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Research Paper

Predicting internal conditions of beehives using precision beekeeping

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Precision beekeeping combines technology and statistics aimed at managing an apiary effectively and reducing the risk of situations that can lead to bee population losses. Databases of the we4bee project of three sensorised beehives were considered for analysis. They contain interior sensor data (temperature, relative humidity, and weight) and data of meteorological events. Static and dynamic vector autoregressive models and linear and nonlinear regression models were constructed to predict the hives' internal variables. They were compared by 100-fold cross-validation adapted for time series. In general, the dynamic vector autoregressive model provided the best predictions, with a feasible computational cost. Only in some specific cases did the static vector autoregressive version produces smaller errors, although the differences were not statistically significant. Generalised additive and dynamic linear models always provided less accurate results than the dynamic vector autoregressive model. There is a need of integrating accurate predictive models, such as the dynamic vector autoregressive one. This predictive model can be integrated into a decision support system to alert the beekeeper of out-of-the-ordinary situations in the hives, and thus aid in their efficient management.

1. Introduction

Beekeeping is an important productive branch of agriculture dedicated to the breeding and maintenance of bees, with the harvesting of different products such as beeswax, propolis, royal jelly, and, above all, honey. In addition, bees play a fundamental environmental role. Being able to transport large quantities of pollen, they are one of the world's main pollinators, facilitating plant reproduction and therefore the production of fruits, nuts, and oils (Patel et al., 2021). Currently, bee colonies are faced with various challenges such as climate change, pesticides, and land uses that affect their growth, reproduction, and sustainability (LeBuhn & Vargas Luna, 2021). The loss of bee colonies is a serious problem leading to reductions not only in the production and quality of honey but also in the pollination service bees provide to ecosystems, with the consequent greater difficulty in maintaining native plants. The assessment report on pollinators, pollination, and food production warned that 37% of European bee populations were declining (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, 2016). The most important losses of honey bee colonies occur during hibernation, causing losses of up to 30% in some European countries (Hristov et al., 2020), and between 8% and 30% worldwide

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(Stara et al., 2019). The report entitled '*The importance of bees and other pollinators for food and agriculture*' warned that bees and other pollinators are under threat, putting at 40% the total proportion of invertebrate pollinator species, especially bees and butterflies, that are at risk of extinction worldwide (Food and Agriculture Organization of the United Nations, 2018). There are also economic consequences since the production of fruits and seeds of many plant species is directly related to bee pollination (Rollin & Garibaldi, 2019).

Precision beekeeping emerged in response to the need to manage beekeeping in an optimal way. It incorporates technology and statistical methods to assist beekeepers in understanding what is happening inside their hives without opening them up and, hence disturbing the colony. The incorporation of sensors into the hives and processing the data they provide gives the beekeeper real-time information about the state of the hives based on the relevant variables without the need to travel to them. This facilitates decision making and minimises the consumption of resources and stress in the colony. Kviesis et al. (2020), for example, applied fuzzy logic decision rules to parameters related to the internal and external temperature of the hive and the season (spring, summer, autumn, or winter) to determine its health status (normal, extreme, or death). Data obtained from recordings of sounds emitted by bees has been used to detect their health status or different events that may take place in the hive, e.g., swarming, hornet attack, or varroa mite infection (Terenzi et al. (2020) reviewed the state of the art of these approaches). Ramsey et al. (2020) studied bee vibrations to detect swarming events. Video monitoring systems have also been used to estimate traffic in and out of the hive and to detect swarming events or varroa mite infection (Tashakkori et al., 2021). Semiconductor gas-sensors can also provide relevant information about the health status of a beehive. Szczurek et al. (2019), for instance, used different kinds of semiconductor gas-sensors to find a direct relationship with the varroa infestation rate of bee colonies.

Although there are sufficient technical resources and hardware for the practical application of precision beekeeping, the market penetration of decision support systems based on sensor data is still very low. The main reason is uncertainly about the economic benefit that using these systems could provide.

There are today several projects incorporating sensor technology into different hives, but most have stayed at a stage of descriptive analysis of the information recorded, using it as a tool for the beekeeper to know the state of the hive at a specific time (Ochoa et al., 2019). In particular, there has been more research on the acquisition of sensor data and its real-time analysis than on the application of robust statistical methods for prediction purposes (Zacepins et al., 2015). The descriptive uses have not had the sufficient impact to produce any real transformation of the sector.

The main focus of most of the studies that have applied statistical methods to sensor data in this context has been on classifying the hive into different classes of health status (Braga et al., 2020), on detecting diseases such as varroa (Szczurek et al., 2019), or on identifying specific events in the hive such as swarming (Davidson et al., 2020). None of them have sought to make predictions. Even though predictive models could be used to anticipate possible changes in the health of the hives, there lack studies in the scientific literature which address this problem. Temperature and relative humidity have been used as indicators of possible changes in hives. Braga et al. (2021) applied neural networks to internal and external temperature, internal humidity, mean fanning, mean colony noise, and weight features in order to make 2-, 10-, and 24-h predictions of the internal temperature. To the best of the authors' knowledge, there have been no other prediction-based studies conducted in this context.

The aim of this work is to implement and compare various predictive models using beekeeping sensor data to forecast the internal temperature and relative humidity of a hive as well as its weight. To this end, endogenous (temperature, relative humidity, and weight) and exogenous (the weather conditions to which the hive is exposed) variables are considered. Using these data, a model comparison is performed, taking into account the goodness-of-fit and the computation time as well as the quality of the predictions in a cross-validation framework. Predictions are made at 1, 3, and 7 days so that the beekeeper has enough time to anticipate and move in response to the different events that may occur, for example, to identify significant weight reductions, loss of thermoregulation or large humidity variations that could endanger the health of the hive. They could also help to detect favourable scenarios for the appearance of some diseases, such as varroa, which are more frequent in certain temperature and relative humidity ranges. The highest reproduction rate of varroa occurs in the temperature range of 32.5 °C–34.5 °C, with no broods being found at temperatures below 31.5 °C. Also, the optimal relative humidity range for the reproduction of this disease is between 55% and 70%, with only limited reproduction taking place when the relative humidity is higher (Nazzi & Le Conte, 2016).

The rest of this article is organised as follows. Section 2 describes the motivating problem and the databases used. Section 3 presents the predictive models, and section 4 the results. Section 5 discusses the results, and finally section 6 presents the conclusions to be drawn from the study.

