

# Spatiotemporal Dynamics of Food Exchange Networks in Honeybees

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## Introduction

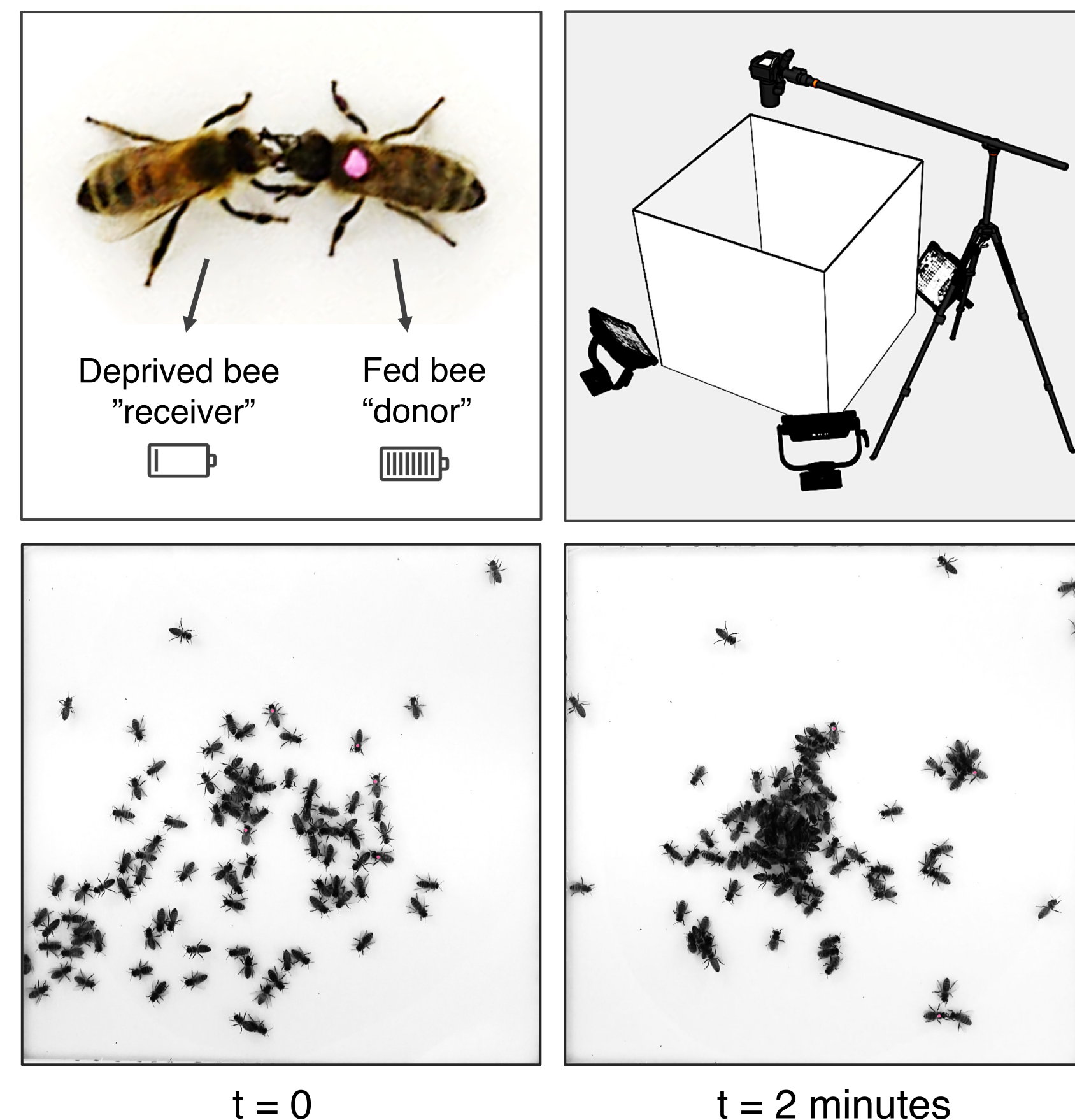
- Trophallaxis*, the direct transfer of food among nestmates serves not only as a feeding mechanism but also as a medium for information exchange among workers, helping them coordinate their activities within the hive [1].
- Using an integrated experimental-modeling approach, we aim to study the dynamics of food distribution among honeybees.

