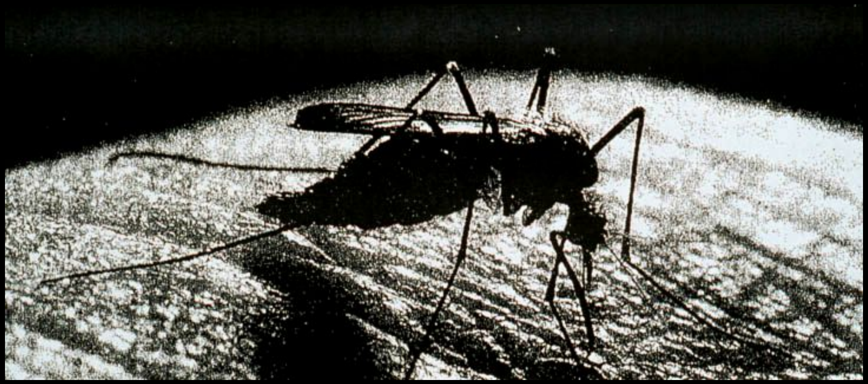
Monitoring mosquitoes of public health importance with TinyML



Cyril Caminade (1), Adrian Tompkins (1) and Jeremy Bouyer (2)
(1) Abdus Salam International Centre for Theoretical Physics, Trieste, Italy
(2) IAEA, Vienna, Austria

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UNIVERSITY OF LIVERPOOL

The Abdus Salam International Centre for Theoretical Physics

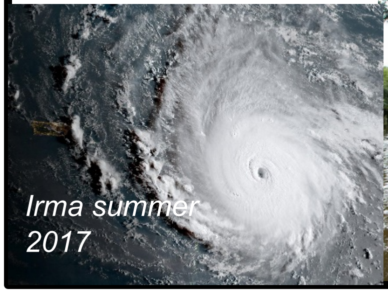
Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture

Climate change impact on health

Heatwaves

An Iraqi man shows a thermometer reading more than fifty degrees Celsius on **July 30, 2015** in Baghdad.

Hurricanes and floods

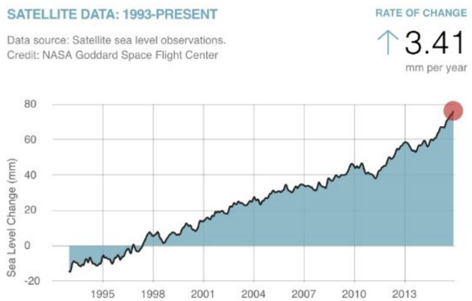

Irma summer 2017


Floods in Florida October 2015

Air pollution


Harbin, China

Sea level rise



Climate sensitive diseases

Arthropods are ectotherms

Vector, water and soil borne pathogens are impacted

Water, agriculture and biodiversity


Scientific American artwork


Starving polar bear National Geographic

Climate refugees and migration

Somali refugees flee flooding in Dabaab, Kenya (UNHCR)

Infrastructures

Genoa Morandi bridge collapsed in Aug 2018 due to heavy rainfall (ABC news)

Forest fires

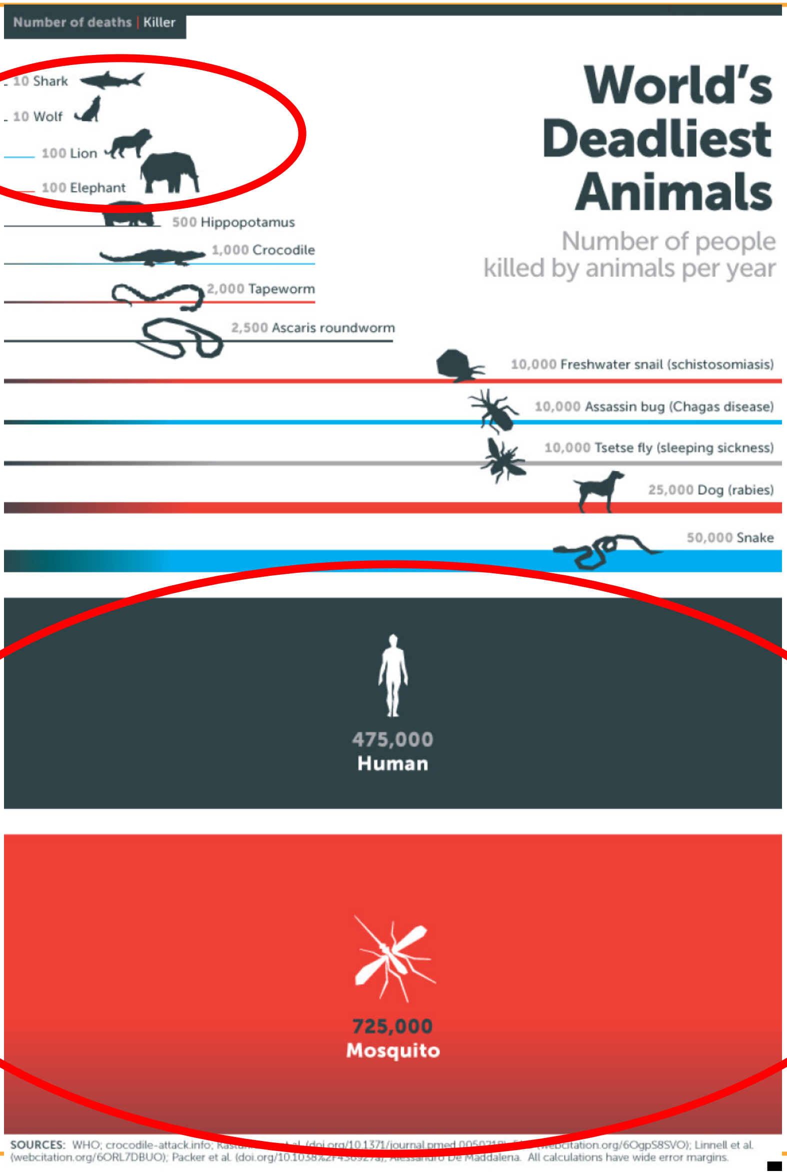
Forest fires in Gironde, France Aug 2022

Direct impacts

Indirect impacts

World’s deadliest animals

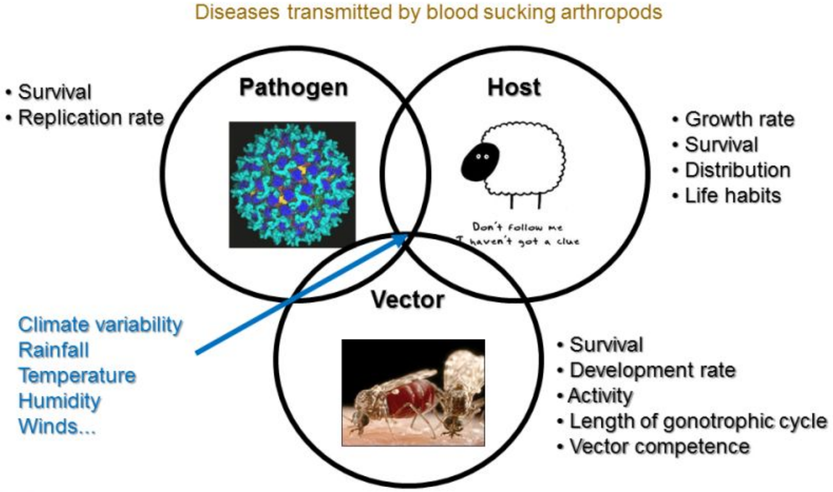
Irrational fear



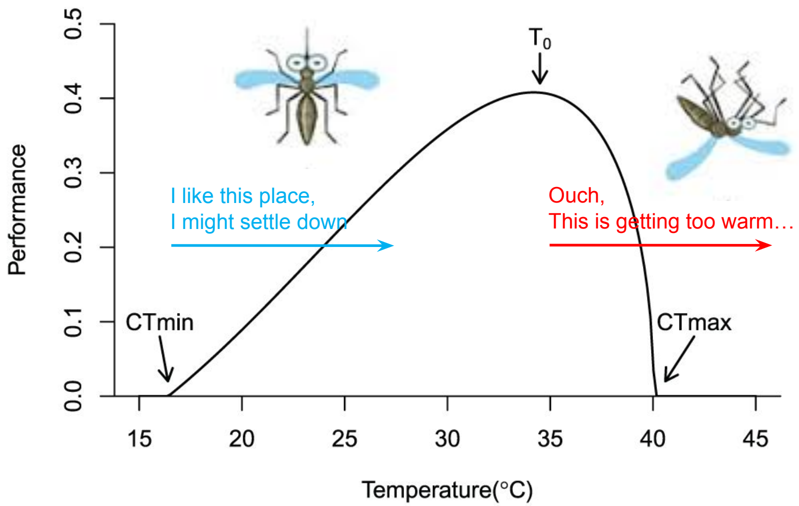
Facts

Climate & vector-borne diseases (VBDs)

VBDs are climate sensitive



Vectorial capacity = F(Tº)



Lafferty KD and Mordecai EA 2016 - F1000Research 2016, 5:2040

Modelling the impact of climate variability on VBD burden, development of early warning systems (seasonal to climate change time scales).

VBD impact

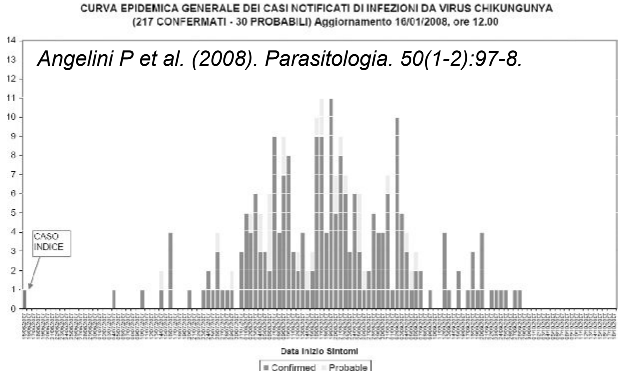
2^nd^ Plague pandemic 14^th^ century

Malaria in Africa

Zika outbreak in Latin America 2015-2016

Bluetongue outbreak in Northern Europe Aug-Sep-Oct 2006

Yellow fever outbreak – Angola DRC 2015-2016



Angelini P et al. (2008). Parasitologia. 50(1-2):97-8.

Biting rates & temperature: **a(Tº)**

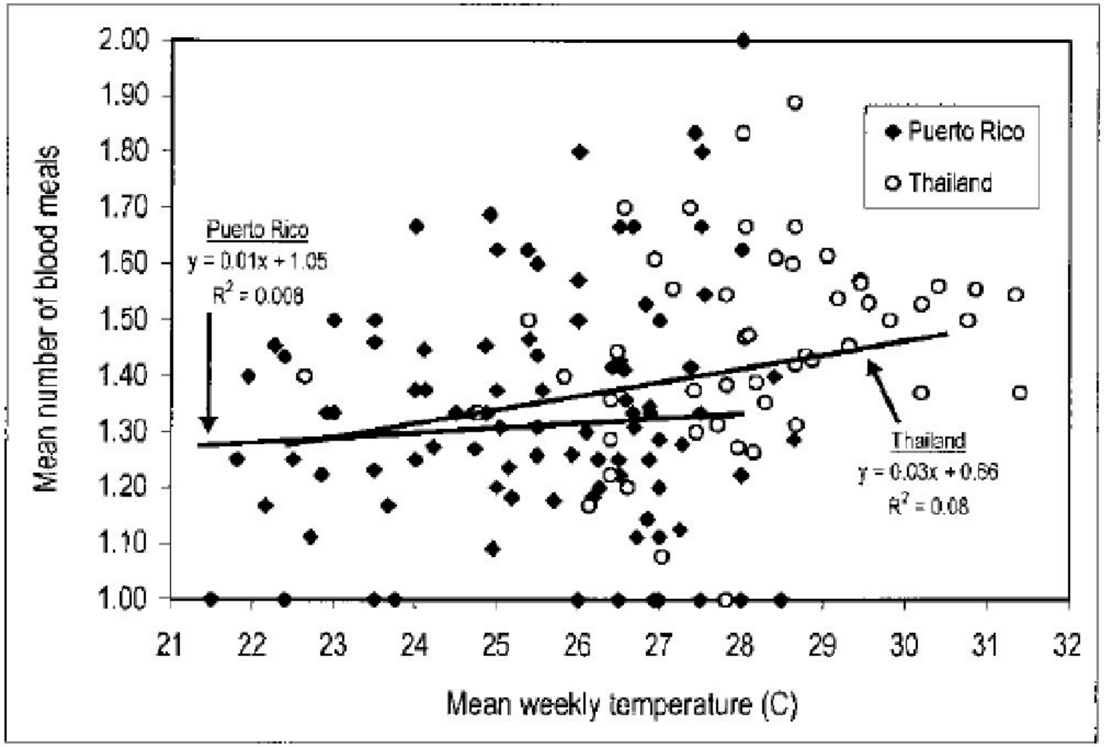


Fig. 5. Relationship between temperature and bloodfeeding frequency of female *Ae. aegypti* collected weekly in Thailand (1990–1992) and Puerto Rico (1991–1993). Linear regression lines and equations for each site are included.