2. Motivating problem

Artificial intelligence can be applied to a broad set of relevant variables obtained from sensors located in the hives in order to predict their health status in a massive data analysis environment. Accurate predictive models involving low computation cost must be integrated into decision support systems specifically designed and implemented for this context. The predictive model would allow the anticipation of different events in the hives.

This work uses data from three beehives of the we4bee project (https://we4bee.org/) fitted with sensors. The we4bee project has Kenya top bar hives, mainly located in schools and educational institutions in Germany, with the aim of raising awareness of bees and their importance to the ecosystem. The hives are made of solid spruce wood and designed for minimally invasive beekeeping rather than prioritising production. Their approximate weight is 25 kg. They could harbour up to about 30,000 bees and were constructed as a flatter and smaller alternative to the typical beehive used for honey production. A decisive advantage of the low overall height lies in the simpler handling of the honeycomb and reduced honeycomb breakage, which makes handling easier. The bees belong to the *Apis mellifera* species. Two of these hives are located in the Bavarian region of southern Germany, and the other one, is located in the North Rhine-Westphalia region of north-west Germany. The first, located in Markt Indersdorf, has data from 1 July 2019 to 14 April 2021. The second, located in Vohburg an der Donau, has data from 17 July 2019 to 4 April 2021, and was later moved to a different location. The third, located in Waltrop, has data from 1 May 2020 to 21 February 2022. The sensors provide information about internal hive variables: temperature (°C), relative humidity (%), and weight (kg). It is important to note that the sensor recording the internal temperature and relative humidity is fixed to the frame of the hive, so the external temperature has a strong influence on the corresponding measurements. Figure 1 shows the recorded internal variables of the three hives analysed for their whole-time range considered. Despite the large variability, the three hives show similar behaviour patterns. Sensors also register the external weather conditions: temperature, humidity, rainfall (ml), wind speed (m s^{-1}), air pressure (hPa), particulate matter ($\mu g\ m^{-3}$), and brightness (lx). Data from all the sensors were stored five times a day at equally spaced time intervals, and were appropriately curated to remove wrong data.

On the one hand, temperature, relative humidity, and weight are variables of great interest to the beekeeper, so they are present in most studies on sensorized hives. On the other, hives are clearly influenced by external weather conditions (Flores et al., 2019), which justifies the relevance of using the variables considered as exogenous in this study.

Exogenous variables can be obtained in two ways: by sensing at the hive itself (the case of the present study) or by extracting the information provided by climatological models since they provide high quality predictions of variables outside the hive. Moreover, sensor data for exogenous variables could be replaced by meteorological data if external sensors are unavailable; the possibility of eliminating external sensors would reduce the costs of fitting sensors to the hive.

Another source of information of great interest is the monitoring of actions that the beekeeper performs on the hive, such as feeding, harvesting, application of treatments against diseases or observation of swarming events, among others. Unfortunately, this information is very sparse in the hives analysed. Indeed, for the Markt Indersdorf hive there is no information available on this type of action, the Waltrop hive data only contain 7 comments on some actions carried out on the hive, while the Vohburg hive is the one with the most detailed monitoring with a total of 45 comments. The comments included by the beekeepers give information on the actions they carry out in the hive, such as feeding, application of varroa treatment, harvesting or just to check that the bees are fine. This information, although sparse, is very useful. A more detailed monitoring of the activities carried out in the hive would allow more accurate results to be obtained.

The main objective of this study was to predict the internal state of a hive, i.e., its temperature, relative humidity, and weight, in order to provide the beekeeper with relevant information about the situation of the hive so that they can anticipate the different events that could lead to a reduction in production. These predictions can be used in an early warning system for different events. For example, there is evidence that certain diseases such as varroa proliferate in cold and humid environments (Harris et al., 2004). If temperature and humidity predictions anticipate this kind of climate event, the beekeeper can be alerted that the hive is at risk of suffering from this disease. Also, it has been reported that there is a significant decrease in hive weight when bees are infected by varroa (Noël et al., 2020). Similarly, temperature and relative humidity predictions are useful to anticipate swarming as it has been shown that swarming is preceded by a decrease in both temperature and relative humidity in the hive (Catania & Vallone, 2020). After a swarming event, the daughter queen bee and about 75% of the worker bees leave the hive, which justifies the importance of anticipating this kind of event. The predictions obtained for these internal features can be useful for beekeepers to alert them to relevant changes in the hives so that they can take action if necessary.

3. Methods

This section explains the models and tools used for model fitting and forecasting the hives' internal variables. It presents the data preprocessing, the four statistical methods considered for prediction, the cross-validation technique, and the evaluation metrics used for model comparison.

3.1. *Preprocessing*

The data were preprocessed before being fed into the predictive models. On the one hand, unfeasible values due to sensor malfunction and/or data acquisition errors were removed. They were identified because they were outside the range of possible values (e.g., negative weights, negative relative humidities, non-realistic temperatures, ...). On the other hand, missing data were filled in by using the Multivariate Imputation by Chained Equations with Random Forest (MICE-Ranger) procedure. This method imputes missing data using an iterative system of predictive models (Wulff & Jeppesen, 2017).

3.2. *Models*

Let T be the time that n variables are observed, and let $\mathbf{y}_t$, $\mathbf{x}_t$, and $\mathbf{c}_t$ be the vectors corresponding to the response, predictor, and covariate variables, respectively. When a vector is univariate, it is denoted without using boldface, i.e., as y_t, x_t, and c_t.

3.2.1. *Vector autoregressive models*

A vector autoregressive model (VAR) is a generalisation of the univariate autoregressive model for predicting time series. It is one of the most efficient and flexible models for multivariate time series analysis (Zivot & Wang, 2006b).

