1 Will climate change affect sugar beet establishment of the 21st century?

2 Insights from a simulation study using a crop emergence model

3 Jay Ram Lamichhane^{1*}, Julie Constantin¹, Jean-Noël Aubertot¹, Carolyne Dürr²

4 ¹INRA, Université Fédérale de Toulouse, UMR 1248 AGIR, F-31326 Castanet-Tolosan,

5 France

⁶ ²INRA, IRHS 1345, 42 rue George Morel, F-49071 Beaucouzé, France

7 *Corresponding author: jay-ram.lamichhane@inra.fr

8 Tel: +33 (0)5 61 28 52 50; Fax: +33 (0)5 61 28 55 37

9 Abstract

Ongoing climate change has been reported to have far-reaching impact on crop 10 development and yield in many regions of the globe including Europe. However, little is 11 known about the potential impact of climate change on specific stages of the crop cycle 12 including crop establishment, although it is a crucial stage of the annual crop cycles. For 13 the first time, we performed a simulation study to pinpoint how sugar beet sowing 14 conditions of the next eight decades will be altered under future climate change and if 15 these variations will affect sowing dates, germination and emergence as well as bolting 16 rates of this crop. We chose Northern France as an important study site, representative of 17 sugar beet growing basin in Northern Europe. Sugar beet emergence simulations were 18 performed for a period between 2020 and 2100, taking into account five sowing dates 19 (mid-February, 1st March, mid-March, 1st April and mid-April). Soil water contents and 20 temperatures in the 0-10 cm soil horizon were first simulated with the STICS soil-crop 21 model using the most pessimistic IPCC scenario (RCP 8.5) to feed the SIMPLE crop 22 emergence model. We also evaluated the probability of field access for the earlier sowings, 23

based on the amount of cumulated rainfall during February and March. When analyzed 24 by sowing date and for successive 20-year period from 2020 to 2100, there was a 25 significant increase in seedbed temperatures by 2°C after 2060 while no change in 26 cumulative rainfall was found before and after sowings, compared with the past. 27 Emergence rate was generally higher for 2081-2100, while time to reach the maximum 28 emergence rate decreased by about one week, compared with other periods, due to higher 29 average seedbed temperatures. The rate of non-germinated seeds decreased, especially 30 for the earlier sowing dates, but the frequency of non-emergence due to water stress 31 increased after 2060 for all sowing dates, including the mid-February sowing. Bolting 32 remains a risk for sowings before mid-March although this risk will be markedly 33 decreased after 2060. The changes in seedbed conditions will be significant after 2060 in 34 35 terms of temperatures. However, the possibility of field access will be a main limiting factor for earlier sowings, as no significant changes in cumulative rainfall, compared with 36 37 the past, will occur under future climate change. When field access is not a constraint, an 38 anticipation of the sowing date, compared to the currently practiced sowing (i.e. mid-March), will lead to decreased risks for the sugar beet crop establishment and bolting. The 39 40 use of future climate scenarios coupled with a crop model allows a precise insight into the future sowing conditions, and provide helpful information to better project future farming 41 42 systems.

Key words: adaptation, seed germination, seedling emergence, seedling mortality, soilsurface crust, temperature, water stress

45 **1. Introduction**

Seed germination and seedling emergence are critical phases of a crop cycle that affect
the success or failure of any crop establishment (Villalobos et al. 2016). These early

phases of crop cycle are affected by several biotic and abiotic factors that may reduce seed 48 germination and seedling emergence rates (Lamichhane et al. 2018). More specifically to 49 abiotic stresses, many factors including seedbed water content, temperature, and the 50 frequency and quantity of cumulated rainfall profoundly impact crop establishment 51 (Gallardo-Carrera et al. 2007; Constantin et al. 2015; Dürr et al. 2016). Several studies 52 reported that climate change will result in increased mean temperature and higher 53 precipitation variability in many regions of the globe including Europe (Pendergrass et al. 54 2017; Kjellström et al. 2018). The effects of ongoing climate change on crop yield have 55 been extensively studied (Lobell et al. 2008; Challinor et al. 2014). For instance, climate 56 change from 1980 to 2008 has resulted in reduced global production of maize by 3.8% 57 and wheat by 5.5% compared with a counterfactual without climate change (Lobell et al. 58 2008). A recent meta-analysis (Challinor et al. 2014) -- based on 1,700 published 59 simulation studies on climate change impacts on yields and adaptation -- showed that 60 without adaptation, there will be losses in production for wheat, rice and maize in both 61 temperate and tropical regions by 2 °C of local warming. 62

While many studies assessed the impact of climate change on crop yields, there is less 63 detailed information about the potential effect of climate change on crop establishment, 64 although it is a crucial stage for annual crops. This prevents stakeholders from mobilizing 65 adaptation strategies that may be helpful to attenuate climate change effects. Rather small 66 adjustments (e.g. changes in varieties, sowing date and density, tillage or tactical pest 67 management) in contrast to more systemic changes (e.g. changes in crop sequences; 68 moving from dryland to irrigated systems or from spring to autumn sowings), may ensure 69 70 successful crop establishment with positive impacts on crop yield (reviewed by Lamichhane et al. 2018). Indeed, either a lack or an excess of soil temperature, water 71 72 content or rainfall may be detrimental to crop establishment. For example, if no precipitation occurs after sowing the seed imbibition process is hindered and seeds cannot germinate. In contrast, if heavy rainfall occurs following sowing soil crusting will occur preventing seedlings from being emerged (Gallardo-Carrera et al. 2007). Spring crops are more sensitive to seedbed sowing conditions than winter crops. The risk of poor crop establishment is higher for these crops also because most of them are not able to compensate a lower plant density via tillering or ramification during their development.

Sugar beet (*Beta vulgaris* L.) is a typical example of spring crop highly sensitive to seedbed 79 sowing conditions. In Northern Europe, these conditions are frequently unfavorable, with 80 81 low temperatures, heavy rainfall followed by dry periods leading to soil surface crusting on loamy soils (Durr and Boiffin 1995). Sugar beet growers have to optimize sowing dates 82 83 and seedbed preparations to ensure successful crop establishment. In addition, sugar beet is subject to bolting, if cold temperatures occur following early sowings (Longden et al. 84 85 1975; Milford et al. 2010), with negative impact on its yield and volunteer plant's control. Simulation studies are useful to help decision-making process. Exploration of adaptation 86 strategies to climate change using process-based models allows crop-level evaluation and 87 adaptation of existing cropping systems (Challinor et al. 2014). While numerous crop 88 models have been developed and used to facilitate decision-making during the crop 89 development phase, only few models focus on the crop establishment phase. 90

The objective of this simulation study was to pinpoint whether sowing conditions of the next decades (2020-2100) will be altered under climate change and if these variations will affect germination and emergence, as well as bolting rates of sugar beet in Northern Europe. A total of 405 sugar beet emergence simulations were performed taking into account five sowing dates. To this aim, we first mobilized the STICS soil-crop model (Brisson et al. 1998, 2003) to generate soil water content and temperature in the seedbed 97 (0–10 cm) using the most pessimistic IPCC scenario. We then used the data obtained as
98 input variables to feed the SIMPLE crop emergence model (Dürr et al. 2001; Constantin et
99 al. 2015). The emergence courses and final rates, and causes of no-seedling emergence
100 are analyzed and discussed. In addition, the possibility of field access was evaluated
101 comparing historical records in relation to future climatic conditions.

102

2. Materials and methods

103 **2.1. Description of the SIMPLE crop emergence model**

A comprehensive description including the functioning of the SIMPLE model and the list 104 of equations and input variables has been previously provided (Dürr et al. 2001). Briefly, 105 the model predicts the germination and emergence process and their final rates in 106 relation to environmental conditions during sowing. The model has previously been 107 108 parameterized for a number of crop species -- including wheat, sugar beet, flax, mustard, French bean, oilseed rape (Dürr et al. 2001; Dorsainvil et al. 2005; Moreau-Valancogne et 109 al. 2008; Dürr et al. 2016), and a plant model Medicago truncatula (Brunel et al. 2009) -110 which allows to compare a range of plant species using the same set of parameters 111 112 (Gardarin et al. 2016).

