Detecting wheat heading stage from daily RGB images

Détection de l'épiaison du blé à partir d'images RVB quotidiennes

DATE

20 Nov 2019

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Wheat phenological stages

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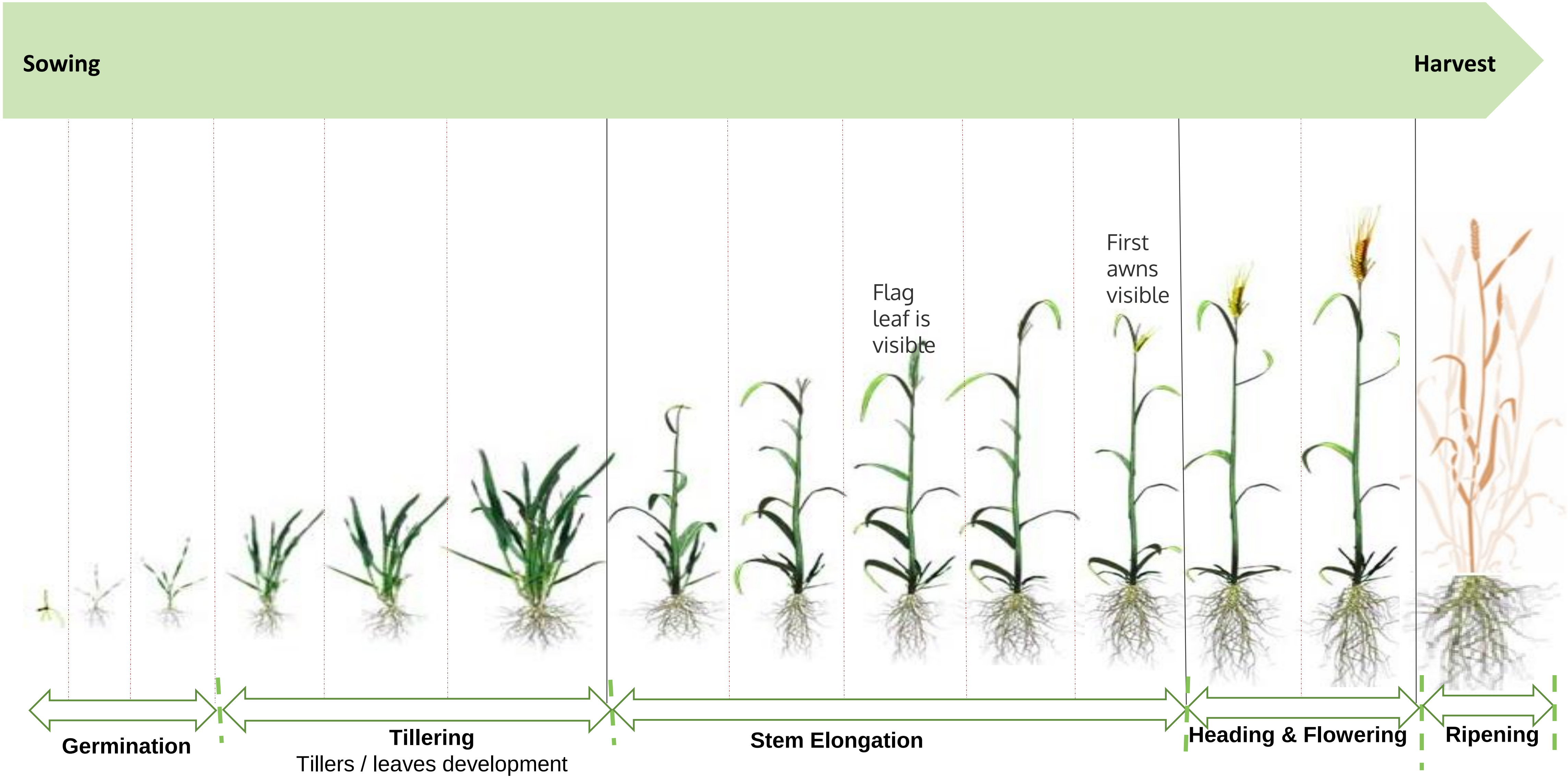
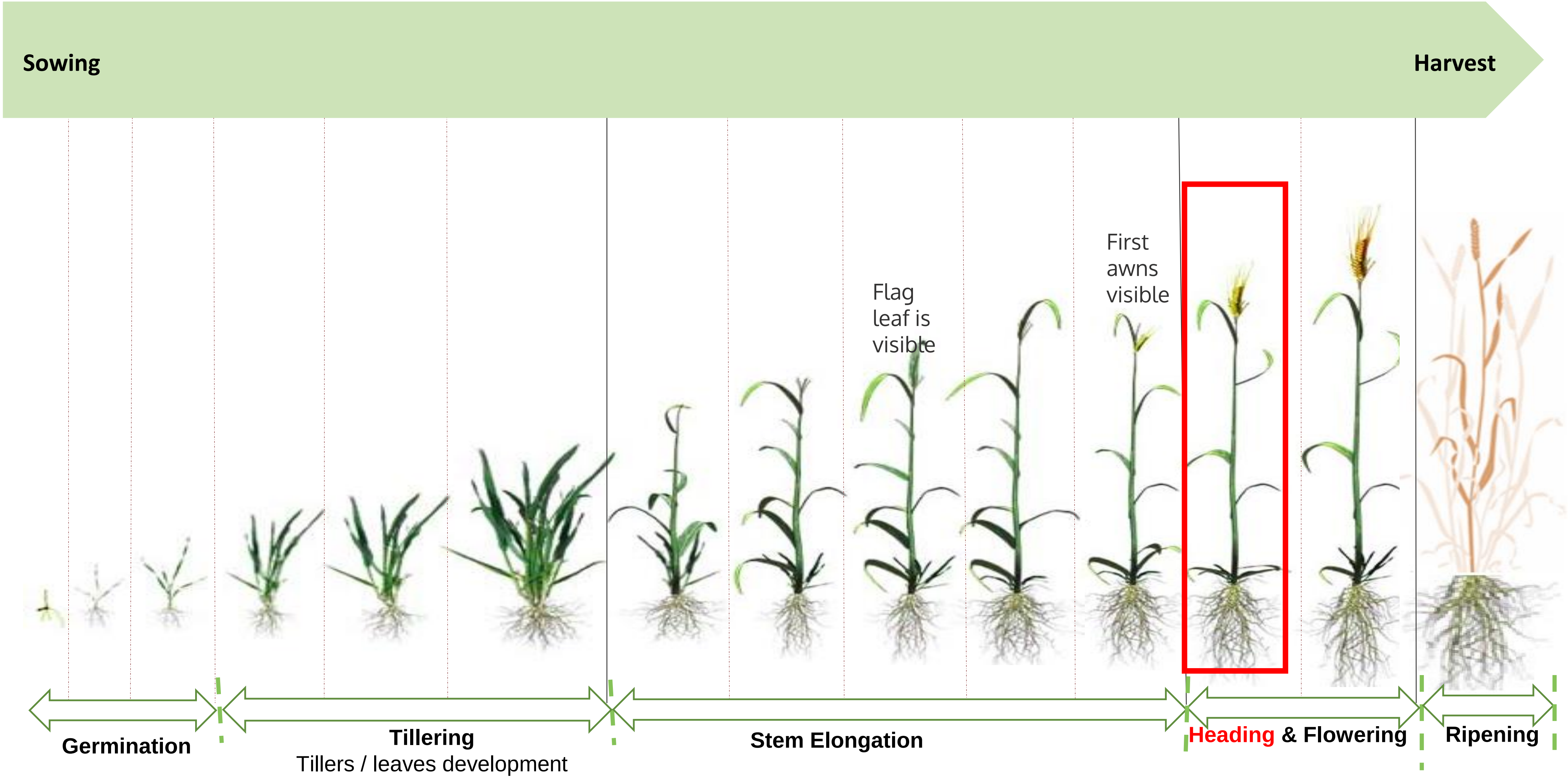


Wheat phenological stages – Heading stage



Wheat heading stage

Importance:

- Stress during this stage affects final yield
- Suitability of cultivar to temperature stress
- Harvest date prediction

Heading date definition :

50% of the wheat ears have emerged from 50% of the plants within the sampling area

