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Review

Bactrocera oleae Control and Smart Farming Technologies for Olive Orchards in the Context of Optimal Olive Oil Quality: A Review

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Abstract: Olive oil production is among the most significant pillars of crop production, especially in the Mediterranean region. The management risks undertaken throughout the olive oil production chain can be minimized using smart tools and applications. This review addressed the influence of the fruit fly of *Bactrocera oleae* (*B. oleae*) or *Dacus oleae* on the quality and antioxidant activity of the olives and their products based on the most recent literature data. Furthermore, in this review, we focused on the latest research achievements in remote sensor systems, features, and monitoring algorithms applied to remotely monitor plant diseases and pests, which are summarized here. Thus, this paper illustrates how precision agriculture technologies can be used to help agricultural decision-makers and to monitor problems associated with integrated pest management for crops and livestock, achieving agricultural sustainability. Moreover, challenges and potential future perspectives for the widespread adoption of these innovative technologies are discussed.

Keywords: *Bactrocera oleae*; olive fruit fly; fruit infestation; insects; virgin olive oil; integrated pest management; pest recognition; risk management; qualitative parameters; antioxidant activity

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1. Introduction

The olive tree (*Olea europaea* L.) was initially discovered in tropical and warm temperate parts of the world. It is a tree well known for its fruits, often known as olives, classified under the Oleaceae family, and it holds a significant commercial value in the Mediterranean as the primary source of olive oil [1]. Although olives are now grown in many other parts of the world, the eastern Mediterranean Basin, which accounts for approximately 98% of global olive cultivation, remains the primary producing zone [2]. Olive yield can reach up to 22 tons of fruit per ha (the weight of a single olive depends on the variety and is usually between 1 and 12 g) [3]. Spain is the largest producer of olives (2.4 million hectares), followed by Italy (1.4 million ha), Greece (1 million ha), and Portugal (0.5 million ha), according to the International Olive Council-IOC [4,5]. In 2011/12–2015/16, the EU was responsible for 70% of global olive oil production, 56% of consumption, and 66% of exports. The primary goal of the European olive oil strategy is to maintain its position in the global market by promoting the development of high-quality products that benefit manufacturers, processors, traders, and consumers.

Olive tree farming is estimated to have begun about seven thousand years ago. Archaeological evidence presented the olive crop cultivation by Greeks and Egyptians used not only as a food product but also for medical benefits [6,7]. For instance, in ancient Egypt,

they utilized the leaves to prepare dead bodies for mummification. Commercially, olive fruit is a valuable product considering its content in high nutritional and edible oil with potential therapeutic properties [8]. Olives are rarely eaten in their natural raw form due to their bitterness; instead, they are consumed as olive oil or table olives. To make olives edible, Oleuropein, the bitterness-causing chemical component, must be removed [2,7].

Given the increasing awareness of the importance of high-quality and nutritious types of food, global consumption of olive and its products has risen significantly worldwide in advanced economies, and as a consequence, this has caused a rapid development of olive-based products [2,9]. In the Mediterranean region, olive oil serves as the main dietary component and is well known for its strong correlation with health issues such as reduced risk for cardiovascular diseases, diabetes, cancer, and cognitive decline associated with age, as well as the decreased probability of metabolic syndrome [2,10,11]. These health benefits are primarily due to the presence of a high content of monounsaturated fatty acids (MUFAs) that contribute to health protection by decreasing low-density lipoprotein levels [6] and functional bioactive compounds such as tocopherols, carotenoids, phospholipids, and phenolics, which have a variety of biological activities [12]. These components are further responsible for the unique taste and flavor of olive oil.

