**Approaches, challenges, and recent advances in automated bee
counting devices – a review**

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18 **ABSTRACT**

19 For nearly 100 years, electronic bee counters have been developed using various
20 technologies to track the foraging activity of mostly honey bee colonies. These counters
21 should enable remote monitoring of the hives without disturbing natural flight behavior
22 while generating precise scientific data. Today, however, there are not many counters on
23 the market, that are able to fulfill this task. One main challenge is the lack of standardized
24 methods to validate a counter's precision, but validation is crucial to categorize and judge
25 the data produced by the counter, especially for scientific purposes. Another challenge is
26 the interpretation of flight data to measure the effects of environmental or anthropogenic
27 sources. Nevertheless, recent developments in the field are promising. This review
28 describes the historic development of automated bee flight measurement and critically
29 compares validation methods to encourage their improvement. Lastly, to increase the
30 comparability of future analyses with bee counters, current advances in data interpretation
31 are also presented.

32 **1 INTRODUCTION**

33 In 1925 the world's first electronic bee counter was described by Lundie (1925). Since
34 then, many devices have been developed, employing state-of-the-art technology from the
35 time they were assembled. The technology used in the very first models was clearly
36 dominated by a combination of mechanical parts and electrical circuits. As technology
37 advances, different sensor types were used to improve the seemingly simple process of
38 counting incoming and outgoing bees from a hive. Even though there is a variety of
39 devices, measuring technology can be narrowed down to five major technological fields.
40 Recently, a trend can be seen regarding the utilization of certain technologies. Optical
41 sensors were dominating the field for more than 40 years. However, within the last
42 decade, the number of video-based counters are rapidly increasing (Fig. 1).

Published work of bee counters

within the past 100 years

43

44 *Figure 1: Published scientific articles that were included in this review describing or*
 45 *using bee counters, categorized by their source technology and plotted against to their*
 46 *publication date. Optical sensors were dominating the field for more than 40 years.*
 47 *However, within the last decade, a rapid increase in video-based counters can be seen.*

48 I will show that every new generation of devices came with new challenges and
 49 limitations. Some remain from day one, some have recently emerged from new insights.
 50 Currently, no commercial counter is available that would suffice scientific needs in terms
 51 of precision and reliability to be used in a field-scale experiment or long-term monitoring
 52 of honey bee colonies.

53 One reason for this is the lack of standardized methods for determining the precision of a
 54 bee counter. However, such a method is essential for the comparability of the counts and,
 55 more importantly, for the correct interpretation of the overall data. So far, 62% of the
 56 scientific articles included in this work do neither provide the precision of their counter

nor a validation method. From the articles that state the precision, 17% do not provide the method used to validate the device. It should be noted, though, that most articles without reference to validation were published before 2000. Nevertheless, lack of validation and corresponding methods remains a major gap that needs to be addressed in the future development of such counters to make them i) comparable and ii) to provide a solid baseline at which data interpretation can be justified. Correct data interpretation is key for the usage of such counters for bee-related ecological, biological, or ecotoxicological questions. For example, currently, there is the hope that loss of forager bees due to pesticide applications could be a useful endpoint of regulatory risk assessment, but this would require that the uncertainty of the forager counts is as low as possible to precisely indicate the background mortality. It is therefore critical to connect hard- and software engineering with beekeeping and bee biology to form the right baseline for the creation of precise counters.

The current development of bee counters can be seen as a process that still is affected by, and can learn from, past experiences. This review aims to present major steps during the historical development and highlights the main technologies on which the different counters are based including their strengths and weaknesses. Furthermore, current methods for counter validation are critically compared to give new momentum for improvement. Lastly, this work compiles indices that focus on simple data interpretation from any given bee counter that measures incoming and outgoing bee traffic and discusses their meaningfulness.

2 COUNTER TECHNOLOGIES

2.1 Mechano-electrical

Historically, the first electronic bee counter described in the literature dates back almost 100 years to the work of Lundie who started his experiments in 1922. He utilized small portals where bees had to pass through a tunnel on which's end a balance arm was attached. The balance was adjusted to let the bodyweight of the bee triggering the arm resulting in an electrical contact forwarding the impulse to a counter (Fig. 2). In total, 30 of these portals were combined in one hive unit – 15 for the incoming and 15 for the outgoing traffic of forager bees arranged about each other. Each portal was connected to

a telephone message register (counter) separately, reading the total impulses in an hourly interval (Lundie 1925).

Adapting the principle of this apparatus, Fabergé introduced his device claiming to have overcome some of Lundie's issues. He at least had implemented all impulses from one set of portals feeding into only one counter, yielding a graph of exits and a graph of entrances to be printed simultaneously on the same sheet of paper (Fabergé 1943).

Figure 2: A single portal for incoming and outgoing bees from Lundie's first electro-mechanical bee counter (Lundie 1925).

Lundie (1925) considered 12 factors introducing errors in the count in his work. The majority of these factors were caused due to the complexity of the mechanics and the resulting high maintenance required. Freeing the parts from bee's debris and fixing mechanical issues required an almost daily cleaning interval of the counter.

Even though Fabergé (1943) improved his version in terms of recording, no other electro-mechanical counters were described besides these two. Lundie's apparatus functioned for a whole season and gave many valuable data, as he also recorded the hive weight and

environmental factors such as temperature and daily sunshine hours. Both counters were furthermore the only affordable way to establish an electronic counter at all, as the photoelectronic technique was very pricey at that time (Brittain 1935).

The very latest approach to implement a mechano-electrical design was published by Liu et al. (1990) in a preliminary test. They considered microswitches as counting units to generate electric impulses whenever a bee walked over the trigger, i.e. when the bodyweight would push it down. They decided, however, to reject this idea because this technique could injure or handicap the bee by passing through.

Worth mentioning, even though presenting only a mechanical but not mechano-electrical device is the counter from Chauvin (1976). He constructed a movable cylinder through which the bees had to pass when leaving the hive. The cylinder was connected to a recording pen which registered the traffic on a paper roll. Parts of the device were treated with a repellent to guide bee traffic as favored by the author. It was stated, that a continuous operation for four months was possible. Even though practically interesting this design offered a simple setup, technically saving data on paper in a field trial does not provide enough safety for data loss and obviously, also the mechanical approach has not been established in future devices.