Heading Date -4 days

2

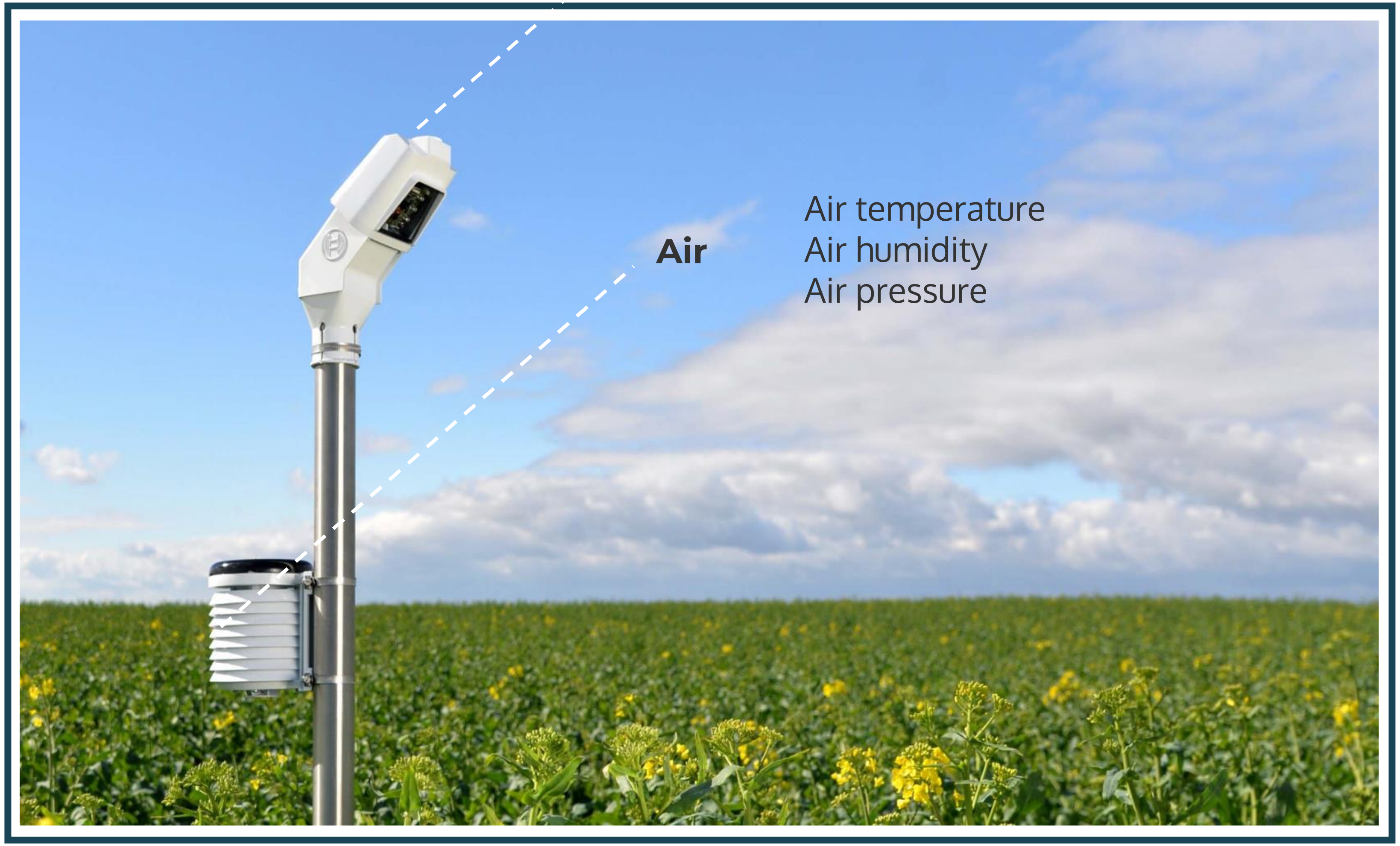
Sensors used

2.1

IoTA Field Sensors

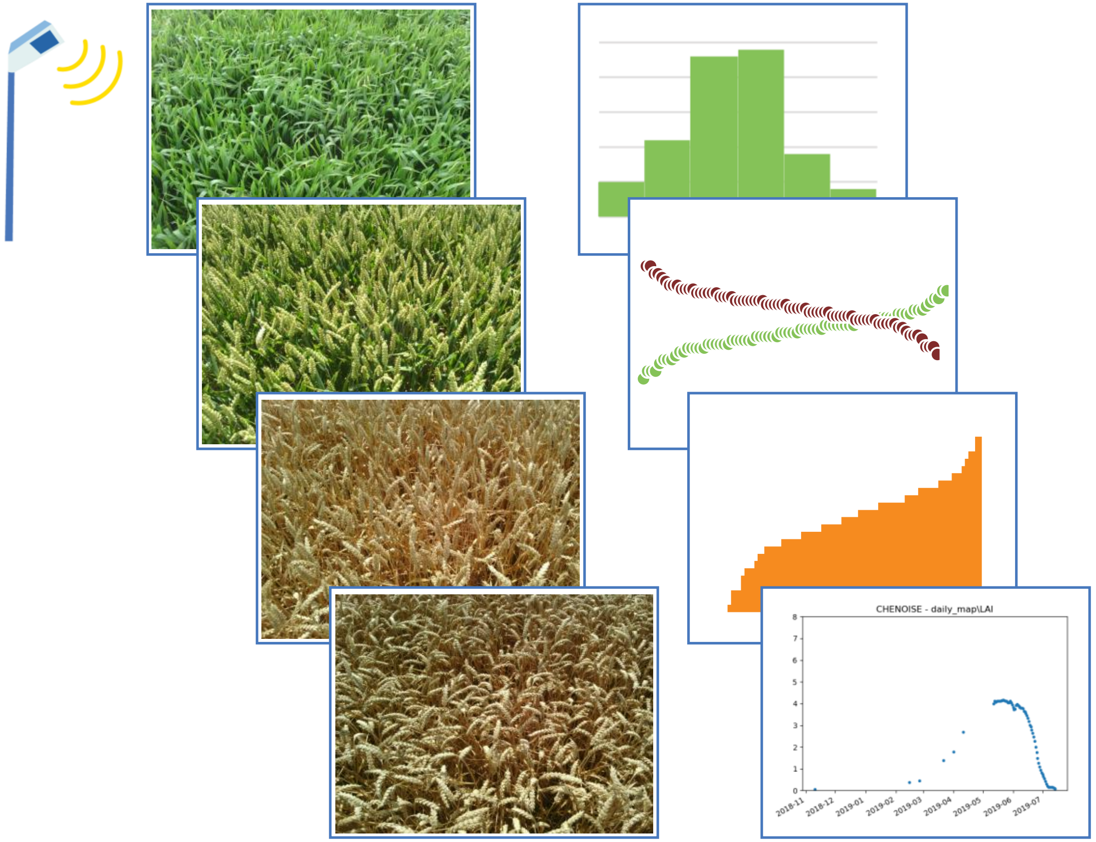
Bosch's Field Sensors can be installed in your field in strategic zones, and transmit data to Bosch's server via cellular networks and other technology (e.g. Lora).

PAR refers to Photosynthetically Active Radiation, i.e. the quantity of light usable for photosynthesis



Inspect crop phenology remotely in almost real-time
to detect important events …

while familiarizing yourself with the data visualisation tools
provided by Hiphen



Data available through our API
https://api.hiphen-plant.com/api/v1/

Data available through our web interface
http://cloverfield.hiphen-plant.com

Daily images and field data from Bosch Field Sensors

Available through the API and our web interface

2.3

Daily Images from Field Sensors

- One image per day, collected throughout the crop growth cycle
- Image dimensions: 1024 x 768 pixels
- Camera is set at approximately 1m above the canopy.
- Inclination angle: 45° and Field of View: 55° x 41°
- Footprint: approx. 10.8 m^2
- Non uniform ground resolution throughout the image, particularly in the vertical direction

