

PHENET Webinar: biotic interaction in agroecosystems

Plant Health: Validated sensors and methodology  
applicable for biotic stresses in wheat

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29 November 2024,  
Online

# Objectives of this webinar

**What question does this presentation address?**

*How to improve the crop resilience to biotic stress ?*

**How did we address this?**

*By building phenotyping tools using different optical sensors and developing models for plant disease detection with real time prediction*

*In particular, by the study of 5 approaches to assess wheat diseases in laboratory and in field*

- *Handheld fluorometer in field (AGROSCOPE)*
- *RGB images in field (GEVES, AGROSCOPE, CRA-W)*
- *Multispectral Visible NIR imaging in laboratory and in field (GEVES)*
- *Hyperspectral NIR imaging in laboratory and in field (CRA-W)*
- *NIR Spectrometer and sorting system in laboratory (CRA-W)*

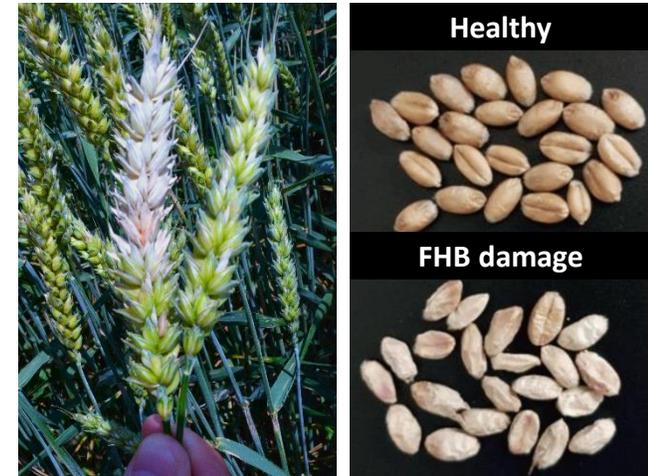
# Study case: Plant Health: Fusarium Head Blight (FHB) in wheat

## What is it? And why this choice?

Wheat is the major grain cereal crop cultivated in Europe

One of the major fungal diseases affecting wheat is Fusarium Head Blight (FHB)

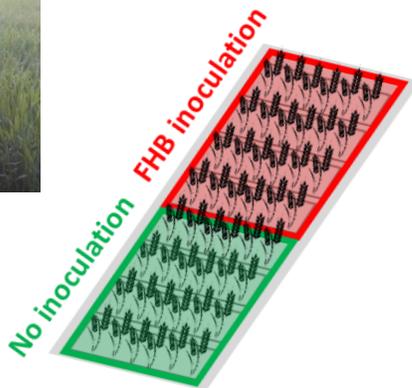
- ❑ Infects the ears at the flowering stage
  - ❑ Damages the kernels
    - yield and quality decrease
  - ❑ Can produce mycotoxins
    - risk for human and animal health
- 
- ➔ Fungicide treatment is only preventive and not fully effective ...
  - ➔ Disease-tolerant varieties are needed
  - ➔ Symptoms observable at the canopy level



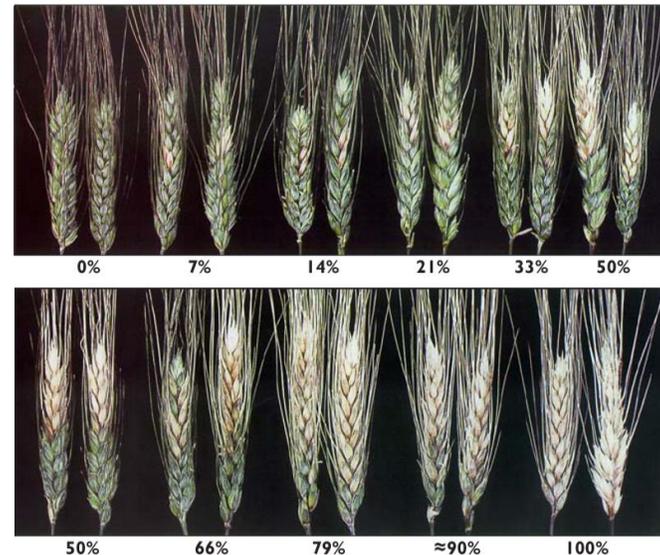
Source: Birr T. et al. (2020)



# Study case: Plant Health: Fusarium Head Blight (FHB) in wheat Experimentation and classical method



A Visual Scale to Estimate Severity of Fusarium Head Blight in Wheat



Source: Stack R.W. & McMullen M. (2011)

Varietal trial

Fusarium Head Blight (FHB) inoculation

Visual observation according to a reference scale  
at ear level (number of spikelets infected by ear)  
at plot level (number of ears infected by plot)



