

Where the bee sucks: a dynamic Bayesian network approach to decision support for pollinator abundance strategies

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Abstract

For policymakers wishing to make evidence-based decisions, one of the challenges is how to combine the relevant information and evidence in a coherent and defensible manner in order to formulate and evaluate candidate policies. Policymakers often need to rely on experts with disparate fields of expertise when making policy choices in complex, multi-faceted, dynamic environments such as those dealing with ecosystem services. The pressures affecting the survival and pollination capabilities of honey bees (*Apis mellifera*), wild bees, and other pollinators is well documented, but incomplete. In order to estimate the potential effectiveness of various candidate policies to support pollination services, there is an urgent need to quantify the effect of various combinations of variables on the pollination ecosystem service, utilising available information, models and expert judgement. In this paper, we present a new application of the integrating decision support system methodology, using dynamic Bayesian networks, for combining inputs from multiple panels of experts to evaluate policies to support an abundant pollinator population.

Keywords: conservation, decision support, dynamic Bayesian network, integrating decision support system, pollination, structured expert judgement elicitation

1 Introduction

In today's ever more interconnected world, decision-making in dynamic environments is often extremely difficult despite vast streams of data and huge models within disparate domains of relevant expertise. Decision support can be valuable, but needs to incorporate all the relevant inputs in a clear and coherent way so that a decision-making team can make a defensible selection among policy options. In these contexts, such decision centres often need to draw together inferences in dynamic, plural environments and integrate together expert judgements coming from a number of different panels of experts where each panel is supported by their own, sometimes very complex, models. These judgements need to be networked together to provide coherent inference for appropriate decision support in increasingly complex scenarios. A formal statistical methodology to network together diverse supporting probabilistic models needed to achieve this, the integrating decision support system (IDSS), was developed in [Smith et al. \(2016\)](#). Here, we capitalise on this exciting new development to construct decision support for policy selection in the domain of pollination ecosystem services. In particular, we use the probabilistic graphical modelling family of dynamic Bayesian networks within the IDSS framework.

In 2014, the UK government issued its first pollinator strategy ([Department for Environment, Food & Rural Affairs, 2014](#)) and more recently the Pollinator Action Plan 2021–2024 ([Department for Environment, Food & Rural Affairs, 2022c](#)) and the Healthy Bees Plan 2030

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(Department for Environment, Food & Rural Affairs, 2020b). The given reason is that bees and other pollinators are an essential part of our environment and play a crucial role in food production—they contribute the equivalent of more than £500 million a year to UK agriculture and food production, by improving crop quality and quantity—and are also vital to our wider, natural ecosystems; critical to our food industry, our green spaces, wider biodiversity and ensuring healthy and productive ecosystems (Department for Environment, Food & Rural Affairs, 2022c).

The importance of pollination services to food production in the UK and worldwide are undisputed (Vanbergen et al., 2014). Pollinator-dependent food products are important contributors to healthy human diets and nutrition (Potts et al., 2016) and it is estimated that over 70% of important food crops worldwide are dependent upon pollinators (Klein et al., 2007). Therefore, the status of bees and other pollinators is of significant concern in global food security (Bailes et al., 2015; Blaauw & Isaacs, 2014; Lonsdorf et al., 2009; Lucas, 2017; Novais et al., 2016; Ollerton, 2012). Pollination has a direct economic value through increasing the yield and quality of insect-dependent crops. In the UK, this includes oilseed rape, orchard fruit, soft fruit, and beans. Many agricultural businesses employ migratory bee services in order to ensure adequate pollination of crops (Bishop et al., 2016; Gordon et al., 2014). Total loss of pollinators could cost up to £440m a year, about 13% of UK income from farming (POST, 2010). Insect-dependent crops can be pollinated by hand, but the cost would be prohibitive (estimated at £1,500 million a year), raising the cost of food in the marketplace and increasing food insecurity and nutrition insecurity substantially.

It is estimated that pollinator loss would reduce world agricultural production by 5% overall, reducing the diversity of food available, particularly affecting ‘Five-a-Day’ crops (POST, 2010), with the obvious downstream effect of increasing burden of disease and health costs. Of course, humans are not the only beneficiaries of pollination services and the social and tourist value of the insects themselves, the other wildlife they support and the floral species reliant on them should not be discounted.

The Pollinator Action Plan defines pollinator health as the state of well-being of wild and managed pollinators that allows individuals to live longer and reproduce more, even in the presence of pathogens, and therefore provide ecosystem services more effectively. Pollinator health is a function of pests, parasites, disease, and other anthropogenic stressors, the availability of appropriate nutrition across life stages, nest sites, host plants, mating areas, and hibernation sites. Honey bee health also depends on the beekeepers managing them. If pollinator health is high, we would expect a greater abundance of pollinators. The strategy includes creating habitats for pollinators on farms, in transport corridors, on industrial sites, in gardens and in woodlands, creating Pollinator (Bees’ Needs) award, a National Pollinator and Pollination Monitoring Framework and sharing knowledge between scientists, conservation practitioners, developers, land owners, managers, users and Non-Governmental organisations. Additionally, the Healthy Bees Plan 2023 (Department for Environment, Food & Rural Affairs, 2020b) includes high standards of bee husbandry and enhancing the skills of beekeepers and bee farmers. These strategies motivated our choice of scenarios in Section 4.

The UK National Pollinator Strategy (Department for Environment, Food & Rural Affairs, 2014) acknowledged that whilst there is an abundance of excellent research in many aspects, the evidence for the system as a whole is patchy. Therefore, there is a need for decision support to identify optimal policies across this complex landscape. There is a need to assess population-level impacts of insect pollinator management actions and the link between insect pollinator population size change and drivers (Department for Environment, Food & Rural Affairs, 2020b, 2022c). This paper seeks to contribute to this need using dynamic Bayesian networks (DBNs) within the IDSS paradigm.

