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Recent developments on precision beekeeping: A systematic literature review

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A B S T R A C T

The aim of this systematic review was to point out the current state of precision beekeeping and to draw implications for future studies. Precision beekeeping is defined as an apiary management strategy based on monitoring individual bee colonies to minimize resource consumption and maximize bee productivity. This subject that has met with a growing interest from researchers in recent years because of its environmental implications. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) was selected to conduct this review. The literature search was carried out in the Scopus database for articles published between 2015 and 2023, being a very recent issue. After two rounds screening and examination, 201 studies were considered to be analysed. They were classified based on the internal parameters of the hive, in turn divided by weight, internal temperature, relative humidity, flight activity, sounds and vibrations, gases, and external parameters, in turn divided by wind speed, rainfall and ambient temperature. The study also considered possible undesirable effects of the use of sensors on bees, economic aspects and applications of Geographic Information System technologies in beekeeping. Based on the review and analysis, some conclusions and further directions were put forward.

1. Introduction

Precision Agriculture (PA) methods have been developed in different fields of agriculture, such as animal husbandry, viticulture, horticulture and forestry [1]. In addition, Precision Beekeeping (PB) has been developed in recent years, firstly defined by Zacepins et al. [2] as an apiary management strategy based on monitoring individual bee colonies to minimize resource consumption and maximize bee productivity. PB supports traditional beekeeping, which provides for the manual and periodic control of the apiaries, often located at considerable distances from each other, this entailing a high cost to reach them. Each hive is inspected on average 15 times a year and, meanwhile, the beekeeper has no insight into the condition of the colonies, making timely action impossible to take [3].

PB uses smart hives, equipped with sensors, aimed at detecting the parameters descriptive of the colonies state of health and providing information to the beekeeper via web-based systems that are accessible also by smartphone, in this way the beekeeper can choose to inspect only the hives that require direct supervision. The sensors are connected to a microprocessor powered by a battery and usually linked to a network to remotely send the data collected by the server. The microprocessor collects data at regular intervals before transferring it to a server, the two main types of microprocessors used today are Arduino and Raspberry Pi [4]. The detected data is sent to the cloud for storage, analysis and alarm generation [5]; in some already tested systems the information is displayed by beekeepers on an application that groups data by hive [6].

In recent years, monitoring systems have greatly advanced through the use of wireless sensor networks (WSN). A WSN consists of embedded devices that can acquire data from different sensors, process them and communicate with a computer and a cloud database [7]. These devices are known as nodes or motes and are the core of the Internet of Things (IoT), defined as a network of Internet-enabled objects connected to web services that interact with these objects [8].

Considering the growing interest of the researchers towards PB, the aim of this paper is to examine and summarize the most recent published articles in the field of PB, especially taking into consideration the monitoring of hive internal and external parameters, in order to make

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detailed and reliable forecasts on the evolution of the behaviour of the bee colony, through the application of suitable methodologies and instruments.

2. Materials and methods

In this study, a systematic literature search method was applied, using the identification, screening and eligibility procedures described by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (https://prisma-statement.org/accessed on 2 January 2023) [9]. It describes new reporting guidelines, reflecting advances in methods for identifying, selecting, evaluating, and summarizing studies published in the literature.

2.1. Identification

The research was conducted in January 2023. The Scopus database was used taking into consideration title, abstract and keywords. It was selected as being the most relevant for publications in the biosystems engineering area. The following criteria were adopted: (1) years (2015–2023), (2) subject areas (Agricultural and Biological Sciences; Environmental Science; Computer Science; Veterinary Science and Veterinary Medicine; Engineering; Chemical Engineering), (3) keywords (precision beekeeping, precision apiculture, honey bee monitoring, smart hive, connected hive) and (4) language (English). A total of 72 articles were identified and exported into an Excel spreadsheet for further analyses.

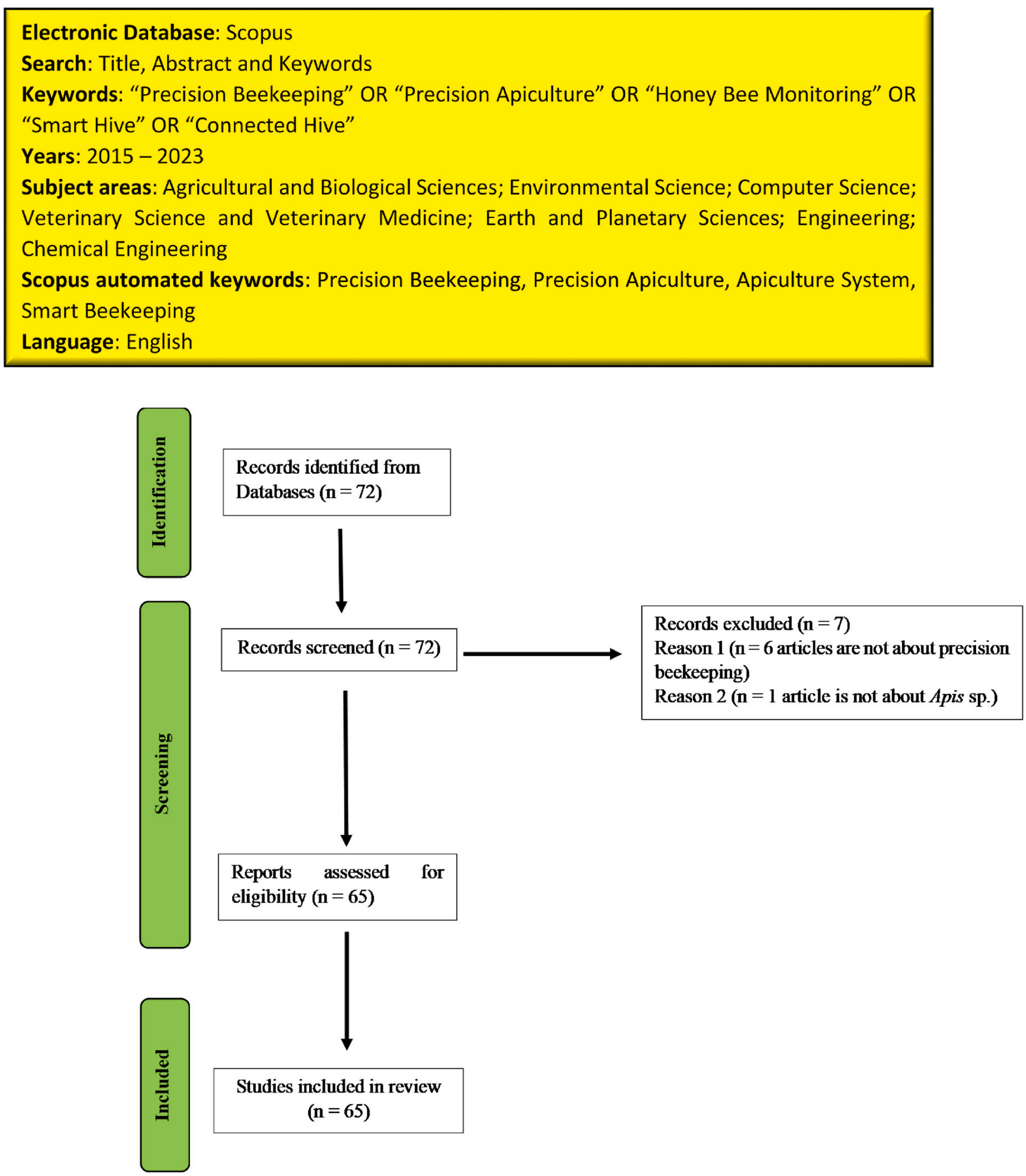

Fig. 1. Flow diagram overview of the consecutive stages applied for the systematic literature review and results at stage 1.