# 1st approach: Fluorescence measurement: acquisition

- +/- 10000 fluorescence measurements in the field by Agroscope

Based on the chlorophyll fluorescence  
Green and at maturity ears

Contact sensing 😞

Low cost 😊

Time consuming 😞

Point to point measurement 😞

Not early detection, need high infection 😞



FluoroPen

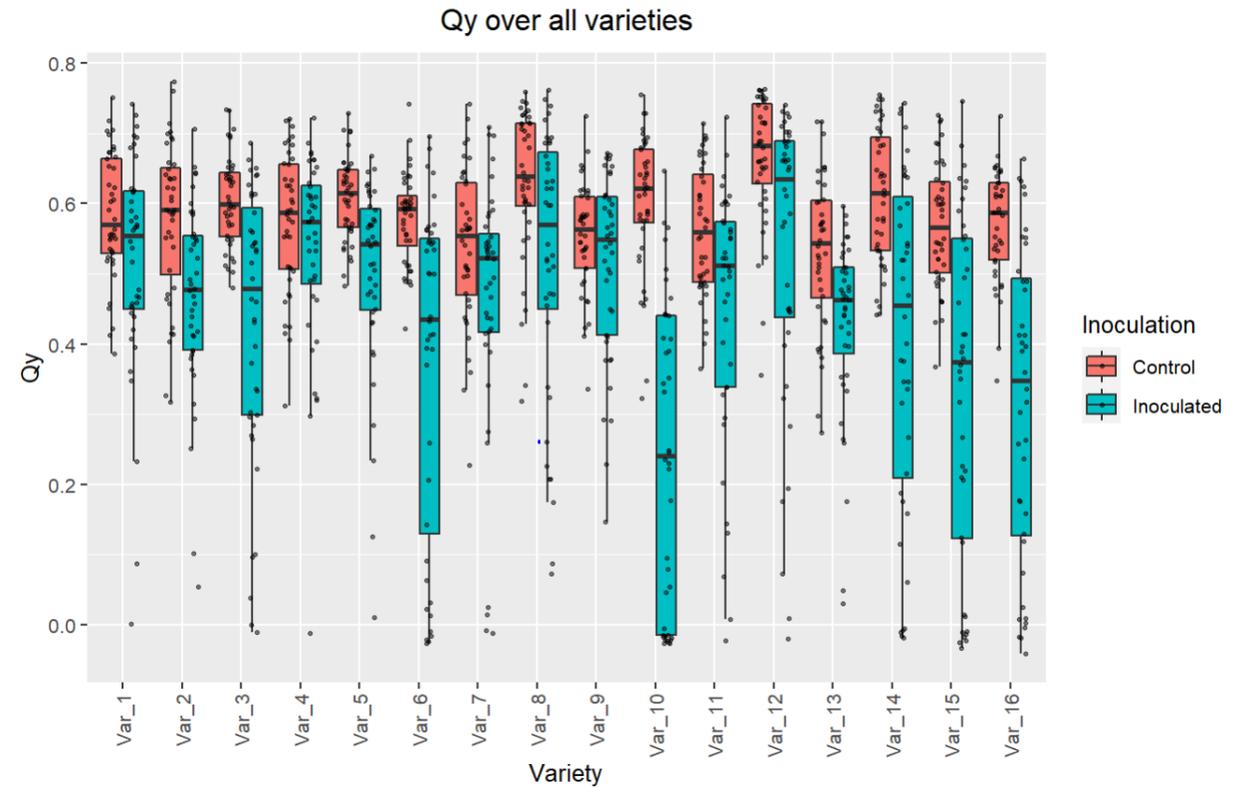


# 1st approach: Fluorescence measurement: results



- *Quantum yield (Qy) results for measurements on ears in the field showing a very large variability in relation to strong infections*

Index	2	3	4	5	6	7
Time	10:27:54 29.3.2018	10:29:29 29.3.2018	10:31:45 29.3.2018	10:35:52 29.3.2018	10:22:44 3.4.2018	10:23:11 3.4.2018
	49° 20.3871' N 16° 28.6379' E	49° 20.3538' N 16° 28.6755' E	49° 20.2923' N 16° 28.6290' E	49° 20.2557' N 16° 28.5246' E	Qy 0.67	Qy 0.04
Qy	0.72	0.65	0.27	0.67	Fo Backgr 378 Fo Flash 3333	Fo Backgr 897 Fo Flash 936
Fo Backgr	299	378	89	438	Fm Backgr 398	Fm Backgr 864
Fo Flash	4985	2711	1069	3110	Fm Flash 9331	Fm Flash 946
Fm Backgr	299	418	92	418		
Fm Flash	17138	7058	1436	8544		



S. Treier (2025). Digital optical lean phenotyping methods in the context of wheat variety testing. Thesis in Agroscope

# 1st approach: Fluorescence measurement: next steps

- Assess its potential application under natural infections in a variety testing network to improve the comparability among campaigns, sites and operators



# 2nd approach: RGB imaging: acquisition

- +/- 3000 RGB images acquired by Agroscope, CRA-W, GEVES

Based on the color (green/white)

Green ears

Proximal sensing 😊

Low cost 😊

Random and quick acquisition 😊

Image on full ears acquired with an angle of 45°/90° 😊

Early detection when one spikelet is infected 😊

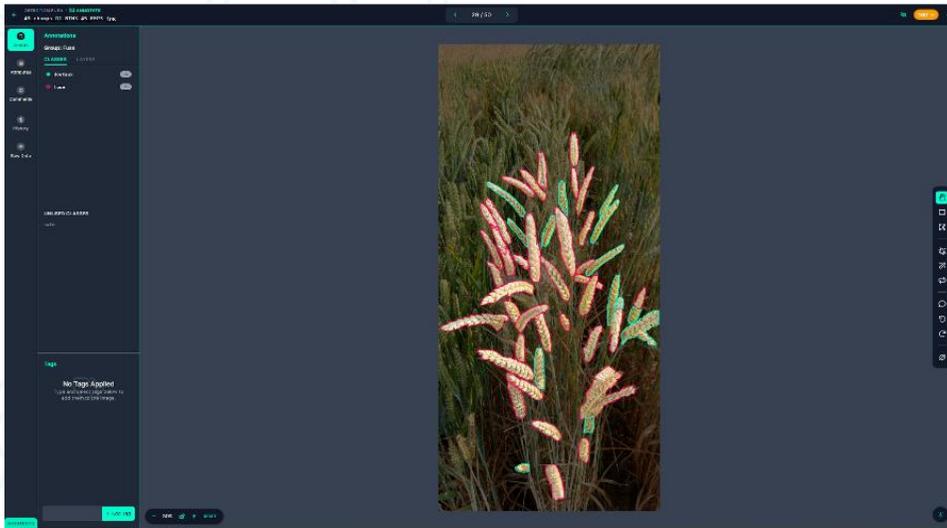


# 2nd approach: RGB imaging: Annotation models

- Plateforme used: **Roboflow**
- Exemple of annotations with **2 classes: healthy / Fusarium**
- 3 methods: manual, **semi-automatic model (« SAM »)** and **development of an automatic model**
- Nb images annotated by GEVES:  $\approx 800$  images=239 from CRA-W + 561 from GEVES