As occurs in other crops, the components and the yields of the agrifood products may vary from 12 to 28% depending on cultivars, agronomic protocol, harvesting systems, machinery, etc. [12]. Olive oil is categorized based on the processes or treatments used. To produce virgin olive oil (VOO), olive juice is extracted naturally by mechanical or physical methods and classified into the following types: (a) extra virgin olive oil (EVOO) with an acidity of equal or less than 0.8% can be obtained from single or multiple cultivars or from a specific geographic region (Protected Designation of Origin); (b) virgin olive oil with 2% acidity; and (c) lampante olive oil with higher than 2% acidity. The latter is produced by refining companies or for technical applications [3].

Temperature and duration are critical elements of the malaxation process for producing high-quality EVOO and VOO with antioxidant potential. The production of extra virgin and virgin olive oils is attained by using a direct extraction procedure that includes olive fruit grinding, so that natural flavor and texture are preserved. This procedure for extracting oil is called “cold pressed”, and it prevents oil from losing its flavor, which can change when it is exposed to high temperatures. Extra virgin olive oil produced without chemical treatments results in organic olive oil. Virgin oil suggests that the oil has not been refined; it is of superior quality; and that, as previously stated, it retains its natural flavor. Additionally, a number of factors may have an effect on the oxidative processes that extend or shorten the shelf-life of olive oil. The unique fatty acid composition in addition to phenolic compounds and tocopherols are the main factors of olive oil resistance to oxidation [13,14]. EVOO is of particular interest due to its high nutritional value and antioxidant compounds than other vegetable oils. The oil consists primarily of triacylglycerols, which account for more than 98% of its weight, as well as over 230 minor chemical compounds, while the compositions differ based on variety, agronomic conditions, manufacturing techniques, and other factors [15–17]. The main minor compounds are sterols, aliphatic and triterpene alcohols, hydrocarbons, and antioxidants such as carotenoids and polyphenols, which contribute to EVOO’s organoleptic qualities, stability, and nutritional value [18,19].

Olive oil quality is also strongly linked to the extent of drupe attack carried out by the olive fruit fly, *B. oleae* (Rossi) or *Dacus oleae* (Gmelin), Diptera: Tephritidae Gmel. It is a monophagous indigenous insect located in the basin of the Mediterranean and attacks olive fruit at an early stage of development. The olive fly’s most significant damage occurs at the fruit level, where females typically deposit a single egg that hatches in 2–4 days, and the larva develops by feeding on the olive’s mesocarp for 10–14 days [20]. This results in the depreciation of table olive prices due to fruit dropping prematurely and skin damage caused by the olive fly’s oviposition. Furthermore, the penetration of fruits by the ovipositor induces infections caused by bacteria and fungi, which causes the acidification of olive oil and weakens its quality and market price [20,21]. In this case and if no treatment is applied,

the olive fly damage to fruit may range from 90 to 100% [22]. At times, under adverse environmental conditions, the production decrease caused by this fly can reach 30%. In 2015, Malheiro et al. reviewed *B. oleae*'s impact on olive products, demonstrating a negative impact on quality, as well as antioxidant and antibacterial activities [23].

Precision agriculture (PA) has presented remarkable growth in the last decades, addressing both pure research topics and applied management issues. PA is the application of field-level technologies to collect more accurate and precise data than conventional methods. The effective use of sensors and real-time processing are viewed as the key challenges for successfully operating agricultural processes based on the principles of PA [24–26].

Plant pest control has been a cornerstone of modern agriculture since the 1960s. In the case of olive fruit, in-field insecticide application remains the most common practice of controlling fruit flies [27], even though it is being restricted by national or EU legislation due to its negative impact on health and the environment, while in parallel provokes resistance in targeted pests. For example, organophosphorus pesticide residues in oil and fruits are identified as a significant threat to consumer health. As a result, the European Union (Regulation EC No. 396/2005) and the Codex Alimentarius Commission of the Food and Agriculture Organization (FAO) set a maximum residual limit (MRL) of 3 mg/kg in olive products [28]. Consequently, the application of PA for pest control has been applied to improve pest control and/or detection. For example, for the control of cotton insect pests, spatially sensitive maps are used to drive a spatially variable insecticide application [29]; fruit fly infestation of mangos is detected by hyperspectral imaging [30]; and medfly insecticide treatments in Israel apply GIS technologies on models to develop more accurate decisions [31].

