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# An agent-based model of a cutaneous leishmaniasis reservoir host, *Meriones shawi*

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## Abstract

*Meriones shawi* (*M.shawi*) is the main reservoir host for zoonotic cutaneous leishmaniasis (ZCL) in Central Tunisia. The incorporation of environmental and climatic effects on the spread of ZCL in *M. shawi* remains difficult. This study presents an agent-based model (ABM) to overcome these difficulties and examine the impact of environment (*i.e.* vegetation cover) and climate (*i.e.* temperature) on *M. shawi* movement and prevalence. The model simulation considers two agents type: rodent agent and field unit agent. We tested the model according to two types of rodent movement: random and thoughtful. We integrated time dependent normalized difference vegetation index (NDVI) in order to test the land cover effects on rodent movement and ZCL transmission. The results confirmed that the spread of the disease depends on rodent movement. We observed that prevalence and distribution are the closest to field data when the vegetation cover is highest and that rodents go for thoughtful movement. In addition, we found that the nature of movement (random or thoughtful) and prevalence depends strongly on minimum food detection.

**Keywords:** Agent based model, Zoonotic cutaneous leishmaniasis, *Meriones shawi*, NDVI, Temperature

## 18 **1. Introduction**

19 Infectious diseases are a global public health problem. It is estimated that 75%  
20 of human infectious diseases originate from an animal reservoir and the majority  
21 are caused by viruses, bacteria, or parasites (Taylor et al., 2001). Among these  
22 diseases, leishmaniasis is predominantly observed, where 350 million people are  
23 at risk of contracting it and approximately 2 million new cases are reported each  
24 year (Arenas et al., 2017). Cutaneous leishmaniasis (CL) is a cutaneous infection  
25 caused by a unicellular parasite (*Leishmania*), transmitted by the bites of a female  
26 insect called phlebotome or sandfly (Dedet, 2009).

27 In Tunisia, zoonotic cutaneous leishmaniasis (ZCL) is caused by the parasite  
28 *Leishmania major* (*L. major*) (Ben Ismail et al., 1986), with its vector *Phlebotomus*  
29 *papatasi* (*P. papatasi*) (Killick-Kendrick, 1999). The latter's reservoir species  
30 include rodents *Psammomys* (*obesus*) (Cretzschmar, 1828), *Meriones* (*shawi*) (Du-  
31 vernoy, 1842), and *Meriones* (*libycus*) (Lichtenstein, 1823).

32 The spatial dynamics of rodent populations involve several endogenous pro-  
33 cesses, such as the availability of food resources or exogenous processes such as  
34 environmental and climatic processes (Chaves and Hernandez, 2004; Bellali et al.,  
35 2017, 2019). According to the literature, *P. obesus* is known for its dietary restric-  
36 tions, and feeds mainly on chenopodiaceae (Ghawar et al., 2011). It is considered  
37 a sedentary rodent with small home ranges (Daly and Daly, 1975; Ghawar et al.,  
38 2011). Furthermore, *M. shawi* is an opportunistic rodent that is able to adapt to its  
39 diet according to the development of cultivated cereals (Adamou-Djerbaoui et al.,  
40 2013); it is considered more mobile compared to *P. obesus* (Ghawar et al., 2015).

41 The Geographic Information System (GIS) data and machine learning are im-  
42 portant for the management of epidemics because they allow the collection, anal-  
43 ysis and display of epidemic spatiotemporal information (Tabasi and Alesheikh,  
44 2019; Mollalo et al., 2018). These approaches were used to study the distribution  
45 of rodent reservoirs and sandfly.

46 In particular, the effect of the environment on the distribution of ZCL has ex-  
47 tensively investigated. Various studies have been conducted to describe the niche  
48 suitability of vectors (Hanafi-Bojd et al., 2015), reservoirs (Gholamrezaei et al.,  
49 2016), or both (Shiravand et al., 2018, 2019) using the MaxEnt algorithm model.  
50 Particularly, (Hanafi-Bojd et al., 2015) proved that moisture, precipitation, and  
51 temperature are determining factors when assessing sandfly density. Furthermore,  
52 Bellali et al. (2017); Talmoudi et al. (2017) have shown a significant correlation  
53 between climate variables (precipitation and temperature) and the incidence of  
54 ZCL and rodent and sandfly density. One possible explanation for the latter ob-

55 servation is the correlation between that rodents and chenopodiaceous densities  
56 (Toumi et al., 2012).

57 Various deterministic models have already been developed for epidemics of  
58 leishmaniasis from different perspectives. Carpenter et al. (1992) and Burattini  
59 et al. (1998) developed structured models for canine leishmaniasis considering  
60 human and sandflies. Chaves and Hernandez (2004) presented a model for the  
61 dynamics of transmission of American Cutaneous Leishmaniasis. They obtained  
62 expressions that allow computing the threshold conditions for the persistence of  
63 the infection. Roy et al. (2015) used the same approach, but rather, considered  
64 the effect of the time lag between the biting of a sandfly and the human infection.  
65 In the other hand, Nadeem et al. (2019) proposed a mathematical model of ZCL  
66 concerning humans, reservoirs, and sandflies. They describe ZCL transmission  
67 and estimate the basic reproduction number  $R_0$  using the next-generation matrix  
68 threshold condition. In addition, they tested different strategies to control the  
69 disease based on the indices of parameters.

70 Even though numerous studies were conducted on this topic, rarely those who  
71 considered the temperature as a factor influencing the ZCL transmission. Up to  
72 our knowledge, only Bacaër and Guernaoui (2006) and Mejhed et al. (2009) have  
73 integrated this factor in their deterministic models.

74 In all these mathematical models, the population and individual interactions  
75 are considered homogeneous. This assumption results in difficulties in represent-  
76 ing the variants of individual microscopic attributes and behaviors and implicitly  
77 assumes that all individuals are subject to the same process (Duan et al., 2015;  
78 Hunter et al., 2018).

79 An agent-based model (ABM) is an integrative approach that takes into ac-  
80 count the individual behavior diversity. The model is defined as a system com-  
81 prising several entities or agents (*e.g.* individual) that operate in an environment,  
82 in which they are located. This agent is characterized by attributes, behaviors, ca-  
83 pacities of perception, and communication (Treuil et al., 2008; Grignard, 2015).  
84 In this context, ABM makes it possible to represent and link different levels of  
85 detail, such as the effect of the spatial dynamics of the reservoir on the trans-  
86 mission of vector-borne diseases (Grimm et al., 2006) or the integration of the  
87 metapopulation model in the context of rodent dynamics (Marilleau et al., 2018).

88 Rajabi et al. (2016) used an ABM with two types of agents, which are the  
89 sandfly and the human in a structured environment (road, land cover, river,...),  
90 knowing that the infection probability depends on the environmental. They were  
91 able to confirm that desertification zones are the main source of ZCL and local  
92 populations are the most exposed to sandflies.

93 Recently, Rajabi et al. (2018) used an ABM to simulate authority interventions  
94 on *Rhombomys opimus* (rodent reservoir of ZCL in Iran) population, to minimize  
95 ZCL incidence. They showed the impact of habitat configurations and human-  
96 made changes on rodent communities and their dynamics.

97 More recently, Tabasi et al. (2020) used an ABM to represent the complete  
98 cycle of ZCL disease, *i.e.* human, sandfly, rodent, and environmental behaviors  
99 using an hybrid model. They showed that the spread of ZCL is important in some  
100 regions like the desert, low altitude areas, and, riverside population centers. They  
101 also confirmed that restricted human movement is an important factor contributing  
102 to the reduction of transmission frequency .

103 In our study, we developed an ABM to determine how the rodents (*i.e.* *M.*  
104 *shawi*) movement types can affect transmission ZCL transmission taking into  
105 account time dependent environmental (*i.e.* vegetation cover) and climate con-  
106 straints (*i.e.* temperature). Indeed, we assumed that vegetation cover is updated  
107 each month using NDVI values and may vary depending on rodent consumption.  
108 In addition, we supposed that rodents decisions (*e.g.* decision to move, choice of  
109 directions . . .) are affected by the vegetation cover (Mollalo et al., 2014; Ghawar  
110 et al., 2015). We simulated two types of rodents movement, a random movement  
111 and a so-called "thoughtful" movement, where rodents can choose their direction  
112 after evaluating the state of vegetation based on their memories. In addition, we  
113 have tested NDVI effects on the transmission of the epidemic.

