dynamAedes: a unified modelling framework for invasive *Aedes* mosquitoes

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Abstract

1		1. Mosquito species belonging to the genus <i>Aedes</i> have attracted the interest of				
2		scientists and public health officers for their invasive species traits and efficient				
3		capacity of transmitting viruses affecting humans. Some of these species were				
4		brought outside their native range by human activities such as trade and tourism,				
5		and colonised new regions thanks to a unique combination of eco-physiological				
6		traits.				
7	2.	Considering mosquito physiological and behavioural traits to understand and				
8		predict the spatial and temporal population dynamics is thus a crucial step to				
9		develop strategies to mitigate the local densities of invasive Aedes populations.				
10	3.	Here, we synthesised the life cycle of four invasive Aedes species (Ae. aegypti,				
11		Ae. albopictus, Ae. japonicus and Ae. koreicus) in a single multi-scale stochas-				
12		tic modelling framework which we coded in the R package dynamAedes. We				
13		designed a stage-based and time-discrete stochastic model driven by tempera-				
14		ture, photo-period and inter-specific larval competition that can be applied to				
15		three different spatial scales: punctual, local and regional. These spatial scales				
16		consider different degrees of spatial complexity and data availability, by ac-				
17		counting for both active and passive dispersal of mosquito species as well as				
18		for the heterogeneity of the input temperature data.				
19	4.	Our overarching aim was to provide a flexible, open-source and user-friendly				
20		tool rooted in the most updated knowledge on species biology which could be				
21		applied to the management of invasive Aedes populations as well as for more				
22		theoretical ecological inquiries.				
23						
24	K	Keywords: Biological invasions; Invasion ecology; Process-based models; Spa-				
25	tial epidemiology; Dispersal; Vector-borne pathogens					

26 **1** Introduction

Some mosquito species within the Aedes taxon have a unique combination of biological 27 traits such as: 1) efficient transmission of viruses debilitating for humans and animals 28 (Gratz, 2004; Hurk et al., 2011; Souza-Neto et al., 2019), 2) eco-physiological plasticity 29 that allows for rapid adaptation (Kramer et al., 2021) and exploitation of novel environ-30 ments created by humans (McBride et al., 2014a), 3) egg stage with high resistance to dry 31 and cold conditions which facilitate displacements over long ecological and geographi-32 cal distances (Thomas et al., 2012; Versteirt et al., 2012; Kaufman and Fonseca, 2014). 33 Some of these species were accidentally brought outside their native areas by human ac-34 tivities and colonised new regions thanks to a unique combination of eco-physiological 35 traits. These mosquitoes, often referred as "Aedes invasive mosquitoes" (AIM), have at-36 tracted the interest of scientists and public health officers and much effort has been done to 37 unravel their physiological and behavioural traits. Among these species, Ae. aegypti, Ae. 38 albopictus, Ae. japonicus and Ae. koreicus showed a rapid expansion of their geographical 39 range, with the first two species often causing an important burden on public health. As 40 a consequence, large experimental and observational datasets on the relationship between 41 water or air temperature and physiological parameters have been collected and used to 42 develop mechanistic models that reproduce the basic life cycle of these four species (e.g., 43 for Ae. aegypti Focks et al., 1993a,b; Otero et al., 2006; Da Re et al., 2021; Caldwell et al., 44 2021; for Ae. albopictus Tran et al., 2013; Erguler et al., 2016; Metelmann et al., 2019; 45 Pasquali et al., 2020; Tran et al., 2020; for Ae. japonicus Wieser et al., 2019; for Ae. kor-46 *eicus* Marini et al., 2019b). The inclusion of such functions, which describe physiological 47 and developmental rates, into modelling frameworks allow for more reliable model extrap-48 olations, as the chances of biological unrealistic outcome may be lower compared to pure 49 correlative model approaches (Kearney, 2006; Kearney and Porter, 2009). Comparisons 50 between modelled and observed population trends showed that such mechanistic models 51 can be used, for example, to understand population dynamics in space and time, and thus 52 can enhance the pest control strategies against AIM (Baldacchino et al., 2015). 53

Models targeting AIM developed so far aimed to simulate the population dynamics 54 of only one species at the time and for a single qualitative (i.e. "individual", "container" 55 or "household") or quantitative (cell in a lattice grid) spatial scale. Moreover, only a few 56 of these models have been made readily operational, for example by organising them in 57 open-access, user-friendly software or libraries with sufficient documentation for practi-58 cal applications (Stallman, 1985). SkeeterBuster, a container-level population dynamical 59 model for Ae. aegypti, has been the first agent-based model for mosquitoes made available 60 as a free (but not open-source) software (Magori et al., 2009). Concerning Ae. albopictus, 61 Erguler et al. (2016) made available a model developed as a Python library that was after-62

wards wrapped into the R package albopictus. More recently, the European Centre 63 for Disease Control (ECDC) has provided a free and open-source adaptation of a model 64 initially developed by Tran et al. (2013), making it accessible via the R Shiny application 65 AedesRisk¹. Similarly, two generic age and stage-structured discrete-time population 66 dynamics models, also applicable to mosquitoes, were proposed in the last few years: 67 stagePop (Kettle and Nutter 2015; applied to Ae. japonicus in Wieser et al. 2019) and 68 sPop (Erguler, 2018). Despite the current availability of models applicable to invasive 69 *Aedes*, none of them can be directly generalised while retaining biological credibility, e.g. 70 species-specific models work only for a single species whereas generic models may over-71 simplify the life cycle structure or are not equipped with species-specific physiological 72 parameters. Hence, if users decide to use generic models, they need to screen the scien-73 tific literature, filter and manipulate experimental data (often scarce and non-standardised) 74 to inform models on the species of interest. Moreover, often models do not consider 75 mosquito dispersal or even completely lack spatial structure. 76

Here, we synthesised the life cycle of four AIM species: Ae. aegypti, Ae. albopictus, 77 Ae. japonicus and Ae. koreicus in a single modelling framework, which we coded in 78 the R package dynamAedes. We designed a stage-based and time discrete stochastic 79 model informed by temperature and photoperiod that can be applied to three different 80 spatial scales: punctual, local and regional. These spatial scales were thought to meet 81 different degrees of spatial complexity and data availability, by accounting for both active 82 and human-mediated passive dispersal of the modelled mosquito species as well as for 83 the heterogeneity of temperature data. Our overarching aim was to provide a flexible and 84 open-source tool which could be used for applications related to the management of AIM 85 populations but also for more theoretical ecological inquiries. We described and assessed 86 the model using observational mosquito data and then showed how to use the R package 87 with coding examples and relevant case studies. 88

2 Materials and methods

2.1 A summary of invasive *Aedes* species ecology

91 2.1.1 Aedes aegypti

Aedes (Stegomyia) aegypti (Linnaeus, 1762), commonly referred to as the "yellow fever
 mosquito", was progressively brought outside sub-Saharan Africa by human trade. It was
 first introduced in the Americas during the 16th century and afterwards to tropical and tem perate regions of Asia and Oceania (Powell et al., 2013). Its invasion was likely favoured

¹AedesRisk v1.0: https://shinyapps.ecdc.europa.eu/shiny/AedesRisk/

by a series of functional traits, such as egg desiccation-resistance, that allows them to 96 withstand dry conditions for months, and egg moderate resistance to cold temperatures 97 (Juliano et al., 2002; Thomas et al., 2012; Kramer et al., 2020). Aedes aegypti efficiently 98 transmit several viruses to humans, including yellow fever, dengue, chikungunya, Zika, 99 Rift Valley, Mayaro and eastern equine encephalitis viruses (Leta et al., 2018; Näslund 100 et al., 2021; da Silva Neves et al., 2021). This is the result of several eco-evolutionary 101 traits that are specific to the species: i) high preference for human hosts (anthropophily), 102 which is channelled by genetic traits linked to behavioural and physiological evolution-103 ary advantages (Harrington et al., 2001; McBride et al., 2014b), ii) exploitation of human 104 dwellings and architectures as shelter, hide and resting indoor sites (endophily) to avoid 105 unfavourable environmental conditions (Dzul-Manzanilla et al., 2017; Gloria-Soria et al., 106 2018), and iii) selection of artificial containers for oviposition and subsequent larval de-107 velopment (eusynantrophy; Christophers, 1960). 108

109 2.1.2 Aedes albopictus

Aedes (Stegomyia) albopictus (Skuse, 1895), commonly referred as the "Asian tiger mosquito", 110 is native of tropical and subtropical regions of Southern-East Asia and Indonesia (Wat-111 son, 1967; Hawley, 1988). It is a competent vector of several viruses, including dengue, 112 chikungunya, Zika, West Nile, eastern equine encephalitis and La Crosse viruses (Koch 113 et al., 2016; McKenzie et al., 2019; Takken and van den Berg, 2019) and it was implicated 114 as the vector species causing local transmission of dengue, chikungunya or Zika virus, 115 even at temperate latitudes outside its native distributional range (Effler et al., 2005; Rezza 116 et al., 2007; Delatte et al., 2008; Venturi et al., 2017; Brady and Hay, 2019; Giron et al., 117 2019; Barzon et al., 2021). This species is a more opportunistic feeder compared to Ae. 118 aegypti (Cebrián-Camisón et al., 2020). It prefers sub-urban habitats with the presence 119 of vegetation, dispersing bites among several species, a behaviour that might decrease the 120 probability of pathogen transmission to humans (Turell et al., 1994; Lounibos and Kramer, 121 2016). Populations of this species located at temperate latitudes show: i) an adaptation to 122 temperate climatic conditions (Marini et al., 2020) and ii) a stronger tendency to laying 123 diapausing eggs at the end of summer (Hawley et al., 1989; Lacour et al., 2015). Dia-124 pausing eggs have been found to be resistant to below-freezing temperatures and probably 125 allowed Ae. albopictus populations to overwinter and spread towards higher latitudes than 126 Ae. aegypti (Hawley et al., 1989; Thomas et al., 2012). 127

