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Validation of a Low-Cost Digital Apiculture System Under Variable Colony Dynamics: A Southern European Case Study

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Abstract

Beekeeping is highly affected by climate change, which alters environmental conditions and challenges colony stability. In this context, digital monitoring technologies can enhance apiary resilience. This study presents the development and field validation of a low-cost hive monitoring system based on a customizable Raspberry Pi architecture, integrating temperature and weight sensors with robust data continuity features. The system was evaluated over one year in Southern Europe (Serbia) against a commercial reference. Results show that correlation between systems depends on both the monitored parameter and the biological state of the colony. For weight, strong agreement was observed only during winter, when reduced biological activity allows reliable comparison, whereas correlations were weak in more active periods. Conversely, temperature monitoring exhibited the highest correlation over long-term datasets, indicating that extended time scales are required for reliable sensor validation. These findings highlight the importance of a context-aware validation approach in apiculture. The proposed system provides a cost-effective and reliable solution for continuous hive monitoring, supporting data-driven management and improved resilience under climate variability.

Keywords: digital agriculture; beekeeping; open-source; low-cost technology

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Academic Editors: Ying Wang, Xuepeng Chi, Hongfang Wang and Zhenguo Liu

Received: 27 April 2026
Revised: 10 June 2026
Accepted: 22 June 2026
Published: 25 June 2026

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1. Introduction

Bees are particularly vulnerable to climate change, which is widely recognized as a major factor threatening their health and productivity at a global scale [1]. Increasingly frequent extreme events such as heat waves and droughts, interspersed with intense cloudbursts, tornadoes, and hailstorms, create conditions of 'climatic chaos' that often exceed the physiological tolerance limits of many bee species, thereby threatening their survival [2,3]. Additionally, these changes disrupt floral resources by altering plant composition and flowering periods in both natural and agricultural ecosystems, ultimately affecting honeybee foraging activity and honey production [4–6]. In this regard, scientists have observed that specific conditions such as drought, strong winds, and extreme temperature fluctuations influence the quantity of nectar produced by plants and, consequently, honey yields by bees [7–9]. To these increasingly severe challenges observed in recent years, additional

issues must be added, including the widespread use of crop hybrids with reduced nectar production for large-scale sowing and the extensive urbanization of territory, which in some areas of Italy significantly reduces the availability of spontaneous flora [10,11].

As a result, the beekeeping sector is compelled to confront a particularly concerning situation, considering that productive activity relies on food resources derived from the external environment and that supplementary feeding is provided by beekeepers only as a stimulus or emergency measure and in limited quantities. Situations of low or null production are becoming increasingly frequent, even in colonies that appear to be in good health, as well as cases of flowering severely compromised by adverse climatic conditions [12,13].

The digitalization of agriculture, through the adoption of precision monitoring systems, sensors, and data-driven decision-support tools, represents a key strategy to mitigate the impacts of climate change by improving resource-use efficiency, enhancing resilience to environmental variability, and, in the beekeeping sector, enabling real-time monitoring of hive conditions to promptly detect stress factors related to climatic extremes, floral resource scarcity, and colony health decline [14–16]. Indeed, recent advancements in precision apiculture (PA) have transformed honeybee management from traditional manual inspections to data-driven, non-invasive monitoring. Current research emphasizes the integration of Internet of Things (IoT) frameworks and Deep Learning to interpret complex colonial dynamics within the hive [17,18]. Key developments include the use of Convolutional Neural Networks (CNNs) for real-time acoustic analysis to identify queen status and generate swarming alerts [19]. Parallelly, the implementation of Computer Vision systems has enabled automated Varroa mite detection and high-precision brood assessment [20]. By correlating weight fluctuations with specific micro-climatic variables, these sensorized hives facilitate the predictive modeling of colony health and honey production [21–23]. Ultimately, these technological synergies significantly reduce hive stress while optimizing apicultural yields through minimal physical intervention.

While digital monitoring systems and commercial solutions have laid the groundwork, evolving environmental challenges and the demand for cost-effective, high-resolution data necessitate next-generation tools for the resilience of modern apiculture. Current commercial digital beehive systems remain inaccessible to many beekeepers due to their high purchase and maintenance costs, as well as restrictive data ownership models, underscoring the need for affordable, open data solutions that can support wider adoption and more inclusive monitoring. In this regard, furthering the development of digital solutions that are functional, scalable, and carefully tailored to the diverse needs of beekeepers worldwide is paramount for honeybee preservation. In this context, we developed a low-cost, customizable, and user-friendly monitoring system based on Raspberry Pi technology to analyze internal beehive activity and track key parameters such as temperature and weight. The first goal of this study was to validate the system architecture, operational reliability, and data continuity of a low-cost beehive monitoring platform, while investigating how continuous, high-resolution monitoring of internal hive temperature and weight can improve the understanding of colony dynamics, environmental stressors, and overall honeybee health, thereby supporting more sustainable and ecologically informed apicultural management. Beyond the development of a low-cost monitoring device, this study introduces a context-aware validation framework for digital apiculture systems, explicitly accounting for biological variability and real-world operating conditions, with the aim of assessing whether low-cost architectures can reliably capture hive dynamics in comparison with commercial solutions.

2. Materials and Methods

The device was developed by the Research Centre for Engineering and Agro-Food Processing (CREA-IT) as part of the ProTechBee project, a collaborative initiative involving the University of Novi Sad's Faculty of Agriculture. The digital system was tested from March 2025 to February 2026 within a family-owned apiary in Bačko Petrovo Selo, Serbia. The experimental site is located in the Municipality of Bečej, South Bačka District, Vojvodina. Throughout the study, environmental conditions were tracked using a weather station integrated into a commercial digital hive infrastructure Melixa Lybra system (Melixa S.r.l, Trento, Italy) installed within the apiary. The commercial Melixa Lybra system, installed on a separate hive within the same apiary, was used as a reference monitoring station. It included a digital scale mounted on an iron frame with a central load cell, five internal temperature probes, and weather sensors. Because the two systems monitored different colonies, the commercial hive was not used for a direct one-to-one validation of sensor accuracy; instead, it served as a reference for seasonal environmental patterns and overall hive dynamics within the apiary. Rather than relying on laboratory-based sensor validation, the comparison between the prototype and the commercial system was performed under field conditions, where biological variability constitutes a major source of signal fluctuation. To address this, the analysis was explicitly structured by separating active and quiescent phases (one-year monitoring). Both digital monitoring systems were installed on a Langstroth hive composed of a brood chamber and a super, each containing ten frames of bees and honey (Figure 1). The colonies were headed by queens hatched in 2024.



Figure 1. Experimental setup showing the prototype digital hive (**A**) and the commercial Melixa Lybra system (**B**).