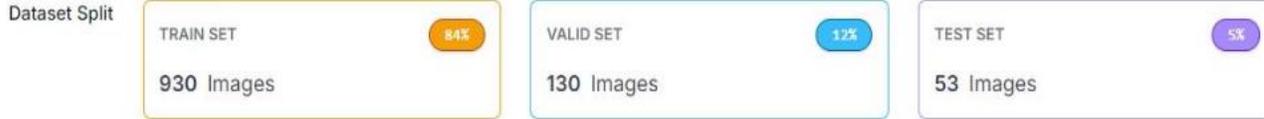
239 Total Images

[View All Images →](#)



# 2nd approach: RGB imaging: method of prediction

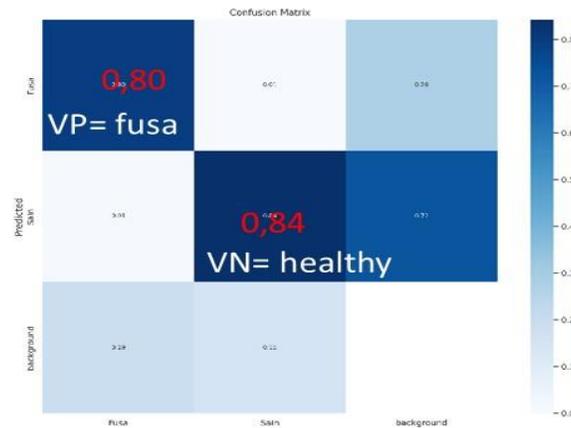
- 1 model selected upon 17 models of Deep learning



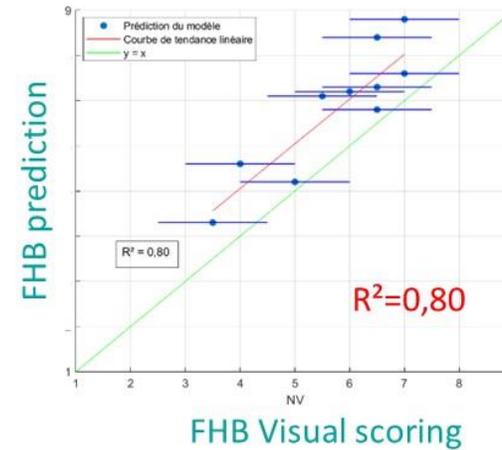
## Segmentation

Class	Precision	Rappel	mAP50	mAP50-95):
all	0.794	0.728	0.806	0.474
Fusa	0.823	0.72	0.808	0.481
Sain	0.766	0.736	0.804	0.468

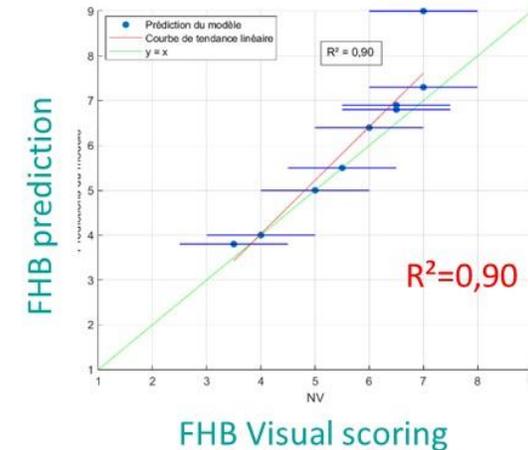
## Confusion matrix



Without detection of spikes



With detection of spikes  
(model coming from Global Wheat Challenge 2021)



High correlation between FHB predictions & visual scorings in field



# 2nd approach: RGB imaging: method of prediction

RGB image  
in perspective



prediction

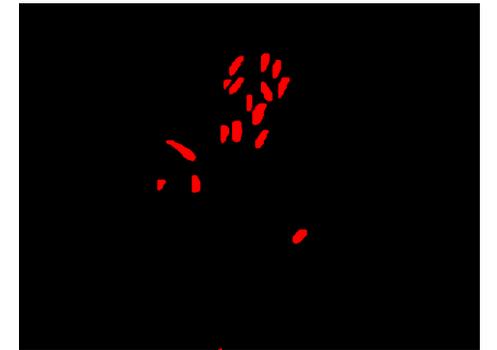
FHB prediction by Deep learning (Yolo V8)



All Mask



Fusa mask



% FHB area = Fusa mask / all mask ; Ex: 9.03 %



# 2nd approach: RGB imaging: comparisons of DL performance between sensors



Camera  
Sony



Smartphone  
Samsung A 54



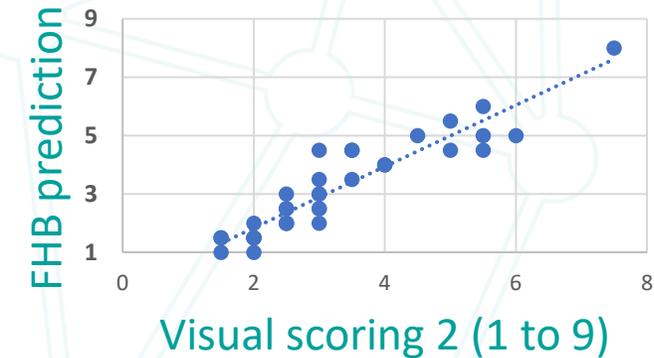
Smartphone  
Google Pixel 8

Groupe	R <sup>2</sup>	REP1	REP2	REP3	MOY
BTH1	D1NV1	0,62	0,60	0,46	0,56
	D2NV2	0,27	0,69	0,76	0,58
BTH2	D3NV2	0,87	0,77	0,74	0,79
BDH	D3NV2	0,58	0,60	0,66	0,61

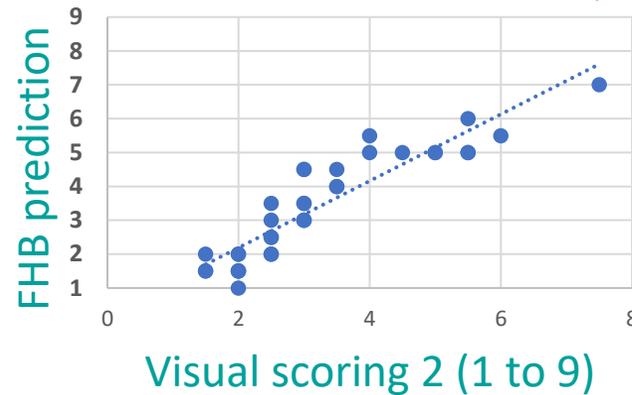
Groupe	R <sup>2</sup>	REP1	REP2	REP3	MOY
BTH1	D1NV1	0,61	0,37	0,37	0,45
	D2NV2	0,46	0,66	0,41	0,51
BTH2	D3NV2	0,83	0,73	0,74	0,77
BDH	D3NV2	0,81	0,55	0,68	0,68