Biting rates:

Left: Relationship between temperature and bloodfeeding frequency of female ***Ae. aegypti*** *collected weekly in Thailand (1990–1992) and Puerto Rico (1991–1993). Linear regression lines and equations for each site are included.*

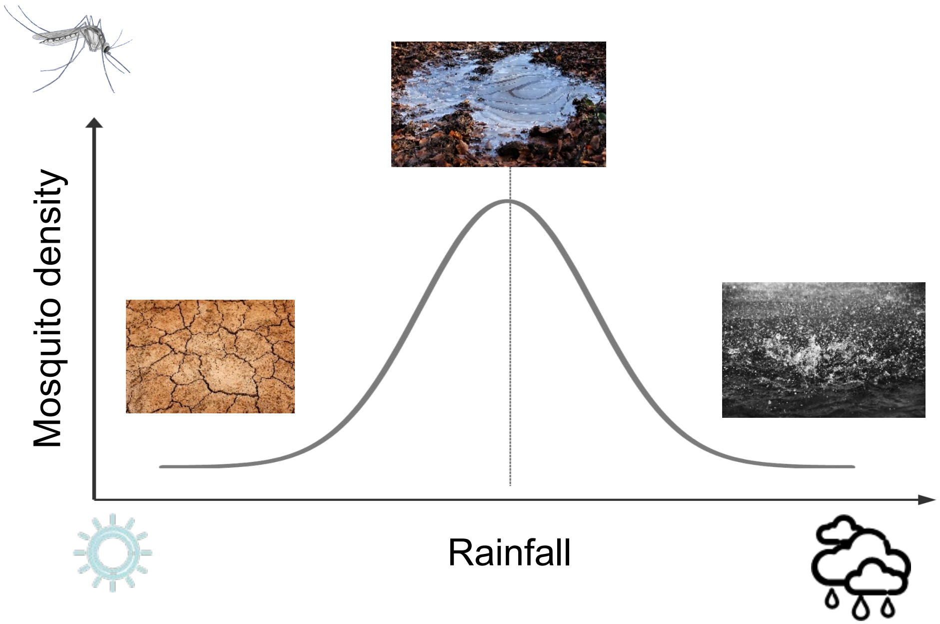
When temperature increases, biting rate increases (up to a certain point).

Fig. 5 - Scott et al. 2000. *J Med Entomol. 37(1): 89-101*
https://doi.org/10.1603/0022-2585-37.1.89

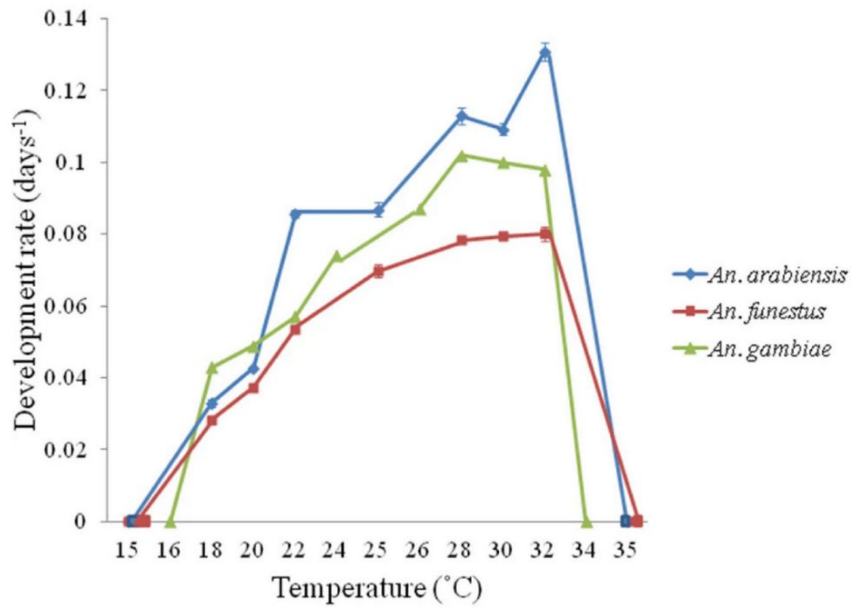
Ae. aegypti, the yellow fever mosquito

Rainfall, temperature & vector mortality : **μ(Tº)**

Bourgouin and Paul, 2021.



Lyons et al., 2013.



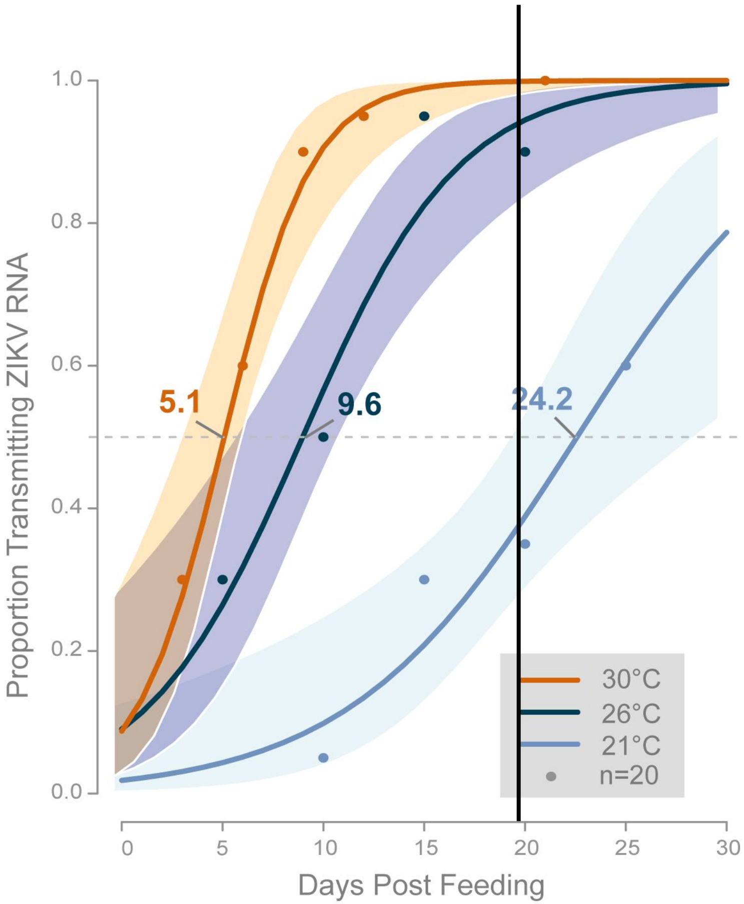
Anopheles **mosquito sensitivity to rainfall (left) and temperature (right).**

•Too little or too much rainfall leads to mosquito death
•Mosquitoes thrive in a specific temperature range

Thanks to A. Chemison

Temperature & Extrinsic Incubation Period: **EIP(Tº)**

Average life span of Ae. aegypti (3 weeks)



Fitted logistic curves showing the proportions of *Ae. aegypti* transmitting ZIKV vRNA over time by temperature.

Each point represents the observed proportion of mosquitoes (of 20 tested) that transmitted at each temperature and time-point. The estimated EIP_{50} is indicated for each temperature.

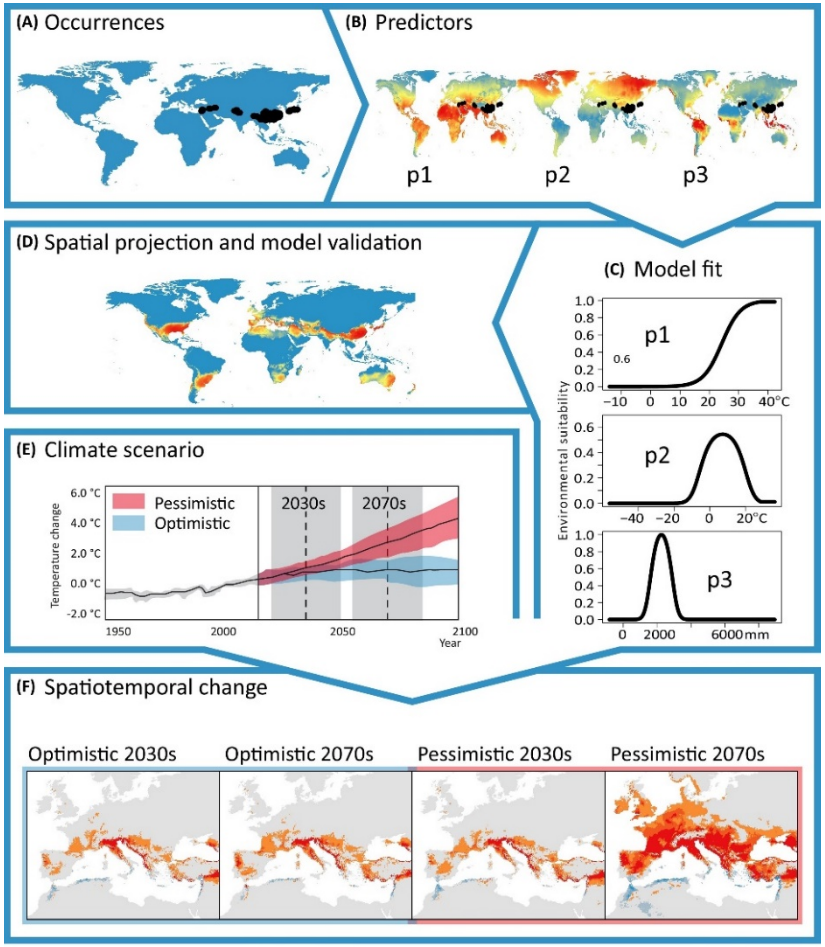
5.1 days at 30ºC
9.6 days at 26ºC
24.2 days at 21ºC

Mosquito life span in the field about **30 days**

Fig. 3 - Winokur et al. 2020. PLoS Negl Trop Dis 14(3): e0008047
https://doi.org/10.1371/journal.pntd.0008047

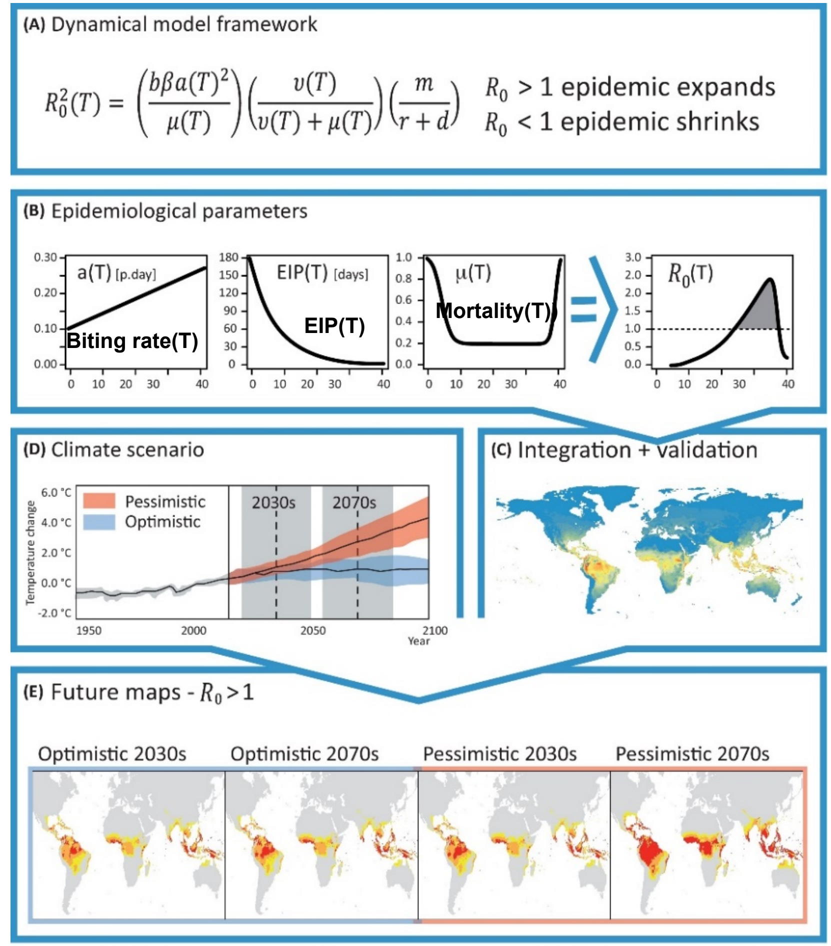
Methods to model vectors and disease risk