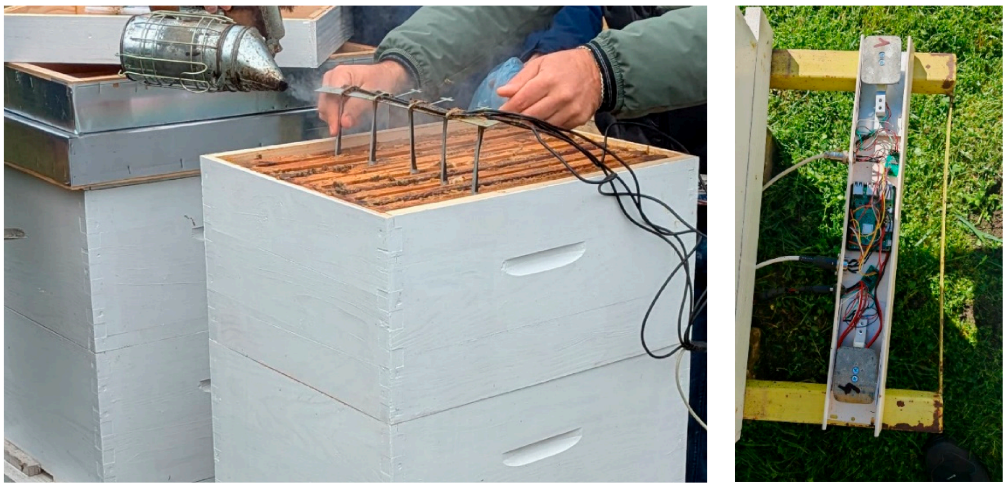
2.1. Technology Description

The digital beehive prototype was developed as an open-source retrofit system, designed for integration with existing traditional hives without altering their structure. The system's primary objective is the continuous monitoring of critical physical parameters during the breeding period, with a specific focus on internal temperature and the overall weight of the hive. The system prototype consists of internal thermal sensors, load cells for weight measurement, and a central processing unit. It is powered by the main electrical grid while data transmission is performed over a domestic Wi-Fi network. To mitigate power interruptions and connectivity failures, the system was equipped with a custom-engineered UPS and a local data-buffering mechanism. This configuration allowed the prototype to continue data logging during temporary network outages and short-term

power failures. The digital monitoring system we developed was based on bottlenecks of commercial systems. In fact, it is lightweight and easy to install on fully populated hives, is considerably more affordable, provides farmer-friendly and directly accessible data, and offers a flexible, customizable configuration that can adapt to evolving management needs.

2.2. Temperature and Weight Monitoring

Internal temperature was monitored using five DS18B20 digital sensors (Maxim Integrated Products, Inc., San Jose, CA, USA) encapsulated in stainless steel probes to ensure mechanical protection and moisture resistance. The sensors were positioned within the spaces between the honeycombs to detect thermal gradients between the hive's core and its peripheral areas. These devices utilize the 1-Wire communication protocol and feature a measurement range of −55 °C to +125 °C, with a declared accuracy of ±0.5 °C. The selection of digital sensors facilitated a reduction in electrical noise and simplified the final wiring architecture. Weight measurement was implemented using four load cells, each with a nominal capacity of 20 kg, installed at the four corners of the hive base to ensure uniform load distribution. The load cells were interfaced via signal conditioning modules based on the HX711 24-bit analog-to-digital converter (ADC) (Avia Semiconductor Co. Ltd., Xiamen, China) a standard component for high-precision weighing applications. This setup enables signal amplification and digitization, significantly improving the resolution and sensitivity of the hive's total weight measurement. The load cells and primary hardware components are housed within a plastic frame. During monitoring, the hive is placed on the plastic frame in direct contact with the load cells (Figure 2).



(**A**) (**B**)

Figure 2. Main hardware components of the prototype system: temperature probes positioned inside the hive (**A**), and the weighing/electronics module including two of the load cells and the Raspberry Pi 3 Model B+ housed in the lower section of the support frame (**B**).

2.3. Data Acquisition and Management

The central control unit is based on a Raspberry Pi 3 Model B+ (Raspberry Pi Foundation, South Cambridgeshire, UK) which manages data acquisition and processing (Figure 3). Sensors are interfaced via GPIO pins, and remote connectivity is established through a Wi-Fi connection. Custom scripts were developed and configured as system services to automate operations and ensure sensor reliability.

Data acquisition occurs at 10 min intervals every day, with records stored in a local MySQL database. The acquisition process is automated and instantaneous: once recorded, the data are stored in the local database and transmitted to the server, with immediate updating of the dashboard. To address frequent internet connectivity issues at the installa-

tion site, a scheduled script synchronizes the local database with a remote server, ensuring data persistence. Finally, a custom-developed Node-RED dashboard allows for real-time data visualization and monitoring of the operational status of both the sensors and the central unit.

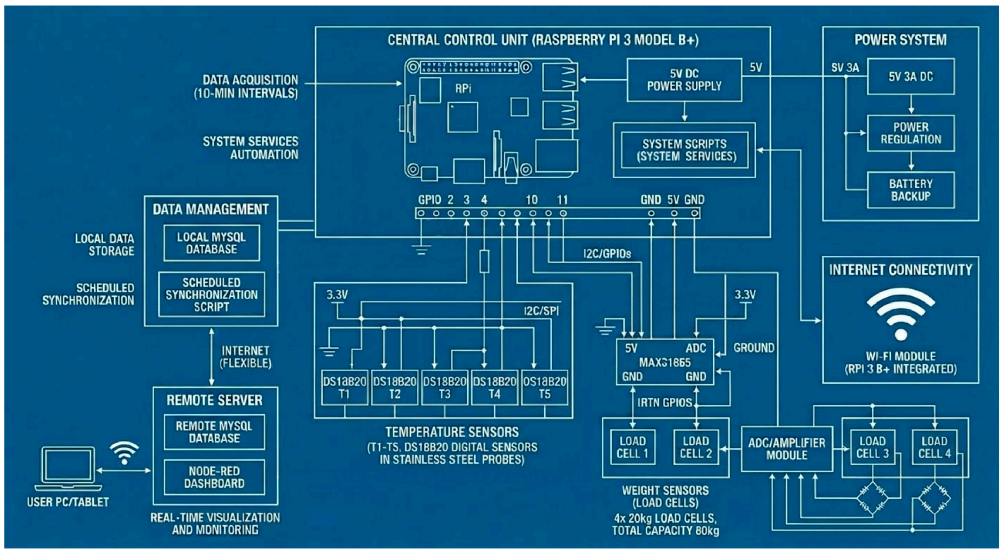


Figure 3. System architecture schematic of the digital beehive monitoring prototype based on the Raspberry Pi 3 Model B+. Image created with AI (Gemini Flash).

2.4. Economic Evaluation

A comprehensive economic evaluation was performed to determine the financial viability of the developed digital beehive. The analysis aimed to quantify the total expenditure required for the hardware integration, focusing on the cost-effectiveness of a custom-built solution compared to pre-assembled alternatives.

The assessment was structured by categorizing the components into their specific functional roles within the system. The analysis included the costs for processing and connectivity, covering the central logic units and telemetry modules, as well as the storage components used for local data logging. The sensing layer was accounted for through the expenditures related to thermal monitoring and the weight measurement hardware, including load cells and their mechanical interfaces. Specialized circuitry for signal conditioning was also factored in to ensure the precision of the analog-to-digital conversion. Unlike remote setups, the power supply for this prototype was designed for connection to the domestic electrical grid, necessitating specific AC/DC transformers and voltage regulation stages rather than solar-based components. Finally, the evaluation included the assembly and housing costs, which comprise the protective enclosures, specialized wiring, and mounting hardware essential for operational longevity. The total cost was calculated based on the purchase price of each component from electronics suppliers, focusing on the Bill of Materials (BOM) adjusted for the current market prices. This methodology excludes the intangible costs of software engineering and manual assembly labor.

2.5. Statistical Analysis

To analytically evaluate the performance of the two monitoring systems, statistical investigations were conducted using the PAST software package (v. 5.4), with the primary objective of assessing operational similarity between the prototype and the commercial reference. The analytical approach was differentiated based on the inherent nature of the variables: for weight measurements, due to the high biological heterogeneity associated with active seasons, the analysis focused exclusively on the winter "quiescent" period (De-

cember 2025–February 2026). This specific timeframe, characterized by the formation of the winter cluster and minimal resource importation, allowed for a more reliable comparison of the systems' baseline stability by reducing biological noise. Conversely, internal hive temperatures were evaluated across the entire annual cycle, as sensors positioned within the confined area of the central frames remain relatively insulated from transient changes in colony mass or foraging success. To quantify the strength of these linear relationships, several statistical coefficients were employed. The Pearson correlation was applied as a bivariate measure for both weight data and specific thermal locations (T1, T3, and T5), while the Mantel test was utilized for temperature data to provide an integrated assessment of global congruence between the similarity matrices of the two systems. Finally, to complement the correlation coefficients that measure trend synchronicity, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated. These metrics provide a direct quantitative measure of the physical gap—in kilograms and degrees Celsius—between the data recorded by the prototype and the commercial reference, offering an impartial evaluation of the absolute numerical divergence between the two hives.