2 Integrating decision support system

2.1 Overview

An IDSS is a unifying statistical framework that enables comparison of candidate policies within complex and evolving systems. It was introduced in Smith et al. (2016), and Leonelli and Smith (2015), and has since been successfully applied to a range of applications, including to support decision-making in household food security (Barons, Fonseca, Davis, et al., 2022), digital

including Bayesian networks (BNs), multiregression dynamic models, chain event graphs, Markov networks and influence diagrams. For our application of assessing candidate strategies for improving the abundance of pollinators, we will use the discrete-time dynamic variant of Bayesian networks known as the *dynamic Bayesian network (DBN)*.

Bayesian networks are a well-established family of probabilistic graphical models that combine together a statistical model that decomposes a complex system into a collection of conditional independence relationships among its defining variables, and a graph that visually represents these conditional independence relationships. The BN model class was first introduced in [Pearl \(1986\)](#) and has been successfully applied to a wide range of domains for reasoning in the presence of uncertainty. In particular, BNs have previously formed the basis of successful risk assessment and decision support tools; for examples in environmental sciences, see [Phan et al. \(2019\)](#), [Davies and Hope \(2015\)](#), [Pollino et al. \(2007\)](#), and [Johnson et al. \(2017\)](#). The nodes of a BN represent the variables of interest and a directed edge between two nodes represents informational or causal dependencies between the two variables. These dependencies are quantified by conditional probabilities of a variable given the values assumed by its parent variables in the network. The BN graphical representation can be easily understood without any formal mathematical or statistical training, enabling domain experts and stakeholders to be drawn in more easily into the modelling process. Formally, a BN is defined as follows.

Definition 1 (Bayesian Network). A Bayesian network (BN) $\mathcal{B} = (\mathcal{G}, P)$ is a probabilistic graphical model over a set of variables $\mathbf{X} = \{X_1, X_2, \dots, X_n\}$. Here, $\mathcal{G} = (V(\mathcal{G}), E(\mathcal{G}))$ is a directed acyclic graph (DAG) whose node set $V(\mathcal{G})$ is given by the variables in \mathbf{X} , and P is a joint probability distribution over the variables \mathbf{X} . The edge set $E(\mathcal{G}) \subseteq V(\mathcal{G}) \times V(\mathcal{G})$ consists of directed arcs such that lack of an edge between two nodes represents conditional independence between the variables represented by the nodes, and similarly, edges between nodes encode conditional dependence. This conditional independence structure allows the joint probability P to be factorised by the chain rule as

$$P(\mathbf{X} = \mathbf{x} | \mathcal{G}) = \prod_{X_i \in \mathbf{X}} p(X_i = x_i | \text{Pa}(X_i) = x_{\text{Pa}(X_i)}),$$

where $\text{Pa}(X_i)$ is the set of parents of the node X_i in \mathcal{G} , $p(\cdot)$ is the probability of an event and $p(\cdot | \cdot)$ is a conditional probability.

Thus, each variable in the BN, represented by a node in its graph, has an associated conditional probability table wherein the conditioning variables are its parents in the graph. The graph of the BN encodes the following conditional independence statements

$$X_i \perp\!\!\!\perp \text{Nd}(X_i) \setminus \text{Pa}(X_i) | \text{Pa}(X_i), \quad (1)$$

where $\text{Nd}(X_i)$ are the non-descendants of X_i , i.e. all the variables in \mathcal{G} that do not have a directed path from X_i to themselves. More advanced conditional independence relationships can be read from the graph of a BN using the d-separation theorem ([Verma & Pearl, 1988](#)) (also known as the global directed Markov property [Lauritzen, 1996](#)).

The decomposition through which BNs are constructed make them a natural choice as a composite model within an IDSS. As a composite model, the nodes of the BN represent the panels or component models within the IDSS. The nodes can still be viewed as variables but each node or variable now has its own underlying model. The dependence structure within the BN represents how the panels interact with each other. All the conditional independence statements encoded by a BN can be read using the d-separation theorem. The realism of these statements should then be discussed with the domain experts and decision-makers to ensure that the structural aspects of the BN are requisite before populating it with any numerical estimates. Further, BNs have the advantage that they are fully transparent with how they process data for estimating the conditional probability parameters, and with how the quantitative effects of any new information is propagated through the network to revise these parameter estimates. In fact, data and

expert judgement can be combined together to uncover the conditional probability distributions of the variables in the system (O'Hagan et al., 2006). Any uncertainties, such as those coming from sampling errors or more often through the subjective probabilistic estimates provided by domain experts, are encoded within the variances of these parameters. Once the structure and parametric estimates of the BN have been agreed upon, it can be used to evaluate candidate policies. The effects of a given candidate policy can be evaluated within the BN by intervening on the variables sought to be changed by the policy, and propagating the effects of these changes through the system. As described in Section 2.1, the varied effects of any candidate policy are typically quantified using a utility score. In the context of decision-making, this refers to expected utility maximisation (for theoretical details, see Smith, 2010). All these factors lend BNs well to transparent and explainable decision-making as well as auditing. Moreover, within a Bayesian framework, they allow for real-time updating which is crucial for decision support in an evolving situation.

However, one key limitation of using a BN is that it is a static model which means that it provides a snapshot of the system at a fixed point in time, called a time-slice. Whilst it can be used in real-time within an evolving system by focusing on decision-making for a single time-slice at each point, it cannot be used for analysing the effects of a policy or decision that occurs over multiple time-slices. Such short-term to medium-term decision-making is exactly what is of interest for evaluating pollinator abundance strategies. For this purpose, we instead use a dynamic variant of the BN known as the dynamic Bayesian network (DBN) (Dean & Kanazawa, 1989). The DBN represents how the system longitudinally evolves in discrete time.