2.2 Sensor-based

After Lundie introduced a mechano-electrical counter, the subsequent generations of devices focused on sensor technology fueled by the invention and availability of cheap photocell and later LED (light-emitting diode) and transistor technology. For over 20 years throughout the seventies, eighties, and nineties, predominantly photocells were used (Fig. 1). When imaging technology became available in the last two decades, the focus turned from LED advanced optical sensors to video-based systems, most recently enhanced by machine learning algorithms.

2.2.1 Optical sensors

2.2.1.1 Photoelectric

In optoelectronics, a light barrier is a system that detects the interruption of a light beam and displays it as an electrical signal. In this way, automatic devices can detect moving objects without contact. For example, obstacles in the case of automatically closing doors

can be detected or intruders through alarm systems. Light barriers consist of a light beam source (the transmitter or emitter) and a sensor (the receiver) for this radiation (ELOVIS 2021).

The first device with this technique was introduced by Brittain in 1935. His and other early attempts used a simple photocell or light-dependent resistor (LDR) (Kerfoot 1966, Spangler 1969, Erickson 1975). Restricted through pricey components (up to 100 USD at the time) the design of Brittain implemented only one gate that counts, assuming to be a representative sample of the whole bee traffic. Other solutions implemented only small colonies on a single frame or a few more, not providing the measure of a full colony (Erickson 1975). This of course could only be seen as a compromise until a solution for complete flight traffic was available.

These designs had also in common that different, rather unreliable, and/or unfavorable light sources were used as a transmitter. Even daylight was used as a light source, which has the huge disadvantage of being inconsistent and massively dependent on the environment. A continuous function of the device can therefore not be maintained (Kerfoot 1966, Spangler 1969). Using a simple light bulb as a light source provides more consistency but introduces two major biases: i) the heat generated by the lamp may obstruct the bee's movement and behavior as well as the ii) emitted visible light may act as obstruction likewise or in combination with the heat, especially at dawn or night. Not to mention the durability of such analog components.

Even though some experimenters suggested addressing the light source issues by using red light (Erickson 1975), limitations due to the use of only one photocell per counting corridor bared further disadvantages. Devices needed a separator that split up incoming and outgoing bees to count them accordingly, especially when there was a lot of traffic that came with the honey flow and stronger colonies. Spangler (1969) tried to guide the bee traffic with a specially designed "maze", separating incoming from outgoing bees (Fig. 3). This study first described a rather complex system on how bees could enter and leave without crossing and being double-counted by walking forth and back or counted as one by two bees walking closely together (Struye et al. 1994).

Figure 3: Top view of the bee counter. *a*, Tube leading from the hive; *b*, tube leading to outside; *c*, outgoing counter tube; *d*, incoming counter tube; *e*, ledge leading to the outgoing tube; *f*, ledge leading to the incoming tube; *g*, light beam hole; *h*, phone jack connecting to photocell from Spangler (1969).

This “maze” was criticized to restrict or slow down normal activity at the hive entrance (Erickson 1975). Another method to improve the separation of incoming and outgoing bees was the implementation of airflow to the system. Erickson (1975) installed separate entrance and exit tubes with counters respectively. In addition, he installed a fan on top of the hive body that resulted in an intake of fresh air at the exit tubes and a low airflow out through the entrance tubes. This technique, however, was not adopted and further enhanced by others.

With the rapid progress in semiconductor fabrication in the sixties, new technology became affordable and Buckley et al. (1978) were the first to use a phototransistor instead of a simple photocell in a full hive setup. This affordable LED technology was widely used in sensor-based bee counters from here on.

2.2.1.2 Infrared

By using LED technology, most of the described disadvantages of the light source disappeared and the first commercially successful bee counter was developed in the nineties by Struye et al. (1991). With LEDs and modern computer technology for data recording, it was possible to use more than one light barrier that bees had to cross while entering or leaving the hive. This made it possible to detect the movement direction of bees and use only one passageway for entries and exits making the beforementioned constructions to separate bee traffic obsolete. Due to their compact size (Fig. 4), it was also much easier to implement more than one passage, which is very important to maintain a certain flow of bees during times of high frequent forager passing (Liu et al. 1990).

Figure 4: Basic setup of an optical sensor in a counting unit utilized in a bee corridor. Usually, two of these sensors are implemented per corridor to track the direction of movement of the bee (after Pešović et al. 2017).

While this advanced technology overcame problems from the past, very soon new difficulties appeared. As most counters so far were tested with hives of low strength, testing full-sized colonies revealed serious new difficulties. At times of high honey flow where several bees enter the corridors one after another in a high frequency, counting

errors were the consequence (Struye et al. 1994). Similar issues appeared from bees changing directions in the corridors or bees aggregating in front of the hive entrance due to high temperatures in the summer or lack of space in the brood chamber (Danka & Beaman 2007, Souza Cunha et al. 2019).

Several authors highlighted the importance to not interfere with the normal behavior of the bees in any way to collect legit and unbiased data (Fabergé 1943, Erickson 1975, Rickli et al. 1989, Struye et al. 1991, Chen et al. 2012). Struye et al. (1991) postulated the following requirements for a “stand-alone continuous monitoring field device”: i) monitoring of all colony sizes, ii) no influence on normal bee behavior, iii) ventilation and orientation should not be compromised, iv) the device should work completely autonomous and under field conditions, v) user friendly and low maintenance construction, vi) the device should be affordable to monitor more than one colony and further vii) have a low energy consumption of the components to allow continuous operation. These requirements still apply today.

Struye et al. (1994) were also the first to clearly state that a key issue in improving counters lies in the identification and elimination of erratic bee movement in the channels. They also implemented user-friendly maintenance automation where their apparatus (named “BeeScan”) brought up an error message when one channel was blocked (by a dead bee, for example) and there was no registration because of a lack of activity. Increasing accuracy was the aim not only of Struye (1999), other authors also suggested improving precision i.e. by adding more than two sensors per passage (Pešović et al. 2017). To date, however, no LED counter is described in the literature that features this suggestion.

Some of the above-described difficulties are still a challenge for modern counters. However, since Struye et al. (1991) postulated their requirements, not much has happened or improved at this stage of sensor technology. Schöne (1996) suggests the average walking speed of a worker bee is between 20 and 120 mm/s, so the bee should break two light barriers in succession within a period between 50 and 300 ms (Pešović et al. 2017). Interruption outside this timeout period is considered as incorrect counting which could fuel an algorithm to correct data appropriately. Further thought to this suggestion was provided recently by Pešović et al. (2017), and could indeed be a benefit for a correction

algorithm that tries to work out so-called borderline cases such as erratic bee movement between sensors or bees getting stuck there somehow (Bermig et al. 2020).

