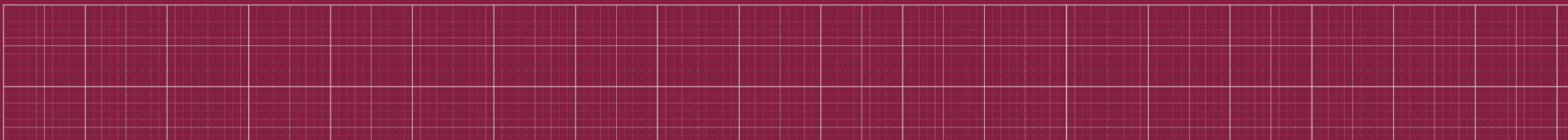




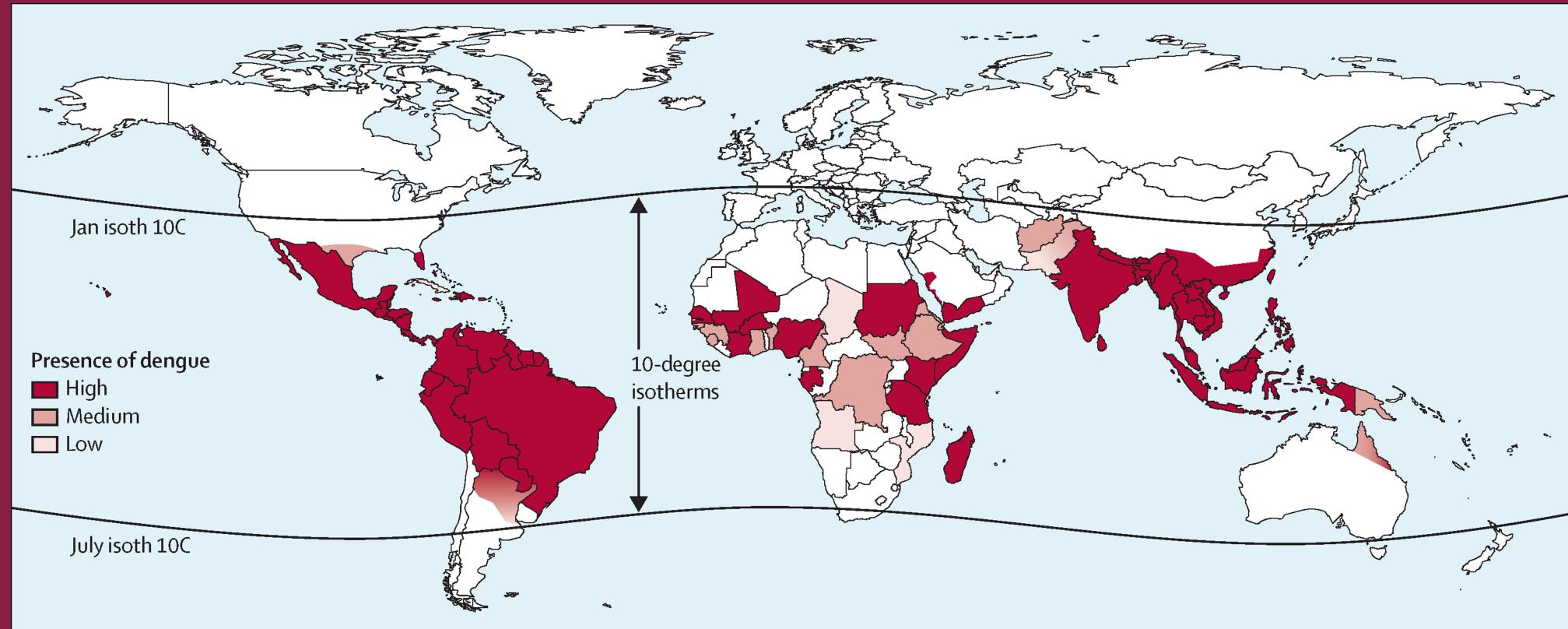
Trait-based approaches to understanding thermal adaptation in arthropods: Potential implications for climate-driven VBD modelling

Paul Huxley
Virginia Tech (Statistics)
Imperial College London (Infectious Disease Epidemiology)



VBDs World-Wide: Dengue

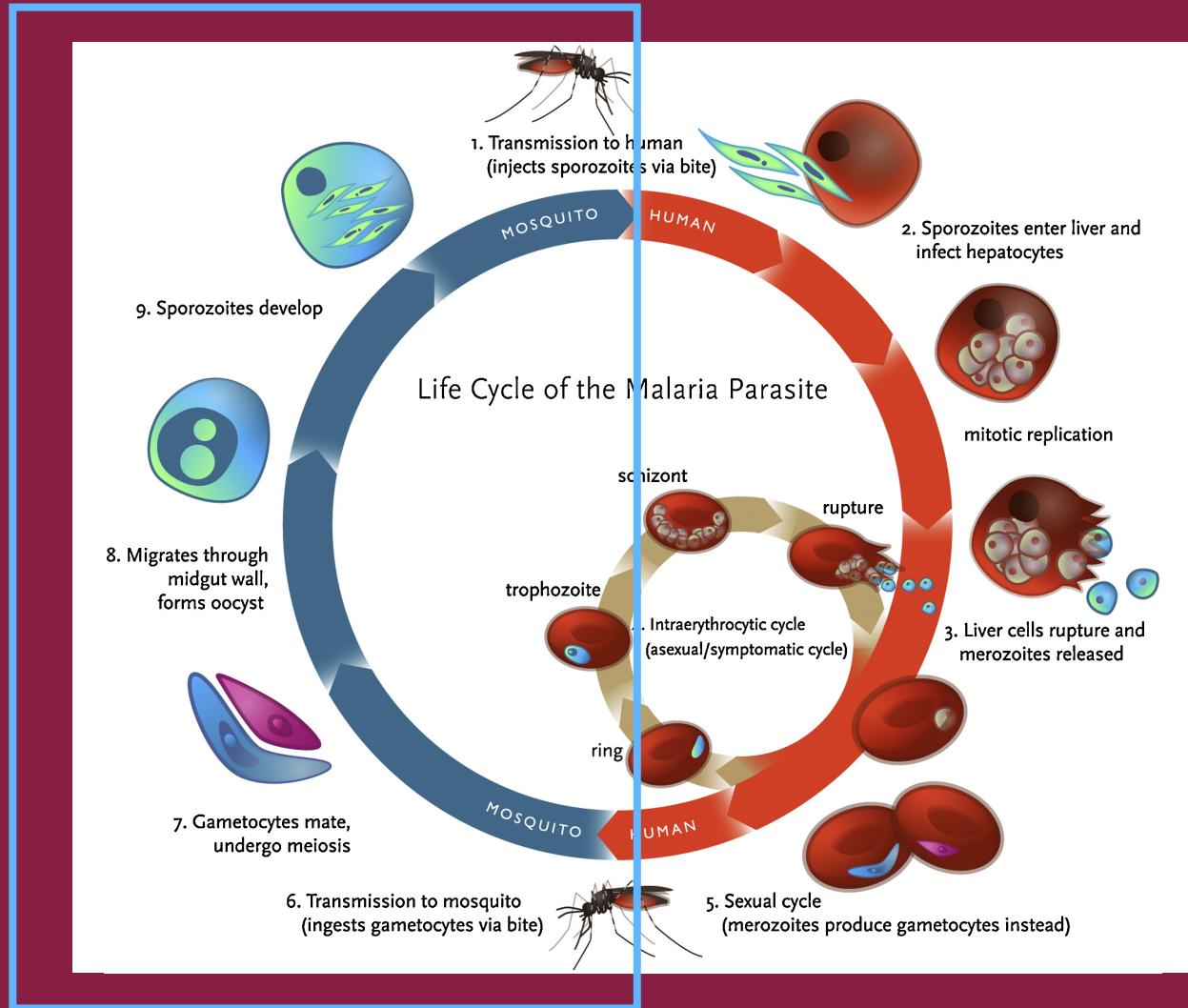
- Causes the greatest human disease burden of any arbovirus
- 10,000 deaths and 100 million symptomatic infections per year in over 125 countries
- Environmental change is expected to shift transmission risk patterns



Guzman & Harris 2014 Lancet

Malaria: The canonical VBD

sensitive to environmental temperature



VBDs: The big picture

- How can we predict when and where VBD burden will be high?
- How much and what kinds of data do we need to make good quantitative predictions, and at what time/spatial scale?
- Can we combine a mechanistic understanding into a ‘tactical’ approach to improve extrapolation?



Ecological/Epidemiological Models

Tactical/Phenomenological

Strategic/Mechanistic

- Describe patterns without elucidating mechanism
- Prediction
- Statistical models (regressions, etc.)

- Focus on mechanisms
- Explanation or understanding
- ODEs, PDEs, IBMS/ABMs

Ecological/Epidemiological Models

Tactical/Phenomenological

Strategic/Mechanistic

How much data?

Some

Some

more than you have (almost always!)