Furthermore, automatic pest monitoring (e.g., electronic traps) provides greater accuracy over the numbers of the targeted pests and, through geolocation, a better understanding of the pest's spatial and temporal distribution. Quick access to time-sensitive pest control information is critical for effective pest and disease management [32]. Electronic systems are now being developed for several plant pest species. More specifically, electronic traps (e-traps) can significantly decrease labor costs for monitoring, particularly for primary pest species, including the Asian citrus psyllid [33], as well as time-consuming identification species such as moths [34]. Several electronic traps for the fruit fly *B. oleae* have been designed for use in pest management systems. The main components of such electronically monitored systems are the following: optical (or optoelectronic) sensors that include an emitter (mostly LED-based) and an array of phototransistors, an electronic circuit to perform frequency band filtering, a power supply system, and a communication system that sends/receives data to the main control system [35,36]. Their core functionalities are to monitor insects that pass through the laser beam, identify them based on their body size and shape, and record them on the main control system.

In this review, based on a thorough literature survey, we assess the influence of the fruit fly of *B. oleae* on the quality and antioxidant activity of the olives and their products. Also, we summarize the state-of-the-art research achievements in smart farming technologies related to olive production, including the potential future trends and challenges of these techniques.

2. Impact of *Bactrocera oleae* Infestation on Oil Qualitative Characteristics

The compounds found in olive oil have been extensively researched in several studies in the past years. In Europe, to be classified as EVOO, the oil needs to fulfill a set of criteria outlined in EU Regulations No. 2568/91 and 1348/2013 [37], which are evaluated through chemical and sensory tests using IOC methods and standards [38]. Quality parameters for olive oil include free acidity, peroxide index, UV absorbance coefficients (K232, K270, and ΔK), fatty acid ethyl esters, and sensory characteristics [38,39]. These fundamental quality parameters, along with fatty acid (oleic acid, palmitic acid, linoleic acid) and sterol (campesterol, stigmasterol) compositions, phospholipid profiles, tocopherols (α-, β-, and γ-tocopherols), phenolic molecules (phenolic acids, flavonoids, phenolic alcohols, lignans),

volatile compounds, pigments (β-carotene, zeaxanthin, lutein, chlorophylls, violaxanthin), hydrocarbons, and others can present valuable information to verify EVOO authenticity and detect any possibly fraudulent activities to it [40–43] (Figure 1).



Figure 1. The main olive oil qualitative parameters affected by *B. oleae.*

The role of pigments, tocopherols, and hydrocarbon fractions have gained great attention due to their potential activities, mainly by reacting with free radicals, resulting in the preservation of other important compounds. This positive impact has been reviewed by Bendini et al. [44], for which the results have been shown to have antioxidant effects; prevent endothelial dysfunction by decreasing the expression of cell adhesion molecules [45], enhance nitric oxide (NO) formation and inducible NO synthesis [46], and eliminate vascular endothelial intracellular free radicals [47]; inhibit platelet-induced aggregation [48]; increase the mRNA transcription of the antioxidant enzyme glutathione peroxidase (GSH-Px); and decrease the bioavailability of food carcinogens and inhibit their metabolic activation [49,50]. However, despite the numerous studies on the fingerprint of olive oil, there remains a literature gap regarding the metabolic pathway of olive oil bioactive constituents such as phenolic acids, flavonoids, lignans, secoiridoids, diacylglycerols, and fatty acids.