3. Results

The meteorological data for Bačko Petrovo Selo reveals a high-amplitude continental climate, with summer temperatures peaking near 34 °C and winter lows dipping below −10 °C. The region experienced significant precipitation variability, notably sharp rainfall events exceeding 25 mm in June and July, followed by a drier period in late summer (Figure 4).

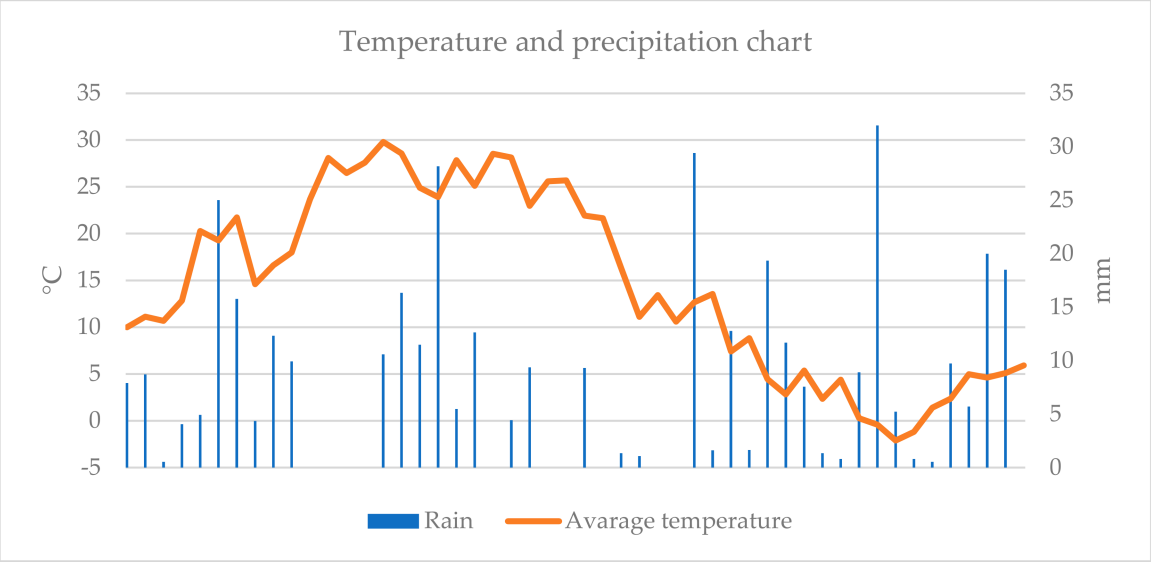


Figure 4. Mean daily temperature and weekly cumulative precipitation data during the monitoring period.

Despite some extreme conditions like mean temperatures below −3 °C, both commercial and experimental beehives did not show permanent failures that compromised their functionalities.

3.1. Comparative Analysis of Weight

Figures 5 and 6 show the results of 1-year weight acquisition by the commercial system and the prototype.

The weight trends demonstrate that both the commercial system and ProTechBee prototype successfully captured the main seasonal increase associated with the summer

nectar flow. The commercial system presents an extremely smooth curve, reaching a peak of approximately 75 kg in July, followed by a sharp decline in August signaling honey extraction. Concurrently, the ProTechBee prototype captured the same production peak, reaching a maximum of 59 kg.



Figure 5. Trend of weight variation during the monitoring period in the commercial hive.

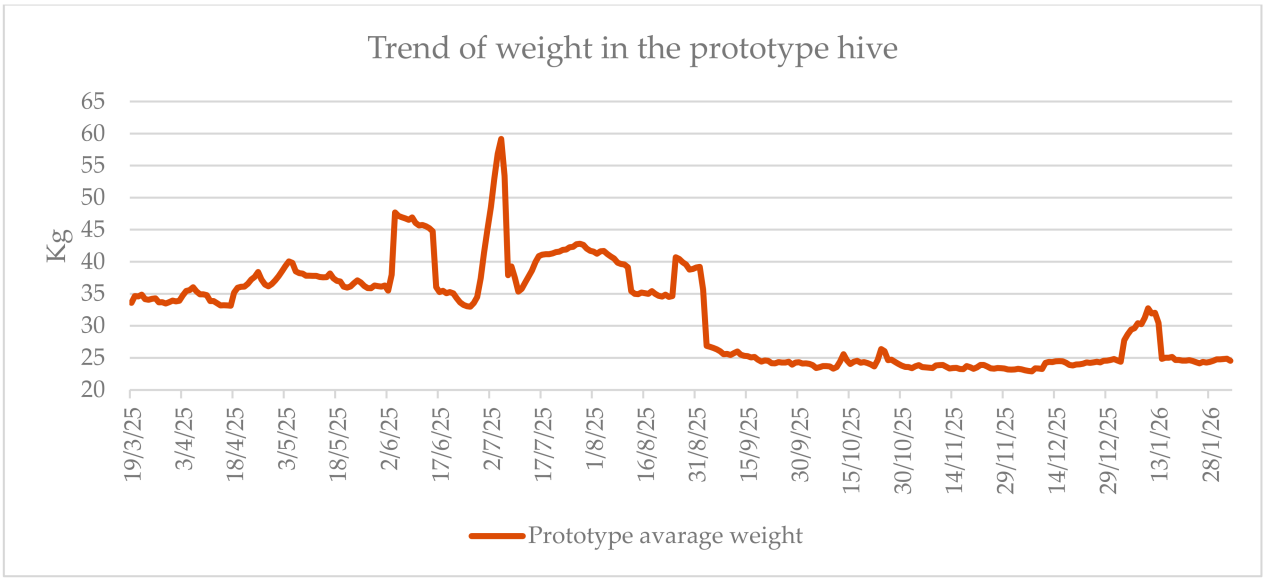


Figure 6. Trend of weight variation during the monitoring period in the prototype hive.

Figures 7 and 8 provide a side-by-side comparison of the weight fluctuations observed in a commercial hive and a prototype hive over the same one-month monitoring period in early 2026. This time window was specifically selected because colony activity was minimal, thereby reducing biologically driven fluctuations and allowing a more interpretable comparison of short-term sensor responses. During the active spring and summer periods, the unique foraging patterns and biological behaviors of individual colonies introduce unpredictable weight fluctuations, which would obscure the direct comparison of the two monitoring systems.

Comparing the two charts reveals a synchronized behavior between the commercial and prototype hives throughout the monitored period.

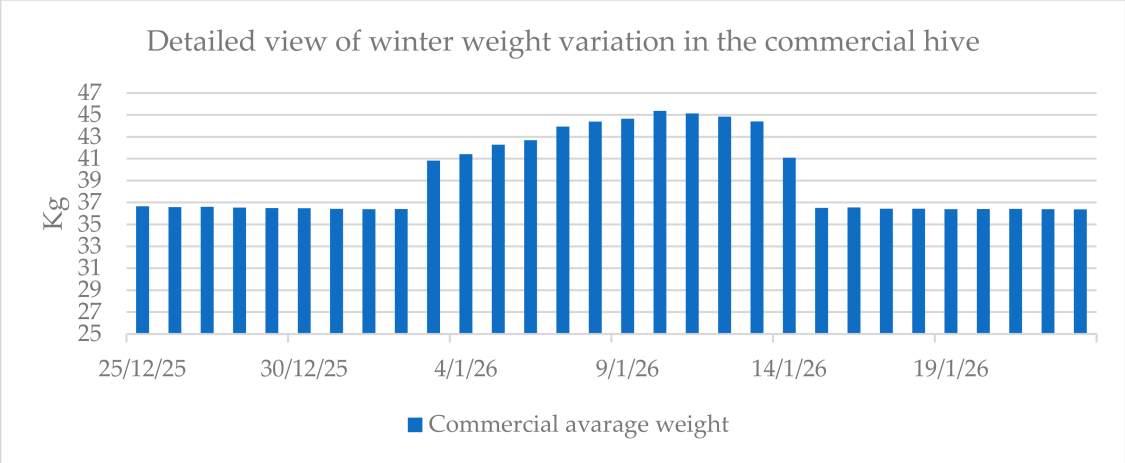


Figure 7. Detailed view of the winter weight variation in the commercial hive during the selected winter period.

