Modeling the spatiotemporal abundance of Aedes species and the risk of arboviral infection in Europe and the Americas

Agnese Zardini[1]

Francesco Menegale[1,2], Andrea Gobbi[3], Mattia Manica[1,4], Giorgio Guzzetta[1,4], Valeria d'Andrea[1], Valentina Marziano[1], Filippo Trentini[1,5], Fabrizio Montarsi[6], Beniamino Caputo[7], Angelo Solimini[7], Cecilia Marques-Toledo[8], André B.B. Wilke[9], Roberto Rosà[10,11], Giovanni Marini[4,10], Daniele Arnoldi[4,10], Ana Pastore y Piontti[12], Andrea Pugliese[2], Gioia Capelli[6], Alessandra della Torre[7], Mauro M Teixeira[8], John C. Beier[13], Annapaola Rizzoli[4,10], Alessandro Vespignani[12], Marco Ajelli[9], Stefano Merler[1,4], Piero Poletti[1,4]

[1] Center for Health Emergencies, Bruno Kessler Foundation, Trento, Italy
[2] Department of Mathematics, University of Trento, Trento, Italy
[3] Digital Industry Center, Bruno Kessler Foundation, Trento, Italy
[4] Epilab-JRU, FEM-FBK Joint Research Unit, Trento, Italy
[5] Dondena Centre for Research on Social Dynamics and Public Policy, Bocconi University, Milan, Italy
[6] Istituto Zooprofilattico Sperimentale delle Venezie, Legnaro, Padua, Italy
[7] Department of Public Health and Infectious Diseases, Sapienza university of Rome, Rome, Italy
[8] Department of Biochemistry and Immunology, Federal University of Minas Gerais, Belo Horizonte, Minas Gerais, Brazil
[9] Department of Epidemiology and Biostatistics, Indiana University School of Public Health, Bloomington, IN, USA
[10] Research and Innovation Centre, Fondazione Edmund Mach, Trento, Italy
[11] Center Agriculture Food Environment, University of Trento, Trento, Italy
[12] Laboratory for the Modeling of Biological and Socio-technical Systems, Northeastern University, Boston, MA, USA
[13] Department of Public Health Sciences, Miller School of Medicine, University of Miami, Miami, FL, USA

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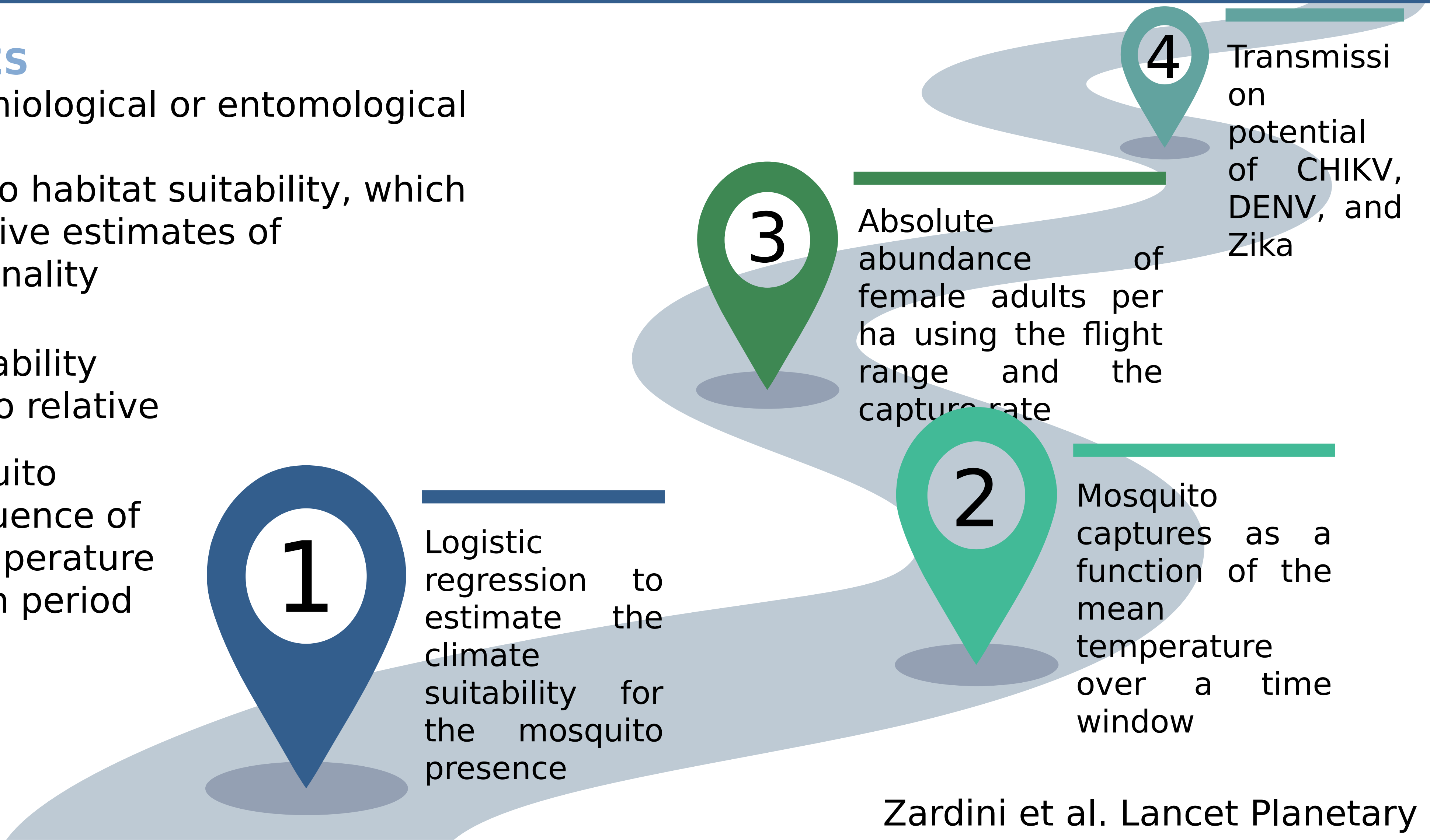
Introduction