The vector autoregressive model of order p with exogenous variables is defined as follows:

$$\mathbf{y}_t = \boldsymbol{\nu} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{C}\mathbf{c}_t + \boldsymbol{e}_t, \quad t = p+1, \ldots, T, \tag{1}$$

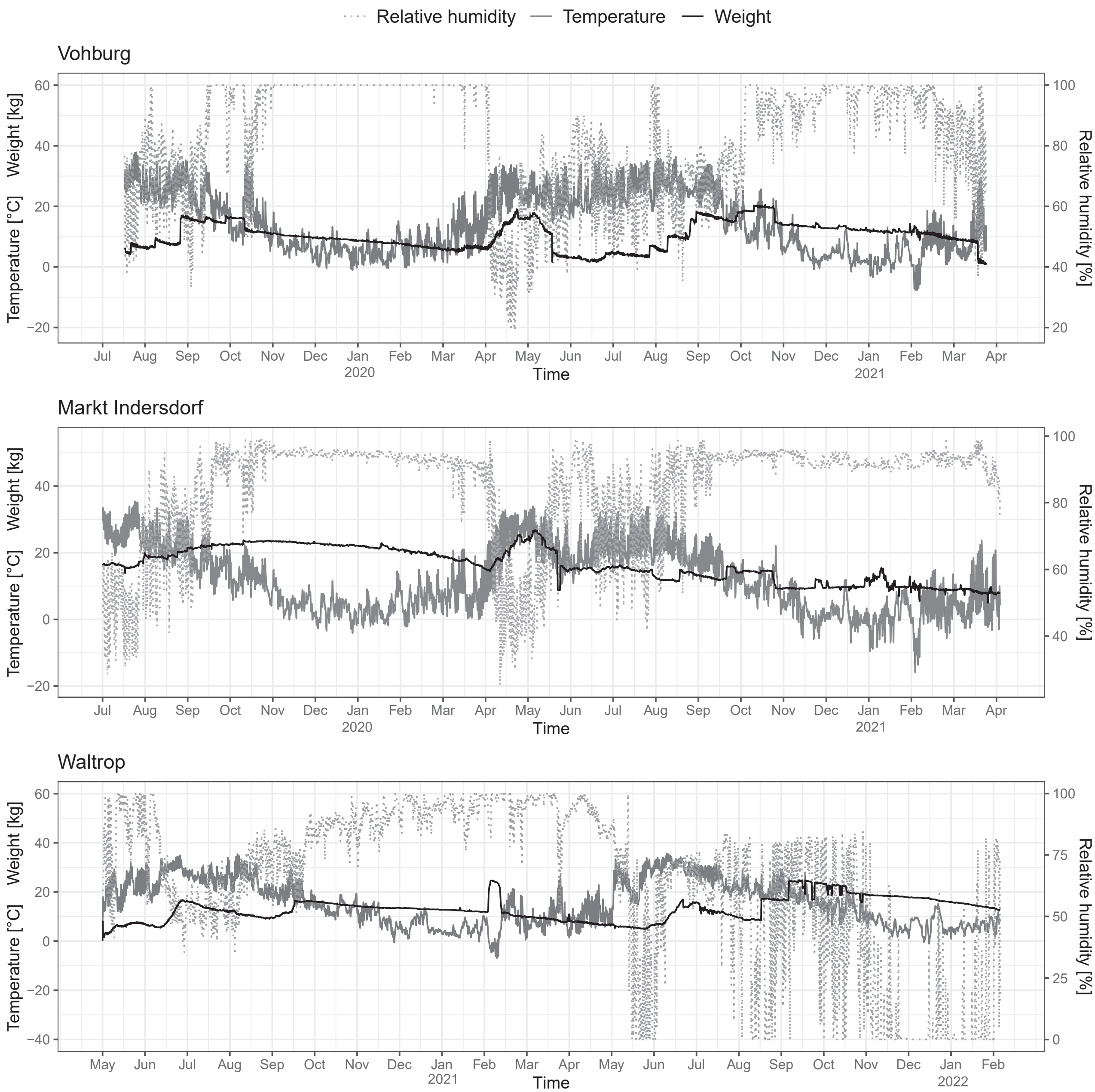

Fig. 1 – Time series of internal temperature (grey continuous line), internal relative humidity (grey dotted line), and weight (black line) of the three hives analysed: Vohburg an der Donau (top), Markt Indersdorf (centre), and Waltrop (bottom). The data were registered from July 2019 to April 2021 for the first two hives, and from May 2020 to February 2022 for the third one. Temperature and weight (continuous lines) are located on the main axis (left), and relative humidity (dotted line) on the secondary axis (right).

where $\boldsymbol{A}_1$, …, $\boldsymbol{A}_p$ are fixed coefficient matrices, $\boldsymbol{\nu}$ the vector of intercept terms, $\mathbf{C}$ the coefficient matrix of covariates, and $\boldsymbol{e}_t$ the vector error term, with $E(e_t) = 0$ and time invariant positive definite covariance matrix with $E(e_t e_t') = \sigma$ (a white noise process).

The order can be determined using different criteria such as Akaike Information (AIC), Hannan-Quinn (HQ), Schwarz (SC), or Forecast Prediction Error (FPE) (Ahmed et al., 2018).

The VAR model with dynamic coefficients or time-varying VAR model (tvVAR) is a modification which assumes that the coefficients involved in the response generating process are dynamic. The tvVAR model can be defined as:

$$\mathbf{y}_t = \boldsymbol{\nu}_t + \mathbf{A}_{1t}\mathbf{y}_{t-1} + \cdots + \mathbf{A}_{pt}\mathbf{y}_{t-p} + \mathbf{C}_t\mathbf{c}_t + \boldsymbol{\upsilon}_t, \quad t = p+1, \ldots, T, \qquad (2)$$

where, in contrast with the static model, the coefficients $\boldsymbol{\nu}_t$, $\boldsymbol{A}_{it}$, and $\mathbf{C}_t$ vary over time. The time-varying coefficients are obtained by combining the ordinary least squares (OLS) estimator and the local polynomial kernel estimator, using one bandwidth per equation automatically selected by leave-one-out cross-validation (Casas et al., 2019).

3.2.2. Dynamic linear model

The dynamic linear model (DLM) is a particular case of dynamic regression models which allows the regression coefficients to vary over time. Dynamic regression can be formulated with a state space representation, so that a DLM provides a generic framework in which to analyse time series data (Laine, 2019, pp. 139–156). The univariate DLM model is defined by:

$$\begin{aligned} y_t &= \mathbf{Z}_t \mathbf{x}_t + \nu_t + \mathbf{C}_1 \mathbf{c}_t + v_t && \text{with } v_t \sim \mathrm{N}(0, r), \\ \mathbf{x}_t &= \mathbf{B}_t \mathbf{x}_{t-1} + \boldsymbol{\eta}_t + \mathbf{C}_2 \mathbf{c}_t + \boldsymbol{u}_t && \text{with } \boldsymbol{u}_t \sim \mathrm{MVN}(0, \mathbf{Q}), \end{aligned} \tag{3}$$

where $\mathbf{Z}_t$ is the vector of regression coefficients at time t, $\mathbf{B}_t$ is the parameter evolution matrix, $\mathbf{C}_1$ and $\mathbf{C}_2$ are the matrices of covariate coefficients, and ν_t and $\boldsymbol{\eta}_t$ are parameters (scalar and vector, respectively).

