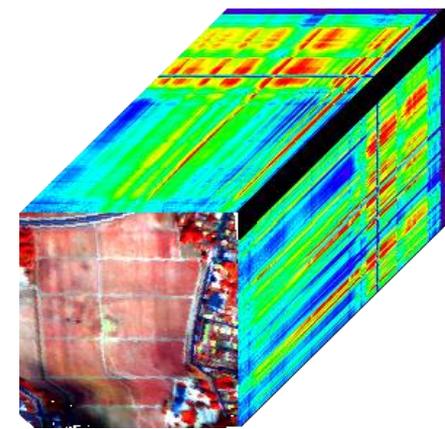


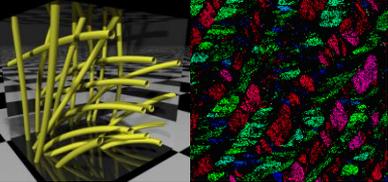
# Téledétection et imagerie embarquée au service de l'agriculture et de l'environnement

**Christian Germain et les chercheurs de l'équipe Motive**  
IMS – UMR CNRS n°5218  
Groupe Signal et Image



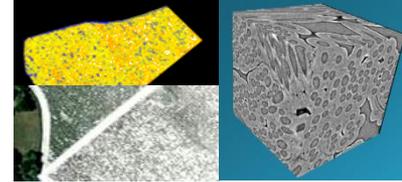
*Journée OASU – 12/10/2017*





# IMS

## Groupe Signal et Image



### Permanents (18)

Professeurs (6)

Maîtres de Conférences (8)

Chargés de Recherches (2)

Ingénieurs (2)

### Non-permanents ( $\approx 20$ )

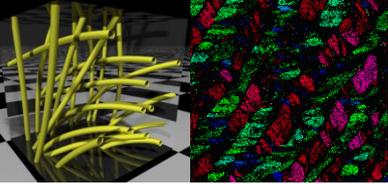
Doctorants / Post-doctorants



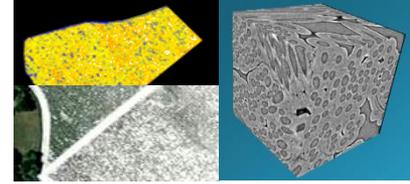
BORDEAUX  
SCIENCES  
AGRO

université  
de BORDEAUX

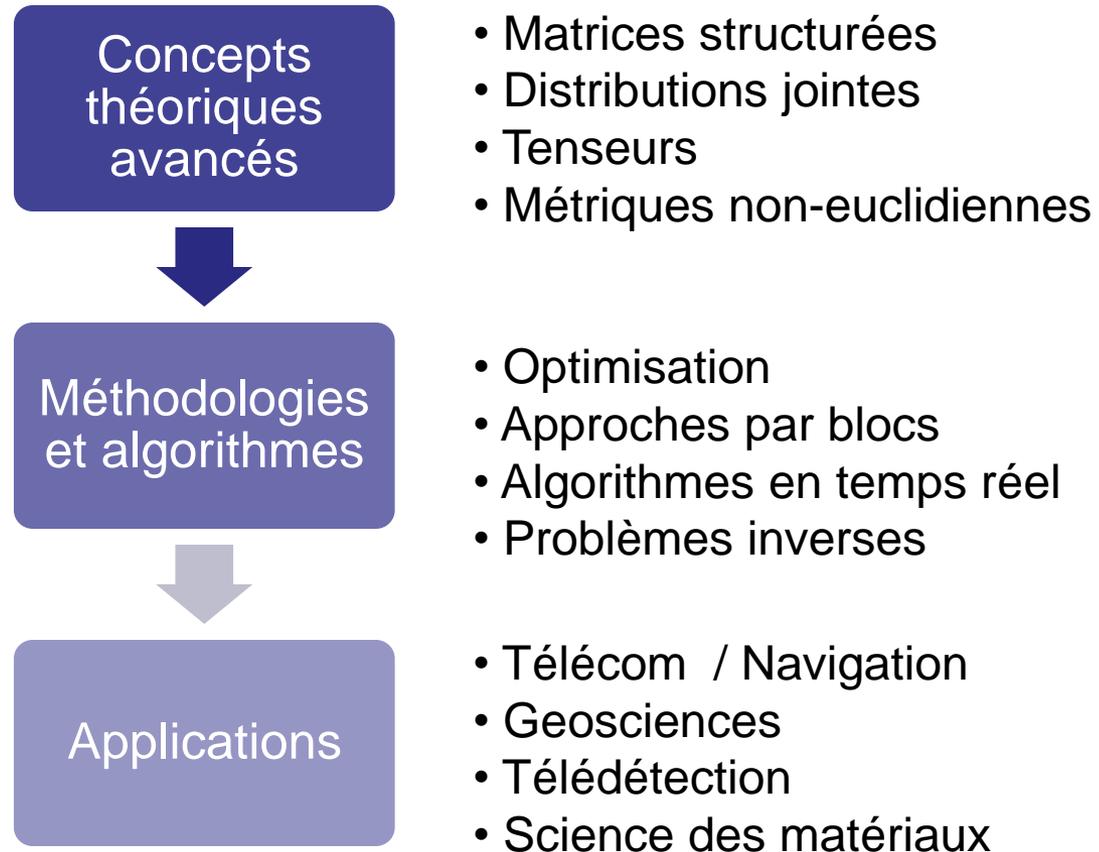




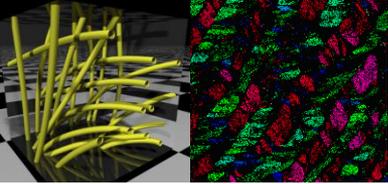
# Stratégie Scientifique



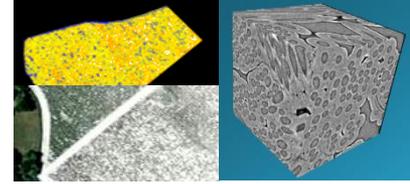
## Recherche Coopérative des Mathématiques à l'Application



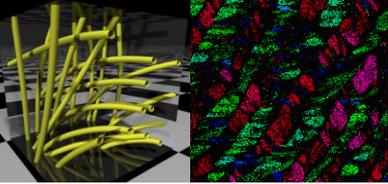
**Partenariats industriels**



# Téledétection: Aspect méthodologiques

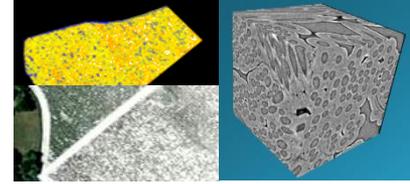


- Modélisation des dépendances
  - Dépendances spatiales : texture
  - Dépendances spectrales: multispectrale / hyperspectrale
  - Dépendances temporelles: séries multi-date
  - Autres dépendances: images polarimétrique (PolSAR)
- Débruitage / Classification / Segmentation
- Détection d'objets
  - Lignes, cercles...