128 2.1.3 Aedes japonicus japonicus

Aedes (Hulecoeteomyia) japonicus japonicus (Theobald, 1901) [Hulecoeteomyia japonica], the "Asian bush mosquito", originated in an area comprised between East China,

East Russia and Japan (Tanaka et al., 1979a). This species may be competent for the trans-131 mission of pathogens of medical importance for humans, such as dengue, West Nile, Zika 132 and Usutu viruses, but only experimental evidences of its role as vector exist (Takashima 133 and Rosen, 1989; Scott, 2003; Schaffner et al., 2011; Westby et al., 2015; Veronesi et al., 134 2018; Jansen et al., 2018; Martinet et al., 2019; De Carlo et al., 2020; Abbo et al., 2020; 135 Hopkins et al., 2020; but see Kilpatrick et al., 2005 for an estimated risk of transmitting 136 WNV by this species). Its likely lesser role as a vector for human pathogens may also be 137 assumed from the tendency to feed on other species than humans as well as the preference 138 for more natural over urbanised areas. Established populations of Ae. japonicus were de-139 tected in North America from 1998 and more recently in European countries (Scott, 2003; 140 Versteirt et al., 2009; Seidel et al., 2016; Eritja et al., 2019; Müller et al., 2020; ECDC, 141 2021). This species is well adapted to cold climates, overwintering either as larvae in the 142 warmer areas, or as diapausing eggs (Krupa et al., 2021) in areas where larval habitats 143 freeze completely (Scott, 2003; Reuss et al., 2018; Day et al., 2020). 144

145 2.1.4 Aedes koreicus

Aedes (Hulecoeteomyia) koreicus (Edwards, 1917) [Hulecoeteomyia koreica] commonly 146 referred to as the "Korean bush mosquito" is native to temperate areas of Northeast Asia 147 comprising Russia, the Korean peninsula, Japan and north-east China (Tanaka et al., 1979b). 148 This species is a suspected vector of *Dirofilaria immitis*, Japanese encephalitis and chikun-149 gunya viruses, but it has not yet been directly implicated in transmission events of zoonotic 150 pathogens (Tanaka et al., 1979b; Montarsi et al., 2015a; Ciocchetta et al., 2018). Aedes 151 koreicus is adapted to temperate climates (Versteirt et al., 2012) and has recently colonised 152 areas of Central Europe while continuing its range expansion (Capelli et al., 2011; Versteirt 153 et al., 2012; Montarsi et al., 2015a; Marcantonio et al., 2016; Werner et al., 2016; Negri 154 et al., 2021; Horváth et al., 2021; Andreeva et al., 2021; Gradoni et al., 2021; ECDC, 2021). 155 Aedes koreicus seems to prefer rural over highly urbanised habitats and has been found to 156 feed on other species than humans (Montarsi et al., 2013, 2014; Cebrián-Camisón et al., 157 2020). In areas where Ae. koreicus lives in sympatry with other invasive Aedes species, 158 the Korean bush mosquito is able to colonise higher altitudes and its development can start 159 earlier in the season with respect to other AIM (Montarsi et al., 2015a; Marcantonio et al., 160 2016). This trait may give them a competitive advantage over other container-breeding 161 mosquitoes whose adults emerge later in the season. 162

163 2.2 The theoretical structure of the model

The basic structure of dynamAedes has been described in Da Re et al. (2021). We amended some components of the model to generalise its structure. Thus, we provide here a short recap of model structure while describing the new model features.

dynamAedes is composed of three main compartments (life stages) that represent a 167 simplified version of Aedes the mosquito life cycle: egg, juvenile and adult stages (Fig. 1). 168 Larval and pupal stages, which can be assumed to have somewhat similar physiological 169 requirements, are fused in a unique "juvenile" compartment. Each compartment is divided 170 into sub-compartments to account for the different physiological states for individuals in 171 the three main compartments (e.g. 1-day old adult females that are not sexually mature). 172 The number of sub-compartments into each compartment is dictated by the known min-173 imum number of days needed by each species to pass to the next stage or complete the 174 gonotrophic cycle (for adults). Thus, the minimum duration of development in each com-175 partment varies among developmental stages as well as among species. As an example, 176 the whole duration of the developmental cycle (i.e. from egg-laying to adult emergence) 177 has a minimum duration of 11 days for Ae. aegypti and Ae. albopictus, whereas 21 days 178 for Ae. koreicus and Ae. japonicus (see Tab S3 in SM for generic model assumptions). 179

In the model, time is treated as a discrete quantity and "day" is the fundamental temporal unit. Therefore, each event in the simulated life cycle occurs once per day and always in the same order. The model can be run with or without a spatial structure. If the model is spatially explicit, space is treated as a discrete quantity. In this case, the fundamental spatial unit is a (user defined) cell of a lattice grid into which the species life cycle takes place and, if relevant (see below), among which adult mosquitoes disperse.

Adult female mosquitoes lay non-diapausing eggs, E, in the summer months or diapausing eggs, Ed, at the end of the season. The embryonic development and hatching of diapausing eggs are activated by increasing daily temperature and photoperiod (typically at the end of winter or early spring). All the developmental and reproductive events considered in the model were treated as stochastic processes with probabilities derived from temperature(or photoperiod)-dependent functions by following the generic formulation:

$$X_{s,t}^{event} \sim Binomial(X_{s,t-1}, \pi_X) \tag{1}$$

where $X_{s,t-1}$ may represent eggs, juveniles or adults that undergo one of the following events in the life cycle: lay eggs, hatch, emerge or survive in cell s, at the end of the day t - 1. π_X is the temperature-dependent (or photoperiod dependent for the hatching of diapausing eggs) daily probability of any of the life cycle events X. All the temperaturedependent functions were calibrated using data from the scientific literature (see Tab S4 in SM) fitted using exponential, polynomial equations, and non-linear Beta density functions,

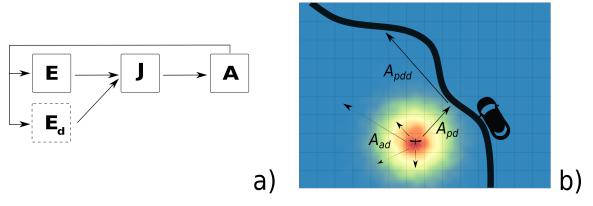


Figure 1: Graphical representation of dynamAedes model structure, adapted from Da Re et al. (2021): a) the life cycle of a generic simulated mosquito species, while in b) a representation of active and passive dispersal processes happening within the Adult (A) compartment at local scale. E: egg compartment; Ed: diapause egg compartment (available for all species except *Ae. aegypti*); J: juvenile compartment; A: adult compartment; Aad: adult active dispersal; Apdd: adult passive dispersal; Apd: adult probability of being caught in a car.

using a combination of drc (non-linear models) and aomisc (Beta function self-starters) 198 R packages (Ritz et al., 2015; Onofri, 2020). The beta function derives from the beta 199 density function and it has been adapted to describe phenomena taking place only within a 200 minimum and a maximum threshold value (threshold model), such as physiological rates 201 with respect to temperatures in the mosquito life cycle (Onofri, 2020). In a similar fashion, 202 adult active dispersal was modelled as species-specific log-normal decaying functions of 203 distances derived from dispersal estimates from field observations for Ae. aegypti and Ae. 204 albopictus (Roche et al. 2015; Marcantonio et al. 2019; Marini et al. 2019a; Müller et al. 205 2020; see Tab S5 in SM for dispersal parameters). In addition to active dispersal, the model 206 also considers dispersal aided by cars along the main road network (a matrix containing 207 the coordinates of the grid cells of the landscape intersecting the road network must be 208 provided, see the "Spatial scales of the model and temperature data sources" section), 209 defined as the "hitchhiking" probability of a female to enter in a car and to be driven 210 and released further away. This probability has been defined for all species by estimates 211 measured for Ae. albopictus (Eritja et al., 2017), while the average distance covered by a 212 single car trip was taken from Pasaoglu et al. (2012). This type of dispersal is thought to 213 be amongst the main drivers of medium-range geographical expansion for invasive Aedes 214 mosquitoes, especially for Ae. aegypti and Ae. albopictus (Marcantonio et al., 2016; Eritja 215 et al., 2017; Müller et al., 2020). 216

Density-dependent survival is an important regulatory factor of mosquito population 217 dynamics (Gilpin and McClelland, 1979). Its regulatory effect for juvenile stages appears 218 to be more common in mosquitoes breeding in container or highly ephemeral habitats 219 (Juliano, 2007), such as invasive Aedes. In dynamAedes we parameterised a density-220 dependent function by extracting observations on Ae. aegypti from Figures 2a and 2b in 221 Hancock et al. (2016) using the Webplot Digitizer (Rohatgi, 2020). We considered the pro-222 portion of juveniles that survived through the juvenile stage (in a 2 L container) reported 223 by these authors as an estimate of juvenile survival probability at different densities. Mor-224 tality probabilities $(1 - proportion \ surviving)$ were converted into rates, which were 225 scaled to a daily time step dividing by the corresponding immature development time (in 226 days) at different densities. Finally, we regressed the natural logarithms of these daily 227 mortality rates on the corresponding densities. The fitted daily survival rate at different 228 densities was then summed to the temperature-dependent juvenile mortality. The resulting 229 probability was then used to inform a binomial random draw (see equation 1) describing 230 overall juvenile daily survival. 231