Moreover, in one of the latest developments, infrared optical sensors were integrated into a wireless sensor network (WSN). The WSN provides automatic and remote data tracking that collects input from the connected sensors in real-time to a gateway. This gateway manages data storage and availability to its users, making it possible to access and inspect the whole system from around the globe (Jiang et al. 2016). Such a network of course is not only limited to sensor-based counters but is open for any kind of device providing relevant input.

Finally, using infrared light spectrum brings the advantage of being invisible to the bee's eye, which lowers any potential influence on natural behavior. Using a non-contact over a contact method in sensor technology excludes the possibility to harm bees when triggering the sensor.

Still, one major disadvantage of optical sensors should be highlighted. Debris and other contaminations by outgoing but in particular by returning foragers make a high maintenance interval necessary to keep the sensors clean and working (Rickli et al. 1989, Struye et al. 1994, Bromenshenk et al. 2015). Interestingly, it was nowhere mentioned how long such an interval would take. Furthermore, it was pointed out, that another obvious disadvantage of optical sensors lies in the registration precision of bees entering or leaving the hives in batches where several bees one after another enter or leave the hive (Liu et al. 1990, Struye et al. 1994). As described by Struye et al. (1994), algorithms are necessary to detect and to clear data about this issue (see also Bermig et al. 2020). Another suggestion to solve this problem was to use capacitive sensors (Rickli et al. 1989, Campbell et al. 2005).

2.2.2 Capacitive sensors

Even though past literature pointed to the advantages of a capacitive sensor system assessing the flight activity of bees, not much research has implemented this technology so far. The technology is cheap, robust, and quite simple. The bee body, like that of all organisms, consists to a certain extent of water. Therefore, it has a dielectric signature that is detectable by its capacitance measured between two electrodes, the so-called

capacitors (Perrault & Teachman 2019). Alterations due to temperature, humidity, and debris inside the corridors of the counter tend to be compensated by assessing the difference in capacitance, i.e. dielectric constant, between the two capacitors. The bees' direction of motion can be tracked by the pair of electrodes first and last responding to a change in capacitance. Its velocity can be calculated by the time required to walk from one set to the other set of electrodes. Interestingly, the change in capacitance is proportional to the body size of the bee; larger bees cause a greater change in capacitance (Campbell et al. 2005), which makes it in theory possible to differentiate between all three casts of honey bees (Fig. 5).

Figure 5: Typical asymmetric double pulses produced by bees in the ring sensor. Pulse (a) is a larger bee exiting the hive while pulse (b) is a smaller bee entering the hive (after Campbell et al. 2005).

Campbell et al. (2005) tested the sensor with live bee specimens. Not only *A. mellifera*, but also *Bombus* sp., *Andrena* sp. and *Megachile rotundata* were included in their experiments. Accordingly, they demonstrated that an increase in bee mass was followed by an increase in voltage. Although there was an overall linear relationship between those two factors, there was still significant variability, particularly for the honey bee and *Andrena*, making identifying different species difficult.

The authors suggest that different shapes of the bees may be the reason for this. *Bombus* species are generally more robust and compact while the *Andrena* and leafcutter species are longer and thinner. More than 10 years after Campbell's publication, this technology

was adopted by Perrault & Teachman (2019) to create a solitary bee counter for *Osmia* sp. with an Arduino single-board microcontroller. Authors believe that with this technique it is possible to determine not just the volume of nesting material and food collected by a single bee but also the type of bee involved. Their sensors detected fluctuations in capacity caused by the bees' movements in the nesting tube. Taken together, this could allow evaluating activity patterns on how long the bees spend outside the nest, how active they are when they return, and how these changes depend on the time of day or other alterations in environmental conditions influencing their behavior. By employing deep learning algorithms over the course of a year the authors believe it should be possible to predict how much pollen each bee has collected and to indicate the general health status of the brood. Therefore, a better understanding of the dynamics of pollinators other than honey bees could be promoted.

Bermig et al. (2020) describe a system called “BeeCheck” where not only seven capacitive sensors per corridor were implemented, but also an algorithm that provides a solution to the difficulties described earlier and by other authors such as erratic bee movement in the corridor or bees coming into contact while moving through the gates (Rickli et al 1989, Struye et al. 1994).

They point out that the high variation in the walking speed of bees is still a challenge. In particular, slow-moving bees or long stays in the corridor, bees that are passing each other or running close behind each other - can all lead to erroneous measurements. Therefore, an algorithm is required that maps the daily balance of incoming and outgoing bees as accurately as possible, factoring out these variations or borderline cases (Bermig et al 2020).

In terms of easy to apply technology, capacitive sensors seem to be superior to the so-far introduced technologies. The “BeeCheck” can be maintained with low effort, as no frequent cleaning of the components is necessary. It is independently operable for more than three months on battery power and exchangeable data memory. The apparatus is currently improved within the consortium of the “VIBee” project (www.vibee-project.net). However, the limitations of this technology are similar to the ones using narrow corridors or entrance tubes generating above mentioned borderline cases. Moreover, ambient air humidity may affect the dielectric constant of moving objects

rendering the sensitivity of the counter up or down ultimately creating false positives rather than negatives. This could be fixed with water-proof housings of the counter.

2.2.3 Electromagnetic sensors

2.2.3.1 RFID

A counter that records the total bee traffic (i.e. activity) is most often incapable of capturing the foraging behavior of individual bees. However, some research questions make it necessary to focus on individuals. For this, up to now direct or video observations are used in combination with colored labels, numbers, or both to differentiate between the subjects of interest (Odemer et al. 2018). Due to a continuous decrease in the size and weight of transponders in the last two decades, however, radio-frequency identification (RFID) technology has been established for bee monitoring.

RFID tags allow automated and continuous monitoring of individual bee flight activity for 24 hours a day, easily outperforming human observers (reviewed in Nunes-Silva et al. 2019). The technology integrates two main components: a transponder (a tag combined with an antenna that is glued on the bee's thorax) and a reader usually installed at the hive entrance. The antenna emits radio signals at a certain frequency that activates the tag. The tag then communicates its stored data such as an identification number (or ID) to the reader using a modulated signal. The ID is then recognized along with a timestamp when the tagged bee was last detected at the entrance (Tenczar et al. 2014).