Example of images acquired through the sensor

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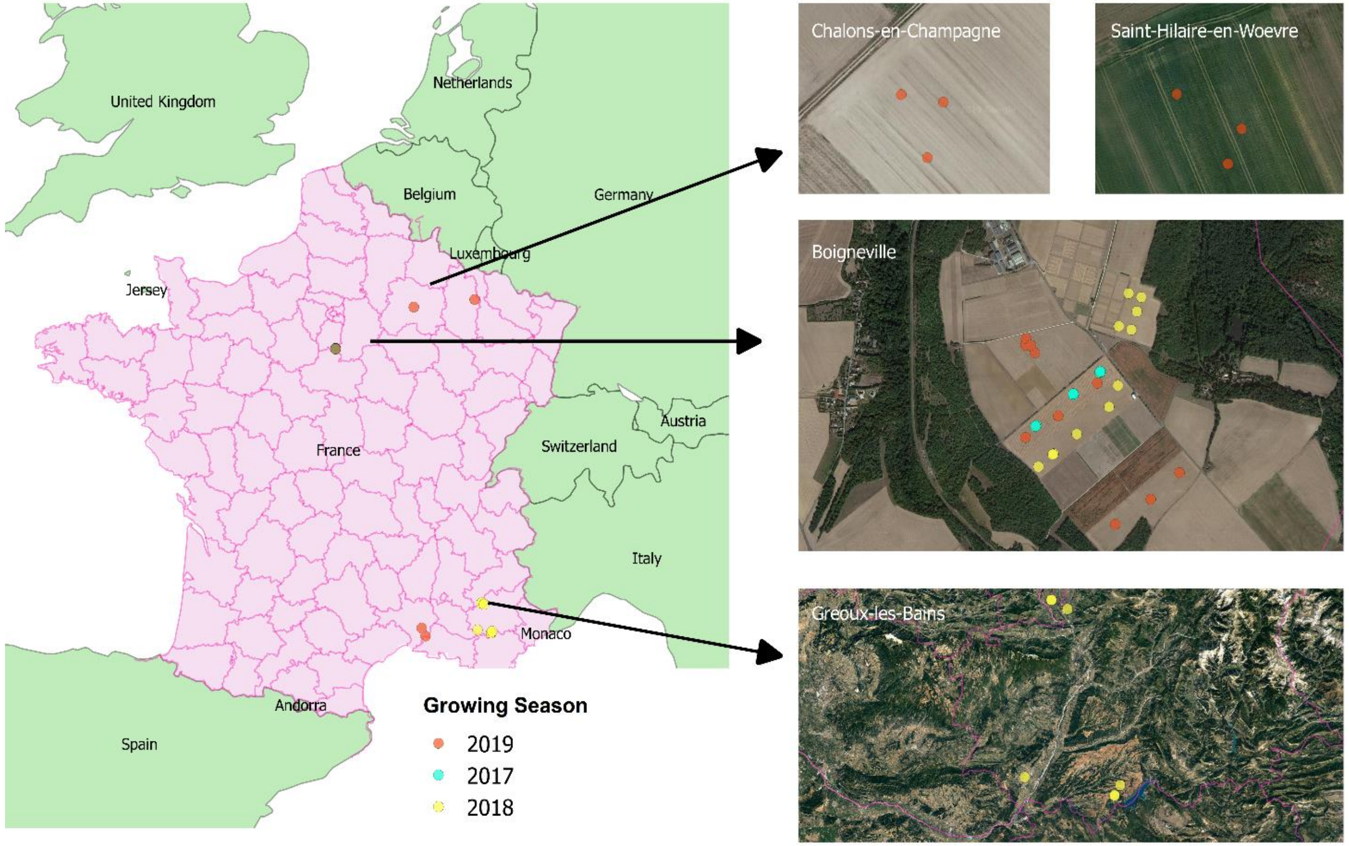
Dataset

Study area

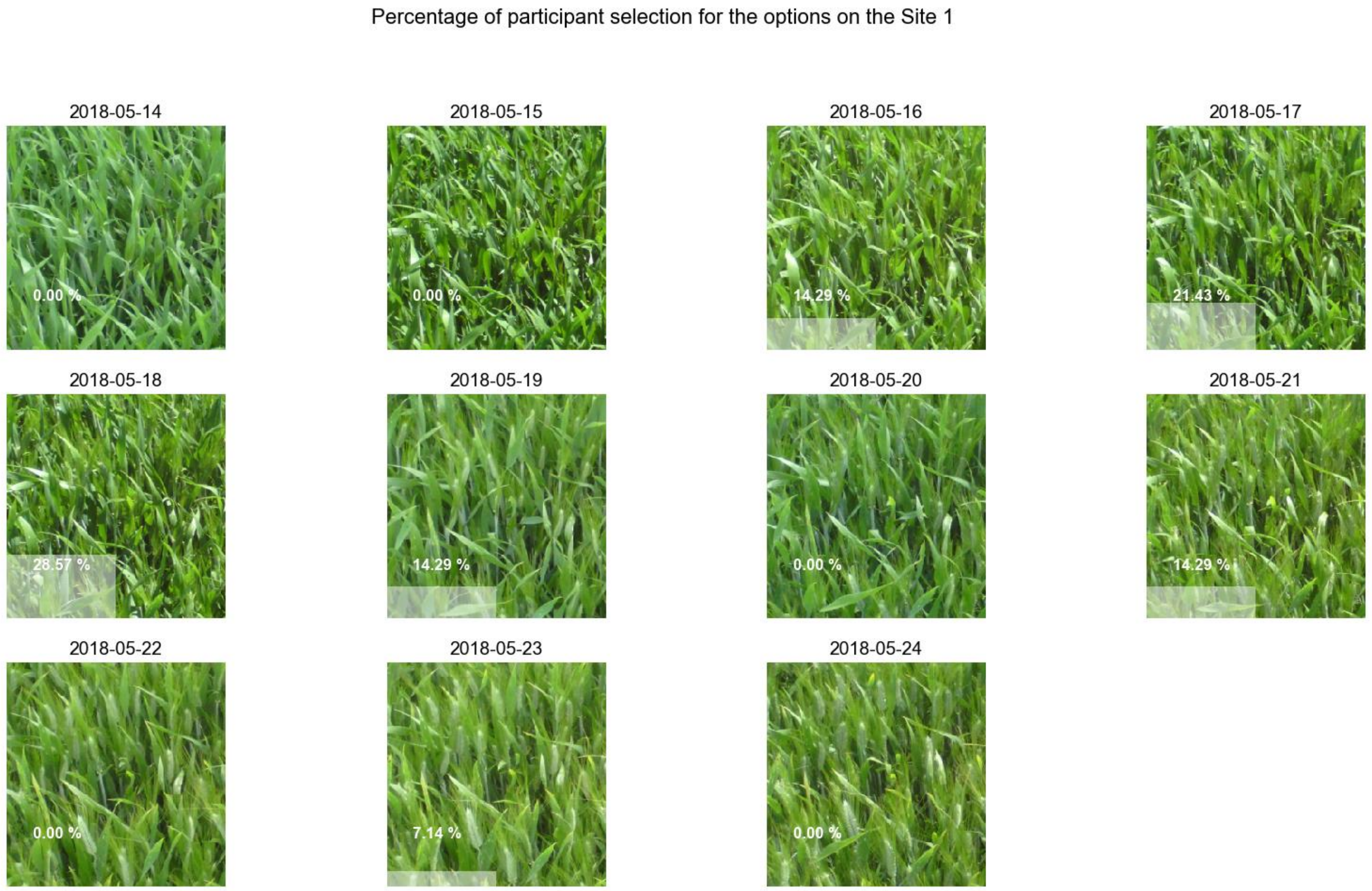


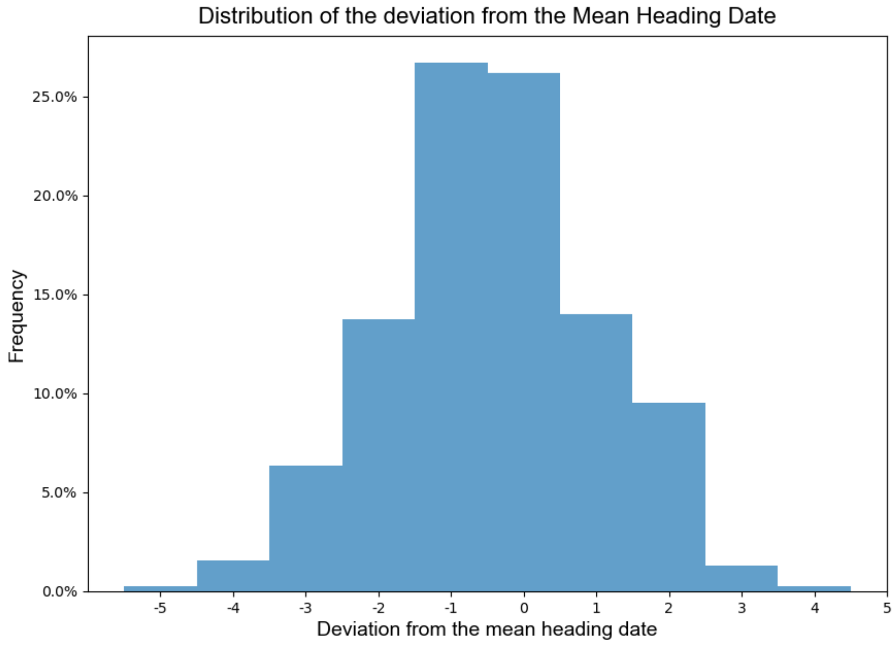
- 3 growing seasons (2017, 2018 and 2019)
- 47 field sensors in different agro-climatic regions in France
- 9 different cultivars

