SWARM OF DRONES FOR ENVIRONMENTAL MONITORING

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OUTLINE

- ENVRONMENTAL MONITORING, SEARCH AND RESCUE: MAIN CHALLENGES
- WHY SWARM ROBOTICS IN ENVIRONMENTAL MONITORING
- COLLECTIVE DECISION MAKING
- A SPECIFIC CASE: BEST-OF-N MODEL
- RESULTS
- CONCLUSIONS

USE OF AUV/DRONES FOR ENVIRONMENTAL MONITORING

Equipment

<u>Sensors:</u>

GPS

camera

IMU (inertial measurement unit)

<u>Communications</u>:

Radio

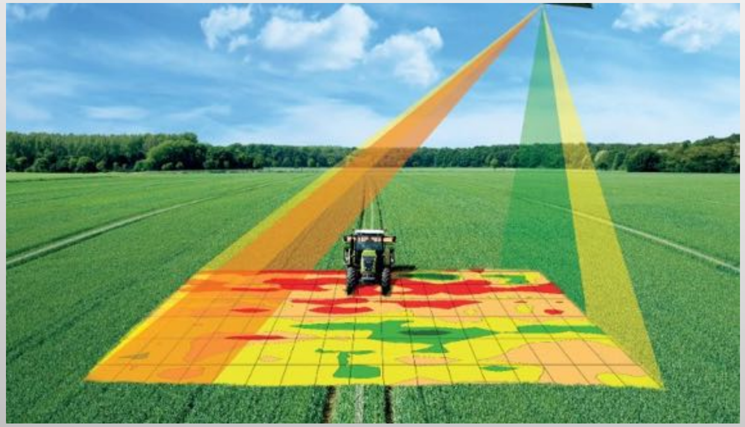
Wireless

M2M\M2C (machine to machine/to cloud)