MOST OF APPROACHES

1. Focus on local epidemiological or entomological data
2. Estimate the mosquito habitat suitability, which do not provide quantitative estimates of transmission risks/seasonality

ASSUMPTIONS:

1. the local climate suitability determines the mosquito relative density
2. increase in the mosquito abundance as a consequence of persisting favorable temperature conditions over a certain period



CENTER FOR HEALTH EMERGENCIES

FONDAZIONE BRUNO KESSLER

Zardini et al. Lancet Planetary

Climate suitability

Logistic regression model

- **Model:**

$$\sigma_i = \frac{1}{1 + e^{-\left(b_0 + \sum_{j=1}^{n} b_j Y_{i,j}\right)}}$$

- **Data:**

Presence-absence records for 1,892 US counties (Monaghan et al. 2019) and 4,372

Parameter	Description	Ae. aegypti		Ae. albopictus (Americas)		Ae. albopictus (Europe)	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
	Intercept	-0.3313192	0.8735	-10.204877	0.003	-17.45971	<0.001
	Coeff. annual mean temperature	0.6406277	<0.001	0.876233	<0.001	0.2383233	<0.001
	Coeff. maximum temperature of the warmest month	-0.2473132	0.001	-0.213569	0.126	0.5374626	<0.001
	Coeff. annual precipitation	-0.0018763	<0.001	0.001792	0.040	0.0008732	<0.001

