# Predictive tools and modelling for mitigating arboviral threats

Oliver Brady 12 December 2023



### Overview



- 1. Understand
- 2. Estimate
- 3. Predict
- 4. Forecast

What developments enabled these and what would the next breakthrough look like?



Model 1

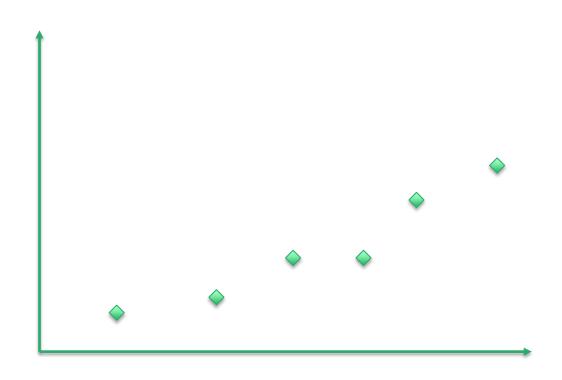


Model 2

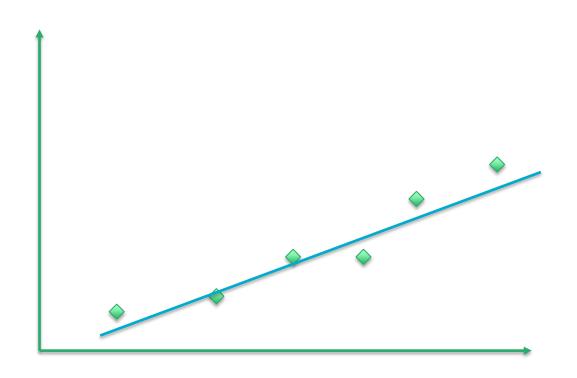




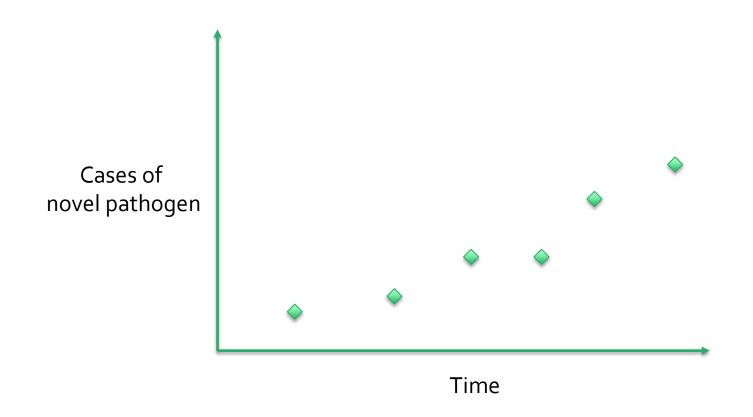




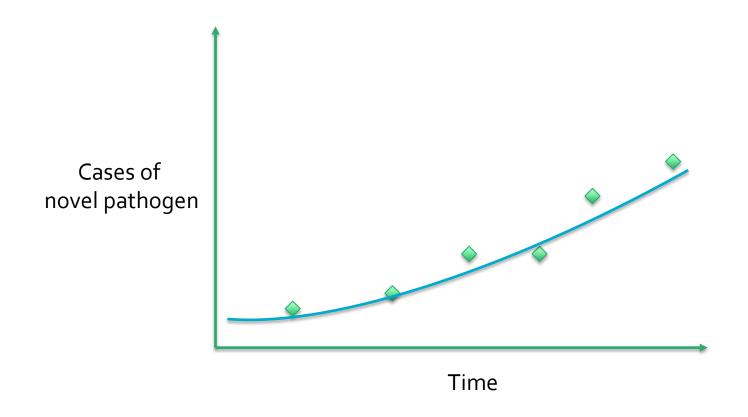




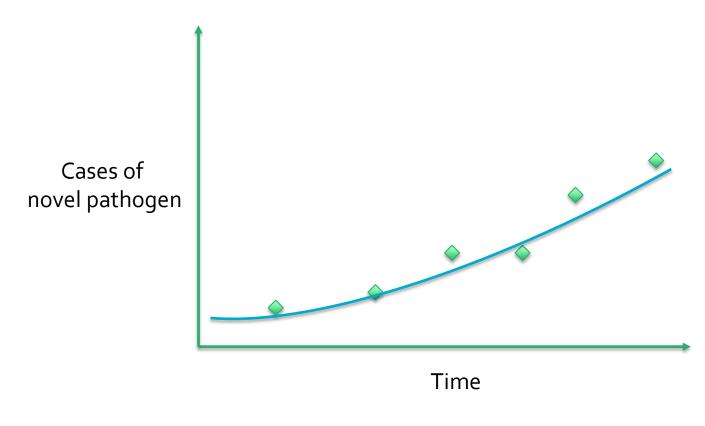












We all use "models"