114 In Section 2, we present the background and hypothesis used in the model.  
115 In Section 3, we describe the model according to the Overview, Design concepts,  
116 and Details (ODD) protocol (Grimm et al., 2010) to standardize its description.  
117 In Section 4, we present the main results. In Section 5, we discuss our results.  
118 Finally, in Section 6, we present the conclusion of our work.

## 119 **2. Background**

120 Climatic and environmental factors impact rodents distribution (Hamidi et al.,  
121 2018). In fact, the rodents reproductive cycle is indirectly influenced by climatic  
122 conditions as the latter influence such as the resource availability (Stenseth, 1999,  
123 2003). Marstona et al. (2007) and Chidodo et al. (2020) showed a correlation  
124 between vegetation cover and rodent distribution. When the resource is abundant,  
125 rodents tend to be close to foraging areas. Otherwise, their movement is random  
126 when the food became rare (Ghawar et al., 2015). This is probably resulting from  
127 rodents ability to assess to food through the information they have on the occupied  
128 area.

129 At the vector level, sandflies are characterized as thermophilic, requiring high  
130 temperatures for their development and survival (Koch et al., 2017) (see Fig. 1).

131 At the parasite level (*L.major*), an increase in temperature increases the rate at  
132 which parasites approach maturity and multiply, which promotes transmission of  
133 the infection (Clémence, 2009). However, when the parasite is in the intestine of  
134 infected sandflies, it remains at the same temperature as his host (Zilberstein and  
135 Shapira, 1994), which considered as the environment temperature (see Fig. 1).

136 Considering temperature or humidity explicitly in the population dynamics  
137 model through the sandfly life cycle is difficult. To overcome this, we assumed  
138 that there is a positive correlation between NDVI and temperature on the one hand  
139 (Wang et al., 2003), and infection probability, on the other (Mollalo et al., 2014;  
140 Shiravand et al., 2018). More precisely, we suppose that the ZCL infection proba-  
141 bility depends linearly on the sandfly density, which depends on temperature via a  
142 bell-like function. The height of the bell depends on NDVI. This hypothesis is not  
143 meaningless as Mollalo et al. (2015); Garni et al. (2014); Shiravand et al. (2018)  
144 developed a model to discuss the associations between NDVI and the incidence  
145 of cutaneous leishmaniasis.

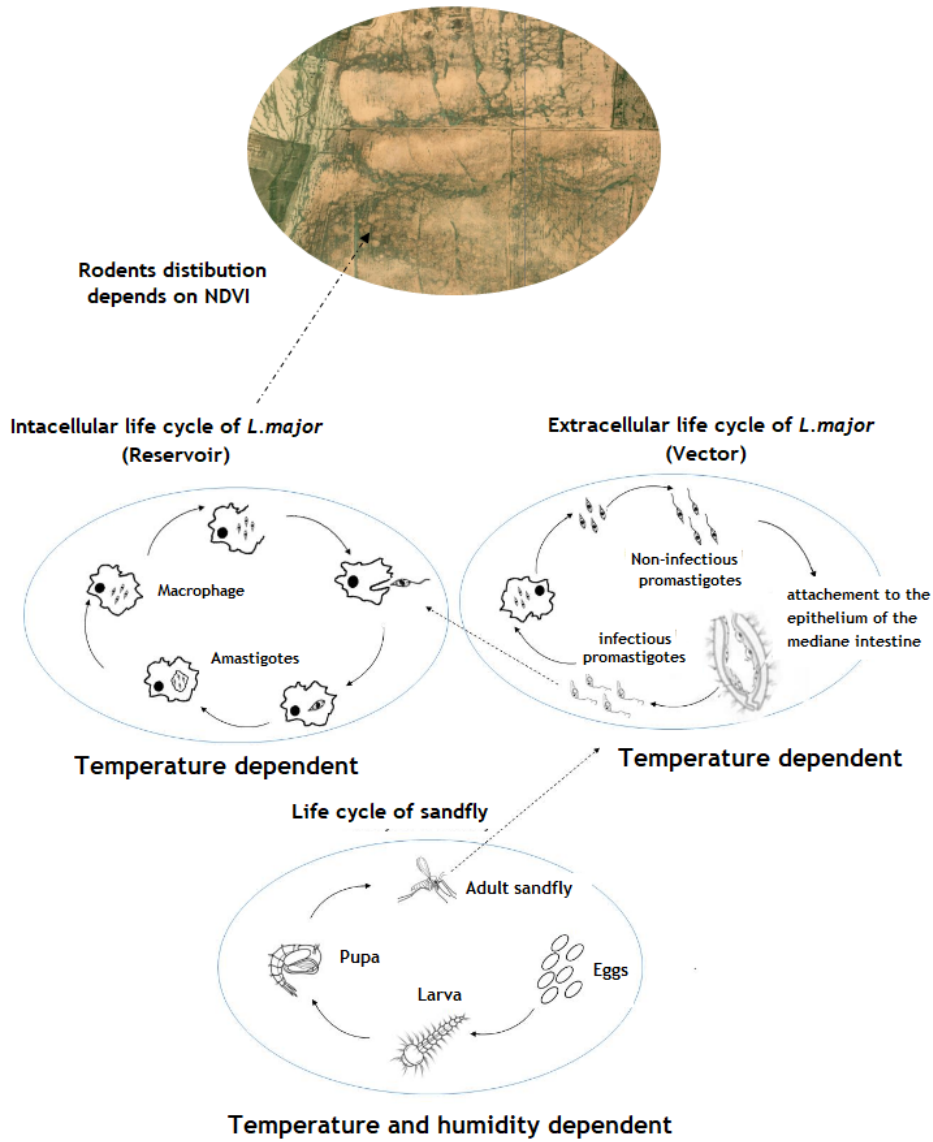


Figure 1: Cycle life of *L. major* and factors influencing sandfly and rodent.

146 Therefore, temperature and NDVI can be considered as good proxies for the  
 147 presence probability of both vectors and reservoirs (Shiravand et al., 2018).

148 Our study presents a simulation of *M. shawi* activity in a spatially heteroge-  
149 neous environment, incorporating individual-based interactions. We used empiri-  
150 cal data on rodents and their habitat and ZCL incidence in El Manara region (aver-  
151 age altitude 80, 8483 m; lat 35°12'36"N, Long 9°49'14"E) in Nasrallah, Kairouan,  
152 Central Tunisia (see Fig. 2). The area is a semiarid plain located at an altitude of  
153 205, 1304 m and is composed of *Arthrophytum sp.*, *Retama sp.*, *Ziziphus mound*,  
154 and *Opuntia hedges* (Ghawar et al., 2011). Additionally, El Manara has long been  
155 known as one of the most important endemic areas of ZCL (Bettaieb et al., 2014),  
156 and *M. shawi* is the main reservoir host of ZCL in this area. The annual inci-  
157 dence rate in Kairouan has been high in recent decades, including approximately  
158 34.4/100,000 inhabits, and the disease has recently emerged in non-endemic re-  
159 gions of the province (Chraiet-Rezgani et al., 2016). Our model does not incorpo-  
160 rate humans as agents. However, human-induced changes are included to explore  
161 the consequences of disease evolution among rodent population dynamics. As  
162 such, the model can be a useful tool for informing healthcare authorities in plan-  
163 ning intervention strategies to control the spread of ZCL.

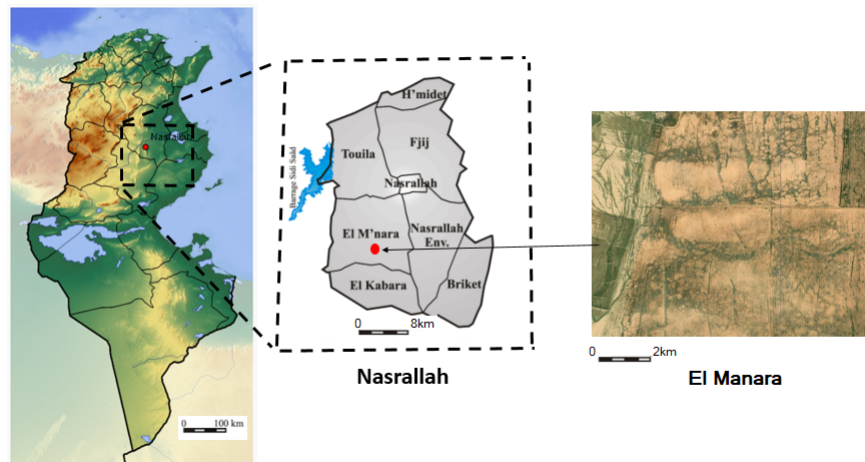


Figure 2: Study area at EL Manara, Nasrallah, Kairouan governorate.