	2017		2018		2019	
Regions	**Sites**	**Cultivars**	**Sites**	**Cultivars**	**Sites**	**Cultivars**
Gréoux	-	-	7	3	2	2
Boigneville	8	1	12	3	12	3
Chalons en Champagne	-	-	-	-	3	1
Saint_Hilaire en Woëvre	-	-	-	-	3	1

Reference heading dates

- **2017 and 2018 sites**: 16 experts in wheat phenology were asked to score the heading date on the daily RGB images collected by field sensors on the 27 sites.
- **2019 sites**: Direct scoring in the field by an expert





An mean absolute deviation of 2.3 is observed

https://www.mentimeter.com/login

Preparing training dataset

- 45 degree – non uniform scale within the image.
- Objects in the background more blurred.
- So we crop and use only the image foreground (this improves the CNN performance in detecting ear presence)

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- 45 degree – non uniform scale within the image.
- Objects in the background more blurred.
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We focus for this study on the lower part of the images

Preparing training dataset

- All images after the heading dates are associated of patches with ear
- A 50% overlap is used to create the different patches

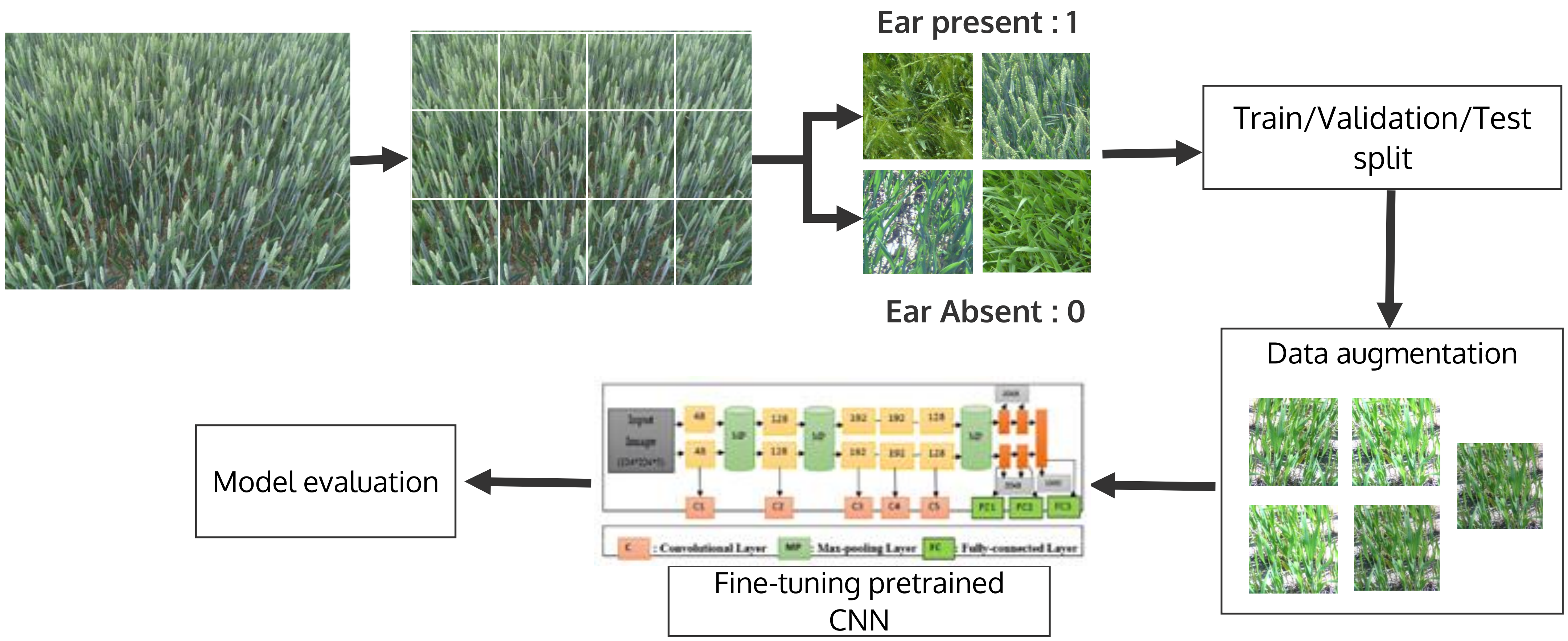
Examples of ear present patches : 1

Examples of ear absent patches : 0

This approach allows us to build a very important dataset very quickly

Method to detect the Heading Date

Training the CNN-classifier

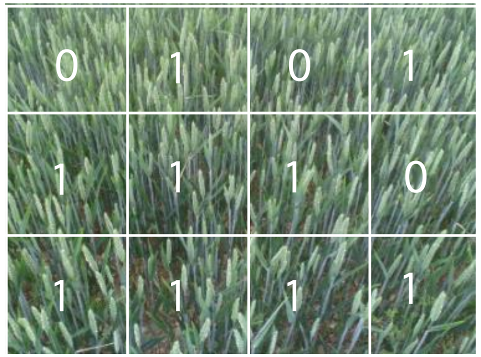


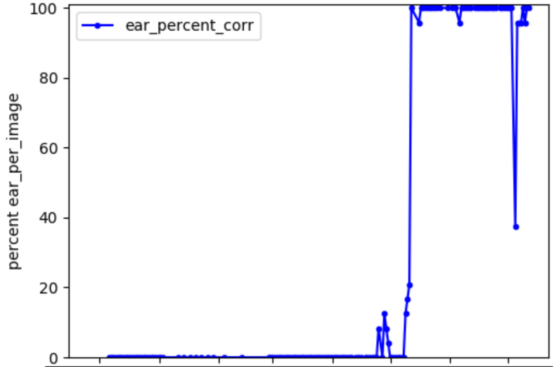
ResNet50 pretrained on ImageNet dataset was finetuned.

- **Data augmentation**: Rotation, flip and brightness range shifts
- **Training strategies:** Learning rate decay and early stopping based on validation AME were employed.