Even though RFID technology is not designed to measure the full traffic of a colony, it has some advantages that should be mentioned. RFID chips are designed to be fitted to individuals (workers, drones, queens) for studying the behavior of a specific cohort of bees (reviewed in Nunes-Silva et al. 2019). Thereby it is possible to precisely determine the onset of flights of freshly hatched bees, flight duration, number of flights, or homing success.

Thought should be given that both technologies, overall bee counter and individual markers, could be combined to increase the resolution of behavior observation at both the colony and individual level. One reason why this RFID technology is not yet extensively used is the relatively high price especially of the tags, that are only reusable by the sacrifice of the bee given the tagged individual can be caught after the observation.

Currently, an OECD guideline is under development (OECD, 2000) where this technology will be used to determine sublethal effects in the regulation of plant protection products (i.e. homing success of worker bees to measure sub-lethal effects), more frequent use of the RFID technology and a drop in prices could be the consequence.

2.2.3.2 RADAR

So far, there have only been two studies using RADAR (Radio Detection And Ranging) technology to measure incoming and outgoing bees from a hive. The beehive activity monitor of Souza Cunha et al. (2020) consists of a Doppler radar, a signal conditioning amplifier, a microcontroller for data acquisition and processing, a real-time clock for time stamping the data, a micro SD card for data storage, and a power management block.

By measuring the total energy output of the Doppler radar at the low-frequency, flight activity of bees could be determined (Fig. 6). This Doppler effect produces velocity data from objects at a distance. A microwave signal bounces off the target, and a computer analyzes how the motion of the bee has altered the frequency of the returned signal. This creates a variation that enables direct and highly accurate measurements of the radial component of a target's velocity relative to the radar (Souza Cunha et al. 2020).

Figure 6: Time-frequency-intensity heat map plot from a 10.5 GHz Doppler radar. The frequencies of forager bees are displayed as vertical tracks approaching 90–150 Hz with yellow and red banding. Tracks can be seen extending throughout the 12 s timeframe of the recording from left to right (after Souza Cunha et al. 2020).

In Aumann et al. (2021) a similar approach is described to monitor rather simple activity events of flying honey bees. Swarming, robbing, and orientation flights could be indicated with Root-Mean-Squared (RMS) counts, also known as the quadratic mean (Jones 2018), which correlates with total power in the Doppler spectrum. This indicates bee activity, but without providing exact numbers. Therefore, evaluating the data and comparing accuracy with other counters is rather difficult at this stage of development. Future improvements are currently being developed. As one example, software can be used to predict radar cross sections (RCS) of flying bees as a precursor to detecting and tracking these insects (Alzaabi et al. 2021). Overall, RADAR could be a promising technology in terms of low cost and durability or even in combination with a sensor or video-based counter.

2.3 Imaging system/ Video-based systems

In 1935 Patterson was the first to describe an image-based bee counter. He illuminated the entrance gates of a bee colony, and by means of a wide-angle lens focused the images of twenty-four gates onto a single strip of continuously moving 35 mm positive film. A single bees' passage was recorded as an interruption of a solid line; this resulted in very high labor of counting these interruptions, and at the time the running cost of the film was considerable (approximately 20.3 m film per minute).

For a long time since then, video-based counters were not considered due to technical complexities and costs. They can therefore be seen as a development of the recent decade (Fig. 1, Tab. 1). Concurrent with the global increase of available smartphone technology in the late 2000s, camera lenses implemented in these phones were the result of lower prices due to the high availability on the world market (Thusu, 2012). As a side effect, this trend made it possible to develop affordable video-based devices such as bee counters in the early 2010s.

One of the first models that can be considered a hybrid of video, optical infrared LEDs, and individual tags was presented by Chen et al. (2012). They used a camera to record individually marked bees under infrared light at the hive entrance, automatically registered by an algorithm. Bees were labeled with a circular character-encoding tag. To identify these tags in the video, a certain algorithm (Hough transformation) was used to

detect the presence of the marked bees (Tarsha-Kurdi et al. 2007). In total, 15 consecutive days could be monitored in a 12,000 bees' strong colony.

This approach combines several advantages of the beforementioned technologies and can be seen as an alternative to RFID tagging. Important benefits are the reduced costs compared to RFID transponders and the range of applications. Bees labeled this way can for instance be deployed to study possible effects of electric fields such as mobile communications radiation (3G-5G) under field conditions, without major interference to be expected with an RFID device that would suffer from the EMF radiation. A similar counter was employed by Dussaubat et al. (2013) to investigate the effects of a *Nosema ceranae* infection on the flight behavior of honey bees.

Chen et al.'s (2012) device was subject to the same limitations as RFID technology (see Section 2.2.3.1). To date, it has been an exception to most other video-based counters and has not been otherwise described besides Dussaubat et al. (2013).

Principles of a modern video-based counter usually include three parts; (i) the first is bee detection. Image transformation algorithms are necessary to make the bee image stand out from the background and differentiate it from other forms. Methods such as background subtraction, shape matching processes, ellipse approximations, hybrid segmentation using both intensity and depth images can be applied (Chiron et al. 2013, Ngo et al. 2019). In the second part (ii), tracking bees (targets) by assuming their future positions to determine whether they are going in or flying out of the hive is accomplished by different algorithms. Most widely used are approaches such as Kalman filters, iterative-Hungarian algorithm tracking (Sahbani & Adiprawita 2016, Yang et al. 2018, Ngo et al. 2019), or 3D multi-target tracking based on a combined Kalman filter and Global Nearest Neighbor (GNN) (Konstantinova et al. 2003, Chiron et al. 2013, Magnier et al. 2018, Ngo et al. 2019). Kalman filters are algorithms that calculate a kind of memory of past measurements and use and continuously update this memory to determine, e.g., the position of an object with high precision (Zarchan & Musoff 2000). Such filters are, for instance, at work in every satellite navigation device and every smartphone. The final part (iii) simply is counting the bees from the results obtained after the first two algorithms have done their part. As pictured in Fig. 1 and Tab. 1, the utilization of such algorithms has just started in recent years and is strongly triggered by affordable video techniques.

Therefore, it can be assumed that development in this sector will most likely have a substantial influence in future bee counters as can be already seen when combined with deep learning approaches (see section 2.3.1).

The technique, however as promising as it may be, has yet some limitations that need to be mentioned. As with photography, every video-based system is inevitably depending on lighting conditions. In an outside setting, these conditions can vary significantly with the time of day, season, and weather (Campbell et al. 2008).

