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Assessing honeybee colony health using temperature time series

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Honeybees face an increasing number of stressors that disrupt the natural behaviour of colonies and, in extreme cases, can lead to their collapse. Quantifying the status and resilience of colonies is essential to measure the impact of stressors and to identify colonies at risk. In this article, we present and apply a methodology to efficiently diagnose the status of a honeybee colony based on a metric of its thermoregulatory capacity. This metric is derived from data-informed analysis of time series, specifically the hive's core temperature in relation to environmental temperature. Healthy honeybee colonies have a remarkable ability to control temperature near the brood area. Our method exploits this fact and quantifies the status of a hive by measuring how resilient they are to extreme environmental temperatures, which act as natural stressors. After analysing 22 hives during different times of the year, including three hives that collapsed, we find the statistical signatures of stress that reveal whether honeybee colonies are stable or are at risk of failure. Based on these analyses, we propose a simple scale of hive status (stable, warning and collapse) that, once calibrated, can be used to diagnose hive status from a few temperature measurements. Our approach offers a lower cost and practical bee-monitoring solution, providing a non-invasive way to track hive conditions and trigger interventions to save colonies from collapse.

1. Introduction

Globally, the annual market of insect pollination has been estimated at around US$212–577 billion [1–3]. Honeybees (*Apis mellifera*) are widely recognized as the most significant pollinators of many crops [1,4–6], and due to their ecological significance, honeybee populations directly impact biodiversity worldwide [7]. The manageability and adaptability characteristics of honeybees make them highly effective as commercial pollinators, resulting in a large number of globally distributed managed hives [8]. This, in turn, has enhanced the impact of honeybees on food supply, global food security and has major financial implications worldwide [5,9,10]. For instance, in the United States, it has been estimated since 2016 that honeybees pollinate crops worth US$15 billion annually [11,12]. Since 2015, bees across the European Union have contributed at least EUR€22 billion annually to the agriculture industry [13,14]. In Australia, the honeybee industry has been valued at approximately AUD$14 billion annually since 2022 [15].

Unfortunately, maintaining the health of honeybee colonies is increasingly challenging [16–18]. Colony failures have been attributed to multifactorial causes that include poor nutrition [19], starvation [20], pesticide exposure [21,22], parasites like *Varroa* mites [23–25]—which also acts as a vector for honeybee-associated viruses [26,27]—queen failure [20] and adverse weather [28]. As global temperature continuously increases [29], resulting in changes

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in local climate conditions [30–32], the escalation of threats and stressors faced by honeybees underscores the importance of identifying stress indicators early and facilitating timely interventions to enhance hive survival.

Extensive efforts have been made to unravel the causes of colony failures and identify early warning signs of stress to prevent honeybee colony collapse. The best-known monitoring approaches require direct manipulation of the hive, the most common being routine inspections [4,33] and toxicological approaches [34]. Unfortunately, these direct approaches can destabilize honeybee colonies if not performed correctly, and they are often restricted by weather conditions to avoid unnecessary risks when opening the hive. On the other hand, more sophisticated mathematical models can provide an approximate representation or estimation of the emerging behaviour of population dynamics of honeybee colonies [35,36]. Although these models significantly enhance the understanding of the underlying mechanism of colonies' transition from a state of apparent health to failure, how to implement them in daily hive management is unclear. An intermediate approach between these methods involves using data obtained from general monitoring systems for beehives (gathered through inspections and automated sensors) and later used to feed models for estimating specific variables of the managed hive. For instance, there are data-centred models with explicit solutions that assist in forecasting brood-rearing rates [37], internal hive temperature variation [38] and the rate of honeybees that leave the hive during the day [39] after processing empirical data. Meanwhile, alternative approaches study the emerging behaviour of colony dynamics as a result of the surrounding environment, integrating accessible real-time measurements such as the weight of the hive and foraging time of bees to extract information that cannot be directly measured, for instance, the number of forager bees within the hive [40] or pupae [41], respectively. After proper model calibration based on expected patterns for a healthy hive, ranging from daily to seasonal cycles, these integrated approaches could reduce the need for frequent physical hive inspections [42,43]. However, the length and precision of the datasets collected directly influence the final result, increasing costs when aiming for higher precision. For example, assessing the individual contribution of each bee to its colony requires meticulous data collection, which, while offering invaluable research insights, does not align with practical needs for routine hive monitoring and scalable management systems.

Recent innovations in beekeeping technology have adopted and scaled high-order data-driven approaches, leading to the development of smart-hive systems. These systems integrate multiple key environmental and hive-specific parameters, such as internal and external temperature, humidity, weight, CO_2 concentration, internal sounds and wind acceleration, to monitor hive health and assess colony status [44–46]. Most of these systems apply machine learning techniques for high-dimensional data analysis, where dimensionality reduction and multivariate regression analysis are prioritized over causal inference [4]. While these systems enable continuous monitoring and early detection of anomalies in hive behaviour and colony dynamics, initial implementation costs for small colonies are estimated at approximately US$350 per hive [44], up to US$1000 for smarter hives [47] assuming access to wired internet and power sources for optimal functionality; otherwise, additional costs may be incurred [48,49]. Furthermore, emerging technologies for image processing are leading to the development of intelligent monitoring systems aimed at estimating the population of foraging bees [50] and detecting infestations [51], but the cost of implementing these systems can rise significantly [52].

Honeybees exhibit circadian rhythms in their locomotor activity, closely linked to meteorological conditions affecting light intensity and environmental temperature [53,54]. Interestingly, from all essential biological mechanisms for the optimal development of honeybee colonies, thermoregulation stands out as one of the most stable characteristics, particularly in the presence of brood [38,55,56]. In response to the significance of these characteristics, researchers have proposed methodologies and models to simulate the thermoregulation dynamics of honeybees, as individual agents or as part of the colony functioning as a superorganism, both within a hive box and when exposed to the environment. Some models incorporate control theory approaches [57,58], while others use deterministic approaches to describe temperature variation based on distance from the nest, using numerous sensors within the hive [38,59] or thermal imaging cameras [60]. Moreover, some physics models link bee behaviour to environmental variables like temperature and airflow [61,62]. These previous approaches have provided valuable insights and opened possibilities for further advances in scientific research on collective behaviour, as a well-established example of how organisms respond to environmental stimuli and in establishing metrics for self-organized thermoregulation and behavioural parameters. In parallel, these findings are particularly relevant to the application of monitoring the health of honeybee colonies and are especially valuable for supporting informed decision-making among beekeepers.