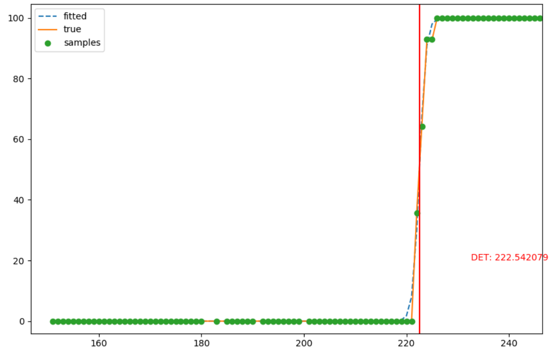
Identifying the Heading Date

Prediction using trained CNN





Calculate % of image-patches with ears

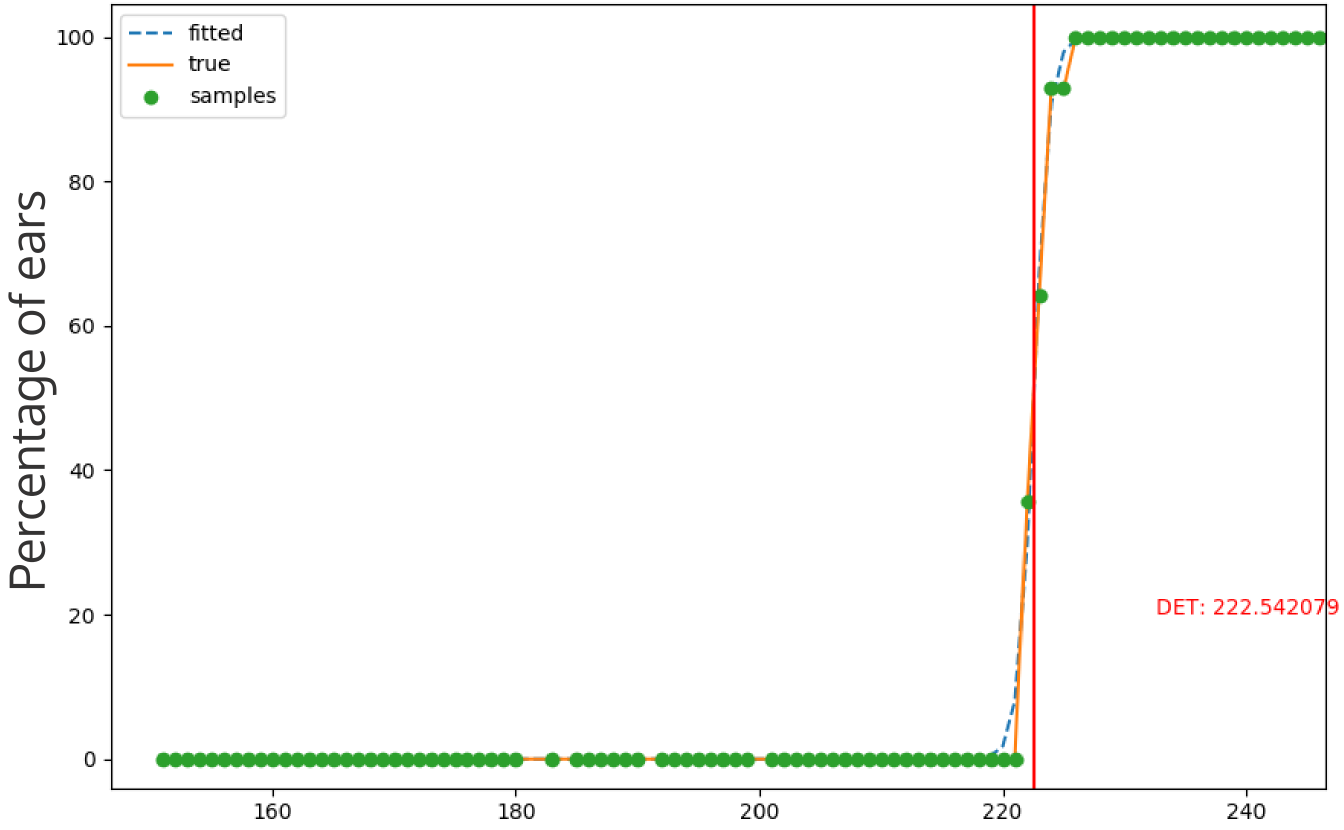


Identify the date at 50% (x°) – logistic curve fitting

Identifying the Heading Date by Logistic curve fitting

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

2 parameter logistic curve:
L = 100
X0 = initialized with x at max(y)
K = initialized at 0.1



Results

Training and testing strategy

Two different strategies (training and testing) are experimented

1

Regions	2017 Sites	2017 Cultivars	2018 Sites	2018 Cultivars
Gréoux	-	-	7	3
Boigneville	8	1	12	3
Chalons en Champagne	-	-	-	-
Saint_Hilaire en Woëvre	-	-	-	-

A total 27 Sites :

13 Sites for training

14 Sites for testing

2

Regions	2017 Sites	2017 Cultivars	2018 Sites	2018 Cultivars	2019 Sites	2019 Cultivars
Gréoux	-	-	7	3	2	2
Boigneville	8	1	12	3	12	3
Chalons en Champagne	-	-	-	-	3	1
Saint_Hilaire en Woëvre	-	-	-	-	3	1

