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State Estimation of Pest Populations subject to Intermittent Measurements

Nicolas Bono Rossello * **Luca Rossini** ** **Stefano Speranza** ** **Emanuele Garone** *

* *Service d'Automatique et d'Analyse des Systèmes: Université Libre de Bruxelles (ULB), Av. F.D. Roosvelt 50, CP 165/55, 1050 - Brussels, Belgium.(e-mail: {Nicolas.Bono.Rossello,Emanuele.Garone}@ulb.be)*

** *Dipartimento di Scienze Agrarie e Forestali: Università degli Studi della Tuscia, via San Camillo De Lellis, 01100 Viterbo, Italy.(e-mail: luca.rossini@unitus.it)*

Abstract: This paper introduces an observer-based scheme to estimate pest populations in agricultural fields. The proposed scheme describes the different stages of the life cycle of insects as a system of ODEs and it uses an Extended Kalman Filter with intermittent observations to provide a state estimation. This scheme aims at providing a general framework to formally combine physiologically-based models and field measurements, contrary to current best practices where both methodologies are used independently in parallel. The presented approach allows to apply this framework to a large number of species of agricultural interest and to take advantage from different counting systems. The improvement of the presented approach with respect to current best practices is demonstrated by means of numerical simulations based on the case of *Drosophila suzukii*.

Keywords: Extended Kalman Filter, Pests, Estimators, Agriculture, System models.

1. INTRODUCTION

Integrated Pest Management (IPM) systems aim at providing an effective and environmentally sensitive approach to pest management (Barzman et al., 2015). IPM schemes use as inputs information on the pests life cycles and environmental conditions. This information, in combination with available pest control tools, is used to define and manage pest damage actions by the most economical means, and with the least possible impact on the environment.

The development of automated detection technologies of pests is fundamental in IPM systems, but not sufficient. Measuring in agriculture is still expensive and many treatments require not only the current status but the future evolution of the infestations. In this context, the use of pest population models is particularly important. Notably, when pest management is performed by release of natural enemies, the effectiveness of the strategies is highly dependant on the pest life cycle given that only certain life stages are susceptible to these actions.

It is worth to remark that insects, like most ectotherms, progress through their life stages with development rates highly dependent on environmental parameters. Among these environmental variables, temperature can be considered the main driven factor (Harcourt, 1969; Damos and Savopoulou-Soultani, 2012). This aspect led the literature to focus on "physiologically-based models" to properly define the pest life cycle dynamics. Conceptually, physiologically-based models can be defined as the union between "phenological models" and "population dynamics models". This type of models describes the development of ectotherm populations over time while considering the stage development driven by environmental factors.

Several physiologically-based models have been proposed in the literature, using ordinary (Banks et al., 2019; Otero et al., 2006) and partial (Rossini et al., 2020b; Von Foerster, 1959; DeAngelis and Huston, 1987) differential equations. However, these models are not completely suited for IPM activities as they are usually developed and tailored for specific insect species. Only after their first successful validation, some models are subsequently adapted and validated to different species. Also, current best practices use these models in *open loop*, i.e., relying only on temperature and humidity measurements from the field. Field population measurements are, in fact, used only to provide time series of the pest abundance in cultivated fields to be compared with the simulations outcome. This approach neglects the helpful information provided by field measurements, and makes predictions susceptible to errors due to migrations or model inaccuracies.

As already mentioned in the early work of Zavaleta and Dixon (1982), combining life cycle models and field measurements is fundamental to improve the quality of model estimations, allowing to reach the full potential of IPM strategies. In this sense, works like Puebla et al. (2018); Boonyaprapasorn et al. (2021) explore the advantages of feedback-control schemes to design pest population control actions. Regarding estimation purposes, works such as (Wiman et al., 2014; Embleton and Petrovskaya, 2013) analyze the combination of data from predictive models and field measurements, with particular attention to uncertainty coming from field data. However, to the best of our knowledge, the combination of measurements and model dynamics has not been yet properly formalized.

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We believe that to achieve this goal, a fundamental element is to define a general model that can be applied to several insects species of agricultural interest while being informative and tractable enough for control purposes. This milestone was recently reached in Rossini et al. (2021).