Statistical models



Stat models: Maxent, BRTs, Bayesian models, Mahalanobis distance…

Mechanistic models



Mechanistic models: SEIR/SIR, R_0, Fuzzy logic, climate envelope…

Fig. 1 &2 *Tjaden et al. (2018). Trends in Parasitology 34(3): 227-245.* *http://dx.doi.org/10.1016/j.pt.2017.11.006*

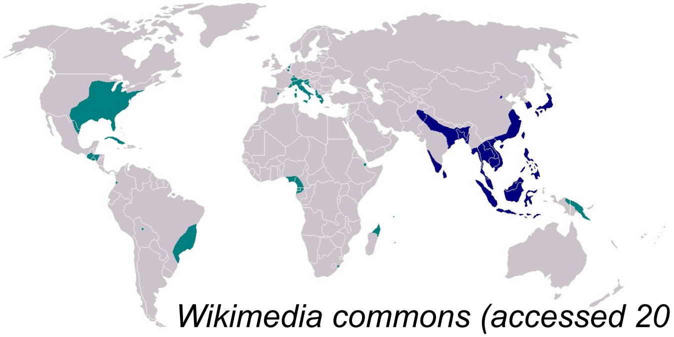
Research examples

The Asian tiger mosquito *Ae. albopictus*

Ae. albopictus

Source: CSIR

Rapid spread worldwide



Wikimedia commons (accessed 2012)

blue: original distribution, cyan: areas where introduced in the last 30 years.

Main introduction routes

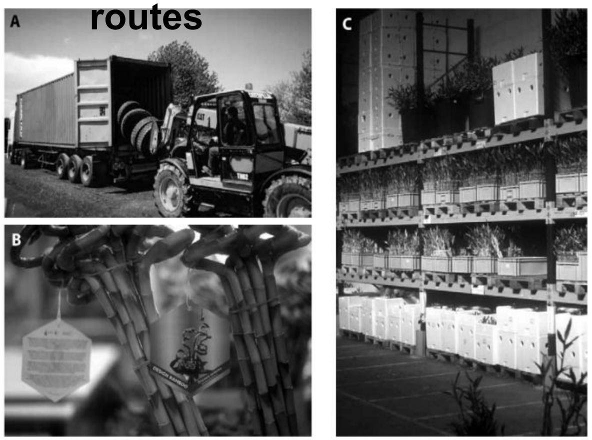


Figure 2. Main Aedes albopictus inroduction routes: (A) Used tyres. (B),(C) Lucky Bamboo (Dracaena spp.).

Scholte & Schaffner, 2007

Rapid spread in Europe

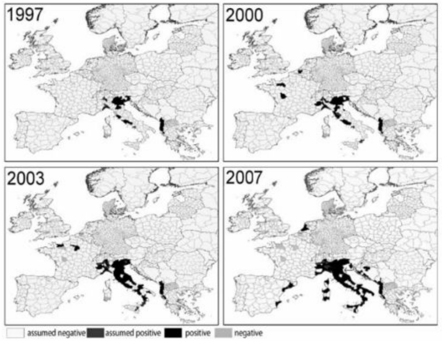
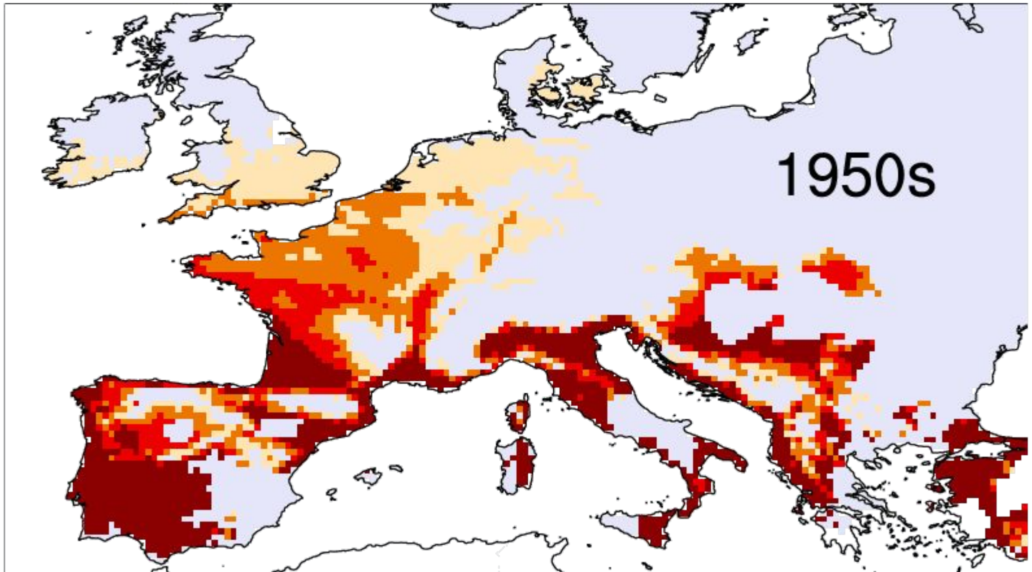


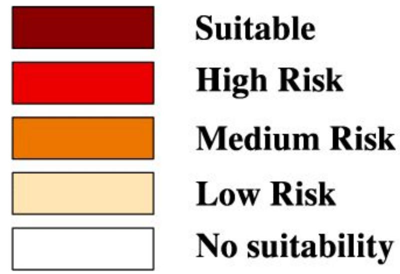
Figure 3. Presence of Aedes albopictus in Europe per province for the years 1997-2007. Data to complete this figure were kindly made available by Roberto Romi (Italy), Roger Eritja and David Roiz (Spain), Eleonora Flacio (Switzerland), Charles Jeannin (France), Anna Klobučar (Croatia), Zoran Lukac (Bosnia and Herzegovina), Igor Pajovic and Dusan Petrić (Serbia and Montenegro), Bjoern Pluskota (Germany), Anna Samanidou-Voyadjoglou (Greece). The map was made by Patrizia Scarpulla. The 2007 outbreak of Chikungunya virus in Italy is indicated with an arrow in the 2007 box.

Scholte & Schaffner, 2007

Ae. albopictus: climate change scenarios

Model





[*Caminade et al. J. R. Soc. Interface* ***2012****, (9), 75, 2708-2717*]

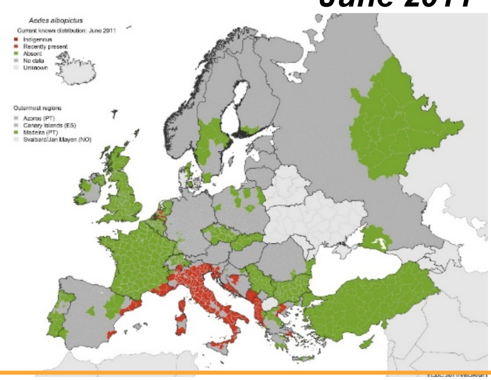
Model 1:
January Temperatures > 0° C, Annual rainfall > 500mm Risk defined for different annual temperature thresholds ([Kobayashi et al, 2002]).

Key results:

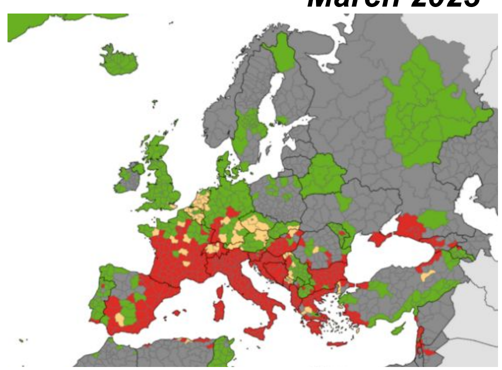
- The mosquito has not filled its potential ecological niche yet
- Risk increases over central / northern Europe while it might decrease over southern Europe in future

Observation

June 2011



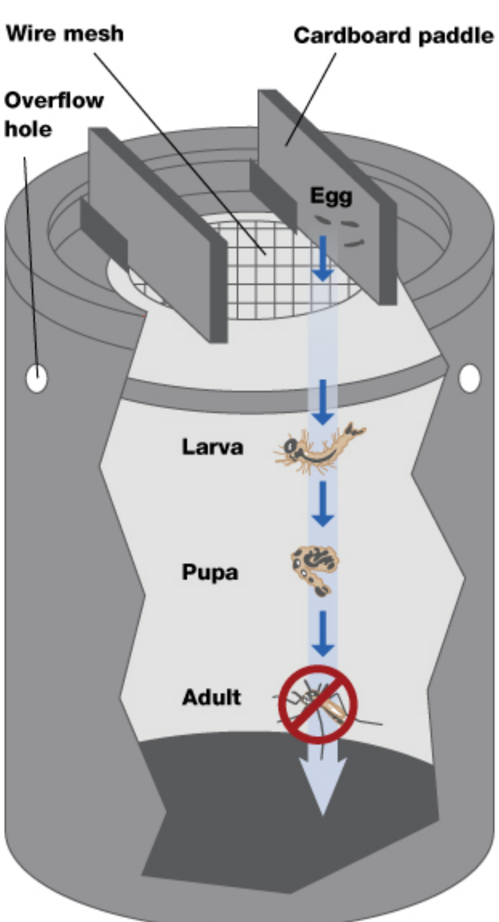
March 2023



Countries at risk based on our model estimates:
Cyprus, Bulgaria, Slovakia, Hungary, Macedonia, Portugal, Turkey, the Benelux, Germany and the UK.