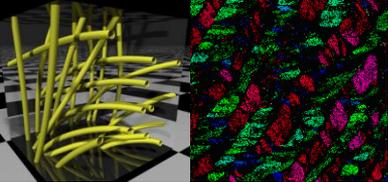


# Téledétection

## Applications

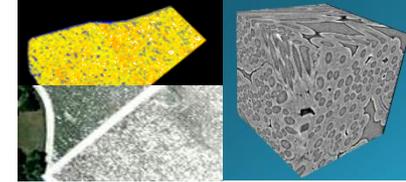


- Télédétection (satellites, avions, drones)
  - Vignes
  - Espaces côtiers
  - Forêts
- Proxidétection (robots, machine agricoles...)
  - Vignes (grappes, feuilles)
  - Verger (fruits, feuilles)
- Permanents impliqués:
  - L. Bombrun, J.P. Da Costa, Ch. Germain, B. Keresztes;
  - + expertise de Y. Berthoumieu, M. Donias, G. Grenier, S. Saïd.

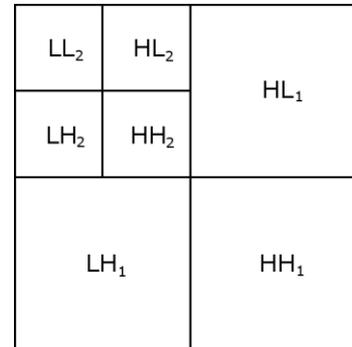


# Modèles de textures

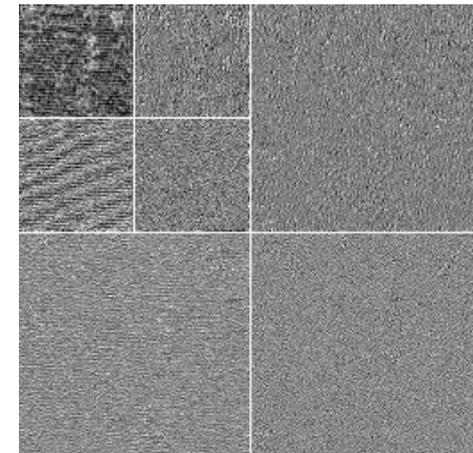
## Classification images



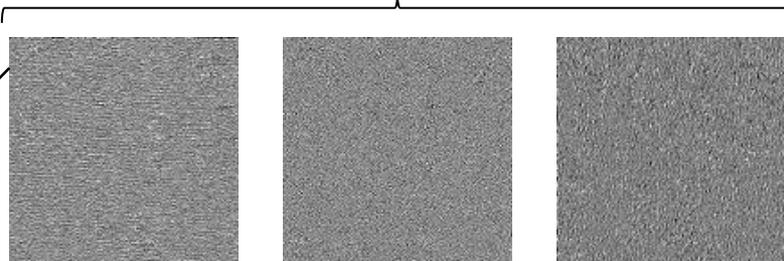
DWT – db4  
nb échelles= 2



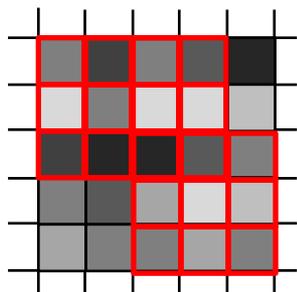
=



1<sup>ère</sup> échelle

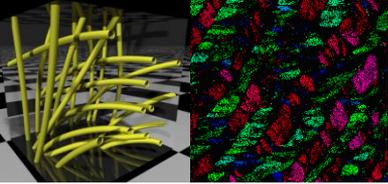


2<sup>nde</sup> échelle



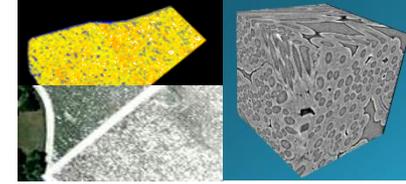
$$\begin{aligned}
 \mathbf{k}_1 &= \text{[row of grayscale blocks]} \\
 \mathbf{k}_2 &= \text{[row of grayscale blocks]} \\
 &\vdots \\
 \mathbf{k}_N &= \text{[row of grayscale blocks]}
 \end{aligned}$$

$N$  vecteurs  $k$  observations de  
la dépendance spatiale  
=  
 $N$  réalisations du processus  
multivaré



# Modèles de textures

## Classification images



### Modèle Gaussien Multivarié

$$\mathbf{k} \sim \mathcal{N}(\mathbf{0}, \mathbf{M}) \quad [\hat{\mathbf{M}}]_{SCM} = \frac{1}{N} \sum_{i=1}^N \mathbf{k}_i \mathbf{k}_i' \quad \rightarrow \text{SCM}$$

### Modèle SIRV (Spherically Invariant Random Vectors)

$$\mathbf{k} = \sqrt{\tau} \mathbf{z} \quad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{M})$$

Si Gamma Inverse sur  $\tau$ , vecteur SIRV  $\mathbf{k}$  = loi G0  $\rightarrow$  **SIRVg0**