### 164 3. The model

165 The model description follows ODD protocol for describing agent-based mod-  
166 els (Grimm et al., 2010). In the remainder of this section and after a brief overview  
167 of the model components and process (see subsection 3.1), the key concepts of



168 model design, including emergence, objective, sensing, adaptation, stochasticity,  
169 and observation , are described (see subsection 3.2). Next, the details of the model  
170 implementation are presented (see subsection 3.3).

### 171 3.1. Overview

172 Our main objective is to design a spatial ABM of the ZCL spread among  
173 rodents, including environmental and climatic data and agent objects. The model  
174 was developed in the GAMA 1.7 platform (Taillandier et al., 2019).

#### 175 3.1.1. Purpose

176 The model was developed to provide a spatiotemporal simulation of the spread  
177 of ZCL between rodents (*M. shawi*). We assumed two types of movement: ran-  
178 dom and thoughtful. The thoughtful movement depends on the vegetation density  
179 where the rodent is able to evaluate the "best" destination. The model includes  
180 climatic factors (e.g., temperature), and environmental (e.g., NDVI) factors influ-  
181 ence the movement and spread of the ZCL between rodents.

#### 182 3.1.2. Entity, state variables, and scales

183 There are two types of agents in the model, rodent agent and field unit agent  
184 representing part of the space (see Fig. 3).

185 *The rodent agents* : They are described by their identifier, position, and epi-  
186 demiological status concerning ZCL (susceptible or infected) and by two matrices  
187  $M_{info}$  and  $M_{food}$  (see Table 1) .

188 *The field unit agents* : They form the grid and represent the environment of the  
189 ABM. They are attributed by their identifier and by  $F_{cell}$ , representing the quantity  
190 of food present in the cell, it changes according to the quantity consumed by the  
191 rodent agent and is updated each month according to the integrated NDVI values.  
192 The grid contains 1530 field units (the area of each unit is  $895 m^2$ ), and its surface  
193 is  $1.37 km^2$ . The choice of the value is based on our observations on the field for  
194 a project to be conducted in 2012 (Ghawar et al., 2015).

195 Regarding temporal resolution, the time step of the simulation was fixed to 1  
196 h. The model has been designed to perform simulations for up to 5 years.

Table 1: Summary of attributes and variables with definitions. In the description of the dimensions, the following symbols are used: – indicates no dimensions, J: Joule, t: time.

Agent	Symbol	Type	Description	Unit	Update period
<b>Rodent</b>	$R_{xy}$	<b>Point</b>	Position of the rodent agent	–	1 hour
	$AF_{consum}$	$\mathbb{R}$	Speed of food consumption made by the rodent agent at each step of the time	$J.t^{-1}$	1 hour
	$AF_{min}$	$\mathbb{R}$	Minimum quantity of food detected by the rodent agent to move	$J$	1 hour
	$q$	$\mathbb{R}$	Quantity of food consumed by rodent agent	$J$	1 hour
	$L_{memory}$	$\mathbb{R}$	Loss memory rate	$t^{-1}$	1 hour
	$M_{info}$	<b>Matrix</b>	Matrix containing information about the presence of food. Its values are between 0 (no information) and 1 (complete information). The size of the matrix corresponds to that of the environment (1530 cells)	–	1 hour
	$M_{food}$	<b>Matrix</b>	Matrix containing the perception of the food values of each cell. The size of the matrix corresponds to that of the environment (1530 cells)	$J$	1 hour
	$V_{min}$	$\mathbb{R}$	Minimum forward term product of the two matrices $M_{info}$ and $M_{food}$	$J$	<b>Fixed</b>
	$p$	$\mathbb{R}$	Infection probability, which depends on temperature and NDVI	–	1 month
	$\gamma$	$\mathbb{R}$	Recovery probability	–	1 week
$\alpha$	$\mathbb{R}$	Infection factor	–	<b>Fixed</b>	
<b>Field unit</b>	$F_{xy}$	<b>Point</b>	Position of the field unit agent	–	<b>Fixed</b>
	$F_{cell}$	$\mathbb{R}$	Quantity of food present in each field unit	$J$	1 hour

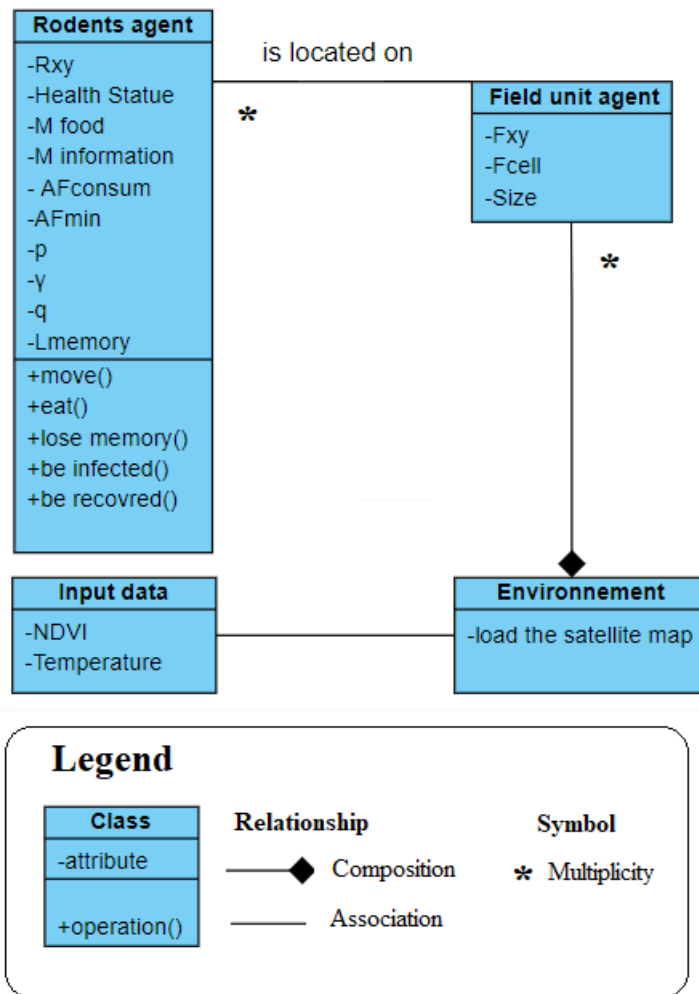


Figure 3: UML (unified modeling language) class diagram represents our ABM, there are two types of agents: rodent agent and field unit agent. Rodent agents are located in field units.

197 *3.1.3. Process overview and scheduling*

198 The simulation time-step represents one hour. Except for the recovery process,  
 199 which is operated every week.

200 *Rodent agent*: First, rodent agents appear in the landscape at different random  
 201 locations. Then, rodent agents are processed using the consumption process under  
 202 particular conditions. When the quantity of food becomes insufficient, the rodent

203 agents choose a destination and move to another cell. Then, the matrix-update  
204 process is activated. Subsequently, the memory loss process is operated (see Fig.  
205 4).

206 *Field unit agent:* First, the field unit values are updated according to the en-  
207 vironmental parameters (NDVI). At each time step, the values of the quantity of  
208 food decrease according to the number of rodent agents present in the cell and  
209 their consumption speed  $AF_{consum}$ . At each month, the field unit values are re-  
210 updated according to the values of the integrated NDVI. The model simulates the  
211 interactions between rodent agents on the one hand and between rodent agents  
212 and field unit agents on the other hand over time. The infected agent rodents per-  
213 ceive susceptible rodents in the same cell. Then, the infection process is activated.  
214 Subsequently, and at each week, the recovery process is performed (see Fig. 5 and  
215 6).