3.2.3. Generalised additive model

A generalised additive model (GAM) is a variation of generalised linear models in which the response variable is given by a sum of smooth functions of at least some (and possibly all) covariates. The smooth functions can take flexible forms and allow for nonlinear relationships between the response variable and the covariates (Wood, 2017). The model is defined as:

$$y_t = \nu + f_1(c_{1t}) + \cdots + f_m(c_{mt}) + v_t, \quad t = 1, \ldots, T, \tag{4}$$

where $f_i(\cdot)$ is a smooth function of exogenous variables.

Different types of smoothing functions can be chosen depending on the data to be analysed. They are based on splines: cubic regression splines, cyclic cubic regression splines, P-splines, thin-plate regression splines, shrinkage smoothers, or tensor product splines.

3.3. Cross-validation

A cross-validation framework is considered in the temporal dimension, i.e., training and testing sets are formed considering the temporal component of the data. A rolling window approach is used (Zivot & Wang, 2006a, pp. 313–360). Rolling analysis is commonly used to back-test a statistical model on historical data in order to assess stability and predictive accuracy.

This cross-validation model works as follows: Initially, the time series is split into a training sample and a test sample. The model is then fitted using the training sample, and γ-step ahead predictions are made for the test sample and errors are calculated. Next, the training sample is rolled ahead a given increment δ, and the estimation and prediction exercise is repeated for the new data collection. This process is repeated for a fixed number of k iterations (k-fold cross-validation) or until no more γ-step predictions are possible. Once each prediction has been calculated, the error is summarised in the form of the mean absolute error (MAE). Finally, the mean and standard deviation of the MAE resulting from the k iterations are reported.

3.4. Statistical test

To study whether the MAE differences between the four models studied were statistically significant, Kruskal–Wallis tests were used, since the applicability conditions (normality and heteroskedasticity) of the one-way ANOVA could not be assumed in any case. When the Kruskal–Wallis test was statistically significant, nonparametric pairwise multiple comparisons were performed considering a family-wise Bonferroni correction. The results were considered statistically significant when the p-values were less than 0.05.

3.5. Implementation

The code necessary to run these models was written in the R programming language (R Core Team, 2020). The libraries used were the *miceRanger* package (Wilson, 2020) for missing data imputation, and the packages *vars* (Pfaff, 2008), *tvReg* (Casas & Fernández-Casal, 2019), *MARSS* (Holmes et al., 2020, pp. 219–229), and *mgcv* (Wood, 2017) to fit the VAR, tvVAR, DLM, and GAM, respectively, and to make predictions.

The experiments were carried out on a compute node with a processor Intel(R) Core(TM) i7-10700 CPU @ 2.90 GHz and 32 GB RAM.

4. Results

This section presents the experimental settings and the results of the different models for fitting, computation time, and prediction.

4.1. Experimental settings

Training series with a length of one year and four months were run, i.e., a total of $T = 2425$ values for each variable. Following Subsection 3.3, a 100-fold cross-validation was performed with a $\delta = 5$ increment and γ steps of 5, 15, and 35 for the 1-, 3-, and 7-day forecasts, respectively.

Knowledge of the external actions that the hives may have been subjected to, such as the addition of food or harvesting (among others), is relevant information, but is not included in the database. A new variable was therefore constructed, representing extreme changes in weight. To create this variable, the differences between two consecutive weights was calculated. Then, a new time series, also of length T, consisting of these differences was stored. The 2.5 and 97.5 percentiles were calculated, and all those values outside this range were considered extreme weight variations, and we assumed that they were due to external causes (feeding, harvesting, ...). This variable was useful for correcting the extreme weight variations.

The numbers of variables are $s = 3$ for the endogenous variables and $m = 8$ for the exogenous ones. The information provided by the sensors installed in the hives was used, but the data related to the exogenous variables could be easily obtainable from public meteorological databases (https://www.dwd.de/EN/).

Measurement errors were considered to have occurred when the measurements lay outside a reasonable or feasible range, i.e., when the temperature is above 43 °C, the humidity is greater than 100% or less than 0%, the weight is less than 0 kg, the rainfall is less than 0 ml or greater than 1 ml (the rain sensor does not pick up values greater than this amount), the wind speed is less than 0 m s^{-1}, or air pressure is less than

0 hPa. In all these cases, the stored values were considered to be sensor failures, and were removed and replaced by imputed values using the MICE-Ranger algorithm.

During certain time intervals, the sensors did not record any data. In order to make efficient use of the MICE ranger imputation method, we included the values of the exogenous variables for that period from meteorological data collected by a nearby hive. This was the case for the Vohburg and the Waltrop hives. The Vohburg hive had only one interval with missing data for all variables, from 27 August 2020 at 09:36 am to 5 September 2020 at 09:36 am, while the Waltrop one had six different periods with missing data for all variables. The first of these periods was the longest, running from 11 July 2021 at 09:36 am to 22 July 2021 at 04:48 am. The remaining intervals with missing data for all sensors were shorter and occurred in October and November 2021. In total, 1.53%, 0.02%, and 3.48% of the data collected by the Vohburg, Markt Indersdorf and Waltrop hive sensors, respectively, were imputed.

The VAR model adjusts for both the trend and the constant of the three response variables, whereas the tvVAR model adjusts for the constant of the three response variables and uses the local constant polynomial kernel estimator. In both models, the incorporation of seasonality did not improve the results. Finally, the AIC was used as the lag selection criterion.

In the case of the DLM model, the matrix $\mathbf{Z}_t$, which contains the information of the hive's internal variables that act as regressor variables, is a matrix with dynamic coefficients, i.e., whose values change over time. The matrices $\mathbf{C}_1$, $\mathbf{C}_2$, and $\mathbf{B}_t$ are set as unconstrained, i.e., each element of the matrix can be different from the rest. Finally, the variance-covariance matrix $\mathbf{Q}$ was set as a diagonal, unequal matrix, i.e., off-diagonal values are zero and on-diagonal values can be different.

