



HAL
open science

An automatic method based on daily in situ images and deep learning to date wheat heading stage

Kaaviya Velumani, Simon Madec, Benoit de Solan, Raul Lopez-Lozano, Jocelyn Gillet, Jeremy Labrosse, Stephane Jezequel, Alexis Comar, Frédéric Baret

► To cite this version:

Kaaviya Velumani, Simon Madec, Benoit de Solan, Raul Lopez-Lozano, Jocelyn Gillet, et al.. An automatic method based on daily in situ images and deep learning to date wheat heading stage. *Field Crops Research*, 2020, 252, pp.107793. 10.1016/j.fcr.2020.107793 . hal-03162912

HAL Id: hal-03162912

<https://hal.inrae.fr/hal-03162912v1>

Submitted on 22 Aug 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

1 An automatic method based on daily *in situ* 2 images and deep learning to date wheat 3 heading stage

4

5 *Kaaviya Velumani^{1,2*}, Simon Madec², Benoit de Solan³, Raul Lopez-Lozano², Jocelyn Gillet¹, Jeremy*
6 *Labrosse¹, Stephane Jezequel³, Alexis Comar¹, Frédéric Baret²*

7 **Corresponding author: kvelumani@hiphen-plant.com; kaaviya.velumani@inra.fr*

8 ¹*Hiphen SAS, 228, route de l'aérodrome – CS 40509, 84914 Avignon Cedex 9 – France*

9 ²*INRAE, Avignon Université, UMR EMMAH, UMT CAPTE, 228, route de l'aérodrome – CS 40509, 84914*
10 *Avignon Cedex 9 – France*

11 ³*Arvalis, 228, route de l'aérodrome – CS 40509, 84914 Avignon Cedex 9 – France*

12 Abstract

13 Accurate and timely observations of wheat phenology and, particularly, of heading date are instrumental
14 for many scientific and technical domains such as wheat ecophysiology, crop breeding, crop
15 management or precision agriculture. Visual annotation of the heading date *in situ* is a labour-intensive
16 task that may become prohibitive in scientific and technical activities where high-throughput is needed.
17 This study presents an automatic method to estimate wheat heading date from a series of daily images
18 acquired by a fixed RGB camera in the field. A convolutional neural network (CNN) is trained to identify

19 the presence of spikes in small patches. The heading date is then estimated from the dynamics of the
20 spike presence in the patches over time. The method is applied and validated over a large set of 47
21 experimental sites located in different regions in France, covering three years with nine wheat cultivars.
22 Results show that our method provides good estimates of the heading dates with a root mean square
23 error close to 2 days when compared to the visual scoring from experts. It outperforms the predictions
24 of a phenological model based on the ARCWHEAT crop model calibrated for our local conditions. The
25 potentials and limits of the proposed methodology towards a possible operational implementation in
26 agronomic applications and decision support systems are finally further discussed.

27 Keywords

28 Phenology, Internet of things for Agriculture, Convolutional Neural Networks, field sensors, phenology
29 modelling

30 1 Introduction

31 Phenological observations are essential in agronomy, as crop management strategies (irrigation,
32 fertilizing or crop protection) are planned considering plant development (Brown et al., 2005;
33 Chmielewski, 2013). In wheat, the heading stage is one of the critical developmental phases as the plant
34 becomes highly sensitive to abiotic stress – heat stress, frost, water constraints – with a strong impact on
35 yield components (Slafer and Rawson, 1994). Several studies have quantified the effect of post-heading
36 abiotic stress on yield (Ferris et al., 1998; Gooding et al., 2003; Wheeler et al., 1996) due to a significant
37 decrease in the grain weight,, along with a fall in the number of grains per plant. More recently, Balla et
38 al., (2019) analysed the possible impact of temperature on yield components at different development
39 stages over a large wheat genotype panel, highlighting the high sensitivity of grain number to heat stress
40 episodes around heading. Also, García et al., (2015) and Lobell and Ortiz-Monasterio, (2007) have shown

41 that the increase in minimum temperature during nights owing to changing climatic conditions
42 accelerates the rate of crop development and reduces yield.

43 The timing and duration of stress through wheat developmental phases are thus essential to understand
44 the impact of environmental factors on yield (Sadras and Slafer, 2012). Wheat phenology is driven by
45 several eco-physiological mechanisms involving the response to temperature, photoperiod and
46 vernalization (Gate, 1995) that are regulated by complex genetic pathways (Guedira et al., 2016; Whittal
47 et al., 2018). Phenology has been traditionally one of the most important traits used to genetically
48 improve wheat adaptation, matching crop development – particularly reproductive and grain-filling
49 phases – to the optimal growing conditions of a target environment (Foulkes et al., 2011; Slafer, 2012).
50 Indeed, phenology constitutes, in wheat breeding programs, one of the main levers enabling to optimize
51 assimilates partitioning while reducing the impact of adverse weather events such as heat stress and
52 frost during the grain-filling stage (Camargo et al., 2016; Chapman et al., 2012; Reynolds et al., 2009).

53 Accurate and timely observations of wheat phenology and, particularly, of heading date are, therefore,
54 instrumental for many scientific and technical domains such as wheat ecophysiology, crop breeding, crop
55 management or precision agriculture. Heading date is commonly scored visually *in situ* by operators that
56 are frequently surveying the crops. It constitutes a labour-intensive task that requires skilled experts. For
57 certain applications like high-throughput phenotyping in crop breeding programs on large genotype
58 panels (Araus and Cairns, 2014; Cabrera-Bosquet et al., 2012) an accurate visual annotation of the
59 heading date –with experts frequently visiting the field– can be difficult to achieve as the number of
60 microplots increase geometrically. In other applications oriented towards crop management,
61 phenological models may represent a valid alternative to *in situ* phenology observations (Bogard et al.,
62 2014; White et al., 2008; Zheng et al., 2012), provided that those models are calibrated for each specific
63 genotypes. However, such genotype-specific calibration necessitates extensive phenology observations
64 from field experiments (Wallach et al., 2019).

65 The recent development of field sensors and unmanned platforms with imaging capabilities –including
66 aerial (UAVs) and ground vehicles (UGVs)– have opened new avenues to monitor automatically crops in
67 near-real time (Baret et al., 2018; Comar et al., 2012; Jay et al., 2017; Madec et al., 2017; White and
68 Conley, 2013; Yang et al., 2017). In parallel, the advances in computational resources and data science
69 achieved in the last years have fostered a significant breakthrough in computer vision and has paved the
70 way to implement advanced algorithms to extract relevant information from high spatial resolution
71 imagery. Deep learning algorithms including convolutional neural network (CNN), have shown excellent
72 performances for object recognition (LeCun et al., 2015). These capabilities have favoured their
73 progressive adoption in the fields of agronomy and phenomics (Kamilaris and Prenafeta-Boldú, 2018;
74 Singh et al., 2018). For instance, they have been successfully used to detect and count individual cereal
75 heads from RGB images (Hasan et al., 2018; Lu et al., 2017; Madec et al., 2019) and LiDAR data
76 (Malambo et al., 2019). Nevertheless, the potential of such algorithms to provide accurate, automatic *in*
77 *situ* estimations of crop phenology remains, up to now, underexploited. The use of well-known
78 capabilities of CNNs to detect plant organs on individual images to derive crop phenology from image
79 series needs to be further explored. At the time of writing this article, only very few studies have
80 attempted to do that. The work of Yalcin (2018) proposing a CNN-based method for the discrimination of
81 phenological stages for several crops, including wheat, seems promising, but no results on the absolute
82 accuracy of the method have been provided. More recently Desai et al., (2019) have developed a deep
83 learning approach to estimate the heading date on rice, but it was only tested over a small number of
84 situations, preventing from drawing general conclusions about its performance under operational
85 conditions.

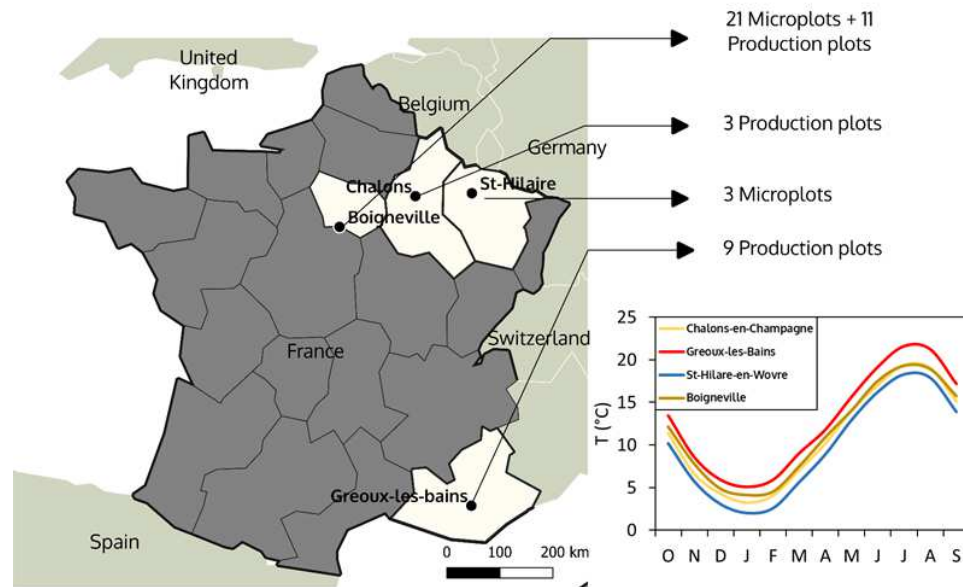
86 The development of operational methods for automatic heading date detection using *in situ* images
87 would enable to increase enormously the acquisition throughput at a reasonable cost. This would

88 represent an important contribution to the afore-mentioned scientific and technical domains, where
89 frequent phenology observations are critical.