In this article, we address the fundamental question of the extent to which useful information about the status of honeybee colonies can be extracted from a single time series of internal hive temperature, when combined with environmental temperature data. We demonstrate that honeybee responses to (extreme) fluctuations in environmental temperature leave identifiable traces in the hive temperature time series. These traces are observable across datasets of varying resolution, from representative data points during extreme environmental conditions to high-resolution datasets. We then show how these traces can be used to quantify the status of the bee colony. Finally, we show how these fundamental findings can be used to develop a methodology that offers a cost-effective and scalable solution for continuous hive-condition assessment. This methodology enables hive-state monitoring from solely two data sources: environmental temperature and the temperature inside the hive (e.g. in the brood area). Once calibrated, we can input datasets for a single day to diagnose the status of the colony's performance. By applying our methodology to 22 independent hives at different times of the year, we successfully classified healthy colonies from those that are struggling and approaching collapse. For simplicity, we use the term 'status of a hive' to refer to the conditions of the honeybee colony within it.

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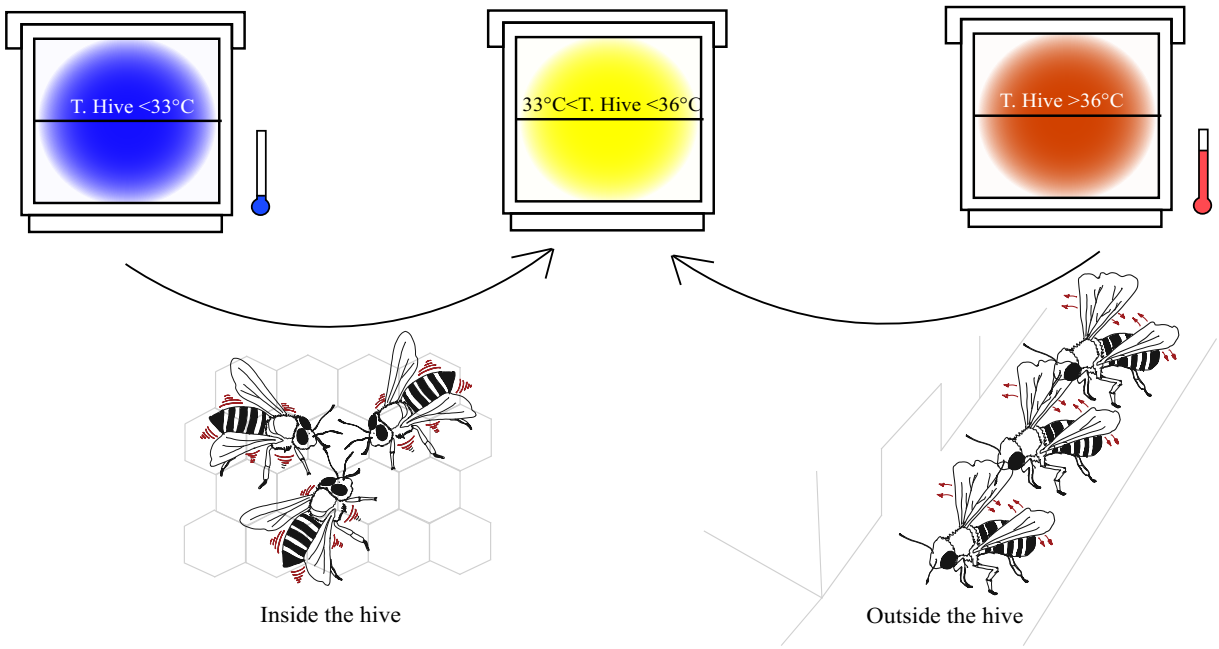


Figure 1. Illustration of hive bee's activities when dealing with temperatures outside the range of 33–36°C. In situations of lower environmental temperatures, when the hive's temperature is much lower than 33°C, especially during cold winters, bees cluster together and generate metabolic heat by contracting and relaxing their flight muscles, a process known as 'shivering'. The result of this vibration is an increase in their thoracic temperature, which allows them to thermally control their hive. On the other hand, when the hive's temperature is higher than 36°C, bees ventilate the hive by fanning the hot air out or using evaporative cooling mechanisms [64].

2. Methodology

2.1. General idea

The starting point for our methodology is the observation that maintaining brood nest temperature between 33°C and 36°C is crucial for normal development of larvae and pupae as well as other in-hive activities [55,62,63]. Honeybees have developed remarkable strategies to collectively thermoregulate hive temperatures [61], as illustrated in figure 1. These strategies require a sufficient number of healthy bees to act in coordination [65]. This motivates the key assumption of our methodology: the status of a hive can be quantified by its ability to bring the hive's core temperature T_H to the desired temperature $T_d \in [33°C, 36°C]$.

An important factor to be considered in this analysis is the environmental temperature T_E. For $T_E \approx T_d$, bees are not challenged, and little information about the status of the hive can be obtained. In contrast, for $T_E \gg T_d$ or $T_E \ll T_d$, the external temperature can be seen as a stressor and only well-prepared hives will be able to bring T_H close to T_d. Therefore, we build our methodology by quantifying the interplay between T_H and T_E, more precisely, quantifying the extent to which T_H is susceptible to variations in T_E. Stable hives are expected to show small susceptibility, while unstable hives display a larger susceptibility. Figure 2 confirms this expectation and illustrates the main effect our methodology explores. For two hives subjected to the same T_E, we see an evident difference in the variation of their T_H. Importantly, we observe a time delay τ between the variations in T_E and T_H, reflecting the thermal inertia of the hive and the reaction of the bees.

2.2. Quantitative methodology

For a given hive, we assume that the hive temperature T_H and the environmental temperature T_E are available at a selection of times $t = 0, 1, \ldots, t_{max}$. Our model is that $T_H = T_H(t + \tau)$, where $\tau > 0$, depends linearly on $T_E = T_E(t)$ and we thus write

$$T_H = (T_E - (T_d - \Delta T))m + T_d, \tag{2.1}$$

where $0 \leq m \leq 1$ is the slope of the linear relationship, T_d the desired temperature and ΔT the temperature change due to intrinsic activities of the bees and their metabolic heat. Together, T_d and ΔT determine the intercept point of the linear dependence of T_H on T_E at $T_E = 0$. Overall, equation (2.1) satisfies $T_H = T_d$ for $m = 0$ (perfectly efficient hive), $T_H = T_E$ for $m = 1$ (totally inefficient hive or empty hive with $\Delta T = 0$) and $T_H = T_d$ for any m if $T_E = T_d - \Delta T$. This last point shows that ΔT can be interpreted as the gap between the most comfortable T_E for the hive and T_d. Indeed, we systematically find $\Delta T > 0$, a reflection of the fact that bees inherently perform heat-generating activities which, in the absence of temperature-controlling activities, would lead to $T_H > T_d$ for $T_E = T_d$. Despite the simplicity of this model and of the linear relationship in equation (2.1), the data analysis reported below confirms that it captures the leading order effect of T_E on T_H and it is sufficient for the data-informed analysis we are undertaking.