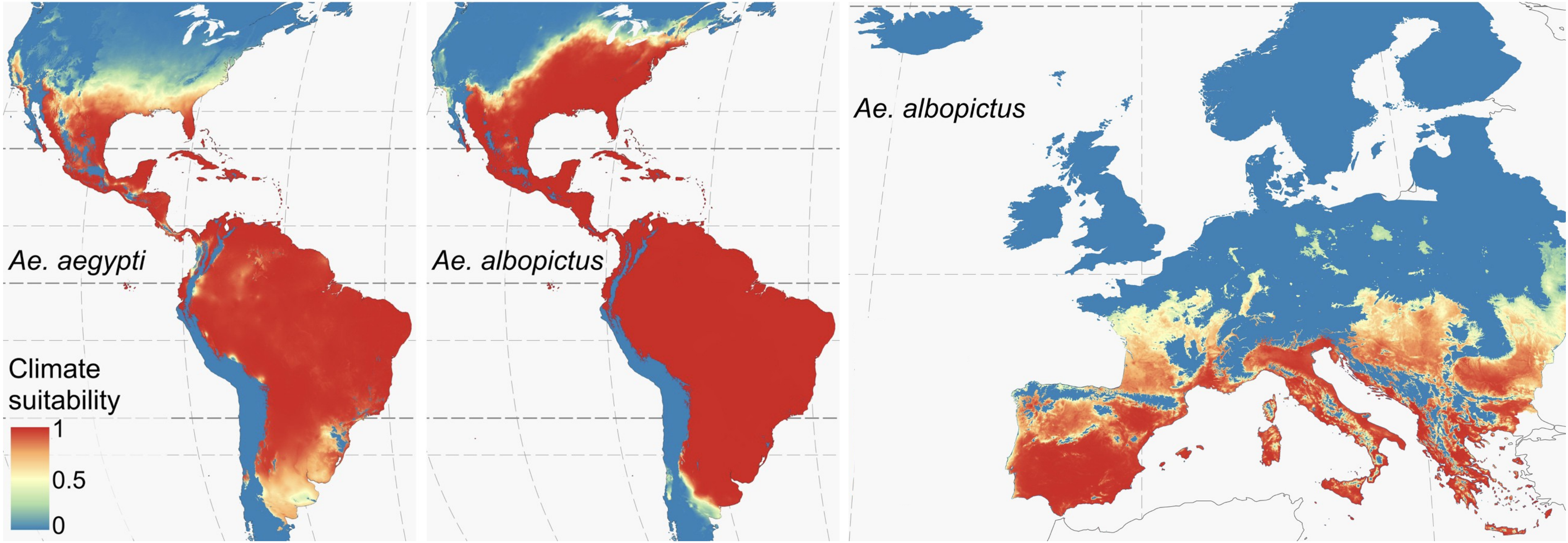
Environmental mask suitability

Annual mean precipitation at least of 200 mm

+

Mosquitoes survive long enough to complete the gonotrophic cycle

Climate suitability



Seasonal population dynamics

Temperature modulation function

$$C(d) = \frac{L}{1 + e^{-k(\widetilde{T}(d,w) - T_0)}}$$

where

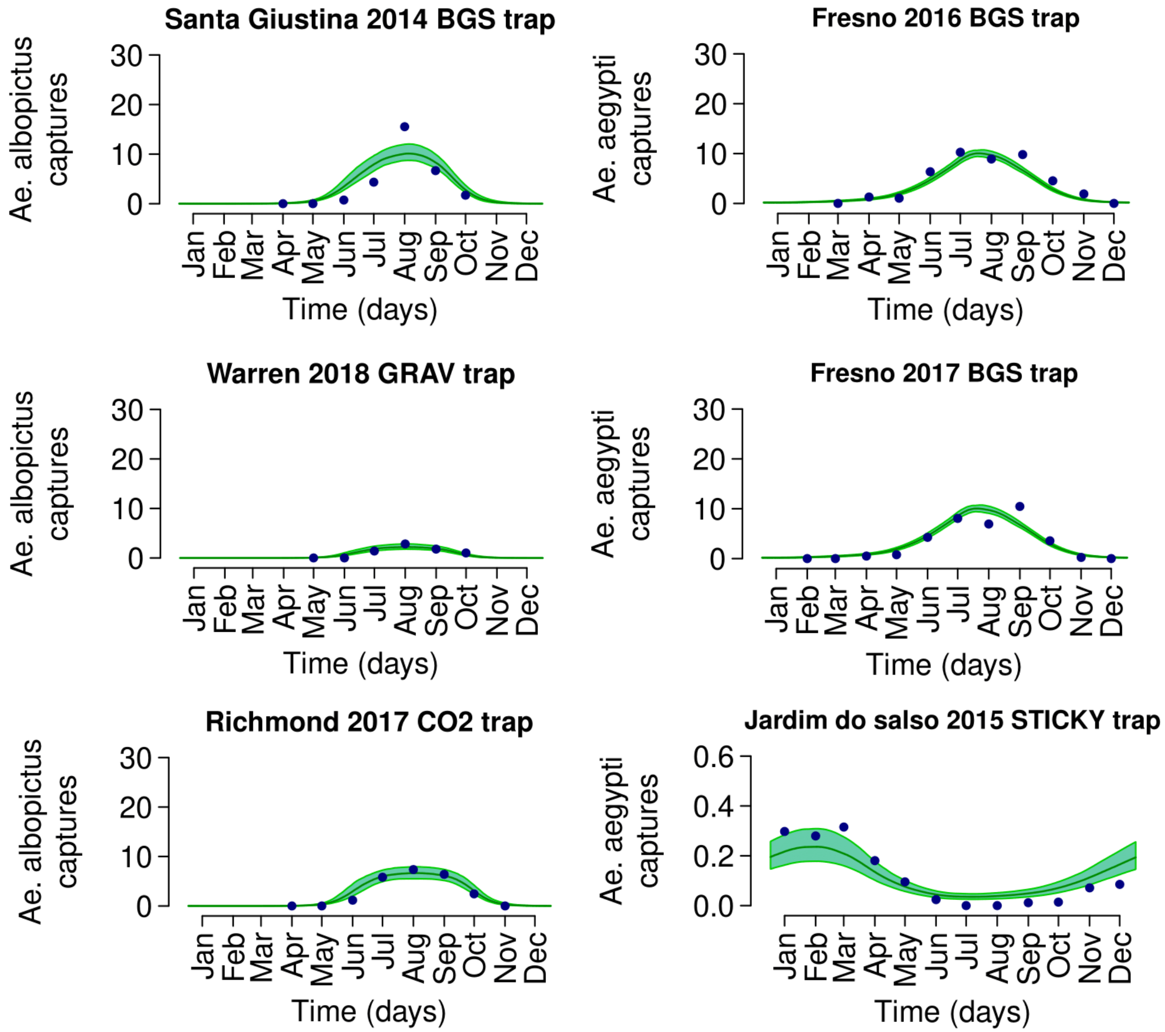
$$\widetilde{T}(d,w) = \frac{1}{w} \sum_{j=d-w+1}^{d} T(j)$$

MCMC calibration based on capture data of female adults collected in 115 locations of Italy, US, Brazil

- : site and trap independent
  - : trap dependent
  - : estimated climate suitability

Absolute abundance: flight range and trap specific

ILLUSTRATIVE FITS



Transmission potential

reproduction number

Average number of mosquitoes infected by a single infectious human host in a population of fully susceptible mosquitoes and hosts:

$$R_{HV} = \chi_V \, \beta \, \phi \, \frac{1}{\gamma} \, \frac{N_V}{N_H} \, \frac{\omega_V}{\omega_V + \mu_V}$$

Average number of hosts infected by a single infectious mosquito introduced in a population of fully susceptible mosquitoes and hosts:

