Simulation Study for Evaluating Efficiency of McPhail Traps in Olive Groves

Nikolaos Avgoustis(✉), Evangelos Alvanitopoulos, Nikolaos Marios Polymenakos, Ioannis Karydis, and Markos Avlonitis

Ionian University, Plateia Tsirigoti 7, Corfu, Greece
{avgoustis,alvanitopoulos,polymenakos,karydis,avlon}@ionio.gr

Abstract. Olive tree production has been of paramount importance to nutrition and culture since the early fifth millennium B.C. The most serious pest of olive groves is the olive fruit fly, known as *Bactrocera Oleae or Dacus Oleae*, which can lead to loss of production up to 80–90%. Nowadays, measuring the olive fruit fly's population in the olive groves is key to most pest control strategies. Accordingly, herein, a simulation of olive fruit fly's population dynamics is presented. Initially, the simulation focuses on the correlation between the ratio of captured olive fruit flies in bait traps in relation to the entirety of population (Trap Efficiency). Subsequently, field and its factors were added in the simulation, such as the ratio of olive fruit flies captured in the traps in relation to flies within the trap's attraction area (Capture Rate), crops' variation, and temperature. The simulation's results initially indicated a correlation between *Trap Efficiency* and *Capture Rate* based on previous field experiments, as well as a significant correlation between *Trap Efficiency* and field *Temperature*, using various *Capture Rates*. These results lead towards a contemporary tool for the estimation of olive fruit fly population as well as, by use of regression, the identification of a model that provides trap efficiency estimation for future pests' traps.

Keywords: Bactrocera Oleae · Simulation · Olive fruit · Trap Efficiency · Temperature · Regression · Pest trap modeling

1 Introduction

The olive fruit fly (also known as *Bactrocera Oleae or Dacus Oleae*) presents a major risk to the cultivation of olives and inflicts damage to olives through its reproductive cycle. The female olive fruit fly lays eggs inside olives by using their ovipositors to puncture the fruit's skin and deposit eggs. After hatching, the larvae consume the pulp of the olives as they mature, which ultimately affects the quality and market value of the fruits due to decay and damage [1].

In order to control the population of olive fruit fly, a plethora of methods have been proposed in the literature such as baited, sticky, or pheromone traps, visual inspections, and degree-day models, among others [2]. These methodologies allow for measurement of the olive fruit fly population rather than their

Published by Springer Nature Switzerland AG 2024
I. Maglogiannis et al. (Eds.): AIAI 2024, IFIP AICT 712, pp. 293–306, 2024.
https://doi.org/10.1007/978-3-031-63215-0_22

elimination. From the aforementioned various measurements, the cultivators can infer the overall population of olive fruit flies in the field and act accordingly in their application of pest management strategies. Traps are essential in pest management as they offer important information on the presence and spread of olive fruit fly populations in olive groves.

Control methods for managing olive fruit flies' infestations in olive groves involve a range of strategies. These can consist of traditional techniques like removing infested fruits through sanitation, employing insecticides for chemical control, introducing natural predators or parasitoids for biological control, and utilizing traps to decrease olive fruit fly populations [3].

1.1 Motivation and Contribution

Several primary reasons drive the motivation to address the olive fruit fly infestation in olive orchards. Initially, addressing this matter is essential for the agricultural industry, affecting both the volume and quality of olive yields [4–6], which in turn has financial consequences for olive farmers and the broader agricultural sector. Secondly, the non-extensive previous research in this field emphasizes the need for further focused investigation and intervention methods. Accurately measuring the population dynamics of the olive fruit fly is crucial for the development of effective pest control techniques, leading to substantial enhancements in the life cycle and overall health of olive trees. The results of this study have broader implications beyond just olive cultivation, offering insights and solutions that can be transferred to other crops dealing with similar pest problems. Many agricultural pests exhibit similar traits and behaviours, including their reproductive patterns, habitat preferences, and susceptibility to control measures, thus helping extend the impact of the research to various agricultural environments.

The main objective of this research is to create an algorithm that simulates the trap's efficiency [5] in an explicit radius in order to calculate the actual population of olive fruit flies. Thus, the aforementioned algorithm will consist of an useful tool for the agronomists and cultivators, that will pave the way for additional population estimation applications, as this modern tool can be adapted and extended according to the needs of each insect. The major contributions of this paper are presented by the following propositions:

- Design and development of a simulation model for evaluating trap's efficiency considering temperature and various types of cultivation,
- Identification of an optimal model, using regression (as part of AI [7]), that provides trap efficiency estimation for future traps' implementation in Olive Groves.