Groupe	Groupe	R <sup>2</sup>	REP1	REP2	REP3	MOY
BTH1	BTH1	D1NV1	0,85	0,55	0,35	0,58
		D2NV2	0,38	0,69	0,44	0,50
BTH2	BTH2	D3NV2	0,89	0,88	0,81	0,86
BDH	BDH	D3NV2	0,59	0,82	0,91	0,77

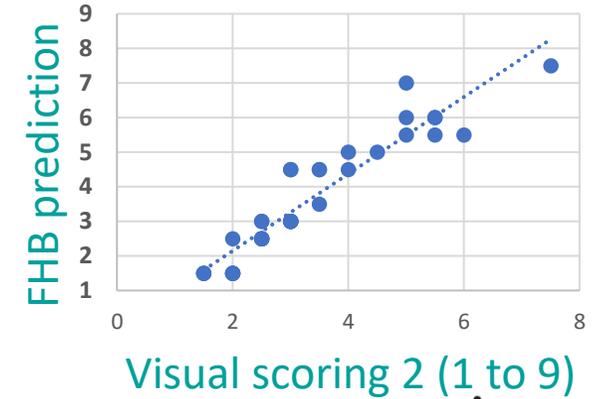
BTH2: D3 NV2 rep1  $R^2 = 0,87$



BTH2: D3 NV2 rep1  $R^2 = 0,83$



BTH2: D3 NV2 rep1  $R^2 = 0,89$



The same Deep Learning model adapted to different low cost RGB sensors



# 2nd approach: RGB imaging: user interface to collect the % FHB area/image

## Analysis for 1 several image

### Détection d'objets YOLOv8 et Visualisation des Masques

Analyse d'une seule image Analyse de plusieurs images

#### Analyse d'une seule image

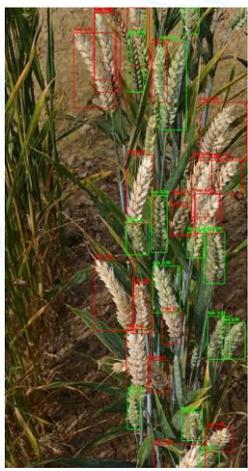
**% FHB area**  
ex : 64,8%

Choisissez une image...

Drag and drop file here  
Limit 200MB per file • JPG, JPEG, PNG

Browse files

crop\_49-Sony-D2-BTH1-2-REP2.JPG 0.7MB



## Analysis for several images

Analyse d'une seule image Analyse de plusieurs images

### Analyse de plusieurs images

Choisissez des images...

Drag and drop files here  
Limit 200MB per file • JPG, JPEG, PNG

Browse files

- crop\_49-Sony-D2-BTH1-41-REP3.JPG 0.8MB
- crop\_49-Sony-D2-BTH1-40-REP3.JPG 1.0MB
- crop\_49-Sony-D2-BTH1-39-REP3.JPG 0.7MB

Showing page 1 of 14

	Image	Pourcentage de Fusa
0	crop_49-Sony-D2-BTH1-1-REP3.JPG	64.8226
1	crop_49-Sony-D2-BTH1-2-REP3.JPG	86.5061
2	crop_49-Sony-D2-BTH1-3-REP3.JPG	80.0881
3	crop_49-Sony-D2-BTH1-4-REP3.JPG	16.9305
4	crop_49-Sony-D2-BTH1-5-REP3.JPG	14.4327
5	crop_49-Sony-D2-BTH1-6-REP3.JPG	88.2476
6	crop_49-Sony-D2-BTH1-7-REP3.JPG	86.6072
7	crop_49-Sony-D2-BTH1-8-REP3.JPG	78.1664
8	crop_49-Sony-D2-BTH1-9-REP3.JPG	77.9965
9	crop_49-Sony-D2-BTH1-10-REP3.JPG	98.9945

Télécharger les résultats en Excel

## % FHB area loaded on Excel

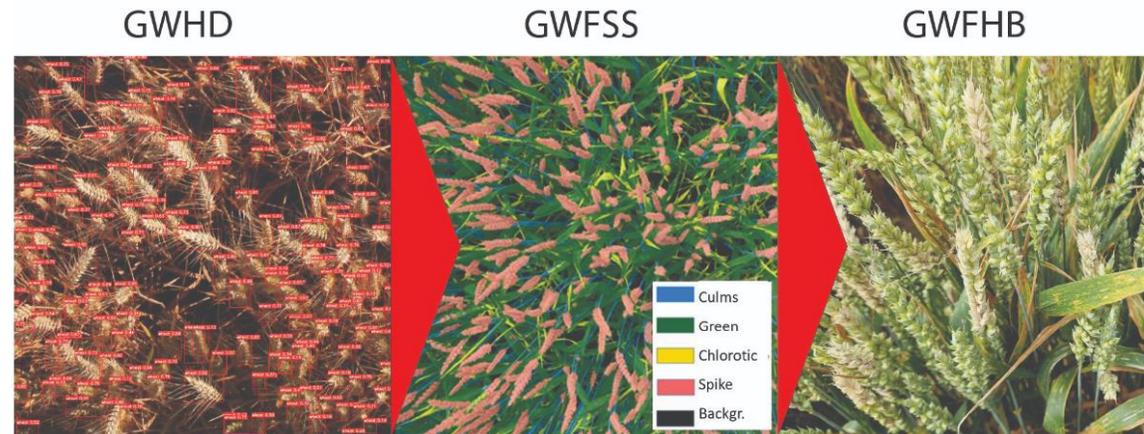
Image	Pourcentage de Fusa
crop_49-Sony-D2-BTH1-1-REP3.JPG	64,82
crop_49-Sony-D2-BTH1-2-REP3.JPG	86,51
crop_49-Sony-D2-BTH1-3-REP3.JPG	80,09
crop_49-Sony-D2-BTH1-4-REP3.JPG	16,93
crop_49-Sony-D2-BTH1-5-REP3.JPG	14,43
crop_49-Sony-D2-BTH1-6-REP3.JPG	88,25
crop_49-Sony-D2-BTH1-7-REP3.JPG	86,61
crop_49-Sony-D2-BTH1-8-REP3.JPG	78,17
crop_49-Sony-D2-BTH1-9-REP3.JPG	78,00
crop_49-Sony-D2-BTH1-10-REP3.JPG	98,99