2.2. Screening

In this phase, the 72 identified articles were examined by reading their titles and abstracts. The inclusion criteria considered to perform the screening were:

- Article on precision beekeeping
- Article on smart hive
- Article on honey bee monitoring

All the 72 articles were reviewed at this stage, but only 65 of them met of the inclusion criteria.

2.3. Eligibility

The authors examined all of the 65 selected articles by reading the full texts. The criteria for inclusion in the next stage were:

- The full text of the article is available
- Article is about precision beekeeping
- Article is about smart hives
- Article about honey bee monitoring
- Article is not a book

In this phase, a total of all 65 articles were processed, meeting the above listed criteria. Fig. 1 shows the review methodology flow chart.

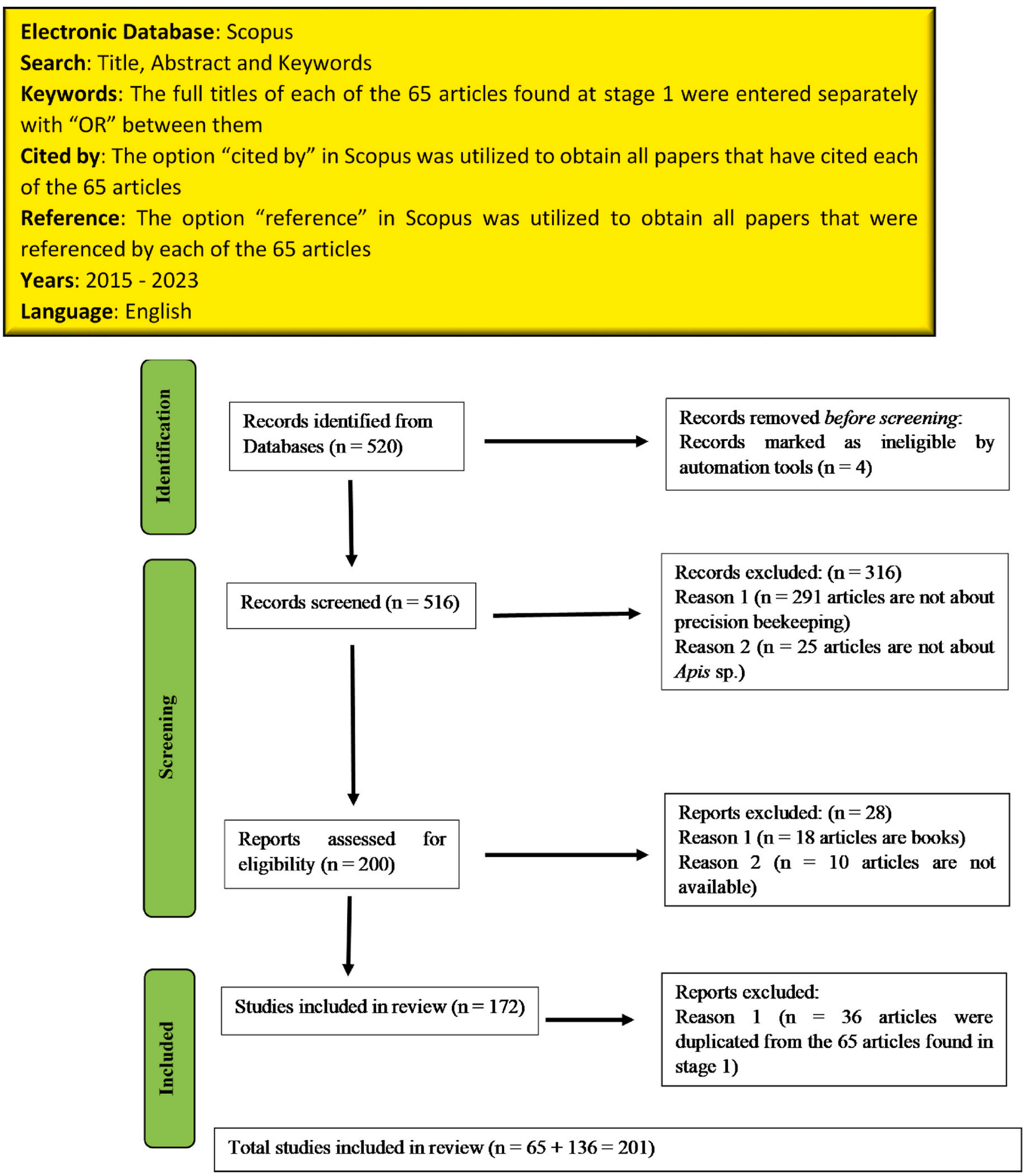

Fig. 2. Flow diagram overview of consecutive stages applied for the systematic literature review and results at stage 2.

2.4. Additional review

To identify additional articles related to precision beekeeping which may be missing from the keyword search, the 65 articles found in Scopus were saved and listed. Then, the automated search options in Scopus electronic database were used to obtain all articles that where either cited or referenced by these 65 articles. In total, 520 articles were identified and exported into an Excel spreadsheet to be analysed. Applying the search criterion language (English) the field narrows down to 516 articles.

The same screening method adopted in section 2.2 was then applied, reducing the 516 articles to 200. The articles were read and only 172 met the criteria reported in section 2.3. However, it turned out that 36 of the 172 articles had already been considered in the first 65. Therefore, these articles were excluded and the remaining 136 were considered. Overall, 201 articles were found and reviewed, i.e. the initial 65 and the additional 136 resulting from the additional review. Fig. 2 shows the flowchart of the methodology used for the additional review.

3. Results

Analyzing the selected papers, internal parameters of the hive are taken into consideration (section 3.1), in turn divided by weight of the hive (section 3.1.1.), internal temperature (section 3.1.2), relative humidity (section 3.1.3), flight activity (section 3.1.4), sounds and vibrations (section 3.1.5), gases (section 3.1.6), and external parameters (section 3.2), in turn divided by wind speed (section 3.2.1), rainfall (section 3.2.2) and ambient temperature (section 3.2.3). Furthermore, this study considered possible undesirable effects of the use of sensors on bees (section 3.3), economic aspects (section 3.4), and applications of Geographic Information System (GIS) technologies in beekeeping (section 3.5).

As regards internal temperature, 98 articles were identified, 69 for relative humidity, 66 for mass in the sense of weight of the hive, 68 for sound, 27 concerning flight activity, specifically entry and exit of the hive (bee inflow/outflow). For the external parameters, that is wind and rain, there were 12 and 14 items respectively. The distribution of the selected papers based on the studied parameters is shown in Fig. 3.

During the examination of the articles, in order to link the above-mentioned parameters to the behaviour of the bee colony, it was considered appropriate to include also some papers concerning the biology of insects, some of them published before the time period examined with reference to PB (2015–2023).

