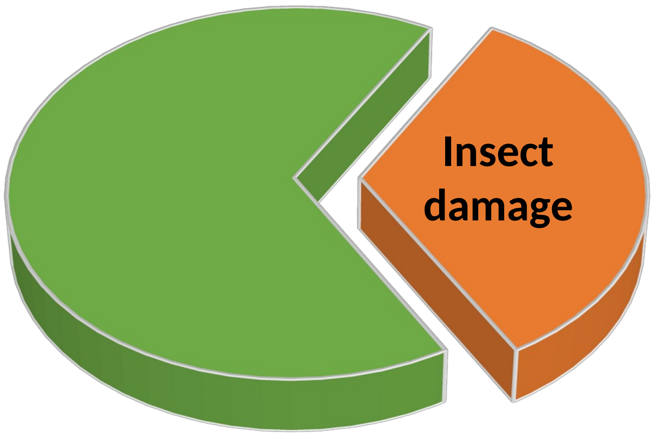
INRAE

Inverse problem for locating insect pests using pheromone detection

Pheromone detection for precision croping

Insects destroy 1/3 of crop production

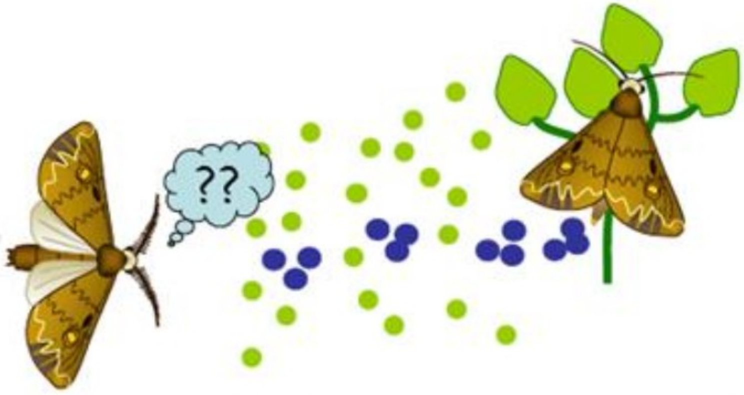


Early detection of insect pests
(before infestation settles)

↓

Targeted biocontrol strategies
Incidence of prophylactic approaches

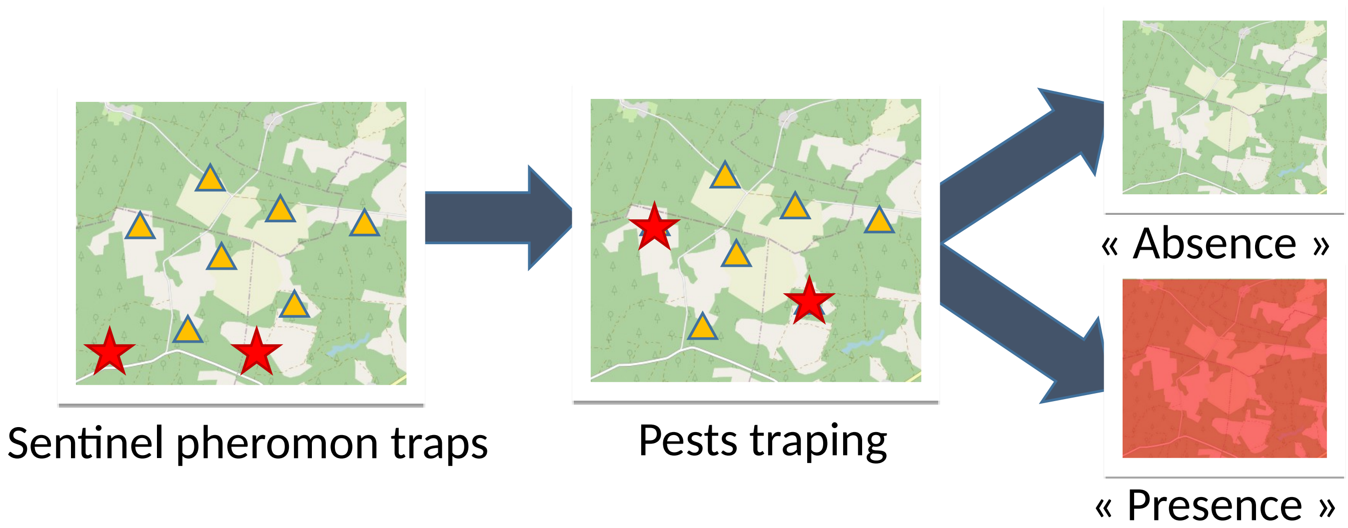
- Insects communicate with species-specific pheromones
- Pheromone system is unique in terms of sensitivity and specificity