SIMPLE creates 3D representations of seedbeds with sowing depth distribution and the 113 114 size, number, and position of soil aggregates as input variables. Daily soil temperature and soil water potential in several layers are also used as input variables for simulations, along 115 116 with plant characteristics for germination and seedling growth. The model predicts germination and emergence, seed by seed, at daily intervals. The time required for 117 germination of the seed i is chosen at random in the distribution of thermal times that 118 characterizes the seed lot used. Cumulative thermal time from sowing is calculated above 119 the base temperature (Tb) for germination, provided that the soil water content at the 120

seed sowing depth is above the base water potential (Ψ b). The Tb and Ψ b thresholds for 121 germination are input variables. If seed i has not germinated after a given time (usually 122 fixed at 30 days for the simulation), the model considers that the seed will never 123 germinate. If the seed germinates, then a seedling grows from the seed. Time is expressed 124 as thermal time using the Tb value. To better include the effect of early water stress on 125 seedling growth, we added a water stress function to the SIMPLE model, which reduces 126 emergence after germination (Constantin et al. 2015). With this function, the fate of 127 seedlings is determined by considering soil water potential in the soil layer in which the 128 radicle grows in the two days following germination. During this period, if soil water 129 potential is lower than Ψ b, the seedling does not emerge and dies the following day. If this 130 is not the case, the time it takes for the seedling to reach the soil surface after germination 131 is calculated by SIMPLE based on the seed's sowing depth, the length of the pathway the 132 shoot takes through the aggregates, and the shoot's elongation function, whose 133 parameters are input variables. The probability of the seedlings remaining blocked under 134 aggregates depends on the size and position of the clods in the seedbed, i.e. laying on the 135 surface or below it. Soil surface crusting depends on cumulative rainfall after sowing; a 136 137 proportion of seedlings remain blocked under the crust depending on daily crust water content (no seedlings are blocked if the crust is wet). Simulations at the individual seed 138 level are run 1000 times to predict the emergence rate and final emergence percentage. 139 The causes of non-emergence simulated by SIMPLE are (i) non-germination, (ii) death of 140 seedlings caused by water stress after germination and (iii) mechanical obstacles (clods 141 or a soil crust). The SIMPLE model does not consider biotic stresses, such as pests and 142 diseases or the effect of high temperatures, which could inhibit germination or cause 143 young seedling death. 144

Bolting risk is represented by a function that was not initially presented in the seminal
paper describing the SIMPLE model (Dürr et al, 2001). This function was derived from
Longden et al (1975) and the probability of bolting μ_b is calculated as:

148
$$\mu_b = c_1 \left(1 - e^{-c_2 n_{ccd}^{c_3}} \right)$$
 Equation 1

where c₁, c₂, c₃ dimensionless coefficients (Table 1); n_{ccd} is the number of cumulative cold
days from sowing to the end of June and is calculated as follows:

151
$$n_{ccd} = \sum_{i=1}^{i=i_{max}} \delta_{\alpha_i \beta_i}$$
 Equation 2

where *i* is a daily index ranging from 1 (sowing day) to i_{max} (day corresponding to the end of June) and $\delta_{\alpha_i\beta_i}$ is the Kronecker symbol with:

154
$$\alpha_i = \beta_i$$
 if $\theta_i < \theta_b$ and $\alpha_i \neq \beta_i$ otherwise Equation 3

where θ_i is the maximum daily temperature at 2 m, and θ_b is the maximum threshold air temperature to define whether a given day is considered as cold or not with regard to bolting **(Table 1)**.

More recent studies (Fauchère et al 2003; Milford 2010) suggested that devernalization can occur if plants are exposed to high temperatures during a specific period of the crop cycle. Based on this information, we analyzed the number of days with Tmax >25°C between 60 to 120 days post sowing (dps). Finally, we established that if this number was >7, the potential risk of having bolted plants became zero.

163 2.2. Climate scenarios and simulations of the seedbed climate

We used the RCP 8.5 emission scenario to generate soil temperature and water content of the seedbed using the STICS soil-crop model (Brisson et al. 2003). This model daily simulates soil water contents and temperatures, according to daily weather and soil characteristics. Variations in soil moisture were predicted using STICS at 0-2, 2-4, 4-6 and
6-10 cm. We selected Estrées-Mons (49°52′44″N 3°00′27″E), located in the typical sugar
beet growing regions of Northern France, as study site. We chose Northern France as
representative sugar beet growing basin of Northern Europe. The soil type considered
had the following soil granulometry and chemical characteristics at the 0-30 cm soil
horizon: 0.197 g.g⁻¹ clay, 0.747 g.g⁻¹ silt and 0.056 g.g⁻¹ sand; 0 g.g⁻¹ CaCO₃, 0.095 g.g⁻¹ C,
0.001 g.g⁻¹N, C/N ratio 9.3, and pH 7.7.

Four weather and soil parameters were analyzed for the year 2020-2100: average soil temperature at sowing, average soil and maximum air temperature 30 dps, and cumulated rainfall 30 dps. The average weather data of the last 19 years (2000-2018) registered at the weather station of the study area were calculated to compare the trend with the simulated weather data of the next 81 years.

179 **2.3. Sugar beet sowing scenarios**

Values of plant input variables of SIMPLE for sugar beet crop are reported in **Table 1**. The seedbed considered in this study is typical of that prepared by growers and was characterized by 15-25% of soil aggregates >20mm in diameter and 70-85% of its aggregates having <20mm in diameter. The simulated sowing depths were 2.5 ± 0.4 cm.

A total of 405 sugar beet emergence simulations was performed for a period between 2020 and 2100, taking into account five sowing dates: mid-February, 1st March, mid-March, 1st April, and mid-April. Farmers in Northern France most often practice mid-March sowing of sugar beet crop but we included both earlier (mid-February and 1st March) and late (1st April and mid-April) sowing dates taking into account a possible shift in future sowing dates due to climate change.

190 **2.4. Analysis of simulation results**

191 Climatic data were pooled and analyzed by sowing date and 20-year period (2000-2018 192 for the past and 2020-2040, 2041-2060, 2061-2080, and 2081-2100 for the future). When 193 data were analyzed by sowing date, the 100 years were treated as replicates. When data 194 were analyzed by 20-year period, the 20 years x five sowing dates (i.e. 100) were treated 195 as replicates. ANOVA was used to determine the potential effect of sowing dates and 196 periods, and their interaction on the four average weather and soil parameters mentioned 197 above.

The variability of germination and emergence rates and their duration was analyzed by 198 establishing three classes of rate or duration, expressed as the frequency of each class 199 over the 20-year period for germination and emergence rates, and their duration. For 200 germination rate, thresholds were poor germination when germination rate was <75% 201 202 and sufficient germination above 75%. For emergence rate, thresholds were poor emergence when the emergence rate was <50%, and sufficient over 50%. For germination 203 204 duration, thresholds were low duration when the number of days required to reach maximum germination (NGmax) was < 14 days and high when NGmax was >14 days. For 205 206 emergence duration, thresholds were low duration when the number of days required to reach maximum emergence (NEmax) was < 28 days, and high when NEmax was >28 days. 207 The frequency of poor germination (<75%) and emergence (<50%) rates as well as high 208 NGmax (>14 days) and NEmax (>28 days) duration were analyzed as they could lead to 209 crop emergence failure and potential re-sowing. 210

The variability of causes of non-emergence was analyzed by establishing two classes of seed and seedling mortality rates for each mortality cause. For non-germination, the two classes were low with <25% and high with >25% non-germinating seeds. For seedling

9

214 mortality due to clod, crust and drought, the two classes were low with <15%, and high 215 with >15% of seedling mortality. Frequency of high risks of non-germination (>25%) and 216 seedling mortality due to clod, crust, and drought (each >15%) cases are presented for 217 the same reason as described above.

The variability of bolting rates was presented as the average predicted percentages of bolted plants over the 20-year periods. This variability was also analyzed by establishing three classes of bolting rates : <0.5%, 0.5-1%, and >1% rate.

To determine significant effects on germination, emergence and bolting rates, and duration as well as on causes of non-emergence, in addition to the same statistical analysis performed for weather data (i.e. only by sowing date and 20-year period pooling all the data), we also analyzed the data by sowing date for each 20-year period separately (hereafter referred to as period). All statistical analyses were conducted using software R (Hothorn and Everitt 2009).