2017 & 2018 for Training 2019 for Testing

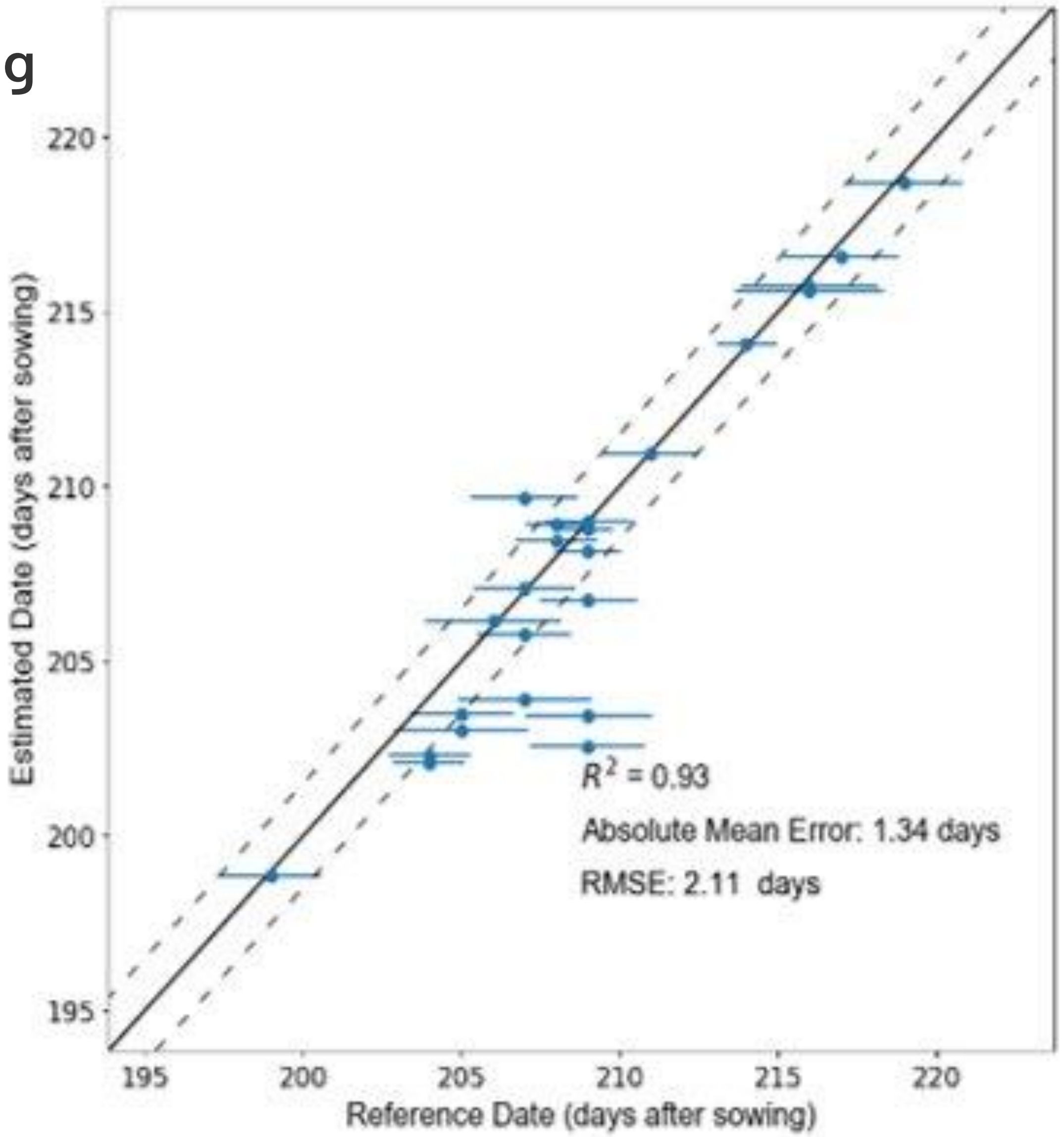
Accuracy of heading date estimations

Sites of 2017&2018 for Testing

- RMSE: 2.11 days

Comparative results between references and estimates dates

Some outliers are observed



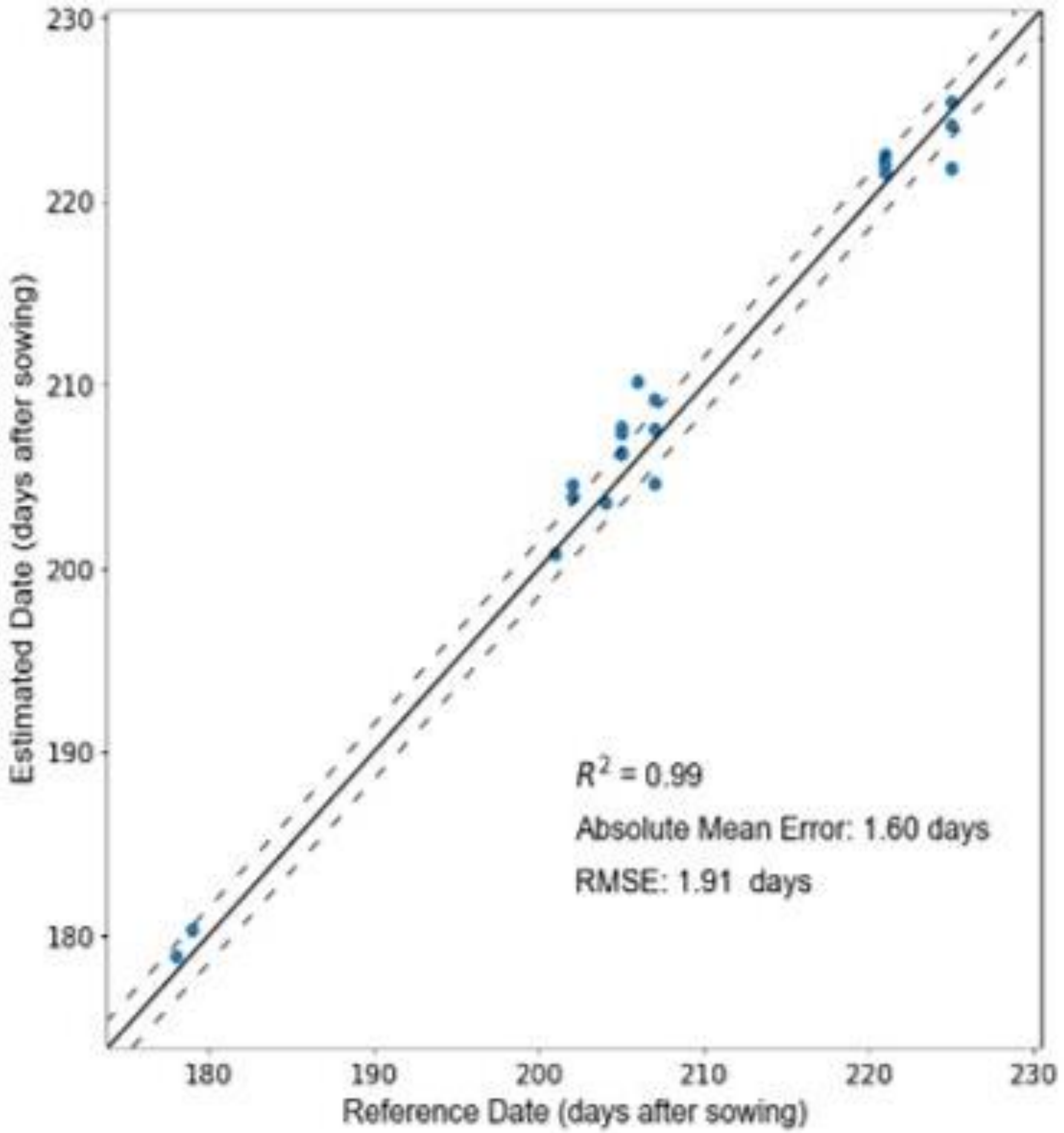
Accuracy of heading date estimations

2019 for Testing

- RMSE: 1.91 days

Training the models with more images (2017&2018) improves the accuracy

Consistent over cultivars not used in training.

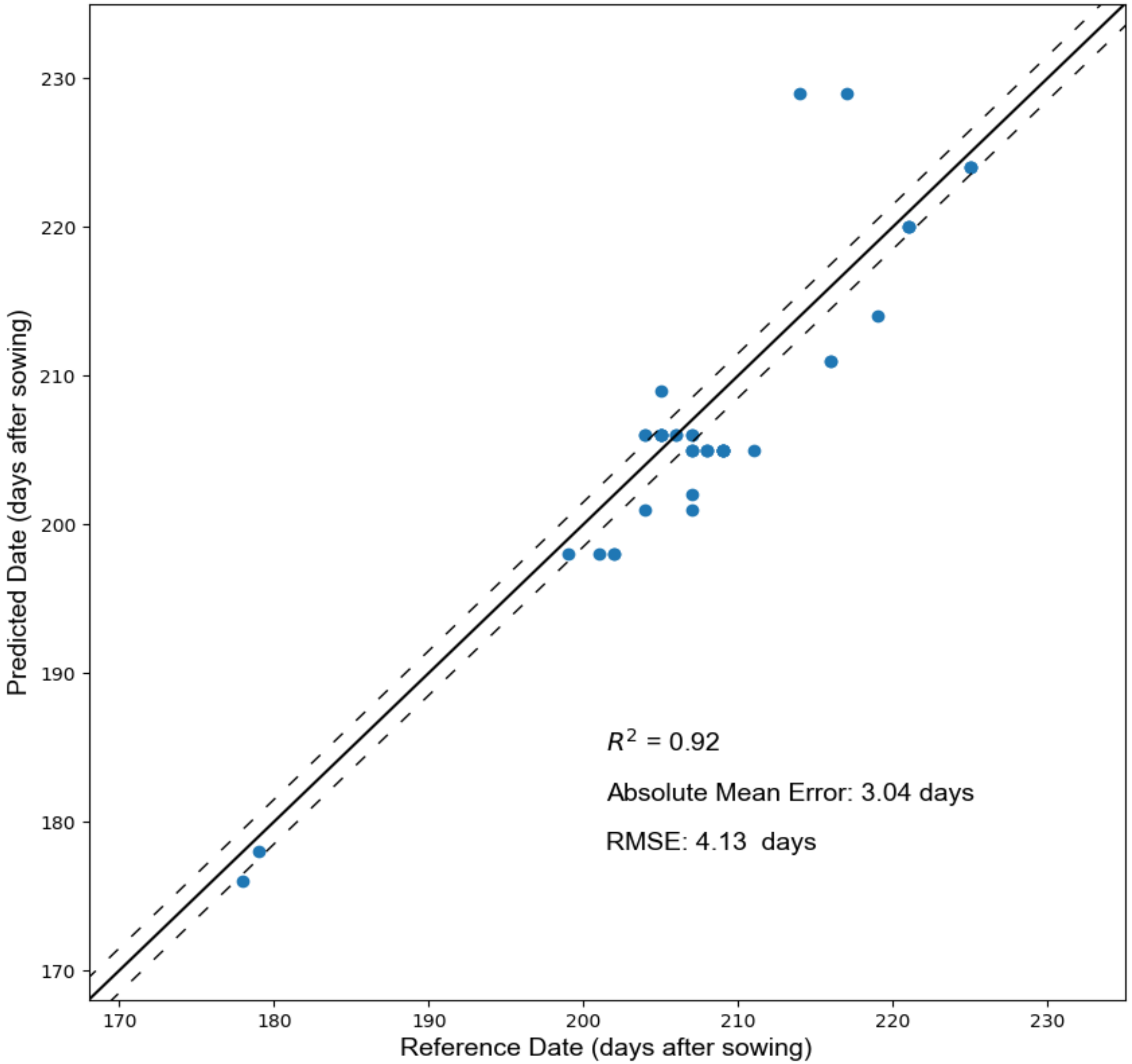


Comparison with phenological model

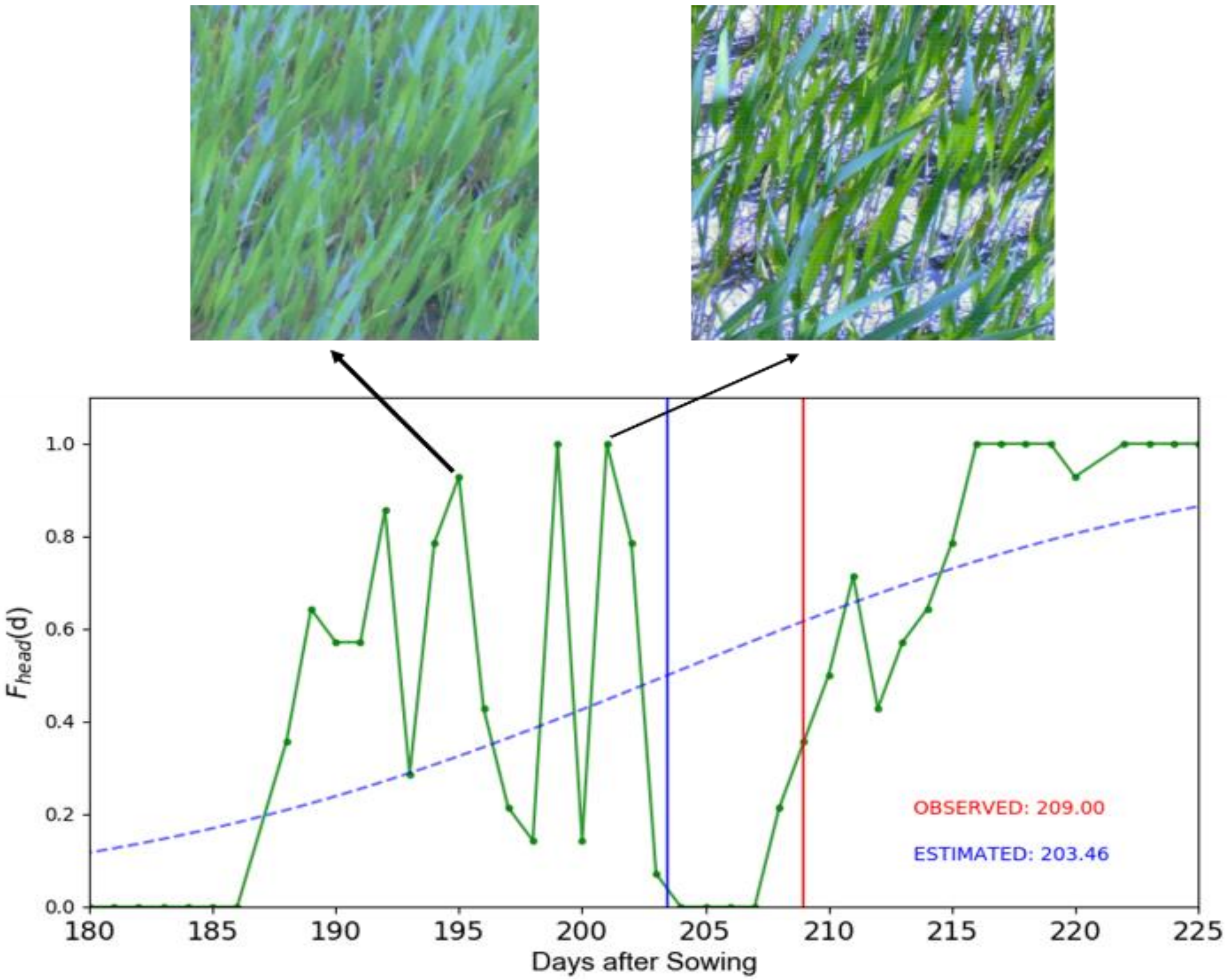
- **ARCWHEAT** modified to French climatic conditions and calibrated to the varieties sown in the sites