Short term

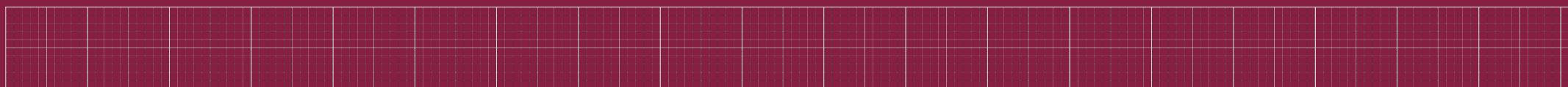
Long term



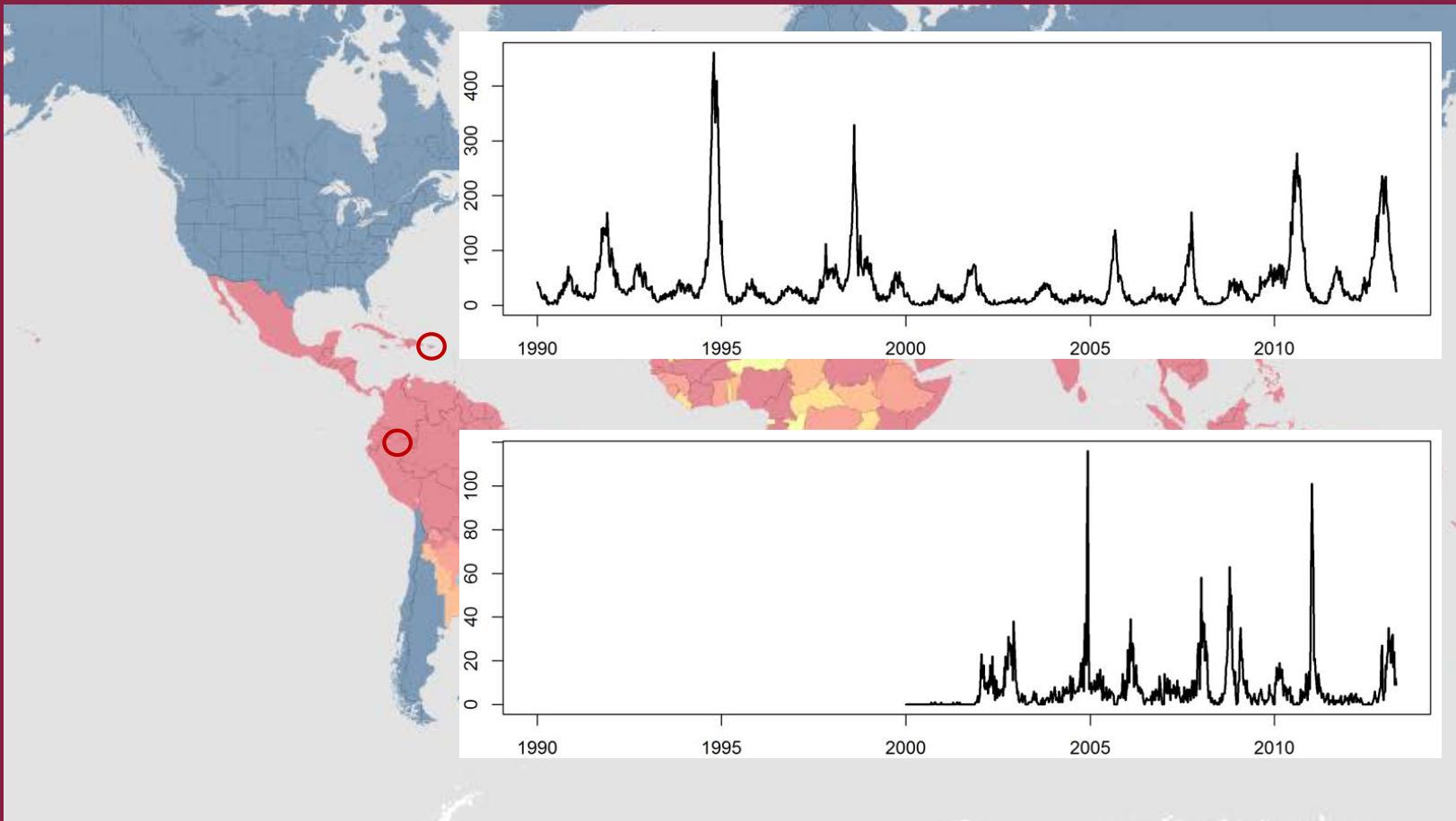
Why more data?

We have to fit the mechanism from the bottom up and validate from the top down!

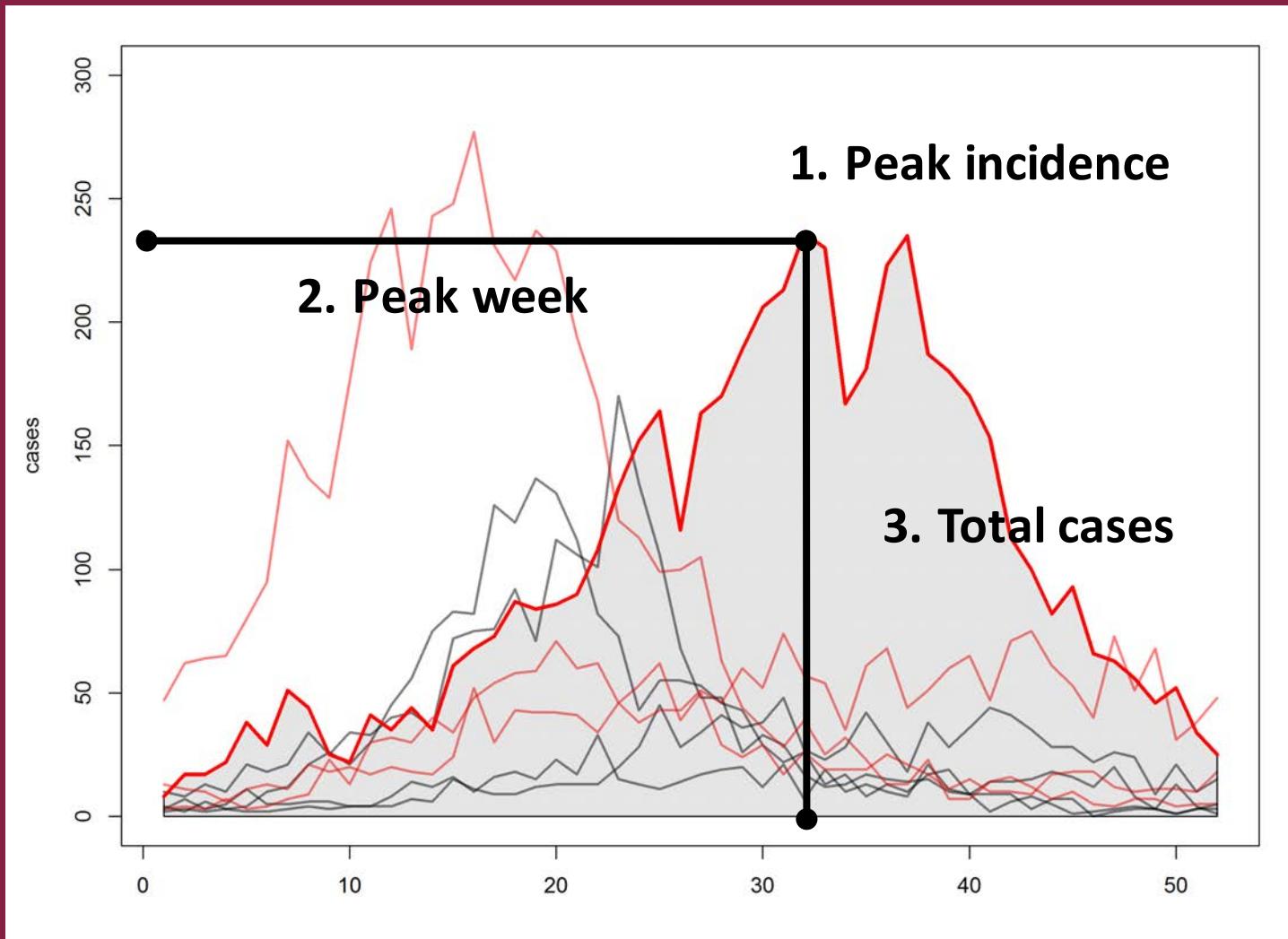
- Twice the work, sometimes twice the data (or more) needed.
- Data available for validation or for fitting parameters for the mechanistic models are often not suitable for those purposes.
- Models may be primarily suitable for a single scale or purpose (prediction vs understanding)



Tactical/Phenomenological VBD models



Tactical/Phenomenological VBD models



Tactical/Phenomenological VBD models

Purely tactical example

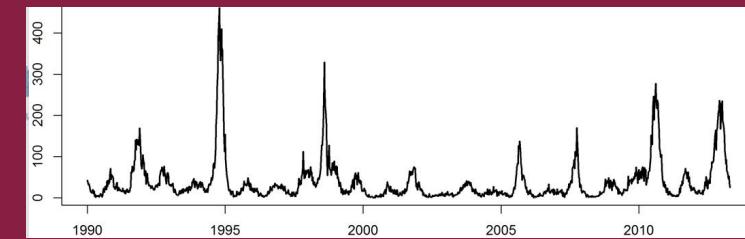
- Based on Gaussian process regression
- Only used dengue incidence data
- Predictors derived from casually observed relationships
(i.e., by looking at the data and identifying some of its characteristics)
- Fully analytic scheme (fast!)
- Heteroskedastic additions for greater flexibility

It's a strategy that is simultaneously simple (in its use of data) and very flexible (non-parametrically estimating nonlinear relationships).

A GP is just a “big multivariate normal”.