227 **2.5. Technical feasibility of sowing**

An earlier sowing than the currently practiced sowing (mid-March) may be possible under future climate change. This shift in sowing date however depends on field access for sowing. We determined whether farmers will have technical possibility for sowing for the simulated sowing dates and years using two following approaches.

i) based on a past historical data set (1987-2005), we observed a correlation between the
quantity of total cumulative rainfall during the sowing in March and the percentage of
sugar beet surface sown in France at the end of this month (Figure 1). We then compared
these past observations with the predicted cumulative future rainfall of the same months
(i.e. February and March).

ii) we supposed that >1 mm rainfall on sowing day will not technically allow field access
for farmers for the sowings in February and March because the soil surface is wet and
evapotranspiration low. Based on this, we calculated the frequency of days >1 mm rainfall
for February and March.

241 **3. Results**

242 **3.1. Sowing conditions and their variability under future scenario**

When analyzed by sowing date, differences between the average soil temperature at sowing, average soil and maximum air temperature 30 dps were statistically significant (P < 0.001) (Table 2). When analyzed by period of time, all average weather values related to temperature increased with time with statistically significant differences (P < 0.001). In contrast, no differences statistically significant were found for average rainfall 30 dps (P = 0.220).

As expected, average soil temperature at sowing increased with later sowing dates. The 249 250 trend was similar for average soil and maximum air temperatures 30 dps. Overall, average soil temperature at sowing ranged between 5 °C for the mid-February sowing to 11 °C for 251 the mid-April sowing, while average soil temperature 30 dps ranged from 6 °C for the mid-252 February sowing to 13 °C for the mid-April sowing. Also average maximum air 253 temperature 30 dps was the lowest (9 °C) for the mid-February sowing while it was the 254 highest (16 °C) for the mid-April sowing. In contrast to the three temperature factors, 255 average rainfall 30 dps did not follow the same pattern: it was high (45-52 mm) for the 256 first four sowing dates with no significant differences, and then decreased drastically for 257 the mid-April sowing (28 mm). 258

When analyzed by period, average soil sowing day temperature was the lowest (7 °C) for 259 the 2020-2040 and 2041-2060 periods, and increased progressively for the 2061-2080 260 and 2081-2100 periods by 8 and 9 °C, respectively. The trend was the same also for 261 average soil temperature 30 dps, which ranged from 9 °C for the 2020-2040 period to 11 262 °C for the 2081-2100 period. These differences were significant between the first two and 263 the last two periods. These changes became significant after 2060. In contrast, mean 264 average maximum air temperature 30 dps varied over periods but with no regular 265 increase. Mean cumulated rainfall 30 dps ranged from 39 to 47 mm, with a high variability 266 between individual years, but without any significant differences until 2100. There was 267 no significant effect of the sowing date x period interaction on any of the analyzed weather 268 data (Table 2). 269

270 **3.2. Emergence rate, duration and frequency**

Year-to-year emergence rate variability for all five sowing dates is described in Figure 2.
Results on the effect of sowing date for each period and their interaction on emergence
rate, duration and frequency are reported in Table 3. Results on the effect of sowing date
and period separately, and their interaction on emergence rate and duration are
presented in Supplementary Table 1.

Year-to-year variability in emergence rate was very high for all sowing dates over the 81
simulated years ranging from 0 to 85%. Emergence rate most often registered between
50 and 85%, but emergence rate <50% were observed in many cases. Simulated average
emergence rate by "sowing date × period" ranged from less than 50% for the midFebruary sowing in 2020-2040 to more than 70% for different sowing dates. The
frequency of poor emergence rate (<50%) ranged from 14 to 48% depending on sowing

date × period. The mid-February sowing in the 2020-2040 period not only had the lowest
average emergence rate but also a high frequency of poor emergence rate.

When data were analyzed by sowing date for each period, the interaction effect of sowing date x period on emergence rate was not statistically significant (P = 0.08). In contrast, the interaction effect was statistically significant (P < 0.001) when all data were pooled and analyzed only by sowing date or period **(Supplementary Table 1)**.

Simulated mean NEmax by sowing date × period ranged from 20 days for the mid-April 288 sowing in the 2081-2100 period to 50 days for the mid-February sowing in the 2041-2060 289 period (Table 3). Mean NEmax decreased over sowing dates and also over periods, by 290 more than one week for the earlier sowing dates and to a lower extent for later sowings. 291 Within each period, mean NEmax was almost no significantly different between the five 292 sowing dates. However, there were statistically significant differences when the data were 293 294 analyzed only by sowing date (P < 0.001) or period (P < 0.001; **Supplementary Table 1**). The frequency of high NEmax (>28 days) ranged from 15 to 100% by sowing date × 295 period. This frequency was higher for earlier sowing dates and also for earlier periods 296 (Table 3). 297

298 **3.4. Causes of non-emergence rates and frequencies**

Results on the main causes of non-emergence are reported in **Table 4**. The major causes of non-emergence were non-germination, followed by soil surface crusting and seedling death due to drought while seedling death due to clod was the least important. Results on the effect of sowing date for each period and their interactions on germination rate, duration and frequency are reported in **Table 5**. Outcomes on the overall effect of sowing date and period, and their interactions on germination rate and duration are presented in **Supplementary Table 1**.

306 **3.4.1. Non-germination**

The mean non-germination rate ranged from less than 5% for several sowing dates after 307 308 the mid-March sowing to 37% for the mid-February sowing in the 2020-2040 period. When data were analyzed by sowing date for each period, and their interaction, no 309 310 statistically significant effect of the sowing date, period, or their interaction was found on non-germination rate except between the 2020-2040 and 2081-2100 periods for the mid-311 312 February sowing. In contrast, non-germination rate differences were statistically significant when the data were combined and analyzed by sowing date (P < 0.001), period 313 (P < 0.01), and their interaction (P < 0.001; **Supplementary Table 2)**. The frequency of 314 high non-germination (>25%) ranged from 0 to 48% (Figure 3) depending on sowing 315 316 date x period and was higher for earlier sowings.

Simulated average NGmax values ranged from 14 to 22 days when data were analyzed by 317 sowing date for each period. These values generally decreased with later sowing dates 318 and periods **(Table 5)**. The frequency of high NGmax (>14 days) ranged from 8 to 21% 319 which generally decreased with later sowings and over the periods. No statistically 320 significant effect of sowing date, period and their interaction (P = 0.98) was found on 321 mean NGmax values when data were analyzed by sowing date for each period. In contrast, 322 when data were analyzed only by sowing date or period, there were statistically 323 significant effects of sowing date (P < 0.001) and period (P < 0.01), but not of their 324 interaction on mean NGmax (Supplementary Table 1). 325

326 **3.4.2. Seedling mortality due to crust**

Seedling mortality rate due to soil surface crust ranged from 6 to 15% (Table 4). Average
mortality rate was generally lower for the 2020-2040 period until the mid-March sowing,
as soil surface crust prevents emergence only when it becomes dry. No statistically

significant effect of sowing date (P = 0.48) or period (P = 0.24) or their interaction was
observed on seedling mortality rate either when the data were analyzed by sowing date
for each period (P = 0.76) or only by sowing date and period (P = 0.22) (Supplementary
Table 2). The frequency of high seedling mortality rate (>15%) ranged from 19 to 45%
(Figure 3). This frequency was lower for the 2020-2040 period until mid-March sowing.

335 **3.4.3. Seedling mortality due to drought**

Seedling mortality rate due to drought ranged from 1 to 14%, and increased with later 336 sowing dates and periods, with some exceptions (Table 4). When data were analyzed by 337 sowing date for each period, no significant effect of sowing date, period or their 338 interaction (P = 0.276) was found on seedling mortality rate. In contrast, when the data 339 were pooled and analyzed only by sowing date and period, statistically significant effect 340 of sowing date (P < 0.001), period (P < 0.001) and their interaction (P < 0.05) was found 341 on seedling mortality rate (Supplementary Table 2). The frequency of high mortality 342 due to drought (>15%) ranged from 0 to 40% (Figure 3). This frequency increased with 343 later sowing dates and periods. It is however remarkable that seedling mortality due to 344 drought appeared for the 2081 – 2100 period even for sowings as early as mid-March or 345 even before. 346

347 **3.4.4. Seedling mortality due to clod**

Seedling mortality rate due to clod ranged from 9 to 12% (Table 4) with little variability among the sowing dates or periods. This was expected because this mortality mostly depends on seedbed structure, which was the same for all simulations, independent of the sowing date and period.