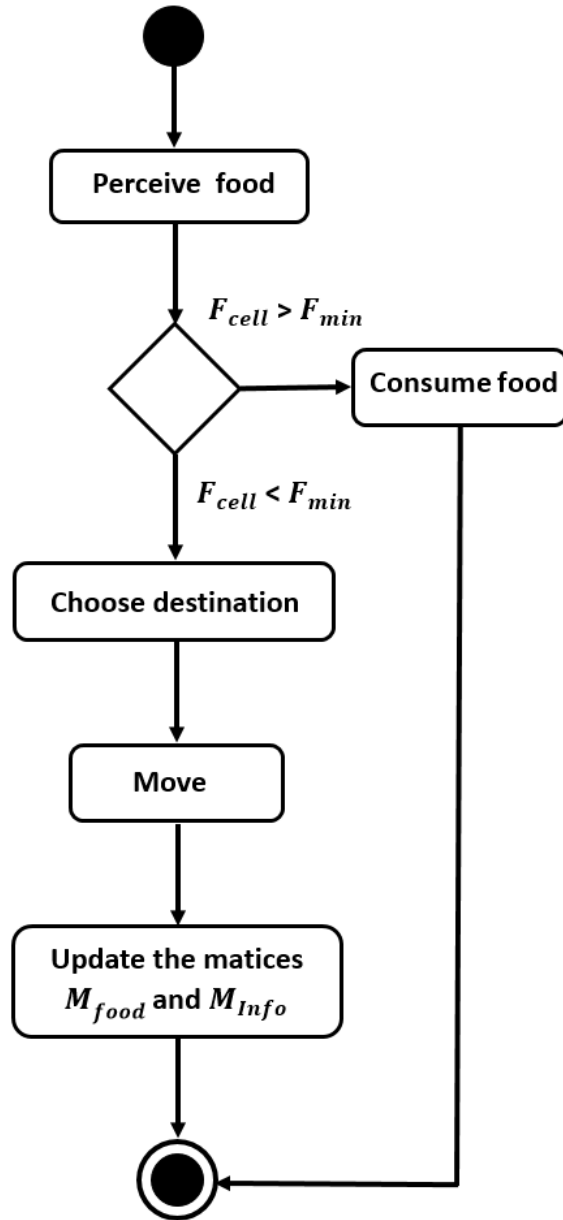


Figure 4: Conceptual view of movement, consumption, and update matrices: the diagram represents an outline of the sequence of processes and the schedule of interactions between agents at each discrete time step.

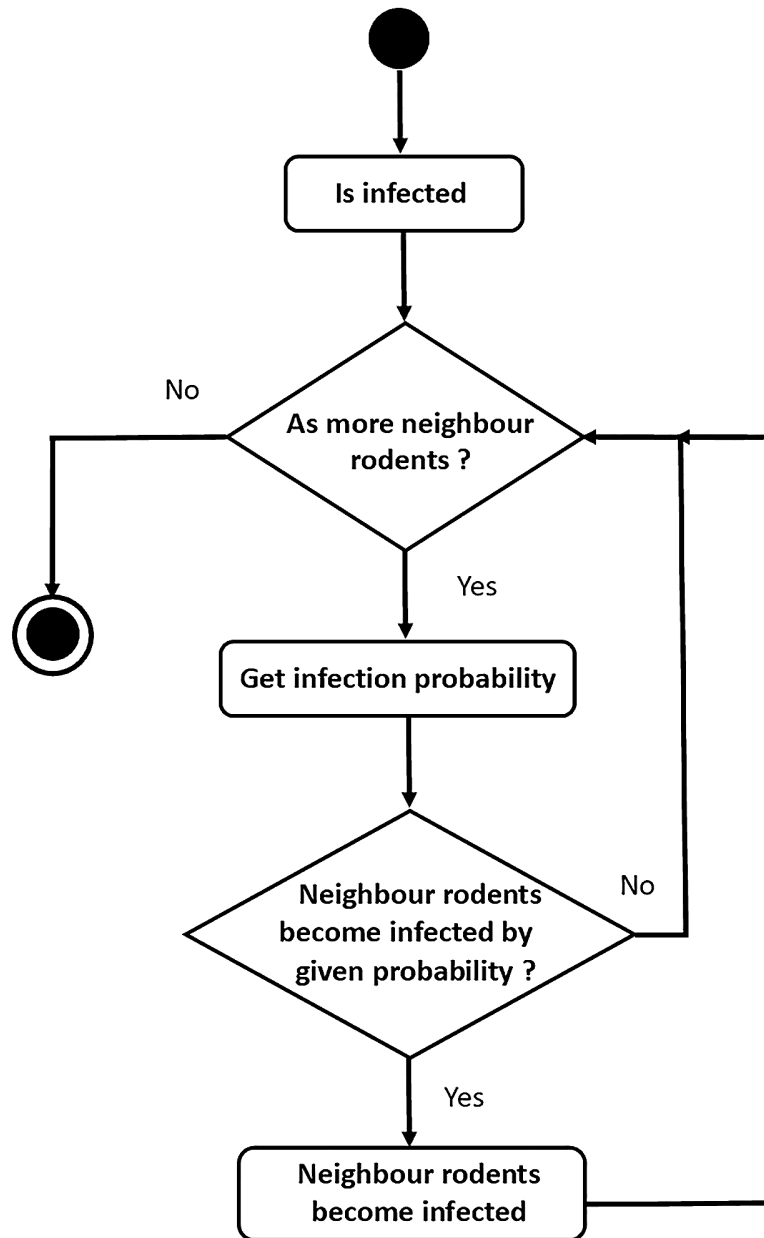


Figure 5: Conceptual view of the infection process (it is activated each time step).

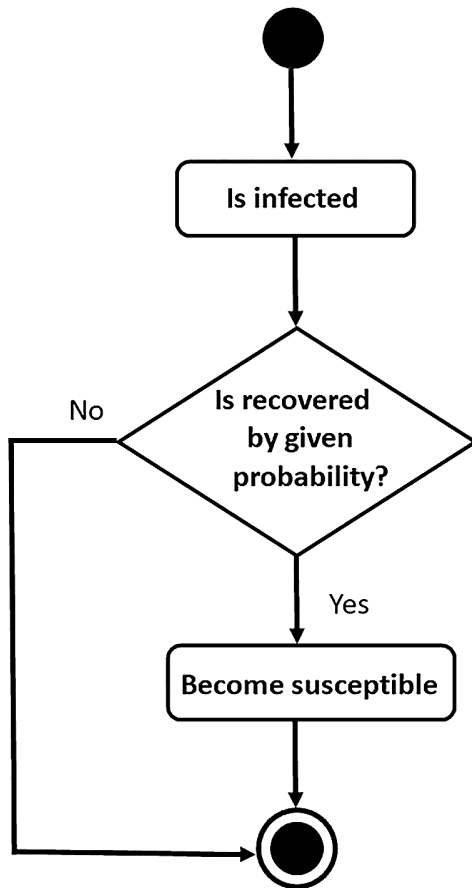


Figure 6: Conceptual view of the recovery process (it is activated each week).

216 *3.2. Design concepts*

217 *3.2.1. Emergence*

218 Depending on the evolution of  $F_{cell}$ , we observe a spread of the epidemic  
 219 that takes into account the mobility, interactions and, characteristics of the rodent  
 220 agents.

221 *3.2.2. Objective*

222 The objective of the agent is to find and consume food. The way to find food  
 223 depends on the type of rodents movement (random or thoughtful).

224 **3.2.3. Sensing**

225 Rodent agents know how to identify suitable habitats within the environment,  
 226 and they perceive the cell information status from  $M_{food}$ . In addition, they can  
 227 perceive other rodent agents located in the same field unit.

228 **3.2.4. Adaptation**

229 The agents adapt their type of movement (random or thoughtful) to the amount  
 230 of food in cells. This adaptation depends on the value of minimum food detection  
 231  $AF_{min}$ .

232 **3.2.5. Stochasticity**

233 The agents move randomly through space by one spatial unit (e.g., grid cells),  
 234 and they choose one of the cells in the proximity. The infection probability follows  
 235 a Gaussian law. In the recovery process, the agent choice of the direction all  
 236 includes elements of stochasticity.

237 **3.2.6. Observation**

238 Spatiotemporal variations in the rodent-level process have been observed in  
 239 the model. These included the number of susceptible and infected rodents at each  
 240 step of the time. We also monitored the number of times the rodent agents passed  
 241 through each agent cell. Moreover, at the end of each simulation, we reported the  
 242 infected density ( prevalence) as  $P = \frac{N_{inf}}{N_0}$ , and the susceptible density noted  $S =$   
 243  $\frac{N_s}{N_0}$ ,  $N_{inf}$  is the number of infected rodent agents,  $N_s$  is the number of susceptible  
 244 rodents, and  $N_0$  is the total number of rodent agents.