Tactical/Phenomenological VBD models

Forecasting Dengue in San Juan: GP model

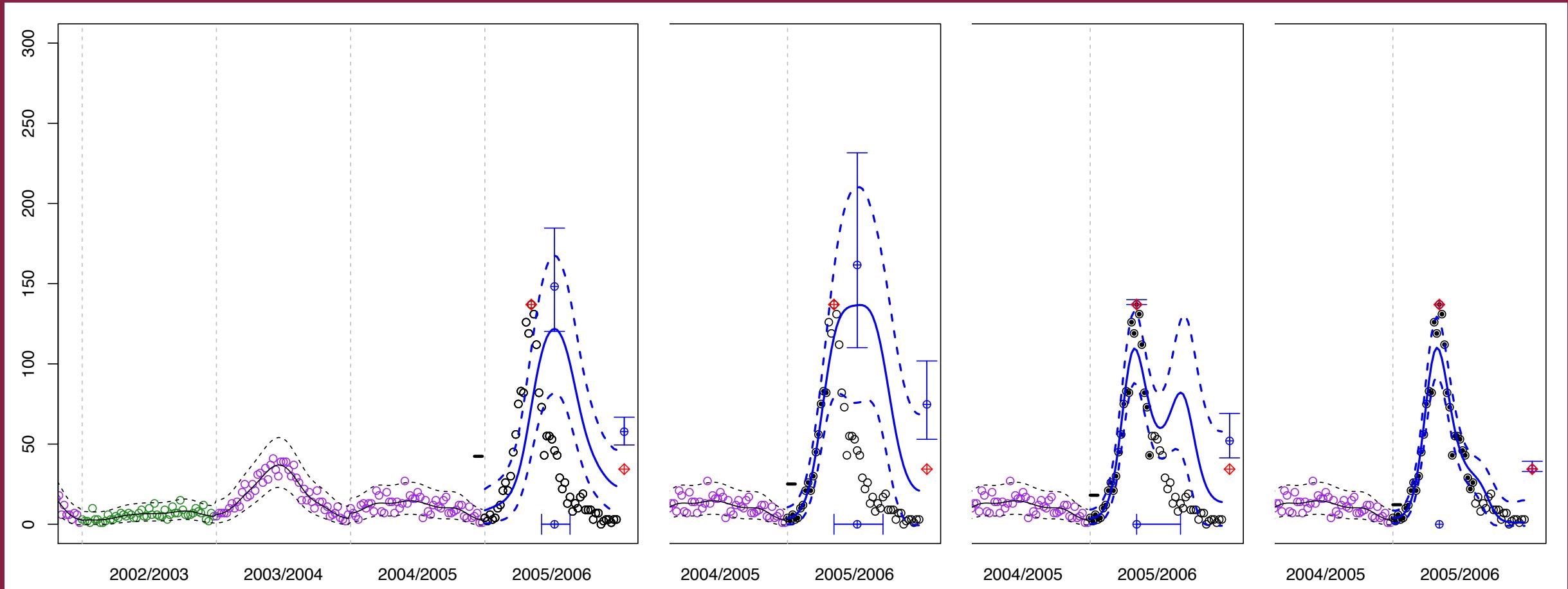


Week 0

Week 16

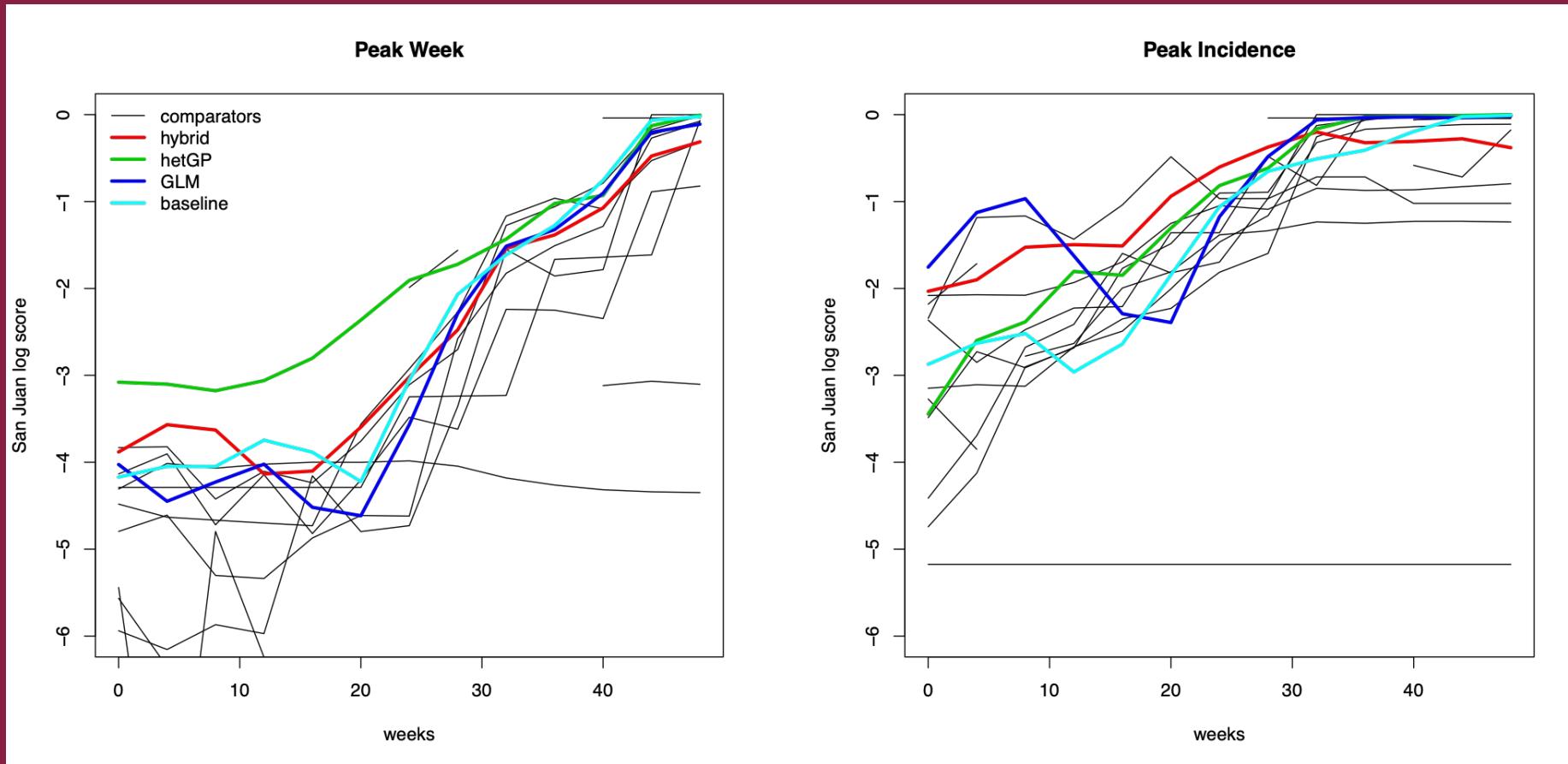
Week 24

Week 32



Tactical/Phenomenological VBD models

Forecasting Dengue in San Juan



Tactical/Phenomenological VBD models

GP Regression

Pros

- Fast, Flexible, **Data Light**
- Can capture uncertainty easily
- Learns from the data as it comes in relatively quickly
- Doesn't care what the underlying processes are so you can't get them wrong!

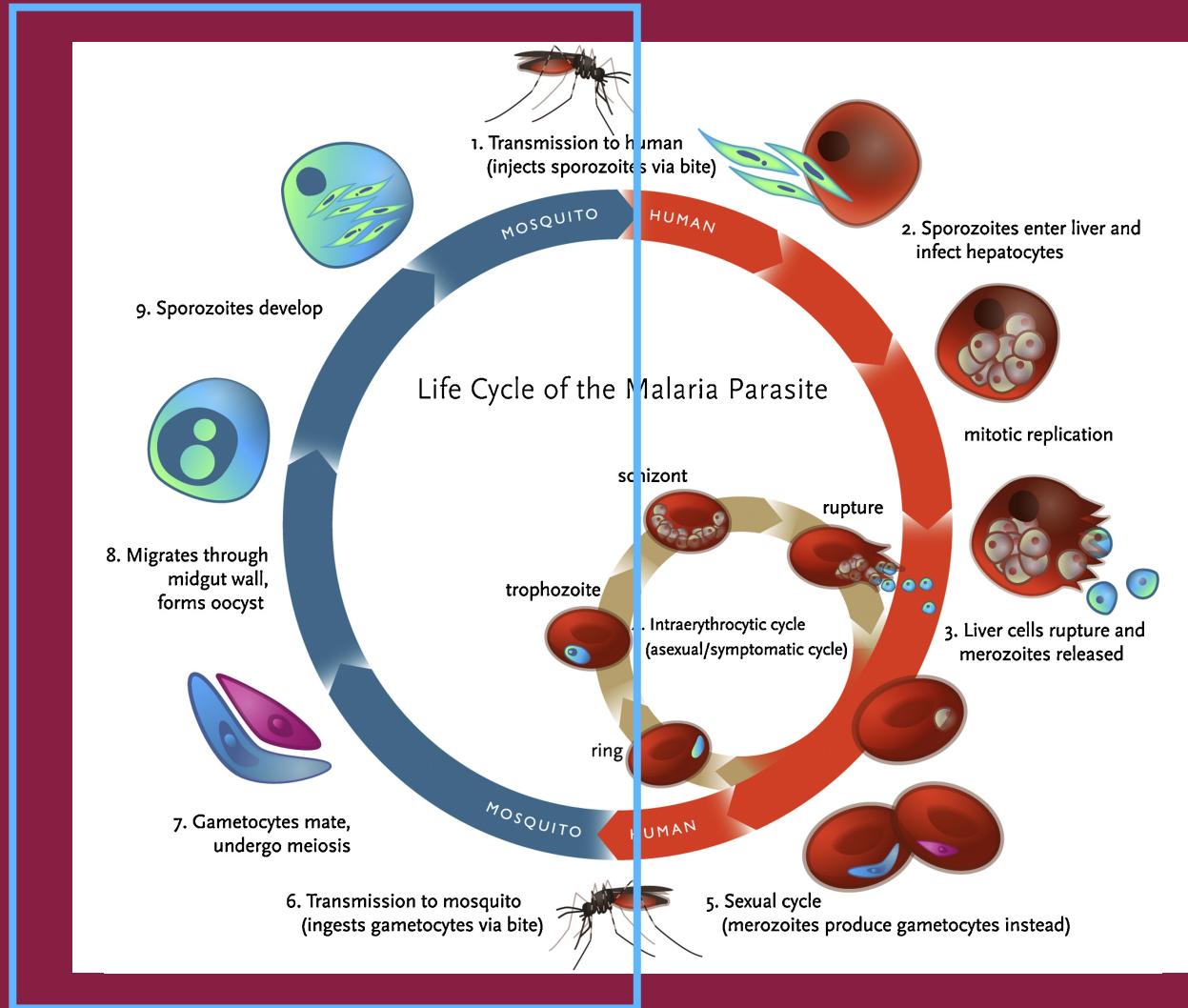
Cons

- Context dependent - can't use a GP (of this type) from one city to predict in another
- Can't be used to learn about impacts of control
- Extrapolation (climate change, invasions....) is problematic

What can you get with a mechanistic model?

Malaria: The canonical VBD

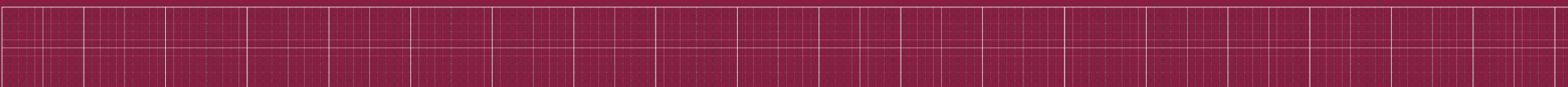
sensitive to environmental and ecological factors



What is a trait?

A trait is any measurable feature of an individual organism.

- Physical (body mass, wing length, wing morphology, etc.)
- Performance (respiration rate, growth rate, flying speed, etc.)
- Behavioural (feeding preference, foraging strategy, thermoregulatory, etc.)



