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Multi-dimensional modelling tools supporting decision-making for the beekeeping sector

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Abstract: Honey bee colonies are fundamental for the provision of goods and ecosystem services. Honey bees are highly influenced by environmental conditions and quality, beekeepers' management practices, socio-economic conditions and policies adopted for cropping and land use. We propose a modelling framework aiming at assessing the bee health status and forecast colony outputs. Two modelling tools are here presented: (i) a Health Status Index (HSI) exploring the consequences of abiotic, biotic drivers and beekeeping actions on bee health; and (ii) predictive models for the estimation of honey production and the provision of pollination service considering abiotic, biotic drivers and HSI. The models proposed represent useful tools for science-based decision support for beekeepers, risk managers and policy-makers.

Keywords: Health Status Index, predictive model, decision support systems, structural equation models, knowledge-based systems, honey bees, beekeeping

1. INTRODUCTION

1.1 Honey bee health

Honey bees are fundamental for the maintenance of sustainable ecosystem services such as pollination of cultivated crops (Bommarco et al., 2012; Potts et al., 2010) and wild plants (Aguilar et al., 2006; Ashman et al., 2004), both important for food security (Rollin et al., 2016; Tscharntkea et al., 2012). In addition, honey bees represent an important source of income for beekeepers (Formato and Smulders, 2011; Mizrahi and Lensky, 2013) contributing to increase the economic value of rural areas (Deloitte, 2013).

In the last decades, managed honey bees faced a widespread decline in Europe as reported in large national and European bee monitoring projects (Genersch et al., 2010; Jacques et al., 2016, 2017; Odoux et al., 2014; Porrini et al., 2016; van Der Zee et al., 2014). The causes that influence honey bee colony health are multiple (Goulson et al., 2015;) and may be subdivided into 5 categories: (1) chemical exposure (Böhme et al., 2017); (2) diseases and biological agents (Higes et al., 2009); (3) change in land use and landscape fragmentation (Henry et al., 2014); (4) climate change and variability (Odoux et al., 2014); (5) beekeeping practices (Jacques et al., 2017).

Furthermore, socio-economic conditions, agricultural and land use policies adopted at Member State level have also a prominent role for the correct maintenance of honey bee colonies and colony productivity (honey production, pollination service etc.). Thus, beekeeping activity is highly related to a set of management strategies applied at various levels of resolution: from the implementation of beekeeping management strategies at the level of beekeeper to the development of policies supporting the beekeeping activity at national and EU level. Despite the increased importance of knowledge-based decision supports, including the development of Decision Support Systems (DSS) in agriculture and environmental management, the beekeeping sector lacks of suitable tools for risk assessment and decision-making which can be used by relevant stakeholders (e.g. beekeepers, risk assessors, policy-makers).

Since 2009, European Food Safety Authority (EFSA) has launched a series of initiatives to support scientific assessment of factors influencing colony health (Hendrikx et al., 2009). EFSA recognised the importance of a holistic approach for the assessment of honey bee health and in 2015 launched the MUST-B project aimed at exploring the influence of multiple stressors and factors on bee health (EFSA, 2016; EFSA AHAW Panel, 2016).

According to EFSA AHAW Panel (2016) bee health is an emerging property of bee colony dynamics within a specific environment and under specific objectives of management. Therefore, it is a complex, dynamical and multidimensional property that results from the interaction between colony demography and energetics, the temporal and spatial pattern of environmental drivers and resources availability in the landscape, the population dynamics and the epidemiology of pests and diseases, the level of contamination in the environmental matrices, and the beekeeping practices. To

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deal with complex and multidimensional beekeeping systems and provide a support for decision-making, it is important to develop modelling tools able to describe the system dynamics and to perform integrated assessment of honey bee health and productivity for the purpose of healthy and sustainable management of beekeeping system in its ecological, economic and social dimension (Rortais et al., 2017).