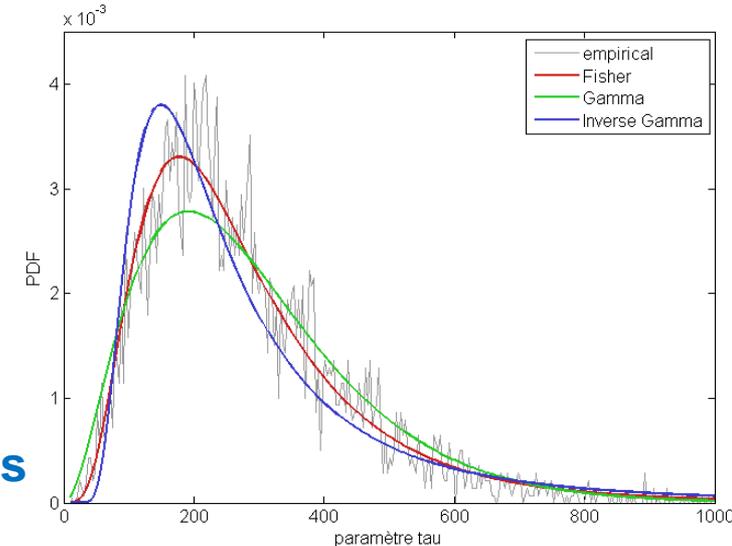
Si Dirac sur  $\tau$ , vecteur SIRV  $\mathbf{k}$  = Gaussien  $\rightarrow$  **SIRVgauss**

$$[\hat{\mathbf{M}}]_{FP} = \frac{p}{N} \sum_{i=1}^N \frac{\mathbf{k}_i \mathbf{k}_i'}{\mathbf{k}_i' [\hat{\mathbf{M}}]_{FP}^{-1} \mathbf{k}_i} \quad \hat{\tau}_i = \frac{\mathbf{k}_i' [\mathbf{M}]^{-1} \mathbf{k}_i}{p}$$

### Modèle Copules

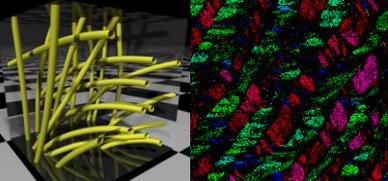
$$F(\mathbf{k}_i) = F(k_{i,1}, \dots, k_{i,p}) = C(F_{i,1}(k_{i,1}), \dots, F_{i,p}(k_{i,p}))$$

$$[\hat{\mathbf{M}}] = \frac{1}{N} \sum_{i=1}^N \mathbf{k}_i^G \mathbf{k}_i^{G'} \quad \begin{array}{l} \text{Gamma multivariées} \\ \text{sur copules} \\ \text{Gaussiennes} \end{array} \quad \rightarrow \text{GCG}$$



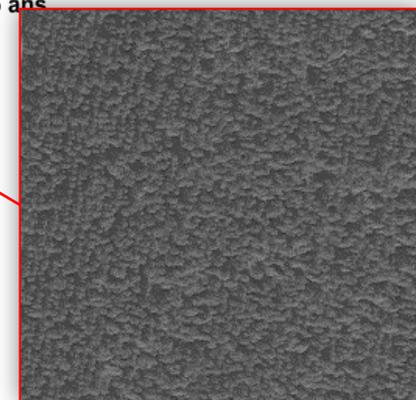
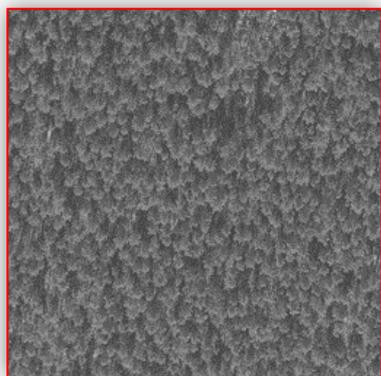
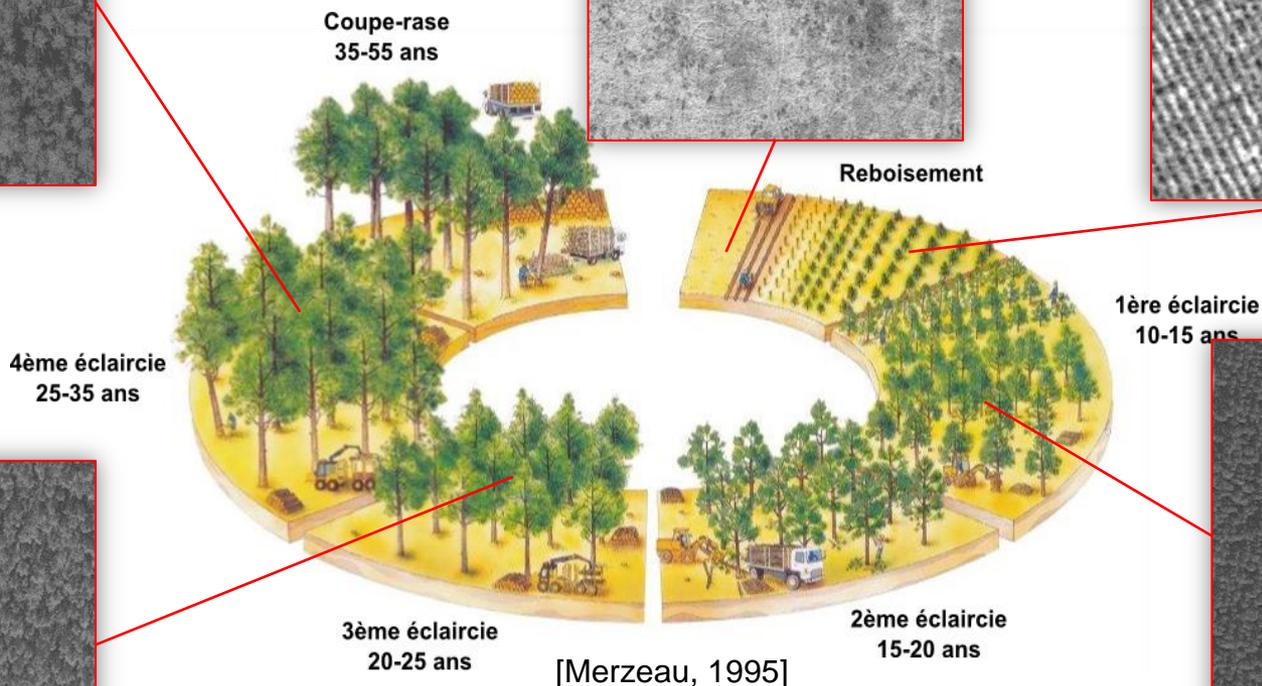
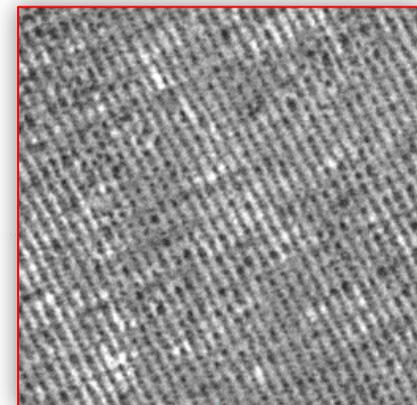
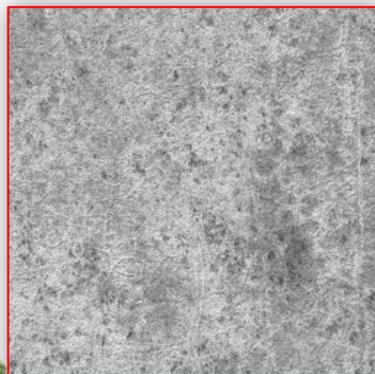
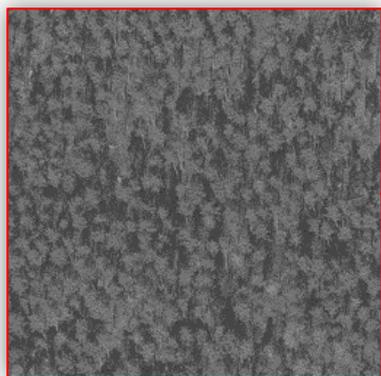
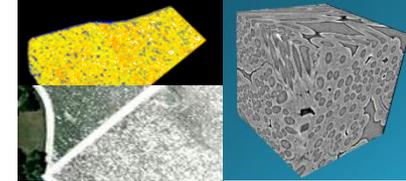
Estimateur de la matrice de  
Covariance  
(+estimation d'autres paramètres)