Counters without an additional light source are dependent on sunlight, which is not permanently available for 24 h. This makes a continuous recording of traffic difficult. Introducing a light source other than the infrared spectrum can cause behavioral alterations of foragers and nest bees which reflects a major disturbance to the natural habits of a colony. Moreover, to cover the whole flight area in front of a hive from a short distance when mounted near the entrance, mostly wide-angle lenses are used. From early on, such imaging systems encountered issues with false-negative registration of bees at the edges of the frame due to optical restrictions and distortions of the lens. False positives occur when bees fly towards the camera and appear larger than usual, generating multiple detections or by occasional shades, leaves, or blades of grass wrongly counted as bees. Complex areas such as a crowded flight board can also cause false-positive events (Campbell et al. 2008, Chiron et al. 2013, Kulyukin & Reka 2016).

Moreover, as expected with any tracker algorithm, the efficiency decreases as the number of targets increases (Chiron et al. 2013). Honey bee colonies tend to strongly vary in flight traffic depending on available food sources, health status, and weather conditions (reviewed in Marchal et al. 2020). To evaluate counters of any type, a certain ground truth or empirical evidence needs to be obtained either by a reference device with a known precision or by human evaluators. Both can be troubled by very high densities of honey bees where one cannot measure in-out activity reliably as bees are almost impossible to separate visually. To improve the process, stronger algorithms and better image quality might solve some of the problems as suggested in Magnier et al. (2018). Lastly, video data generate large amounts of disk space that cannot easily be transferred from the storage to the user online. When future high-speed 5G networks are more commonly accessible, this issue, however, should belong to the past.

2.3.1 AI-BASED SYSTEMS & DEEP LEARNING

Artificial Intelligence (AI) is a branch of computer science focused on algorithms that mimic intelligent learning and problem-solving. An important and increasingly used approach within AI is deep learning, a class of machine learning algorithms that uses multiple layers of a neural network to progressively extract higher-level features from the raw input data. Neural networks are algorithms that can be trained to detect certain signals, for example, images. Most commonly applied to analyzing visual imagery, a convolutional neural network (CNN) is employed as a class of deep neural networks that basically represents an input-output mapping. When combined with video-based counters it can be a powerful tool to detect more than simply honey bees flying in and out from their hives.

The CNN converts raw sensory data on the input side (e.g. a picture) into a classification or keywording (e.g. a text description of the object shown in the picture). The input data is entered into the network, where a series of intermediate layers in the network subsequently extract increasingly abstract “features” of the image. A feature is an attribute that the network “learns” from the data (Fig. 7).

Figure 7: Convolution and pooling layers act as feature extractors from the input image while fully connected layers act as a classifier. Since the input image is a bee, the target probability is 1 for the bee class and 0 for the other three classes.

Based on such algorithms, Marstaller et al. (2019) and Tausch et al. (2020) present a visual monitoring system being able to detect flight activity and background mortality of honey bee hives.

An advantage of using deep learning algorithms in visual bee counters is the ability to extract other features from image data than only honey bees. As demonstrated by Babic et al. (2016), Yang et al. (2018) and, Yang & Collins (2019) deep learning can already be utilized to differentiate between pollen and non-pollen foragers to detect corbicular pollen carriers. By utilizing regional data of flowering periods from possible bee-attractive food plants, correlations of pollen color could indirectly indicate food availability in the flight radius and time of the observed beehives and season. This could provide valuable input for developing policies that support diverse and continuous pollen supply in rural and agricultural landscapes. Ideally, these AI-based counters could be embedded in monitoring programs or wireless sensor networks to evaluate such policies (Ratnayake et al. 2021).

Moreover, it is also possible to detect Varroa-infested bees when a phoretic mite is attached to the bee body (Schurischuster et al. 2018, Bjerger et al. 2019). Berge et al. (2019) for instance developed a so-called Infestation Level Estimator (ILE) algorithm, that is able to analyze image data by counting the number of bees and estimating positions of found varroa mites. It seems only logical to implement feature extraction to detect all genera of bees such as drones, queens, and workers as well as other insects who possibly threaten hives as robbers or parasites such as the small hive beetle *Aethina tumida* or the Asian hornet *Vespa velutina* (reviewed in Abou-Shaara & Staron 2019).

Another possibility to utilize deep learning to detect Varroa mites is object detection. Bilik et al. (2021) used YOLO (you only look once) and SSD (single shot detector) object detectors to be implemented in a real-time computer vision-based honey bee inspection system. This system can be used as online monitoring tool where video or photo data are analyzed. Finally, a non-scientific use by beekeepers to quickly screen their apiary or monitoring area for current Varroa prevalence could be enabled and may be a benefit for treatment strategies in the future. By applying generic counters with such features, technological advances could ultimately be used for nationwide health monitoring, where not only food availability but also parasitism levels can be remotely tracked, and through rapid intervention, situations could be improved.

In parallel and as a further step, deep learning techniques are used for automated pollen detection when combined with using multispectral imaging flow cytometry (Dunker et

al. 2020). This is a very promising development in the field of palynology as it requires less effort and expertise to perform a reliable pollen analysis. Combined with a bee counter and pollen trap, monitoring of food resources for pollinators at the landscape scale could be established – not only to measure the impact of steps to improve bee nutrition but also to monitor pollinator health.

3 COUNTER VALIDATION METHODS

A prerequisite and very important step in developing a bee counter is validation. It is not only necessary to assemble the right apparatus that doesn't interfere with bees' behavior and using components that are cheap, durable, and functional to maintain a stand-alone continuous monitoring field device. Without validation, the device may be recoding in and outgoing numbers of bees, however to an unknown precision.

Using a bee counter for scientific purposes, therefore, needs to be validated by applying standard methods. This would make it possible to compare the performance of different types of counters and foster the development of the best technology. From the counters presented in Tab 1, 70.3% did not indicate a validation method, which was criticized by Rickli et al. (1989) already. They found that without validation, neither devices nor the data generated could be compared. Those papers that stated a method, manual counting bees on video or in front of the hive was most common (75%). The remaining studies used specific methods.

This lack of standardization points out clearly that there is an urgent need for methods that are easy to apply and comparable amongst the different types of counters. In this section, the most promising two approaches are given further thoughts, i.e. visual observation and robbers test. Moreover, the user should not only be aware of the counter's principle precision, but one also needs means to monitor the current precision of counters in operation. This would correspond to a laboratory balance, which can easily be gauged by using calibration weights. While this routine significantly reduces the opportunity for problems to remain undetected, most balances these days have additional self-check systems of various levels of sophistication that provide some degree of confidence that the system is operating correctly. This should be implemented in bee counter systems too, as realized by Struye et al. (1994) and Bromenshenk et al. (2015).