Olive oil bioactive compounds are detected at trace levels, and for this reason, the olive fruit sample needs to be extracted, cleaned up, and concentrated to achieve an effective separation and detection. Most techniques for EVOO/VOO phenolic analysis are based on liquid–liquid extraction (LLE) [51–54] and solid phase extraction (SPE) [55,56]. More recently, LLE and SPE were applied to pre-treatment olive oil samples, and the comparative findings showed no significant variations in the degree of extraction of the investigated phenolic compounds when comparing the two procedures. Identification and quantitation analysis of a wide variety of compounds, such as phenolic compounds,

amino acids, proteins, and carbohydrates, are based traditionally on high-performance liquid chromatography (HPLC) coupled with ultraviolet or diode array detection (PDA), electrochemical detection, and mass spectrometry (MS) analyzer (i.e., quadrupole, ion trap, time-of-flight). Gas chromatography (GC) is also widely applied as the principal tool in the determination of fatty acids and volatile compounds in olive oil, which have been identified as authenticity markers [57,58]. Of particular interest is the coupling of LC with MS. This coupling improves performance by providing high sensitivity, selectivity, and short analysis time, thus enabling the determination of the entire molecular composition of complex systems, such as olive oil [59]. Recent developments in high-resolution mass spectrometry (HRMS) platforms have improved the simultaneous determination and resolution of thousands of compounds and the identification of new contaminants without prior knowledge. LC-HRMS enables reliable target analysis with reference standards and screening for suspect and non-target compounds often occurring in olive oil (i.e., flavonoids, lignans, phenolic acids, secoiridoids, or simple phenols). TOF provides the highest resolution for relatively high m/z ion masses. Additionally, hybrid tandem mass instruments, such as the Q-TOF-MS, provide relevant structural information by obtaining product ion full spectra at accurate mass. Q-TOF-MS/MS experiments confirm the existence of potential positives and permit the elucidation of unknown compounds. LC-Q-TOF-MS could be a powerful tool for determining new bioactive compounds, metabolic profiling, and the thorough characterization of the olive oil fruit. However, its application is still very limited [42,43,60,61].

During the last few years, researchers have focused on electrochemical (bio)sensors and how they can detect various antioxidant substances or contaminators in EVOO/VOOs. Recently, Bounegru et al. (2021) published an interesting review on the use of these devices for monitoring bioactive compounds in olive oil. In the same review, the authors highlighted the main advantages and limitations of several electrochemical sensors, sensor arrays, and biosensors used to evaluate olive oil quality [62]. The findings indicate that carbon nanomaterials are more favorable for sensor creation, but there are significant benefits when they are utilized with mediators, which improve electron flow and sensitivity. As with electrochemical sensors, concerns may arise, particularly in contaminating the active surface, especially when measuring the levels of phenolic chemicals, due to the accumulation of an antioxidant product that inhibits further oxidation. This obstacle can be removed by the proper functionalization of the material. Electrochemical methods based on sensors or sensor arrays signify the development of innovative technologies for EVOO/VOO analysis by being precise, ecological, rapid, and less expensive [62,63].

Olive fly (*B. oleae*) is one of the main menaces for olive crops worldwide, affecting their fruit development and oil production, and it has spread in the last decades to newly cultivated areas. Olive orchards display different susceptibilities to this pest, with some cultivars having a systematically low fly infestation, while others are usually more heavily affected under the same agroecosystem. The global impact of *B. oleae* in olive crops, from the tree to the table, has been previously reviewed by Malheiro et al. [23]. In their study, the data collected showed that oil production, olive oil quality indicators (free fatty acid, peroxide value, K232 and K270, oxidation stability), bioactive compounds (fatty acids and tocopherols, and total phenols and flavonoids), and antioxidant (reducing power, FRAP, β-carotene bleaching inhibition, ABTS, and DPPH) as well as antibacterial (against eight referenced human enteropathogenic bacteria by the agar disc diffusion method) properties are negatively correlated with olive infestation level, leading to increased quality degradation, namely, hydrolysis and oxidation, which causes significant change in oil stability. However, several studies have been published so far involving monitoring infestation levels of different olive cultivars from different geographical origins. Some examine aspects not covered earlier, such as regional climatic conditions, light intensity, and nitrogen fertilization, allowing for a better understanding of the damage caused by the olive fruit fly.