## Research Questions

- What spatiotemporal patterns arise during food exchange interactions?
- Can we characterize phase changes in the collective behavior?
- What is the effect of aggregation for food exchange?
- What communication mechanism among bees leads to aggregation formation?

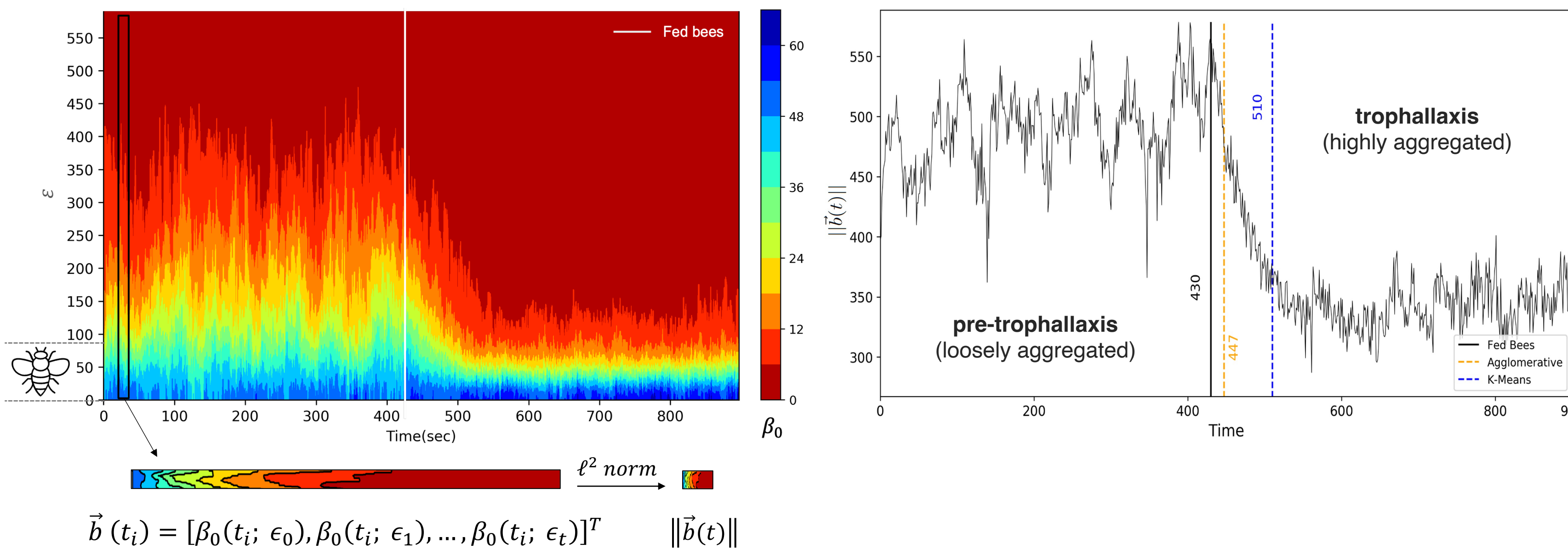
## Behavioral Experiments

- Six different colonies of honeybees *Apis mellifera* L. were divided into two groups.
- One group was *deprived* of food for 24 hours before each experiment, while others had constant access to food.
- These *fed* bees, which comprised ~10% of the whole population in each experiment, were carefully marked with a pink circle on their thorax.



