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1Future development of apricot blossom blight under climate change in Southern France

2

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22

23Abstract

24

25Climate change will have several consequences for agro-systems, one of which will concern

26changes to the development of pathogens. Because of the losses it causes, particularly in

27organic farming, *Monilinia laxa* is an important pathogen affecting apricot crops. This study
28focuses on the consequences of climate change regarding blossom and twig blight (*Monilinia*
29*laxa*) of apricot. To achieve this, a Climatic Index of cumulated Blight risk (CIB) was built, to
30obtain the weighted sum of blossom blight incidence throughout the blooming period. An
31epidemiological model to calculate the incidence of blossom blight during every potentially
32infectious episode and based on biological parameters, was calibrated using a trap pot
33experiment where trees were placed in orchards and subject to various meteorological
34conditions. The CIB derived from this model was evaluated on field data, and was shown to
35be a robust and useful tool to predict the effects of climate change on the development of
36apricot blight. Then, using the CIB with a phenological model to predict blooming periods in
37the future, we estimated the risks of apricot blight until 2100 on four contrasted apricot
38cultivars and in three geographical zones under climate change scenarios RCP 4.5 and 8.5.
39This study revealed different effects of climate change depending on the cultivar and altitude.
40Apricot trees would bloom earlier (up to a difference of 50 days between 1950 and 2100)
41under climate change. Under the combined effects of these shifts of blooming period and
42changing climatic conditions, late cultivars such as Bergarouge might see a reduction in the
43risk of blossom blight (down to 31%) because of warmer but dryer blooming periods. Other
44varieties (e.g.: Bergeron) could experience an increase in this risk by up to 27% with a shift of
45the blooming period towards rainier conditions at the highest altitudes. The results of this
46study could be used to anticipate future changes as well as be used at present as a decision-
47support tool for farmers.

48

49**Key words**

50Blossom blight, *Monilinia laxa*, apricot orchards, *Prunus armeniaca* L., climate change,
51modelling, phenology

52

531. Introduction

54

55

56 Climatic changes such as increase of air temperature and rainfall variability can directly
57 and/or indirectly affect pathogens and the plant diseases they are causing, which has been
58 recently reviewed (Trebicki and Finlay, 2019). All important life cycle stages of fungal
59 pathogens are more or less directly influenced by the prevailing environmental conditions.
60 The infection process is particularly dependent on the species specific temperature and
61 humidity requirements of the pathogens. According to the review article by Juroszek and
62 Tiedemann (2015) infection risk is the most frequently investigated plant disease parameter in
63 disease risk simulation studies, where crop disease models have been linked to climate
64 scenarios including, for example, downy mildew infection risk of grapevine (*Vitis vinifera* L.)
65 published by Launay et al. (2014). As well as direct effects on pathogens, climate change will
66 also affect plant phenology (Körner and Basler, 2010) and thus modify host-pathogen
67 synchronism (Caubel et al., 2017). This indirect effect of climate change on disease
68 development will be all the more crucial regarding pathogens that infect plants during a short
69 and sensitive phenological stage, such as infectious diseases which attack during blooming
70 periods.

71 Apricot (*Prunus armeniaca* L.) is an important crop in the Mediterranean region (14,000 ha
72 planted and 180,000 T of fruit produced in 2014) and particularly in southern France (third
73 most important fruit crop) (Lichou and Jay, 2012), but like other such crops, apricot requires
74 repeated fungicide treatments to secure production. In 2012, an average apricot orchard in
75 France received 11.8 treatments, including 8.1 against fungi (AGRESTE, 2014). Among the
76 different fungi that affect apricot, *Monilinia spp.* causes the most losses (Hrustić et al., 2012;

77Oliveira Lino et al., 2016). Three species of *Monilinia* have a significant economic impact:
78*Monilinia laxa*, *Monilinia fructicola* and *Monilinia fructigena* (Hrustić et al., 2012; Oliveira
79Lino et al., 2016). The latter has been the subject of the most study because of the damages it
80also causes to apple and pear crops. However, infections affecting stone fruits are mainly due
81to *Monilinia laxa* and *Monilinia fructicola* (Oliveira Lino et al., 2016). *Monilinia laxa* can
82infect apricot blossom, twigs and fruit. Blossom and twig blight are the principal concerns,
83particularly for organic farmers, and can cause losses of up to 90% in Southern France
84(Parveau et al., 2016).

85Apricot blossom is sensitive to blight (whether this is caused by *M. laxa* or *M. fructicola*) at
86flowering. The flowers have been shown to be the most susceptible when they are wide open
87(BBCH Stage 65; Hack et al., 1992) (Luo et al., 2001). In some cases, infected blossoms can
88then convey infection to the twigs, generating a necrosis of internal tissues. Moreover, twig
89blight can only be caused when transmitted via infected blossom (Agrios, 2005). During the
90present study, we focused on twig and blossom blight, as there is a causal relationship
91between the two, and did not address the problem of fruit rot.

92The development of *Monilinia* fungal infection on stone fruit blossom is linked to
93meteorological conditions in several ways, as has been demonstrated by previous studies.
94Experimenting in a growth chamber, Tamm et al. (1995) revealed the effects of the duration of
95petal wetness and temperature on the development of blossom blight caused by *M. laxa* on
96cherry (*Prunus avium* L.). Luo et al., (2001) produced similar results in 2001 in their study on
97plums (*Prunus domestica* L.) infected by *M. fructicola*. Relative humidity and water activity
98have also been shown to affect the development of *M. fructicola* on cherry blossom petals
99(Koball et al., 1997). Casals et al., (2010) highlighted the importance of the same weather
100factors to the germination of *M. fructicola* on Petri dishes (Casals et al., 2010). However,
101although the effects of climate on the development of *Monilinia* have been studied before, to

102our knowledge this has only been done under controlled conditions. It may be difficult to
103ensure reliable recordings of the variables used to describe incidence, mycelial development
104or conidia germination in the field. For example, leaf wetness duration is widely used in crop-
105disease epidemiological models but remains difficult to measure accurately (Gleason et al.,
1062008).