➡ RMSE from phenological model predictions was x2 more than the RMSE from the automatic method

IOT sensors and deep learning-based methodology are more accurate than crop model

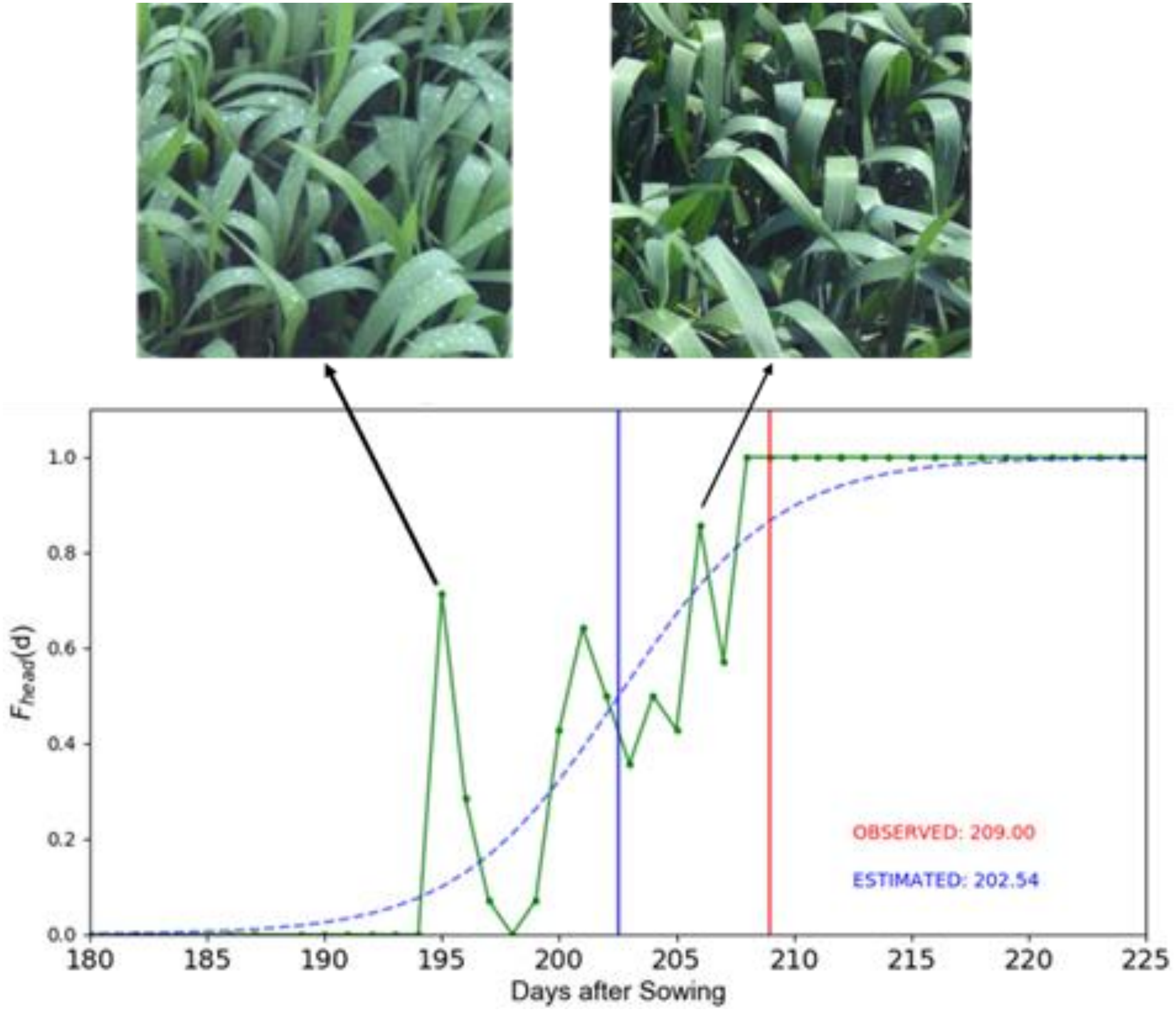


Example of failure



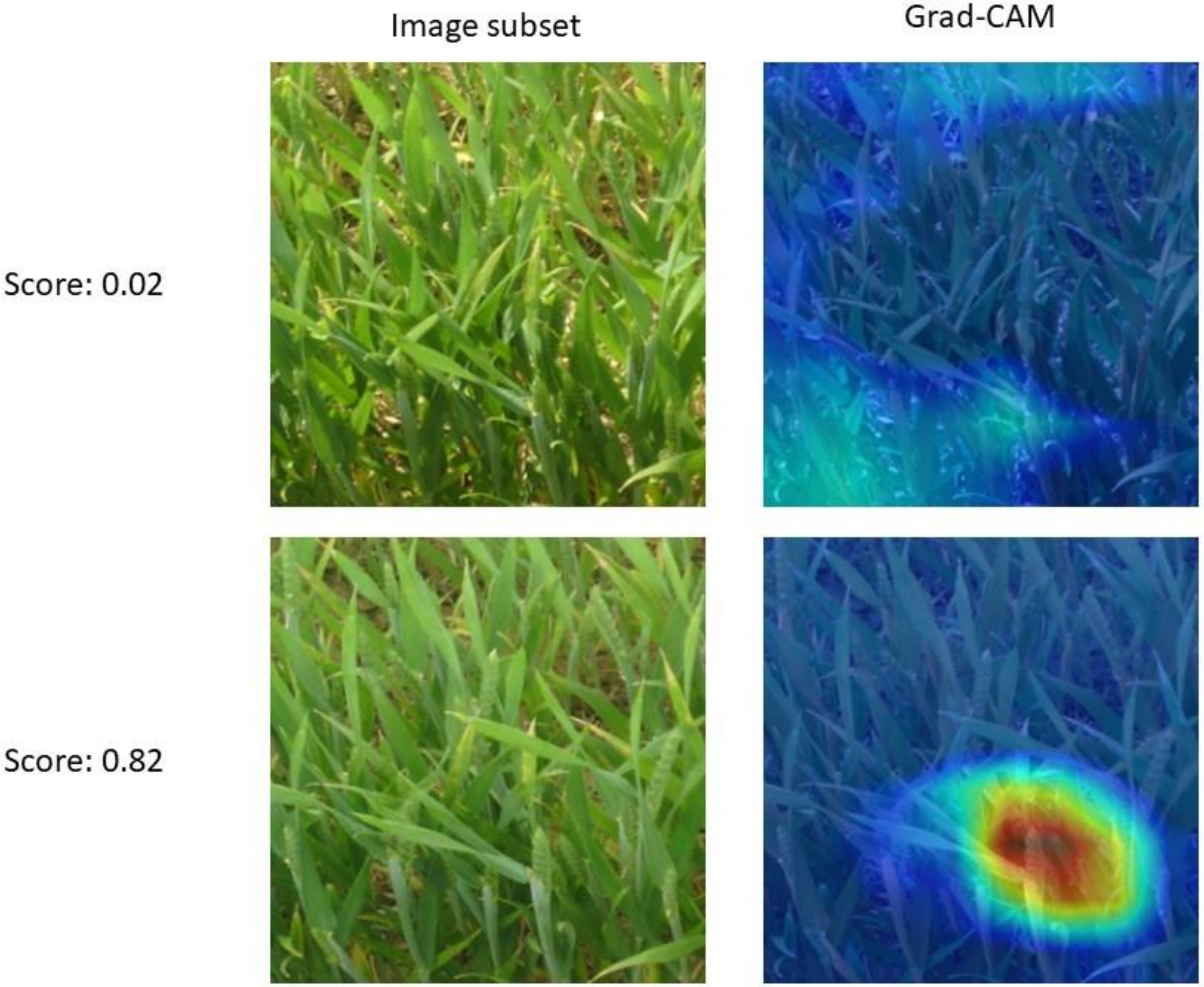
- Error: 5.6 days
- Patches without ears were misclassified as "Ears Present".
- Classification error could be related to image quality: poor white balance setup in camera was causing leaf blades to appear blue.
- Issue was fixed on day 203, but these quality issues introduced substantial noise in the time-series and impacted the logistic curve fit.