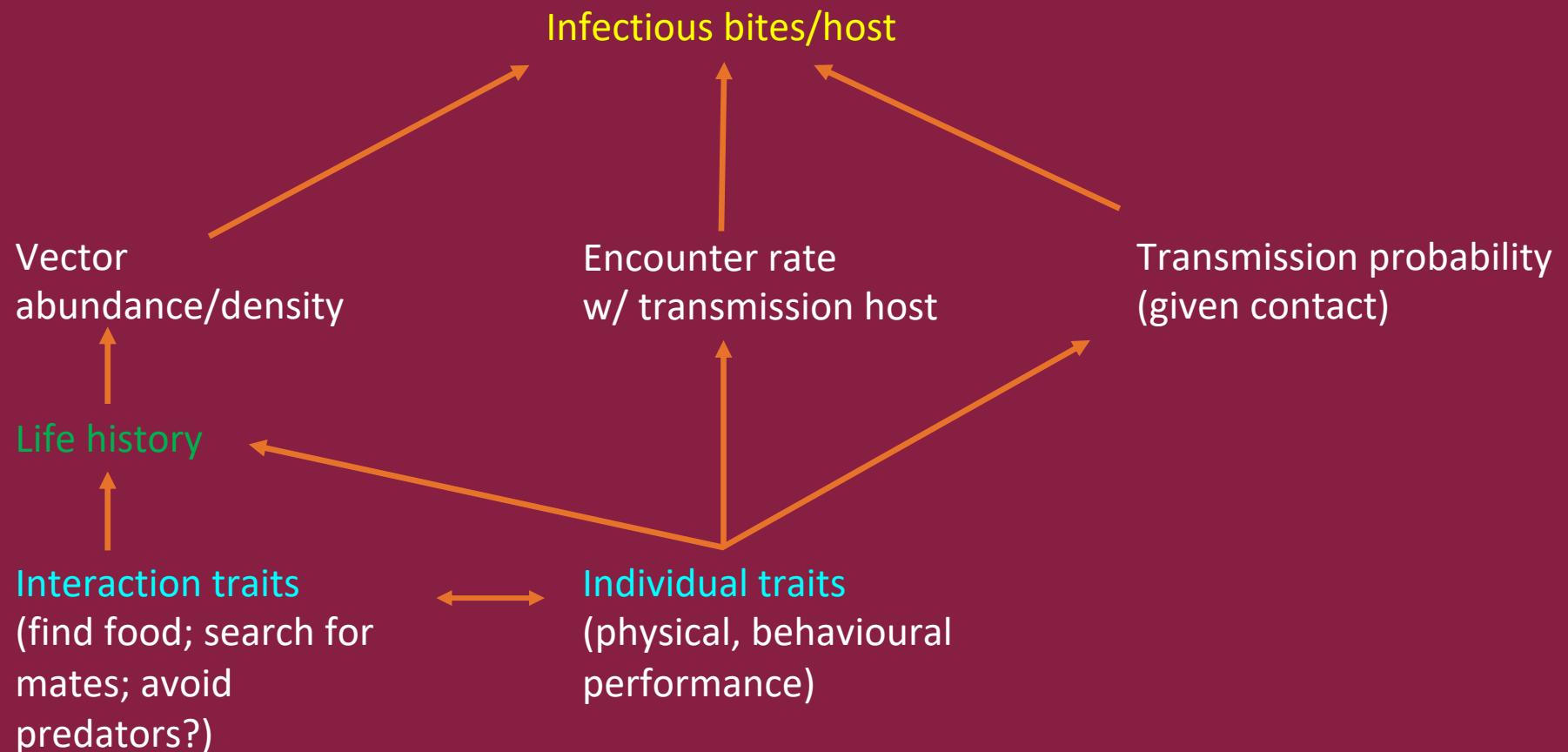
What is a trait?

A trait is any measurable feature of an individual organism.

- Physical (body mass, wing length, wing morphology, etc.)
- Performance (respiration rate, growth rate, flying speed, etc.)
- Behavioural (feeding preference, foraging strategy, thermoregulatory, etc.)

Why are traits important?

Strategic/Mechanistic VBD models



Mechanistic VBD models

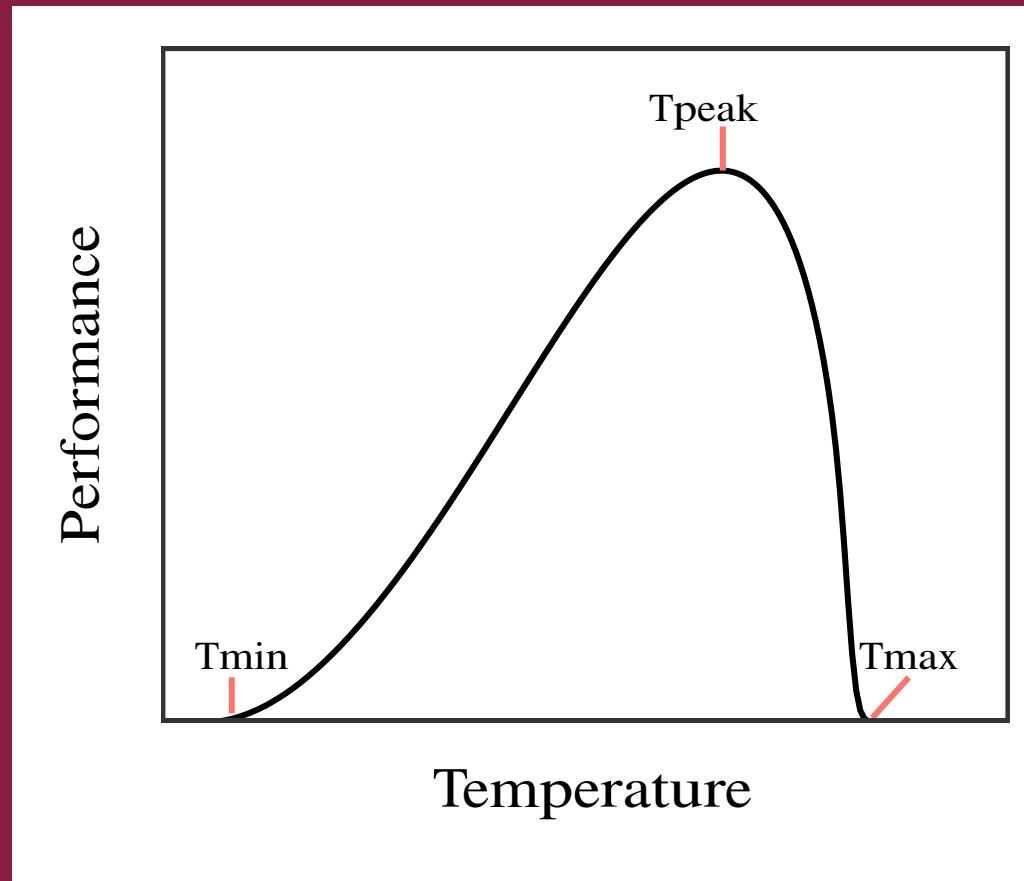
Expected number of secondary cases arising from an initial case in a naïve population

$$R_0 = \sqrt{\frac{M}{Nr} \frac{a^2 b c e^{-\mu EIP}}{\mu}}$$

- M - mosquito population
 a - biting rate (1/gonotrophic cycle length)
 bc - vector competence
EIP - parasite extrinsic incubation period
 μ - mosquito mortality rate
 N - human population
 r - recovery rate

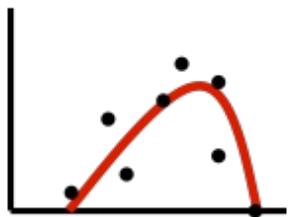
Mechanistic VBD models

Many biological rate processes respond to temperature in a predictable way.



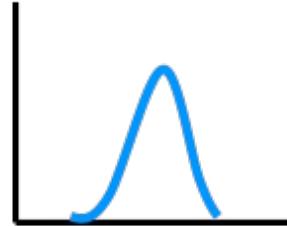
Mechanistic VBD models

Fit physiological responses to data



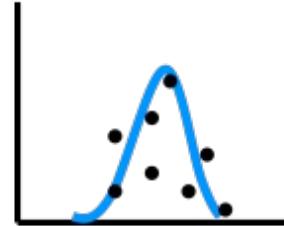
symmetric & asymmetric
(linear for comparison)
fit with Bayesian method

Calculate $R_0(T)$
based on fitted curves



$$R_0 = \sqrt{\frac{M}{Nr} \frac{a^2 b c e^{-\mu EIP}}{\mu}}$$

Validate with field data



field transmission -
observed incidence

Temperature response data for R_0

$$R_0 = \sqrt{\frac{M}{Nr} \frac{a^2 bce^{-\mu EIP}}{\mu}}$$

$$M = \frac{EFD \times p_{EA} \times MDR}{\mu^2}$$

M -	mosquito population
a -	biting rate (1/gonotrophic cycle length)
bc -	vector competence
EIP -	parasite extrinsic incubation period
μ -	mosquito mortality rate
N -	human population
r -	recovery rate

