



DECISION MAKING IN SWARM INTELLIGENCE: REPLICATING AND EXPANDING AN AGENT-BASED MODEL OF NEST-SITE CHOICE BY HONEYBEE SWARMS

Bachelor's Project Thesis

Philipp Bischoff, S3534626, p.bischoff@student.rug.nl,
Supervisor: Prof. Dr. D. Grossi

Abstract: The organisation of organisms as a group yields many advantages. However, to develop and maintain group cohesion, the group will have to make decisions as a whole. The fact that many animals exhibit limited information-sharing capacities and still manage to act and solve problems as a whole indicates the need to further investigate the dynamics of decision making in groups. This emergent property known as Swarm Intelligence can be modelled through an agent-based model. This study replicated and validated a previously conducted agent-based simulation of a honeybee swarm's ability to choose the best possible nest site in regards to their independence and interdependence. Furthermore, this paper expands previous research by simulating habitat and population loss and their effect on the groups' decision making capabilities. Results showed a successful replication of the agent-based model and the expansion illustrated a negative effect on nest-site choice when population and habitats are reduced.

1 Introduction

The phenomena of individual animals gathering and living in groups can be observed throughout nature from complex mammals to simple invertebrates. While the specific dynamics of group-living widely differ, there are fundamental evolutionary reasons that foster the development of groups within species including the reduction of predatory threats (Dehn, 1990) or the enhanced access to information and the subsequent improvement of foraging capabilities (Ward and Webster, 2016). Groups can be presented with problems that require the individuals to make decisions as a whole in order to sustain the group cohesion and thus maintain the advantages of group living. Collective decision making however is not limited to human societies. Gorillas use vocalisation to collectively decide when to conclude a resting period and return to traveling and feeding activities (Stewart and Harcourt, 1994), Swans use head-neck movements to indicate flight departure of the flock (Black, 1988), and Bees use waggle-dances to decide on potential nest sites (Seeley and Visscher, 2004). The ability to collectively make a decision is a funda-

mental part of the social lives of animals (Conradt and Roper, 2005). The collective behaviour that emerges due to the individuals acting within the context of the group appears to be capable of solving cognitive problems that would be unsolvable for the individual itself. This is commonly known as Swarm Intelligence (SI) (Krause et al., 2010). These behavioural phenomena can be simulated using agent-based simulations. In these simulations autonomous agents interact with each other to produce an emergent group behaviour whose complexity far exceeds the capabilities of an individual agent.

A remarkable example of SI in nature is the behaviour of the honeybee (*Apis mellifera*). Once a honeybee swarm gets to a certain size, it splits up where part of the swarm stays at the current nesting site and others gather to search for a new site to build a new hive. Research by Seeley and Buhrman (2001) has revealed that the swarm manages to choose the best possible site out of a set of possible sites that differ in quality. This raises the question of how a hive made up of insects that have little information sharing capabilities manages to

collectively make a decision and chose an optimum nesting site. The process that gives rise to this behaviour involves scouting bees which fly out and inspect potential sites and upon inspecting a site return to the hive and advertise for the found site by doing a figure-eight movement known as a 'waggle-dance'. This movement encompasses, among other informational pieces, the perceived quality of the site that has been found.

In light of agent-based systems, the topic of this paper is the simulation of these behaviours and the investigation into an array of different behavioural parameters and their influence on nest-site choice. List et al. (2008) used an agent-based model to investigate a bee swarm's ability to collectively make a decision on which nest-site to chose to build a new hive. The model of the bees' decision-making ability was tested under a variety of different parameters. The investigation concentrated on two behavioural parameters especially: the bee's independence and the bee's interdependence. The independence is a factor that determines how likely the bees are to find a nest site on their own whereas the interdependence is a factor that determines the degree to which their nest site choice is influenced by the advertising dance of other bees.

The objective of this paper can be divided into three parts. The main objective is to use the model descriptions provided in List et al. (2008) and to reconstruct and *replicate* the simulation. Once the model has been reconstructed, it is used to *validate* the behaviour of the simulation. This is achieved by applying the same parameter settings to our model and subsequently comparing the results. To broaden the investigation on collective decision making and gather insights on bee swarms behaviour, the model is furthermore *explored* by testing additional parameters that simulate the effect of habitat and population loss and examine what kind of effect they have on the ability of the group to find the best possible site.

1.1 Preliminary Results

The system was successfully replicated, in that it produced comparable results over all parameter settings. The expansion of the research by changing behavioural parameters to simulate habitat and population loss resulted in two behavioural effects.