107In the context of climate change, the increasing threat of apricot blight makes it necessary to
108develop tools that will enable us to define/imagine crop systems adapted to future conditions.
109There is therefore a need for bioclimatic modelling to anticipate the changes to come and
110adapt our agro-systems (Jeschke and Strayer, 2008). Current epidemiological models that are
111used as Decision Support Systems (DSS) are often of a purely statistical nature. They are
112calibrated on current data for use at present but may lack robustness regarding any changes to
113conditions which fall outside their domain of validity. On the other hand, bioclimatic and
114physiological models are calibrated under controlled conditions (Petri dishes, growth
115chambers, greenhouses) that may not reflect the reality in the field, so are once again
116deficient. Faced with the future uncertainties inherent in climate change, our models need to
117be adaptable and valid under different conditions (Maier et al., 2016).

118The study we present here only concerned *M. laxa*, as several identification tests performed
119during the experiments based on the Lane identification key (Lane, 2002) had reported a great
120majority of *M. laxa* cases (93.7%), rather than *M. fructicola* (6.3%) and *M. fructigena* (none).

121

122The aims of this study were to (1) produce a climatic index of blight risk thanks to an
123epidemiological model simulating the incidence of blossom and twig blight caused by *M.*
124*laxa* on apricot. This model, including biological parameters, was calibrated on field data
125from a trap pot experiment and then evaluated on independent data from a network of
126orchards;

127(2) determine the effects of climate change on apricot blossom blight. To do so, we first of all
128applied a phenological process-based model to simulate flowering changes, and then
129implemented our epidemiological model to calculate the incidence of blossom blight on four
130contrasted apricot cultivars in three geographical ranges and under two climate change
131scenarios.

132

1332. Materials and methods

134

135 2.1. Building a climatic index of cumulated blight risk

136The Climatic Index of cumulated Blight risk (CIB) that we propose is built in several sections.
137A blossom incidence I is calculated using a modified version of the epidemiological model
138proposed by Tamm et al. in 1995. This factor reflects primary blossom infection due to
139inoculum dispersal and infection as a function of rainfall and temperature. This blossom
140infection can then be transmitted to twigs. This transmission is not equal at all stages of
141blossom development so incidence I is weighted according to the proportion of disease-
142sensitive stages at the time of infection, to form a Weighted Incidence WI . The twig blight
143observed at the end of blooming is thus the result of several infectious episodes and the
144different WI experienced by an orchard are then summed to obtain a Climatic Index of
145cumulated Blight risk (CIB) that reflects twig infection.

146

147 2.1.1. Incidence of blossom blight

148The epidemiological model we used for this study was a modified version of that proposed by
149Tamm et al., (1995) to describe the incidence of *M. laxa* blossom blight (*number of*
150*symptomatic blossoms/total number of blossoms*) on sour cherry trees (Tamm et al., 1995).
151This model describes a continuous response surface for any given temperature and wetness

152duration, making it usable under different conditions and appropriate for the study of climate
153change. We nevertheless made several modifications to this model.

154First, Tamm's model takes wetness duration and temperature as input variables to generate
155incidence data. During our study, we preferred to use rainfall rather than wetness duration to
156explain blight incidence (see Supplementary Materials 1 for a comparison between wetness
157duration and rainfall). One of the advantages of this approach is that rainfall data are easier to
158measure accurately in the field.

159Second, in order to prevent the model from generating positive incidence values in the
160absence of rainfall (as the trees displayed no symptoms under dry conditions), we added a
161corrective term taking a zero-value for null rainfall and a one-value otherwise. In this context,
162a supplementary factor built on precipitation (p) and a constant ε , $p/(p + \varepsilon)$ with $\varepsilon \neq 0$, was
163added to force the model to return no incidence if the rainfall is null.

164The equation of our modified version of the Tamm model is therefore as follows (eq.1):

165

$$166 I(p, T) = \frac{p}{p + \varepsilon} * i_{max} * \left\{ 1 - \left(1 - i_0(T)^{(1-m)} \right) * e^{-r(T)*p} \right\}^{\frac{1}{1-m}} \quad (1)$$

167with,

$$168 i_0(T) = \gamma_1 * \phi^{\gamma_2} * (1 - \phi) \quad (2)$$

$$169 r(T) = \rho_1 * \phi^{\rho_2} * (1 - \phi) \quad (3)$$

170where,

$$171 \phi = \frac{(T - T_{min})}{(T_{max} - T_{min})} \quad (4)$$

172

173The model returns the incidence I for a given rainfall p and temperature T . The model takes as
174known parameters i_{max} (the maximum observed incidence), and T_{min} and T_{max} the minimal and
175maximal cardinal temperatures for *M. laxa* development. The fit parameters ρ_1 , ρ_2 , γ_1 , γ_2 and ε

176 were estimated during model fitting. The shape parameter m was set at 0.9 as advised by
177 Tamm (Tamm et al., 1995). The ϕ factor describes a “bell curve” response to temperature. The
178 $i_0(T)$ factor was originally designed to return an incidence in the absence of wetness duration.
179 We retained it despite the supplementary factor that we added because we saw a rapid
180 increase in the incidence observed on trees under low rainfall levels. This factor therefore
181 describes incidence at low rainfall values. The $r(T)$ factor is a rate parameter describing the
182 response to rainfall.

183

184 In addition to this model, we also tested two others (see Supplementary Materials 2.): (i) a
185 simple generic infection model based on epidemiological knowledge and proposed by
186 Magarey and colleagues (Magarey et al., 2005, referred to below as “Magarey”), and (ii) a
187 purely statistical model (linear regression, referred to as “LM”) established from our trap pot
188 experiment dataset. We chose the modified Tamm model we because of its greater robustness
189 and suitability for climate change studies (for details see Supplementary Materials 2.).

190

191 **2.1.2. Transmission to twigs**

192 As the proportion of disease-sensitive blossoms is evolving with phenology, I has to be
193 weighted for rainy events that occur at different times during blooming.

194 Different blooming stages are susceptible in different ways to blossom blight (Luo et al.,
195 2001). We observed that 58 to 65 BBCH stages (flower opening) displayed comparable
196 sensitivity and the 57 stage (sepals opening) had less sensitivity; 57 stage infections were only
197 possible in the context of a highly infectious event and were observed at lower proportions
198 (data not shown). The Weighted Incidence WI was thus defined as:

199

$$200 WI = \frac{I \times (0,25 S_{57} + S_{5865})}{S_{57} + S_{5865}} \text{ if } I \geq 0,5 \quad (5)$$

$$WI = \frac{I \times S_{5865}}{S_{57} + S_{5865}} \text{ if } I < 0,5 \quad (6)$$

With S_{57} being the number of flowers at BBCH stage 57 and S_{5865} being the number of flowers at BBCH stages 58 to 65.