The aim of this work is to propose an estimation framework where information from physiologically-based models and pest population measurements can be formally combined. In this paper, this objective is achieved by means of an Extended Kalman Filter scheme. We believe that this approach can substantially improve the monitoring part of IPM strategies.

To prove the efficiency and applicability of this approach we focus on a species of major agricultural interest, as it is the case of the *Drosophila suzukii* (Asplen et al., 2015). Based on the model validated on (Rossini et al., 2021), we generate synthetic data simulating a *D. suzukii* infestation based on the meteorological data retrieved by the weather station of the PANTHEON project (Giustarini et al., 2020). The results show how combining realistic sparse measurements of the current insect population with model predictions heavily improves the accuracy of the physiologically-based model.

The rest of the paper is organized as follows. In Section 2 we introduce the general model describing the life cycle of ectotherms. Sections 3 and 4 present the sensing and the observer structure, respectively. In Section 5, numerical simulations are carried out to show the performance of the presented approach, and in Section 6 we draw some conclusions and discuss future works.

2. MODEL DESCRIPTION

In this section we introduce the general ODE-based model used to describe the evolution of pest populations.

Ectotherms' life cycle is divided into discrete age classes, each representing an "identifiable" life stage. More specifically, a life stage is defined as identifiable if it shows a series of taxonomic features that are commonly defined for the majority of the known species. This is an important aspect, since it allows a simple description of the main mechanisms of insects' development as a succession of discrete life stages, and fits with our definition of "physiological age". The progress of the insects through these stages, their mortality and fertility aspects are commonly characterized by different "rate functions" (Rossini et al., 2019; Gilioli et al., 2016).

A general scheme of life cycle is depicted in Fig. 1. The general scheme considers an egg stage, a variable number of larval instars, and up to two adult stages. Note that adult stages are divided by sex. This is a necessary feature to describe species where the two sexes have different characteristics. Also notice that the female adult stage is, in turn, divided into two different sub-stages, allowing to represent, for example, mated and non-mated females as well as younger and older females (Otero et al., 2006).

We associate to each stage a scalar state $x_i(t)$, $i = e, L_1, \dots, L_n, A_m, A_{f,1}, A_{f,2}$ representing the number of individuals in the population that at time t are in the stage i. Each stage population variation over time is then represented by an ODE which depends on the inflows and outflows of individuals associated to that stage.

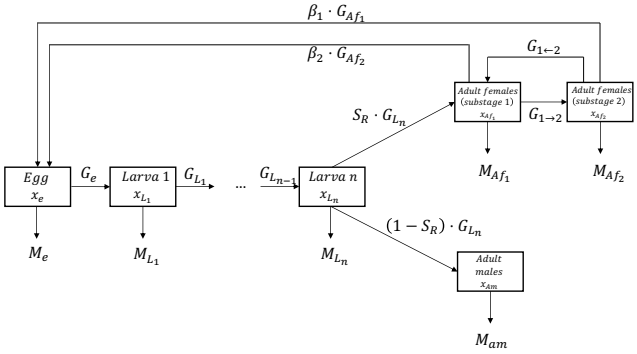

Fig. 1. Schematic representation of the life cycle.

As previously mentioned, the flow of individuals leaving or entering the stages is determined by rate functions. These rates are specific to each species, and depend mainly on environmental parameters (e.g., temperature or relative humidity). Note that, the estimation of these rates is performed through laboratory experiments subject to inaccuracies. Additionally, simulations to evaluate them are based on field temperature measurements also subject to noise. In this work, we consider this uncertainty related to the computation of the rates by introducing an additive term $\omega_{i,j}(t)$ associated to the stage $i = e, L_1, \dots, L_n, A_m, A_{f,1}, A_{f,2}$ and the rate function j. This term is defined as

$$\omega_{i,j}(t) = \omega^1_{i,j}(t) + \omega^2_{i,j}(t)$$

where $\omega^1_{i,j}(t) \backsim N(0, Q^1_{i,j})$ describes the uncertainty related to the parameters estimation and $\omega^2_{i,j}(t) \backsim N(0, Q^2_{i,j})$ defines the noise introduced by temperature measurements. Since we assume both terms to be Gaussian with zero means, it holds that

$$E[\omega_{i,j}(t)] = E[\omega^1_{i,j}(t)] + E[\omega^2_{i,j}(t)] = 0 \tag{1}$$

and

$$Cov(\omega_{i,j}(t)) = Q^1_{i,j} + Q^2_{i,j} = Q_{i,j} \tag{2}$$

with $\omega_{i,j}(t) \backsim N(0, Q_{i,j})$.