The remainder of this work is organised as follows: Sect. 2 examines previous research on the olive fruit fly, including its impact on olive trees, methods for managing its population, and the importance of trap precision. Section 3 outlines the suggested methodology, followed by a the methodology's results in Sect. 4, continuing with Sect. 5 discussing the results obtained. Finally, the paper is concluded in Sect. 6.

2 Background

Dacus Oleae (Diptera: Tephritidae), also known as the olive fruit fly, is considered to be one of the main parasites of olive trees mainly around Mediterranean countries. Nevertheless, there are a significant number of records in other regions like America, Asia, and South Africa, that are either lately (year 2018) invading, or have not developed, or have not yet been discovered, as seen on Fig. 1 [8]. According to the work by Kalamatianos et al. [1], the olive fruit fly can cause great damage to the production of olive oil and table olives. Additionally, the olive fruit fly is most active during the summer and the population reaches it's highest levels during autumn. It hibernates during winter and early spring, remaining dormant until the environment becomes suitable for re-emergence [1]. The control measures against the olive fruit fly mainly involve the use of insecticides, which require several applications and highly specific favorable conditions in order to protect the trees [5].

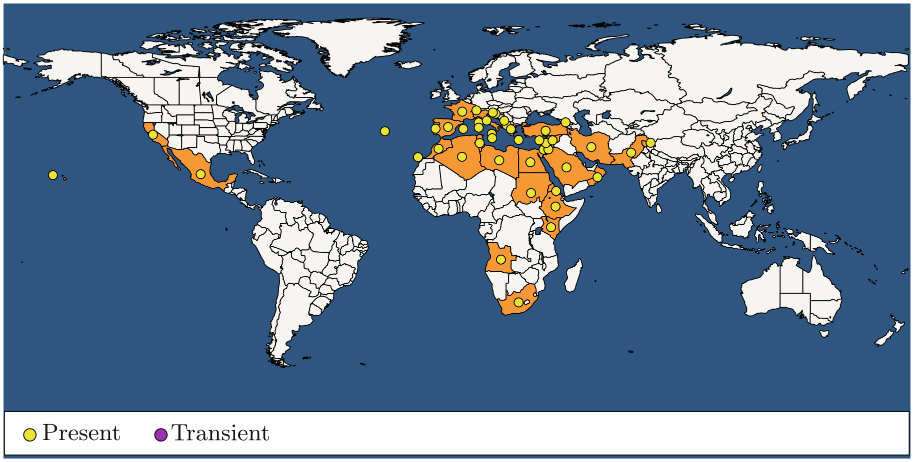


Fig. 1. Olive fruit fly's incidents around the world

As mentioned above, the olive fruit fly causes infestation during its life cycle. Fletcher et al. [9,10] mention that the population growth of olive fruit flies and the extent of infestation in olive groves are affected by wide variety of environmental factors, such as: temperature, humidity, fruit production, olive grove orientation, olive's varieties, spatial spread of olive trees, and interaction between neighbouring microclimates. In any case, the primary factors that affect the activity of the olive fruit fly are temperature [11] and relative humidity [10].

According to the work by Haniotakis et al. [4], the impact of the olive fruit flies can be substantial: without timely control measures, at least 10% of the yield may be lost, and without treatment in olive groves, the loss of production could potentially reach 90% [5]. Other issues include premature fruit shedding prior to harvest, considered highly severe as it leads to complete loss for cultivators. Another challenge, although minor unless infestation is too extensive, is larval consumption of some pulp, resulting in reduced quantity of olive oil. Additionally, there is a risk of deterioration in olive oil quality in infested fruits due to increased acidity levels [6].

Amr et al., in their work [2], mention that the effect of damage caused by olive fruit fly is influenced by the degree of infestation which can be observed by the presence of exit holes created by the full-grown larvae. These holes damage the fruit skin, exposing it to the atmospheric conditions and other destructive factors like fungi. This results in the acceleration of hydrolytic and oxidative types of rancidity which can be estimated by measuring oil acidity (FFA) and peroxide value (PV).

The mobility of the olive fruit fly is significantly influenced by ambient temperature within the grove, as highlighted in previous studies [9,12]. For instance, research conducted in Greece revealed notable temperature thresholds affecting the flight behaviour of the olive fruit fly. When the average temperature fell below 9 °C, observations indicated a cessation of flight activity among the olive fruit flies. Conversely, as temperatures exceeded 29 °C, adult flies exhibited heightened agitation, with a subsequent loss of motion occurring above 35 °C. These findings underscore the profound impact of temperature fluctuations on the behavioural patterns of the olive fruit fly, with implications for pest management strategies in agricultural settings.