Finally, to fit the GLM model, thin-plate regression splines, given by the negative log restricted maximum likelihood (ReML) procedure, were used for each exogenous variable individually, and a joint thin-plate regression spline for two of the covariates (external temperature and external humidity).

4.2. *Experimental results*

This subsection will describe the results for the fit, the computation time, and the prediction of the internal variables for each hive studied. Firstly, Table 1 lists the means and standard deviations of the MAE obtained in fitting the models.

The results in terms of the fits to the temperature, relative humidity, and weight time series are fairly robust regardless of the hive analysed, i.e., the errors for the three hives are relatively close within each method. The best fit is with the tvVAR, and the poorest with GAM. There is no clear difference between the VAR and DLM models, with the better of the two depending on the variable and hive analysed.

Table 2 lists the computation times for model fitting. The VAR model is the most efficient for all tree time series. It uses less than one second to fit the internal variables of the Vohburg, Markt Indersdorf, and Waltrop hives (0.29, 0.43, and 0.42 s, respectively). The two slowest methods (taking about 20 min) are tvVAR and DLM. The table's ratio column shows how much faster the VAR model is than the three others.

Considering both the goodness-of-fit (Table 1) and the computation time (Table 2) results, one can see that the VAR model achieves a good trade-off between accuracy and time. However, most (more than 95%) of the computation time used by the tvVAR model is spent in bandwidth estimation. If the bandwidth parameters were fixed, the computation time would be sharply reduced from around 20 min to less than 1 min (54.45, 36.49, and 27.8 s to fit the Vohburg, Markt Indersdorf, and Waltrop internal conditions, respectively). Note that these parameters could be updated with new data from time to time. This would make tvVAR very competitive since it would provide accurate fits at low computation cost.

The following results refer to the four models' forecasting performance. Table 3 lists the means and standard deviations of the MAE, highlighting in grey those cells that, after performing the Kruskal–Wallis tests and the pairwise comparisons, showed no significant differences with respect to the model that gave the most accurate prediction (marked in boldface).

In Table 3, it can be observed that, for temperature and relative humidity, tvVAR provides the most accurate forecasts and GAM the least accurate, while which of the other two models is better depends on the hive analysed. After applying the Kruskall–Wallis test, statistically significant differences were observed between the MAEs given by the tvVAR and GAM models in the prediction of temperature in all hives. Practically the same is the case with relative humidity, although for the Waltrop hive no significant differences were detected between the MAE given by tvVAR and GAM. The MAE values from the different models in the relative humidity predictions are greater for the Waltrop hive than for the other two. This can be explained by considering the large variability of the data provided by the relative humidity sensor in this hive, especially at the end of the time series, with fluctuations between 0% and 75% relative humidity (see Fig. 1). In analysing the weight, the poorest models in terms of forecasting accuracy are DLM (third ranked) and GAM (the worst), and VAR is the best for the Vohburg hive in general and for the Markt Indersdorf hive in the short-term (1-day) forecasts, while the tvVAR model is the best in the longer-term (3- and 7-day) forecasts for the Markt Indersdorf and the Waltrop hives. In general, the results for the VAR and tvVAR models are fairly similar, this is clearly seen in Table 3, since there are no significant differences in the MAEs made by these two models when estimating the weight.

Note that the computational time now plays no relevant role since the forecasting itself, which simply applies the best model parameters, is very straightforward computationally.

Figure 2 shows violin plots of the distribution of these errors. To compare the three hives, their corresponding plots have been superposed, shifting slightly the axes of each one so that the differences can be appreciated. The lighter plot belongs to the Vohburg hive, the medium grey colour to the Markt Indersdorf hive, and the darker one to the Waltrop hive. The plots clearly show that the MAE distributions for weight and temperature are very similar in the three hives, while those for relative humidity are dissimilar, with this also being the variable presenting the greatest dispersion in terms of forecasting errors. The GAM model is clearly the poorest performer in weight prediction, with a greater than 6 kg MAE

Table 1 – Mean (standard deviation) of the MAE obtained by the different models in their fit to the Vohburg, Markt Indersdorf and Waltrop hives' internal variables over one year and four months.

		VAR	tvVAR	DLM	GAM
Vohburg	Temperature (°C)	0.712 ± 0.661	0.565 ± 0.557	0.787 ± 0.800	1.380 ± 1.157
	R. humidity (%)	2.628 ± 2.801	2.053 ± 2.506	2.595 ± 3.230	5.864 ± 5.948
	Weight (kg)	0.097 ± 0.100	0.096 ± 0.098	0.384 ± 0.473	1.316 ± 1.276
Markt I.	Temperature (°C)	0.748 ± 0.739	0.455 ± 0.485	0.642 ± 0.686	1.519 ± 1.521
	R. humidity (%)	1.997 ± 2.440	1.359 ± 1.882	1.666 ± 2.486	5.179 ± 5.378
	Weight (kg)	0.089 ± 0.089	0.079 ± 0.078	0.265 ± 0.295	1.216 ± 1.197
Waltrop	Temperature (°C)	0.672 ± 0.780	0.463 ± 0.543	0.644 ± 0.811	1.241 ± 1.199
	R. humidity (%)	5.898 ± 7.399	4.885 ± 6.375	6.530 ± 8.481	12.368 ± 11.421
	Weight (kg)	0.059 ± 0.060	0.050 ± 0.052	0.240 ± 0.352	1.384 ± 1.471

Table 2 – Time (min) taken by each model to fit the internal variables of each hive over a period of one year and four months, and the computation time ratio relative to the fastest model.

	Vohburg		Markt Indersdorf		Waltrop	
	Time (min)	Ratio	Time (min)	Ratio	Time (min)	Ratio
VAR	< 0.01	1.00	< 0.01	1.00	< 0.01	1.00
tvVAR	23.71	4905.24	18.04	2517.51	14.24	2034.79
DLM	18.83	3895.41	18.80	2623.19	19.75	2821.12
GAM	2.29	472.24	1.49	207.51	1.66	237.71

in some cases. Figure 3 displays the forecasts for all the time points up to 7 days (the actual values are shown with dots and the different model forecasts with lines). The dates corresponding to the forecasts are 31 March to 6 April 2021 for the Vohburg hive, 8 to 14 April 2021 for the Markt Indersdorf hive, and 15 to 21 February 2022 for the Waltrop hive. The predictions of the VAR and tvVAR models are very similar at the beginning, and differ as time progresses, generally being good (especially the 1-day predictions) for all three variables analysed. Overall, the behaviour shown in Fig. 3 is in agreement with the results obtained both in model fitting and after cross-validation evaluation of the predictions.