$$R_{VH} = \beta \, \phi \, \frac{\chi_H}{\mu_V}$$

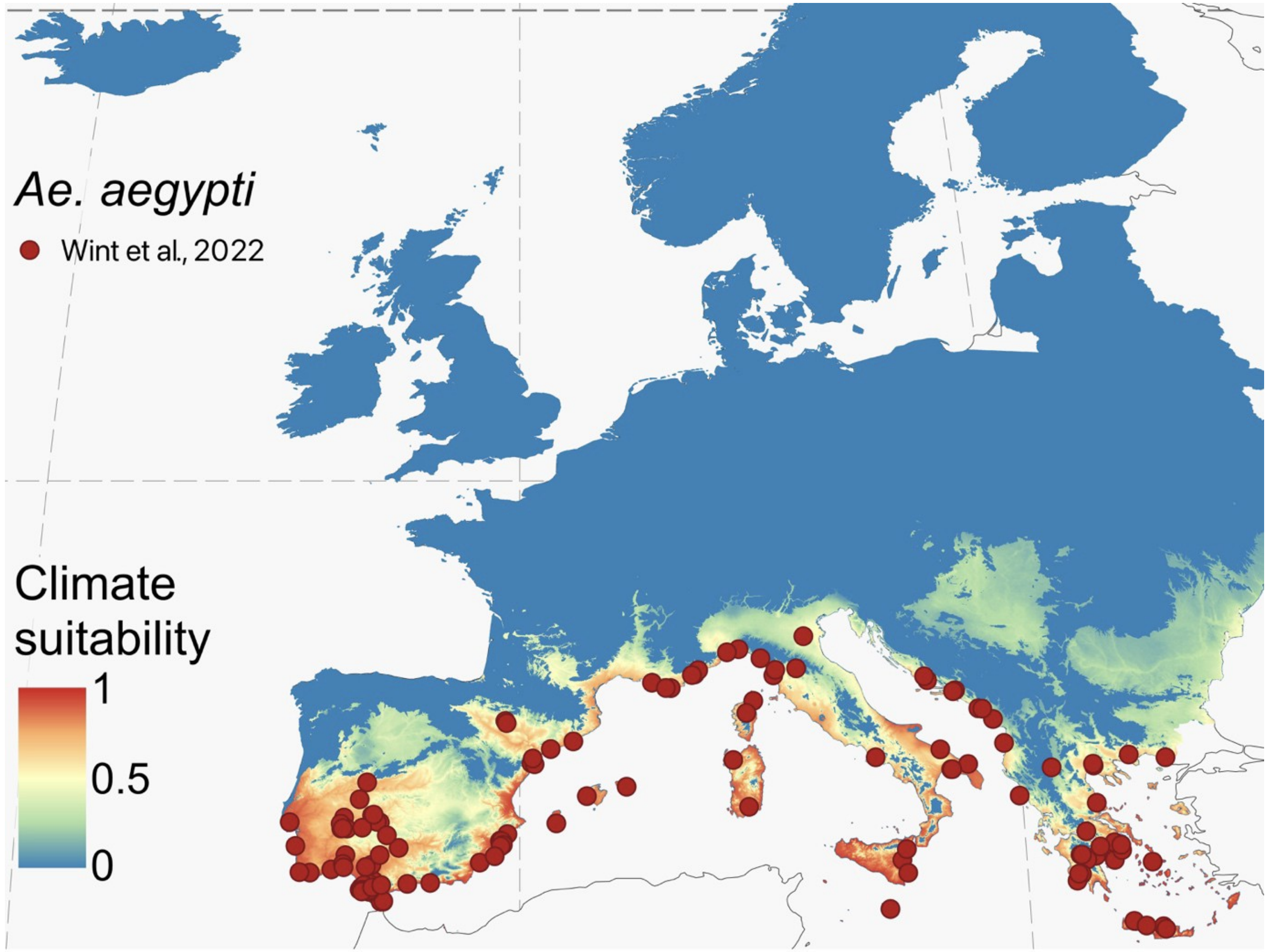
Reproduction number:

$$R_0 = R_{HV} \, R_{VH}$$

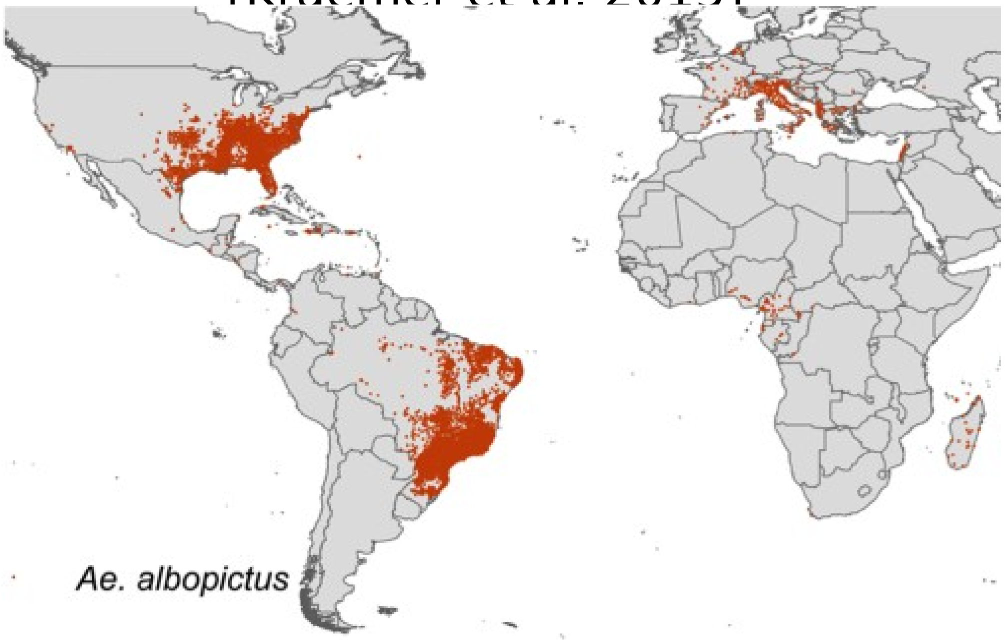
Diekmann O et al. 2009 (J R Soc Interface)
Lloyd AL et al. 2007 (J R Soc Interface)

Model vs entomological evidence

Historical records for Ae. aegypti [1900-1955]