Modelling is just a way of expressing those assumption and ideas in a mathematical form

# Challenges of summarising a broad field



#### Mechanistic models

#### Review

Mathematical models for dengue fever epidemiology: A 10-year systematic review

Maíra Aguiar a,b,c,\*, Vizda Anam a, Konstantin B. Blyuss f, Carlo Delfin S. Estadilla a, Bruno V. Guerrero a, Damián Knopoff a,c, Bob W. Kooi d, Akhil Kumar Srivastav a, Vanessa Steindorf a, Nico Stollenwerk a,b

Aguiar et al. Phy. of Life Rev 2022 <a href="https://doi.org/10.1016/j.plrev.20">https://doi.org/10.1016/j.plrev.20</a> <a href="https://doi.org/10.1016/j.plrev.20">22.02.001</a>

#### Forecasting models

#### RESEARCH ARTICLE

A systematic review of dengue outbreak prediction models: Current scenario and future directions

Xing Yu Leung<sup>1</sup>, Rakibul M. Islam<sup>1</sup>, Mohammadmehdi Adhami<sup>1</sup>, Dragan Ilic<sup>1</sup>, Lara McDonald<sup>1</sup>, Shanika Palawaththa<sup>1</sup>, Basia Diug<sup>1</sup>, Saif U. Munshi<sup>2</sup>, Md Nazmul Karimo<sup>1</sup>\*

Leung et al. PLoS NTDs 2023 https://doi.org/10.1371/journal.p ntd.0010631

#### Risk mapping models

A systematic review of the data, methods and environmental covariates used to map *Aedes*-borne arbovirus transmission risk



Ah-Young Lim<sup>1,2\*</sup>, Yalda Jafari<sup>3,4</sup>, Jamie M. Caldwell<sup>5</sup>, Hannah E. Clapham<sup>6</sup>, Katy A. M. Gaythorpe<sup>7</sup>,
Laith Hussain-Alkhateeb<sup>8,9</sup>, Michael A. Johansson<sup>10</sup>, Moritz U. G. Kraemer<sup>11</sup>, Richard J. Maude<sup>3,4</sup>, Clare P. McCormack<sup>7</sup>,
Jane P. Messina<sup>12,13</sup>, Erin A. Mordecal<sup>14</sup>, Ingrid B. Rabe<sup>15</sup>, Robert C. Reiner Jr<sup>16,17</sup>, Sadie J. Ryan<sup>18</sup>, Henrik Salje<sup>19</sup>,
Jan C. Semenza<sup>80</sup>, Diana P. Roias<sup>15</sup> and Oliver J. Bradv<sup>1,2</sup>

Lim et al. BMC Infect. Dis.2023 https://doi.org/10.1186/s12879-023-08717-8



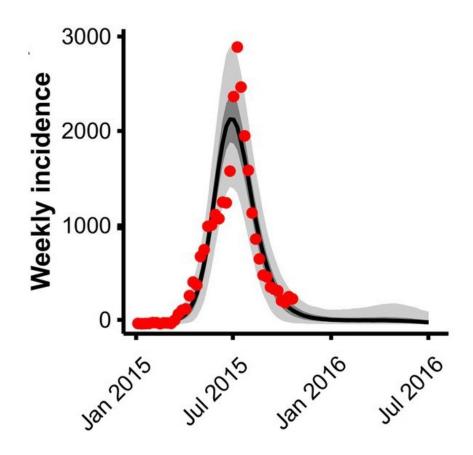
### Using model to test hypotheses about:

- Immunity
- Climate
- Environment
- Origins of epidemics
- **—** ...