ECDC Vectornet -
https://www.ecdc.europa.eu/en/disease-vectors/surveillance-and-disease-data/mosquito-maps

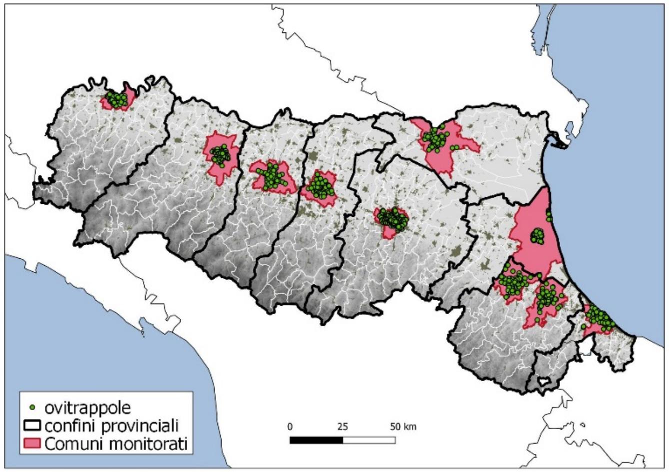
Trapping mosquitoes - ovitraps (Eggs)



https://www.nature.com/scitable/content/ovitrap-22404316/

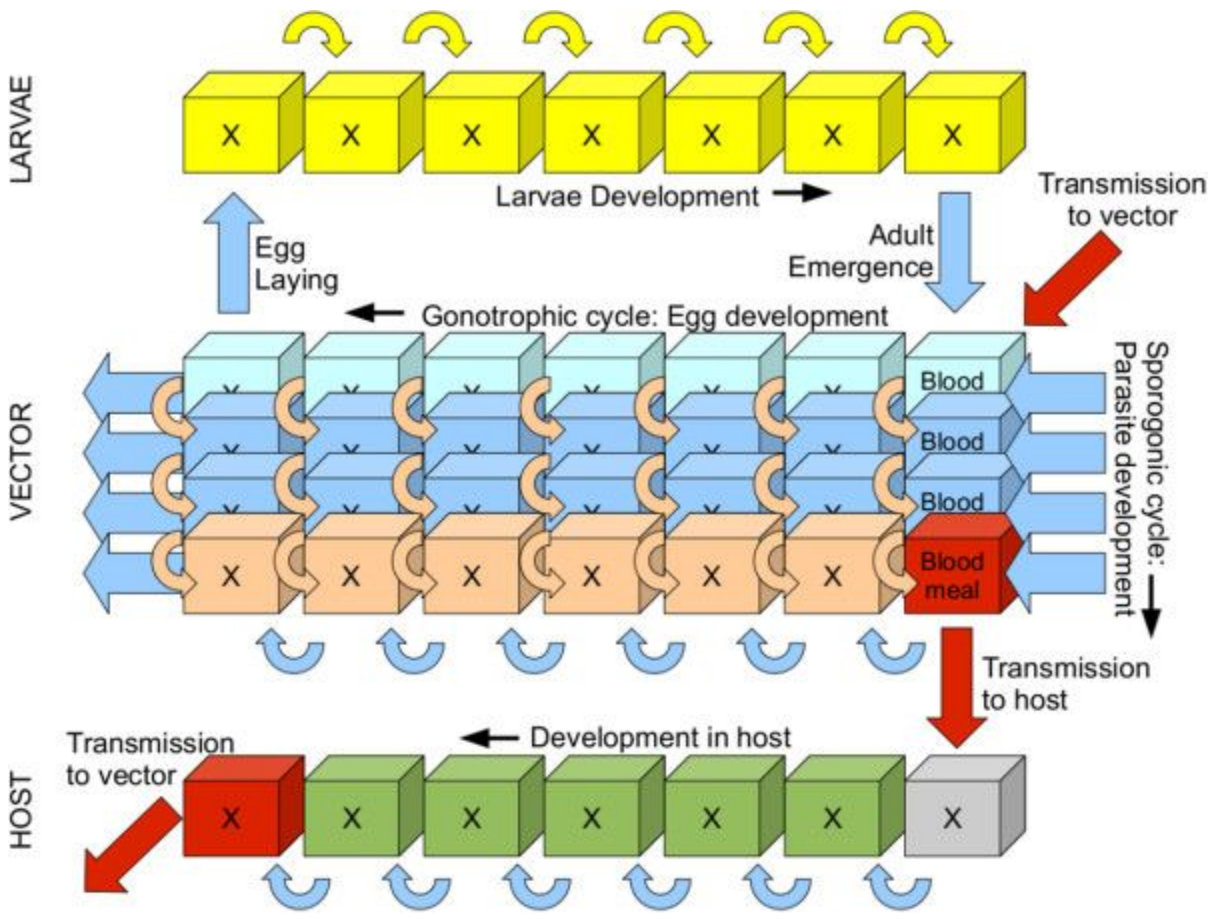
Ovitrap CAA14GG model (**Left**) used in Emilia Romagna to monitor *Ae. albopictus* population since 2010 (**bottom**) every two weeks.

Source: https://zanzaratigreonline.it/it/monitoraggio/informazioni-tecniche



Ovitrap
An ovitrap is a mosquito trap. It is a black, cylindrical container filled with water that appears to be an ideal location for a female *Aedes aegypti* to lay eggs. The female lays her eggs on the cardboard paddles. The eggs then fall through the mesh into the water, where the larvae hatch and develop into pupas. When the adult mosquitoes emerge, they are trapped beneath the mesh and are unable to escape from the ovitrap.

The VECTRI model

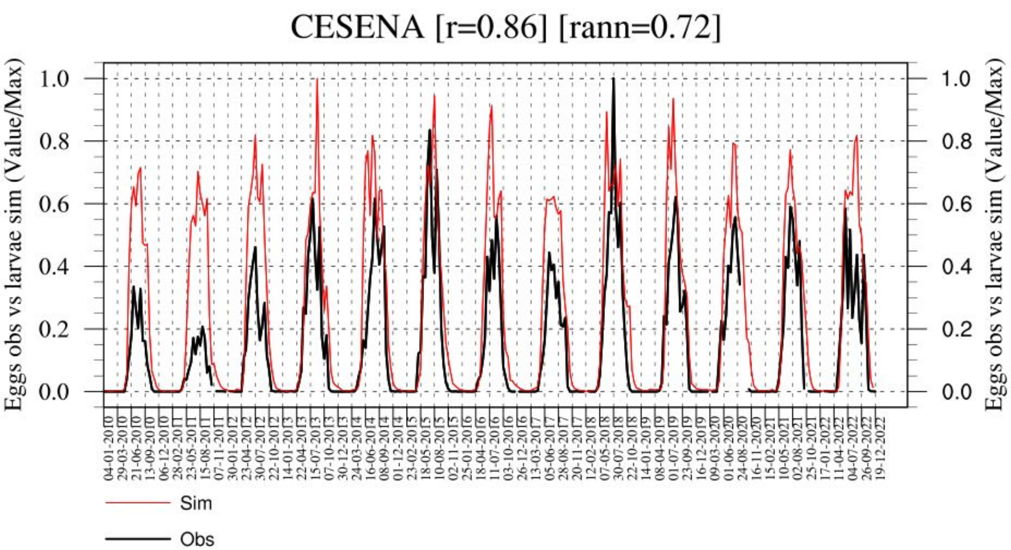


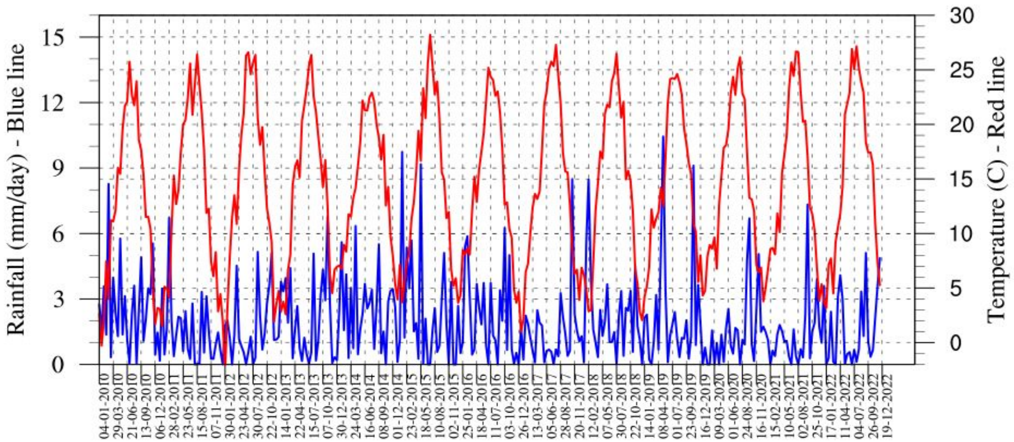
Schematic of the VECTRI model originally developed for malaria and An. gambiae. Tompkins & Ermert, Malar J **12**, 65 (**2013**)

VECTRI model adapted for *Ae. albopictus* *(Caminade & Tompkins):*

- ***Parameters update**: wperm = 0.5% e.g. smaller dependency to rainfall with respect to An. gambiae. Adult mortality scheme derived from Metelmann et al., J. of the Roy. Soc. Int. 16*, 20180761 *(**2019**).*
- ***Inputs**: rainfall and temperature data based on EOBS v27 : rainfall and temperature data based on EOBS v27 (0.25° x 0.25°); Human population data from GPWv4 (UN-adjusted 2015; data was interpolated on the same 0.25° grid).*

Model validation, ovitrap data Cesena, Italy





VECTRI EOBS simulations for *Ae. albopictus:*

•*Comparison of standardized simulated larval density with ovitrap data for Emilia Romagna*
•*Seasonality well reproduced; interannual variability fine in some locations but to be improved*

•***Results are promising with correlations > 0.8 for 10 sites in Italy (mostly related to seasonality) – annual correlations are lower***

Trapping mosquitoes: Human Landing catches (adults)

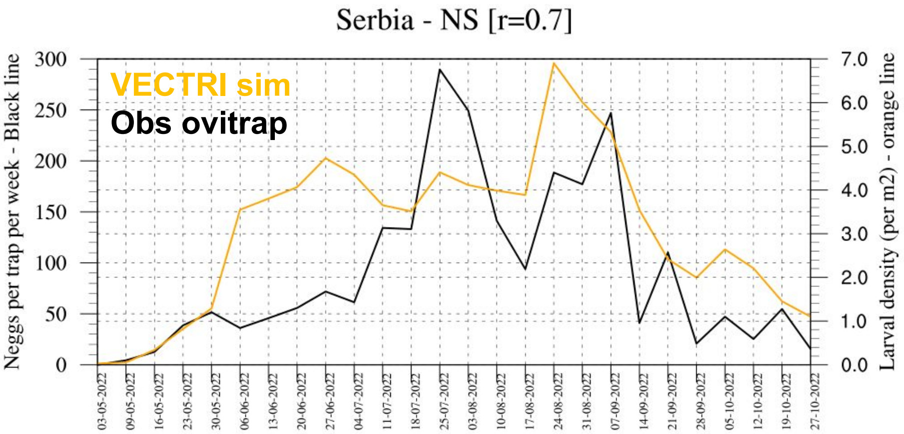
Colucci, B., Müller, P. *Nat. Sci Rep* **8**, 12578 (2018). https://doi.org/10.1038/s41598-018-30998-2

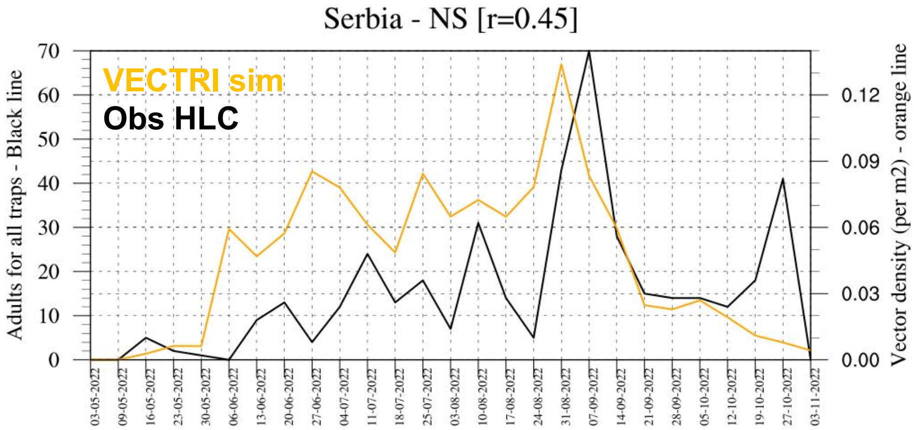
Human landing catches (HLC) are **an entomological collection technique in which humans are used as attractants to capture medically relevant host-seeking mosquitoes**. The use of this method has been a topic of extensive debate for decades mainly due to ethical concerns.