90 In that context, the objective of this study is to present an automatic method to estimate wheat heading
91 date from daily high-resolution images taken in the field from fixed cameras. The method developed rely
92 on deep learning techniques: daily images are interpreted using a CNN classifier that detects the
93 presence of wheat spikes in the image, and the dynamics of the presence of spikes along the season
94 permits to determine the heading date. A major aspect that differentiates this study against the existing
95 works on this subject is the use of an extensive dataset of observations used to validate the method
96 proposed, which enables to discuss its possible implementation under operational conditions. The
97 dataset comprises 47 field plots sown with several soft and durum wheat cultivars in different regions of
98 France, where fixed cameras were installed, and actual heading dates were annotated by experts. The
99 performance of our CNN-based method to estimate the actual heading date are also concurrently
100 compared with those of a phenology model based on ARCWHEAT (Weir et al., 1984) and calibrated for
101 local conditions. The robustness of our method and its potential operational implementation are
102 discussed with emphasis on possible limitations—e.g. image quality issues, environmental conditions
103 during image acquisition— that may impact the performances.

104 2 Materials and Methods

105 2.1 Study sites



106
 107 *Figure 1. Location of the 4 regions where field sensors installed during the 2017, 2018 and 2019 growing seasons. The graph*
 108 *indicates the average monthly temperatures in the period 1986-2018 observed in 4 near weather stations from INRA and Meteo*
 109 *france: St. Gilles (Gréoux-les-Bains), Gif-sur-Yvette (Boigneville, only since 1999), Erneville (St-Hilare-en-Wovre), and Fagnieres*
 110 *(Chalons-en-Champagne).*

111 This study was conducted during the years 2017, 2018 and 2019 in different commercial and
 112 experimental fields belonging to four contrasted agro-climatic regions around the following cities:
 113 Gréoux-les-Bains (43.8° N, 5.9° E) in the south-east of France, Boigneville (48.3° N 2.4° E) in the center of
 114 France; Chalons-en-Champagne (49.0° N, 4.4° E) and Saint-Hilaire-en-Woèvre (49.1° N, 5.7° E) in the
 115 north-east of France (Figure 1).

116 The climate in Gréoux-les-Bains is Mediterranean (Kottek et al., 2006), with a maximum average
 117 temperature of 20°C, 690 mm of rainfall. In Boigneville, the climate is temperate and humid, with a
 118 maximum average temperature of 15.3°C over the year and rainfall of 677 mm (Meteo France). The

119 climate in Chalons-en-Champagne is similar to that of Boigneville, whereas in Saint Hilaire-en-Wovre
 120 conditions are slightly colder, especially during winter (Figure 1), and more humid (average precipitation
 121 close to 1000 mm/year).

122 Among these four sites, 24 field sensors equipped with RGB cameras (see 2.2) were installed in
 123 microplots with a size of 10 x 2 meters belonging to larger experimental fields. The remaining 23 sensors
 124 were installed in production plots, with a size similar to a commercial field (around 800 x 200 meters).
 125 Often, the production plots are subdivided in homogeneous units with different cultivars or agro
 126 management. In the sites at the north of France, production plots and microplots are sown with winter
 127 soft wheat (*Triticum aestivum*) cultivars Descartes, Oregrain, Fructidor, RGT Sacramento, Matheo and
 128 Rebelde. In *Gréoux-les-Bains*, the winter durum wheat (*Triticum durum*) cultivars RGT Voilur, Anvergur
 129 and Toscadou were grown. A summary of the 47 sites considered is given in Table 1. Please refer to Table
 130 A in Appendix for a detailed description of the sites, their location and average temperature over the
 131 growing season. The field sensors were installed in relatively homogenous areas of the fields which
 132 provided daily information over a footprint of about 10m² (see 2.2). During the installation, special
 133 attention was paid to orientate the camera field-of-view towards the centre of the microplot to prevent
 134 possible border effects.

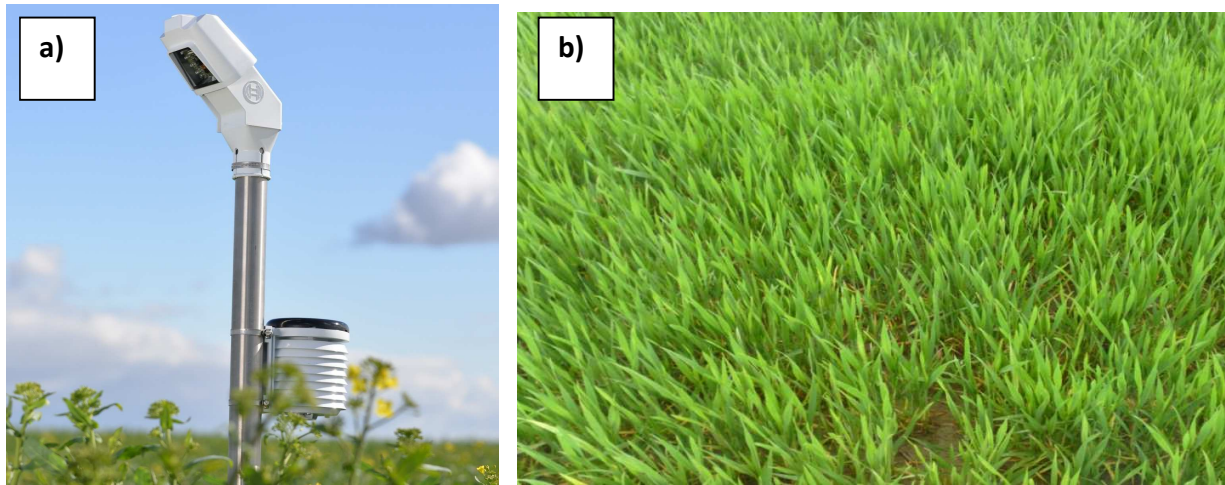
135 *Table 1 Description of the distribution of the 47 sites across years and regions. The number of sites available each year per region*
 136 *and year is indicated along with the corresponding number of cultivars.*

Locations	2017		2018		2019	
	Sites	Cultivars	Sites	Cultivars	Sites	Cultivars
Gréoux-les-Bains	-	-	7	3	2	2
Boigneville	8	1	12	3	12	3
Chalons en Champagne	-	-	-	-	3	1

Saint_Hilaire en Woëvre	-	-	-	-	3	1
-------------------------	---	---	---	---	---	---

137 2.2 Acquisition of daily images of the canopy with IoT systems

138 The field observation systems installed in the 47 sites were developed by Bosch and Hiphen
139 (www.hiphen-plant.com/our-solutions/iot-field-sensor) and are named IoT (Internet of Things for
140 Agriculture). They consist of a telescopic pole placed vertically and equipped with an RGB camera as well
141 as meteorological sensors (Figure 2a). The RGB camera takes one image (Figure 2b) each day at solar
142 noon, and automatically uploads it to a cloud storage system through a GSM network. The image
143 dimensions are 1024 x 768 pixels and is recorded in PNG format. The camera was set up at a height of
144 approximately 1m above the top of the crop (installed after emergence), with a 45° inclination angle
145 oriented in a compass direction perpendicular to the row. In some of the fields of 2017 and 2018, the
146 length of the pole was adjusted mid-growing campaign to ensure that the camera was always well above
147 the plant canopy. In the 2019 campaign, the height of the pole was fixed at 1.5 m to avoid this mid-
148 campaign intervention. It has a field of view (FOV) of 55° x 41° providing a footprint of 10.8 m². Because
149 of the relatively large FOV, the ground resolution is non-uniform throughout the image, particularly in
150 the vertical direction (Figure 2b).



151

152 *Figure 2 a) The IoT systems installed in a field. The top part inclined at 45° hosts the RGB camera. The cylinder attached to the*
 153 *vertical pole includes sensors to monitor the local air temperature and moisture. b) An example of a raw image.*

154 2.3 Heading date determined by experts

155 The heading stage corresponds to the emergence of the developing spike from the flag leaf sheath.
 156 (Bonnett, 1936; Zadoks et al., 1974). In the field, the heading stage is identified according to the
 157 definition given by Zadoks et al., (1974): 50% stems with spikes, at least, half-emerged, corresponding to
 158 the phase code 54 of the Zadoks scale. For the 27 sites monitored in 2017 and 2018 (Table 1), an online
 159 questionnaire was prepared with IoT images covering a 9 to 13 consecutive days period approximately
 160 centered on the heading date. A panel of 14 experts was asked to identify the reference heading date for
 161 all the sites by applying the definition of Zadoks *et al.*, (1974) for heading stage: 50% stems with spikes at
 162 least half-emerged. The experts could view the images at their full resolution. Eight of the experts had
 163 more than 10 years of experience in working with wheat phenology and only four of them had less than
 164 two years of experience. The reference heading date for each of the 27 sites was considered as the
 165 average date of all the 14 experts. The standard deviation of the heading dates for each site was also
 166 calculated to quantify the variability of the expert replies.

167 In 2019, the actual heading dates were determined *in situ* by experts on all the 20 available sites (Table
168 1). They followed the definition by Zadoks *et al.* (1974) and visited the fields every two or three days.
169 Note that this reference heading date might be different from the one derived from the 2017-2018
170 questionnaire since experts were scoring the heading date from images, not from direct observation of
171 the crop in the field.

172 2.4 Heading date estimation from IoT images and CNN

173 2.4.1 Image preparation

174 To get a more uniform ground pixel size, each image was first cropped into 1024 x 384 pixels by
175 removing the top region of the image where the crop-sensor distance is too large, resulting in blurred
176 objects (Figure 2b). Then 14 overlapping patches of size 256 x 256 pixels were extracted from the
177 cropped image. The overlap between patches was 50% in either vertical or horizontal directions to
178 minimize possible border effects. Working with patches permits to benefit from the full resolution of the
179 IoT image while avoiding memory issues.