Definition 2 (Dynamic Bayesian Network). A DBN is a dynamic variant of the BN that evolves in discrete time. A DBN, defined over a set of variables $\mathcal{X}(t) = \{X_1(t), X_2(t), \dots, X_n(t)\}$ representing a time-series, is given by the tuple $(\mathcal{B}_1, \dots, \mathcal{B}_n)$ where \mathcal{B}_1 is the initial BN over $\mathcal{X}(1)$ and each subsequent BN \mathcal{B}_t represents the state of the system at time-slice t over $\mathcal{X}(t)$ for $t \geq 2$. Assuming the system satisfies the first-order Markov property, the BN \mathcal{B}_t is connected to the BN \mathcal{B}_{t+1} by directed inter-slice temporal arcs to represent the effect of the variables at time t on the variables at time $t + 1$.

A common simplification of the DBN is to assume stationarity of the graphical structure and the model parameters over time. Such a DBN is called a 2-time-slice DBN and can be compactly given by the tuple $(\mathcal{B}_1, \mathcal{B}_{\rightarrow})$, where \mathcal{B}_1 is the initial BN and $\mathcal{B}_{\rightarrow}$ is the transition BN that describes the dependencies of a variable X at time t given the values of its parents in time-slices t and $t - 1$. Edges that begin in one time-slice and end in the next are called temporal edges. The DBN inherits all the advantages of the BN as mentioned above, and thus, is suitable for short-term to medium-term decision-making within an evolving system.

2.3 Evaluation of scenarios

Each candidate policy describes a complex scenario. In order for it to be evaluated using a DBN, we require that the candidate policy can be stated in terms of changes to the probabilities associated with one or more of the variables in the DBN. For example, assume that the level of pesticide use is a binary variable in our DBN for evaluating pollinator abundance strategies which is categorised as 'High' or 'Low'. A policy that provides subsidies for using integrated pest management (IPM) techniques and thereby, reducing the use of pesticides can be stated in terms of changes to the probability that the level of pesticide use is 'High'.

We use the Netica software (Norsys, 1994–2010) provided by Norsys for creating and analysing the DBN. Within Netica, for a node without any parents, it is straightforward to modify the probabilities associated with that variable. The effect of such changes are automatically propagated to the descendants of this node by the software. For nodes with parents, changing the probabilities within Netica results in the effects of these changes also being propagated to its parents. Realistically, a policy can only affect downstream variables. Therefore, for a node with parents, a policy affecting that variable is implemented by setting a fixed value for that variable. For example, the effects of the IPM strategy described earlier can be analysed by setting the level of pesticide use being 'Low' with the probability of 1.

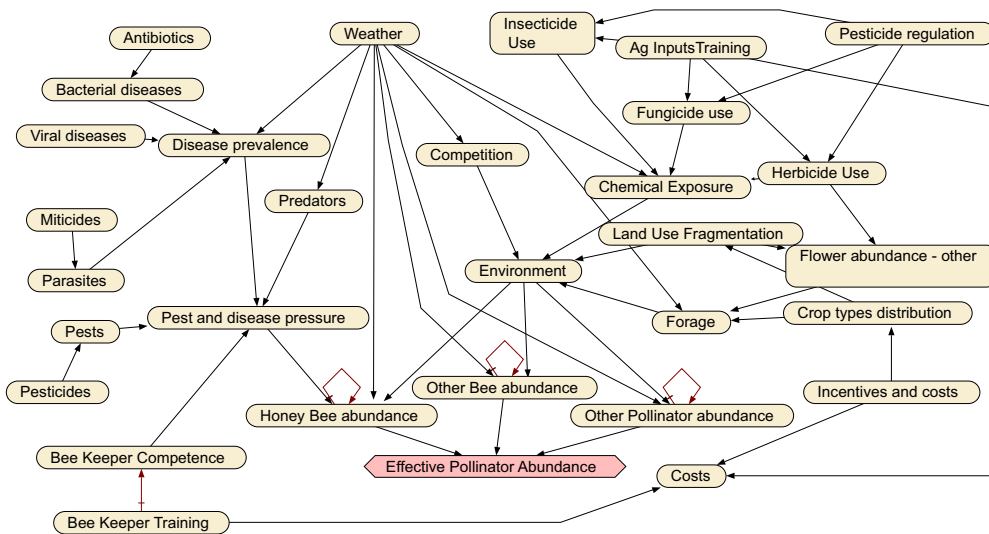


Figure 1. Structure of DBN (dynamic Bayesian network) at time-slice t including all variables affecting pollinator populations based on domain literature and expert opinion.

discretisation is done carefully, the granularity added by retaining variables as continuous does not qualitatively affect the decision-making process.

3.2 Expert panels for the IDSS

Having identified the key variables and their conditional independence relationships in Figure 1, we then identify the natural panels of experts who might oversee those variables. For example, the Met Office would be best placed to provide information relating to the ‘Weather’ variable, whereas various different units at the Department for Environment, Food and Rural Affairs (DEFRA) would be able to provide information relating to variables such as ‘Predators’, ‘Disease Prevalence’, ‘Honey Bee abundance’, ‘Other Bee abundance’ and ‘Other Pollinator abundance’. Below we describe how the variables in the DBN in Figure 1 are organised into realistic panels based on the UK organisational setting:

- **Weather:** Weather;
- **Disease and Pest Pressures:** Disease prevalence, Pest and disease pressure, Predators, Parasites, Miticides, Pests, Pesticides, Viral diseases, Bacterial diseases, Antibiotics;
- **Pesticide Use:** Insecticide use, Pesticide regulation, Agricultural inputs training, Fungicide use, Herbicide use, Chemical exposure;
- **Land Use Fragmentation:** Land use fragmentation;
- **Food Supply:** Forage, Crop types distribution, Flower abundance;
- **Social Attitudes & Incentives:** Incentives;
- **Environment:** Competition, Environment.

The panels for the abundances of honey bees, other bees, and other pollinators are kept separate as in the DBN in Figure 1. Thus, the DBN in Figure 1 can be decomposed into a panel-based structure such as the one shown in Figure 2. Each panel will have its own separate model for the inputs they provide. Transforming the full DBN model into a panel-based DBN makes it an IDSS. We have not included the variables associated with bee keeper training or any associated costs as these are likely to be estimated or decided by the decision-makers.