However this technique provides the most realistic estimates of potential biting rates for a given mosquito species…

https://www.reddit.com/r/mildlyinteresting/comments/dlzcii/this_bigfoot_research_project_ad_for_human_bait/

Model validation: ovitrap & HLC data AIMS-surv





***Left**: Simulated larval density (orange line) vs averaged number of eggs per trap per week (black line) for Novi Sad in Serbia in 2022. **Right**: Total number of Aedes mosquitoes based on HLC data. VECTRI simulations were driven by EOBS v27 rainfall and temperature data.*

Funded by the European Union

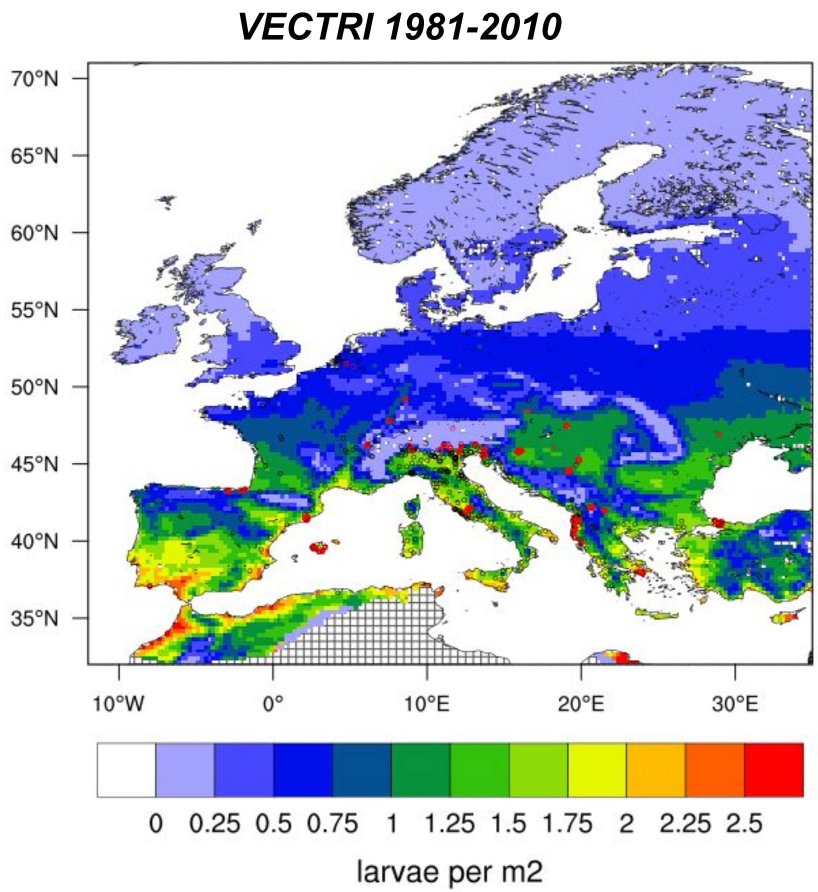
AIM Aedes Invasive Mosquitoes

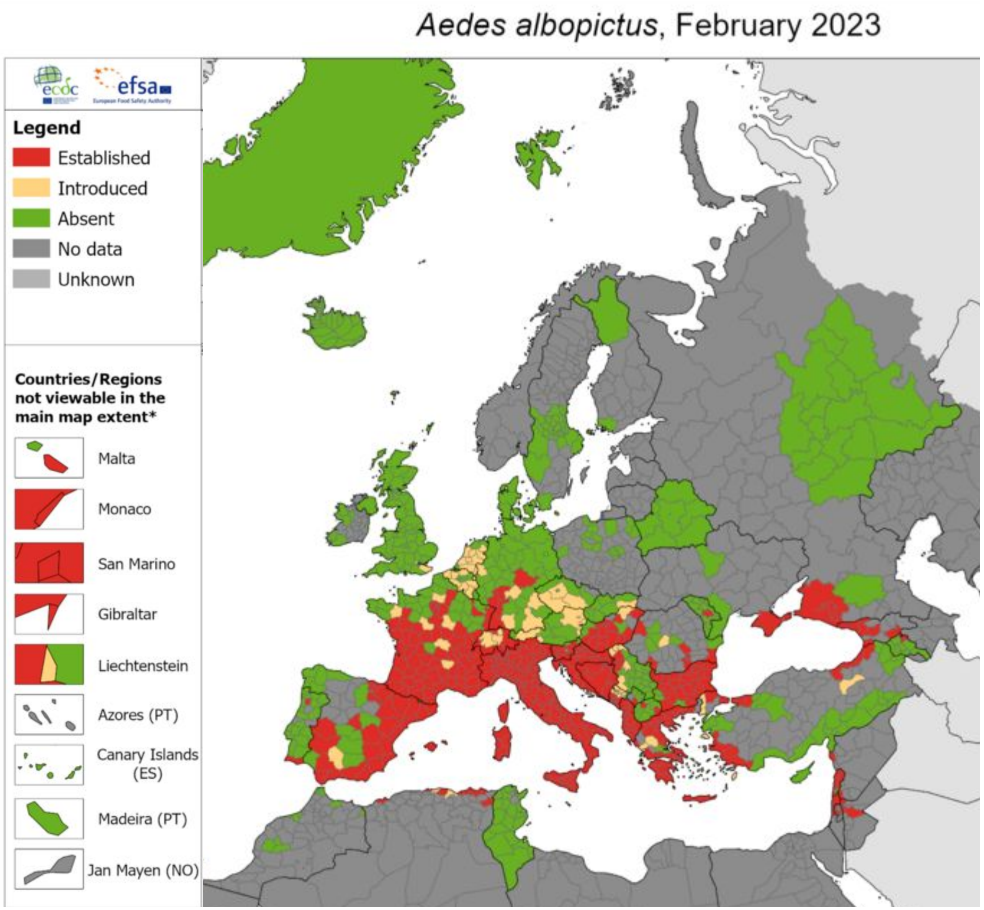
cost EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

https://www.aedescost.eu/

https://indico.ictp.it/event/10172

VECTRI model validation in Europe

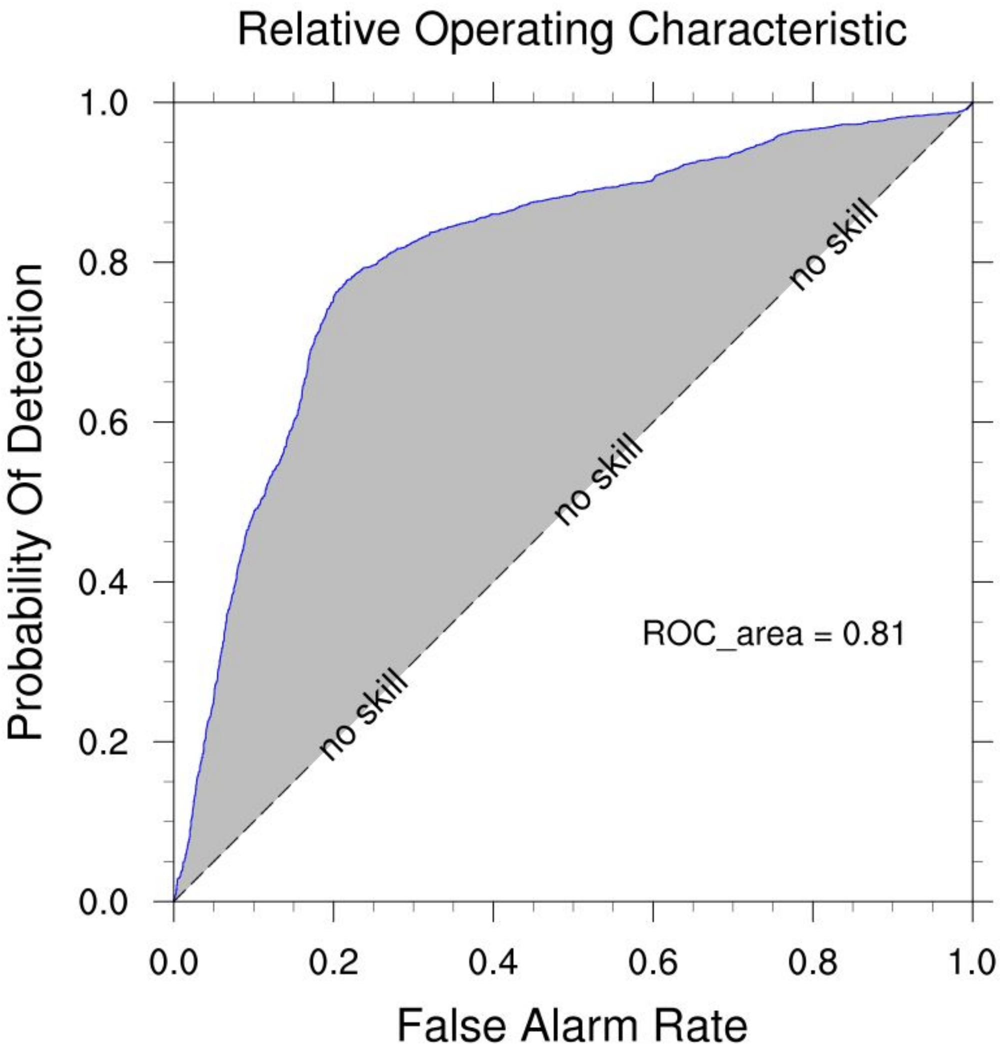




Left: Mean annual larval density (1981-2010) as simulated by the VECTRI model (input EOBS data). Black dots GBIF data; Red dots AIMS-EU data

Right: Observed presence of *Ae. albopictus* in Europe (ECDC data, Feb 2023)
https://www.ecdc.europa.eu/en/publications-data/aedes-albopictus-current-known-distribution-february-2023

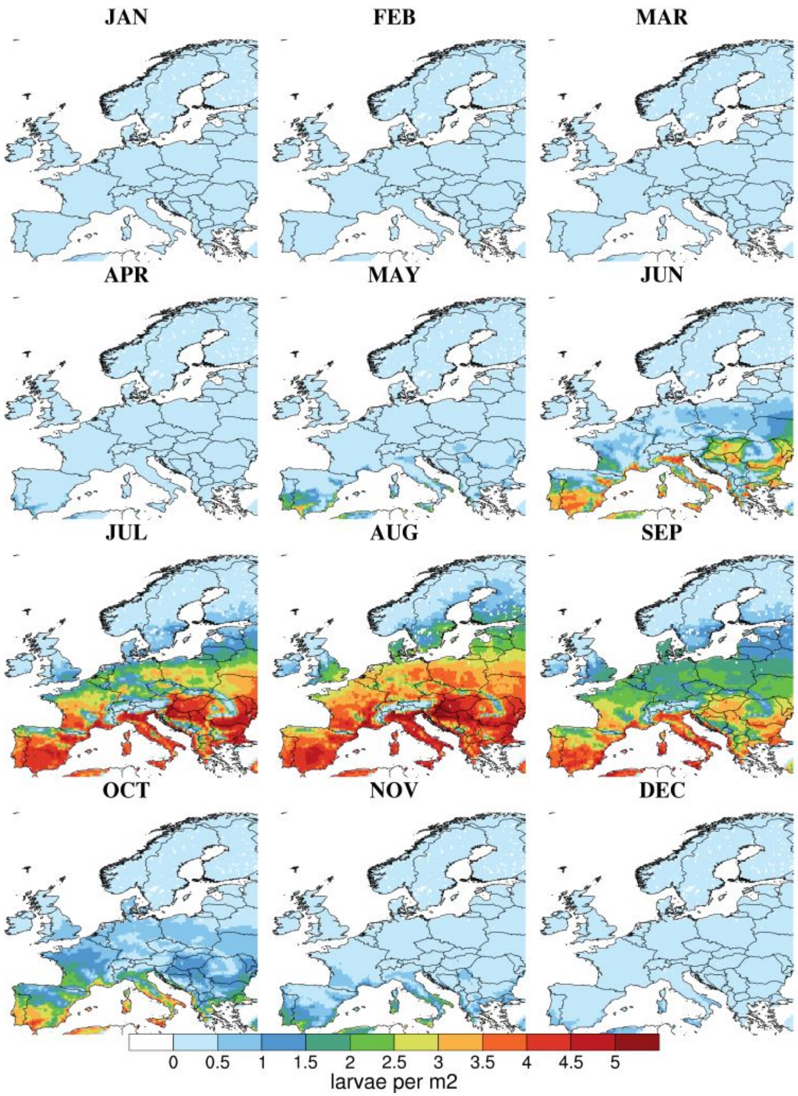
Ae. albopictus: VECTRI model AUC Europe



ROC curve
Simulated mean larval density (1981-2010) vs ECDC occurrence data (0-1 – NUTS3 admin level)