Usually using observational data

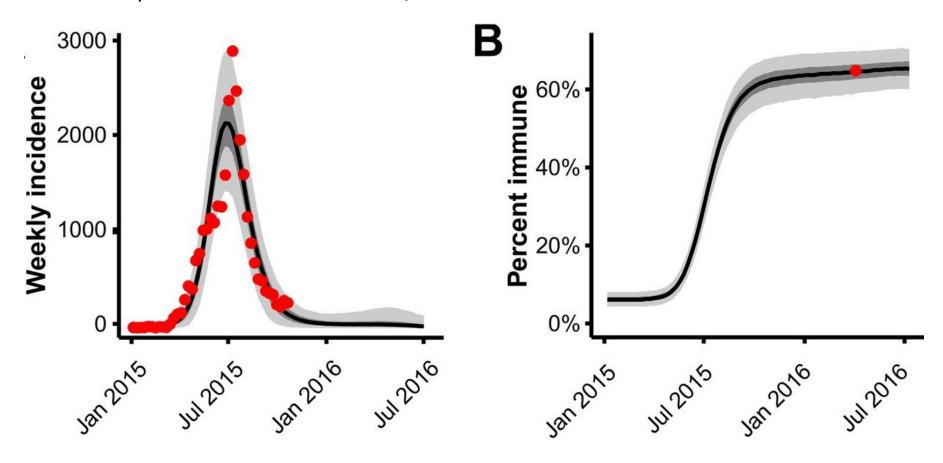


Why did the Zika epidemic decline in Salvador, Brazil?





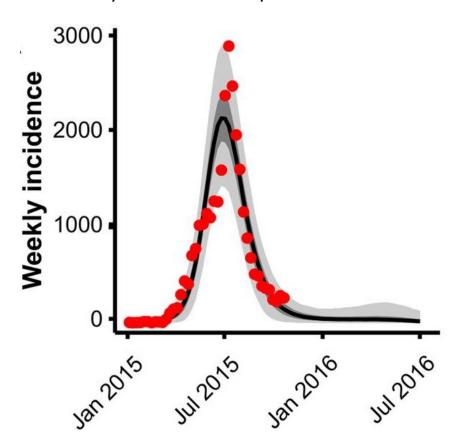
Why did the Zika epidemic decline in Salvador, Brazil?