352 **3.5. Risks of bolting**

When data were analyzed by sowing date for each 20-year period, significant effect of 353 sowing date, period or their interaction (P < 0.001) was found on potential bolting rate 354 and devernalization conditions. The average predicted potential bolting rates ranged 355 from 0.04% to 1.65%. As expected, bolting rates were higher for sowings in February and 356 decreased with later sowing dates. Our results showed that the predicted bolting rates 357 decreased progressively and significantly after 2060 for all simulated sowing dates 358 (Table 6). Likewise, the potential for devernalization highly increased due to an increased 359 number of days with Tmax > 25°C at the end of spring (Table 6). Based on these results, 360 the average risk of bolting will be lower after 2060, even for the earliest sowing dates. 361

362 **3.6. Technical feasibility of sowing**

Results on the probability of field access for February and March over periods are reported in **Table 7**. When considering cumulated rainfall over one month or the number of days >1 mm rainfall in February or March (i.e. the earliest sowing periods), there were no statistically significant differences between the two months and over the 20-year periods. This means that the technical feasibility of sowings will remain the same as nowadays, as shown in **Figure 1**.

369 4. Discussion

370 4.1. Seedbed micro-climatic conditions under future scenarios

We used the STICS soil-crop model based on the RCP 8.5 emission scenario to generate climate data. This model has been reported to be sensitive enough to generate realistic soil data such as soil moisture (Constantin et al. 2015; Dürr et al. 2016; Tribouillois et al. 2018). Predictions of the STICS soil-crop model showed that during the sowing period of sugar beet, mean seedbed temperatures will increase over time and that a higher variability of rainfall will occur, without an overall increase of its cumulated values. The
trends we found here are coherent with those generally expressed for global climate
changes, and the use of the STICS model allows to evaluate more precisely these changes
specifically in the seedbed and for the sowing period of sugar beet in Northern France or
Europe.

Under the most pessimistic climate scenario that we used, the predicted rise in mean soil 381 temperature at sowing remained 0 °C until 2060 and became +2 °C after 2080. When 382 climatic data of the next eight decades were compared with the past two decades, we 383 384 found that average soil temperature 30 dps of the last 19 years were similar to those predicted until 2060, but higher over the last two periods. This highlights that the impact 385 of climate change will become more remarkable after 2060 with warmer soil 386 temperatures during the last two decades of the 21st century. Interestingly, when 387 388 maximum air temperature at sowing was considered, mean values 30 dps showed a very high year-to-year variability, but without any regular increase over the years. 389

In contrast to predicted seedbed temperatures, cumulative rainfall did not change over time and were more or less the same for the first four sowing dates. A delay of two weeks in sowing from 1st to mid-April resulted in an increased drought risk under future climate change.

4.2. Sugar beet crop establishment under future climate

Several previous studies compared results of field observation and simulation using the SIMPLE crop emergence model and found its prediction similar to observed data (Dorsainvil et al. 2005; Brunel-Muguet et al. 2011; Constantin et al. 2015; Dürr et al. 2016). Therefore, prediction of germination and emergence rates reported in this study can be considered reliable. Even by using the most pessimistic climate scenario, predictions based on the SIMPLE crop emergence model showed that, in most cases, there
will be a sufficient level of sugar beet crop emergence in Northern France and Europe
under future climate change.

Despite performing simulation studies using only one climate scenario, the results of this 403 404 study represent an important outcome for decision making related to sugar beet sowing not only in Northern France, but in Northern Europe in general due to similar climatic 405 406 conditions and sowing dates. The inclusion of the most pessimistic climate scenario for simulation did not render necessary the use of other less pessimistic climate scenarios 407 408 (i.e. RCP 2.6, 4.5 and 6). This is because we did not find any dramatic changes in sugar beet emergence rate which would have been less impacted with simulation studies 409 410 including less drastic future climate scenarios. Nevertheless, our results are based on only one study site which represents a limit and thus future studies taking into account several 411 412 study sites over space could shed more light in this regard.

The most important finding of this study is that there are no important variability in terms 413 414 of emergence rate among sowing dates, except for the earliest one for which emergence rate was predicted to be higher and less variable after 2060. Sowing date adaptation is, 415 by far, the most frequently investigated climate change adaptation option (White et al. 416 2011). Sugar beet farmers in France and Northern Europe, who currently practice the 417 mid-March sowing, may thus anticipate sowing under future climate scenarios, given that 418 earlier sowing provides higher yield benefits. This is due to a prolonged vegetation period 419 and the higher amount of intercepted solar radiation, as it is the case for many field crops 420 (Van Ittersum and Rabbinge 1997). 421

Bolting causes yield penalties in sugar beet , and contribute to gene flow, seed dispersion,
and volunteer plant development in the next crops (Longden et al 1975; Sester et al 2008).

18

Therefore, bolting risks could be a limiting factor even when there are possibilities for 424 earlier sowing. Our results showed that the predicted bolting risk will decrease over time 425 and will become reduced for the mid-February sowing and very limited for the 1st March 426 sowing, especially after 2060. 427

428

4.3. Causes of non-emergence of seedlings under future scenarios

In terms of the total percentage of emergence failure, the one due to non-germination was 429 the most important followed by soil surface crusting and drought. Seedling mortality rates 430 under clod did not vary over sowing dates or periods since it strictly depends on the 431 seedbed structure chosen for simulations. It is also the reason why the maximum 432 simulated emergence rate remained always around 85%, due to about 5% non-433 germinating seeds in the simulated seed lot and about 10% non-emerging seedlings due 434 to the simulated seedbed structure. Both germination and emergence were affected by 435 the considered abiotic stresses. At the germination stage, very low temperature with 436 earlier sowings, and very low or no rainfall during the later sowings affected the seed 437 germination process. During the emergence phase, the frequency of emergence failure 438 was either related to seedling mortality due to a soil surface crust with all sowing dates, 439 or to water stress with later sowings. The average risk of crop emergence failure remains 440 similar with sowing dates or periods but the prevalence of individual stress factor changes 441 according to sowing dates and periods. After 2060 and to a greater extent after 2080, 442 higher risks of seedling mortality due to drought appear even for the earliest sowing date. 443 Such an analysis of non-emergence results can be obtained only with a simulation 444 approach. Even in the current situation, field observations are rarely undertaken since 445 they are difficult, time consuming and cannot be performed in a high number of fields. 446

Although the SIMPLE model does not consider the effect of high temperatures that could
inhibit germination, we exclude the impact of this stress, given that all sowing were
performed in spring and under North European conditions.

Seed germination and seedling emergence rates of sugar beet simulated by the SIMPLE 450 451 crop emergence model could be overestimated because this model does not take into account the effect of biotic stresses (Constantin et al. 2015). Nevertheless, the risk related 452 to biotic stress could be still limited under current cropping practices for two reasons. 453 First, pelleting of sugar beet seeds containing protectants (fungicides, insecticides, and 454 455 nematicides) and biostimulants -- is performed to date on 100% seeds (Agreste 2014) which may limit risks of the sugar beet crop establishment due to biotic stresses. Although 456 457 several diseases of sugar beet caused by soil-borne pathogens, including Rhizoctonia root rot and damping-off, have been reported in Northern France (Motisi et al. 2009), the 458 disease pressure is generally low when seeds are treated. Secondly, sugar beet crop is 459 often rotated with other crops including wheat, to reduce pest inocula sensu lato, although 460 some of the crops introduced into the rotation scheme may also be affected by the same 461 soil-borne pathogens affecting sugar beet (Motisi et al. 2009). This is due to a wide host 462 range of most soil-borne pathogens affecting the crop establishment phase (Lamichhane 463 et al. 2017). Therefore, risks related to biotic stresses may be a limiting factor to sugar 464 beet crop establishment under two conditions: i) when seeds are not treated with 465 conventional pesticides and when farmers plan to anticipate sowing, especially under 466 climate change. As shown in this study, an anticipation of sowing, compared to the 467 currently practiced sowing (i.e. mid-March) may be beneficial in terms of yield, but it has 468 469 to take into account potential risks due to biotic stresses. The latter is generally increased when crops are sown into cold and humid soil conditions and without chemical seed 470 471 treatment (Serrano and Robertson 2018). Therefore, future studies should integrate the

biotic determinants affecting crop establishment into the SIMPLE crop emergence model
since the sustainability of chemical pesticides in general and those used for seed
treatment in particular is increasingly questioned, especially in the European Union for
human health and environmental reasons (Lamichhane et al. 2016). This has led to the
recent ban of neonicotinoids in the EU which were widely used for seed treatment (Gross
2013).