Simply reducing the population of the swarm reduced the frequency in which the group found the best site and increased the amount of time in which they were not able to form a consensus. However, if we simulate a population loss as well as a habitat loss at the same time, the swarm's decision making skill appears to not just diminish in the frequency of finding the best possible site but also in their ability to distinguish the sites from each other resulting in low-quality sites being chosen more often.

2 System Description

The simulation was created in *Python 3.8.5*. If not otherwise mentioned the justifications for implementation choices stem from List et al. (2008).

2.1 Simulation

The bee swarm consists of n bees participating in the simulation. Each bee b is defined as $b_0, b_1, b_2 \dots b_n$. There are additionally k sites labeled $k_0, k_1, k_2 \dots k_k$, where each site j contains a quality q_j . The simulation runs for T iterations, where each iteration t is a discrete value labeled $t_0, t_1, t_2, \dots t_t$. In each iteration t , the behaviour of all n bees is simulated.

The state of bee b at iteration t is defined as the vector

$$b_t = \begin{bmatrix} s_{b,t} \\ d_{b,t} \end{bmatrix} \quad (2.1)$$

- $s_{b,t} \in \{0, 1, 2, \dots, k\}$ represents the site for which bee b is dancing at iteration t . $s_{b,t} = 0$ when the bee is dancing for no site at all.
- $d_{b,t} \geq 0$ is the remaining duration of the dance activity of bee b at iteration t .

The model is initialized by creating all bees with no dance activity and no site advertised for. The state vector at the $t = 0$ is initially the same for every bee b namely:

$$b_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (2.2)$$

Which means that there is no site being advertised for and no dance activity for all bees.

2.2 Agent Behaviour

The behaviour of the bees can be separated into two different categories. They have either not found a site and are currently looking for a new one or they are currently advocating for a site by their dance activity.

2.2.1 Searching for a Site

Each site s has a probability that it will be found and advertised for at $t+1$. This probability $p_{s,t+1}$ is defined by

$$p_{s,t+1} = (1 - \lambda)\pi_s + \lambda f_{s,t} \quad (2.3)$$

consisting of the following factors:

- An *a priori* probability π_s , made up of the initial likelihood of the site, capturing how likely a site is to be discovered by a bee without the advertisement of others.
- $f_{s,t}$ measuring the proportion of bees currently dancing for site s
- $\lambda = \{ \lambda \mid 0 \leq \lambda \leq 1 \}$. A value used to model the amount of interdependence between bees. If $\lambda = 0$ there is no interdependence between the bees and the probability is simply determined by the *a priori* probability of the site and if $\lambda = 1$ the probability is solely determined by the proportion of bees dancing for a site.

Once a site has been found, we need to determine how long the dance activity $d_{b,t+1}$ is going to last. As dance duration is related to the quality to the site, this simulates a bee judging the quality of a site. Formally, this is defined by

$$d_{b,t+1} = \begin{cases} q_j \exp(T_\sigma) & \text{with probability } 1 - \mu \\ K \exp(T_\sigma) & \text{with probability } \mu \end{cases} \quad (2.4)$$

μ is essentially a factor that describes how independent the bees are at assessing the quality of a site. If $\mu = 0$ the duration of the dance activity of a bee that has found site is closely related to the respective quality and the bees always perform an independent assessment of the site. Whereas when $\mu = 1$ the actual quality of the site is irrelevant,

and only the mimicking factor λ decides how long the bees are dancing for a site. For $\lambda = 1$ the dance duration is mainly influenced by how many bees are currently at a specific site. T_σ is a normally distributed random variable with a mean of 0 and a standard deviation of $\sigma \geq 0$. The purpose of this variable is to model a bee's reliability. A low σ will yield values that are close to the original objective quality of the site, whereas a high σ will yield values that have a broader distribution around the original site quality. $K > 0$ is a factor that plays a role in the case where the bees assess a site depending on how many bees are already advocating for it.

2.2.2 Currently Dancing

If the bees are currently engaged in an advertising dance, the dance duration will be reduced by one in the next time step until the dance time has ended. This is defined by

$$b_{t+1} = \begin{cases} (s_{b,t}, d_{b,t} - 1) & \text{if } d_{b,t} > 0 \\ (0, 0) & \text{otherwise} \end{cases} \quad (2.5)$$

2.2.3 Consensus

As previously mentioned, the ability to make decisions is an integral part of a functioning swarm. This requires the formation of a consensus within the group. The simulation offers two types of decision thresholds indicating a consensus within the swarm.