Based on this, the general life cycle can be modelled as follows.

The dynamics of the egg stage are described as

$$\begin{aligned}\dot{x}_e(t) = {} & (G_{A_{f_1}}(t)\beta_1(t) + \omega_{e,1}(t))x_{A_{f_1}}(t) + (G_{A_{f_2}}(t)\beta_2(t) + \\ & \omega_{e,2}(t))x_{A_{f_2}}(t) - (G_e(t) + \omega_{e,3}(t))x_e(t) - \\ & (M_e(t) + \omega_{e,4}(t))x_e(t),\end{aligned} \tag{3}$$

where $G_e(t)$ is the development rate associated to the egg stage, $M_e(t)$ is the mortality at this stage and $\beta_i(t)$ $(i = 1,2)$ the fertility rates associated to the 2 adult female sub-stages. On the other hand, $\omega_{e,i}(t)$ $(i = 1,2,3,4)$ represent the process noise associated to each of these rates.

A generic preimmaginal stage is defined as follows

$$\begin{aligned}\dot{x}_{L_i}(t) = {} & (G_{L_{i-1}}(t) + \omega_{L_i,1}(t))x_{i-1}(t) - (G_{L_i}(t) + \omega_{L_i,2}(t))x_{L_i}(t) \\ & -(M_{L_i}(t) + \omega_{L_i,3}(t))x_{L_i}(t),\end{aligned} \tag{4}$$

being $G_{Li-1}(t)$ the development rate associated to the previous preimmaginal stage, where $L_0 = e$ denotes the egg stage, $G_{L_i}(t)$ is the rate of the population that develops into the next stage and $M_{L_i}(t)$ the mortality rate.

The male adult stage is defined as

$$\begin{aligned}\dot{x}_{A_m}(t) = {} & (1 - S_R(t)) \cdot (G_{L_4}(t) + \omega_{A_m,1}(t)) \cdot x_{L_4}(t) \\ & -(M_{A_m}(t) + \omega_{A_m,2}(t))x_{A_m}(t),\end{aligned} \tag{5}$$

with $S_R(t)$ as the sex ratio, indicating the distribution in between sexes of individuals that arrive to the adult stage. Note that, for the sake of simplicity, previous stages do not consider this separation. This is due to the fact that previous stages are not actively part of the reproduction process and therefore this distinction would not affect the population dynamics.

As mentioned before, we assume two female adult sub-stages, where the first female stage is defined as

$$\begin{aligned}\dot{x}_{A_{f_1}}(t) = {} & S_R(t)(G_{L_4}(t)+\omega_{A_{f_1},1}(t))x_{L_4}(t)+(G_{2\to1}(t)\\ & +\omega_{A_{f_1},2}(t))x_{A_{f_2}}(t)-(G_{1\to2}(t)+\omega_{A_{f_1},3}(t))x_{A_{f_1}}(t)\\ & -(M_{A_{f_1}}(t)+\omega_{A_{f_1},4}(t))x_{A_{f_1}}(t),\end{aligned} \tag{6}$$

where $G_{1\to2}(t)$ represents the rate of individuals that advance to the next stage while $G_{2\to1}(t)$ is associated to the inflow of individuals that move back from the *Female stage 2*. Note that these rates might have different meanings depending on the species, including cases where $G_{2\to1}(t)=0$.

Equivalently, the second stage associated to adult females is described as

$$\begin{aligned}\dot{x}_{A_{f_2}}(t) = {} & (G_{1\to2}(t)+\omega_{A_{f_2},1}(t))x_{A_{f_1}}(t)-(G_{2\to1}(t)\\ & +\omega_{A_{f_1},3}(t))x_{A_{f_2}}(t)-(M_{A_{f_2}}(t)+\omega_{A_{f_2},2})x_{A_{f_2}}(t).\end{aligned} \tag{7}$$