# 2nd approach: RGB imaging: results



➤ Contribution to the GWFHB: **G**lobal **W**heat **F**usarium **H**ead **B**light



Head  
Detection

Full Semantic  
Segmentation

Fusarium  
Head Blight

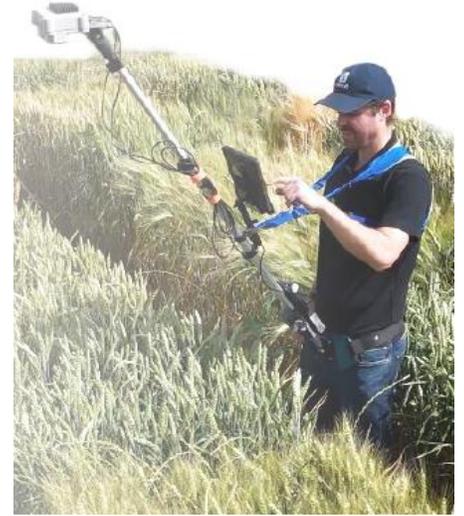


<https://www.global-wheat.com/gwss.html>



# 2nd approach: RGB imaging: next steps

- Guidelines document for images
  - (semi-automatic) annotating to assess biotic stress
- Use of the annotated images
  - for model development by GEVES
- Use of this model to extend the portfolio of agronomics traits on existing phenotyping device such as:
  - the Mobile-based Rapid Phenotyping (MoRPH) application developed by WUR
  - the Literal stick developed by Hiphen



# 3rd approach: VNIR multispectral imaging: acquisition



- 383 images (1658 spikes) acquired in laboratory by GEVES
- 560 images acquired on 7 sites in field by GEVES

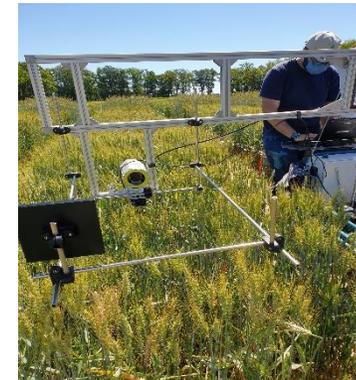


Multispectral imaging - plane scan  
CMS 4: 4 wavelengths for FHB  
detection (3 RGB & 1 NIR bands)



- Based mainly on the Chlorophyll content
- Green and yellow ears (until 550°day post inoculation)
- Proximal sensing 😊
- Rather specific of FHB (≠Microdochium or Yellow rust) 😊
- High cost 😞
- Time consuming 😞
- Image on full ears acquired in frontal view (1 row of ears) 😊
- Possible early detection when one spikelet is infected 😊

In laboratory



In field

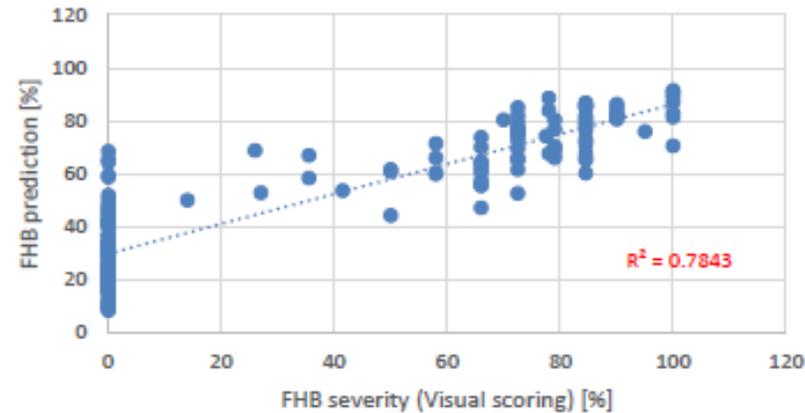
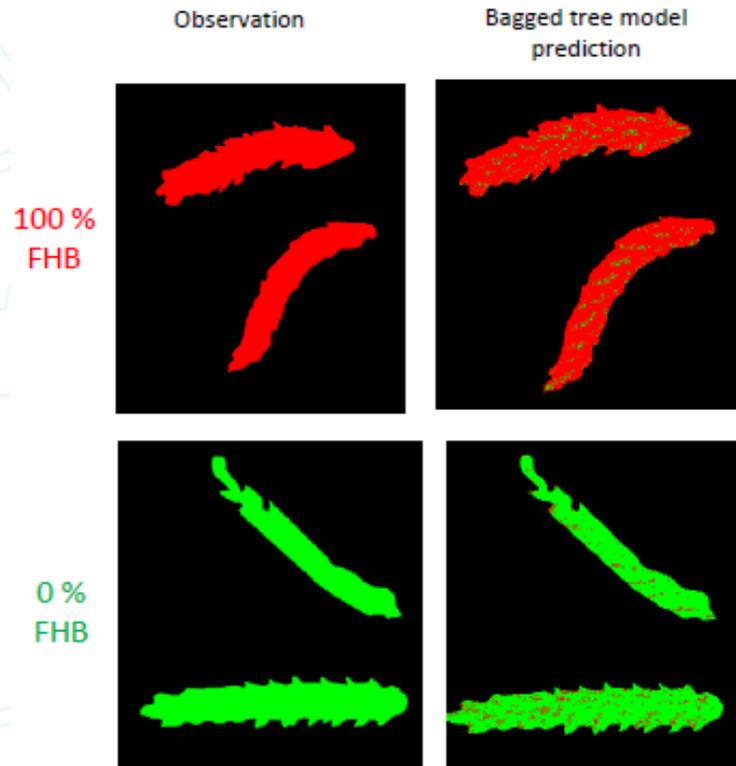