The number of bees at site j at time t is defined as

$$n_{j,t} = |\{b : s_{b,t} = j\}| \quad (2.6)$$

There are two ways in which a consensus is measured. One involves a simple majority vote whereas the other combines a majority vote with 2 more conditions:

Weak Criterion According to the weak criterion site j at time t is the winner if it receives the most support out of all other sites. Formally defined as $n_{j,t} > n_{h,t}$ for any $h \neq j$ and $h \neq 0$

Strong Criterion The stronger criterion demands the winning site to have more than twice the amount of bees dancing for it than the second highest. $n_{j,t} > 2 * n_{h,t}$ for any $h \neq j$ and $h \neq 0$ and more than 20 percent of the bees have to be engaged with a site ($n_{0,t} < 0.8n$)

2.3 System Expansion

Pollinating animals provide an important ecosystem service that is currently threatened globally (Seeley and Visscher, 2004). Among factors like climate change and pesticide use, the loss of natural habitat remains as one of the most detrimental influences to healthy bee populations (Kline and Josh, 2020). Habitat loss generally reduces the availability of habitat patches and this reduction furthermore might lead to a diminished gene flow and a subsequent reduction in population sizes (Ferreira et al., 2015). These phenomena are integrated into the system by investigating the swarm’s ability to make an optimal decision in a situation where there are less bees to simulate the loss in populations size and a situation in which the population size is reduced as well as the quality of the sites.

To describe this more formally, the amount of bees is sequentially reduced from originally 200 bees to 150, 100 and 50 to simulate the population loss. In order to simulate the habitat loss the qualities of the site have to be altered. The quality of the site q was originally defined as $q \in \{1, 3, 5, 7, 9\}$, for our adaption we reduced the difference between the qualities and the range of values that the sites can have to $q \in \{3.5, 4, 4.5, 5, 5.5\}$

3 Results

3.1 Original Investigation

To re-emphasise, the paper that we aimed to replicate investigated two factors mainly: the independence and the interdependence of the bees.

3.1.1 Interdependence

To properly investigate the interdependence, the influence of the independence is kept at the same value to prevent it from diluting or confounding

the investigation. This is achieved by setting the value of μ to 0. Consulting 2.4, we can see that this prevents any form of mimicking, creating a simulation in which there is always an independent assessment of the site by the bees. Thus achieving a situation in which the bees’ interdependence can take different values, but their independence is always fully given.

To actually change the interdependence of the bees, the variables λ and σ are altered. The independence factor is modelled through the λ value. Looking at 2.3 we can see that λ determines if and to which extent either the *a priori* site quality (π) or the proportion of bees already dancing for a site (f) play a role in the likelihood of a site being found by a bee. This is interpreted as their level of interdependence. Another attribute that is being changed as part of the investigation into the interdependence of the bees is the σ value. It determines the standard deviation in the distribution from which the bees can receive a subjective assessment of the objective site quality, a higher σ value will, in turn, lead to more judgments that are further away from the actual site-quality, and a smaller σ value will consequently make the bees judgment more accurate or closer to the actual value. This in turn can be interpreted as the bee’s level of reliability.

3.1.2 Independence

With the insights gained from the previously outlined parameter settings, the authors continued to investigate the independence. The parameters for λ and σ stayed at values that gave optimum results ($\lambda = 0.8$, $\sigma = 0.2$) and the parameter μ was changed, to generate behaviours with different levels of independence. Additionally, some test with an additional λ and μ values was performed.

List et al. (2008) found that the swarm essentially *needs* the interplay of interdependence and independence to unfold its optimum decision-making potential.

3.2 Replication

Before we demonstrate the results further, considering the main goal of this paper was to replicate and validate the system as proposed in List et al.

(2008), it is integral to investigate our system’s replicative validity.

We can give an indication of the applicability of the system by calculating an average mean deviation between the results of the original parameter settings and the accuracy of the same settings in our system.

$$AMD_{System} = \frac{1}{n} \sum_{i=1}^n |x_i - y_i| \quad (3.1)$$

For n parameter settings, we sum the absolute difference between the original result x_i and the result of the replication of the same parameter setting y_i and consequently calculate the overall average or difference in results.