180 2.4.2 Spikes Labelling

181 The patches from the 27 sites observed during the 2017 and 2018 growing seasons were labelled into
182 two classes: “spikes present” or “spikes absent”. This represents a total of 40,500 patches out of which
183 17,000 were labelled as “spikes present” and 23,500 as “spikes absent”. All the patches belonging to
184 images acquired until five days before the actual heading date determined by experts were automatically
185 assigned to the “spikes absent” class. Similarly, the patches from the images acquired from five days
186 after the actual heading date onwards were assigned to the “spikes present” class. Therefore, only those
187 patches within a window of ± 5 days around the actual heading date were visually attributed to their
188 respective classes. Few patches with unclear assignation, such as emerging and sparse spikes were

189 excluded from the training dataset. A few examples belonging to the two classes can be found in Figure
 190 3.



191
 192 *Figure 3 Samples extracted from patches belonging to the 9 wheat varieties monitored in our study. The patches were classified*
 193 *as ‘spikes present’ (top row) and ‘spikes absent’ (bottom row).*

194 2.4.3 Identifying the presence of wheat spikes with the ResNet50

195 Wheat spikes were identified in the images using the ResNet50 (He et al., 2016), which obtained the best
 196 results in object detection at the ImageNet Large Scale Visual Recognition Challenge 2015 (Russakovsky
 197 et al., 2015). This network has a depth of 50 layers and uses residual blocks with identity mappings. The
 198 ResNet50 pre-trained on the ImageNet dataset which is available in the Keras Python deep learning
 199 library (Chollet, 2015) was used.

200 We replaced the original top layers of the pre-trained ResNet50 by two fully connected layers with
 201 dimensions, respectively of 512 and 1 to build a binary classifier (spikes present/absent). The network
 202 was re-trained with the labelled image patches by fine-tuning the weights of the entire network with a
 203 low learning rate to identify only the high-level features which were relevant to detect spikes and classify
 204 the patches as “spikes present” or “spikes absent”. This strategy, called transfer learning, performs
 205 generally better than training the full network from scratch (Lee et al., 2015; Tajbakhsh et al., 2016). The

206 training dataset comprises the 27 sites available in 2017 and 2018. First-order data augmentation was
207 applied to the patches: translation, rotation, zoom, flip and changes in brightness levels. This improves
208 the generalization capacity of the neural network and increases the size of the training set at marginal
209 cost. Two different training and validation schemes were followed:

- 210 • **Twofold-cross validation on 2017 and 2018 sites:** the 27 sites available in 2017 and 2018 were
211 divided randomly into folds of 13 and 14 sites with approximately 19500 and 21000 labelled
212 patches in each fold. ResNet50 was re-trained on each of the two folds independently and
213 validated with the other one.
- 214 • **Independent validation on 2019 sites:** In this second scheme, a unique set of the 27 sites
215 corresponding to 40500 patches from the 2017 and 2018 sites is used for fine-tuning ResNet50.
216 The purpose of this scheme is to mimic the operational conditions when CNNs are trained with
217 data from the previous years: the CNN is trained on data acquired in years different from those
218 used for the validation.

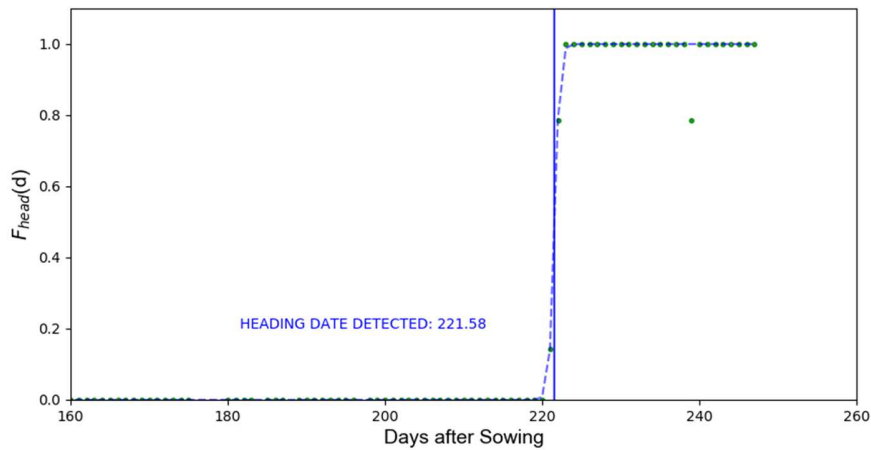
219 In both schemes, 20% of the data were held back for performance testing at the end of each epoch of
220 the ResNet50 re-training. The “binary cross entropy loss” available in the Keras library was used as the
221 loss function. To avoid over-fitting, we reduced the learning rate by a factor of 0.5 when the validation
222 mean absolute error did not improve after three consecutive epochs and stopped the training when the
223 validation mean absolute error did not improve after five consecutive epochs. The pertinence of the
224 ResNet50 network was further evaluated using Gradient-weighted Class Activation Maps (Grad-CAM,
225 developed by Selvaraju *et al.* , 2016). These maps highlight the regions that contribute to the output
226 score using the gradient values input to the final convolutional layer (shown in Figure 6 and Figure 8).

227 2.4.4 Heading date estimation

228 The heading date is determined from the dynamics of the presence of spikes in the images. For each day,
 229 d , the fraction of patches per image classified by the CNN as ‘spikes present’, $f_{head}(d)$, is calculated
 230 along the growing season (Figure 4). It provides a fair approximation of the Zadoks definition followed by
 231 the experts: the proportion of patches with emerged spikes in an image is a reasonable proxy to the
 232 proportion of stems with spikes emerged in the image. Then, a three-parameter logistic function is fitted
 233 to the time-series of $f_{head}(d)$ for every site:

$$f_{head}(d) = \frac{L}{1+e^{-k(d-d_0)}} \quad \text{Eq. 1}$$

234 where L is the maximum value of $f_{head}(d)$, fixed by construction to $L = 1.0$ (Figure 4). The maximum
 235 growth rate, k , and d_0 are estimated using the Scipy Python package (Jones et al., 2001). Parameter d_0
 236 represents the date when 50% of the patches have spikes.



237
 238 *Figure 4 Typical dynamics of the fraction of patches with spikes (f_{head} shown as green dots). The logistic curve fitted to the*
 239 *dynamics of f_{head} is shown using dashed blue line. The heading date estimated from adjusted parameter d_0 is represented by*
 240 *the vertical blue line.*

241 2.5 Heading date from ARCWHEAT model

242 A version of the phenology module of ARCWHEAT (Weir et al., 1984) adapted to the French local
 243 conditions by Gate (1995) was used. It is based on cumulated temperature with the effects of
 244 vernalization and photoperiod (Gouache et al., 2012). The model was run with actual daily temperatures
 245 collected by the Meteo France weather stations that are the closest to the sites in the period 2016-2019.
 246 Cultivar-specific parameters for vernalization and photoperiod corresponding to the nine cultivars
 247 observed in this study were adjusted using optimization algorithms based on independent field
 248 experiments (Thépot, 2014).

249 2.6 Performance metrics

250 The accuracy of the CNN classification was evaluated based on the overall accuracy (OA):

$$251 \quad OA = \frac{T_p + T_n}{N} \quad \text{Eq. 2}$$

252 where T_p and T_n are, respectively, the number of patches correctly classified as “spikes present” (true
 253 positive) and “spikes absent” (true negative); and N is the total number of patches in the test dataset.

254 The root mean squared error (RMSE) was computed to quantify the errors between estimated and
 255 observed heading dates:

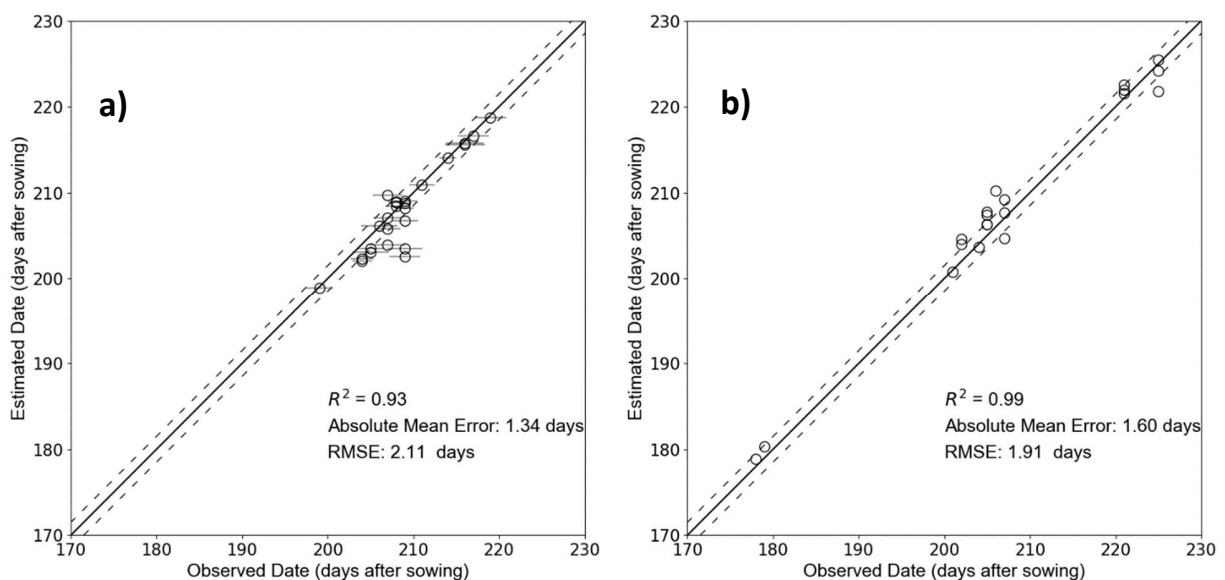
$$RMSE = \sqrt{\frac{\sum_{i=1}^N (HD_r - HD_e)^2}{N}} \quad \text{Eq. 3}$$

256 where HD_r is the reference heading date obtained from experts, HD_e is the heading date estimated by
 257 the indirect method (CNNs or phenology model) and N is the number of sites used.