The overall system can be written as the following system of ODEs:

$$\begin{cases}\dot{x}_e(t) = (G_{A_{f_1}}(t)\beta_1(t)+\omega_{e,1}(t))x_{A_{f_1}}(t)+(G_{A_{f_2}}(t)\beta_2(t)+\\ \quad \omega_{e,2}(t))x_{A_{f_2}}(t)-(G_e(t)+\omega_{e,3}(t))x_e(t)-\\ \quad (M_e(t)+\omega_{e,4}(t))x_e(t)\\ \dot{x}_{L_1}(t) = (G_e(t)+\omega_{e,1}(t))x_e(t)-(G_{L_1}(t)+\omega_{L_1,2}(t))x_{L_1}(t)\\ \quad -(M_{L_1}(t)+\omega_{L_1,3}(t))x_{L_1}(t)\\ \quad\vdots\qquad\vdots\qquad\vdots\qquad\vdots\qquad\vdots\\ \dot{x}_{L_n}(t) = (G_{L_{n-1}}(t)+\omega_{L_n,1}(t))x_{n-1}(t)-(G_{L_n}(t)+\omega_{L_n,2}(t))x_{L_n}(t)\\ \quad -(M_{L_n}(t)+\omega_{L_n,3}(t))x_{L_n}(t)\\ \dot{x}_{A_m}(t) = (1-S_R(t))\cdot(G_{L_4}(t)+\omega_{A_m,1}(t))\cdot x_{L_4}(t)\\ \quad -(M_{A_m}(t)+\omega_{A_m,2}(t))x_{A_m}(t)\\ \dot{x}_{A_{f_1}}(t) = S_R(t)(G_{L_4}(t)+\omega_{A_{f_1},1}(t))x_{L_4}(t)-(G_{1\to2}(t)\\ \quad +\omega_{A_{f_1},2}(t))x_{A_{f_1}}(t)-(M_{A_{f_1}}(t)+\omega_{A_{f_1},2}(t))x_{A_{f_1}}(t)\\ \dot{x}_{A_{f_2}}(t) = (G_{1\to2}(t)+\omega_{A_{f_2},1}(t))x_{A_{f_1}}(t)-(G_{2\to1}(t)\\ \quad +\omega_{A_{f_1},2}(t))x_{A_{f_2}}(t)-(M_{A_{f_2}}(t)+\omega_{A_{f_2},2})x_{A_{f_2}}(t).\end{cases} \tag{8}$$

For the sake of readability, the presented system subject to stochastic noise can be represented in compact form as

$$\dot{x}(t) = f(x(t),\omega(t)) \tag{9}$$

with the state vector

$$x(t)=\begin{bmatrix}x_e(t)\\ x_{L_1}(t)\\ \vdots\\ x_{Am}(t)\\ x_{Af1}(t)\\ x_{Af2}(t)\end{bmatrix}$$

and the noise vector

$$\omega(t)=\begin{bmatrix}\omega_{e,1}(t)\\ \vdots\\ \omega_{A_{f_2},2}(t)\end{bmatrix}$$

with $\omega(t)\backsim N(0,Q)$ and $Q\in\mathbb{R}^{m\times m}$, where m is a number that varies based on the number of preimmaginal stages considered in the model.

3. SENSING STRUCTURE

We assume that the state of the population can be measured at some instants thanks to the use of traps or automatic counting systems. Assuming a constant sampling time of the system and by using the approximated forward Euler method we obtained following discrete-time system

$$x_{k+1} = f(x_k,\omega_k) \tag{10}$$

where $x_k = x(kT_s)$ with $k\in\mathbb{N}$ and $T_s\in\mathbb{R}_+$ the sampling time. In this work, as it is common in ecological literature, we assume that $T_s = 1\ \ day$.

It is important to remark that in this kind of systems, measurements are intermittent due to the amount of resources required for each counting action. In particular, let us define the binary variable $\gamma_k\in(0,1)$, which takes the value 1 if a trap or vision system is used at the time instant k, and 0 otherwise.

We define the measurement equation as

$$y_k = \gamma_k(Cx_k+\nu_k) \tag{11}$$

where $\nu_k\in\mathbb{R}^l$ represents stochastic sensor noise which is assumed $\nu\backsim N(0,R)$ with $R\in\mathbb{R}^{l\times l}$ the noise covariance matrix.