Because the parameter settings for the change in μ have been given visually, rather than numerically, we will proceed to judge our replication of the system by comparing the numerical values given in the paper, which were only given for the values $\lambda \in \{0.8, 0.5, 0.2\}$ and $\phi \in \{0.2, 1\}$. However, a thorough investigation for all parameters has been conducted with the system, yielding similar behaviours and results. An application of 3.1 to our data results in 3.8119%, indicating that our results as a mean average only differed 3.8119% from the original results. This is indicative of an applicable and accurate replication of the original paper’s results. An exact reproduction of the results is unfeasible considering there is an inherent stochastic dynamic in the simulation and each simulation has been repeated 250 times. The only parameter setting that was a slight outlier compared to what was found in the original paper was the parameter setting $\lambda = 0.8$ and $\sigma = 1$ modelling a high interdependence and low individual reliability (see Figure 3.1). This parameter settings results in $AMD = 8.3666\%$.

However, considering the general trend of all parameter settings and the similarity of the results, we can still conclude that we have an applicable replication of the original paper allowing us to further explore other parameter settings and their effect on the swarm’s decision making.

For a thorough comparison for all parameter settings consult Appendix A.

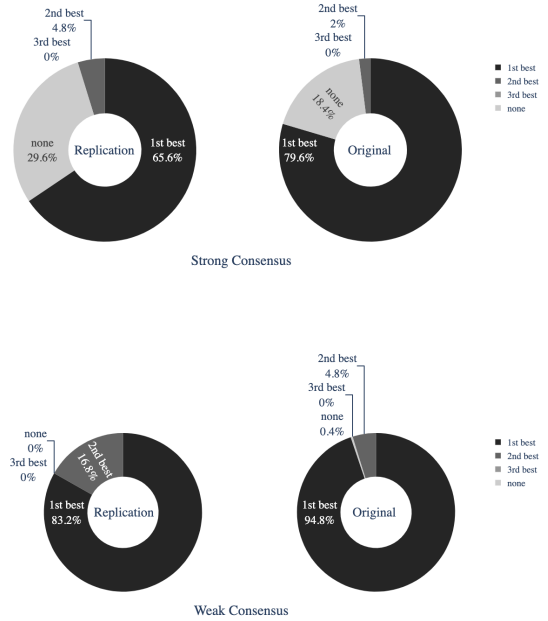


Figure 3.1: Replication results for $\lambda = 0.8$ and $\sigma = 1$

3.3 Expansion

3.3.1 Population Loss

When we first look at just the reduction of the population we see that initially a reduction of 25 % (150 bees) still leads to an optimal site-choice in 89% of the repetitions for the strong consensus and 97.2 % for the weak consensus. If judged by the strong consensus, the swarm comes to no consensus 10% of the time. The weak consensus results in very little activity for the 2nd best site and almost exclusively for the highest quality site.

A further reduction to 50% of the original population size (100 bees) increases the less optimum site-choice. The optimum choice in the strong consensus drops down to 82% and no site is chosen 11,2% of the time. We start to see a bit of activity for the 2nd highest site at 2.8%. The weak consensus shows the same results as previously, but with less activity for the 1st best site and more activity for the 2nd best site.

If the population is reduced by 75 % (50 bees), we see an even greater emphasis on the reduced site-choice ability. The best site is only chosen 75 % of

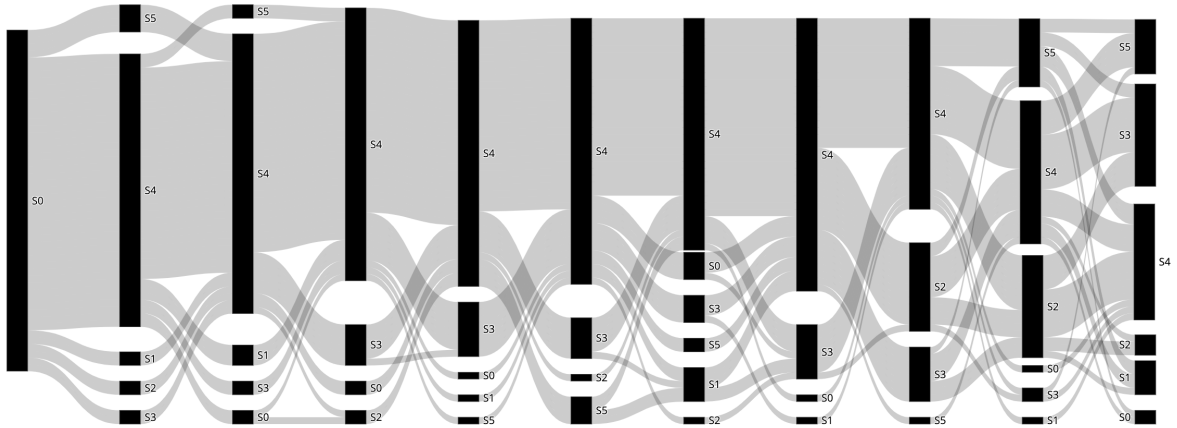


Figure 3.2: Site activity over 300 iterations with 50 bees and a reduced site quality distribution