From P.Lucas

Sensors should provide more precision to build risk maps

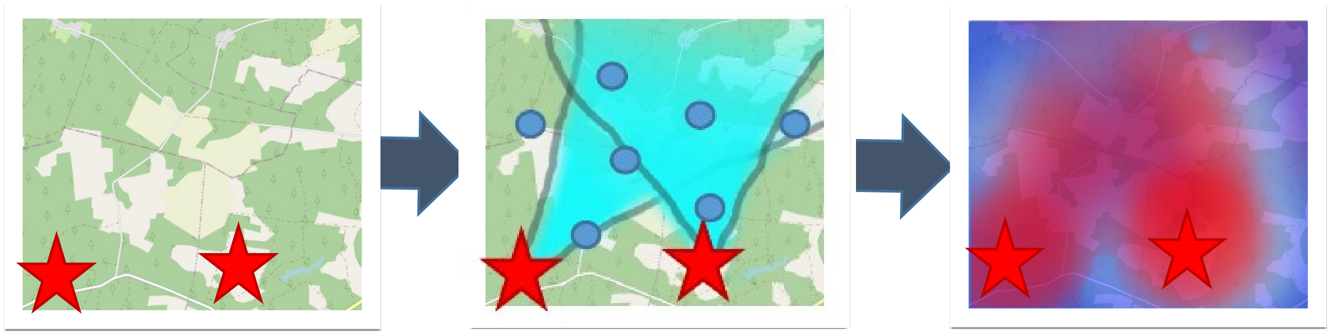
Pheromon traps



Pests natural location still unknown

Sensors should provide more precision to build risk maps

Pheromon sensors



Pheromon sensors — Plume detection — Risk maps for **Targeted treatment**

Pests localization for targeted treatment in their natural habitats

Pherosensor

Biological sensors

Sentinel flies

Physical sensors

Pheromone receptors on chip

Field studies

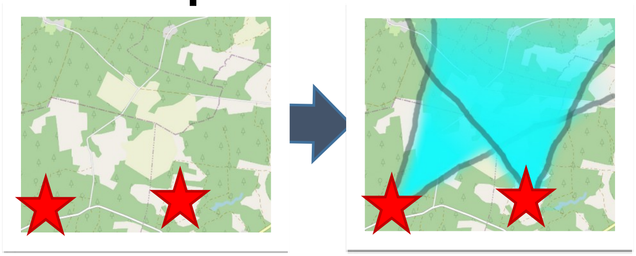
Green house → Open field

Risk map construction

Direct problem | Inverse problem | Optimal placement

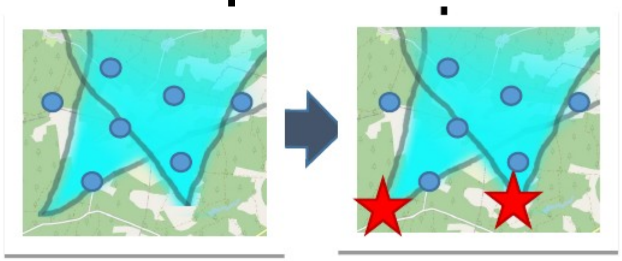
Different mathematical problems

Direct problem



Knowing : pest location + environmental covariables
Predict : pheromone plumes

Inverse problem



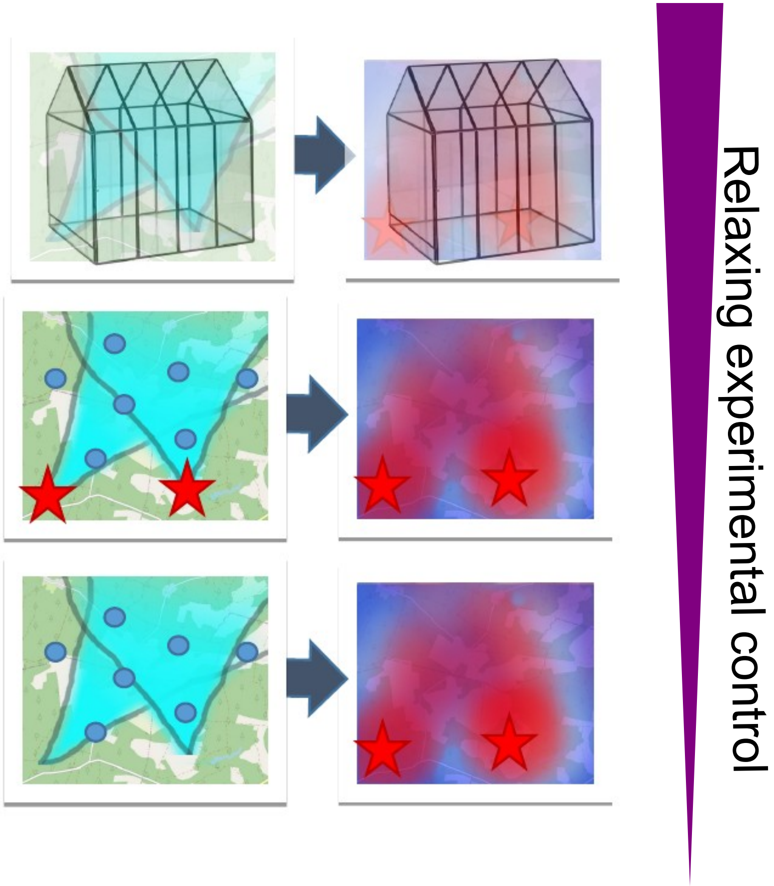
Knowing : sensor location and signals + environmental covariables
Predict : pheromone plumes sources (i.e. pests location)

Optimal design