258 3 Results

259 3.1 Accuracy of heading date estimates from the CNN model

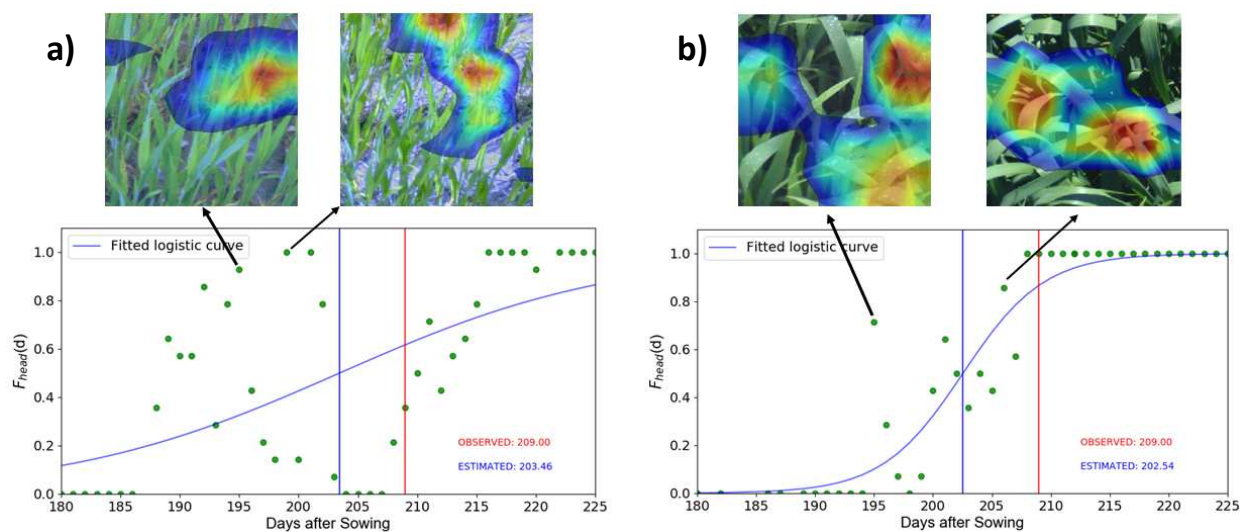
260 The automatic method proposed estimated the heading date with a RMSE close to 2.0 days (Figure 5), as
 261 compared to the reference dates given by the experts. Moreover, the errors when the CNN is trained
 262 and validated with images from years 2017 and 2018 using a twofold cross-validation (Figure 5a) are
 263 similar to those obtained when validating the method against a completely independent set of images
 264 from year 2019 (Figure 5b). Moreover, the coefficient of determination R^2 is very close to 1 especially in
 265 2019, where the variability in the time to heading among the plots monitored is large. In that year,
 266 heading was observed about 180 days after sowing for two durum wheat plots (varieties Anvergur and
 267 RGT Voilur) at Greoux-les-Bains, more than 20 days earlier than both varieties in 2018. This is explained
 268 by higher seasonal temperatures in the 2019 season compared to the 2018 season (seasonal average of
 269 13.3 °C in 2019, against 10.1°C in 2018, see details in the Appendix Table A).



270
 271 *Figure 5 Comparison of reference heading dates and those estimated by our CNN-based method. a) 2017 and 2018, using a*
 272 *twofold cross-validation for years 2017 and 2018; b) independent validation over year 2019. Horizontal error bars represent the*

273 *standard deviation of the expert annotations for each site in 2017 and 2018. The dotted black lines represent the standard*
274 *deviation (1.5 days) between experts when identifying the heading dates from photographs.*

275 For two sites at Boigneville monitored in 2018 (Figure 5a), the CNN estimations show discrepancies
276 reaching up to 6 days with the reference dates from the experts. The dynamics of spike appearance for
277 these two sites are shown in Figure 6 along with the GradCAM (Gradient Class Activation Maps) which
278 highlights the regions that influence the CNN prediction. In one of the sites (Figure 6a) the
279 misclassification was due to the poor quality of the images: leaf blades appear bluish because of a poor
280 white balance camera setup that was fixed only after day 203 (Figure 6a). These quality issues introduced
281 substantial artifacts in the time-series that impacted the logistic curve fit. In the second site (Figure 6b),
282 the water droplets on leaves observed on days 195 and 196 after sowing were wrongly identified by the
283 CNN as spikes. Although the CNN seems to slightly over-detect the presence of spikes in this site (Figure
284 6b) even when no droplets were observed, the errors due to presence of droplets contributed to
285 increase substantially the discrepancies against observed dates. Besides these two specific cases, the
286 issues of CNN misclassification were marginal over the whole dataset. The cross-validation conducted
287 with images from 2017 and 2018 revealed an overall accuracy of 98.45% for classifying individual patches
288 as spikes present/absent. Moreover, the classification errors observed did not exhibit any systematic
289 bias.



290

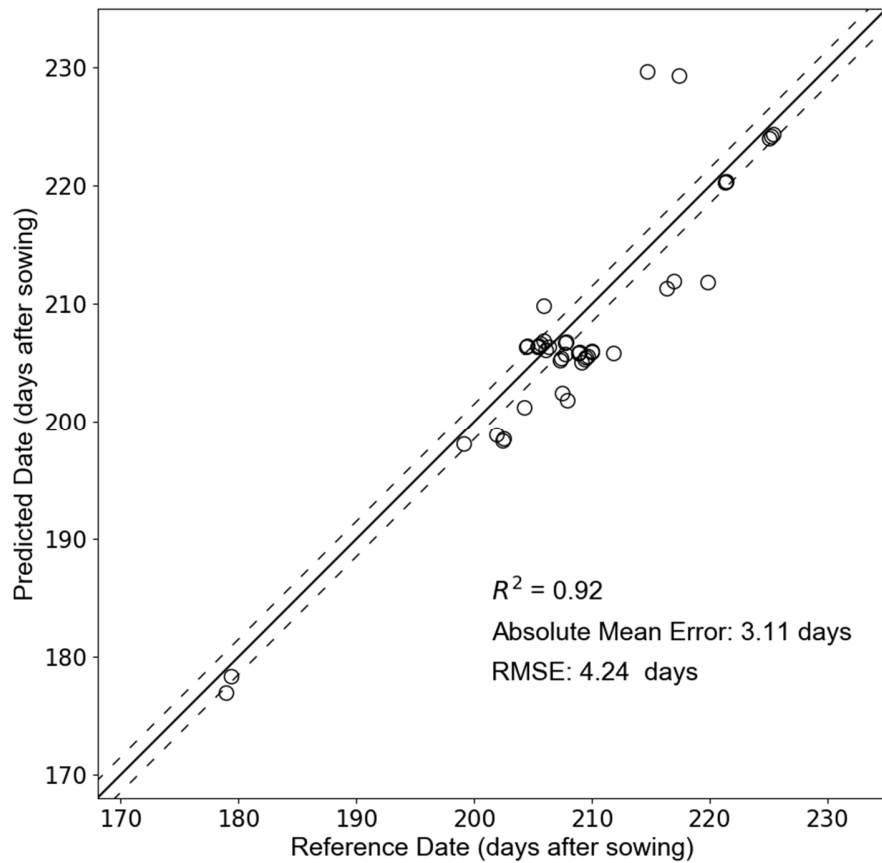
291 Figure 6 Dynamics of f_{head} for two sites in Boigneville in 2018 where large errors on heading date estimations by the CNN
 292 method were observed due to non-optimal image quality (a); image misclassification due to the presence of water droplets (b).

293 3.2 Accuracy of heading date prediction by the ARCWHEAT phenology model

294 The ARCWHEAT crop model, adapted to French conditions had an RMSE of 4.1 days to predict the
 295 heading date for the 47 sites monitored from 2017 to 2019 (Figure 7). This represents twice the error
 296 yielded by our CNN based method. A similar study conducted by Bogard *et al.* (2014), which evaluated
 297 the use of phenology models specifically calibrated for different cultivars to predict heading dates,
 298 reported errors comparable to those given by ARCWHEAT in this study. Other works where phenology
 299 models are applied at the regional or continental scale with no cultivar-specific calibration show even
 300 larger discrepancies reaching up to 20 days (McMaster and Smika, 1988; Ceglar *et al.*, 2019).

301 Although the ARCWHEAT model is capable to simulate the variability of the heading date among sites
 302 and years ($R^2=0.92$), it clearly underperformed when compared to the automatic method based on CNN.
 303 Only 37% of the sites were within the ± 1.5 days interval that represent the variability of the heading
 304 dates determined by the experts. Moreover the discrepancies between the model predictions and the

305 observed heading dates were above 10 days for two sites (Figure 7), which is not acceptable for precision
306 agriculture or phenotyping applications.