# 3rd approach: VNIR multispectral imaging: results



## In laboratory

Annotated and predicted images



H. Garbougé (2022). Deep learning applied to multi-component imagery for variety testing problems. Thesis in U.Angers



# 3rd approach: VNIR multispectral imaging: results



## In field in frontal view

### Annotations

Annotations of the 1st row of ears



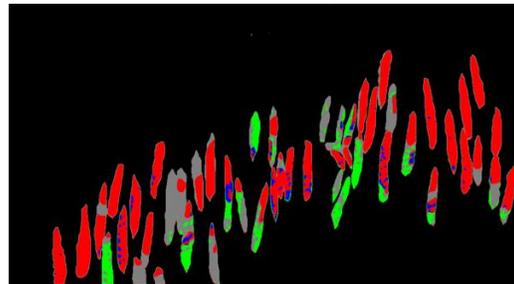
### Creation of 2 algorithms :

Ear segmentation (U-NET)

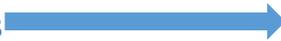


H. Garbougé (2022).  
Thesis in U.Angers

Fusarium quantification  
prediction (Machine learning)

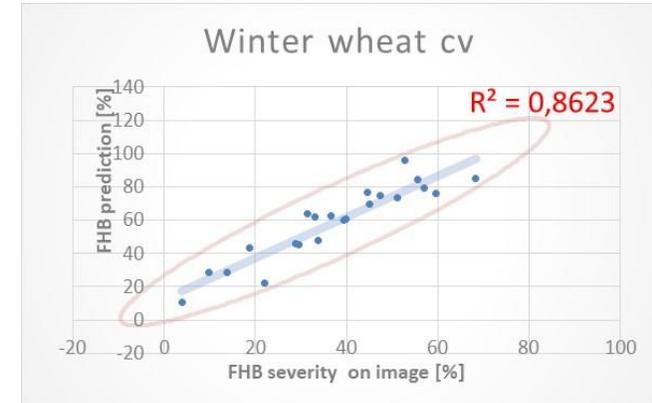


Fusarium annotations



Fusarium pixels

### FHB prediction results



- Usable for assesment of FHB cv resistance
- 🤩 **High correlation with annotations:**  
in case of good acquisition conditions & high FHB pressure.



VP='Fusarium' pixels predicted as 'Fusarium'  
FP='Healthy' pixels predicted as 'Fusarium'  
FN='Healthy' predicted 'Fusarium' pixels  
FN='Healthy' pixels predicted as 'Healthy'

# 3rd approach: VNIR multispectral imaging: next steps

- Develop a semi-automatic annotation method to assess biotic stress



# 4th approach: VNIR hyperspectral imaging: acquisition



- 614 images acquired in laboratory by CRA-W
- 100 images acquired on 1 site in field by CRA-W

Hyperspectral imaging - line scan (Specim)  
(400-1000, 1000-1700, 1000-2500 nm)

Based on the chlorophyll and water content  
Green and at maturity ears

Proximal sensing 😊

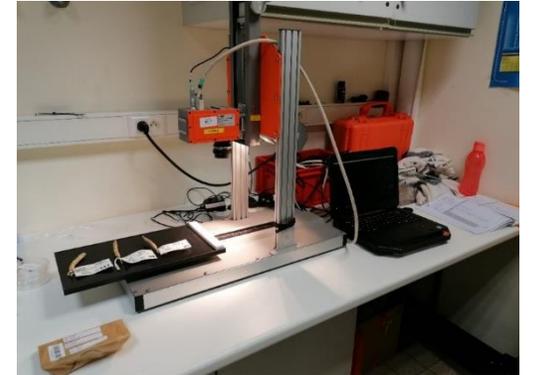
High cost 😞

Time consuming 😞

Image on ears acquired in vertical view (line scan camera) 😊

Possible detection on a wider area (100 ears or 1m<sup>2</sup>/plot) 😊

In laboratory



In field



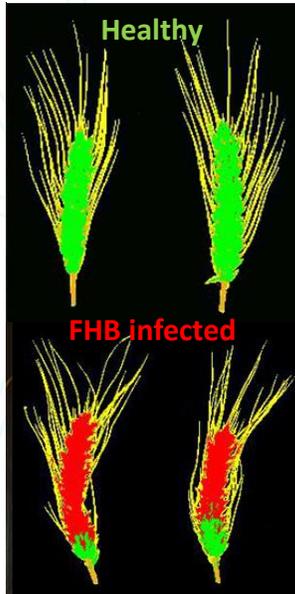
# 4th approach: VNIR hyperspectral imaging: results



In laboratory

NIR-HSI predicted images

MODEL VALIDATION (PLSDA)



Infected or not

Predicted results by ear

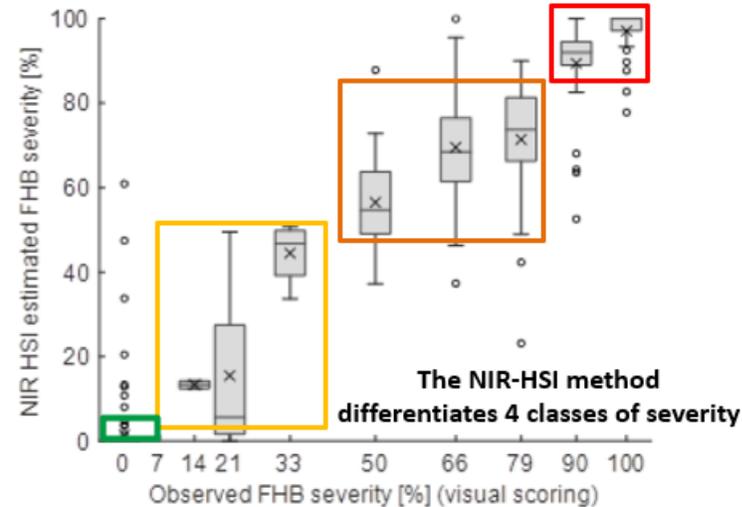
	Actual class	
	FHB-infected	Healthy
Predicted as FHB-infected	152	13
Predicted as Healthy	2	141