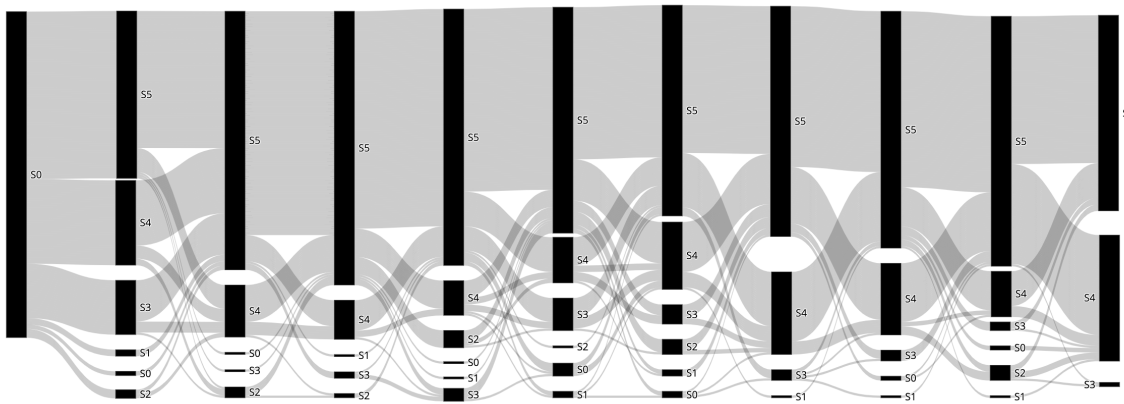


Figure 3.3: Site activity over 300 iterations with 150 bees and a normal site quality distribution

Table 3.1: Nest-site choice results for different parameter settings

		Normal Site Quality		Habitat Loss	
		Strong Consensus	Weak Consensus	Strong Consensus	Weak Consensus
150 Bees	1st Best	224 (89%)	243 (97.2%)	204 (81%)	238 (95.2%)
	2nd Best	1 (0.4%)	7 (2.8) %	4 (1.6%)	12 (4.8%)
	3rd Best	0	0	0	0
	None	25 (10%)	0	42 (16.8%)	0
100 Bees	1st Best	205 (82%)	230 (92%)	188 (75%)	224 (89%)
	2nd Best	7 (2.8%)	20 (8%)	4 (1.6%)	22 (8.8%)
	3rd Best	0	0	1 (0.4%)	4 (1.6%)
	None	28 (11.2%)	0	57 (22.8%)	0
50 Bees	1st Best	185 (74%)	216 (86.4%)	157 (62.8%)	190 (76%)
	2nd best	27 (10.8%)	34 (13.6%)	23 (9.2%)	42 (16.8%)
	3rd Best	0	0	5 (2%)	14 (5.6%)
	None	38 (15.2%)	0	64 (25.6%)	0

the time, the 2nd best site 10.8 % and for 15.2 % of the trials no consensus emerged. A similar situation unfolds in the weak consensus, where 86.4% of the repetitions resulted in the best site being chosen. The 2nd best site received 13.6 %.

The reduction in population size thus appears to lead to the swarm losing its ability to choose the best possible site (see Table 3.1). Judged by strong consensus criteria, the swarm tends to come to no consensus, rather than choosing different sites. However, this effect also diminishes when the population loss is severe (50 bees), because we start to see more activity for the 2nd best site as well.

3.3.2 Population Loss and Habitat Loss

The same step-wise reduction in population size applied to the situation in which the quality range within the sites has been reduced as well illustrates a slightly new behavioural effect. While we still see a reduction in the capability of choosing the *best possible site*, we also see that that swarm becomes more and more incapable of differentiating *between* the sites, leading to more failures on consensus formation and/or consensus on sub-optimal sites. While this is to be expected, given our changes to the simulation, it does give a glimpse into two separate effects that population loss and habitat loss could have on the decision making capability of a swarm.