Example of failure



- Error: 5.5 days
- the texture of water droplets on leaves was wrongly identified by the CNN as ears in the days 195 and 196 after sowing.
- Although in that site the CNN would have anyhow underestimated the heading date –at the date determined by experts, the CNN already detected ears in 100% of the patches– the misclassification of images with water droplets multiplied those discrepancies.

Trying to understand the model..



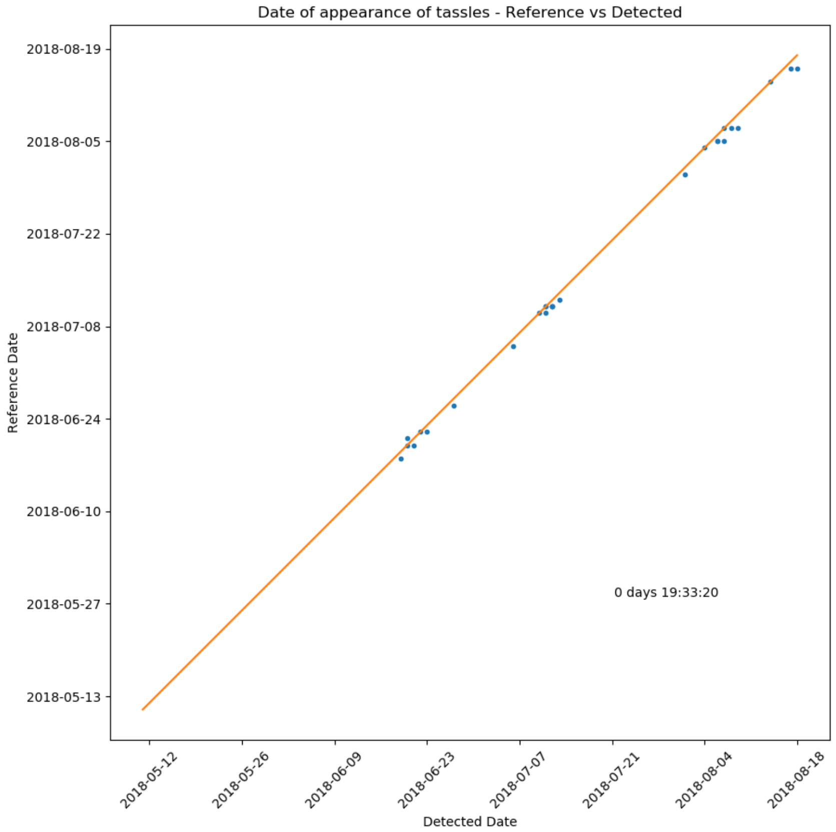
Conclusion

Conclusion

- easy to implement since the labelling of patches is not time-consuming as compared to individual object annotation required for other CNN models used for object identification or counting
- satisfactory performances with RMSE≈2.0 days, which is close to the uncertainties of expert annotations
- substantially better than phenological models specifically calibrated for the cultivars monitored.
- Could be made operational in phenotyping experiments, especially with new cultivars which lack model calibration

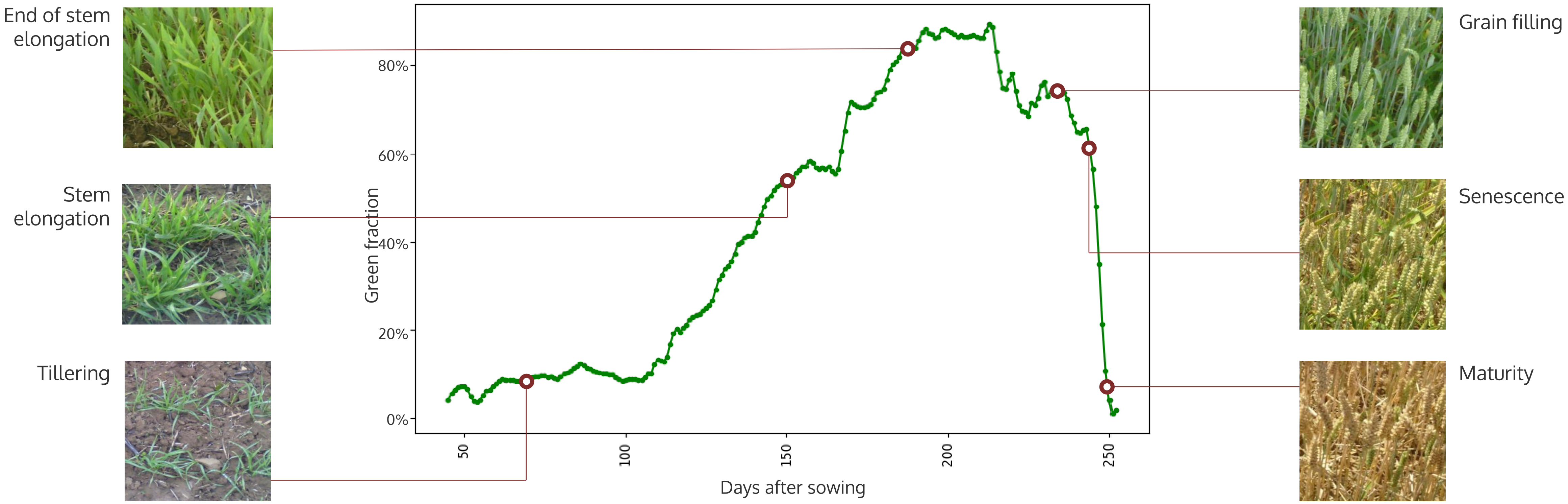
Perspective

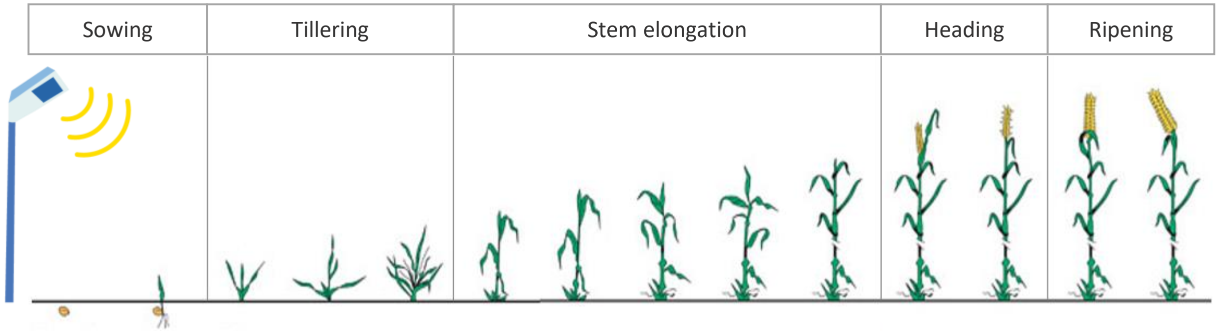
Application to maïze tasseling



- Same methodology applied for maize tasseling is more accurate
- From an image analysis point of view, wheat is a more challenging crop to monitor

Wheat phenological stages from Green Fraction





Perspective

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- The representativeness of such small footprint estimations to characterize phenology over large and heterogenous fields remains an open question for future works

- Similar approaches could be transposed to time series of images from other vectors used in phenotyping experiments, such as unmanned ground and aerial vehicles, providing that the revisit time and resolution are sufficient.

- The method could be adapted to identify other crop growth stages associated with the identification of certain organs, such as the appearance of anthers for wheat to date flowering, or the appearance of tassels for the male flowering in maize

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