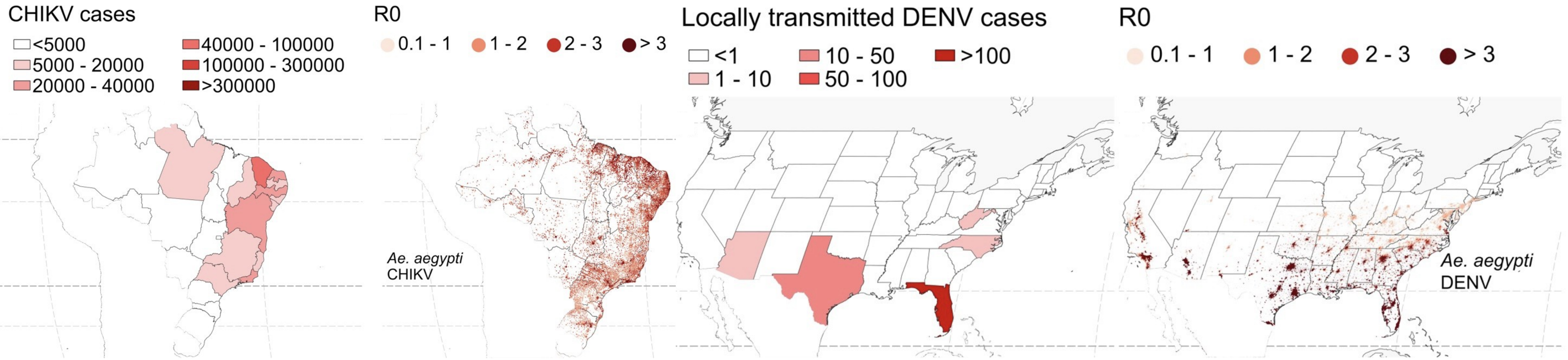


Occurrence records in Europe and the Americas
[Kraemer et al. 2015]



	True Positive
Ae. albopictus	99%
Ae. aegypti	98%

Model vs epidemiological evidence



Modeling exercise

Standardized the abundance of Ae. albopictus with respect to the maximum value predicted in Bologna

Number of consecutive days associated with a standardized mosquito abundance

Conclusions

- Innovative method to estimate the overall abundance of mosquitoes over time, based on freely available eco-climatic data
- Provide estimates in areas where entomological data are scarce or unavailable
- High temporal and spatial resolution

LIMITATIONS:

- Limited entomological data available for South America and Europe
- Climate suitability of the Americas calibrated against data aggregated at county level
- Dependence on estimates of capture rate
- Not account for progressive expansion and competition of mosquito species, and control measures
- Human mobility, level of immunity, case importations