Various methods are available for trapping olive fruit flies and assessing their presence in olive groves. According to the work by Zalom et al. [13], one of the most efficient methodologies to monitor the presence of olive fruit fly is by using McPhail traps [14], with effective bait for the current season.

Traps designed to capture olive fruit flies are crucial tools for monitoring population levels and implementing focused control strategies. According to the work by Doitsidis et al. [15] the accuracy of trap data is vital for efficient pest management, as it influences decisions concerning the timing and extent of control measures. Strategic positioning and effective attraction methods are essential for ensuring that traps consistently attract and capture olive fruit flies. Furthermore, the effectiveness of traps depends on variables such as design, bait appeal, and environmental conditions like temperature and humidity, highlighting the requirement for accuracy and thoroughness in the deployment and maintenance of traps. The McPhail traps have been utilized for more than five decades in various Mediterranean nations and are commonly employed in Greece to monitor the olive fruit fly [16]. The traps are typically baited with different attractants, tailored to the specific location and environmental factors, in order to optimize their efficiency in capturing the insects targeted in olive groves [5].

Additional methodology to trap olive fruit flies, as presented in [5], included placing collection nets under the olive trees and then the application of spray to affect the olive fruit flies population. After allowing some time for the treatment to take effect, counting of the flies occurred in order to estimate the local population, and thus estimate the wider population.

Yet another method to measure olive fruit flies focuses on measuring larvae pupating in the soil [17]. During the initial phase of their life-cycle, the majority of larvae go through pupation inside the fruit. However, as the environmental variables changing according to each season, a varying proportion of larvae exit the fruit and undergo pupation in the soil. To assess the quantity of larvae entering the soil, traps were deployed under olive trees to capture both falling larvae and fruits. These traps were constructed using high-sided rectangular plastic containers filled with water and equipped with drainage holes covered by fine mesh to prevent flooding during rainy periods. After that the fallen larvae were accurately counted and recorded for analysis. Then, to estimate the number of olive fruit flies emerging from the soil after reaching adulthood, emergence traps shaped like pyramids were placed beneath each olive tree. These pyramid-shaped emergence traps were designed based on preliminary studies [17] suggesting that their effectiveness at catching nearly all immature adults as they emerge from the soil.

Recent advancements in machine learning have paved the way for innovative approaches in detecting and counting olive fruit flies [18,19], or even predicting outbreaks as in work of Kalamatianos et al. [20].

3 Proposed Methodology

In [5], Varikou et al. conducted an experiment in 2008 and 2009 on the island of Crete, Greece to monitor the population of fruit olive fly. Ten McPhail traps were set up in an area, along with bait sprays applied throughout the experimentation grove. Infestation levels in olive fruits were monitored, while temperature and relative humidity data were collected from an official weather station near the experimentation site.

The population estimation procedure for olive fruit flies involved using collection nets, applying cover sprays to the trees, and installing traps. Olive fruit flies' counts were conducted at various time intervals after each treatment to minimise overestimation due to fly dispersal.

Six population sampling traps installations were conducted in 2008 and sixteen during the following year. New neighboring trees were chosen for each trap to avoid insecticide residual effects. Data analysis included calculation of the number of dropped adult olive fruit flies from olive trees by trap as well as captures of olive fruit flies.

3.1 Simulation Methodology Approach

With the simulation framework proposed herein, the study endeavors to replicate the behavioural dynamics of olive fruit flies as described in previous literature, thereby facilitating a more accurate assessment of catch rates under varying environmental conditions.

The simulation proceeds through the following steps (see also Fig. 3): Firstly (Fig. 3a), essential variables and simulation parameters are initialised. Subsequently, the simulation environment is constructed based on these parameters, and initial positions are assigned to each fly. The main simulation loop (Fig. 3b) is then initiated, comprising of several key operations. Within this loop, new random moves and states are generated for each fly. Depending on the presence or absence of attracting trees, a drift towards the tree is incorporated for flies within the tree's radius. Fly's positions are updated accordingly, followed by boundary condition checks. Subsequently, a check for flies within the trap radius is conducted, and captured flies are removed from the simulation. Following completion of the main loop, the *Trap Efficiency* metric is computed and recorded. This systematic approach provides a comprehensive understanding of fly behaviour within the simulation environment.