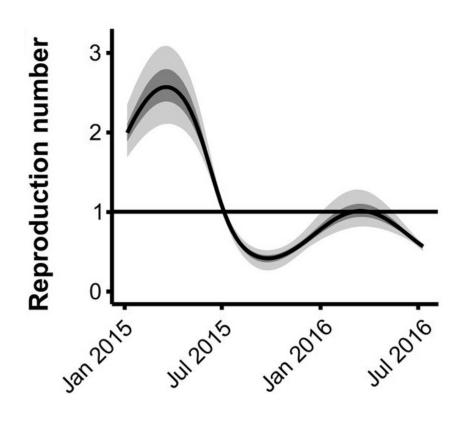


Netto et al. 2017 mBio https://doi.org/10.1128/mbio.01390-17



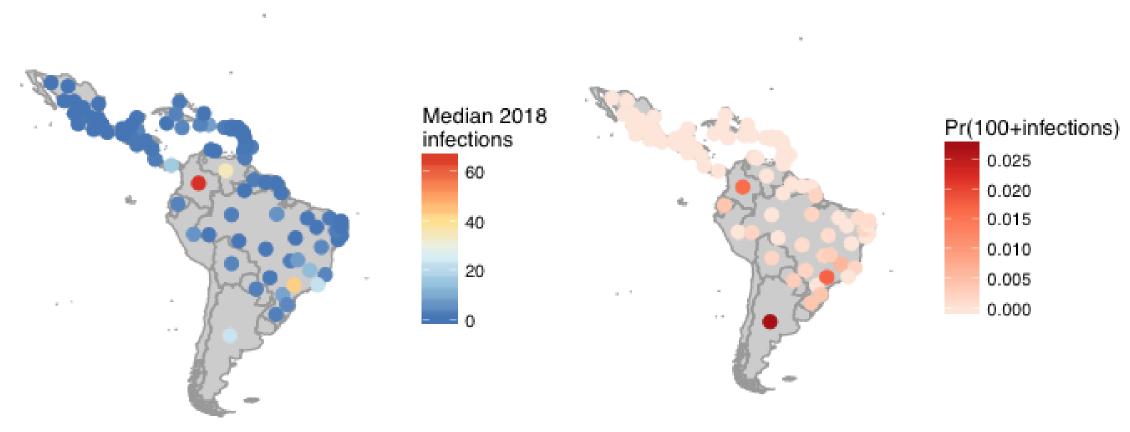
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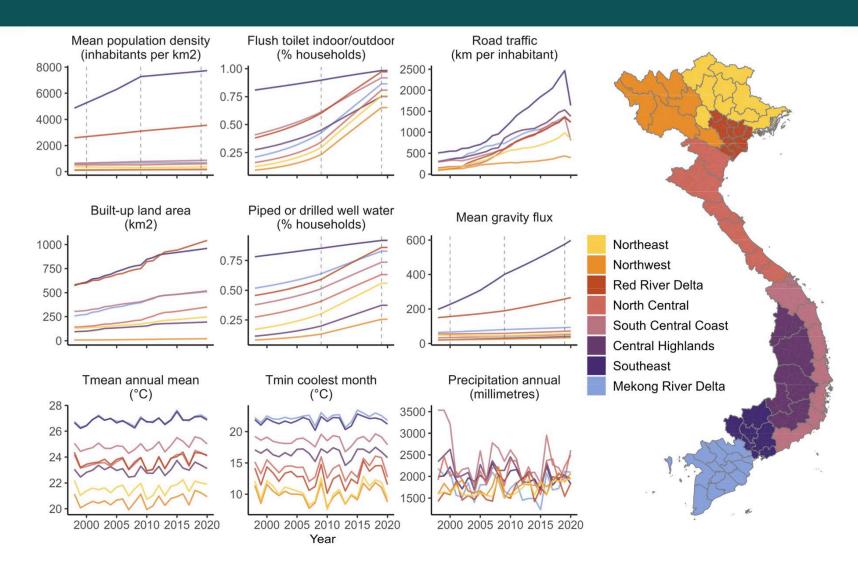


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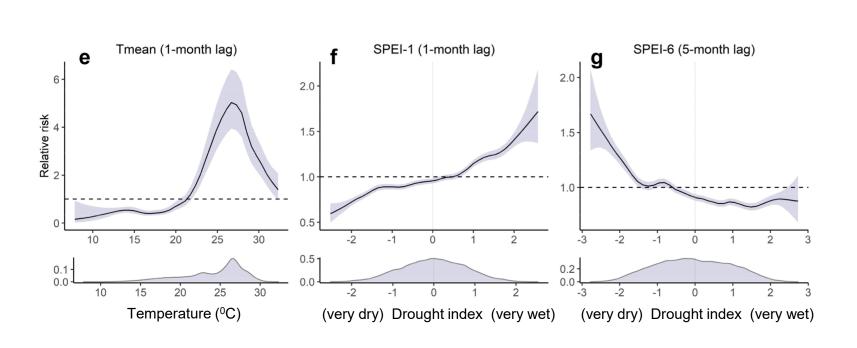


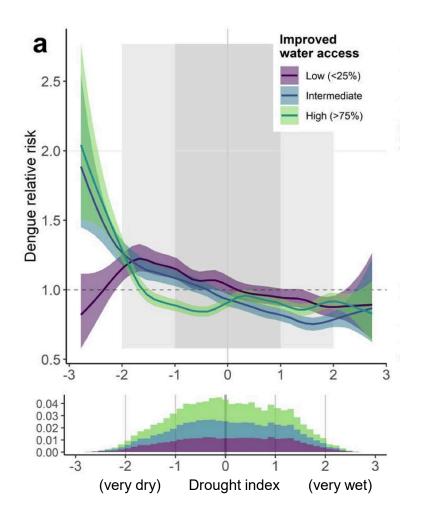
O'Reilly et al. 2018 BMC Med <a href="https://doi.org/10.1186/s12916-018-1158-8">https://doi.org/10.1186/s12916-018-1158-8</a>