Because twig infection is caused by infected blossoms, use of these weightings was necessary to correctly describe transmission of the infection to twigs.

206

207 **2.1.3. Climatic index of cumulated blight risk**

The twig infection observed was the result of several blossom infections, each being caused by a rainy event during blooming. We chose to identify a single rainy event during the blooming period as a record of rainfall separated from another rainfall episode by at least 4 hours without rain or leaf wetness. We estimated that 4 hours was sufficiently long for the wetness caused by the rain to dry, so that the next event could be considered separately. Finally, by summing the WI associated with different rainy events, we were able to build a **Climatic Index of cumulated Blight risk** (CIB) reflecting the history of infectious events (eq. 7).

$$CIB = \sum_{i=1}^n WI_i \quad (7) \quad n \text{ being the number of recorded rainy events}$$

217

218 **2.2. Data**

219

220 **2.2.1. Trap pot experiment for model calibration**

CIB parameters corresponding to those enabling calculation of the blossom infection (I) component were optimised with data from a trap pot experiment. This trap pot experiment was performed under semi-controlled conditions: we chose the weather events to which the pots would be exposed by taking them out into the orchard or returning them to the

225greenhouse. In the orchard, they continued to be exposed to field inoculums and current
226weather conditions. The fact that we could choose the events to which the trees were exposed
227enabled us to cover a broad range of weather conditions for model calibration, and at the same
228time this contributed robustness to our model as the calibration was performed using field
229data.

230The trap pot experiment for model calibration was carried out at the INRA Gotheron Research
231Station (Southern France, 44° 58' 37" N, 4° 55' 48" E) over a two-year period, *i.e.* 2017 and
2322018.

233Trap apricot trees in pots were set out in the orchard for a defined period of time (around 24
234hours), during which they were exposed to recorded meteorological conditions (see 3.1.2) and
235outdoor *Monilinia* inoculum. The pots were then moved to a greenhouse in which the
236conditions were controlled and favourable to the expression of blossom blight.

237Apricot trees of the Bergarouge cultivar (Bergarouge® (A2914) Avirine (cov)) were used as
238the trap pot trees. This cultivar is known to be very sensitive to blossom blight (Parveau et al.,
2392016). The expression of symptoms in the event of exposure to *M. laxa* and favourable
240climatic conditions for infection was therefore ensured. The orchard comprised three lines of
24125 trees along a south-north axis.

242We used seven groups of six Bergarouge trees in pots during 2017 and nine groups of five
243trees in 2018. Before exposure, the trees were maintained in a cold room (4°C) to keep their
244phenology under control. Each tree within a group was exposed for the same period in the
245orchard between the BBCH 57 and BBCH 65 stages (disease-sensitive stages) and during the
246blooming period of the Bergeval orchard. The first group of trees was exposed on 27 February
247and the last on 10 March in 2017, while in 2018 the trees were exposed for periods between 7
248and 28 March. After exposure, pots were placed in a greenhouse under controlled conditions
249(relative humidity >40%, ambient temperature between 5°C and 25°C).

250 With each group, a control tree was left in the greenhouse to prove the absence of any
251 inoculum inside the greenhouse.

252

253 **2.2.2. Orchard network for model evaluation**

254 The model was tested on independent data by studying an orchard network in Southern
255 France. The CIB was calculated for the orchards and compared versus a measured Twig
256 Blight Incidence (TBI).

257

258 The network comprised 15 orchards located in the Drôme and Ardèche regions (Rhône Valley,
259 France, ranging between 4°48'29"E - 4°58'54"E and between 45°14'52"N - 44°41'51"N).
260 Thirteen orchards were studied in both 2017 and 2018 and two were studied in 2018, thus
261 providing a total of 28 siteXyear measurements of Twig Blight Incidence. None of the
262 orchards was treated against fungal diseases.

263 These 15 orchards were planted with two moderately sensitive cultivars: ten with the
264 Bergeron cultivar (Bergeron (660)) and five with the Bergeval cultivar (Parveau et al., 2016).
265 These cultivars are less sensitive to blossom blight than the Bergarouge trees used for the
266 blossom blight model. However, this was not expected to alter the performance of the model
267 (see Discussion).

268

269 Blighted twigs were counted on five random main branches per orchard to obtain one TBI
270 notation per orchard:

$$271 TBI = \frac{\text{number of blighted twigs}}{\text{total number of twigs}} \quad (8)$$

272

273 The evolution of blossom phenological stages was recorded regularly (three times a week) on
274 ten trees in each orchard. On several occasions, the proportion of blossom at each stage was

275estimated. The proportion of blossom at any time during the different stages was then
276extrapolated linearly between two estimation dates.

277

278 **2.2.3. Recorded meteorological data**

279A weather station (IMT 200 Pessl Instruments, Weiz, Austria) was placed in the middle of
280each orchard (trap pot experiment and each orchard in the orchard network) at a height of 1.80
281m. Rainfall (mm), temperature (°C) and leaf wetness (min) were recorded at an hourly time
282step using a rain gauge, temperature sensor and filter paper leaf sensor, respectively. Leaf
283wetness was also measured with an electric resistance sensor to assess the reliability of the
284measurements (this variable is used in Supplementary Materials 1).

285

286 **2.2.4. Future climate data**

287We performed the study using the predicted rainfall and temperature data of 46 DRIAS grids
288(French climate change modelling project, <http://www.drias-climat.fr>), which are 8 x 8 km
289wide. They were selected in the Rhône Valley at locations where apricot is currently being
290cultivated.

291

292For more clarity we decided to group the DRIAS grids thus employed in several clusters. A
293Hierarchical Ascending Classification was performed (mean temperature and mean rainfall as
294entry variables) and reflected groups as a function of altitude (see Supplementary Materials
2953). The following clusters were thus used (see *Fig. 1*):

296Cluster 1: altitude <100m

297Cluster 2: 100m ≤ altitude ≤ 400m

298Cluster 3: altitude > 400m

299

300 Present and future climatic conditions (between 1950 and 2100) were applied using the
301 ALADIN-Climate regional climate model nested within the global ARPEGE model (Deque,
302 2010). Three periods were simulated: the ‘recent past’ (RP, 1970–1999), ‘near future’ (NF,
303 2020–2049) and ‘far future’ (FF, 2070–2099) according to two ‘representative concentration
304 pathway’ emission scenarios, RCP4.5 (median) and RCP8.5 (pessimistic) (Pachauri et al.,
305 2014).