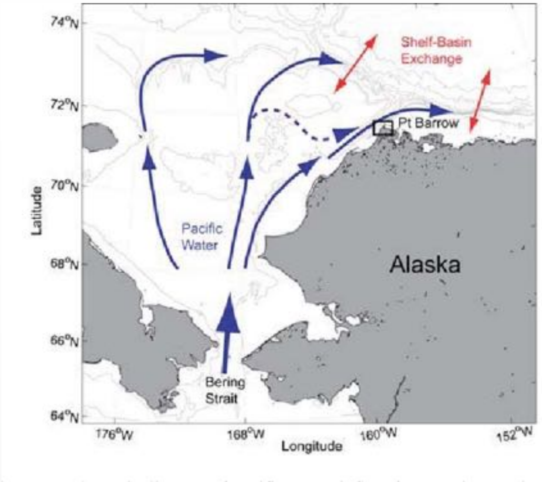
Post-tsunami or cyclones

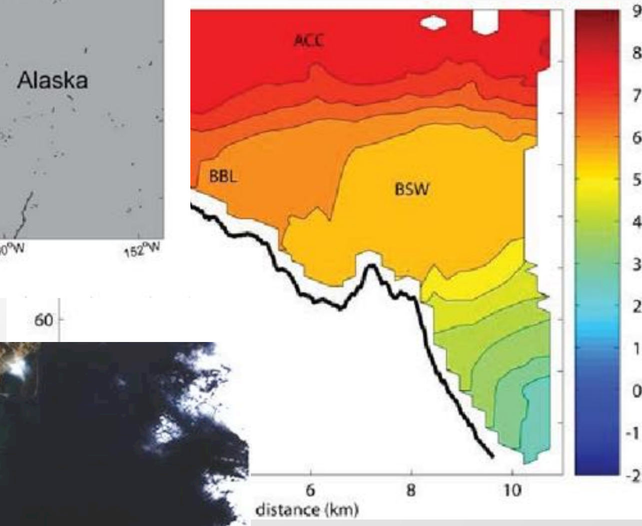
Post-earthquake

Precision agricolture



Arctic coastal hydrography





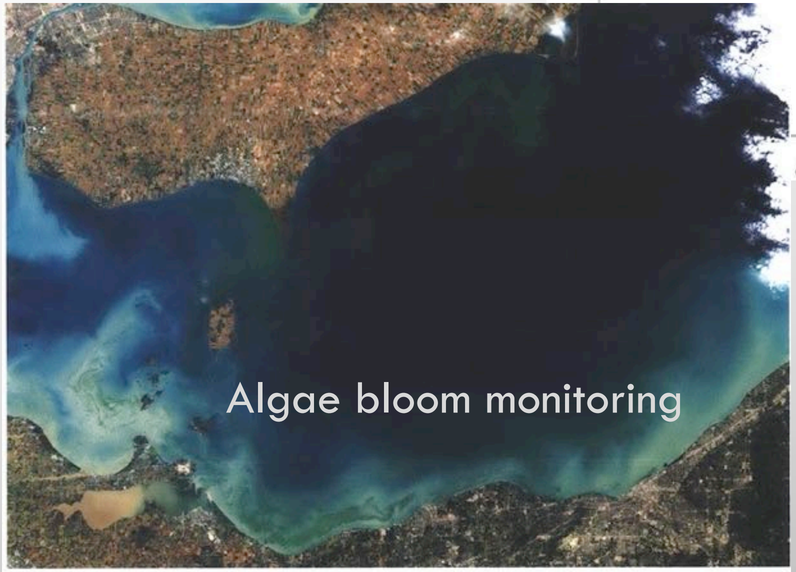


Figure 3. Satellite image courtesy of NASA shows an algae bloom on the western side of Lake Erie. (Kate Abbey-Lambertz, Aug 6 2014, "These Disturbing Photos Show Why Algae Blooms Are A Growing Global Water Threat" *The Huffington Post*)