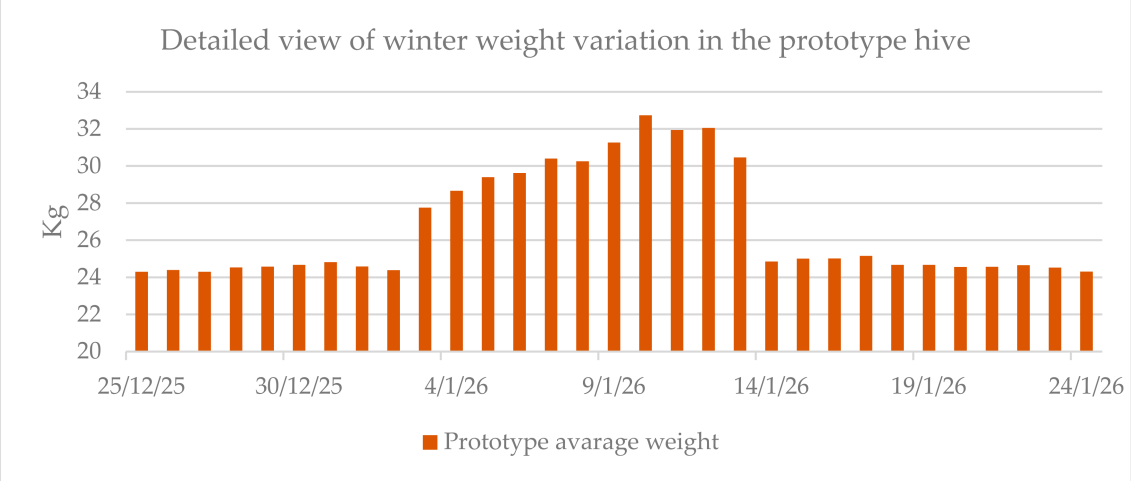


Figure 8. Detailed view of the winter weight variation in the prototype hive during the selected winter period.

Below, a scatter plot (Figure 9) providing a visual representation of the Pearson correlation analysis is shown, while Table 1 shows the statistical coefficients and the absolute numerical deviations between the commercial reference system and the prototype for winter weight comparison.

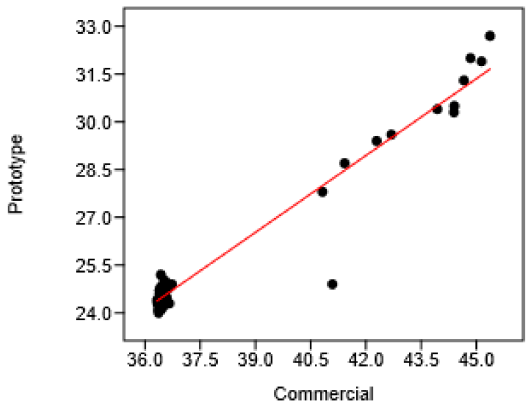


Figure 9. Bivariate scatter plot comparing winter weight data of the commercial reference hive against the prototype.

Table 1. Statistical indices comparing the weight monitoring performance of the commercial reference and the prototype during different time intervals.

	1 Year	Spring–Summer	Spring	Summer	Fall	Winter
r	0.65	0.47	0.69	0.65	0.3	**0.97**
R^2	0.44	0.22	0.48	0.42	0.09	**0.94**
RMSE	**3.26**	18.90	6.00	26.10	12.12	12.38
MAE	**2.86**	14.10	4.90	23.40	12.09	12.35

The analysis focused on this winter period shows that the two weighing platforms are highly synchronized in tracking the temporal dynamics of the hives. This is further supported by the statistical indices reported in Table 1, where winter exhibits the highest correlation coefficient (r = 0.97) and coefficient of determination (R^2 = 0.94), confirming that both systems accurately capture the same weight dynamics under these conditions. On the other hand, considerably lower correlations are observed across the other seasons, with r values ranging from 0.30 (fall) to 0.69 (spring). Under such conditions, direct comparison and correlation between the prototype and reference system are not reliable, as biological variability can obscure measurement consistency.

The MAE and RMSE values indicate the presence of a systematic offset between the two datasets across all periods. This discrepancy can be attributed to differences in initial conditions, particularly the total hive mass at the start of measurements, which depends on varying amounts of food reserves and colony biomass rather than measurement inaccuracy.

3.2. Comparative Analysis on Thermal Dynamics

The thermal monitoring performance of the ProTechBee prototype was evaluated against the Melixa commercial system over a one-year experimental period. To ensure graphical clarity and avoid data overlap, the representations for both systems do not include the full range of available sensors. Instead, the analysis focuses on three specific probes: the central probe (T3), located within the core of the brood nest (or the winter cluster), and the two most external probes (T1 and T5). This selection provides a representative cross-section of the hive's thermal gradient, capturing both the maximum metabolic heat production at the center and the influence of ambient environmental conditions at the periphery (Figures 10 and 11).

During the peak foraging season, from March to August, both digital systems identified stable brood-area temperatures, with internal measurements generally remaining within the 30–35 °C range. In January 2026, when mean ambient temperatures approached −5 °C, the central probe remained consistently warmer than the peripheral probes, reflecting the thermal buffering effect of the winter cluster. In the Melixa system, the selected probes showed strong convergence during the coldest period, suggesting a stable and coherent thermal response. The ProTechBee prototype recorded a similar seasonal decline, although the peripheral probes exhibited greater short-term variability. In particular, probe T1 maintained a slightly higher thermal profile during late winter, which may indicate closer proximity to the surviving winter cluster.

Figure 12 depicts scatter plots that provide a visual representation of the Pearson correlation analysis (Figure 12), while Tables 2 and 3 show the statistical coefficients and the absolute numerical deviations between the commercial reference system and the prototype for the thermal probes (T1, T3, and T5) analyzed individually.

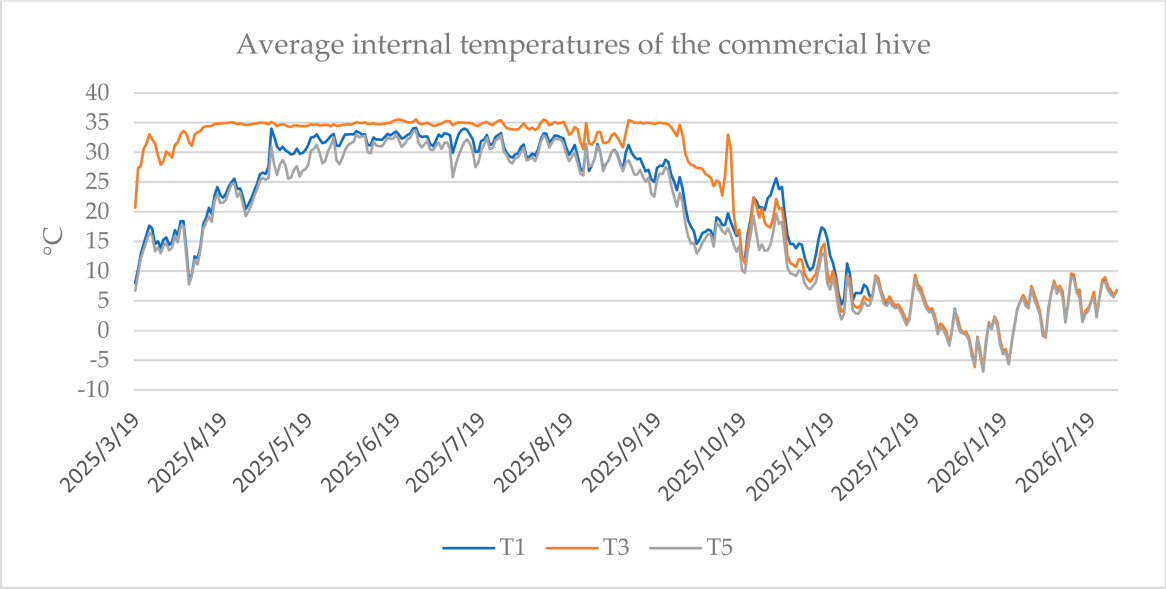


Figure 10. Trend of temperature during the monitoring period in the prototype hive.