The description above suggests that we consider two quantitative indicators of the status of the hive, ΔT and $\Pi \equiv -\log m$. The motivation for taking Π as a nonlinear transformation of m is that it uniquely maps $m \in (0, 1]$ into $\Pi \in [0, \infty)$, providing a better distinction between the stable or efficient (small m or large Π) and unstable or inefficient (large m or small Π) hives. Moreover, both measures can be taken as comparable measures of performance because they have the same range $\Delta T \geq 0$ and $\Pi \geq 0$, with

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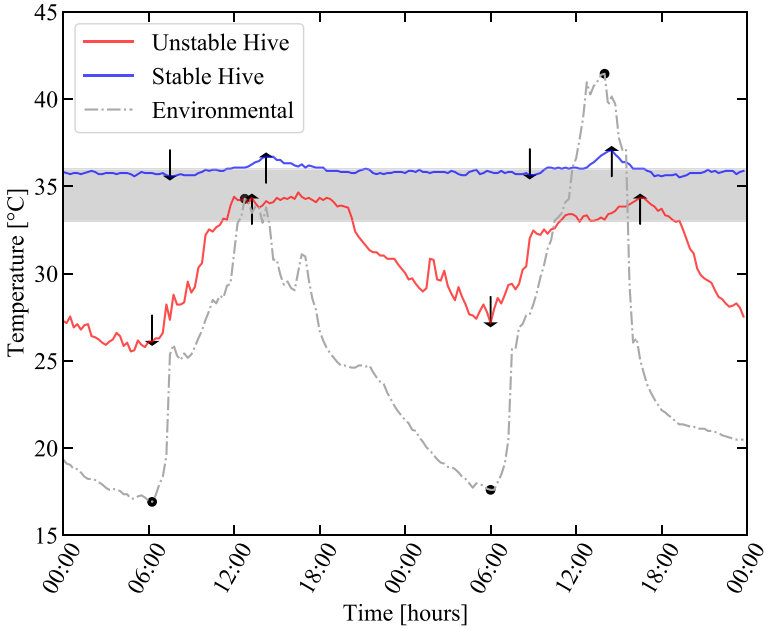


Figure 2. Low- and high-environmental temperatures affect the hive's core temperature. The plot shows the variation in the temperature of two hives (coloured lines) subject to the same environmental conditions (dot-dashed line) in a period of 48 h. Extremes in the environmental temperature T_ϵ (denoted by •) lead to peaks (top arrow ↑) and valleys (bottom arrow ↓) in the core temperature of both hives. These variations are large in an unstable hive (red line) and small in a stable one (blue line), confirming the resilience of hive to environmental temperature change as the result of hive bee activities. The shade regime reflects the desired hive temperature.

$\Delta T = 0$ and $\Pi = 0$ for empty hives (no bee activities), and they increase as hive performance gets better. In practice, we observe that healthy hives typically show $\Delta T \approx 10$ and $\Pi \approx 3$, so values higher than these are considered irrelevant. We compute ΔT and Π using two different methods, as described below.

2.2.1. Method 1: extreme temperatures

We extract the maximum and minimum environmental temperatures daily from $T_E(t)$ and analyse the hive's temperature response $H(t+\tau)$ for τ up to 2 h, which is adaptively selected after either the minimum or maximum environmental temperature was recorded. Then, we compute Π and ΔT over a specific time window t_w from equation (2.1) directly.

In figure 3a,b, we depict the possible responses of a hive where a threshold of $\Pi = 2.66$ corresponds to a hive temperature within the desired range, given an environmental temperature difference up to 42°C. From $0 \leq \Pi < 2.66$, a grey zone represents a transition area, lying outside the desired range and extending towards collapse ($\Pi = 0$). In both cases, the T_d was determined from the average core temperature of the hive when the analysed hive was in good condition, and the ΔT was chosen after solving for the equation (2.1), note that for any $\Pi > 2.66$ the $\Delta T = 10$°C represents a closer match to an ideal condition.

2.2.2. Method 2: cross-correlations

Instead of looking for a peak in T_H after an extreme in T_E, in our second method we explore the connection between T_H and T_E in the entire datasets of the hive and environmental temperatures by calculating the cross-correlation between the time series. The cross-correlation between the hive temperature at time $t+\tau$ and the environmental temperature at time t is given by [66]

$$\rho(\tau) = \frac{\gamma(\tau)}{\sigma_{T_E}\sigma_{T_H}} = \frac{\sum_{t=1}^{N}\left[\left(T_E(t)-\overline{T_E}\right)\left(T_H(t+\tau)-\overline{T_H}\right)\right]}{\sqrt{\sum_{t=1}^{N}\left(T_E(t)-\overline{T_E}\right)^2 \sum_{t=1}^{N}\left(T_H(t+\tau)-\overline{T_H}\right)^2}}, \tag{2.2}$$

where $\gamma(\tau)$ is the cross-covariance function and N is the total number of points (temperature records in the time window under consideration). Figure 4 shows how the cross-correlation $\rho(\tau)$ depends on the delay time τ. Confirming our previous discussion of the delayed impact of T_E on T_H, we see that $\rho(\tau)$ is positive and peaks with a lag of approximately 1.5 h for set 1 and 0.5 h for set 2.

Details for the hives that comprise each set can be found in electronic supplementary material (S1). For simplicity, we use fixed delay times $\tau = \tau^*$ (1.5 h for set 1 and 0.5 h for set 2), disregarding their potential dependence on seasons and hive conditions. We now connect the cross-correlation to the observables of interest m (and $\Pi = -\log m$) and ΔT appearing in equation (2.1) and used in the first method. This is done by noting that, at a fixed τ, the cross-correlation ρ is connected to the least-squared estimator $\hat{m}$ of the slope between the $T_E(t)$ and $T_H(t+\tau)$ data as

$$m = \rho(\tau)\frac{\sigma_{T_H}}{\sigma_{T_E}}, \tag{2.3}$$

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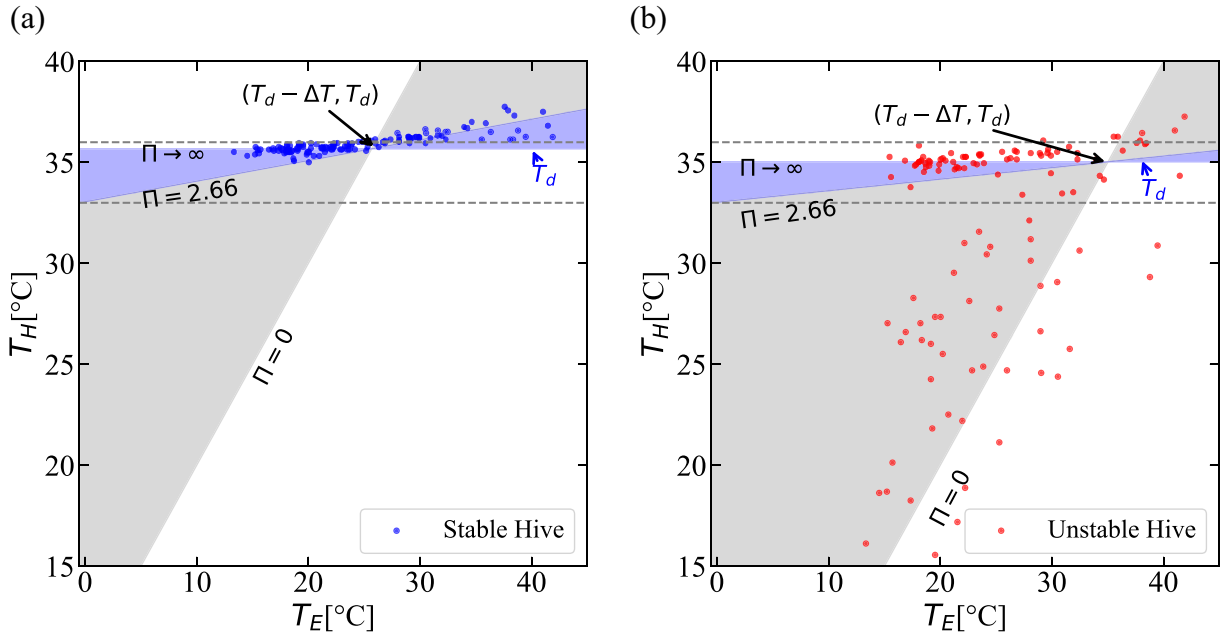