To address the need of tools supporting decision-making for the beekeeping sector we are involved in the development of both dynamical systems modelling and advanced statistical approaches. The first approach is developed under the EFSA MUST-B framework and it is based on a mechanistic model for the integrated risk assessment of stressors affecting honey bee colonies (EFSA, 2016). In this paper, we present the methodological basis and a preliminary test of a statistical approach to bee health and productivity assessment based on Structural Equation Models (SEMs) (Bollen, 1989; Simonetto, 2012). SEMs present important advantages for the analysis of multidimensional complex systems characterized by emerging properties not directly measurable. SEMs allow to (i) take into account various sources of data; (ii) analyse causal relationships between variables; (iii) use real data to test the reliability of a conceptual framework; (iv) provide estimates of latent variables that can be used in predictive models.

SEMs are used for system analysis, decision support, including comparison of management scenarios and the selection of mitigation actions in ecological (Arhonditsis et al., 2006; Villeneuve et al., 2018) and human health-related (Boniface and Tefft, 1997; Cheung and Hong, 2017) issues. SEMs' characteristics make them fundamental tools to provide scientific support for risk assessment and decision-making for the beekeeping system at different levels.

In this paper, we propose two modelling tools based on SEMs, able to capture the complexity of the beekeeping system. The models proposed are:

- A honey bee Health Status Index (HSI): a multi-dimensional construct that defines and detects short-term fluctuations in honey bee colony health by a multi-dimensional analysis of abiotic and biotic variables;
- Predictive models for Colony Outputs (PCO): a multi-dimensional tool that predicts honey productivity and pollination service provided by honey bees based on HSI and relevant biotic and abiotic variables.

2. MATERIALS AND METHODS

2.1 HSI model definition

For the development of the HSI we applied the Partial Least Squares Path Modelling (PLS-PM) approach (Tenenhaus and Vinzi, 2005), designed to study complex multivariate relationships among two or more latent variables and a set of blocks of observed variables (indicators). The overall model structure is defined *a priori* and the hypothesized relationships between latent variables and indicators are tested by data.

A full PLS-PM is composed by two sub-models: the inner model (or structural model) defining the relationships between latent variables and the outer model (or measurement model) defining the links between latent variables and their respective indicators.

Starting from EFSA AHAW Panel (2016) we defined the conceptual model underlying the HSI, represented as the synthesis of the construct "Colony attributes", strictly influenced by the construct "External drivers" (Fig. 1).

Fig. 1: Conceptual path relating the constructs

External drivers influencing honey bee health are represented by 3 latent variables: Resource Providing Unit (RPU), Environmental Drivers (ENV) and Beekeeping Management Practices (BMP). Colony attributes defining honey bee colony health status are represented by 6 latent variables: Queen (QUE), In-hive Product (IHP), Contamination (CON), Disease-Infection-Infestation (DII), Demography (DEM) and Behaviour and Physiology (BEH). The reflective indicators related to these 9 latent variables are shown in Fig. 2.

The HSI, by definition, is a second-order construct because it involves more than one dimension (the 6 latent variables representing colony attributes) and it has none indicators. To model HSI we considered the indicators of lower-order construct (colony attributes), as suggested by Sanchez (2013).

A graphic description of this model is showed in Fig.2 and Fig.3.

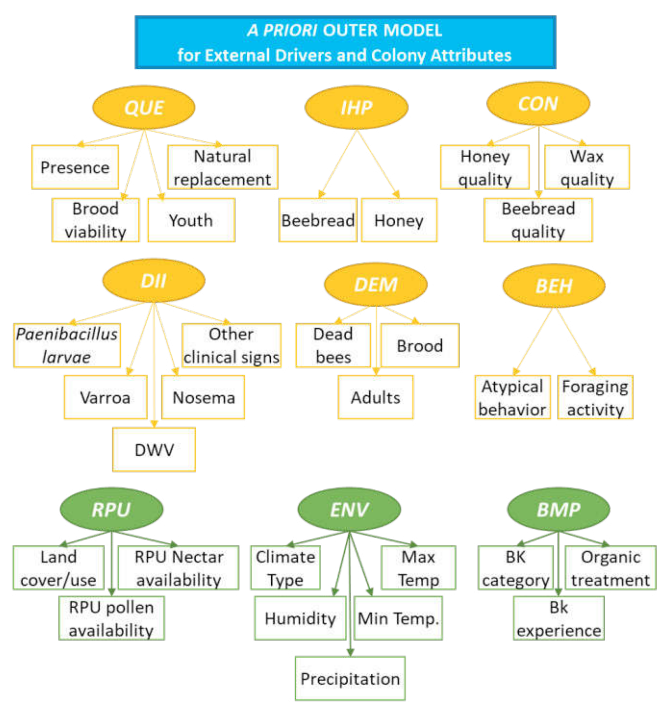

Fig. 2: *A priori* outer model for external drivers and colony attributes latent variables