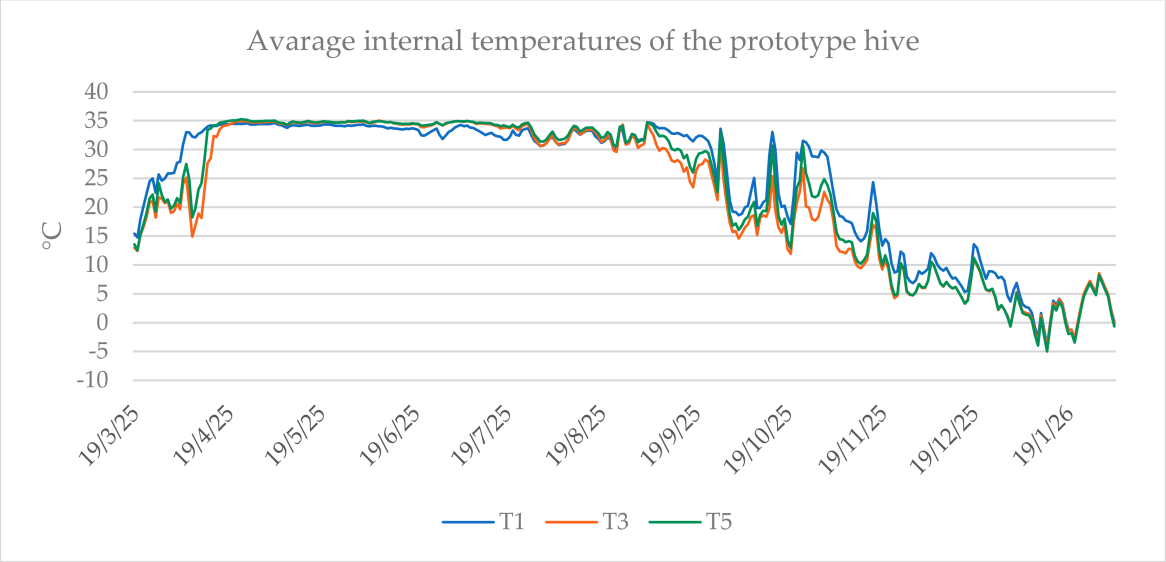


Figure 11. Trend of temperature during the monitoring period in the commercial hive.

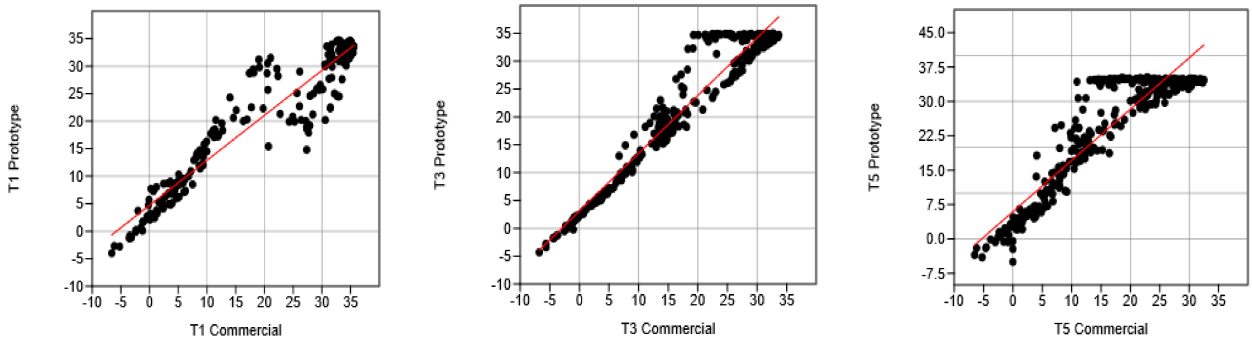


Figure 12. Bivariate scatter plots showing the relationship between temperatures measured by the commercial monitoring system (*x*-axis) and the prototype (*y*-axis) at three different spatial locations within the hives. The red line represents the regression line, illustrating the linear correlation trend. Data corresponds to the complete annual monitoring cycle.

Table 2. Statistical summary of the comparative thermal monitoring ($p < 0.001$) between the commercial hive (c) and the prototype hive (p), based on measurements from probes located at the same positions throughout different time periods.

	1-Year			**Spring–Summer**			**Spring**			**Summer**			**Fall**			**Winter**		
	T1c, T1p	T3c, T3p	T5c, T5p	T1c, T1p	T3c, T3p	T5c, T5p	T1c, T1p	T3c, T3	T5c, T5p	T1c, T1p	T3c, T3p	T5c, T5p	T1c, T1p	T3c, T3p	T5c, T5p	T1c, T1p	T3c, T3p	T5c, T5p
R	**0.96**	**0.97**	**0.914**	0.81	0.83	0.64	0.89	0.87	0.71	0.32	0.84	0.56	0.96	0.96	0.91	0.88	0.99	0.85
R^2	**0.93**	**0.94**	**0.83**	0.66	0.69	0.41	0.80	0.77	0.5	0.10	0.70	0.31	0.93	0.93	0.82	0.78	0.98	0.73
RMSE	3.9	4.8	9.3	2.6	5.8	11,1	3.0	7.6	13,8	2.2	2.9	7.5	5.9	3.0	7.0	**3.4**	**2.2**	**3.0**
MAE	2.9	3.8	7.8	1.8	4.7	9.9	1.6	6.8	12,9	2.0	2.5	6.9	5.3	2.6	6.0	**3.0**	**2.2**	**2.5**

The statistical coefficients (Table 2) indicate that, over the one-year monitoring period, the prototype closely replicates the reference system's sensitivity to hive thermal dynamics, demonstrating strong agreement in capturing internal temperature fluctuations. However, when shorter time intervals are considered, correlation values decrease. This suggests that shorter-term analyses are more affected by transient variability, reducing comparability between systems. Therefore, reliable evaluation of temperature monitoring performance is better achieved over longer time scales, where the influence of short-term fluctuations is minimized.

Analyzing the two systems holistically without distinguishing between specific probes, the Mantel test yielded a correlation coefficient of $R = 0.94$, indicating a very strong and positive linear association between the commercial hive and the prototype (Table 3). The statistical significance ($p = 0.0001$ based on 9999 permutations) allows for the rejection of the null hypothesis, confirming that the prototype faithfully replicates the thermal response of the reference system.

On the other hand, the relatively high error metrics (RMSE and MAE) reveal an absolute divergence between the datasets, reflecting the inherent lack of perfect numerical identity between two distinct biological systems.

Figures 13 and 14 show the combined graphs (weight and temperature) for both prototype and commercial hives.