Figure 3. Illustration of the minimum and maximum environmental temperature registered *in situ* against the core's hive temperature. For the (a) stable hive and for the (b) unstable hive, both of them are under the same temporal and spatial conditions. The unstable hive loses control of the temperature gradually ($\Pi < 2.66$) until it eventually collapses ($\Pi = 0$).

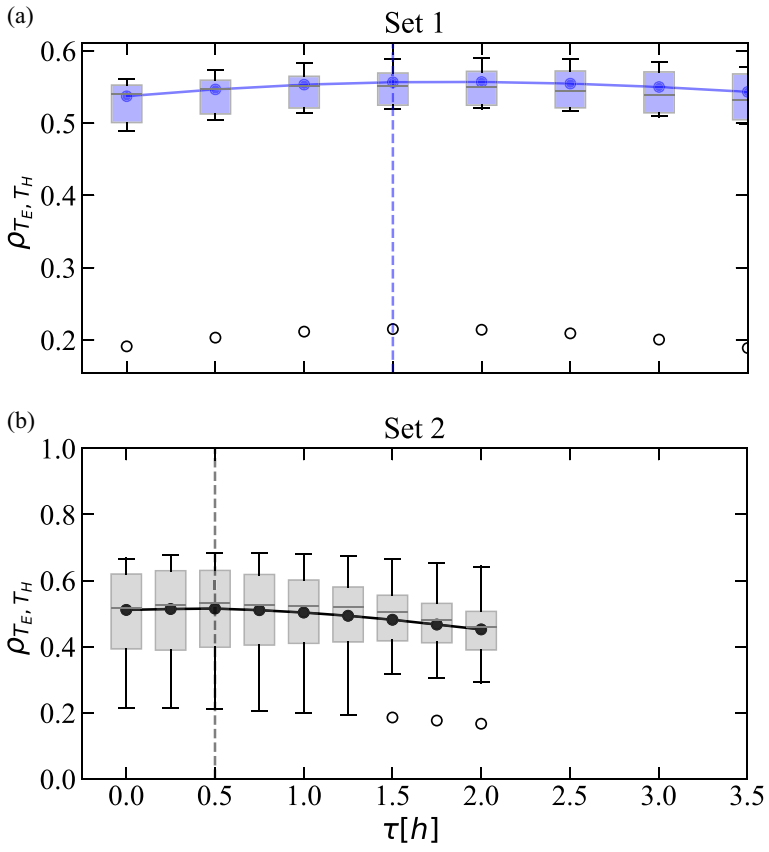


Figure 4. The maximum cross-correlation between the hive temperature T_H and environmental temperature T_E happens after a delay time τ of around 1 h. Each panel shows the dependence of the cross-correlation in equation (2.2) as a function of τ computed over a set of hives (the box plots mark the median and quartiles, while the dots ∘ indicate the outlier points). The top panel (a) shows the results for our set 1 of hives, with a maximum around $\tau^* = 1.5$ h. The bottom panel (b) shows the results for our set 2 of hives, with a maximum around $\tau^* = 0.5$ h. Set 1 consists of six hives and set 2 consists of 16 hives; the sets were formed based on the time of data collection; refer to §3.1 and electronic supplementary material (S1) for detailed information.

where σ_T is the standard deviation of the corresponding time series of T. We fix a small time window of 7 days around a time t and determine both the slope $m(t)$, therefore $\Pi(t)$, at each time step with length t_{max} (see electronic supplementary material (S2) for a more detailed derivation). This allows us to estimate $\Pi = -\log m$ from m in equation (2.2), which is computed at the delay time

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τ^* with maximum correlation, i.e. $\rho = \rho(\tau = \tau^*)$. Similarly, ΔT is estimated from equation (2.1) as $\Delta T = \frac{\overline{T_H} - \overline{T_d}}{m} + \overline{T_d} - \overline{T_E}$, where all terms on the right-hand side are computed (averaged) over the same time window.

3. Results

3.1. Datasets

Our analysis was based on data obtained from hives located on-site at the campus of Macquarie University (33°46′05.1″ S 151°06′46.4″ E, Macquarie Park, NSW, Australia). The analysed hives are two-storey, eight-frame wooden Langstroth hives with plain bases and lids equipped with four small vents. Vent lids are frequently used in warmer regions of Australia to help bees handle high humidity. All evaluated hives were established under identical initial conditions and received the same treatment, beginning as stable colonies. Temperature was measured using a Thermochron iButton placed at the centre of the hive, positioned between frames 4 and 5, at the midpoint of the frames at the bottom box where the brood was located. The data were collected *in situ* using a DS1922L data logger from the iButton® device, which has temperature accuracy of ±0.5°C from −10°C to +65°C (DS1922L), ±0.5°C from +20°C to +75°C (DS1922T), with Software Corrections and resolution of 0.0625°C.

We analysed a time series of honeybee hives from two distinct datasets. Set 1 consists of six hives monitored from 18 November 2016 to 28 September 2017 at 30 min frequency, while set 2 consists of 16 hives. Set 2 includes data from 11 hives monitored from 21 January to 22 March 2020, two hives from 21 January to 3 March 2020, and three hives that eventually collapsed between January and March 2020. The data from hives in set 2 was recorded with a frequency of 15 min. To avoid incomplete data and potential bias due to initial set-up, we exclude one or two days of initial recordings. For set 1, our methodologies are presented starting from 20 November, two days after the installation of the devices, while for set 2, our methodologies are presented starting from 22 January, as the data from 21 January is incomplete. Environmental data were recorded *in situ* for the entire apiary site using an iButton Temperature Logger, placed between the hives, hanging under a table to protect it from direct sunlight while keeping it at the same level as the hives. The environmental temperature was recorded at the same time resolution as the brood hive temperature dataset. For more information and detailed time frames for each hive, see electronic supplementary material (S1). Pre-processing details are provided in electronic supplementary material (S3).