478 **4.4. Technical feasibility of sowing**

The feasibility of technical field operations depends on water content of the soil top layers and thus also on climate change and sowing dates. We evaluated the possibility to enter into the field with agricultural equipments including a seeder for each simulated sowing date and year, using past historical data on earlier sowing dates. Our results suggest that, field access will represent the main limit for earlier sowings in the future as rainfall during early spring will not decrease, compared with the past.

485 **5. Conclusions**

Climate impact studies are dominated by those on crop yields (Wollenberg et al. 2016). 486 Little is known about the impact of changing climate on specific stages of the crop cycle. 487 especially the crop establishment phase. To achieve an acceptable level of yield it is 488 essential to optimize conditions that favor crop establishment. Despite several 489 490 limitations, simulation studies represent an important means when it comes to predict 491 food security of the 21st century under future climate change. The present study provides important information that was not possible without mobilizing simulation approach 492 493 using process-based models. Despite some possibilities of crop emergence failure, the quality of crop establishment will be acceptable under future scenarios, which was not 494 495 easy to predict without simulations. An anticipation of sowing, compared to the currently

- 496 practiced sowing (i.e. mid-March), will be viable under future climate change, with
- 497 possibility of compensating increasing drought risks during summer. However, the
- 498 possibility of filed access will remain a limiting factor due to extremely variable and high
- 499 cumulative rainfall values in late winter across our study sites.

500 Acknowledgements

- 501 This study was supported by a starter grant of the INRA's Environment and Agronomy
- 502 Division to the first author. The authors thank the colleagues from technical institute of
- sugar beet (ITB) for useful discussion on this topic.

504 **References**

- Agreste (2014) La protection des cultures. 21:49–64.
- Brisson N, Gary C, Justes E, et al (2003) An overview of the crop model STICS. Eur J Agron
 18:309–332. doi: 10.1016/S1161-0301(02)00110-7
- Brisson N, Mary B, Ripoche D, et al (1998) STICS: a generic model for the simulation of
 crops and their water and nitrogen balances. I. Theory and parameterization applied
 to wheat and corn. Agronomie. doi: 10.1051/agro:19980501
- Brunel-Muguet S, Aubertot J-N, Durr C (2011) Simulating the impact of genetic diversity
 of *Medicago truncatula* on germination and emergence using a crop emergence
 model for ideotype breeding. Ann Bot. doi: 10.1093/aob/mcr071
- Brunel S, Teulat-Merah B, Wagner M-H, et al (2009) Using a model-based framework for
 analysing genetic diversity during germination and heterotrophic growth of
 Medicago truncatula. Ann Bot 103:1103–1117. doi: 10.1093/aob/mcp040
- 517 Challinor AJ, Watson J, Lobell DB, et al (2014) A meta-analysis of crop yield under climate
 518 change and adaptation. Nat Clim Chang 4:287. doi: 10.1038/nclimate2153
- Constantin J, Dürr C, Tribouillois H, Justes E (2015) Catch crop emergence success
 depends on weather and soil seedbed conditions in interaction with sowing date: A
 simulation study using the SIMPLE emergence model. F Crop Res 176:22–33. doi:
 10.1016/j.fcr.2015.02.017
- Dorsainvil F, Durr C, Justes E, Carrera A (2005) Characterisation and modelling of white
 mustard (*Sinapis alba* L.) emergence under several sowing conditions. Eur J Agron
 23:146–158. doi: 10.1016/j.eja.2004.11.002
- Dürr C, Aubertot JN, Richard G, et al (2001) SIMPLE: a model for SIMulation of PLant
 Emergence predicting the effects of soil tillage and sowing operations. Soil Sci Soc Am
 J 65:414–442. doi: 10.2136/sssaj2001.652414x

- Dürr C, Boiffin J (1995) Sugarbeet seedling growth from germination to first leaf stage. J
 Agric Sci 124:427–435. doi: 10.1017/S002185960007338X
- Dürr C, Constantin J, Wagner M-H, et al (2016) Virtual modeling based on deep
 phenotyping provides complementary data to field experiments to predict plant
 emergence in oilseed rape genotypes. Eur J Agron 79:90–99. doi:
 10.1016/j.eja.2016.06.001
- Fauchère J, Richard-Molard M, Souverai, F, et al (2003). Cartographie des risques de montées en France en relation avec les températures de printemps et d'été – conséquences sur l'expérimentation et le conseil. In: Proceedings of the 1st Joint International Institut de Recherches sur la Betterave/American Society of Sugar Beet Technologists Conference, San Antonio, Texas, 2003, pp. 189–205. Brussels & Denver, CO: IIRB & ASSBT.
- Gallardo-Carrera A, Léonard J, Duval Y, Dürr C (2007) Effects of seedbed structure and
 water content at sowing on the development of soil surface crusting under rainfall.
 Soil Tillage Res 95:207–217. doi: 10.1016/j.still.2007.01.001
- Gardarin A, Coste F, Wagner M-H, Dürr C (2016) How do seed and seedling traits influence
 germination and emergence parameters in crop species? A comparative analysis.
 Seed Sci Res 26:317–331. doi: 10.1017/S0960258516000210
- Gross M (2013) EU ban puts spotlight on complex effects of neonicotinoids. Curr Biol. doi:
 10.1016/j.cub.2013.05.030
- Hothorn T, Everitt B (2009) A Handbook of Statistical Analyses Using R, Second Edition
- Kjellström E, Nikulin G, Strandberg G, et al (2018) European climate change at global
 mean temperature increases of 1.5 and 2}C above pre-industrial conditions as
 simulated by the EURO-CORDEX regional climate models. Earth Syst Dyn 9:459–478.
 doi: 10.5194/esd-9-459-2018
- Lamichhane JR, Dachbrodt-Saaydeh S, Kudsk P, Messéan A (2016) Toward a reduced
 reliance on conventional pesticides in European agriculture. Plant Dis 100:10-24.
 doi: 10.1094/PDIS-05-15-0574-FE
- Lamichhane JR, Debaeke P, Steinberg C, et al (2018) Abiotic and biotic factors affecting
 crop seed germination and seedling emergence: a conceptual framework. Plant Soil
 432:1–28. doi: 10.1007/s11104-018-3780-9
- Lamichhane JR, Dürr C, Schwanck AA, et al (2017) Integrated management of damping off diseases. A review. Agron Sustain Dev 37:10. doi: 10.1007/s13593-017-0417-y
- Lobell DB, Burke MB, Tebaldi C, et al (2008) Prioritizing Climate Change Adaptation Needs
 for Food Security in 2030. Science (80-) 319:607-610. doi:
 10.1126/science.1152339
- Longden P, Scott RK, Tyldesley JB (1975) Bolting of sugar beet grown in England. Outlook
 Agric 8:188–193. doi: 10.1177/003072707500800406
- Milford GFJ, Jarvis PJ, Walters C (2010) A vernalization-intensity model to predict bolting
 in sugar beet. J Agric Sci 148:127–137. doi: 10.1017/S0021859609990323
- 569 Moreau-Valancogne P, Coste F, Crozat Y, Dürr C (2008) Assessing emergence of bean