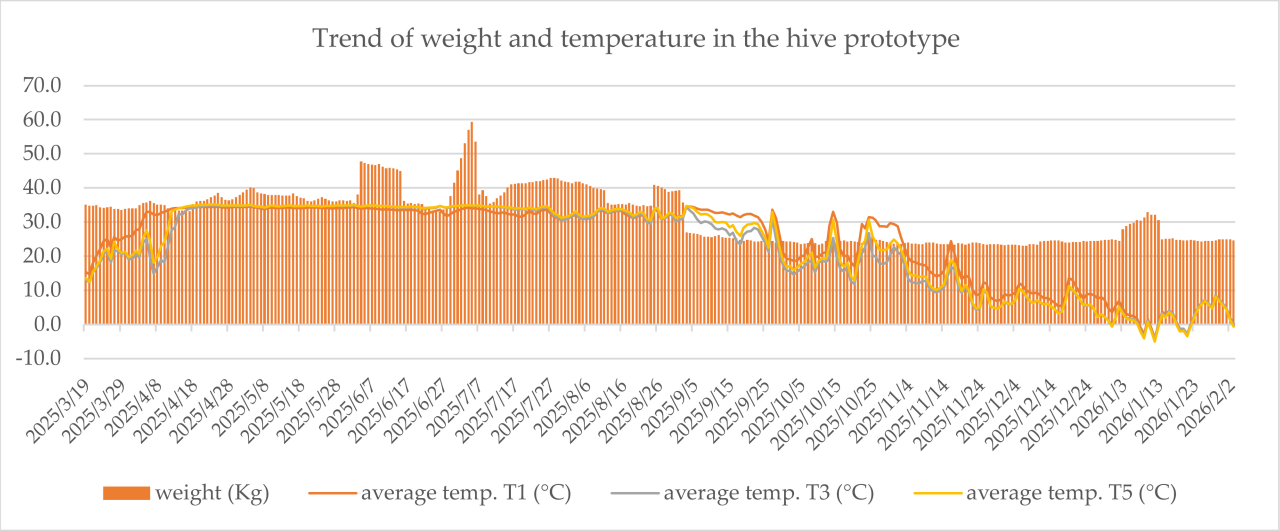


Figure 13. Combined graph of temperature and weight variation during the monitoring period in the prototype hive.

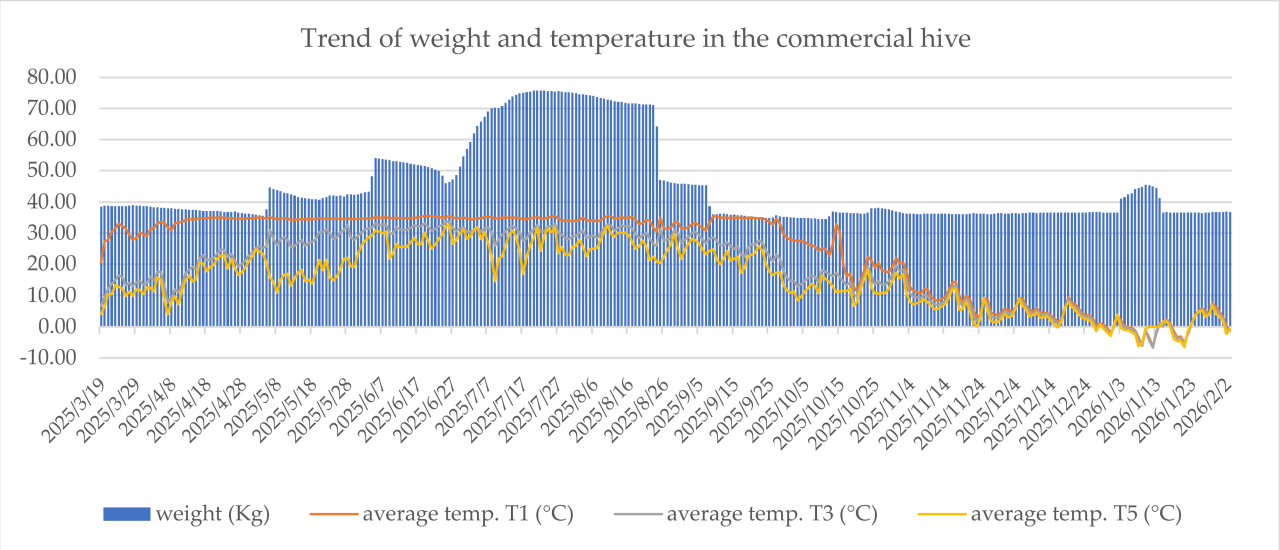


Figure 14. Combined graph of temperature and weight variation during the monitoring period in the commercial hive.

Table 3. Results of the Mantel test applied to the thermal monitoring of the two systems.

Mantel (*r*)		0.94	
p		<0.001	
RMSE	3.93	4.78	9.32
MAE	2.94	3.77	7.8

3.3. Economic Assessment

Table 4, shown below, describes the cost for realization of the digital system.

Table 4. Bill of materials for the prototype system and corresponding component cost range.

Component Category	Item Description	Cost (€) *
Processing & Connectivity	Raspberry Pi 3 Model B+ (Central Unit)	35–45
Storage	MicroSD Card (Operating System & MySQL Database)	8–12
Thermal Monitoring	5× DS18B20 Digital Sensors (Stainless Steel Probes)	16–24
Weight Measurement	4 × 20 kg Load Cells (Uniform Load Distribution)	22–28
Signal Conditioning	HX711 24-bit Analog-to-Digital Converter (ADC)	3–7
Power Supply	Main Grid Adapter	7–13
Uninterruptible Power Supply (UPS) Infrastructure	Switching Power Supply Unit, Lead–Acid Battery, DC-DC Converter, Case	70–90
Assembly & Housing	IP67 Waterproof Enclosure, Wiring, and Connectors	35–45
Range of Total Cost		196–264

* Figures were rounded to reflect current market values and eliminate decimal notation.

The average estimated budget for the system was 230 €, covering all essential components from data processing to final assembly. The primary expenses are the UPS Infrastructure and central unit, a Raspberry Pi 3 Model B+, supported by a robust power supply system featuring a main grid adapter and battery backup. For data collection, the design integrates five DS18B20 digital thermal sensors and a weight measurement kit consisting of four 20 kg load cells paired with an HX711 24-bit ADC. Rounding out the hardware are a MicroSD card for OS and MySQL database storage, and an IP67 waterproof

enclosure to ensure environmental protection. This configuration represents a cost-effective yet professional-grade solution for remote monitoring and weighing applications.

4. Discussion

The comparative monitoring was conducted over the entire year; however, specific time intervals were also analyzed to identify periods with higher correlation between the prototype and the reference system. This approach allowed us to determine when the agreement between the two systems is maximized and, consequently, to identify the most suitable periods for reliable comparison.

Regarding weight monitoring, both systems were able to document abrupt weight drops associated with maintenance and harvesting operations, which supports the robustness of the data acquisition chain. The uninterrupted continuity of the recorded traces validates the effectiveness of the system's architecture in mitigating operational risks. By coupling the Raspberry Pi 3 B+ and MySQL database with an Uninterruptible Power Supply (UPS) and a local data-caching system, the prototype successfully prevented data loss during both power grid failures and internet outages. As identified in other studies, these measures ensured reliable data persistence throughout the experimental year, proving that the system can maintain a consistent high-resolution dataset despite the frequent connectivity and power supply disruptions typical of remote apicultural sites [22,24]. It is relevant to point out that these results confirm the operational reliability of the system, but they should be interpreted as evidence from a limited set of deployments.