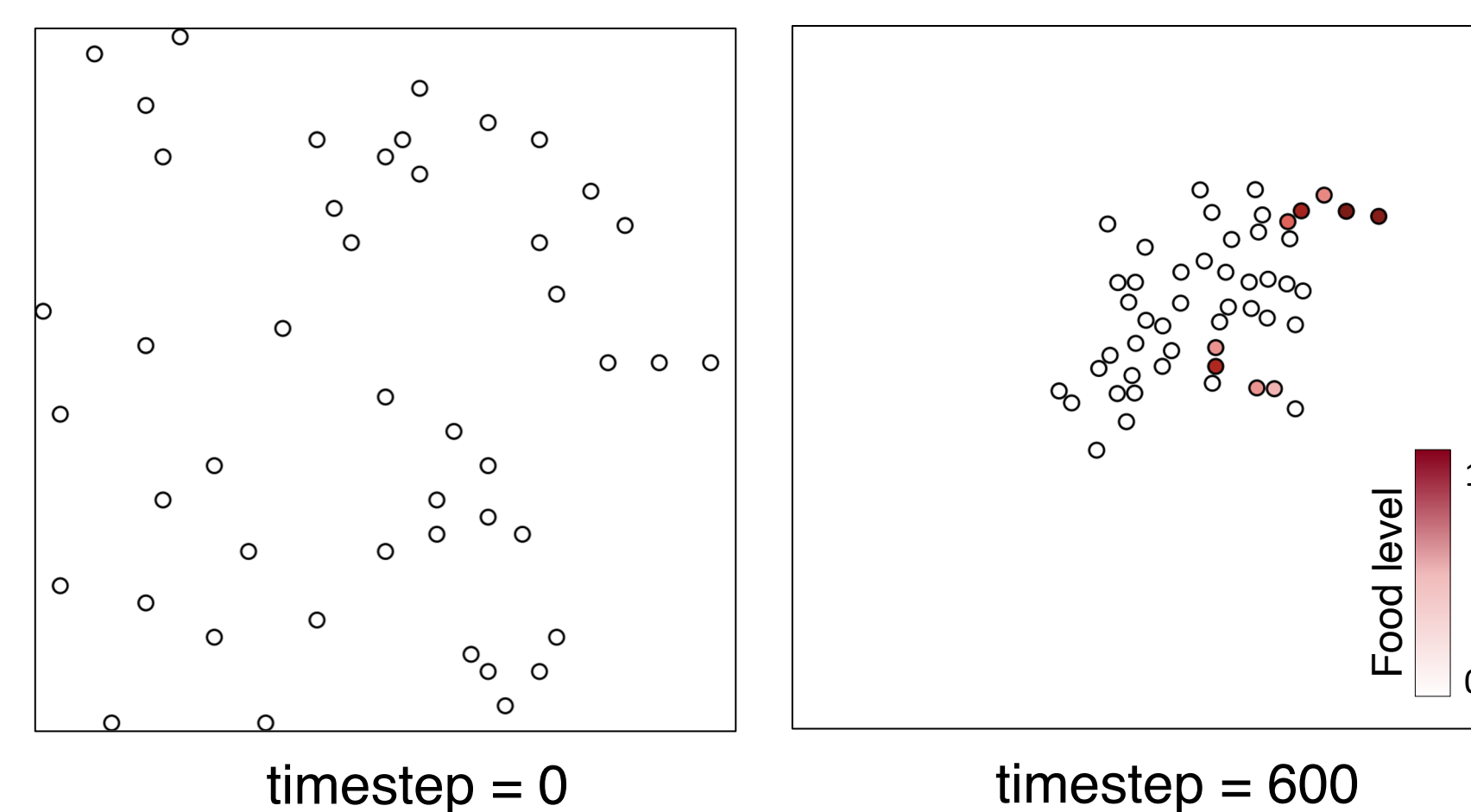