$\rightarrow$  **SIGNATURE TEXTURALE**

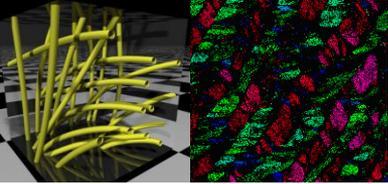


# Peuplements forestiers

## Texture / Pléiades

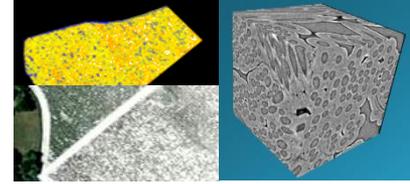


**Corrélation entre les variables de structures forestières et la distribution spatiale des arbres**



# Peuplements forestiers

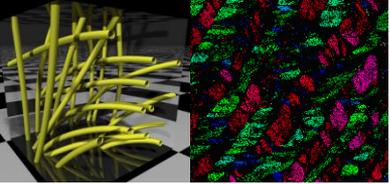
## Texture / Pléiades



**Classe d'âge 1** : peuplements de 0 à 9 ans

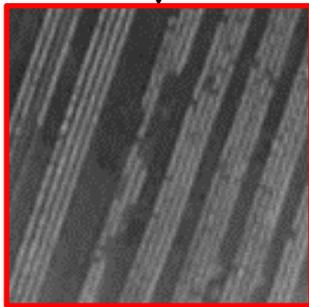
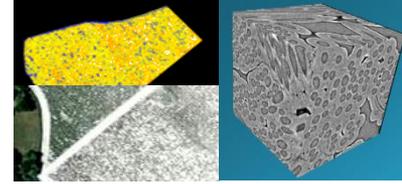
**Classe d'âge 2** : peuplements de 10 à 19 ans

**Classe d'âge 3** : peuplements de plus de 19 ans

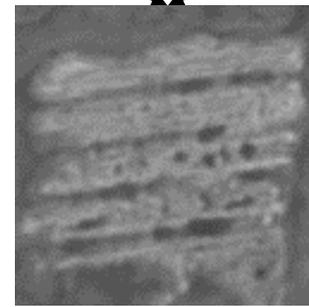


# Cultures ostréicoles

## Texture / Pléiades



**Cultures sur  
tables**

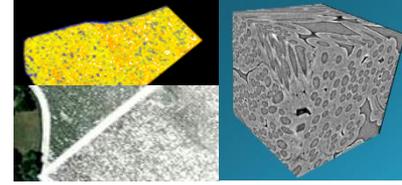
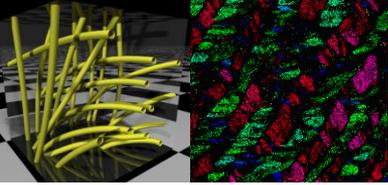