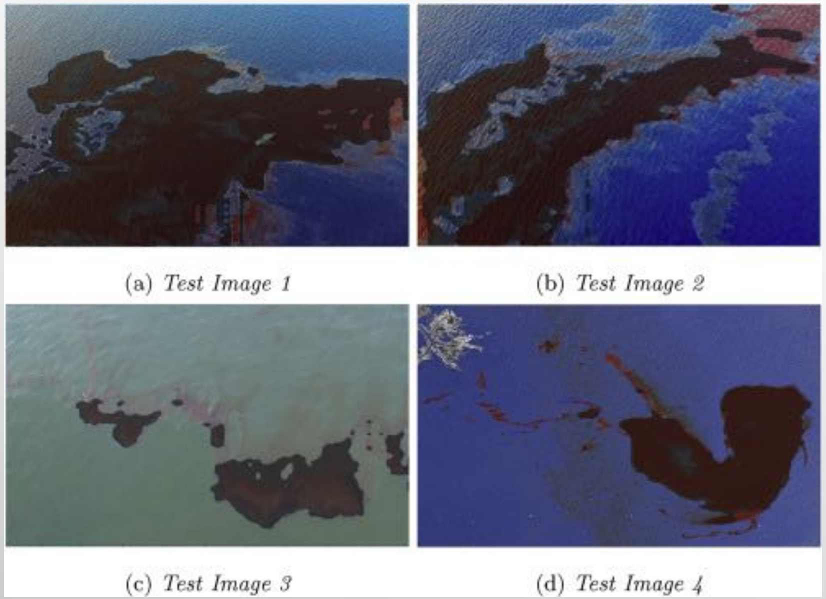
USE OF DRONES FOR *DYNAMIC* ENVIRONMENTAL MONITORING

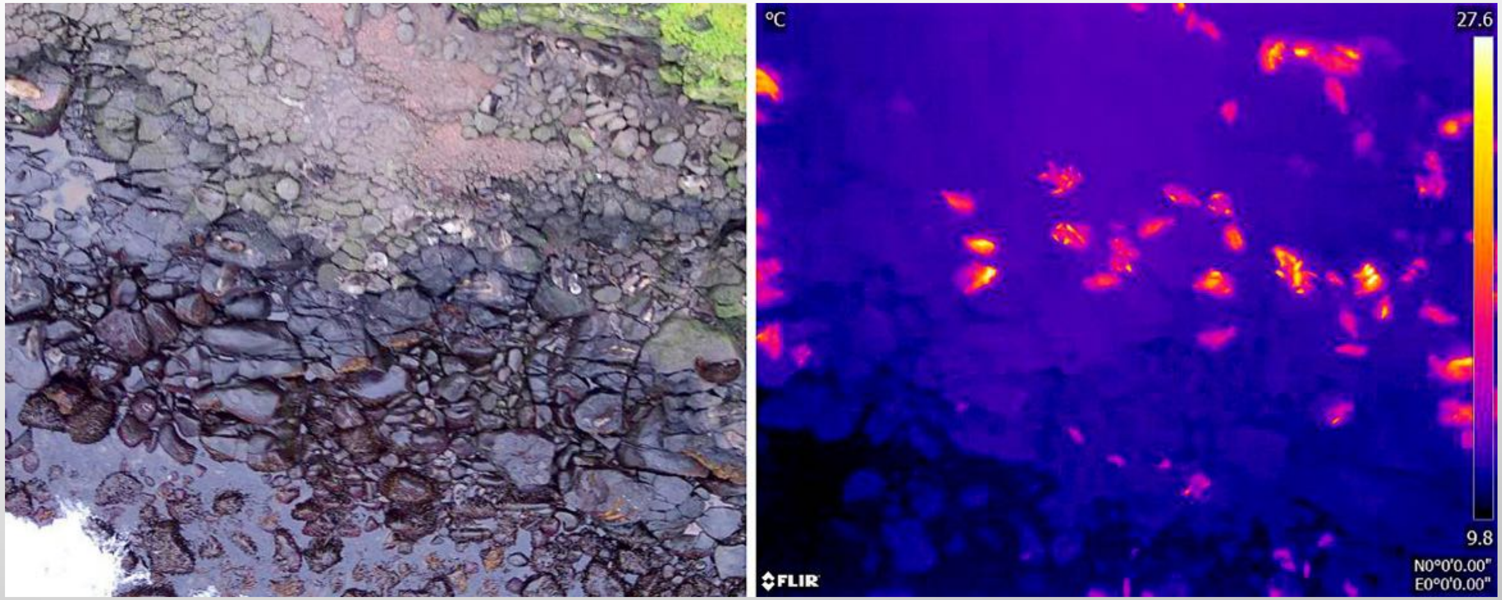
Environment is intrinsically dynamic.

Monitoring of endangered species