307
308 *Figure 7 A comparison between the heading date predictions from the crop phenology model with the reference heading date for*
309 *all the 47 sites in our study from the 3 growing seasons. The dashed lines around the 1:1 line corresponds to the 1.5 days interval.*
310 *To ensure that all the 47 points are visible on the graph despite the overlap, a negligible random noise was added while plotting*
311 *the points.*

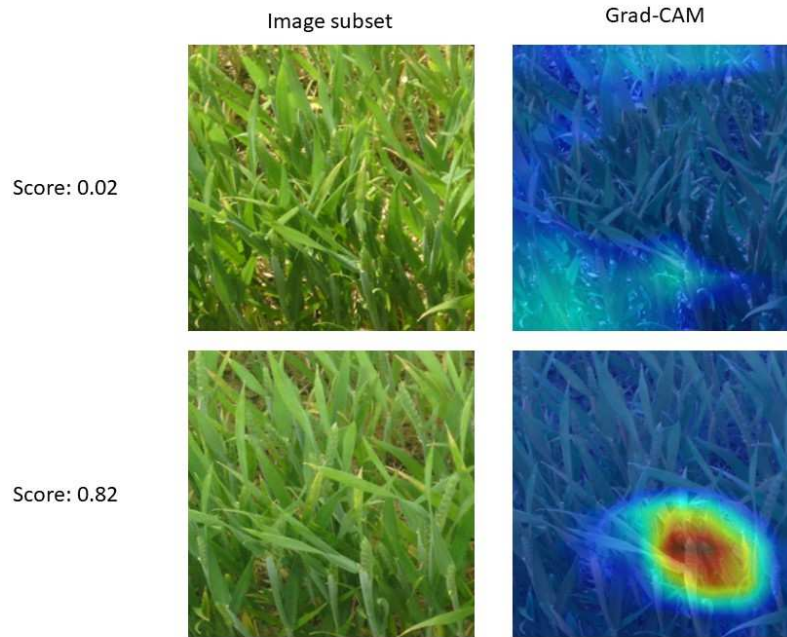
312 4 Discussion

313 4.1 Suitability of the automatic CNN-based methodology to estimate wheat heading 314 date in operational applications

315 Our proposed CNN based method estimated heading dates with about 2 days uncertainties as evaluated
316 over the 47 sites spanning across several regions, years and cultivars. The performances of the method
317 proposed are considered satisfactory since the errors are close to the standard deviation of the expert
318 panel replies provided for years 2017 and 2018. Moreover, this is close to the expected accuracy of an
319 expert visiting the fields every two or three days to annotate crop development stage. The recent study
320 of Desai et al., (2019) reported estimation errors between one and two days using also a CNN-based
321 approach for paddy rice heading date, but the number of observations and sites were substantially
322 smaller than in our study. Further, among the 20 sites monitored in the 2019 validation dataset, 6 of
323 them were sown with cultivars that were not included in the training set of the CNN, indicating that the
324 method is resistant to possible morphological differences among spikes between cultivars. The
325 robustness of our method is essentially due to three factors: the reliability of the ResNet50 CNN to
326 identify the presence of spikes in the patches; the statistics computed across patches within each image
327 that smooth out individual errors; and the use of a logistic fit to determine the heading date from the
328 daily statistics.

329 The ResNet50 CNN was used here to classify the patches with spikes. This approach was preferred to
330 directly identifying spikes in the image and counting them (Madec et al., 2019). Using CNN for image
331 classification increases the efficiency with which the training dataset is generated. Indeed, assigning
332 individual images to the spikes present/absent classes is relatively straightforward: it permitted to
333 generate a training dataset of more than 40,000 patches that contributed to improve the robustness of
334 ResNet50. By contrast, annotating images for spikes identification or spikes counting is time-consuming.

335 Although CNN-based classification provides much less information than object counting/detection
336 algorithms, the results indicate that this approach is sufficient for heading date estimation. In Figure 8,
337 the first image (top row) spikes are not yet emerged and the Grad-CAM heat map shows low confidence,
338 whereas in the second one (bottom row) the presence of emerged spikes is obvious, and the probability
339 increases up to 0.82. ResNet50 may only detect the presence of a proportion of the spikes present in the
340 patch, but this appears sufficient to correctly classify it. This makes the classification approach more
341 robust for phenology identification as compared to the approaches based on object detection or
342 counting by regression, where the variability of spike size and shape among cultivars or environmental
343 conditions during image acquisition may severely affect the performances (Park et al., 2010). The
344 presence of water droplets induced only a moderate bias in heading date estimation in two of the sites
345 (Figure 6b). Images with droplets represent less than 1% of the training dataset cases. That was probably
346 not sufficient to teach the CNN to distinguish between droplets and spikes. These issues can only be
347 solved by increasing the variability by including more images taken under diverse environmental
348 conditions.



349

350 *Figure 8 Patches extracted from two images of the same IoT system and acquired on the reference heading date (top) and one*
 351 *day after (bottom) with their corresponding class activation maps. The confidence score provided by the CNN towards the*
 352 *presence of spikes is shown along with the Grad-CAM heat map which shows the areas which influence the CNN output*

353 The logistic function smooths the daily values of $f_{head}(d)$, and reduces the influence of possible
 354 unsystematic classification errors on the heading date estimation. Furthermore, to minimize the possible
 355 impact of classification errors, in operational conditions it would be possible to prevent unrealistic
 356 estimations by imposing some constraints on the logistic model based on prior knowledge of the heading
 357 date:

$$\begin{aligned}
 f_{head}(d) &= 0.0 & \text{if } d < d_{prior} - \delta \\
 f_{head}(d) &= 1.0 & \text{if } d > d_{prior} + \delta
 \end{aligned}
 \tag{Eq. 4}$$

359 With d_{prior} being the prior value of the heading date derived from previous years observations or from
 360 phenological models, and δ being the associated maximum error. Anyhow, the use of a logistic function
 361 fit makes difficult to estimate the heading date in real time. The correct function fit is only possible *a*
 362 *posteriori*, i.e. when some images where $f_{head}(d) = 1.0$ have been already observed, which may only

363 happen 5 to 10 days after the actual heading date. This may limit the use of the method proposed on
364 operational applications of crop management requiring a rapid assessment of the heading date.

365 Compared to a phenological model calibrated under local conditions, our CNN-based method provides
366 better accuracy while not requiring ancillary information (e.g. sowing dates, variety-specific model
367 parameters) or daily weather data. This is an important advantage, since the accuracy achieved by
368 ARCWHEAT over the 47 sites monitored in this study (RMSE= 4 days) was mainly due to the cultivar-
369 specific calibration of model parameters. However, such a cultivar-specific calibration is time-consuming
370 and requires frequent observations throughout the crop cycle, repeated over several locations and years
371 (Cabelguenne et al., 1990; Jégo et al., 2010). Moreover, phenological models largely rely on the quality of
372 meteorological variables, which sometimes are interpolated from weather stations that are far from the
373 sites to be monitored without accounting for possible microclimatic effects (Joly et al., 2011; Monestiez
374 et al., 2001). In any case, mechanistic modelling of plant phenology remains always necessary on
375 prospective studies and to predict cultivar performance under a range of climatic scenarios. It also
376 constitutes an attractive alternative for heading date estimation for some applications where the
377 acquisition of high-throughput canopy images is not feasible. Phenological models can also largely
378 benefit from the method developed in this paper: the use of IoT field systems and deep learning
379 approaches would substantially reduce the cost of calibration experiments and would permit also to
380 increase the environmental variability of the field trials giving access to frequent observations from
381 remote locations.

382 Our CNN based method constitutes a robust and cost-efficient approach for heading date estimation for
383 operational applications when daily images of the canopy are available, as it is the case for some high-
384 throughput phenotyping platforms. In those platforms, vectors such as unmanned ground vehicles and
385 hand-pushed carts are often used to frequently monitor the plant development and characterize
386 biophysical traits of the different cultivars using optical images (Deery et al., 2014; Mueller-Sim et al.,

387 2017; White and Conley, 2013). In such applications, the proposed automatic method showcased in this
388 study could be directly integrated into other data processing pipelines at almost no cost to estimate
389 heading date from the existing RGB images.

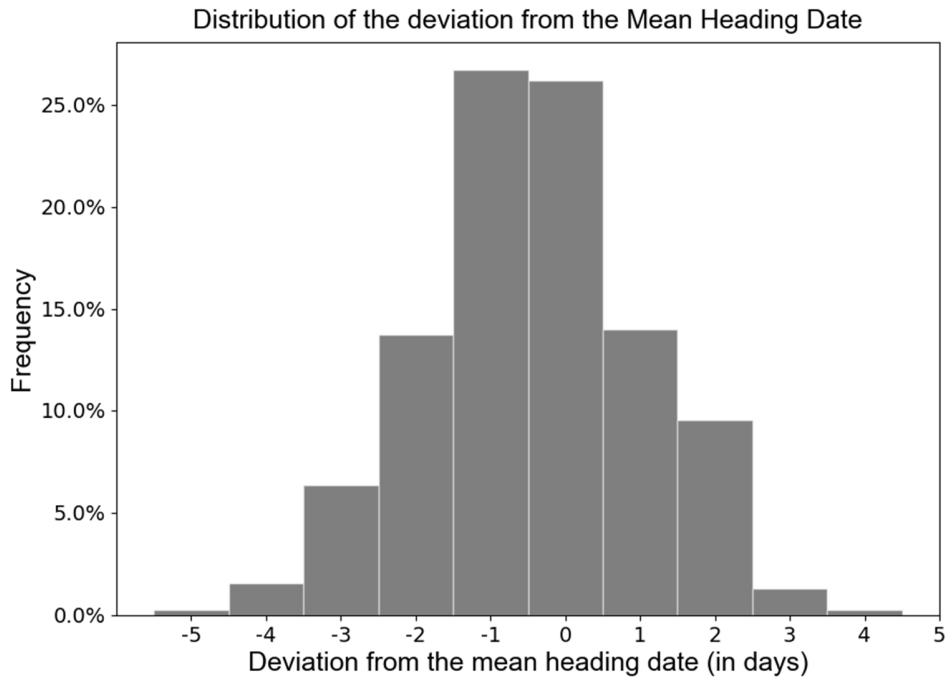
390 In agronomic or breeding applications where the phenology on distant fields need to be monitored –e.g.
391 regional or national networks of agricultural fields– the whole system presented, including the fixed
392 camera and the CNN-based method to estimate heading dates, may present important advantages in
393 terms of costs compared to in situ visual annotation. The initial investment in each camera (including the
394 pole, batteries and the hardware for data transmission) raises up to, approximately, 650 €; and the
395 yearly costs of system maintenance and real-time data transmission by GSM is about 150 € per camera.
396 The cost-efficiency –and the benefits in terms of environmental impact– of a system based on network
397 of cameras compared to expert visits has to be determined case by case, and will largely depend on the
398 distance between the fields to be monitored: the larger the network is, the more efficient remote
399 observations are compared to field visits.

400 4.2 Subjectivity of visual annotations of the heading date from experts using RGB 401 images

402 The visual determination of heading date is a task that includes some degree of subjectivity. For the 27
403 sites monitored in 2017 and 2018, the panel of 14 experts provided different estimates of the heading
404 dates after inspecting visually the IoT images. In most of the cases, the panel members selected 5 to 7
405 different dates per site out of those proposed in the questionnaire, although they were asked to follow
406 the same definition of the heading date (Zadoks *et al.* 1974). The distribution of the deviations between
407 individual replies and the average date for each site was roughly Gaussian with a standard deviation of
408 1.5 days (Figure 9), very close to the RMSE of our CNN based method proposed in this paper.