Traps, or other measuring devices, usually track only certain stages of the life cycle, namely adults (Preti et al., 2021). In this work, we assume that the 3 adult stages of the general model can be measured. This provides the following observation matrix

$$C=\begin{bmatrix}0_{1\times6} & \kappa & 0 & 0\\ 0_{1\times6} & 0 & \kappa & 0\\ 0_{1\times6} & 0 & 0 & \kappa\end{bmatrix}, \tag{12}$$

where $\kappa\in\mathbb{R}_+$ is the estimated counting efficiency, providing the percentage of insects out of the whole population that can be count during the period $[k-1,k]$.

Remark 1. In line of principle, when using traps, the measurement actions should incorporate an additional mortality to the adult stages. This additional mortality is commonly neglected by the ecological community given that the use of traps *attracts* additional insects from outside the field. This external inflow tends to balance the additional mortality by the arrival of new individuals to the system, while the measurements obtained can be still assumed accurate.

Thus, the overall pest population dynamics system can be described as

$$\begin{cases}x_{k+1|k} = f(x_k,\omega_k)\\ y_k = \gamma_k(Cx_k+\nu_k).\end{cases} \tag{13}$$

4. OBSERVER

To estimate the state of the population we propose the use of an Extended Kalman Filter (EKF) with intermittent observations based on the arrival of system measurements.

We assume that the distribution of the initial conditions of the system is known with $p(x_0) \backsim N(\bar{x_0}, P_0)$. Providing

$$\hat{x}_{0|0} = \bar{x_0} \quad \text{and} \quad P_{0|0} = P_0 \tag{14}$$

as the initial estimate and covariance of the EKF, respectively.

The estimation scheme of the EKF can be summarized as follows. The prediction step is

$$\hat{x}_{k+1|k} = f(x_k) \tag{15}$$

$$P_{k+1|k} = AP_{k|k}A^T + L_k Q L_k^T, \tag{16}$$

with

$$L_{k-1} = \left.\frac{\partial f}{\partial \omega}\right|_{\hat{x}_{k|k}} \tag{17}$$

and the correction step is

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + \gamma_k K_{k+1}(y_{k+1} - C\hat{x}_{k+1|k}) \tag{18}$$

$$K_{k+1} = P_{k+1|k}C^T(CP_{k+1|k}C^T + R)^{-1} \tag{19}$$

$$P_{k+1|k+1} = P_{k+1|k} - \gamma_k K_{k+1} C P_{k+1|k}, \tag{20}$$

where $\hat{x}_{k|k}$ is the estimated value of the state at time k given the information available at time k, and $P_{k|k}$ is the error covariance matrix of the estimation at time k.

Note that when $\gamma_k = 0$, i.e., there are no new measurements, the correction step does not modify the prediction step, relying uniquely on the estimate given by the model dynamics. Specifically,

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k}$$
$$P_{k+1|k+1} = P_{k+1|k}.$$

5. SIMULATION RESULTS

In this section, we provide a numerical validation of the presented approach based on the case study of a species of agricultural interest as it is *D. suzukii*.

5.1 Case Study: Drosophila Suzukii

The spotted wing drosophila *D. suzukii* is a harmful pest worldwide. In most countries it represents an invasive species of more or less recent introduction.

D. suzukii life cycle consists of an egg stage, three larval instars, pupa stage, and adult stages. Accordingly, the total number of equations in the model (8) is 8: one for the egg stage, four for the larval stages (pupa is considered as the last larval instar), and one for the adult males, non-mated females, and mated females, respectively.

Due to its harmfulness, the dependence of *D. suzukii* development, fertility and mortality rates on temperature has been studied by several authors (Tochen et al., 2014; Asplen et al., 2015) providing validated temperature-based rate functions. These rate functions for the case of the *D. suzukii* are presented in the following.

Regarding the development rate $G_i(t)$, the Briére function, (Briere et al., 1999), provides very good results describing the relationship between *D. suzukii* development rate and environmental temperature. Mathematically, the Briére function is defined as

$$G(t) = a \cdot T(t) \cdot (T(t) - T_L)(T_M - T(t))^{\frac{1}{m}}, \tag{21}$$

where a and m are empirical parameters, T_L and T_M are the lower and upper temperature thresholds below and above which the development of the species theoretically does not occur.