Aedes albopictus



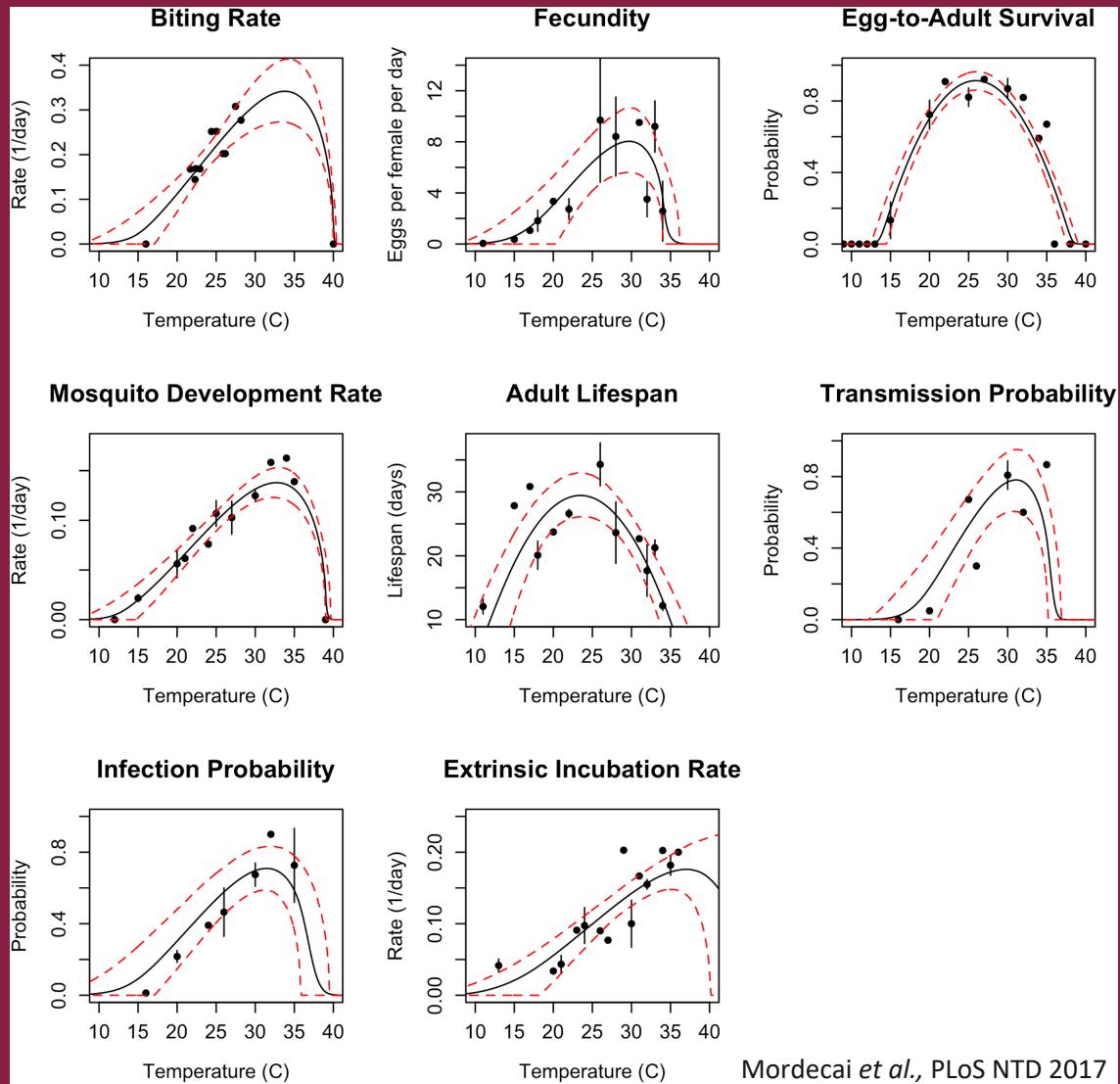
James Gathany

Aedes aegypti



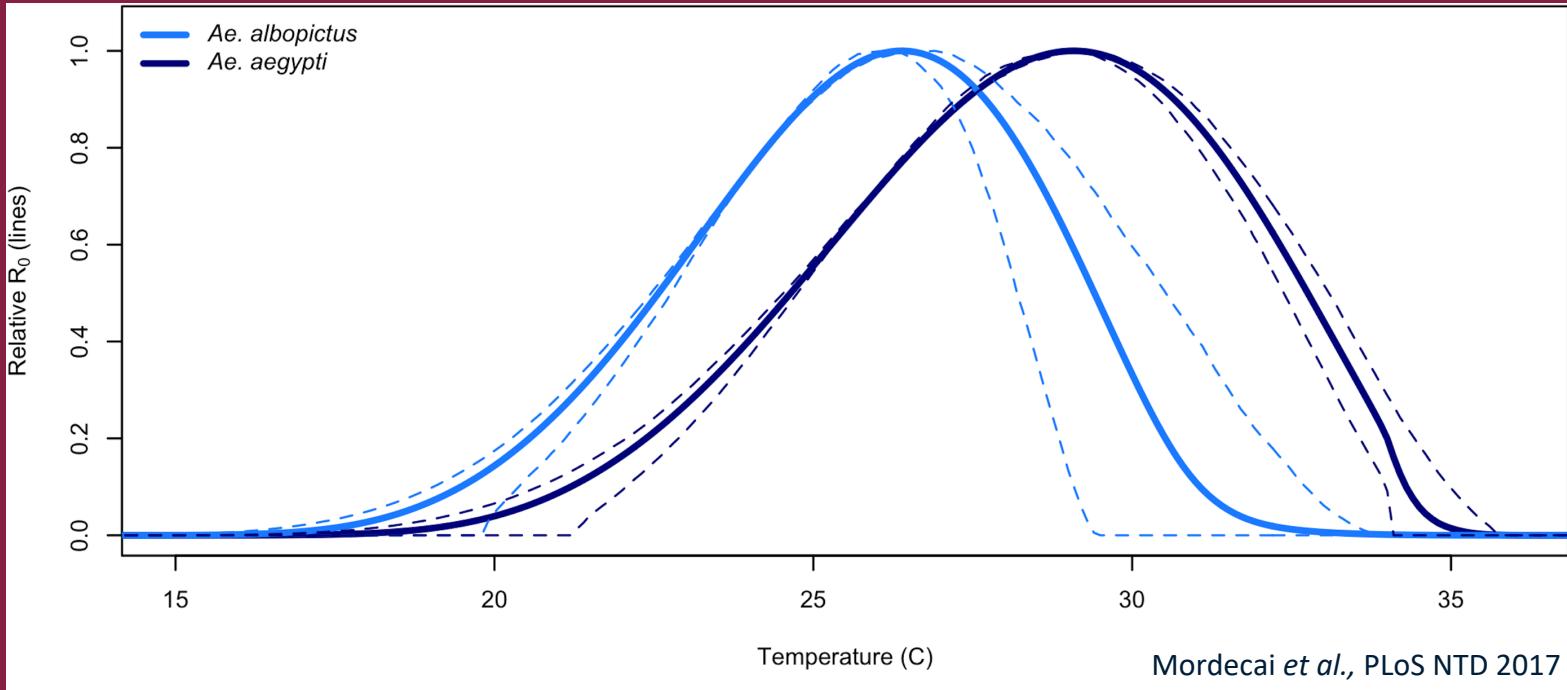
Muhammad Mahdi Karim

Temperature-dependent components of $R_0(T)$

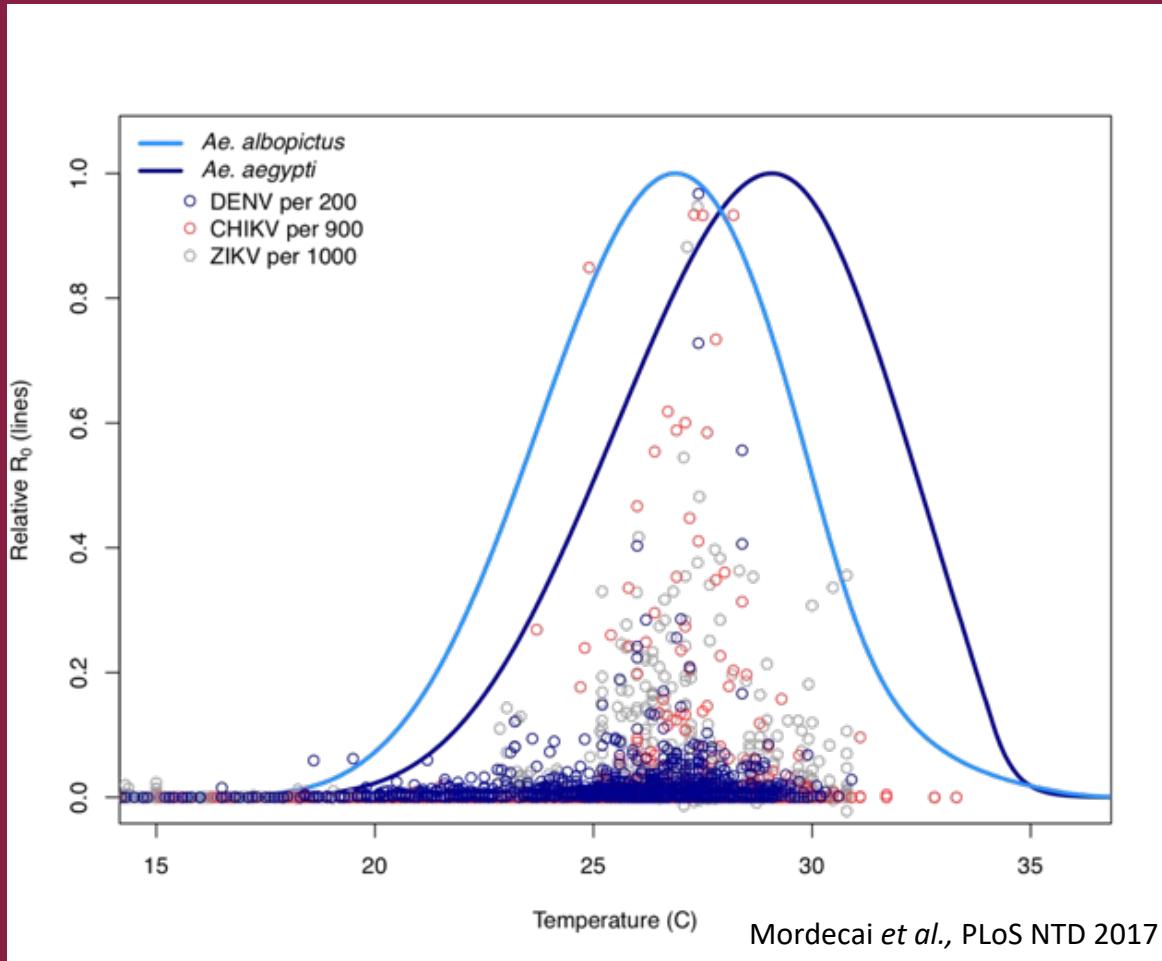


Mordecai et al., PLoS NTD 2017

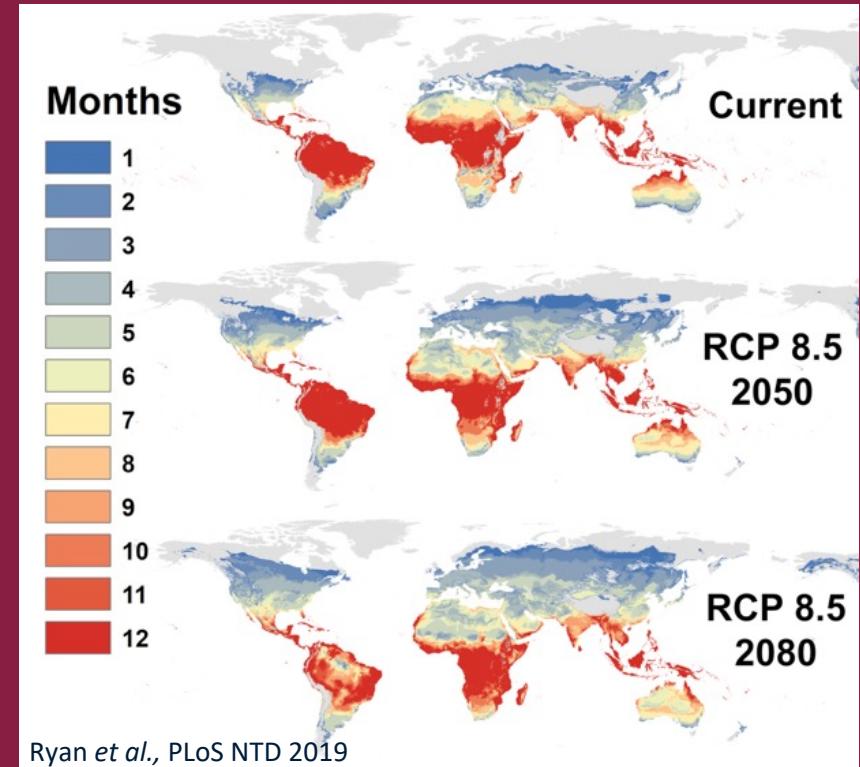
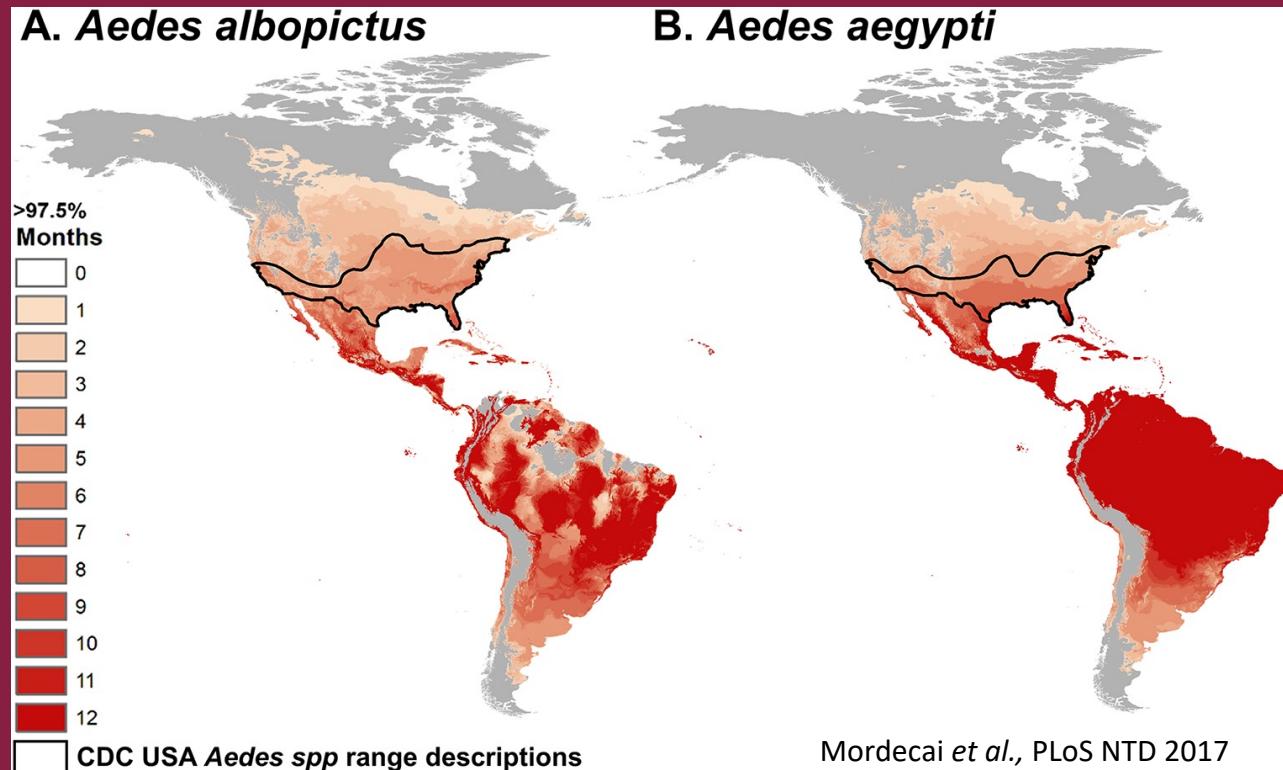
Bayesian estimate of $R_0(T)$



Temperature dependence: $R_0(T)$ for Dengue/Zika/CHIKV

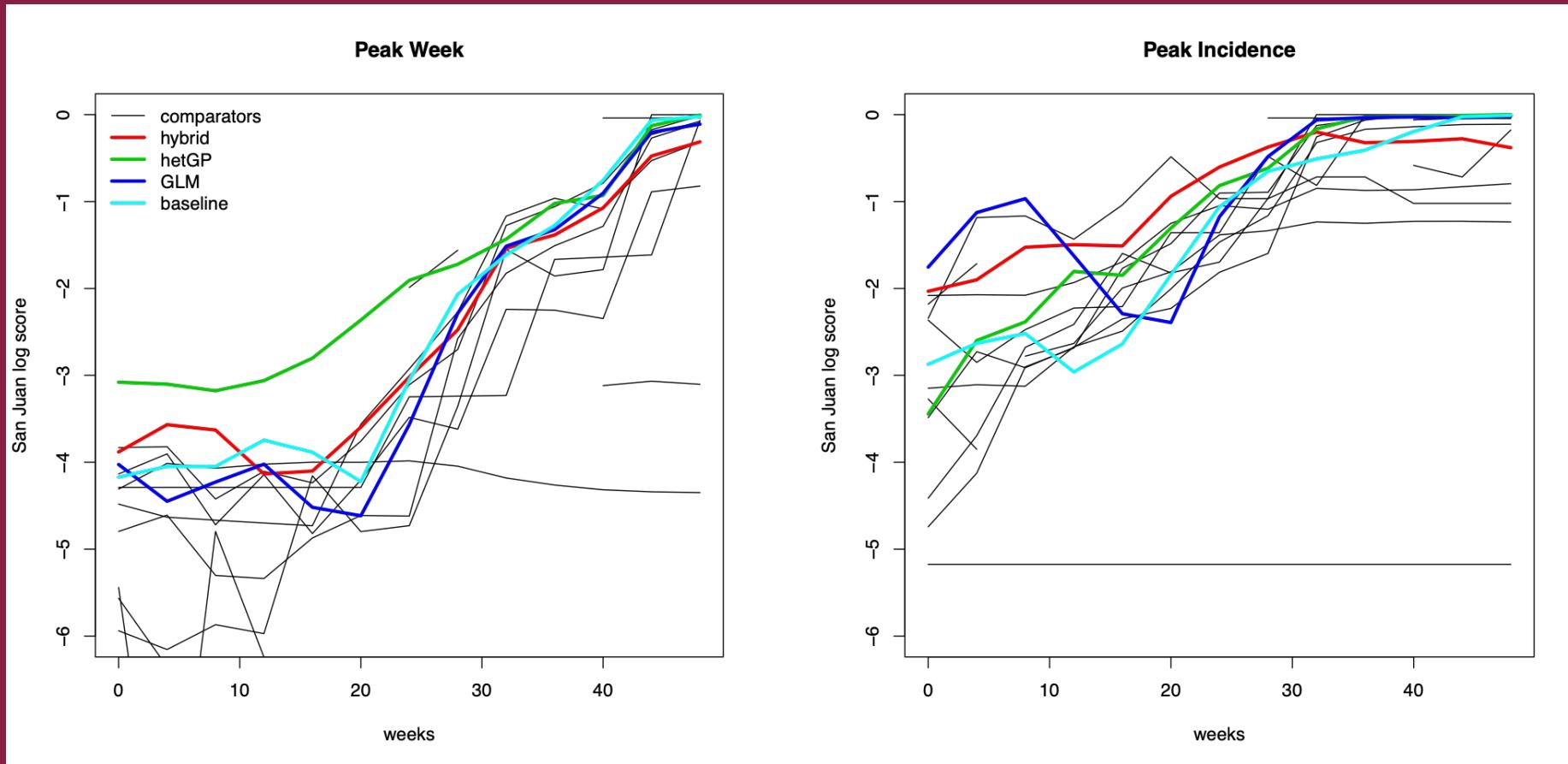


Risk mapping using temperature-dependent R_0



Strategic/Mechanistic VBD models

Forecasting Dengue in San Juan



Strategic/Mechanistic VBD models

GLM Regression

Pros

- Simple and familiar approach