The country of origin of the first author was also considered, with reference to the geographical position of the publication. Most of the publications come from Latvia with 28 articles, followed by USA with 26. Germany has 20 articles, Italy and United Kingdom 11 have publications each. China appears with 10 publications, followed by France, Brazil, and Mexico with 8, 7 and 6 respectively. Canada and Spain have 5 publications, while 4 publications were found for Poland, Turkey, Ethiopia, Bulgaria, New Zealand, followed by India, Africa, Slovenia with 3 articles and finally Serbia, South Korea, Greece, Russia, Bosnia and Herzegovina, Japan, Romania, Belgium, Australia, Denmark, Hungary, Philippines, Vietnam, Sweden, Egypt, Arizona, Ireland, Luxembourg with 1–2 papers (Fig. 4).

On average, 23 papers were published per year between 2015 and 2022. Fig. 5 shows a growing trend starting from 2017, a year with 17 published papers, to reach the maximum of 38 published articles in 2020, while in 2021 and 2022 there were respectively 23 and 16 papers.

3.1. Hive internal parameters

Regardless of their use (e.g. research, beekeeping, awareness raising on various issues, such as environmental ones), the main objective of smart hives is to provide real-time information on the state of health of the colony and the quality of its internal environment. It is therefore

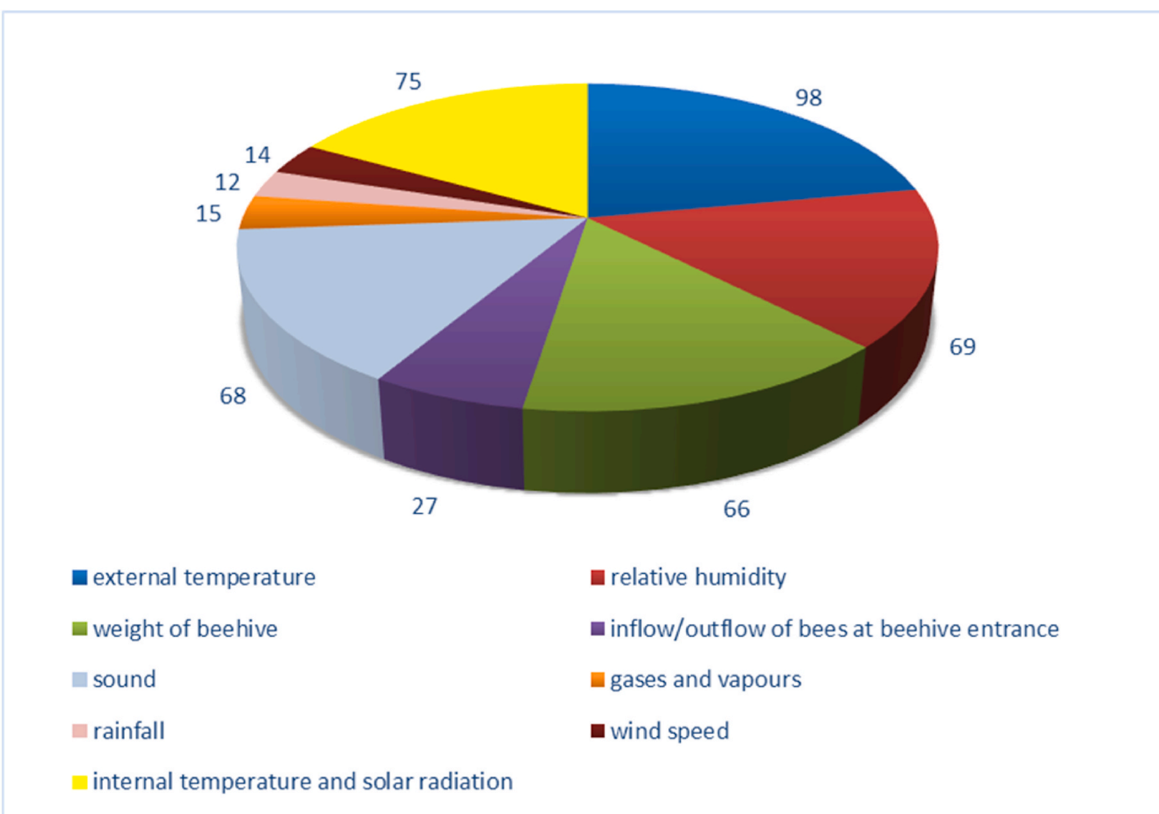

Fig. 3. Distribution of the selected papers based on the studied parameters.

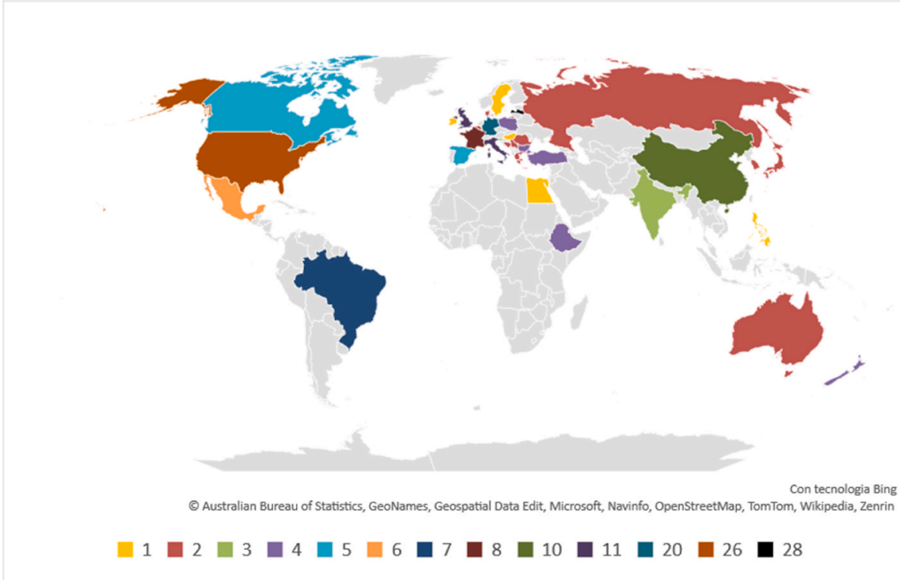

Fig. 4. Geographic distribution of the selected articles in the period 2015–2023.

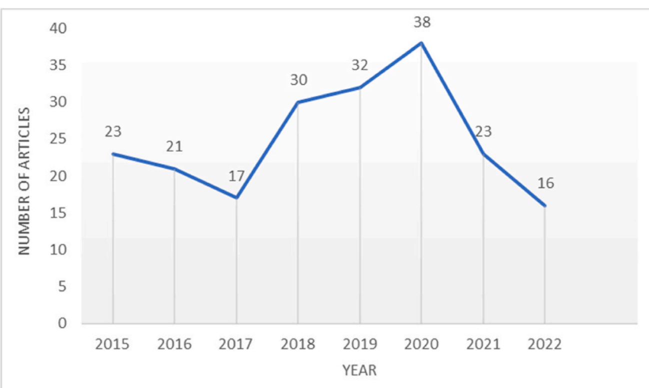

Fig. 5. Annual distribution of the selected articles in the period 2015–2022.

important to control parameters inside the hive such as weight, temperature and relative humidity, sounds and vibrations. These parameters and the main technologies used to monitor them are described in the following sections.

3.1.1. *Weight of the hive*

The weight of a hive provides important information on the size and activity of the colony; its increase suggests a production of honey and an expansion of the population, on the contrary, a decrease may indicate the consumption of honey, typical of the winter season, but at other time periods it may be related to swarming or mortality events (poisoning, diseases, etc.) [10].