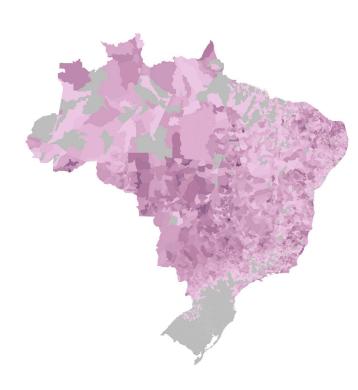


### Enabling factors:

- Higher spatial and temporal resolution data
  - Of cases
  - Of explanatory variables (infrastructure, human movement)



- Integration of causal inference methods into modelling
  - DAGs



### Models for estimation



Can improve experimental estimates of epidemiological parameters or estimate relevant new parameters:

- Reproduction number
- Burden
- Effectiveness

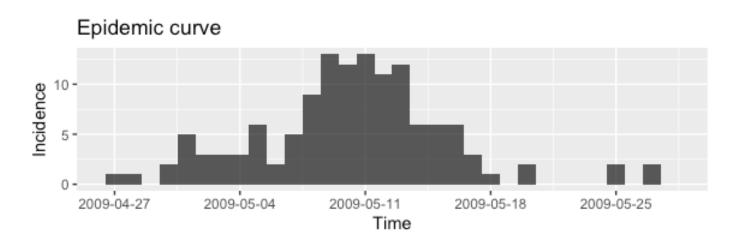
Models fill the gap where experimental measurement is impractical or impossible

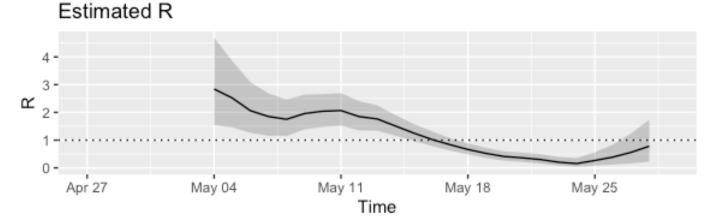
### Models for estimation -Rt



#### Effective reproduction number (R<sub>t</sub>)

- Number of new infections generated by the average infected individual
- Critical for outbreak management
- Difficult to directly measure
- Can be inferred from case data using models





Cori et al. EpiEstim vignette <a href="https://cran.r-">https://cran.r-</a>
<a href="project.org/web/packages/EpiEstim/vignettes/demo.html">project.org/web/packages/EpiEstim/vignettes/demo.html</a>

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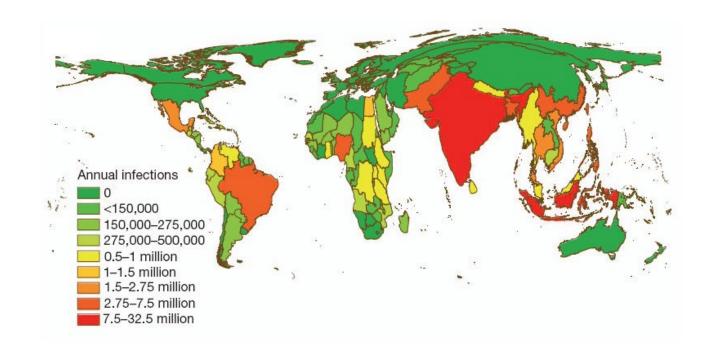