More specifically, eight olive cultivars (Abani, Aellah, Blanquette de Guelma, Chemlal, Ferkani, Limli, Rougette de Mitidja, and Souidi) with varying degrees of fly infestation (0%, not attacked; 100%, all attacked; and real attack %) and different maturation indices, Verbascoside, tyrosol, and hydroxytyrosol, were the most adversely affected compounds [64]. In addition, Helvaci et al. (2018) investigated the effect of olive fruit flies on Northern Cyprus olive cultivars and provided valuable information on their ecology within the Mediterranean climate [65]. Research results showed that insect populations considerably affected the infestation rate. They also noted a positive correlation between air temperature and infestation rate, while a weak correlation was reported between altitude and infestation rate, and that lower humidity causes an increase in the population of *B. oleae*. In this sense, in Turkish olive cultivars, free fatty acids (FFA), peroxide value, total phenolics, o-diphenol, and α-tocopherol amounts are also linked to the infestation status of olive fruits attacked by *B. oleae*, as examined by Abacıgil et al. (2023) [66]. The same pattern was verified by Notario et al. (2022) after finding a significant content increase for certain volatile compounds such as (E)-hex-2-enal, ethanol, ethyl acetate, and β-ocimene and a drastic decrease of the phenolic contents in oils (cvs. Picual, Manzanilla, and Hojiblanca) from *B. oleae*-infested fruits [67]. The information of Malheiro et al. (2019) suggests that in both field and laboratory bioassays, olive cultivar and maturation are crucial parameters in the oviposition preference of female olive flies and influence the longevity of adults [68]. From a practical point of view, Kokkari et al. (2017) investigated the role of olive fruit under light conditions [69]. They support that fruit contact and/or volatile fruit stimuli significantly affect the extent of mating and egg production of the olive fly and that this influence is modulated by the light intensity degree. More specifically, mating percentages were significantly higher at dusk and under low light intensity.

3. Smart Farming Technologies and Practices for Detecting *Bactrocera oleae*

Smart farming overall is multidimensional and is correlated with a series of concepts and systems. Such systems include Farm Management Information Systems that aim to transform agricultural production into a fully controlled system [70]. Towards this direction, technologies based on cloud architecture combined with high computational speed make feasible the use of multiple micro-services and the communication of various devices across the cloud [71]. Another pillar of smart farming is agricultural robotics. Here, the synergy of unmanned aerial and ground vehicles, along with their interaction with humans in arable, orchard, or horticultural farming systems, may be developed [72]. Agricultural robotics development should focus on indoor/outdoor awareness and navigation; autonomous data acquisition; and high accuracy control for mission, route, and task planning [73,74]. Machine learning applications are particularly useful in solving problems in agriculture. Nowadays, with the unprecedented use of IoT and cloud computing, it is possible to train models with a huge variety of data from multiple sources and discover new patterns [75]. The use of classification, clustering algorithms, and artificial neural networks (ANN) for weed detection, yield prediction, insect detection, weather forecasting, and operations management are a few examples [3,76,77]. Finally, precision agriculture is the management of fields at the subfield level, applying the right treatment, in the right amount, to the right place at the right time. In order to define all these parameters for the correct application, a series of sensors and other sources of information concerning the fields of interest can be employed [78–80]. Precision agriculture systems use remote and proximal sensing and wireless sensor systems as stationary sensors. All these layers of information can be combined through data fusion procedures to support farmers in decision making [81,82].