3.2. Analysis

In this section, we test and apply the methodology introduced in §2 to data from 22 hives, which are divided into two groups as described in the previous section, sets 1 and 2. The data and code used in our analysis and to validate our results are available in our repository [67,68].

We start by comparing how our two methods perform in a stable hive and in a hive that eventually collapses. The results in figure 5 show that both methods lead to similar estimations of $\Pi(t)$ and $\Delta T(t)$, succeeding in differentiating between the two hives and showing the decay in the status of the fragile hive ahead of the collapse.

The results from both hives, which are part of set 2, were analysed during the summer (brood-rearing season), under the same spatio-temporal conditions. Methodologies 1 and 2 were computed over the same rolling time window of 7 days, and both outputs consistently reveal that the unstable hive is unable to regulate its internal temperature (figure 5d–f) compared with the stable hive (figure 5a–c), even for warmer temperatures. This plot shows that both methodologies can determine if a hive is unstable or performing at a lower level than others. The grey-shaded region marked as 'Collapse' represents the timeframe during which colony collapse symptoms were observed, including an accelerated decline in thermoregulation stability, and was inferred based on two basic statistical indicators that consistently reflect thermal instability: (i) optimal hive temperature core range outside (33–36°C) and (ii) temperature fluctuations inside the hive vary in accordance with environmental temperature fluctuations. Later, information about this hive and all others that collapsed was reviewed using field notes and inspection records. Since all hives were opened and inspected approximately every two weeks (fortnightly), observations indicating signs of instability or late-stage collapse were noted by the experimentalist at least one week after the onset of this identified period labelled as 'Collapsed'. For more information about how the onset of the collapse period was determined statistically, see electronic supplementary material (S4). The onset of this collapse occurs once $\Pi \approx 1.5$ for both cases.

We extend the analysis and report the results obtained from our two independent datasets (22 hives) for methods 1 and 2, respectively. We present the results in a two-dimensional grid (cells of 0.5 × 0.5 units) based on the Π and ΔT variables, allowing us to visualize where each result falls within defined regions or zones. Figure 6a,b displays the analysis of the earlier dataset, set 1 (six hives), where no hive failures were identified over approximately a year of study. We coloured specific cells to distinguish outputs from different seasons. If results from multiple seasons converge into the same cell, the cell is coloured based on the season with the highest relative frequency, which is displayed as a percentage in figure 6a,b. The outcome for set 2 (16 hives) is shown in figure 6c,d and covers the summer and early fall of the first quarter of 2020, including the transition of three stable hives to instability until the ultimate collapse. After applying methods 1 and 2 to the 22 hives, we established that for these hives $\Pi < 3.5$ and $\Delta T < 8$ should raise concern and promote closer monitoring of them, except in winter. Results obtained during the winter season defined a lower threshold $\Pi < 1.5$ and $\Delta T < 4$, which typically dropped from normal average but recovered quickly in spring. Notably, no stable hive has a $\Pi < 1.0$ even during winter for both methods.

Figure 6e contains a simple summary of the results. The three zones were defined considering the values obtained for Π and ΔT together from sets 1 and 2 by inspecting the patterns obtained from stable and the three hives that eventually collapsed. First, we identify the cells in common between those containing only data from the collapsed hives (three hives from set 2) and those

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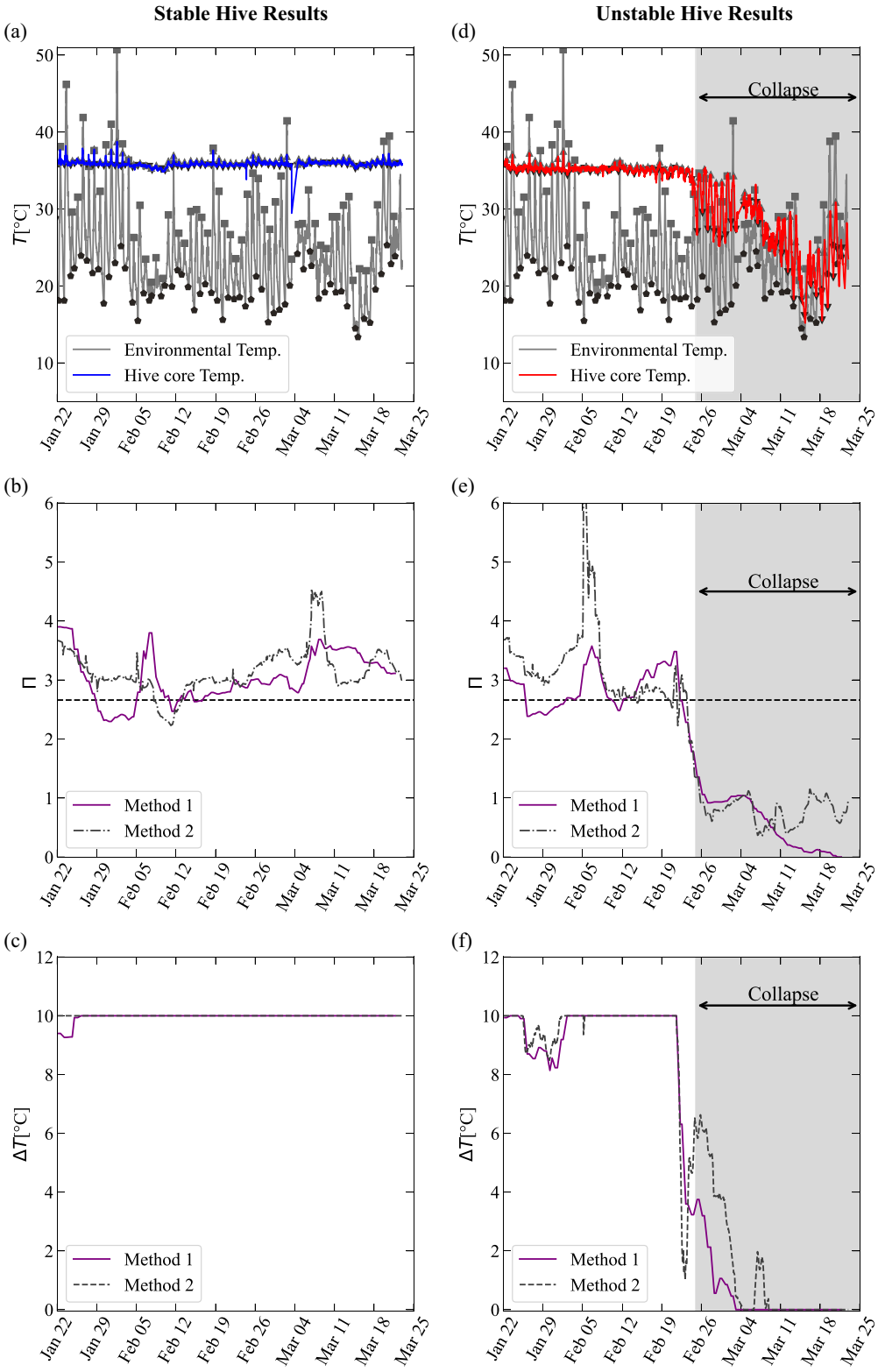