**Friches  
ostréicoles**



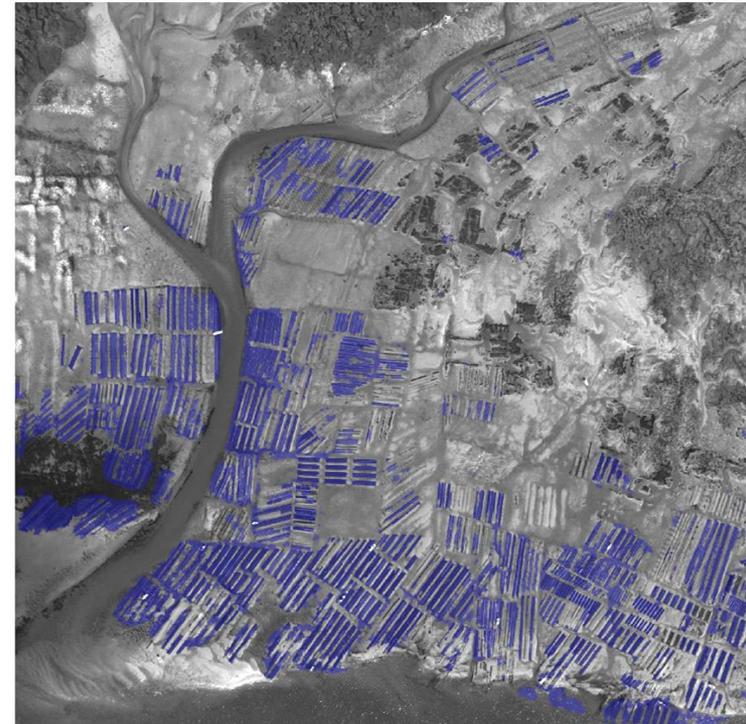
# Cultures ostréicoles

## Texture / Pléiades

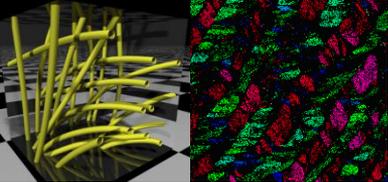


Cultures ostréicoles sur table					
Cultures ostréicoles en friche					
Estran					

Base de données d'apprentissage

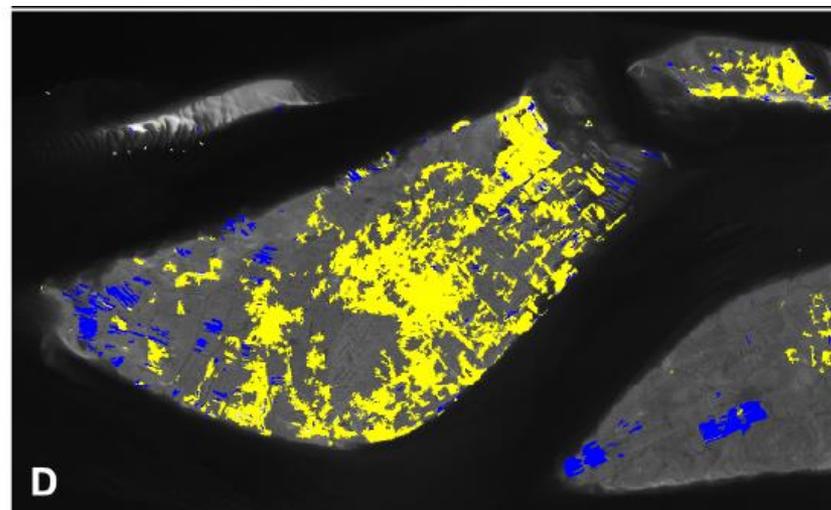
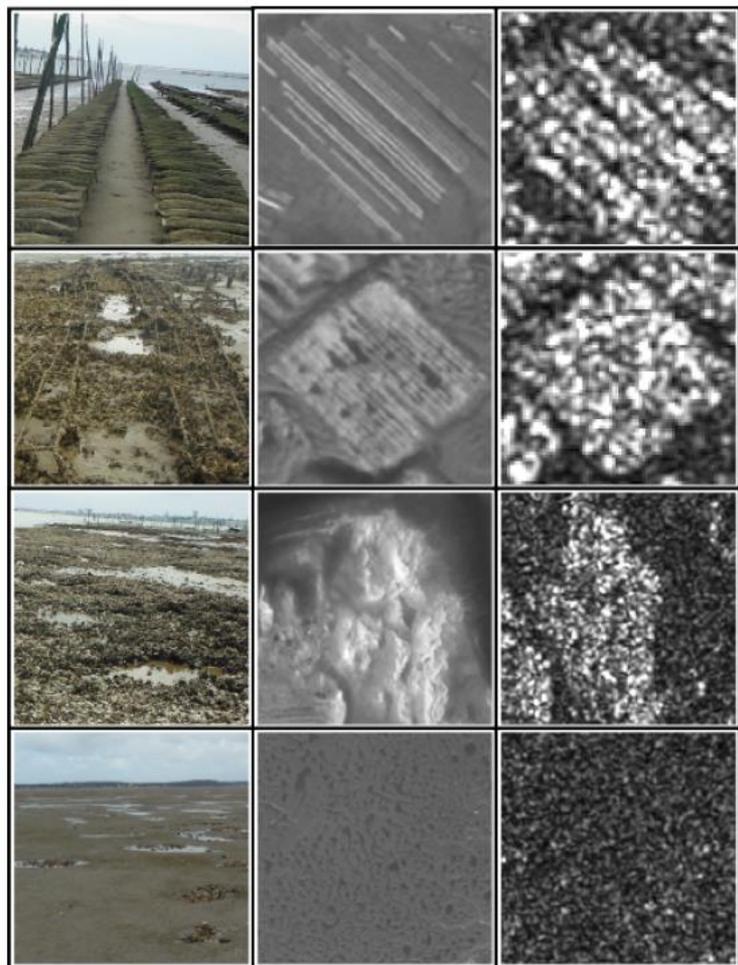
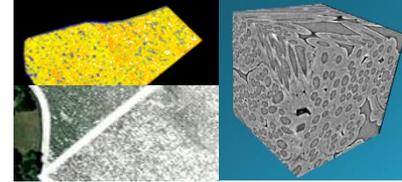


Exemple de détection des  
parcs cultivés sur une image  
Pléiades



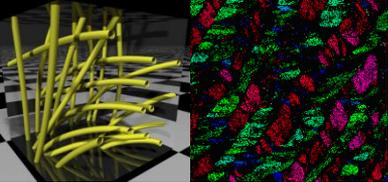
# Cultures ostréicoles

## Fusion de données optique/radar

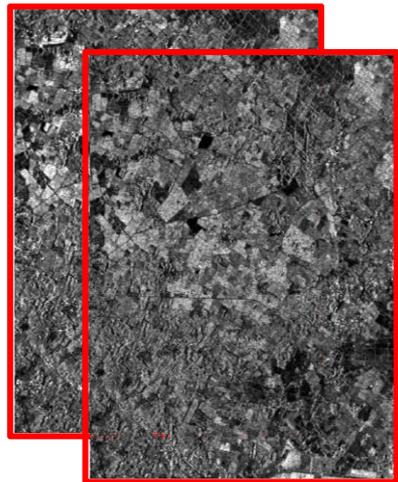
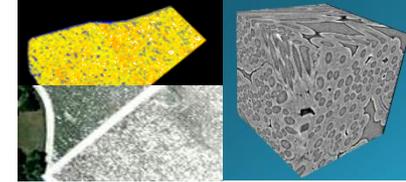