An abnormal variation in the weight of the hive may also indicate theft [11]. During the day, there are variations in the weight of the hive that can be considered normal: in the morning, when the bees go out to forage, there is a drop of about 300–500 g, while with the return of the bees laden with pollen and nectar, the weight gradually increases until just before sunset. During the night, this parameter may undergo a decrease due to the consumption of honey by bees [12], a reduction of 200 g per night was recorded by Catania & Vallone [13] for the entire monitoring period. During the cold season the bees rarely go out to forage, consuming the internal stocks of the hive, and consequently the weight of the colony tends to decrease by 30–80 g per day [14]. This result was obtained in China, Tai' an City, Shandong Province, an area with 12.9 °C annual average temperature, 26.4 °C highest monthly average temperature in July, and −2.6 °C lowest monthly average temperature in January.

The scales used in most researches are placed externally at the base of the hive and detect the total weight of the hive. In the low cost platform by Seritan et al. [15], the mass sensor is composed of a single load cell (Fig. 6 a), it has an accuracy of ±100 g and detects up to a maximum of 200 kg, while the system proposed by Ochoa et al. [16] uses four load cells placed at each corner of the base of the hive (Fig. 6 b). On the other hand, the system proposed by Sakanovic & Kevric [17] detect the weight of each individual frame of the hive using twenty sensors, two for each frame. In the model proposed in Ref. [14] by Li et al. the sensor for detecting mass is placed in an internal structure of the hive the frames are placed on, in order to measure only the total weight of the frames.

The weight monitoring system of the hives proposed by Zacepinz et al. [18] uses a single point load cell, this monitoring can help identify the beginning and end of the nectar flow and evaluate the foraging activity of the colony.

When analysing the weight of the hive, some meteorological factors such as precipitation and wind, can influence the data [10]. To overcome the problem of moisture absorbed by the wood of the hive, Zacepins et al. [19] recommend the use of polystyrene hives, alternatively they recommend taking into consideration the mass variations of an empty hive placed under the same environmental conditions.

3.1.2. *Temperature*

Internal hive temperature is the primary indicator of a colony's health. The ability of a colony to thermoregulate is influenced by the subspecies and, within this, by the genetic diversity of the colony [10]. Bees maintain a temperature of 34 ± 1.5 °C near the brood [16]. Temperature variations can occur in correspondence with natural events, such as swarming, or adverse events, such as a weakening of the colony, which is unable to keep the temperature stable. Indeed, by measuring temperature, swarming can be predicted, since temperature inside the hive tends to increase in the immediately preceding period [12]. In the model proposed by Andrijević et al. [5] a push notification is set up and sent, informing about changes in the hive, especially when the internal temperature exceeds 35 °C. On the contrary, in the model proposed by Ochoa et al. [16], when the temperature drops below the threshold of

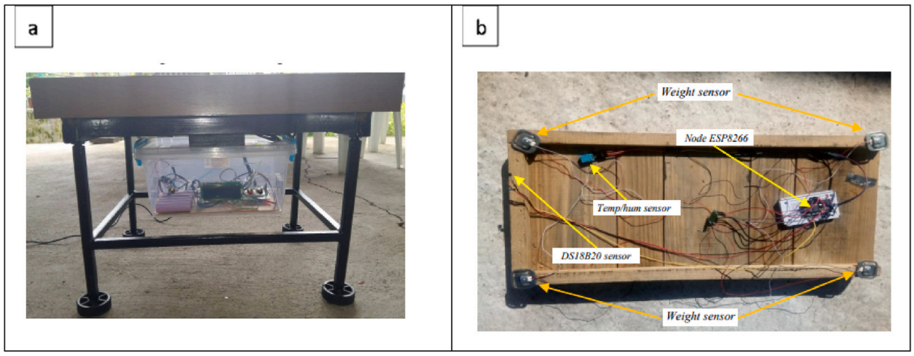

Fig. 6. (a) Implementation of the platform in Ref. [15], (b) Instrumented bottom board of the hive in Ref. [16].

20 °C near the brood, an alarm sends a voice call, an e-mail and an SMS.

When monitoring the internal temperature of the hive it is important to consider the position of the sensors; those placed close to the brood, in the central and warmest part of the hive, are less affected by external conditions, while in the periphery, closer to the walls of the hive, they will be more affected [3]. Individual sensors can be inserted in a small box placed longitudinally in the center of a normal frame [20] or suspended in the center of the hive near the brood [21], or in the center of a frame which is positioned between the body of the hive and the honeycomb [22]. In the model proposed by Zabasta et al. [23] two more sensors are added to the central one between the external frames, while in Ref. [24] the authors use two Humidity Temperature Sensors (DHT22) installed in the center of lateral side and in the center of the back side, directly in the wood panels of the hive. Finally, in Ref. [14] two sensors are arranged on the internal wall near the entrance to the hive. Fig. 7 shows some examples of sensor installation.

On the other hand, in some studies the location of the sensors is not indicated so the reported values are difficult to compare; for example, in Ref. [25] the authors indicate a stable brood temperature between 28 °C and 32 °C, lower than in other studies. The machine learning model based on the long-term memory algorithm (LSTM) has also been used to detect when a bee colony is about to lose control of its temperature [26].