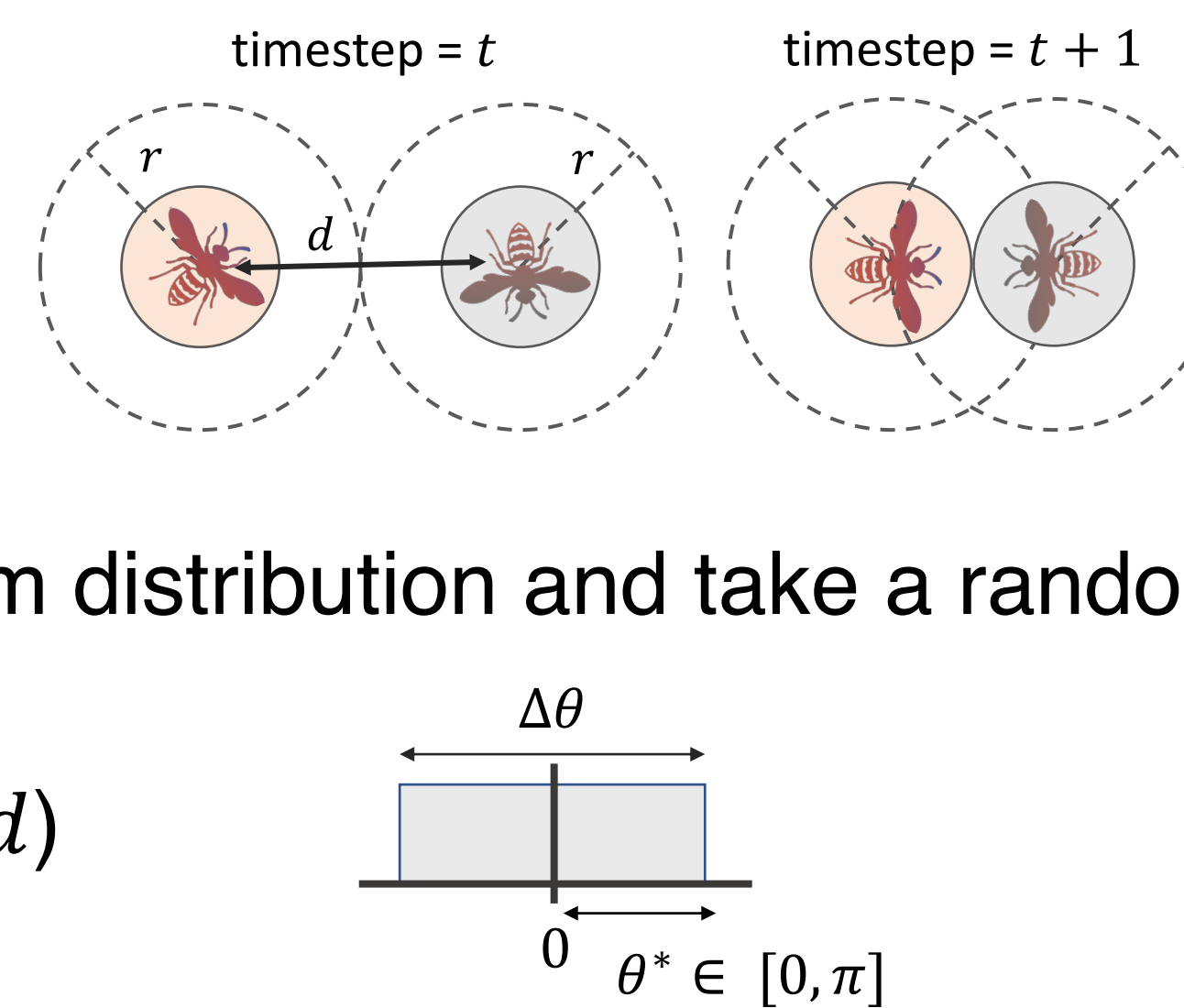
## Topological Data Analysis