Thank you for your attention

contact: zardini@fbk.eu

A SPECIAL THANK TO:
Francesco Menegale, Piero Poletti, Stefano Merler

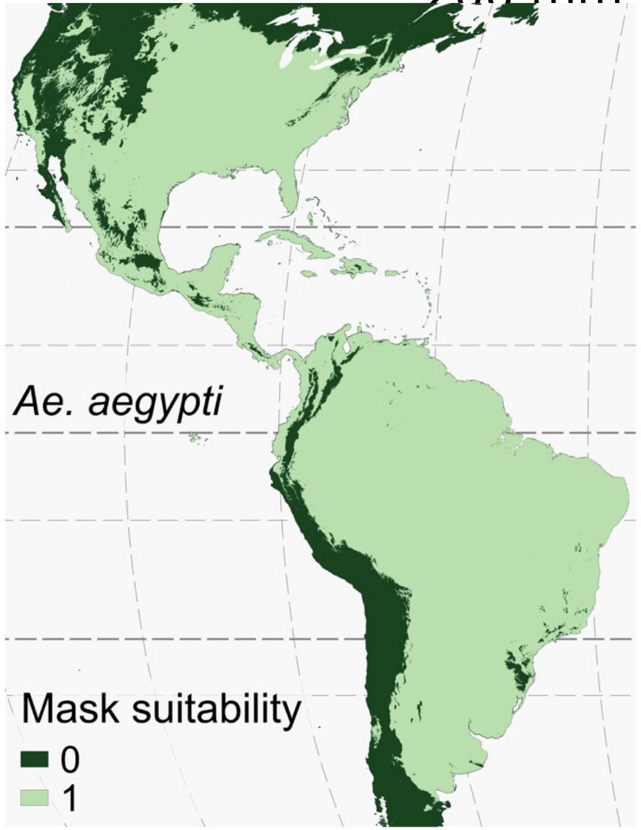
Climate suitability

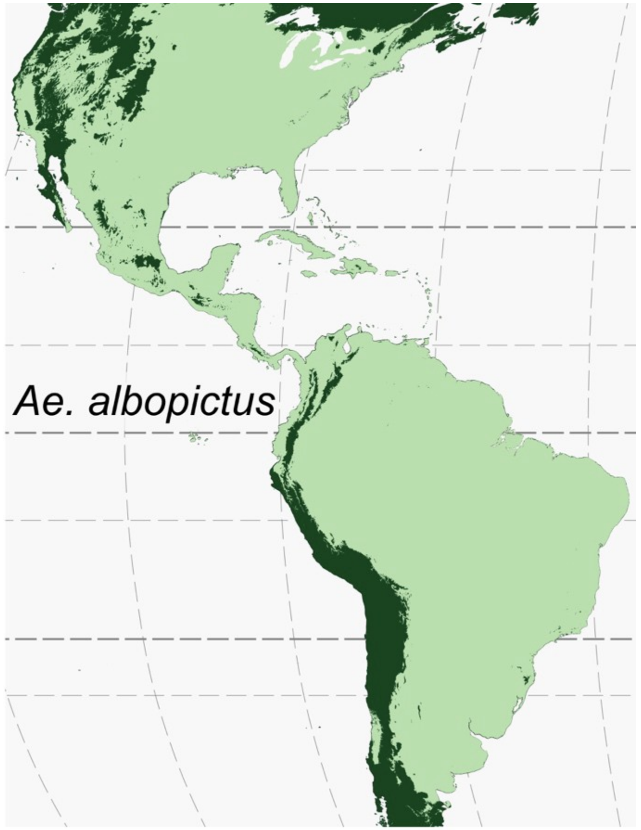
Environmental mask suitability

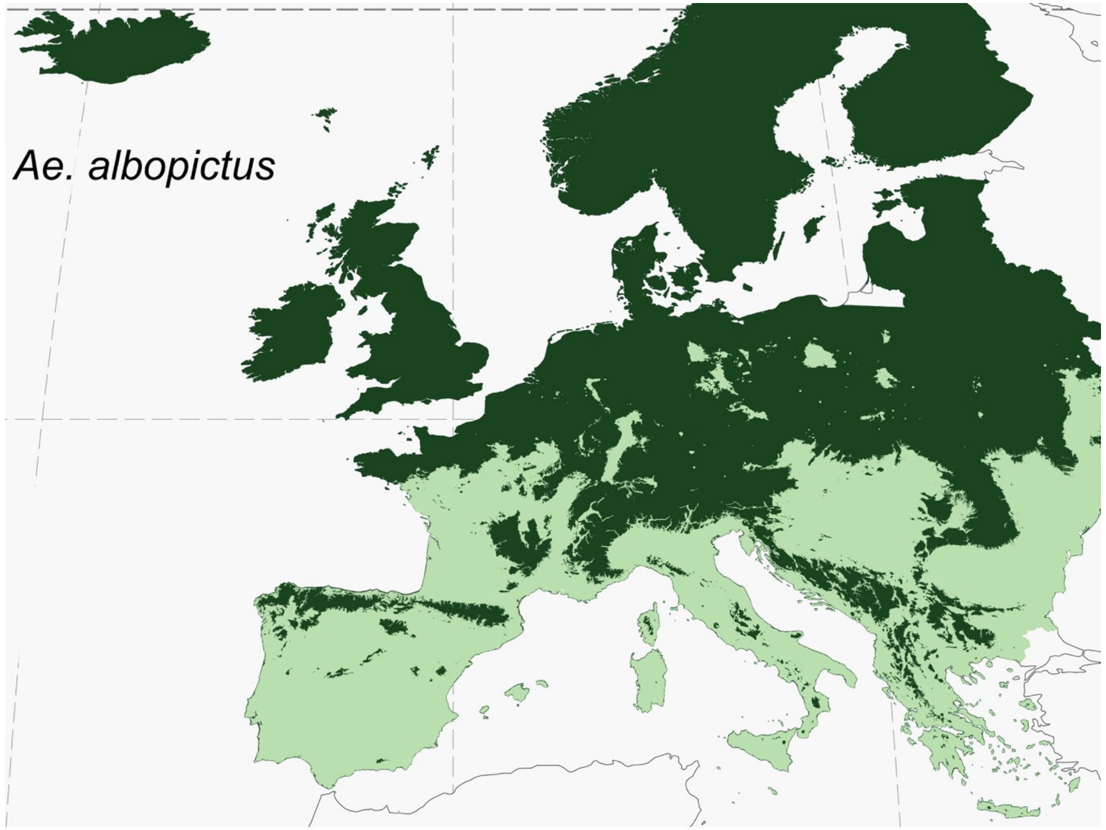
Annual mean precipitation at least of 200 mm

+

Mosquitoes survive long enough to complete the gonotrophic cycle







Climate suitability

Logistic regression model

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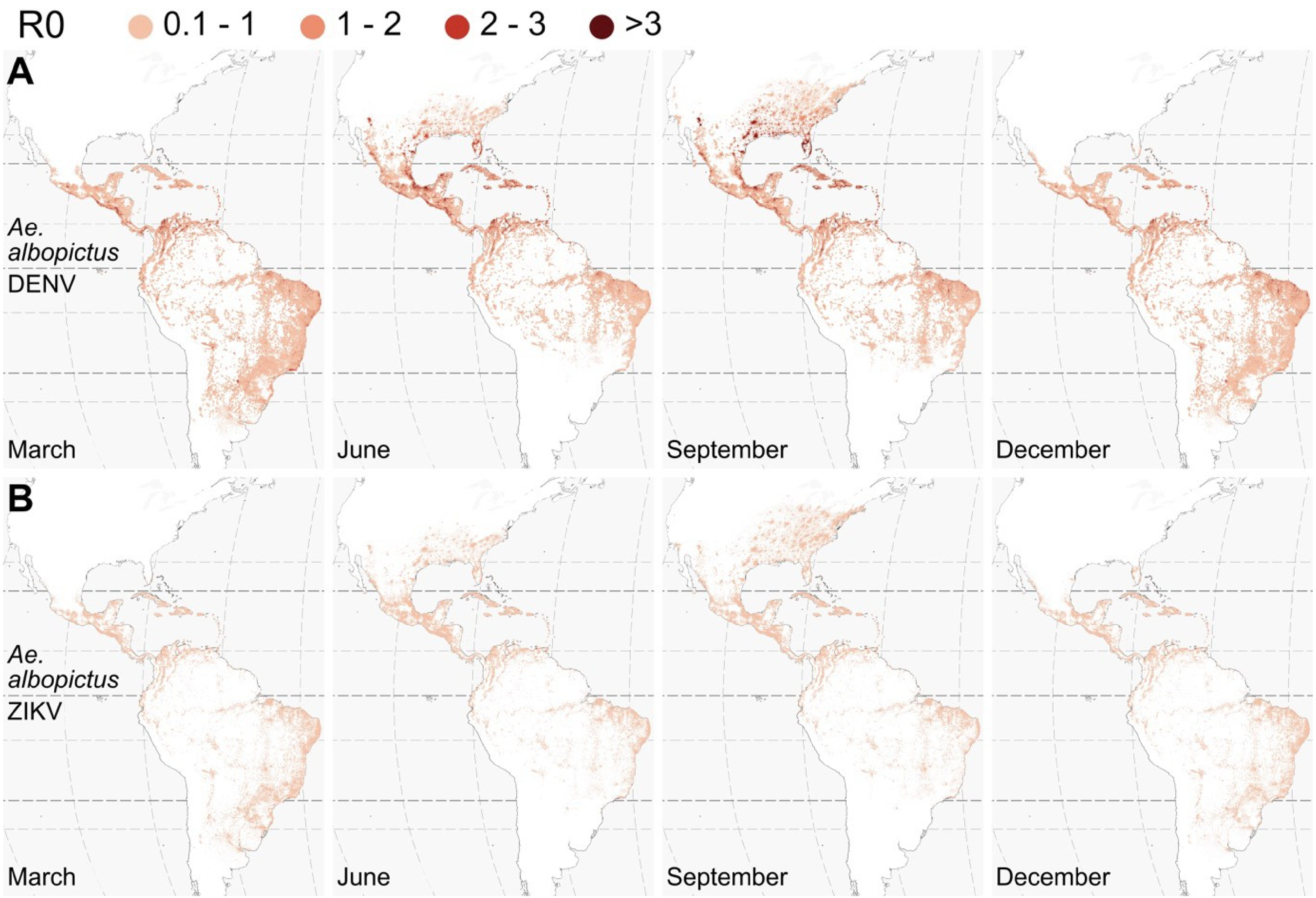
Presence-absence records for 1,892 US counties (Monaghan et al. 2019) and 4,372 European locations (ECDC)