539 Tab. 1: Automated bee counting devices that were described in the scientific literature (i.e. in journal articles, preprints, conference
540 proceedings, and theses). An online search was conducted using Google Scholar, ResearchGate, and literature references in review articles.
541 The search process is further described in the supplementary material. *Without claiming completeness.*

Type	Light source	Species	Validation method	Precision	Source
Mechano-electrical	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Lundie 1925
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Fabérge 1943
Optical sensor	Light bulb	<i>A. mellifera</i>	n.a.	n.a.	Brittain 1935
	Daylight	<i>Agapostemon texanus</i>	n.a.	n.a.	Kerfoot 1966
	Light bulb	<i>A. mellifera</i>	n.a.	n.a.	Spangler 1969
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Burrill and Dietz 1973
	Light bulb	<i>A. mellifera</i>	n.a.	n.a.	Erickson et al. 1975
	Daylight	<i>A. mellifera</i>	n.a.	n.a.	Buckley et al. 1978
	Infrared (LED)	<i>A. mellifera</i>	Liebefeld Method (Gerig et al. 1987)	up to 7.5 fold higher loss rate than estimated	Rickli et al. 1989
	Infrared (LED)	<i>A. mellifera</i>	n.a.	n.a.	Liu et al. 1990
	Red light (LED)	<i>A. mellifera</i>	Flight cage	99.7-99.8%	Struye et al. 1994
	Infrared (LED)	<i>A. mellifera</i>	Robbers Test	n.a.	Struye 1999
	Infrared (LED)	<i>A. mellifera</i>	n.a.	n.a.	Bromenshenk 2001
	Infrared (LED)	<i>A. mellifera</i>	Manual counting bees on video	84.92% incoming and 85.95% outgoing	Jiang et al. 2016

	Infrared (LED)	<i>A. cerana</i>	n.a.	n.a.	Pešović et al. 2017
	Infrared (LED)	<i>A. mellifera</i>	n.a.	n.a.	Qiuzi et al. 2017
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Clarke & Robert 2018
	Infrared (LED)	<i>A. mellifera</i>	Manual counting bees on video images	95.57 % incoming and 96.11 % outgoing	Son et al. 2019
Mechanical	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Chauvin 1976
Capacitive sensor	n.a.	<i>Bombus sp.</i> <i>A. mellifera</i> <i>Andrena sp.</i> <i>Megachile rotundata</i>	n.a.	86.80%	Campbell et al. 2005
	n.a.	<i>Osmia sp.</i>	n.a.	n.a.	Perrault & Teachman 2019
	n.a.	<i>A. mellifera</i>	Robbers Test and manual counting bees on video	~ 95 % ⁺	Bermig et al. 2020
Video based	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Patterson 1935
	n.a.	<i>A. mellifera</i>	n.a.	94%	Campbell et al. 2008
	Infrared (LED)	<i>A. mellifera</i>	n.a.	n.a.	Chen et al. 2012
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Chiron et al. 2013
	n.a.	<i>A. mellifera</i>	n.a.	96-97%	Dussaubat et al. 2013
	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	80.5 - 85.5% (total bees on flightboard within a margin of 10 bees)	Kulyukin & Reka 2016*
	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	95.3% incoming and 88.8% outgoing	Tu et al. 2016

	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	94 - 99% (total bees on flightboard within a margin of 10 - 15 bees)	Kulyukin 2017*
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Tashakkori et al. 2017
	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	75%	Magnier et al. 2018
	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	93.9%	Ngo et al. 2019
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Tausch et al. 2020
	n.a.	<i>A. mellifera</i>	Manual counting bees on video images	97.5% (82.4 – 100%)	Kulyukin et al. 2021*
RADAR	n.a.	<i>A. mellifera</i>	Manual counting bees in front of the hive / BeeScan (Struye et al. 1999)	76.6% visual, 70.3-76.3% BeeScan	Souza Cunha et al. 2020
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Aumann et al. 2021
n.a.	n.a.	<i>A. mellifera</i>	n.a.	97.7%	Marceau et al. 1990
	n.a.	<i>A. mellifera</i>	n.a.	n.a.	Hong et al. 2020

542

543 (n.a.) not applicable or not available

544 (*) The author(s) used the same technique but different counting algorithms. Therefore, in Fig. 1 only the first of these publications was
545 considered.

546 (+) personal communication

547

3.1 Visual observation

Manual counting of bees to compare the flight activity with the numbers provided by the counting device seems reasonable to be the first step evaluating a counter's performance. Counting the entire traffic of one flight day of a full-sized honey bee colony would be impossible for a human observer when done manually, but with the help of the video technique, this task is partly solvable. However, it still requires an operator that has to square both datasets appropriately.

Manual evaluation of video footage for determining counting accuracy, therefore, requires a standardized approach. Jiang et al. (2016) suggested the following equations to calculate the percentage error (PE) of measuring incoming and outgoing bees. The *Actual Number* (AN) represents the number of bees assessed visually, the *Counted Number* (CN) defines the bees counted by the device:

$$PE_{in} = \left[\frac{AN_{in} - CN_{in}}{AN_{in}} \right] \times 100 \quad (1)$$

and

$$PE_{out} = \left[\frac{AN_{out} - CN_{out}}{AN_{out}} \right] \times 100 \quad (2)$$

The average percentage error ($AvgPE$) of the incoming and outgoing accuracy was respectively defined as

$$AvgPE_{in} = \frac{\sum PE_{in}}{Trial_{total}} \quad (3)$$

and

$$AvgPE_{out} = \frac{\sum PE_{out}}{Trial_{total}} \quad (4)$$

Note that $Trial_{total}$ represents the total number of test trial observations during the experimental validation period.

Bermig et al. (2020) suggest using colonies of a strength ranging from 5,000 to 10,000 bees to obtain flight traffic a human observer can handle. Moreover, they suggest

evaluating videos of 3-minute length with a playing speed of x0.3 (slow motion) to capture all movements appropriately.

An important factor when assessing bee flight manually is the foraging conditions at the apiary. Favorable conditions with temperatures above 14 °C (Clarke & Robert 2018) and mass flowering food sources are the higher end of the scale providing solid large flight traffic. However, Jiang et al. (2016) highlight that for instance, lower temperatures are suitable to cover the lower range of flight traffic. Including both scenarios, and detect a possible gradient of the accuracy of the counter is equally important.