Our main contribution in this paper is developing and illustrating the use of this proof of concept IDSS for evaluating candidate policies to improve the abundance of pollinators. Therefore, we will henceforth work with the IDSS shown in Figure 2. Note that whilst the ‘Costs’ variable features in the full DBN, we have not included it into the IDSS which we use for illustrative

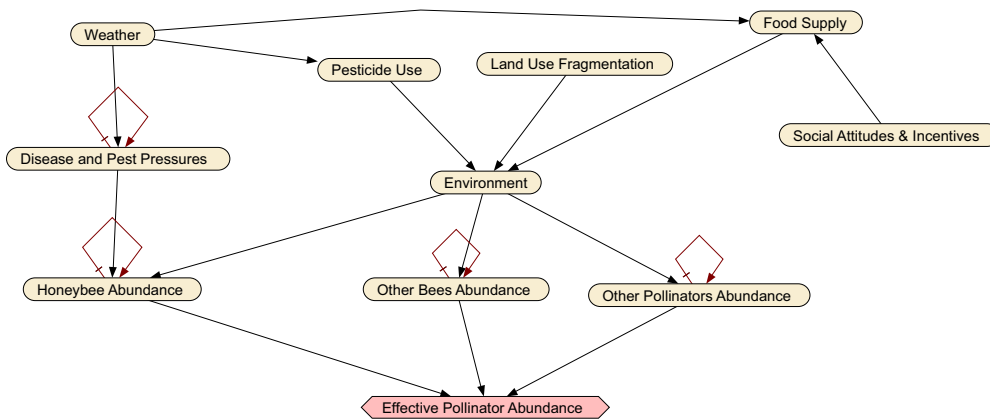


Figure 2. Panel view of the DBN (dynamic Bayesian network) for evaluating pollinator abundance strategies.

purposes in the remainder of the paper. In practice, a cost–benefit analysis is an essential aspect in the comparison of candidate policies. However, since the IDSS is designed to aid evidence informed decision-making by policymakers, and not automated decision-making, considerations not included in the IDSS can be considered alongside IDSS outputs (e.g. political acceptability). One time step in our IDSS is a year, since in the UK most pollinators have a break in brood cycle over winter. However, depending on the level of data available, timing of the decision-making cycle and the type of policies considered, decision-makers are at liberty to decide to use more granularity in the IDSS, e.g. a seasonal time step (see further discussion in Section 5).

In this paper, we directly estimate the outputs of each of the models for the IDSS using a combination of expert elicitation and domain information due to the lack of complete data for all the variables needed as inputs into the various models that form the panel-based DBN. We previously carried out a structured expert elicitation exercise, reported in Barons, Hanea, et al. (2018) based on the IDEA (Investigate, Discuss, Estimate and Aggregate) protocol (Hanea et al., 2017) to estimate the probability of good pollinator abundance given different weather, disease pressure, and environmental scenarios. We use this as a starting point for estimating the parameters in our panel-based DBN. The remaining probabilities are extracted from domain information available in academic journals and technical reports prepared by environmental and governmental bodies (such as the National Pollinator Strategy prepared by DEFRA). We do not yet have the input from such panels, but full details of this estimation process are given in Appendix A of the online supplementary material. The probability values for the BN initialising our panel-based DBN are given in Figure 3.

3.3 Utility

To quantify the effect of a given candidate policy, we use the following utility function:

$$\begin{aligned} \text{Utility} = & \frac{1}{3} \times p(\text{Honeybees abundance} = \text{Good}) + \frac{1}{3} \times p(\text{Other bees abundance} = \text{Good}) \\ & + \frac{1}{3} \times p(\text{Other pollinators abundance} = \text{Good}). \end{aligned} \quad (4)$$

This is the simplest form of a linear utility score which gives equal weighting to the abundances of the three types of pollinators that we consider here. The decision-makers can adapt this utility function to appropriately reflect their level of risk aversion and priorities. For example, they can choose to use a higher weighting on the abundance of honeybees to reflect the emphasis of abundance strategies typically being on improving the numbers of domesticated honeybees as compared to feral honey bee populations, other wild bees, and other pollinators.

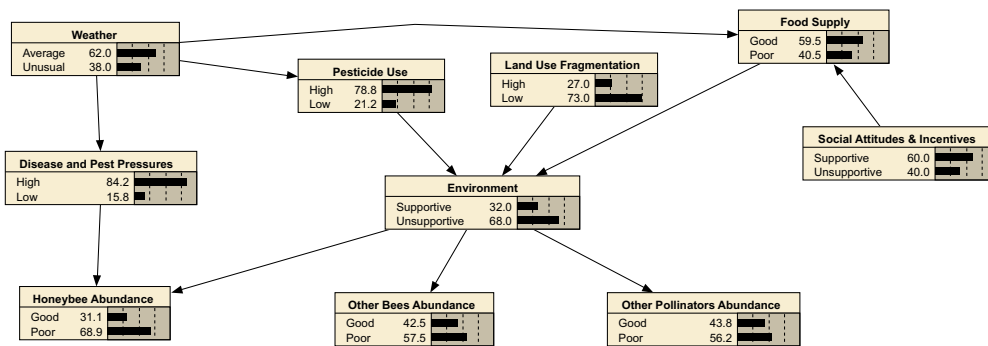


Figure 3. The Bayesian network initialising our panel-based DBN IDSS. Note that the parameter estimates for the initialising BN when the DBN is unrolled to 10 time-slices as in Section 4 are not exactly as given here due to the temporal links.