306

307 **2.3. Application to climate change**

308

309 **2.3.1. Phenological model**

310 In order to apply our model to the context of climate change, it was necessary to forecast
311 apricot blooming periods in the future. We therefore implemented a two-step phenological
312 model on future climatic data.

313

314 **2.3.1.1. Estimation of the mid-blooming date**

315 To simulate the blooming period for apricot we used the sequential phenological process-
316 based model proposed by Andreini et al. (2014). The date of budbreak is simulated using the
317 Smoothed Utah function (Bonhomme et al., 2010, advised by Andreini et al. 2014) and the
318 time between budbreak and mid-blooming (F50) is simulated with a sigmoid model (Chuine
319 et al., 2016). We estimated the mid-blooming dates for four cultivars chosen to have different
320 precocities in terms of dormancy release and blooming: cv. Beliana (Beliana® Sayeb)
321 (median to early blooming period), cv. Bergarouge (used during the trap pot experiment,
322 median blooming period), cv. Bergeron (late blooming period, widely used in the Rhône
323 Valley) and cv. Rouge du Roussillon (Rouge du Roussillon (A157)) (early blooming period).

324The models we used to estimate the F50 date had already been calibrated for the different
325cultivars (Andreini et al., 2014, Chuine et al., 2016), (Garcia de Cortazar-Atauri et al., 2013).

326

327 **2.3.1.2. Estimation of the blooming period**

328The expand of the blooming period was estimated by studying the phenological data recorded
329by the orchard network. No significant differences were found between the expands of the
330blooming periods of Bergeron and Bergeval (T-test, p-value = 0.2196). Recordings on the two
331cultivars were then grouped. We found that the proportion of disease sensitive stages during
332blooming (degree-days) could be approximated using a Gaussian curve centred on the
333maximum proportion of opened flowers (around 100% of opened flowers) and of a 28 degree-
334day standard deviation. It was then possible to estimate the expand of the blooming period at
335around F50, starting 122 degree-days before F50 and ending 133 degree-days after F50.

336

337 **2.4. Data analysis**

338Statistical analysis and computations were performed using R 3.4.3. Computations for
339phenological modelling were performed using Phenology-Modeling-Platform 5.5
340(<http://www.cefe.cnrs.fr/fr/recherche/ef/forecast/phenology-modelling-platform>) (Chuine et
341al., 2013).

342

343 **2.4.1. Model calibration**

344Goodness-of-fit was assessed using the Root Mean Square Error (RMSE, eq.9) and Relative
345Root Mean Square Error (RRMSE, eq.10).

346

$$347 RMSE = \sqrt{\frac{\sum (S_i - O_i)^2}{n}} \quad (9) \quad \text{and} \quad RRMSE = \frac{RMSE}{\bar{O}} \quad (10)$$

348

349 Where n is the number of observations, S_i the simulated value and \bar{O} the average of observed
350 values O_i . RMSE can be broken down into two components representing systematic (bias or
351 RMSEs) and unsystematic (dispersion or RMSEu) error (Willmott, 1981).

352

$$353 RMSE_s = \sqrt{\frac{\sum (\hat{S}_i - O_i)^2}{n}} \quad (11)$$

$$354 RMSE_u = \sqrt{\frac{\sum (\hat{S}_i - S_i)^2}{n}} \quad (12)$$

355

356 With \hat{S}_i being derived from the linear regression of observed versus simulated values:

357 $\hat{S}_i = a + b * O_i$ with a and b being the parameters of the regression.

358

359 **2.4.2. Model evaluation**

360 The performance of our model was then assessed from the correlation between the observed
361 Twig Blight Incidence of orchards in the network and their respective calculated CIB.

362

363 **2.4.3. Algorithm for climate change study**

364 The method used for computation is described in Figure 2.

365

366 **3. Results**

367

368 **3.1. Model fitting and evaluation**

369 Our model revealed a RMSE of 6.12% incidence when comparing the simulated incidence on
370 flowers with those observed in the calibration dataset. Given that the average incidence was
371 27.34%, the RRMSE of our model was 22.43%, which could be considered to be a

372satisfactory performance. A comparison between simulated and observed incidences is
373illustrated in Figure 3.

374

375

376Furthermore, the RMSEs was 1.86% whereas the RMSEu was 5.84%, meaning that the error
377was mostly due to dispersal of the points (*i.e.* biological variability) and not to bias in the
378chosen formalism. This can also be seen in Figure 4 which represents the residuals associated
379with each point.

380

381The parameter values we obtained after optimisation are shown in Table 1.

382

383The CIB calculated using our model was correlated with Twig Blight Infection at $R^2 = 0.46$
384(Fig.5). Given the numerous parameters varying between the orchards (see Discussion), we
385considered this performance to be satisfactory.

386

387 **3.2. Evolution of blooming dates**

388The predictions of the phenological model indicated a shift of all mid-blooming dates to an
389earlier day in the year (DOY) for all cultivar and clusters. Under climate change scenario
390RCP4.5, the median blooming date was 20 days earlier, from 89.9 DOY (*i.e.* 31 March in
3911950) to 72.2 DOY (March 12 in 2100). This shift was more marked under scenario RCP8.5,
392where the F50 date moved to 61.5 DOY (1st March) in 2100 (Fig. 6). Rouge du Roussillon and
393Beliana displayed similar but moderated shifts toward earlier blooming dates (of around 20
394days), but the Bergeron cultivar notably experienced a shift of almost 50 days in its mid-
395blooming date in all clusters under the RCP8.5 scenario. Therefore, by 2100, the differences
396in blooming periods between Bergeron and other cultivars would no longer be significant. On

397the contrary, Bergarouge experienced less variation in its blooming date and would thus
398become the latest blooming cultivar by 2100 in both cluster 1 and cluster 2. We concluded
399that under the RCP4.5 and RCP8.5 scenarios, but particularly with the latter, a shift towards
400earlier blooming periods and a convergence between the blooming periods of different
401cultivars would be observed, with consequences regarding the climatic conditions during
402blooming and thus the risk of blossom blight.