As occurs in every crop production system, to achieve optimum management of the olive oil supply chain, a Farm Management Information System (FMIS) is required. FMIS is the most significant tool in managing smart farming applications and technologies [70]. The most important field operations that are implemented each year in olive groves include soil cultivation, fertilization, pest control, irrigation, pruning, and harvesting. On top of these, crop monitoring by using proximal, aerial (e.g., UAV—unmanned aerial vehicles)

and satellite means contribute to optimal olive grove management with high precision levels [83]. The olive crop production system is a complex system that requires optimal use of resources and equipment (tractors and implements) to increase yield and productivity. In Table 1, an indicative list of research publications related to the use of smart farming systems in various stages of the olive crop production cycle is presented. Disease control, pest management, irrigation, and water and nutrients need evaluation are only some examples. Overall, the optimal management of all field operations may have a positive impact on olive oil quality.

Table 1. Smart farming solutions in various olive production stages.

Field Operation/Crop Focus Stage	Platform Means	Country	Reference
Disease control, tree identification, vigor	UAV	Greece	[84]
Fertilization, vigor	UAV	Spain	[85]
Irrigation	Satellite	Tunisia	[86]
Fertilization, vigor	UAV	Spain	[87]
Disease control	Satellite, manned flight	Italy	[88]
Vigor, tree identification	UAV	Spain	[89]
Yield prediction, vigor	UAV	Greece	[90]
Irrigation, vigor	UAV	Spain	[91]
Disease control, vigor	Unmanned ground vehicle	Italy	[92]
Vigor, tree/row identification	Satellite	Italy	[93]
Vigor, irrigation	UAV	Spain	[94]
Pruning biomass assessment	Manned flight	Spain	[95]
Variety/phenology, vigor	Proximal measurements	Spain	[96]

Focusing on the detection and treatment of *B. oleae*, various practices and methods have been reported and reviewed in [97–99]. The most important and indicative of them are presented in Table 2, including their core methodological approaches and indicative results. Some refer to strategic planning or following specific management protocols to face olive fly, while others include smart technologies and applications. Management strategies of the Mediterranean fruit fly have been reviewed in [100]. Decision making (decision support systems—DSS) in modern agriculture includes data-driven information systems that are used for problem solving and the optimization of crop production systems' performance [101,102]. In this scope, a decision support system has been demonstrated, taking into account spatial and temporal patterns of the olive fruit fly population in an orchard where all trees were georeferenced in order to increase the accuracy and precision of sprays in time and space, resulting in a reduction of about 37% of the insecticide volume usage, and, as a consequence, decreasing the environmental and financial impact on natural enemies [103]. Similarly, a pest management control of olive fruit fly that is based on a location-aware agro-environmental system (LAS) that is based on spatiotemporal data could provide useful information about the olive products' traceability. In this study, significant results were extracted, i.e., reduction of the spray solution up to ~5% and an increase of the spray effectiveness up to 6% [104].

Table 2. Indicative studies that include smart farming technologies towards *Bactrocera oleae.*

Type of Control [1]	Methodological Approach	Results	Reference
T	DSS demonstration (software and hardware)	37% insecticide reduction, 42% reduction of spray duration	[103]
T	GIS-based LAS system	Reduced spray solution (5%), increased spray effectiveness (6%)	[104]
T	DL-based approach for olive flies' recognition	>90% identification accuracy	[105]
T	DL framework for detection and counting of flies	Average detection precision ~97%	[106]
P/T	Female *B. oleae* pheromone detection by using MEMS device	Detection limit ~ 0.297 ppq	[107]
T	Remote monitoring by McPhail trap	Accuracy counting ~75%	[108]
T	McPhail trap demonstration (hardware)	App. 7.5% false alarms	[109]
T	Image recognition toolkit demonstration (hardware)	Accuracy app. 92%	[110]
P/T	DL-based detection approach	Precision rate 93%	[111]
T	NIR spectroscopy for hidden *B. oleae* damage detection	Classification accuracy ~94%	[112]
T	Olive oil quality based on infestation level and maturity	Early ripening stage min. damage by *B. oleae*	[113]
T	NN-based classification for microclimate identification methods for olive fly detection	Algorithm performance app. 66%	[114]

[1] P: prevention, T: treatment.