- 570 (*Phaseolus vulgaris* L.) seed lots in France: Field observations and simulations. Eur J
 571 Agron 28:309–320. doi: 10.1016/j.eja.2007.09.003
- Motisi N, Montfort F, Doré T, et al (2009) Duration of control of two soilborne pathogens
 following incorporation of above- and below-ground residues of *Brassica juncea* into
 soil. Plant Pathol. doi: 10.1111/j.1365-3059.2008.02017.x
- Pendergrass AG, Knutti R, Lehner F, et al (2017) Precipitation variability increases in a
 warmer climate. Sci Rep 7:17966. doi: 10.1038/s41598-017-17966-y
- Serrano M, Robertson AE (2018) The effect of cold stress on damping-off of soybean
 caused by *Pythium sylvaticum*. Plant Dis 102:2194–2200. doi: 10.1094/PDIS-12-171963-RE
- Sester M, Tricault Y, Darmency H, et al (2008) GeneSys-Beet: A model of the effects of
 cropping systems on gene flow between sugar beet and weed beet. F Crop Res.
 107:245-256. doi: 10.1016/j.fcr.2008.02.011
- Tribouillois H, Constantin J, Justes E (2018) Analysis and modeling of cover crop
 emergence: Accuracy of a static model and the dynamic STICS soil-crop model. Eur J
 Agron. 93:73-81. doi: 10.1016/j.eja.2017.12.004
- Van Ittersum MK, Rabbinge R (1997) Concepts in production ecology for analysis and
 quantification of agricultural input-output combinations. F Crop Res. doi:
 10.1016/S0378-4290(97)00037-3
- Villalobos FJ, Orgaz F, Fereres E (2016) Sowing and Planting. In: Villalobos FJ, Fereres E
 (eds) Principles of Agronomy for Sustainable Agriculture. Springer International
 Publishing, Cham, pp 217–227
- Wallach D, Makowski D, Jones J, Brun F (2018). Working with Dynamic Crop Models.
 Methods, Tools and Examples for Agriculture and Environment. 3rd Edition Academic
 Press, p. 613.
- White JW, Hoogenboom G, Kimball BA, Wall GW (2011) Methodologies for simulating
 impacts of climate change on crop production. F Crop Res. doi:
 10.1016/j.fcr.2011.07.001

598

Parameter	Value	Unit
Germination		
Base temperature, T _{b,germ}	3.5	°C
Germination percentages per thermal time class STT _g		°Cd (%)
20-25	3	
25-30	12	
30-35	12	
35-40	32	
40-45	15	
45-50	15	
50-55	6	
55-60	1	
Residual percentage of non-germinated seeds	4	
Base water potential $\Psi_{b,germ}$	1.94	МРа
Heterotrophic growth		
Base temperature for elongation T _{b,elon}	3.5	°C
Parameters of the Weibull elongation function		
(i) for hypocotyl		
a	59.06358	mm
b	0.01696	°C-1d-1
С	2.6095	
(ii) for radicle		
V	0.7	mm °C-1d-1
Mechanical obstacles - clods		
Parameters of the probability function of seedling death under clod (i) Buried clods		
α_{b}	0.031	mm ⁻¹

Table 1. Values of the input variables of SIMPLE for sugar beet used in this study

L_{0b}	10.37	mm
ii) Clods laid on the soil surface		
α_{ss}	0.021	mm ⁻¹
L_{0ss}	23.16	mm
Mechanical obstacles - soil surface crust		
Probability (p) for a seedling to emerge through a dry crust	60	%
Daily rain threshold causing the appearance of a crust	5	mm
Cumulative rain-threshold causing the appearance of a crust	12	mm
Daily rain threshold causing humidification of the crust during the last 3 days	3.5	mm
Parameters of the bolting function		
	1.407769	
C ₁	10-1	
	2.500000	
C_2	10-5	
C3	2.197334	
θ_b , threshold for the daily maximum air temperature at 2 m for bolting	12	°C

Table 2. Differences among weather data (means ± standard deviation) of the study site when analyzed by sowing date, 20-year period and their
interaction

Sowing date	ASTS (°C)	AST 30 dps (°C)	ATairmax 30 dps (°C)	TR 30 dps (mm)
Mid-February	5 ^a ± 3	6ª ± 2	9ª ± 2	$46^{b} \pm 30$
1 st March	$7^{b} \pm 3$	8 ^b ± 2	11 ^b ± 2	45 ^b ± 28
Mid-March	$7^{b} \pm 3$	9° ± 2	12° ± 2	$49^{\rm b} \pm 27$
1 st April	9 ^c ± 3	11 ^d ± 2	15 ^d ± 2	52 ^b ± 26
Mid-April	11 ^d ± 3	13 ^e ± 2	16 ^e ± 2	$28^{a} \pm 19$
Df	4	4	4	4
Significance level	***	***	***	***
Period				
2000-2018	7 ^a ± 3	9ª ± 3	$13^{b} \pm 4$	$40^{a} \pm 27$
2020-2040	$7^{a} \pm 4$	9ª ± 3	12ª ± 3	43 ^a ± 21
2041-2060	$7^{a} \pm 3$	9ª ±3	12ª ± 3	$46^{a} \pm 27$
2061-2080	$8^{b} \pm 3$	$10^{b} \pm 3$	13 ^b ± 3	$39^{a} \pm 27$
2081-2100	$9^{b} \pm 3$	11 ^b ± 3	14 ^b ± 3	$47^{a} \pm 33$
Df	4	4	4	4
Significance level	***	***	***	NS
Sowing date X Period				
Df	12	12	12	12
Significance level	NS	NS	NS	NS

Means followed by the same letter are not significantly different within the year or sowing date categories; ***P < 0.001; **P < 0.01; *P < 0.05 NS: not significant; dps: days post sowing; ASTS: average soil temperature at sowing; AST: average soil temperature; ATairmax: average daily maximum air temperature; TR: total cumulated rainfall

Sowing date	Period	Emergence (%)	Frequency (%) of emergence rate <50%	NEmax (days)	Frequency (%) of NEmax >28 days
Mid-February	2020-2040	$48^{a} \pm 32$	48	$45^{a} \pm 24$	95
	2041-2060	$62^{a} \pm 24$	25	$50^{a} \pm 12$	100
	2061-2080	$63^{a} \pm 20$	30	$40^{a} \pm 13$	80
	2081-2100	$68^{a} \pm 20$	25	$37^{a} \pm 10$	70
1 st March	2020-2040	66ª ± 20	24	43 ^b ± 13	90
	2041-2060	$59^{a} \pm 28$	30	$40^{ab} \pm 16$	85
	2061-2080	$60^{a} \pm 20$	30	$36^{ab} \pm 11$	65
	2081-2100	67 ^a ± 19	30	$32^{a} \pm 12$	60
Mid-March	2020-2040	73ª ± 16	24	$38^{a} \pm 11$	81
	2041-2060	$64^{a} \pm 21$	35	$35^{a} \pm 11$	75
	2061-2080	$62^{a} \pm 23$	30	29 ^a ± 11	70
	2081-2100	$68^{a} \pm 20$	35	$29^{a} \pm 10$	65
1 st April	2020-2040	69ª ± 15	14	$28^{a} \pm 7$	43
-	2041-2060	$70^{a} \pm 15$	25	$27^{a} \pm 7$	40
	2061-2080	$66^{a} \pm 21$	25	$26^{a} \pm 10$	50
	2081-2100	$74^{a} \pm 15$	25	$23^{a} \pm 8$	30
Mid-April	2020-2040	$74^{ab} \pm 14$	33	$23^{a} \pm 7$	33

Table 3. Emergence rate and duration (means ± standard deviation) and frequencies with <50% emergence rate and >28 days to reach the maximum emergence when analyzed by sowing date for each 20-year period and their interaction

	2041-2060	$74^{b} \pm 11$	20	$24^{a} \pm 7$	30
	2061-2080	$66^{a} \pm 16$	60	$22^{a} \pm 7$	20
	2081-2100	72 ^b ± 15	25	$20^{a} \pm 7$	15
Sowing date X	Df	12		12	
Period	Significance level	NS		NS	

Means followed by the same letter are not significantly different; number of days required to reach maximum emergence (NEmax); NS: not significant