The core simulation was achieved using the Python programming language due to its widespread usage/popularity and the rich ecosystem of libraries. The simulation is based on stochastic diffusion involving olive fruit flies moving within a pre-defined area, potentially being caught by a McPhail trap positioned at the center of the simulation area. The setting parameters of the simulation include the area's size, time step, *Capture Rate* and the presence or absence of other olive trees acting as attracting entities. In the context of more precise definition, the above parameters are defined in Sect. 3.2. Information kept on individual olive fruit flies focused on their positions and movement behaviour, per each step of the simulation. The simulation progresses through designated steps, encompassing olive fruit flies's movement and the possibility of trap capture based on their positions, capture probabilities and temperature. Results are then analysed to ascertain the captured olive fruit flies's absolute count and percentage in relation to overall population. The simulation provides a versatile framework for researching stochastic diffusion dynamics using Random Walk methods [21] and examining how varying capture probabilities, presence or absence of other attracting olive trees, and temperature impact capture rates.

The simulations begin with the assumption of a uniform distribution of olive fruit flies within the 20-meter radius surrounding the trap (see Fig. 2a). The first set of simulations are grounded on empirical observations, proposing that olive fruit flies allocate their time primarily to walking, with intermittent periods of flight and rest. In each iteration of the simulation, individual flies have the capability to move in one of eight directions of North, Northeast, East, Southeast, South, Southwest, West, Northwest with their respective coordinates relative to the individual fly's location being (0, 1), (1, 1), (1, 0), (1, −1), (0, −1), (−1, −1), (−1, 0), (−1, 1) and with the distance travelled determined by predefined probabilities based on field observations [6,22,23]: there is a 20% chance of flight for a distance of 1 m, a 20% chance of remaining stationary, and a 60% chance of walking a distance of 0.05 m. Subsequently, four attracting trees are strategically positioned near each corner of the experimentation space, effectively integrating a drift factor into the movement dynamics of the olive fruit fly (see Fig. 2b). This approach allows for the exploration the nuanced influence of proximity to these trees on the flies' directional movement, contributing to a comprehensive understanding of pest behaviour in agricultural ecosystems. In the second set of simulations the assumption that the movement of the olive fruit flies depends on the temperature is introduced and the probabilities of flight, walking or remaining stationary are affected by the weekly temperature following the formalisation shown in sequel:

$$P(fly) = 1 - f(t) \tag{1}$$

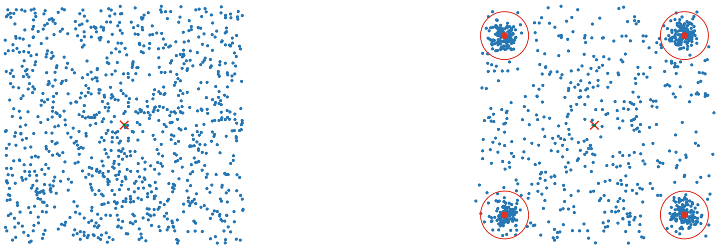
$$P(walk) = 1 - f(t) \tag{2}$$

$$P(stationary) = 1 - P(fly) - P(walk) \tag{3}$$

where $f(t)$ is a logistic equation with input the mean weekly temperature and

$$f(t) = \frac{1}{1 + e^{-k(t-25)}} \tag{4}$$

The use of the logistic function aims to represent a threshold behaviour, where there is a critical temperature range within which certain biological processes or events occur. For example, in the case of insect activity, there might be a temperature range between 20 and 32 °C where the likelihood of a specific behaviour (e.g., flight activity) is significantly higher compared to temperatures outside this range.