409 The subjectivity when determining visually heading date from images is obviously higher compared to *in*
410 *situ* scoring. Issues regarding the image quality exacerbated the discrepancies among experts. According
411 to the feedback provided by the panel, image saturation and blur due to a suboptimal camera setup
412 made difficult to see the emergence of spikes in some of the images. Further, spikes were harder to
413 identify in images taken under direct illumination conditions due to low image contrast, as well as for
414 cultivars with awns.

415 The variability of expert replies evaluated in the 27 sites constitutes a good benchmark for our CNN
416 based method, as image quality issues may also affect the identification of spikes by ResNet50 when
417 classifying patches. The similarity between the 2 days RMSE associated to our CNN based method with
418 the 1.5 days confidence interval of the expert date demonstrates that the performances of our CNN
419 based method can be considered comparable to the expert reply when observing the same images.



420
 421 *Figure 9 Distribution of the difference in days between the individual heading date identified by the experts and the mean*
 422 *heading date value.*

423 5 Conclusion

424 In this study, we propose a CNN based method to estimate the heading date from daily images acquired
 425 over wheat crops using an RGB camera fixed in the field. Images are processed per patch based on a
 426 binary CNN-classifier to construct the dynamics of spikes appearance. Our method is easy to implement
 427 since the labelling of patches is not time-consuming as compared to individual object annotation
 428 required for other CNN models used for object identification or counting. The reliability of the CNN-
 429 classifier to identify the presence of emerged spikes was marginally affected by the illumination
 430 conditions and cultivar diversity, since the training dataset included images acquired under diverse
 431 environmental conditions. Our method achieved satisfactory performances with $RMSE \approx 2.0$ days, which is
 432 close to the uncertainties of expert annotations, and substantially better than phenological models
 433 specifically calibrated for the cultivars monitored.

434 The proven robustness of the proposed method suggests a strong potential for cost-efficient operational
435 applications in the field of phenotyping and agronomic applications. However, our method is limited by
436 the image footprint close to 5 m² if only the bottom half of the image is used, as done in our study.
437 However, the good consistency with expert observations taken over a larger sampling area demonstrates
438 that our restricted sampling was sufficient. Nevertheless, the representativeness of such small footprint
439 estimations to characterize phenology over large and heterogenous fields remains an open question for
440 future works.

441 This method has been developed using a camera looking to the crop in a fixed position, but a similar
442 approach could be transposed to time series of images from other vectors used in phenotyping
443 experiments, such as unmanned ground and aerial vehicles, providing that the revisit time and resolution
444 are sufficient. Further, the method could be adapted to identify other crop development stages
445 associated with the identification of certain organs, such as the appearance of anthers for wheat to date
446 flowering, or the appearance of tassels for the male flowering in maize.

447 Acknowledgements

448 The authors would like to thank the Association Nationale de Recherche Technologique (ANRT) for their
449 grant CIFRE. The authors acknowledge Guy Deshayes (Arvalis) for his kind support with consolidating the
450 reference data from the experts in the field.

451 6 References

- 452 Araus, J.L., Cairns, J.E., 2014. Field high-throughput phenotyping: the new crop breeding frontier. *Trends*
453 *Plant Sci.* 19, 52–61. <https://doi.org/10.1016/j.tplants.2013.09.008>
- 454 Balla, K., Karsai, I., Bónis, P., Kiss, T., Berki, Z., Horváth, Á., Mayer, M., Bencze, S., Veisz, O., 2019. Heat
455 stress responses in a large set of winter wheat cultivars (*Triticum aestivum* L.) depend on the timing

- 456 and duration of stress. *PLoS One* 14, e0222639. <https://doi.org/10.1371/journal.pone.0222639>
- 457 Baret, F., Madec, S., Irfan, K., Lopez, J., Comar, A., Hemmerlé, M., Dutartre, D., Praud, S., Tixier, M.H.,
458 2018. Leaf-rolling in maize crops: from leaf scoring to canopy-level measurements for phenotyping.
459 *J. Exp. Bot.* 69, 2705–2716. <https://doi.org/10.1093/jxb/ery071>
- 460 Bogard, M., Ravel, C., Paux, E., Bordes, J., Balfourier, F., Chapman, S.C., Le Gouis, J., Allard, V., 2014.
461 Predictions of heading date in bread wheat (*Triticum aestivum* L.) using QTL-based parameters of
462 an ecophysiological model. *J. Exp. Bot.* 65, 5849–5865. <https://doi.org/10.1093/jxb/eru328>
- 463 Bonnett, O.T., 1936. The development of the wheat spike. *J. Agric. Res.* 53, 445–451.
- 464 Brown, B., Westcott, M., Christensen, N., Pan, B., Stark, J., 2005. Nitrogen management for hard wheat
465 protien enhancement. *Pacific Northwest Ext. Publ.* 578, 1–14.
- 466 Cabelguenne, M., Jones, C.A., Marty, J.R., Dyke, P.T., Williams, J.R., 1990. Calibration and validation of
467 EPIC for crop rotations in southern France. *Agric. Syst.* 33, 153–171. [https://doi.org/10.1016/0308-](https://doi.org/10.1016/0308-521X(90)90078-5)
468 [521X\(90\)90078-5](https://doi.org/10.1016/0308-521X(90)90078-5)
- 469 Cabrera-Bosquet, L., Crossa, J., von Zitzewitz, J., Serret, M.D., Luis Araus, J., 2012. High-throughput
470 Phenotyping and Genomic Selection: The Frontiers of Crop Breeding ConvergeF. *J. Integr. Plant Biol.*
471 54, 312–320. <https://doi.org/10.1111/j.1744-7909.2012.01116.x>
- 472 Camargo, A. V., Mott, R., Gardner, K.A., Mackay, I.J., Corke, F., Doonan, J.H., Kim, J.T., Bentley, A.R., 2016.
473 Determining Phenological Patterns Associated with the Onset of Senescence in a Wheat MAGIC
474 Mapping Population. *Front. Plant Sci.* 7, 1540. <https://doi.org/10.3389/fpls.2016.01540>
- 475 Ceglar, A., van der Wijngaart, R., de Wit, A., Lecerf, R., Boogaard, H., Seguini, L., van den Berg, M., Toreti,
476 A., Zampieri, M., Fumagalli, D., Baruth, B., 2019. Improving WOFOST model to simulate winter
477 wheat phenology in Europe: Evaluation and effects on yield. *Agric. Syst.* 168, 168–180.

478 <https://doi.org/10.1016/j.agsy.2018.05.002>

479 Chapman, S.C., Chakraborty, S., Dreccer, M.F., Howden, S.M., 2012. Plant adaptation to climate change—
480 opportunities and priorities in breeding. *Crop Pasture Sci.* 63, 251.
481 <https://doi.org/10.1071/CP11303>

482 Chmielewski, F.-M., 2013. Phenology in Agriculture and Horticulture, in: Schwartz, M.D. (Ed.), *Phenology:
483 An Integrative Environmental Science*. Springer Netherlands, Dordrecht, pp. 539–561.
484 https://doi.org/10.1007/978-94-007-6925-0_29

485 Chollet, F., 2015. Keras. <https://keras.io>.

486 Comar, A., Burger, P., de Solan, B., Baret, F., Daumard, F., Hanocq, J.-F., 2012. A semi-automatic system
487 for high throughput phenotyping wheat cultivars in-field conditions: description and first results.
488 *Funct. Plant Biol.* 39, 914. <https://doi.org/10.1071/FP12065>

489 Deery, D., Jimenez-Berni, J., Jones, H., Sirault, X., Furbank, R., 2014. Proximal Remote Sensing Buggies
490 and Potential Applications for Field-Based Phenotyping. *Agronomy* 4, 349–379.
491 <https://doi.org/10.3390/agronomy4030349>

492 Desai, S.V., Balasubramanian, V.N., Fukatsu, T., Ninomiya, S., Guo, W., 2019. Automatic estimation of
493 heading date of paddy rice using deep learning. *Plant Methods* 15, 76.
494 <https://doi.org/10.1186/s13007-019-0457-1>

495 Ferris, R., Ellis, R.H., Wheeler, T.R., Hadley, P., 1998. Effect of High Temperature Stress at Anthesis on
496 Grain Yield and Biomass of Field-grown Crops of Wheat. *Ann. Bot.* 82, 631–639.
497 <https://doi.org/10.1006/anbo.1998.0740>

498 Foulkes, M.J., Slafer, G.A., Davies, W.J., Berry, P.M., Sylvester-Bradley, R., Martre, P., Calderini, D.F.,
499 Griffiths, S., Reynolds, M.P., 2011. Raising yield potential of wheat. III. Optimizing partitioning to