Table 3 – Mean ± standard deviation of the MAE of the 1-, 3-, and 7-day forecasts given by the four models for the variables temperature, relative humidity, and weight of the Vohburg, Markt Indersdorf and Waltrop hives when performing 100-fold cross-validation with $\delta = 5$. Cells highlighted in grey represent the models whose MAE does not differ significantly from the best one (marked in boldface).

			VAR	tvVAR	DLM	GAM
Vohburg	Temp.	1 day	0.739 ± 0.414	**0.701 ± 0.403**	0.897 ± 0.618	1.666 ± 0.963
		3 days	0.831 ± 0.347	**0.802 ± 0.392**	1.051 ± 0.715	1.749 ± 1.080
		7 days	0.897 ± 0.309	**0.846 ± 0.314**	1.147 ± 0.825	1.888 ± 1.211
	R. hum.	1 day	3.760 ± 2.579	**3.386 ± 2.733**	4.297 ± 2.805	4.997 ± 3.348
		3 days	4.324 ± 2.179	**3.752 ± 2.212**	4.926 ± 3.587	5.246 ± 3.968
		7 days	4.959 ± 2.341	**4.349 ± 2.108**	5.608 ± 4.366	5.634 ± 4.430
	Weight	1 day	**0.168 ± 0.142**	0.184 ± 0.157	0.418 ± 0.236	0.865 ± 0.312
		3 days	**0.289 ± 0.235**	0.324 ± 0.308	0.599 ± 0.364	0.963 ± 0.453
		7 days	**0.444 ± 0.328**	0.554 ± 0.461	0.872 ± 0.512	1.134 ± 0.607
Markt Indersdorf	Temp.	1 day	0.929 ± 0.447	**0.562 ± 0.277**	0.809 ± 0.541	1.382 ± 0.836
		3 days	1.128 ± 0.453	**0.576 ± 0.217**	0.850 ± 0.588	1.448 ± 0.892
		7 days	1.426 ± 0.543	**0.588 ± 0.205**	0.870 ± 0.638	1.543 ± 0.972
	R. hum.	1 day	2.638 ± 1.506	**0.924 ± 0.564**	1.359 ± 0.865	3.726 ± 2.167
		3 days	3.881 ± 2.419	**1.108 ± 0.786**	1.740 ± 1.145	3.997 ± 2.506
		7 days	5.510 ± 3.328	**1.382 ± 1.086**	2.117 ± 1.368	4.338 ± 2.923
	Weight	1 day	**0.170 ± 0.153**	0.172 ± 0.146	0.423 ± 0.258	1.068 ± 0.492
		3 days	0.264 ± 0.240	**0.261 ± 0.202**	0.555 ± 0.351	1.131 ± 0.632
		7 days	0.413 ± 0.331	**0.381 ± 0.229**	0.684 ± 0.430	1.239 ± 0.767
Waltrop	Temp.	1 day	0.713 ± 0.452	**0.544 ± 0.364**	1.127 ± 0.734	1.050 ± 0.611
		3 days	0.922 ± 0.446	**0.692 ± 0.420**	1.850 ± 1.125	1.101 ± 0.682
		7 days	0.998 ± 0.366	**0.849 ± 0.538**	2.530 ± 1.516	1.199 ± 0.740
	R. hum.	1 day	9.745 ± 10.125	**7.039 ± 6.625**	9.559 ± 6.438	11.371 ± 5.801
		3 days	11.478 ± 10.216	**7.620 ± 5.764**	10.790 ± 8.564	12.153 ± 7.752
		7 days	13.386 ± 9.871	**7.958 ± 5.006**	11.376 ± 10.301	12.905 ± 9.441
	Weight	1 day	0.062 ± 0.041	**0.061 ± 0.038**	0.598 ± 0.341	1.806 ± 0.340
		3 days	0.114 ± 0.066	**0.101 ± 0.065**	0.957 ± 0.539	1.936 ± 0.484
		7 days	0.194 ± 0.115	**0.162 ± 0.123**	1.301 ± 0.738	2.161 ± 0.635