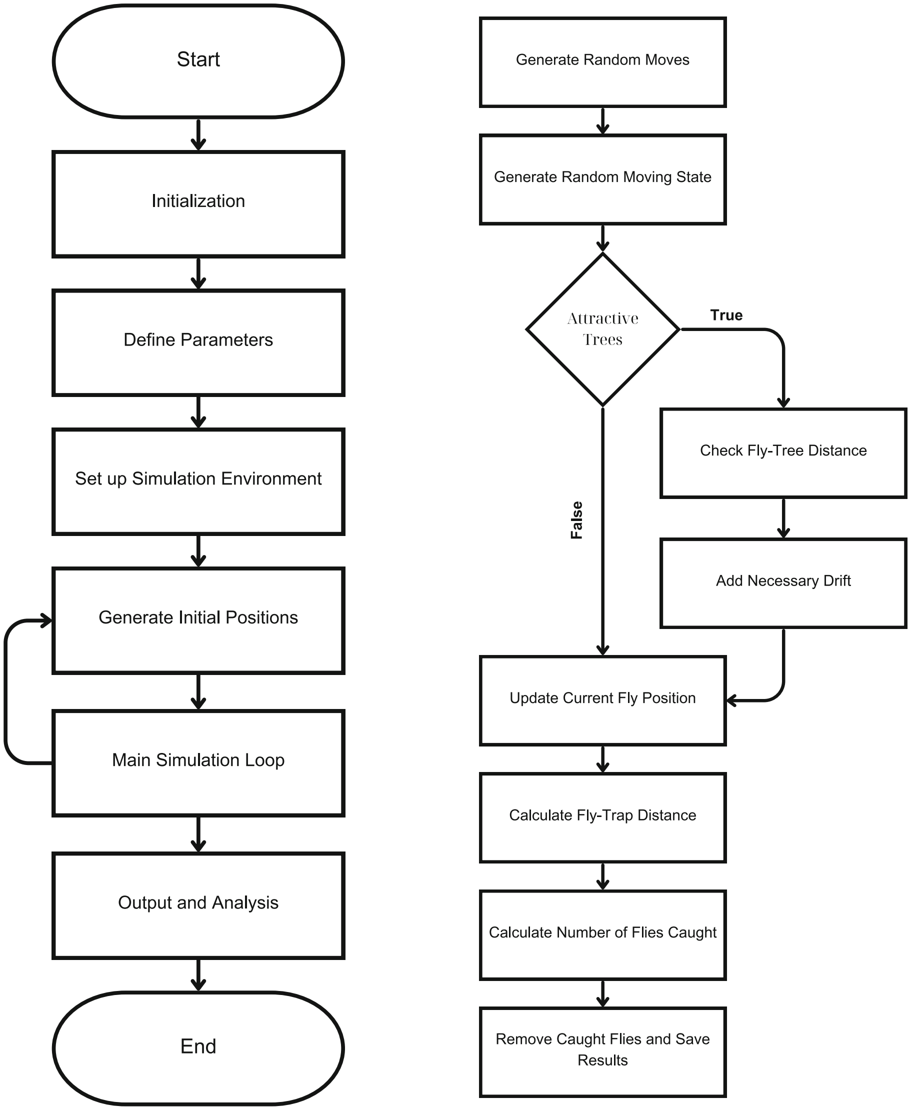
(a) (b)

Fig. 2. Olive fruit fly distribution with the presence (a) and absence (b) of attractive trees

As per the results of the studies [5,6] and to retain comparable results, each simulation corresponds to a one-week time-frame. Within each week, the simulation is executed ten times, and the average catch rate is computed based on the results of these iterations with the purpose to address the stochasticity introduced in numerous parameters of the simulation, like the random movement of the fruit fly and the different number of the trapped olive fruit flies on each simulation run.

3.2 Inputs and Outputs of the Model

The methodology employed herein draws upon the findings of Varikou et al. [5] as a foundational basis and integrates insights from earlier works by Economopoulos et al. [12] and Fletcher et al. [9] to construct two distinct models.



(a) Diagram of the simulation process (b) Diagram of the main simulation loop

Fig. 3. Architecture diagram of the simulation model

The first model is a linear model which correlates trap efficiency with capture rate, building upon a theoretical framework calibrated against empirical data. This framework posits that a McPhail trap captures approximately 0.5% of the actual olive fruit fly population within a 20-m radius.

The second model extends this approach by integrating mean weekly temperature data from the grove. It adjusts the probabilities of olive fruit fly movement based on the observed trap's efficiencies and corresponding temperature conditions. A polynomial model is then fitted to derive a theoretical equation for calculating trap efficiency considering both capture rate and mean temperature.

The simulation framework was developed using Python, leveraging additional input variables to enhance algorithmic accuracy. These variables include Radius, Step Time, Duration Day, Fly Size, Population, Capture Rate, Fly Speed, and Temperature as outlined in Table 1 and further detailed in the sequel.

As mentioned before, Radius is defined as the efficient radius of the trap, accordingly to [5]. For simulation performance reasons *Step Time* is set to 3 s, and refers to the time that passes between two movements of olive fruit flies. For optimal performance, *Duration Day* is considered as the duration of one day in the simulation, since at night the olive fruit fly is considered not as active as the day. The *Fly Size* is the actual size of the olive fruit fly in the simulation. The *Population* is the number of flies initialised. *Capture Rate* (CR) is defined as the probability of the fly to be captured after being in close proximity or above the trap, and is considered to be from 0 to 100%. *Fly Speed* of the flies is set as three different values depending on the states of the movement of the fly. While flies are flying speed is considered to be as 1, walking is equal to 0.05 and stationary is equal to 0 [6,22,23]. Finally, the last input variable is the mean weekly *Temperature* with integer values in range of [20, 32] °C per week, following the methodology of [9,12].