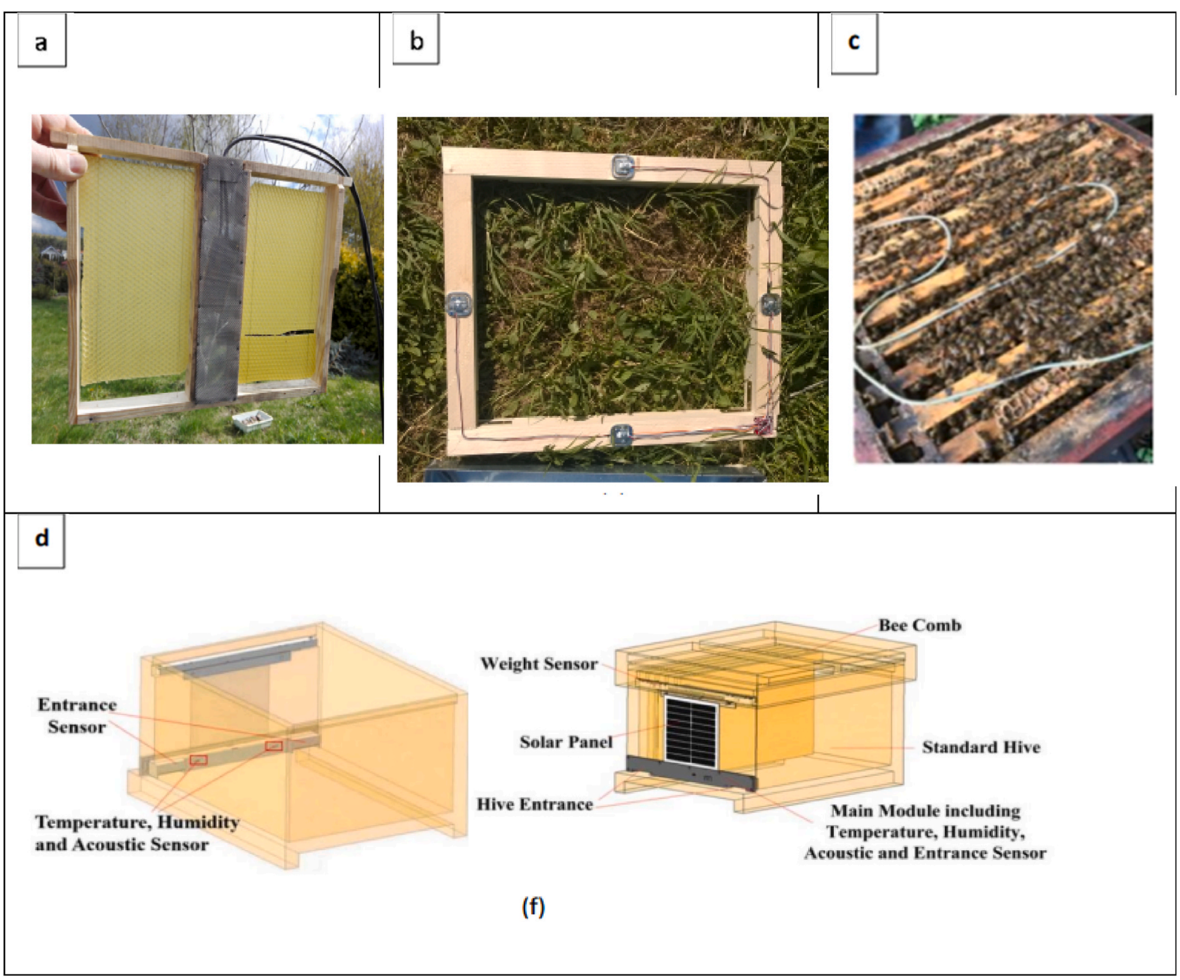

Fig. 7. (a) Sensor placed in the center of a normal frame in Ref. [20], (b) frame with four load cells applied in Ref. [24], (c) sensor placed in the center of the hive in three different points [23], (d) 3D representation of an intelligent hive with relative positioning of the sensors in Ref. [14].

The predictive model analyzes internal temperature and relative humidity, external temperature, weight and sound.

3.1.3. Relative humidity

Relative Humidity (RH) inside the hive can be considered as an indicator of health and optimal development of the bee colonies, which the bees are able to maintain at stable values of around 70% [13].

For egg hatching, the optimal RH range goes from 90 to 95%, while values lower than 50% hinder this phase [27]. RH can also influence the development of parasites and pathogens; specifically, values between 55% and 70% favor the reproduction of varroa (*Varroa destructor*), while higher values reduce its reproduction [28].

A good correlation between hive internal parameters and weather conditions is important for production purposes; RH inside the hive appears to respond to the external weather conditions. An increase in RH (>95% RH) was detected on days with high levels of precipitation [29].

Similarly to temperature, RH is a useful parameter for predicting swarming, as it has been observed that this event is preceded by a decrease in RH due probably to ventilations, consisting in a rapid flitting of bee wings [30]. In Ref. [24], the DHT22 sensor is also used for RH measurement, having a 0–100% RH measurement range with 2% accuracy and 0.1% resolution. The authors noticed that bees were able to keep the internal RH quite stable during the year of observation.

3.1.4. Flight activity

Bee flight activity is defined as the number of bees entering and/or leaving the hive in a given time interval. In spring, more than 100,000 flights departing and arriving in a day can be recorded in a well-developed hive [31]. The number of bees leaving the hive to forage is positively correlated to the increase in environmental temperature and solar radiation and negatively to environmental relative humidity [32]. Flight activity provides information on colony populations and foraging activity; it is also an important parameter to monitor when evaluating the impact of pesticides on bees [33].

Flight activity has been negatively correlated to the presence of predators, especially bee-eaters (*Merops apiaster*) [34] and hornet (*Vespa* spp.).

Standard methods for estimating bee flight activity involves the use of two observers both having a hand-held counting device and one keeping time [35]. The use of human observation, while likely accurate, limits the amount of time that the hive can be observed.

In recent years, automated counting methods have been adopted to reduce human error and time [10]. Flight activity can be monitored through images continuously acquired at the hive entrance. In Ref. [36] the camera is attached to the front wall of the hive, about 30 cm above the entrance, and pointing downwards; moreover, a white table is positioned in front of the entrance to better distinguish the bees (Fig. 8). In Ref. [32] the webcam is placed in front of the hive entrance inside an observation box with a red LED lighting panel. In this study the bees are detected using the background subtraction method, using the Kalman filter to predict the future position of the bees and applying a suitable algorithm to assign detection to existing targets which allows counting with a precision of 94%. Object tracking algorithms were applied to count the number of bees that enter and leave the hive based on a pre-set boundary surrounding the hive entrance in Ref. [37]. They obtained an over count of departures by 18% and arrivals by 44%. The Long Short-Term Memory (LSTM) recurrent neural network model achieved good results in bee activity prediction as found in Ref. [5]. The authors obtained an error of 8.9 missed bees per hour for bees outbound and 7.8 missed bees per hour for bees inbound at the hive. However, the surveys were made in autumn and the authors expected to find higher errors per hour for measurements carried out during spring and summer.

As stated by Ref. [38], in the last decade, promising approaches have been made by using enhanced video-based systems to record bee flight activity utilising deep learning and artificial intelligence. Commercially available bee in-and-out activity counting devices are usually installed at the hive entrance and use infrared (IR) radiation to detect bees departing and arriving to the hive [3]. Whereas in Ref. [39], foraging activity monitoring is based on the use of Wireless Sensor Networks (WSN), with an average counting accuracy of 84.92% and 85.95% for in and out, respectively.

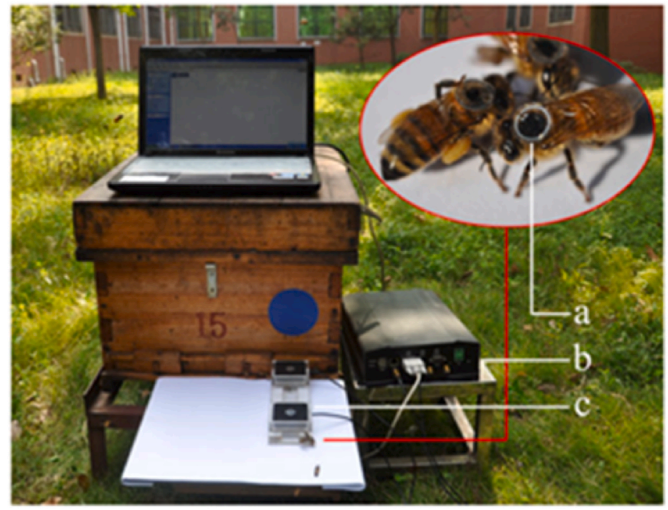

Fig. 8. The beehive and camera setup in Ref. [36].

The BeeCheck counting device validated in Ref. [33], distinguishes incoming and outgoing bees, consists of 24 entrance tubes made of polyethylene, with seven capacitive sensors installed in each tube; the passage of the bees causes a change in electrical capacity which acts as a signal. The authors proved capacitive sensors to be superior, since they measure more precisely and were less susceptible to dirt and propolisation from bees compared to optical sensors, such as infrared, where frequent failure is reported as signals are jammed by contaminants. However, bee counter devices have some drawbacks; when the flight activity is high, counting errors may occur due to bees trying to enter the hive at the same time [40].