The results in Figures 7 and 8 (details of a winter period) demonstrate highly synchronized performance between the two digital systems, characterized by stable baselines followed by a simultaneous weight surge between 9 and 10 January. Given that both systems return to their initial values by 14 January, these fluctuations are likely attributable to shared external factors (i.e., supplemental feeding provided by the farmer) rather than divergent honeybee colony dynamics. In support of this, by restricting the statistical weight analysis to the winter months, the influence of stochastic biological variables—such as foraging flux and swarming events—was effectively neutralized. Under these controlled conditions, the two weighing platforms demonstrated high temporal synchronicity, indicating that the prototype's structural response to resource depletion is functionally equivalent to that of the commercial reference.

Conversely, when correlations are evaluated over periods outside winter, substantially lower values are observed. This suggests that the increased biological activity characterizing spring, summer, and fall introduces variability that can obscure the intrinsic agreement between systems. Therefore, in the context of testing and validating weight sensors in apiculture, seasonal biological dynamics must be carefully considered, as they can significantly affect the apparent synchronization between measurement platforms.

For temperature monitoring, both systems demonstrate a highly synchronized thermal response, showing nearly identical tracking patterns from the onset of spring through the peak of summer, where both achieve consistent thermal equilibrium near 35 °C. Furthermore, both systems exhibit a unified decay in thermal readings as seasonal temperatures drop, confirming that the two architectures maintain reliable data collection parity throughout the transition into winter dormancy.

The overall statistical framework on temperature analysis reveals a duality in the monitoring data. On one hand, the high Pearson and Mantel correlation coefficients indicate that the prototype and the commercial system are technically synchronous. This means that the sensors respond similarly to thermal stimuli, capturing the same heating and cooling trends with high sensitivity. Notably, unlike the weight analysis, the highest and most stable correlations are observed when considering the full annual dataset. This indicates that

temperature monitoring benefits from long-term integration, where transient fluctuations are smoothed and system agreement becomes more evident. These findings suggest that, in the context of apicultural sensor validation, temperature monitoring systems should be evaluated over extended time periods. Long-term datasets are essential to reliably assess sensor performance and inter-system synchronicity, as they reduce the influence of short-term colony thermoregulation dynamics and provide a more robust representation of the systems' operational consistency within the hive environment.

Moreover, the relatively high values of RMSE and MAE (particularly for T5) indicate a significant absolute temperature gap between the two monitored environments. In a controlled laboratory setting, such differences might suggest calibration issues; however, in in vivo apiary conditions, they may reflect biological and micro-environmental variability between individual hives. Given the limited number of monitored colonies, this interpretation should be considered preliminary and warrants further investigation through replicated measurements.

The total cost for the construction of the digital beehive prototype amounted to approximately 230 euros. This figure reflects the cumulative expense of all functional subsystems, including processing units, sensing hardware, and the housing components. The weight measurement and processing and connectivity modules represented the most significant portions of the budget, while the decision to utilize a domestic grid power supply helped maintain a low cost profile by avoiding the need for expensive high-capacity batteries and solar controllers.

When compared to the current market landscape, this result underscores a significant economic advantage. While specific prices for commercial digital hives vary depending on the manufacturer, they consistently exhibit significantly higher costs. The low-cost nature of the solution makes it a viable option for small-scale beekeepers or research projects that require the deployment of multiple units on a limited budget.

Overall, the results of this study should be interpreted not as a definitive validation of the system's performance across diverse conditions, but as a field-level proof-of-concept demonstrating the feasibility and operational reliability of a low-cost, open-source monitoring architecture. In this respect, the main contribution lies in the adoption of a context-aware validation strategy, where system performance is assessed as a function of the biological state of the colony. More specifically, the analysis revealed contrasting behaviors between weight and temperature measurements. In the case of weight sensors, the high correlation observed during winter is primarily driven by the biological stability of the colony in this period. Reduced activity minimizes stochastic fluctuations, allowing a clear and robust comparison between systems. Conversely, during the rest of the year—or when considering the full annual dataset—correlation becomes weak and less meaningful, as intensified biological dynamics introduce variability that can obscure system agreement and potentially mislead comparisons.

In contrast, temperature monitoring exhibits the opposite trend. Here, longer monitoring periods result in stronger correlations between the two systems, indicating that reliable validation for this parameter requires extended temporal scales. This suggests that, for hive temperature assessment, long-term data integration is essential to capture consistent system behavior and to properly evaluate sensor performance and synchronicity.

In our case, the findings support the hypothesis that low-cost, open-source monitoring systems, when coupled with appropriate validation methodologies, can provide scientifically reliable insights into hive dynamics. This has important implications not only for the accessibility of precision apiculture technologies but also for the reproducibility and scalability of data-driven approaches in the sector.

4.1. System Limitations

The ProTechBee system represents a low-cost solution developed to support the ongoing digitalization of apiculture. However, its current architecture—particularly its dependence on grid power and domestic Wi-Fi connectivity—introduces both operational and scalability limitations. Although risk mitigation measures were implemented, such as the integration of a small Uninterruptible Power Supply (UPS) and a local data-caching system to prevent data loss during internet outages, the use of a microcomputer powered directly by the grid significantly limits system scalability.

This configuration confines the apiary to the immediate vicinity of residential buildings, effectively excluding applications in migratory beekeeping or monitoring in remote natural reserves, where colonies impacted by climate change are often most vulnerable. In contrast, the Melixa system integrates a solar panel for energy supply and a SIM card for web connectivity and data transmission, enabling installation in off-grid locations.

Furthermore, although the Raspberry Pi 3 Model B+ offers high computational power and ease of programming, we observed that the lack of a native deep-sleep state and its high idle current draw make it ill-suited for prolonged field deployment.

Although the study was conducted on a single hive per monitoring system and limited to one season, this constraint is not considered critical, as the primary objective was to assess system functionality, performance, and reliability. Under these conditions, the data obtained are sufficiently robust to support our conclusions.

4.2. Future Directions

To evolve this prototype into a resilient, next-generation tool, future iterations should prioritize a transition toward ultra-low-power microcontrollers, such as the ESP32 or STM32. These devices require only a fraction of the energy consumed by the Raspberry Pi and offer deep-sleep modes that could enable long-term autonomous operation using a small solar panel and a $LiFePO_4$ battery, finally untethering the apiary from the electrical grid. Connectivity should ideally transition from domestic Wi-Fi to LoRaWAN, a protocol particularly suited to agricultural IoT applications because it enables long-range, low-power data transmission. This protocol is specifically designed for agricultural IoT, offering the capacity to transmit data over several kilometers through dense vegetation and hive walls with minimal energy expenditure. By bypassing domestic infrastructure, the system would achieve the robustness required for professional apiculture. Future work will focus on expanding the experimental design to include a larger number of colonies, including the deployment of a higher-density network of temperature sensors to enable spatial mapping of the winter cluster dynamics, providing additional insights into colony behavior. In parallel, the developed hardware platform will be leveraged to design, implement, and quantitatively evaluate targeted interventions in bee colonies (e.g., feeding strategies, thermal regulation, or health treatments), enabling data-driven assessment of colony responses under controlled conditions.

5. Conclusions

In summary, this study presented a low-cost, customizable honeybee hive monitoring system based on Raspberry Pi and evaluated its performance through a one-year comparison with a commercial reference station. The results highlighted the importance of adopting a context-aware validation approach, explicitly accounting for the biological state of the colony. For weight measurements, system agreement was strongly dependent on seasonal biological dynamics. A high correlation was achieved during the winter period, when reduced colony activity ensured stable conditions and minimized variability. In contrast, correlations during the rest of the year or over the full annual dataset were substantially

lower and less informative, as intense biological activity introduced fluctuations that can obscure true measurement consistency and potentially mislead system comparisons. Conversely, temperature monitoring showed an opposite behavior. The strongest correlations between the prototype and the commercial system emerged when considering long-term datasets, indicating that reliable validation of hive temperature sensors requires extended monitoring periods. This reflects the more integrative nature of thermal dynamics within the colony, where long-term trends better capture system synchronicity.