Based on the dependence of the mortality on temperature studied by (Ryan et al., 2016), and to avoid the overestimation of the mortality rates in close-to-optimal conditions, a fourth order polynomial function (Wang et al., 2002) is used to describe the mortality rate. Mathematically,

$$M[T(t)] = a_1\,[T(t)]^4 + b_1\,[T(t)]^3 + c_1\,[T(t)]^2 + d_1\,[T(t)] + e_1 \tag{22}$$

where a_1, b_1, c_1, d_1 and e_1 are parameters estimated using the dataset published by Ryan et al. (2016).

Lastly, for the temperature-dependent birth rate function $\beta_2(t)$ we consider the equation provided by Ryan et al. (2016), which fits their experimental data with the Gaussian-like function

$$\beta_2[T(t)] = \begin{cases} \alpha\left[\frac{\gamma+1}{\pi\lambda^{2\gamma+2}}\left(\lambda^2 - \left([T(t)-\tau]^2 + \delta^2\right)\right)^{\gamma}\right] \\ \qquad\qquad if\ T_{min} < T(t) < T_{max} \\ 0 \qquad otherwise, \end{cases} \tag{23}$$

being T_{min} and T_{max} the lower and upper temperature thresholds where the oviposition occurs. The parameters α, γ, λ, δ and τ are empirical and with no biological meaning. Note that in the case of the *D. suzukii* the adult females substages are defined as non-mated and mated, such that $\beta_1(t) = 0$.

The validation of this model for *D. suzukii* was presented in Rossini et al. (2021), and the parameters used for the simulations in this paper are summarized in Table 1.

Table 1. List of parameters.

Rate function	Parameter	Reference
Development (21)	$a = (1.20 \pm 0.15) \cdot 10^{-4}$ $T_L = 3 \pm 2$ $T_M = 30 \pm 1$ $m = 6 \pm 3$	Rossini et al. (2020a) Tochen et al. (2014)
Mortality (22)	$a_1 = (-5 \pm 1) \cdot 10^{-5}$ $b_1 = (5 \pm 8) \cdot 10^{-4}$ $c_1 = 0.1 \pm 0.2$ $d_1 = (2.2 \pm 0.3) \cdot 10^{-5}$ $e_1 = 1.3 \pm 0.9$	Ryan et al. (2016)
Fertility (23)	$\alpha = 659.06$ $\gamma = 88.53$ $\lambda = 52.32$ $\delta = 6.06$ $\tau = 22.87$ $T_{min} = 5$ $T_{max} = 30$	Ryan et al. (2016)

5.2 Numerical simulations

The simulations use generated synthetic data to reproduce an insect infestation in a crop field. This infestation is generated based on real field temperature data retrieved during 2020 from the meteorological station of the H2020 PANTHEON project, located in an experimental field in the municipality of Caprarola, Italy. Simulations are performed from March to December so to provide several life cycles of the *D. suzukii*.

Simulations compare:

- Synthetic data of population dynamics based on measured real data (*reference*).
- Prediction based on the open loop model and noisy temperature measurements (*traditional approach*).

- Estimation based on the EKF using noisy counting measurements and noisy temperature measurements (*presented approach*).

Simulations consider initials conditions $x_{e,0} = 1000000$ and $x_{A_{f,2},0} = 1000000$ individuals with $x_{i,0} = 0$ for $i = L_1, \ldots, L_4, A_{f,1}$. Regarding the estimation of these initial conditions we assume an error of $\pm\sigma_0 = 10000$.

We assume daily temperature measurements with an error of $\pm\sigma_T = 0.2$ degrees Celsius with respect to the synthetic data used as reference. Then, the uncertainty in the estimation of the rates is randomly generated from the available experimental data given the general propagation of uncertainty formula

$$\sigma_f = \sqrt{\sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i}\right)^2 \sigma_{x_i}^2} \tag{24}$$

where $f(x_1, \ldots, x_n)$ is the rate function, x_i are the different parameters associated to it and the values of σ_{x_i} can be retrieved from Table 1. Note from Table 1 that the parameter estimation error is not available for the fertility rate. For the sake of exposition, this error is randomly generated in the simulations using the error of the other two rates as bounds.

Regarding field measurements, we assume 20 trap measurements available during the span of a year. This amount of measurements is common in pest population monitoring, as a higher amount becomes excessively costly. These measurements are randomly distributed along the year with an additive measurement noise variance of $\pm\sigma_y = 2$.