403

404 **3.3. Evolution of climatic conditions during the blooming period**

405This future convergence of blooming periods caused a convergence of the climatic conditions
406prevailing during the blooming of different cultivars. In particular, Bergeron and Bergarouge
407experienced opposite and strong shifts. The blooming conditions for Bergarouge shifted
408towards warmer but dryer conditions, and would be 2°C warmer in the far future than in the
409past in all clusters and under both scenarios, the trees receiving 10 to 20 mm less rainfall
410during blooming (Fig. 7). On the other hand, Bergeron saw a marked shift of its blooming
411period towards earlier dates, so that this cultivar would experience cultivar conditions that
412would be colder (2.8°C lower in cluster 3 and RCP8.5) and rainier (especially in cluster 1).
413Rouge du Roussillon and Beliana saw more moderate shifts; those in cluster 3 shifted towards
414dryer conditions while cluster 1 saw a temperature-related shift towards warmer conditions.

415

416From an epidemiological standpoint, the impacts of these changes to climatic conditions
417during blooming could indeed be assessed by the CIB computation.

418

419 **3.4. Future risk of apricot blight**

420Significant differences in future CIB were only found in the eventuality of the RCP8.5
421scenario, so this is the only one described in greater detail below.

422The CIB calculated by the model revealed different consequences of climate change that
423varied according to the clusters and cultivars studied (Fig.8). Variations in the CIB between
424past and far future ranged from +27% (Bergeron cluster 1) to -31% (Bergarouge, cluster 1).
425However, cluster 1 (lowest altitudes) displayed greater inter-annual variations, although these
426differences were not always significant.

427

428We noted a significant in the risk to which Bergarouge is exposed, in all clusters. This could
429be linked to the shift of its blooming period to warmer but dryer conditions, the expected
430positive effect from rising temperatures being counter-balanced by the negative effect of
431lower rainfall (Fig. 7). On the other hand, an increase in risk may be possible in the near
432future (nf) for Bergeron in cluster 3 (altitudes higher than 400 m) because of colder but rainier
433blooming conditions. Beliana and Rouge du Roussillon experienced more diverse conditions
434depending on the cluster, with a general trend regarding disease risk that stagnated or
435diminished in the far future.

436

4374. Discussion

438This study generated a climatic index of cumulated blight risk based on an epidemiological
439model, describing the blossom and twig blight caused by *M. laxa* on apricot. The model we
440used was built using biological parameters driving development of the fungus (optimal
441growth temperatures, response to rain). This gave the model robustness, enabling its use
442within the framework of a changing climate. Furthermore, by comparison to the original
443Tamm model, this model was calibrated and evaluated on easily measurable variables and in
444the field, so that it is more applicable and closer to observed incidence. To our knowledge,
445this approach – integrating the incidence of both blossom and twig blight in the same CIB

446index, based on biological parameters and easily accessible weather inputs (daily temperature
447and rainfall), and valuable under field conditions – is entirely new.

448To estimate the effects of climate change on blight risks, we first of all determined the
449sensitivity periods of several cultivars. By estimating the present and future CIB at different
450altitudes (and even latitudes to a lesser extent), we were able to reveal different changes as a
451function of the precocities of the trees and their altitudes. The late blooming cultivar Bergeron
452might bloom earlier and face rainier conditions, leading to an increase in the incidence of twig
453blight; on the other hand, the median cultivar Bergarouge might shift towards later blooming
454and dryer conditions, accompanied by a lower blight incidence at all altitudes.

455

456 **4.1. Variabilities affecting evaluation**

457The results of evaluating this model using data from the orchard network could be considered
458as satisfactory ($R^2 = 0.44$). Indeed, numerous parameters varied between orchards in the
459network. For example, the amount of *Monilinia* inoculum could vary at the landscape or
460regional levels. Furthermore, the fitting performances of the epidemiological model
461(RRMSE = 0.22) were equal to or better than the fitting performances regarded as satisfactory
462by recent comparable studies (e.g.: Gouache et al., 2015; Morales et al., 2018).

463We set blossom-twig transmission according to our empirical observations. However,
464variations in twig infection via blossom could impact the performance of the model. For
465instance, blossom-twig transmission could also depend on climatic conditions. A large part of
466the correlation between the calculated CIB and observed TBI was due to the choice of
467weightings. More observations might help to improve our understanding of blossom-twig
468transmission. For example, orchards that experienced rain at the end of the blooming period
469displayed greater sensitivity to twig blight infection. This factor could be determined by
470means of other trap pot experiments or the analysis of a larger orchard network experiencing a

471 variety of conditions, with a broader range of latitudes; for example, combining
472 Mediterranean and more continental climatic conditions.

473 The biological construction of our epidemiological model means that it could be used to
474 address future conditions at a single location (in the present case, the Rhône Valley) but
475 should also make the model usable at various geographical locations. For example, testing our
476 model in other apricot growing regions such as Spain or Turkey would further assess the
477 robustness of the model we propose here.

478 It should be noted that the model used to calculate blossom blight infection was calibrated on
479 Bergarouge trees, which are more sensitive to blossom blight than Bergeval and Bergeron
480 (Parveau et al., 2016). However, because Bergeron and Bergeval display comparable
481 sensitivity (and thus comparable differences in sensitivity versus Bergarouge), the correlation
482 between CIB and TBI should not be affected mathematically by a difference in sensitivity
483 between Bergarouge and Bergeron or Bergeval.

484

485 **4.2. Working hypotheses**

486 We only studied climate-related factors during this study, in order to assess changes to the
487 infection risk in line with climate change. Nevertheless, factors of a genetic (e.g. resistance),
488 physiological (e.g. water stress) or epidemiological (e.g. inoculum repartition) nature should
489 also be taken into account.

490 Here, the apricot cultivars were only compared through the lens of precocities, but a factor
491 reflecting varietal sensitivity could be added. Such study would enable assessment of the
492 respective roles of phenology and genetics: is it better for a tree to avoid blight or resist it?

493 As for physiological factors, two types of interactions have been documented to date: "cross-
494 protection" for plants whose resistance to biotic stresses is increased by the onset of abiotic
495 stress, and "cross-vulnerability" for plants whose susceptibility to biotic stress is increased

496under abiotic stress (Fones and Gurr, 2017). These processes might modify the host response
497to increased biotic and abiotic stresses under climate change, and should therefore be
498considered under a more integrative modelling approach.

499Further, inoculum levels may vary at a landscape or regional level. For example, they may be
500affected by the provenance of air masses, as has already been shown for *Botrytis cinerea*
501(Leyronas and Nicot, 2013). Moreover, amounts of primary inoculum may also vary as a
502function of previous disease levels or orchard management practices (Lichou and Jay, 2012).