Knowing : environmental covariables
Predict : optimal sensor placement for reduced risk map uncertainty

Risk maps assessment

Risk maps in decreasingly uncontrolled environments



Modeling odor plume dispersion including environmental conditions

Direct problem
State variable:
concentration in pheromone c.

Environmental input data:
- wind field $\vec{u}(x, y, t)$,
- isotropic diffusion tensor $\mathbf{K}(x, y, t)$,
- ***vegetation dependent loss coefficient*** $\tau_{loss}(x, y)$.

Task 3.1.1: 2D model for pheromone dispersion:

$$\frac{\partial c}{\partial t} \underbrace{-\nabla \cdot (\mathbf{K}\nabla c)}_{diffusion} + \underbrace{\nabla \cdot (\vec{u} c)}_{wind} + \underbrace{\tau_{loss} c}_{deposition} = \underbrace{s}_{emission}$$

Quantity of pheromone emitted by pest $s(x, y, t)$.

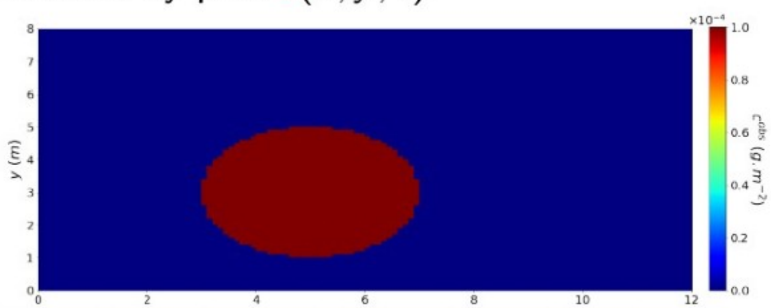


Figure: Pest density p uniformly located in a circle with a constant emission rate q leads to s^{circ}.

Concentration in pheromone c given a source term s.