Figure 5. Evolution of Π and ΔT values across two months using methods 1 and 2, recalling the stable and unstable hives from figure 3. The variations of Π and ΔT reflect the collapse over time for the unstable hive. The analysis was made considering a rolling time window with a span of 7 days. The grey shade represents the collapsed regime where the hive lost control of regulating its internal temperature.

from the stable hives (6 hives from set 1 and 13 hives from set 2) through methods 1 and 2. The common cells for set 1 correspond to fully or partially filled cells, associated with the winter season, indicative of the broodless period. In contrast, the common cells in set 2 mainly comprise data from hives that ultimately collapsed. Based on this, we delineated this region as 'Broodless' or 'Warning Zone'. Second, the remaining cells that contain only data from collapsed hives defined the 'Collapsed Zone'. Finally, the zone composed of cells with stable hive data is defined as the 'Stable Zone'. The cells without data from any of the datasets or methodologies were left blank. Additionally, figure 6e displays the percentage of stable hive records, calculated over the total records collected within each of the three different zones—stable, warning and collapsed—from the hive temperature data of set

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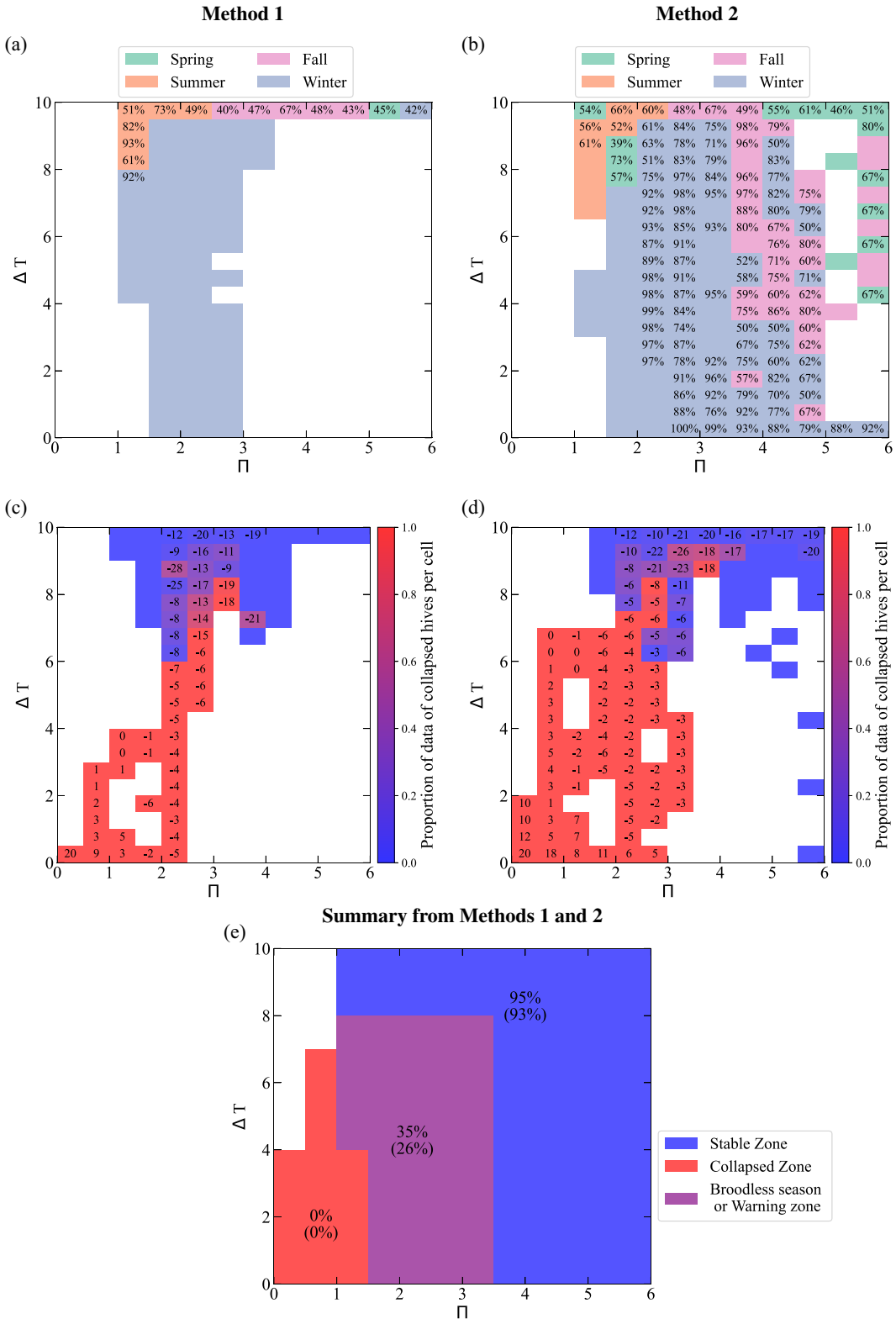


Figure 6. Classification of the status of beehives based on methods 1 (left plots) and 2 (right plots). (a,b) Results of set 1 over approximately a year, where none of the hives collapsed. We coloured specific cells to distinguish output from different seasons. If data from multiple seasons converge in the same cell, it is coloured based on the season with the highest frequency, expressed as a percentage. (c,d) Relationship between Π and ΔT for set 2, where three of them eventually collapsed. The numbers indicate the average number of days from the current state to the onset of collapse for the affected hives. (e) Summary of stable and collapse zones and their transitions identified by methods 1 and 2 in subplots (a–d). Percentages show the proportion of healthy records in each zone for set 2. A value of 0% (0%) means no stable hive data overlaps with the 'Collapsed Zone' in method 1 (or method 2). See electronic supplementary material (S5) for more details.

2. The percentage supports the proposed threshold of Π and ΔT, where 0% (0 %) indicates no record from any stable hive touches the area marked as 'Collapsed Zone' from method 1 (method 2), respectively.