We also report the entropy  $H$  of the occupied site distribution. We assumed that the random variable  $X = (X_1, \dots, X_m)$ , where  $X_i$  is "the number of times the site  $i \leq m$  is visited" random variable follows a multinomial distribution of parameter  $(N, p_1, \dots, p_m)$ , where  $m$  is the site number ( $m = 1531$ ),  $X_1 + \dots + X_m = N$ ,  $N$  is the total number of rodent movements, and  $p_i$ ,  $i \leq m$  is the probability that a rodent has occupied site  $i$ , we have  $\sum_{i=1}^m p_i = 1$ . Therefore, we have:

$$f(x_1, \dots, x_k; n, p_1, \dots, p_k) = \Pr(X_1 = x_1 \text{ and } \dots \text{ and } X_k = x_k), \quad (1)$$

$$= \begin{cases} \frac{N!}{x_1! \cdots x_k!} p_1^{x_1} \cdots p_k^{x_k}, & \text{when } \sum_{i=1}^k x_i = N \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$



245 In the case where sites are chosen equiprobably - *e.g.* no food on site and  
 246 rodents have no sensory organs or memory and move randomly, the law is an  
 247 equi-distributed multinomial and  $p_i = p = 1/m$ . We have:

$$f(x_1, \dots, x_k; n, p, \dots, p) = \Pr(X_1 = x_1 \text{ and } \dots \text{ and } X_k = x_k), \quad (3)$$

$$= \begin{cases} \frac{N!}{x_1! \dots x_k!} p^N, & \text{when } \sum_{i=1}^k x_i = N \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

248 To evaluate the values of  $p_i$ , and as each simulation has a different total number  
 249 of movements, we normalize  $N$  to 5000. A good estimator of  $p_i$  is  $\tilde{p}_i = N_i/N$ ,  
 250 where  $N_i$  is the normalized number of site visits  $i$  calculated from either field  
 251 observation data or simulation data.

### 252 3.3. Details

#### 253 3.3.1. Initialization

254 50 rodents were randomly created throughout the environment with a suscep-  
 255 tible status. Only one infected rodent were randomly selected; the initial values of  
 256  $M_{food}$  and  $M_{info}$  were 0. Table 2 represents the model initialization parameters.

Table 2: Parameters and input values of the rodent agent and field unit agent. In the description of the dimensions, the following symbols are used: – indicates no dimensions, J: Joule, t:Time, A: Authors' estimation, E: Experts' judgments.

Symbol	Default value	Range	Unit	Source
$N_0$	50	<b>Fixed</b>	–	<b>A</b>
$N_{inf}$	1	<b>Fixed</b>	–	<b>A</b>
$\gamma$	0.001	0.009 – 0.011	–	<b>E</b>
$\alpha$	1	0.9 – 1.1	–	<b>A</b>
$AF_{consum}$	0.001	0.009 – 0.011	$J.t^{-1}$	<b>E</b>
$L_{memory}$	0.8	0.79 – 0.81	$t^{-1}$	<b>E</b>
$AF_{min}$	{0.2; 0.7}	0.19 – 0.21	$J$	<b>A</b>
$V_{min}$	0.0001	<b>Fixed</b>	$J$	<b>A</b>

#### 257 3.3.2. Input Data

258 At the beginning of each month, a satellite map is included containing the  
 259 NDVI values of each cell, representing the amount of resources produced. The

260 maps (with a surface area of  $1.37 \text{ km}^2$ ) were downloaded for each month using the  
261 *Landsat 8* sensor (30 m resolution), and processed in ArcGis 10.3. We calculated  
262 the monthly NDVI values for each cell (between 0 and 1). To test their effects on  
263 the model simulation, we integrated three types of NDVI:

- 264 •  $NDVI_{max}$ : These are the maximum monthly values of the NDVI (collected  
265 on 2014) whose plant density is considered the highest.
- 266 •  $NDVI_{mean}$ : These are the average monthly values of the NDVI between  
267 2013 and 2017.
- 268 •  $NDVI_{min}$ : These are the minimum monthly values of the NDVI (collected  
269 on 2015) whose plant density is considered the lowest.

270 Average monthly temperatures were obtained from a weather forecasting station  
271 that was implemented in the study area in 2012 (data not shown).

### 272 3.3.3. Submodels

273 *Consumption submodel.* If  $F_{cell}$  is  $\geq AF_{min}$ , the rodent agent consumes food with  
274 a consumption rate of  $AF_{consum}$ . The variation in food quantity  $F_{cell}$  is governed  
275 by the following equation:

$$F_{cell}(t + \delta t) = F_{cell}(t) - \min(F_{cell}, AF_{consum}) \quad (5)$$

276 *Matrices update process:*. For each time step, the following algorithm, which  
277 describes the matrices update, is run :

---

**Algorithm 1** Algorithm represents the update of  $M_{food}$  and  $M_{info}$ . For each field unit  $i$ , we note that  $(i_x, i_y)$  for the coordinates in the matrix  $M_{food}$  and  $M_{info}$  associated with  $i$ . We recall that  $M_{food}$  is the matrix containing information about the presence of food and  $M_{info}$  is the matrix containing the perception of the food values of each *cell*, both have the same dimension as field units.  $Neighb(i)$  represents the neighboring field unit  $i$ . *MyCell*: is the field unit where agent rodents are.

---

```

 $M_{info}(MyCell_x, MyCell_y) \leftarrow 1$ 
if  $F_{cell}(MyCell) > F_{min}$  then
   $M_{food}(MyCell_x, MyCell_y) \leftarrow F_{cell}(MyCell)$ 
else
   $M_{food}(MyCell_x, MyCell_y) \leftarrow 0$ 
end if
 $Minformation \leftarrow M_{info}$ 
 $M_{food} \leftarrow M_{food}$ 
for  $i$  in  $Neighb(MyCell)$  do
   $Minfo(i_x, i_y) \leftarrow \max(\text{mean}_{k \in Neighb(i)}(M_{info}(k_x, k_y)), M_{info}(i_x, i_y))$ 
  if  $M_{info}(i_x, i_y) \neq 1$  then
     $M_{food}(i_x, i_y) \leftarrow \text{mean}_{k \in Neighb(i)}(M_{food}(k_x, k_y))$ 
  end if
end for
 $M_{info} \leftarrow Minformation$ 
 $M_{food} \leftarrow M_{food}$ 

```

---

278 *Movement submodel.* We performed the two scenarios of movement by setting  
 279 parameters that affect the type of movement (random versus thoughtful)  $AF_{consum}$ ,  
 280  $AF_{min}$ , and  $L_{memory}$ . Two different dispersal behaviors were identified:

- 281 • **Random:** The rodent agent moves cell by cell. From a cell, the rodent ran-  
 282 domly chooses the next neighboring cells. This behavior is applied to each  
 283 agent at each step when  $AF_{min}$  is high ( $AF_{min} = 0.7$ ). In this case, the mini-  
 284 mum quantity of food that the agent must detect (in order to move) is greater  
 285 than that available in neighboring cells, so the rodent moves randomly.
- 286 • **Thoughtful:** The rodent agent makes a selection of a neighboring cell. This  
 287 choice is made with regard to the values of  $M_{food}$  and  $M_{info}$ . Rodent moves  
 288 according to the information collected on the vegetation status of neighbor-  
 289 ing cells. The cell chosen is the one that maximizes the forward term prod-

290 uct of the two matrices  $M_{info}$  and  $M_{food}$ . If this maximum is less than a  
 291 certain value previously set (noted  $V_{min}$ ), the movement will be random.

292 *Memory loss submodel.* In the model, we assumed that the rodent agent can forget  
 293 information about a cell that has visited before. For this purpose, the values of the  
 294  $M_{food}$  matrix are multiplied by a previously set rate,  $L_{memory}$ .

295 *Infection submodel.* At every step, susceptible rodent agents can be contaminated  
 296 with an infection probability  $p$  that depends on the temperature and NDVI, since  
 297 these two factors have an impact on the transmission of the epidemic.  $p$  follows  
 298 a Gaussian law based on the assumption that plants grow if the temperature in-  
 299 creases, except that above a set value, plant density decreases. On the other hand,  
 300 we supposed that each susceptible agent observes at the infected agents in its prox-  
 301 imity at a distance of  $R_{infection}$  (set at 0), we assumed that the transmission of the  
 302 epidemic can only occur if a susceptible and an infected agent occupy the same  
 303 cell.

$$p = \frac{\alpha(\text{NDVI})}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(T - T_{optimal})^2}{2\sigma^2}\right) \quad (6)$$

304 where  $\sigma = \sqrt{\frac{(T_{max} - T_{optimal})^2 + (T_{min} - T_{optimal})^2}{2}}$ ,  $T$  is the field temperature,  $T_{optimal}$   
 305 is the average temperature,  $T_{max}$  is the maximum temperature,  $T_{min}$  is the mini-  
 306 mum temperature and  $\alpha$  is the infection factor.