The timing of the measurements is randomly selected in each simulation in order to mimic the uncertainty regarding the availability of data in the field. We perform 100 simulations of the presented scenario to ensure the robustness of the results. Figure 2 depicts one of these simulations.

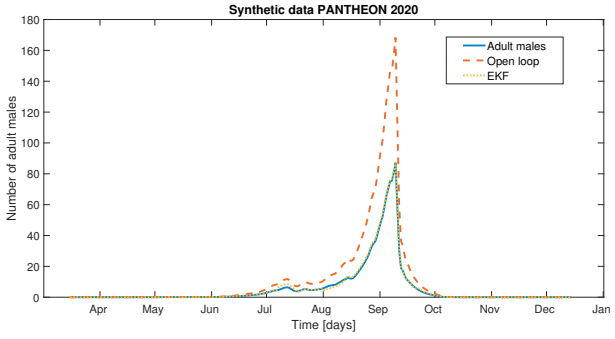

Fig. 2. Evolution of the number of adult males provided by one of the performed simulations.

From Fig. 2 it can be appreciated that the use of information from certain measurements helps to estimate more accurately the peak of insects. This aspect can be really useful in the case of pest control actions.

To provide a synoptic overview of the results, we compute the root mean squared error (RMSE) and the coefficient of determination (R^2) for each simulation with respect to the *reference* data. Results are plotted in Figures 3 and 4.

From these plots we can observe the clear improvement in the estimation of the evolution of the pest population obtained by incorporating some noisy measurements. It must be noted that this improvement is obtained by only 20 measurements

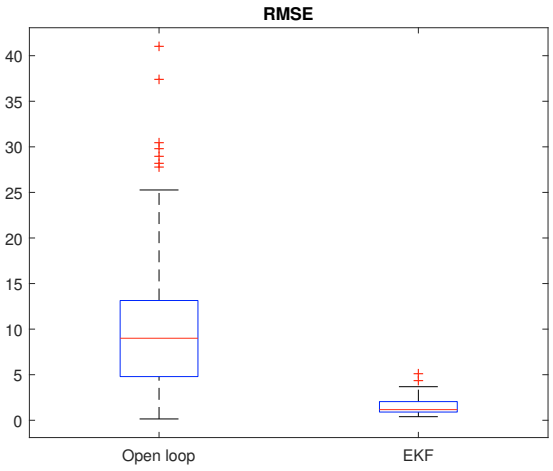

Fig. 3. Root mean square error distribution of the simulations.

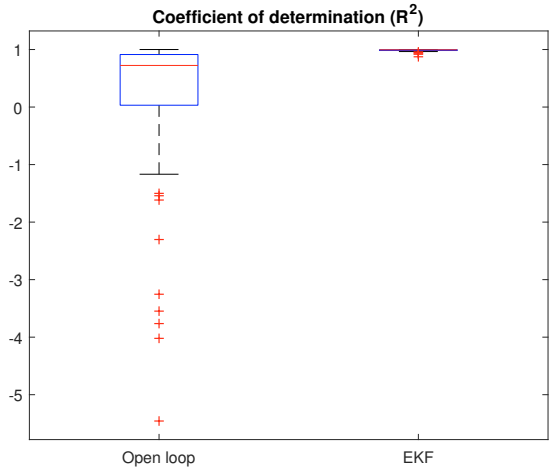

Fig. 4. Coefficient of determination for the 100 simulations.

randomly selected over the time span of a year, showing the potential of this approach.

The temperature dataset, computed parameters from Table 1 and Matlab script simulations are publicly available at the GitHub page `https://github.com/Niboros91/Ectotherms-estimation`.

6. CONCLUSIONS

In this paper we presented an Extended Kalman Filter with intermittent observations to estimate the evolution of pest populations. The proposed scheme is general enough to be applied to several species of agricultural and ecological interest and to formally incorporate field measurements from different sources into the estimation.

In simulations, we show how the combination of field measurements and physiologically-based models clearly improves the estimation accuracy of traditional strategies only based on temperature measurements. Results, based on the case of *D. suzukii*, show that with a low and realistic number of field measurements the EKF scheme provides a significant improvement.

Future works will focus, first, on the field validation of this approach as already done for the dynamics model. Also, future lines of research will focus on how to sample the population in order to improve the outcome of the EKF and the application of this approach to larger areas subject to spatial redistribution.

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