503The *Monilinia* inoculum may differ in terms of both quantity and quality involving a change
504to the predominant *Monilinia* species. For instance, because it is better suited to warmer
505temperatures (Casals et al., 2010) and displays pesticide resistance (Lichou and Jay, 2012),
506*Monilinia fructicola* may become more important than *Monilinia laxa* in the European
507inoculum landscape as climate change progresses. In addition, the sexual reproduction of
508*Monilinia laxa* has not yet been observed under natural conditions in Europe (Hrustić et al.,
5092012) but warmer temperatures could trigger this development cycle (Agrios, 2005). Such a
510change would render obsolete the model we present here, as this aspect of development
511remains a limiting factor. These features could also affect epidemiological concerns over the
512coming decades. Epidemiological studies on *M. fructicola* under semi-controlled conditions
513would then be of value in the context of future research.

514

515 **4.3. Uncertainty of climatic variables**

516Variations affecting the risk predicted by the model were mainly due to rainfall. However, this
517variable is hard to predict in climate change scenarios, and climatic models can generate
518markedly different predictions (Jouzel et al., 2014). For instance, the DRIAS data we used are
519based on the ALADIN model proposed by the French National Weather Research Centre
520(Centre National de Recherches Météorologiques) and used to forecast weather in the context

521of climate change; it predicts an overall reduction of rainfall in France between [1976-2005]
522and [2071-2100] under the RCP8.5 scenario in summer (-0.38 mm.day⁻¹). On the other hand,
523the WRF (Weather Research and Forecasting) model proposed by the US National Center for
524Atmospheric Research predicts an overall increase of rainfall of the same scope (+0.32
525mm.day⁻¹) (Jouzel et al., 2014), hence the uncertainty attached to ongoing modelling
526approaches used to study future impacts of climate change.

527

5285. Conclusion

529The Climatic Index of cumulated Blight risk we propose here offers an efficient reflection of
530twig blight infection calculated from the weighted sum of blossom blight infection episodes
531($R^2 = 0.44$ with independent evaluation). Blossom blight infections were estimated with a
532good fit to an epidemiological model (RRMSE = 0.22, largely due to unsystematic error).
533This model, calibrated and evaluated on field data (using easily measurable variables such as
534rainfall) and based on biological parameters, was shown to be a robust and useful tool to
535predict the consequences of climate change regarding the development of apricot blight.
536Because of a shift of the blooming period, the Bergarouge apricot cultivar could experience a
537long term reduction in the climatic risk to which it is exposed (in the far future). By contrast,
538cultivars such as Beliana or Bergeron could see a medium-term (near future) increase of this
539risk of blossom blight at altitudes above 100 m. The various conditions under which our
540model can be employed means that it could be applied to conditions other than those in the
541Rhône Valley, and possibly worldwide.

542

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Fig.1: Localisation of the grids studied and their associated clusters (Best viewed in colour).

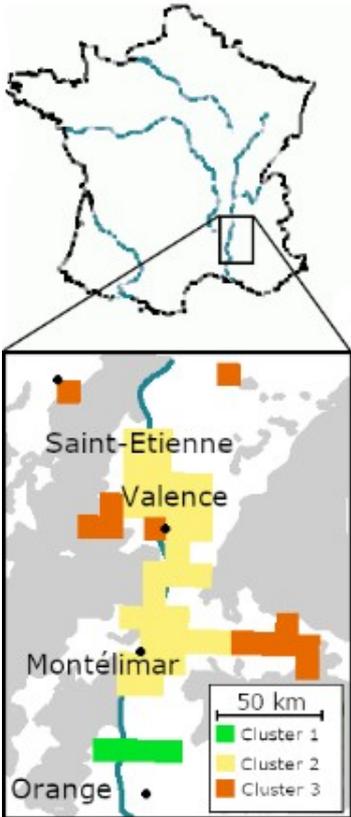


Fig. 2: Method used to calculate climate change for a given year n and cultivar. (1) Computations for year n start on the 15th of October of year $n-1$. For the dormancy model, it is assumed that the cold needs of apricot have not started to be fulfilled prior to this date. (2) Phenological models compute the F50 date given the daily average temperature. (3) The expand of the blooming period around F50 is estimated given the distribution of disease-sensitive stages. (4) Daily rainfall and temperature during the blooming period are extracted and (5) CIB is calculated for year n

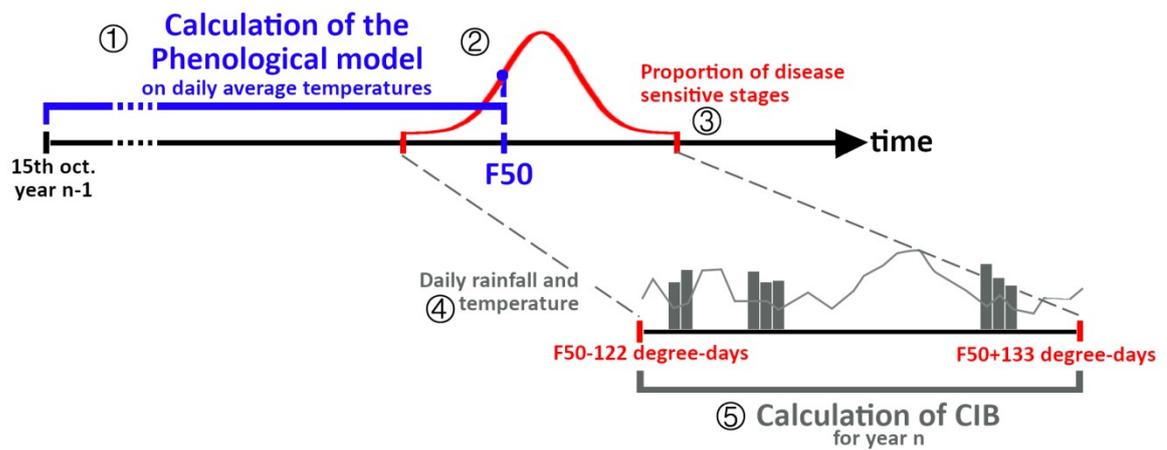


Fig 3: Simulated vs. Observed values for blossom blight incidence (I , dimensionless). $R^2 = 0.941$,

Intercept = 0.009; slope = 0.935.