The use of a camera does not interfere in any way with the normal behavior of the bees and allows to collect other data: predation by hornets, detection of parasites such as varroa [41] and loads of corbicular pollen [42,43].

3.1.5. Sounds and vibrations

Bees communicate within the colony through vibrations and sound signals [44]. Continuous sound monitoring can provide important information on bee health. It can be used to detect the presence of the queen [20], predict swarming [45] or pillaging [46], colony strength [47], the presence of parasites and predators [44].

Queen bees emit sounds of different frequencies: before flickering, they produce a series of short pulses with a frequency of about 350 Hz; as soon as they emerge, they emit sounds with a frequency of 400 Hz during the first day and about 500 Hz from two to four days after birth. They start with around 17 short pulses, and the number decreases to around 7 after several days [48].

Before swarming, bees make a special sound that spreads at a distance of 5–6 m from the hive at a frequency of 1500 Hz [49]. When they feel threatened by predators such as hornets (*Vespa* spp.) and bee-eaters (*M. apiaster*) they emit a hissing sound with a frequency ranging from 300 to 3600 Hz [50].

The analysis and classification of the vibroacoustic signal involves the acquisition of sound using microphones or accelerometers; the recorded signal is usually filtered to remove background noise and unwanted frequencies. Finally, the data are classified for subsequent analyses [51]. Different types of microphones placed inside or outside the hive can be used. Their position varies based on different scientific approaches. Electret microphones are used in Ref. [25], clip microphones in Ref. [52] and MEMS (Micro Electro-Mechanical Systems) microphones in Ref. [24], in Ref. [53] accelerometers were used. In Ref. [54] the position of the microphones was chosen to monitor different parts of the colony, placing one near the hive entrance and the other near the brood.

Vibrations and sounds data are extremely difficult to explain, because the meaning of the sound or its variations can only be interpreted if associated with the simultaneous observation of what is happening in the colony; moreover, the different sensitivity of the microphones makes it difficult to compare the data [47].

Papers related in hive sound analysis generally use data preprocessing with systems that are able to recognize bee sounds and discriminate them from other captured sounds. In Ref. [30], the authors applied a Butterworth filter with cut-off frequencies 100 Hz and 2000 Hz to remove all sound signals disturbing the bee frequencies. Kulyukin et al. [52], compared several deep learning (DL) and standard machine learning (ML) methods in classifying audio samples from microphones deployed approximately 10 cm above Langstroth beehives' landing pads. Audio classification algorithms they designed were able to discriminate bee buzzing, cricket chirping, and ambient noise.

Most of the bee-unrelated sounds are short-lived compared to beehive sounds. In Ref. [55] the authors used a method based on a Fast Fourier Transform (FFT) and Self-Organising Map (SOM) to investigate how the sounds produced by honeybees in hives changed after their queen had been removed. The model achieved high accuracy of 92% discriminating between queen-absent and queen-present hives. In Ref. [56] the author achieved the best performance in swarming prediction with the system based on Hidden Markov Model (HMM) acoustic models and Mel-Frequency Cepstral Coefficients (MFCC) features, although Convolutional Neural Networks (CNN) system provided high accuracy when large amounts of acoustic training material are available, but demanding higher computational power.

3.1.6. Gases

Few studies describe gas monitoring in beehives. Carbon dioxide (CO_2) measurement plays an important role in analyzing hive behavior. It is related to bee metabolism, as a variation in its respiratory emission is associated with the metabolic heating of a bee in its normal activity. Furthermore, when CO_2 inside the hive reaches levels higher than the atmospheric value, the bees begin to ventilate to control and keep it at an acceptable level, i.e. between 0.1% and 4.3% [57,58]. This parameter is also related to the hive internal relative humidity and temperature and the amount of sound generated by bees, which correlates with respiration and gas exchange events [24]. In Ref. [29] the authors monitored the presence of CO_2 inside the hive; they also evaluated the presence of polluting gases such as: nitrogen dioxide (NO_2), ethanol (CH_3CH_2OH), ammonia (NH_3), carbon monoxide (CO) and methane (CH_4). The authors confirmed that low CO_2 levels could indicate the loss of bees due to disease, poisoning, attack by predatory animals or family queenless, thus requiring immediate action by the beekeeper.

The presence of some gases can be used as an indicator of honey bee disease. According to Ref. [59] valeric acid, caprylic acid and isocaprylic acid may be indicator of the presence of Paenibacillus larvae, the causative agent of American foulbrood (AFB). They developed a device equipped with semiconductor gas sensors, with a sampling probe placed in the middle of the beehive (Fig. 9). In Ref. [60] the authors identified 40 compounds as volatile biomarkers for AFB infections, particularly 2, 5-Dimethylpyrazine showed the greatest sensitivity and accuracy for diagnosing AFB, it was exclusively detected in AFB-disease larvae and was detectable in beehives with $<$10 AFB-symptomatic larvae. The authors state that these biomarkers are prime candidates to be targeted by a portable sensor device for rapid and non-invasive diagnosis of AFB in beehives.

Fig. 9. Gas sampling probe positioned in the middle of the beehive [59].

3.2. Hive external parameters

Subspecies of *A. mellifera* are found in a wide range of climates, from hot and dry to tropical and temperate [27]. Hives are evidently affected by the external weather conditions [61]. Ngo et al. [32] show the correlation between environmental data and colony activity (in terms of pollen collection). The results show that temperature, relative humidity, wind speed, rainfall and light intensity influence pollen collection. For example, heavy rains or a light breeze negatively affect the quantity of collected pollen. Climate also indirectly influences pollinator activity by altering the amount and sugar concentration of nectar in flowers [62].

The hive can only be inspected during the day with no rain and the ambient temperature is in the range 15 °C–38 °C [63]. Monitoring climatic conditions is therefore essential to keep bees healthy.

3.2.1. Wind speed

The flight of insects is energetically expensive, and this cost is also influenced by the presence and intensity of wind; indeed, bees have a lower foraging rate as wind speed increases. Furthermore, in case of long windy periods, bees refrain from going out to forage and honey production stops. In Ref. [64] the authors found that a wind speed of just 2.75 m/s results in a 37% decrease in flower visits.

Wind is measured and related to honey production in Ref. [13]. Decreases in honey production were observed at wind peaks of over 4 m/s. The reduction in honey was attributable to the lack of exit of the bees and their consumption of honey. Therefore, the choice of the site must provide for poor wind conditions, as it represents a strong environmental factor limiting honey production.

3.2.2. Rainfall

In [39] the authors state that bees are not active in rainy days when the ambient relative humidity is higher than 80%.

Honey bees can predict future rainfall by increasing foraging activity. He et al. [65], with Radio Frequency Identification (RFID) monitoring, demonstrated that foragers work more intensely in the days preceding rains than in those following a sunny day.

3.2.3. Ambient temperature

Honey bees use all their strength to heat the hive; being heterothermic insects, their body temperature is prone to significant changes. However, bees possess an extraordinary power of thermoregulation, this function of their body is able to stabilize the body's heat according to the environment and the different needs and this allows them to maintain colonies throughout the year [66].