The results are consist of the outputs shown in Table 2: *Captured Flies*, *Trap Efficiency*, and *Regression Models*. The *Captured Flies* are the unit of *Population* that finally trapped during the simulation. The terminology *Trap Efficiency* (TE), first discussed in [9,11], is set as the percentage of population that finally was trapped. Lastly, the *Regression Models* (Linear and Polynomial) are expressed as equations.

Through this integrated approach, the study aims to provide a comprehensive understanding of olive fruit fly behaviour in relation to *Trap Efficiency* and Temperature dynamics, facilitating more effective pest management strategies.

Table 1. Inputs that used for simulation

Inputs	Value	Variable unit
Radius	20	m
Step Time	3	s
Duration Day	12	h
Fly Size	1×1	px
Population	1000	num
Capture Rate	0.1–1	%
Fly Speed	1, 0.05, 0	m/s
Temperature	20–32	mean °C/week

Table 2. Outputs of the simulation

Outputs	Variable unit
Captured Flies	Individuals per trap
Trap Efficiency	%
Regression Models	Equations

4 Results

The first model establishes a correlation between Trap Efficiency and Capture Rate of a fly being captured upon crossing the trap in two distinct scenarios: initially the impact of tree distribution within a 20-m radius is explored in Eq. 5, contrasting instances where the trees exhibit homogeneity and where they do not, as seen in Eq. 6. Utilising as linear regression approach, the model is refined to achieve the best fit to the simulated data. The resulting equations for the best fit lines for the simulation with and without trees are displayed below, along with its corresponding coefficient of determination (R-squared value):

$$TE = 0.0479CR + 0.4435 \tag{5}$$

With

$$R^2 = 0.9842$$

$$TE = 0.0177CR + 0.1518 \tag{6}$$

With

$$R^2 = 0.9620$$

As expected, the resulting line from the simulation with homogeneity exhibits a steeper slope compared to the scenario without homogeneity, as illustrated in Fig. 4. This discrepancy suggests that in an orchard with varying types of olive trees, the *Trap Efficiency* metric may not accurately represent the actual *Capture Rate* and subsequent control of olive fruit flies. The steeper slope implies that the presence of different olive tree varieties could significantly influence the effectiveness of trapping methods. This phenomenon may occur due to the diversion of flies towards more attractive trees, diminishing their presence in the traps. Hence, accounting for tree heterogeneity is crucial for refining pest management strategies in agricultural settings.

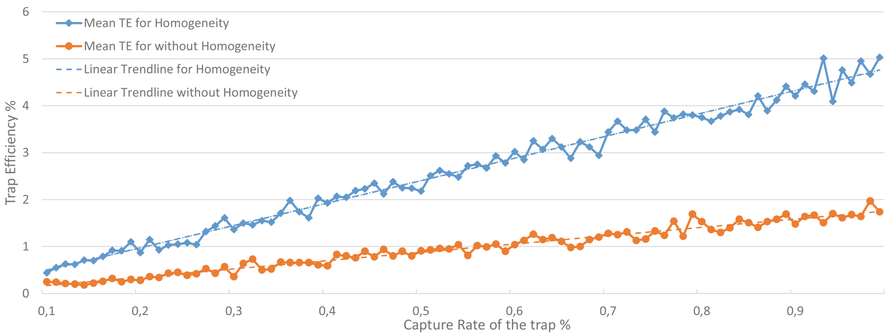


Fig. 4. Correlation of Trap Efficiency and Capture Rate.

The second model explores the relationship between *Trap Efficiency* and the average weekly temperature. Employing polynomial regression analysis, the model is optimised to provide the most accurate representation of the observed data. Fitted equations for selected *Capture Rates*, along with its corresponding coefficient of determination (R-squared value), are:

For Capture Rate of 0.2%

$$TE = 0.0023T^3 - 0.0528T^2 + 0.2558T + 0.6606 \tag{7}$$

With

$$R^2 = 0.8973$$

For Capture Rate of 0.5%

$$TE = 0.0032T^3 - 0.0717T^2 + 0.2314T + 2.1571 \tag{8}$$

With

$$R^2 = 0.9863$$

For Capture Rate of 0.8%

$$TE = 0.0077T^3 - 0.1717T^2 + 0.6777T + 3.326 \tag{9}$$

With

$$R^2 = 0.9906$$

The simulation results depict a marginal increase in *Trap Efficiency* followed by a decline as temperature rises across each of the distinct *Capture Rates* as shown in Fig. 5.