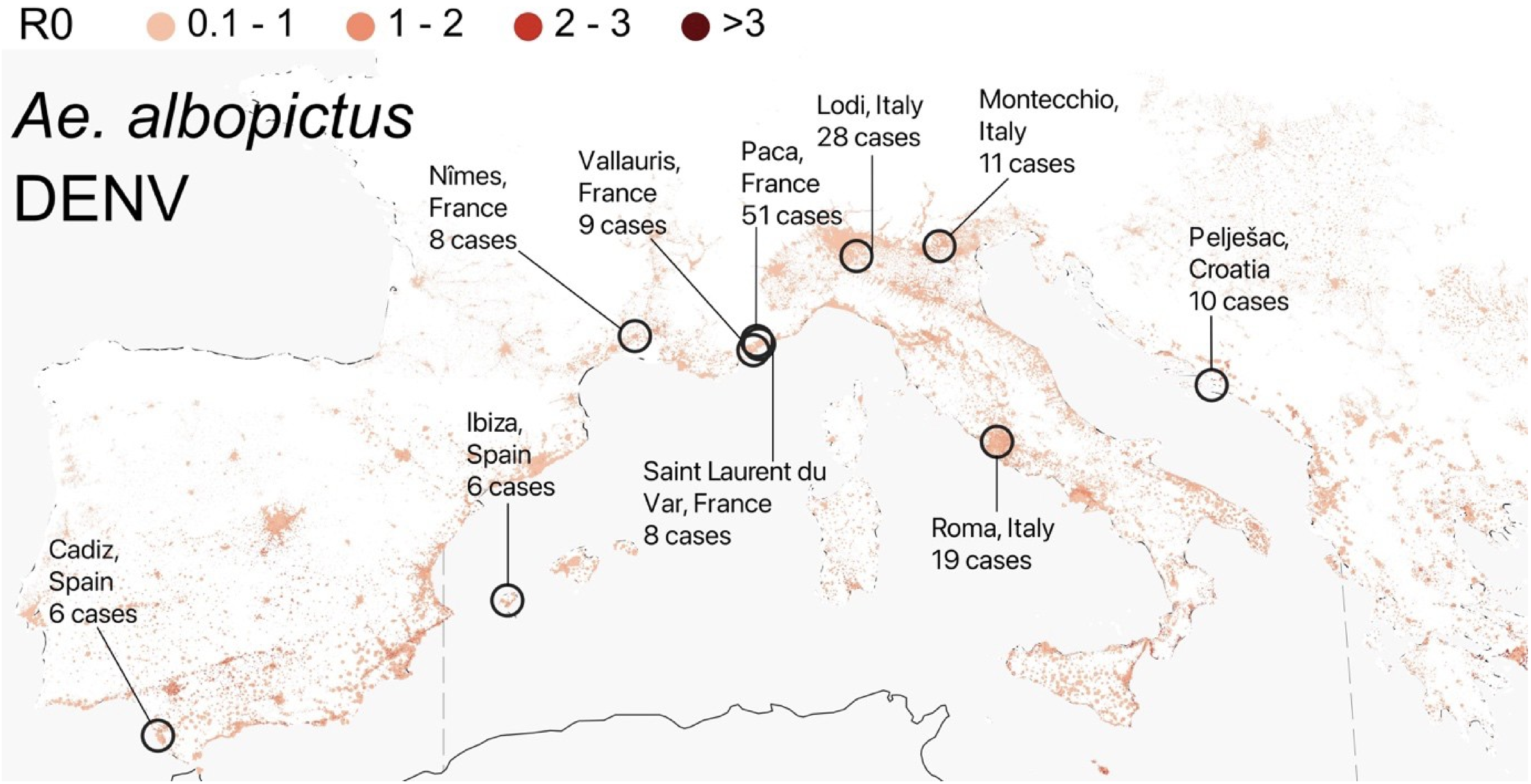
Parameter	Description	Ae. aegypti			Ae. albopictus (Americas)			Ae. albopictus (Europe)		
		Estimate	Std. error	p-value	Estimate	Std. error	p-value	Estimate	Std. error	p-value
	Intercept	-0.3313192	2.0802373	0.8735	-10.204877	3.418939	0.003	-17.45971	0.8290	<0.001
	Coeff. annual mean temperature	0.6406277	0.0580453	<0.001	0.876233	0.130634	<0.001	0.2383233	0.03409	<0.001
	Coeff. maximum temperature of the warmest month	-0.2473132	0.0774989	0.001	-0.213569	0.139544	0.126	0.5374626	0.03245	<0.001
	[illegible]	-[illegible]	[illegible]	[illegible]		[illegible]		[illegible]	[illegible]	