Overall, rather than providing a universal validation across all conditions, this work demonstrates the feasibility and operational reliability of a low-cost, open-source architecture for apicultural monitoring. By reducing economic barriers to continuous data collection, the proposed system can support wider adoption of non-invasive monitoring tools, enabling improved assessment of colony status and contributing to honeybee health management and ecosystem resilience.

Author Contributions: Conceptualization, E.R., S.B., A.F., S.F. and S.V.; methodology, A.S. and S.B.; software, E.R., S.F., A.F. and S.V.; formal analysis, A.S., Z.S. and K.K.; investigation, A.S. and M.M.K.; resources, A.S.; data curation, R.C., A.S., M.M.K., Z.S. and K.K.; writing—original draft preparation, A.S.; writing—review and editing, S.B., M.M.K. and A.S.; project administration, A.S. and M.M.K.; funding acquisition, A.S. and M.M.K. All authors have read and agreed to the published version of the manuscript.

Funding: The work has been funded by the ProTechBee project. This project is part of the Know-how Exchange Programme (KEP) and received funding from the CEI fund at EBRD under Grant agreement n. 304.4.2023.004. This project is also financed with a contribution from the Ministry of Foreign Affairs and International Cooperation of the Italian Republic.

Data Availability Statement: The data presented in this study are available on request from the corresponding author (data are part of an ongoing study).

Acknowledgments: We thank the host family Bugarski for accommodating the experimental hives and for their valuable support in hive management during the monitoring period.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Rahimi, E.; Jung, C. Global trends in climate suitability of bees: Ups and downs in a warming world. *Insects* **2024**, *15*, 127. [CrossRef]
2. Liu, Q.; Fu, C.; Xu, Z.; Ding, A. Global warming intensifies extreme day-to-day temperature changes in mid–low latitudes. *Nat. Clim. Change* **2026**, *16*, 69–76. [CrossRef]
3. Jawad, S.; Thirthar, A.A.; Nisar, K.S. The impact of climate change on flowering plants–bees–Vespa orientalis model. *Results Control Optim.* **2025**, *20*, 100583. [CrossRef]
4. Huang, S.; Jiang, F.; Dong, Q.; Yu, J.; Fan, K.; Wang, Z.; Hao, S.; Qiao, Y. The impact of climate change induced extreme weather events on microbial dynamics and public health: An in-depth review on water quality and ecosystem resilience. *Front. Environ. Sci.* **2025**, *13*, 1674490. [CrossRef]
5. Quaresma, A.; Baveco, J.M.; Brodschneider, R.; Buddendorf, W.B.; Carreck, N.L.; Gratzer, K.; Hatjina, F.; Kilpinen, O.; Roessink, I.; Vejsnaes, F.; et al. Honey bee food resources under threat from climate change. *Nat. Commun.* **2026**, *17*, 1331. [CrossRef] [PubMed]
6. Landaverde, R.; Rodriguez, M.T.; Parrella, J.A. Honey production and climate change: Beekeepers' perceptions, farm adaptation strategies, and information needs. *Insects* **2023**, *14*, 493. [CrossRef]
7. Takkis, K.; Tscheulin, T.; Petanidou, T. Differential effects of climate warming on the nectar secretion of early- and late-flowering Mediterranean plants. *Front. Plant Sci.* **2018**, *9*, 874. [CrossRef] [PubMed]
8. Frigero, M.L.P.; Boaro, C.S.F.; Galetto, L.; Tunes, P.; Guimarães, E. Extreme events induced by climate change alter nectar offer to pollinators in cross pollination-dependent crops. *Sci. Rep.* **2025**, *15*, 10852. [CrossRef] [PubMed]
9. Furtak, K.; Wolińska, A. The impact of extreme weather events as a consequence of climate change on soil moisture and on the quality of the soil environment and agriculture—A review. *Catena* **2023**, *231*, 107378. [CrossRef]

10. Bergonzoli, S.; Romano, E.; Beni, C.; Latterini, F.; Lo Scalzo, R.; Scarfone, A. Nectar dynamics and pollinators preference in sunflower. *Insects* **2022**, *13*, 717. [CrossRef]
11. Salinitro, M.; Alessandrini, A.; Zappi, A.; Tassoni, A. Impact of climate change and urban development on the flora of a southern European city: Analysis of biodiversity change over a 120-year period. *Sci. Rep.* **2019**, *9*, 9464. [CrossRef] [PubMed]
12. Niu, S.; Luo, Y.; Li, D.; Cao, S.; Xia, J.; Li, J.; Smith, M.D. Plant growth and mortality under climatic extremes: An overview. *Environ. Exp. Bot.* **2014**, *98*, 13–19. [CrossRef]
13. Gajardo-Rojas, M.; Muñoz, A.A.; Barichivich, J.; Klock-Barría, K.; Gayo, E.M.; E Fontúrbel, F.; Olea, M.; Lucas, C.M.; Veas, C. Declining honey production and beekeeper adaptation to climate change in Chile. *Prog. Phys. Geogr. Earth Environ.* **2022**, *46*, 737–756. [CrossRef]
14. Scutaru, D.; Bergonzoli, S.; Costa, C.; Violino, S.; Costa, C.; Albertazzi, S.; Capano, V.; Kostić, M.M.; Scarfone, A. An AI-based digital scanner for Varroa destructor detection in beekeeping. *Insects* **2025**, *16*, 75. [CrossRef]
15. Lee, H.G.; Kim, M.-J.; Kim, S.-B.; Lee, S.; Lee, H.; Sin, J.Y.; Mo, C. Identifying an image-processing method for detection of bee mite in honey bee based on keypoint analysis. *Agriculture* **2023**, *13*, 1511. [CrossRef]
16. Sevïn, S.; Tutun, H.; Mutlu, S. Detection of varroa mites from honey bee hives by smart technology VARGOR: A hive monitoring and image processing device. *Turk. J. Vet. Anim. Sci.* **2021**, *45*, 487–491. [CrossRef]
17. König, A. IndusBee 4.0–integrated intelligent sensory systems for advanced bee hive instrumentation and hive keepers' assistance systems. *Sens. Transducers* **2019**, *237*, 109–121.
18. Voudiotis, G.; Moraiti, A.; Kontogiannis, S. Deep Learning Beehive Monitoring System for Early Detection of the Varroa Mite. *Signals* **2022**, *3*, 506–523. [CrossRef]
19. Kontogiannis, S. Beehive smart detector device for the detection of critical conditions that utilize edge device computations and deep learning inferences. *Sensors* **2024**, *24*, 5444. [CrossRef]
20. Rathore, N.; Agrawal, D. Automated precision beekeeping for accessing bee brood development and behaviour using deep CNN. *Bull. Èntomol. Res.* **2024**, *114*, 77–87. [CrossRef] [PubMed]
21. Catania, P.; Vallone, M. Application of a precision apiculture system to monitor honey daily production. *Sensors* **2020**, *20*, 2012. [CrossRef]
22. Kurdin, I.; Kurdina, A. Internet of Things smart beehive network: Homogeneous data, modeling, and forecasting the honey robbing phenomenon. *Inventions* **2025**, *10*, 23. [CrossRef]
23. Zaman, A.; Dorin, A. A framework for better sensor-based beehive health monitoring. *Comput. Electron. Agric.* **2023**, *210*, 107906. [CrossRef]
24. Hunor, B.; Bodor, Z.; Keresztesi, Á.; Gârbacea, G.; György, D.; Monica, M.; Laslo, L.; Boboc, M.; Elena, H.; Szép, R. Advances in Beehive Monitoring Systems: Low-Cost Integrating Sensor Technology for Improved Apiculture Management. *E3S Web Conf.* **2024**, *589*, 04001. [CrossRef]

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