307 *Recovery submodel.* At the end of each week, infected rodents can be recovered  
 308 with a fixed recovery probability  $\gamma$ .

309 *Food evolution submodel.* The evolution of  $F_{cell}$  is related to the values of the  
 310 integrated NDVI, which represents the initial quantity of food (at the beginning of  
 311 each month  $F_{cell} = \text{NDVI}$ ). NDVI is integrated in the form of a monthly satellite  
 312 map of the EL Manara region. These images provide us with information on the  
 313 vegetation status of the field. This process is operated every month; once the  
 314 consumption process is activated,  $F_{cell}$  decreases with the agent consumption.

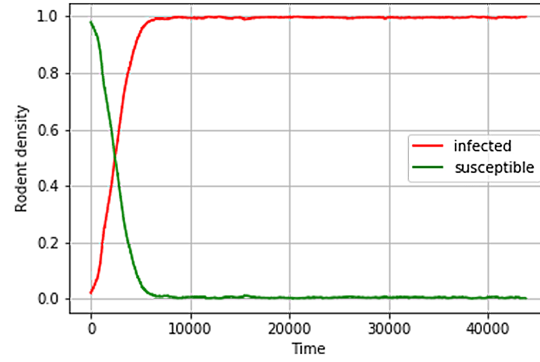
## 315 4. Results

316 Simulations were performed using the Gama 1.7.0 platform to develop the  
 317 agent-based simulator Python 3 to generate the experiment plan and sensitivity  
 318 analysis.

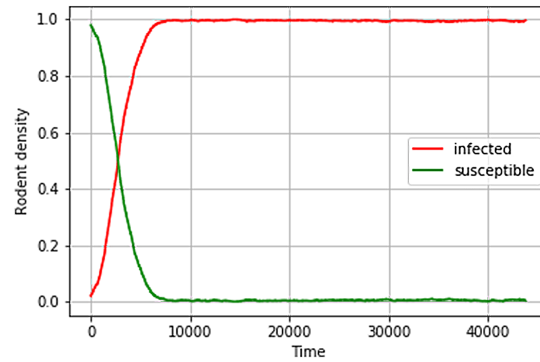
319 To see the movement effect (i.e., random or thoughtful) and the NDVI choice  
 320 (i.e.,  $NDVI_{min}$ ,  $NDVI_{mean}$ , and  $NDVI_{max}$ ) on the spread of the epidemic (i.e.,

321 the infected versus susceptible rodents), we performed a simulation of 50 agents  
322 over 5 years. Each simulation was repeated 30 times. We have represented on Fig.  
323 7 and Fig. 8 the average of infected density and susceptible density on the simula-  
324 tions. In the thoughtful movement, we set  $AF_{consum} = 0.001$ ,  $AF_{min} = 0.2$ , and  
325  $L_{memory} = 0.8$ . However, to obtain a random movement, we fixed  $AF_{min} = 0.7$ .

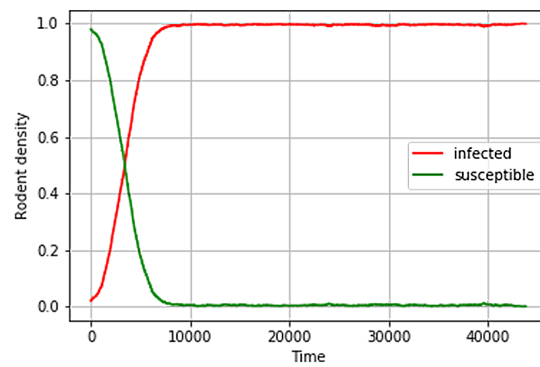
326 We tested the model using an exhaustive method that consists all the possible  
327 combinations of the parameters (basic and modified) and reviewing those that give  
328 prevalence close to that of reality. To the best of our knowledge, there is only one  
329 study in Central Tunisia that demonstrated the prevalence of *L. major* infection  
330 among *M. shawi* rodents (Ghawar et al., 2011). The prevalence of *L. major* for  
331 indirect fluorescent antibody test was 0.33.



(a) NDVImax

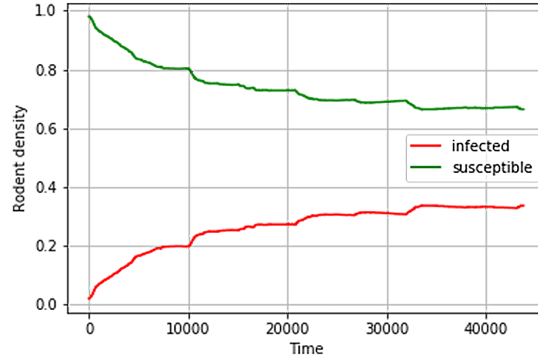


(b) NDVImean

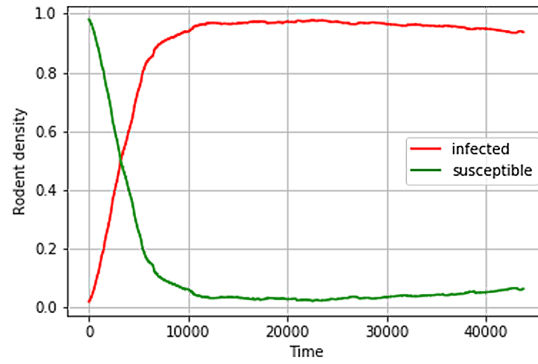


(c) NDVimin

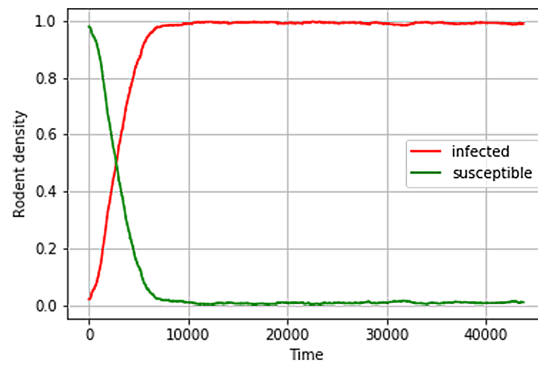
Figure 7: Figures representing the dynamics of infected rodents (red curve) and susceptible rodents (green curve) with varying NDVI in random movement case.



(a) NDVImax



(b) NDVImean



(c) NDVimin

Figure 8: Figures representing the dynamics of infected rodents (red curve) and susceptible rodents (green curve) with varying NDVI in thoughtful movement case.

332 We noted that the type of movement affects the variation in infected density.  
 333 In the random movement case, all rodents become infected (see Fig. 7). The same  
 334 behavior can also be observed in the case of  $NDVI_{min}$  when the movement is  
 335 thoughtful (Fig. 8c). In the  $NDVI_{mean}$  case (thoughtful movement), the majority  
 336 of rodents are infected (between 94% and 98%). We also observed a slight de-  
 337 crease in the infected density over the last 2 years (see Fig. 8b). In  $NDVI_{max}$   
 338 case when the movement is thoughtful (Fig. 8a), there is a small increase in the  
 339 infected density with a stability at the end of the simulation (30% of rodents are  
 340 infected).

341 We calculated the average prevalence (in the last 3 years) that  $\overline{P_{max}}$ ,  $\overline{P_{mean}}$ ,  
 342 and  $\overline{P_{min}}$  (corresponding to  $NDVI_{max}$ ,  $NDVI_{mean}$ , and  $NDVI_{min}$ , respectively).  
 343 It can be seen that they are greater in the first scenario (random movement). Thus,  
 344 we noticed that the average prevalence is inversely proportional to the NDVI val-  
 345 ues in the case of thoughtful movement (see Table 3).

Table 3: Mean prevalence and standard deviation (SD) values calculated over the last 3 years.

Type of movement	Type of prevalence	Value of prevalence	SD
<b>Random</b>	$\overline{P_{max}}$	0.99	0.06
	$\overline{P_{mean}}$	0.99	0.06
	$\overline{P_{min}}$	0.99	0.06
<b>Thoughtful</b>	$\overline{P_{max}}$	0.34	0.006
	$\overline{P_{mean}}$	0.92	0.01
	$\overline{P_{min}}$	0.99	0.006

346 To examine the distribution of rodents in the cells and compare them with  
 347 those in the field, we calculated the entropies noted  $H_{max}^r$ ,  $H_{mean}^r$ , and  $H_{min}^r$  cor-  
 348 responding to the first scenario (random movement) and  $H_{max}^{th}$ ,  $H_{mean}^{th}$ , and  $H_{min}^{th}$   
 349 corresponding to the second scenario (thoughtful movement). We calculated the  
 350 entropy ratio  $r = \frac{H}{H_{field}}$  ( $H_{field}$  is the entropy of the real distribution of rodents in  
 351 the field) to compare the model entropies and field data (Fig. 9).