- Parcs cultivés
- Friches ostréicoles

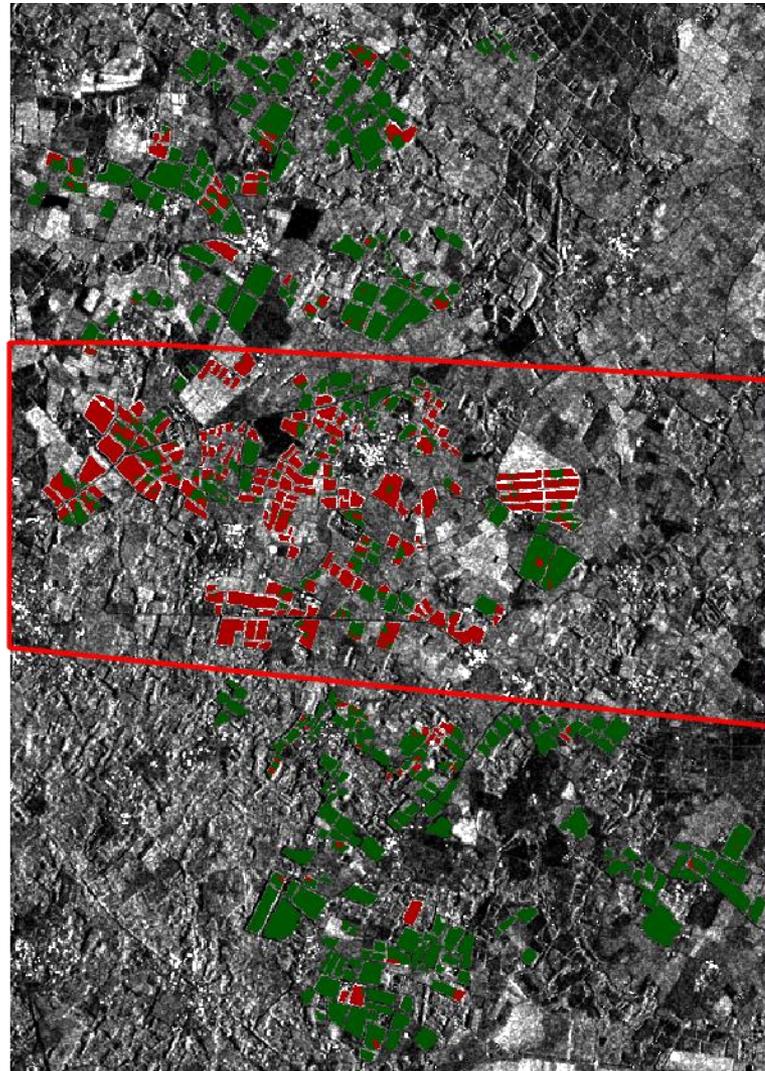




# Dégât de grêle sur vigne données radar multi-temporelles

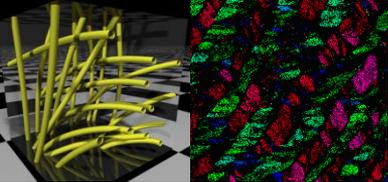


2 images  
CosmoSkyMed  
(HH, 3m résolution)  
avant et après la grêle



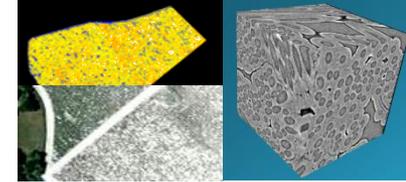
-  zones épargnées
-  zones touchées
-  couloir de grêle  
estimé à dire d'expert.



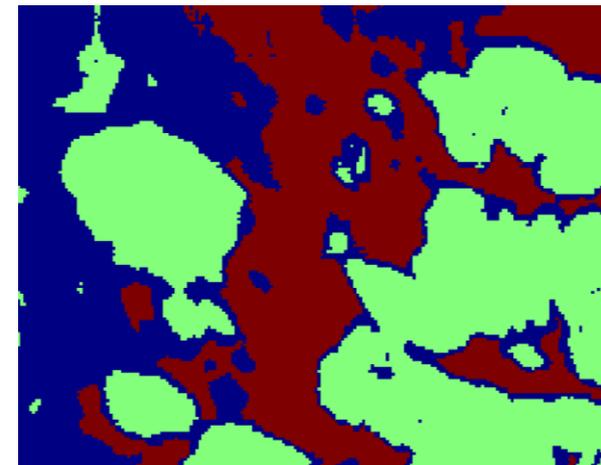
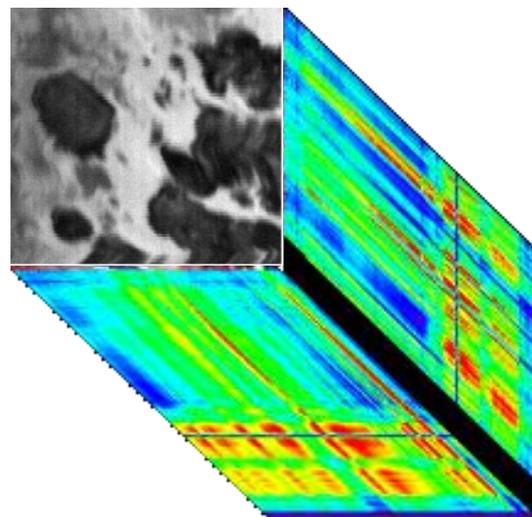


# Habitats naturels côtiers

## images hyperspectrales

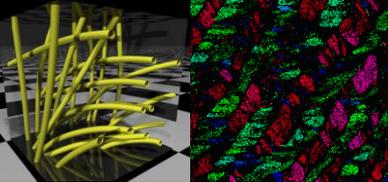


- Classification des spartines (*spartina anglica*/*spartina maritima*)