3.4 Sensitivity analysis

We performed a sensitivity analysis to identify the variables that had large effects on the abundances of honey bees, other bees, and other pollinators. This also enables us to see how the probabilities for the abundances change under different conditions. Since the panel-based DBN we use is a two time-slice DBN (see Section 2.2), we perform the sensitivity analysis on abundances at the second time-slice as the first time-slice is the initialising BN. We use the standard metrics of mutual information (based on entropy) and variance of belief (posterior probabilities) which are directly available within the Netica software (Norsys, 1994–2010). Mutual information ($I(X; Y)$) between two nodes X and Y is defined as follows:

$$\begin{aligned}
 I(X; Y) &= H(X) - H(X | Y) \\
 &= \sum_x \sum_y \log_2 \frac{p(x, y)}{p(x) \cdot p(y)},
 \end{aligned}
 \tag{5}$$

where $H(X)$ is the marginal entropy of X , $H(X | Y)$ is the conditional entropy of X given Y and $I(X; Y)$ is measured in bits. The mutual information metric for X and Y is non-negative (ranges from $[0, H(X)]$), symmetric and indicates how much information X communicates about Y . Thus, a higher value of $I(X; Y)$ indicates that changes in Y have a strong impact on X . Within Netica, $I(X; Y)$ is also expressed as a percentage of the entropy of $I(X)$. The second metric we use, i.e. the variance of belief $S^2(X; Y)$ metric is calculated as follows:

$$S^2(X; Y) = \sum_y \sum_x x p(x, y) [p(x | y) - p(x)]^2.
 \tag{6}$$

$S^2(X; Y)$ ranges from $[0, 1]$ gives the squared values of the expected changes in the beliefs of X , taken over all its states, as a result of the information contained in Y .

Table 1 shows the top 10 nodes that affect the abundances of honeybees at the second time-slice. Similar tables are given in Appendix B of the online supplementary material for other bees, and other pollinators. These tables shows the sensitivity of the population of honey bees, other bees, and other pollinators to a finding at other nodes in the first and second time-slices (indicated as [1] and [2], respectively, after the variable name) in terms of the mutual information score, percentage of entropy of the specific pollinator’s abundance and variance of belief. It is clear from these tables that the environment in the first and second time-slices has a strong influence on the populations of all three categories of pollinators. Further, disease and pest pressure has a strong influence on the abundance of honeybees. These sensitivity checks are also useful as a diagnostic tool so that experts can check whether the influence of the various nodes or panels are as expected.

Table 1. Top 10 nodes affecting the abundance of honeybees at the second time-slice

Variable	Mutual information (<i>I</i>)	Percentage of entropy	Variance of belief (S^2)
Disease and pest pressure [2]	0.06487	10.5	0.0140673
Environment [2]	0.03101	5	0.0059849
Honeybee abundance [1]	0.02988	4.81	0.0064502
Disease and pest pressure [1]	0.01078	1.74	0.0021470
Other bees abundance [2]	0.00605	0.975	0.0011491
Other pollinators abundance [2]	0.00574	0.924	0.0010831
Food supply [2]	0.00358	0.577	0.0006341
Weather [2]	0.00296	0.477	0.0005228
Pesticide use [2]	0.00173	0.278	0.0003256
Environment [1]	0.00136	0.219	0.0002503

4 Scenarios

The aim of our IDSS is to model the variables influencing the populations of pollinators in the UK ecosystem sufficiently well to analyse the short-term and medium-term effects of various candidate policies. To demonstrate how such an IDSS can be used in practice, we will analyse various hypothetical but realistic policy and event scenarios as they affect pollinator populations over 10 time-slices, i.e. 10 years. These scenarios are inspired by changes in the influential variables affecting pollinator populations (in particular, environment, and disease and pest pressure; see Section 3.4) that are discussed in key strategic publications such as the National Pollination Strategy (Department for Environment, Food & Rural Affairs, 2014, 2022c). The first two scenarios focus on policies that can lead to making the physical environment more supportive for pollinating insects, the third focuses on reducing disease and pest pressure on pollinating insects, the fourth combines both of the above and finally, the fifth does not consider a policy but looks at likely impacts of climate change on pollinator populations in the absence of any ameliorating strategies. Each of the five scenarios is described below in detail; the changes in the probabilities associated with ‘Good’ abundances of the pollinators and the utility scores can be seen in Figures 4 and 5. Note that the points on the graphs in Figure 4 are jittered to enable data points under different scenarios that obtain the same value to be visible next to each other. The exact values of the utilities are given in Appendix C of the online supplementary material.

4.1 Scenario 1: Decreasing pesticide use

There are three expert panels providing estimates to the environment panel as can be seen in Figure 2, namely, pesticide use, land use fragmentation and food supply which is directly affected by social attitudes and incentives. The first scenario we consider is one where we attempt to make the environment more supportive by decreasing the use of pesticides. Reducing the dependence on pesticides is a critical way forward towards making the environment safer for pollinators as pesticides can have severe and adverse effects on bees (Henry et al., 2014). In the UK, pesticides legislation is regulated by the Chemicals Regulation Directorate (CRD), which is a sub-division of the Health and Safety Executive (HSE). The CRD supports the work of the HSE and DEFRA in ensuring pesticides are used safely, without risk to either spray operators, the general public or the environment. Under the National Action Plan for the Sustainable Use of Pesticides, the UK Governments aim to ‘reduce the use of pesticides by utilising alternatives and promoting natural processes’ (Department for Environment, Food & Rural Affairs, 2020a). In line with this, their action plan includes increasing the uptake of IPM techniques. Therefore, for our first scenario, we consider the effects of reducing pesticide use through the adoption of techniques such as IPM.

To analyse the effect of reducing pesticide use, we set pesticide use to ‘Low’. We consider three cases within this scenario. The first (Scenario 1a) is where pesticide use is set to ‘Low’ for only one year, the second (Scenario 1b) sets it to ‘Low’ for five years and the third (Scenario 1c) for 10 years.