We can furthermore conduct a visual investigation as illustrated in 3.2 and 3.3, in which we can see the development of the nest site choice throughout one simulation. 30 iterations pass between one horizontal alignment and the numbers connected to the bars represent the difference site, where the size of the bar represents the number of bees currently advertising for them. Within the scope of the investigation, 3.2 shows a typical simulation with the worst parameter setting (full population and habitat loss), whereas 3.3 shows the best possible setting (only 25% population loss and a normal site distribution). 3.2 shows that while there is notable amount of advertisement for the second-highest site (S4) at the beginning of the simulation, the dance activity for other sites picks up leading to the situation where there is a lot of back and forth between all sites, resulting in similar amounts of dance activity for the first, second and third highest site, indicating a lack of consensus within the swarm. If we compare this to the best-case scenario in 3.3 we see that the bees establish and maintain an optimal decision throughout the simulation. The other sites do get activity as well, considering that exploration of all sites is an important component in the process of eventually finding the best possible site, but in the end, the highest quality site gets a substantial amount of activity and a consensus is formed.

When we compare these two settings in the simulation, we see that the success of the swarm also seems to depend on having a robust consensus on the optimum site throughout the simulation, while still being able to tolerate activity for other sites. Once this tolerance is undermined, as indicated in 3.2, the swarm starts to lose its ability to *collectively* decide which site to chose.

4 Discussion

We replicated an agent-based system as proposed by List et al. (2008). The system simulates how a swarm of bees gathers information, forms a consensus and subsequently makes a decision. The replication produced satisfactory results. Taking the inherent stochasticity of the simulations into account, our system exhibited comparable behaviour for all parameter settings, which included independence, interdependence and reliability of the bees. This is indicative of the reproducibility of the system. The fact that the simulations showed the same behaviours strengthens the empirical insights that the original authors have gained. To furthermore explore the behaviour of the swarm additional parameters were explored. The population size, as well as the quality of the sites, were altered. The range in quality that the sites could exhibit was also made more narrow. A reduction in population size generally resulted in a decline in the swarm's ability to find the best possible site. The consensus was more likely not to be formed, rather than choosing a low quality site. However once the population loss was compounded with a decrease in absolute site quality and range of site qualities, the swarm was also less likely to form an optimum decision and additionally more likely to choose lower-quality sites.

Possible points of improvement in the simulation could include a more expansive investigation into parameters and their influence on the collective decision-making ability. Possible directions for example could include changing the number of sites rather than changing the quality of the site.

On a bit broader scale, the insights we can gather from the simulation could benefit from adding a temporal-spatial component to the agent simulation. This could be achieved by either adding a graphical component in which the bees actually physically explore the simulation or simply adding

a variable that could represent this fact of reality. The distances to and the location of sites are important factors that determine a swarm's behaviour, which are not represented in the current simulation.

4.1 Conclusion

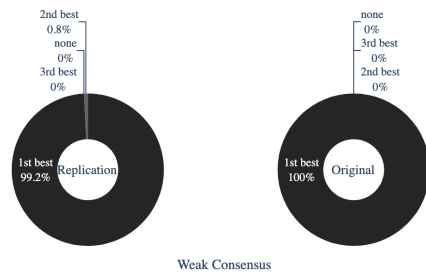
The simulation illustrates a powerful potential that agent-based simulation can have on the observation of and the research into animals' behaviour that are difficult to conduct in real life. Field studies are limited by the researcher's ability to observe and their vicinity to the animals which is far from a trivial task. Environmental factors and the animals' tolerance of human presence can undermine and limit the quality and amount of data one can generate on their respective behaviour. While a simulation will always be an abstraction of real life processes, they nevertheless can give insights into behaviour and capabilities that one could otherwise not get.

References

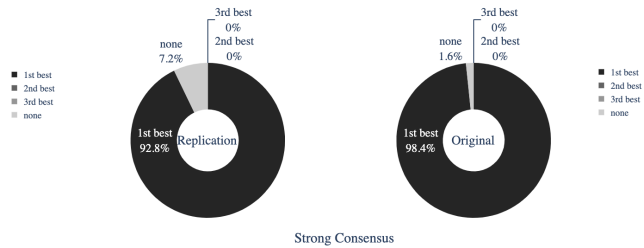
- Black, J. M. (1988). Preflight signalling in swans: A mechanism for group cohesion and flock formation. *Ethology*, 79(2):143–157.
- Conradt, L. and Roper, J. T. (2005). Consensus decision making in animals. *Trends in Ecology Evolution*, 20(8):449–456.
- Dehn, M. M. (1990). Vigilance for predators: Detection and dilution effects. *Behavioral Ecology and Sociobiology*, 26(5):337–342.
- Ferreira, P. A., Boscolo, D., Carvalheiro, L. G., Biesmeijer, J. C., Rocha, P. L. B., and Viana, B. F. (2015). Responses of bees to habitat loss in fragmented landscapes of brazilian atlantic rainforest. *Landscape Ecology*, 30(10):2067–2078.
- Kline, O. and Josh, N. K. (2020). Mitigating the effects of habitat loss on solitary bees in agricultural ecosystems. *Agriculture*, 10(4):115.
- Krause, J., Graeme, D. R., and Krause, S. (2010). Swarm intelligence in animals and humans. *Trends in Ecology Evolution*, 25(1):28–34.