- 500 grain while maintaining lodging resistance. *J. Exp. Bot.* 62, 469–486.
501 <https://doi.org/10.1093/jxb/erq300>
- 502 García, G.A., Dreccer, M.F., Miralles, D.J., Serrago, R.A., 2015. High night temperatures during grain
503 number determination reduce wheat and barley grain yield: a field study. *Glob. Chang. Biol.* 21,
504 4153–4164. <https://doi.org/10.1111/gcb.13009>
- 505 Gate, P., 1995. *Ecophysiologie du blé*. Tec & Doc-Lavoisier, France.
- 506 Gooding, M.J., Ellis, R.H., Shewry, P.R., Schofield, J.D., 2003. Effects of Restricted Water Availability and
507 Increased Temperature on the Grain Filling, Drying and Quality of Winter Wheat. *J. Cereal Sci.* 37,
508 295–309. <https://doi.org/10.1006/jcrs.2002.0501>
- 509 Gouache, D., Le Bris, X., Bogard, M., Deudon, O., Pagé, C., Gate, P., 2012. Evaluating agronomic
510 adaptation options to increasing heat stress under climate change during wheat grain filling in
511 France. *Eur. J. Agron.* 39, 62–70. <https://doi.org/10.1016/j.eja.2012.01.009>
- 512 Guedira, M., Xiong, M., Hao, Y.F., Johnson, J., Harrison, S., Marshall, D., Brown-Guedira, G., 2016.
513 Heading Date QTL in Winter Wheat (*Triticum aestivum* L.) Coincide with Major Developmental
514 Genes *VERNALIZATION1* and *PHOTOPERIOD1*. *PLoS One* 11, e0154242.
515 <https://doi.org/10.1371/journal.pone.0154242>
- 516 Hasan, M.M., Chopin, J.P., Laga, H., Miklavcic, S.J., 2018. Detection and analysis of wheat spikes using
517 Convolutional Neural Networks. *Plant Methods* 14, 100. [https://doi.org/10.1186/s13007-018-0366-](https://doi.org/10.1186/s13007-018-0366-8)
518 8
- 519 He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep Residual Learning for Image Recognition, in: *Proceedings of*
520 *the IEEE Conference on Computer Vision and Pattern Recognition*. pp. 770–778.
- 521 Jay, S., Maupas, F., Bendoula, R., Gorretta, N., 2017. Retrieving LAI, chlorophyll and nitrogen contents in

- 522 sugar beet crops from multi-angular optical remote sensing: Comparison of vegetation indices and
523 PROSAIL inversion for field phenotyping. *F. Crop. Res.* 210, 33–46.
524 <https://doi.org/10.1016/j.fcr.2017.05.005>
- 525 Jégo, G., Pattey, E., Bourgeois, G., Morrison, M.J., Drury, C.F., Tremblay, N., Tremblay, G., 2010.
526 Calibration and performance evaluation of soybean and spring wheat cultivars using the STICS crop
527 model in Eastern Canada. *F. Crop. Res.* 117, 183–196. <https://doi.org/10.1016/j.fcr.2010.03.008>
- 528 Joly, D., Brossard, T., Cardot, H., Cavailhes, J., Hilal, M., Wavresky, P., 2011. Temperature interpolation
529 based on local information: the example of France. *Int. J. Climatol.* 31, 2141–2153.
530 <https://doi.org/10.1002/joc.2220>
- 531 Jones, E., Oliphant, T., Peterson, P., others, 2001. SciPy: Open source scientific tools for Python.
532 <https://www.scipy.org>.
- 533 Kamilaris, A., Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: A survey. *Comput. Electron. Agric.*
534 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- 535 Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World Map of the Köppen-Geiger climate
536 classification updated. *Meteorol. Zeitschrift* 15, 259–263. [https://doi.org/10.1127/0941-](https://doi.org/10.1127/0941-2948/2006/0130)
537 [2948/2006/0130](https://doi.org/10.1127/0941-2948/2006/0130)
- 538 LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. *Nature* 521, 436–444.
539 <https://doi.org/10.1038/nature14539>
- 540 Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P., 2015. Deep-plant: Plant identification with convolutional
541 neural networks, in: 2015 IEEE International Conference on Image Processing (ICIP). IEEE, pp. 452–
542 456. <https://doi.org/10.1109/ICIP.2015.7350839>
- 543 Lobell, D.B., Ortiz-Monasterio, J.I., 2007. Impacts of day versus night temperatures on spring wheat

- 544 yields: A comparison of empirical and CERES model predictions in three locations, in: *Agronomy*
545 *Journal. American Society of Agronomy*, pp. 469–477. <https://doi.org/10.2134/agronj2006.0209>
- 546 Lu, H., Cao, Z., Xiao, Y., Zhuang, B., Shen, C., 2017. TasselNet: counting maize tassels in the wild via local
547 counts regression network. *Plant Methods* 13, 79. <https://doi.org/10.1186/s13007-017-0224-0>
- 548 Madec, S., Baret, F., de Solan, B., Thomas, S., Dutartre, D., Jezequel, S., Hemmerlé, M., Colombeu, G.,
549 Comar, A., 2017. High-Throughput Phenotyping of Plant Height: Comparing Unmanned Aerial
550 Vehicles and Ground LiDAR Estimates. *Front. Plant Sci.* 8, 1–14.
551 <https://doi.org/10.3389/fpls.2017.02002>
- 552 Madec, S., Jin, X., Lu, H., De Solan, B., Liu, S., Duyme, F., Heritier, E., Baret, F., 2019. Ear density
553 estimation from high resolution RGB imagery using deep learning technique. *Agric. For. Meteorol.*
554 264, 225–234. <https://doi.org/10.1016/j.agrformet.2018.10.013>
- 555 Malambo, L., Popescu, S.C., Horne, D.W., Pugh, N.A., Rooney, W.L., 2019. Automated detection and
556 measurement of individual sorghum panicles using density-based clustering of terrestrial lidar data.
557 *ISPRS J. Photogramm. Remote Sens.* 149, 1–13. <https://doi.org/10.1016/j.isprsjprs.2018.12.015>
- 558 McMaster, G.S., Smika, D.E., 1988. Estimation and evaluation of winter wheat phenology in the central
559 Great Plains. *Agric. For. Meteorol.* 43, 1–18. [https://doi.org/10.1016/0168-1923\(88\)90002-0](https://doi.org/10.1016/0168-1923(88)90002-0)
- 560 Monestiez, P., Courault, D., Allard, D., Ruget, F., 2001. Spatial interpolation of air temperature using
561 environmental context: Application to a crop model. *Environ. Ecol. Stat.* 8, 297–309.
562 <https://doi.org/10.1023/A:1012726317935>
- 563 Mueller-Sim, T., Jenkins, M., Abel, J., Kantor, G., 2017. The Robotanist: A ground-based agricultural robot
564 for high-throughput crop phenotyping, in: *Proceedings - IEEE International Conference on Robotics*
565 *and Automation. Institute of Electrical and Electronics Engineers Inc.*, pp. 3634–3639.

- 566 <https://doi.org/10.1109/ICRA.2017.7989418>
- 567 Park, D., Ramanan, D., Fowlkes, C., 2010. Multiresolution Models for Object Detection, in: Daniilidis, K.,
568 Maragos, P., Paragios, N. (Eds.), *Computer Vision – ECCV 2010*. Springer, Berlin, Heidelberg, pp.
569 241–254. https://doi.org/10.1007/978-3-642-15561-1_18
- 570 Reynolds, M., Foulkes, M.J., Slafer, G.A., Berry, P., Parry, M.A.J., Snape, J.W., Angus, W.J., 2009. Raising
571 yield potential in wheat. *J. Exp. Bot.* 60, 1899–1918. <https://doi.org/10.1093/jxb/erp016>
- 572 Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A.,
573 Bernstein, M., Berg, A.C., Fei-Fei, L., 2015. ImageNet Large Scale Visual Recognition Challenge. *Int. J.*
574 *Comput. Vis.* 115, 211–252. <https://doi.org/10.1007/s11263-015-0816-y>
- 575 Sadras, V.O., Slafer, G.A., 2012. Environmental modulation of yield components in cereals: Heritabilities
576 reveal a hierarchy of phenotypic plasticities. *F. Crop. Res.* 127, 215–224.
577 <https://doi.org/10.1016/j.fcr.2011.11.014>
- 578 Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., Batra, D., 2017. Grad-CAM: Visual
579 Explanations From Deep Networks via Gradient-Based Localization, in: *The IEEE International*
580 *Conference on Computer Vision (ICCV)*. pp. 618–626.
- 581 Singh, A.K., Ganapathysubramanian, B., Sarkar, S., Singh, A., 2018. Deep Learning for Plant Stress
582 Phenotyping: Trends and Future Perspectives. *Trends Plant Sci.* 23, 883–898.
583 <https://doi.org/10.1016/j.tplants.2018.07.004>
- 584 Slafer, G., 2012. Wheat development: its role in phenotyping and improving crop adaptation, in:
585 Reynolds, M., Pask, A., Mullan, D. (Eds.), *WHEAT Physiological Breeding I: Interdisciplinary*
586 *Approaches to Improve Crop Adaptation*. CIMMYT, Mexico, pp. 107–121.
- 587 Slafer, G., Rawson, H., 1994. Sensitivity of Wheat Phasic Development to Major Environmental Factors: a

- 588 Re-Examination of Some Assumptions Made by Physiologists and Modellers. *Funct. Plant Biol.* 21,
589 393. <https://doi.org/10.1071/PP9940393>
- 590 Tajbakhsh, N., Shin, J.Y., Gurudu, S.R., Hurst, R.T., Kendall, C.B., Gotway, M.B., Liang, J., 2016.
591 Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? *IEEE Trans.*
592 *Med. Imaging* 35, 1299–1312. <https://doi.org/10.1109/TMI.2016.2535302>
- 593 Thépot, S., 2014. Utilisation d'une population multi-parentale et hautement recombinante de blé tendre
594 pour l'étude de l'architecture génétique de la précocité de floraison. Util. d'une Popul. multi-
595 parentale hautement Recomb. blé Tendr. pour l'étude l'architecture génétique la précocité
596 floraison, Univ. Paris Sud (Paris 11)(2014). Université Paris Sud 11.
- 597 Wallach, D., Palosuo, T., Thorburn, P., Seidel, S.J., Gourdain, E., Asseng, S., Basso, B., Buis, S., Crout, N.,
598 Dibari, C., Dumont, B., Ferrise, R., Gaiser, T., Garcia, C., Gayler, S., Ghahramani, A., Hochman, Z.,
599 Hoek, S., Horan, H., Hoogenboom, G., Huang, M., Jabloun, M., Jing, Q., Justes, E., Kersebaum, K.C.,
600 Klosterhalfen, A., Launay, M., Luo, Q., Maestrini, B., Moriondo, M., Zadeh, H.N., Olesen, J.E., Poyda,
601 A., Priesack, E., Pullens, J.W.M., Qian, B., Schütze, N., Shelia, V., Souissi, A., Specka, X., Srivastava,
602 A.K., Stella, T., Streck, T., Trombi, G., Wallor, E., Wang, J., Weber, T.K.D., Weihermüller, L., Wit, A.
603 de, Wöhling, T., Xiao, L., Zhao, C., Zhu, Y., 2019. How well do crop models predict phenology, with
604 emphasis on the effect of calibration? *bioRxiv* 708578.
605 <https://doi.org/https://doi.org/10.1101/708578>
- 606 Weir, A.H., Bragg, P.L., Porter, J.R., Rayner, J.H., 1984. A winter wheat crop simulation model without
607 water or nutrient limitations. *J. Agric. Sci.* 102, 371–382.
608 <https://doi.org/10.1017/S0021859600042702>
- 609 Wheeler, T.R., Hong, T.D., Ellis, R.H., Batts, G.R., Morison, J.I.L., Hadley, P., 1996. The duration and rate of
610 grain growth, and harvest index, of wheat (*Triticum aestivum* L.) in response to temperature and