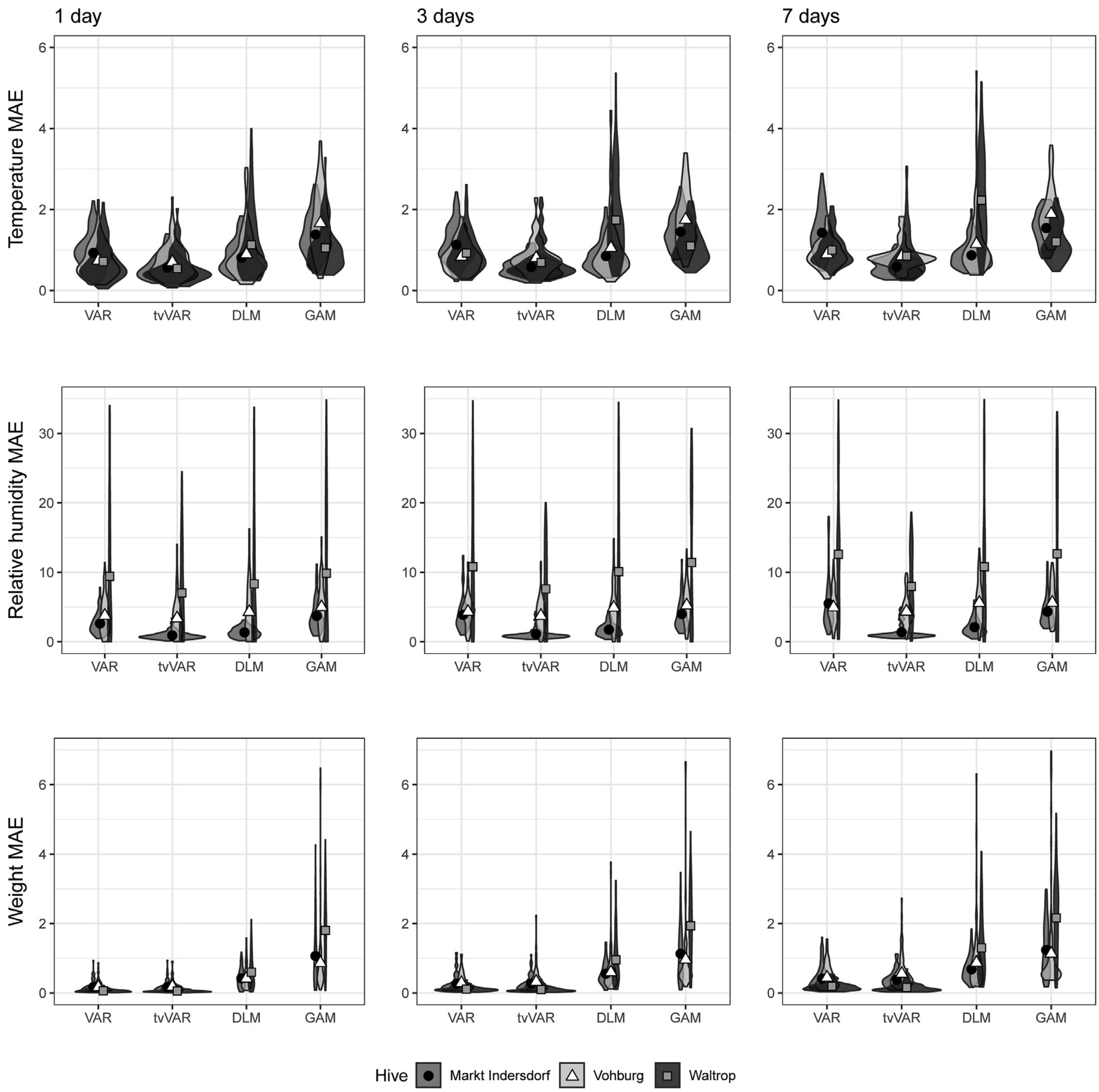

Fig. 2 – Distribution of the MAEs of the 1- (left), 3- (centre), and 7- (right) day forecasts for temperature (top), relative humidity (centre), and weight (bottom) of the Vohburg, Markt Indersdorf and Waltrop hives. The means of the MAE distributions are marked with a white triangle, a black circle or a grey square for the Vohburg, Markt Indersdorf and Waltrop hives, respectively. The vertical axes of the violins corresponding to the different hives are slightly offset from each other so that the difference between the three distributions can be better appreciated.

In general, in terms of the model fitting, computation time, and predictions given by the different models, tvVAR is the most appropriate method for this kind of data. This is supported by the Kruskal–Wallis test, whose results indicated that tvVAR is the best model or there is no significant difference between tvVAR and the best model. It was the best at model fitting and prediction, and, despite requiring more computation time, it is totally feasible since about 20 min are needed to complete the whole process if the bandwidth parameter estimates have to be included, and less than 1 min otherwise.

In order to test the effect of the number of daily measurements analysed, a study was carried out on the Markt Indersdorf hive, evaluating the results of the different models with 3, 5, 6, and 12 daily measurements. After carrying out this experiment, no clear differences were detected among the errors obtained for different numbers of measurements. The model with most statistically significant differences was tvVAR, where it can be observed that the model was most accurate for estimating temperature when 12 measurements were taken, although these differences were not so clear for relative humidity and weight. It must be borne in mind that, as

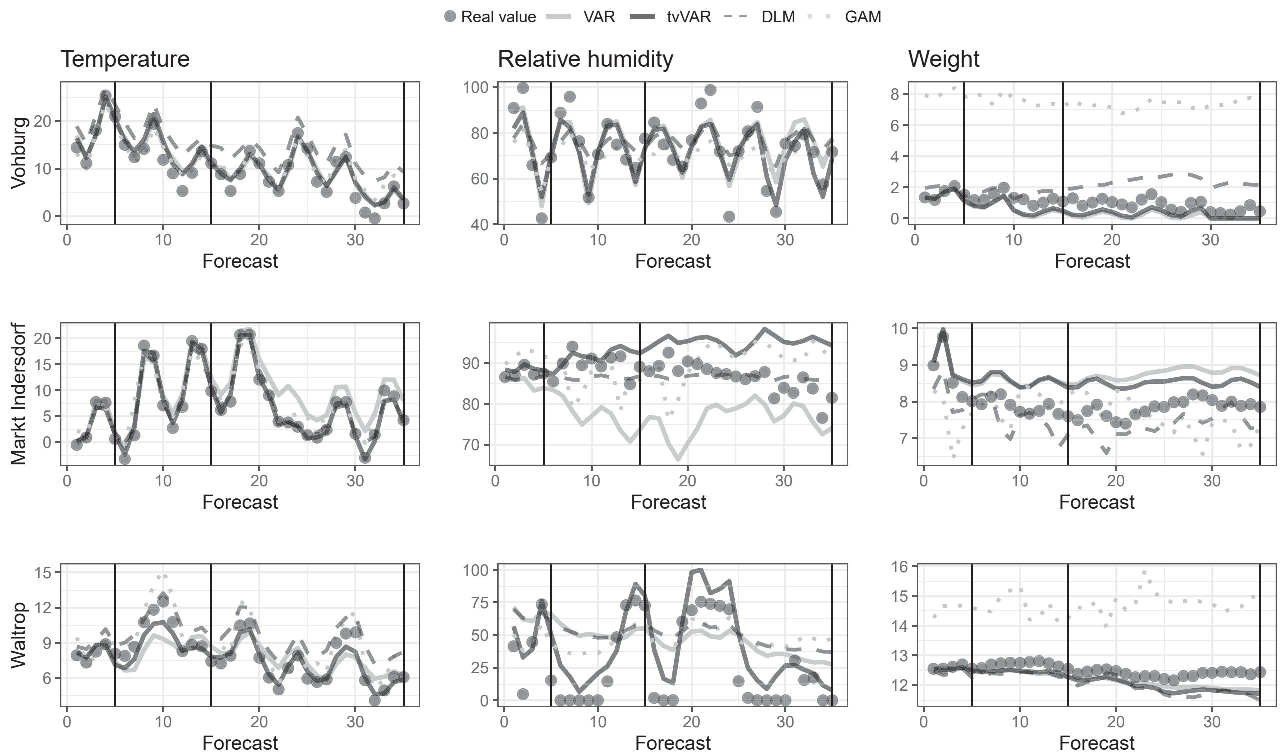

Fig. 3 – Forecasts resulting from the different models for temperature (left), relative humidity (centre), and weight (right) recorded in the last seven days in the Vohburg (top), Markt Indersdorf (centre) and Waltrop (bottom) hives. Limits for 1, 3, and 7 days are marked by vertical lines. The *x*-axis corresponds to the 35 forecasts (5 per day).

the number of measurements increases, the required computational time to fit the models also increases.