- Our experimental analysis described in [2] suggests that bees aggregate to share food.
- We use TDA, a framework from applied mathematics, to analyze the complex morphology of our data.
- The goal is to characterize the group's dynamics via the time evolution of topological invariants called Betti( $\beta$ ) numbers, accounting for persistence of topological features across multiple scales. Our focus is on tracking the value of  $\beta_0$  (*i.e.*, number of connected components).
- We use the CROCKER plot [3] representation of our results and then perform clustering on the norms of the CROCKER slices to detect any possible regime shift.



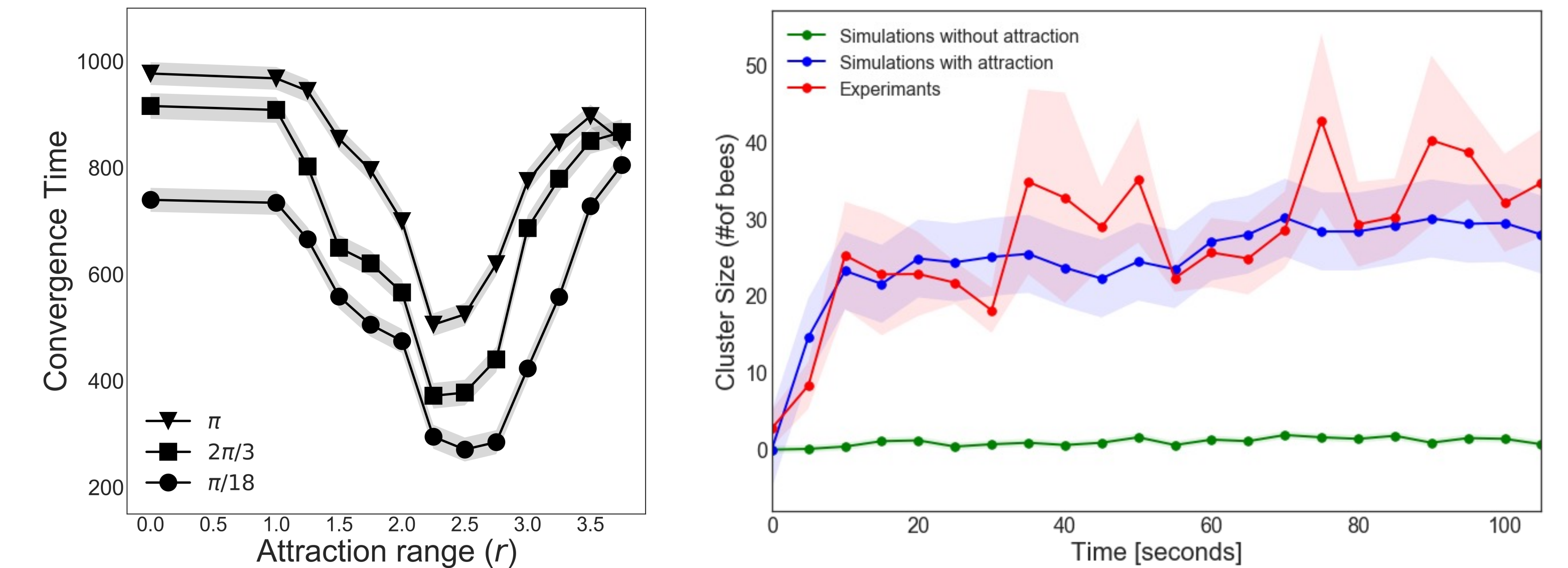
## Data-Driven Agent-Based Model

- Check immediate  $r$  –neighborhood, If  $d \leq 2r$ , then agents will move one step toward each other at the next timestep (attraction parameter  $r$ )
- Modify heading by  $\Delta\theta$  drawn from a uniform distribution and take a random walk step (angle parameter  $\theta^*$ )
- Check for encounter (distance parameter  $d$ )
- Exchange food:  $f_i(t+1) = f_i(t) \pm \frac{\Delta f(t)}{2}$
- Loop until the food distribution is uniform (variance threshold)
  - Convergence:  $\sigma^2(t) \leq \sigma_{threshold}^2$   
 $\sigma^2(t+1) - \sigma^2(t) \leq \Delta\sigma_{threshold}^2$