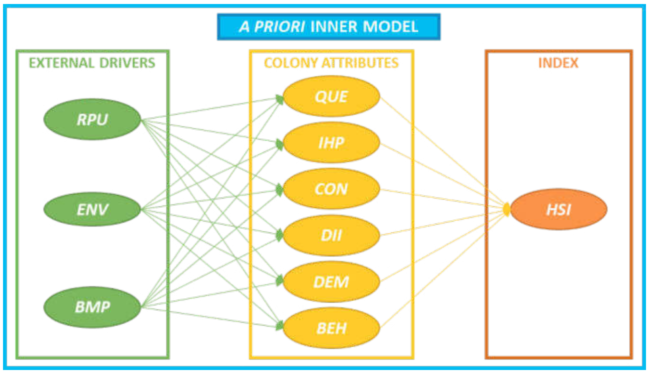

Fig. 3: *A priori* HSI inner model

2.2 PCO definition

The outputs provided by honey bees are represented by pollination service provided at landscape level and honey harvested by the beekeeper. Given a set of input data, PCO allows to predict:

- The total amount of honey (in Kg) that can be harvested by the beekeeper in the month following the data collection;
- The capacity of the honey bee colony to satisfy the landscape demand for honey bee pollination in the week following the data collection. It is measured by an index ranging from 0 (no capacity to satisfy the demand) to 1 (full capacity to satisfy the demand). The index is defined under the hypothesis of no competition with wild pollinators.

HSI and the latent variables representing external drivers (RPU, BMP, ENV) have been considered as possible independent variables. To investigate the causal link between these variables and the two colony outputs (considered as dependent variables), we applied a stepwise linear regression on a training dataset (random sample of 75% of the source data) and we checked the goodness of fit of the model on a test set (random sample of 25% of the source data). With PCO, it is possible to detect the most significant linear relationships between dependent and independent variables (stepwise techniques) and to evaluate the strength and the direction of these relationships (regression coefficients).

2.3 Scenario development and data generation

To make a preliminary test of the proposed methodology, we considered a data set generated by a semi-formal expert knowledge elicitation (EKE) procedure (EFSA, 2014, 2018) applied to beekeeping in Greece. We developed a set of 7 scenarios, based on 5 sites in Greece, representing realistic conditions faced by beekeepers in different areas of Greece. We considered one optimal case (high availability of pollen and nectar and low level of infection), three critical cases (with high prevalence of varroa, *Penibacillus larvae* and/or low availability of pollen or nectar), and three combinations of drivers and attributes representing intermediate conditions. For each scenario, the variables referred to the external drivers were assigned according to real values of each site considered, at the time of reference. The values of the DII indicators were set a priori to define the scenarios (high or low level of infection). Based on this information, experts were asked to estimate the distribution of the colony attributes indicators (excluding DII) and of colony output. Initially bee experts participating to EKE worked separately and were asked to provide uncertainty distributions of indicators and justification of their estimation. Based on first estimations, in a second round bee experts worked together to defined a unique uncertainty distribution for each indicator.

Starting from these uncertainty distributions, we randomly generated a database of 1000 observations. Each of the 7 scenarios was represented in this database proportionally to the probability of realization estimated by the experts.

Analyses were performed using R (version 3.4.2) and package plspm (Sanchez, 2013).

3. RESULTS

3.1 HSI estimation

The analysis of coefficient estimates (showed in Table 3) confirm the validity of the outer model structure defined *a priori*.

With the exception of ENV and HSI, all the latent variables are positively related to their indicators: as the value of the indicators increase, the score of the latent variable increases. In the case of ENV, the coefficient estimates of two temperature-related indicators are strongly negative, showing a quite strong inverse relation with the ENV latent variable, (i.e. the environmental score decreases with increasing temperature). The other set of negative coefficient estimates are those of DII indicators linked directly to the HSI index. High values of these indicators suggest a colony state of suffering leading to a reduction in the HSI score.