- Killer whales monitoring in British Columbia
- Northern fur seals in Alaska

Oil spill monitoring

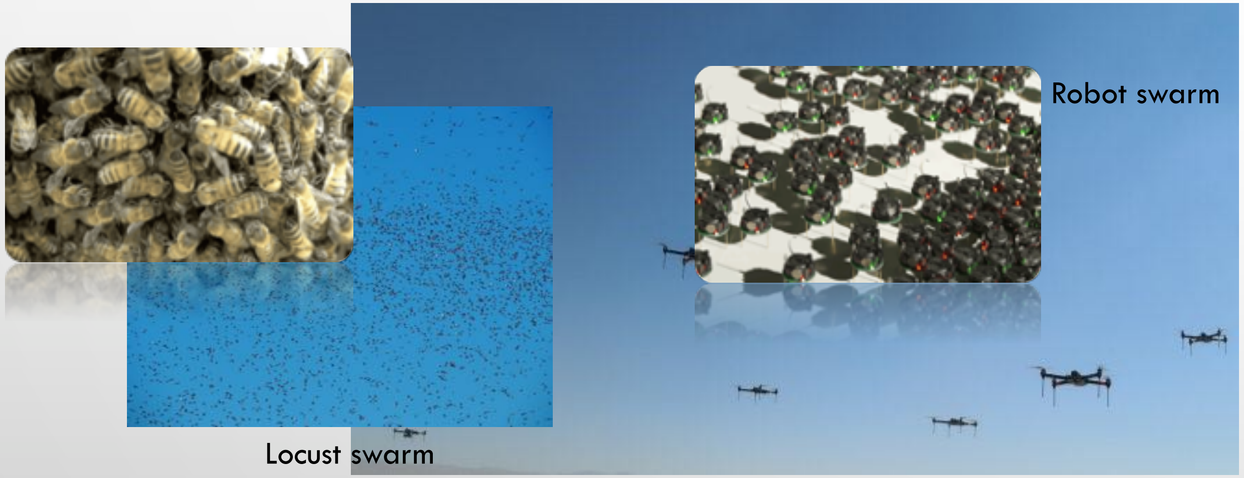




The use of single drones is well established.
The application of a swarm of drones is under study.