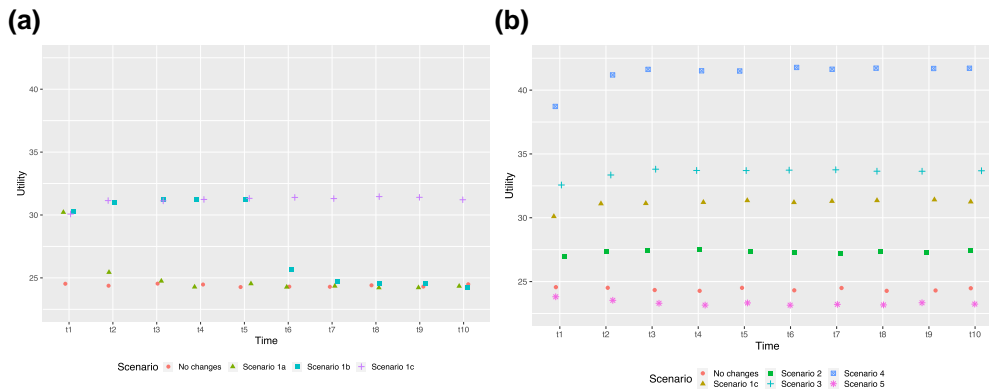


Figure 4. Plots showing the utility scores for each of the 10 years under (a) the three cases of Scenario 1 (reducing pesticide use) and (b) under Scenario 1c (low pesticide use for 10 years) and Scenarios 2 (improving social attitudes and reducing land use fragmentation), 3 (reducing disease and pest pressure), 4 (decreasing pesticide use and reducing disease and pest pressure), and 5 (worsening weather conditions) when compared to having no changes in the IDSS.

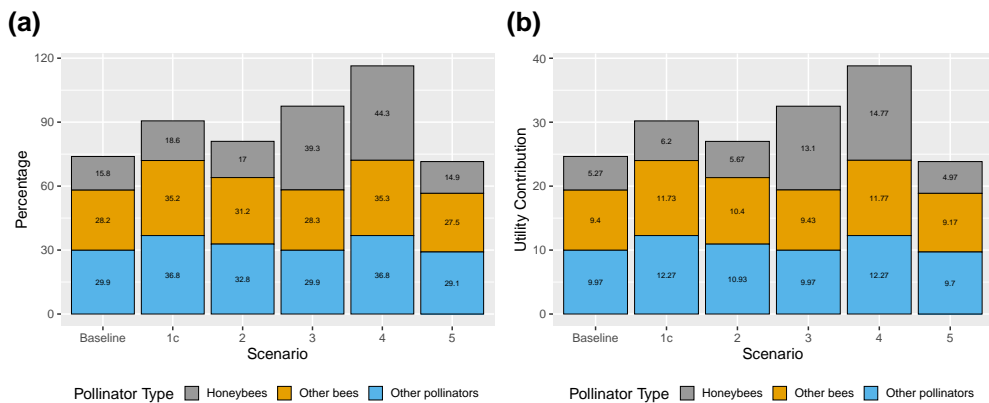


Figure 5. Stacked bar charts illustrating two sets of visualisations of a type that have been used to aid a decision-maker. We have shown in (a) an illustration of the changes in percentages associated with ‘Good’ abundances for the pollinators under each of the five scenarios as compared to the baseline, and (b) illustration of the changes in contribution to the utility score by the pollinators under each of the five scenarios as compared to the baseline.

The first two cases assume that once the policy is discontinued, the probabilities revert to pre-policy levels. Under Scenario 1a, we find that there is an immediate effect in the increase in the probability of the environment being ‘Supportive’ from 32% to 49.3% and the probabilities for the abundance of honeybees, other bees, and other pollinators being ‘Good’ goes up from 15.8%, 28.2%, and 29.9% to 18.6%, 35.2%, and 36.8%, respectively. (These probabilities are reported as percentages rather than as values in [0,1] as in our experience, decision-makers find percentages more intuitive.) Thus, there is a strong positive effect of reducing the dependence of pesticides. However, this effect quickly drops off in the subsequent years. Similarly, under Scenario 1b, the positive effects of the policy tapers off quickly once the policy has been discontinued after five years. Under Scenario 1c, the effects are sustained throughout the 10 years. The utility values for each year under the three cases can be seen in Figure 4a.

The drop-off in utility scores when a policy is discontinued can be seen in all other scenarios considered in this paper. In reality, we may expect that there is a lag in observing the effects of a new policy and correspondingly, also a lag in observing a drop-off in the effects once the policy

on insect pollinators). The former positively benefits all three categories of pollinators whilst the latter mostly benefits only honeybee populations. The combination of both these policies gives the highest improvement in the utility score among all scenarios considered in this paper. It has the immediate effect of increasing the probability of honeybee, other bees, and other pollinators populations being ‘Good’ from 15.8%, 28.2%, and 29.9% to 44.3%, 35.3%, and 36.8% respectively. The utility score reaches and stays at the maximum value of 41.63 from the fourth year. This maximum value is 1.7 times the maximum utility score under no changes to the estimated panel-based DBN.

4.5 Scenario 5: Worsening weather conditions

In this final scenario, we consider the impact of implementing no new beneficial policies under a warming climate. The UK Climate Projections (Met Office, 2022) provides national climate projections for the UK and is developed by the Met Office in collaboration with DEFRA, Department for Business, Energy and Industrial Strategy, and the Environment Agency. The findings report that under a high emission scenario, the seasonal average warming in the UK could amount between 1.3°C and 5.1°C in summer and between 0.6°C and 3.8°C in winter. By mid-century, hot summers are expected to be 50% more common. Thereafter, their prevalence strongly depends on whether we are in a low or high emission scenario. A warming climate adversely impacts the health and population of pollinators, their food supply, and their interactions with plants (see, e.g. Dormann et al., 2008; Hegland et al., 2009; Memmott et al., 2007; Potts et al., 2010). Under this scenario, we analyse the effects of the weather becoming more unusual. It must be noted that a warming climate is likely to have other far-ranging societal impacts that could have a knock-on effect on pollinators and the various variables affecting them. Here, we only consider the impacts that are quantified within our IDSS.