From the analysis of path coefficient estimates (graphically showed in Fig. 4) it emerges a complex system of relationships between the latent variables.

The RPU represents the quality of the landscape around the hive. It increases as the production of nectar and pollen increases and decreases with the degree of pressure of human activities on the environment. High scores of RPU positively influence the score of QUE, IHP and DEM, while there is a negative relationship with CON and DII. The estimate of the path coefficient on BEH is not significant.

BMP summarizes the outcomes of honeybee colony management tactics and strategies. Its score increases in the presence of expert and professional beekeepers adopting organic management strategies. BMP is not significantly related to QUE, while the coefficient estimates of IHP, CON, DII, DEM, BEH are all negative.

ENV represents a synthesis of the climatic and meteorological conditions in the environment surrounding the hive. It increases with increasing precipitation and humidity, while it decreases with increasing temperature. ENV is positively related to IHP and DEM and negatively related to CON and DII. With favourable weather and climate conditions, the hive population and the amount of honey and beebread increase, while there is a lower level of contamination of honey, beebread and wax and a low level of infection inside the hive. The estimates of path coefficients versus QUE and BEH are non-significant.

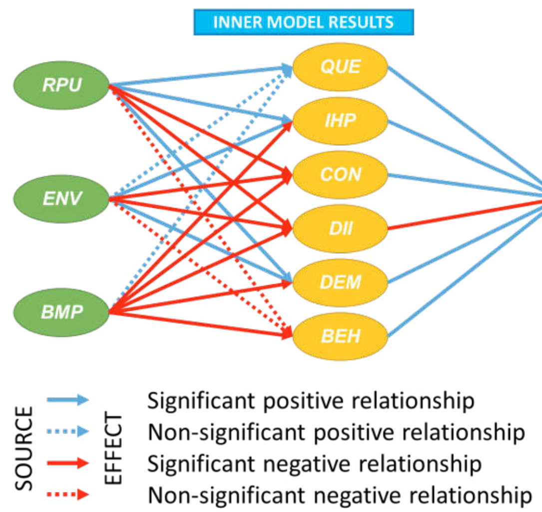

Fig. 4: HSI inner model results. Blue arrows indicate a positive relationship between the source latent variables (starting point of the arrow) and the effect latent variables (end point of the arrow). The red arrows indicate a negative relationship (inversely proportional relationship). The continuous arrows indicate a statistically significant coefficient estimate ($p < 0.05$), the dashed arrows indicate a non-statistically significant estimate

All the coefficient estimates between the latent variable of colony attributes and HSI are statistically significant. There is only one negative path coefficient and it concerns the DII attribute. This indicates that as the DII score increases, the colony health status decreases.

3.2 PCO estimation

3.2.1 Honey harvest

From the stepwise linear regression, all independent variables have been considered relevant and their regression coefficient estimates ($\hat{\beta}_j$) are all statistically significant (Table 1).

The results, obtained on training set, show a positive linear relationship between the health status of the honey bee colony and the amount of harvested honey, and a negative linear relationship between the external drivers and the amount of harvested honey. The adjusted R^2 computed on test set (25% of data) is equal to 0.734, showing a good fit of the model.

Table 1: Results of PCO for honey harvest on training set (75% of data)

Variable	$\hat{\beta}_j$	Std. error	t value	P-value
Intercept	3.85	0.03	111.59	<0.001
HSI	1.04	0.04	25.85	<0.001
RPU	-0.96	0.05	-18.44	<0.001
ENV	-1.08	0.04	-24.26	<0.001
BMP	-0.54	0.04	-12.67	<0.001

3.2.2 Pollination service

The stepwise procedure selected the model including all independent variables. The regression coefficient estimates ($\hat{\beta}_j$) are all statistically significant and positive, thus all the independent variables have a positive relationship with pollination service. Results obtained on training set are reported in Table 2. The model fits very well the data (adjusted R^2 on test set is equal to 0.94).