FROM NATURAL TO ARTIFICIAL SWARMS

In nature, many animals' societies are based on **collective decision making**, where the single individuals coordinate to get to take a common decision



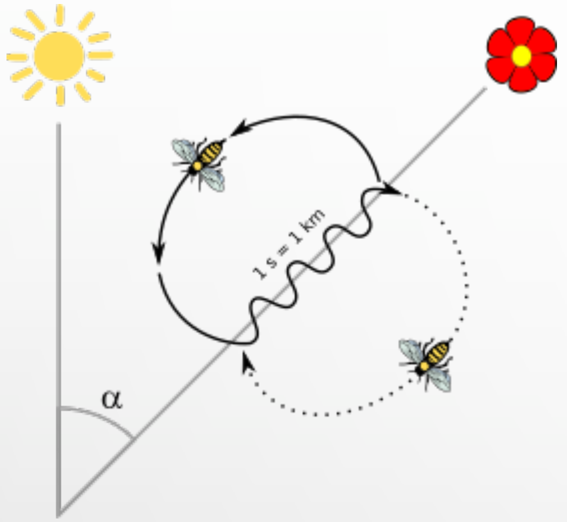
Engineering: Can we design artificial swarms of drones to achieve a specific task?

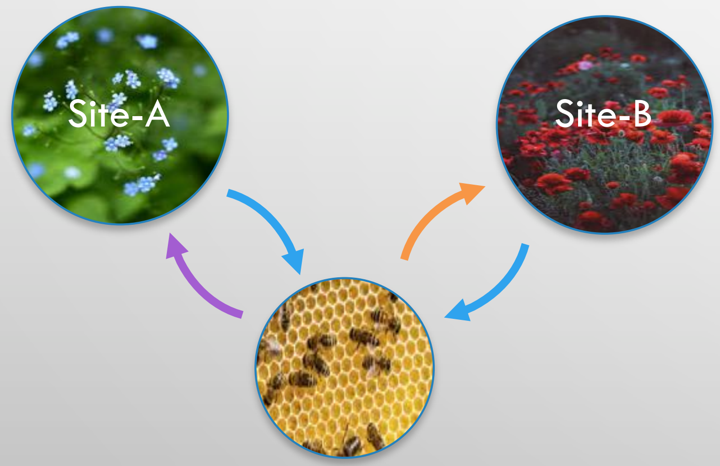
BEST-OF-N MODELS

- The ability to collectively **choose the best** among a finite set of alternatives
- **Social insects,** such as honeybees and ants, are able to collectively choose and commit to a single suitable nest site, using collective and distributed information processing
- **Social animals**, like schools of fish, flocks of birds, and wild baboons are able to move coherently in a common direction using only local interactions with their neighbors
- It is a fundamental cognitive skill also for **robot swarms**
- Application to environmental monitoring:
    - **marine mammals**
    - **fire monitoring**