AUC = 0.81 for Europe

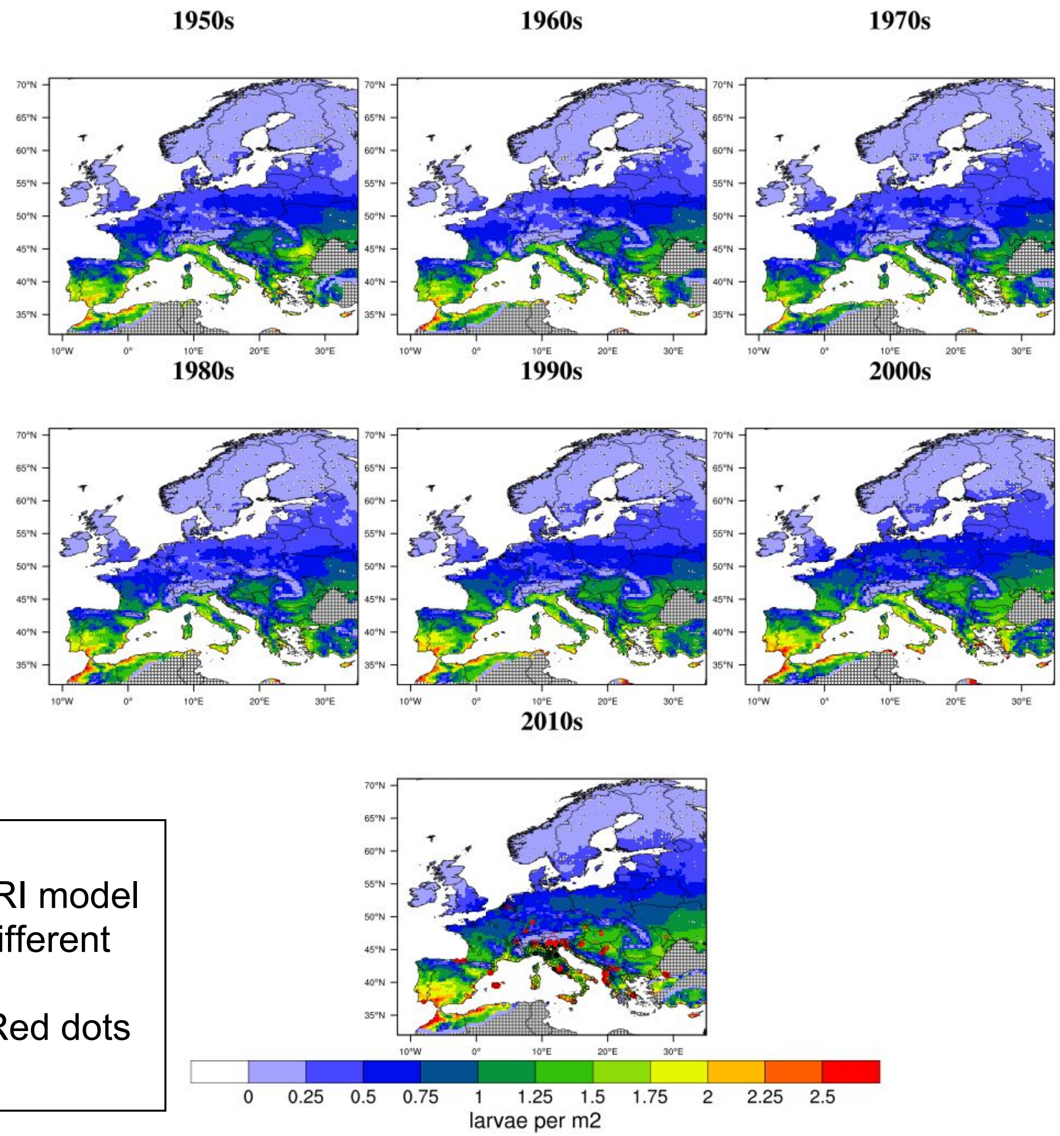
Ae. albopictus: simulated seasonal cycle



- Hotspots in France, Germany, Benelux, over the coasts of the Adriatic and the Mediterranean sea are well reproduced by the model
- Minimums over altitude regions (Alps, Pyreneans, Massif Central, Carpathian mountains…)
- Risk overestimation over Spain and Portugal
- Overall, seasonality looks realistic (May-Oct; and lasts until Nov in some southernmost locations of Europe)

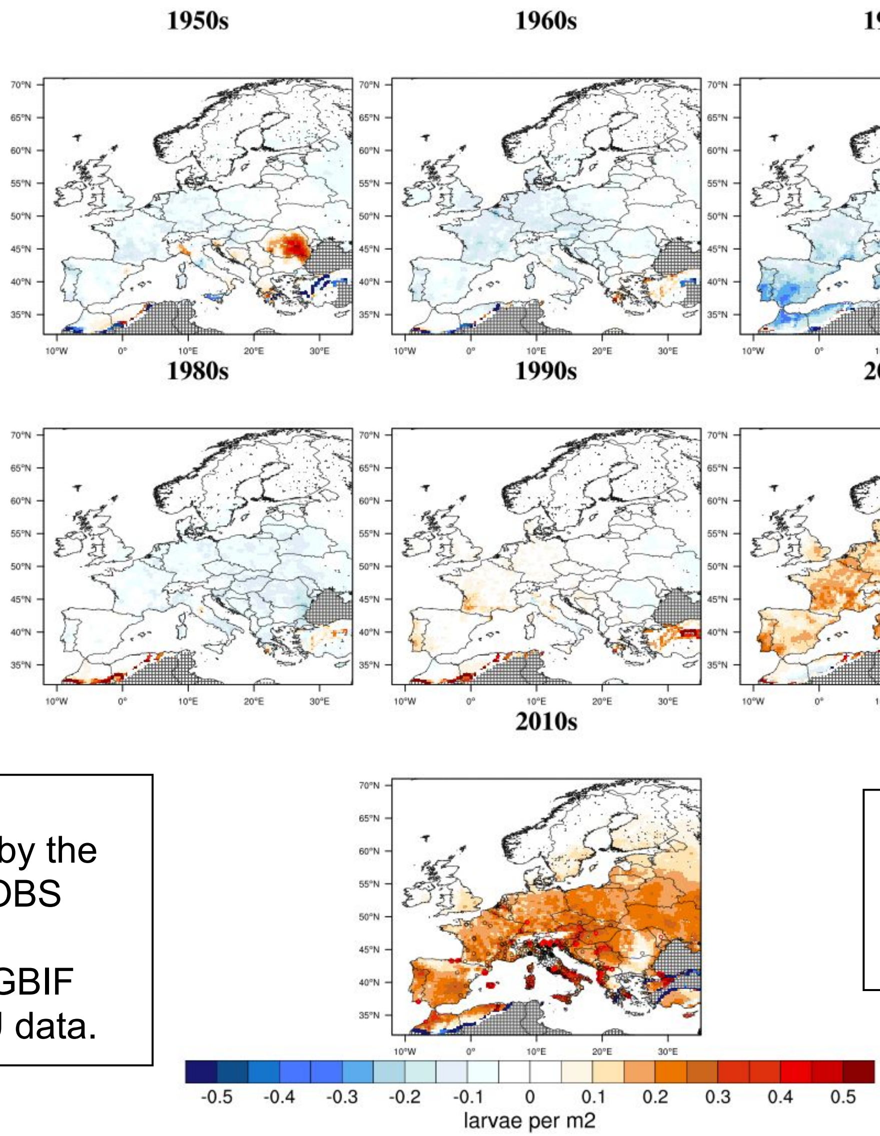
Left: Mean monthly larval density (2011-2021) as simulated by the VECTRI model over Europe.

Ae. albopictus: decadal variability



Mean larval density as simulated by the VECTRI model (input EOBS data) for different decades.
Black dots GBIF data; Red dots AIMS-EU data.

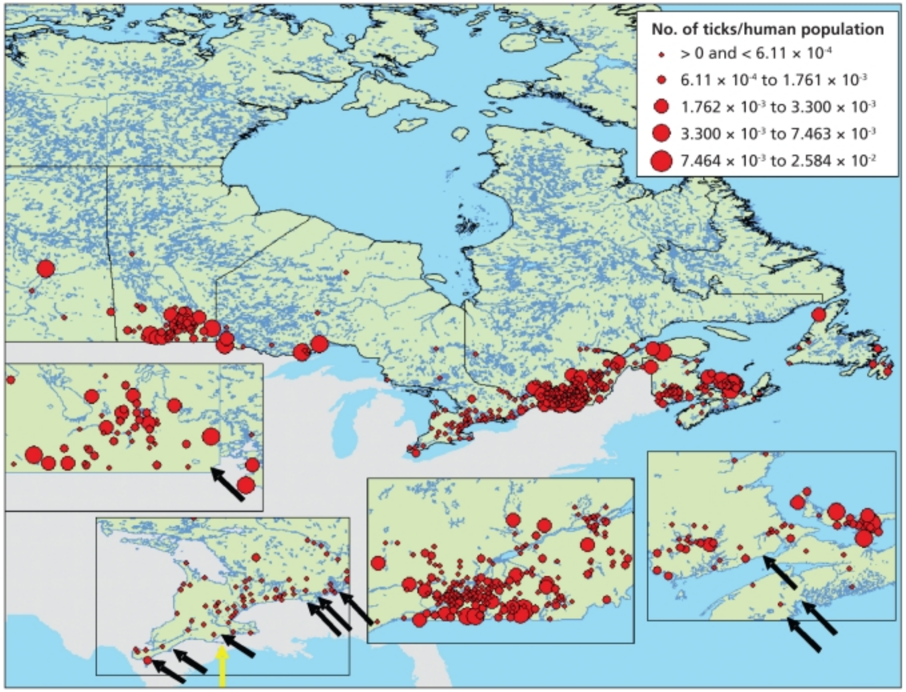
Ae. albopictus: decadal variability



Larval density decadal anomalies as simulated by the VECTRI model (input EOBS data) with respect to the 1951-2019. Black dots GBIF data; Red dots AIMS-EU data.

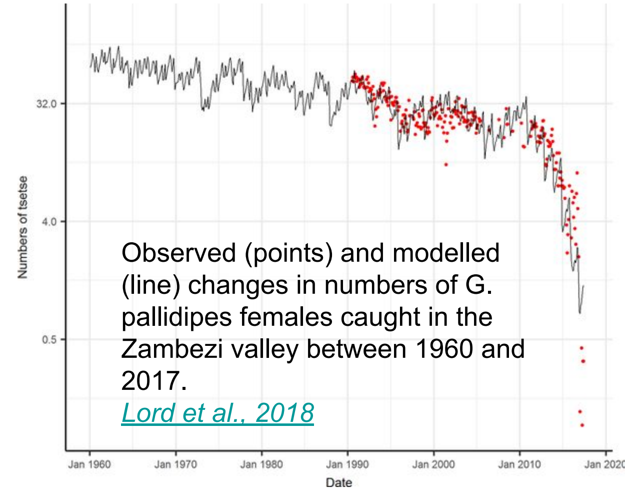
Climatic conditions during the 2000s and 2010s were highly suitable for the establishment of *Ae. albopictus* in Europe.