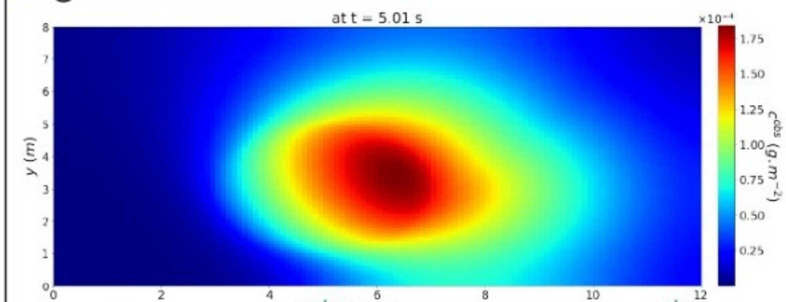


Figure: Concentration $c(s^{circ})$ with the circular source s^{circ}, at a given time.

Inverse problem to build risk maps

Sensors

Observations m^{obs}

Inverse problem
Control variable: pest density s.

Task 3.2.1: Optimization problem:

$$\begin{cases} \text{find } s_a(x,y,t) \text{ such that} \\ s_a(x,y,t) = \arg\min_{s(x,y,t)} \left(j_{obs}(s) + j_{reg}(s)\right) \end{cases}$$

with j_{reg} ***a regularization term*** and
$j_{obs}(s) = \|m(c(s)) - m^{obs}\|_2^2$.

Optimal source term s_a:
pest distribution that makes the direct model fits at best the observations m^{obs}.

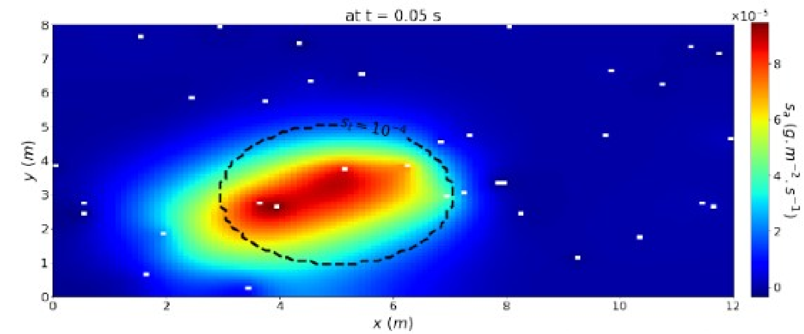


Figure: Optimal source term s_a and target s_t (dashed line). The white dots are the locations of the sensors.

Prediction of the observed variable $m(c(s))$.

Direct model

Sensors

Finite difference vs Variational method

Finite difference

$$\text{compute } \langle \nabla j_{obs}(s), \delta s \rangle \simeq \frac{j_{obs}(s + \varepsilon \delta s) - j_{obs}(s)}{\varepsilon}, \text{ for all } \delta s$$

$$(N_x \times N_y \times N_t + 1) \text{ PDE resolution}$$

Finite difference vs Variational method

Variational method

$$\langle \nabla j_{obs}(s), \delta s \rangle = \langle \nabla_m j_{obs}, \partial_c m \cdot \partial_s c \cdot \delta s \rangle$$
$$= \langle (\partial_c m)^* \nabla_m j_{obs}, w \rangle$$

$$\text{with } w = \partial_s c \cdot \delta s$$

Finite difference vs Variational method

Variational method

$$\langle \nabla j_{obs}(s), \delta s \rangle = \langle \nabla_m j_{obs}, \partial_c m \cdot \partial_s c \cdot \delta s \rangle$$
$$= \langle (\partial_c m)^* \nabla_m j_{obs}, w \rangle$$

$$\text{with } w = \partial_s c \cdot \delta s$$

Writing the PDE equation as $\mathcal{L}(s, c(s)) = 0$ We have (tangent linear)

$$d_s \mathcal{L}(s, c(s)) \cdot \delta s = \partial_s \mathcal{L}(s, c(s)) \cdot \delta s + \partial_c \mathcal{L}(s, c(s)) \cdot w = 0$$