The remaining question is how early we can detect a hive that is on its way to collapse. We assessed the hives that collapsed collectively and individually. We note that hives that eventually collapsed maintained internal temperatures within the optimal range until a week before collapsing. A more detailed overview of Π and ΔT can be observed in figure 6c,d, where the numbers in

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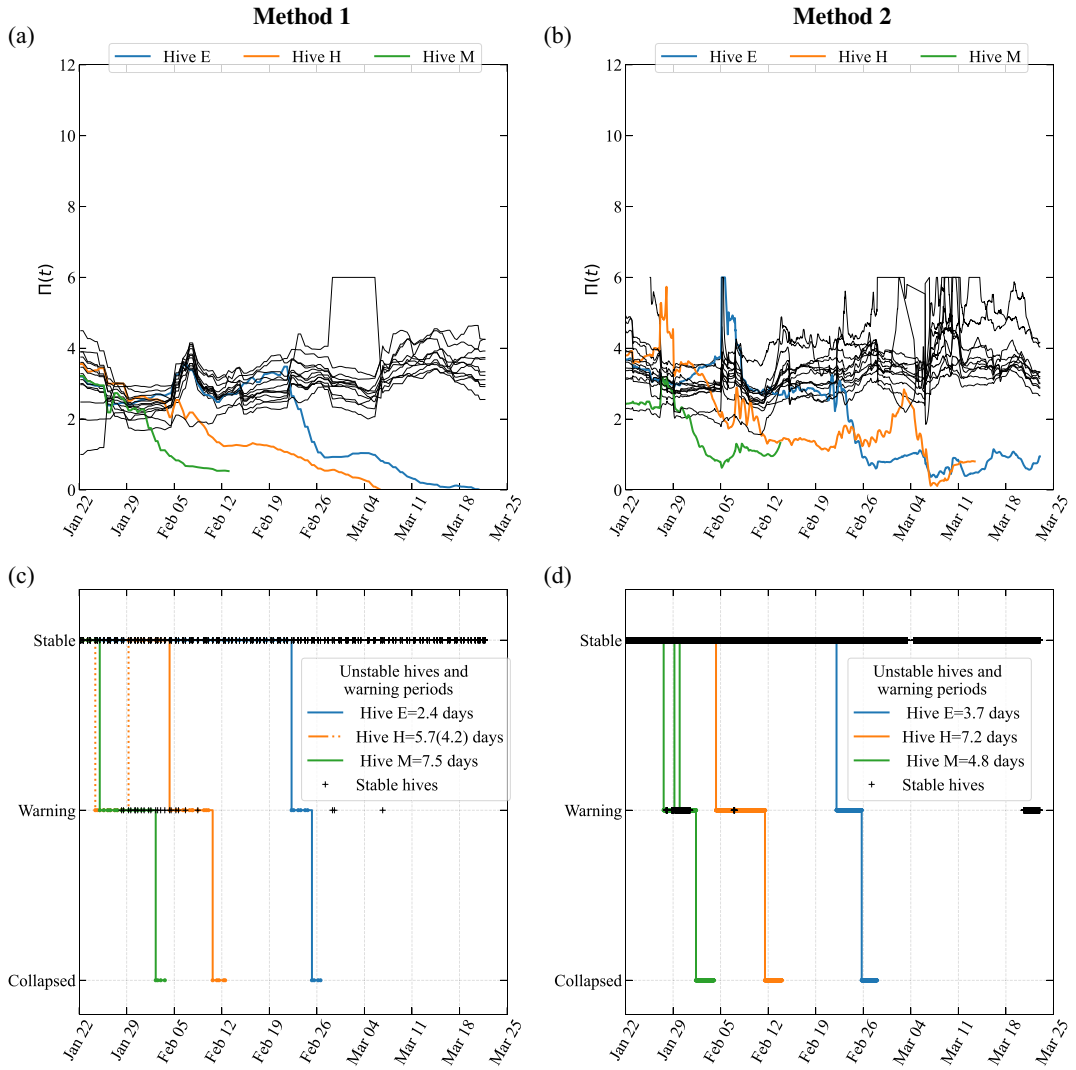


Figure 7. Temporal dependence of the status of 16 hives, all from set 2 (electronic supplementary material S1), including the three hives that eventually collapsed (E, H and M) in a different colour. (a) Value of the indicator Π computed with method 1; (b) Value of the indicator Π computed with method 2. (c,d) Change in status of the hives for method 1 (c) and 2 (d), respectively. A warning period before the collapse of hives is clearly visible.

each cell represent the difference of days between the current state and the collapsed state, averaged over all points that fall into the same cell and across three hives (hives E, H and M). Later on, we evaluated each hive that eventually collapsed individually and compared them with the stable hives during the same evaluation period (set 2). Our focus is on the early detection of signs of decline, before collapse symptoms become evident.

We characterized the time-dependent status of each hive (stable, warning and collapsed) in set 2 based on the results obtained from methods 1 and 2, respectively. While the outputs show certain similarities, they are not identical (figure 7). A hive is labelled as collapsed if, for two consecutive days, the Π and ΔT records consistently fall within the 'Collapsed Zone' defined in figure 6e. For method 1 (figure 7c), we found that two of the three hives that eventually collapsed exhibited a smooth transition from stability to collapse, with warning periods lasting between 2.4 and 7.5 days. In contrast, among the three hives, hive H showed a more complex pattern, with a warning period of 4.2 days, followed by a recovery, and then a final warning period of 5.7 days before an imminent collapse. Under method 2[1] (figure 7d), the same hive displayed a single warning period lasting 7.2 days.

Furthermore, we found that, of the three hives that eventually collapsed, method 1 displayed an earlier collapsed state in two of them (hives E and H). Interestingly, both methods agreed in identifying hive E as having the fastest transition from stable to collapsed, while hives H and M remained in a warning state for at least 5 days, providing more time for a successful intervention. It is important to note that the onset of collapse in the identified cases corresponds to at least one week before experimentalists observed evident signs of instability within the hives. The honeybee hive colonies were later declared dead on specific subsequent dates: hive E on 22 March, hive H on 12 March and hive M on 13 February. This supports our belief that the collapse period corresponds to the late stage of hive decline, where the onset of failure marks entry into the 'Collapsed Zone' and recovery is unlikely. The warning stage corresponds to mid-stage indicators of hive decline, where timely and sustained intervention may prevent progression to irreversible collapse. Field notes and inspection data were used to investigate potential causal factors contributing to the collapse of these three hives: hive E was noted as queenless on 3 March, hive H, which had a hive beetle infestation confirmed

[1]Negative cross-correlation values are disregarded, as they indicate a negative slope between the environmental temperature and the hive temperature.

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on the same day it was declared dead, and hive M, with no single specific documented cause, although a honey removal was documented on 6 February. Although the three hives collapsed due to different causes, both of our methods successfully identified the stages of decline in each case. Importantly, the methods showed potential for detecting hives at risk in advance—the onset of failure at least two weeks before official colony death was recorded. For hives H and M, the models provided an additional 5 days of warning, and for hive E, a lead time of 2.4 to 3.7 days, offering a valuable window for potential intervention and colony rescue.