Sowing date	Period	Non- Germination (%)	Clod (%)	Crust (%)	Drought (%)
Mid-February	2020-2040	$37^{b} \pm 39$	9ª ± 5	$7^{a} \pm 10$	1ª ± 3
	2041-2060	$17^{ab} \pm 27$	11ª ± 4	11ª ± 13	1ª ± 2
	2061-2080	$17^{ab} \pm 22$	11ª ± 3	9ª ± 13	1ª ± 1
	2081-2100	13ª ± 17	11 ^a ± 2	8ª ± 13	2ª ± 6
1 st March	2020-2040	$14^{a} \pm 18$	11 ^a ± 2	9ª ± 12	1ª ± 2
	2041-2060	21 ^a ± 32	$10^{a} \pm 4$	$10^{a} \pm 12$	1ª ± 1
	2061-2080	$16^{a} \pm 24$	11ª ± 3	$13^{a} \pm 14$	$2^{a} \pm 3$
	2081-2100	12 ^a ± 19	11 ^a ± 2	10 ^a ± 13	$4^{a} \pm 12$
Mid-March	2020-2040	9 ^a ± 16	12 ^a ± 2	6 ^a ± 10	1ª ± 4
	2041-2060	11 ^a ± 18	12 ^a ± 3	$13^{a} \pm 14$	1ª ± 2
	2061-2080	$17^{a} \pm 28$	11ª ± 4	$10^{a} \pm 12$	3ª ± 6
	2081-2100	9ª ± 14	12 ^a ± 2	$12^{a} \pm 14$	7ª ± 15
1 st April	2020-2040	5 ^a ± 7	12 ^a ± 1	13ª ± 12	2 ^a ± 5
	2041-2060	$7^{a} \pm 10$	12 ^a ± 2	11ª ± 13	$4^{a} \pm 10$
	2061-2080	$11^{a} \pm 22$	11 ^a ± 3	$11^{a} \pm 12$	$5^{a} \pm 12$
	2081-2100	$6^{a} \pm 8$	12 ^a ± 1	9ª ± 12	9ª ± 14
Mid-April	2020-2040	4 ^a ± 1	12ª ± 1	$10^{a} \pm 13$	7ª ± 11
	2041-2060	5 ^a ± 4	12ª ± 1	9ª ± 9	5ª ± 11

Table 4. Rates of non-emergence causes (means ± standard deviation) of seedlings as analyzed by sowing date for each 20-year period and their interaction

	2061-2080	8 ^a ± 11	$12^{a} \pm 2$	$15^{a} \pm 14$	$14^{a} \pm 19$
	2081-2100	$6^a \pm 8$	12ª ± 1	$10^{a} \pm 12$	$6^{a} \pm 14$
Sowing date	Df	12	12	12	12
X Period	Df Significance level	NS	NS	NS	NS

Means followed by the same letter are not significantly different within the sowing date categories; NS: not significant

Sowing date	Period	Germination (%)	Frequency (%) of germination rate <75%	NGmax (days)	Frequency (%) of NGmax >14days
Mid- February	2020-2040	63ª ± 39	48	$21^{a} \pm 10$	21
5	2041-2060	$83^{ab} \pm 27$	15	$22^{a} \pm 5$	20
	2061-2080	$83^{ab} \pm 22$	25	$20^{a} \pm 6$	15
	2081-2100	87 ^b ± 17	20	$18^{a} \pm 7$	13
1 st March	2020-2040	86ª ± 18	14	22ª ± 7	17
	2041-2060	$79^{a} \pm 32$	25	$20^{a} \pm 8$	16
	2061-2080	$84^{a} \pm 24$	25	$20^{a} \pm 8$	13
	2081-2100	88ª ± 19	15	18ª ± 8	14
Mid-March	2020-2040	91ª ± 16	10	22ª ± 7	18
	2041-2060	89 ^a ± 18	10	21ª ± 7	16
	2061-2080	$83^{a} \pm 28$	20	19 ^a ± 9	16
	2081-2100	91ª ± 14	10	19 ^a ± 8	13
1 st April	2020-2040	95ª ± 7	5	17ª ± 6	14
-	2041-2060	$93^{a} \pm 10$	5	$16^{a} \pm 5$	13
	2061-2080	$89^{a} \pm 22$	15	18 ^a ± 8	14
	2081-2100	94 ^a ± 8	5	16 ^a ± 7	11

Table 5. Germination rate and duration (means ± standard deviation) and frequencies with <75% germination rate and >14 days to reach the maximum germination when analyzed by sowing date for each 20-year period and their interaction

Mid-April	2020-2040	96ª ± 1	0	15 ^a ± 8	11
	2041-2060	$95^{a} \pm 4$	0	17 ^a ± 7	12
	2061-2080	$92^{a} \pm 11$	10	15 ^a ± 7	10
	2081-2100	$94^{a} \pm 8$	5	$14^{a} \pm 7$	8
Sowing	Df	12		12	
date X Period	Significance level	NS		NS	

Means followed by the same letter are not significantly different; number of days required to reach maximum germination (NGmax); NS: not significant

Table 6. Bolting rate (means ± standard deviation), without the devernalization effect, and frequency when analyzed by sowing date for each 20-year period and their interaction and potential devernalization due to high temperatures (7 days with Tmax > 25°C) 60 to 120 days after sowing.

Sowing date	Year categories	Potential bolting rate (%)	Frequency of potential bolting rates (%)			Number of days with Tmax > 25°C, 60-120 days after sowing
			<0.5%	0.5-1%	>1%	
Mid-February	2020-2040	1.65 ^b ± 0.59	0	3	18	3ª ± 3
	2041-2060	$1.60^{b} \pm 0.76$	2	2	16	4 ^{ab} ± 6
	2061-2080	$0.97^{a} \pm 0.41$	4	5	11	7 ^{ab} ± 4
	2081-2100	$0.79^{a} \pm 0.54$	7	8	5	8 ^b ± 7
1 st March	2020-2040	$0.89^{b} \pm 0.38$	3	9	9	4ª±4
	2041-2060	$0.88^{b} \pm 0.52$	5	7	8	7 ^{ab} ± 7
	2061-2080	$0.47^{a} \pm 0.26$	12	8	0	13 ^{bc} ± 7
	2081-2100	$0.40^{a} \pm 0.33$	13	6	1	15 ^c ± 9
Mid-March	2020-2040	$0.40^{b} \pm 0.21$	16	5	0	6ª ± 6
	2041-2060	$0.40^{b} \pm 0.28$	13	6	1	13 ^{ab} ± 8
	2061-2080	$0.17^{a} \pm 0.13$	20	0	0	20 ^{bc} ± 10
	2081-2100	$0.16^{a} \pm 0.17$	19	1	0	23 ^c ± 12
1 st April	2020-2040	$0.11^{bc} \pm 0.08$	21	0	0	8ª ± 8

	2041-2060	0.13 ^c ± 0.14	19	1	0	17 ^{ab} ± 10
	2061-2080	$0.04^{ab} \pm 0.05$	20	0	0	26 ^{bc} ± 12
	2081-2100	$0.02^{a} \pm 0.03$	20	0	0	32 ^c ± 12
Mid-April	2020-2040	$0.02^{ab} \pm 0.02$	21	0	0	13 ^a ± 11
	2041-2060	$0.03^{b} \pm 0.04$	20	0	0	26 ^b ± 12
	2061-2080	$0.01^{ab} \pm 0.01$	20	0	0	33 ^{bc} ± 12
	2081-2100	$0.00^{a} \pm 0.01$	20	0	0	42 ^c ± 11
Sowing dates X	Df	12				12
Periods	Significance level	***				***

Means followed by the same letter are not significantly different within the sowing dates or periods; ***P < 0.001; **P < 0.01; *P < 0.05; NS: not significant

Period of time	Period	Average cumulated rainfall 30 days before sowing (mm)	Number of days with >1mm	
1st February – end of February	2000-2018	$38^{a} \pm 3$	$8^{a} \pm 0.45$	
	2020-2040	$47^{a} \pm 3$	$11^{a} \pm 0.47$	
	2041-2060	51ª ± 3	11 ^a ± 0.48	
	2061-2080	51 ^a ± 4	$10^{a} \pm 0.47$	
	2081-2100	52ª ± 3	11 ^a ± 0.47	
1 st March –end of March	2000-2018	45ª ± 3	$8^{a} \pm 0.43$	
	2020-2040	$48^{a} \pm 3$	$10^{a} \pm 0.45$	
	2041-2060	$50^{a} \pm 3$	$9^{a} \pm 0.44$	
	2061-2080	$37^{a} \pm 3$	7 = 0.42	
	2081-2100	$50^{a} \pm 4$	$9^{a} \pm 0.45$	