So that

$$\langle \nabla j_{obs}(s), \delta s \rangle = \langle (\partial_c m)^* \nabla_m j_{obs}, w \rangle + \langle \partial_s \mathcal{L}(s, c(s)) \cdot \delta s, z \rangle + \langle \partial_c \mathcal{L}(s, c(s)) \cdot w, z \rangle$$

$$\text{for any } z$$

Finite difference vs Variational method

Variational method

$$\langle \nabla j_{obs}(s), \delta s\rangle = \langle \nabla_m j_{obs}, \partial_c m \cdot \partial_s c \cdot \delta s\rangle$$
$$= \langle (\partial_c m)^* \nabla_m j_{obs}, w\rangle$$

with $w = \partial_s c \cdot \delta s$

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So that

$$\langle \nabla j_{obs}(s), \delta s\rangle = \langle (\partial_c m)^* \nabla_m j_{obs}, w\rangle + \langle \partial_s \mathcal{L}(s, c(s)) \cdot \delta s, z\rangle + \langle \partial_c \mathcal{L}(s, c(s)) \cdot w, z\rangle$$

for any z

Taking Z solution of $\mathcal{L}(s, c(s))^* z + (\partial_c m)^* \nabla_m j_{obs} = 0$

$$\langle \nabla j_{obs}(s), \delta s\rangle = \langle \partial_s \mathcal{L}(s, c(s)) \cdot \delta s, Z\rangle$$

2 PDEs

Sensors

Inverse problem
Control variable: pest density s.

Observations m^{obs}

Task 3.2.1: Optimization problem:

$$\begin{cases} \text{find } s_a(x,y,t) \text{ such that} \\ s_a(x,y,t) = \arg\min_{s(x,y,t)} \left(j_{obs}(s) + j_{reg}(s) \right) \end{cases}$$

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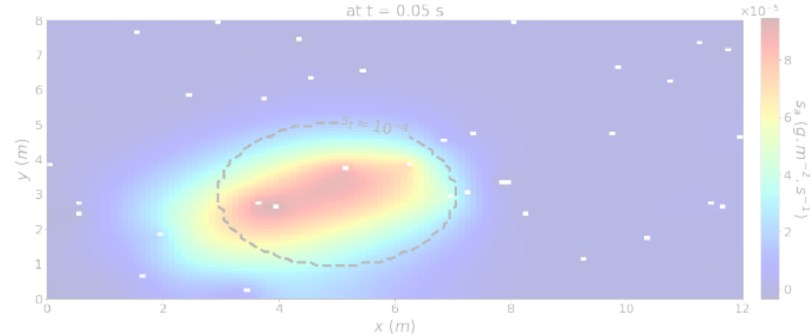

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Prediction of the observed variable $m(c(s))$.

Direct model

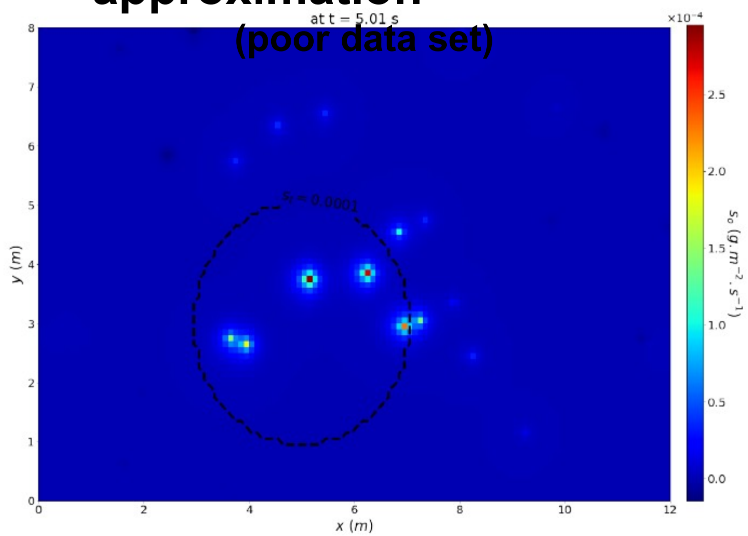
Sensors

Regularization term

Statistical characteristic: (sparsity, smoothness)