InfoDengue <a href="https://info.dengue.mat.br">https://info.dengue.mat.br</a>

### Models for estimation -Burden

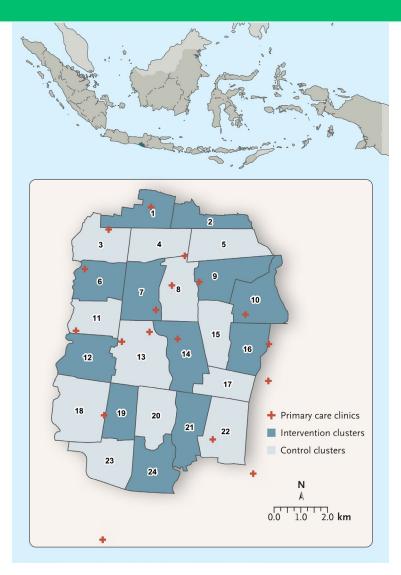


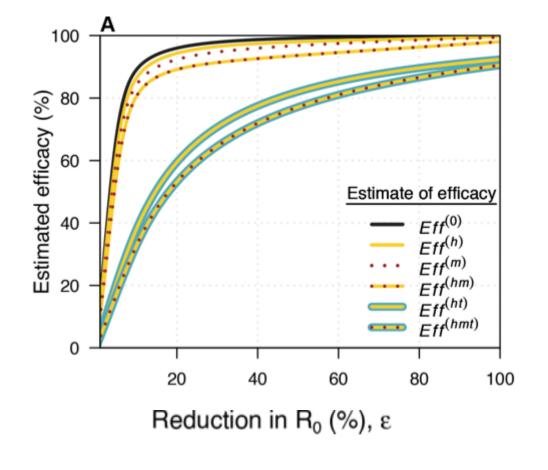
- Measuring incidence of infections is expensive
- Data sparsity necessitates extrapolation
- Importance of different approaches



### Models for estimation -Effectiveness







### Models for estimation



### Enabling factors:

- Accessibility and speed of computational methods
- Recognition of modelled estimates

### Future developments:

- Integration across more disciplines
  - Routinely measuring effectiveness of vector control
  - Model-informed trial design
  - Targeted data collection to improve modelled estimates

# Models for prediction



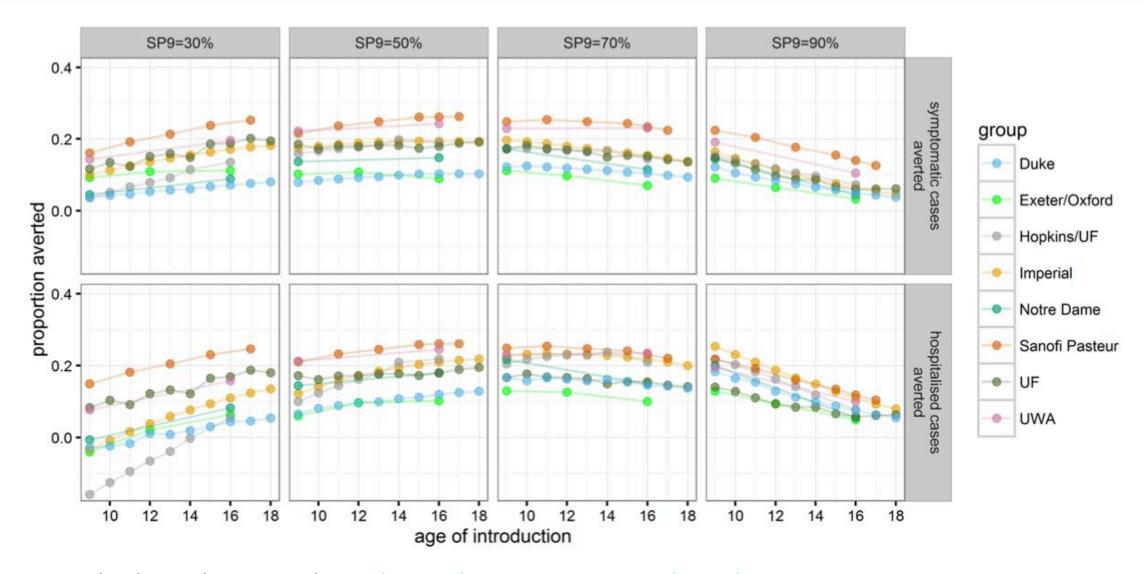
Predicting the consequences of different intervention choices:

- Best long-term usage strategy for an intervention
- How to best combine interventions

Increasingly critical piece of evidence needed for investment in new interventions