A prerequisite in a decision support system is the capability to monitor the orchard remotely via a management information system [99]. On top of that, it is crucial to detect and identify the olive fruit flies to avoid extracting misleading results on counting fruit flies [105,106]. To this scope, smart farming hardware tools (optical or acoustical sensors) should be used for optimal monitoring and detection [115]. These sensors along with a communication system could be very important tools for remote monitoring and preventing potentially damaging insect infestation. An innovative study presents the use of MEMS (microelectromechanical system) devices in the detection of the presence of female *B. oleae* via highly sensitive pheromone nanosensors with a detection limit of a value as low as 0.297 ppq [107]. This contributes significantly as a prevention tool before insect attack. Other smart insect control applications include, for example, a novel automated McPhail e-trap that remotely monitors the population of olive fly and presented an accuracy of counting around 75% via image processing [108], while a similar electronic McPhail trap presented about 7.5% false alarms due to multiple events triggering [109], and an image recognition toolkit, called DIRT (Dacus Image Recognition Toolkit), achieved accuracy up to approximately 92% in Dacus identification [110].

Deep learning (DL) can be a driving force in smart farming and in the overall digitalization of agriculture [116]. More specifically, for olive oil production, various approaches have been based on deep learning for insect species identification (including *B. oleae*) with a precision rate of up to 93% [111] and a mean average precision rate of ~97% [106]. All of them are making use of optical and acoustical high-tech sensors together with deep learning-based algorithms to optimize the accuracy of the system.

Finally, a huge chapter that affects infestation level and potential damage is related to the agricultural operations and post-harvest processes throughout the production cycle. First, the infested olive fruit is an important negative factor for olive fruit milling processing because the infestation might not be visually detectable on the olives' surface. Spectroscopical methods could be a solution for this [112]. Of course, the maturity of olives plays a crucial role in the quantitative and qualitative characteristics of the produced olive oil for various insect infestation levels [113]. The use of chabazite zeolite and other types of zeolite through foliar applications may act as a controller on the olive fly, while in parallel affecting the quality of olive oil [117]. It is well known that climate and microclimate conditions are highly related to the olive fly's life cycle. In this light, various olive grove locations have been assessed by using statistical analysis and neural-network-based classification algorithms [114]. On top of this, an IoT platform that focuses on the optimization of irrigation scheduling in olive groves could send alerts to farmers/agronomists when weather conditions are suitable for the potential growth of *B. oleae* [118].

4. Discussion

The basis of the interest (both in scientific and farmer's level) in olive oil production is understanding the key factors that determine the presence of the olive fruit fly. Significant research on state-of-the-art technologies suggests promising prevention and treatment methods and processes. Of course, the lifelong learning and training of farmers, consultants, and agronomists may contribute to the decreasing of the environmental impact of insecticides by minimizing their use, and, in parallel, improving olive oil quality and food safety in the olive oil production cycle. In the natural environment, insects are often stressed by adverse factors, mainly weather parameters (Figure 2).

More specifically, the temperature is among the most significant weather factors due to its high impact on insects' life cycle. Several studies have revealed that the population of the fruit fly *B. oleae* is positively correlated with the maximum temperature, whereas the minimum temperature is not suitable for the growth and development of fruit fly. Regarding relative humidity, results have shown that the infestation rate decreases when relative humidity increases. Specifically, the correlation of *B. oleae* with morning relative humidity and rainfall seems to be negatively correlated. In addition, a negative weak correlation has also been observed between the altitude and infestation rate. Furthermore,

the fruit fly population was observed to be affected by the maturation stage. Results have shown that early harvesting seems to have an attractive effect on olive fly females, thus decreasing its infestation levels, while fly species infestation increased as fruits ripened. Thus, fruit infestation risk can be minimized by harvesting fruits at the green-mature stage. Last, the olive cultivar is a crucial aspect in olive fly preference, also influencing the fruit infestation level. Changes in volatile chemicals during fruit ripening could also be involved in the host preferences of fruit flies. In the stage of olive fruit ripening, a number of changes in the physico-chemical features occur simultaneously, making it difficult to determine their significance in host preference.