Table 2: Results of PCO for pollination service on training set (75 % of data)

Variable	$\hat{\beta}_j$	Std. error	t value	P-value
Intercept	0.65	0.002	256.08	<0.001
HSI	0.16	0.003	54.52	<0.001
RPU	0.14	0.004	35.93	<0.001
ENV	0.05	0.003	14.64	<0.001
BMP	0.02	0.003	6.38	<0.001

4. DISCUSSION

In this paper, we presented a methodological framework for the development of two modelling tools aiming at supporting management decisions for the beekeeping sector suitable by beekeepers, risk assessors and risk managers. The models proposed were parameterized using simulated data, and provided good capacity to integrate multiple types of variables such as the influence of environmental drivers, pressure of human activities and management strategies on honey bee colony health and productivity.

The estimated Heath Status Index can be used for assessing honey bee colony health status and for the implementation of (i) point-based risk analysis at colony level and (ii) risk analysis at regional and EU levels through the development of risk maps using GIS. HSI can also be suitable for the comparative assessment of different management scenarios, from (i) the evaluation of different beekeeping management strategies (e.g. organic VS conventional beekeeping), to (ii) the evaluation of management decision at policy level (e.g. comparing different land use scenarios). Furthermore, HSI outputs can be used as a proxy for environmental quality assessment based on the sensitivity of honey bees to environmental stressors (also taking into account the role of the beekeeper and how it influences honey bee health).

Predictive models for honey harvesting and pollination service could be used for (i) the evaluation of the profitability of the beekeeping activity and (ii) the exploration of scenarios for pesticide use in cropping and land use. The information provided by the predictive models might be suitable for the development of successful business models for the beekeeping sector and for the evaluation of sustainability of agriculture (e.g. evaluation of costs and benefits of pesticides use, different agricultural practices etc.).

The tools proposed could be integrated in a framework for the holistic assessment of honey bee colony health and productivity at EU level, based on an adaptive management approach (Allen and Garmestani, 2015) in which monitoring, data analysis, model implementation and decision support are put into a self-evolving system. This system may be supported by multi-stakeholders community (beekeepers, farmers, risk assessors, risk managers etc.) towards a healthy and sustainable beekeeping in the EU.

Table 3: HSI loadings estimates (in grey estimates not statistically significant, $p \geq 0.05$)

LV	Indicator	Loading	Std. Error
HSI	Presence	0,50	0,03
	Brood viability	0,41	0,03
	Youth	0,49	0,03
	Natural replecement	0,49	0,06
	Beebread	0,75	0,10
	Honey	0,58	0,07
	Beebread quality	0,69	0,05
	Honey quality	0,77	0,04
	Wax quality	0,66	0,06
	P. larvae	-0,08	0,03
	Varroa	-0,47	0,13
	Nosema	-0,25	0,11
	DWV	-0,46	0,13
	Other clinical signs	-0,33	0,09
	Atypical behavior	0,58	0,05
	Foraging activity	0,67	0,04
	Dead bees	0,49	0,04
	Brood	0,69	0,10
	Adults	0,58	0,03

LV	Indicator	Loading	Std. Error
RPU	Land cover/use	0,81	0,01
	RPU pollen availability	0,93	0,00
	RPU nectar availability	0,23	0,04
BMP	Bk category	0,98	0,00
	Bk experience	0,59	0,04
	Organic treatment	0,68	0,03
ENV	Climate type	0,47	0,03
	Humidity	0,04	0,95
	Precipitation	0,03	0,82
	Min Temp.	-0,04	0,97
	Max Temp.	-0,03	0,83
QUE	Presence	0,83	0,12
	Brood viability	0,80	0,10
	Youth	0,77	0,04
	Natural replecement	0,37	0,18

LV	Indicator	Loading	Std. Error
IHP	Beebread	0,99	0,00
	Honey	0,22	0,05
CON	Beebread quality	0,88	0,01
	Honey quality	0,96	0,00
	Wax quality	0,96	0,00
DII	*P. larvae*	0,08	0,03
	Varroa	0,97	0,00
	Nosema	0,77	0,02
	DWV	0,97	0,00
	Other clinical signs	0,69	0,02
BEH	Atypical behavior	0,88	0,01
	Foraging activity	0,91	0,01
DEM	Dead bees	0,34	0,05
	Brood	0,95	0,00
	Adults	0,73	0,03

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