Since the weather node has no parents in the IDSS (see Figure 2), we can modify the probability distribution associated with this variable as given in equation 2 rather than setting it to a specific fixed value. We modify the weather variable to have a 57% probability of being unusual relative to current data (up from 38%) and 43% probability of being average (down from 62%). The immediate impact of such a change is that the probability of honeybee, other bees, and other pollinators populations being ‘Good’ drops from 15.8%, 28.2%, and 29.9% to 14.9%, 27.5%, and 29.1%, respectively. As expected, the utility scores are the worst under this scenario compared to the earlier four scenarios. By the fourth year, the utility score drops down to 23.3 and then stays there for the remaining 6 years.

5 Discussion

We have presented a proof of concept IDSS based on DBNs for comparing candidate policies aimed at improving the population of pollinators. We demonstrated the efficacy of this IDSS in evaluating various scenarios that could be implemented by relevant policymakers. The IDSS presented here consists of variables affecting pollinator populations in the UK based on its unique social, economic, and climatic conditions. Therefore, for such an IDSS to be developed and used in another country, steps similar to those detailed in this paper would need to be followed whilst keeping in mind the unique conditions of that country. Indeed, this work is currently being adapted for use in Australia, which has recently suffered an incursion of the *Varroa* mite and has different climates and governmental and beekeeping practices to encode in the IDSS.

To operationalise this work for use in the UK, the DEFRA, as overseer of the National Pollinator Strategy, would be the most natural decision-maker, with its departments providing the majority of expertise for the expert panels along with the UK Met Office for weather and climate. In addition to the sensitivity to findings in Section 3.4, it may be considered prudent to investigate the impact of possible misspecification of priors over the parameters of the BN arising from the structured expert judgement elicitation; Smith and Daneshkhah (2010) provide a method for this.

A decision-maker can further tailor their specific requirements into this IDSS to fully operationalise it. We used a simple linear utility function for illustrative purposes. A risk averse decision-maker can use a different utility function such as an exponential functional of the form $U(x) = 1 - \exp(-ax)$ for $a > 0$. Due to the uncertainty tower rules, for such a utility function, a high variance in X will be directly influential on the resultant utility score (Smith, 2010). Further, we note that for

illustration, we considered an IDSS that evolves over a yearly time step. In practise, variables such as weather, disease and pest pressure, pesticide use etc. depend heavily on the season. Therefore, a seasonal time step might be considered by policymakers to be more appropriate for this system. This would result in a four time-slice DBN. However, one major drawback to consider here is that in the absence of complete data, this will largely increase the burden of estimating the parameters from domain experts until relevant data can be collected. This has to be weighed against the benefits of using a seasonal time step. The implementation and temporal evolution of the policies under consideration will also need to be considered when choosing the most appropriate time step (see also discussion on choosing the time step in Section 2.1).

In Section 4, the policies we implemented had immediate effects when they were implemented and when they were discontinued. In practise, there will be a lag associated with both types of changes. Due to the immediate implementation assumption, the largest effect of a given policy on the abundances of the pollinators was observed in the same time step that it was implemented for each scenario. Therefore, we found it useful in Section 4 to highlight the changes (as compared to the baseline of ‘No changes’) to the probabilities of the abundances of the pollinators at the first time step for each scenario. It must be noted that good visualisation plays a crucial role in effectively communicating the effects of the various candidate policies to decision-makers; see, e.g. Levontin et al. (2020), Walton et al. (2022), and Barons, Fonseca, Merwood, et al. (2022). In Figure 5, we illustrate a set of such visualisations for the five scenarios considered in Section 4. For instance, from Figure 5a and b it is clear that the beneficial effects of the policy in Scenario 1c is larger for other bees and pollinators than for honeybees, whereas under the policy in Scenario 3, the largest effect is seen for honeybees. Finally, for the decision-makers to choose the most appropriate policy, a cost–benefit analysis will be needed to complement the analysis provided by the IDSS.

6 Conclusion

In this paper, we have demonstrated that an IDSS based on a DBN can support decision-making for policies aimed at improving pollinator abundances. We illustrated, through five different scenarios, how our IDSS can quantify the effects of changes to the system. We have also shown here that for any policy to be beneficial in the long run, it needs to be sustained over that period of time.

The National Pollinator Strategy identified the key components of the environment and pollinator system which affect insect pollinators. What this work adds is a way to evaluate the efficacy of the policies the National Pollinator Strategy implies in a quantitative manner. This quantification aids policymakers to prioritise actions and combinations of actions that give the greatest probability of good pollinator abundance and allows then to construct a business case based on comparison of cost and benefits.

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Where The Bee Sucks (There Suck I), this song from *The Tempest* by William Shakespeare is sung by Ariel, a spirit who is in the service of the sorcerer Prospero. Act Five, Scene 1, Lines 88–95.

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Data availability

All data used in this paper was sourced from publicly available sources and are given in online supplementary Section A.

