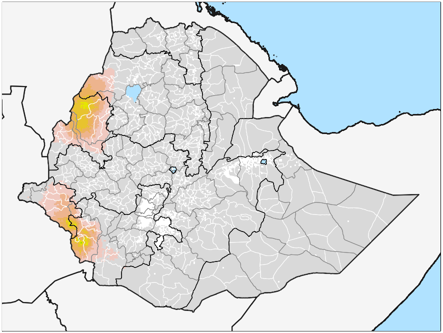
Future Intervention Strategies

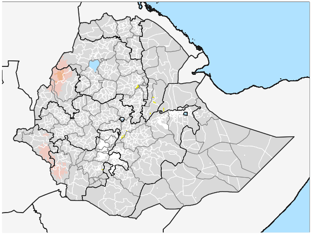
- In the case of LF Ethiopia is advised to perform Mass Drug Administration (MDA), Ivermectin (IVM) + Albendazole (ALB) with 65% coverage, once a year.
- We tested 4 future intervention strategies:
  1. No intervention or if already started complete 5 rounds of MDA.
  2. MDA with 65% coverage, once a year for unlimited rounds.
  3. MDA with 80% coverage, once a year for unlimited rounds.
  4. MDA with 65% coverage, twice a year for unlimited rounds.
- Different groups have various backgrounds of historical treatments, ie. MDA and/or bed-nets → **104 scenarios**.
- We consider 3 different models for LF in Ethiopia:
  → TRANSFIL (University of Warwick).
  → EPIFIL (University of Notre Dame).
  → LYMFASIM (Erasmus MC).