BEST-OF-2 MODELS

Inspired by bee waggle dance



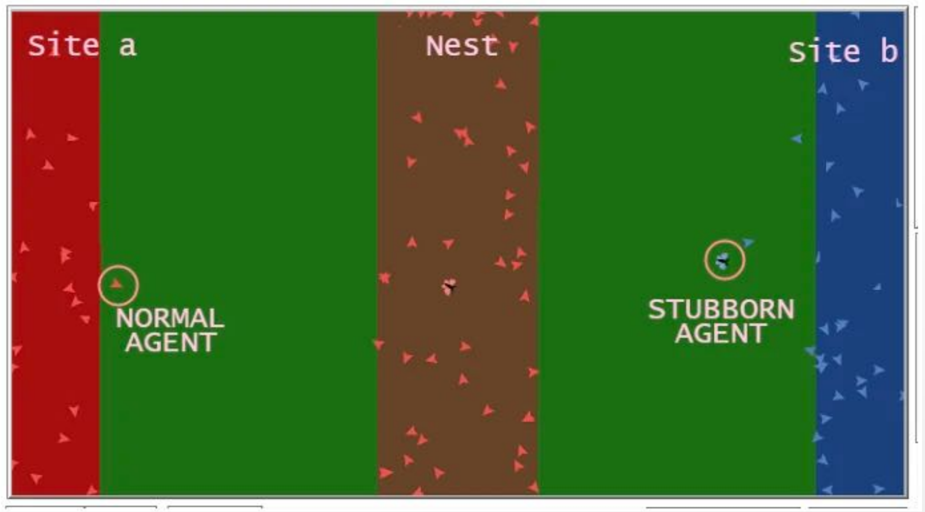


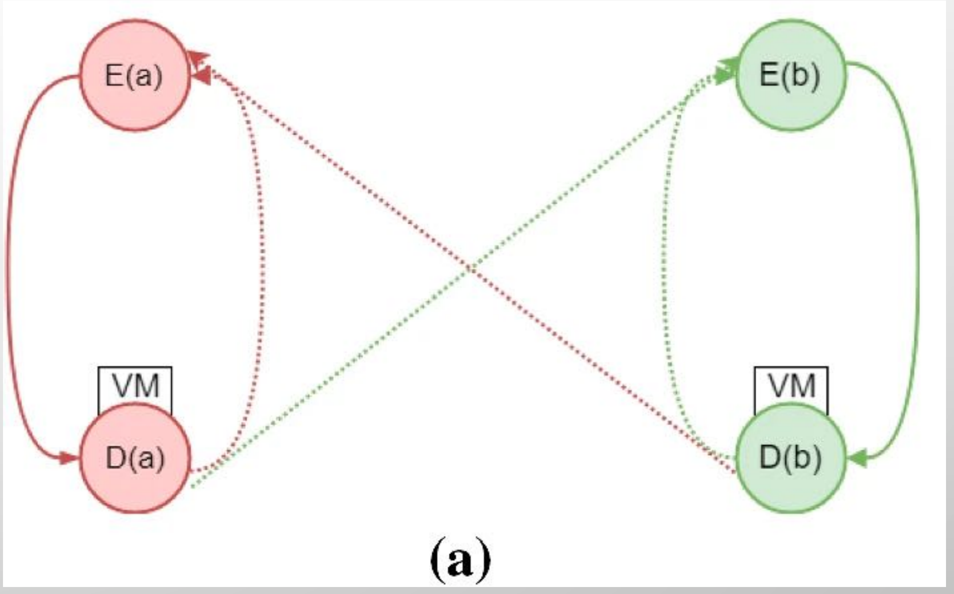
Initial quality ratio
$\rho_A/\rho_B = \rho_1/\rho_2$

at time = t, the quality will be swapped - **Dynamic!**
$\rho_A/\rho_B = \rho_2/\rho_1$

Nest - Voting happens here using *Positive Feedback Modulation*
(the better the site, the longer the bee promotes it)

Netlogo Implementation





Corresponding Finite State Machine

The system of 8 ODEs with 8 state variables is given by:

$$\dot{d}_A = -\frac{1}{\rho_A g} d_A + \frac{1}{q} e_A \tag{1}$$

$$\dot{d}_B = -\frac{1}{\rho_B g} d_B + \frac{1}{q} e_B \tag{2}$$

$$\dot{e}_A = -\frac{1}{q} e_A + \frac{\sigma_{AS}}{\rho_A g} d_A + \frac{\sigma_{AS}}{\rho_B g} d_B \tag{3}$$

$$\dot{e}_B = -\frac{1}{q} e_B + \frac{1 - \sigma_{AS}}{\rho_A g} d_A + \frac{1 - \sigma_{AS}}{\rho_B g} d_B \tag{4}$$

$$\dot{d}_{AS} = -\frac{1}{\rho_A g} d_{AS} + \frac{1}{q} e_{AS} \tag{5}$$

$$\dot{d}_{BS} = -\frac{1}{\rho_B g} d_{BS} + \frac{1}{q} e_{BS} \tag{6}$$

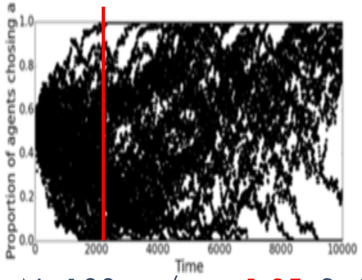
$$\dot{e}_{AS} = -\frac{1}{q} e_{AS} + \frac{1}{\rho_A g} d_{AS} \tag{7}$$

$$\dot{e}_{BS} = -\frac{1}{q} e_{BS} + \frac{1}{\rho_B g} d_{BS} \tag{8}$$

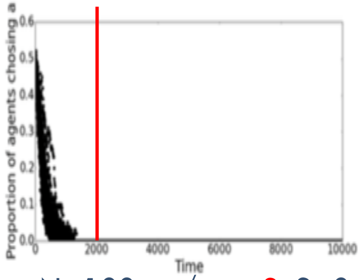
THE MODEL

Collective decision making in dynamic environments, J. Prasetyo, G. De Masi, E. Ferrante, Swarm Intelligence, Jun 2019, pp 1-27