Some invasive Aedes can lay eggs resistant to low temperature commonly referred 232 to as "diapausing eggs" (Thomas et al., 2012; Lacour et al., 2015; Krupa et al., 2021). 233 Diapause describes the evolutionary adaptation exploited by insect species to overcome 234 unfavourable environmental conditions by passing through an alternative and dormant 235 physiological stage. In Ae. albopictus, maternal photoperiod is the environmental stim-236 ulus implied to induce oviposition of "diapausing eggs" (Pumpuni et al., 1992; Lacour 237 et al., 2015). In dynamAedes, the oviposition of diapausing/non-diapausing eggs was 238 integrated as a species-specific exponential function on the incidence of diapausing eggs 239 given photoperiod length (and thus geographically-dependent; Urbanski et al. 2012; Petrić 240 et al. 2021). The function is based on data from Lacour et al. (2015) for Ae. albopictus and 241 Krupa et al. (2021) for Ae. japonicus. We applied the same diapausing function developed 242 for Ae. japoncus to Ae. koreicus due to the close phylogeny of these species and the lack 243 of data for Ae. koreicus (see Tab. S6). The daily survival of diapausing eggs was set to 244 be constant (0.99) only for Ae. japonicus and Ae. koreicus, while for Ae. albopictus we 245 used the exponential function described in Metelmann et al. (2019). The hatching rate 246 of diapause eggs was triggered by an increasing photoperiod regime (spring) from 11.44 247 hours of light for Ae. albopictus (95th percentile estimated from Petrić et al. 2021) and 248 10.71 hours for Ae. japonicus or Ae. koreicus (Krupa et al., 2021). 249

250 2.3 Overview of the R package

The function dynamAedes.m calls the model and allows to customise the simulated scenario through a suite of options. As for the simplest application of the model (no explicit

spatial dimension, scale="ws", see next paragraph for further details), the user has to 253 define what species to model through the argument species (default "aeqypti"), the 254 "type" and number of introduced propagules through intro.eggs, intro.juvenile 255 or intro.adults (default intro.eqqs=100, intro.juvenile=0, intro.adults=0), 256 and the volume (L) of water habitats wanted in each spatial unit with the argument lhwv 257 (larval-habitat water volume, parameterised from Hancock et al. 2016; default lhwv=2; 258 see Fig S13 for a sensitivity analysis of this parameter). Moreover, the argument temps.matrix 259 takes the matrix of daily average temperature (in Celsius degree) used to fit the life cycle 260 rates. This matrix must be organised with the daily temperature observations as columns 261 and the geographic position of the *i*-grid cell as rows (it follows that the matrix will have 262 only one row when scale="ws"). The day of start, end and number of iterations are 263 defined by startd, endd and iter, respectively. The model has been optimised for 264 parallel computing and the number of parallel processes can be specified through the op-265 tion n.clusters. If the modelled species is Ae. albopictus, Ae. japonicus or Ae. 266 koreicus (e.g., species="albopictus") then the arguments defining latitude (lat), 267 longitude (long) and year of introduction (intro.year) should be adequately defined 268 to allow a correct switch to and from the egg diapausing stage. 269

The default output of dynamAedes consists of a list of numerical matrices containing, 270 for each iteration, the number of individuals in each life stage per day (and for each grid 271 cell of the study area if scale="lc" or "rg"). If the argument compressed.output=FALSE 272 (default TRUE), the model returns the daily number of individuals in each life stage sub-273 compartment. The model, coded in the R statistical language (R Core Team, 2021), 274 and adapted for parallel computation, is available on the the following link https: 275 //github.com/mattmar/dynamAedes (it has meanwhile been submitted to the 276 CRAN). 277