352 The results showed that when the movement is random, the entropy ratio is  
 353 almost equal to the maximum entropy ratio  $r_{uniform}$  (the most disordered state).  
 354 Moreover, we noted that when the movement is thoughtful, the entropy ratio is  
 355 close to that of the field. The value of the entropy ratio closest to that of the field  
 356 is in the case of  $NDVI = NDVI_{max}$ , and it has been noted that if the simulation  
 357 time is greater, the ratio entropy  $r_{max}^{th}$  is close to the value 1 ( $r_{field}$ ).



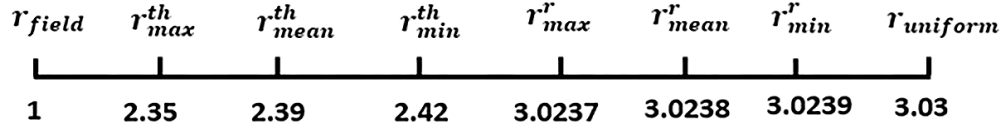


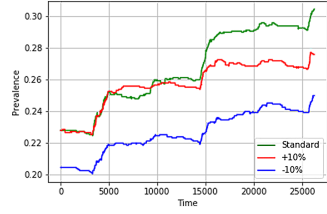
Figure 9: The entropy ratios: All entropies are normalized with respect to the field entropy  $H_{field}$ ,  $r_{field} = \frac{H_{field}}{H_{field}} = 1$ ,  $r_{max}^{th} = \frac{H_{max}^{th}}{H_{field}}$ ,  $r_{mean}^{th} = \frac{H_{mean}^{th}}{H_{field}}$ ,  $r_{min}^{th} = \frac{H_{min}^{th}}{H_{field}}$ ,  $r_{max}^r = \frac{H_{max}^r}{H_{field}}$ ,  $r_{mean}^r = \frac{H_{mean}^r}{H_{field}}$ ,  $r_{min}^r = \frac{H_{min}^r}{H_{field}}$ ,  $r_{uniform} = \frac{H_{uniform}}{H_{field}}$ .  $H_{uniform}$  denotes the uniform distribution entropy. In the description of the entropy ratios, the following symbols are used: r: random movement, th: thoughtful movement, max:  $NDVI_{max}$ , mean:  $NDVI_{mean}$  and min:  $NDVI_{min}$ .

358 Finally, we performed a sensitivity analysis to determine the parameters that  
359 could influence the prevalence. This analysis was applied in the thoughtful move-  
360 ment case when the NDVI was maximum. Thus, we used the one-factor-at-a-time  
361 (Cariboni et al., 2007; Saltelli et al., 2008) sensitivity analysis method that con-  
362 sists of selecting a base parameter setting and varying one parameter by  $\pm 10\%$   
363 at a time while keeping all other parameters fixed. Each simulation was repeated 30  
364 times. The infection factor  $\alpha$ , recovery probability  $\gamma$ , consumption rate  $AF_{consum}$ ,  
365 minimum food detected  $AF_{min}$ , and loss memory rate  $L_{memory}$  parameters were  
366 tested.

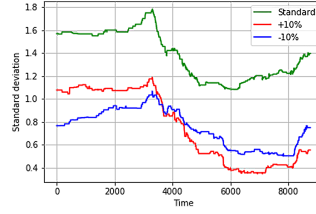
367 Fig. 10 shows the variations in prevalence and standard deviation according to  
368 the modified parameters. In addition, a linear regression analysis was performed  
369 for each case. We estimated the coefficient of determination, slope, and intercept  
370 for each curve (Table 4)

371 The results show the effect of seasonality on the variation in prevalence and  
372 standard deviation. In addition, we noted that practically all the curves have the  
373 same slope, which is very low (in the order of  $10^{-4}$ ). This weakness can be ex-  
374 plained by the stability of prevalence in the last 3 years.

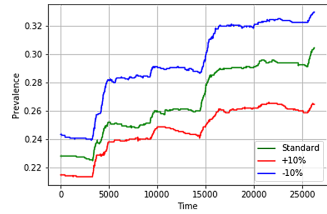
375 In addition, we noted the impact of the parameters on prevalence and SD val-  
376 ues. For example, in Fig. 10c, when the recovery probability  $\gamma$  is high, the preva-  
377 lence value becomes lower. In the figure, when  $AF_{consum}$  is high, the prevalence  
378 value increases.



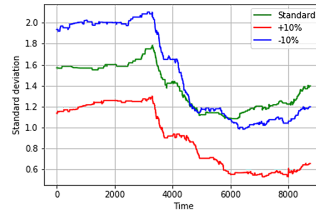
(a)



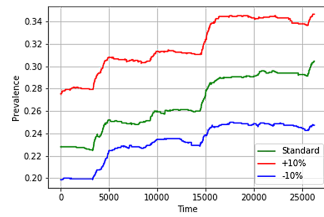
(b)



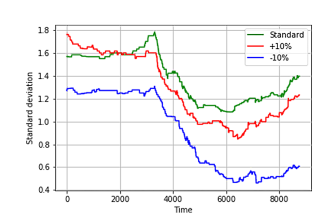
(c)



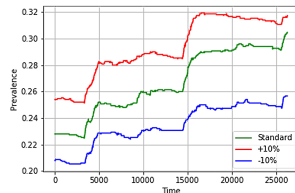
(d)



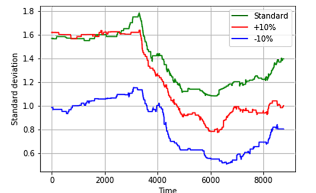
(e)



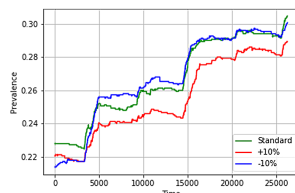
(f)



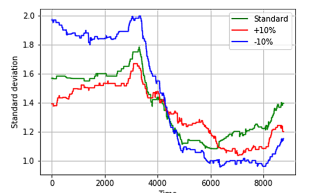
(g)



(h)



(i)



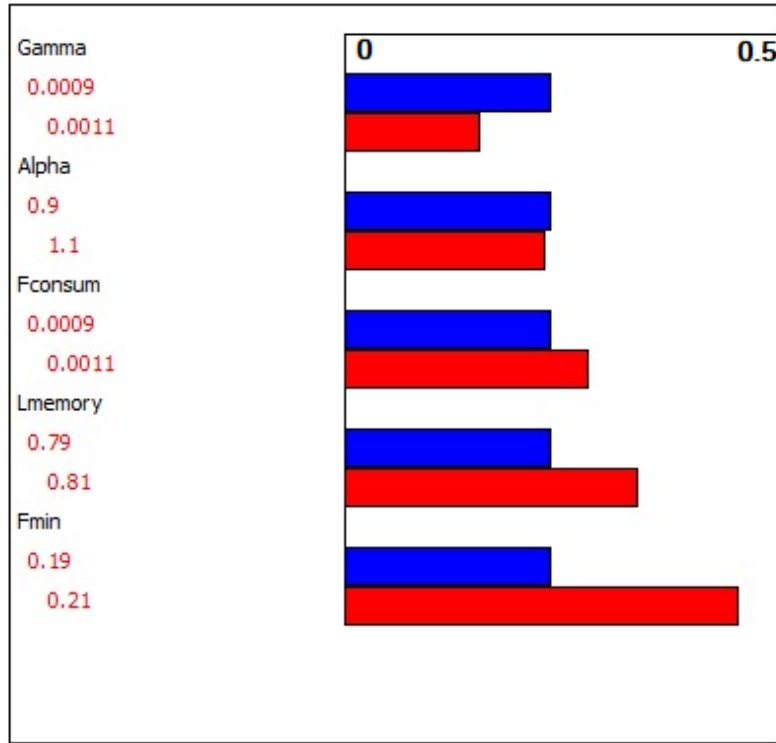
(j)

Figure 10: Figures (a), (c), (e), (g), and (i) represent the prevalence for different values of parameters  $\alpha$ ,  $\gamma$ ,  $AF_{min}$ ,  $AF_{consum}$ , and  $L_{memory}$  respectively. Figures (b), (d), (f), (h), and (j) represent SD for different values of  $\alpha$ ,  $\gamma$ ,  $AF_{min}$ ,  $AF_{consum}$ , and  $L_{memory}$ , respectively