## Insights from the Model

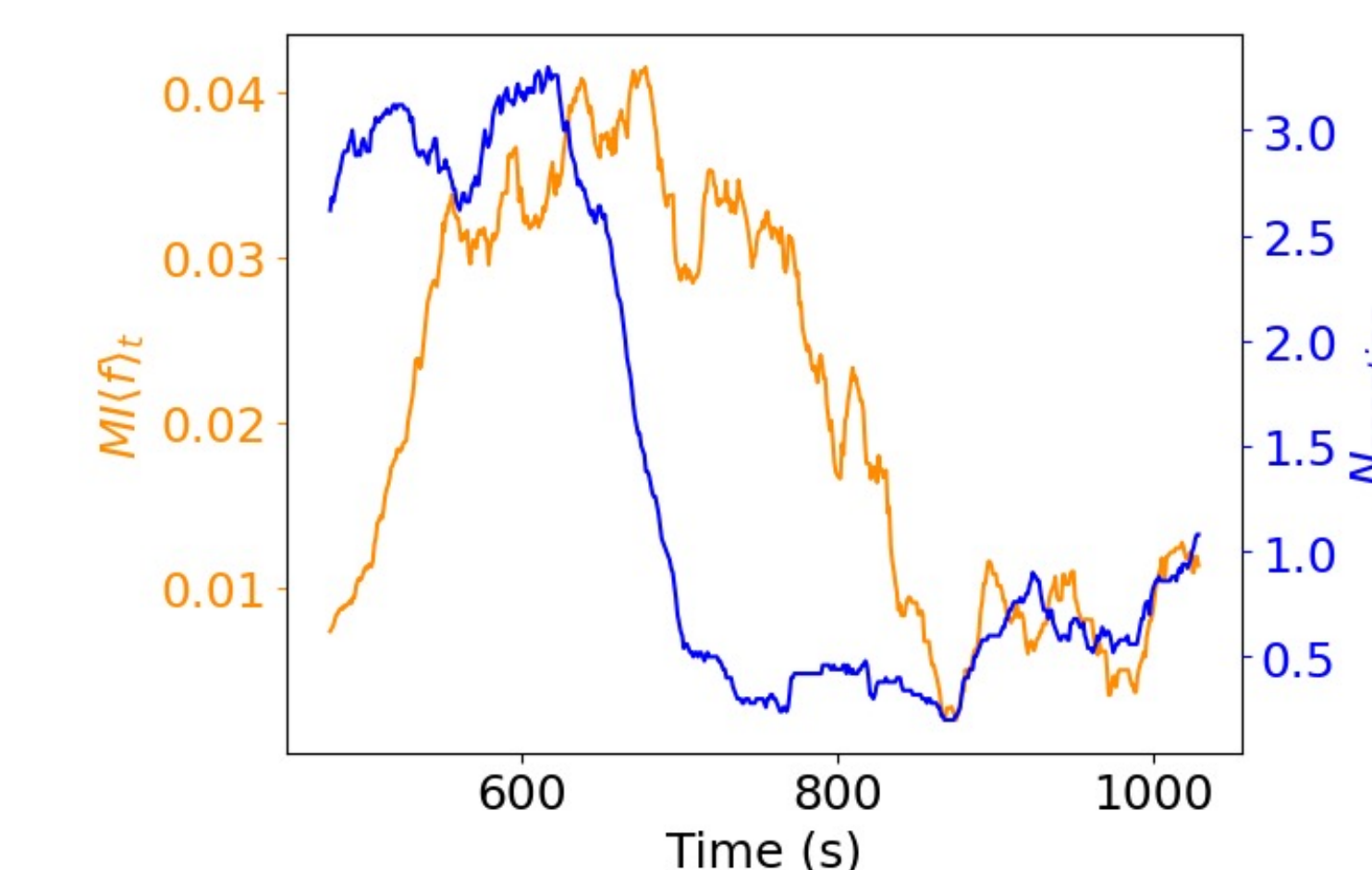
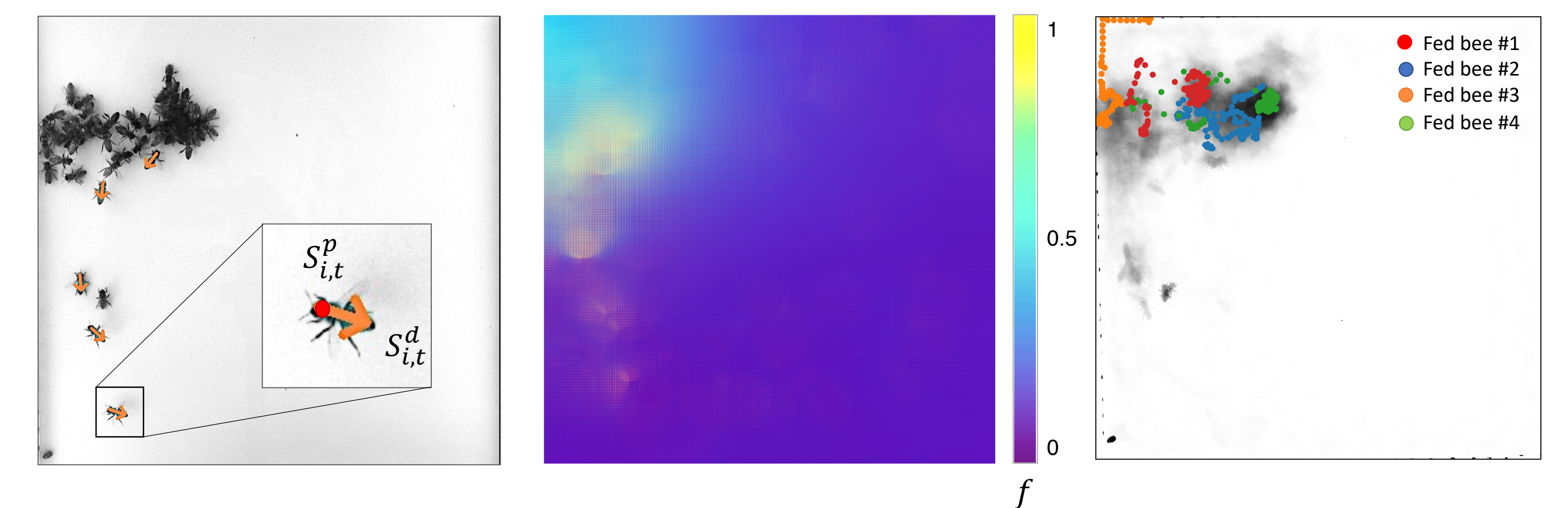
- Short range attractions* increase the efficiency of food distribution.
- Comparing the cluster sizes across real and simulated bees show that model with attraction is a better match to the natural behavior of the bees compared to a homogenous random walk [3].