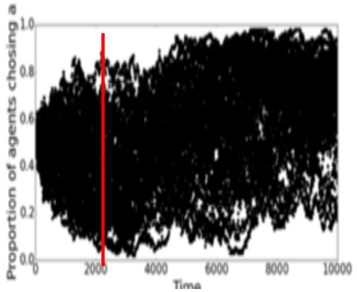
PREVIOUS RESULTS



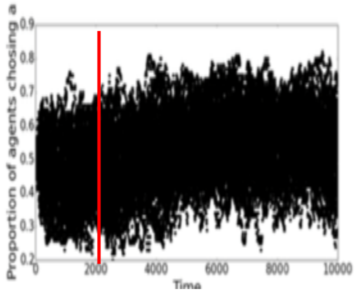
N=100, ρ_A/ρ_B = **1.05**, S=0



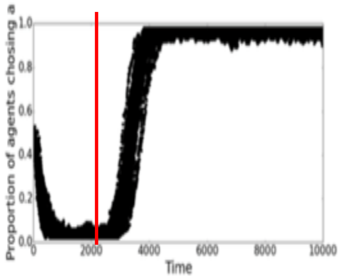
N=100, ρ_A/ρ_B = **3**, S=0



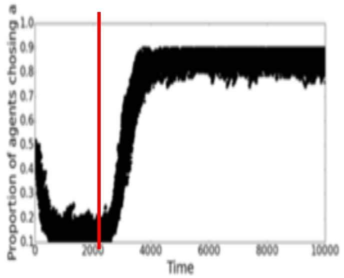
N=100, ρ_A/ρ_B = 1.05, S=**5%**



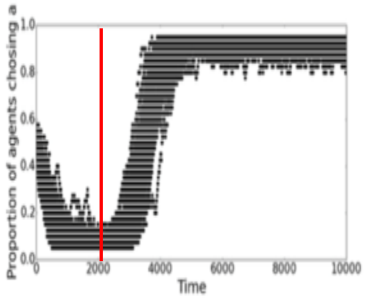
N=100, ρ_A/ρ_B = 1.05, S=**20%**



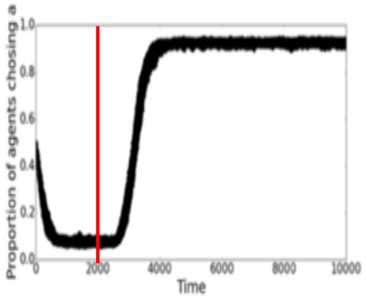
N=100, ρ_A/ρ_B = 3, S=**5%**



N=100, ρ_A/ρ_B = 3, S=**20%**



N=40, ρ_A/ρ_B = 3, S=5%

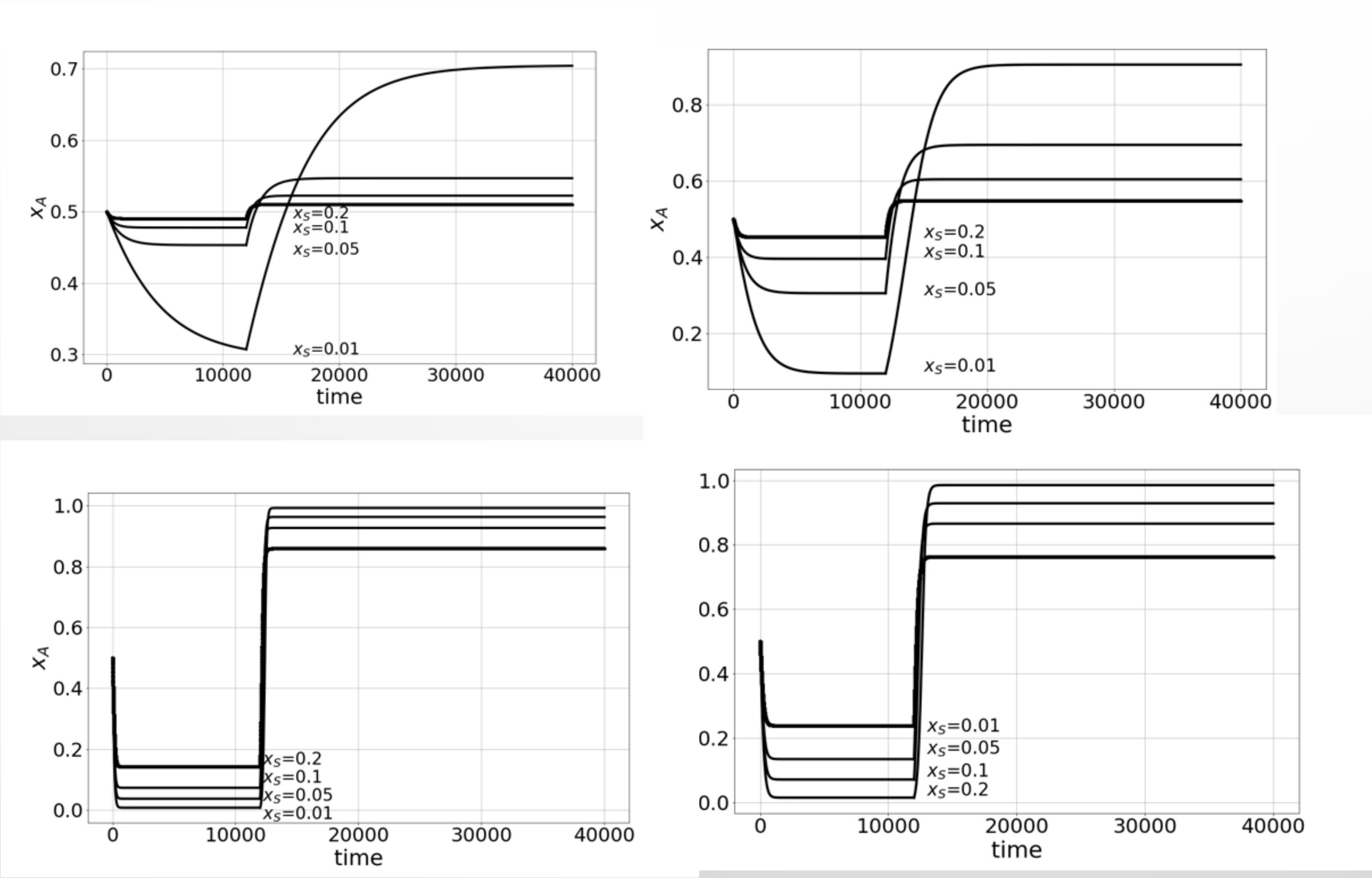


N=500, ρ_A/ρ_B = 3, S=5%

Collective decision making in dynamic environments, J. Prasetyo, G. De Masi, E. Ferrante, Swarm Intelligence, Jun 2019, pp 1-27