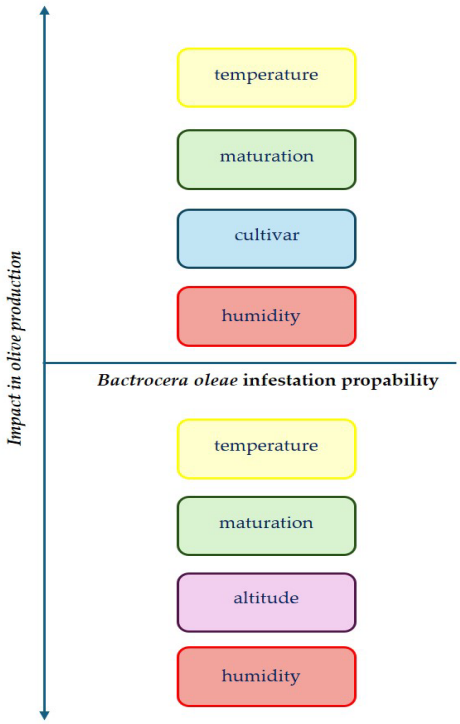


Figure 2. Preference parameters of the fruit fly, *Bactrocera oleae*, in olive tree orchards.

In addition to the above, the olive fly (*B. oleae*) in olive groves can be controlled by smart farming applications and tools, either before the infestation occurs, or as a treatment following infestation. As outlined in this review, a group of such technologies includes the use of deep learning, artificial neural networks, sensors and nanosensors, e-traps, and more. Based on the results, the detection accuracy is reported as being as high as ~97% in the identification and counting of infested olive trees. Additionally, smart spraying machines contribute to minimizing environmental impact by the use of insecticides along with decreasing production costs. However, the use of smart farming technologies cannot stand alone. The agronomic protocol, the applied field applications, and the post-harvest management operations in olive oil production systems may provoke potential infestation or act as a barrier and protect from olive fruit flies' presence.

5. Future Research

In this study, the influence of *B. oleae* on olive oil quality along with the state-of-the-art research achievements in smart farming technologies related to olive production was discussed. For the first stage with a focus on olive oil nutritional value and its correlation with human disease prevention, further research is needed in assessing the nutraceutical activities of EVOOs. On the same track, even though there are several studies on in vivo and in vitro applications of olive oil to determine the bioavailability of olive, more methodological approaches should be employed.

Looking forward to the future, from an agronomic point of view, the basis for overall research in olive crop production should be focused not only on digital transformation of primary in-field and post-harvest processes and operations, but also on conserving high agri-food safety and sustainability. Sustainability includes not only optimization of yields, from a financial point of view, but also the minimization of environmental impact. The use of smart farming and precision agriculture systems could be the means towards this direction, both at the in-field level and at the final product level. New directions in the development of sensors, biosensors, and smart technologies that are user-friendly, eco-friendly, portable, and economical could be of high interest.

Being more focused on the olive fruit fly, the early detection of infested trees would contribute to minimum losses, the development of biosensors and related technologies, database development, and big data algorithms. Additionally, the ecological and biological parameters (temperature, humidity, host fruit, resistance in pest control methods) that play a deterministic role in the growth and distribution of olive fruit fly should be considered for further investigation. At this level, climatic changes and microclimatic variations in parallel with their relationship with the development of insect pests and their natural enemies should be assessed. Overall, from an agronomic point of view, the related technological advances should be directed towards the main natural resources (as pillars) of crop production systems, i.e., soil, water, air, and biodiversity. More specifically, they should be focused on soil property and nutrient conservation, irrigation water quality and savings, ecological pest and disease management, conserving the optimal olive crop cultivars, and overall field management. This is critical for specific countries as olive oil production is among the most significant from a financial point of view, especially in the Mediterranean region.

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