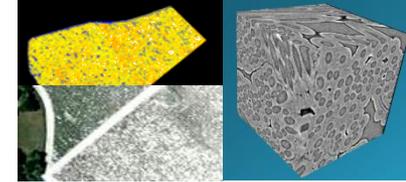
EPOC

ims

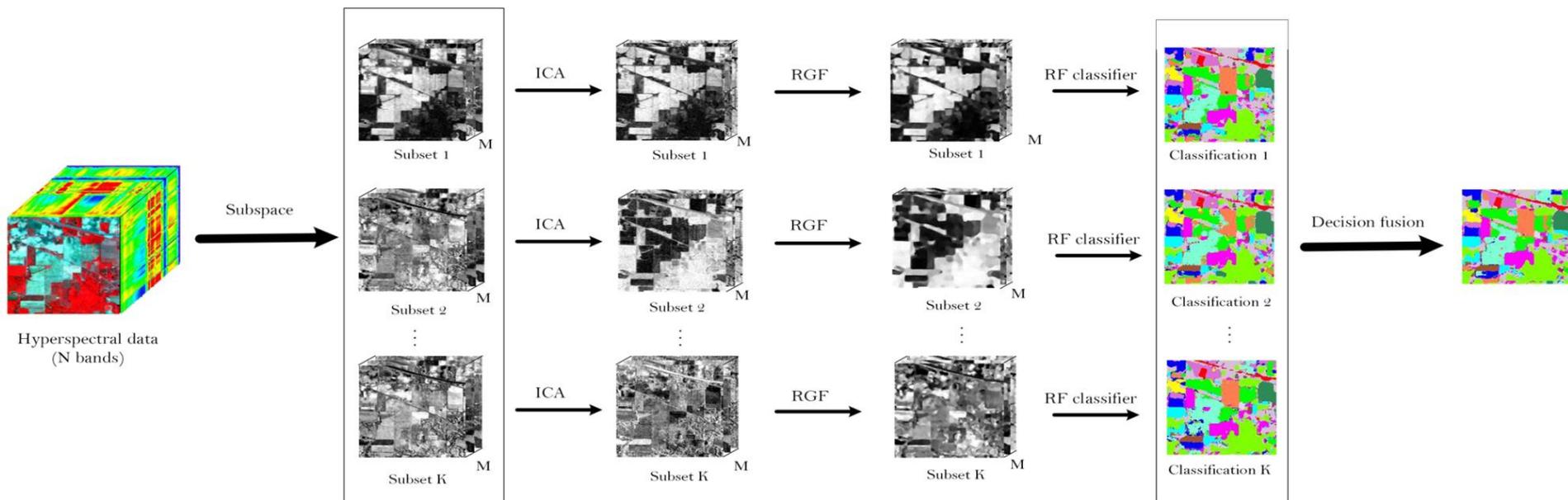


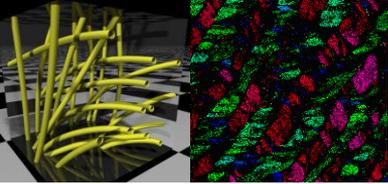
# Images hyperspectrales

## Aspects méthodologiques

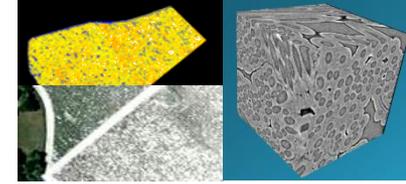


- Approches multi-classifieurs (random forest, rotation forest, ...) pour la classification d'images hyperspectrales

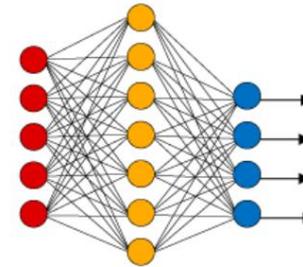




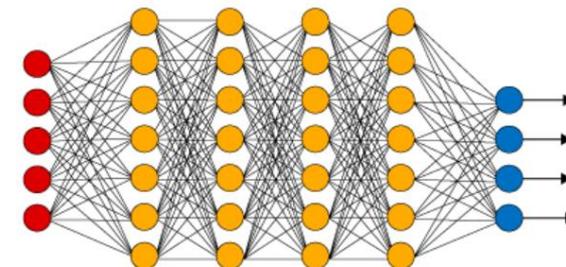
# Milieux naturels littoraux deep learning / hyperspectral



Simple Neural Network



Deep Learning Neural Network



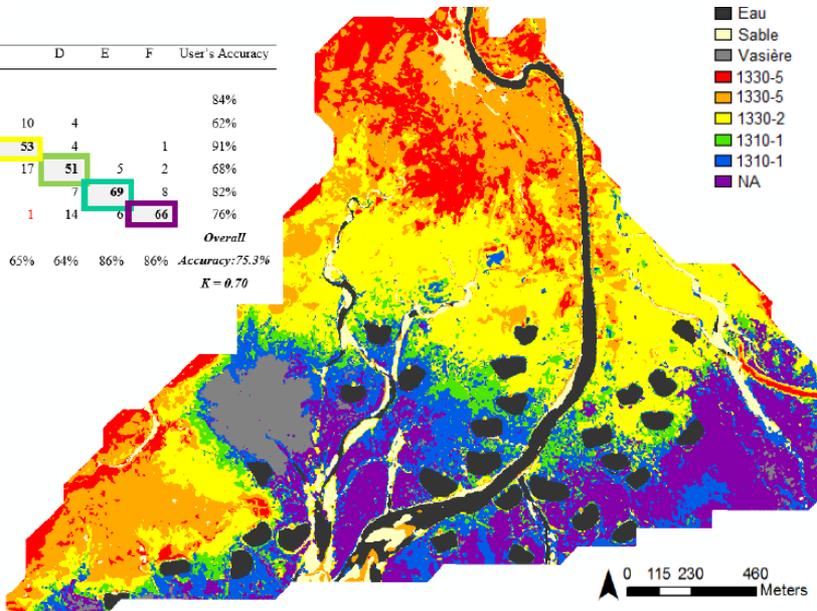
● Input Layer

● Hidden Layer

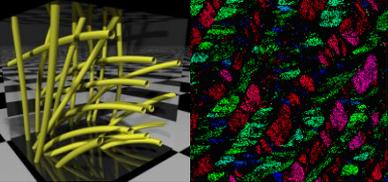
● Output Layer

A	B	C	D	E	F	User's Accuracy
51	10					84%
29	70					62%
		10	4			91%
		53	4		1	68%
		17	51	5	2	82%
			7	69	8	76%
			1	14	6	66%
<b>Overall</b>						
64%	88%	65%	64%	86%	86%	Accuracy: 75.3%
						$K = 0.70$

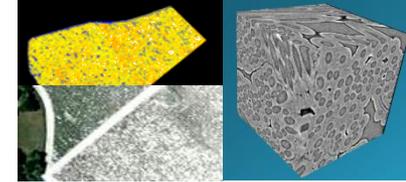
- Eau
- Sable
- Vasière
- 1330-5
- 1330-5
- 1330-2
- 1310-1
- 1310-1
- NA