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#model parameters
cl=47 #number of cluster
it=100 #number of iterations
ie=500 #number of introduced eggs
str=1 #day intro
endr=ncol(ww1) #day end simulations
aeg.cal <- dynamAedes(species="aegypti",</pre>
                         scale="rg",
                         temps.matrix=ww1,
                         startd=str, endd=endr,
                         n.clusters=cl,
                         iter=it,
                         intro.eggs=ie,
                         ihwv=100,
                         verbose=FALSE)
albo.cal <- dynamAedes(species="albopictus",</pre>
                         lat=37, long=-120,
                         intro.year=2015,
                         scale="rg",
                         temps.matrix=ww1,
                         startd=str, endd=endr,
                         n.clusters=cl,
                         iter=it,
                         intro.eggs=ie,
                         ihwv=100,
                         verbose=FALSE)
```

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279 2.3.1 Spatial scales of the model and input temperature data

The selection of the geographical scale for population dynamics is a crucial aspect of the whole package and the temperature dataset provided to dynamAedes function must reflect this decision. Along with the photoperiod, temperature is the other only environmental driver of our model, which is dictated by its central role in mosquito development and activity. The measurement of temperature is inevitably scale-dependent, thus we structured the model to allow for temperature datasets relevant for different measurement spatial scales (Fig. 2) and to match the different hypotheses that users may want to test.

The punctual or "weather station" scale (scale="ws") is the smallest geographic scale (i.g., no spatial dimension) available in dynamAedes and the environment mod-

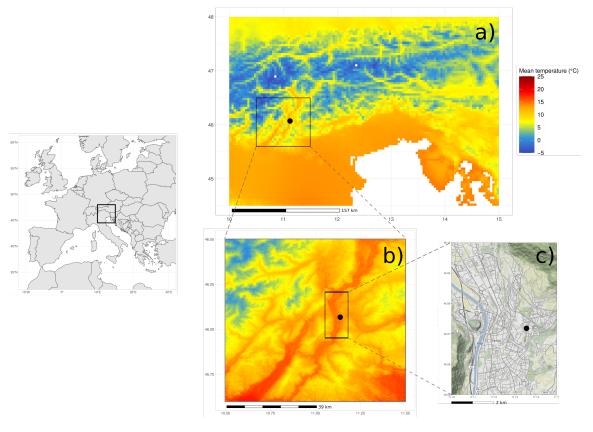


Figure 2: dynamAedes allows to simulate *Aedes* mosquitoes population dynamics at three different spatial scales: a) regional, b) local, and c) punctual (weather station). Passive and active dispersal is enabled only at local spatial scale.

elled is assumed to be what represented by the chosen weather station (or any other dataloggers). In this case, the model has no spatial structure, thus dispersal is not considered:
the model will return the temporal trend of population dynamics given the chosen temperature, larval-habitat water volume and photoperiod conditions.

The "local" scale (scale= "lc") represents those scenarios and spatial resolutions 293 at which species dispersal and local microclimate variability are relevant for users. We 294 suggest to keep the resolution of the matrix of temperatures equal or smaller than the 295 maximum daily dispersal range of the mosquito species (i.e., usually under 1 km for 296 Aedes species; Guerra et al., 2014). The optional arguments cellsize, dispbins 297 and maxadisp are available to fine tune the dispersal kernel which drives the spatial 298 behaviour of the simulated mosquito populations. The argument cellsize (default 299 "cellsize=250" meters) sets the minimal distance of the dispersal kernel and should 300

match the size of the cell to avoid inconsistencies (i.e., mosquitoes dispersing at a finer 301 or bigger grain than the arena), maxadisp sets the maximum daily dispersal (default 302 maxadisp=600 meters), and dispbins the resolution of the dispersal kernel (de-303 fault dispbins=10). Passive dispersal is also implemented and it requires i) a matrix 304 containing the coordinates of the grid cells of the landscape intersecting the road network 305 (argument road.dist.matrix), and ii) to specify the average car trip distance through 306 the argument country, which can be defined by the user or considering estimates for 307 the following countries: France, Germany, Italy, Poland, Spain and the United Kingdom 308 Pasaoglu et al. (2012). An extensive example of model application at local spatial scales 309 is described in Da Re et al. (2021). 310

The rationale behind the third spatial scale considered in the model, the "regional" scale (scale= "rg") was to return an overview of invasive *Aedes* population dynamics over large extents (i.e., larger than 1 km). The model in regional scale does not account for species dispersal, introductions happen separately (but at the same time) in each grid cell which hence are closed systems. The output of the model at "regional" scale can be compared to those produced by correlative species distribution models (SDMs), with the advantage of mechanistic rather than purely correlative model foundations.

The amount of water available for larval development in each spatial unit(s) (at any model spatial scale) was set as 2 L that is the water volume considered in the experiments we used to parametrise model functions Hancock et al. (2016). It is likely that for many real-world model applications, the relative availability of breeding habitats is much higher, and we encourage users to set a value based on their scenarios and hypotheses (i.e. through the model option lhwv; Hartemink et al. 2015).

324 2.3.2 Auxiliary functions

Several auxiliary functions are available to analyse model outputs. The function psi re-325 turns the proportion of model iterations that resulted in a viable population for the given 326 date. It works for all spatial scales and the output can reflect either the overall grid or 327 each single cell. Likewise, summaries of mosquito abundance at each life stage for each 328 day can be obtained through adci, which by default returns the inter-quartile range abun-329 dance of each life stage. Similarly, icci returns a summary of the number of invaded cells 330 over model iterations. Estimates of dispersal spread (in km^2) of the simulated mosquito 331 populations is provided by the function dici, which is available only for model results 332 computed at the local scale (the only scale which integrates dispersal). Finally, the function 333 get_rates_spatial, returns the output of the temperature-dependent physiological 334 functions used by dynamAedes to derive the daily rates. It can be used to better under-335 stand the outcome of model simulations, by highlighting those areas where the predicted 336

values of the temperature-dependent functions are maximised or minimised, or to derive
causal-based physiological estimations that, for example, could be used as inputs for correlative SDMs (e.g., Kearney and Porter, 2009; Mathewson et al., 2017).

340 3 Case studies and model validation

We applied the model to three case studies representing different geographical scales and areas, species and invasion trajectories. The case studies were chosen considering the availability of optimal mosquito data-sets to show model strength and weakness. We did not report any example for the "local scale" as it had already been provided in Da Re et al. (2021), who applied a previous version of dynamAedes.

346 3.1 Regional scale models

347 3.1.1 Likelihood of successful introductions of *Ae. albopictus* and *Ae. aegypti* across 348 California, USA

We used dynamAedes at "regional" scale to assess the likelihood of successful intro-349 ductions for two invasive Aedes across California: Ae. aegypti and Ae. albopictus which 350 are considered established from 2011 and 2013, respectively (Fujioka, 2012; Gloria-Soria 351 et al., 2014). California is among the few areas where established populations of these two 352 species were detected during the last decade and their progressive spread was documented 353 in great detail². We downloaded daily minimum and maximum temperature data from the 354 NASA Daily Surface Weather Data on a 1-km Grid for North America (DAYMET), Ver-355 sion 4 (Thornton et al., 2020) from 1 January 2011 to the 31 December 2018. These two 356 sets of data (in netCDF raster format) were clipped to the boundary of California and ag-357 gregated at a spatial resolution of 2.5 km by using a combination of GDAL (GDAL/OGR 358 contributors, 2021) and Climate Data Operators (CDO; Schulzweida, 2019) software. The 359 two sets of raster layers were then imported in R 4.0.4 (R Core Team, 2021), transformed 360 in matrices, averaged and converted to integers to obtain a single average daily temper-361 ature integer matrix with cell id as observations (rows) and days as variables (columns). 362 This dataset was used as the input temperature matrix for the model. We run 80 model 363 iterations for five years, introducing 500 eggs in each cell of the gridded landscape on 15 364 May 2011 and 2013 for Ae. aegypti and Ae. albopictus respectively. By using the auxil-365 iary function psi, we then derived a map showing the proportion of iterations with viable 366 population of both Ae. aegypti and Ae. albopictus at the end of the simulated period (15 367

²See https://maps.vectorsurv.org/

May 2016 and 2018). The photoperiod was set to match conditions in the geographical center of California (Lat 37° N, Lo -120° W) and the amount of breeding habitat was set to 100 L (per cell), which we assumed to be representative of the potential water larval habitats available given cell size and overall regional climate.