Sensitivity: 98,7%



Specificity: 91,6 %

Severity



D. Vincke et al. (2023). Near infrared hyperspectral imaging method to assess Fusarium Head Blight infection on winter wheat ears. *Micromechanical Journal* 191, 108812

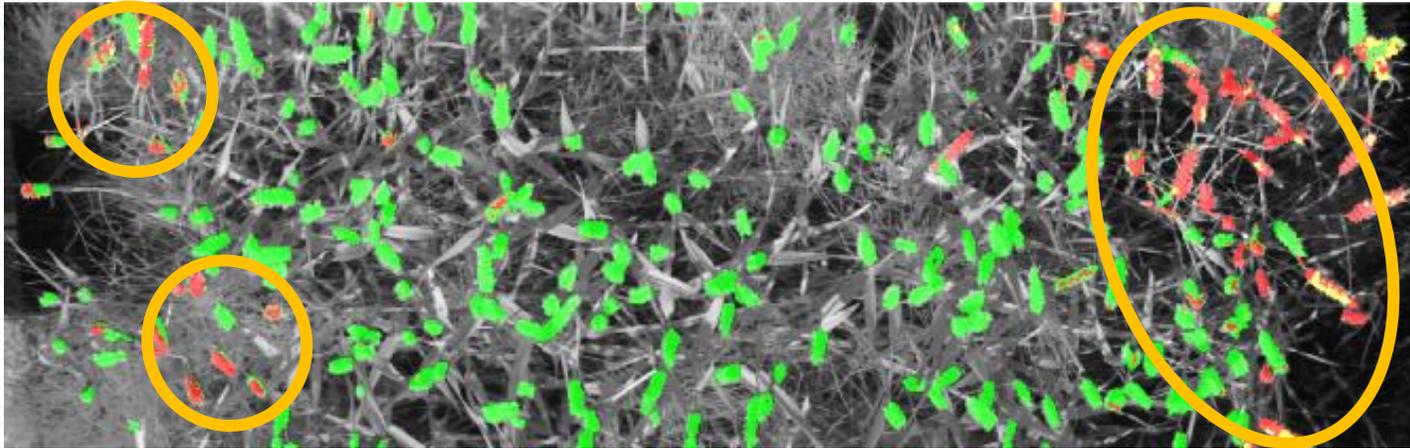


# 4th approach: VNIR hyperspectral imaging: results



In field

Predicted images



- Healthy
- FHB infected
- Take-all infected

Date	FHB <span style="color: red;">✗</span>		Take-all <span style="color: red;">✗</span>		Overall stress <span style="color: green;">✓</span>	
	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>
28-06-22	0,7	0,08	4,1	0,39	2,0	0,85
04-07-22	0,6	0,26	7,8	0,56	4,2	0,87
14-07-22	0,5	0,42	5,4	0,79	1,8	0,98

D. Vincke (2024). Evaluation of fusarium head blight infection on winter wheat using near infrared hyperspectral imaging from the laboratory to the field. Thesis in U.Liège Gembloux Agro-Bio Tech

The method can assess the overall stress of the ears but ...  
It is not specific enough to differentiate two diseases with similar symptoms.



# 4th approach: VNIR hyperspectral imaging: next steps



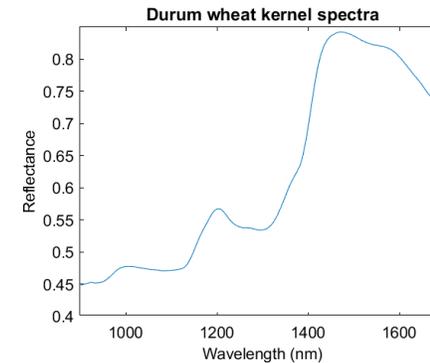
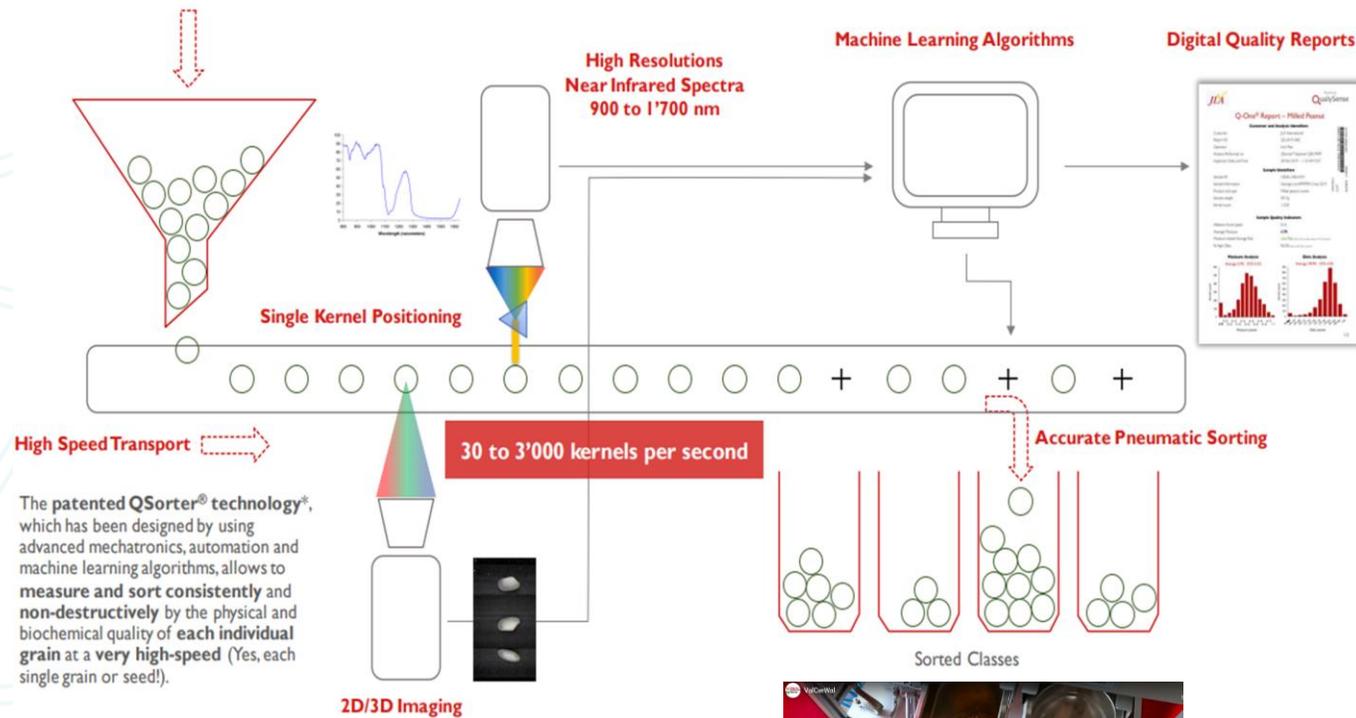
- Transfer to a tractor platform & adaptation with blackout box (natural light control) with angle 45 or vertical view
- Model optimisation: specificity prediction in real time