- 611 CO 2. *J. Exp. Bot.* 47, 623–630. <https://doi.org/10.1093/jxb/47.5.623>
- 612 White, J.W., Conley, M.M., 2013. A Flexible, Low-Cost Cart for Proximal Sensing. *Crop Sci.* 53, 1646.
613 <https://doi.org/10.2135/cropsci2013.01.0054>
- 614 White, J.W., Herndl, M., Hunt, L.A., Payne, T.S., Hoogenboom, G., 2008. Simulation-Based Analysis of
615 Effects of and Loci on Flowering in Wheat. *Crop Sci.* 48, 678.
616 <https://doi.org/10.2135/cropsci2007.06.0318>
- 617 Whittal, A., Kaviani, M., Graf, R., Humphreys, G., Navabi, A., 2018. Allelic variation of vernalization and
618 photoperiod response genes in a diverse set of North American high latitude winter wheat
619 genotypes. *PLoS One* 13, e0203068. <https://doi.org/10.1371/journal.pone.0203068>
- 620 Yalcin, H., 2018. Phenology recognition using deep learning: DeepPheno, in: 2018 26th Signal Processing
621 and Communications Applications Conference (SIU). IEEE, pp. 1–4.
622 <https://doi.org/10.1109/SIU.2018.8404165>
- 623 Yang, G., Liu, J., Zhao, C., Li, Zhenhong, Huang, Y., Yu, H., Xu, B., Yang, X., Zhu, D., Zhang, X., Zhang, R.,
624 Feng, H., Zhao, X., Li, Zhenhai, Li, H., Yang, H., 2017. Unmanned Aerial Vehicle Remote Sensing for
625 Field-Based Crop Phenotyping: Current Status and Perspectives. *Front. Plant Sci.* 8, 1111.
626 <https://doi.org/10.3389/fpls.2017.01111>
- 627 Zadoks, J.C., Chang, T.T., Konzak, C.F., 1974. A decimal code for the growth stages of cereals. *Weed Res.*
628 14, 415–421. <https://doi.org/10.1111/j.1365-3180.1974.tb01084.x>
- 629 Zheng, B., Chenu, K., Fernanda Dreccer, M., Chapman, S.C., 2012. Breeding for the future: what are the
630 potential impacts of future frost and heat events on sowing and flowering time requirements for
631 Australian bread wheat (*Triticum aestivum*) varieties? *Glob. Chang. Biol.* 18, 2899–2914.
632 <https://doi.org/10.1111/j.1365-2486.2012.02724.x>

633

634 Appendix

635 *Table A Description of the 47 sites considered in our study over 3 growing seasons and 9 different varieties of wheat*

Field Id	Coordinates	Year	Mean Seasonal Temperature Oct to July (°C)	Growing Degree Days °C (sowing to heading)	Heading date	Variety	Sowing date	Harvest date	Comments
D-D1	48.322452, 2.383738	2017	11.43	1518.15	17-05-2017	Descartes	20-10-2016	-	Experimental plots
D-D2	48.322483, 2.383812	2017	11.43	1518.15	16-05-2017	Descartes	20-10-2016	-	
D-D3	48.321520, 2.382034	2017	11.43	1518.15	17-05-2017	Descartes	20-10-2016	-	
D-I1	48.321570, 2.382026	2017	11.43	1518.15	17-05-2017	Descartes	20-10-2016	-	
D-I2	48.321530, 2.383126	2017	11.43	1518.15	16-05-2017	Descartes	20-10-2016	-	
D-I3	48.322499, 2.383748	2017	11.43	1518.15	17-05-2017	Descartes	20-10-2016	-	
D-S1	48.320248, 2.379639	2017	11.43	1518.15	18-05-2017	Descartes	20-10-2016	-	
D-S2	48.320221, 2.379579	2017	11.43	1518.15	19-05-2017	Descartes	20-10-2016	-	

E-A	44.238959, 5.928383	2018	7.45	1612.904	11-05-2018	RGT Voilur	25-10-2017	-	Production plots
E-ME	44.261415, 5.870530	2018	8.61	1841.848	06-05-2018	Anvergur	04-10-2017	-	
E-MO	44.262088, 5.869253	2018	8.61	1894.37	09-05-2018	Anvergur	04-10-2017	-	
E-MN	43.766323, 6.098798	2018	10.08	1780.29	17-05-2018	Toscadou	10-10-2017	-	
E-MS	43.765653, 6.100184	2018	10.15	1754.06	14-05-2018	Toscadou	10-10-2017	-	
E-S	43.812474, 5.772345	2018	11.22	1620.32	09-05-2018	RGT Voilur	22-10-2017	-	
E-V	43.791706, 6.120393	2018	10.08	1878.21	14-05-2018	Toscadou	10-10-2017	-	
A-201	48.323864, 2.378989	2018	10.06	1586.40	11-05-2018	Oregrain	16-10-2017	10-07-2018	
A-207	48.348859, 2.432 189	2018	10.06	1575.05	10-05-2018	Oregrain	16-10-2017	10-07-2018	
A-210	48.345231, 2.432945	2018	10.06	1613.05	13-05-2018	Oregrain	16-10-2017	10-07-2018	
A-301	48.349030, 2.432 504	2018	10.06	1586.40	11-05-2018	Oregrain	16-10-2017	10-07-2018	
A-305	48.323589, 2.378951	2018	10.06	1601.60	12-05-2018	Oregrain	16-10-2017	10-07-2018	

A-308	48.347419, 2.43389	2018	10.06	1586.40	11-05-2018	Oregrain	16-10-2017	10-07-2018	
A-310	48.344959, 2.432586	2018	10.06	1613.05	13-05-2018	Oregrain	16-10-2017	10-07-2018	
22-DS	48.325583, 2.386405	2018	10.06	1624.20	14-05-2018	Fructidor	20-10-2017	09-07-2018	Production plots
22-SS	48.324231, 2.385779	2018	10.06	1639.85	15-05-2018	Fructidor	20-10-2017	09-07-2018	
331- MS	48.321029, 2.384333	2018	10.06	1613.05	13-05-2018	RGT Sacramen to	20-10-2017	09-07-2018	
331- SS1	48.319074, 2.380753	2018	10.06	1601.60	12-05-2018	RGT Sacramen to	20-10-2017	09-07-2018	
331- SS2	48.319046, 2.380693	2018	10.06	1601.60	12-05-2018	RGT Sacramen to	20-10-2017	09-07-2018	
SI-1	49.073911, 5.704641	2019	8.80	1582.76	27-05-2019	Fructidor	14-10-2018	-	
SI-2	49.073735, 5.704535	2019	8.80	1582.76	27-05-2019	Fructidor	14-10-2018	-	
SI-3	49.074086, 5.704128	2019	8.80	1582.76	27-05-2019	Fructidor	14-10-2018	-	
C-B1	48.958538, 4.253838	2019	9.48	1671.19	23-05-2019	Matheo	14-10-2018	-	
C-B2	48.958576,	2019	9.48	1671.19	23-05-2019	Matheo	14-10-2018	-	

	4.253507								
C-B3	48.95826, 4.253713	2019	9.48	1671.19	23-05-2019	Matheo	14-10-2018	-	
T-217	48.323273, 2.379553	2019	9.62	1529.25	16-05-2019	Oregrain	23-10-2018	-	Experimental plots with different nitrogen management
T-205	48.323624, 2.379038	2019	9.62	1529.25	16-05-2019	Oregrain	23-10-2018	-	
T-202	48.323761, 2.378927	2019	9.62	1543.0	17-05-2019	Oregrain	23-10-2018	-	
T-305	48.323589, 2.378951	2019	9.62	1529.25	16-05-2019	Oregrain	23-10-2018	-	
T-201	48.323864, 2.378989	2019	9.62	1557.70	18-05-2019	Oregrain	23-10-2018	-	
T-110	48.323586, 2.379289	2019	9.62	1529.25	16-05-2019	Oregrain	23-10-2018	-	
332-DS	48.32201, 2.383564	2019	9.62	1518.65	16-05-2019	Rebelde	24-10-2018	-	
332-SS	48.319752, 2.37894	2019	9.62	1558.70	19-05-2019	Rebelde	24-10-2018	-	
332-MS	48.320652, 2.381057	2019	9.62	1558.70	19-05-2019	Rebelde	24-10-2018	-	
411-SS	48.317192, 2.387024	2019	9.62	1570.45	27-05-2019	Fructidor	06-11-2018	-	
411-DS	48.318287, 2.388875	2019	9.62	1553.5	26-05-2019	Fructidor	06-11-2018	-	
411-	48.316154,	2019	9.62	1570.45	27-05-2019	Fructidor	06-11-2018	-	

MS	2.384733								
E-F1	43.710176, 4.534401	2019	13.31	1854.88	21-04-2019	RGT Voilur	25-10-2018	-	
E-M1	43.843360, 4.442453	2019	13.12	1874.5	22-04-2019	Anvergur	25-10-2018	-	

636