We validated model prediction using maps of cities in California with known species 372 presence updated to 2021 by the California Department of Public Health (CDPH³). We 373 derived the average predicted probability of successful introduction for each city and com-374 puted the Area Under the ROC Curve (AUC) score which defines the probability that a 375 randomly chosen positive city will be ranked higher than a randomly chosen negative city. 376 An AUC score > 0.5 indicates that the model is performing better than random, while a 377 score of 1 indicates perfect prediction. In addition, we calculated the percentage of posi-378 tive cities that fell into a grid cell that had a probability of establishment higher or equal to 379 1% (e.g., at least 1 out of the n_{th} iterations reported a viable mosquito population in that 380 cell). 381

The predicted spatial pattern of areas with a high likelihood of Ae. aegypti and Ae. 382 albopictus successful introduction is in general consistent with updated information on 383 the presence of this species (Fig. 3). Predictions show moderate-to-high probabilities of a 384 successful introduction in all counties with known presence of these species, except for the 385 extreme South-East coastal part of the state, where Ae. aegypti was predicted to have a low 386 probability of successful introduction whereas being well established (Fig. 3). This may 387 be due to the high micro-climatic variability that characterises coastal areas of California 388 which may not be resolved by the temperature datasets that we have considered in this case 389 study. On the contrary, areas predicted to be suitable for Ae. albopictus exceeded by far the 390 known current distribution of this species. Factors other than temperature and photoperiod, 391 more nuanced aspects of species invasion history and the extremely low humidity during 392 the dry season in the Central Valley of California or the Inland Empire, may hinder species 393 establishment in these areas. Nevertheless, recently Ae. albopictus was found as north as 394 Redding, Shasta County, thus it is not unlikely that this species is also present (perhaps at 395 low densities), but not yet detected, at southern latitudes in California. 396

Both models had over 75% of successful introduction scores (calculated as the proportion of pixels with species observations and simulated proportion of invasion > 1%) when validated at city levels (Tab. 1). Still, only the prediction for *Ae. aegypti* validated at city levels reported an AUC score bigger than 0.5 (Tab. 1), whereas validating the model by averaging the predictions at county level resulted in an AUC bigger than 0.5 for both species (0.892 and 0.717 for *Ae. aegypti* and *Ae. albopictus* respectively; Fig. S14).

³California Department of Public Health, "Map and City List of *Aedes aegypti* and *Aedes albopictus* Mosquitoes in CA, 2011-2021" (accessed on 28th October 2021): https://www.cdph.ca.gov/ Programs/CID/DCDC/Pages/VBDS.aspx

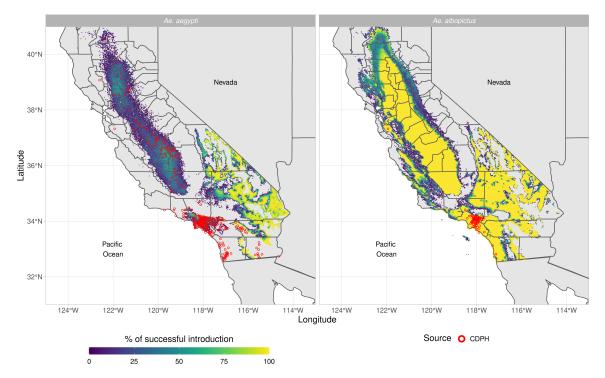


Figure 3: Predicted percentage of established introductions of *Ae. aegypti Ae. albopictus* in California (USA) for the years 2011-2016 and 2013-2018, respectively. The red dots represent the centroids of the Californian municipalities with established populations as reported by the Californian Department of Public Health (CDPH).

403 3.1.2 Likelihood of successful *Aedes albopictus* introductions in France

Aedes albopictus was first detected in metropolitan France in 1999 (Schaffner et al., 2000) 404 and since 2004 it has established populations in the southern part of the country while 405 still expanding its distribution range (ECDC, 2021). We used dynamAedes model at 406 "regional" scale to assess the success of introductions of Ae. albopictus for the whole 407 metropolitan France. We processed ERA5-Land (Muñoz-Sabater et al., 2021) hourly air 408 temperature measured at 2 m above surface from January 1st 2015 to December 31st 2020 409 in the Climate Data Store (CDS) Toolbox⁴ to get the daily mean temperature of the period 410 considered for the whole metropolitan France, at the spatial resolution of ~ 9 km. The 411 netCDF file obtained was imported in R 4.0.4 (R Core Team, 2021), where was clipped 412 to the extent of metropolitan France, converted from degrees Kelvin to Celsius and con-413 verted to integer to obtain a single average daily temperature integer matrix with cell id 414

⁴CDS Toolbox: https://cds.climate.copernicus.eu/toolbox/doc/index.html

as observations (rows) and days as variables (columns). This dataset was then used as the input temperature matrix for the model. We run 100 simulations for five years, introducing 100 eggs in each cell of the gridded landscape on 15 May 2015. By using the auxiliary function psi, we derived a probability map of the areas showing the proportions of iterations that produced a viable population of *Ae. albopictus* five years after the simulated introductions.

We validate the model predictions using the list of the 3419 French municipality re-421 porting established Ae. albopictus until 2020 provided by the French Health Ministry (data 422 collected thanks to active monitoring from French mosquito operators and passive surveil-423 lance⁵). Similarly to the previous case study, we computed both the AUC as well as the 424 proportion of positive location falling into a grid cell that had a percentage of established 425 introductions higher than or equal to 1%. The spatial pattern of the areas predicted to have 426 a high likelihood of successful Ae. albopictus introduction (Fig. 4) is consistent with up-427 dated observational data (Ae. albopictus map; ECDC, 2020) as well as with the results of 428 other mechanistic models (see for instance Metelmann et al., 2019; Pasquali et al., 2020). 429 The Mediterranean French coast and the Rhone valley are the areas where our model pre-430 dicted the highest percentage of successful introduction. Similarly, the Aquitaine region on 431 the Atlantic coast and the Alsace region in the North-East part of France showed relatively 432 high predicted percentage of successful introduction. The northern and the central part of 433 France, as well as the Pyrenees areas, show low percentage of successful introduction un-434 der the current climatic conditions. However, the resolution of the pixel, approximately 10 435 km, may have played a role influencing the model outcomes especially in topographically 436 complex areas such as the Pyrenees or the French Alps, where the microclimate of the 437 valleys may be underestimated. Similarly, the model was not able to predict the successful 438 introduction of the species in areas such as Paris, where Ae. albopictus is established and 439 probably favoured by i) local climatic factors such as the urban heat island effect, and ii) 440 the continuous inflow of *Ae. albopictus* propagules to Paris from areas where the species 441 is already established. Indeed, most railways, flights and highways have a connection with 442 Paris, and the Paris-Lyon-Mediterranée axis is the main artery of France, with an average 443 of >60,000 cars/day on the highway⁶ and 240 trains per day⁷, thus the quantity of imported 444 mosquitoes can compensates for the less favorable climatic conditions of Paris compared 445 to the Mediterranean region (recent phylogeographic findings support this hypothesis, see 446 Sherpa et al., 2019). All the model performances metrics assessed support the capacity of 447 the model to discriminate between areas where the species can or cannot be established 448

⁵https://signalement-moustique.anses.fr/signalement_albopictus/

⁶https://www.data.gouv.fr/fr/datasets/trafic-moyen-journalier-annuel-sur-le-reseau-re ⁷https://www.leparisien.fr/economie/l-europe-fait-passer-la-lgv-paris-lyon-a-l-heure php

449 (Tab. 1).

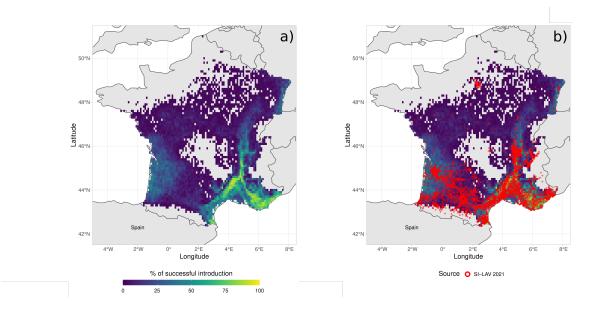


Figure 4: Percentage of successful introduction for *Ae. albopictus* in France for the years 2015-2020: a) Model prediction, b) Model prediction and in red the centroids of the French Municipalities with established population of *Ae. albopictus* reported by the French Health Ministry (SI-LAV).

3.2 Punctual population dynamics temporal trends

451 3.2.1 Aedes albopictus population dynamics in Nice, South-East France

Aedes albopictus is established mainly in the southern part of metropolitan France where 452 more than 40% of municipalities are colonized⁸ and it is still expanding in other areas. We 453 computed the population dynamics of the species informing dynamAedes model at punc-454 tual spatial scale using temperature observations downloaded from the National Oceanic 455 and Atmospheric Administration (NOAA) network via the R package rnooa. The obser-456 vations of the NOAA weather station located in Nice area (usaf code = 076900, Lat 43° 457 42' 00" N, Lon 7° 13' 12" E, 3.7 m a.s.l.), spanning from January 1st 2013 to December 458 31st 2018, were linearly interpolated to fill missing values at hourly and daily level. Af-459 terwards, the daily average for all observations was computed. We run 100 simulations 460 for five years, introducing 500 eggs on 15 May 2013. By using the auxiliary function 461 adci, we then derived the daily abundance inter-quantile range for each life stage and the 462 abundance of newly-laid eggs per day. 463

The model was validated comparing the simulated newly laid eggs per day to egg counts from mosquito ovitrap data, following the validation approach presented in Tran et al. (2013). During the years 2014-2018, fifty ovitraps were installed in the Nice area and inspected fortnightly from April-May to November-December (data collected and kindly provided by EID Méditerranée). We computed the Spearman's *rho* correlation coefficient between the weekly-aggregated simulated newly-laid eggs and the mean observed eggs per day.