# Models for prediction- Intervention strategy

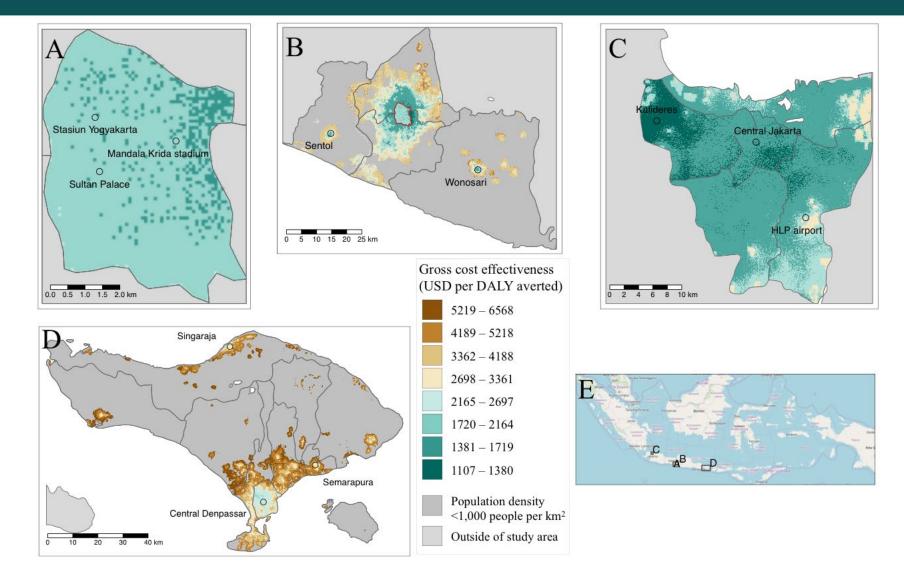




Flasche et al. PLoS Med. 2016 https://doi.org/10.1371/journal.pmed.1002181

# Models for prediction- Intervention strategy

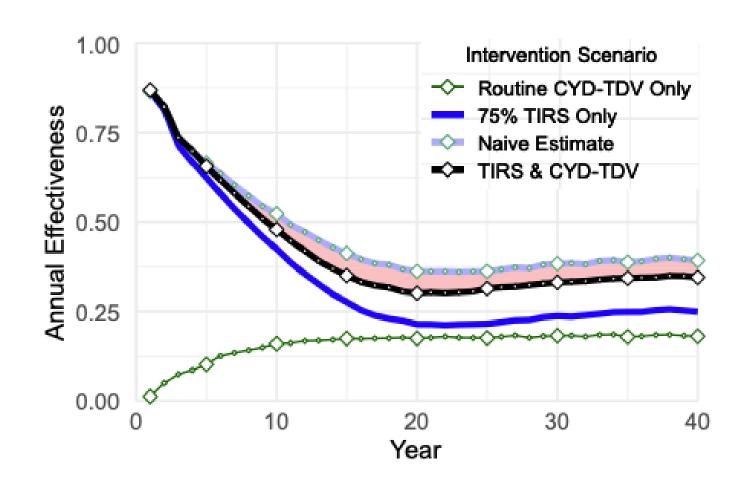




Brady et al. *BMC Med*. 2020 <a href="https://doi.org/10.1186/s12916-020-01638-2">https://doi.org/10.1186/s12916-020-01638-2</a>

### Models for prediction- combining interventions





# Models for prediction

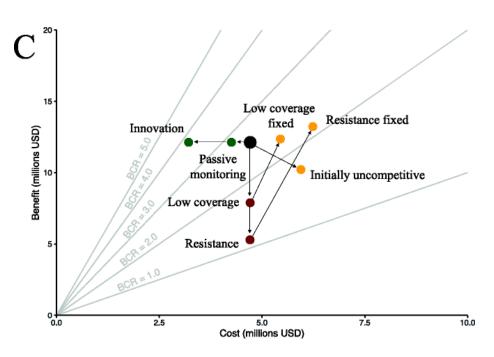


### Enabling factors:

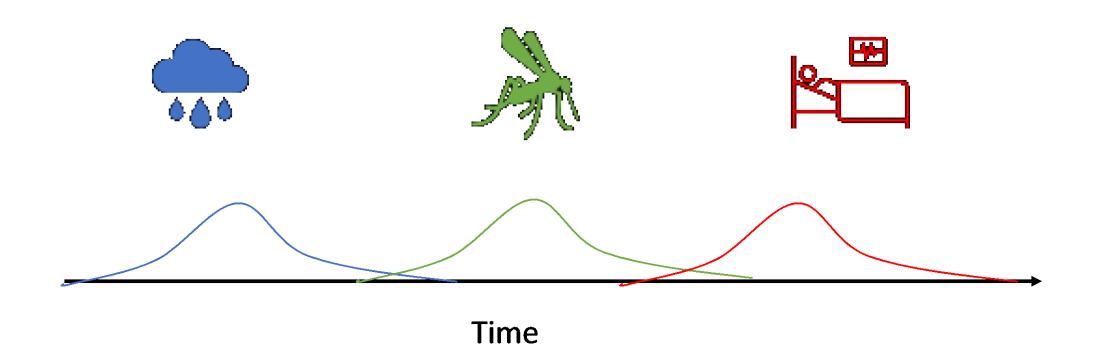
- Good collaborations with intervention developers, governments and international health organisations
- Consensus among models