Possible limitations of this method lie in its impracticability to capture periods of very high traffic. Tu et al. (2016) reported that it was impossible to count bees on the flight board by human observers not only due to the vast number of bees but also due to various layers of incoming and outgoing bees. Even with second by second resolved pictures from a video, counting bees accurately is not possible (Chiron et al 2013). Moreover, behavioral traits such as short-term flights from newly assigned hive bees, aggregating bees at the hive entrance due to higher temperatures, or any other behavior that interferes with a clear vision on the entrance could bias the count (Danka & Beaman 2007, Souza Cunha et al. 2019). These challenges also indicate that it is important to clearly define what we mean by “flight activity” detected by counters. It is actually the number of bees leaving and entering the hive, but it does not necessarily reflect foraging activity 100%.

Nevertheless, manual counting is suitable to establish a certain degree of ground truth. At least for an activity level that can be handled by a human observer if considering that accuracy tends to decrease with traffic (Jiang et al. 2016). This is important in terms of setting a minimum level of comparability.

3.2 Robbers test

Contrasting manual validation of bee traffic, Struye et al. (1994) were also the first to introduce a simple but solid verification method managed without human participation called “Robbers test”.

By applying this method, the counter is placed under an empty box with a food source attracting honey bees and encouraged them to “rob” the box. Bees have to access the food by entering and leaving through the counter. At the end of the day, the sum of in and

outgoing bees has to be zero as bees tend to fly home after temperature drops lower and daylight is reduced. Any deviation from zero is considered as a benchmark of the precision of the device.

This can be outlined as the first standardized approach to measure the precision of a bee counter, independent of a human observer. Apart from Bermig et al. (2020), no one else had applied this test so far, probably due to the lack of visibility as it was merely published in the proceedings of a conference (ICPPR, Struye 1999).

Bermig et al. (2020) suggest using more standardized conditions such as a tunnel tent instead of free-ranging foragers to limit the access to the counter to only one single colony and limiting the risk that robbing spreads to weaker colonies at the apiary. This makes it possible to select a gradient of colony strengths as it was mentioned by different authors that with increasing traffic most counters lose precision (Struye et al. 1994; Jiang et al. 2016). As a limitation of the tunnel, however, flight traffic may not be as intense as with free-flying bees.

Taking all this into account, future research should focus on the development of a robust validation method to make the performance of a bee counter transparent and reproducible. The Robbers test has the potential to become such a standard method. Bermig et al. (2020) and Struye et al. (1994) calculated their counters total percentage error (PE_{total}) with the following equations:

$$CN_{diff} = \sum CN_{in} - \sum CN_{out} \quad (5)$$

For CN_{diff} it was chosen to subtract the total number of incoming (CN_{in}) from the total number of outgoing bees (CN_{out}). Usually one assumes the other way would be more appropriate to measure how many bees remained outside the hive after a flight day. However, in Robbers tests, traffic is first generated by incoming bees and not *vice versa*. Note that CN is the counted number of either incoming or outgoing bees (see 3.1).

$$PE_{total} = \left[\frac{100}{\sum CN_{in}} \right] \times CN_{diff} \quad (6)$$

Where $PE_{total} > 0$ means that x% of incoming bees remained in the box, and suggests checking the box after each flight day for dead bees inside the box. These bees should be

added to CN_{out} as a correction. $PE_{total} < 0$ means that $y\%$ more bees flew out than came in, which is not possible and indicates inaccuracy of the counter. $PE_{total} = 0$ would be 100% accuracy or 0% error of the device.

4 DATA INTERPRETATION

Rickli et al. (1989) and Struye (1999) were the first to specify indices related to how data from bee counters can be used to provide evidence for the health and vitality status of a honey bee colony, later complemented by Ngo et al. (2019). Such indices are, like the validation of the counters, very important in terms of standardization and comparability of the created dataset. Moreover, these indices contain clearly specified terms, that allow interpretation and visualization of the data.

As a basic feature, a bee counter should ideally record incoming and outgoing bees for 24 h a day. Although no flight activity is expected before sunrise and after sunset, activity may be detected at the hive entrance during events such as fanning due to hot temperatures and should be recorded. Thereby, the timely resolution should be as high as possible to cover the slightest possible fluctuation that may represent an unnatural flight behavior indicating either an internal or external interference. A 1 min interval has proven to be sufficient for that purpose (Bermig et al. 2020).

If we take a pesticide spray scenario as an example, it would make sense to compare flight data from a treated and untreated area where bees were foraging before, during, and after the spray application (event) as indicators for (sublethal) effects. Sublethal effects may involve, for example, delayed return or departure of bees to neighboring colonies. To do so, extracting timeframes with cumulative flight counts (C) from incoming and outgoing bees as a function of the hour (h) can be resolved with the following equations:

$$C_{in}(h) = \sum_0^{59} C_{in}(min) \quad (i)$$

and

$$C_{out}(h) = \sum_0^{59} C_{out}(min) \quad (ii)$$

This can be condensed to cumulative flight counts per day (d) if the event may not need such a high resolution to be displayed with the use of equations (iii) and (iv):

$$C_{in}(d) = \sum_0^{23} C_{in}(h) \quad (iii)$$

and

$$C_{out}(d) = \sum_0^{23} C_{out}(h) \quad (iv)$$

These indices can be applied to compare events of significant change in flight behavior such as swarming or pesticide exposure by feeding (Struye et al., 1994; Ngo et al. 2019). Moreover, it may be of higher interest to examine incoming (i.e. returning) bees when events tend to affect foragers on their trip outside of the hive in terms of homing success. Examination of outgoing bees may be more relevant when internal exposure is expected as the source of the event.