Results showed that the model was able to correctly reproduce the seasonal dynamics 471 of the new-laid eggs over five years (Spearman's rho = 0.753, p.value < 0.001). The first 472 simulated eggs were laid during the late spring each year, confirming the fact that the first 473 overwintering eggs hatch at the end of the winter season or at the beginning of spring. 474 The ovipositing season seem to last until the late autumn accordingly to the observations, 475 while our model seems to predict a shorter length of the ovipositing period. Nevertheless 476 the model is able to correctly infer the peak of the ovipositing season during the summer 477 months (Fig. 5). 478

479 3.2.2 Aedes koreicus population dynamics in Trento, North-East Italy

Aedes koreicus was first detected in Trento Autonomous Province (NE Italy) in 2013, soon
 after the first Italian detection in the neighboring Belluno province (Capelli et al., 2011).

⁸https://solidarites-sante.gouv.fr/sante-et-environnement/ risques-microbiologiques-physiques-et-chimiques/especes-nuisibles-et-parasites/ article/cartes-de-presence-du-moustique-tigre-aedes-albopictus-en-france-metropolitain

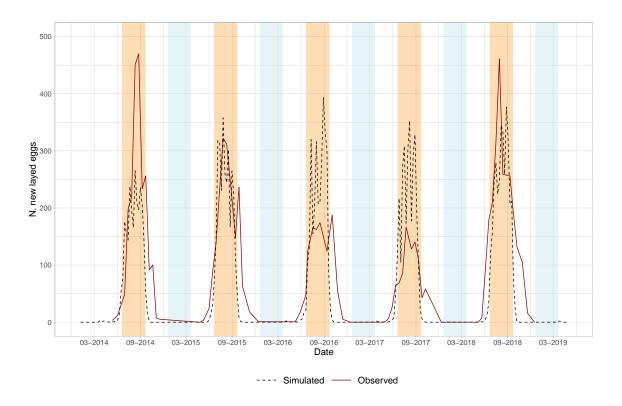


Figure 5: Temporal trend reporting the simulated and observed new-laid eggs of *Ae. albopictus* years 2014-2018 in Nice, SE France. The light blue bands represent the winter seasons, while the orange bands the summer seasons. The simulated data were rescaled for graphical purpose using as rescaling factor the ratio between the maximum observed value and the maximum median simulated values.

We computed the population dynamics of the species informing dynamAedes model 482 at punctual spatial scale using temperature observations downloaded from the local net-483 work of weather stations⁹. The daily average temperature observations from the "Trento 484 Laste" weather station (Lat 46° 04' 18.5" N, Lon 11° 08' 08.5" E, 312 m a.s.l.) spanning 485 from 1 January 2015 to 31 December 2018 were linearly interpolated to fill missing val-486 ues. We run 100 simulations for five years, introducing 500 eggs on 15 May 2015. Using 487 the auxiliary function adci, we then derived the daily inter-quartile range abundance for 488 each life stage and for the daily host-seeking female sub-compartment. 489

The model was validated computing Spearman's *rho* correlation coefficient between the monthly-aggregated simulated host-seeking females and the observations gathered

⁹www.meteotrentino.it

from four BG-Sentinel traps installed in Trento municipality from April to November during the years 2016, 2017, and 2018 (data obtained from Marini et al. 2019b). In order to compare observed and simulated data, the whole simulated host-seeking females abundance was multiplied by a BG-sentinel catching rate equal to 0.157, as estimated by Marini et al. (2019b) and similar to what already reported for *Ae. albopictus* in previous studies (Guzzetta et al., 2017).

The simulated population dynamics showed that *Ae. koreicus* could be successfully introduced in the study area. The model correctly predicted the start of the seasonal activity in early spring, while the higher abundance of female host-seeking mosquitoes was predicted to be in late summer. Considering the three years together, our model was able to reproduce the observed seasonal population dynamics, where the 76.2% (47.6%) of the observed captures lie within the 95% (50%) credible intervals of model predictions (Tab S7). Similarly, the Spearman's rho for the three yeas was 0.735 (p.value < 0.001) (Tab. 1)

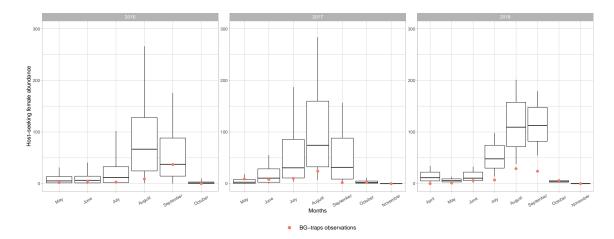


Figure 6: Temporal trend reporting the boxplot of simulated and observed host-seeking *Ae. koreicus* females for the years 2016-2018 in Trento, NE Italy.

Species	Geographic location	Scale	AUC	Specificity	Sensitivity	Sensitivity 1%	Spearman's ρ
Ae. aegypti	California	Regional	0.658 (0.401-0.914)	0.8	0.642	0.795	-
Ae. albopictus	California	Regional	0.435 (0.367-0.502)	0.241	0.641	1	-
Ae. albopictus	France	Regional	0.874 (0.867-0.880)	0.788	0.802	0.848	-
Ae. albopictus	S-E France	Punctual	-	-	-	-	0.753***
Ae. koreicus	N-E Italy	Punctual	-	-	-	-	0.735***

Table 1: Model validation. The column "Sensitivity 1%" reports the proportion of cities predicted to have at least one successful introduction over the total number of iterations (predicted introduction success equal or over 1%. *** p.value < 0.001).

505 **4 Discussion**

From an ecological perspective, our modelling approach focuses on the species funda-506 mental thermal niche (sensu Hutchinson, 1957), since we considered temperature as the 507 main driver of population growth and dynamics. In light of this, our model was able to in-508 fer spatial and temporal population dynamics of different species, at different geographic 509 scales and locations. The model showed overall good validation performance, and the ar-510 eas predicted to likely support Aedes mosquito populations largely matched what reported 511 by observational studies and other existing models (Kraemer et al., 2015, 2019; Oliveira 512 et al., 2021). 513

Nevertheless, we raise the attention on two aspects that should be considered when 514 applying dynamAedes and interpreting model results. First, good quality information on 515 survival and developmental rates is largely available for Ae. aegypti and Ae. albopictus, 516 whereas much less for the other two species. Similarly, mosquito observational datasets 517 with sufficient longitudinal depth for model validation are scarce for Ae. koreicus and 518 presently absent, to the best of our knowledge, for Ae. japonicus. Thus, whilst we have 519 built the foundations for an open-source modelling framework that can be progressively 520 expanded, life cycle functions and thus outputs for Ae. japonicus and Ae. koreicus should 521 be interpreted more carefully. 522

Secondly, we recognise that pixel size may influence model outcome because of the 523 aggregating effect of the Modifiable Unit Areal Problem (Jelinski and Wu, 1996; Da Re 524 et al., 2020). While the consequences of this artifact are well known in SDMs applications, 525 they are rarely mentioned or addressed (but see Peterson, 2014). Thus, the correct choice 526 of temperature datasets is crucial to investigate species population dynamics and interpret 527 model results (Bütikofer et al., 2020). Climatic reanalysis and Global/Regional Circula-528 tion Models are reliable data sources with high temporal resolution for present climatic 529 conditions and robust future projections, though they have a coarse spatial resolution that 530 may underestimate the effect of microclimate on species biology (Metelmann et al., 2019; 531

Liu-Helmersson et al., 2019). Coarse resolution of input temperature data is rather com-532 mon since temperature is often estimated over large extents, and can become an issue in 533 topographically complex regions where the effect of microclimatic variation on population 534 dynamics may pass undetected. The results showed in Fig. 3–4 may be better interpreted 535 considering the coarse resolution of temperature data which may have caused lower pro-536 portion of established populations in topographically complex areas such as the Pyrenees 537 or the Peninsular Ranges. Interpolated local micro-climatic conditions, for example esti-538 mated with the microclima R package (Maclean et al., 2019), have the advantage of 539 providing fine spatial and temporal resolution datasets. But, they need to be first properly 540 validated with field data which are typically difficult to gather also over small geograph-541 ical extents. Temperature measured with classical weather stations may be considered as 542 the most accurate available observations of local climatic conditions. Though it is not al-543 ways easy to deal with such data due to the limited number of weather stations and gaps 544 in the time series, they are suited for statistical downscaling or bias adjustment for climate 545 change projections (Bedia et al., 2020). 546

547 4.1 Model assumptions

Model structure has been designed to be as ecologically relevant as possible considering available data, however, when data were limited, we relied on a set of "expert-based" assumptions that must be clearly stated.

The interplay of multiple environmental factors drives the population dynamics of 551 Aedes mosquitoes but we chose to mold our model framework just on established infor-552 mation available for temperature and photo-period (Pumpuni et al., 1992; Waldock et al., 553 2013; Eisen et al., 2014). This choice was suggested by a generalised lack of clear relation-554 ships between other environmental factors and *Aedes* population dynamics. For example, 555 concerning the role of precipitations, different studies report contrasting results (Koen-556 raadt and Harrington, 2008; Tran et al., 2013; Caldwell et al., 2021). Moreover, invasive 557 Aedes mosquitoes mostly thrive in urban or suburban landscapes where the presence of 558 standing water is often independent from precipitations (except for extreme rainfall events 559 (Roiz et al., 2015). We suggest that, at the present stage, dynamAedes it is better suited 560 for applications in temperate climates, where temperature seasonality is a more important 561 limiting factor than in tropical climates, where other factors may limit mosquito life cycle 562 Lega et al. (2017). 563