5. Discussion

In this work, the tvVAR model was found to make fairly reliable predictions of internal hive variables, regardless of the hive analysed. On average, after using cross-validation, the MAEs of 1-day predictions of temperature, relative humidity, and weight were less than 1 °C, 7.1%, and 200 g, respectively, making the short-term predictions useful for the beekeeper. Moreover, the 7-day prediction results were still quite good, keeping the MAEs below 1 °C in temperature, 8% in relative humidity, and 600 g mass.

With respect to temperature, there has been very little work attempting to predict the internal temperature of a beehive. So far, the only study to perform this task that we found in the scientific literature is that by Braga et al. (2021). This applied neural networks and walk-forward validation to data collected every two hours. The longest prediction horizon considered was 1 day. Observing the prediction graphs provided, we compared the hive for which they obtained a better result in making 1-day predictions with our predictions for the Markt Indersdorf hive. We could appreciate graphically that their predictions had a MAE greater than the 0.562 °C that we obtained using the tvVAR model. Furthermore, it was clear that, unlike the predictions we achieved with this model, their 1-day predictions of internal temperature were not good fits to the real values of the time series.

With respect to relative humidity or weight of a beehive, we could find no work making predictions of these parameters, so that we cannot make any comparison of the present results with any others in the literature. Nonetheless, in absolute terms, the results we have obtained for both relative humidity and weight are good.

Another important feature of the tvVAR model is that it performs the fit and the prediction process relatively quickly, taking around 20 min if the bandwidths are to be calculated automatically. Furthermore, if the bandwidth values for each variable can be input instead of calculated, there is a major reduction in computation time to less than 1 min, thus allowing real-time predictions to be made. This option is totally feasible since it is possible to obtain the bandwidth values parametrically, and update them periodically when the beekeeper will not be affected, at night for instance. The fact that a model takes a short time to fit the time series is of great importance in an environment of massive data analysis, especially when it comes to real-time forecasting since, if the model is too slow, the user will be prevented from making short-term predictions.

Therefore, the values obtained from the predictions of temperature, relative humidity, and weight by the tvVAR model can be used to detect in advance different events that may take place inside the hive, such as winter mortality or the risk of varroa or nosema diseases. A direct extension of this study would be to collect data by applying a much finer grid. Then, it would be necessary to apply Big Data techniques, which would allow us to analyse and predict continuously over time. For example, more complex events such as swarming could be predicted, since it has been reported that the hive temperature increases linearly in the first 20–60 min before swarming (Zhu et al., 2019). Zacepins et al. (2021) found that remote hive monitoring generates economic benefits for the beekeeper, coming especially from detection of swarming events. Those researchers created an application to estimate the economic benefit of swarm detection as a function of the beekeeper's distance from the apiary. Depending on the hive's geographical location, the maximum benefit from swarm detection was between 50 and 170 euros approximately. This benefit decreased as the distance to the apiary increased since, by 3 h after the swarm formation, all the bees forming the swarm had usually left the hive. This fact justifies the need to use methods such as the tvVAR model and to develop new models or adaptions of existing ones to handle Big Data analysis, for example, considering parallelisation or distributed computing. This may help to accurately predict the hives' internal variables, thus reducing the beekeeper's response time to events related with the internal conditions and increasing economic profitability.

The sustainability of any sensor-based apiculture system must take into account its scalability, efficiency, and economic cost as well as the return on the investment. In the scientific literature, there is a sparsity of articles addressing all these topics simultaneously, since there are many factors involved and systems that are difficult to compare. Hadjur et al. (2022) described recent advances in precision beekeeping as systems and as services. They estimated the sustainability of the proposed solutions and showed that there is a great variability in terms of scalability, efficiency, costs, and benefits.

The present work has some limitations. On the one hand, all colonies used in this study were located in Germany, so that the applicability of the results to other locations with different kinds of climate needs to be checked. Nevertheless, the models are general enough to maintain their usefulness and quality regardless of the location of the hive. And on the other hand, it is important to note that there is hardly any information on the beekeepers' actual management practices. A detailed analysis of the processes carried out on the hives would probably reduce the forecasting errors.

6. Conclusions

This article has addressed elements that had as yet been little studied in the precision beekeeping field. Good predictions of the internal variables of sensorized hives were achieved. Vector autoregressive models proved to be reliable in making predictions based on this type of data. It was observed that both the tvVAR and the VAR models give accurate predictions. The computation time cost of the tvVAR model is really manageable, especially when bandwidths are calculated parametrically and then incorporated into the model. The fact that a model performs the entire fitting and prediction process in a short time is becoming increasingly important, especially in big data environments.

The accuracy of these predictions makes these approaches very useful for integration into a decision support system to help beekeepers manage their hives effectively. Furthermore, all the algorithms are easily extensible to accommodate other factors, such as hive activity, types of crops near the hive, flowering season of these crops, feeding, harvesting, etc., being sufficiently flexible to be adapted to any context the beekeeper requires. Once implemented in a remote hive monitoring system, they could help the beekeeper by providing early warning of problems, for example, by identifying sharp weight losses, significant falls in temperature, or large variations in relative humidity that could endanger the health of a hive. Such an alert system can be easily implemented, thus extending the benefits of precision beekeeping, and making it more attractive to beekeepers.

There is a need to apply predictive modelling in the beekeeping industry, and to continue developing new predictive models, e.g., ones based on neural networks that could improve the methods being applied. Another challenge is to integrate these tools into decision making systems.

As a continuation of this research, it would be interesting to collect data from our own experiment and adapt the methodological approach to be capable of handling a Big Data analysis environment. Collecting internal information of the hives with a shorter temporal window (for example, 10–15 min) could contribute to providing more reliable and detailed predictions of the evolution of the hives' behaviour.

Declaration of competing interest

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

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