# 5th approach: NIR + RGB imaging for sorting grains

## ➤ Single-kernel analyzer: Qsorter explorer (Qualisense)

- NIR range 900-1700 nm
- 3D RGB imaging
- Information acquired from each individual grain



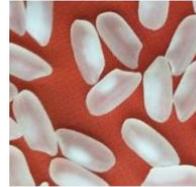
# 5th approach: NIR + RGB imaging for sorting grains

## ➤ High-speed pneumatic sorting system

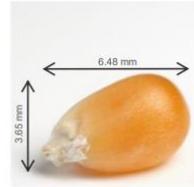
- Sorting based on **physical** and/or **biochemical** characteristics of grains
- Quality inspection in real time at **high throughput**
- In-depth batch **characterization** and better contaminant **management**
- **Individual grain** phenotyping for the development of new varieties



INSECT DAMAGE



BROKEN KERNELS



GEOMETRY



DISEASES  
(FUSARIUM)



IDENTIFY IMPURITIES

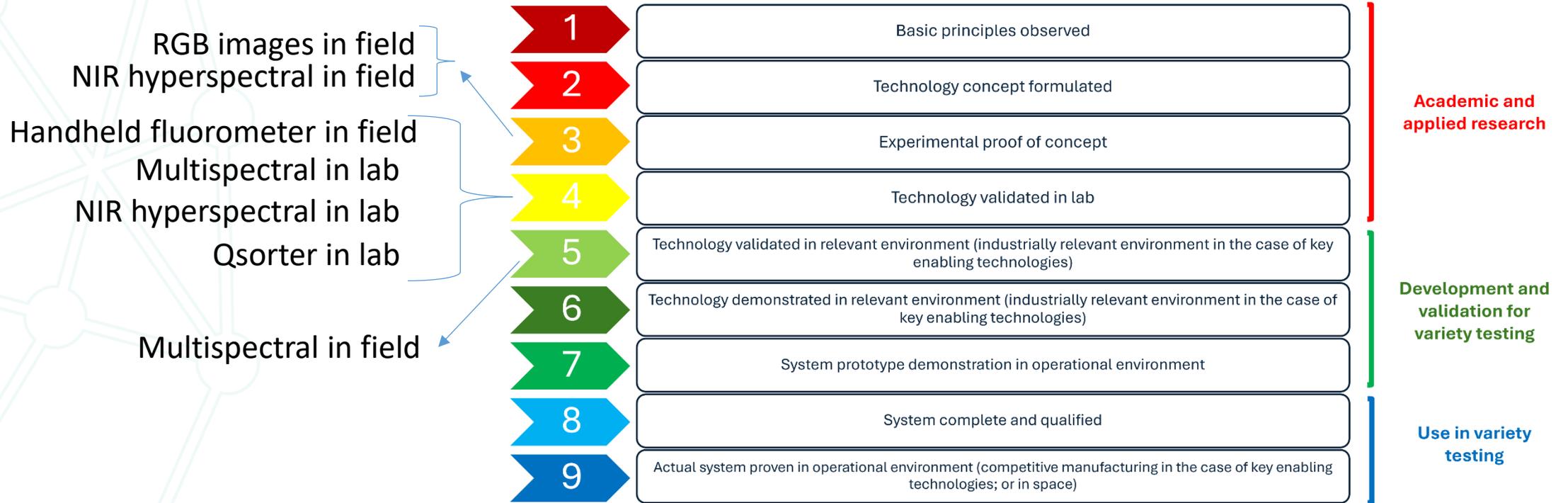


Image	Spectra	Protein [%]	Moisture [%]	Length [mm]	Width [mm]	Area [sqmm]	Elongation Factor [-]	Prediction Index	Label
		12.23	12.34	9.21	2.45	22.58	4.58	1.02	Oat
		13.65	11.21	8.76	2.76	24.21	4.48	1.12	Oat
		11.42	12.13	7.78	2.57	20.00	3.85	1.08	Oat
		15.35	11.05	7.25	3.97	28.78	3.97	0.92	Contaminant
		12.78	10.98	11.58	3.12	36.17	4.72	1.01	Oat

Various compositional properties:  
protein, fatty acids, sugar...



# Readiness of the tools



*"Technology readiness levels (TRL); Extract from Part 19 - Commission Decision C(2014)4995" (PDF). ec.europa.eu.*

# Next steps

## Extension to other diseases

### ☐ Head diseases

Bunt (*Tilletia caries*): contamination of grain lots by spores  
transfer methodology to other head disease (CRA-W)

Orange wheat blossom midge larvae – *Cecidomyia* – Yield loss  
counting of larvae from RGB image (CRA-W, GEVES)

### ☐ Leaf diseases

Barley yellow dwarf virus (BYDV)- Vector: aphids - Yield loss  
assess BYDV symptoms on leaves with the perch Phenoman (GEVES)



# Acknowledgements



**PHENET**

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David Rousseau (UA)

Joseph Peller (WUR)



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**PHENWHEAT**

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**VALCERWAL**

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**Fus'eye**

Valérie Cadot (GEVES)