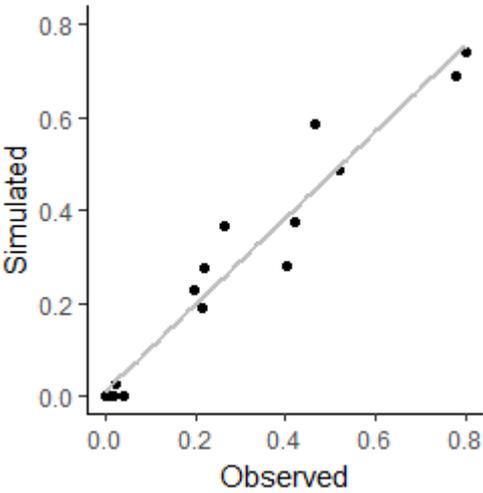


Fig 4: 3D representation of our model as a surface response of blossom blight incidence to rainfall (mm) and temperature (°C) (left) and residuals associated with each point of the dataset as a function of rainfall and temperature (right). The size of each point represents the value of the residual and the colour the sign of the residual. Lines correspond to different predicted levels of incidence.

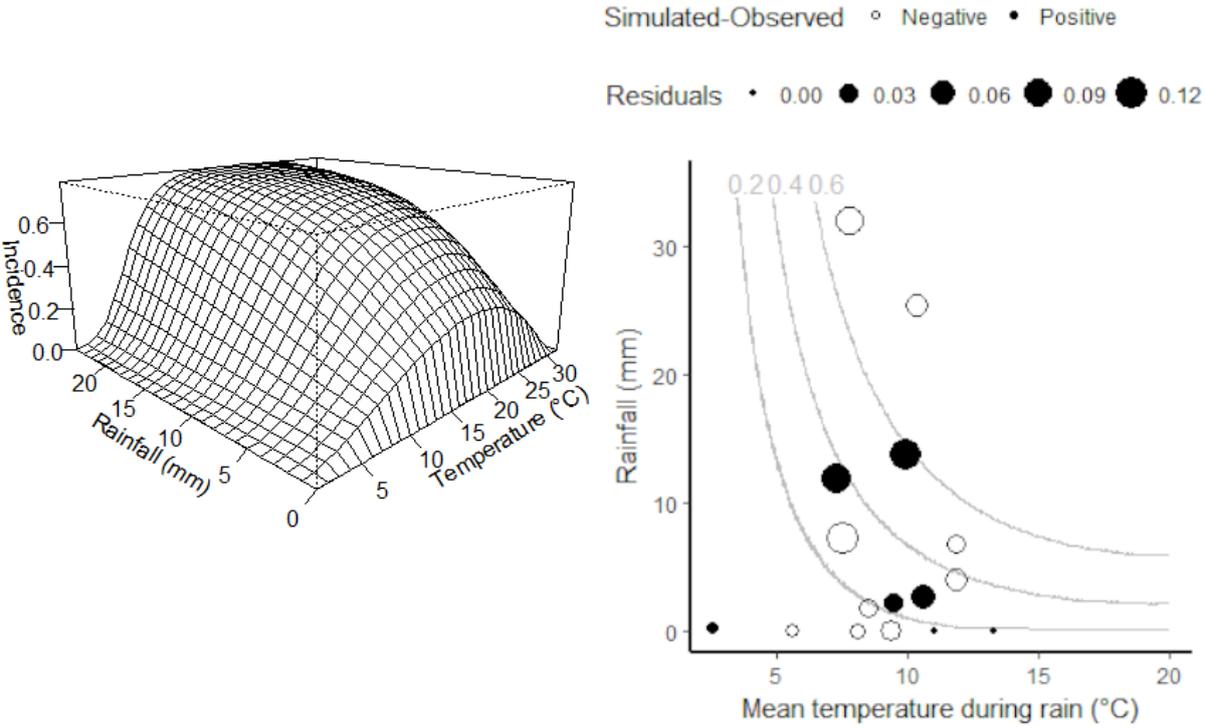


Fig 5: Predicted Climatic Index of cumulated Blight risk (CIB, cumulated %) versus observed Twig Blight Incidence (TBI, dimensionless).

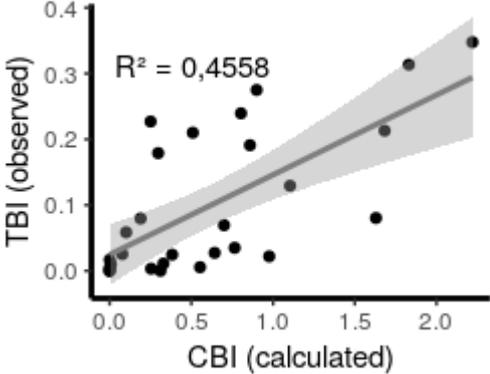
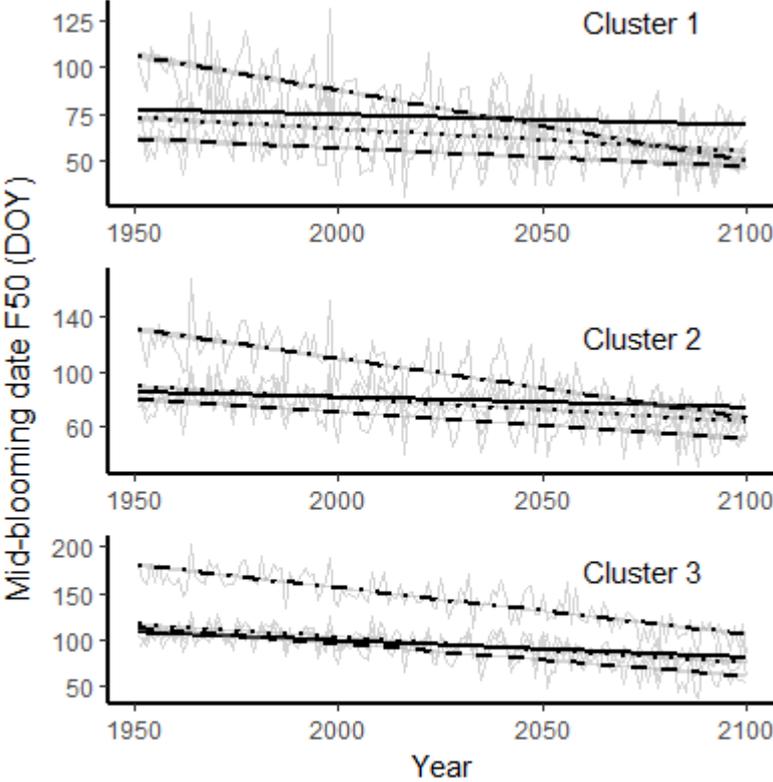


Fig 6: Evolution of the mid-blooming date (DOY) for the different cultivars and clusters under scenario RCP8.5. Linear regression lines are shown for clarity.