### Future developments:

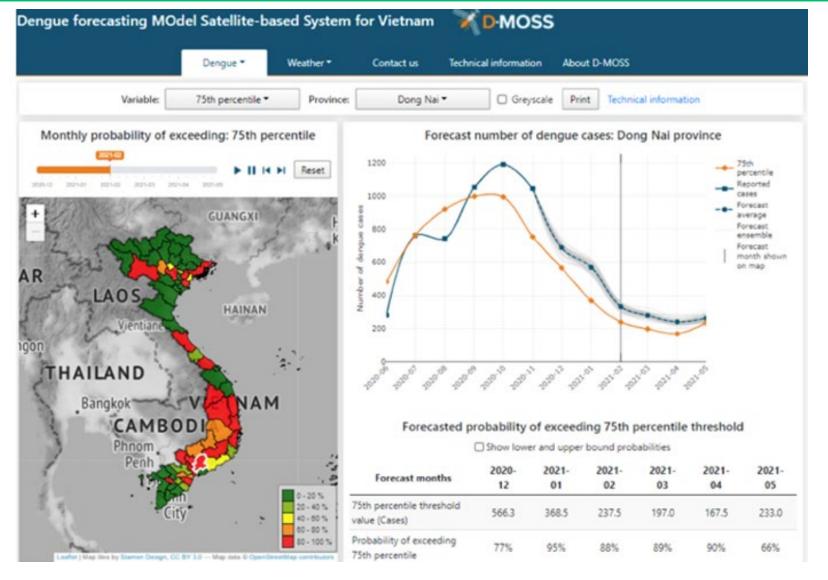
More realistic and locally-relevant predictions to improve robustness





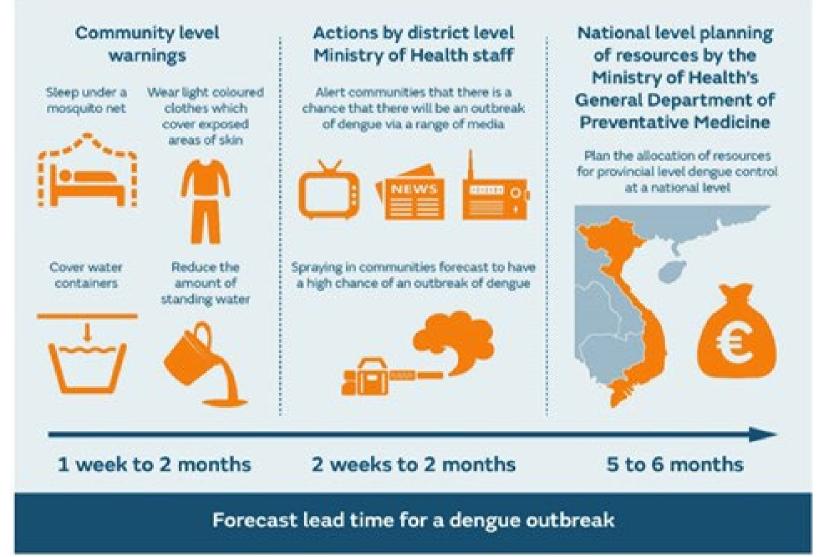






https://www.d-moss.org and Colon-Gonzalez et al. 2021 PLoS Med https://doi.org/10.1371/journal.pmed.1003542





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### Enabling factors:

- Better understanding of drivers of arboviruses
- Efficient Bayesian inference methods
- More relevant approaches to validation developed with ministries of health

### Future developments:

- More prospective evaluation of forecasts
- cRCT of forecast-informed outbreak prevention

# Summary



Purpose	Enabling developments	Future opportunities
Understand	More abundant and detailed case data	Use of causal inference methods
Estimate	New answers to difficult questions and rapid and easy to use frameworks	Routine use of models in data dashboard and study design
Predict	Collaborations with intervention developers and between modelling groups	More specific and realistic predictions for context-specific decision making
Forecast	Capitalising on improved understanding of dynamics and closer collaboration with users	Better evaluation of operational performance and epidemiological effectiveness