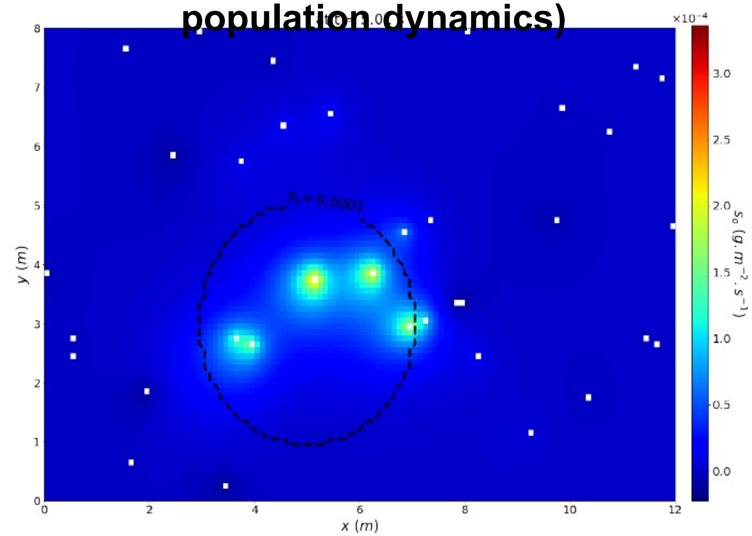
Biological characteristic :
- favorite pest habitat (Thikonov)
- population dynamic model

Very bad approximation
(poor data set)



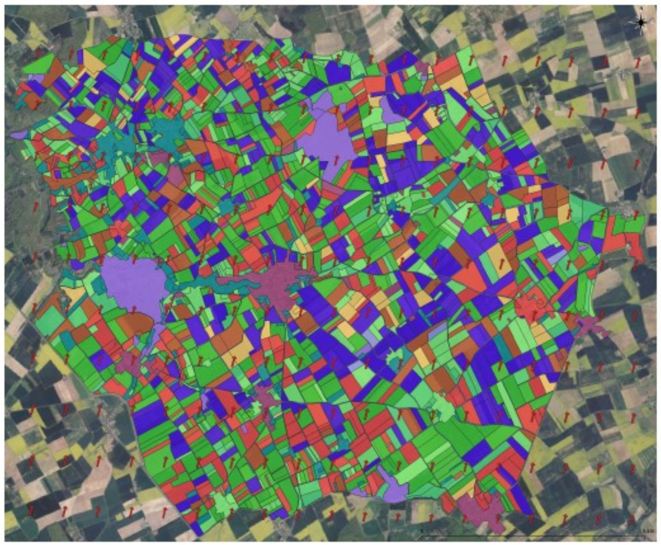
(a) no regularization

Enhanced approximation
(data supplemented by population dynamics)