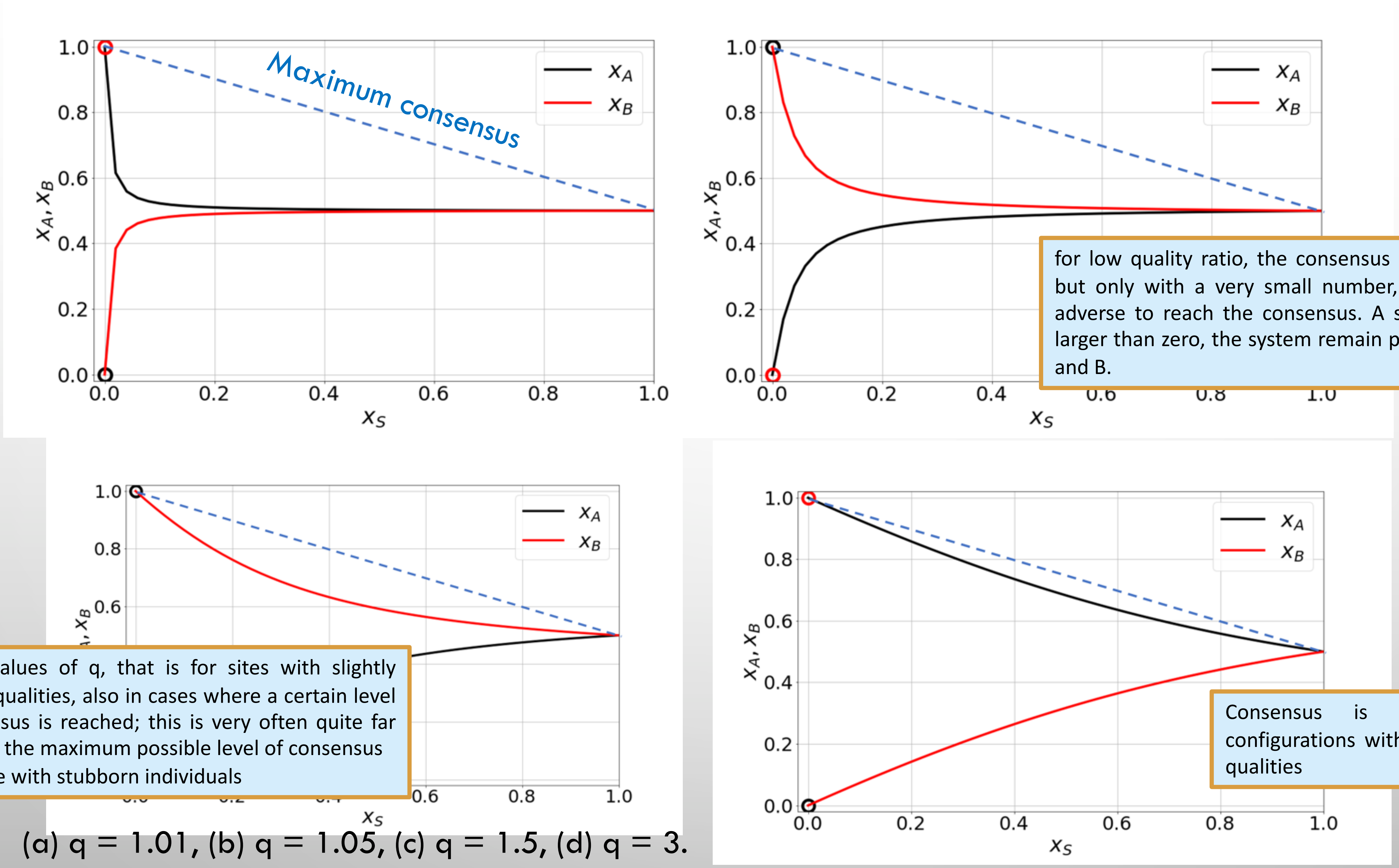
- The mere presence of the stubborn agents is enough to achieve adaptability, but increasing its number has detrimental effects on the performance;
- The difference in site quality plays a crucial role, whereby higher level of adaptability is observed with increasing ratio between the qualities
- The system adaptation increases with increasing swarm size, while it does not depend on agents' density, unless this is below a critical threshold;

TEMPORAL EVOLUTION OF EQUILIBRIUM IN DYNAMIC ENVIRONMENT



Temporal evolution of equilibrium in dynamic environment (t_{switch} = 12000) for different x_S values, for 4 different values of quality ratio: (a) q = 1.01, (b) q = 1.05, (c) q = 1.5, (d) q = 3.

CONSENSUS TO A AND B



(a) q = 1.01, (b) q = 1.05, (c) q = 1.5, (d) q = 3.

for low quality ratio, the consensus is reached with stubborn, but only with a very small number, being an higher number adverse to reach the consensus. A soon as the value of x_S is larger than zero, the system remain polarized in two opinions A and B.

for low values of q, that is for sites with slightly different qualities, also in cases where a certain level of consensus is reached; this is very often quite far from $x_{max\,A}$, the maximum possible level of consensus achievable with stubborn individuals

Consensus is actually achieved for configurations with sites with very different qualities

CONCLUSIONS

- **ABRUPT CHANGES** IN SITE QUALITIES MAY LEAD SWARMS TO CHOOSE **BAD OPTIONS**
- INTRODUCING **STUBBORN AGENT ALLOWS SWARMS TO ADAPT** TO ABRUPT CHANGES IN SITE QUALITIES IN COLLECTIVE DECISION-MAKING.
- **IMPACT OF QUALITY RATIO ON THE LEVEL OF CONSENSUS**: THE MAXIMUM ACHIEVABLE CONSENSUS IS REALLY ACHIEVED ONLY FOR HIGH QUALITY DIFFERENCE WHILE FOR LOW QUALITY DIFFERENCE THE REAL CONSENSUS IS MUCH LOWER THAN THE EXPECTED ONE. THIS CAN BE EXPLAINED IN TERMS OF **POLARIZATION**.
- APPLICATIONS TO **MARINE MAMMALS** AND **FIRE** MONITORING

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