Cultivar ··· Beliana — Bergarouge ·-· Bergeron - - Rouge

Fig 7: Mean temperature (°C) and mean cumulated rainfall (mm) experienced during blooming for the different cultivars and clusters. The start of the line represents the situation during the [1970-1999] period and the head of the arrow the situation forecasted for the [2070-2099] period.

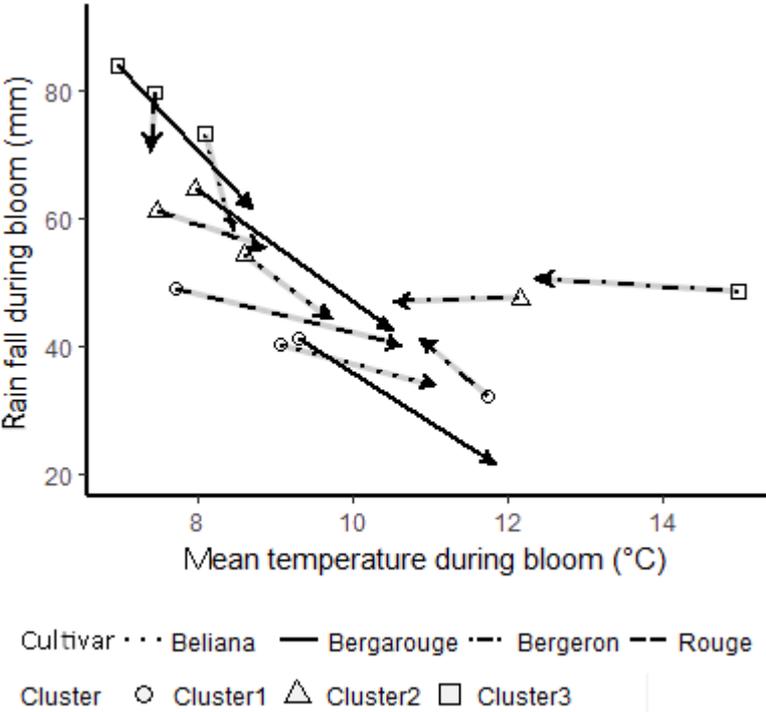


Fig 8: Mean simulated CIB (\pm one standard deviation) by period (p: past, nf: near future, pf: far future) for each cluster and cultivar under RCP 8.5. The colours are red for a significant increase in the risk and green for a significant reduction in the risk. Letters are the result of the Kruskal-Wallis comparison between periods within one Cultivar-Cluster panel (best viewed in colour).

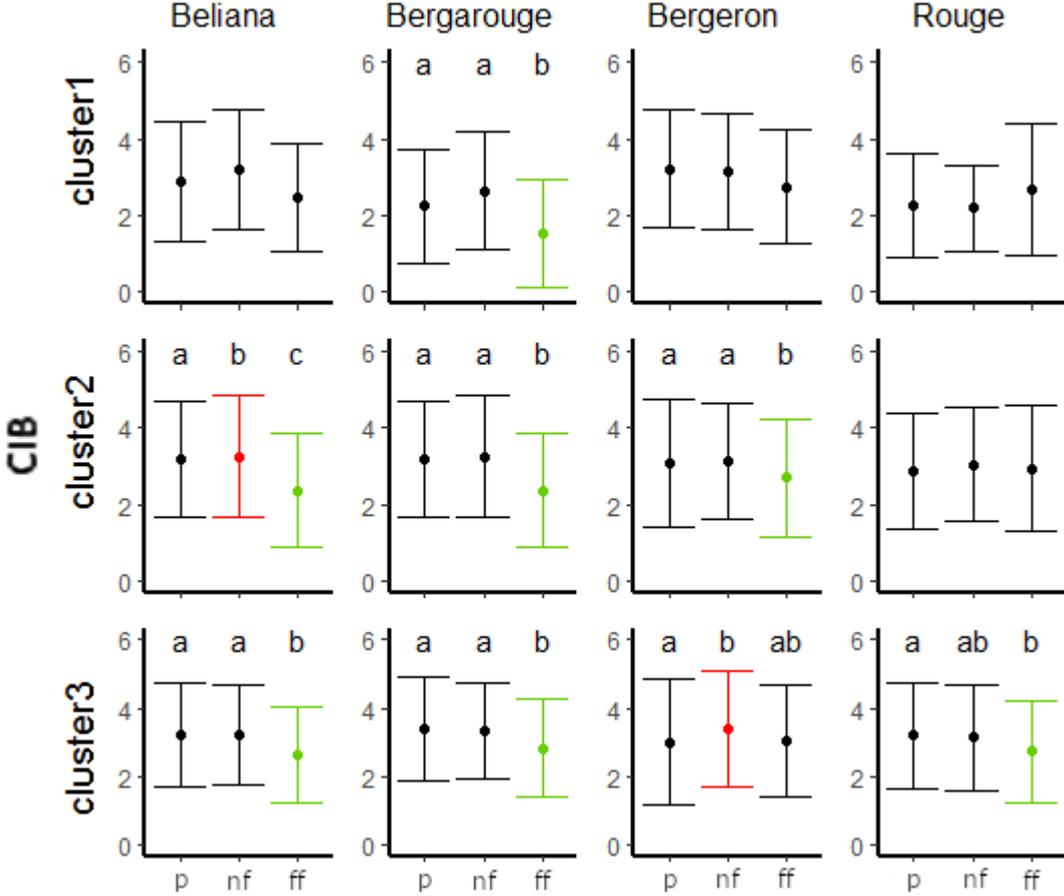


Table.1: Parameter values of the fitted model. Bolt parameters were chosen priori to optimisation according to the method described by Tamm et al. 1995

Parameter	Value
T_{\min}	0
T_{\max}	31
E	0.029
i_{\max}	0.79
m	0.9
ρ_1	1.575
ρ_2	1.965
γ_1	1.709
γ_2	1.472