- Can include environmental predictors and biological knowledge
- Can be implemented in R without too much trouble
- Can use model selection to tell you what's important

Cons

- Computationally intensive for predictors
- Non-linear dynamics beholden to unpredictable events (extreme temps/precipitation, SOI ...)
- Regime changes season-to-season are hard to predict

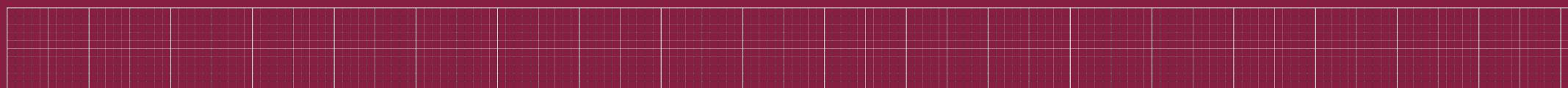
Complements GP, but slower and needs more data

Strategic/Mechanistic VBD models

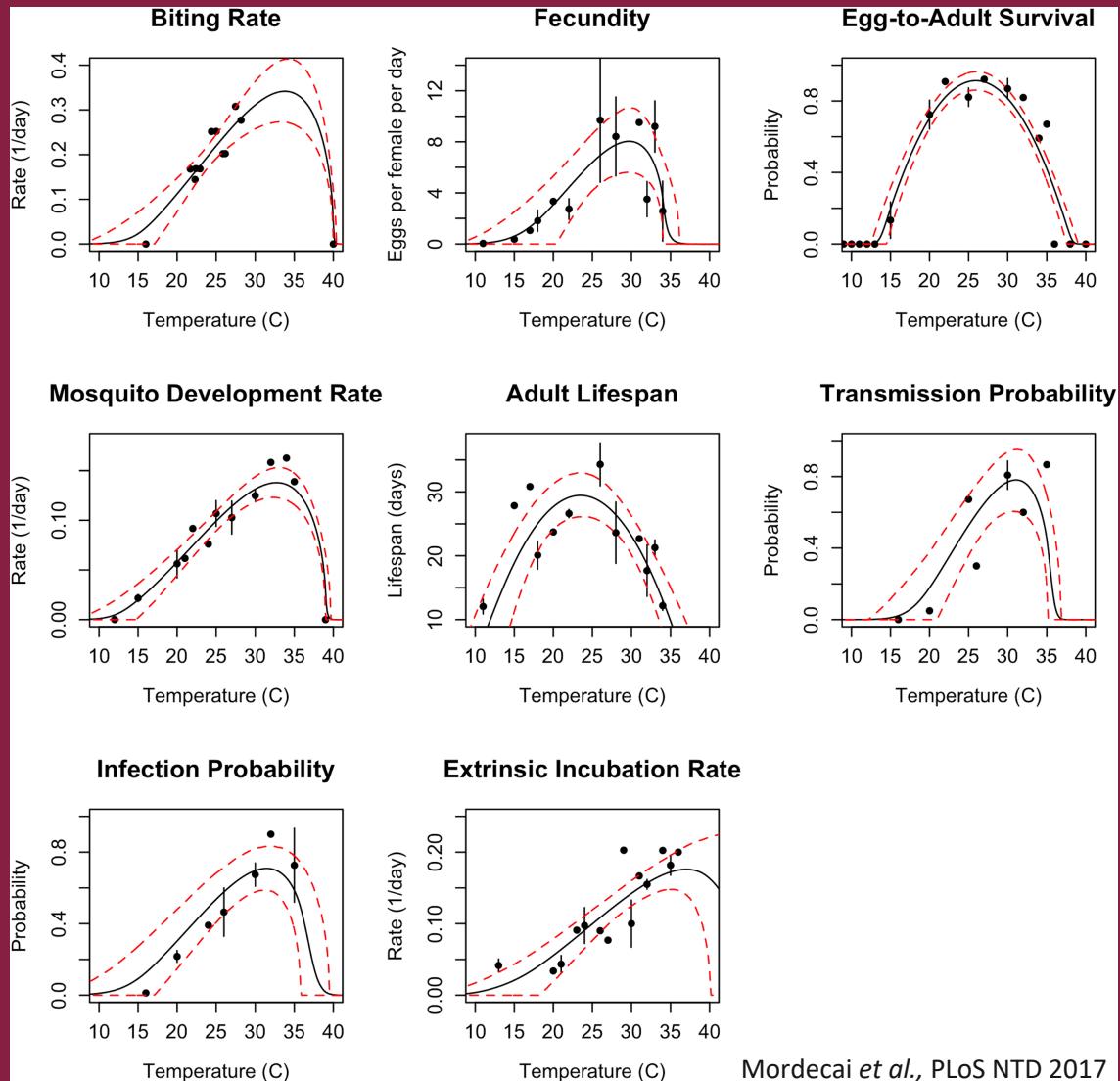
Combining mechanistic models with tactical approaches should enable us to make better predictions about patterns of transmission in the face of climate change, including at intermediate times scales (e.g., 5-10 years).