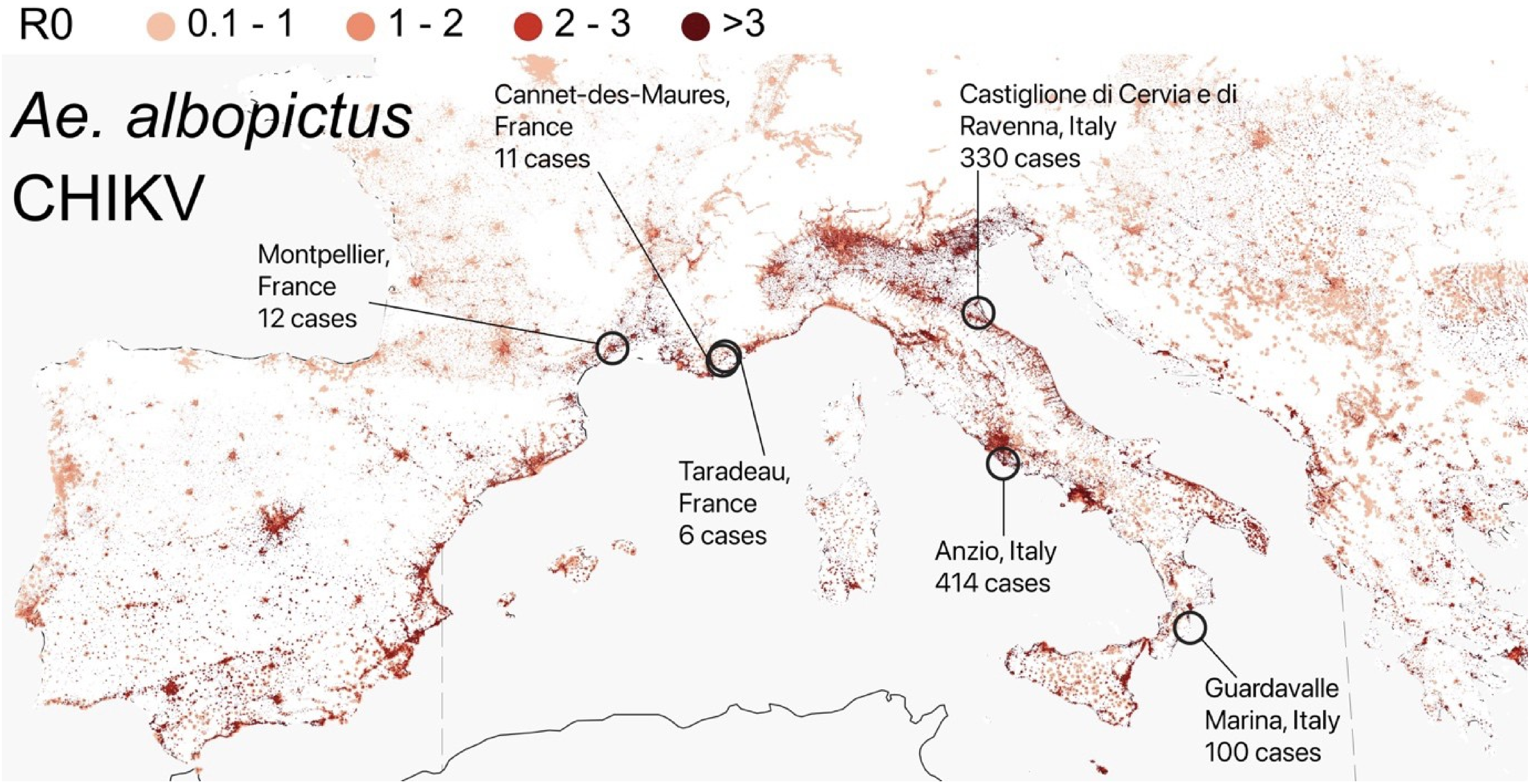
	Reference	Threshold 0.5		Threshold 0.3		Threshold 0.7	
		True Positive	False Positive	True Positive	False Positive	True Positive	False Positive
Ae. albopictus (US)	Monaghan et al. 2019	99%	13%	99%	22%	98%	8%
Ae. albopictus (Europe)	ECDC	99%	38%	99%	46%	94%	29%
Ae. aegypti	Monaghan et al. 2019	67%	7%	76%	13%	49%	4%

127 time series

173 time series


R0
0.1 - 1
1 - 2
2 - 3
>3
A
Ae.
albopictus
DENV
March
June
September
December
B
Ae.
albopictus
ZIKV
March
June
September
December


R0
0.1 - 1
1 - 2
2 - 3
>3
Ae. albopictus
DENV
Nîmes, France 8 cases
Vallauris, France 9 cases
Paca, France 51 cases
Lodi, Italy 28 cases
Montecchio, Italy 11 cases
Pelješac, Croatia 10 cases
Ibiza, Spain 6 cases
Saint Laurent du Var, France 8 cases
Roma, Italy 19 cases
Cadiz, Spain 6 cases



R0
0.1 - 1
1 - 2
2 - 3
>3
Ae. albopictus
CHIKV
Cannet-des-Maures, France 11 cases
Castiglione di Cervia e di Ravenna, Italy 330 cases
Montpellier, France 12 cases
Taradeau, France 6 cases
Anzio, Italy 414 cases
Guardavalle Marina, Italy 100 cases

transmission potential

duration epidemic risk

Number of consecutive days associated with an