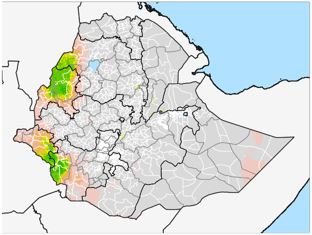
Geo-Spatial Maps Of Prevalence



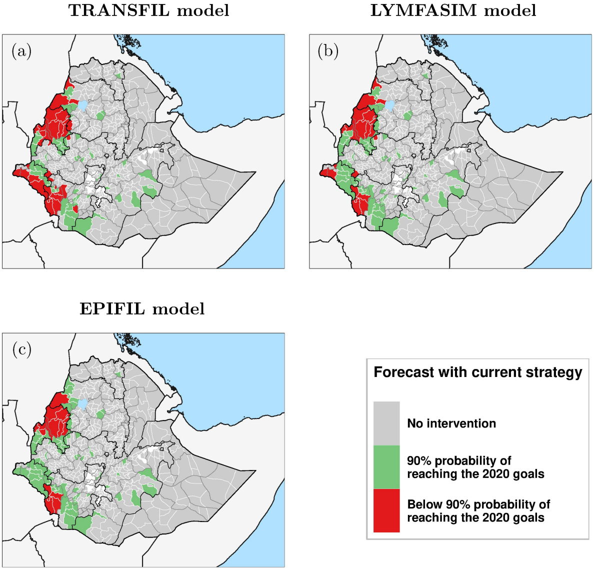
Estimated TRANSFIL Maps Of Prevalence



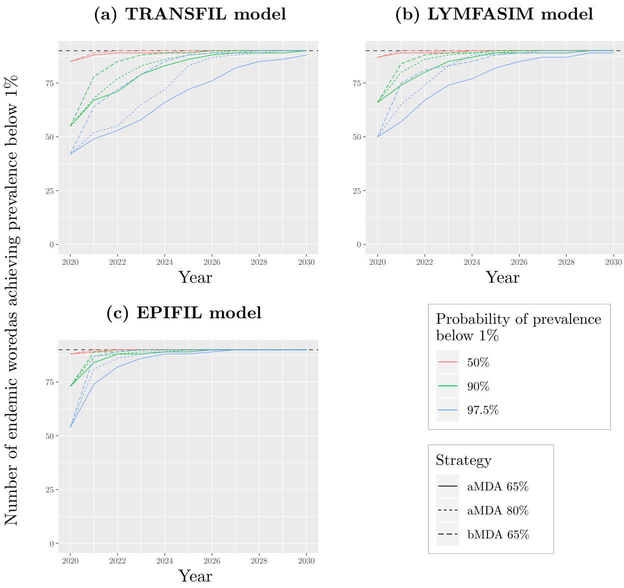




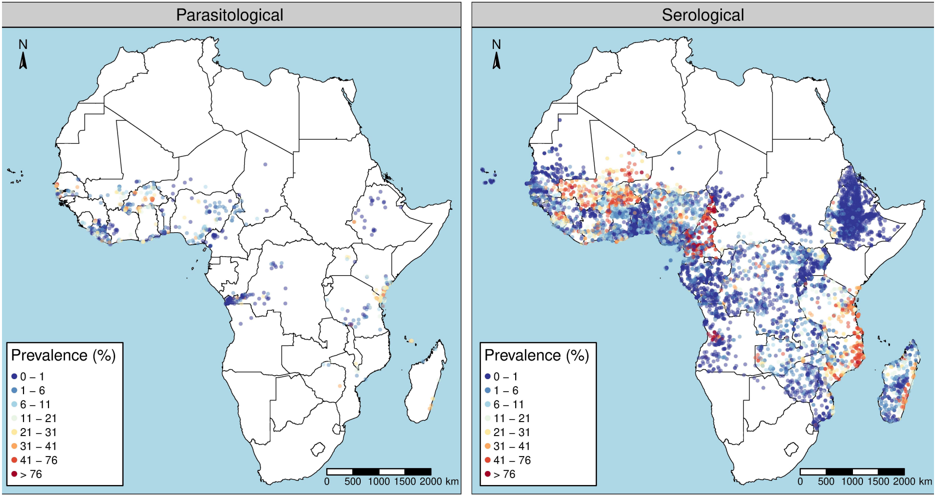
Forecast Current Strategy: IU level



Predicted Year Of Elimination



Application 2: LF In Africa



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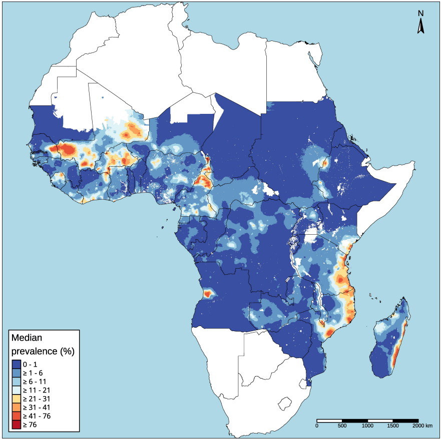
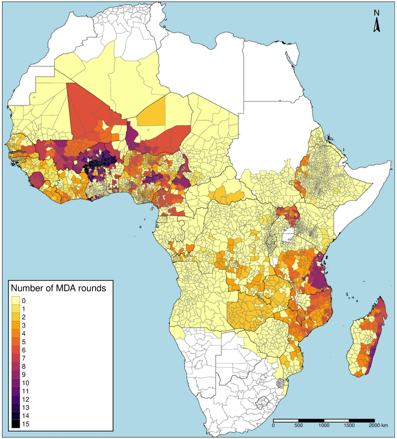


(a) Pre-control geo-spatial map provided by Claudio Fronterre (pixel scale 5km^2).



(b) ESPEN's historic MDA interventions provided by Jorge Cano.

Technical Details

- Geographical data:
  - **Historic MDA** interventions: gap between reported and true coverage (we considered 0%, 15% or 65%).
  - **Bed-net coverage** for each year, extracted from the Malaria Atlas Programme (we considered 0%, 25%, 50% or 75%).
  - WorldPop **population data**.

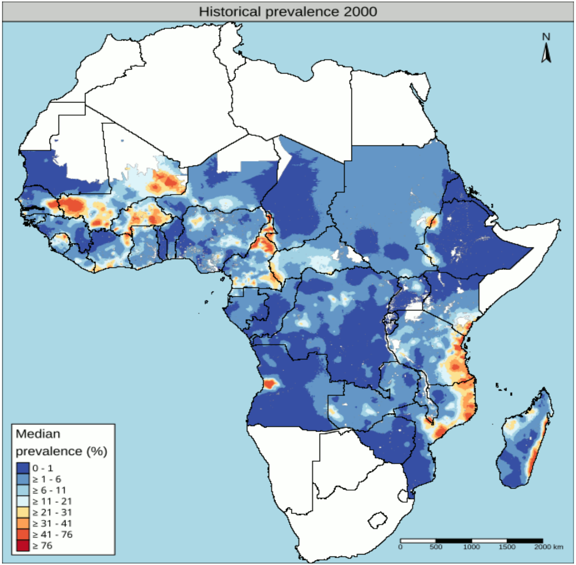
- We considered **4 future intervention strategies**:
  1. No intervention,
  2. WHO guidelines specified for each region for unlimited rounds,
     - Annual Ivermectin (IVM) + Albendazole (ALB) with 65% coverage
     - Annual Diethylcarbamazine (DEC) + ALB with 65% coverage
     - Biannual ALB with 65% coverage
     - Annual IVM + DEC + ALB with 65% coverage
  3. Increased coverage for unlimited rounds,
  4. Increased frequency for unlimited rounds.