- List, C., Esholtz, C., and Seeley, T. D. (2008). Independence and interdependence in collective decision making: an agent-based model of nest-site choice by honeybee swarms. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364:755–762.
- Seeley, T. D. and Buhrman, S. C. (2001). Nest-site selection in honey bees: how well do swarms implement the ‘best-of- n ’ decision rule? *Behav. Ecol. Sociobiol.*, 49:416–427.
- Seeley, T. D. and Visscher, P. K. (2004). Group decision making in nest-site selection by honey bees. *Apidologie*, 35(2):101–116.
- Stewart, K. J. and Harcourt, A. H. (1994). Gorillas’ vocalizations during rest periods: Signals of impending departure. *Behaviour*, 130(1-2):29–40.
- Ward, A. and Webster, M. (2016). Other benefits and costs of grouping. In *Sociality: The Behaviour of Group-Living Animals*. Springer.

A Appendix



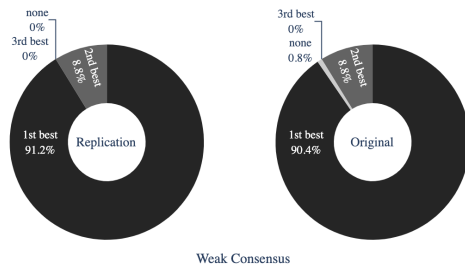
Weak Consensus



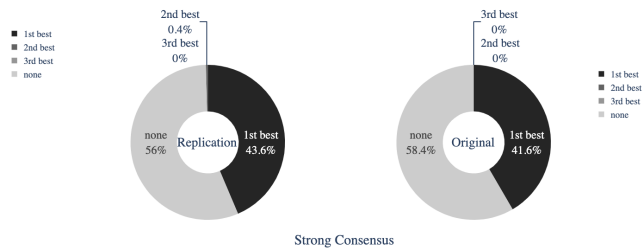
Strong Consensus

Figure A.1: Weak Consensus comparison for $\lambda = 0.8$ and $\sigma = 0.2$

Figure A.2: Strong Consensus comparison for $\lambda = 0.8$ and $\sigma = 0.2$



Weak Consensus