On the one hand, we did not consider in the model biotic interactions such as preypredator or food and space competition with other mosquito taxa during the larval stages, despite this is another factor that influences the trajectory of introduced populations (Armistead et al., 2008; Tripet et al., 2011; Reiskind and Lounibos, 2013; Montarsi et al., 2013, ⁵⁶⁸ 2015b; Müller et al., 2018). On the other hand, we considered the effect of intra-specific ⁵⁶⁹ competition on larval survival (but not development). We generalised the information ⁵⁷⁰ available for *Ae. aegypti* to the other *Aedes* species due to the lack of species-specific ex-⁵⁷¹ periments (Hancock et al., 2016). We recognise that this is not optimal under many facets, ⁵⁷² but intra-specific larval interactions were a key driver of mosquito-population dynamics ⁵⁷³ that could not be excluded by model structure.

Finally, we did not consider evolutionary processes in our model which may affect invasion success over medium-long time spans. Given the reproductive strategy of *Aedes* mosquitoes, rapid evolutionary processes may take place over relatively short temporal periods (e.g. decades), making introduced populations able to extend their original niche (McBride et al., 2014b).

579 4.2 Proposed research directions

dynamAedes is an open-source tool for testing ecological hypothesis and/or to support 580 management plans concerning AIMs. Selecting areas at risk of AIM establishment or pe-581 riods when abundances are more likely to peak should be considered as facets of AIM 582 surveillance. The importance of such early information becomes fundamental for protect-583 ing human health when treating AIM involved in pathogen transmission, as early informa-584 tion on new trajectories of AIM populations becomes critical in the current climate change 585 era. Mosquitoes are affected by temperature changes in, often, predictable ways, though 586 changes in population dynamics can be extremely rapid. Modelling population dynamics 587 under climate change scenarios may thus provide information for anticipating both AIM 588 population changes in space and time and human health risks. 589

The conceptualisation and design of dynamAedes required the review of up-to-date 590 ecological and physiological literature available on four Aedes species, which was in-591 tegrated with feedback from expert ecologists and medical entomologists. It emerged 592 that knowledge on some ecological aspects of these species is highly fragmented or poor 593 (e.g., Cebrián-Camisón et al. 2020), and often dependant on experimental settings and 594 lab strain (e.g., Kramer et al. 2020). Thus, the exploitation of such sets of information 595 for process-based models and, hence, for AIM management would greatly benefit from a 596 standardised review effort and possibly centralised repositories, as already done in other 597 scientific fields such as plant functional traits (Kattge et al., 2020) or systems biology 598 (Tsigkinopoulou et al., 2018). Moreover, experiments on Ae. japonicus and Ae. koreicus 599 life cycles are just starting to unravel these species eco-physiological rates (Ae. koreicus: 600 (Ciocchetta et al., 2017; Marini et al., 2019b); Ae. japonicus: (Scott, 2003; Reuss et al., 601 2018; Wieser et al., 2019) and much work remain to be done on this species. On the con-602 trary, there is large information concerning Ae. aegypti and Ae. albopictus physiological 603

rates which anyhow have been shown to be highly heterogeneous (Eisen et al., 2014) likely
due to non-standardised experimental designs and ecological plasticity of *Aedes* populations (*sensu* Kramer et al. 2021). Information regarding mosquito dispersal is even scarcer
and available only for *Ae. aegypti* and *Ae. albopictus*, while passive dispersal through
auto-vehicles has been estimated only for *Ae. albopictus* (Eritja et al., 2017) despite the
worldwide spread of *Aedes* species was most likely caused by means of passive dispersal.
From a biological perspective, future developments of dynamAedes may consider

also the addition of a strain argument, where the physiological temperature-dependent function can be fitted on geographically different mosquito strains, such as tropical, mediterranean or temperate (Marini et al., 2020; Kramer et al., 2021). Moreover, if observational data are available, calibration of some parameters values, such as the juvenile densitydependent mortality rate, might be implemented following for instance a Bayesian approach (Marini et al., 2019b).

We believe that a closer interaction between modelers and experimenters will motivate the collection of standardised data on unknown eco-physiological AIM rates that would lead to more accurate model predictions. This project was inspired by such interactions and, in this spirit, dynamAedes was meant to be modified or extended to relax its assumptions and limitations with new available information by anyone having basic R programming skills.

5 Conclusion

In this study, we presented dynamAedes, a mechanistic process-based model to infer 624 invasive Aedes mosquito spatio-temporal population dynamics. This first version of the 625 model showed to be often reliable in terms of both biological realism and statistical ac-626 curacy. The open-source nature and programming language accessibility and flexibility 627 of the project offers great potential to further develop the model, allowing to better tune 628 the temperature-dependent functions when new physiological observations and findings 629 become available. Abundance estimations derived from dynamAedes could be used to 630 inform epidemiological models (e.g., SIR or SEIR) and thus obtain estimations on the risk 631 of pathogens transmission. Finally, it does not seem unrealistic to extend the model appli-632 cation to other species of the genus Aedes such as Ae. notoscriptus or to species belonging 633 to other genus of medical interest belonging to the *Culicidae* family, such as *Anopheles*, 634 or even to other blood-sucking insects belonging to different taxa such as *Culicoides*. 635

636 6 Acknowledgements

⁶³⁷ No conflict of interest has been declared by the author(s).

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556 7 Authors contribution

MM and DDR conceived the ideas, designed the methodology and analysed the data; WVB, FR, RM, SB, FM, SC, DA, GM, AP, GLA, GL and CJMK provided expert opinion on mosquito biology as well as observational datasets to validate the model; DDR, MM and SOV led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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41

A Review of mechanistic model for invasive *Aedes*

Name	Year Species	es	Biological resolution	Time	Space	Biological resolution Time Space Programming language	Reference
SkeeterBooster 20	2009 Ae. aegypti	2gypti	Agent-based			C++	Magori et al. (2009)
stagePop 20	600		Process-based			R	Kettle and Nutter (2015)
	018					C++, R, Python	Erguler (2018)
albopictus 20	019 Ae. all	bopictus	albopictus Process-based			C++, R, Python 4	Erguler et al. (2016, 2017)
2	019 Ae. all	bopictus	Process-based			Octave v4.2.1, Runge-Kutta 4	Metelmann et al. (2019)
2	019 Ae. all	bopictus	Ae. albopictus Process-based			R, Ocelet	Tran et al. (2013, 2020)
2	020 Ae. ae	28ypti	Process-based			R	Iwamura et al. (2020)
2	020 Ae. ko	koreicus	Process-based			R	Kurucz et al. (2020)

Table 2: Description of mechanistic codes for invasive *Aedes* made available as software or scripts.

B Parameters used in dynamAedes

Species	Stage	Parameters	Main data source	Origin	Value	Comments
Ae. aegypti and Ae. al-	Eggs	min number of days for eggs de-	Christophers 1960; Delatte et	Literature therein; La	4	
bopictus Ae. aegypti and Ao aL	Invanilae	velopment min number of dave for imma-	al 2009 Christophers 1060- Delatta at	Reunion (France) Literature	v	
bopictus	Juv 2000-20	ture development	al 2009	(Fran	5	
Ae. aegypti and Ae. al- bopictus	Adults	day otrop	Christophers 1960; Delatte et al 2009	Literature therein; La Reunion (France)	4	
Ae. koreicus and Ae. japon- icus	Eggs	min number of days for eggs de- velopment	ioldi ied re: <i>korei</i> i	Trento (NE Italy)	×	
Ae. koreicus and Ae. japon- icus	Juveniles	min number of days for imma- ture development	Dr Damele Arnoldi unpub- lished results for Ae. koreicus; Wieser et al. (2019)	Trento (NE Italy)	6	min 10 days for <i>Ae. koreicus</i> , min 8 days for <i>Ae. japonicus</i> . Assumed 9 for both species
Ae. koreicus and Ae. japon- icus	Adults	min number of days for gonotrophic cycle	Assumed the same of Ae. aegypti	ı	4	Since the probability of complete the gonothropic cycle is roughly 1/3 of <i>Ae. aegypti</i> , we kept the same leght the same lenght of <i>Ae. aegypti</i>
All species	Juveniles	Survival rate (density- dependent)	Hancock et al. 2016	Tropical (NE Australia)	Log- normal distri- bution	1-density dependant survival rate is additive to 1- temperature-dependent survial rate; the estimates made for <i>Ae. aegypti</i> were extended to the other three species
	Adults	Sex ratio 1:1				General modelling assumption widely taken in process-based modelling literature

Table 3: Other model features

Species	Stage	Model parameter	Data source	Origin	Function	Comments