Technical Details

- Different regions have various backgrounds of historical treatments, ie. MDA and/or bed-nets:
  - ➢ **2611 total number of scenarios**.
- We consider 3 different models for LF in Africa:
  - ➢ **TRANSFIL** (Warwick/Oxford),
  - ➢ **LYMFASIM** (Erasmus MC),
  - ➢ **EPIFIL** (Notre Dame).
- Ensemble model.

Impact Of Current Interventions

Thanks to **Claudio Fronterre** for the video and for all the remaining figures!!!



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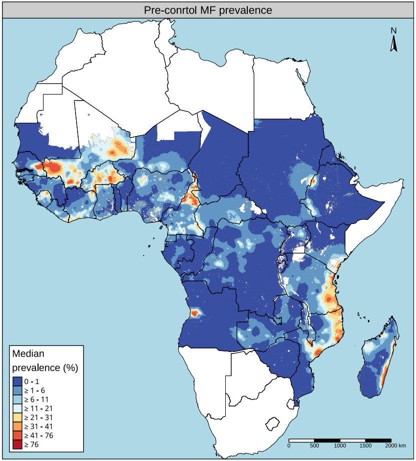
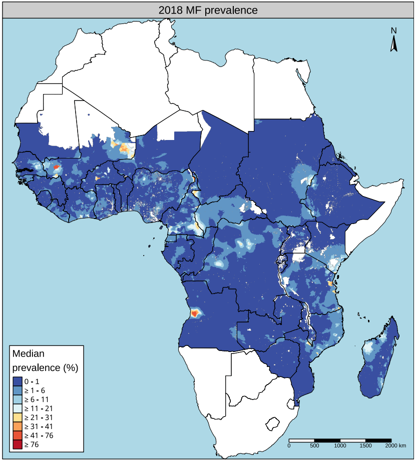
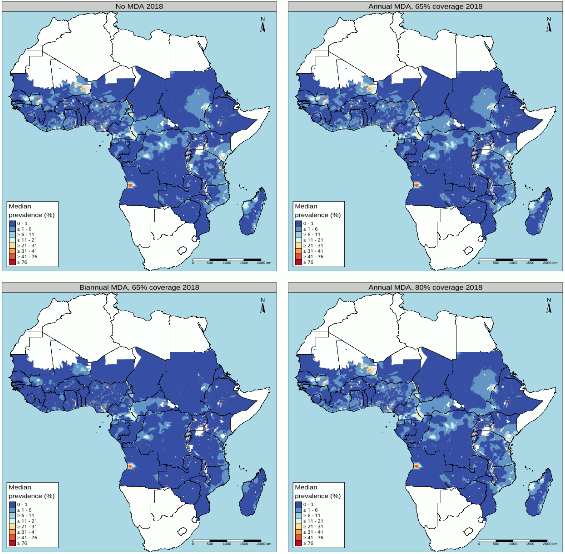


(a) Pre-control prevalence.

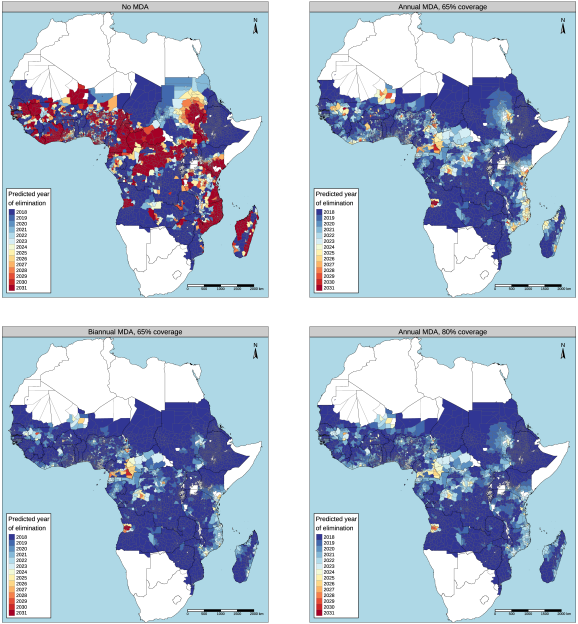


(b) Prevalence at 2018.

Impact Of Future Interventions



Projected Year Of Elimination



Discussion

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Conclusions:

- Bayesian methodology that integrates the uncertainty over multiple sources.
- Method reproduces spatial maps of disease prevalence well and carefully propagates uncertainty forward in time.
- Methodology can readily applied to different models/diseases.
- Evaluate impact of current and future intervention strategies.

Future work:

- Combine simulations from multiple models: Model comparison?
- Transmission assessment survey (TAS) data: We can use the TAS data for model validation.
- Gap between reported and true coverage.
- Weaknesses of our approach: Independent pixels.

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