Foraging activity takes place in a wide range of temperatures, from 10 to 40 °C [27]. Ambient temperature interferes with the life of the colonies; when temperature is too high or too low compared to the temperature of 35 °C which guarantees regular breeding of the brood, bees have to invest significant energy resources to cool or heat the hive, respectively. In Ref. [67] costs of thermoregulation, however, were rather independent of ambient temperature when in the range 13–30 °C.

As the resources needed to fuel thermoregulation are strongly limited, honey bee colonies should refrain from brood rearing under cold environmental conditions. When ambient temperature is low, bees go into cold stress, worker bees tend to remain relatively inactive and cluster densely in the so-called winter cluster to reduce heat loss from the colony, while individual workers actively produce heat by flight muscle shivering to keep the cluster core temperature above ambient temperature [68].

3.3. Possible undesirable effects of sensor use on bees

A major concern of the effects of Radio Frequency Electromagnetic Radiation (RF-EMR) on animals is tissue heating due to the specific absorption rate of the propagated wave. Short-term exposure to Extremely Low Frequency-ElectroMagnetic Fields (ELF-EMF) at 50 Hz, comparable to those found around power lines, reduced learning performance and increased bee aggression in Ref. [69].

Wireless sensor networks used in precision farming systems need not raise pollinator health concerns. A study carried out by Henry et al. [70] indicate that 2.4 GHz signal strength levels over 72-h periods did not affect temperature, humidity, and acoustic measurements compared to hives that did not receive exposure to long term RF-EMR.

The use of sensor protection is suggested to prevent them from being propolized, as in Ref. [22] where coating with mesh <0.2 mm is recommended.

3.4. Economic aspects

Beekeepers are not usually willing to invest in digital solutions; therefore, the cost of smart hives becomes a crucial aspect, and should be reduced to the minimum possible [18].

In [15] the authors realized a low-cost platform to monitor the health of bees and the quantity of honey produced, already described in section 3.1.1., the cost of which is approximately € 300. The data collection system of weight, temperature and relative humidity can range from 17 to 35 USD per hive in Ref. [16]. The cost calculated for the prototype is € 192 in Ref. [18] and € 170 in Ref. [22] excluding the Global System for Mobile Communications (GSM).

Although there are sufficient hardware and technical resources for the practical application of precision beekeeping, the market uptake of sensor-based decision support systems is still very low. The main reason is the uncertainty about the economic benefit that using these systems could provide [71]. To reduce costs, only a part of the hives per apiary could therefore be equipped with sensors, assuming that different colonies in the same environment are in similar conditions [4].

3.5. Geographic Information System (GIS) applications in apiculture

Normally beekeepers choose to locate apiaries based on their experience and sometimes the location may not be optimal for bee colonies. An apiary should normally consist of 30–80 colonies for practical purposes, the most important question determining the optimal number is the amount of forage available in a given area [72]. In some countries, such as Indonesia [73], nomadism is very common, and beekeepers are forced to change the location of the apiary very often to provide food sources for their colonies.

In [74] the authors developed a model using the Python programming language, with the help of aerial and satellite images of agricultural fields detected using Google Maps with the aim of providing support to beekeepers in the search and selection of suitable apiary locations. In the first step of the process, the fields in the aerial image of the region were annotated with a polygons and an estimated value of resources on that field was given, obtaining a semantically annotated map. In the second step, the method calculated a value function assigning each location on the map an estimated amount of resources to be collected at that location (Fig. 10).

This model was then improved in Ref. [72] in terms of details by proposing a system capable of identifying the ideal number of bee colonies necessary for optimal foraging. The new model considered multiple factors as the number of fields in the area, field productivity, possible level of contamination, presence of infrastructures. For example, the authors coded the fields by colour according to their pesticide applications, ranging from bright red to bright green (Fig. 11). The region with the value equal to zero (field without pesticides) have its polygon coloured bright green.

The geographical characterization of an area can be considered a useful tool for honey production. Using GIS, allowing the acquisition, recording, analysis, display and return of information deriving from geo-referenced geographical data, thematic maps can be created to describe that area. In Ref. [75] the authors also used GIS to identify the best locations for new apiaries within a given area, thanks to a set of specific data: availability of flowering plants, land slope, distance from water resources and roads, the distance between apiaries, as well as climatic factors such as temperature, relative humidity and rainfall.

Furthermore, GIS has been used to predict the sites invaded by parasites and to trace the movements of invasive species within new environments in order to allow for the identification of the most effective interventions against parasites [76].

In [77] an interactive map was designed, using Google Maps, as a decision support tool in solving spatial problems associated with the American Foulbrood disease. By selecting a position on the map, the beekeeper has the possibility of identifying potential risks of infection and consequently being able to decide on a new position for the hive (Fig. 12).

GIS can be used alone or in combination with other technologies, as well as Remote Sensing (RS), which acquires information from satellite or aerial images of the site, then included into the GIS analysis to provide more information on the study area [78].

Vegetation land cover variations can be studied using GIS and RS to understand the impacts on honey production [79].

Maps from such systems are an effective aid to beekeepers in selecting the most appropriate locations for their apiary. In Al-Baha

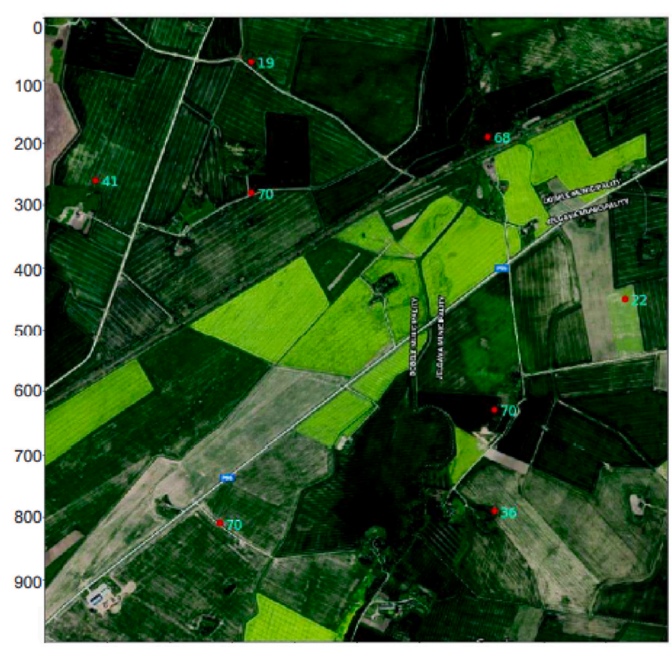

Fig. 10. Results of the model in Ref. [73] to determine the optimal apiary locations.