By deriving these models from the simulation results, the study provides insights into the factors influencing *Trap Efficiency* of the McPhail trap, thus contributing to the refinement of pest management strategies in agricultural ecosystems. This offers a clearer understanding of the intricate interplay between *Trap Efficiency*, environmental temperature, and non uniform terrain. Moreover, by elucidating the complex relationships between these variables, the study enhances our ability to predict and mitigate pest infestations effectively.

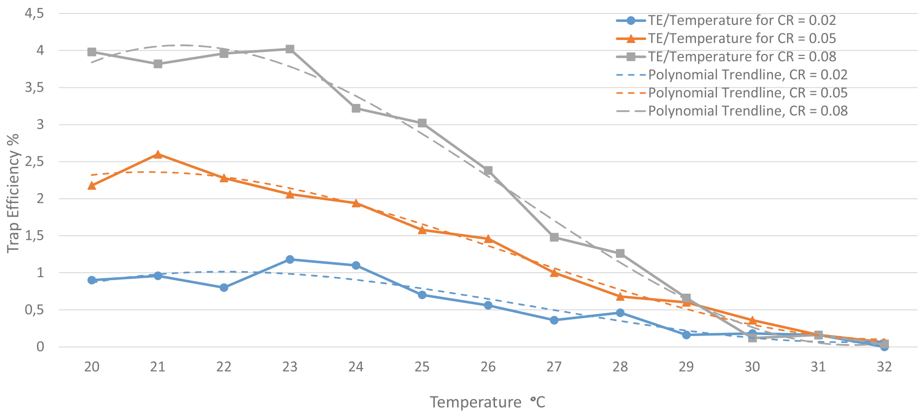


Fig. 5. Correlation of Trap Efficiency and Temperature.

5 Discussion

Based on the findings of the suggested methodology, it can be inferred that when a specific quantity of olive fruit flies is captured by the McPhail trap on olive trees, then the population in the orchard approximates to a number of individuals. This data is valuable for developing a strategy to manage the population of olive fruit flies and mitigate their infestation on olive trees.

By integrating temperature data into our simulation models, it was possible to develop predictive equations that accurately reflect the relationship between *Trap Efficiency* and *Temperature* variations, offering valuable insights for precision pest management.

Furthermore, the analysis of *Trap Efficiency* provides interesting insights regarding the efficacy of trapping methods for estimating olive fruit fly population. By calibrating simulation models against empirical data, it is able to derive regression equations that are able to predict *Trap Efficiency* based on *Capture Rates*. These models offer a practical tool for agronomists and trap manufacturers to improve trap design and positioning, thereby enhancing the effectiveness of pest monitoring and control endeavors.

Overall, this study contributes to the growing body of research aimed at improving pest management practices in olive groves. By leveraging advanced simulation techniques and mathematical modeling, it provides a deeper understanding of the complex interactions between environmental factors, trap efficiency, and olive fruit fly behaviour in non uniform field patterns.

6 Conclusion

In this study, a comprehensive analysis of olive fruit fly (*Bactrocera Oleae*) population dynamics had been presented, focusing on the correlation between *Trap* *efficiency* and field factors such as *Capture Rate*, various crops, and *Temperature*. Through a combination of empirical observations, mathematical modeling, and simulation techniques, it was aimed to shed light the underlying factors influencing olive fruit fly behaviour and their implications for pest management strategies in olive groves.

The results of the first simulation concluded in correlation between *Trap Efficiency* and *Capture Rate* based on previous experiments. On the second simulation the results showed that there is a significant correlation between *Trap Efficiency* and *Temperature*, using various *Capture Rates*, leading towards a contemporary tool for the estimation of olive fruit fly population.

Future research could include the development of more sophisticated simulation models and the integration of additional parameters to further refine pest management strategies in agricultural settings. Moreover, this study has the potential to be extended in the future by leveraging techniques such as Spatial Skyline Queries [24,25], where different clusters based on trees' attractions, olive fruit flies behaviour, and microclimates can be identified. Finally, the results and methods could be transferred on other kind of crops and pests.

Acknowledgment. The authors gratefully acknowledge the financial support of the Ionian University, Greece.