BUT we need more data!

- **Traits** - laboratory and field data on vector traits and characteristics linked to environmental variables
- **Vector dynamics** - population measures for vector model validation, and as input into mechanistic models
- **Human case data**
- How do vector traits and behaviours impact transmission?
- Model output as data for comparing methods



Most current projections of arbovirus transmission risk are based on idealised trait TPCs



Mordecai *et al.*, PLoS NTD 2017

$$R_0 = \sqrt{\frac{M}{Nr} \frac{a^2 b c e^{-\mu EIP}}{\mu}}$$

$$M = \frac{EFD \times p_{EA} \times MDR}{\mu^2}$$

M - mosquito population

a - biting rate (1/gonotrophic cycle length)

bc - vector competence

EIP - parasite extrinsic incubation period

μ - mosquito mortality rate

N - human population

r - recovery rate

Thermal adaption in *Aedes* mosquitoes

Background

- Most current projections of how climatic warming will affect VBD assume that all populations of a given vector species respond similarly to temperature.
- Variation in environmental temperatures is a selection pressure that can lead to local adaptation. If species are made-up of multiple locally adapted populations, assuming a single species-level response might lead to inaccurate predictions of future VBD risk.

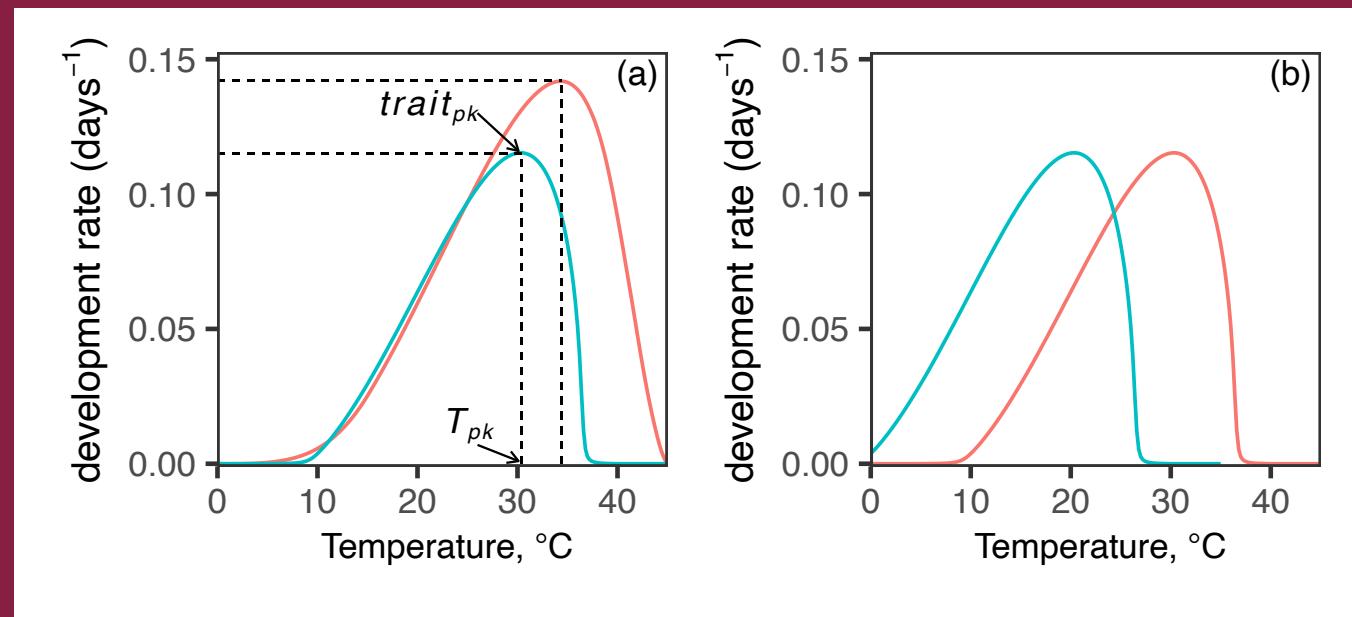


Table 1. Proportion of ovipositing females, duration of preoviposition and oviposition periods, longevity, and fecundity of *Tetranychus mcdanieli* at different temperatures

Temperature (°C)	n ^a	Ovipositing females (%)	Preoviposition period ^b (days)	Oviposition period ^b (days)	Female longevity ^b (days)	Female fecundity ^b (eggs)
14	8	87.5	4.0 ± 1.9	29.1 ± 12.5	36.2 ± 14.2	43.8 ± 27.3
16	30	83.3	3.7 ± 0.6	28.5 ± 12.9	35.0 ± 13.7	57.5 ± 37.2
20	41	90.2	2.2 ± 0.5	25.5 ± 15.1	28.8 ± 15.9	91.7 ± 68.9
24	32	97.0	1.2 ± 0.3	21.9 ± 9.7	24.0 ± 10.0	151.5 ± 70.9
28	39	100	1.2 ± 0.4	15.1 ± 7.5	17.0 ± 8.0	129.8 ± 58.8
30	21	100	1.0 ± 0.3	6.7 ± 3.6	7.7 ± 3.7	79.2 ± 47.2
32	47	91.5	1.1 ± 0.5	8.2 ± 5.4	9.6 ± 5.6	52.0 ± 45.3
34	35	100	0.8 ± 0.9	4.8 ± 2.7	6.1 ± 3.4	30.2 ± 18.0
36	15	100	0.8 ± 0.2	5.4 ± 2.0	6.5 ± 2.4	12.7 ± 2.3

^aNumber of females that survived to the adult stage.

^bValues are means ± standard deviation.

 Cold Spring Harbor Laboratory

bioRxiv

THE PREPRINT SERVER FOR BIOLOGY

HOME | SUBMIT | FAQ | BLOG | ALERTS / RSS | RESOURCES | ABOUT | CHANNELS

Search 

Advanced Search

New Results  Previous 

bayesTPC: Bayesian inference for Thermal Performance Curves in R Posted April 28, 2024.

Sean Sorek, John W. Smith Jr., Paul J. Huxley,  Leah R. Johnson

doi: <https://doi.org/10.1101/2024.04.25.591212>

This article is a preprint and has not been certified by peer review [what does this mean?].



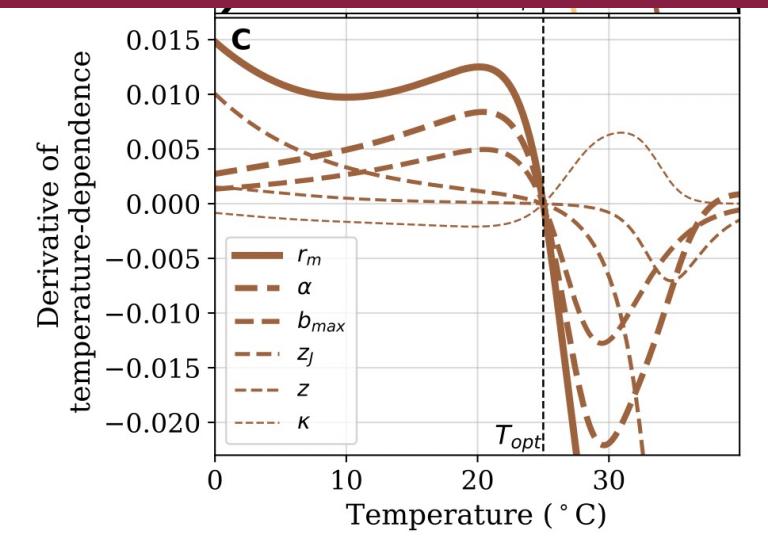
Abstract Full Text Info/History Metrics  

Email 
Share 
Citation Tools 
Get QR code 

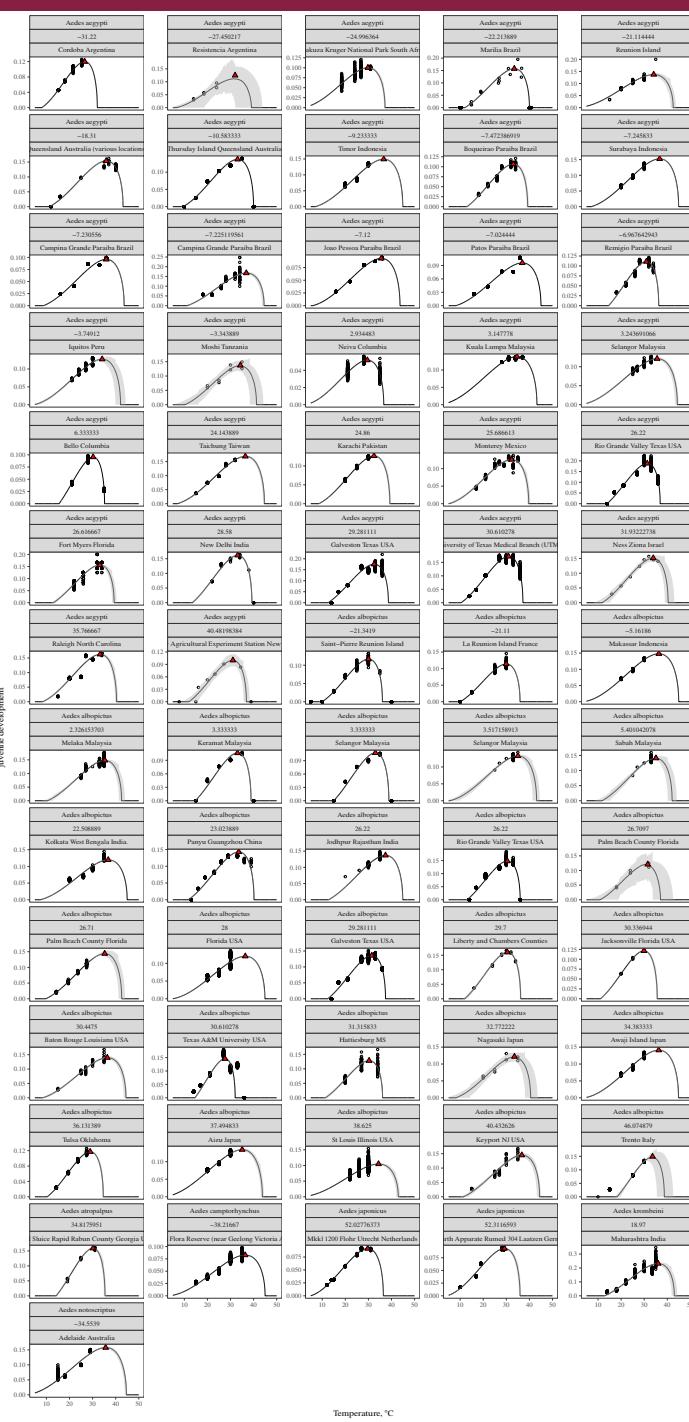
Analytic r_m model

$$r_m \approx \frac{(\kappa + z) \left(\log \left(\frac{b_{max}}{\kappa+z} \right) - \alpha z_J \right)}{\alpha(\kappa + z) + 1}.$$