Table 7. Indicators for field accessibility for farmers to perform sowing for early sowing dates and periods

Means followed by the same letter are not significantly different within the sowing dates or periods

Supplementary Table 1. Germination and emergence rates and duration of sugar beet (means ± standard deviation) when analyzed by sowing date
and 20-year period

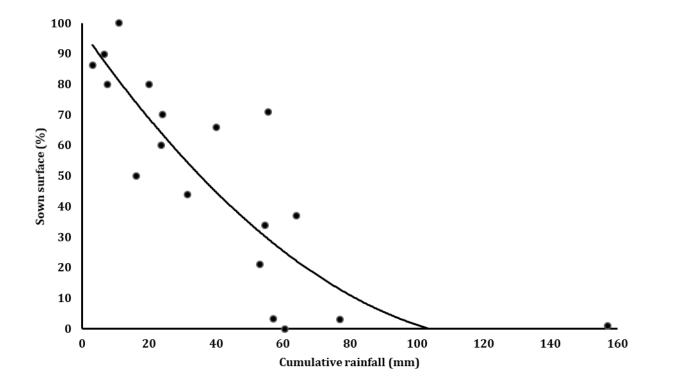
Sowing date	Germination (%)	Emergence (%)	NGmax (days)	NEmax (days)
Mid-February	$79^{a} \pm 29$	59ª ± 25	17ª±7	26 ^b ±8
1 st March	$84^{ab} \pm 23$	$61^{a} \pm 22$	20 ^b ±7	38 ^d ±14
Mid-March	$89^{bc} \pm 19$	$64^{a} \pm 21$	15ª±7	22ª±7
1 st April	93 ^c ± 13	$64^{a} \pm 20$	20 ^b ±7	43º±16
Mid-April	94 ^c ± 7	$63^{a} \pm 20$	20 ^b ±8	33°±11
Df	4	4	4	4
Significance level	***	NS	***	***
Period				
2020-2040	$86^{a} \pm 23$	$63^{ab} \pm 23$	19 ^b ±8	35 ^b ±16
2041-2060	$88^{a} \pm 21$	$63^{ab} \pm 21$	19 ^b ±7	$35^{b} \pm 14$
2061-2080	$86^{a} \pm 22$	$58^{a} \pm 22$	$18^{ab}\pm8$	31ª±12
2081-2100	$91^{a} \pm 14$	64 ^b ± 21	17ª±7	29ª±11
Df	3	3	3	3
Significance level	NS	*	**	***
Sowing date X Period				
Df	12	12	12	12
Significance level	***	***	NS	NS

Means followed by the same letter are not significantly different within the year or sowing date categories; ***P < 0.001; **P < 0.01; *P < 0.05; NS: not significant; NGmax and NEmax: number of days required to reach the maximum germination and emergence respectively **Supplementary Table 2.** Causes of non-emergence rates of sugar beet (means ± standard deviation) when analyzed by sowing date and 20-year period

Sowing date	Non-Germination (%)	Clod (%)	Crust (%)	Drought (%)
Mid-February	7ª ± 13	$10^{a} \pm 4$	9ª ± 12	$2^{a} \pm 4$
1 st March	$16^{bc} \pm 23$	$11^{ab} \pm 3$	$10^{a} \pm 12$	3ª ± 6
Mid-March	6 ^a ± 7	$11^{bc} \pm 3$	$10^{a} \pm 12$	$4^{ab} \pm 8$
1 st April	21°±29	12 ^c ± 2	$11^{a} \pm 12$	$6^{bc} \pm 11$
Mid-April	$11^{ab} \pm 19$	12 ^c ± 1	$11^{a} \pm 12$	9 ^c ± 14
Df	4	4	4	4
Significance level	***	***	NS	***
Period				
2020-2040	$14^{a} \pm 23$	11ª ± 3	9 ^a ± 12	$3^{a} \pm 7$
2041-2060	12 ^a ± 21	11ª ± 3	$10^{a} \pm 12$	3ª ± 7
2061-2080	$14^{a} \pm 22$	11ª ± 3	$11^{a} \pm 13$	$6^{b} \pm 12$
2081-2100	$9^{a} \pm 14$	11ª ± 2	$10^{a} \pm 12$	$6^{b} \pm 12$
Df	3	3	3	3
Significance level	**	NS	NS	***
Sowing date X Period				
Df	12	12	12	12
Significance level	***	***	NS	*

Means followed by the same letter are not significantly different within the year or sowing date categories; ***P < 0.001; **P < 0.01; *P < 0.05; NS: not significant

Figure 1. Relationship between cumulative rainfall (measured at Estrées-Mons ; 49°52′44″N 3°00′27″E) and percentage of sown surface recorded at the end of March across the sugar beet growing area in France (1987-2005).



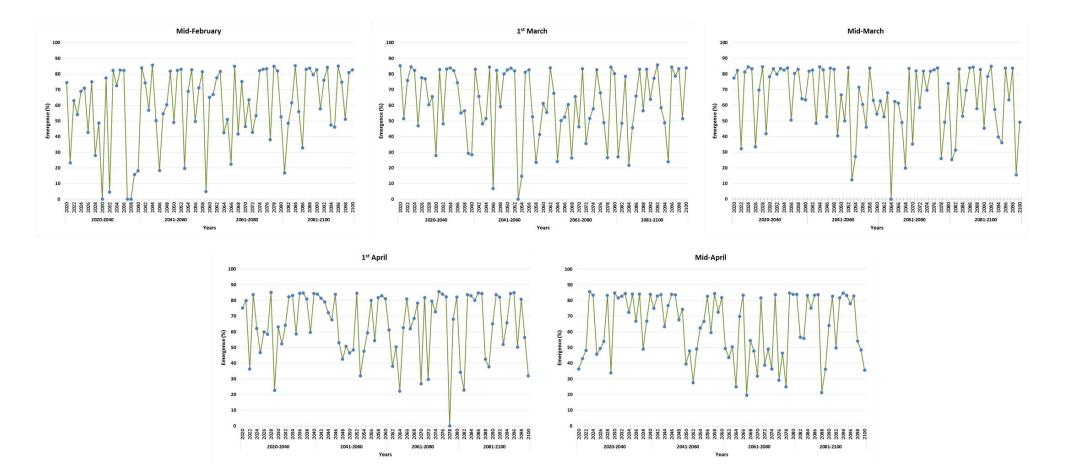
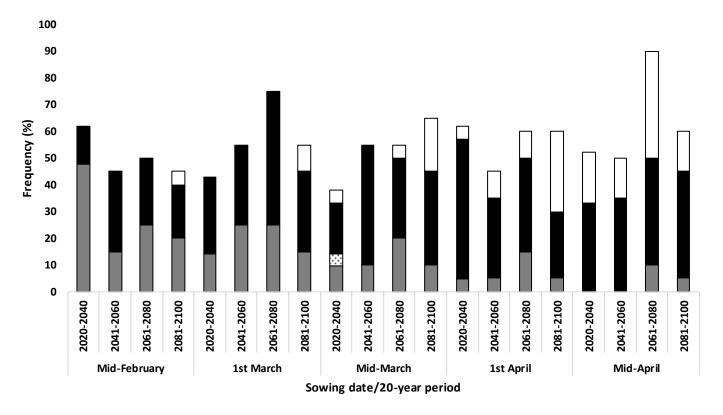


Figure. 2. Year-to-year emergence rate variability of sugar beet by sowing date under future climate scenario

Figure 3. Frequencies (%) of non-emergence causes when analyzed by sowing date for each 20-year period. Only causes with a high frequency that could pose risks of crop emergence failure were considered which included frequency of non-germination >25% and frequency of seedling mortality due to clod, crust and drought, each >15%



■ Non-Germination>25% □ Clod>15% ■ Crust>15% □ Drought>15%