Biodiversité, gènes & communautés



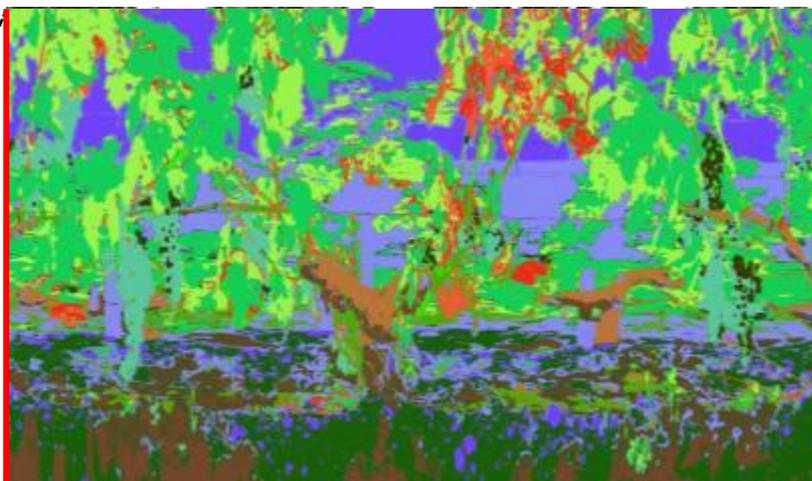
# Détection précoce des maladies (Vignes / Fruits)

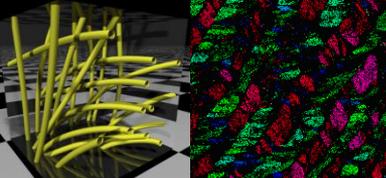


La caméra (pushbroom) acquiert des colonnes de pixel

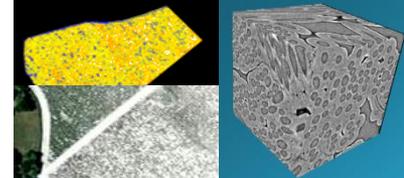
L'image obtenue représente le spectre des pixels

Le chariot se déplace dans un rang de vigne/vergers





# Rendement de la vigne



Estimer précocement le rendement par l'analyse d'images



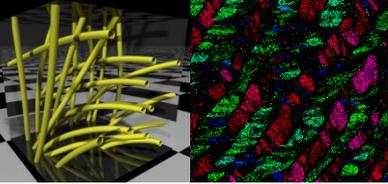
Dispositif autonome d'analyse d'images :

- 1 caméra + 1 flash
- 1 ordinateur industriel
- 1 antenne GPS + 1 capteur ultra-son

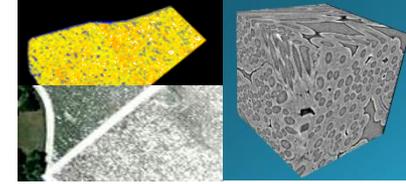


Traitement en 2 étapes:

- Détection des baies: nombre, position et taille de chaque baie détectée,
- Extrapolation au rendement: nombre de baies détectées => rendement en tonnes.

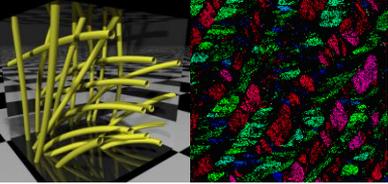


# Cartographie des maladies (Vigne)

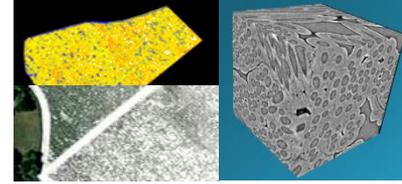


**1<sup>ère</sup> étape:**  
Segmenter les organes  
de la plante  
(Texture + tenseur  
généralisé)





# Conclusion



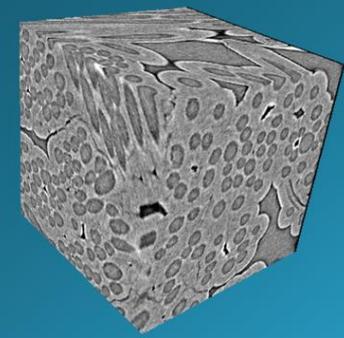
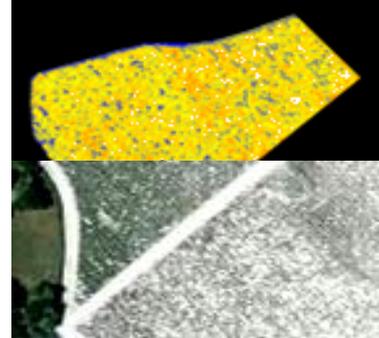
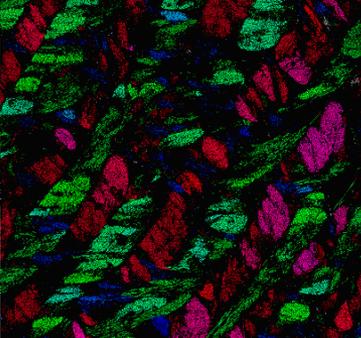
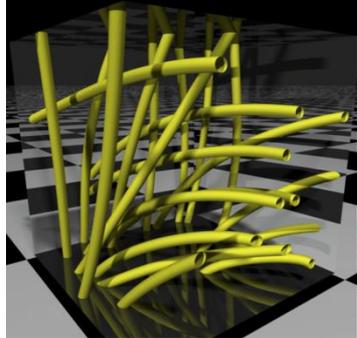
## BILAN

- L'image toujours au cœur de nos travaux.
  - Son acquisition est un domaine assez nouveau pour nous
- Des sujets difficiles en lien avec les problématiques sociétales sensibles: les maladies de la vigne par exemple



## PERSPECTIVES

- Poursuite des axes en cours (vigne, forêts, vergers)
- Nouvelles pistes méthodologiques avec le Deep Learning
- Extensions en cours ou prévues:
  - Capteurs connectés, Vigne. Projet européen IOF 2020 (en cours)
  - Désherbage robotisé en maraichage: Challenge ANR ROSE (déposé)



# Téledétection et imagerie embarquée au service de l'agriculture et de l'environnement

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