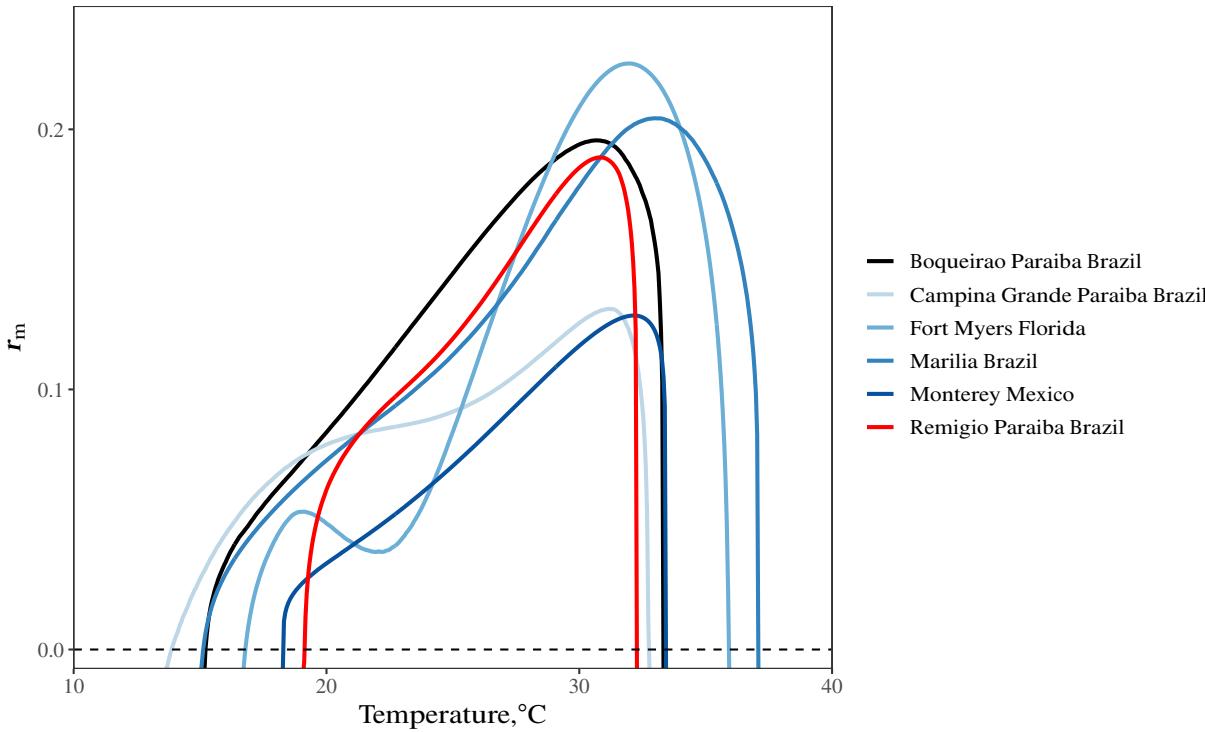
Parameter	Units	Description
r_m	day ⁻¹	Maximal population growth rate
α	days	Egg to adult development time
b_{max}	eggs × (female × day) ⁻¹	Maximum fecundity rate
κ	day ⁻¹	Fecundity loss rate
z	day ⁻¹	Adult mortality rate
z_J	day ⁻¹	Mortality rate averaged across juvenile stages

Variation in temperature dependence of *Aedes* life history traits

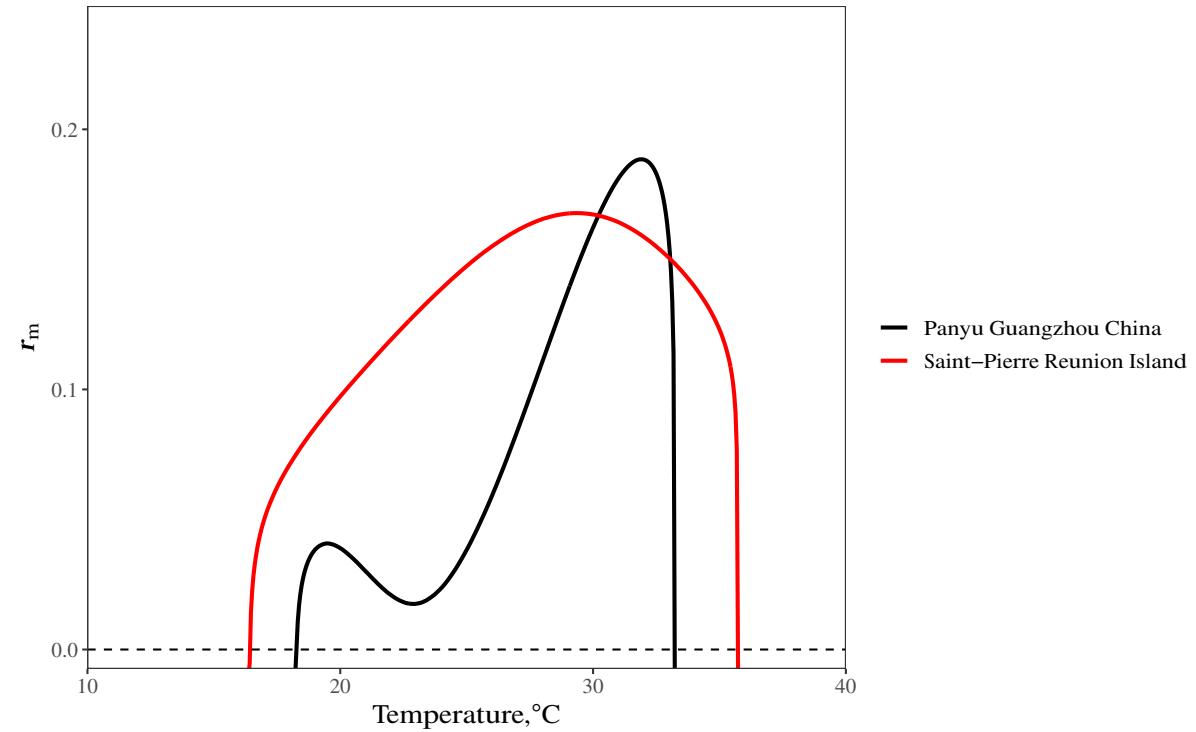


Evidence of thermal adaption of population fitness in *Aedes*

Aedes aegypti



Aedes albopictus



Da Re et al., in prep.



Instructions +

Search by phrase...

Select a column

Select an operator

Enter a search term...

- +

Click any row in the table to view its details page or click the checkbox beside any number of rows and then click the download button to download their data.

Search

Clear

Download

572 records returned

Select	Dataset ID	Original Trait Name	Variables	Interactor1Stage	Interactor1Genus	Interactor1Species	Interactor2Genus	Interactor2Species	Citation
<input type="checkbox"/>	1	development time	Interactor1Temp	juvenile	Acyrthosiphon	pisum			Ahn et al. 2010
<input type="checkbox"/>	2	fecundity	Interactor1Temp	adult	Acyrthosiphon	pisum			Ahn et al. 2010
<input type="checkbox"/>	3	longevity	Interactor1Temp	adult	Acyrthosiphon	pisum			Ahn et al. 2010
<input type="checkbox"/>	4	reproductive period	Interactor1Temp	adult	Acyrthosiphon	pisum			Ahn et al. 2010
<input type="checkbox"/>	5	survival	Interactor1Temp	juvenile (not inc egg st...)	Acyrthosiphon	pisum			Ahn et al. 2010
<input type="checkbox"/>	6	mortality rate	Interactor1Temp	adult	Aedes	albopictus			Alto and Julian 2010
<input type="checkbox"/>	7	development time	Interactor1Temp	juvenile (inc egg st...)	Paracoccus	marginatus			Amarasekar et al. 2010
<input type="checkbox"/>	8	fecundity	Interactor1Temp	adult	Paracoccus	marginatus			Amarasekar et al. 2010
<input type="checkbox"/>	9	longevity	Interactor1Temp	adult	Paracoccus	marginatus			Amarasekar et al. 2010
<input type="checkbox"/>	10	ovipositional period	Interactor1Temp	adult	Paracoccus	marginatus			Amarasekar et al. 2010
<input type="checkbox"/>	11	survival	Interactor1Temp	juvenile (inc egg st...)	Paracoccus	marginatus			Amarasekar et al. 2010
<input type="checkbox"/>	12	development time	Interactor1Temp	egg	Sitona	lepidus			Arbab and Naseem 2010
<input type="checkbox"/>	13	survival	Interactor1Temp	egg	Sitona	lepidus			Arbab and Naseem 2010
<input type="checkbox"/>	14	survival	Interactor1Temp, LocationText	juvenile	Bemisia	tabaci			Aregbesola et al. 2010
<input type="checkbox"/>	15	development time	Interactor1Temp	juvenile	Bemisia	tabaci			Aregbesola et al. 2010
<input type="checkbox"/>	16	longevity	Interactor1Temp	adult	Bemisia	tabaci			Aregbesola et al. 2010

Acknowledgements

Leah Johnson (VT)

Samraat Pawar (Imperial College London)

Lauren Cator (Imperial College London)

VectorByte RCN

Ilaria Dorigatti (Imperial College London)



UNIVERSITY OF
NOTRE DAME



VIRGINIA
TECH

UF UNIVERSITY of
FLORIDA

Imperial College
London



NERC

SCIENCE OF THE
ENVIRONMENT