	Egg	Survival rate	Thomas et al. 2012, Eisen et al. 2014	Laboratory colony(Tropical Asia origin); Literature review	Beta	Data for T>0 taken from Eisen 2014, data for T<0 taken from Thomas et al. 2012
Ae. aegypti		Hatching rate	Christophers 1960; Farnesi et al 2009; Mohammed and Chadee 2011	Literature therein; Rock- feller strain; Trinidad and Tobago	Beta	48h estimates from Mohammed and Chadee 2011 divided by two to get a daily rate. Additional data: 0 hatching a 7° C from Christophers and 0.025 at 12° C daily hatching from Farnesi et al. (2009)
	Juvenile	Survival rate (temperature- dependent)	Yang et al. 2009	NW of São Paulo State (Brazil)	Beta	Table 8 from Yang et al. 2009 Appendix1
		Emergence rate	Yang et al. 2009; Grech et al (2015)	NW of São Paulo State (Brazil); Cordoba (Argentina)	Beta	Data from Yang et al. (2009) refer to all immature stages, we corrected them to match only pupa using information present in Grech et al (2015) by taking the ratio between the mimimum pupation time of the two experiment as a scaling factor
		Survival rate	Yang et al. 2009	NW of São Paulo State (Brazil)	Beta	Table 4
	Adult	Gonotrophic cycle	Yang et al. 2009	NW of São Paulo State (Brazil)	Beta	Table 5
		Oviposition: num- ber of eggs	Christophers 1960; Yang et al. 2009	therein; NW of São Paulo State (Brazil)	Beta	Table 5 from Yang et al (2009) rescaled using the average number of eggs/female reported in Christophers (1960)
		Survival rate (non- diapausing)	Metelmann et al. 2019; Expert based	Literature therein	nonlinear	Polynomial function taken from the SM manually adapted to get no survival at T>40°C
	Egg	Survival rate (dia- pausing)	Metelmann et al. 2019	Literature therein	nonlinear	Polynomial function taken from the SM
Ae. albopictus			Delatte et al. 2009	La Reunion (France)	Beta	Table 1; column Egg-L1
		rate (ı	Assumed the same as for non-diapausing eggs
	Juvenile	Survival rate (temperature- dependent)	Metelmann et al. 2019	Literature therein	nonlinear	Polynomial function taken from the SM
		Emergence rate	. 2009	La Reunion (France)	Beta	Table 1; column Pupae-adult
	A ժո1+	Survival rate	Metelmann et al. 2019	Literature therein	nonlinear	Polynomial function taken from the SM
	1mmv /	Gonotrophic cycle	Delatte et al. 2009	La Reunion (France)	Beta	Table 6

Species	Stage	Model parameter	Data source	Origin	Function	Comments
		Oviposition: num- ber of eggs	Delatte et al. 2009	Reu	Beta	Table 6
	Есе	Survival rate	Wieser et al. 2019	Biberach (SW Germanv)	Beta	Observation taken from Fig. 1 in Wieser et al (2019)
A innuine	۵ ۵	Hatch rate	Wieser et al. 2019		Beta	Reuss et al., unpublished. Hatching observed also below a thin ice layer $(T < 0)$
Ac. Juponuus	Juvenile	Survival rate	Wieser et al. 2019	Biberach (SW Germanv)	Beta	Reuss et al., unpublished
		Emergence rate	Reuss et al. 2018 SM		Beta	Table S2; survival upper temperature limit was adapted by accounting for expert opinion.
		Survival rate	Reuss et al. 2018 SM	Biberach (SW Germany)	Beta	Fig. 2
	Adult	Gonotrophic cycle			Beta	No information available, assumed the same of Ae. kore- icus due to their phylogenetic and biogeographic similar- ity
		Oviposition: num- ber of eggs	Reuss et al. 2018	Biberach (SW Germany)	Beta	Number of eggs estimated by mean female wing length, using the formula taken from Armistead et al. (2009), their Fig. 5; we divided the estimated eggs per female per gonotrophic cycle by a factor of two, due the two oviposit-
	Egg	Survival rate	Marini et al. 2019; Expert Based	Trento (NE Italy)	nonlinear	ing days we are accounting in the model. Polynomial function F3 and parameters values taken from Tab. 5 in Marini et al (2019) adjusted using observations provided in Arnoldi et al., unpublished observations
Ae. koreicus		Hatching rate	Marini et al. 2019; Expert Based	Trento (NE Italy)	Beta	Table 1 scaled with unpublished data to account for non- embryonated eggs; Arnoldi et al., unpublished observa- tions
	Juvenile	Survival rate (temperature- dependent)	Marini et al. 2019; Expert Based	Trento (NE Italy)	Beta	Table 1 averaged from instar 1 to 4; the the upper limit has been adapted accordingly to expert opinions by Cioc- chetta et al., unpublished observations and Arnoldi et al., unpublished observations
		Emergence rate	Marini et al. 2019 Marini et al. 2010:	Trento (NE Italy)	Beta	Table 2
	- 1- T	Survival rate		Trento (NE Italy)	Beta	Table 3
	Adult	Gonotrophic cycle Oviposition: num-	Marini et al. 2019 Evnert Rased	Trento (NE Italy) Trento (NE Italy)	Beta Reta	Table 3 Arroddi et al mmuhlished observations
		ber of eggs	Experiences		DCIA	ALINOIS CLAI, UIPUDIISING UDSCIVATIOUS

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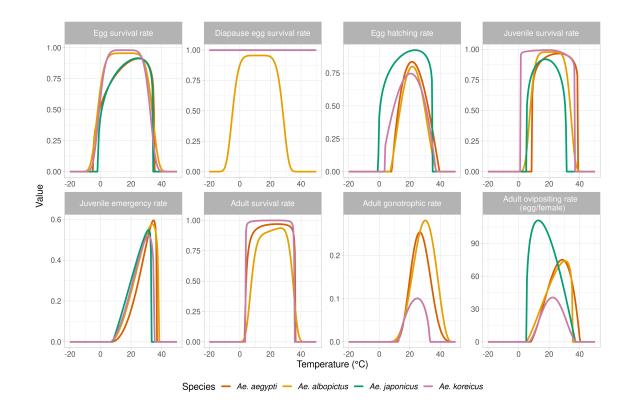
Table 4: Species-specific temperature-dependent physiological parameters

Species	Stage	Parameters	Main source	Origin	Distribution	Comments
Ae. aegypti	Adults	Active dispersal	Marcantonio et al. 2019	California (USA)	Log-normal	Table 3
Ae. albopic- tus	Adults	Active dispersal	Marini et al. 2019B	Rome (Italy)	Log-normal	Figure 2a; Data from the 3 MRR were fit with several distributions, best distribution chosen using AIC
Ae. japoni- cus	Adults	Active dispersal	ı	ı	Log-normal	No information available, assumed the same of <i>Ae. albopictus</i>
Ae. koreicus	Adults	Active dispersal	ı		Log-normal	No information available, assumed the same of <i>Ae. albopictus</i>
	All species	Passive dispersal (average trip distance)	Pasaoglu et al. 2012	,	,	Trip distance weighted average for ITA, DEU, FRA, ESP, POL, UK. Data taken from Figure 4.4 Average trip distance (km) by trip
All species	Adults	Passive dispersal (Hitch- hiking probability)	Eritjia et al. 2017	Mediterranean (Catalonia, Spain)	gamma distribu- tion	for the species as estimated by Eritja et al. 2017 for Ae. albopictus

Table 5: Species specific dispersal parameters

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Species Stage		Model p ter	parame-	Data source	Origin	Function	Comments
Ae. ae- gypti	<i>Ae. ae</i> - Diapaus €)iapause gy <i>pti</i> Egg dence	Diapause dence	inci-	inci- Lacour et al. 2015	Ovitraps (Provence, Southern France)	Exponential	
Ae. japoni- cus	DiapausDiapause Egg dence	Diapause dence	inci-	inci- Krupa et al. 2021	Ovitraps (Bas- Rhin, Northeast Exponential France)	Exponential	
Ae. kor- eicus	<i>Ae. kor</i> Diapaus Diapause <i>eicus</i> Egg dence	Diapause dence	inci-	inci- Krupa et al. 2021	Ovitraps (Bas- Rhin, Northeast Exponential France)	Exponential	We used the same exponential function used for <i>Ae. japon-icus</i> due to the close philogenetic relationship between these two species
			Table (5: Species spec	Table 6: Species specific photoperiod parameters	ameters	



A Aedes sp. response curve

Figure 7: Overview of the temperature-dependent functions used in the model for the four *Aedes species*

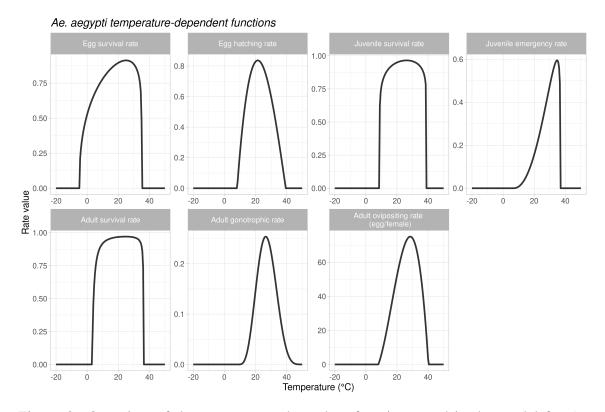


Figure 8: Overview of the temperature-dependent functions used in the model for Ae. aegypti

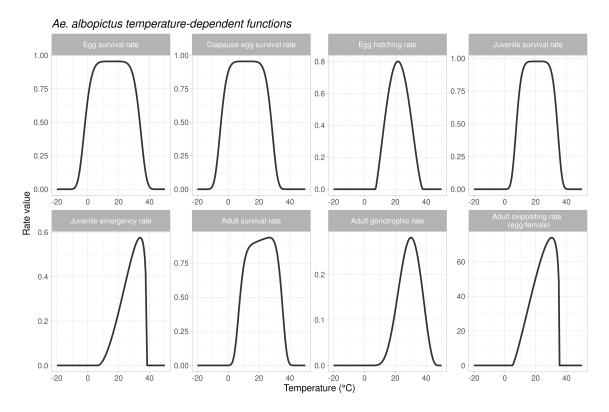


Figure 9: Overview of the temperature-dependent functions used in the model for Ae. albopictus

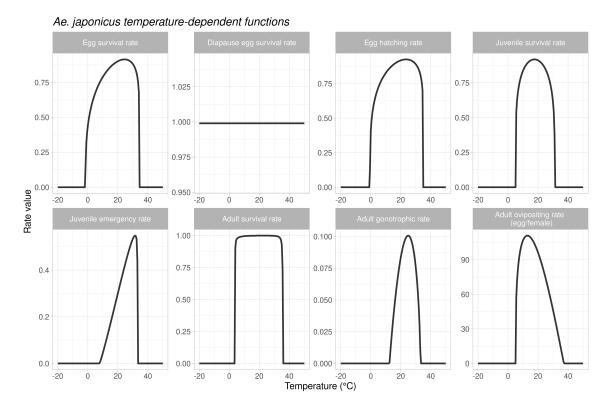


Figure 10: Overview of the temperature-dependent functions used in the model for Ae. *japonicus*

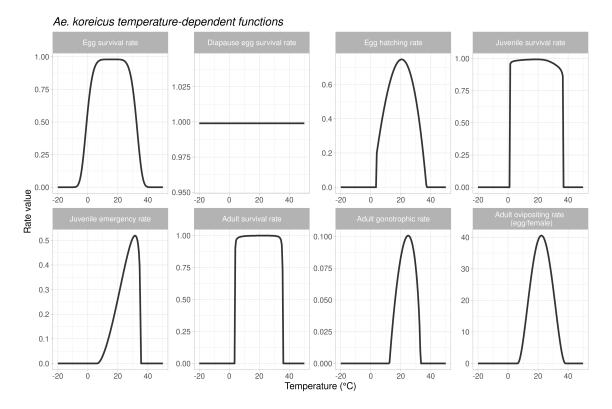


Figure 11: Overview of the temperature-dependent functions used in the model for *Ae*. *koreicus*

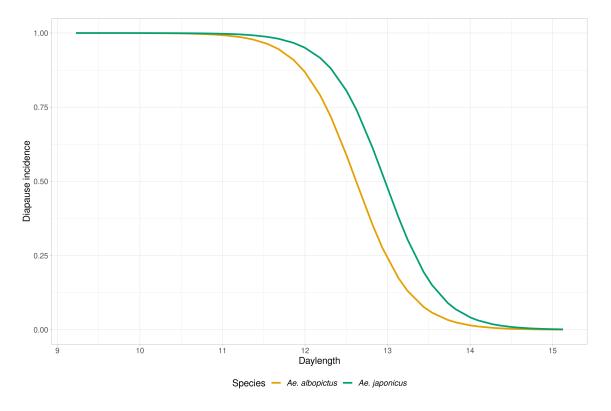


Figure 12: Overview of the photoperiod-dependent diapause incidence function used to in the model for *Ae. albopictus* and *Ae. japonicus*. The *Ae. japonicus* function was used for *Ae. koreicus* as well.

B Larval habitat water volume parameter sensitivity



Figure 13: Sensitivity analysis on the effect of the lhwv parameter on the estimated number of individuals. In this example, we used the temperature observations of the Nice weather station used in the case study and varied the amount of water volume. The seasonal trend remained the same but, as expected, the simulated number of individuals increase as the lhwv parameter increase.

¹¹¹⁹ C Aedes aegypti and Ae. albopictus regional scale case ¹¹²⁰ study

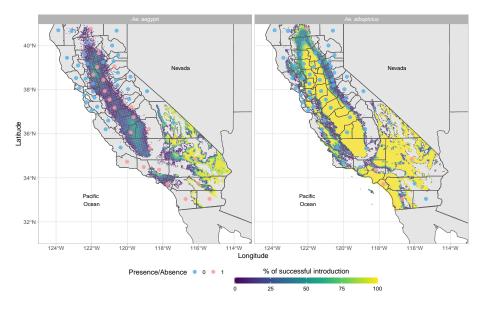


Figure 14: Predicted percentage of establishment of *Ae. aegypti Ae. albopictus* in California (USA) for the years 2011-2016 and 2013-2018, respectively. Only pixels having a probability of successful introduction >0 are shown. The red dots represent the counties where the species have been found.

¹¹²¹ D Aedes koreicus population dynamics punctual scale case ¹¹²² study

Year	Month	CI 2.5%	CI 25%	CI 50%	CI 75%	CI 97.5%	Observed Ae. Koreicus
2016	May	0.00	1.45	5.26	13.74	31.22	2
2016	June	0.00	1.37	6.36	14.40	40.64	5
2016	July	0.00	2.32	11.85	32.62	101.76	3
2016	August	0.70	24.57	66.65	128.03	266.00	9
2016	September	0.18	14.52	37.37	88.27	175.66	37
2016	October	0.00	0.24	1.18	3.14	10.17	0
2017	May	0.02	0.51	2.67	7.85	18.44	9
2017	June	0.29	2.75	10.60	28.57	55.28	8
2017	July	3.67	10.91	30.62	85.53	186.93	10
2017	August	7.24	32.50	74.18	159.67	283.74	24
2017	September	0.61	8.79	31.48	88.08	156.47	2
2017	October	0.08	0.82	2.20	4.98	11.06	2
2017	November	0.00	0.00	0.00	0.00	0.14	0
2018	April	1.66	5.26	11.54	22.25	34.30	0
2018	May	1.73	3.22	5.73	9.18	13.21	1
2018	June	1.57	5.81	10.52	22.29	32.89	6
2018	July	13.74	29.99	48.04	74.34	98.01	7
2018	August	37.83	71.67	109.27	157.55	201.00	29
2018	September	54.55	82.03	112.57	147.58	179.09	24
2018	October	2.13	2.90	3.77	5.89	7.80	6
2018	November	0.00	0.00	0.00	0.08	0.15	0

Table 7: Model validation for Aedes koreicus model in Trento (NE Italy)