Vector-Borne Diseases & climate change



The distribution of ***Ixodes scapularis* ticks**, reflecting information submitted to provincial and federal public health agencies from January 1990 to December 2003 and to the Lyme Disease Association of Ontario for 1993 to 1999 *Ogden et al., 2008*

African Trypanosomiasis in Zambezi valley



Observed (points) and modelled (line) changes in numbers of G. pallidipes females caught in the Zambezi valley between 1960 and 2017.
Lord et al., 2018

Tick-borne encephalitis northern Russia

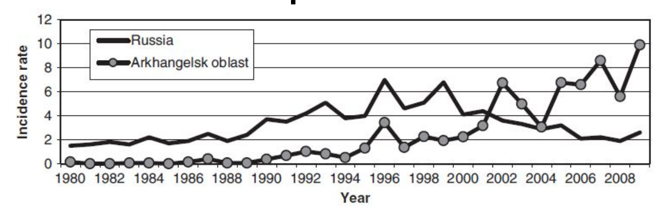
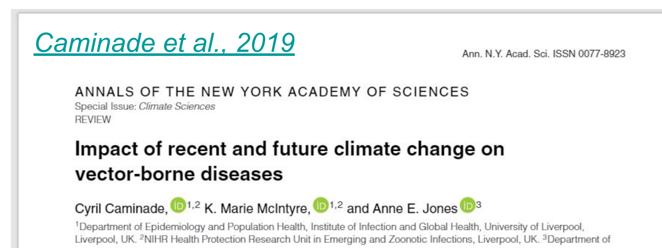


Fig. 3. TBE incidence in AO and in Russia as a whole in 1980—2009. *Tokarevich et al., 2011*


Caminade et al., 2019

Ann. N.Y. Acad. Sci. ISSN 0077-8923

ANNALS OF THE NEW YORK ACADEMY OF SCIENCES
Special Issue: *Climate Sciences*
REVIEW

Impact of recent and future climate change on vector-borne diseases

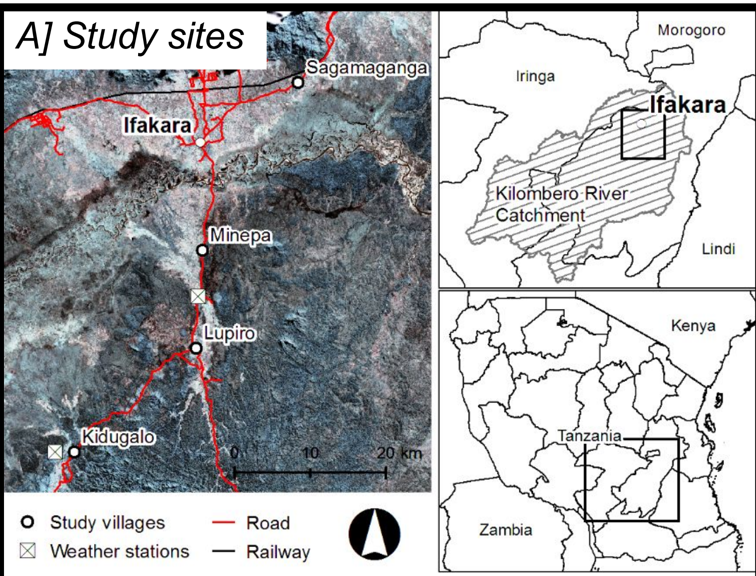
Cyril Caminade,[1,2] K. Marie McIntyre,[1,2] and Anne E. Jones[3]

[1]Department of Epidemiology and Population Health, Institute of Infection and Global Health, University of Liverpool, Liverpool, UK. [2]NIHR Health Protection Research Unit in Emerging and Zoonotic Infections, Liverpool, UK. [3]Department of Mathematical Sciences, University of Liverpool, Liverpool, UK

Field work – research examples

Malaria vectors in Tanzania NERC project in pictures

A] Study sites



B] A day of work in Lupiro


1) IHI technicians set up mosquito traps in Lupiro in Tanzania (6.00 pm)


2) Ready for 12 hours of trapping (6.00pm – 6.00am)


3) Anopheles counting & identification the following morning (7.00 am-9.00 am)


4) Data of the day! (11.00am)

C] Downloading fresh weather station data

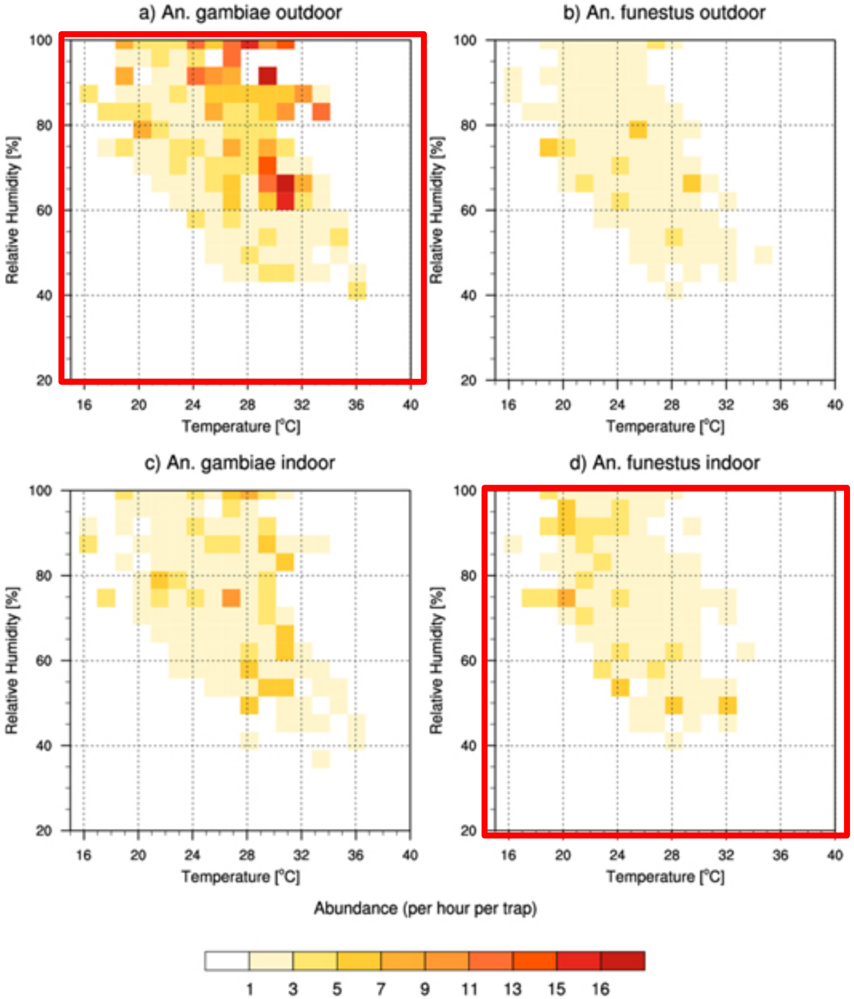
D] Outreach with village elders

E] Daily catch

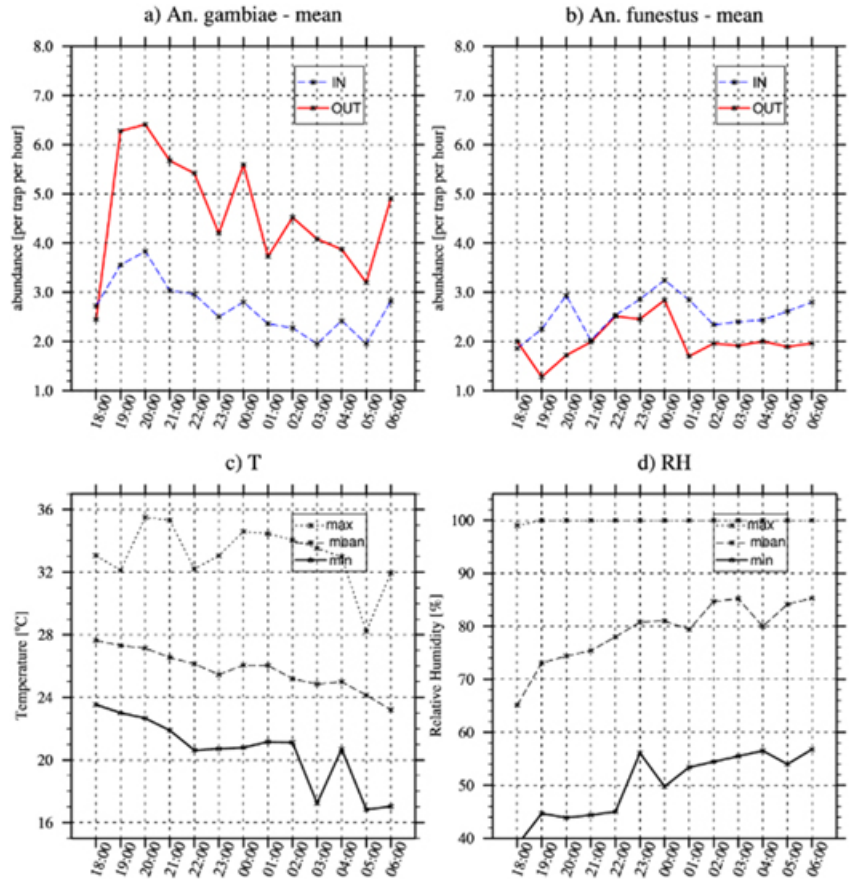
Malaria vectors in Tanzania NERC project in pictures

Field work is hard work…

Malaria vectors in Tanzania NERC project



Mosquito abundance (catch per trap per hour based on the MET) dependencies to **temperature** (°C—*x*-axis) and **relative humidity** (%—*y*-axis). Results are shown for (**a**) *An. gambiae* caught outdoor and (**c**) indoor and (**b**) *An. funestus* caught outdoor and (**d**) indoor.



Hourly abundance for (**a**) *An. arabiensis* and (**b**) *An. funestus* (indoor and outdoor, per trap per night based on the MET data) averaged for all villages. (**c**) Hourly temperature (°C) and (**d**) relative humidity (%). All data are averaged for all villages. The mean, minimum and maximum were calculated using daily data from May 2016 to September 2017.

Kreppel *et al.* 2019 [*Environ. Res. Lett.* **14** 075009]

UNIVERSITY OF LIVERPOOL

IFAKARA HEALTH INSTITUTE

University of Glasgow

BBSRC bluetongue disease and its *Culicoides* vectors in the UK

Some thoughts…

- Mosquito **identification** is usually carried out using **morphological features**, though this exercise is sometimes difficult in the field…

- Formal mosquito data validation usually involves sending a subset of collected mosquitoes to the laboratory for further Q-PCR / PCR testing. These techniques are **costly** but required to benchmark any trapping and identification method.

- Power of **citizen science projects** using pictures and machine learning techniques for **identification**. Data is often double checked by experts, in particular if the data has to be deposited on the *Global Biodiversity Information Facility* (GBIF) database.

- What about sound recognition and use of TinyML to identify mosquitoes of public health importance?

Using mosquito wingbeat to identify mosquitoes

Classifying mosquito wingbeat sound using TinyML

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Acoustic detection of mosquitoes has been studied for long and Machine Learning can be used to automatically identify mosquito species by their wingbeat.

A solution based on an openly available dataset, the Edge Impulse platform and three commercially-available TinyML devices was developed for classification of two species of mosquitoes (*Aedes aegypti* and *Aedes albopictus*).

The proposed solution is low-power, low-cost, scalable, and can run without human intervention in resource-constrained areas.

Data is transmitted using LoRaWAN technology, allowing scientists to analyze the results and add more sensors (such as temperature and humidity) if needed.

GoodIT '22: Proceedings of the 2022 ACM Conference on Information Technology for Social Good September 2022, Pages 132–137, https://doi.org/10.1145/3524458.3547258

Slide from Prof. Pietrosemoli

Framework

1. Out of a public dataset of 20 different mosquito wingbeat sounds, we selected those of *Aedes aegypti* and *Aedes albopictus*, and added mixed samples and background noise, for a total of 4 classes.
2. Resampling to obtain uniform WAV sound and creation of "images" of the sound based on their frequency feature generated spectrograms.
3. Each image has 5,135 features (model input tensor), given by its length (65 columns) times its height (79 lines). The output of the model is the probability of each of the 4 classes: "*aegypti*", "*albopictus*", "*noise*", "*other*"

Figure 1: Workflow diagram of a TinyML project, including the deployment to an embedded device

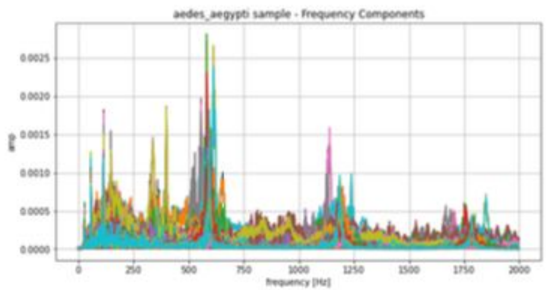

Figure 2: Frequency components of the Aedes Aegypti

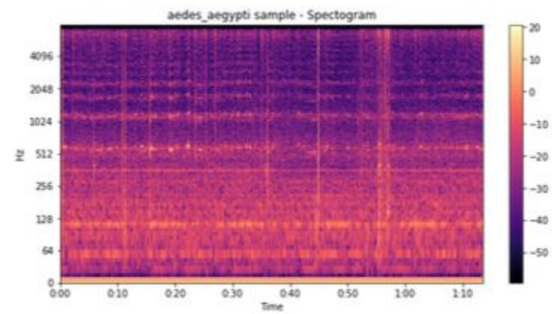

Figure 3: Spectrogram of a Aedes Aegypti sound measurement

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Deployment results

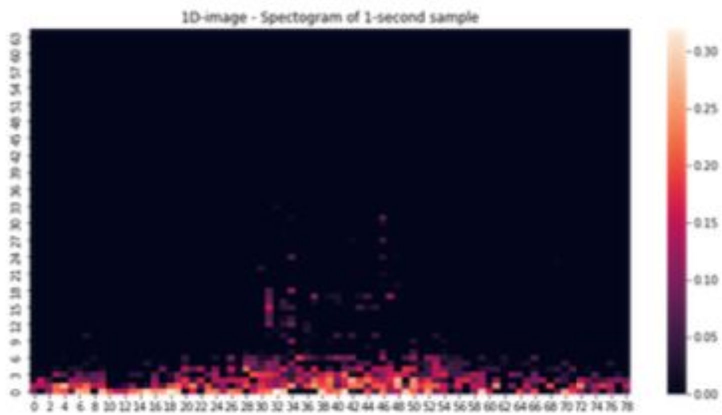

Figure 4: 1D image, obtained through the spectrogram creation of a 1-second window of raw data