To finally quantify the total daily loss (L) of a honey bee colony, equation (v) can be used to determine the total number of bees not returning to the hive at the end of the day. This measure has a more informative value to judge for striking events such as forager loss due to a spray application or rotary mowers used on blooming clover harvest for instance.

$$L(d) = C_{out}(d) - C_{in}(d) \quad (v)$$

The same index was used by Bortolotti et al. (2003) to measure the effect of the neonicotinoid imidacloprid on the homing success of bees. In general, flight traffic hinges, amongst others, on internal factors such as size, composition, and health status of a colony (Clarke & Robert 2018, Bermig et al. 2020). These factors can vary significantly amongst different colonies. To avoid such bias, Struye (1999) and Ngo et al. (2019) suggested utilizing a normalized or relative loss rate (LR) to better categorize the increase or decline of forager bees per time and independent of colony factors. With the following equation (vi) the daily loss can be expressed as a ratio to the cumulative outgoing flight counts in percent (%):

$$LR(d) = \left[\frac{C_{out}(d) - C_{in}(d)}{C_{out}(d)} \right] \times 100 \quad (vi)$$

Furthermore, the accumulated loss of foragers (L_{acc}) that had not returned to the hive during N days can be calculated by equation (vii):

$$L_{acc}(N) = \sum_1^N L(d) \quad (vii)$$

Lastly, the accumulated loss rate (LR_{acc}) stands for the percentage loss of bees during N days and can be calculated by equation (viii):

$$LR_{acc}(N) = \sum_1^N LR(d) \quad (viii)$$

Indices (vi) and (vii) are particularly useful to reveal external influences on bees' flight behavior for both, short-term and long-term periods (Struye 1999, Ngo et al. 2019). For future work with electronic counting devices, the above-introduced indices can not only help to interpret data but are also mandatory to create comparable and standardized results as scientific output.

5 CONCLUSIONS AND PERSPECTIVE

Since the first invention of an electronic bee counter, the research field has only slowly developed. For a long time, sensor-based systems dominated the sector of such devices. The strength of sensors lies in their robustness and a rather simple design. There is still, however, no commercial model available that can generate reliable scientific data. In the last decade, it seems that promising approaches were made by using enhanced video-based systems to record flight activity utilizing deep learning and artificial intelligence to disentangle complex flight behavior of the honey bee superorganism (Fig. 1). Thereby we can see also a trend of not simply recording incoming and outgoing bees. With the increased complexity and capabilities of the technique, it is even possible to record details rendering sensor-based systems inferior. Automatic food source recognition represents such a detail, identifying the pollen loads of returning foragers. Another detail sensor-based counters cannot register is the presence of parasites attached to the bees' body by additionally including an image recognition algorithm to observe the degree of infestation with *Varroa* mites (Cecci et al. 2020). In a future scenario, mites could be detected at the hive entrance, and statistics on the infestation rate could be made available by a web interface for neighboring beekeepers. As an ultimate approach to fight *Varroa destructor*

without chemicals the coordinates of the mites are to be detected and a laser will be used to kill them (Chazette et al. 2016).

There is promising evidence that the former implementation in video-based systems could be of success. The recent development of computer vision and deep learning enables monitoring of biodiversity in a fully autonomous and non-invasive way for whole seasons which is not limited to honey bees (Hoye et al. 2021, Ratnayake et al. 2021). Such an instrument can also enhance the processing of samples in the laboratory, where automated imaging, in particular, can provide a new way of identifying and counting specimens to measure the abundance of different bee pollinators. This was impressively demonstrated by Hoye et al. (2021) with examples of sensors and devices relevant to the field of entomology. They provide evidence of how deep learning tools can easily convert big data streams into ecological information. This trend is currently commercialized with products to remotely monitor bee health for the everyday beekeeper. Weather conditions, hive weight, brood temperature, and flight data are being recommended to monitor. Even though some techniques are well-engineered, the market is rather intransparent due to the lack of standards and without provision of counter precision, data may be useless at least for scientific use.

This is also an issue that we encounter with current scientific literature. The majority of the here reviewed articles did not provide any information on the validity of their bee counters. As a counter represents a precision tool similar to a laboratory balance, it is not enough to simply state that it counts incoming and outgoing bees. It is mandatory for correct data interpretation at what range of precision the device operates. If the daily loss of forager bees accumulates to an unrealistic number suggesting the hive would be empty after a week, it is questionable if such data can be trusted. By providing a percentage error after validation with a standard test method, data are far more comparable and the user can judge data more easily. Therefore, urging the need to define a common standard in counter validation seems legit. First thoughts on method development have been provided earlier in this review and could form the basis for future validation concepts.

Once a device is validated, it is equally important to enable proper interpretation of the flight data. If counters should be used to measure the ecotoxicological significance of plant protection products on bees' flight behavior and ultimately on colony development,

comparing daily incoming and outgoing bees from treated and untreated colonies may not give enough resolution to detect sublethal effects. By utilizing a normalized loss rate (LR), however, the temporal resolution can easily be adapted to hourly or even smaller intervals independent of colony factors. Such “indices” were first compiled by Struye (1999) and Ngo et al. (2019) and slightly refined in this review.

The so-called background mortality of a honey bee colony stands for those bees which die naturally outside the hive in a certain time (e.g. daily, weekly, in spring, in the summer hole, etc.) (Dukas 2008). Only with a counter that has a stable and low error rate, even during periods of intense flight activity, would it be possible to reliably determine this mortality. However, as can be seen from the work presented here, standards for determining the error rate must first be established to make such an approach feasible.

So far, it is not yet possible to collect this kind of data accurately and particularly not over longer time intervals. This would however benefit the environmental risk assessment (ERA) for higher-tier studies. Obtaining accurate information on bee mortality rates induced solely by the substance of interest would be a valuable endpoint. In addition, the effects of a spray application could be measured more or less live while the farmer is operating the field sprayer.

Whether or not a certain loss of foragers poses a significant risk to the colony, for example in terms of its winter mortality, would be difficult, if not impossible, to determine empirically but can be checked using simulation models that are realistic enough, i.e. simultaneously reproduce a range of observed features of a colony and its response to different environmental conditions. BEEHAVE is such a model (Becher et al. 2014). It has been thoroughly examined by the European Food Safety Authority (EFSA 2015) and considered suitable for simulating unstressed, or reference colonies (EFSA 2021). EFSA itself has a model under development which will be based on the ALMaSS (Animal, Landscape and Man Simulation System) framework of representing agricultural landscapes and their management, including considerably more details than BEEHAVE, and include modules for diseases and pesticide effects (EFSA 2016).

Considering the most recent development of bee counters, promising progress has been made indicating a major leap towards solving the here discussed issues and shortcomings

within the current decade. Connected hives and beekeeping networks will provide a tremendous number of data including bee traffic, weight change, weather conditions, and overall colony development – acting all together as indicators for bee and colony health. Compiling the current knowledge of state-of-the-art electronic counting devices should enable future work to be more focused to easier overcome the outlined issues.

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