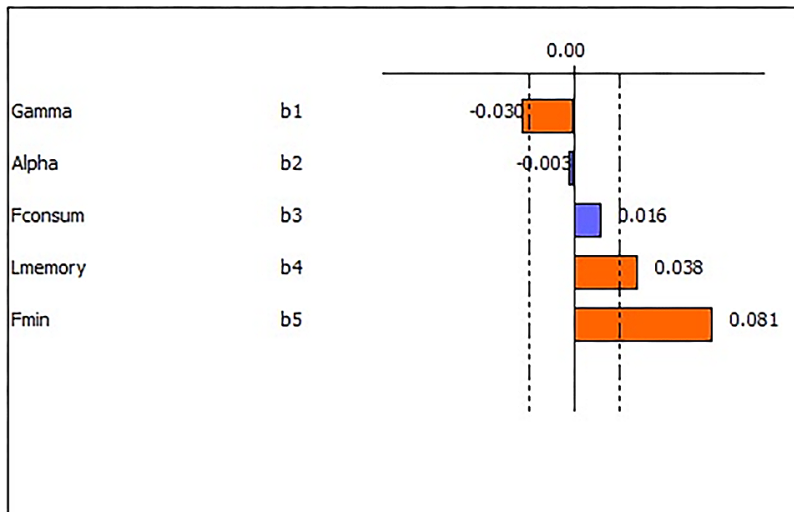
Table 4: Coefficient of determination, slope, and intercept of linear regression line for each modified parameter. In the case of based parameters,  $R^2 = 0.93$ , slope =  $10^{-4}$ , and intercept = 11.33

<b>Parameter</b>	<b>Variation</b>	<b>Coefficient of determination</b>	<b>Slope</b>	<b>Intercept</b>
$\alpha$	+10%	0.79	$8.10^{-5}$	11.74
	-10%	0.92	$8.10^{-5}$	10.23
$\gamma$	+10%	0.85	$9.10^{-5}$	11
	-10%	0.88	$10^{-4}$	12.46
$AF_{consum}$	+10%	0.85	$10^{-4}$	12.88
	-10%	0.88	$9.10^{-5}$	10.48
$AF_{min}$	+10%	0.86	$10^{-4}$	14.12
	-10%	0.8	$10^{-4}$	10.34
$L_{memory}$	+10%	0.88	$10^{-4}$	11.25
	-10%	0.93	$10^{-4}$	10.82

379 We then performed a sensitivity analysis to determine the effect of the 5 pa-  
380 rameters on the mean prevalence over the last 3 years. We observe that the min-  
381 imum food detected  $AF_{min}$  has a major effect on the mean prevalence, which  
382 increases by 0.2. The minimum food detected,  $AF_{min}$ , and the loss memory rate  
383  $L_{memory}$  have a positive effect ; however, the recovery probability  $\gamma$  has a negative  
384 effect. (see Fig. 11a and Fig. 11b).



(a)



(b)

Figure 11: Factors influencing the mean prevalence

Table 5: Screening parameters for the mean prevalence.  $b_i$  correspond to the model regression coefficients.  $\bar{Y} = b_0 + b_1 \gamma + b_2 \alpha + b_3 AF_{consum} + b_4 L_{memory} + b_5 AF_{min}$ .

Parameter	Coefficient	Value	Inflation factor	SD
	$b_0$	0.2808	1	0.0062
$\gamma$	$b_1$	-0.0301	1	0.0062
$\alpha$	$b_2$	-0.0027	1	0.0062
$AF_{consum}$	$b_3$	0.0162	1	0.0062
$L_{memory}$	$b_4$	0.0380	1	0.0062
$AF_{min}$	$b_5$	0.0814	1	0.0062

## 385 5. Discussion

386 Our results highlight the importance of considering the type of movement (ran-  
387 dom or thoughtful) of reservoir rodents considering their influence on the trans-  
388 mission of the epidemic. In the first scenario (random movement), the prevalence  
389 values were higher than those in the second scenario. This difference can be  
390 explained by the activity of rodents who forage randomly. The fact that the move-  
391 ment is random implies that the probability of an encounter is a product of the fre-  
392 quencies of the infected and susceptible rodents (i.e., mass action law). Thus, in  
393 this case, our model is "close" to an SIS model (susceptible-infected-susceptible  
394 epidemiological model). The term "close" refers to the fact that rodents spend the  
395 maximum of their time foraging *i.e.*, the case where  $NDVI = NDVI_{mean}$  and  
396  $NDVI = NDVI_{min}$ . In the case where  $NDVI = NDVI_{max}$ , the fluctuations  
397 may be due to the fact that rodents spend more time consuming food; thus, there  
398 is a lower possibility of being infected.

399 In the second scenario, when rodents accessed food more rapidly, the risk of  
400 infection was reduced because the probability of an encounter was lower. This  
401 explanation is supported by the fact that in the case where NDVI is weak (i.e.,  
402  $NDVI = NDVI_{min}$ ), the number of infected rodents becomes high again. If  
403 food is scarce, the information on feeding sites is low; therefore, the rodents adopt  
404 random movement.

405 Regarding temperature, its effect can only appear through the infection prob-  
406 ability  $p$  (see formula (6)). Note that the effect of NDVI also appears through  
407 the movement of rodents (which influences the probability of encounter). In the  
408 model, the simulations show that NDVI has a more dominant effect than temper-  
409 ature. Moreover, in the second scenario, we noticed that the effect of temperature  
410 is observed in the fluctuations in Fig. 8a and Fig. 8b. Additionally, when NDVI

411 increases, the prevalence decreases (Fig. 8).

412 This result was also observed by Shirzadi et al. (2015) and Shiravand et al.  
413 (2018), which showed that the incidence of leishmaniasis increased in areas where  
414 vegetation coverage was low. In the same context, Mollalo et al. (2014) showed  
415 that the decrease of the vegetation cover is accompanied by increase of epidemic  
416 occurrence and vice versa.

417 The prevalence and rodents strategies that provides closest results to those  
418 observed in the field, are when the rodents movement is thoughtful and when  
419  $NDVI = NDVI_{max}$  (Ghawar et al., 2011).

420 Moreover, figure 9 demonstrated that the thoughtful movement is similar to  
421 the field rodents motion. These results are consistent with Rajabi et al. (2018).  
422 The latter found that rodents adapt their direction and movement depending on  
423 food suitability and availability. Field observation of Ghawar et al. (2015) showed  
424 that the higher vegetation cover is, the more new active burrows are detected,  
425 indicating that *M.shawi* is able to assess the vegetation abundance.

426 Even though relevant findings are reported in this current study, a more com-  
427 prehensive multispecies model which includes human and sandflies parameters  
428 would provide a deeper understanding of the ZCL transmission cycle. The lack  
429 of data on sandfly densities in Tunisia and on its association with plant density  
430 (NDVI) makes such the achievement of such study currently difficult. Moreover,  
431 no studies have been conducted on the demographic processes (births, deaths) in  
432 rodent reservoirs.

433 Other climatic factors, such as rainfall and humidity, which influence the trans-  
434 mission of ZCL are also important. However, in our case, these data were insuffi-  
435 cient; thus, we used NDVI as an environmental factor (which depends on rainfall  
436 and humidity). It can be used when climate data as well as environmental charac-  
437 teristics of the site are not available (Gaudart et al., 2009).

## 438 6. Conclusion

439 In conclusion, our study provides an overview of the effects of climate (*i.e.*  
440 temperature) and environmental (*i.e.* NDVI) parameters on the rodents move-  
441 ments in a limited geographical area by using an ABM in order to simulate the  
442 transmission of ZCL among rodents. We considered two types of rodents move-  
443 ment (random or thoughtful). We observed that NDVI has a more dominant effect  
444 than temperature, and the transmission of ZCL was increased by decreasing the  
445 value of NDVI.

446 The findings reported in this current study would improve comprehension of  
447 the ZCL spread dynamics in larger areas, and thus to be subsequently used to  
448 implement prevention and control strategies of the epidemic.

## 449 **7. Acknowledgements**

450 We thank Professor Afif Ben Salah and the *Department of Medical Epidemi-*  
451 *ology* for their support and for providing references and unpublished information  
452 about temperature and *M. shawi*. We would also like to show our gratitude to Dr  
453 Dhafer Laouini for his financial support.

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