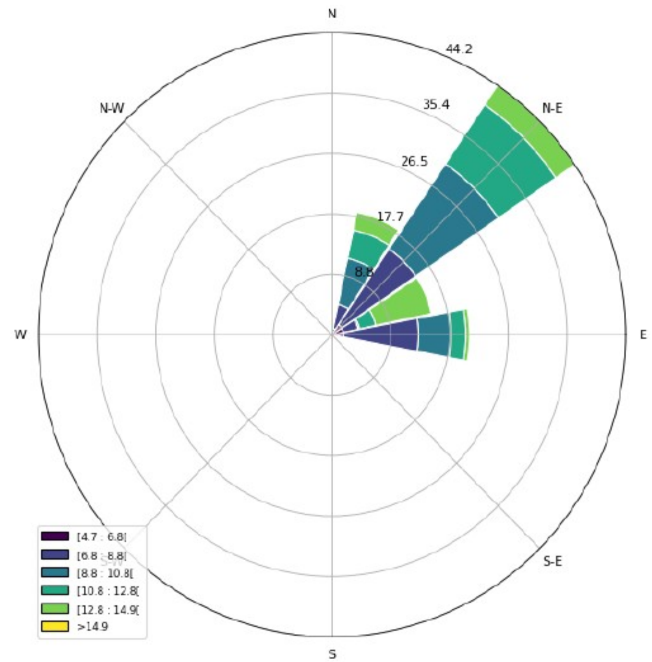


(b) stationnary population dynamique regularization

Application to a more realistic environmental conditions



(a) map of the test case with the land occupation and wind field at a given time

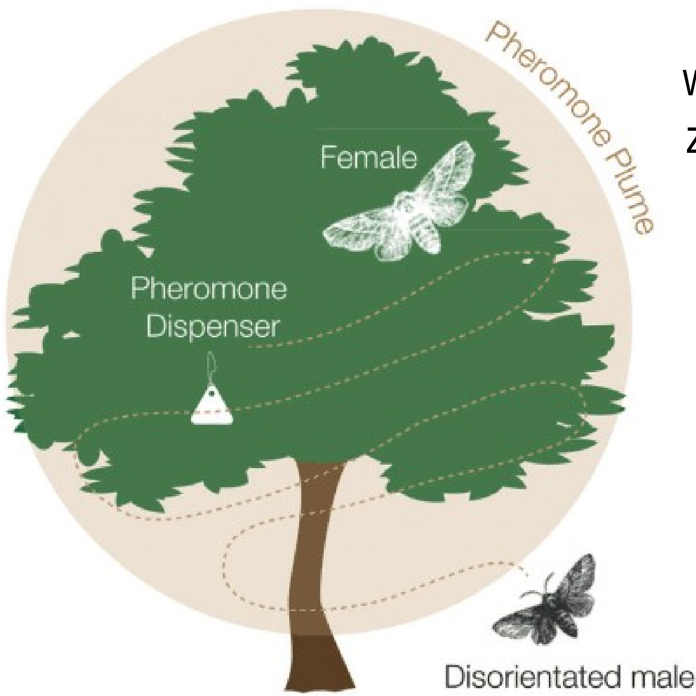


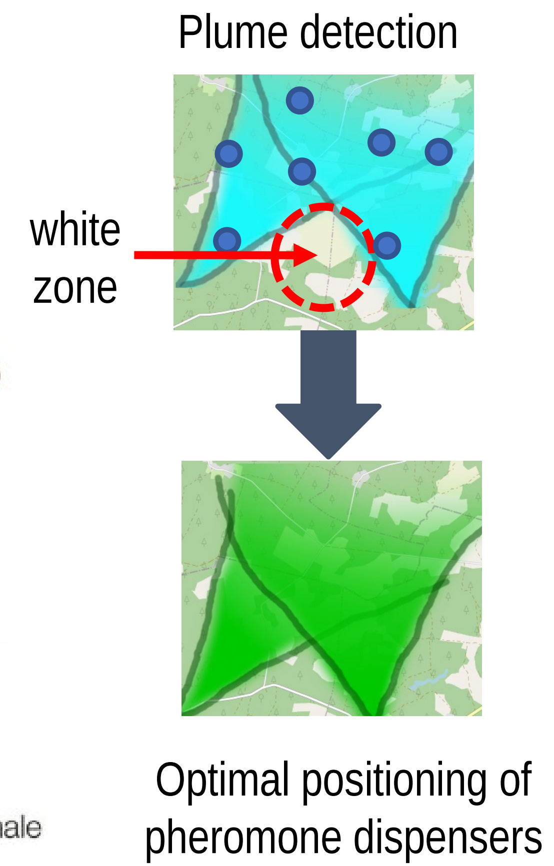
(b) wind rose over the test case and the whole time window (one day)

Figure: Test case around the village of Selommes between 16/11/2022 12:00 and 17/11/2022 12:00 (one day time window)

Related problem on “mating disruption optimization”

Detection of "white zones"
during mating disruption





Conclusion

- Inverse problem for pheromone emission source detection
- Variational inversion method
- Main work on regularization (biologically informed inverse problem)
- Pratical issues (input data, sensor data, computing method)

- Additional maths : optimal placement, surrogate models, sensitivity analysis

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- Pherosensor WP3 colleagues
  - T.Malou
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  - B.Laroche
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