## Communication for Aggregation

- We train a machine learning algorithm developed in [4] to identify the positions and directions of the scenting events in our experiments.
- We then correlate the scenting events with the spatiotemporal density of bees by treating the positions ( $S_{i,t}^p$ ) and directions ( $S_{i,t}^d$ ) vectors as a set of gradients that define a minimal surface of height  $f(x, y, t)$ .
- We compute the value of normalized mutual information  $MI\langle f \rangle_t$  between the attractive surface averaged over 10 minutes after the fed bees are in and the density of the bees  $\rho(x, y, t)$ .
- Our results confirm that there is strong correlation,  $MI\langle f \rangle_t = 0.44$ , between scenting events and the location of the food exchange aggregations.

$$MI(f(x, y, t); \rho(x, y, t)) = \sum_{f_i \in f} \sum_{\rho_i \in \rho} P_{(f, \rho)}(f_i, \rho_i) \log \frac{P_{(f, \rho)}(f_i, \rho_i)}{P_{(f)}(f_i) P_{(\rho)}(\rho_i)}$$



## References

- [1] Greenwald *et al.* *Scientific Reports*, 2015.
- [2] Gharooni Fard *et al.* *MIT Press*, 2020.
- [3] Ulmer *et al.* *PLOS ONE*, 2019.
- [4] Nguyen *et al.* *PNAS*, 2020.