	Train Result		Test Result	
Evaluation / Metrics	Accuracy	F1-Score	Accuracy	F1-Score
General Test Result	98.2%		93.8%	
aegypti	98.1%	0.99	97.2%	0.97
albopiticus	98.3%	0.98	86.9%	0.93
noise	98.3%	0.99	100%	0.95
other	98.2%	0.98	99.6%	0.94

Table 1: Model Train and Test performance

Name	MCU	Microphone	Memory	Clock speed	LoRa	Price
Arduino Nano 33 TinyML kit	Cortex-M0+	MP34DT05	1MB	64MHz	External Grove sensor RFM95 module	USD 70
Arduino Portenta H7	Cortex M7 and Cortex M4	2 x MP34DT05	16MB	M7 at 480 MHz and M4 at 240 MHz.	External with Arduino Portenta Vision Shield ABZ-093 LoRa Module with ARM Cortex-M0	USD 153
Wio Terminal	Cortex-M4F	Electret Condenser	4MB	120MHz	External Grove sensor RFM95 module	USD 60

Table 2: Technical characteristics of the three TinyML devices

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Blind test

Culex quinquefasciatus (male)

Aedes aegypti (female)

Aedes albopictus (female)

Culex quinquefasciatus (female)

Audio sources: https://humbug.ox.ac.uk/soundAudio sources: https://humbug.ox.ac.uk/sound & https://github.com/Mirovai/wingbeat-mosquito-tinyml/blob/main/dataset/

Aedes aegypti
Yellow fever mosquito

https://en.wikipedia.org/wiki/Aedes_aegypti#/media/File:Aedes_aegypti.jpg

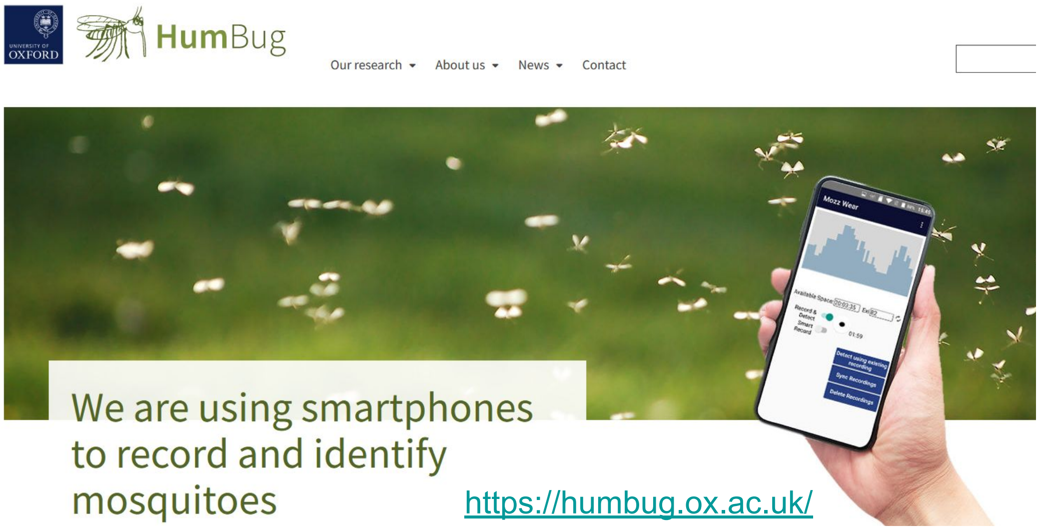
Aedes albopictus
The Asian tiger mosquito

https://en.wikipedia.org/wiki/Aedes_albopictus#/media/File:CDC-Gathany-Aedes-albopictus-1.jpg

Culex quinquefasciatus
The southern house mosquito

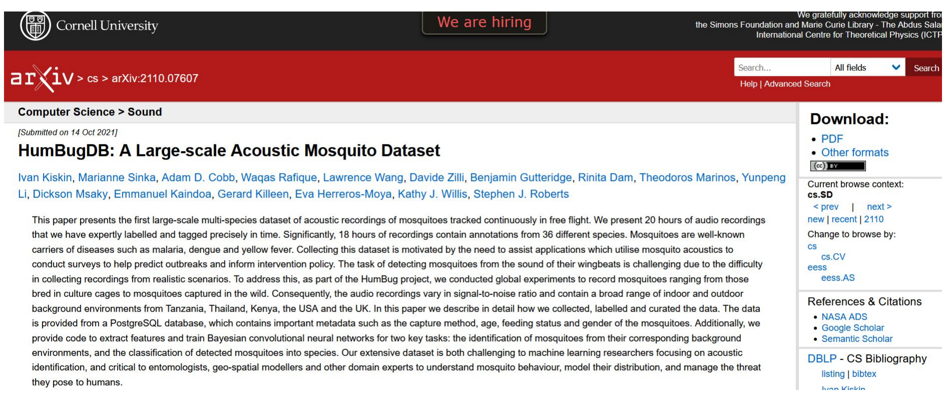
https://entnemdept.ufl.edu/creatures/aquatic/southern_house_mosquito.htm

Novel mosquito sound database: HumBug project



https://humbug.ox.ac.uk/

Right: *A visual representation of a clearly audible mosquito in flight for 5 seconds. The audio wave file is given in the first row. The second row is a short-time Fourier transform spectrogram, which shows how the magnitude of frequency components vary over time. If we think of the buzz of a mosquito as a musical note, we can show that this particular mosquito keeps a near-constant pitch of F# in the bottom row.*



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arXiv > cs > arXiv:2110.07607

Computer Science > Sound

[Submitted on 14 Oct 2021]

HumBugDB: A Large-scale Acoustic Mosquito Dataset

Ivan Kiskin, Marianne Sinka, Adam D. Cobb, Waqas Rafique, Lawrence Wang, Davide Zilli, Benjamin Gutteridge, Rinita Dam, Theodoros Marinos, Yunpeng Li, Dickson Msaky, Emmanuel Kaindoa, Gerard Killeen, Eva Herreros-Moya, Kathy J. Willis, Stephen J. Roberts

This paper presents the first large-scale multi-species dataset of acoustic recordings of mosquitoes tracked continuously in free flight. We present 20 hours of audio recordings that we have expertly labelled and tagged precisely in time. Significantly, 18 hours of recordings contain annotations from 36 different species. Mosquitoes are well-known carriers of diseases such as malaria, dengue and yellow fever. Collecting this dataset is motivated by the need to assist applications which utilise mosquito acoustics to conduct surveys to help predict outbreaks and inform intervention policy. The task of detecting mosquitoes from the sound of their wingbeats is challenging due to the difficulty in collecting recordings from realistic scenarios. To address this, as part of the HumBug project, we conducted global experiments to record mosquitoes ranging from those bred in culture cages to mosquitoes captured in the wild. Consequently, the audio recordings vary in signal-to-noise ratio and contain a broad range of indoor and outdoor background environments from Tanzania, Thailand, Kenya, the USA and the UK. In this paper we describe in detail how we collected, labelled and curated the data. The data is provided from a PostgreSQL database, which contains important metadata such as the capture method, age, feeding status and gender of the mosquitoes. Additionally, we provide code to extract features and train Bayesian convolutional neural networks for two key tasks: the identification of mosquitoes from their corresponding background environments, and the classification of detected mosquitoes into species. Our extensive dataset is both challenging to machine learning researchers focusing on acoustic identification, and critical to entomologists, geo-spatial modellers and other domain experts to understand mosquito behaviour, model their distribution, and manage the threat they pose to humans.

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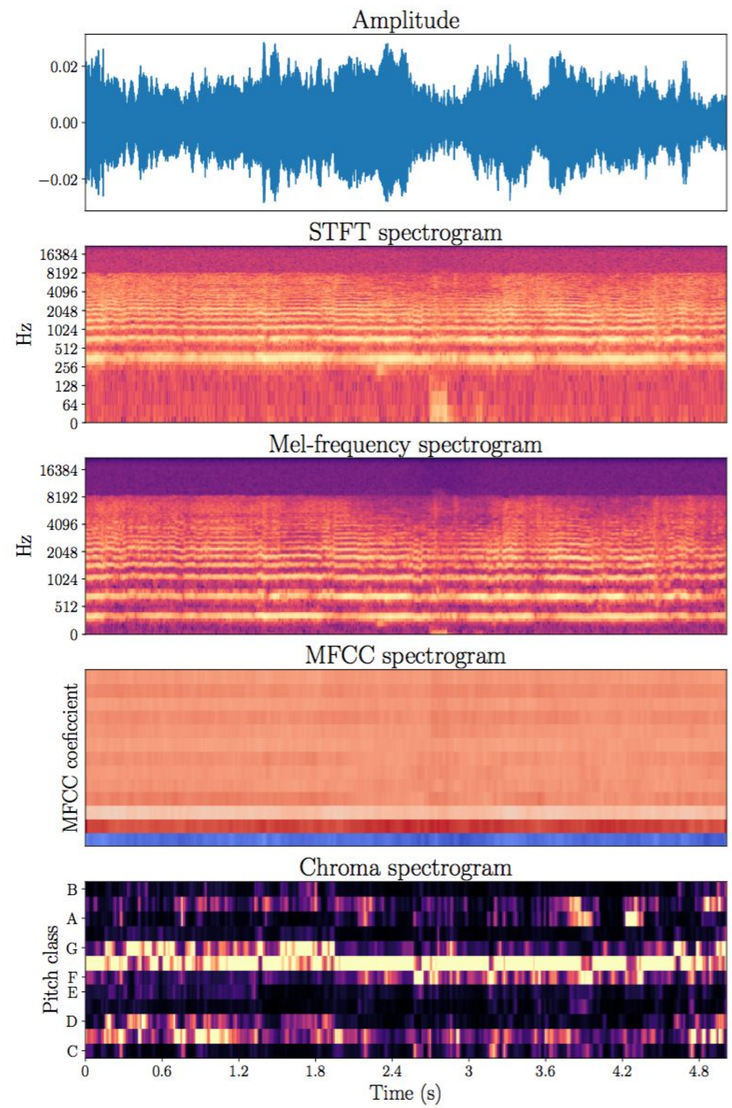

Final thoughts & conclusion

- Increasing evidences that climate change already impacted the distribution of important vectors over the past 20 years: worrying vector trends have been observed in different temperate, arctic and highland regions (**higher altitudes and latitudes**). Many factors drive the emergence of vector-borne diseases.
- **Climate change** will alter the distribution and seasonality of some infectious diseases (vector-borne and water-borne) affecting **humans** and **animals: Need for One Health framework.**
- **Reported autochthonous transmission of DENV, CHIKV in southern Europe (France, Italy, Spain…) and WNV over south-eastern Europe (Italy, Romania, Greece…)**

- Mosquito identification is costly (manpower and equipment wise) and field work is hard work. Harmonization of trapping techniques is work in progress (fan power – substrate chemical composition…)
- Potential of **TinyML** to develop **low-cost** techniques for **mosquito monitoring and identification** with significant value for surveillance system and **public health services**.
- **Wingbeat audio example** but other **ML techniques** can also be applied for **ecological niche modelling** and **insect identification** using the power of citizen sciences project and image recognition techniques.

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