- Jack C. J., & Ellis J. D. (2021). Integrated pest management control of *Varroa destructor* (Acari: Varroidae), the most damaging pest of (*Apis mellifera* L. (Hymenoptera: Apidae)) colonies. *Journal of Insect Science*, 21(5), 6. <https://doi.org/10.1093/jisesa/ieab058>
- Johnson S., Logan M., Fox D., Kirkwood J., Pinto U., & Mengersen K. (2017). Environmental decision-making using Bayesian networks: Creating an environmental report card. *Applied Stochastic Models in Business and Industry*, 33, 335–347. <https://doi.org/10.1002/asmb.2190>
- Klein A.-M., Vaissière B. E., Cane J. H., Steffan-Dewenter I., Cunningham S. A., Kremen C., & Tscharntke T. (2007). Importance of pollinators in changing landscapes for world crops. *Proceedings of the Royal Society B: Biological Sciences*, 274(1608), 303–313. <https://doi.org/10.1098/rspb.2006.3721>
- Lauritzen S. L. (1996). *Graphical models* (Vol. 17). Clarendon Press.
- Leonelli M., & Smith J. Q. (2015). Bayesian decision support for complex systems with many distributed experts. *Annals of Operations Research*, 235(1), 517–542. <https://doi.org/10.1007/s10479-015-1957-7>
- Levontin P., Walton J., Kleineberg J., Barons M., French S., Aufegger L., McBride M., Smith J., Barons E., & Houssineau J. (2020). *Visualising uncertainty: A short introduction* (Technical Report). AU4DM.
- Lonsdorf E., Kremen C., Ricketts T., Winfree R., & Greenleaf N. W. S. (2009). Modelling pollination services across agricultural landscapes. *Annals of Botany*, 103(9), 1589–1600. <https://doi.org/10.1093/aob/mcp069>
- Lucas A. (2017). *The role of hoverflies as pollinators in Welsh conservation grasslands* [PhD thesis]. Swansea University.
- Memmott J., Craze P. G., Waser N. M., & Price M. V. (2007). Global warming and the disruption of plant–pollinator interactions. *Ecology Letters*, 10(8), 710–717. <https://doi.org/10.1111/ele.2007.10.issue-8>
- Met Office. (2022). *UK climate projections: Headline findings* (Technical Report). Met Office. <https://www.metoffice.gov.uk/research/approach/collaboration/ukcp/summaries/headline-findings>
- Norsys. (1994–2010). *Netica*. Norsys. <https://www.norsys.com/netica.html>
- Novais S. M. A., Nunes C. A., Santos N. B., D'Amico A. R., Fernandes G. W., Quesada M., Braga R. F., & Neves A. C. O. (2016). Effects of a possible pollinator crisis on food crop production in Brazil. *PLoS ONE*, 11(11), e0167292. <https://doi.org/10.1371/journal.pone.0167292>
- O'Hagan A., Buck C. E., Daneshkhan A., Eiser J. R., Garthwaite P. H., Jenkinson D. J., Oakley J. E., & Rakow T. (2006). *Uncertain judgements: Eliciting experts' probabilities*. John Wiley & Sons.
- Ollerton J. (2012). The importance of native pollinators. *The Plantsman*, 11(2), 86–89. <https://www.academia.edu/16681012>
- Owen R. (2020). *The likely effect of Varroa destructor on Australian honey bee populations* [PhD thesis]. University of Melbourne.
- Pearl J. (1986). Fusion, propagation, and structuring in belief networks. *Artificial Intelligence*, 29(3), 241–288. [https://doi.org/10.1016/0004-3702\(86\)90072-X](https://doi.org/10.1016/0004-3702(86)90072-X)
- Pearl J. (1995). Causal diagrams for empirical research. *Biometrika*, 82(4), 669–688. <https://doi.org/10.1093/biomet/82.4.669>
- Phan T. D., Smart J. C., Stewart-Koster B., Sahin O., Hadwen W. L., Dinh L. T., Tahmasbian I., & Capon S. J. (2019). Applications of Bayesian networks as decision support tools for water resource management under climate change and socio-economic stressors: A critical appraisal. *Water*, 11(12), 2642. <https://doi.org/10.3390/w11122642>
- Phillips L. D. (1984). A theory of requisite decision models. *Acta Psychologica*, 56(1–3), 29–48. [https://doi.org/10.1016/0001-6918\(84\)90005-2](https://doi.org/10.1016/0001-6918(84)90005-2)
- Pollino C. A., Woodberry O., Nicholson A., Korb K., & Hart B. T. (2007). Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. *Environmental Modelling & Software*, 22(8), 1140–1152. <https://doi.org/10.1016/j.envsoft.2006.03.006>
- POST. (2010). *Insect pollination POST note 348* (Technical Report). Parliamentary Office of Science and Technology.
- Potts S. G., Biesmeijer J. C., Kremen C., Neumann P., Schweiger O., & Kunin W. E. (2010). Global pollinator declines: Trends, impacts and drivers. *Trends in Ecology & Evolution*, 25(6), 345–353. <https://doi.org/10.1016/j.tree.2010.01.007>
- Potts S. G., Imperatriz Fonseca V., Ngo H. T., Biesmeijer J. C., Breeze T. D., Dicks L., Garibaldi L. A., Hill R., Settele J., & Vanbergen A. J. (2016). *Summary for policymakers of the assessment report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services on pollinators, pollination and food production* (Technical Report). Secretariat of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.
- Shenvi A., Bunnin F. O., & Smith J. Q. (2023). A Bayesian decision support system for counteracting activities of terrorist groups. *Journal of the Royal Statistical Society Series A*, 186(3), 294–312. <https://doi.org/10.1093/jrssa/qnac019>
- Smith J. Q. (2010). *Bayesian decision analysis: Principles and practice*. Cambridge University Press.
- Smith J. Q., Barons M. J., & Leonelli M. (2016). 'Coherent frameworks for statistical inference serving integrating decision support systems', arXiv, arXiv:1507.07394, preprint: not peer reviewed.

- Smith J. Q., & Daneshkhah A. (2010). On the robustness of Bayesian networks to learning from non-conjugate sampling. *International Journal of Approximate Reasoning*, 51(5), 558–572. <https://doi.org/10.1016/j.ijar.2010.01.013>
- The National Archives. (2021). DiAGRAM—The digital archiving graphical risk assessment model. <https://diagram.nationalarchives.gov.uk/>
- Vanbergen A. J., Heard M. S., Breeze T., Potts S. G., & Hanley N. (2014). *Status and value of pollinators and pollination services: A report to the Department for Environment, Food and Rural Affairs (DEFRA)* (Technical Report). DEFRA.
- Verma T., & Pearl J. (1988). Causal networks: Semantics and expressiveness. In *Proceedings of the Fourth International Conference on Uncertainty in Artificial Intelligence* (pp. 352–359). Elsevier.
- Walton J., Levontin P., Barons M., Workman M., Mackie E., & Kleineberg J. (2022). *Communicating climate risk: A toolkit* (Technical Report). AU4DM.