Regarding false positives, the frequency with which a stable hive was identified as being at risk of collapse or in a warning state, both methods 1 and 2 flagged two stable hives (hives A and O), classifying them as in a warning state. Under method 1, hive A displayed a single warning record on 6 March. In contrast, under method 2, it was flagged as being in a warning state at an average frequency of every 20 min (closer to the highest possible frequency) for 2.4 days, from 20 to 22 March. On the other hand, under method 1, hive O was classified as being in a warning state with an average frequency of approximately 12 h (closer to the highest possible frequency for daily extreme temperatures) over 11 days, from 28 January to 8 February. Later, the same hive displayed warning behaviour for only one day, 28 February. Method 2 yielded a similar result, with hive O being flagged with an average frequency of about 50 min over 10 days, starting on 27 January, and overlapping nearly the same initial warning period flagged by method 1. After reviewing field notes, we did not find specific causes for these false positives, as inspections were carried out approximately every fortnight. However, we identified a potential reason for the false positive recorded on 28 February for hive O as the temperature sensor was moved during an inspection and later repositioned. Figure 7c,d, presents these records for methods 1 and 2, respectively.

4. Conclusion

We introduced and tested two methods to quantify the status of honeybee hives based on their response to environmental temperature fluctuations, enabling faster and more cost-effective beehive health monitoring. Building on previous studies demonstrating that in-hive bee response thresholds modulate temperature within their hive's brood nest between 33°C and 36°C, our study quantifies their ability or inability to control temperature and links this to the status of the hive. The significance of our results is that it assesses hive stability based only on data that can be easily collected (time series of hives and environmental temperatures), providing a cheaper (and potentially complementary) diagnostic when compared with alternative approaches that considered hive structure [38], genetic variance [69], hive weight [40], colony dynamics [70] or collective thermoregulation [62,71].

We applied our approach to the study of 22 hives, including three hives that collapsed. We found that both our methods succeed in separating healthy from unhealthy hives, motivating us to propose a monitoring scale that alerts beekeepers when hives are at risk. This approach offers a more affordable alternative, as it requires only a single sensor per hive and benefits from the simplicity of linear approximation for easy calculation. We note that while this scale is applicable, it is unlikely to be universal. For an accurate threshold nomination, a calibration will be necessary to include different hive construction, bee genetics and geographical location. Furthermore, each of the presented methods has its own advantages and limitations. Although method 1 detects collapse risks or *warning* states a bit earlier by focusing solely on extreme temperatures, method 2 offers a more detailed data analysis and a more straightforward approach. The strengths of each method are influenced by the length of the datasets and the slightly different approach used to select the time lag between environmental and hive temperatures, τ. For method 1, the lag is adaptively selected by identifying the highest or lowest corresponding hive temperature within the 2 hours following the recorded daily extreme environmental temperature. Although honeybee behavioural responses such as fanning or clustering occur within minutes [72,73], hive temperature stabilization can take hours. Then, method 1 is ideal and more accurate when hives are exposed to temporary extreme temperatures within a short time interval, as it allows us to inspect the highest or lowest temperature experienced in the brood area resulting from these daily extremes. It captures more precisely temperature changes due to intrinsic activities of the bees, ΔT and the colony strength, Π, in response to a specific, high-magnitude environmental temperature deviation from the desired temperature. On the other hand, method 2 gets the τ based on the point where the cross-correlation between environmental temperature and hive temperature datasets peaks for each stable hive, and then averages these values across each set. This lag of time, τ^*, can also be interpreted as the average critical time at which fluctuations in the centre of the hive temperature are greatest and most strongly correlated with the environmental temperature. One of the major benefits of method 2 is that it accounts for the duration of persistent extreme temperature challenges by considering the full temperature records. As we might intuit, facing a temporary extreme temperature within a short time window is not the same as experiencing it persistently over several hours due to colony fatigue. Given both methodological options and considering that a slope represents the rate of change between two variables, the simplest estimation (method 1) can be made using the lowest and highest environmental temperatures of the day (e.g. at the peak of solar radiation in the afternoon for the maximum and at the early morning hours before sunrise for the minimum). Alternatively, one can use weather forecast estimates of when the maximum and minimum environmental temperatures are expected to occur and then compute the corresponding hive temperature within a 2-hour window following these key times.

Considering both methods, we have established that a hive should be flagged for concern if our key quantification measure Π is at $\Pi < \Pi_1$, where $\Pi_1 = 3.5$ for our hives set-up, and elevated to collapse status if $\Pi < \Pi_2$, where $\Pi_2 = 1.5$ in our experiment, as this is the threshold for their survival. We anticipated these thresholds would be valid from spring to autumn. In winter, the warning threshold should be elevated only for $\Pi < \Pi_2$. This difference correlates with the fact that winter is a broodless period for honeybees, during which temperature maintenance is less critical to the hive. Brood rearing commonly starts in late winter and rises until summer [74–77]. It is important to note that simple statistical measures allow us to identify when the hive loses full control of its internal temperature. However, we are not only interested in recognizing when the hive colony has collapsed; we also aim to detect when the colony begins to struggle. Among the three hives that eventually collapsed, we identified possible causes in two of them (hives H and M). Using our proposed approach, we could detect warning signs before they became visible—at least

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5 days before the onset of colony failure. Notably, this onset (Π_2) occurs approximately two weeks before the colony is officially declared dead. In cases like hive E, which presented a rapid decline in the colony's thermoregulation capacity, the approach still offers a valuable window to raise a warning flag for prompting inspection and enabling management actions focused on either preventing disease spread or salvaging resources.

In our study, we observed that two stable hives were temporarily flagged as false positives during a short time period. Given the inherent complexity of honeybee hives, it is unlikely to not have false positives. However, the proposed model reduces the need for manual inspections and provides earlier warnings, offering a few days for intervention when a true issue arises. Most importantly, we have not observed any false negatives as our method has consistently detected issues at least a week before visible signs of hive failure were noticed during physical inspections. While a false positive leads to some extra inspections for beekeepers, the cost is minimal compared with a false negative. False negatives would lead to a loss often valued at several hundred dollars in equipment, bees, honey production, or pollination contracts for each hive (commercial beekeepers). This occurs because false negatives can delay treatment, leading to irreversible damage, depending on the stressor, as it directly affects the time of intervention for the hive.

Our results and repository [67,68] open up a potential opportunity for comparison with other early warning indicators of collapse, such as signs of approaching tipping points. Motivated by the fact that maintaining an optimal temperature during the brood-rearing season depends on both beehive population and brood-rearing rate [74,78], we expect that, with suitable calibration, the key quantities identified in our method (e.g. Π and ΔT) can be used to detect hives approaching tipping-point collapses, such as the ones predicted by beehive models [35].

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. Repositories for results validation are available at [67].

Supplementary material is available online [79].

Declaration of AI use. I pre-proofread the Introduction and Conclusion sections using the Grammarly app, which currently uses AI.

Authors' contributions. K.A.-C.: conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, writing—original draft; T.C.: conceptualization, data curation, investigation, resources, writing—original draft; T.L.: conceptualization, funding acquisition, supervision, writing—review and editing; M.M.: conceptualization, funding acquisition, supervision, writing—review and editing; E.G.A.: conceptualization, funding acquisition, supervision, validation, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interest declaration. We declare we have no competing interests.

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