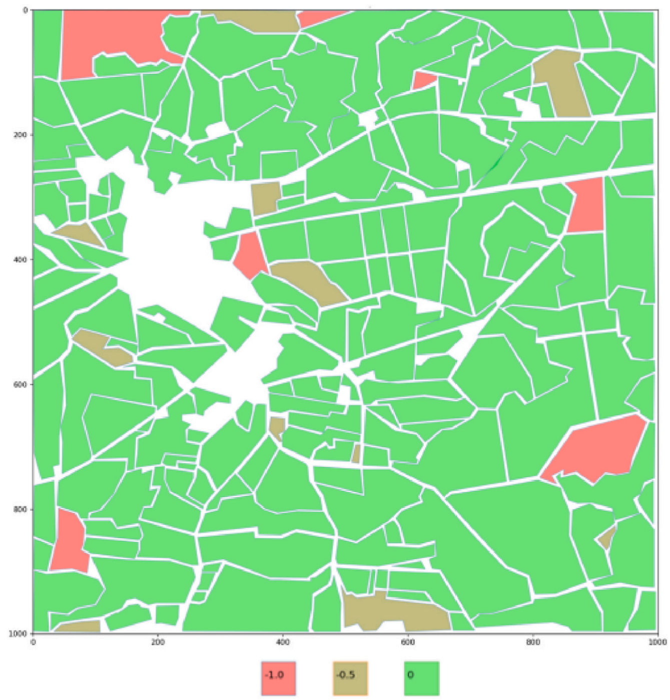

Fig. 11. Encoding of the potential volume of pesticides in the fields in Ref. [72].

region of Saudi Arabia, Adgaba et al. [80] mapped the spatio-temporal distribution of bee forage using GIS. Specifically, the data was stored and processed using the Trimble GPS supported with ArcGIS10 software program. Subsequently, the data was used to estimate frequency, density, abundance and diversity of the species present and above all their apicultural value. Furthermore, Remotely Sensed Satellite Image was obtained and processed using the Hopfield Artificial Neural Network technique. The results clearly showed the distribution of flowering plants and their area in the study site, helping to estimate area coverage of the different species, the honey production potential and the expected flowering period. Migratory beekeepers can be helped in evaluating the available resources in different times and places.

In [81] a model to map monthly nectar and pollen production via land cover maps was developed to better manage floral resources for bees. It can contribute to management decisions such as the location of the hives depending on floral resources and where nectar limited areas may be found. It can also contribute to planning areas for bee protection.

4. Discussion

Precision beekeeping was born in response to the need of optimizing beekeeping management with sensors and specific programs, with the aim of helping beekeepers understand what is happening inside the hives without necessarily making inspections. Smart hives remotely provide real-time information about the hives, thereby minimizing management costs and at the same time minimizing stress in the colony [71].

Weight monitoring provides one of the most important data for beekeepers about the colonies, as it is related to significant activities such as the start of nectar collection and the consumption of food reserves by the colonies which can indicate the need for additional power supply. Continuous monitoring of the weight of at least one reference colony at the apiary, can help to identify the beginning and end of nectariferous flow and evaluate the foraging activity of the colony [18].

Monitoring the internal temperature of the hives gives indications on the health state of the colonies, which in optimal conditions are able to keep constant relative humidity and temperature. If the temperature inside the hive is correlated to the ambient temperature and the day/night temperature range, it means that the hive is unable to do thermoregulation and requires timely intervention.

Monitoring the external environmental parameters is also essential to correctly understand the state of bee colonies [18].

Some researchers [47,82,83] integrated the data collected by the sensors placed inside the hive with meteorological data and weekly inspections, obtaining a high precision model (Healthy Colony Checklist, HCC). The standardized HCC inspection form indicates the size of the brood, the quantity of adult bees, the presence of the queen, the abundance of food, the absence of stress and adequate space. This is an original approach that allows to better interpret the data collected by the sensors and to train the forecasting algorithms [82].

Another source of information of great interest is represented by the actions that beekeepers perform on the hives, such as feeding, harvesting, applying treatments against diseases, and their effects on the colony [71]. The latest precision beekeeping systems provide the same information in digital format that beekeepers would have recorded during a traditional visual inspection, allowing to reduce the number of seasonal visits to the apiary.

In [3] the main commercial solutions for precision beekeeping are analysed. The Israeli company Beewise created container-type hives with 24 colonies inside, equipped with a system that can get every single frame and take a picture of it. The Beehold system, on the other hand, uses sensors placed inside each frame, capable of processing a digital image and determining the content of each single cell.

There are few studies on the prediction of the future conditions of the hives using statistical methods. In Ref. [25] the authors used a Long-Term Memory Algorithm (LSTM) to anticipate temperature drops in hives, while in Ref. [71] the authors use the time-varying Vector

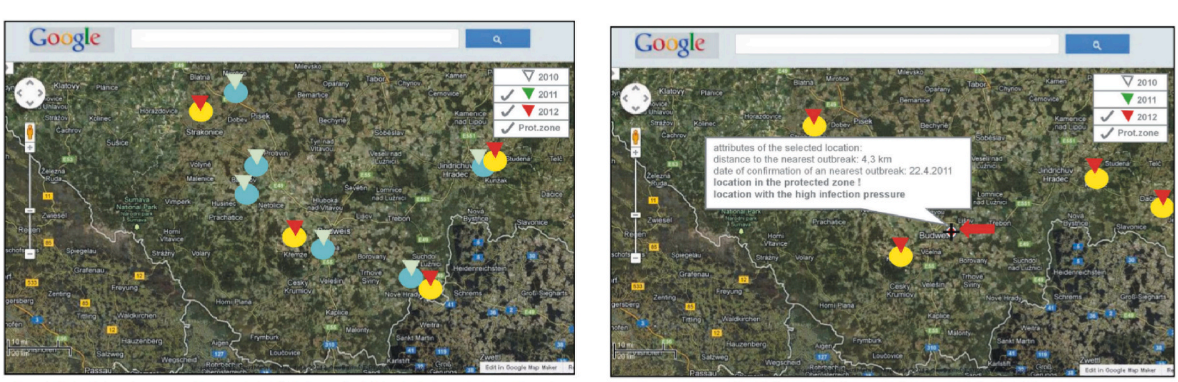

Fig. 12. Interactive map designed by Ref. [77] and representation of the infection pressure from the environment.

Autoregressive Models (tvVAR) to make 1-, 3-, and 7-day forecasts of internal hive variables (temperature, relative humidity, and mass). In Ref. [5] a prediction model capable of estimating the volume of bee outflows and inflows per hour, which simulates the dependence between environmental conditions and bee activity was developed.

5. Conclusions

The numerous papers published in the period 2015–2023 taken into consideration in this study demonstrate that the future of beekeeping is digital; it is therefore necessary to implement the various monitoring systems for the remote and optimized management of bee colonies. These systems may help to accurately predict the hives' internal variables, thus reducing the beekeeper's response time to events related with the internal conditions with positive economic consequences.

The health status of the hives can be monitored through the use of sensors to detect temperature, relative humidity, sounds, images, weight, etc. Each parameter alone can provide useful indication, however, several parameters simultaneously detected allow to have a complete view of what is happening in the hive, as evidenced by the studies in which complex forecasting models are built.

Finally, some recommendations for future studies emerge from this literature review.

Marchal et al. [84] underlined that new sensors are needed to study the multifactorial impact of environmental stressors on bee colony health, such as a predator counter. Indeed, predators such as hornets (*Vespa* spp.) have a significant impact on honeybee populations in Europe and eastern Asia, but there is a lack of quantitative data on the relationship between predation and parameters characterizing colonies. Correlating hornet predation pressure with bee colony health metrics may provide important answers for developing control strategies for such aggressors.

Remote sensing and the application of sensors will have to be used in synergy for better territorial planning of the beekeeping monitoring and surveillance activity, useful for defining the traceability of honey production and protecting its quality.

The use of precision beekeeping will make it possible to counteract the negative impact of climate change on the life of bees. Furthermore, the introduction of artificial intelligence with specific algorithms will make it possible to reduce the use of pesticides which represents one of the threats to the survival of the bee colonies.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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