Strong Consensus

Figure A.3: Weak Consensus comparison for $\lambda = 0.5$ and $\sigma = 0.2$

Figure A.4: Strong Consensus comparison for $\lambda = 0.5$ and $\sigma = 0.2$

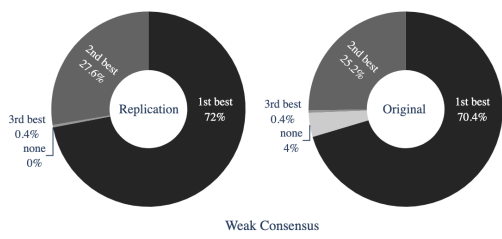


Figure A.5: Weak Consensus comparison for $\lambda = 0.2$ and $\sigma = 0.2$

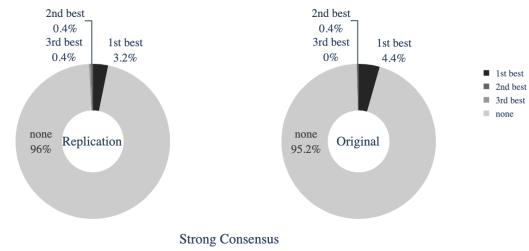


Figure A.6: Strong Consensus comparison for $\lambda = 0.2$ and $\sigma = 0.2$

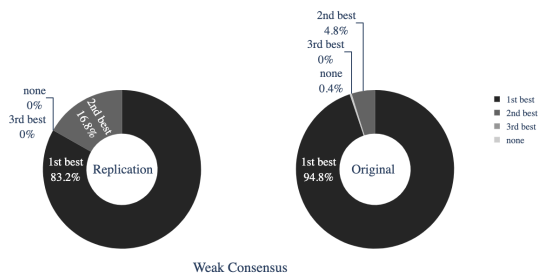


Figure A.7: Weak Consensus comparison for $\lambda = 0.8$ and $\sigma = 1$

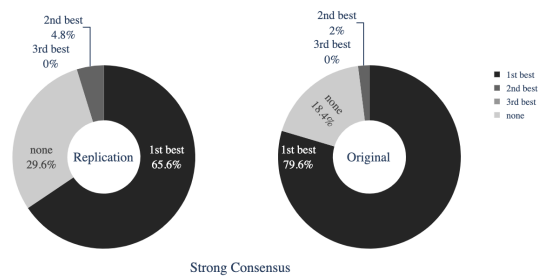


Figure A.8: Strong Consensus comparison for $\lambda = 0.8$ and $\sigma = 1$

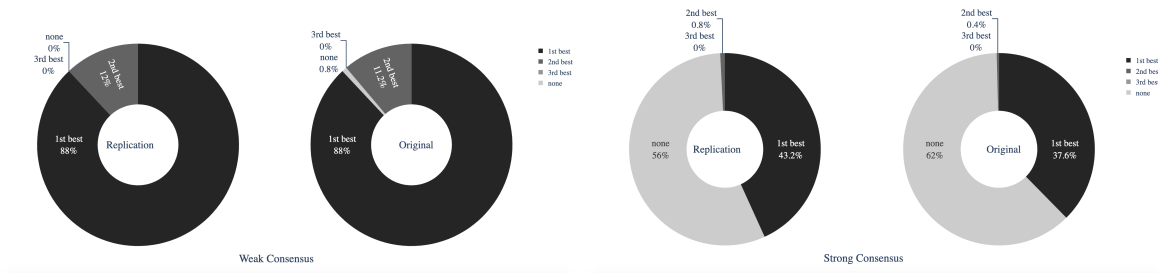


Figure A.9: Weak Consensus comparison for $\lambda = 0.5$ and $\sigma = 1$

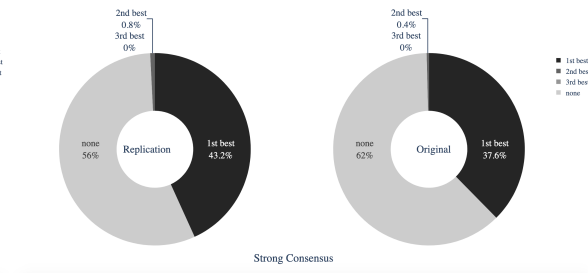


Figure A.10: Strong Consensus comparison for $\lambda = 0.5$ and $\sigma = 1$

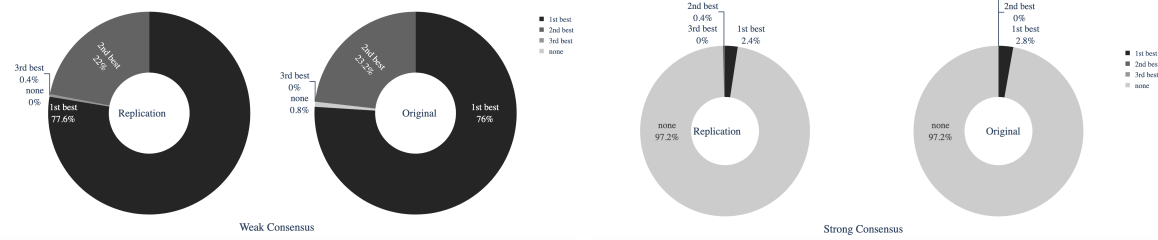


Figure A.11: Weak Consensus comparison for $\lambda = 0.2$ and $\sigma = 1$

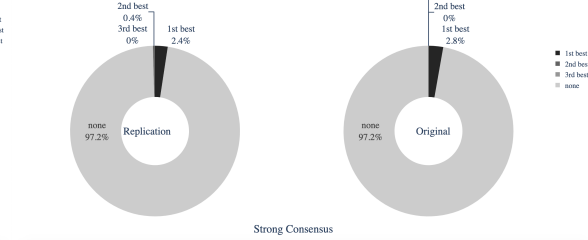


Figure A.12: Strong Consensus comparison for $\lambda = 0.2$ and $\sigma = 1$