References

1. Kalamatianos, R., Kermanidis, K., Avlonitis, M., Karydis, I.: Environmental impact on predicting olive fruit fly population using trap measurements. In: Iliadis, L., Maglogiannis, I. (eds.) AIAI 2016. IAICT, vol. 475, pp. 180–190. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-44944-9_16
2. Amr, A., Sadder, M., Sakarneh, N., et al.: Review article olive fruit fly bacterocera oleae infestation of olives: effect on quality and detection in olive oil. Jordan J. Agric. Sci. **19**(1), 81–94 (2023)
3. Haniotakis, G., Kozyrakis, M., Fitsakis, T.H., Antonidakj, A.: An effective mass trapping method for the control of dacus oleae (diptera: Tephritidae). J. Econ. Entomol. **84**(2), 564–569 (1991)
4. Haniotakis, G.E., et al.: Olive pest control: present status and prospects. IOBC WPRS Bull. **28**(9), 1 (2005)
5. Varikou, K., Alexandrakis, V., Gika, V., Birouraki, A., Marnelakis, Ch., Sergentani, C.: Estimation of fly population density of bactrocera oleae in olive groves of Crete. Phytoparasitica **41**(1), 105–111 (2013)
6. Kapatos, E.T., Fletcher, B.S.: An assessment of components of crop loss due to infestation by dacus oleae, in corfu. Entomologia Hellenica **1**, 7–16 (1983)
7. Kesavaraj, G., Sukumaran, S.: A study on classification techniques in data mining. In: 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), pp. 1–7 (2013)
8. [World distribution]| EPPO Global Database: Bactrocera oleae (dacuol), 1989–2023 (n.d.)
9. Fletcher, B.S.: Temperature-development rate relationships of the immature stages and adults of tephritid fruit flies. In: Fruit Flies Their Biology, Natural Enemies and Control, vol. 3, pp. 273–289 (1989)

10. Broufas, G.D., Pappas, M.L., Koveos, D.S.: Effect of relative humidity on longevity, ovarian maturation, and egg production in the olive fruit fly (diptera: Tephritidae). Ann. Entomol. Soc. Am. **102**(1), 70–75 (2009)
11. Kapatos, E., Fletcher, B.S.: Seasonal changes in the efficiency of McPhail traps and a model for estimating olive fly densities from trap catches using temperature data. Entomol. Exp. Appl. **33**(1), 20–26 (1983)
12. Economopoulos, A.P., et al.: Population studies on the olive fruit fly, dacus oleae (gmel.) (dipt., tephritidae) in Western Crete. Zeitschrift für Angewandte Entomologie **93**(1–5), 463–476 (1982)
13. University of California Agriculture & Natural Resources: Olive fruit fly management guidelines, Revised 2/09
14. Steyskal, G.C.: History and use of the McPhail trap. Florida Entomol. 11–16 (1977)
15. Doitsidis, L., et al.: Remote monitoring of the bactrocera oleae (gmelin) (diptera: Tephritidae) population using an automated McPhail trap. Comput. Electron. Agric. **137**, 69–78 (2017)
16. Haniotakis, G.E., Skyrianos, G.: Attraction of the olive fruit fly to pheromone, McPhail, and color traps. J. Econ. Entomol. **74**(1), 58–60 (1981)
17. Kapatos, E.T., Fletcher, B.S.: The phenology of the olive fly, dacus oleae (gmel.) (diptera, tephritidae), in corfu. Zeitschrift für Angewandte Entomologie **97**(1–5), 360–370 (1984)
18. Mamdouh, N., Khattab, A.: Yolo-based deep learning framework for olive fruit fly detection and counting. IEEE Access **9**, 84252–84262 (2021)
19. Molina-Rotger, M., Morán, A., Miranda, M.Á., Alorda, B.: Remote fruit fly detection using computer vision and machine learning-based electronic trap. Front. Plant Sci. **14** (2023)
20. Kalamatianos, R., Kermanidis, K.L., Karydis, I., Avlonitis, M.: Treating stochasticity of olive-fruit fly's outbreaks via machine learning algorithms. Neurocomputing (Amsterdam) **280**, 135–146 (2018)
21. Pearson, K.: The problem of the random walk. Nature **72**, 294 (1905)
22. Sexton, C.: Fruit flies can travel six million times their body length. Earth.com, April 2021
23. Leitch, K.J., Ponce, F.V., Dickson, W., Van Breugel, F., Dickinson, M.H.: The long-distance flight behavior of drosophila supports an agent-based model for wind-assisted dispersal in insects. Proc. Natl. Acad. Sci. USA **118**(17) (2021)
24. Borzsony, S., Kossmann, D., Stocker, K.: The skyline operator. In: Proceedings 17th International Conference on Data Engineering, pp. 421–430. IEEE (2001)
25. Bavirthi, S.S., Supreethi, K.P.: Systematic review of indexing spatial skyline queries for decision support. Int. J. Decis. Support Syst. Technol. (IJDSST) **14**(1), 1–15 (2022)